POLITECNICO DI MILANO
DEPARTMENT OF ENERGY

DOCTORAL PROGRAMME IN
ENERGY AND NUCLEAR SCIENCE AND TECHNOLOGY

A MULTI-DIMENSIONAL APPROACH TO THE MODELLING OF POWER PLANT FLEXIBILITY

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Year 2015 - XXVIII Cycle

“Here some one thrust these cards into these old hands of mine, swears that I must play them, and no others.
[…] Ahab, but thou actest right, live in the game, and die in it.”

Herman Melville

Moby Dick, 1851

Alla mia famiglia

Acknowledgements

In the first place, I express my gratitude to prof. Emanuela Colombo and prof. Fabio Inzoli for supporting this research from the very beginning. From our discussions the idea came to look at the issues in the Italian energy market from a wider perspective, diving into the principles of Game Theory and energy systems analysis. Thanks to their advice, my experiences with a number of research groups at Politecnico and abroad became possible.

I thank prof. Roberto Lucchetti and prof. Nicola Gatti for orienting my first steps in the field of Game Theory and starting with our group the search for new mathematical tools in energy modelling. The numerous chats with Nicola opened my mind to this fascinating world, and the discussions we had, armed with pen and paper, were some of the most genuine experiences of this research.

I express very special thanks to Eleonora Della Bartolomea, Mauro Fiale, all the staff and the Direction of Enel La Casella power plant, for constantly providing me with their support and expertise and working side by side during two years.

I thank prof. Mohammad Hesamzadeh, for leading me in the study of electricity markets and working at my side in developing the Game Theory model. I owe him my satisfaction for seeing the core of this work realised on this paper.

Finally, I thank prof. Mark Howells, Abhishek Shivakumar, Constantinos Taliotis and all the staff at KTH division of Energy System Analysis. Their supervision on my work during the period I spent in Stockholm allowed this thesis to bring a value added in the field of energy system analysis. However, not only was my period there a highly valuable professional experience, but also a wonderful and funny human experience among friends.

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General nomenclature

In this section, only the acronyms and abbreviations employed in the whole dissertation are illustrated. The nomenclature specific to the models is listed at the beginning of Chapters 3, 4, 5 and 6.

Acronyms, abbreviations

CAES	Compressed Air Energy Storage
CCGT	Combined Cycle Gas Turbine
CCS	Carbon Capture and Sequestration
CSP	Concentrated Solar Power
DSC	Direct Specific Consumption
EOH	Equivalent Operating Hours
GenCO	Generation Company
GHG	Greenhouse Gas
HRSG	Heat Recovery Steam Generator
ICE	Internal Combustion Engine
IGVs	Inlet Guide Vanes
ISC	Indirect Specific Consumption
KKT	Karush-Kuhn-Tucker
MCP	Market Clearing Price
MGP	Mercato del Giorno Prima
MI	Mercato Infragiornaliero
MILP	Mixed-Integer Linear Program
MINLP	Mixed-Integer Non Linear Program
MSD	Mercato dei Servizi di Dispacciamento
OCGT	Open Cycle Gas Turbine
PHS	Pumped-Hydro Storage
PUN	Prezzo Unico Nazionale
PV	Solar Photovoltaic
TCL	Technical Control Load
TIT	Turbine Inlet Temperature
TOT	Turbine Outlet Temperature
TSO	Transmission System Operator
VoLL	Value of Lost Load

Summary

In light of the challenges of a fast developing world and an increasing need for energy, the energy supply system of the European Union suffers from structural weaknesses. To address them, the European Commission issued long-term strategies for the development of the energy system: the Climate and Energy Package and the Energy Roadmap identify the pathways to 2020 and 2050, respectively. According to these strategies, one of the keys to achieve higher levels of sustainability, security and competitiveness is to decarbonise the energy system, i.e. to reduce the reliance on fossil fuels and increase the penetration of renewable sources.

A number of mathematical models have been designed, to turn these generic indications into a more concrete energy technology and generation mix. These models seek for the mix which complies with the decarbonisation objectives set by the European Commission and guarantees the system's adequacy at the minimum global cost. The European Union, in response, issues policies and directives for this mix to be pursued. All of the models tend to agree over one point: the future energy system, and particularly the electricity grid, will have to become more flexible.

A flexible electricity system must integrate storage technologies, demand response technologies and fast ramping fossil-fuel fired units. A relevant amount of research work is produced about the integration of storage and demand-side technologies in the future electricity system. However, these are still at a development stage, while flexible fossil-fuel fired units are already commercially widespread. Therefore, at present, the flexibility of the energy system relies almost only on such power plants. In order to balance the fluctuations of renewables, these power plants are gradually shifting their operation profiles from base- to peak-load, reducing the average load factor and increasing the number and slope of deep ramps and starts. This change is deepened by the interaction of two more factors: the decrease of the final electricity consumptions due to the financial crisis and the fluctuation of the gas prices.

The shift towards peak-load operation brings about a set of new problems and a chain reaction in the whole electricity supply system: power plant cycling has a cost; this causes the price bids of the companies on the market to increase and their share and revenues to decrease; this, in turn, may cause a number of companies to decommission or relocate several power plants at the same time, thus undermining the adequacy of the system. The models employed to predict the optimal long-term energy technology and generation mix do not take into account these dynamics of flexibility. Consequently, there is a risk the policies of the European Union aimed at pursuing this mix will be ineffective: the actual mix may happen to be different, the costs of the system higher, the adequacy undermined. The research of the author had an overall objective to address this risk and this doctoral dissertation describes how such objective was pursued.

The first part of the dissertation provides an introduction to the whole work. In the first place, it briefly discusses how the need for flexible energy and electricity systems arose from the new paradigm of sustainable energy supply. Subsequently, it states the overall objectives of this PhD research and how they are intended to contribute to the scientific literature.

The second part looks into the issue of power plant flexibility and synthesizes its main features. The author analyses how the need for flexible operation of fossil-fuel fired power plants arises, stemming from the European and national long-term strategies. Thereafter, the implications of power plant flexibility on the energy supply are described. It emerges there are implications on three scales: the power plant, the electricity market and the whole energy system. At each one of these scales the requirement for flexible electricity supply causes costs and reactions of the actors to reduce these costs.

At the power plant scale, the operators experience higher costs for components wear and decreased efficiency. Their decisions to lower these costs involve power plant modifications, actions on the control systems and new O&M practices.
At the electricity market scale, the companies see the costs of the power plants increase, and they are forced into making higher bids. This reduces their market share and, therefore, their revenues. The decisions to regain competitiveness range from decommissioning or relocating capacity to trying new opportunities for revenues, such as the reserve capacity markets.
At the energy system scale, the costs arise when the dynamics related to flexibility are not taken into account and the energy mix ends up different from what envisaged by the planners. The decisions at this scale consist in anticipating the costs and reactions to flexibility at a power plant and electricity market scale, and update the forecasts and pathways to decarbonisation.
As can be seen, these three scales are related to one another and they involve dynamic interactions between power plant operators, companies and energy system planners. In order for these dynamics to be fully captured, an interdisciplinary research had to be carried out. It ranged from Thermodynamics and power plant Engineering, to Decision Support and Macroeconomics. The author considers the elaboration of a multi-dimensional picture of the impact of flexibility on the energy system as the very innovative core of this PhD research.
In the third part of the dissertation, the weaknesses of the models for long-term energy system planning are discussed and addressed. If the flexibility of the electricity supply impacts the system on three scales, mathematical models to represent this impact at the three scales are needed. The author designed models to meet these needs.
The costs of flexibility and the reactions of the operators at a power plant scale are represented through two kinds of models: a thermodynamic model of a fossil-fuel fired power plant, set up with the help of Thermoflex simulation environment, and an analytical formulation of global performance indices, embeddable in electricity market and energy system models.
The thermodynamic model consists in a quasi-stationary off-design model, featuring all the relevant control logics employed in real operation. It was set up in collaboration with the operators of a power plant in the North of Italy. Its purpose is to provide the operators with an interface for predicting the thermodynamic costs of flexibility and evaluating feasible solutions for increasing the ramping capability. In line with such objective, the output of the model is indices about the off-design performance of the power plant and of the individual components, through First and Second Law of Thermodynamics quantities, respectively. The power plant model is applied to an industrially relevant case study, which is the detailed off-design performance prediction of the whole cycle and the individual components of a CCGT operating in the North of Italy, as a function of different control logics. This allowed the operators to evaluate new strategies for enhancing the cycling capability of the power plant, such as the decrease of the minimum load of the power plant.
The analytical formulation consists in equations for computing aggregate performance indices of the power plant in flexible operation. Specifically, the cost of the starts, the fuel cost for decreased efficiency at partial load and the cycling capability as a function of the power plant configuration are modelled. These equations provide the link between the power plant scale and the electricity market or energy system scales: when embedded into electricity market or energy system planning models, they allow the global thermodynamic costs computed with power plant models to be fed into the electricity market or energy system models.
The costs of flexibility and the reactions of the companies at the electricity market scale are represented through a model based on Game Theory. Among the decision making methodologies, Game Theory is the most suitable in all problems where several objectives and several decision makers are involved. The proposed electricity market model is, in Game Theory terms, a

Stackelberg stochastic game. It is a nonlinear two-level optimisation program, which is reduced, thanks to the duality theory, to a one-level mixed-integer linear program. In addition to traditional generation dispatch models, it endogenously computes the quantity and price bids and the generation expansion strategies which guarantee each company the maximum profit, given the decisions of the other companies. The novelty of the model developed by the author with respect to others in literature lies in three major characteristics:

- A number of features of flexible electricity markets are gathered and represented together in the model, while in literature they are represented separately, by different models.
- The costs of flexibility are accounted, through the equations formulated at the power plant scale.
- The demand for electricity, the demand for capacity reserve and the cycling costs are considered stochastic and not deterministic quantities.

Only the theoretical formulation of the model is presented. Its application to a country-wide electricity system and its translation into a formulation to be embedded in energy system planning models turned out to be long-term research activities. They were not finalised during the PhD research.

Finally, the cost of flexibility at an energy system scale is computed by modifying an existing open source energy system planning model, OSeMOSYS. This is a partial equilibrium model, consisting in a multi-period, multi-regional linear program. The mathematical formulation derived for the cost of the starts, the costs for decreased efficiency and the cycling capability at a power plant scale is introduced into the model with proper adaptations. As other energy system models, OSeMOSYS computes the least cost long-term energy technology and generation mix, subject to constraints dictated by the European decarbonisation objectives. In addition, the introduced modifications allow the costs and dynamics of flexibility to be accounted. The risk for European energy planners to face unforeseen shifts and costs of the energy mix due to flexibility is thus reduced when employing this model.

The modified energy system model is applied to a test case study and to a real case study. The test case study proves that the impact of power plant flexibility on the energy system planning can be relevant; the real case study, the long-term energy planning of Cyprus, provides a small scale example of how flexibility may impact a larger system like Europe. The costs of flexibility computed through the power plant model are given as inputs to the energy system case studies. When taken into account, they cause the optimal long-term energy mix to be sensibly different from the reference case where they are not taken into account. This proves the power plant and the energy system scales are dynamically related and the energy policies must be informed with the impact of flexibility.

PART I - Introduction

For centuries, primary energy resources were extensively deployed to foster the industrial development of a limited number of countries. Recently, with the steeper growth of the global population, the demand for energy has begun to increase faster than ever experienced. The Governments are faced with problems related to the energy supply, for in many regions and countries it seems to lack the fundamental requirements of sustainability, secureness and competitiveness.

Energy systems must be sustainable on three dimensions: social, economic, environmental. The social sustainability of an energy system may be identified with its capability to contribute to the development of a society; the economic sustainability looks at the cost of the energy system, including the investment and operation costs as well as the cost of the externalities; the environmental sustainability requires that the availability of primary resources, the availability of renewable resources and the environmental impact of energy conversion systems be cared about. Currently, some of the widest energy systems, like those of the European Union, the United States or the BRIC countries (Brazil, Russia, India, China), particularly lack environmental sustainability: the deployment of non-renewable primary resources for their industrial development implied huge amounts of environmentally harming emissions on one side, and the gradual depletion of the primary resources on the other side.

As far as the secureness of the energy systems is concerned, it is related in large part to the energy independence of the countries. Many economies rely much on the import of primary resources like gas and oil, and this exposes them to the political instability of the regions from where the resources are supplied.

Finally, the competitiveness of the energy systems lies in their capability of meeting the demand at affordable global costs and with least exposure to price fluctuations. The energy supply mix of a country should be diversified enough for its global costs not to depend too much on the affordability of one of the sources. Currently, most energy systems rely heavily on non-renewable primary resources, which are being depleted and are sold at highly fluctuating prices.

If the weaknesses of the energy systems with respect to these three dimensions are not addressed, the development of the remaining part of the world economies may be prevented and the global society may be exposed to severe consequences. Such issue has been brought to the general attention by the political debate in the last decades, starting from COP3 in 1997, when the Kyoto Protocol was signed, down to COP15 and the Copenhagen Agreement, and to the recent COP21. In the frame of these Conferences of Parties, the Governmental Organisations and the individual states started to review the traditional paradigm of energy supply, and to identify long-term pathways for restructuring the energy systems. Most of these pathways envisage a deep twist from a fossil-fuel fired to a renewable-based energy supply mix, in order to increase the environmental sustainability, the energy independence and the competitiveness of the energy systems.

The high penetration of renewable energy sources in the energy supply mix represents a radical change for traditional systems, and it calls for an equally radical mutation of the attitudes of the energy suppliers: it requires that the operators of the energy conversion plants upgrade the operation strategies; it forces the generation companies to reconsider their portfolio investments and decisions; it implies that Transmission System Operators (TSOs), Authorities and Governments, in charge of guaranteeing the security and the adequacy of the energy supply, upgrade the technological level of the supply chains, the rules of the energy markets and the long-term policies.

These dynamics are particularly relevant in the electricity supply sector, where the demand for electricity must be met instantaneously by the supply, but energy can be stored only to a limited amount. Under these conditions, the high penetration of intermittent and non-controllable renewable energy sources in the electricity generation mix forces the planners to consider investments and new technological options for guaranteeing a flexible matching between demand and supply. A need for flexibility of the electricity supply system arises.

Different definitions of flexibility exist. According to planners it describes the extent to which an electricity system can adapt the pattern of electricity generation and consumption in order to balance supply and demand; according to generation companies and power plant operators, it defines the ability of a power plant to vary its generation output as fast as possible, without harming the components. From these definitions, it can be imagined that when the need for flexible electricity supply arises, it carries impacts at different scales, from the individual power plant to the electricity market and the whole system.

In order for the energy system planners to best address the weaknesses of the energy system and draw effective pathways for restructuring it, they need to understand how the need for flexibility at each scale can be met, at what cost and at what consequences. They must consider the demand and supply of flexibility as a multi-dimensional problem, because the impact of flexibility at one scale is likely to be related to the impact at another scale. If they do not develop such perspective, their long-term pathways for restructuring the national or regional energy systems may turn more expensive than they predict, or ineffective.

This research moves one step into the elaboration of a comprehensive, multi-dimensional picture of the flexibility of electricity systems. It specifically aims at identifying and mathematically formulating the impact of the flexible operation of fossil-fuel fired power plants on the energy system at different scales. The core of the research is divided in two parts. In PART II the need for flexible operation of fossil-fuel fired power plants, its causes and its consequences are investigated. A multi-dimensional picture of the impact of flexibility on the energy system is elaborated, starting from information scattered in the scientific literature and industrial datasets. In PART III, models and mathematical formulations of the impact of flexibility are developed, able to capture its multi-dimensional nature. These models are then applied to numerical examples and real case studies, to predict how the decision makers at different scales will change their strategies when updated with the costs and benefits of flexibility.

PART II - Understanding the multi-dimensional nature of power plant flexibility

In this part of the PhD dissertation, the author presents an in-depth analysis of the issue of power plant flexibility. The analysis aims at gradually bringing to surface that the flexibility of the electricity systems envisaged by the European decarbonisation scenarios has impacts on different temporal and spatial scales. Though not yet entering the modelling details, which are discussed in PART III, this section represents the actual innovative core of the research: in literature, the issue of flexibility has not been looked at from a global perspective, due to its multi-dimensional nature. Mono-thematic researches about issues related either with power plant or market operation are scattered around and the results of studies at a power plant scale do not feed the studies at the electricity market scale. Building all the information together and proposing a 3D view of power plant flexibility and its multi-dimensional impact on the energy system required a wide-spectrum research, diving into diverse scientific disciplines.

In Chapter 1, a context analysis is carried out. The author first explains where the issue of power plant flexibility originates from and what its general features are at a European and national scale. In Chapter 2, the author gathers data existing in literature and details the present impact of flexibility at three scales: the power plant, the electricity market and the energy system. Eventually, in Chapter 3, the models for predicting the future impact of flexibility at the three scales are reviewed, and their weaknesses highlighted. PART II ends with the statement of the needs and objectives which drive the following modelling part of the dissertation.

1.
Context

1.1. The energy policy in Europe

In the introduction to this thesis, it was highlighted that the fast development of the economies worldwide is exposing several energy systems to structural weaknesses in three dimensions: sustainability, secureness and competitiveness. The European Commission has recently discussed why the European energy sector suffers from these weaknesses, separating the causes into the three dimensions [1]:

- *Sustainability*. In the last decades, increasing concerns have been arisen about the depletion of primary resources and the potentially harmful effect of greenhouse gases (GHGs) and polluting emissions. The Intergovernmental Panel On Climate Change (IPCC), established by the United Nations in 1988, also argue that greenhouse gases emissions may contribute to the global warming [2]. In Europe, 80% of all GHGs emissions are ascribable to energy uses.
- *Secureness*. With business as usual, the energy dependence of Europe from imports is expected to grow: by 2030, the reliance on imports is projected to grow from 57% to 84% for natural gas, from 82% to 93% for oil. This carries economic and political instability.
- *Competitiveness*. The reliance of the European Union on fossil fuel reserves owned by few suppliers exposes the countries to the exercise of market power and prevents them from fully benefitting from the liberalisation of the energy markets.

The European Commission argues that failing to address these weaknesses or delaying the action would put unbearable costs on the whole European Union. The first step in creating a competitive environment in the energy sector across Europe was the creation of energy markets by individual Member States since the mid ‘90s. However, the liberalisation process was not enough for the necessary levels of sustainability, secureness and competitiveness to be reached, for two main reasons: in the first place the national markets of some countries never became fully competitive; in the second place, the decentralisation of the energy planning fragmented the European energy system even more, with the risk of undermining the security of supply in the continent. Based on these considerations, the European Council stated that the energy policy of the Member States had to be given common guidelines and objectives. The Strategic Energy Technology Plan (SET-Plan) [3] served this purpose and set for the first time objectives and guidelines for a long-term European energy strategy. The first operative entailment of the SET-Plan was the Climate and Energy Package [4], which gave birth to the Europe 2020 Strategy [5]. Its well-known targets are:

- 20% reduction of greenhouse gases emissions by 2020, compared to 1990 levels. This addresses the scarce environmental sustainability of the energy system, on both the demand and supply sides.
- Increase of the production from renewable energy sources, in order for renewable energy to achieve 20% share in the overall EU energy consumption. This mostly promotes the security of supply, and consequently the political and economic stability of the region.
- 20% reduction in the primary energy consumption, compared to 2020 projections, through energy efficiency measures. This helps reaching higher competitiveness, by

making the consumers less energy-dependent. It also contributes to reducing the environmental harm due to local emissions.

The SET-Plan also introduced a longer-term vision to 2050, with the aim of nearly decarbonising the energy sector. This vision was embodied into the Energy Roadmap 2050 [6], which set an objective of abating the energy-related GHGs emissions by 80 to 95% by 2050.

Introducing such long-term time horizon brought a totally new perspective in energy system planning and raised the question of how to meet the 2050 goals. The decarbonisation envisaged by the Energy Roadmap 2050 is much more ambitious than the objectives set by Europe 2020. These last can be reached through many pathways and every Member State has many degrees of freedom in their choice. On the contrary, the possible pathways to reach full decarbonisation by 2050 are much less than those to reach the 2020 targets, so they must be firmly negotiated among the States far in advance. Apart from huge diplomacy efforts, this also calls for high resolution energy system forecasting and planning models, and for the elaboration of a number of energy scenarios at the European scale. These scenarios must give insights about the possible energy technology and energy production mix until 2050. In [6], the European Commission identifies a number of scenarios, based on different assumptions about the commitment of the Member States in the future:

- *High Energy Efficiency*: it reflects a political commitment on reducing final consumptions through energy efficiency measures and establishment of saving obligations.
- *Diversified Supply Technologies*: all the energy technologies compete in markets with no specific support measures. Carbon pricing is applied and Carbon Capture and Sequestration (CCS) is considered.
- *High Renewable Energy Sources*: it accounts for strong incentives to renewable energy technologies, which would lead them to reach 97% share in electricity consumption.
- *Delayed CCS*: similar to the Diversified Supply Technologies scenario, but with delay in the employment of CCS, assuming its learning curve is longer.
- *Low Nuclear*: again similar to Diversified Supply Technologies scenario, but assuming no new nuclear is built, due to the concerns about nuclear security after Fukushima incident.

The preliminary predictions for these scenarios agree on some qualitative conclusions. The first and most relevant change envisaged to reach decarbonisation is the highly increasing role of electricity in the energy mix. This implies that particular care will have to be taken for low carbon electricity generation technologies. Linked to this, the penetration of renewable sources in the energy and, particularly, electricity supply must increase by great amount. Since most of the renewable energy technologies have not reached grid parity, yet, they shall be still financially supported for a number of years. With time, however, the investments should shift towards the integration of new markets, development of the grid and development of storage technologies. Gas-fired electricity generation will play an increasing role in all scenarios and it will be critical for the transformation of the electricity sector at least until 2030. Gas-fired power plants will have a chance to become low-carbon technologies if equipped with CCS, provided it turns competitive. Also nuclear-fired generation will play a fundamental role in driving towards a low-carbon energy system, unless the safety concerns lead most countries to ban this technology. The role of nuclear will be more significant, the more the transport sector is electrified. Eventually, and linked to this all, the energy system will have to become smarter, more decentralised and more interconnected.

Though the European Commission is clear about the possible pathways to the decarbonisation of the energy sector, their preliminary predictions do not identify the possible configurations of the energy technology and production mix, needed to meet the decarbonisation objectives.

1.1.1. Pathways for the decarbonisation of the electricity sector

In view of the energy policy set by the Energy Roadmap 2050, the analysts started studying which pathways would allow the European Union to meet the decarbonisation objectives. Such pathways are typically based on an economic cost minimisation criterion: they aim at finding the energy technology and production mix which minimises the discounted global cost of the energy system in the timeframe considered, given the constraints on emissions and the predicted costs of the technologies.

The pathways identified upon the objectives of the Energy Roadmap 2050 describe the technological implications of the policy framework designed by the European Commission. In the following, a focus is made on the electricity sector, which is the object of this thesis. In [7] the feasibility and the challenges of realising 80% GHG emissions abatement in Europe by 2050, as envisaged in the Energy Roadmap, are discussed. Three pathways are investigated, with 40, 60, 80% share of renewable energy sources in the electricity generation, respectively. In Figure 1 the share of different technologies in the electricity generation [TWh] from 2010 to 2050 according to the three pathways is shown. In all cases, meeting an 80% decarbonisation objective means 95% GHG abatement in the power sector. Nonetheless, fossil-fuel fired generation, in particular gas-fired generation, maintains a key role in the transition in all the scenarios. Even in the 80% renewables scenario, it is forecasted that in 2050 part of the generation will still be in charge to gas-fired power plants, equipped with CCS. Most of this generation, in such high renewables scenario, will be supplied by backup power plants, which are expected to share around 14% of the installed capacity and 5 to 8% of the total generation. According to the authors, the backup power plants should be mostly highly flexible power plants like Open Cycle Gas Turbines (OCGTs), because Combined Cycle Gas Turbines (CCGTs) equipped with CCS are expected to require too long warm start-up times. Similar conclusions are drawn in other studies focussing on the infrastructure needed to support the high renewables scenarios [8–10].

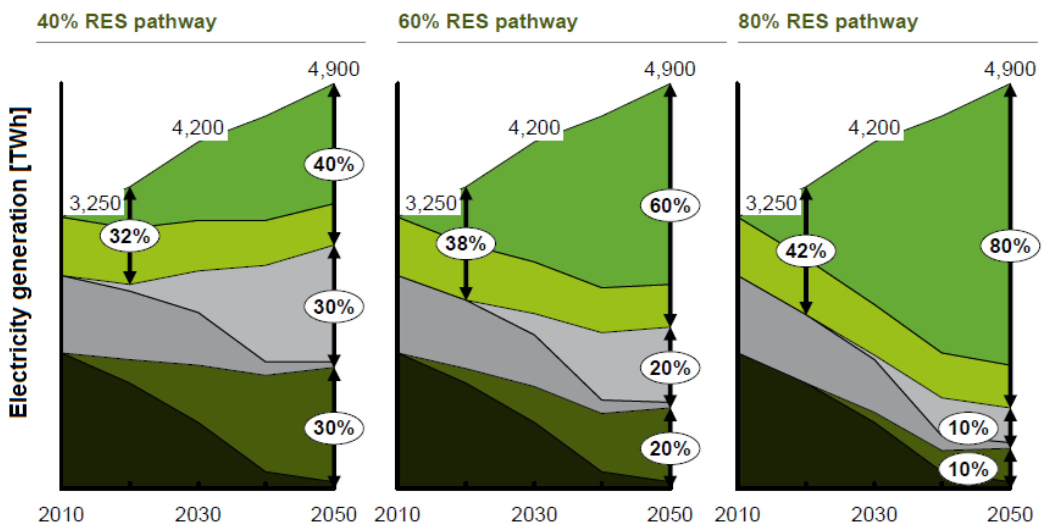

Figure 1. *Shares of electricity generation [TWh] in three decarbonisation pathways. Source:* [7].

Another authoritative insight about the possible long-term energy technology and generation mix is provided by the IEA World Energy Outlook [11]. The study makes projections to 2040, according to three scenarios: the Current Policies, the New Policies and the 450. The features of the scenarios are listed in Table 1. Scenario 450 mirrors the 80% GHG abatement scenario by the European Commission.

	Current Policies	New Policies	450
Rationale	Comply with Europe 2020 strategy; included policies formally adopted until mid-2014	Partial implementation of Europe 2020 strategy; policies formally adopted until mid-2014 and relevant new proposals	Keep the increase in global average temperature within 2 °C, with 50% probability
Key measures	20% reduction of GHGs by 2020; 20% increase of RES in final energy consumption by 2020; 20% reduction of final energy consumption by 2020; Current ETS scheme;	partial implementation of 20% reduction of consumption target; partial implementation of EU Energy Efficiency Directive; National Energy Efficiency Action Plans;	30% reduction of GHGs by 2030; reinforcement of ETS scheme; full implementation of EU Energy Efficiency Directive;
Common Measures	financial support to RES; financial support to CCS; Industrial Emissions Directive; removal of barriers to CHP; retirement of all nuclear in Germany by 2022.		

Table 1. *Features of the World Energy Outlook scenarios.*

In Figure 2 through Figure 4, the results of the forecasting models, in terms of installed capacity and electricity generation, are presented for each of the three scenarios.

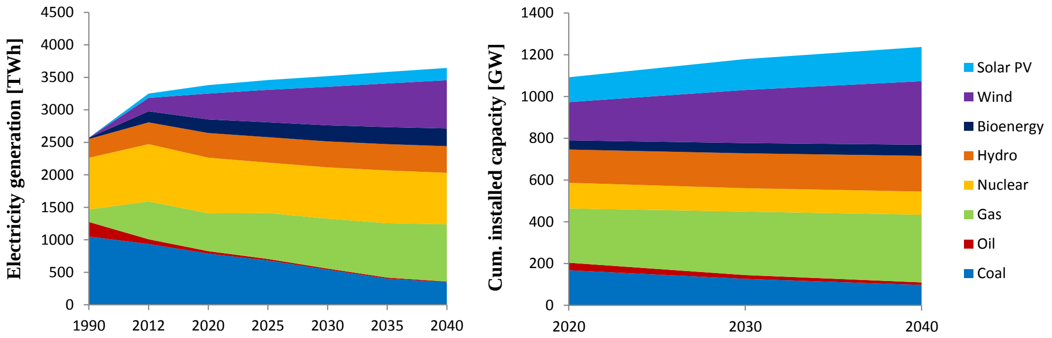

Figure 2. *Electricity generation and cumulative installed capacity in the EU according to the New Policies Scenario.*

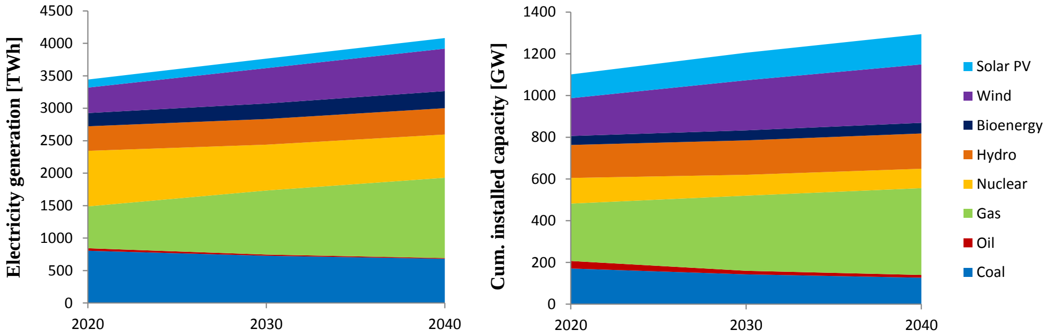

Figure 3. *Electricity generation and cumulative installed capacity in the EU according to the Current Policies Scenario.*

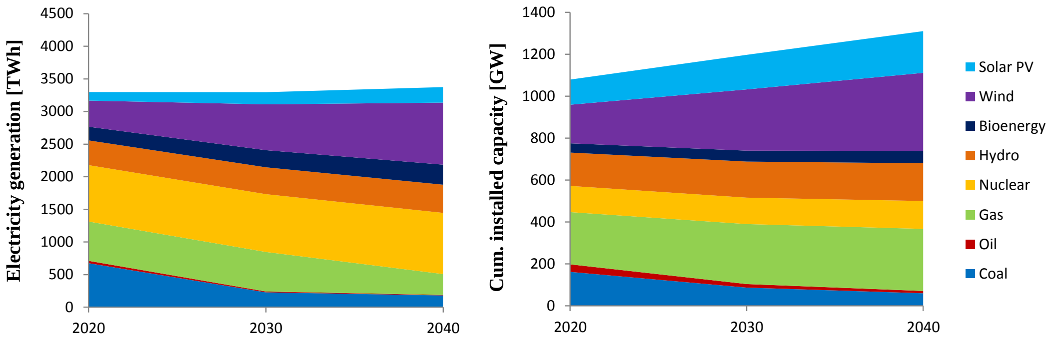

Figure 4. *Electricity generation and cumulative installed capacity in the EU according to the 450 Scenario.*

It is clear from the graphs that the generation from renewables is expected to grow in all cases, little in the Current Policies Scenario, by great amount in the other two. Nuclear power remains quite a big player as well. On the contrary, most uncertainty is cast over the role of natural gas: in the New Policies Scenario its weigh increases, both in terms of absolute values and of share. On the contrary, in the 450 Scenario, which draws on the recommendations of the Energy Roadmap 2050 (80% GHG abatement by 2050), the gas-fired generation is expected to decrease, while the installed capacity will increase. This means that gas-fired power plants would be operating with much lower load factors, as backup power plants for intermittent renewables.

1.1.2. Present and future role of gas-fired electricity generation in Europe

IEA considers the New Policies Scenario the most likely to occur, given the direction the national and international policies are taking. This entails that the ambitious objectives set by the Energy Roadmap 2050 are unlikely to be met. However, one feature is common through all the scenarios, independently from the assumptions they build on. With increasing penetration of renewables, the electricity supply must gradually become more flexible. According to the definition by IEA, 'flexibility describes the extent to which an electricity system can adapt the pattern of electricity generation and consumption in order to balance supply and demand'. Generically, system flexibility can be pursued in four ways: integration of electricity networks, electricity storage, demand response and generation from dispatchable power plants. Several technologies can provide either of these services, and IEA makes a deep review about their maturity in [12].

The integration of electricity networks can bring benefits only in the long term, since it requires investments in new interconnectors and new market rules. Moreover, the need for investments may be mitigated if storage, demand response and dispatchable generation technologies are developed.

As for storage technologies, IEA underlines that they are not in general mature enough to be addressed as game changers in the short and medium term. To date, storage shares 3% of the total installed capacity worldwide. 99% of it is Pumped-Hydro Storage (PHS), almost all of the remaining part is Compressed Air Energy Storage (CAES). Both are medium-term storage options (hours to weeks). Most of the sites eligible for PHS have been deployed, therefore PHS is not expected to grow, while its costs are. Current CAES technology has 50-60% efficiency, comparable to CCGTs. It is claimed the only big potential may come from adiabatic or isothermal CAES, still far to be commercially widespread. Research effort is still needed for hydrogen storage, suitable for seasonal storage. Batteries have potential for small appliances, off-grid small scale generation and the transport sector.

As far as demand response is concerned, the technology which is expected to contribute most is smart grids. To date, the rate of dissemination of smart grids is unlikely to meet the 450 scenario targets, but their penetration is growing steadily. In 2013, the global penetration of smart meters was 20%, projected to rise to 55% by 2020.

The generation from dispatchable fossil-fuel fired power plants is, at present, the most competitive option for meeting the requirements of flexibility in the electricity network. Therefore, they are expected to contribute significantly to the adequacy of the system in the next decades, while they will probably compete with the other flexible technologies in the longer term. Currently, these thermal units are increasingly called upon to balance the fluctuations of intermittent renewables, and their operation becomes flexible under several respects:

- The average load factors, defined as the ratio between the effective Equivalent Operating Hours and the hours in one year, decrease, as shown in Figure 5. This means that: on one side the power plants operate more time at highly partial load; on the other side they are awarded generation on the markets for less time.
- The number of start-up cycles increases up to daily, and the load ramps become deeper.

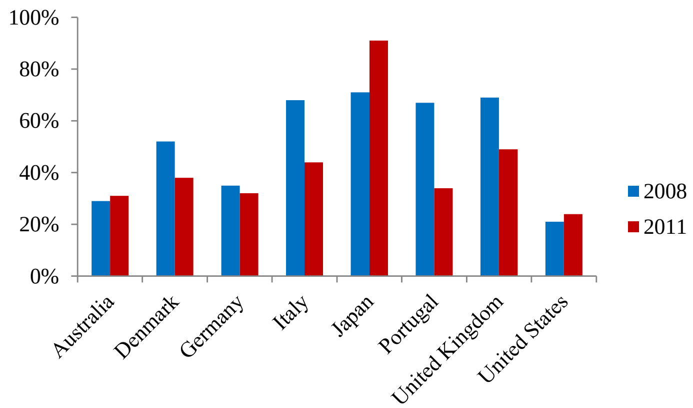

Figure 5. *Gas-fired power plants capacity factors. Source: IEA, 2014* [12].

IEA does not draw univocal conclusions about which technology, among the fossil-fuel fired, is the best candidate for backing up intermittent renewables in the long term. Either OCGTs, CCGTs or Internal Combustion Engines (ICEs) are generally suitable for cycling and off-design operation, mostly due to their ramping characteristics. However, which one would allow for flexible electricity supply at the minimum cost of the system also depends on other factors. Among them, the most relevant are the price of the fuels, the carbon taxes, the efficiency of the technologies and the pattern of the final electricity consumption.

Price of fuels and carbon taxes

With a current price of coal of around 12 €/MWh, the Levelised Cost of Electricity (LCOE) of CCGTs is on average lower than that of coal-fired power plants for a gas price lower than 28 €/MWh [12], as happened throughout the early 2000s until 2012. This means that CCGTs are more competitive also for base-load generation. If the price of coal lowers or the price of gas increases, the figure turns upside down, and the competitiveness of CCGTs might be limited to the supply of peak-load. At present, this element casts great uncertainty over which technology will be most convenient and for which kind of operation, given the wide fluctuations of the gas prices on the wholesale market in the last decade. However, in the long term the gas prices are expected to grow, on average, and this is going to reduce the share of gas-fired power plants as base-load suppliers.

Also the carbon tax plays a role in determining whether shifting from coal to gas is convenient, LCOE-wise. At recent gas prices of around 30 €/MWh, a carbon price higher than 10 €/tCO_2 is sufficient for the LCOE of CCGTs to be lower. Since the carbon price is forecasted to grow through the next decades, it should favour gas-fired generation, counterbalancing the effect of the fuel prices.

Efficiency of the technologies

CCGTs have the highest efficiency among the fossil-fuel fired power plants. The Best Available Technology efficiency outreaches 60% and is expected to increase up to 65% in the next five years [12]. However, at small scales or at highly partial loads the efficiency decays below that of some ICEs or OCGTs. For this reason, the last two technologies may be preferred in case the power plants are expected to operate mostly with low load factors. However, the turbine suppliers currently put much effort in increasing the full-load efficiency of the machinery, while the power plant operators are considering retrofits to increase the part-load and minimum-load efficiency of CCGTs. These elements, together with retrofits to increase the ramping capability of CCGTs, may turn these plants competitive in the whole range of load factors.

Historic trend of the electricity consumption

At the beginning of the 2000s, when most electricity sectors in Europe were liberalised, the final electricity consumption was steadily increasing in the Union, as shown in Figure 6 [13].

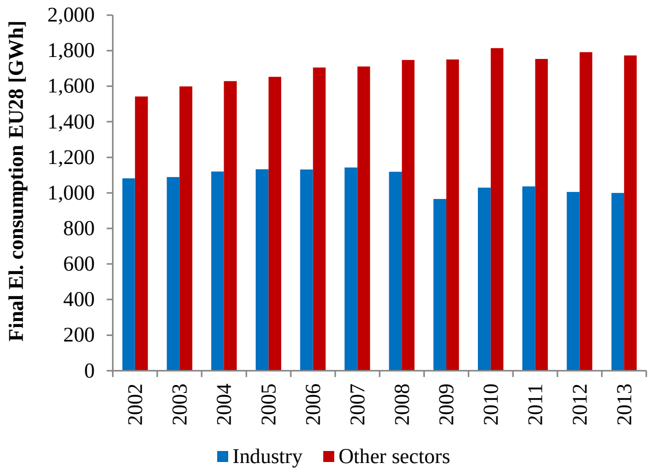

Figure 6. *Final electricity consumption in the EU.*

At the same time, the wholesale price of natural gas was low. This conjuncture raised large interest in big sized gas-fired generation, i.e. CCGTs, since it represented the most efficient and most profitable option for generating electricity on large scale. A huge number of CCGTs were built or repowered from old coal- or oil-fired boilers. However, when the financial crisis came, the electricity consumption dropped, mostly due to the decrease of the industrial consumption (blue columns in Figure 6). Suddenly, many national electricity systems turned out to be highly oversized. This contributed, together with the increasing penetration of renewables, to decrease the load factor of the CCGTs and relegate them to peak-load or backup power plants. This situation is not expected to change deeply, since the European energy policies aim at reducing the final consumption. With this perspective, many companies started decommissioning part of their installed capacity, and they still do. This is a natural consequence, in competitive markets. However, with increasing penetration of renewables the energy system may require in the long-term a consistent backup capacity of gas-fired power plants, as described above. Part of the present overcapacity of CCGTs may take on this role. If too much capacity is dismissed now, this may affect the adequacy of the electricity systems in the future.
From the context analysis a scenario emerges where the European energy system is facing a deep change. Many of the challenges will have to be played on the electricity system, where strict objectives of decarbonisation were set out: the penetration of renewables is due to increase more than ever experienced, the need for flexible electricity supply is urgent. Since flexibility is a new requirement in the planning of energy systems, it must be still understood which technological mix will allow the highest degree of flexibility to be reached at the lowest cost. Among the fossil-fuel fired technologies, CCGTs, OCGTs, ICEs may all have a prominent role as peak-load or backup units, depending on their prospective costs, possibilities of retrofit, capability to cycle and operate at partial loads. Moreover, their competitiveness in the future electricity systems is highly sensitive to external conditions, such as the prices of the fuels, the carbon taxes and the final electricity consumption. More reliable predictions about the expected future energy technology mix may be obtained if more specific contexts are considered, such as individual countries.

1.2. A country insight: the case of Italy

With some exceptions (such as Norway, which relies on hydroelectric by almost 97% [14]), many European countries are expected to face the transformations predicted for the Union as a whole. The most critical situations are already occurring in United Kingdom, France and Italy [15]. In the following sections, the case of Italy is briefly introduced, as it is fully representative of the issues brought about by the flexibility in the electricity sector.

1.2.1. The National Energy Strategy

It is useful to start from the performance of Italy with respect to the three core weaknesses of the European energy system. Despite being virtuous on the sustainability point of view, with higher energy efficiency than the European average, Italy is weaker on the security and competitiveness sides [16]:

- 84% of the primary energy demand relies on imports, compared to an average 53% in the European Union. This is also due to the peculiar electricity mix, with no nuclear and almost all the fossil-fuel fired generation provided by gas-fired power plants.
- The energy mix is not competitive: the price of energy, particularly of electricity, to the final consumers is significantly higher than the European average. The spot prices of electricity are on average 70% higher than in Spain, France and Germany. This is due to

several factors. The first one is the electricity generation mix, mainly based on renewables and on gas-fired generation: the incentives to renewables have been up to 100% higher than the European average, while the wholesale prices of gas have been 25% higher. The second factor is related to many extra expenses charged onto the bills, like the dismissal of nuclear plants, incentives for certain categories of consumers, incentives to some kind of non-renewable generation, bottlenecks in the electricity grid.

In response to these weaknesses and in compliance with the guidelines of the Climate and Energy Package, the Italian Government elaborated in 2010 the 'Piano di Azione Nazionale' [17], which was embodied in the National Energy Strategy [16]. In the first place, the Strategy raises on the objectives of the Climate and Energy Package:

- 24% reduction of the primary energy consumption with respect to what predicted by 2020.
- 21% GHG emissions abatement with respect to 1990 levels.
- Increase of the production from renewables so as to achieve 23% share of the final gross energy consumption.

In addition, it also sets objectives for 2050:

- Reduction of the primary energy consumption by 17% to 26% in 2050 with respect to 2010.
- Increase of the penetration of renewables so as to achieve 60% in final gross consumption, and 85 to 90% in final electricity consumption.
- Extensive electrification of the energy sector, with focus on the transportation sector.
- Fostering gas-fired electricity generation as a bridge towards a decarbonised electricity sector.

The pathway for meeting such goals does not differ significantly from those identified at a European level, but for the absence of nuclear generation, as a consequence of the Referendum in 1987, which banned nuclear production in Italy. Ministero per lo Sviluppo Economico and ENEA predicted the least cost energy technology and generation mix which would allow these long-term objectives to be fulfilled. The key conclusions are presented in [18] and illustrated in Figure 7. The projections for the global electricity generation in a Reference Scenario and the electricity generation by source in a Roadmap Scenario are shown.

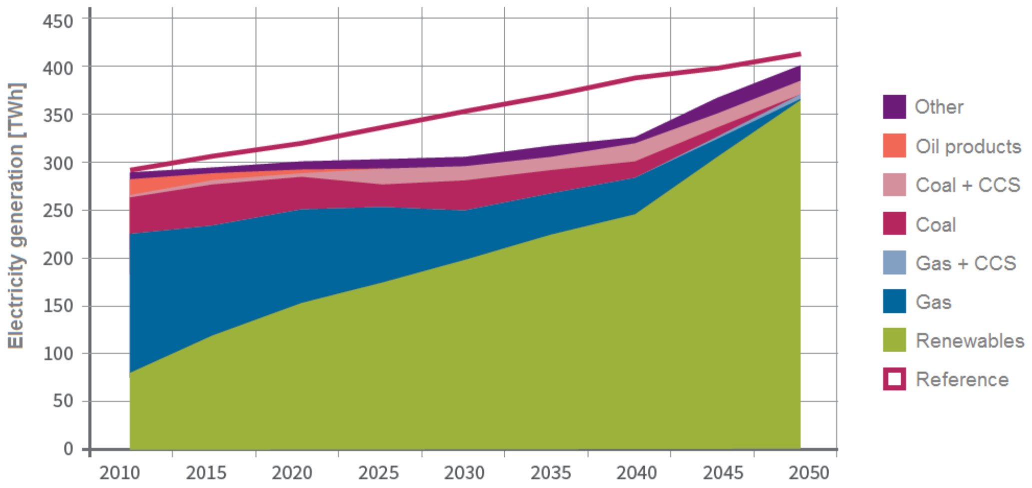

Figure 7. *Projections for the electricity generation in Italy by source for the Roadmap Scenario and global projections for the Reference Scenario. Source:* [18].

In Figure 7, the Reference Scenario is a current policies scenario, which assumes that the Europe 2020 objectives are met, while the Roadmap Scenario is set so as to achieve 80% in GHGs emissions, as envisaged by the Energy Roadmap 2050. In line with the predictions at a European scale, also in Italy renewables will increase their share until they cover nearly the whole electricity generation in 2050. Gas-fired CCGTs currently cover most of the electricity supply. With time, their share will decrease and they will bridge the transition towards a decarbonised electricity system, while in 2050 they will serve only as backup capacity. Also coal-fired power plants, equipped with CCS, will contribute as backup capacity.

1.2.2. Present and future role of gas-fired electricity generation in Italy

For the deep restructuring of the electricity system envisaged by the National Energy Strategy to effectively take place, it had to start as soon as possible. This is why the Italian Government put in place mechanisms for incentivising the generation from renewable sources, and fostered the penetration of renewable energy technologies into the market. Thereafter, in the last decade the generation profiles of fossil-fuel fired power plants began to shift from base- to peak-load, and they started taking up the role of bridging technology towards a decarbonised electricity system. This occurred particularly for CCGTs, because in Italy they have traditionally shared most of the installed capacity and electricity generation.

This bridging role is confirmed by studies about the implications of the penetration of renewable energy technologies on the adequacy of the grid. Apart from fossil-fuel fired generation, smart grids and storage technologies could take up the role of backup for the intermittent renewables. Italy is pioneer in the diffusion of the smart grid technology, with an almost full penetration of smart meters in the residential sector [19]. However, smart grids are still prevented from turning into a solid market structure for demand response, able to contribute to the adequacy of the system, due to limited investments, scarce responsiveness of the consumers, and the absence of an integrated European market. As far as storage is concerned, the most significant source is PHS, with 7 GW installed capacity in 2013. Nonetheless, this storage is not competitive now and it is not expected to be, at least until 2020 [18]. No other technology is expected to give a relevant contribution to storage [20]. Therefore, gas-fired generation is expected to be essential for the adequacy of the electricity system at least in the medium term [16].

The shift of combined cycles towards a role of peaking and backup power plants is intensified by the overlapping of other dynamics recently occurred in the Italian electricity system. First of all, the peculiar history of the national generation portfolio plays a role. Until the early 90s the fossil-fuel fired power plants fleet in Italy consisted mainly of heavy oil-fired boilers. Since around 1990, the low prices of gas and, later on, the liberalisation of the electricity market induced companies to invest in CCGTs, either of new construction or repowered from the oil-fired power plants. Around 40 GW new thermal units were built from 1990 to 2012, making CCGTs the main generation technology in the country. With the sudden penetration of renewables since 2006, the installed thermal capacity started to be redundant. This led to substantial overcapacity of the electricity system: the available capacity in 2013 was around 78 GW (out of 130 GW globally installed), face a peak demand of 54 GW [21].

Also the trend of the final electricity consumption played a role in the recent evolution of the pattern of the electricity supply. While it increased steadily until around 2007, it started decreasing thereafter, mostly due to the financial crisis, in line with most of the European Union [13]. The trend of the final electricity consumption, as from data recorded by the Italian TSO, Terna S.p.A, is shown in Figure 8 [21].

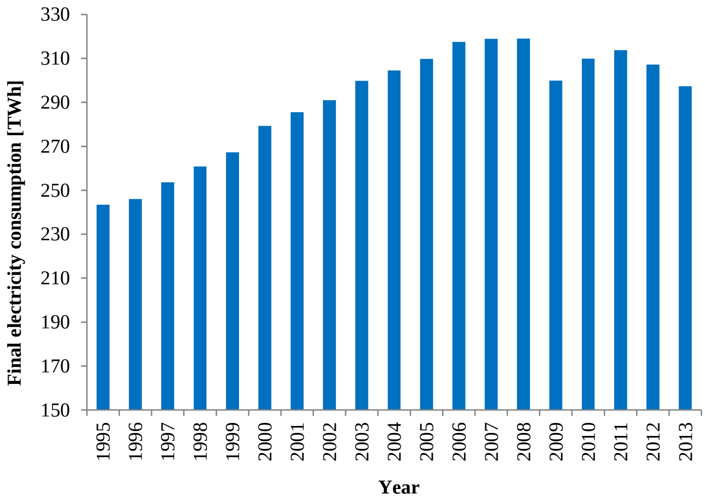

Figure 8. *Final electricity consumption in Italy [TWh].*

Eventually, the fluctuation of the gas prices impacted the gas-fired generation in Italy. The variations of the prices of gas on the main European hubs since 2008 are shown in Figure 9. At the end of 2008 and 2011 the gas prices in Italy experienced peaks. Moreover, until 2012 they were higher than the European average. In the last years they have aligned and decreased, but they are expected to increase again [18].

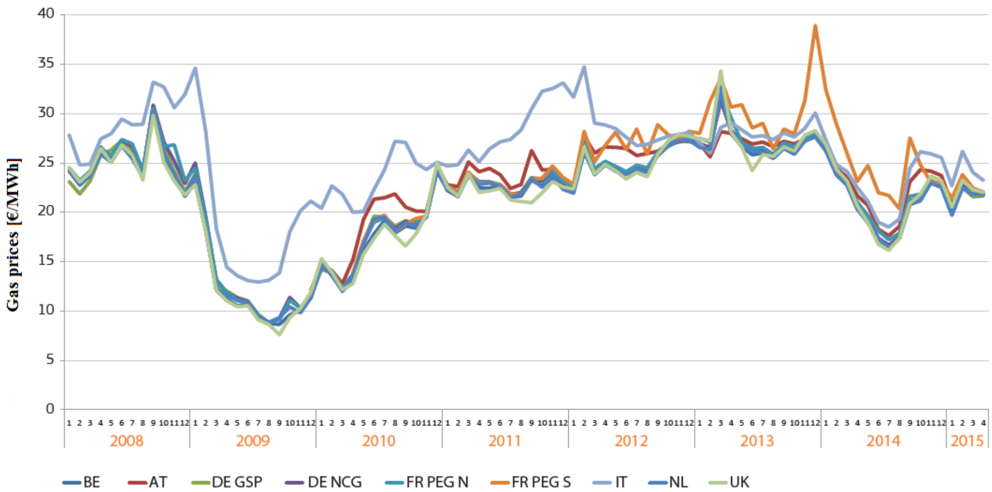

Figure 9. *Average wholesale day-ahead prices on gas hubs in the EU. Source:* [22].

All of these dynamics acted jointly in reducing the share of gas-fired power plants in the last decade. In Figure 10 the historic trend of the annual generation in Italy since 1990 is shown. The global reduction from 2006 is mostly ascribable to the flection in gas-fired generation.

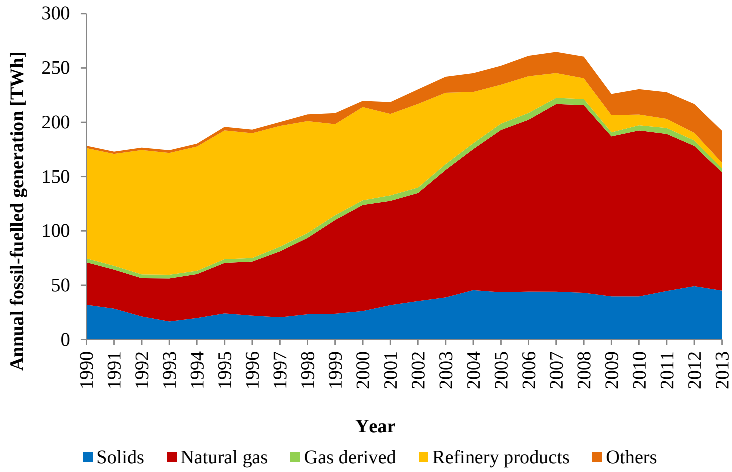

Figure 10. *Annual fossil-fuel fired generation in Italy [TWh].*

CCGTs designed to operate 4000 to 5000 Equivalent Operating Hours (EOH) reduced their operation from 5100 EOH on average in 2006 to 3100 in 2008 [23]. Besides this, they also varied deeply their production profile: while in the early 2000s the power plants experienced few starts per year, now they undergo daily starts [21], with deep and frequent ramps. An example is provided by the operation profile of a CCGT at Castel San Giovanni (PC), representative of many others in Italy. From 2006 to 2013, the EOH more than halved from 7600 to 3500 and the number of hot starts increased on average from 50 to 200. This cycling operation is well mirrored into its weekly operation, shown in Figure 11.

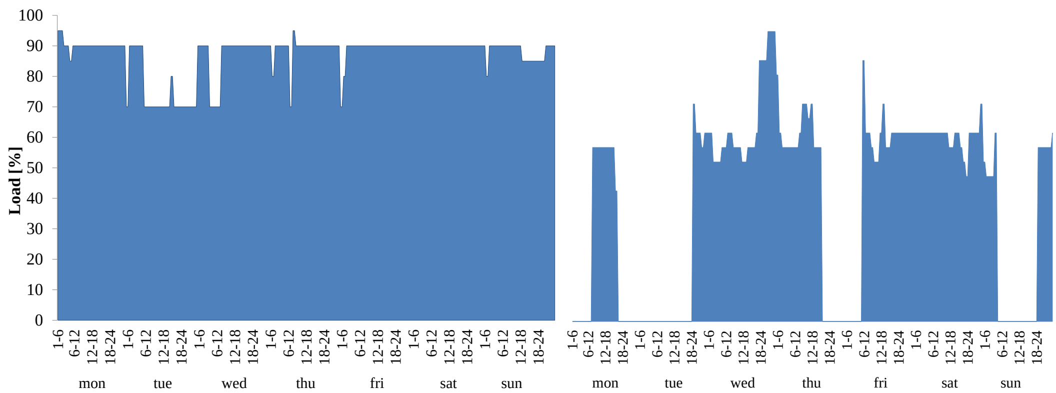

Figure 11. *Sample load profile of a CCGT power plant in northern Italy in 2006 and 2013.*

The predictions by Ministero dello Sviluppo Economico for the next decades confirm the electricity system will evolve in this direction, given that the gas prices and the carbon tax will increase significantly and the final consumption will at most keep constant [18]. Ricerca Sistema Energetico (RSE) simulated the day-ahead market in 2020, to study how the electricity generation mix may vary in the medium-term [20]. The study assumes that the objectives set by the National Energy Strategy for the generation from renewables are fulfilled. Moreover, a price of 38 €/MWh and of 14 €/MWh are set for gas and coal, respectively. As expected, they are higher than the European average. The carbon tax is 25 €/t CO_2. Under these assumptions, CCGTs are predicted to be called into operation 2300 EOH, while coal-fired power plants provide the base-load generation

(6600 EOH). However, if this is the case, the minimum primary reserve requirement is not fulfilled for 1000 hours and the transmission bottlenecks between the south and the north of Italy cause high price differentials. A sensitivity analysis over the installed capacity of solar photovoltaic (PV) highlights that with higher PV penetration the price differentials and the electricity price decrease compared to the reference case. However, the number of hours when the reserve requirements are not fulfilled increase, therefore the adequacy of the system is weaker. This indicates a higher need for backup capacity and generation.

2.
Assessing the current impact of flexibility: review of the existing data

From Chapter 1, it can be concluded that the future adequacy of the electricity system of Italy may depend on the extent to which fossil-fuel fired power plants will contribute to the reserve and backup capacity. This in turn depends primarily on the long-term energy policies at a national and European level, but also on the structure of the electricity market, the characteristics of the technologies, their learning curves and the reactions of the generation companies. These elements may impact the costs borne by the power plant operators and the companies for generating electricity, and the costs borne by the system operator (intended as the market operator or, more in general, the State) to guarantee the adequacy of the whole energy system. These can be called 'costs of flexibility', since they derive from the necessity for power plants to operate with flexible, cycling profiles. In the following sections, the impact of flexibility on different spatial and temporal scales is discussed. From the introduction and the context analysis, three scales can be identified:

1. *Power plant scale*. It is a small-size, short-term scale. The flexible production profiles cause the components of the power plants to wear, since they were designed for base-load operation. This causes the operation costs to increase, and they can be reduced through decisions taken by the operators of the individual power plants, concerning retrofits or the adoption of new control logics. Both the costs of flexible operation and the benefits of decisions to reduce them need to be quantified. They will impact the costs and the decision making at the electricity market scale.
2. *Electricity market scale*. It is a large-size, short-term scale. Due to both the additional operation costs of flexibility and to other market variables, fossil-fuel fired power plants loose competitiveness and market share. This impacts the profits of the generation companies. There are a number of decisions the companies may make on the whole generation fleet to regain competitiveness, acting on several market variables: the share of capacity to be decommissioned, expanded or renovated, the bidding strategies, the choice between the energy-only and the reserve capacity market. These decisions are influenced also by decisions made by the system operator to adjust the market structure, like those introducing taxation or incentive policies. Market models must be developed, which quantify the impact of flexible operation, strategic decisions of the companies, decisions of the system operator on the revenues of the companies and the global welfare. This impact will, in turn, influence the costs at the energy system scale.
3. *The energy system scale*. It is a large-size, long-term scale. The European Commission and the individual Governments usually plan the energy system in an economic cost optimisation perspective, subject to the objectives of the Energy Roadmap 2050 and the national strategies. The resulting scenarios indicate the share each technology should have in the global installed capacity and generation along the years, so as to meet the long-term objectives at the least possible cost of the whole system. If the costs of flexibility are not accounted for, the actual cost of the system may be higher than predicted and other pathways to the decarbonisation may be neglected, which are actually more convenient. Energy system planning models accounting for the costs of flexibility

must be developed. The long-term energy system pathways drawn from these models will impact back the costs and decisions at the power plant and electricity market scale.

2.1. Power plant costs of flexibility

CCGTs are one of the most suitable technologies for backing up intermittent renewables in the long-term scenarios for the European and the Italian energy system. This is confirmed by the existing literature about the power plant cycling costs, almost only focussing on CCGTs. Therefore, the CCGTs costs of flexibility are analysed in this section, and they will be referred to in the following ones. A large amount of literature provides data about the Levelised Cost of Electricity (LCOE) of CCGTs, both present [24–33] and projected [34–37]. The projections are usually done only with respect to the expected cost of natural gas or to the learning curves of the technology. Few references are made to the new operation profiles of CCGTs and the costs of flexibility. A focus on the hot topics in this regard is made in this section. The new operation profiles of CCGTs present:

- Reduced load factors.
- Increased number of starts and load ramps.

The load factors have decreased in recent years for two reasons: in the first place, the power plants are called on to produce for fewer hours; secondly, when they do produce, they operate at partial load. As can be seen in Figure 12, featuring the performance of a CCGT as from [38], the efficiency decreases with the load, and it has different values, depending on the control logics of the power plant. Therefore, the specific cost of fuel increases and this impacts the production costs by a great amount, because for CCGTs the cost of fuel represents around 75% of the LCOE [12].

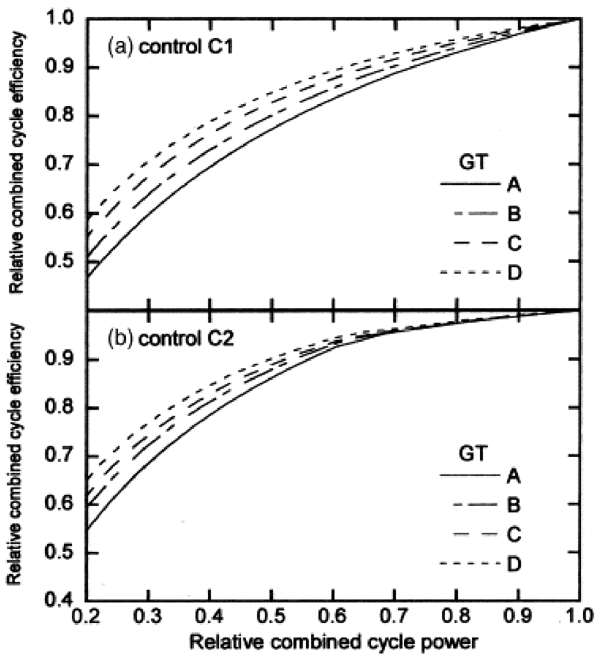

Figure 12. *Net electric efficiency of a CCGT. Source:* [38].

Moreover, at partial load the NO_x and CO emissions increase [39]. In Figure 13, the typical concentration of NO_x and CO in the flue gases is shown [40]. It refers to a MS6001B gas turbine from General Electric, equipped with a 6B DLN-1 Dry-Low-NO_x combustion system, the state of the art in 2010.

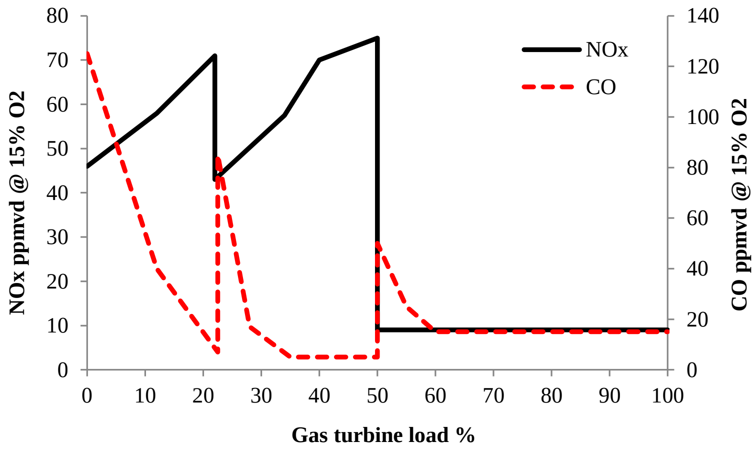

Figure 13. *NO_x and CO emissions of a gas turbine as functions of the load. Source:* [40].

NO_x emissions increase with decreasing load, because they depend on the combustion regime in the gas turbine. From 100% down to 50% of the gas turbine load the combustion is premixed and the NO_x emissions are as low as 9 ppmvd @ 15% O_2. At lower loads the combustion regime changes and the emissions increase sharply. The CO emissions increase with decreasing load as well, but due to the decreasing temperature in the combustion chamber. They start increasing already with the premixed flame, below 60% of the gas turbine load. In Italy the emission limits for CCGTs are 30 mg/Nm^3, for both NO_x and CO [41], corresponding to around 15 and 25 ppmvd @ 15% O_2, respectively . In this case, the gas turbine would not be allowed to generate electricity below 50% of the load, since the NO_x emission limits would be exceeded by far. However, depending on the characteristics of each individual power plant, in some cases the CO emissions may become constraining before the NO_x emissions do. In either case, the gas turbine minimum load is lower-limited by the emission constraints. This represents an indirect economic loss in flexible operation, since the power plant operator cannot make offers on the market for loads lower than the Minimum Environmental Load, i.e. the load at which the emissions reach the maximum value allowed by law.

The number of CCGTs starts has increased up to daily starts, as mentioned in Section 1.2.2, and the ramps have become countless, as well as deeper and steeper. With respect to the number of starts, ramps and the EOH, the current operation profiles of CCGTs can be considered half-way between cyclic and peaking duty [42,43]. The CCGT technology was conceived for base-load operation. The components wear with cycling operation and the risk of damage increases. While continuous duty is mainly interested by creep, cyclic duty also introduces thermal fatigue in the hot gas path of the gas turbine. The combination of the two mechanisms results in more frequent cracking. The same is said for the heat exchangers tubes in the Heat Recovery Steam Generator (HRSG), which is the bottoming steam cycle in CCGTs. Statistical analyses about the frequency of the forced outages in large CCGTs fleets subject to flexible operation have been carried out [42,44]. They refer to CCGTs subject to more than weekly stops. The key findings are condensed in Table 2: the components which cause the highest unavailability are presented and ordered by importance, along with the main causes of the damages.

Component	N°/h outages per year	Damage mechanism
Gas turbine	9.1/154	Erosion/corrosion/thermal fatigue and fatigue crack growth, mostly on combustor liners and compressor/ turbine blades; sintering or loss of thermal barrier coating; malfunctioning of control instrumentation; vibrations of the rotor
Auxiliaries	4.1/87.7	Failures at the transformer and the cooling tower; feedwater valves and pumps failures; condenser piping leaks
Steam turbine	1.9/57.7	Failures of valves and control instrumentation; thermal fatigue on LP turbine blades and piping; vibrations of the rotor
Alternator	1.2/30.6	Failures of control instrumentation and the exciter; cooling problems
HRSG	0.2/4.5	Failure of valves; stress from uneven flow rates and from laning of gas and low steam flows during cycling; overheating in duct fired units; failures in feedwater heater and tube/header connections, from high thermal differentials in adjacent tubes during starts or ramps; thermal quench of bottom headers from un-drained condensate; flow assisted corrosion in LP carbon steel piping

Table 2. *Frequency and mechanisms of damage in the main components of a CCGT.*

The failures of the components cause the power plant operators to bear direct and indirect costs: the direct costs are related to the repair interventions and to the substitution of the damaged parts; the indirect costs are due to the unavailability of the power plant. They can be roughly computed as the product of the number of hours the power plant is unavailable by the average price the power plant would be awarded on the market if it sold electricity. If the maintenance and inspections plan is rescheduled to account for the increased forced outage rate, the costs of the outages decrease, but the costs of maintenance increase. To sum up, if the operators want to keep the outage rate constant in flexible operation, they will have to increase the maintenance costs. In the common industrial practice, two ways are identified to schedule the maintenance interventions as a function of both the EOH and the number of starts:

- Each intervention is scheduled after a fixed number of starts or EOH [42]. This number is corrected with factors accounting for the different kinds of starts (cold, warm, hot) and for different steepness of the ramps.
- Each start is converted into EOH, as if it caused an increased life consumption of the components [31,37]. The maintenance interventions are scheduled as a function of the EOH so that, if the power plant undergoes more starts in a given timeframe, the interventions will be more frequent.

With the second methodology one more consequence of cyclic duty is made explicit: the decrease of useful life of the components, due to their deterioration.

The most complete work about the cycling costs of CCGTs is a study for National Renewable Energy Laboratory [33]. It is based on a 20 years statistical study on hundreds of units in USA. The result is a quantification of the average cost of starts and ramps for state of the art combined cycles and Best Available Technology combined cycles. It is a capitalized cost, which accounts for:

- Increases in maintenance, operation and overhaul capital expenditures.
- Cost of heat rate changes due to low load and variable load operation.
- Cost of fuel, auxiliary power, chemicals, and extra manpower for start-up procedures.
- Cost of long-term heat rate increases (i.e., efficiency loss due to degradation).
- Long-term generation capacity cost increases due to unit life shortening.

The outcomes of the study are shown in Table 3.

	State of art power plant			**BAT power plant**
	Median	25^{th} %ile	75^{th} %ile	Median
Base-load O&M cost [€/MWh]	0.79	0.66	0.91	0.86
Hot start cost [€/MW]	27	22	44	24
Warm start cost [€/MW]	43	25	72	34
Cold start cost [€/MW]	61	36	79	47
Load follows cost [€/MW]	0.50	0.23	0.58	0.26
Fast-ramp factor: 1.1 to 2x	0.9 to 3.1	-	-	0.9 to 3.1

**conversion factor 1 € = 1.2848 USD, average conversion factor in 2012. Source: European Central Bank.*

Table 3. *Cost of starts and ramps for state of the art and Best Available Technology CCGTs.*

2.1.1. Decisions at the power plant scale

The cycling capability of a CCGT and the cycling costs can vary upon variations of the control logics at partial load and modifications of the power plant. Therefore, the operators are trying to act in this direction, to reduce the costs of cycling and increase the revenues from the sale of electricity and reserve capacity. In the following, the options currently available to the power plant operators for meeting such need are described.

In [45–48] reviews of the state of the art retrofits for enhancing the flexibility of existing CCGTs are provided. The main ones are:

- Installation of once through HRSGs, evaporator steam sparging, stack damper for reducing heat losses during short shut-downs.
- Installation of an auxiliary boiler for feeding the steam sparging system.
- Installation of de-superheaters in the high pressure and hot reheat steam lines, to control the steam turbines inlet temperatures during the starts and reduce the thermal fatigue over the hot path.
- Switching from sequential to parallel start-up of the gas turbine and the steam turbine: the gas turbine is accelerated and loaded to base-load; the hot gases heading to the steam generator are no more dumped to the condenser, but they are used to produce low temperature steam, which is employed to accelerate and load the steam turbine.
- Installation of throttling valves at the steam turbines inlets. Currently, these are usually operated in sliding pressure. With the throttling valves, the inlet pressure to the steam turbines is controlled, therefore the steam production and finally the power output. The delay which is typical of the current steam-follows control logic is reduced.
- Installation of a condensate polisher for avoiding deposits in the HRSG and, therefore, reducing the pressure losses.
- Installation of mechanical vacuum pumps for maintaining vacuum in the condenser overnight.
- Installation of stress and fatigue monitoring systems for the thick walled components of the HRSG and the steam turbine. These provide online evaluation about life consumption

and residual lifetime, which help optimise the start-up ramp rates. This way, unnecessary hold-up times are avoided, without damaging the components.

- Installation of Digital Control Systems for fast start sequencing.

Employing these retrofits allows the hot start-up times of large CCGTs to be halved, from around 70 to around 35 minutes. Also the warm and cold start-up times are significantly reduced. Consequently, also the fuel and electricity costs for starts can drop by 50 to 60%. All these conclusions by the manufacturers and the power plant operators are conveyed in the estimations by IEA about the ramping rates of Best Available Technology combined cycles (Figure 14).

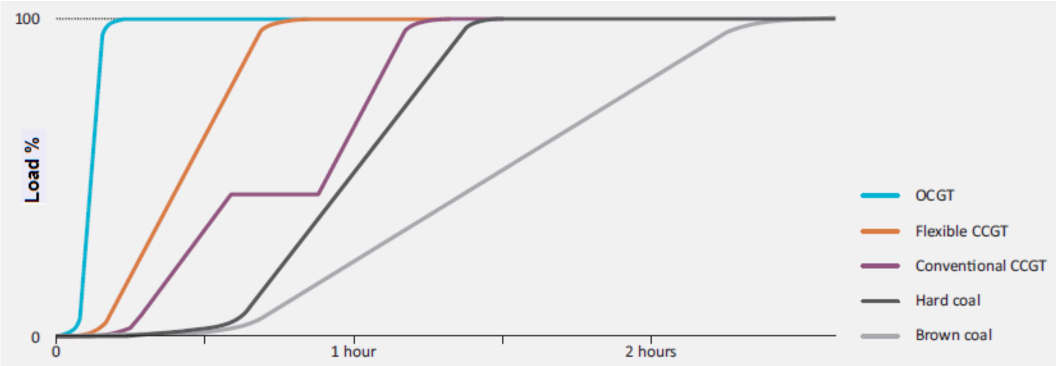

Figure 14. *Load ramps of different fossil-fuel fired power plants. Source:* [12].

The investment costs for the listed retrofits are hardly found in literature. Rough indications are provided in [47]. More specific information is obtained by the individual power plant operators, who are commissioning technical and economic feasibility studies for different kinds of retrofits. Such data are employed in this research.

2.2. Electricity market costs of flexibility

The evolution of the electricity market, due to the penetration of renewables, the reduction of the final electricity consumption, the increase of the gas prices, has deeply changed the share and the role of CCGTs. This implied a loss of competitiveness and a loss of revenues for the operators of these units. Understanding how the loss occurred helps identify the decisions companies are likely to make, in order to regain market share. The analysis starts from the description of the Italian electricity sector and continues with the explanation of the main mechanisms which pulled CCGTs out of the market. Eventually, the market opportunities for CCGTs in a flexible electricity system are discussed.

2.2.1. Features of the Italian electricity market

The Italian electricity system was a monopoly until 1999, when the electricity market (known as IPEX, Italian Power Exchange) was created, with D.Lgs. n. 79/99 [49]. The market became operative on April 1st, 2004, when the stock exchange for trading electricity between suppliers and consumers opened. The trade occurs in three phases [50]:

- Day-Ahead market (Mercato del Giorno Prima, MGP).
- Intra-Day market (Mercato Infragiornaliero, MI).
- Market for Dispatch Services (Mercato dei Servizi di Dispacciamento, MSD).

MGP and MI are energy-only markets, where consumers and producers make electricity buying and selling bids each hour. The consumers bid the minimum quantity of energy they are willing to buy and the maximum price they will pay for it, the producers bid the maximum quantity they are willing to produce and the minimum price which they will sell it for. In the absence of market power, the market is perfectly competitive, and the offered price mirrors the marginal cost of the generator. The quantity and the price each participant is awarded are determined every hour by the System Operator, through the mechanism of the Marginal Price: cumulative curves of the price/quantity offers from consumers and producers are built and the point where they meet determines the global quantity traded on the market and the global Market Clearing Price (MCP). The mechanism is shown, in a simplified fashion, in Figure 15. The highest offers accepted (the last on the right) are the ones which determine the MCP, and the power plants making those offers are called price-setter plants. When a plant is price-setter, the electricity price it is awarded is equal to its offer. Therefore, from the sale it is able to pay back only the marginal costs, which are equal to the variable costs, while it cannot pay back the fixed costs. In order to gradually pay these back, the power plant must seek, at least for a number of hours per year, to sell electricity during peak times, when the MCP is higher enough than its marginal costs.

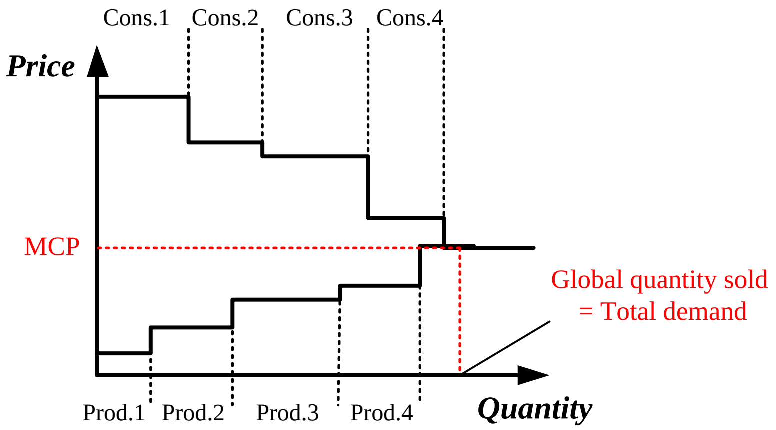

Figure 15. *Example of derivation of the Market Clearing Price.*

In Figure 15, the abbreviation ‘Prod.’ stands for producer and ‘Cons.’ stands for consumer. The real aggregated curve of the consumers is almost vertical, due to the scarce elasticity of the demand for electricity. The price elasticity of the electricity demand is defined as the responsiveness of the demanded quantity Q to changes in the price P:

$$e_P = \frac{dQ/Q}{dP/P} \tag{2.1}$$

The limits on the transmission capacity between different nodes of the electricity network create unbalances that affect the price the production units are awarded: power plants which are located in congested areas will be paid more for the sale of electricity, because there are limits on the electricity that can flow from outside. Therefore, the global Market Clearing Price is always corrected, at a second stage of the market, to account for the constraints over the transmission capacity. Different selling prices emerge in different nodes of the network, based on the congestions. These prices are averaged by zones, and all the power plants operating in a certain zone are paid the Zonal Price. This is why the IPEX is called a zonal market. On the contrary, all the consumers in Italy pay the same price for the electricity they buy, determined every hour. This is an average of the Zonal Prices, called PUN (Prezzo Unico Nazionale).

MSD is devoted to real time balance and trade of primary, secondary and tertiary capacity reserve. The need for this parallel market comes from the necessity to perfectly match the demand and the supply of electricity in every instant, in order for the frequency of the network to be constant. The capacity reserve is supplied by different dispatchable technologies and it is a part of the installed capacity which can be called in or out the network within seconds or minutes, whenever a sudden peak or drop of demand occurs. The presence of a reserve of capacity guarantees that the demand for energy is always met with certain quality requirements (in terms of voltage and frequency), both in the short-term and in the long-term. The provision of primary reserve is mandatory for all the units with capacity no less than 10 MVA connected to the grid and, at present, it is not traded. It must be at least 1.5% of the efficient capacity of the unit and it must be provided within 15 to 30 s upon request. The secondary reserve is mandatory for qualified units and it must be provided within 15 minutes since when it is requested. It is at least 15% of the efficient capacity for hydroelectric units and 6% for thermal units. It is traded in the MSD. The tertiary reserve consists in Prompt Reserve and Substitution Reserve: the Prompt Reserve must be delivered within 15 minutes since the request by Terna with a gradient no lower than 50 MW/min; the Substitution Reserve must be delivered within 120 minutes upon request. Both are traded in the MSD. The trade of reserve capacity is similar to the trade of electricity, but the remuneration system is different: the accepted offers are paid with a pay-as-bid mechanism.

The clue characteristic of the Italian electricity market emerging from this description is that it offers the possibility to power plant operators to compete for the supply of either electricity or reserve capacity, based on their marginal costs. When the marginal costs change, the shares of supplied electricity and reserve and the offers on the market do.

2.2.2. Costs of flexibility in the electricity market

The penetration of renewables deeply impacted the profitability of the companies operating CCGTs in two ways:

- Directly, by reducing their share in the energy-only electricity market.
- Indirectly, by causing the operation costs, therefore the price bids on the market, to increase.

The *direct impact* is due to the fact that the penetration of renewable energy sources modified the electricity price. Since 2006, the incentives to renewable energy technologies allowed their costs to decrease and fostered their penetration into the generation mix. Increasing incentives were released up to 2015, stabilising around 12.5 billion € [51]. They should start decreasing not before 2018. Since the marginal costs of renewables are close to zero, they can afford to make much lower offers than the other suppliers on MGP, and the offers are always accepted. This caused the offers of the other suppliers to shift to the right of the aggregated supply curve, the accepted offers from fossil-fuel fired power plants to become fewer (at constant global demand), the market prices to decrease, as shown in Figure 16.

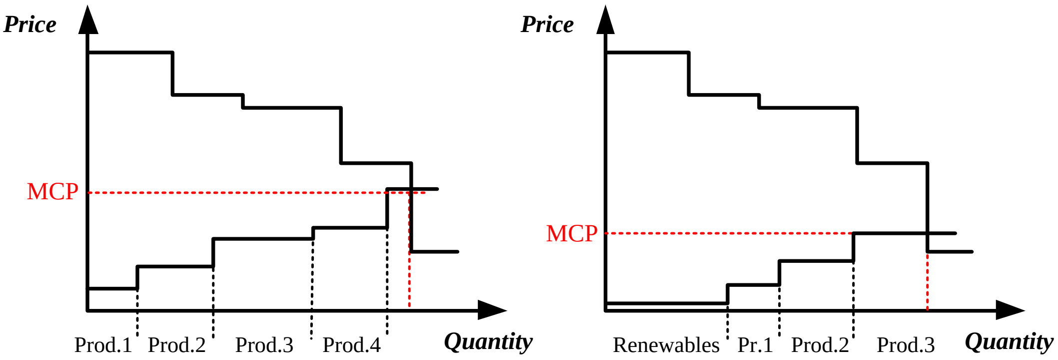

Figure 16. *Shifting of the merit order and decrease of the MCP due to the penetration of renewable energy sources.*

The average reduction of the MCP can be noticed in the reduction of the average PUN occurred in the last years, as obtained from historical data provided by Terna (Figure 17) [21].

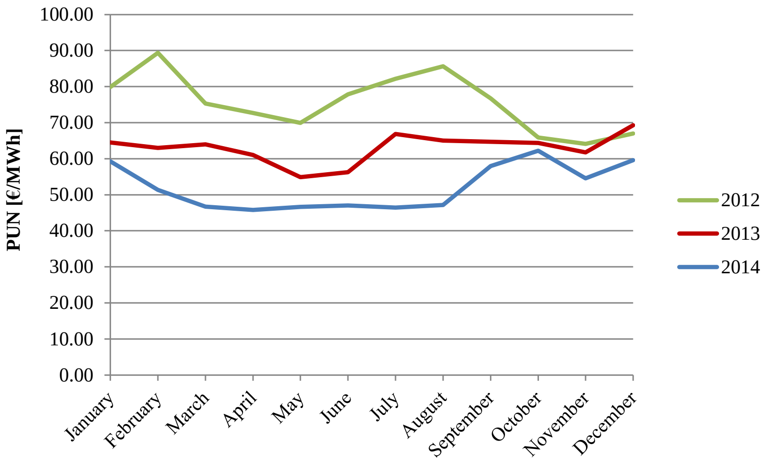

Figure 17. *Historic trends of the PUN in years 2012 to 2014.*

The average value of the PUN in 2014 was 52 €/MWh, fairly close to the marginal cost of CCGTs [52]. This proves that CCGTs have become almost constantly price-setter plants. The least competitive among them are pulled out of the market, while the most competitive ones fall within the merit order, but they are able to pay back only their marginal costs. This inability to pay back the investment costs of price-setter power plants is called 'missing money' problem in literature [15,53]. The price-setter power plants must be able to ramp up fast during the peak times at least for a number of hours per year, in order to take advantage of the higher market price in these hours and pay back part of the fixed costs. If they are not, they end up being no more profitable as well, in the long term.

The *indirect impact* comes mostly from the effect that renewables have on the bids of CCGTs. As shown in Section 2.1, the cycling profiles of CCGTs due to the penetration of renewables (and fostered by other elements) cause them to bear costs for the increased life consumption of the components. These additional operation costs must be paid back by the sale of electricity. This forces the companies to make higher bids on the market and contributes to further decrease their profitability.

Another source of indirect impact is the higher uncertainty over some of the market variables, both in the MGP and MSD. Those variables are described in the following.

Generation from intermittent renewables

The increasing installed capacity on the transmission grid causes the uncertainty over the electricity supply to increase, while the increasing distributed capacity impacts the uncertainty over the demand. On one side, this uncertainty calls for higher reserve, therefore it represents a chance for fossil-fuel fired power plants to contribute more to the reserve capacity market; on the other side, the higher uncertainty affects the bidding strategies of the fossil-fuel fired power plants. Every company makes its own predictions about the generation from renewable energy sources day by day. If one company predicts high renewable generation for the day after, this means that high reserve should be required. Therefore, the company bids little in the energy-only market and more in the reserve market. If, then, the predictions turn out to be wrong and renewables generate little, the company misses both the opportunity to generate in the energy-only market and the chance to sell reserve capacity. The opposite happens when the company predicts little renewable generation for the day after. This case is even more severe, because costs for preparing the power plant for generation are incurred, but no revenues are gained. Companies with better forecast models for renewables are more competitive and gain higher market share.

Cost of cycling

As mentioned, even the power plant operators do not know the exact cycling costs of their power plants. This uncertainty must be taken into account when making price offers on the market. If no cycling costs are taken into account, the price bid is lower and the power plant has more chances to be dispatched; on the other side, the cycling costs are not covered and this will turn into a loss in the long-term. If high cycling costs are taken into account, the power plant reduces the risk in the long-term, but it is more unlikely to be dispatched. A trade-off must be found between these two extremes.

Parameters for selecting the best candidates in the MSD

The offers of reserve capacity in the MSD are accepted or rejected not based on a merit order (like in the MGP), but based on several parameters, which describe the ramping capability of the power plant [54]. The main parameters are:

- Maximum and minimum power [MW].
- Upward and downward ramping rate [MW/min].
- Response time, which is the time the power plant takes to start executing the required ramps [min].
- Start-up and shut-down time [min].
- Maximum secondary reserve capacity [MW].

At every node of the electricity network there may be more than one power plant competing for the supply of reserve capacity. The operators know the abovementioned parameters for their own power plant, but they have scarce information about the values for the competing power plants. This casts uncertainty over the price they offer for the provision of reserve capacity in the MSD and over the opportunity of interventions aimed at improving their capability of providing reserve (e.g. increasing the ramping rates).

2.2.3. Decisions at the electricity market scale

From the analysis carried out so far, some indications can be drawn, about the opportunities the companies have in the electricity market to increase their competitive margin.

The first one is a no-cost solution, consisting in a mere observation. Apart from the average reduction of the PUN, one effect of the penetration of renewables is the peak shaving of the daily market prices: while previously the maximum electricity price occurred on daylight hours, coinciding with the peak of the energy demand, now, because of the increase of PV generation, it occurs during early evening hours (between 5 p.m. and 9 p.m.), when PV facilities end their operation [51]. A progressive increase of the price with respect to the yearly average during early evening hours and a reduction during daylight hours has been noticed in the last years [55]. The fossil-fuel fired power plants must shift their operation towards the evening hours, to take advantage of the peak shaving effect.

The second one consists in taking advantage of the increased need for reserve capacity in the reserve market. To do this, the market divisions of the energy companies must adjust the bidding strategies in the MGP and the MSD for all the power plants they own: a shift from the MGP to the MSD may be convenient on the nodes where the transmission limits are more constraining and the need for reserve is more stringent, due to the presence of intermittent renewables. Of course, such solution relies on the actions taken at the power plant scale: the cycling capability of the power plants must be increased. A study in [37] assesses the impact of the choice of the operation profile on the profitability of a CCGT in Italy. The choice is between two profiles:

- A reference profile, where the power plant is shut-down whenever the difference between the expected revenues and the marginal costs is negative for more than 18 hours. If the expected profit is negative for less than 18 hours, the power plant is not shut-down, but operated at the Minimum Environmental Load.
- A flexible profile, where the power plant is shut-down whenever the difference between the expected revenue and the marginal costs is negative for more than 8 hours. If the expected profit is negative for less than 8 hours, the power plant is not shut-down, but operated at the Minimum Environmental Load. An additional cost due to the increased life consumption of the components and due to the higher forced outage rate is taken into account in this case.

The flexible profile results more profitable than the reference profile, despite the higher costs due to flexible operation. Increasing the participation into the reserve market may become even more profitable if it is incentivised by the system operator.

The generation companies are not the only decision makers in the electricity market. Also the energy system planners, such as the Governments or, generically, the policy makers, may make decisions to influence the market outcomes. The introduction of market tools like taxations, incentives, and new market mechanisms is an example of such decisions. In a recent consultation paper, the European Union evaluated the necessity of additional remuneration mechanisms for the provision of reserve capacity [15]. The study reflected some concerns about the capability of the future European electricity system to ensure the required adequacy and proposed new market mechanisms as one of the possible solutions. While some countries refused to adopt such market mechanisms, as they distort the market competition, others adopted them. Currently, the mechanisms implemented in Europe can be grouped into four [56].

- *Capacity payments*. They are the only price-based mechanism. They consist in a fixed price paid by an Authority for the available capacity. This mechanism influences the behaviour of the generation companies in that it reduces the investment risk of the generators and stimulates investments in new generation capacity. However, the prices depend on assumptions on the future demand and the investment response to the payments. Therefore, they rely on detailed future energy scenarios. Failing to design such scenarios could make it necessary to adjust the prices. The adjustments would in turn affect the investment risk. The capacity payments are employed in Spain, Portugal, Ireland and Northern Ireland.

- *Strategic reserve*. It is a hybrid price- and quantity-based mechanism and it consists in an amount of emergency capacity held by the system operator and activated at risk of shortage of electricity. It is paid again at a fixed price. If the electricity market is efficient enough, this mechanism should distort it little, since it will be activated rarely. However, again the setting of the fixed price is crucial, because it may act as a price cap and discourage investment in more flexible technologies. The strategic reserve is implemented in Sweden, Norway and Finland, and it is under evaluation in Belgium and Germany.
- *Capacity requirements*. It is a quantity-based mechanism. It introduces a trading mechanism for capacity credits, like the emission trading scheme. A global demand for reserve capacity is set. Suppliers of capacity are paid a price determined by the market, between zero and a fixed cap; consumers are obliged to buy capacity credits according to their expected peak demand. This mechanism is probably the most efficient in ensuring the right amount of reserve capacity is supplied, but it is the most difficult to implement. Currently, it exists in North America.
- *Reliability contracts*. It is a quantity-based mechanism. It is an evolution of the Capacity requirements and it establishes a real market for capacity reserve, parallel and similar to the energy-only market. Like the energy-only market, it is based on auctions. In addition, a strike price is set by the system operator. There is no experience about this mechanism. However, it is claimed it would give strong incentives to generation companies to provide reserve capacity. In the United Kingdom a similar mechanism has been approved in 2012 [57,58] and started in 2014, while in Italy it is under evaluation by Ministero dello Sviluppo Economico [59].

The last option consists in decommissioning generation capacity where it cannot be profitable anymore, or expanding the generation capacity where it is convenient, in Italy or abroad. An example of such decisions comes from Enel S.p.A., a generation company in Italy, which recently started decommissioning around 14 GW fossil-fuel fired power plants. 7.7 GW of these are combined cycles, corresponding to 6 power plants [60]. At the same time, the company invested in the repowering of power plants abroad, like in the case of SuGRes CCGT in Russia, operative from 2011.

2.3. Energy system costs of flexibility

The National Energy Strategy sets the decarbonisation objectives for the energy and the electricity sector up to 2050. The pathways to meet such objectives are identified in a welfare maximisation, or equivalently cost minimisation, perspective. Therefore, the technology and the generation mix envisaged for the short-, medium- and long-term is a least cost one. As seen through the description of the electricity market, the system operator can put in place market tools, taxations, incentives, to steer the technology and generation mix towards the identified optimal one. The system operator decides the amount of the investments in such tools based on the information he has about the costs of the technologies. If this information is wrong or incomplete, in the long term the investments may result misplaced, for two main reasons:

- The resulting energy technology and generation mix may be different from the one envisaged by the system operator and more costly, due to operation costs which were not taken into account when planning, e.g. those of flexibility. Indeed, the technologies which were assumed to be profitable may be not, due to the aforementioned missing money problem, and their operators may decide to decommission capacity. New capacity of other technologies will replace it, but this could lead to higher global costs of the system, therefore lower welfare.

- The market tools, taxations, incentives put in place by the system operator at his own cost for ensuring the decarbonisation objectives are met may end up incentivising technologies which are not the least cost option.

[47] and [61] provide an example of how the first cost source may affect the energy system planning in a cost minimisation perspective. The study focusses on the electricity generation fleet of the U.S. portion of the Western Interconnection, comprising of around 13 GW thermal units. In a 2020 scenario for this electricity system, with 33% penetration of wind and solar, the annual cycling costs of the thermal units are expected to range from 35 to 157 M$. In order to lower the costs of flexibility in the system, a scenario where 1.6 out of 6.3 GW CCGTs are retrofitted to increase their cycling capability is studied. The results show that such choice leads the retrofitted capacity to cycle more and the non-retrofitted capacity to switch back to base-load operation. This turns into 2 M$ net savings for the whole energy system. However, the new situation turns into positive revenues only for one third of the installed CCGTs, while the remaining two thirds are not profitable. If this is not taken into account, the companies will choose to shut-down and decommission those power plants and the system operator will have to replace them. The results show that the system operator cannot plan the energy system without accounting for the costs and revenues of flexible operation at a power plant level and for the reaction of the companies at the electricity market scale.

An additional evaluation in [47] gives a rough idea of the impact of the second cost source on the energy system. A scenario similar to the one just presented is formulated, but this time coal-fired units are retrofitted, instead of CCGTs. Though the two scenarios are not fully comparable, since some assumptions are different, it is shown that retrofitting coal units determines higher net economic benefit for the system than retrofitting CCGTs. Moreover, in this case, all the units increase their profitability in the new situation, as opposed to the former case. This indicates that incentivising investments in different technologies, in this case CCGTs rather than coal-fired units, may result in a lower social welfare.

2.3.1. Decisions at the energy system scale

The discussion about what decisions can be made at an energy system scale pertains much more to politics than to engineering. Nonetheless, some considerations are derived from the previous analyses. At the energy system scale, the system operators, or more generically the national Governments or international organisations, issue the directives aimed at reaching the decarbonisation objectives set by the Energy Roadmap 2050 and the National Energy Strategies. Through these directives, they can indirectly decide on the future technology and generation mix by directly acting on a number of regulatory tools. For the regulations to be effective, the energy scenarios which the directives are based on must rely on full information about the cost and benefits of each implemented measure. This means the system operators must include in the elaboration of the scenarios evaluations about how their decisions will impact the costs and the reactions of other actors at an electricity market scale and a power plant scale. They must predict how the utility of the other actors will be affected, in order to anticipate their moves and propose least-cost, best trade-off pathways to decarbonisation. In literature, it is debated that proposing decarbonisation solutions without accounting for these dynamics may even have caused international agreements to fail [62].

2.4. Interaction between the three scales

From the description of the impact of flexibility on the three scales, two main conclusions are drawn.

In the first place, the power plant, electricity market, energy system scales dynamically interact with each other, since what happens at one of them causes reactions in the others. Power plant operators, companies and system operators are not static entities. They are economic agents who aim at maximising some welfare function, subject to the current energy scenario and their predictions about the future one. Therefore, if flexibility is expected to bring costs, all the actors will make decisions to minimise these costs. These decisions will change the technology and generation mix with respect to the predicted one. More specifically, the power plant costs of flexibility and the retrofit decisions of the operators impact the competitiveness of the companies and the decisions of the players of the electricity market; these, in turn, impact the energy system costs and the long-term decisions of the policy makers; the long-term decisions of the policy makers impact back the costs and decisions at the power plant and electricity market scale. These interactions are summarised in Figure 18. The dynamic connections between the three scales must be brought to the surface. If they are not, the impact of flexibility may be understood only partially and it may be wrongly quantified.

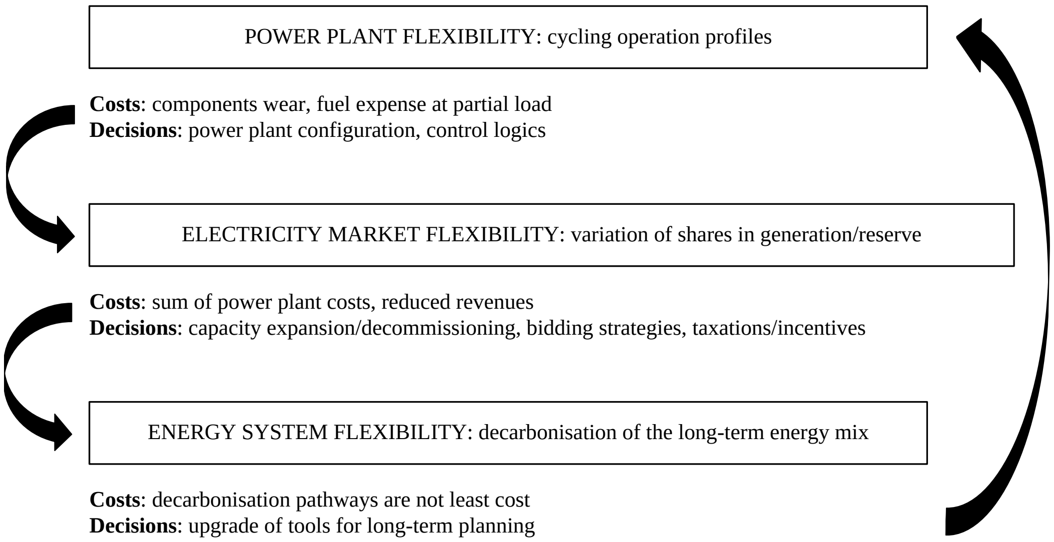

Figure 18. *Interactions between the power plant, electricity market and energy system scales.*

In the second place, the problem of flexibility is multi-dimensional. Besides Engineering, the evaluation of the costs and the decisions of the operators at a power plant scale involve Thermodynamics, the study of markets involves Decision Support methodologies, the energy system planning involves Macroeconomics. Elements of these disciplines must be integrated to have a full picture of the impact of flexibility on the three scales. This is the most complicated task in the research about flexibility, and the newest aspect.

To conclude, for the energy system planning to result in the desired future technology and generation mix, the Governments must consider the multi-scale, multi-dimensional and dynamic nature of flexibility. If they set up some policy, it will have both direct (expected) and indirect (possibly not expected) effects. The indirect effects may cause the energy mix to be different from the desired one, and the long-term policies to be ineffective. A first step to understand the complex nature of the problem of flexibility is to have a snapshot of its current impact on the system. This is obtained collecting the existing data about the costs of cycling (power plant scale), the current quantity and price market offers (electricity market scale), the overall burdens of flexibility (energy system scale). Such static picture may give an idea of the expected future impacts of flexibility, and it was given in Sections 2.1, 2.2 and 2.3. However, it is not enough for providing the Governments with a reliable prediction of the short- and long-term impact. Therefore, it turns out necessary to develop a dynamic representation of the impact of flexibility on the three scales. This may come from models, able to mathematically formulate the dynamic interactions.

3.
Predicting the future impact of flexibility: review of the existing models

As described in Chapter 2, a fair amount of data about the current costs of flexibility at the power plant, electricity market and energy system scale are available in literature. However, for the dynamic interactions between the three scales to be properly represented, these data should be fed into mathematical models able to make predictions. In this chapter, the existing power plant, electricity market and energy system models are reviewed, with respect to their capability of representing aspects related to flexibility. The discussion is preceded by the nomenclature specific to this chapter. The same will be done in Chapter 4, 5 and 6, since all of them present models referring to different disciplines, each involving a different use of symbols and indices.

Nomenclature

Symbols

c_i	operation cost
$\underline{c}_i$	investment cost for generation capacity
$curt$	curtailed load
d	demand
$\dot{E}x$	exergy
$E(\pi_i)$	expected profit of company i
F	transmission limit
G_i	generation capacity decision variable
$G_{i,min}, G_{i,max}$	minimum and maximum generation capacity for company i
$g_i(b,\vartheta_i,\vartheta_{-i}), g_i(b,\vartheta_i)$	dispatched generation capacity and generation capacity bid
H	Matrix of Power Transfer Distribution Factors
MCP	Market Clearing Price
N	number of companies
$P_{r,i}$	price of the reserve
$P_{c,j}$	price of the curtailed load
p	probability
$r_i(b,\vartheta_i,\vartheta_{-i}), r_i(b,\vartheta_i)$	dispatched reserve capacity and reserve bid
S	set of possible moves of one player
s	move of one player
t_b	duration of time block b
u	utility
y_D	exergy destruction ratio
η	efficiency
Θ	set of all types

Indices

b	time block

ϑ_i	type of company i
ϑ_{-i}	type of all companies but i

Subscripts

ex	exergy
i	generic player/company
k	component
l	transmission line
n	node
$prod$	product of a component
$resource$	resource of a component

3.1. Power plant models

3.1.1. State of the art modelling of power plants in flexible operation

Mathematical modelling may provide the analyst with functional relations between the operation profiles of the power plants and given performance parameters. In this way, the cost of flexible operation can be predicted also for power plants which have never experienced cycling duty. Moreover, the expected benefits deriving from retrofits of the power plants can be predicted. The major cost sources of flexible operation are the life consumption of the components due to cycling operation, the use of fuel and electricity during start-ups, the additional fuel consumption due to the decreased efficiency at partial loads.

As for the cycling costs, the models able to quantify them are divided into bottom-up and top-down models. Bottom-up models compute the life consumption of the components, then the cycling costs, as functions of the production profiles, by means of thermo-mechanic correlations for creep-fatigue interaction. An example of such models is [46], where the damage mechanisms in the components are endogenously represented through detailed models of the same components. Top-down models compute the cycling costs, starting from statistical analyses of big operational datasets from real power plants. This is done, for instance, in [33,44].

As far as the use of fuel and electricity during start-ups and the decreased efficiency at partial loads are concerned, they have much more to do with how the combined cycle works. Therefore, these costs can be quantified through models of the whole power plants, representing the thermodynamic cycle on one side and the control logics on the other side. A huge amount of such models have been presented in literature, but they can be broadly grouped into a few categories, according to the kind of thermodynamic analysis they perform and to their purpose.

The thermodynamic analysis can be based on First Law or Second Law of Thermodynamics quantities: the models based on the First Law of Thermodynamics allow global performance evaluations to be carried out, while the Second Law of Thermodynamics provides tools for comparing the performance of individual components and optimising networks of components.

The purpose is usually on- or off-design analysis/optimisation. The on-design models are stationary, since they analyse one operating condition at a time, the design one. The off-design models can be quasi-stationary or dynamic: quasi-stationary models discretise the variable operation profile into a number of stationary operating conditions, so they do not account for transients; dynamic models fully represent the dynamic behaviour of the system, including the transients. In the following, the existing power plant models based on the First Law and on the Second Law of Thermodynamics are reviewed. The discussion is introduced by Table 4, which gives an overview of the groups and anticipates the subdivision of the reviewed models among them.

	Purpose		
	On-design	Quasi-stationary off-design	Dynamic off-design
First Law of Td.	[63,64]	[65,66]	[67]
Second Law of Td.	[68–81]	[82–93]	[52]

Table 4. *Summary and grouping of the referenced thermodynamic models.*

3.1.1.1. Models based on the First Law of Thermodynamics

The models based on the First Law of Thermodynamics allow the analyst to compute all the energy and material flows in the power plant, the energy efficiency of the components and the net electric efficiency of the power plant, reciprocal of the specific fuel consumption. They are useful as accounting tools, when applied to existing power plants, or as tools for optimising the design and operation of new power plants. [63] provides an example of accounting tool, where the performance of a three-level pressure CCGT with hot reheat is assessed. More advanced models carry out multi-objective optimisation, taking into account environmental constraints, in line with the European directives. Bernier et al. [64] carry out the design optimisation of a CCGT with CO_2 capture, simultaneously minimising the LCOE and the Global Warming Potential in a Life Cycle perspective.

Relevant applications of first law models are found in the analysis and optimisation of the off-design performance. Much effort is lately put on minimising the fuel consumption at partial load operation: for CCGTs, for instance, fuel expenses account for around 75% of the LCOE already at full load and their share increases at lower loads. In [65], Judes et al. carry out the design optimisation of a cogeneration system, considering not a single operating point (design operation) but an operation profile with several points at partial load. A mixed-integer nonlinear program is developed to carry out the quasi-stationary design optimisation. The model is mixed-integer, since it allows for discrete decisions, such as the introduction of additional gas turbines, post-firing burners, de-superheaters. Papalexandri et al. [66] apply the same concept to a steam turbines network. However, they introduce a slightly different perspective. Though the model is still quasi-stationary, the time domain is split into periods and sub-periods. Across sub-periods, only the most flexible components are allowed to adjust their operation; across periods, also slower components. In this way, a much more realistic representation of the implementable control logics of a process is given, without complicating the analysis with dynamic terms. An example of a dynamic off-design optimisation model is found in the work of Garduno-Ramirez and Lee [67]. The authors develop a nonlinear program for the multi-objective optimisation of the load-tracking delay and the heat rate of an oil-fired power plant, by regulation of the pressure set point in the boiler.

First law models allow a picture of the global performance of the cycle to be quickly and easily obtained. However, they lack capability in pinpointing the sources of irreversibility inside the power plant and their causes. Therefore, they prevent predictions about the efficiencies of the individual components and the diagnosis of malfunctions in cases where streams at different temperature are present, typically in heat exchangers networks like those of the HRSG.

3.1.1.2. Models based on the Second Law of Thermodynamics

The Second Law of Thermodynamics provides information about the irreversibility of the heat exchange between sources at different temperature and the corresponding loss of capability to provide mechanical work. Though introducing some computational complexity, this concept turns useful in the analysis and optimisation of processes involving flows at different temperatures, like boilers or the HRSG in CCGTs. For this reason, power plant models based on the Second Law of Thermodynamics are useful to assess and predict the performance of individual components and to optimise heat exchanger networks.

Currently, most works based on the Second Law of Thermodynamics employ exergy as a metrics, since it comfortably condenses the First and Second Law and represents the capability of a system in a given thermodynamic state to produce mechanical work. The definitions of exergy and its possible uses in thermal plant analysis are discussed in Kotas [94], Bejan et al. [95], Moran and Shapiro [96], Querol [97] and others [98,99].

Equivalently to First Law methods, one application of exergy analysis is the design of steam or combined cycles. Woudstra et al. [68] assessed the effect of increasing the number of pressure levels on the exergy destruction in the HRSG of a combined cycle and the exergy loss at the stack. The results indicate that exergy is a proper numerical for computing the avoidable and unavoidable contribution of each component of the HRSG to the efficiency loss. However, no indication of potential for improvement is drawn from the analysis. Ersayin and Ozgener [69] perform a detailed exergy analysis of a CCGT, in order to draw indications for potential improvements. Their analysis relies on two performance indices: the exergy efficiency of each component k, defined as $\eta_{ex,k} = \dot{Ex}_{prod,k}/\dot{Ex}_{resource,k}$, and representing the ratio between the exergy of the useful product of the component and the resource introduced in the component to obtain it; the exergy destruction ratio, defined as $y_D = \dot{Ex}_{des,k}/\dot{Ex}_{fuel,tot}$, representing the ratio between the exergy destroyed by the component and that of the fuel to the whole power plant. The indications for improvements the authors draw from these indices are not supported by any feasibility evaluation, though. Moreover, the authors base their evaluations on operating data from a power plant, without considering that these might be affected by measurement errors or that some components may be malfunctioning. The same considerations can be made about an analogous work by Ameri et al. [70]. Ataei and Yoo [71] more successfully combine exergy and pinch-point analysis, for improving certain operational parameters, such as pressure and mass discharge of steam extractions. Petrakopoulou et al. [72] consider again the exergy destruction ratio of each component and distinguish between avoidable and unavoidable exergy destruction. This is based on a definition made in [100]. This approach marks a step forward into understating which components can be effectively improved and how much. From the work it results the compressor and the expander of the gas turbine can be improved. However, nothing is said about whether this is practical or not. More on-design models based on Second Law can be found in [73–77].

A widely employed formalisation of these analytical methods is provided by Thermoeconomics. This discipline combines thermodynamic and economic evaluations and provides the analyst with a smart methodology to compute the specific cost (in exergy or monetary units) of the product of each component in a system. The foundations of Thermoeconomics were laid through the Structural Theory of Thermoeconomics [101]. It provided a methodology for representing the productive structure of a system and the interconnections between resources and products of all the components. Standard applications of Thermoeconomics to the design of CCGTs are found in [78–81].

The most relevant applications of Thermoeconomics relate to the off-design analysis and optimisation of power plants. Like in the case of First Law models, most effort is put in developing quasi-stationary off-design models where the design features of the power plants are optimised based on the expected operation profiles. One example of such studies was performed by Rovira et al. [82], who minimise the generation cost of different CCGT configurations over different flexible operation scenarios. The optimisation is carried out modifying design parameters such as pinch-points, pressures and temperatures in the HRSG. Piacentino and Cardona develop a complex algorithm for the joint optimisation of the design and operation of a power plant [83]. However, it can be applied to simple layouts, due to its symbolic and analytic derivative nature. Similar thermoeconomic optimisation techniques are developed in [84,85] and applied to systems other than power plants, but always subject to highly flexible operation. All of these models perform the quasi-stationary optimisation of the design of thermodynamic cycles, taking into account expected operation profiles. Therefore, they represent evaluations made at a step before the power plant starts to operate. The degrees of freedom in the optimisation are more than those the operators actually have when the power plant is already operating.

Among the off-design thermoeconomic methodologies there is Thermoeconomic Diagnosis. This discipline may be of stronger industrial interest, since it is dedicated to identifying, locating and quantifying the inefficiencies originating from malfunctions of components within the system [86,93]. Several aspects of this method have been discussed and formalised along the years [102–107]. Verda et al. [93,108] focussed on separating the direct effect of a malfunction on the power plant performance (intrinsic malfunction) from the indirect effects due to induced malfunctions on other components and the action of the control systems. They also proposed a methodology for evaluating the expected energy savings obtained removing each malfunction. To meet these purposes, symbolic, derivative algorithms were developed, and applied to case studies where the systems are modelled as sets of balance equations. Many applications of Thermoeconomic Diagnosis are found in literature [86–92]. Again, none of these applications is dynamic.

The application of the Second Law of Thermodynamics to the dynamic off-design modelling of power plants is very limited, because the additional computational effort does not add any useful information to the performance analysis of the components, with respect to quasi-stationary off-design models. In [52], a dynamic analysis of the HRSG of a combined cycle is performed, with the aim of computing the ramping rates of given start-up procedures. The thermodynamic properties of the inlet and outlet flows of all the components are computed through thermo-fluid-dynamic correlations, and the exergy is computed consequently.

3.1.2. Needs in power plant modelling

It is necessary to understand which models, among those presented in the previous section, allow the best quantification of the impact of flexible operation on the power plants and of the benefits of asset modifications.

By definition, assessing the impact of flexible operation requires off-design models. On-design models are, therefore, of no interest for the present study. Many models were found in literature, which carry out performance analyses and optimisation of power plants in off-design operation. Few of them are dynamic, while most are quasi-stationary and optimise the operation parameters considering production profiles discrete in the time domain. Dynamic behaviours such as the thermal transients of the machinery cannot be neglected, when the aim of the study is to assess the response time of the CCGT to load variations. Specifically, dynamic models are crucial in the design and the transient performance assessment of the HRSG. However, quasi-stationary models are enough when carrying out averaged evaluations over the CCGT, like the quantification of the yearly costs due to specific production profiles. Therefore, this last class of models is taken into account for the present research, and their capability with respect to the study of flexibility is evaluated.

The choice between models base on the First and Second Law of Thermodynamics for the impact assessment of flexibility depends on what information is needed. In light of the analysis of Chapter 2, this question can be answered.

- At the *power plant scale*, the operators need to know how the power plant responds to the new operating profiles. Specifically, this means: identifying which components undergo faster performance degradation in cycling operation and quantifying the dependence of the degradation on the operation profiles; predicting the performance decay in a number of off-design operation scenarios, with different generation profiles and load control logics; predicting the thermodynamic benefits of retrofitting the power plant or modifying some control logics. When evaluations on the components are required, Second Law models are needed, while for predictions of the global performance, First Law models are enough. To carry out all these kinds of analyses, models implemented in simulation environments are preferred: the simulations are faster and the results can be promptly interpreted graphically; this abates possible barriers for an industrial use of the models.

- At the *electricity market scale*, the competitiveness of a power plant in the new operating regime depends on its price bids in the auctioning sessions of MGP. The price bids depend, in turn, on the variable costs of the power plant. In this case, determining the overall impact of a flexible operation profile on the cost of the generated electricity is sufficient. The impact is computed in terms of increased consumption of fuel and average ramping cost. These are global accounting quantities. Therefore, First Law models are enough to meet this purpose.

In light of these considerations, both First and Second Law quantities are necessary, to cover all the needs of the power plant operators and the companies. Among the analysed first law models, the one closest to meet such needs is [66]. However, it is conceived for design optimisation, therefore it misses some fundamental features: an existing power plant is a huge network of components with given characteristic curves and the feasible operation points are dictated by the matching between all the components. Therefore, the study of new configurations is much more constrained than it is for plants to be designed. An off-design model of a power plant for studying operational improvements in flexibility should be based on the rationale expressed in [66], but featuring in detail all the control logics. Among the Second Law models, [82] is applicable to the needs of the present study, but it suffers from the same weaknesses as [66]. On the contrary, adapting the model in [83] to a power plant would be ideal. The algorithm could be implemented in the control software of the power plant for the optimisation of the operation strategy. However, the algorithm is solvable for very simple layouts, since it relies on analytical and derivable relations. Extending it to a very complex system like an actual CCGT would require an unreasonable effort, for the purpose of the present research. Models based on Thermoeconomic Diagnosis particularly fit the need for the performance prediction of individual components in different off-design conditions and the analysis of malfunctions due to cycling operation profiles. However, they are less suitable for predicting the benefits of asset modifications, changes in the configuration, or new control logics, because these must be first turned into symbolic and derivative expressions. This is an exercise of thermodynamic modelling, normally carried out by academicians, but not always by power plant operators. Therefore, it could rise barriers between the scientific research and the industrial practice, and prevent the thermodynamic models from becoming a tool directly employed by power plant operators for performance predictions and retrofit decisions. To conclude, it emerges that a number of quasi-stationary off-design models based on the Second Law of Thermodynamics may serve the needs of power plant operators and generation companies, but their relevance is measured also on their practicality and ease of use. One step in this direction may be setting up thermodynamic models based on simulation environments and graphical representations similar to those utilised in the control rooms of the power plants, to be with time integrated with well-developed analytic tools in literature.

3.1.3. Tools for power plant modelling

Many of the power plant models reviewed in Section 3.1.1 are set up with the aid of software, where the equations representing the thermodynamic behaviour of the components are already built in through component libraries. On one hand, employing modelling software and interfaces may limit the degrees of freedom in the representation of the system, on the other hand it may allow the user to quickly add, remove or modify components in the power plant. In this way, modelling software may simplify the elaboration of production scenarios where the control logics of the power plant are parametrised, or a number of possible retrofits are alternatively implemented. Diverse software is employed in process and systems engineering. The capability of the main commercial software in modelling power plants and assessing the impact of flexibility was compared during dedicated activities of this research.

3.1.3.1. Aspen Hysys®

Most employed in the process engineering is Aspen Hysys® [109]. It allows lumped parameters models of industrial plants to be designed, by juxtaposition and connection of components chosen from built in libraries. It proved not to add significant value to a model set up manually by writing balance and constraint equations for the individual components. The elaboration of production scenarios with new control logics or component retrofits is not straightforward and this prevents an easy and fast analysis of the impact of flexibility. Indeed, while many components utilised in the chemical industry are built in and modelled in detail, few components of the power industry are present in the libraries. In order for a whole CCGT to be properly modelled, most components and control logics must be user-defined and created from scratch. The only peculiar capability of Aspen Hysys® is the characterisation of the thermodynamic properties of the gas mixtures, since several Equations of State are embedded and can be chosen by the user. However, this possibility is of minor importance in the range of gas temperatures and pressures typical of CCGTs.

3.1.3.2. Flownex®

Different were the conclusions drawn by the use of Flownex® simulation environment [110]. This is a one-dimensional computational fluid dynamics software, usually employed to simulate thermal-fluid networks, such as air distribution circuits, water piping, power plants, etc. The model solves the mass, momentum and energy equations to obtain the mass flow, temperature and pressure distribution along the network. The thermo-fluid-dynamic correlations employed by one-dimensional models to characterise the properties of the fluids are unfit to model the components in detail, especially when 3D phenomena like turbulence are involved. However, when the components have already been designed, these models allow accurate information about the dynamic behaviour of the whole system to be drawn with reasonable computational time and effort.

In order to prove the capability of Flownex® simulation environment in the modelling power plants in flexible operation, a dual pressure HRSG was modelled and validated with data from literature [111]. The sketch of the system is shown in Figure 19.

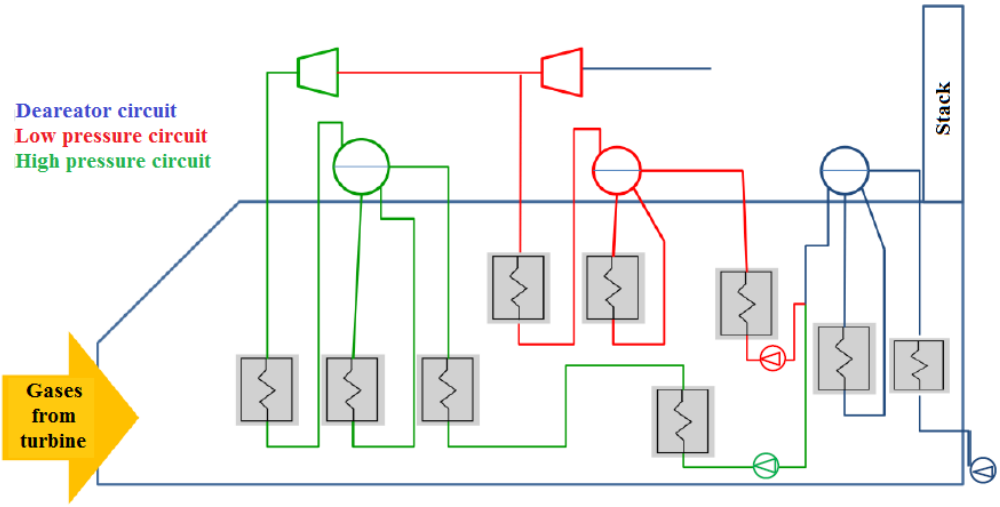

Figure 19. *Scheme of the HRSG modelled in Flownex®.*

Since the gas turbine has a much faster response than the HRSG to load variations, for this study it was assumed to undergo instant transients and it was modelled as a boundary condition on the mass flow rate and temperature of the gases. Both the global and component outputs were computed. The most relevant global outputs are the power output and the power plant efficiency. In Figure 20, the power output of the turbogas, the steam cycle and the whole power plant as functions of time, during an unloading ramp, are shown. In Figure 21, the trend of the efficiency for a loading ramp is compared to the one achieved with a quasi-stationary model.

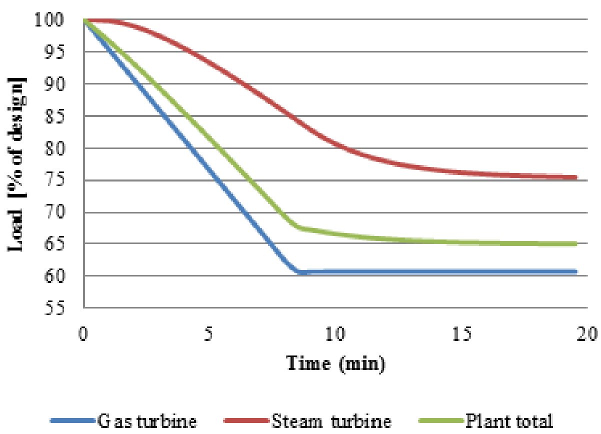

Figure 20. *Dynamic load profiles during an unloading ramp.*

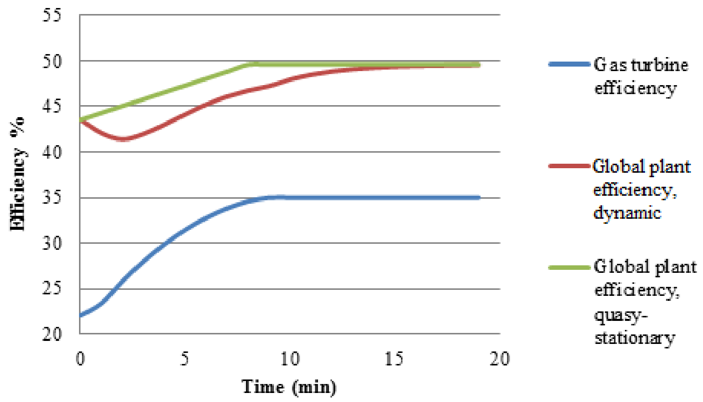

Figure 21. *Comparison between a dynamic and a quasi-stationary model during a load ramp.*

Computing in detail the power output and the efficiency of the HRSG during ramps allows the operator to predict how fast the power plant is able to respond to load variations and at what cost. The fuel expense during the ramp can be obtained by integrating the reciprocal of the efficiency over the time of the ramp. By the difference between the green and the red curves in Figure 21 it can be inferred that a dynamic model computes higher fuel consumption during the ramp, with respect to a quasi-stationary model. Multiplied by countless ramps in a year, this might result in a significant fuel cost. On the other side, the load profile of each component can be translated into life consumption by creep-fatigue interaction models, then into cycling costs. The dynamic model also allows the operator to predict how much the ramping capability of the power plant can be improved through interventions on the components or on the control logics of the HRSG.

In spite of these advantages, the use of this simulation environment presented some drawbacks for the application to CCGTs. First of all, the higher computational time and memory required by a 1D model with respect to lumped parameters models reduces the number of simulations that can be carried out, therefore the number of scenarios that can be analysed. Moreover, the library of Flownex® does not include gas turbines. In order for the CCGT to be fully modelled, these should be added as user-defined components. Modelling the gas turbine from scratch may be far too demanding, when off-design evaluations are required, because the compressor and turbine maps, the performance of the combustor and the control logics of the gas turbine (CO and NO_x emissions, combustion temperature, TOT and TIT, gas by-pass lines) must be modelled.

These considerations add to practicality considerations. The reasons why off-design thermodynamic power plant models are needed were widely discussed in Chapter 2: the impact of flexibility on the power plant costs and the benefits deriving from possible retrofits or updates of the control logics need to be assessed. Such costs and benefits are numbers to be communicated to the market divisions of the companies in order for them to formulate new market strategies. Therefore, they should come from internal evaluations of the individual power plant operators. Two approaches can be followed to compute these quantities:

- To set up dynamic models like the one abovementioned. These models allow detailed predictions of the ramping rates and costs to be made, as functions of different power plant assets, but they are not handy for the power plant operators to be employed. They are slow, little integrated into interfaces, hardly implementable in the control software of the power plants, due to the number and complexity of the thermodynamic correlations they employ. Therefore, the operators would hardly be empowered the know-how deriving from such models and they would need to subcontract every retrofit or maintenance study, from the most complex to the simplest ones, with higher decision times and costs. This acts as a barrier for power plant operators against the study of flexible operation solutions for CCGTs.

- To set up quasi-stationary models, which serve as prediction tools for the costs and benefits of flexible operation, but are handy enough for the operators to quickly draw indications from them. In this case, dynamic indices like the ramping rates and costs would be drawn from literature (or from studies subcontracted to specialised companies), while other indices related to the off-design quasi-stationary operation would be computed internally. Such tools can be embedded in the control software of the power plants. The operators would be able to compute the average fuel costs of different operation profiles, predict the benefit of all the possible retrofits or control strategies not related to the power plant transients, plan new maintenance schedules of the components.

Given the impact of flexibility at a power plant level is much related to the understanding the operators have about its costs and to their decisions, in this research the second approach was followed. Tools allowing this kind of evaluations were searched for.

3.1.3.3. Thermoflex

Thermoflex is a flexible simulation environment for the design and off-design modelling of power plants. It allows for quasi-stationary, lumped parameters models to be simulated. It is employed by numerous industrial users [112] and in the scientific literature [113–116]. The built-in library features a wide number of components employed in different kinds of power plants and presents for each component a set of models actually employed in the industry. For instance, around a hundred models of industrial gas turbines are featured in the library, provided with the design characteristics and the maps as communicated by the producers. The interface is modular and the representation of the system is alike the one found in the control room of the power plants: the individual components can be viewed and their design interacted by selecting them from the main view of the power plant. In Figure 22 and Figure 23 a combined cycle as viewed on the graphical interface of the control room of the power plant and on the interface of Thermoflex is represented, respectively.

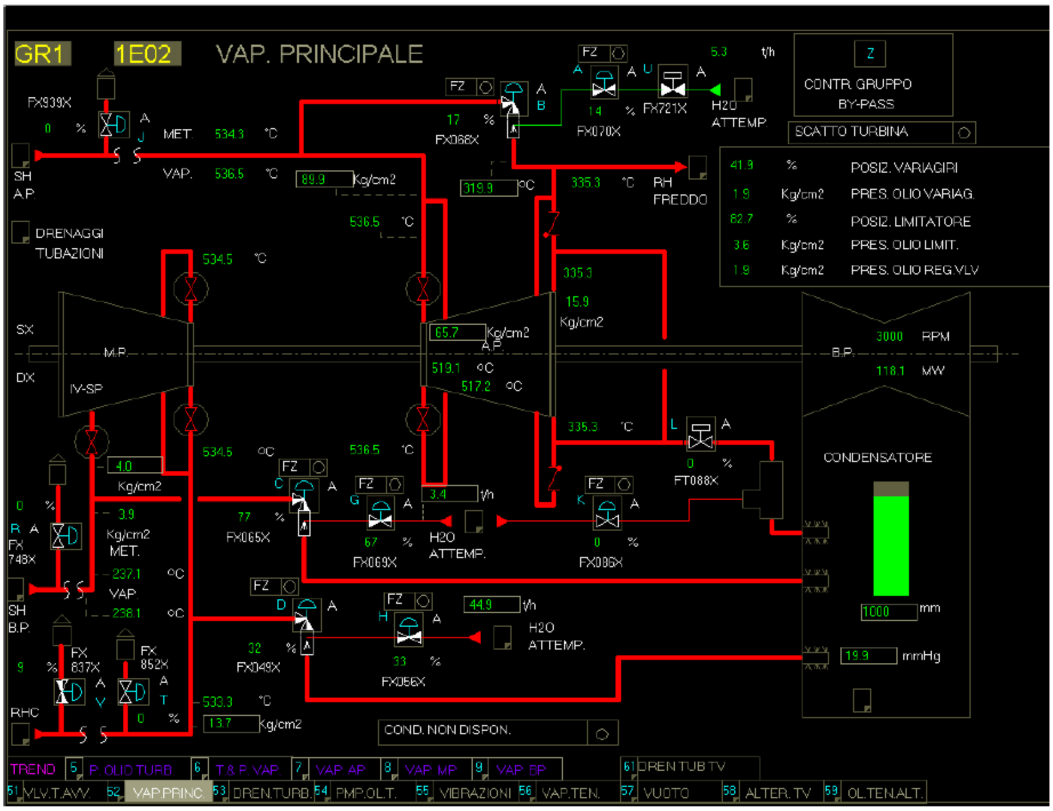

Figure 22. *View of a CCGT from the interface of the online monitoring system.*

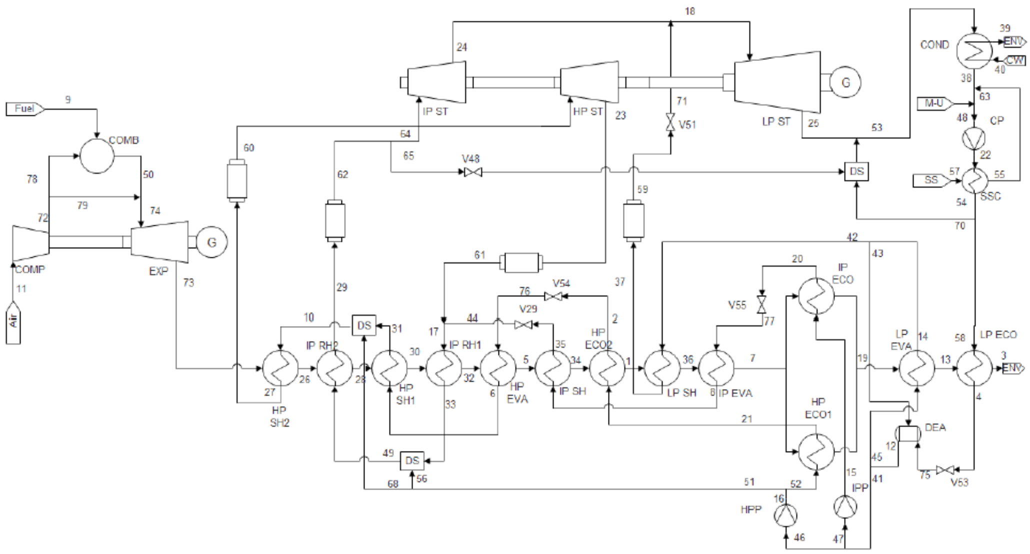

Figure 23. *View of a CCGT from the interface of Thermoflex simulation environment.*

The affinity between the online system of the power plant and the simulation environment of Thermoflex contributes to make it an appropriate tool for operators, for analyses and predictions about the off-design performance of the power plant.

Thermoflex allows the analyst to model a power plant through consecutive steps:

- *Thermodynamic design mode*. The scheme of the system and the boundary conditions are given as fixed inputs and the program computes preliminary heat and mass balances and designs the overall geometric characteristics of the components, without engineering detail.
- *Engineering design mode*. The analyst is allowed to define more detailed design parameters of each component (e.g. number of tubes and configuration of the heat exchangers, overall heat transfer coefficient, etc.) and the software computes again the heat and mass balance. This phase corresponds to the real design phase in the project of power plants.
- *Off-design mode*. The design characteristics and the defined geometry of the components are fixed in this case, while the boundary conditions and the control logics of the system can be changed, so as to compute its off-design performance, for analysis, prediction, diagnosis purposes.

The inputs and outputs of these three steps are summarised in Table 5.

Mode	**Inputs**	**Outputs**
Thermodynamic design	Scheme of the power plant; boundary conditions (e.g. T, P, mass flow rate of flows into the system).	Global geometric characteristics of the components; thermodynamic properties of all the flows; performance of the system and of the components.
Engineering design	Detailed design parameters of components (e.g. number and configuration of tubes).	Revised thermodynamic properties of all the flows; revised performance of the system and of the components.
Off-design	Boundary conditions; control logics of the components and of the power plant.	Thermodynamic properties of all the flows for every off-design condition; performance of the system and of the components for every off-design condition.

Table 5. *Inputs and outputs to the thermodynamic, engineering, off-design modes of Thermoflex.*

The off-design mode allows additional evaluations to be carried out, with respect to those the power plant operators are able to make. Usually, the operators or, generically, the companies, perform off-design evaluations during the design phase of a power plant: the expected performance under different plausible operation scenarios and different configurations is computed, in order to choose the configuration which is optimal for the highest number of scenarios. The characteristics and parameters of the components are designed consequent to such evaluations. On the contrary, when the power plant is already operating, the online control software allows only the actual performance of the power plant to be measured, since it just collects operation data. It has no thermodynamic model of the components embedded, therefore it is not able to predict how the performance may vary under different operating conditions or control logics, or after retrofits of the components. The operators can only make qualitative evaluations about these aspects.

The possibility of running off-design simulations in Thermoflex punctually responds to these needs. In the first place, the off-design mode gives the possibility of computing the performance of

the components and the power plant under different scenarios, for design optimisation. This is equivalent to what the operators already do.
Secondly, and more importantly, it allows predictions of the performance after retrofits or modifications of the control logics for existing power plants. The analysis and optimisation of existing power plants is conceptually different from that of power plants to be designed: the number of decision variables is limited, and they must be chosen only among those parameters which can be changed during operation.
Based on these considerations, Thermoflex was chosen as the most appropriate tool for modelling CCGTs under flexibility and computing the impact of flexibility at the power plant scale, among those analysed. It represents the best compromise between the required characteristics of modularity, detailed component design, affinity and possibility of integration with the software of the power plant control rooms, capability of off-design modelling of the system and its control logics, velocity of simulation also for multiple scenarios.

3.2. Electricity market models

3.2.1. State of the art modelling of electricity markets

The thermodynamic models of power plants provide numerical outputs about the costs of flexible operation and the benefits deriving from feasible retrofits or modifications of the control logics in the already existing power plants. As discussed in Chapter 2, when summed up over all the generators, these costs and benefits impact the market share of the whole company and influence its strategies on the electricity market. The present impact of flexibility can be observed through market data, while the impact in the near- to long-term future needs to be predicted. Mathematical models can serve this purpose: the costs and benefits at a power plant scale and the various market constraints can be fed as inputs, and the reactions of the companies and of the system operator will be provided as outputs. The electricity market is an economic environment where various players make decisions with the aim of maximising some utility: the companies maximise the expected profit, the system operator maximises the social welfare. Therefore, the best mathematical models to represent the dynamics of the market are optimisation models. The models in the domain of the optimisation theory can be grouped within a few frameworks, depending on the number of decision makers and objectives involved, and on the degree of information the decision makers have. There might be one or more decision makers, each having one or more objectives. Every decision maker has some information about the possible decisions and the related outcomes of the others. If this information is full and known by everyone with certainty (i.e., no decision maker has private information), the problem is said to be of complete information. If some decision makers have some private information or, similarly, if some player has uncertain information about the others, then the problem is of incomplete information.
The grouping of the optimisation methodologies is sketched in Figure 24 [117]. Eight points can be identified, each corresponding to a decision making problem with particular characteristics. They are briefly described in the following.

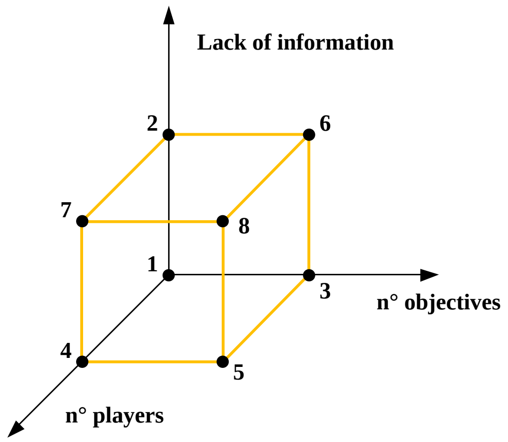

Figure 24. *Possible situations in decision making. Source:* [117].

1. The optimisation methods involving one player, one objective and complete information pertain to the paradigms of traditional *Mathematical Programming* (linear, nonlinear, mixed-integer programming, etc.).
2. The methods involving one player and one objective, but incomplete information, fall under the category of *Risk Analysis*.
3. The methods involving one player, complete information, but more than one objective are in the domain of *Multi-objective* or *Multi-criteria* decision making.
4. When more decision makers deal with one objective, under complete information, the optimisation methods pertain to the *Social Choice theory*.

5, 6, 7, 8. The other situations, involving more than one decision maker and objective, and possibly involving incomplete information, fall under the framework of *Game Theory*.

As previously described, the mathematical modelling of the reactions and strategies of the companies and the system operator in the electricity market involve several decision makers, different objectives and incomplete information. For this reason, Game Theory may be considered the most appropriate paradigm for this kind of modelling. In Subsection 3.2.1.1, a definition of Game Theory and an explanation of its relevance to the modelling of the electricity markets are provided; in Subsection 3.2.1.2, a review of the existing models of the electricity markets based on Game Theory is made.

3.2.1.1. Game Theory and its relevance to the modelling of electricity markets

Game Theory was first conceived in 1944 in the work of von Neumann and Morgenstern [118] and formalised in some of its aspects by Nash afterwards [119]. It is a framework which helps mathematically model the strategic interactions between self-interested agents, called players, making decisions in a specific context. This context is called game, since every participant must obey some rules when deciding. Football or chess matches, discussions among friends for the planning of the night, as well as auctioning sessions, elections, negotiations for international agreements may be regarded as games [62,120–129]. Each decision of a player turns into an action, a move in the game. Every player makes moves aimed at maximising its own payoff (i.e. its utility). The most important assumption underlying this concept is that the players are rational. This means that each player is considered as a perfect calculator and flawless follower of its best strategy, not influenced by any feeling or irrational behaviour. Now, in order to obtain the best outcome, the rational player must take into account how the other players will react to its decisions. This is the core concept of Game Theory: in general, an economic agent never makes decisions in isolation; on the contrary its decisions affect and are affected by those of the other agents. Not considering these strategic interactions between agents may lead the agents themselves or the planners above them to wrongly predict the outcomes of a game. The players may implement their actions collectively, through agreements, or individually. The study of situations in which there can be agreements or not pertains to two completely different branches of Game Theory: Cooperative and Non-Cooperative. In Cooperative Game Theory, joint-action agreements are enforceable, in Non-Cooperative Game Theory they are not [120]. In the study of auctioning markets, both the Cooperative and Non-Cooperative approaches are employed. The Non-Cooperative approach is the most employed for the electricity markets, though, given the high number of players and the complexity of the market structure. The most known didactic example in Non-Cooperative Game Theory is the Prisoner's Dilemma. In this game, two robbers are caught and separately interrogated by the police commissioner. He wants the robbers to accuse each other in order to gather evidence that both were involved in the robbery. Therefore, he offers them that:

- If A testifies against B and B remains silent, A is set free and B serves 3 years in prison (and vice versa).
- If A and B testify against each other, they both serve 2 years in prison.
- If A and B remain silent, they both serve 1 year in prison.

If A and B were allowed to talk to each other, they would decide to remain silent, so that they both serve 1 year in prison, and no one risks the maximum punishment. This would be the so called 'welfare optimum' solution. The commissioner knows this well, so he does not allow them to communicate. In this case, remaining silent is too risky for B, since if A testifies against him he will get the worst payoff. The same is said for A. Therefore, if they cannot communicate to each other, the two robbers end up testifying against each other. This result is called Nash Equilibrium, defined as the outcome from which no player is interested to deviate. It is shown, in a matrix form, in Figure 25.

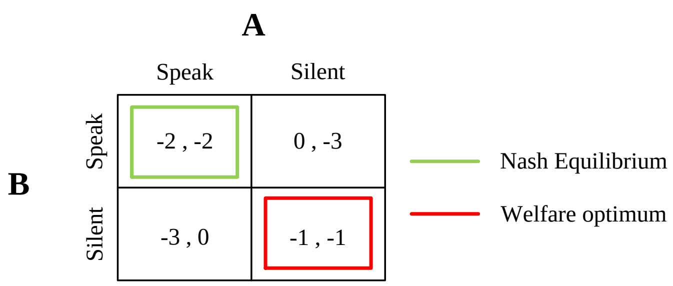

Figure 25. *Matrix representation of the Prisoner's Dilemma.*

The interest of this result is that, because of fear of the other, A and B make the choice which does not guarantee the best outcome to any of them, nor the welfare optimum. The equilibrium of a situation where different agents interact may deviate from the mathematically optimal solution (i.e. the welfare optimum solution), due to the expectations of each agent about the others. This concept may turn useful also in the study of electricity markets: the computation of the generation dispatch carried out by the system operator is usually based on the concept of welfare optimisation. However, the individual decisions of the companies in the market, based on their private interest, could distort the optimal dispatch and divert it from the welfare optimum.

In order to understand how this can happen, it is necessary to put the concept of Nash Equilibrium into mathematical terms. In a game with N players, a Nash Equilibrium is a set of moves of the players, such that, for all the players:

$$\forall\ i = 1,...,N\ \&\ \forall\ s_i \in S_i \qquad u_i\left(s_i^*, s_{-i}^*\right) \geq u_i\left(s_i, s_{-i}^*\right) \tag{3.1}$$

Where i identifies one player, $-i$ identifies all the players but i, s is a move, S is the set of all possible moves, u_i is the utility of player i and the superscript $*$ identifies a Best Response move. A Best Response move of one player is the one that awards it the highest payoff against all possible moves of the other players. Then, in few words, a Nash Equilibrium is a situation where all the players have played Best Responses against the others and no one is interested in deviating from the outcome. If the players were playing in isolation, they could probably obtain better outcomes, but not if they all play. This concept is still valid when the players play under incomplete information, as happens in the electricity market, but some correction must be made to the mathematical formulation. One of the ways to solve games of incomplete information is to employ the notion of Bayesian Equilibrium. As opposed to the Nash Equilibrium, Bayesian Equilibrium involves probability distributions and the concept of 'type'. Type ϑ_i identifies a realisation of the uncertain variable(s) for player i. A given set of actions of all the players is a Bayesian Equilibrium if:

$$\forall\ i = 1,...,N \qquad s_i \in \underset{s_i^{'} \in S_i^{\vartheta}}{\operatorname{argmax}} \sum_{\vartheta_i} \sum_{\vartheta_{-i}} p\left(\vartheta_i, \vartheta_{-i}\right) u_i\left(s_i^{'}\left(\vartheta_i\right), s_{-i}\left(\vartheta_{-i}\right), \left(\vartheta_i, \vartheta_{-i}\right)\right) \tag{3.2}$$

where $p(\vartheta_i, \vartheta_{-i})$ is the probability that the type of player i is ϑ_i when the types of the opponents are ϑ_{-i}. This formulation is equivalent to the Nash Equilibrium, apart from the additional term $p(\vartheta_i, \vartheta_{-i})$, where all the uncertainty is condensed. If the utility functions are the profit functions of the generation companies and constraints related to market operation are added, the formulation in (3.2) turns into a market optimisation problem. One such problem is shown in (3.3) to (3.11). It refers to a formulation in [130], here slightly simplified for convenience. In this formulation, $E(\pi_i)$ is the expected profit of company i, MCP is the market price of the electricity, $g(b, \vartheta_i, \vartheta_{-i})$ and $g(b, \vartheta_i)$ are the generation dispatch decision and the generation bid, respectively, c is the generation cost, P_r is the remuneration price for the reserve capacity, $r(b, \vartheta_i, \vartheta_{-i})$ and $r(b, \vartheta_i)$ are the dispatched and the bid reserve capacity, respectively, G is the global dispatchable capacity and $curt$ is the curtailed load. For the complete nomenclature, the reader may refer to the dedicated section at the beginning of this chapter.

$$\max\ E\left(\pi_i\right) = \sum_{\vartheta_i \in \Theta_i} \sum_{\vartheta_{-i} \in \Theta_{-i}} \left\{ \begin{bmatrix} \sum_{b=1}^{B} Dt_b \begin{pmatrix} MCP\left(b, \vartheta_i, \vartheta_{-i}\right) \cdot g_i\left(b, \vartheta_i, \vartheta_{-i}\right) - c_i\left(\vartheta_i\right) \cdot g_i\left(b, \vartheta_i, \vartheta_{-i}\right) \\ + P_{r,i} \cdot r_i\left(b, \vartheta_i, \vartheta_{-i}\right) \end{pmatrix} \\ -\underline{c}_i \cdot G_i\left(\vartheta_i\right) \end{bmatrix} \\ \cdot p\left(\vartheta_{-i} \middle| \vartheta_i\right) \cdot p\left(\vartheta_i\right) \right\} \tag{3.3}$$

$$\text{s.t.} \qquad G_{i,min}\left(\vartheta_i\right) \leq G_i\left(\vartheta_i\right) \leq G_{i,max}\left(\vartheta_i\right) \tag{3.4}$$

$$G_i\left(\vartheta_i\right) = g_i\left(b, \vartheta_i\right) + r_i\left(b, \vartheta_i\right) \tag{3.5}$$

$$\min \left[\sum_{i=1}^{K} \left(g_i\left(b, \vartheta_i, \vartheta_{-i}\right) \cdot c_i\left(\vartheta_i\right) + r_i\left(b, \vartheta_i, \vartheta_{-i}\right) \cdot P_{r,i}\left(\vartheta_i\right) \right) + \sum_{j=1}^{ND} curt_j\left(b, \vartheta_i, \vartheta_{-i}\right) \cdot P_{C,j} \right] \tag{3.6}$$

$$\text{s.t.} \qquad \sum_{i=1}^{K} g_i\left(b, \vartheta_i, \vartheta_{-i}\right) + \sum_{j=1}^{ND} curt_j\left(b, \vartheta_i, \vartheta_{-i}\right) = d\left(b\right) \tag{3.7}$$

$$-F_l \leq \sum_n H_{ln}\left(g_n\left(b, \vartheta_i, \vartheta_{-i}\right) + curt_n\left(b, \vartheta_i, \vartheta_{-i}\right) - d_n\left(b, \vartheta_i, \vartheta_{-i}\right)\right) \leq F_l \tag{3.8}$$

$$0 \le \mathrm{curt}_j\left(b, \vartheta_i, \vartheta_{-i}\right) \le d_j\left(b\right) \tag{3.9}$$

$$0 \le g_i\left(b, \vartheta_i, \vartheta_{-i}\right) \le g_i\left(b, \vartheta_i\right) + r_i\left(b, \vartheta_i, \vartheta_{-i}\right) \tag{3.10}$$

$$0 \le r_i\left(b, \vartheta_i, \vartheta_{-i}\right) \le r_i\left(b, \vartheta_i\right) \tag{3.11}$$

This is a two-level optimisation problem, where in the lower level problem ((3.6) to (3.11)) the electricity market operator decides how much generation and reserve will be provided by every company, while in the upper level problem ((3.3) to (3.6)) company i decides its quantity bids for the generation and the reserve, in order to maximise its expected profit. Notice that (3.6) is indicated as part of both the upper and the lower level problem: indeed, it is a constraint for the upper level problem, and the optimisation function for the lower level problem.

Looking more into the structure of this model, (3.3) is the objective function of the upper level problem, and it is equivalent to (3.2). The utility function u is, in this case, the expected profit of generation company i. It consists in the algebraic summation of the revenues from the sale of electricity and of reserve, and the generation and investment costs. Since the game is Bayesian, the profit is multiplied by the probability distribution of the types. (3.4) imposes lower and upper limits to the total installed capacity of the generation company, while (3.5) states that the sum of the generation and reserve bids of the company must equal to the available capacity of the generator. (3.6) is the objective function of the lower level problem, corresponding to the global cost minimisation by the market operator. (3.7) defines the matching between demand and supply, (3.8) sets the limit for the flows over the transmission lines, (3.9) constrains the possibility of load shedding, (3.10) and (3.11) constrain the maximum generation and reserve that can be supplied by every generation company.

In this example, the specific contribution of Game Theory to the modelling of the electricity market can be highlighted. Specifically, in this case, it lies within the upper level optimisation problem. The lower level problem represents the traditional market clearing problem solved every day by system operators. It involves one objective, the welfare maximisation, and one player, the system operator itself. The upper level problem introduces multiple players and multiple objectives, making the formulation exactly equivalent to the one of (3.1) or (3.2). Therefore, recalling Figure 24, the two-level problem falls under the domain of Game Theory. The optimal solution is a Nash Equilibrium point and it is found by solving the two-level problem for all the players, and for all their possible moves. This does not introduce any new solution concept: well-known solution algorithms, such as co-evolutionary algorithms, iterative procedures, Simulated Annealing can be employed to solve the program. In some cases, the problem can be reduced even to a standard nonlinear or linear program, thanks to the duality theory. Game Theory must not be seen as a set of solution algorithms, but as a framework for turning real-life situations of interaction among several players with possibly conflicting objectives into solvable mathematical structures. Without a Game Theory perspective, the electricity market would have been modelled as in the lower level problem of the example described above, neglecting the interactions among the players.

A number of Game Theory models of deregulated electricity markets have been developed in the last twenty years, not necessarily based on the two-level setting. In the following subsection, a review of the most significant ones is made. Their features are looked into, in order to sort out those elements which allow the dynamics of the Italian electricity market and of flexible operation to be represented.

3.2.1.2. Game Theory models of electricity markets

A relevant overview of the existing models is given by one literature survey carried out in 2000 [131]. Though not recent, it categorises well most of the modelling approaches in literature. It focusses on the strategies employed by the companies to maximise their expected profits on the electricity market. When the market is not perfectly competitive, the companies have an incentive to bid higher prices than their marginal costs. This behaviour is called strategic bidding. There are three ways companies can optimise their bidding strategies, face the market outcomes and the behaviours of the competitors:

- Making statistical estimations of the MCP in the next trading period and bid just below that price.
- Estimating the bidding behaviour of the competitors by means of probability distributions and choosing a more competitive one.
- Estimating the market outcomes as functions of their decisions and the reactions of the competitors by means of Game Theory models. This approach makes use of Supply Function Equilibrium (SFE), Stackelberg, Bertrand or Cournot models.

The third family of methodologies provides the best picture of the strategic interactions among the players in the market and of their implications on the market outcomes. The reliability of such models depends on the number and type of assumptions they are built on.

In SFE models, the bidding strategy of each company is represented by a curve, usually quadratic: it features the bidding price as a function of the generation. Therefore, the choice of the optimal bidding strategy lies in the choice of the coefficients of the curve. This approach results in nonlinear programming models. When incomplete information is considered, i.e. uncertainty over the generation costs, the coefficients of the bidding strategy curves become uncertain as well, and the program becomes stochastic. Most SFE models are of this kind [132–134]. All of these models may give a rather good approximation of how the price bid of the company depends on the generation level. However, in real markets the price bid may also be decoupled from the generation level in some cases.

Many models are based on Cournot oligopoly competition. As opposed to Bertrand competition, where the participants make price bids on the market, in the Cournot competition the participants make quantity offers (e.g. maximum electricity they are willing to generate). Both Bertrand and Cournot competition models are simplifications for the electricity markets, where usually both price and quantity bids are made [135]. Nonetheless, in some cases, such as in Serbia and Austria, companies also have the possibility of bidding only the quantity. This is more frequent in the electricity markets. The characterising features of Cournot competition are:

- The competition only occurs in quantities (electricity offered to the market).
- The product is non-storable and homogeneous.
- The market price is determined by auctions.
- No entry occurs during the game.
- The moves of the players are simultaneous.

Examples of Cournot models are presented in [136–138]. In [139], Zhang et al. couple the SFE concept with the Cournot competition model.

A big number of studies are based on Stackelberg models. In a Stackelberg game, the players do not make decisions simultaneously. Rather, they move sequentially: at the upper/outer level there is the ‘leader’, who moves first; at the lower/inner level, there is the ‘follower’, who moves after observing what the leader has done. Such structure was employed in economics for the first time in 1934 by Von Stackelberg and it was named Stackelberg duopoly after him. Due to its nature, it is also called leader-follower game or simply bi-level game. In this game, the leader has a competitive advantage over the follower and it can influence the game so that the outcome will be as it wishes. This is clear from the structure of the game itself. Let $f_1(x,y)$ and $f_2(x,y)$ be the objective functions of the leader and the follower, respectively. They both depend on two vectors of variables, x and y. x is the decision variable of the leader, y of the follower. If the leader acts first, choosing x, the follower will take x as given and will act on y to maximise its outcome. The optimum value of the follower's objective function is $f_2^*(x,y^*)$, therefore the optimum value of y is $y^* = f_2^{-1*}(x)$. If the leader knows f_2, it can maximise its output in advance, by choosing x such that $f_1^*(x^*,y) = max f_1\left(x, f_2^{-1*}(x)\right)$. The Stackelberg structure is applied to the modelling of electricity markets in different ways, assuming either the system operator, some other social planner or the companies as leaders, in order to study what competitive advantages they may have in every case and what the market outcomes could be. Some works in literature assume the network planners are the leaders and they optimise the transmission network investments in the upper level, subject to the market clearing in the lower level [140]. Huppman et al. [141] employ such setting, but structure the problem into three levels, rather than two. In [130,142,143] the market operator, or, equivalently, a so-called market monitoring board, are assumed as the leaders, while the generation companies are the followers. On the contrary, in [144–146] the generation companies are the leaders and the market operator is the follower. Other Stackelberg models, or multi-level models with similar features, are given in [147–149]. Many of the models described so far are reviewed and categorised in a recent literature survey [150]. The Stackelberg setting where the generation companies are the leaders and the system operator is the follower appears to fit most the dynamics of the electricity market described in Chapter 2. The traditional dispatch optimisation models run by the system operators consist only in one level, the welfare maximisation problem. Here, the only player is the system operator, which chooses the generation schedule in order to obtain the least cost market clearing. These models do not allow the analyst to predict how the reactions of the companies to the need for flexible electricity supply could impact the market outcomes. Let us consider now a Stackelberg setting where the market clearing is the lower level problem, therefore the system operator is the follower. An upper level problem adds to this one, with the generation companies as the leaders. This setting not only models the market clearing, but also how the companies may act to influence the market and increase their own competitiveness. Therefore, it adheres better to the reality of increasingly flexible electricity systems.

The treatment of the uncertainty in all of the presented models deserves particular attention. In Subsection 3.2.1.1 it was explained that the concept of Bayesian Equilibrium is employed in many models to deal with the incomplete information on the side of the companies. In the reviewed models it is always assumed that the players lack information about the generation costs of the competitors, therefore the types of each player represent realisations of the generation costs [139,151,152]. All the players usually share a common prior over the generation costs, this meaning that everyone knows that the generation costs of the others obey some particular probability distribution. This distribution is known to everyone, be it discrete or continuous. Bayesian Equilibrium, however, is not the only solution concept for representing the uncertainty in electricity markets. Some models utilise a stochastic approach [145,153]: the standard Nash Equilibrium as formulated in (3.1) is searched for, rather than the Bayesian Equilibrium expressed in (3.2), and the uncertainty is introduced by means of stochastic parameters in the problem.

3.2.2. Needs in electricity market modelling

As anticipated, in order for the dynamics caused by flexibility in the electricity market to be properly represented and their impact on the market outcomes computed, mathematical models with particular features are needed. Most importantly, the models need to predict how the reactions of the generation companies to the request for flexible operation may impact the generation dispatch and the system's adequacy. The models in literature which seem to meet most this need are the Game Theory models based on the Stackelberg setting. Particularly, those models considering the generation companies as the leaders and the system operator as the follower suit best the situation of the Italian market. They conveniently capture that the market clearing and the strategic decisions of the companies are made on different grounds: when carrying out the market clearing, the system operator 'observes' the current generation fleet of the different companies, their generation and reserve capacity, their strategies. Therefore, the system operator acts as a follower. The companies, knowing the rules of the market, and its average outcomes, can decide their bidding strategies and their generation expansion/decommission plans in advance and submit them to the system operator. Therefore, they act as the leaders. The two-level setting traditionally proposed by the Stackelberg models may be even brought further and turned into a three-level model. As discussed, this setting has been employed in literature to represent the different grounds of decision making for the transmission expansion planning. In the case of flexibility, a three-level model may turn useful to add to the market clearing and the profit maximisation another decision making ground: the choice of taxation/incentive policies by the Government. Therefore, at the upmost level the Government would choose the policy, at the intermediate level the companies would choose their strategies, at the lower level the system operator would operate the market clearing.

Two mainstreams emerge in literature about the ways to treat the uncertainty over the market variables: the search for Bayesian Equilibria or the use of stochastic models. The difference between the two approaches has not been investigated, yet, in terms of market outcomes. At a first analysis, the Bayesian approach seems to be less appropriate for the representation of all the uncertain variables in the problem: they should be all included in the term $p(\vartheta_i, \vartheta_{-i})$ of equation (3.2), but it is not always clear how the joint probability distributions of the types are derived, starting from the distributions over the individual parameters. With stochastic models, it seems easier to include uncertain parameters of diverse nature, related and not related to the generation costs of the companies, since they can be included separately. Referring to the analysis of Chapter 2, the uncertain parameters which should be added to the models, for the impact of flexibility at the electricity market scale to be properly computed, are:

- Generation costs of company i, which are uncertain for the same company, due to the unknown costs of flexible operation.
- Generation costs of the competitors of company i.
- Uncertainty over the generation from renewables, therefore over the residual electricity demand to be met by fossil-fuel fired power plants.
- Uncertainty over the demand for reserve capacity.

Another point where all of the existing electricity market models fail is that none is able to fully represent the current dynamics of a real flexible electricity market altogether. For instance, the structure of the Italian market is more complex than what presented in these models. In the first place, no Cournot or Bertrand competition model fits it, because the companies make both price and quantity bids. Secondly, the reserve capacity demand and supply play a fundamental role in the strategic decisions of the companies. This part is neglected in most models, and superficially included in the others, without considering the technological constraints to the provision of reserve. Eventually, no discussion is ever made about the constraints, costs, benefits related to the flexible operation of fossil-fuel fired power plants. None of the models in literature is conceived to endogenously compute the impact of the flexible operation of the power plants owned by the companies on the strategic decisions of the companies themselves and on the market outcomes.

The equations of the models must be updated with constraints and mathematical formulations introducing features representing the performance of power plants in flexible operation, such as:

- Costs of cycling operation and costs of the starts.
- Fuel costs of partial load operation.
- Possibility for the existing generators to be retrofitted or operated with new control logics, in order to enhance their cycling capability.

The mathematical formulations for these cost and performance items may come from thermodynamic models of the individual power plants, such as those described in Section 3.1. However, at present, no model exists which soft-links power plant and electricity market models. They pertain to different domains of research and different disciplines.

3.2.3. Tools for electricity market modelling

The most employed simulation environments for the analysis and optimisation of electricity markets are PLEXOS [154], GTMax [155] and GridView [156]. These tools are both employed by system operators and in literature, usually for predicting the short-term optimum welfare generation dispatch, like the one carried out every day by every market operator. The algorithms to compute the optimum dispatch usually solve the power flow equations for each node of a given electricity network and determine the nodal prices in every trading interval. Typically, the time domain of the models is hours or days, at most one year, given the huge computational effort they require. The advantage of employing such widespread tools for research purposes is that the models designed with them are fully compatible with those commonly used in by market operators, and interfaces are available. However, these simulation environments and the solution algorithms they are based on do not support Game Theory settings for the optimisation of electricity markets.

The Game Theory models reviewed in Section 3.2.1 introduce a new perspective in the modelling of electricity markets, which turns into new mathematical structures. The optimisation programs of these models do not consider only one player (the System Operator) and one objective (the welfare maximisation) anymore, but several players and objectives, along with several optimisation levels. Moreover, longer-term time domains may be needed, since strategic elements decided at least yearly by the companies are introduced, like the generation expansion planning. Also the power plant cycling costs and the retrofit or operating decisions for enhancing the cycling capability pertain to time domains longer than one year. Finally, in order to compute the costs and benefits of the flexible operation of power plants, it may be necessary to define parameters and variables, which are currently not available in the optimisation models supported by the mentioned simulation environments.

Therefore, ad hoc mathematical models must be developed for the Game Theory representation of flexible electricity markets, and the codes written outside the simulation environments. The most commonly utilised tool to meet this purpose is the General Algebraic Modelling System (GAMS) [157]. It is a modelling system for mathematical programming and optimisation, consisting in a language compiler and a wide set of stable solvers for linear, nonlinear, mixed-integer programs. The language GAMS is built on is much more intuitive and user-friendly than other languages, like C++, Fortran, Python. Therefore, it allows large problems to be easily written almost in the same shape as in their mathematical formulation. The objective functions and the constraints are quickly traceable and modifiable in the codes. The drawback of this ease of use is the scarce flexibility of the language, which makes the simulations more computationally demanding.

3.3. Energy system models

The impact of flexibility and the decisions made at both the power plant and the electricity market scales may affect the outcomes of the policies at the energy system scale. These are designed based on the objectives of the planner and on the available data about the technologies and the markets. If some cost items or reactions of the players are not foreseen by the planner, the policy he designs may fail to pursue the least cost decarbonisation pathway. Mathematical models for energy system planning may solve this issue. They can be set up so as to take these costs and reactions into account and provide the least cost energy system planning under flexibility constraints.

As described in Chapter 1, the elaboration of European directives for indicating the decarbonisation pathways required models able to elaborate long-term scenarios of the regional, national or continental energy technology mix. This gave birth to a number of energy system models, employed by different international organisations or Governments. First of all, in the field of energy planning, the expression 'energy system' refers to a national or continental system of energy technologies and energy vectors to meet a certain demand for electricity, heating, cooling, transportation, etc. Therefore, the energy system of one country may be the ensemble of the technological chains which transform the primary resources into energy vectors to the final users, including the importation and exportation through the national boundaries. Secondly, with 'planning', the optimisation of the energy technology and generation mix (particularly in terms of installed capacity and forecasted production), by a Government, a system operator, or a generic planner for a given time horizon is usually intended. Such time horizon is typically long-term, up to decades, like the one of the European Energy Roadmap 2050. The optimisation is carried out according to one or more objectives, and a number of constraints, specific to the system to be optimised. In most cases, the Governments or international agencies carry out the optimisation based on a minimisation of the present cost of the system for the whole time domain considered. The decarbonisation or environmental objectives are included as constraints, e.g. limits on the generation from fossil fuels, lower limits on the generation from renewables, caps on the emissions, etc. This is done because the national or supranational Governments are constrained by the financial balance and they must give account of everything they plan in economic terms.

Given the temporal and spatial extension of the scenarios, the time and space resolution of these models is coarse. They do not compute the hourly nodal generation dispatch over transmission networks, like the electricity dispatch models; on the contrary, they compute the balances of installed capacity and energy generation over whole countries or regions for each year or fractions of the year. The time steps in which the time domain is divided are commonly named time slices. A time slice is defined as the fraction of the year occupied by all the hours of a specific kind. For instance, the time domain of a case study may be divided into 8 time slices, representing night and day of each season. The time slice for the winter-night sums up all the hours of all the nights in winter and does not make a difference between days.

The use of a coarser time and space resolution with respect to electricity market models allows the computational time and memory to be reduced and scenarios up to decades to be computed. In the following, a brief description of the main energy system models is presented.

3.3.1. State of the art modelling of energy systems

The most known energy system models are usually partial equilibrium models, computing the equilibrium prices and quantities resulting from the matching between supply and demand in the energy sector. PRIMES is one of these [158]. It was developed in the '90s by the National

Technical University of Athens in collaboration with the European Commission and it served to quantify impact assessments and energy outlook scenarios for the European Union since 1990 [8–10,159]. PRIMES simulates the energy systems and markets of the whole Union on a country-by-country base, for a number of time periods. It performs a full scale representation of the energy system, covering all sectors and chains, from the energy supply, to the technological chains for transforming primary resources into final vectors, to the energy demand. It makes an in-depth representation of the energy demand through separate objective functions, one per energy vector. This makes the problem huge and computationally demanding. Therefore, the predictions of future energy scenarios are elaborated in steps of five years, with assumptions for the years in between. Another well-known energy system model is MARKAL [160], developed by the Energy Technology Systems Analysis Programme (ETSAP) of the IEA. It is different from PRIMES in that it has a more aggregate representation of the energy sectors and the energy demand and a single objective function. It consists in a linear programming multi-regional and multi-period model. It again represents all the energy sectors and chains and it computes the least cost energy system based on the matching between supply and demand for energy carriers. In one year, six time slices are assumed (day and night of a winter, summer and intermediate season). This model has recently been incorporated into a newer energy system model: TIMES (The Integrated MARKAL-EFOM System) [161,162]. The structure of the two models is the same. In TIMES, some variables of MARKAL are modified and additional features introduced. This model has been extensively employed for simulating a number of long-term energy and climate scenarios [163–165].

Another family of energy system models has been developed in the last decades. All of them are defined as dynamic (multi-regional and multi-period) linear programming models. Their structure is simplified with respect to the models just described. The demand for energy is assumed to be inelastic to the price, therefore it is fixed and fed as a user-defined input. No equilibrium prices and quantities are computed from the interactions between consumers and producers, but only the energy technology mix which fulfils the overall balances of demand and supply at the least cost. Some of these models are the World Energy Model [166], employed by IEA for computing the scenarios of the World Energy Outlook since 1993, MESSAGE [167], developed by IIASA in the 80s, LEAP [168] and OSeMOSYS [169,170].

3.3.2. Needs in energy system modelling

All of the models described in the previous section were conceived to inform the policy makers about the optimal pathways for designing the future energy system. According to predefined objectives, environmental constraints and characteristics of the available and prospective technologies, they indicate the optimal energy technology and generation mix. If the costs or the characteristics of some technology change with time, this can be taken into account by the model and the scenarios updated.

Nonetheless, in their formulation no variable or user-defined parameter exists, which allows for the costs of flexibility at the power plant or the electricity system scale to be taken into account. The user cannot enter the costs of cycling, the additional fuel costs due to partial load operation, or the chance for existing generators to be modified as inputs, in order to assess the impact on the costs of the system and the generation mix. One exception is represented by MESSAGE, where the increased fuel cost at partial load operation is taken into account by assuming a given kind of power plant can operate in two discrete modes, one at full load with higher efficiency, one at a fixed partial load with lower efficiency. Moreover, in the models which do not perform the equilibrium between demand and supply, the market strategies and the reactions of the companies to the increasing flexibility of the electricity market cannot be taken into account. For instance, they do not consider that a technology is unlikely to operate very little, because it may be not profitable and the companies may decide to shut it down, instead.

Therefore, whichever model is chosen, its source code should be modified by introduction of new variables, parameters and constraints, for the impact of flexibility at the power plant and electricity market scales to be fully computed. Of all the models, the only one whose source code is accessible is OSeMOSYS. Its source code is available on the web and it can be modified to account for the dynamics related to flexibility. For this reason, the author chose it as the modelling tool for the energy system scale and modified its source code, as explained in PART III of this dissertation.

3.3.3. Tools for energy system modelling

OSeMOSYS is a deterministic linear programming model developed in 2011 [169]. Since its publication, it has been widely employed in literature for the elaboration of long-term energy scenarios [171–176]. It is designed to require only open source software, therefore it is written in GNU MathProg programming language on a text file and it can be run through GLPK linear programming solver. The objective function is the minimisation of the net present cost of a generic energy system throughout the given time period, subject to defined constraints. The philosophy of the model is based on a set of ‘fuels’ and a set of ‘technologies’. The fuels are generic energy vectors which enter and exit different technologies with given conversion efficiencies. The technologies are black boxes with parameters defined by the user. In this way, different sectors can be modelled, from the transport sector (where one technology may be a car, the input fuel any product from oil refining, the output fuel driven km) to the electricity sector (where the technologies are different power plants, the input fuels are fossil fuels or renewable resources, the output fuels are electricity and capacity reserve).

OSeMOSYS is conceived as a puzzle of blocks of functionality, each consisting in a set of constraint equations which receive user-defined inputs and compute a number of output variables. The organisation into functionality blocks facilitates the modification and update of the source code, since it easily allows the users to add new blocks or modify the existing ones. For each block, a contextual English description, the algebraic formulation of the English description and finally the model implementation in the programming language are provided in the documentation of the model.

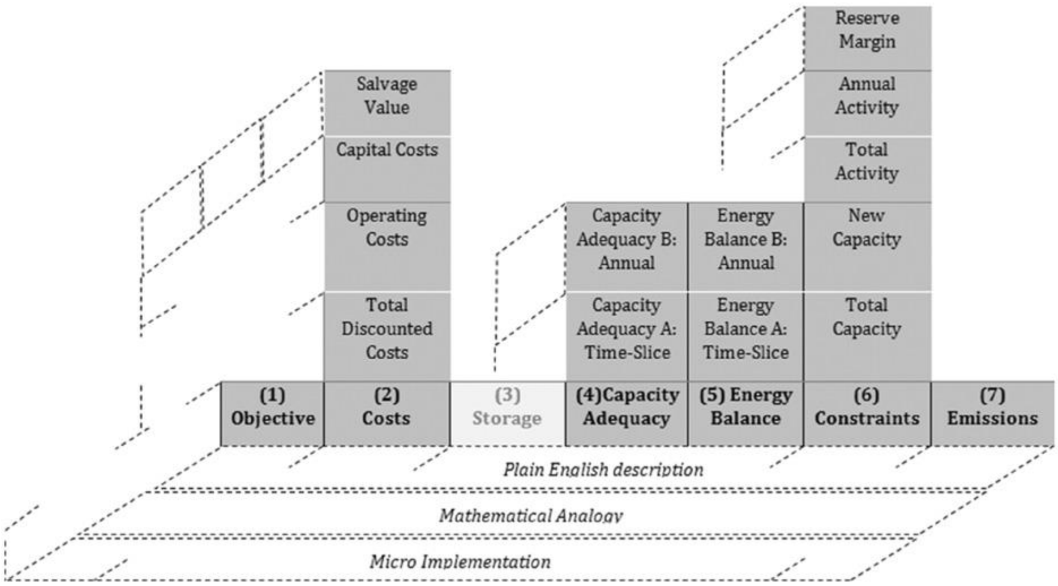

Figure 26. *Structure of OSeMOSYS.*

In Figure 26, the functionality blocks are numbered at the bottom. They are:

- *Objective*: to estimate the lowest NPV of an energy system to meet given demand(s) for energy throughout the time domain of the study.
- *Costs*: a set of variables and constraints which account for all the costs (O&M, fuel, investment, etc.) incurred by each technology (e.g. coal-fired, gas-fired, nuclear, wind, solar, biomass power plants, etc.) in each year and region.
- *Capacity adequacy*: a set of variables and constraints which ensure that each technology meets its production requirements. They are defined both for each time slice and for each year.
- *Energy balance*: the energy generation of each technology is calculated for each time slice and each year. The energy production, use and demand balances must be fulfilled in each time slice and year.
- *Constraints*: additional constraints accounting for
    - Maximum/minimum limits on the capacity of each technology allowed for a year, for the whole time domain, for a region.
    - Maximum/minimum limits on the new capacity of each technology for a year, for a region.
    - Maximum/minimum limits on the energy generation of each technology for a year, for the whole time domain, for a region.
    - Matching between primary/secondary reserve capacity demand and supply.
    - Ramping characteristics of each technology and minimum stable operation level (Minimum Environmental Load).
- *Emissions*: the emissions of different pollutants are determined by multiplying exogenously defined parameters representing the emissions per unit generation by the total annual generation of each technology. A cost for the emissions may be included.

The main outputs globally resulting from the functionality blocks are:

- Global NPV of the energy system and costs of the individual technologies.
- Yearly installed capacity and energy generation of each technology, included the storage, for all the years of the selected timeframe.

- Total use of fuel by each technology.
- Emissions of different pollutants by each technology and related penalties, if any.
- Trade of electricity between regions within the system or through the boundaries of the system.

In the file of the model, both the variables and the user-defined parameters, i.e. the boundary conditions of the problem, are defined and their name declared. In an additional text file, the data file, the user recalls the names of the parameters and assigns values to each of them. The scenarios are computed through a command window, by calling the model file, the data file and the executable of the solver. In this way, the necessity of an interface for running the energy system models is avoided. However, also an interface was created, Answer OSeMOSYS. Though not publically available, it is useful for users who only aim at designing scenarios. The energy system model LEAP [168] is OSeMOSYS integrated, as well, and provides an interface for it.

3.4. Summary of the modelling needs

In the previous sections, the research needs in the context of power plant flexibility were identified, at three scales. They can be summarised as follows:

1. *Need to model the costs of flexibility and the benefits deriving from retrofits and new operation logics at the power plant scale*. Models in simulation environments and mathematical formulations need to be developed. The models set up through simulation environments must be off-design power plant models, and must provide the operators with practical tools for analysing the performance of the power plants, and predicting the benefits of new configurations. The mathematical formulations must synthesize key performance indices of the power plants and provide equations to be embedded into electricity market and energy system models, for the impact of flexibility to be assessed and the three scales to be soft-linked.
2. *Need for mathematical models of the electricity market, able to represent the actions and reactions of the generation companies and the policy makers in decarbonisation scenarios*. The models must include the mathematical formulations developed at a power plant scale, for computing the costs and the strategies of the companies and the policy makers also as functions of the costs of power plant flexibility.
3. *Need for mathematical models of the energy system, able to represent how the optimal pathways to decarbonisation designed by the policy makers shall change, if the dynamics of flexibility are taken into account*. The models must receive as inputs numerical values representing the costs and benefits of flexibility computed at a power plant scale and the actions and reactions of the generation companies at the electricity market scale; through the mathematical formulations developed at a power plant scale and the relevant Game Theory dynamics modelled at the electricity market scale, the energy technology and generation mix they compute shall also be a function of flexibility.

3.5. Objectives of the modelling activity

From the needs, the objectives of the modelling phase are derived.

1. *To model the costs of flexibility and the benefits deriving from retrofits and new operation logics at the power plant scale*.
   1.1. To develop the off-design thermodynamic model of a power plant through a simulation environment, compatible with the online software of power plants. The model shall

provide the operators with the capability of predicting the performance of the power plant in diverse flexible operation scenarios.

1.2. To develop a mathematical formulation of the most relevant global performance indices of the power plant in flexible operation. These formulations shall be embeddable in electricity market and energy system models.

2. *To develop models of the electricity market, able to represent the actions and reactions of the generation companies and the policy makers in decarbonisation scenarios*.
3. *To develop energy system models, able to represent how the optimal pathways to decarbonisation designed by the policy makers shall change, if the dynamics of flexibility are taken into account*.
   3.1. To develop models able to receive as inputs numerical values representing the costs and benefits of flexibility computed at a power plant scale and derive their impact at an energy system scale.
   3.2. To develop models able to receive as inputs numerical values representing the actions and reactions computed at an electricity market scale and derive their impact at an energy system scale.

During the research activity, Objective 3.2 turned out to require the design of a completely new energy system model, integrated with Game Theory. Considering the development of the energy system models presented in Section 3.3.1 required years and the joint work of pools of scientists, this objective was put aside, as a long-term research objective. In PART III, the fulfilment of Objectives 1.1, 1.2, 2, 3.1 and the relative models are described. The models are then applied to different case studies in the frame of joint projects with an Italian generation company, a European university and European institutions.

PART III - Modelling the multi-dimensional nature of power plant flexibility

Stemming from the statement of the needs and objectives at the end of PART II, this section enters the modelling core of the PhD research. Models are derived, able to prove and quantify the impact of the flexible operation of fossil-fuel fired power plants at the three scales, and the links between the three scales.

In Chapter 4 the off-design thermodynamic model of a fossil-fuel fired power plant is set up, for quantifying its performance in flexible operation, under different control logics and configurations actually employed by the operators. The outputs of the model can be used by the operators, to drive the choice of new operation strategies or hardware modifications, by the companies, to quantify the global costs of flexible operation and review the market strategies, and by the energy planners, to assess the system costs of flexibility and draw updated decarbonisation pathways. A mathematical formulation for relevant global performance indices of the power plant is also developed, to be embedded into electricity market and energy system models. Specifically, equations for computing the fuel consumption at partial load, the cycling capability as a function of the power plant configuration, and the cost of the starts are derived. These provide the physical link between the three scales identified in PART II, because they receive numerical inputs from the power plant model and provide outputs for the electricity market and energy system model. Specifically:

- The fuel consumption as a function of the load receives the values of the maximum and minimum load and efficiency under different control logics as inputs, and extrapolates the efficiency as a continuous function of the load.
- The cycling capability as a discrete function of the power plant configuration receives the values of the Minimum Environmental Load, efficiency, ramping rates, cost of the starts, and cost of retrofits under different control logics as inputs, and computes the economically optimal quantity of generators to be retrofitted to new configurations and control logics.
- The cost of the starts receives the values of the specific cost of start-up ramps per unit capacity as input and computes the global annual cost of cycling operation due to the dispatch decisions of the electricity market.

In Chapter 5, a Game Theory electricity market model is developed, including relevant features of a flexible electricity system and embedding the mathematical formulations previously derived. The outputs of the model can be employed by the generation companies and the electricity system operators, to plan for short- to long-term market strategies.

Finally, in Chapter 6, an open source energy system model is modified, again by introduction of the mathematical formulations previously derived. This allows the model to assess the impact of power plant flexibility on the energy system. Figure 27 shows how the output variables link them the models at the three scales with one another.

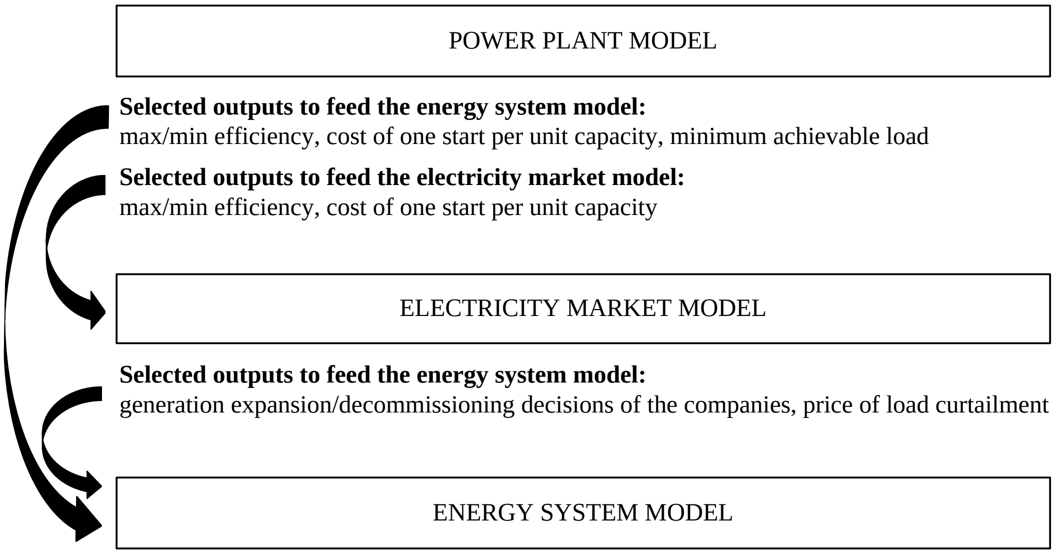

Figure 27. *Outputs specifically linking the models with one another.*

Chapter 7 provides applications of the models developed in Chapter 4 and 6, while the application of the electricity market model is not developed. The results show the value added of the approach proposed in this thesis. The power plant model provides the operators with information about the costs and benefits of flexible configurations. If these are not quantified, the operators cannot change the configuration of the power plants and be aligned with the decarbonisation pathways envisaged by the Government. The modified energy system model allows the planners to take the costs and benefits of flexibility into account when planning long-term energy strategies. When this is not done, the decarbonisation pathways drawn from the long-term scenarios are different, and adhere less to the reality. Relying on such pathways may result in higher costs of the energy system, and it may cause long-term policies to be ineffective.

4. Power plant model

This chapter is devoted to the fulfilment of Objective 1 of the modelling activity, split in Objectives 1.1 and 1.2. They are here recalled:

1. *To model the costs of flexibility and the benefits deriving from retrofits and new operation logics at the power plant scale.*
    1.1. To develop the off-design thermodynamic model of a power plant through a simulation environment, compatible with the online software of the power plant. The model shall provide the operators with the capability of predicting the performance in diverse flexible operation scenarios.
    1.2. To develop a mathematical formulation of the most relevant indices of the global performance of the power plant in flexible operation. These formulations shall be embeddable in electricity market and energy system models.

Objective 1.1 is pursued setting up a thermodynamic model of a power plant, able to predict the performance under diverse flexible operation scenarios. This model will give global and nodal outputs. The global outputs must help the power plant operators with global accounting evaluations, while the nodal outputs must provide them with detailed information about the performance of the components, for diagnostic purposes. While the nodal outputs will be employed internally by the power plant operators, the global outputs may be useful also at an electricity market and energy system scale: the efficiency of the power plant or its achievable minimum load are data typically employed by the companies for elaborating the best bidding strategies, and by the planners for computing the long-term energy system mix. Therefore, a mathematical formulation of these global outputs is developed, which can be embedded in electricity market and energy system models. This will allow the impact of the flexible operation of power plants to be taken into account. In Section 4.1, the thermodynamic model of the power plant is described and its outputs are discussed in Section 4.2. In Section 4.3, the mathematical formulation of the global performance indices is derived.

Nomenclature

Symbols

C_{starts}, c_{starts}	global and specific cost of the starts
$f_{\dot{E},i}$	variation of power due to parameter i
$f_{SC,i}$	variation of specific consumption due to parameter i
$E, E_{full\ load}$	supplied energy at actual and full load
$\dot{E}$	power
$\dot{E}_{CCGT,net}$	net electric power of the CCGT
$\dot{E}x$	exergy
FC, FC_{nom}	total fuel consumption, total fuel consumption assuming constant efficiency
k	additional fuel use
K_1, K_2, K_3	constants for the computation of the corrected Turbine Outlet Temperature

LHV_{fuel}	Lower Heating Value of the fuel
$\dot{m}_{fuel}$	fuel mass flow rate
n, n_0	actual and nominal rotational speed
$\dot{E}, \dot{E}_{corr}$	power and corrected power
SC_{nom}	specific consumption of fuel assuming costant efficiency
SC_{ref}	reference specific consumption
T_{out}	temperature at the outlet of the component
T_{VI}	temperature at the inlet of the compressor
y_D	exergy destruction ratio
η	efficiency

Subscripts

des	destruction
ex	exergy
$fuel$	fuel
k	component
nom	nominal
$prod$	product of a component
$resource$	resource of a component
t	time slice

4.1. Thermodynamic model of a power plant in flexible operation

The model of the costs of flexibility and the benefits deriving from retrofits or new control logics at a power plant scale must be industrially relevant. This means that, first of all, it must reproduce in detail an actual power plant and its control logics. Secondly, it must be applicable to power plants undergoing flexible operation profiles. Eventually, it must allow the user to analyse the impact of retrofits or control logics which are feasible and actually under evaluation by power plant operators. For these needs to be met, the model must be developed in collaboration with generation companies.

The author developed in Thermoflex simulation environment a model reproducing La Casella power plant, a CCGT in the North of Italy, with the support and expertise of the operators. The power plant is owned and operated by Enel Production S.p.A., a major generation company in Italy. La Casella CCGT is representative of the reality of combined cycle flexibility, for two reasons.

The first one is that the power plant itself, in the last years, has experienced a deep change in the operation profile, from base- to peak-load. Sample load profiles of the last decade were shown in Figure 11. From base-load operation until 2006, the profile rapidly shifted to daily cycling by 2013. During the online times, an average load factor of around 50-60% can be noticed, along with several fast and deep ramps up to 30% of the load. Therefore, all the issues related to flexible operation and described in Chapter 2 can be observed. The second reason is that La Casella CCGT power plant acts as a hub for operation data coming from other combined cycles operated by Enel S.p.A. across Italy and some in Europe. Specifically, six CCGTs in Italy (Porto Corsini, Pietrafitta, Priolo Gargallo, Termini Imerese, La Spezia, Arezzo) and three abroad (Marcinelle in Belgium, Ngres and Sugres in Russia) are monitored [177]. All the thermodynamic and operation data

recorded by the control rooms of these combined cycles is accessed at La Casella power plant, providing a picture of the operation profiles in a wide range of different contexts.
It may be noticed that setting up a model on a real power plant represents already an application, and limits the generality of the model. However, a model including all the relevant control logics of the power plant in detail cannot be set up independently from a real case. Moreover, the observation that this comes with loss of generality is not entirely true. First of all, the CCGTs of late installation have similar plant layouts. Secondly, even when the configuration or the control logics must be changed, the simulation environment is modular enough for the changes to be performed promptly. The rationale of designing the model based on the on- and off-design characteristics and parameters of La Casella power plant lies in the necessity of adhering as much as possible to the reality, for none of the actual operational issues to be neglected.
The present structure of La Casella CCGT power plant results from the repowering of a conventional oil-fired steam cycle in 2000. The combined cycle consists in four multi-shaft units, each coupling one turbogas with a vertical HRSG. The HRSG is on three pressure levels, with reheating of the intermediate pressure steam and de-superheating of the high and intermediate pressure steam before the turbines. No post-firing is utilised. The water-cooled condenser is fed with water of river Po. The main design parameters of the power plant are listed in Table 6. Whenever the design conditions are mentioned in this work, they refer to the nominal operation of the power plant and to ISO environmental conditions. These are the reference conditions commonly adopted by power plant operators and they are 15 °C, 1.013 bar, and 60% relative humidity.

Combined cycle net electric power	405 MW
Gas turbine net electric power	277 MW
Full-load net electric efficiency	55.6 %
Temperature of hot gases to the HRSG	569 °C
Temperature of gases to the stack	88.6 °C
Condensation pressure	0.033 bar
Temperature of steam to HP, IP, LP steam turbines	520, 520, 340 °C
Pressure of steam to HP, IP, LP steam turbines	86, 13, 3.5 bar

Table 6. *Main design parameters of the modelled power plant.*

The gas turbines are Siemens V94.3A. The main design parameters of the turbogas are given in Table 7.

Frequency	50 Hz
N. of compression stages	15
N. of expansion stages	4
N. of burners	24
Type of burners	VeLoNOX
Outlet mass flow rate at ISO conditions [kg/s]	687.7

Table 7*. Main design characteristics of the gas turbine.*

4.1.1. Design

Since the four groups of La Casella CCGT are identical, only one of them was modelled. Thermoflex simulation environment was employed. The scheme of the modelled power plant is presented in Figure 28.

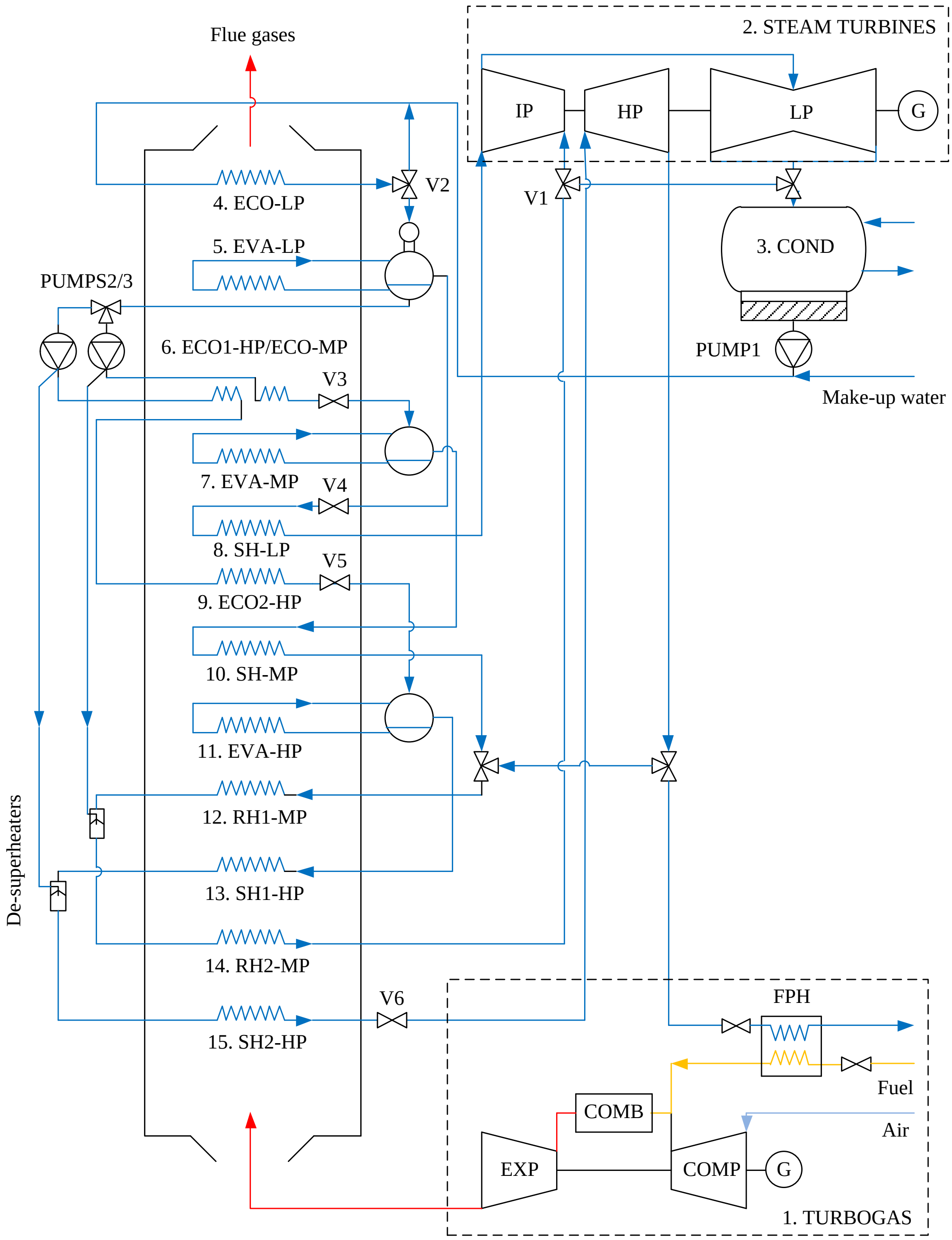

Figure 28. *Scheme of La Casella CCGT power plant.*

All the relevant components of the thermodynamic cycle and control components were modelled. The components in the scheme are described in the following list. The numbers of the listed items correspond to the numbers in the scheme.

1. *Gas turbine.* The air filters are modelled as pressure drops on the air upstream the compressor. The fuel is natural gas, assumed to contain no sulphur. It is preheated by steam exiting the intermediate pressure steam turbine, properly expanded.

2. *Steam turbines.* They are the same turbines of the old steam power plant, divided into four bodies, one of high pressure, one of intermediate pressure, two of low-pressure.
3. *Condenser.* It is water-cooled, through water of river Po. A maximum increase of 6 °C is fixed for the cooling water, due to environmental constraints. A water make-up duct balances the mass flow losses on the steam side.
4. *Low pressure economiser.* It is a unique component together with valve V2. This controls the water recirculation from the outlet to the inlet of the economiser, in order to keep the temperature of the outlet gases above a threshold and prevent condensation of acids.
5. *Evaporator of low pressure.* It is preceded by valve V2, which also controls the pressure at the inlet of this component. In the scheme of Figure 28, it is integrated with the de-areator, which utilises low-pressure steam to strip the incondensable gases contained in the water flow exiting the economiser. Part of the water in the drum is extracted by pumps 2 and 3 and sent to the intermediate and high pressure lines. In the actual power plant, only one pump is present, from which the water at the intermediate pressure is extracted as a bleed.
6. *First economiser of high pressure and economiser of intermediate pressure.* They are incorporated in the same heat exchanger, in parallel configuration.
7. *Evaporator of intermediate pressure.* It is preceded by valve V3, which controls the pressure in the drum.
8. *Superheater of low pressure.* The steam at its outlet is mixed with the steam at the outlet of the intermediate pressure steam turbine and conveyed to the low pressure steam turbine. The heat losses and pressure drops in the connection pipes are considered, as for all the other connection pipes. This is done because the length of the pipes is considerable.
9. *Second economiser of high pressure.*
10. *Superheater of intermediate pressure.* The steam at its outlet is mixed with the steam exiting the high pressure steam turbine and conveyed to the first reheater.
11. *Evaporator of high pressure.* The pressure in the drum is controlled by valve V5.
12. *First reheater of intermediate pressure.* Its outlet enters the intermediate pressure de-superheater, which is fed by water coming from the feedwater pump and sprayed over the steam.
13. *First superheater of high pressure.* Its outlet enters the high pressure de-superheater, which is fed by water coming from the feedwater pump and sprayed over the steam.
14. *Second reheater of intermediate pressure.* Its outlet is conveyed to the intermediate pressure steam turbine. Through valve V1, part of the steam can be by-passed to the condenser, for regulating the power generation at the Minimum Environmental Load.
15. *Second superheater of high pressure.* Its outlet flows to the high pressure steam turbine.

The Temperature VS Heat Transfer diagram of the HRSG (T-Q diagram) referring to the on-design conditions is shown in Figure 29. From the diagram, the temperature levels of all the heat transfers in the HRSG can be appreciated, as well as the pinch-points and the levels of subcooling at the outlet of the economisers. The numbers below the names of the heat exchangers are the thermal powers transferred in each of them, in kW.

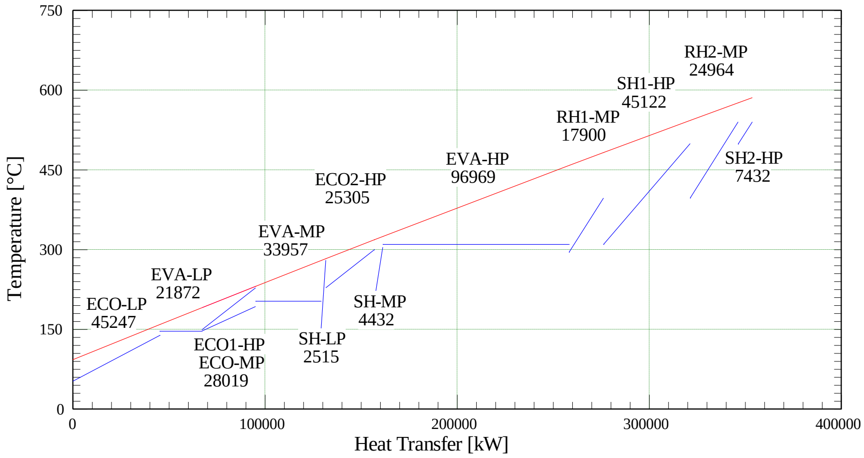

Figure 29. *Temperature-Heat Transfer diagram of La Casella CCGT at full load.*

4.1.2. Off-design control logics

Currently, the power plant undergoes highly cycling operation. Therefore, part of the time it is off, part of the time it experiences load ramps and part of the time it operates constantly at partial load, if not at the minimum load. From this, it is clear that the power plant operates almost always in load control mode and that determining what 'minimum load' means is fundamental. As discussed in Chapter 2, the minimum load is lower-limited by the maximum CO and NO_x emissions allowed by law. When the emission limit is reached, the power plant is operating at the MEL. In the case of La Casella CCGT, due to the structure of the turbogas, the CO emissions are more constraining. Different load control logics are implemented in case the emissions are lower than the limits or in case they reach the limits. They are described separately in the following two subsections.

4.1.2.1. Load control in case CO emissions are lower than the law limits

The load of the power plant is controlled through the load of the gas turbine. This one is controlled modifying the air inlet mass flow rate, by means of the Inlet Guide Vanes (IGVs) of the compressor. When the aperture of the IGVs is reduced, the mass flow rate is reduced consequently. The fuel flow rate is regulated accordingly, in order to control the Turbine Inlet Temperature (TIT). This is critical for the creep resistance of the blades, therefore it must not exceed a pre-determined set point. Since the TIT cannot be measured directly, the set point is imposed over the Turbine Outlet Temperature (TOT), corrected to keep into account the temperature at the compressor inlet and the rotational speed, according to (4.1):

$$\mathrm{TOT_K} = \mathrm{TOT} - \left(\mathrm{K_1} + \mathrm{K_3} \cdot \mathrm{T_{VI}}\right) \cdot \mathrm{T_{VI}} - \mathrm{K_2} \cdot \left(1 - \frac{\mathrm{n}}{\mathrm{n_0}}\right) \tag{4.1}$$

where TOT_K is the 'corrected' turbine outlet temperature, TOT is the turbine outlet temperature in °C, as measured by the thermocouples, T_{VI} is the compressor inlet temperature in °C, n and n_0 are the actual and the nominal turbine rotational speeds, K_1, K_2, and K_3 are constants, obtained from experimental tests. The set point of TOT_K as a function of the load is shown in Figure 30.

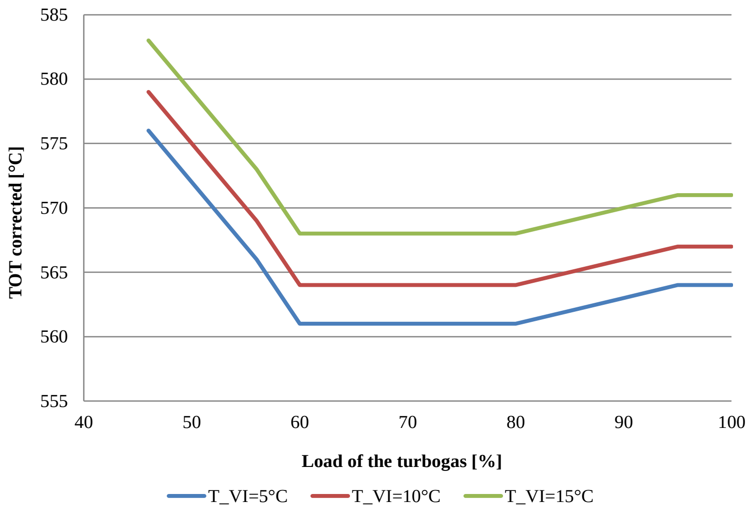

Figure 30. *Set point of the corrected TOT as a function of the gas turbine load.*

The HRSG follows the load regulation of the gas turbine. This means that: the mass flow rate and temperature of the steam adjusts automatically as a function of the varying mass flow rate and temperature of the gases; the steam turbines work in sliding pressure, therefore the inlet pressure decreases as the mass flow rate of steam does, due their characteristic curves; the power output of the steam turbines decreases, because the mass flow rate and the pressure of the steam are lower. The temperature and the pressure of the steam at some nodes of the network are controlled, in order to avoid issues at partial load. Specifically:

- The pressure at the low pressure evaporator is always kept at its design value, to avoid the risk of cavitation at the suction of the feedwater pump (PUMP1) when the load decreases.
- The pressure at the intermediate pressure evaporator is regulated through a valve placed downstream the superheater (V4), and set equal to a set point, function of the mass flow rate at the superheater. The curve of the set point is shown in Figure 31.
- There is no pressure control on the high pressure line. However, a valve at the inlet of the steam turbine (V6) ensures the pressure does not drop below 50% of its nominal value when the load decreases.
- The de-superheaters on the intermediate and high pressure lines ensure the temperature of the steam at the inlet of the turbines does not exceed 540 °C. This happens when the mass flow rate of the steam decreases, since the temperature differences between the water and the gases in the heat exchangers narrow. The mass flow rate of the steam can decrease in two cases:
    1. When the load of the gas turbine decreases. In this case the IGVs close, the mass flow rate of the gases decreases, and consequently the steam flow rates in the HRSG do.
    2. When the environmental temperature increases. In this case the density of the air decreases, so, at constant IGV aperture, the air mass flow rate decreases. Again, if this decreases, so do the steam flows.

Indeed, the de-superheaters happen to be in operation only when the environmental temperature is high.

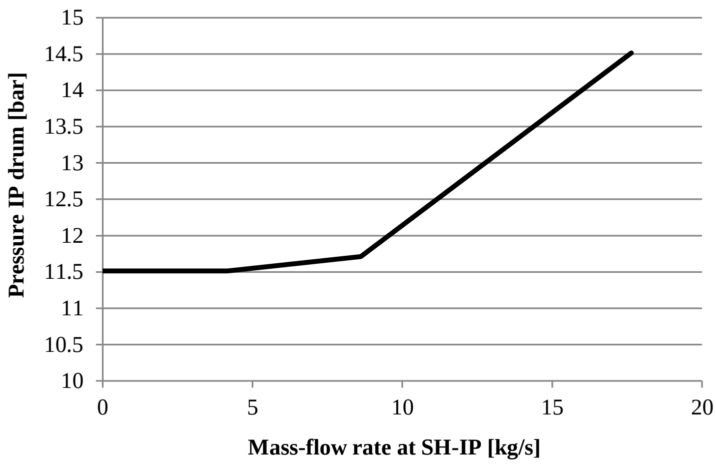

Figure 31. *Pressure set point in the IP drum.*

4.1.2.2. Load control at the Minimum Environmental Load

The load of the combined cycle is controlled by closure of the compressor's IGVs until the Technical Control Load (TCL) is reached. It corresponds to the minimum load at which it is possible to keep the temperatures of the superheated and reheated steam at their nominal values. At this point, the IGVs are not completely closed. Below the TCL, the air mass flow rate to the compressor (i.e. the closure of the IGVs) is kept constant, and the load is reduced decreasing the fuel mass flow rate, until the Minimum Environmental Load is reached. This corresponds to the minimum load achievable without harming the integrity of the components and complying with the CO and NO_x emission limits. It was experimentally noticed that at the Minimum Environmental Load the CO emissions are constraining. At this point, the turbogas generates 115 MW, corresponding to 41.5% of its nominal load, while the combined cycle generates around 190 MW. To further decrease the load of the combined cycle, valve V1 is gradually opened and intermediate pressure steam is discharged to the condenser. However, this operation causes the efficiency to drop: when the load decreases as low as 170 MW the efficiency drops by 6% with respect to the situation with valve V1 completely closed at 190 MW. Therefore, the load is never decreased below 170 MW.

4.1.3. Validation

The model was validated by comparison with operation data of La Casella power plant at five loads from full-load to the TCL. These data were recorded during tests of the power plant after a major retrofit and inspection, therefore they are assumed to represent the reference operation, without malfunctions. The five loads correspond to 100, 89.4, 58.7, 30.2, 7.1% aperture of the IGVs. The inputs to the model are the operation conditions of the power plant during the tests. They are listed in Table 8.

IGVs aperture %	100%	89.4%	58.7%	30.2%	7.1%
Ambient temperature [°C]	10.9	9.4	6.8	7.0	10.4
Ambient pressure [bar]	1.012	1.012	1.013	1.016	1.015
Ambient relative humidity [%]	89	95	100	98	85
Cooling water temperature [°C]	9.4	9.3	9.2	9.1	9.3
Fuel temperature [°C]	32.5	33.0	32.7	32.7	32.8
Fuel LHV [kJ/kg]	48764	48764	47444	47375	47375
Fuel mass flow rate [kg/s]	14.5	13.9	12.0	10.0	8.0
SH-IP outlet pressure [bar]	14.420	14.140	13.120	12.060	11.070
SH-LP outlet pressure [bar]	3.930	3.770	3.830	3.920	3.960

Table 8. *Numerical inputs for the validation of the thermodynamic model.*

As can be seen, most of the inputs are environmental conditions, which slightly vary from case to case, since the tests were taken along one day. Among the environmental conditions, also the temperature and LHV of the fuel are considered, since they depend on the fuel supply. In addition, the fuel mass flow rate is controlled, since it must be regulated according to the aperture of the IGVs. Also the pressure at the outlet of the low and intermediate pressure superheaters are controlled, because of structural constraints, as anticipated in Subsection 4.1.2.1. When these inputs are introduced in the model and the simulations are run, a perfect agreement of the model with the data at 100% is noticed, while an increasing shift at lower loads occurs. Specifically, the highest error appears in the pressure of the condenser: at partial loads the pressure computed by the model results lower than in the reality and the difference increases with decreasing loads. This is found to be due not to the model, but to a problem in the real condenser. When the load decreases, a higher fraction of incondensable gases leaks into the condenser since this cannot guarantee a perfect void. This is supported by observing the fraction of oxygen in the condensate water, which is higher than expected. Therefore, in the model the fraction of incondensable gases is adjusted, in order for the condensation pressure to match the real one. In Table 9 and Table 10, the key outputs of the adjusted model for the cases corresponding to 100% and 7.1% aperture of the IGVs are presented, respectively. The case with 7.1% aperture represents the worst case, with the highest errors between the model and the real data, since it is the furthest from the design condition.

Variable	Real	Model	Δ
CCGT electric efficiency %	56.0	56.1	0.1%
CCGT net electric power [MW]	397.7	398.1	0.1%
Steam turbine net electric power [MW]	127.6	127.5	0.0%
Gas turbine net electric power [MW]	277.2	277.1	0.0%
T at compressor outlet [°C]	413.6	413.6	0.0 °C
P at compressor outlet [bar]	18.3	18.3	0.0 bar
Mass flow rate at compressor inlet [kg/s]	682.9	683.0	0.1 kg/s
T at gas turbine outlet [°C]	569.2	569.1	-0.1 °C
T gases at stack [°C]	88.4	86.6	-1.8 °C
T, P, mass flow rate at HP-ST inlet [°C, bar, kg/s]	519.3	518.7	-0.6 °C
	86.3	86.3	0.0 bar
	73.4	73.4	0.0 kg/s
T, P, mass flow rate at IP-ST inlet [°C, bar, kg/s]	521.2	520.9	-0.3 °C
	13.0	13.0	0.0 bar
	88.9	88.9	0.0 kg/s
T, P, mass flow rate at LP-ST inlet [°C, bar, kg/s]	339.4	339.3	-0.1 °C
	3.5	3.5	0.0 bar
	102.2	102.1	0.0 kg/s

Table 9. *Outputs of the validation at 100% aperture of the IGVs.*

Variable	Real	Model	Δ
CCGT electric efficiency %	49.4	50.2	1.6%
CCGT net electric power [MW]	187.7	190.6	1.5%
Steam turbine net electric power [MW]	78.1	80.1	2.5%
Gas turbine net electric power [MW]	115.1	114.4	-0.6%
T at compressor outlet [°C]	345.7	362.7	17 °C
P at compressor outlet [bar]	10.7	10.6	-0.1 bar
Mass flow rate at compressor inlet [kg/s]	415.4	415.4	0.0 kg/s
T at gas turbine outlet [°C]	574.0	579.3	5.3 °C
T gases at stack [°C]	80.7	79.0	-1.7 °C
T, P, mass flow rate at HP-ST inlet [°C, bar, kg/s]	535.5	543.6	8.1 °C
	57.1	58.3	1.2 bar
	47.8	48.2	0.4 kg/s
T, P, mass flow rate at IP-ST inlet [°C, bar, kg/s]	530.2	537.4	7.2 °C
	8.2	8.3	0.1 bar
	55.0	55.9	0.9 kg/s
T, P, mass flow rate at LP-ST inlet [°C, bar, kg/s]	345.5	352.0	6.5 °C
	2.1	2.2	0.1 bar
	62.1	62.2	0.0 kg/s

***Table 10**. Outputs of the validation at 7.1% aperture of the IGVs.*

The values for the other loads are reported in Appendix A. At full load, all the errors are negligible. At very low loads, non-negligible differences between the model and the real operation data can be noticed in some temperatures in the HRSG. This is due to differences in the heat exchange rates through the tubes, probably deriving from differences in the design characteristics between the model and the real power plant, or from fouling in the real heat exchangers. Also temperature differences in the gas turbine are noticed. These are clearly ascribable to the design of the compressor. Pre-defined maps were employed for describing the off-design behaviour of the compressor, since the real maps are property of the manufacturers and they are not released to the power plant operators. The differences with the real maps cause the air mass flow rate at various apertures of the IGVs to be slightly different and, consequently, the outlet temperature.

Notwithstanding these differences, the errors in the steam mass flow rates and pressures are very limited in all the nodes and the percentage errors in the global power and efficiency are low compared to other works in literature [113]. Based on these considerations, the errors are deemed acceptable and the model validated.

4.2. Outputs of the thermodynamic model

The outputs of the model can be divided in two groups: global and nodal. The global outputs include the electric efficiency, the minimum achievable environmental load, the cost of the starts and other performance indices of the whole CCGT.

They are useful to the power plant operators for accounting purposes, in that they allow the technical constraints for the generation and the fuel expenses to be predicted in every operating condition. They are also useful for the companies: when a reliable quantification of these variables is available, it is communicated to the central market division of the company and the optimal dispatch of the power plant is decided. The market division, indeed, elaborates the information about the performance of all the power plants owned by the company, and it decides which power plants are worth presenting on the market. A higher efficiency at partial load can save a power plant from being decommissioned. Eventually, these outputs are useful at an energy system scale: the energy system planning models rely, among others, on data about the global performance of the technologies. When detailed data are available from thermodynamic models of the power plants, these can be given as numerical inputs to the energy system models. The long-term optimal energy technology and generation mix may change deeply as a function of the performance of different technologies. In the end, the global outputs are useful not only to the power plant operators, but also to the companies and the energy system planners. For this reason, they are the ones which shall be introduced into electricity market and energy system models in the next chapters.

The nodal outputs are the thermodynamic properties of the streams at each node of the cycle, i.e. at the inlet and outlet of each component. These are not useful for accounting purposes, nor for evaluations at an electricity market or energy system scale. Nonetheless, they are equally important for the power plant operators for diagnostic purposes: the deviation of some quantity from the values predicted by the model indicates an anomaly in some of the components. Through methods well-known in literature, the anomaly can be located and its effect on the performance of the other components and of the whole plant quantified [93]. Moreover, through methodologies based on the Second Law of Thermodynamics, it is possible to compare the efficiency of different heat exchangers in the HRSG and decide which to intervene on, in case multiple anomalies arise.

In the following sections, some of the relevant outputs are described. As for the global outputs, the fuel consumption and indices related to the cycling capability of the power plant are described. These are highly related to flexible operation. The cost of the start is as well, but it is computed in literature through thermo-mechanic models of the components wear, rather than through thermodynamic models. As for the nodal outputs, a discussion about the performance indices of the heat exchangers is made.

4.2.1. Global outputs

4.2.1.1. Fuel consumption

The specific consumption of fuel is the reciprocal of the CCGT net electric efficiency. When a power plant is expected to operate mostly at partial/minimum load, like La Casella CCGT and

others in Italy, the fuel consumption becomes fundamental: at full load it already accounts for around 75% of the LCOE of a CCGT on average, and it increases at lower loads. Moreover, at partial loads it highly depends on the control logics adopted by the operators.
Additionally, the fuel consumption is fundamental for the power plant operators, for accounting purposes. It is worth briefly explaining what this means. Generically, the actual fuel expense is known to the operators, since it comes from the bills of the gas utilities. However, the operators cannot understand if this expense can be reduced, unless they are provided appropriate analytical tools. At present, they make this kind of evaluation by computing the specific consumption with two methods and comparing the results. The methods are:

- *Direct method*: the actual specific consumption of fuel is computed as the ratio between the measured inlet heat rate and the electricity produced by the power plant.
- *Indirect method*: a theoretical specific consumption is computed as the summation between the expected consumption at ISO conditions and the variations due to the deviation of several parameters from the ISO conditions. Correction curves provided by the manufacturers at the time the power plant went into operation are employed for this computation.

With the direct method, the 'Direct Specific Consumption' of fuel (DSC) is computed as:

$$\mathrm{DSC} = \frac{\dot{\mathrm{m}}_{\mathrm{fuel}} \cdot \mathrm{LHV}_{\mathrm{fuel}}}{\dot{\mathrm{E}}_{\mathrm{CCGT,net}}} \tag{4.2}$$

where $\dot{m}_{fuel}$ is the fuel mass flow rate, LHV is the Lower Heating Value, $\dot{E}_{CCGT,net}$ is the net electric power generated by the CCGT. Though this may seem a straightforward computation, it requires the measurement of

- fuel mass flow rate
- LHV of the fuel

for the heat rate input, while it requires the measurement of

- gross electric power generated by all the sections, included the emergency units
- electric power absorbed by the auxiliary services
- transformation losses

for the net electricity output. The number of variables to be measured introduces many uncertainties, the biggest of which is the fuel mass flow rate. This is measured for the whole power plant, not for the single gas turbine units, with errors up to 5%. Therefore, the DSC is a highly uncertain quantity. In order to provide reliable information, it must be cross-checked with the Indirect Specific Consumption (ISC). This is computed as:

$$\mathrm{ISC} = \mathrm{SC}_{\mathrm{ref}} + \sum_{\mathrm{i}} \mathrm{f}_{\mathrm{SC,i}} \tag{4.3}$$

Here, $f_{SC,i}$ is the variation of the specific consumption of the power plant due to the deviation of parameter i from its nominal value. The overall variation is the summation of the variations over all the parameters which can affect the specific consumption by significant amounts. Polynomial curves displaying $f_{SC,i}$ as functions of the deviations of the parameters i are provided by the manufacturers for the following parameters:

- Ambient temperature, pressure and relative humidity.
- Pressure drop on the air filters at the compressor inlet.
- Gas turbine outlet pressure.

- LHV of the fuel.
- Power absorbed by the auxiliaries.
- Air temperature difference due to the anti-acing system.
- Gas turbine EOH.
- Steam turbine discharge pressure.
- Make-up water mass flow rate.

SC_{ref} is the reference specific consumption of the power plant, at ISO conditions at a given load. Starting from an operation point at some load different from the full load and some environmental condition different from the ISO conditions, it is computed in two steps:

1. The gross 'corrected' power is computed. It is the power the CCGT would be providing if all the parameters listed above were at their nominal value. The corrected power is computed summing to the actual gross power the deviations $f_{\dot{E},i}$ due to the abovementioned parameters not being at their nominal value.

$$\dot{E}_{corr} = \dot{E} + \sum_i f_{\dot{E},i} \tag{4.4}$$

   The deviations are read on curves provided by the manufacturers. The curves are again polynomial, like those of the correction factors $f_{SC,i}$.

2. Secondly, the reference specific consumption is derived as a function of the gross corrected power, using a curve recorded by the operators during operation tests of the power plant in reference conditions:

$$SC_{ref} = f\left(\dot{E}_{corr}\right) \tag{4.5}$$

The DSC and the ISC are both subject to errors. However, their comparison allows a number of indications to be drawn. If there is a significant difference between the two values (La Casella operators consider as significant a difference bigger than 105 kJ/kWh), this means that a) some measurement error has occurred due to anomalies in the measurement equipment; b) there is a loss of performance somewhere in the cycle, which is recorded by the DSC and not by the ISC. First of all, the possible failure of some measurement equipment is checked. If all the equipment is working and the DSC is higher than the ISC, the explanation falls on the loss of performance: the DSC computes the real specific consumption, which is higher than the ideal consumption represented by the ISC because some component is malfunctioning. When this is the case, the cause of the malfunction can be searched for and the specific consumption brought again to normality.
Therefore, it is fundamental for the operators that the correction curves for the power and the specific consumption employed in the indirect method are as reliable as possible. The detailed off-design thermodynamic model set up in this research provides a tool for elaborating the curves in-house, without relying on the possibly obsolete information from the manufacturers. An example is provided in Chapter 7.

4.2.1.2. Cycling capability of the power plant

An ideal thermodynamic model of a power plant in flexible operation should be at the same time user-friendly, preferably set up in a simulation environment, computationally not demanding, detailed in representing the control logics, dynamic. This last feature allows the ramping rates to be computed, but contrasts with other requirements: it makes the model less user-friendly and it makes the simulations much slower. Therefore, in this research the author preferred setting up a quasi-stationary model. Though this kind of model does not allow for the ramping rates to be computed, it allows other predictions about the cycling performance to be made. For instance, the variation of the Minimum Environmental Load when different control logics are employed can be computed. A decrease of the Minimum Environmental Load widens the range of loads at which the power plant can operate and increases its probability to be dispatched. A case study about the reduction of the Minimum Environmental Load is presented in Chapter 7.

4.2.2. Nodal outputs

One of the most urgent needs of the power plant operators is to have a thermodynamic scheme of the HRSG. At present, it is almost a black box, for which the operators know the properties of the inlet and outlet flows and a few quantities inside. When some issue occurs inside the HRSG, it is complicated to locate and quantify the anomaly. If, for instance, the temperature of the flue gases at the stack increases, the operators assume it is due to the fouling of the last heat exchanger in the hot gas path, the low pressure economiser. However, it cannot be verified whether other and/or more malfunctions contribute to this anomaly. Methodologies for the diagnosis of malfunctions like [93] are probably the best options for meeting this need. The thermodynamic model provides a ground for them to be applied, thanks to its capability of representing a number of possible off-design conditions and configurations of the control systems.

The computation of Second Law performance indices is the first step into the diagnosis of malfunctions. Since the heat exchangers operate at different temperatures, the best indices based on which they can be compared are the exergy efficiency and the exergy destruction ratio, reported in (4.6) and (4.7), respectively.

$$\eta_{ex,k} = \frac{\dot{E}x_{prod,k}}{\dot{E}x_{resource,k}} \tag{4.6}$$

$$y_{D,k} = \frac{\dot{E}x_{des,k}}{\dot{E}x_{fuel}} \tag{4.7}$$

As regards the exergy efficiency, it requires a definition of the product and the resource for every component. A wide bibliography exists about the most appropriate definitions, starting from [95,178]. The assumptions made in this study, regarding the resources and the products of the main components are illustrated in Figure 32 and Table 11.

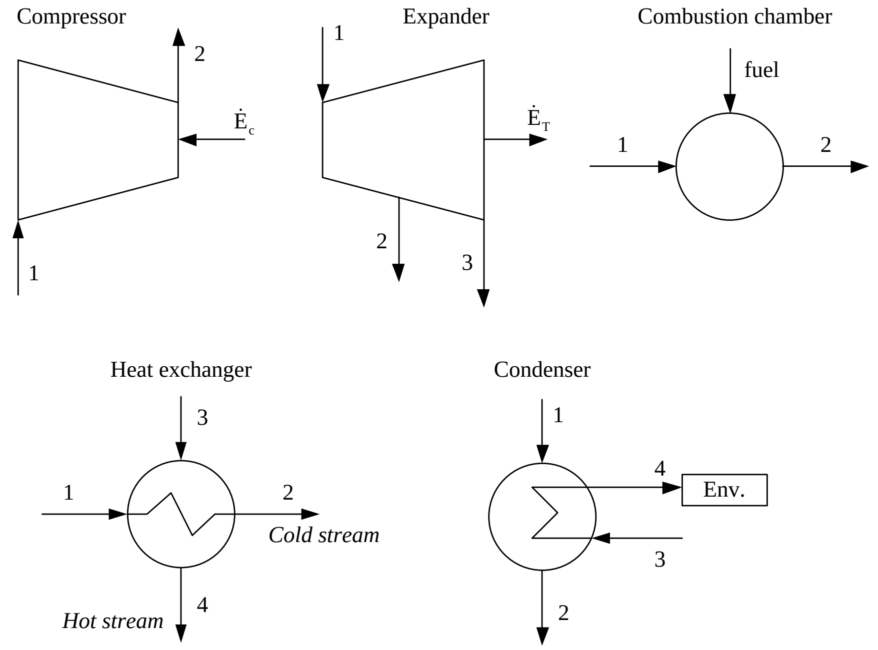

Figure 32. *Exergy flows across the components of the CCGT.*

	Compressor	Expander	Comb. chamber	Heat exch.	Condenser
Resource	$\dot{E}_C$	$\dot{E}_1 - \dot{E}_2 - \dot{E}_3$	$\dot{E}_{fuel}$	$\dot{E}_3 - \dot{E}_4$	$\dot{E}_1 - \dot{E}_2 + \dot{E}_3$
Product	$\dot{E}_2 - \dot{E}_1$	$\dot{E}_T$	$\dot{E}_2 - \dot{E}_1$	$\dot{E}_2 - \dot{E}_1$	
Loss					$\dot{E}_4$

Table 11. *Resource – product – loss assumptions for the components of the CCGT.*

In Table 11, the loss is an exergy stream which does not constitute a useful product, notwithstanding its thermodynamic value, because it is rejected to the environment.

As regards the exergy destruction ratio, it represents the contribution of the component to the global exergy destruction in the power plant. All the components in the power plant can be compared and sorted by exergy destruction ratio, even those working at different temperatures or with different fluids. Those with the highest value of the index must be cared about most. Among the heat exchangers, a good part of the exergy destruction is due to temperature differences between the gases and the water/steam. Such contribution is hardly avoidable in the case of an operating power plant: the pressure and temperature levels are constrained on one side by the structure of the heat exchangers, on the other by the set points of valves and pumps. This represents a major difference with respect to most models in literature, which perform the optimisation of power plants in their design phase, as discussed in Chapter 3. Nonetheless, with time an avoidable contribution to the exergy destruction may add up, due to the fouling of the heat exchangers. Having a ranking of $y_{D,k}$ for the heat exchangers in the HRSG informs the operators about those for which the fouling should be cared most. An application is shown in Chapter 7.

A further step into the diagnosis of anomalies inside the HRSG consists in analysing the correlation between the changes in the properties at the inlet and outlet of different heat exchangers. In this case, more than the exergy efficiency or the exergy destruction ratio, the temperature may be a relevant variable. The key question the operators need to answer in this case is: how do the temperatures in the other heat exchangers vary when the outlet temperature at one of them does? Through parametric simulations with the thermodynamic model this information is easily obtained, and a matrix like this can be drawn:

$$\begin{pmatrix} \frac{\partial T_{out,1}}{\partial T_{out,1}} & \cdots & \frac{\partial T_{out,n}}{\partial T_{out,1}} \\ \vdots & \ddots & \vdots \\ \frac{\partial T_{out,1}}{\partial T_{out,m}} & \cdots & \frac{\partial T_{out,n}}{\partial T_{out,m}} \end{pmatrix} \tag{4.8}$$

The information coming from these analyses can be efficiently elaborated by means of thermoeconomic diagnosis methodologies like [93], and/or with the aid of Input-Output methodologies, as discussed in [179]. This is still an open research field.

4.3. Mathematical formulation of global performance indices

As anticipated, global performance indices like those described in Section 4.2.1 are useful not only for power plant operators, but also for companies and energy system planners. This is why including them in electricity market or energy system models may be important. However, how to embed the information coming from detailed thermodynamic models in larger scale models is not trivial.

For instance, in the CCGT model described in Section 4.1, the specific fuel consumption of the power plant (or its reciprocal, the efficiency) is what results from a complex network of components, each having its own control logics. If such a model was to be fully linked to an electricity market model or an energy system model, the global code would be far too complicated and time consuming to run. Therefore, a different approach is proposed in this research. Stand-alone mathematical formulations of key global performance indices are derived from the thermodynamic model in two steps:

- Parametric simulations are run with the thermodynamic model, and global performance indices of the power plant are computed as functions of some variable or control logic. Therefore, curves of the performance index VS the chosen variable or control logic are obtained.
- The function representing this curve is extrapolated, or a proper approximation of it.

Once the mathematical formulation is obtained, it is introduced in the electricity market or energy system models as a constraint equation (or a set of constraint equations). This way, the models are given the capability to compute endogenously the selected index as a function of the operation profile and take into account specific technological constraints. The mathematical formulation is simple enough not to slow the computation down, but it is model-based, thus adhering to the reality with good approximation, depending on how much the thermodynamic model adheres to the reality.

In the following sections, the author describes how the mathematical relation for some global performance indices was derived. The choice of which indices to model was based on the context analysis carried out in PART II and it focussed on those indices which are most affected by flexible operation: the fuel consumption at partial load, the cycling performance as a function of different configurations or control logics, the cost of the starts. As briefly mentioned, the numerical values for this last index are not obtained through the thermodynamic model, since they are generally computed in other ways. Available data from literature were employed for extrapolating the relations for the, instead of the thermodynamic model developed in Section 4.1.

4.3.1. Fuel consumption at partial load

Obtaining a mathematical formulation for the fuel consumption at partial load which could be embedded in electricity market and energy system models was a key issue of the modelling activity. The electricity market and energy system models compute scenarios based on available data about the technological characteristics of the technologies. The data in literature are pretty much aggregated, therefore most times a single number is provided as the efficiency of a technology: the full-load (i.e. nominal) efficiency. For this reason, none of the existing models, to the knowledge of the author, considers the efficiency as a variable. The most advanced models consider for every technology two values of the efficiency, one at full load, one at partial load [167,173]. Usually, the only input the user gives these models is the nominal efficiency (or its reciprocal, the specific consumption). Based on it, the models compute the consumption of fuel in a given time frame, i.e. a time slice, as the product of the specific consumption by the generation in that time slice.

$$\mathrm{FC_{nom}} = \mathrm{SC_{nom}} \cdot \mathrm{E} \tag{4.9}$$

where E is the generation, SC_{nom} the nominal specific consumption of fuel, FC_{nom} the global consumption of fuel obtained if the efficiency is assumed to be constant and equal to its nominal value. From (4.9), if the efficiency is constant and equal to the nominal value, as occurs now in all models, also SC_{nom} is constant, therefore FC_{nom} decreases linearly with the load. A problem arises when a variable efficiency is introduced. If the efficiency varies with the generation E, so does SC_{nom}, and the curve of FC_{nom} becomes nonlinear. Electricity market and energy system models are usually linear programs, since nonlinear programs would require much higher computational times to analyse large time and space domains. Therefore, if any new equation is to be introduced in these models, it should be linear. To overcome this problem, the functional relation of the efficiency on the load can be introduced in a different way. The fuel consumption FC at some load lower than the full load can be considered as the summation of the fuel consumption FC_{nom} in case the efficiency is constant and equal to its nominal value, plus a term of additional fuel consumption, proportional to the load partialisation. Such concept is expressed in (4.10):

$$\mathrm{FC} = \mathrm{FC_{nom}} + \mathrm{k} \cdot \left(\mathrm{E_{full\ load}} - \mathrm{E}\right) \tag{4.10}$$

Here, the first term in the right hand side is the fuel consumption at load E, in case the efficiency is equal to its nominal value. It is calculated as in (4.9). The second term is an additional term of fuel consumption at load E, due to the decrease in the efficiency. k is a constant and it represents the additional fuel consumption per unit load. $E_{full\ load}$ is the energy the power plant would generate in the given time slice if it was operating constantly at full load. In this equation, FC is a linear function of E, as desired. Electricity market models usually compute the electricity dispatch, this meaning that they compute, among others, the generation E from every generator and the fuel consumption FC_{nom}. Energy system models compute the energy technology and generation mix in every time slice and every year. Therefore, they compute the same variables as electricity market models, on a wider time frame. In the end, (4.10) is easily introduced in such models by the addition of the term $k \cdot (E_{full\ load} - E)$, and the only additional parameter is k. Now it must be determined whether employing the linear formulation (4.10) for the fuel consumption leads to a good approximation of the functional relation of the efficiency with the load. This relation is usually nonlinear, as shown in Figure 33. Here, the curve of the efficiency as a function of the load for La Casella CCGT power plant is presented. Actually, it is one of the results of the case studies described later on in Chapter 7, but it is worth also calling now, because it shows the trend of the efficiency for a real power plant when particular load control logics are employed. In this case the curve presents a discontinuity, due to the activation of the control logic for decreasing the load when the CO emission limit is met, described in Section 4.1.2.2. The reader may remember this control logic consists in opening a steam by-pass from the inlet of the intermediate pressure steam turbine to the condenser, which causes the efficiency to drop at a higher slope than for higher loads.

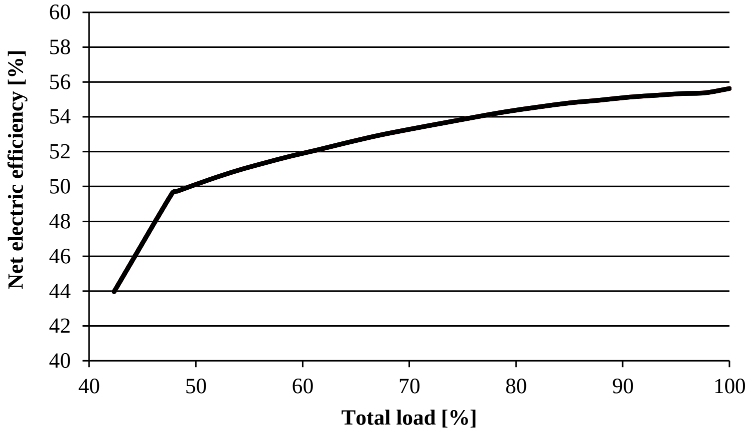

Figure 33. *Net electric efficiency of a CCGT as a function of the load.*

First of all, it is necessary to understand whether the formulation in (4.10) results in a nonlinear trend of the efficiency with the load. If (4.10) is re-written in terms of efficiency, as in (4.11), it is noticed that this is actually the case (4.12):

$$\frac{1}{\eta}\cdot \mathrm{E} = \frac{1}{\eta_{\mathrm{nom}}}\cdot \mathrm{E} + \mathrm{k}\cdot\left(\mathrm{E}_{\mathrm{full\ load}} - \mathrm{E}\right) \tag{4.11}$$

$$\eta = \frac{\eta_{\mathrm{nom}}\cdot \mathrm{E}}{\mathrm{E} + \eta_{\mathrm{nom}}\cdot \mathrm{k}\cdot\left(\mathrm{E}_{\mathrm{full\ load}} - \mathrm{E}\right)} \tag{4.12}$$

This is the first desired effect.

As a second step, the agreement of the nonlinear trend as from the mathematical formulation and the data from real power plants must be verified. This depends on the value of k, which can be computed from (4.11): if the nominal efficiency, the minimum load and the efficiency at the minimum load of the real power plant are known, by replacing them in (4.11), k is found. Let us consider the efficiency curve shown in Figure 33. The nominal efficiency is 55.62%, while the minimum load and efficiency depend on the range of loads taken into account. If the whole range of loads until the Minimum Environmental Load is considered, including the discontinuity due to the opening of the steam by-pass, the minimum load is 42.3% and the corresponding efficiency 44%. Replacing these values in (4.11), (4.13) is obtained:

$$\frac{1}{0.44}\cdot 0.423 = \frac{1}{0.556}\cdot 0.423 + \mathrm{k}\cdot\left(1 - 0.423\right) \tag{4.13}$$

from where k results equal to 0.35. If this value is utilised in (4.12), a trend of the efficiency is obtained, as in the red curve of Figure 34.

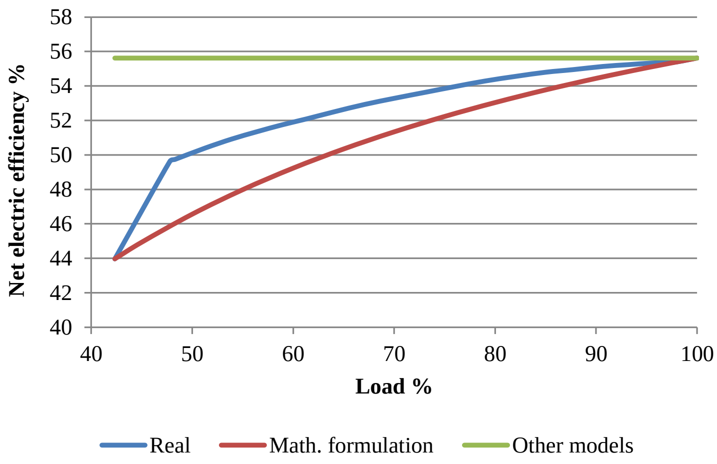

Figure 34. *Comparison between the curves of the efficiency as from the mathematical formulation, models in literature, and a real CCGT. Case 1.*

The agreement between the mathematical formulation and the real case is scarce, because the efficiency of the discontinuity at low loads. The mathematical formulation is not able to follow discontinuities. However, some considerations are due. First of all, usually the efficiency curves of the power plants do not present so sharp discontinuities. Refer, for instance, to [38,180,181]. Moreover, with respect to the existing electricity market and energy system models, this formulation represents a step forward: at present, these models only consider a fixed value for the efficiency, equal to the nominal one (green curve in Figure 34). Eventually, the efficiency predicted in this case is lower than the one of the thermodynamic model, therefore the formulation is conservative with respect to the fuel costs. This leads to the elaboration of more conservative scenarios.

If the agreement of the mathematical formulation and the thermodynamic model in the higher part of the load range is preferred, for example in cases where the technology is expected to operate a loads generally higher than the minimum, k can be computed in a different way. The values of η and E in (4.11) can be replaced with the efficiency and the corresponding load just before the discontinuity of the curve of the model. The result is shown in Figure 35.

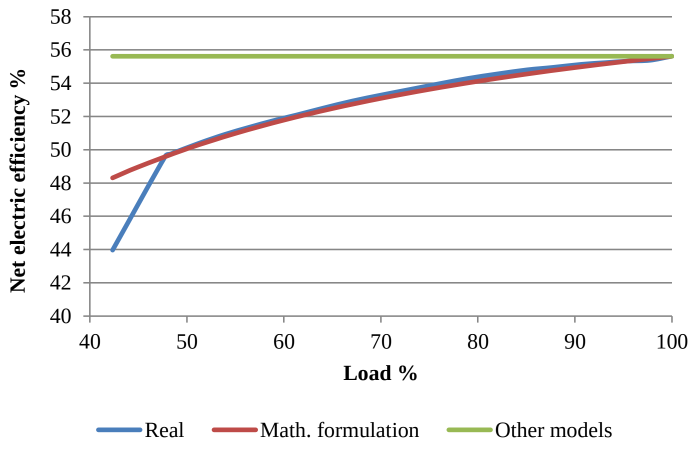

Figure 35. *Comparison between the curves of the efficiency as from the mathematical formulation, models in literature, and a real CCGT. Case 2.*

The trend of the mathematical formulation agrees almost perfectly with the one of the power plant, except after the discontinuity due to the opening of the steam by-pass.

4.3.2. Cycling performance as a function of the power plant configuration

In Section 4.1 it was explained that the cycling performance is a function of the power plant configuration. For instance, if the Minimum Environmental Load of the power plant is considered as an indicator of the cycling performance, it depends on the employed load control logic and so does the corresponding efficiency: at La Casella CCGT the Minimum Environmental Load is 47.8% and the corresponding efficiency 49.6%, when the steam by-pass is not employed, while they are 42.3% and 44% when the by-pass is employed. It was also pointed out how the choice of different configurations for enhancing the cycling capability may lead the power plants to be dispatched more, with consequences at an electricity market and energy system scale. Therefore, the power plant configuration and the corresponding cycling capability must not be seen as fixed parameters, but as variables. In the existing models, they are entered in the electricity market and energy system models as fixed parameters. The author searched for a set of equations which allowed the power plant configuration to become a variable and the cycling capability to be a function of the configuration. In this case, the shape of the equations strictly depends on the model they are written for, therefore no unique formulation can be presented. At this stage, it is useful just to explain the rationale of the equations. Electricity market and energy system models model power plants as black boxes where fuels enter and energy vectors exit. The rate at which these streams flow in and out depends on the characteristics of the technologies, defined by parameters (such as the efficiency, the minimum load, the ramping rates, etc.). If a power plant can be retrofitted or its control logics changed for enhancing the cycling capability, these parameters must become variables, and the model must be able to change them endogenously as a function of the control logics and of the power plant configuration. As a first step in this direction, the author derived a number of equations for allowing the control logics and the power plant configuration to vary discretely, and making the characteristics of the technology functions of these discrete variables. This was done assuming the simplest case, the one where two configurations are allowed, an old and a new one. These are introduced in the code as two ‘versions’ of a technology. The old version represents the original power plant, the new version the retrofitted one. The user defines a priori the characteristics of the two versions, by assigning values to all the parameters of each one. The model is allowed at every moment to decommission part of the installed capacity of the old version and install at most a corresponding capacity of the new version. This is done with a cost corresponding to the sole cost of retrofit. An example of complete mathematical formulation for introducing the cycling capability as a function of the configuration in an energy system model will be described in Chapter 6.

4.3.3. Cost of the starts

The cost of the starts is a fundamental index of the cycling performance of a power plant. When a power plant undergoes daily start-up and shut-down cycles, this cost item becomes significant in the annual balance. As other global performance indices, it may have an impact on electricity market and energy system models. Thus, it is fundamental to provide a mathematical formulation for the cost of the starts as a function of the operation profile of the power plants, to be embedded in those models. As mentioned previously, the cost of the starts sums up a number of cost sources. The main ones are the cost of fuel and electricity, the cost for the personnel, and the cost of the components' wear. None of these can be evaluated through thermodynamic models, therefore the cost of the starts is not an output of the model described in Section 4.1. However, it has been quantified in literature, through models like the one in [33]. In the following, it is explained how the equations for computing the cost of the starts are formulated.
Both electricity market and energy system models divide the time domain in 'time slices'. Independently from the duration of the time slices, in both kinds of models the spinning capacity of every generator (or, generically, technology) is always computed for every time slice. Let us assume the case where the time slices represent parts of the day (such as morning, afternoon, evening, night). The cost of the daily starts can be computed as the summation of the costs of ramping up and down capacity between one time slice and the other, over a whole day:

$$\mathrm{C_{starts}} = \sum_{\mathrm{day}} \frac{\mathrm{c_{starts}}}{2} \cdot \left| \dot{\mathrm{E}}_{\mathrm{t}} - \dot{\mathrm{E}}_{\mathrm{t-1}} \right| \tag{4.14}$$

c_{starts} is the cost of a shut-down/start-up cycle per unit capacity; $\left|\dot{E}_t - \dot{E}_{t-1}\right|$ is the difference in the capacity on-grid between a time slice and the previous one; the operator $\sum_{day}\cdot$ indicates the cost of daily starts is computed summing up the variations of on-grid capacity between the time slices over one day. In electricity market models, (4.14) is usually written for every single generator. Therefore, when the generator is shut down or started up $\left|\dot{E}_t - \dot{E}_{t-1}\right|$is equal to its capacity; when it is kept in operation, $\left|\dot{E}_t - \dot{E}_{t-1}\right|$ is equal to 0. In energy system models, (4.14) is usually written for a group of generators, e.g. for all the power plants of the same kind. In this case, it frequently occurs that only part of the generators is shut down. Therefore, in general, in energy system models $\left|\dot{E}_t - \dot{E}_{t-1}\right|$is always different from zero. A graphical example helps understand why c_{starts} is divided by two and the absolute value is present. Let us consider a group of power plants, such as all the CCGTs in Italy, part of which is shut down daily. Let us also consider one average day and assume all the days are equal to each other. If the day is split in four time slices, for instance, a situation like the one shown in Figure 36 may occur.

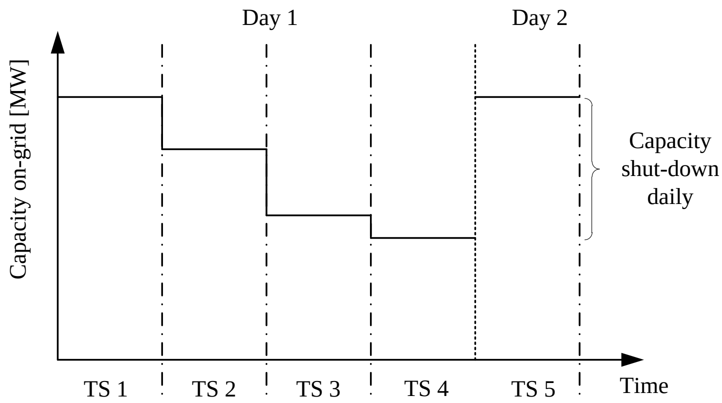

Figure 36. *Sample subdivision of a day in time slices.*

In Day 1, part of the capacity is gradually shut down across the time slices from TS1 to TS4. At the beginning of Day 2, the capacity on-grid is again the one in TS1 of the day before, since all the days are assumed to be equal. It can be noticed that the sum of the capacity which is shut down from TS1 to TS4 corresponds to the capacity which is restarted from TS4 to the beginning of Day 2 (TS5):

$$\left|\dot{E}_2 - \dot{E}_1\right| + \left|\dot{E}_3 - \dot{E}_2\right| + \left|\dot{E}_4 - \dot{E}_3\right| = \left|\dot{E}_5 - \dot{E}_4\right| \tag{4.15}$$

Therefore, as indicated in Figure 36, the amount of capacity corresponding to $|P_5 - P_4|$ undergoes daily cycling. If (4.15) is replaced into (4.14), (4.16) is obtained:

$$C_{start} = \frac{c_{start}}{2} \cdot \left|\dot{E}_2 - \dot{E}_1\right| + \frac{c_{start}}{2} \cdot \left|\dot{E}_3 - \dot{E}_2\right| + \frac{c_{start}}{2} \cdot \left|\dot{E}_4 - \dot{E}_3\right| + \frac{c_{start}}{2} \cdot \left|\dot{E}_5 - \dot{E}_4\right| \tag{4.16}$$

This corresponds to:

$$C_{start} = \frac{c_{start}}{2} \cdot \left(\left|\dot{E}_2 - \dot{E}_1\right| + \left|\dot{E}_3 - \dot{E}_2\right| + \left|\dot{E}_4 - \dot{E}_3\right|\right) + \frac{c_{start}}{2} \cdot \left|\dot{E}_5 - \dot{E}_4\right| \tag{4.17}$$

$$C_{start} = \frac{c_{start}}{2} \cdot \left|\dot{E}_5 - \dot{E}_4\right| + \frac{c_{start}}{2} \cdot \left|\dot{E}_5 - \dot{E}_4\right| \tag{4.18}$$

$$C_{start} = c_{start} \cdot \left|\dot{E}_5 - \dot{E}_4\right| \tag{4.19}$$

In conclusion, summing up half of the cost of the starts for the Δ capacity in every time slice leads to computing the cost of a whole start over a day. It is easily proven that this formulation is valid for every possible number of time slices the day is divided into, from one upwards. A different case occurs when the time slices are coarser than one day. Let us consider, for instance, the time domain is divided in two time slices, representing two sample weeks. Though the author could not find any such case in literature, this may occur. In this case the formulation is still valid, but the operator $\sum_{day} \cdot$ must be replaced by $\sum_{2\ weeks} \cdot$ and the term c_{starts} must be redefined. Typically, it will not include any cost of the components wear, since the start is much slower.

4.4. Power plant model: conclusions

Chapter 4 was dedicated to the achievement of Objectives 1.1 and 1.2 of the modelling activity. Objective 1.1 was pursued by setting up the off-design thermodynamic model of a CCGT in Thermoflex simulation environment. The outputs of the model consist in global and nodal outputs. The global outputs, such as the fuel consumption and the cycling capability as a function of the power plant configuration, can be used by the operators for accounting purposes. The nodal outputs, such as the thermodynamic properties and a number of Second Law of Thermodynamics performance indices of all the components, allow diagnostic evaluations to be carried out. Both provide the operators with predictions about the performance of the power plant under flexible operation profiles. Objective 1.2 was pursued by formulating linear equations able to represent: the variation of the efficiency as a function of the load, the variation of the cycling capability as a function of different power plant configurations and the cost of the starts. These equations were formulated in such way as to employ variables and parameters already used in electricity market and energy system models. In this way, when the equations are embedded in those models, they shall be least perturbed.

5.
Electricity market model

This chapter focusses on Objective 2 of the modelling activity: t*o develop models of the electricity market, able to represent the actions and reactions of the generation companies and the policy makers in decarbonisation scenarios*.
To pursue the objective, a Game Theory model was developed, in collaboration with the Department of Electric Power Systems at KTH Royal Institute of Technology. An existing model [145] was modified, by addition of elements characterising the Italian electricity market, and by introduction of two of the mathematical formulations developed in Chapter 4. In this way, all the relevant dynamics taking place between generation companies and system operators when flexible electricity supply is requested are modelled. Reference is made to the Italian electricity market, because it is particularly representative of markets where a significant request for flexible electricity supply is emerging. However, this does not imply any loss of generality, because the same characteristics and the same request for flexible electricity generation are noticed also in several other electricity markets.
The model in [145] is stochastic, and so is the one developed in the present chapter. As discussed in Subsection 3.2.1.2, a stochastic model more easily allows the different sources of uncertainty to be taken into account.

Nomenclature

General notation

$\tilde{\cdot}$	variable
$\underset{\smile}{\cdot}$	bid quantity
$\hat{\cdot}$	uncertain parameter

Symbols

B	set of the new generators
$c, \underset{\smile}{\tilde{c}}$	cost and cost bid
$\tilde{c}urt$	curtailed load
d	demand
E	expected value
$f(x, y)$	generic function of the vectors x and y
$\tilde{g}, \underset{\smile}{\tilde{g}}_{\max}, g_{max}$	generation, generation bid, maximum generation
$g_i(x, y)$	inequality constraint i
H	Matrix of Power Transfer Distribution Factors
$h_j(x, y)$	equality constraint j
k	binary variable of the Bernoulli distribution
L	Lagrangian
M	generic big number
N, N_A, N_B, N_G, N_D	number of nodes, all generators of a company, new generators of a company, all generators on the market, demand points
P_{curt}	price of the curtailed load (VoLL)

$\tilde{P}_r$	price bid for the reserve
$\tilde{p}$	price determined by the market clearing
$\tilde{r}, r_{max}$	reserve, maximum reserve
m_g, m_d	matrices for grouping the generators/demand points by nodes
W	generic welfare function
x	variable of the Bernoulli distribution
y, v, w, k, t, u, h	auxiliary variables
$\tilde{z}$	binary variable with Bernoulli distribution
ΔG	generic generation expansion
∇	Nabla operator
$\alpha, \beta, \gamma, \delta, \varepsilon, \zeta, \vartheta, \lambda, \mu, \nu, \tau$	KKT multipliers
θ	current exiting a node
Π_t	profit of company t

Indices

b	demand block
j	generator or demand point
l	transmission line
n	node
s	step of the cost curve

Subscripts

0	optimal
A	set of all generators of a company
B	set of new generators of a company
b	demand block
$curt$	curtailed load
D	set of all demand points
d	demand point
e, el	electricity
G	set of all the generators in the market
g	generator
i	generic item
j	generator or demand point
inv	investment
l	transmission line
$fuel$	fuel
r, res	reserve
$ramp$	ramp

Superscripts

low	lower limit
up	upper limit
$*$	optimal value

5.1. A Game Theory model of a flexible electricity market

As inferred from the discussion in PART II, several agents play a role in the Italian electricity market. In the first place, the system operator (in the Italian case this is Gestore dei Mercati Energetici) computes the optimal electricity dispatch every hour and every day, based on welfare optimisation algorithms. It is a neutral agent, running a traditional mathematical program, subject to a number of constraints related to the structure of the electricity network. On a different ground, there are the generation companies, offering their bids to the system operator on an hourly basis, and making generation expansion decisions on a yearly basis. The companies make decisions before participating into the auctioning sessions of the market. Therefore, the electricity market may be seen as a leader-follower framework, where the companies are the leaders and the system operator carrying out the market clearing is the follower. This is the so-called Stackelberg duopoly problem, already introduced. Eventually, there appears the planner, which may be identified in the Government, or the Authority. This may decide to introduce incentives, taxations, price caps or other tools to condition the market, for the long-term decarbonisation objectives to be pursued. For instance, the capacity market, currently under evaluation in a number of European countries, is one of these tools: even though concerns are cast about the distortive effects such mechanisms may have [53], they are claimed to be a way to control the 'missing money' problem in markets characterised by substantial flexibility. The planner moves even before the companies, since it decides in principle the rules of the electricity market. Therefore, another leader-follower structure adds to the existing one: the leader is in this case the planner, the follower is the ensemble of the companies and the system operator. In the end, a three-level problem emerges. This situation may be sketched as in Figure 37.

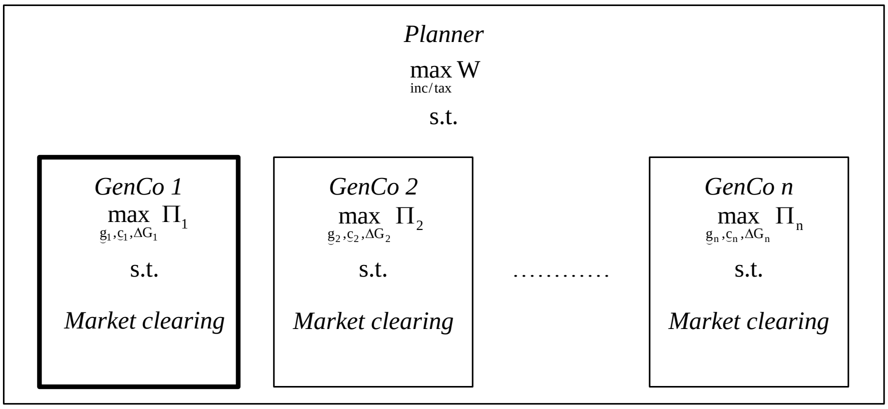

Figure 37. *Three-level Game Theory setting of the electricity market.*

At the upmost level, the planner maximises a long-term social welfare function W, deciding on incentives, taxations or other market tools. The welfare maximisation is subject to a number of constraints, each consisting in a two-level optimisation problem: at the upper level the generation company (GenCo) maximises its profit in the electricity market, deciding on the price and quantity bids and on the generation expansion strategies; at the lower level, the system operator carries out the market clearing. The market clearing in the lower level is a constraint of the maximisation of the profit in the upper level. n two-level problems are written and solved, one for every company in the market.

The depicted structure clearly simplifies the complex interrelations between the numerous agents of the Italian electricity market, but it captures the essential aspects. The modelling activity of this research focussed on one of the two-level problems between one generation company and the market clearing, identified by the bold frame in Figure 37. This bi-level setting was formulated as a Stackelberg stochastic game by Hesamzadeh et al. [145] at KTH Royal Institute of Technology. The structure of their model is reported.

$$\underset{\underset{\smile}{\tilde{g}}_{max,j},\tilde{z}_j}{\mathrm{Max}}\ \Pi_t = E\left[\sum_{j=1}^{N_A}\left(\tilde{p}_j - c(j)\right)\cdot\tilde{g}(j) - \sum_{j=1}^{N_B} c_{inv}(j)\cdot\tilde{z}(j)\right] \tag{4.20}$$

$$\text{s.t.}\quad 0 \le \underset{\smile}{\tilde{g}}_{max}(j) \le g_{max}(j) \qquad j = 1,\ldots,N_A \tag{4.21}$$

$$0 \le \underset{\smile}{\tilde{g}}_{max}(j) \le \tilde{z}(j)\cdot g_{max}(j) \qquad j = 1,\ldots,N_B \tag{4.22}$$

$$f\left(\tilde{z}(j) = k\right) = x(j)^k \cdot \left(1 - x(j)\right)^{1-k} \qquad k=\{0,1\} \tag{4.23}$$

$$\underset{\tilde{g}_j}{\mathrm{Max}} - \sum_{j\in G} \underset{\smile}{\tilde{c}}(j)\cdot\tilde{g}(j) \tag{4.24}$$

$$\text{s.t.}\quad 0 \le \tilde{g}(j) \le \underset{\smile}{\tilde{g}}_{max}(j) \qquad j = 1,\ldots,N_G \tag{4.25}$$

$$\sum_{j=1}^{N-1} B(n,j)\cdot\tilde{\theta}(j) = \sum_{j\in G_n}\tilde{g}(j) - \sum_{j\in D_n}\tilde{d}(j) \qquad n = 1,\ldots,N \tag{4.26}$$

$$-F(l) \le \sum_{n=1}^{N-1} H(l,n)\cdot\tilde{\theta}(n) \le F(l) \qquad l = 1,\ldots,L \tag{4.27}$$

For the complete nomenclature, the reader may refer to the dedicated section at the beginning of this chapter. In (4.20) to (4.27), as in the following, $\sim$ indicates the variables, $\smile$ indicates the quantities bid by the companies in the auctioning sessions of the market.

(4.20) is the optimisation function of the upper level problem. It represents the maximisation of the expected profit Π_t of company t. Each company owns a number of generators j and can decide to build new generators. The profit consists in two terms: the first term is the summation over the generators j of the difference between the market price p_j and the generation cost $c(j)$, multiplied by the awarded generation $\tilde{g}(j)$. The price is determined for each node of the network; the second term is related to the new units the company may decide to build, and it is the product of the investment cost $c_{inv}(j)$ by a binary decision variable with Bernoulli distribution $\tilde{z}(j)$. A is the set of all the generating units of company t, B is the set of the new units, where $B \subset A$. The company maximises its profit deciding on the variables $\underset{\smile}{\tilde{g}}_{max}(j)$ and $\tilde{z}(j)$, where $\underset{\smile}{\tilde{g}}_{max}(j)$ is the quantity bid of the company, i.e. the maximum generation it is willing to provide through generator j.

(4.21) states that the quantity bid by the company for generator j cannot exceed the maximum generation capacity $g_{max}(j)$ of the generator. (4.22) is equivalent to (4.21), but it refers to the sole new units. (4.23) introduces the variable with Bernoulli distribution $\tilde{z}(j)$, as a function of the binary variable $k = \{0,1\}$.

(4.24) is the objective function of the lower level problem and it is at the same time a constraint of the upper level problem. It represents the market clearing carried out by the system operator, considering the demand for electricity inelastic to the market prices. It consists in the maximisation of the global welfare, by decision of the generation $\tilde{g}(j)$ to be awarded to every generator. The welfare is the inverse of the system's generation cost, and it is computed by summing the product of the cost bid $\underset{\smile}{\tilde{c}}(j)$ and the dispatched generation $\tilde{g}(j)$ over all the generators G of all the companies.

(4.25) states that the quantity the system operator decides to dispatch from every generator must not exceed the bid $\underset{\smile}{\tilde{g}}_{max}(j)$ made by the company. (4.26) is the matching between demand and

supply at each node n, and it states that the difference between the supply $\sum_{j\in G_n}\tilde{g}(j)$ and the demand $\sum_{j\in D_n}\tilde{d}(j)$ at each node must equal the net flow exiting the node $\sum_{j=1}^{N-1}B(j,n)\cdot\tilde{\theta}(j)$. (4.27) introduces the flow limits on the transmission lines between nodes, through the concept of the Matrix of the Power Transfer Distribution Factors [53]. An element $H(l,n)$ of the matrix is the amount by which the flows over the transmission line l vary with a change in the injection at each node n. The product $\sum_{n=1}^{N-1}H(l,n)\cdot\theta(n)$ is the flow over one link.
In the Matrix of Power Transfer Distribution Factors, by definition, the transmission lines are represented by the rows of the matrix, the nodes by the columns. In the columns, all the nodes appear, but one, which is assumed as a reference node. For instance, consider a three-node network like in Figure 38.

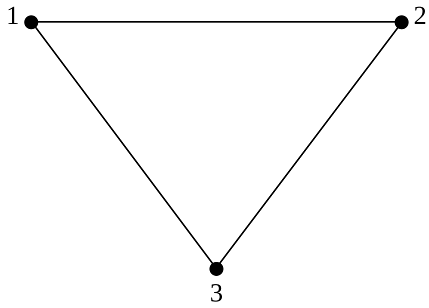

Figure 38. *Sample three-node network.*

If node 3 is assumed to be the reference node and all the links to have the same impedance, the Matrix of Power Transfer Distribution Factors for the network in Figure 38 results as in (4.28):

$$\mathrm{H} = \begin{array}{c c} & \begin{array}{cc} \mathrm{n1} & \mathrm{n2} \end{array} \\ \begin{array}{c} 1\rightarrow 2 \\ 2\rightarrow 3 \\ 1\rightarrow 3 \end{array} & \begin{pmatrix} 1/3 & -1/3 \\ 1/3 & 2/3 \\ 2/3 & 1/3 \end{pmatrix} \end{array} \tag{4.28}$$

The elements in the left column, must be read like this: 1/3 of the current exiting node 1 flows on both the lines from 1 to 2 and from 2 to 3; 2/3 of the current exiting node 1 flow on the link from 1 to 3. A similar reasoning is made for the right column, i.e. the current exiting node 2. Therefore, for instance, the total current flowing from 2 to 3 is:

$$\mathrm{f}_{2\rightarrow 3} = 1/3\tilde{\theta}_1 + 2/3\tilde{\theta}_2 \tag{4.29}$$

Through the matrix, the expression above can also be written as:

$$\sum_{n=1}^{2}\mathrm{H}(2\rightarrow 3,\mathrm{n})\cdot\tilde{\theta}(\mathrm{n}) \tag{4.30}$$

In the described electricity market model, Greek letters show up aside the constraints of the lower level problem. These are the Karush-Kuhn-Tucker (KKT) multipliers of the optimisation problem. Their meaning and their use will be illustrated further on. This model must be significantly modified to fit the current and forecasted situation of the Italian electricity market. Some fundamental characteristics are missing:

- *Need for capacity reserve and the option for supplying it*. Currently, in the Italian market these two elements play a dominant role in the strategies of the companies owning CCGTs. While the penetration of renewables reduces the share of CCGTs in electricity generation, and the revenues from the MGP decrease, these power plants have an option to profit from the MSD.
- *Opportunity of introducing demand-response measures, such as load shedding*. When the renewables are highly fluctuating and balancing them through fossil-fuel fired power plants becomes too costly, it may be convenient to curtail part of the load. This does not correspond to anything actually existing in the Italian market, but it may result a convenient option in the future.
- *More realistic representation of the generation costs*. Usually, the total generation cost is a non-decreasing quadratic function of the generation. This means the specific cost $c(j)$ is not actually a constant, but rather a variable, linearly increasing with the generation: $\tilde{c}(j) = a_j + b_j \cdot \tilde{g}(j)$. The Supply Function Equilibrium models discussed in Section 3.2.1.2 employ such formulations. However, when the specific cost is multiplied by the generation in the upper level objective function, the cost curve becomes quadratic. Introducing a quadratic cost function makes the model nonlinear and much slower to run. Therefore, such formulation is avoided. The author chose a different approach: the quadratic cost function is approximated by a stepwise constant function, like in Figure 39.

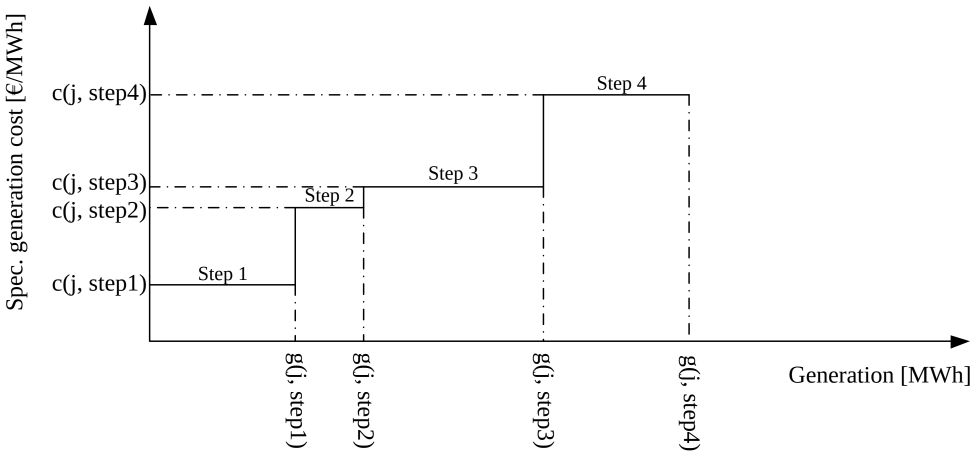

Figure 39. *Stepwise constant curve of the generation cost.*

  In this way, the specific generation cost becomes a function of both the generator and the step in the step curve: $c(j, s)$.

- *Uncertainty of renewable generation*. As discussed in PART II, the higher is the penetration of the renewable energy sources, the more the bids of the generation companies in the MGP depend on their predictions about the generation from the renewables in the day after. The uncertainty over the generation from the renewables can be taken into account indirectly, through the demand for electricity and for reserve. The uncertainty shall be placed over these two variables.
- *Costs for the flexible operation of fossil-fuel fired power plan*ts. In scenarios where the penetration of renewables is significantly increasing, these items may be critical in

determining the dispatch of fossil-fuel fired units and also the bids of the companies. The main costs of flexible operation can be taken into account by introducing in the model the mathematical formulations developed for the fuel consumption at partial load, the cycling performance, the cost of the starts. However, the addition of the cycling performance as a function of the configuration would have complicated the model by far. Given the already complex structure, with three optimisation levels and a number of stochastic variables, this item was not introduced. Only the fuel consumption at partial load and the cost of the starts were added, with proper adaptations, among the formulations derived in Section 4.3. The cost of the starts is assumed as a stochastic quantity, since it includes the wear of the components, which is uncertain.

- *Subdivision of the time domain into time slices/demand blocks*. The introduction of the cost of the starts as formulated in Section 4.3.3 required another significant modification to the whole model: the cost is originated by the difference of on-grid capacity between one time slice and the previous one. Therefore, the time slices must be introduced. In the new formulation, it was assumed that the day is split into a number of demand blocks *b*, representing the time slices.

After adding all these modifications, the model becomes as follows.

$$\max_{\underset{\smile}{\tilde{g}}_{max,j},\tilde{c}_j,\underset{\smile}{\tilde{P}}_{r,j},\tilde{z}_j} \Pi_t = E\left\{\begin{array}{l} \sum_b \sum_{j\in A} \sum_s \left(p_{el,b,j} - c(j,s)\right)\cdot \tilde{g}(j,b,s) + \\ + \sum_b \sum_{j\in A} p_{res,b,j} \cdot \tilde{r}(j,b) + \\ - \sum_b \sum_{j\in A} c_{fuel}(j)\cdot\left(g_{max}(j) - \sum_s \tilde{g}(j,b,s)\right) + \\ - \sum_{b>0} \sum_{j\in A} \hat{c}_{ramp}(j)\cdot\left|\sum_s \tilde{g}(j,b,s) - \sum_s \tilde{g}(j,b-1,s)\right| + \\ - \sum_{j\in B} c_{inv}(j)\cdot\tilde{z}(j) \end{array}\right\} \tag{4.31}$$

s.t.

$$0 \le \underset{\smile}{\tilde{g}}_{max}(j,b) \le g_{max}(j) \qquad j = 1,\ldots,N_A \tag{4.32}$$

$$0 \le \underset{\smile}{\tilde{g}}_{max}(j,b) \le \tilde{z}(j)\cdot g_{max}(j) \qquad j = 1,\ldots,N_B \tag{4.33}$$

$$f\left(\tilde{z}(j) = k\right) = x(j)^k\left(1 - x(j)\right)^{1-k} \qquad k \in \{0,1\} \tag{4.34}$$

$$\max_{\tilde{g}_{j,b,s}} -\sum_b \left\{ \sum_{j\in G} \left\{ \sum_s \tilde{g}(j,b,s)\cdot \underset{\smile}{\tilde{c}}(j,b) + \tilde{r}(j,b)\cdot \underset{\smile}{\tilde{P}}_r(j,b) \right\} + \sum_{j\in D} \tilde{c}urt(j,b)\cdot P_{curt} \right\} \tag{4.35}$$

s.t.

$$0 \le \sum_s \tilde{g}(j,b,s) \le \underset{\smile}{\tilde{g}}_{max}(j,b) \qquad j = 1,\ldots,N_G \;\leftrightarrow\; \alpha_{j,b} \tag{4.36}$$

$$0 \le \tilde{g}(j,b,s) \le g_{max}(j,b,s) \qquad j = 1,\ldots,N_G \;\leftrightarrow\; \beta_{j,b,s} \tag{4.37}$$

$$\begin{array}{l} \sum_{k=1}^{N-1} B(n,k)\cdot\tilde{\theta}(k) = \sum_{j\in G}\sum_s \tilde{g}(j,b,s)\cdot m_g(j,n) + \sum_{j\in D} \tilde{c}urt(j,b)\cdot m_d(j,n) + \\ -\sum_{j\in D} \hat{d}_e(j,b)\cdot m_d(j,n) \qquad n = 1,\ldots N \leftrightarrow\; p_{el,b,n} \end{array} \tag{4.38}$$

$$\sum_{j\in G} \tilde{r}(j,b)\cdot m_g(j,n) = \sum_{j\in D} \hat{d}_r(j,b)\cdot m_d(j,n) \qquad n = 1,\ldots N \leftrightarrow\; p_{res,b,n} \tag{4.39}$$

$$-F(l) \le \sum_{n=1}^{N-1} H(l,n)\cdot\tilde{\theta}(n) \le F(l) \qquad l = 1,\ldots,L \leftrightarrow\; \gamma_{l,b}^{up},\gamma_{l,b}^{low} \tag{4.40}$$

$$0 \le \tilde{r}(j,b) \le g_{max}(j) - \underset{\smile}{\tilde{g}}_{max}(j,b) \qquad j = 1,\ldots,N_G \;\leftrightarrow\; \delta_{j,b}^{up},\delta_{j,b}^{low} \tag{4.41}$$

$$0 \le \tilde{r}(j,b) \le \tilde{g}_{max}(j,b) \quad j = 1,...,N_G \quad \leftrightarrow \; \zeta^{up}_{j,b}, \zeta^{low}_{j,b} \tag{4.42}$$

$$0 \le \tilde{r}(j,b) \le r_{max}(j) \quad j = 1,...,N_G \quad \leftrightarrow \; \vartheta^{up}_{j,b}, \vartheta^{low}_{j,b} \tag{4.43}$$

$$0 \le \tilde{c}urt(j,b) \le \hat{d}_e(j,b) \quad j = 1,...,N_D \quad \leftrightarrow \; \varepsilon^{up}_{j,b}, \varepsilon^{low}_{j,b} \tag{4.44}$$

A number of new features appear in this formulation. First of all, the optimisation problem becomes multi-period, due to the presence of the demand blocks b. Therefore, all the variables become also functions of the demand blocks, with respect to the original formulation in [145].

In (4.31), the objective function of the upper level problem, new items are added. The company maximises its expected profit by deciding on more variables: in addition to the quantity bid and the generation expansion, also the price bids on the energy and reserve markets appear.

The second term in the right hand side of (4.31) is the revenues from the supply of reserve capacity. It is the product of the price $p_{res,b,j}$ awarded by the generator for the provision of reserve and the supplied reserve $\tilde{r}(j,b)$. Notice that in Italy the MSD is a pay-as-bid market, where the reserve is paid at the price bid by the company. The author decided to have the price determined by the market, to keep the problem as general as possible, but this does not prevent the pay-as-bid case to be easily represented, as a simplification of this formulation.

The third term is the additional cost of fuel due to the decreased efficiency at partial load operation. It corresponds exactly to the second term in the right hand side of (4.10), in Section 4.3.1. $c_{fuel}(j)$ is the factor k, while $(g_{max}(j) - \sum_s \tilde{g}(j,b,s))$ corresponds to $\left(E_{full\ load} - E\right)$. The first term of the formulation (4.10) in Section 4.3.1 is not taken into account, since it is already accounted in the cost item $c(j)$.

The fourth term conceptually recalls the formulation of the cost of the starts, derived in Section 4.3.3, but it is slightly different, due to computational constraints. The mathematical formulation in 4.3.3 implies that the on-grid capacity of the generator is a variable. In this model the only variable related to the electricity production is $\tilde{g}(j,b,s)$, the generation from generator j, while the capacity of the generator is a user-defined parameter. If $\tilde{g}(j,b,s)$ is 0, the generator is off, otherwise it is generating. To employ the exact formulation derived in Section 4.3.3, binary variables should be introduced, but the computational burden would increase significantly. Therefore, the author decided to modify the cost for the starts into a cost for the ramps, proportional to the variation of the generation from one time slice to the other. Compared to the formulation (4.14) in Section 4.3.3, $\sum_{b>0}\cdot$ corresponds to $\sum_{day}\cdot$, $\hat{c}_{ramp}(j)$ replaces $c_{starts}/2$ and the difference in generation $|\sum_s \tilde{g}(j,b,s) - \sum_s \tilde{g}(j,b-1,s)|$ replaces the difference in on-grid capacity $\left|\dot{E}_t - \dot{E}_{t-1}\right|$. Notice that $\hat{c}_{ramp}(j)$ is in this case a stochastic parameter.

Another major difference between the model in [145] and the current formulation lies in the objective function of the lower level problem. Here, two new items add up. The first one is the global cost for the supply of reserve capacity. It is the product of the reserve provided by each generator $\tilde{r}(j,b)$ by the price bid for the reserve, summed over all the generators of all the companies. The second item is the global cost for the curtailment of the loads, technically called global Value of Lost Load (VoLL). It consists in the product of the curtailed load at each demand point $\tilde{c}urt(j,b)$ by the price of load curtailment P_{curt}, summed over all the demand points. The price is assumed as fixed by the Authority and unique for all the demand points. It indirectly represents a price cap: whenever the price of the electricity determined on the market exceeds this value, no more generation offer is accepted and load is cut off instead.

A number of new constraints are also introduced, in the lower level problem. They are mostly related to the introduction of the demand and supply of reserve capacity.

(4.36) states that the total generation of each unit in every time slice is upper-limited by the generation bid of the company for that unit. The total generation is the sum $\sum_s \tilde{g}(j,b,s)$ of the generation from all the steps of the step curve in Figure 39. (4.37) states that the generation in each step of the curve is lower-limited by 0 and upper-limited by the value $g_{max}(j,b,s)$, indicated as $g(j, step\ n)$ in Figure 39. This is necessary, for the cost of generation to follow the stepwise trend.
(4.38) imposes the matching between demand and supply of electricity. It is equivalent to the original model, but this time also the curtailed load plays a role: in each node, the sum of the generation and the curtailed load must equal the demand. The demand for electricity is stochastic. Notice that in the current formulation the generation at each node is represented as the sum over j of the product between the generation of each generator by the matrix $m_g(j,n)$. Equivalently, the demand and the curtailed load at each node are respectively the products of the demand and the curtailed load at each demand point by the matrix $m_d(j,n)$. For example, the demand at node n and demand block b is $\sum_{j\epsilon D} \hat{d}_e(j,b) \cdot m_d(j,n)$. (4.39) is equivalent to (4.38), but it imposes the matching between the demand $\tilde{d}_r(j,b)$ and supply $\tilde{r}(j,b)$ of reserve capacity at each node. Also the demand for reserve is stochastic. (4.40) sets limits on the flow over the transmission lines.
(4.41) states that the reserve supplied by every generator in every time slice must be less than the difference between the maximum generation capacity and the generation bid for the same time slice. That is, if a generator is to supply reserve capacity, its load must be partialised enough. This constraint implicitly defines the reserve as upward reserve: the formulation here introduced does not cover a need for downward reserve. The constraint introduces another approximation: actually, the supplied reserve should be constrained by the difference between the generation capacity and the actual generation in the time slice. Here, the actual generation is replaced by the generation bid, which is the maximum generation the unit is willing to provide and it is in general higher than the actual generation. Therefore, in the current formulation the reserve is more constrained than it should be and it will result lower. With a few algebraic passages it can be demonstrated that such approximation was necessary, for preventing the problem from becoming nonlinear.
(4.42) states that the reserve must be less than or equal to the generation bid. This does not necessarily occur in reality, but the constraint is introduced to approximate the limits on the reserve which can be provided. Actually, in the proposed model of the electricity market, the provision of reserve turns out to be decoupled from the generation: the reserve capacity can be provided also by power plants which are off. In principle, this would be possible for very fast ramping generators, which can be started up in less time than what is requested for providing reserve. However, most generators take a very long time to start up, therefore they must be already spinning to provide reserve. In light of these considerations, the current formulation is not realistic. However, all the few models in literature accounting for the provision of reserve make the same assumptions, because removing them would make the problem non-convex. No solution algorithms are known in literature for such cases, yet. (4.42) tries to partly solve this issue: imposing that the reserve be less than the generation bid, this constraint also implies that if a generator does not bid anything, i.e. it plans to be off, it cannot provide reserve.
(4.43) imposes that the reserve be less than a pre-defined value. This value is computed exogenously, and represents the limits on the ramping rates of the power plant. Eventually, (4.44) states that the curtailed load at every demand point cannot exceed the demand in the same point.
The model from (4.31) to (4.44) is a bi-level mixed-integer nonlinear optimisation problem (MINLP). Three features make the problem particularly difficult to solve:

- The presence of two optimisation levels. These two levels are linked: first of all, because the lower level optimisation function is a constraint of the upper level problem; secondly, because two of the KKT multipliers of the lower level problem are multiplied by variables of the upper level problem.

- The nonlinearity, introduced by the first and second term in the upper level optimisation function and by the first and second term in the lower level optimisation function.
- The mixed-integer terms in the upper level optimisation function, consisting in the presence of the absolute value and in the binary variable $k = \{0,1\}$.

The presence of the two mixed-integer terms cannot be avoided. On the contrary, the other two issues can be solved by use of definitions and theorems from the duality theory.

- The bi-level problem can be reduced to a one-level program by writing the Lagrangian of the lower level optimisation problem and deriving the Karush-Kuhn-Tucker optimality conditions. This is shown in Section 5.1.1.
- The nonlinear terms can be linearised by rearranging the complementary slackness and the stationarity conditions, as described in Section 5.1.2.

In [145], a procedure based on these two techniques is developed and applied for turning the optimisation problem into a one-level mixed-integer linear program (MILP). This procedure is applied to the modified formulation in the two following sections, with proper adaptations.

5.1.1. Reduction to a one-level problem

An optimisation problem can be generically defined as:

$$\begin{aligned} &\text{maximise } \mathrm{f}(\mathrm{x},\mathrm{y}) \\ &\text{subject to } \mathrm{g}_\mathrm{i}(\mathrm{x},\mathrm{y}) \le 0 \\ &\qquad\qquad \mathrm{h}_\mathrm{j}(\mathrm{x},\mathrm{y}) = 0 \end{aligned} \tag{4.45}$$

where g_i are the inequality constraints, h_j are the equality constraints and x and y are vectors of variables. The Lagrangian of the optimisation problem is defined as:

$$\mathrm{L}(\mathrm{x},\mathrm{y},\mu_\mathrm{i},\lambda_\mathrm{j}) = \mathrm{f}(\mathrm{x},\mathrm{y}) + \sum_\mathrm{i} \mu_\mathrm{i} \cdot \mathrm{g}_\mathrm{i}(\mathrm{x},\mathrm{y}) + \sum_\mathrm{j} \lambda_\mathrm{j} \cdot \mathrm{h}_\mathrm{j}(\mathrm{x},\mathrm{y}) \tag{4.46}$$

where and μ_i and λ_j are the Karush-Kuhn-Tucker (KKT) multipliers. The usefulness of the KKT multipliers is clear in what follows: if $f(x_0, y_0)$ is a maximum of $f(x, y)$ in the original problem, then there exist values $\mu_{0,i}$ and $\lambda_{0,j}$ for which $L(x_0, y_0, \mu_{0,i}, \lambda_{0,j})$ is a maximum of the Lagrangian. The method of the KKT multipliers allows an optimisation problem consisting in several equations to be turned into a single equation. In line with these definitions, and naming the KKT multipliers as in (4.36) to (4.44), the Lagrangian of the lower level optimisation problem presented above can be written.

$$\begin{aligned}
\mathrm{L} = &-\sum_\mathrm{b} \left\{ \sum_{\mathrm{j}\in\mathrm{G}} \left\{ \sum_\mathrm{s} \tilde{\mathrm{g}}(\mathrm{j},\mathrm{b},\mathrm{s}) \cdot \undertilde{\mathrm{c}}(\mathrm{j},\mathrm{b}) + \tilde{\mathrm{r}}(\mathrm{j},\mathrm{b}) \cdot \undertilde{\tilde{\mathrm{P}}}_\mathrm{r}(\mathrm{j},\mathrm{b}) \right\} + \sum_{\mathrm{j}\in\mathrm{D}} \tilde{\mathrm{c}}\mathrm{urt}(\mathrm{j},\mathrm{b}) \cdot \mathrm{P}_\mathrm{curt} \right\} + \\
&+ \sum_\mathrm{b} \sum_\mathrm{n} \mathrm{p}_{\mathrm{el},\mathrm{b},\mathrm{n}} \begin{pmatrix} -\sum_{\mathrm{j}=1}^{\mathrm{N}-1} \mathrm{B}(\mathrm{n},\mathrm{j}) \cdot \tilde{\theta}(\mathrm{j}) + \sum_{\mathrm{j}\in\mathrm{G}} \sum_\mathrm{s} \tilde{\mathrm{g}}(\mathrm{j},\mathrm{b},\mathrm{s}) \cdot \mathrm{m}_\mathrm{g}(\mathrm{j},\mathrm{n}) + \sum_{\mathrm{j}\in\mathrm{D}} \tilde{\mathrm{c}}\mathrm{urt}(\mathrm{j},\mathrm{b}) \cdot \mathrm{m}_\mathrm{d}(\mathrm{j},\mathrm{n}) \\ -\sum_{\mathrm{j}\in\mathrm{D}} \hat{\mathrm{d}}_\mathrm{e}(\mathrm{j},\mathrm{b}) \cdot \mathrm{m}_\mathrm{d}(\mathrm{j},\mathrm{n}) \end{pmatrix} + \\
&+ \sum_\mathrm{b} \sum_\mathrm{n} \mathrm{p}_{\mathrm{res},\mathrm{b},\mathrm{n}} \cdot \left(\sum_{\mathrm{j}\in\mathrm{G}} \tilde{\mathrm{r}}(\mathrm{j},\mathrm{b}) \cdot \mathrm{m}_\mathrm{g}(\mathrm{j},\mathrm{n}) - \sum_{\mathrm{j}\in\mathrm{D}} \hat{\mathrm{d}}_\mathrm{r}(\mathrm{j},\mathrm{b}) \cdot \mathrm{m}_\mathrm{d}(\mathrm{j},\mathrm{n}) \right) +
\end{aligned}$$

$$
\begin{aligned}
&+\sum_{b}\sum_{l}\gamma_{l,b}^{up}\cdot\left(F(l)-\sum_{n}H(l,n)\cdot\tilde{\theta}(n)\right)+\sum_{b}\sum_{l}\gamma_{l,b}^{low}\cdot\left(F(l)+\sum_{n}H(l,n)\cdot\tilde{\theta}(n)\right)+\\
&+\sum_{b}\sum_{j\in G}\alpha_{j,b}^{up}\cdot\left(\underset{\smile}{\tilde{g}}_{max}(j,b)-\sum_{s}\tilde{g}(j,b,s)\right)+\sum_{b}\sum_{j\in G}\alpha_{j,b}^{low}\cdot\sum_{s}\tilde{g}(j,b,s)+\\
&+\sum_{b}\sum_{j\in G}\sum_{s}\beta_{j,b,s}^{up}\cdot\left(g_{max}(j,b,s)-\tilde{g}(j,b,s)\right)+\sum_{b}\sum_{j\in G}\sum_{s}\beta_{j,b,s}^{low}\cdot\tilde{g}(j,b,s)+\\
&+\sum_{b}\sum_{j\in G}\delta_{j,b}^{up}\cdot\left(g_{max}(j)-\underset{\smile}{\tilde{g}}_{max}(j,b)-\tilde{r}(j,b)\right)+\sum_{b}\sum_{j\in G}\delta_{j,b}^{low}\cdot\tilde{r}(j,b)+\\
&+\sum_{b}\sum_{j\in G}\zeta_{j,b}^{up}\left(\underset{\smile}{\tilde{g}}_{max}(j,b)-\tilde{r}(j,b)\right)+\sum_{b}\sum_{j\in G}\zeta_{j,b}^{low}\tilde{r}(j,b)+\\
&+\sum_{b}\sum_{j\in G}\vartheta_{j,b}^{up}\left(r_{max}(j)-\tilde{r}(j,b)\right)+\sum_{b}\sum_{j\in G}\vartheta_{j,b}^{low}\tilde{r}(j,b)+\\
&+\sum_{b}\sum_{j\in D}\varepsilon_{j,b}^{up}\cdot\left(\hat{d}_{e}(j,b)-\tilde{c}urt(j,b)\right)+\sum_{b}\sum_{j\in D}\varepsilon_{j,b}^{low}\cdot\tilde{c}urt(j,b)
\end{aligned}
\tag{4.47}
$$

From the Lagrangian, the KKT optimality conditions can be derived. These are first order necessary conditions for the solution of a program to be optimal. They are also sufficient, in case the objective function is concave, the inequality constraints are continuously differentiable convex functions, the equality constraints are affine functions. All of these conditions are verified in the lower level problem of the present electricity market model, therefore the KKT optimality conditions are both necessary and sufficient, in the present case. The KKT conditions are theoretically defined as:

Stationarity conditions

$$\nabla f\left(x^{*},y^{*}\right)=\sum_{i}\mu_{i}\cdot\nabla g_{i}\left(x^{*},y^{*}\right)+\sum_{j}\lambda_{j}\cdot\nabla h_{j}\left(x^{*},y^{*}\right)\tag{4.48}$$

where x^{*} and y^{*} are vectors of local optima.

Primal feasibility conditions

$$g_{i}\left(x^{*},y^{*}\right)\le 0\quad\forall i\tag{4.49}$$
$$h_{j}\left(x^{*},y^{*}\right)=0\quad\forall j\tag{4.50}$$

Dual feasibility conditions

$$\mu_{i}\ge 0\quad\forall i\tag{4.51}$$

Complementary slackness conditions

$$\mu_{i}\cdot g_{i}\left(x^{*},y^{*}\right)=0\quad\forall i\tag{4.52}$$

When applied to the current optimisation problem, the KKT optimality conditions result as follows.

Stationarity conditions

$$-\underset{\smile}{\tilde{c}}\left(j,b\right)+\sum_{n}p_{el,b,n}\cdot m_{g}\left(j,n\right)-\alpha_{j,b}^{up}+\alpha_{j,b}^{low}-\sum_{s}\beta_{j,b,s}^{up}+\sum_{s}\beta_{j,b,s}^{low}=0 \quad j=1,\ldots,N_{G} \tag{4.53}$$

$$-\sum_{k}p_{el,b,n}\cdot B\left(k,n\right)-\sum_{l}\gamma_{l,b}^{up}\cdot H\left(l,n\right)+\sum_{l}\gamma_{l,b}^{low}\cdot H\left(l,n\right)=0 \quad n=1,\ldots,N\text{-}1 \tag{4.54}$$

$$-P_{curt}+\sum_{n}p_{el,b,n}\cdot m_{d}\left(j,n\right)-\varepsilon_{j,b}^{up}+\varepsilon_{j,b}^{low}=0 \quad j=1,\ldots,N_{D} \tag{4.55}$$

$$-\underset{\smile}{\tilde{P}}_{r}\left(j,b\right)+\sum_{n}p_{res,b,n}\cdot m_{g}\left(j,n\right)-\delta_{j,b}^{up}+\delta_{j,b}^{low}-\zeta_{j,b}^{up}+\zeta_{j,b}^{low}-\vartheta_{j,b}^{up}+\vartheta_{j,b}^{low}=0 \quad j=1,\ldots,N_{G} \tag{4.56}$$

Primal feasibility conditions

$$0\leq\sum_{s}\tilde{g}\left(j,b,s\right)\leq\underset{\smile}{\tilde{g}}_{max}\left(j,b\right) \quad j=1,\ldots,N_{G} \tag{4.57}$$

$$0\leq\tilde{g}\left(j,b,s\right)\leq g_{max}\left(j,b,s\right) \quad j=1,\ldots,N_{G} \tag{4.58}$$

$$\begin{aligned}&\sum_{j=1}^{N-1}B\left(n,j\right)\cdot\tilde{\theta}\left(j\right)=\sum_{j\in G}\sum_{s}\tilde{g}\left(j,b,s\right)\cdot m_{g}\left(j,n\right)+\\&+\sum_{j\in D}\tilde{c}urt\left(j,b\right)\cdot m_{d}\left(j,n\right)-\sum_{j\in D}\hat{d}_{e}\left(j,b\right)\cdot m_{d}\left(j,n\right) \quad n=1,\ldots,N\end{aligned} \tag{4.59}$$

$$\sum_{j\in G}\tilde{r}\left(j,b\right)\cdot m_{g}\left(j,n\right)=\sum_{j\in D}\hat{d}_{r}\left(j,b\right)\cdot m_{d}\left(j,n\right) \quad n=1,\ldots,N \tag{4.60}$$

$$-F\left(l\right)\leq\sum_{n=1}^{N-1}H\left(l,n\right)\cdot\tilde{\theta}\left(n\right)\leq F\left(l\right) \quad l=1,\ldots,L \tag{4.61}$$

$$0\leq\tilde{r}\left(j,b\right)\leq g_{max}\left(j\right)-\underset{\smile}{\tilde{g}}_{max}\left(j,b\right) \quad j=1,\ldots,N_{G} \tag{4.62}$$

$$0\leq\tilde{r}\left(j,b\right)\leq\underset{\smile}{\tilde{g}}_{max}\left(j,b\right) \quad j=1,\ldots,N_{G} \tag{4.63}$$

$$0\leq\tilde{r}\left(j,b\right)\leq r_{max}\left(j\right) \quad j=1,\ldots,N_{G} \tag{4.64}$$

$$0\leq\tilde{c}urt\left(j,b\right)\leq\hat{d}_{e}\left(j,b\right) \quad j=1,\ldots,N_{D} \tag{4.65}$$

Dual feasibility conditions

$$\begin{aligned}&\alpha_{j,b}\geq 0,\beta_{j,b,s}\geq 0,\gamma_{j,b}^{up}\geq 0,\gamma_{j,b}^{low}\geq 0,\delta_{j,b}^{up}\geq 0,\delta_{j,b}^{low}\geq 0,\\&\zeta_{j,b}^{up}\geq 0,\zeta_{j,b}^{low}\geq 0,\vartheta_{j,b}^{up}\geq 0,\vartheta_{j,b}^{low}\geq 0,\varepsilon_{j,b}^{up}\geq 0,\varepsilon_{j,b}^{low}\geq 0\end{aligned} \tag{4.66}$$

Complementary slackness conditions

$$\gamma_{l,b}^{up}\cdot\left(F\left(l\right)-\sum_{n}H\left(l,n\right)\cdot\tilde{\theta}\left(n\right)\right)=0 \tag{4.67}$$

$$\gamma_{l,b}^{low}\cdot\left(F\left(l\right)+\sum_{n}H\left(l,n\right)\cdot\tilde{\theta}\left(n\right)\right)=0 \tag{4.68}$$

$$\alpha_{j,b}^{up}\cdot\left(\underset{\smile}{\tilde{g}}_{max}\left(j,b\right)-\sum_{s}\tilde{g}\left(j,b,s\right)\right)=0 \tag{4.69}$$

$$\alpha_{j,b}^{low}\cdot\sum_{s}\tilde{g}\left(j,b,s\right)=0 \tag{4.70}$$

$$\beta_{j,b,s}^{up}\cdot\left(g_{max}\left(j,b,s\right)-\tilde{g}\left(j,b,s\right)\right)=0 \tag{4.71}$$

$$\beta^{low}_{j,b,s} \cdot \tilde{g}(j,b,s) = 0 \tag{4.72}$$

$$\delta^{up}_{j,b} \cdot \left(g_{max}(j) - \tilde{\underset{\smile}{g}}_{max}(j,b) - \tilde{r}(j,b)\right) = 0 \tag{4.73}$$

$$\delta^{low}_{j,b} \cdot \tilde{r}(j,b) = 0 \tag{4.74}$$

$$\zeta^{up}_{j,b}\left(\tilde{\underset{\smile}{g}}_{max}(j,b) - \tilde{r}(j,b)\right) = 0 \tag{4.75}$$

$$\zeta^{low}_{j,b}\tilde{r}(j,b) = 0 \tag{4.76}$$

$$\vartheta^{up}_{j,b}\left(r_{max}(j) - \tilde{r}(j,b)\right) = 0 \tag{4.77}$$

$$\vartheta^{low}_{j,b}\tilde{r}(j,b) = 0 \tag{4.78}$$

$$\varepsilon^{up}_{j,b} \cdot \left(\hat{d}_e(j,b) - \tilde{c}urt(j,b)\right) = 0 \tag{4.79}$$

$$\varepsilon^{low}_{j,b} \cdot \tilde{c}urt(j,b) = 0 \tag{4.80}$$

As anticipated, the KKT conditions are necessary and sufficient for the vectors of the variables to be solutions of the optimisation problem. Therefore, the lower level optimisation problem can be replaced by its KKT conditions and the whole problem thus becomes a one-level program. The so obtained algorithm is reported in Appendix B. The nonlinear lower level optimisation function has been replaced by linear terms. However, the upper level optimisation function is still nonlinear. In addition, new nonlinear terms appear, in the complementary slackness conditions: they are the products of KKT multipliers by variables. In the following section, these nonlinearities are solved.

5.1.2. Treating the nonlinear terms

The nonlinearity of the complementary slackness conditions can be solved thanks to an approach developed by Fortuny Amat and McCarl [182], who considered their disjunctive nature. Generically, the complementary slackness conditions can be written as:

$$w_T \cdot \left(a_1 x_1 + a_2 x_2 + b\right) = 0 \tag{4.81}$$

where w_T is the KKT multiplier and x_1 and x_2 are variables. If a new variable

$$y = a_1 x_1 + a_2 x_2 + b \tag{4.82}$$

is defined, (4.81) can be rewritten as

$$w_T y = 0 \tag{4.83}$$

(4.83) implies that either w_T or y must be equal to 0. This condition can be met by introducing a new zero-one binary variable η, such that:

$$w_T \le (1-\eta)M \tag{4.84}$$

$$y = a_1 x_1 + a_2 x_2 + b \le \eta M \tag{4.85}$$

where M is a very large positive number. In this way the problem becomes much larger, but it is turned from a nonlinear program into a linear mixed-integer program. Employing this approach, the complementary slackness conditions can be linearised and replaced by the following equations.

$$-M\left(1-y_{l,b}^{up}\right) \le \left(F(l)-\sum_{n=1}^{N-1} H(l,n)\cdot\tilde{\theta}(n)\right) \le M\left(1-y_{l,b}^{up}\right) \tag{4.86}$$

$$-My_{l,b}^{up} \le \gamma_{b,l}^{up} \le My_{l,b}^{up} \tag{4.87}$$

$$-M\left(1-y_{l,b}^{low}\right) \le \left(F(l)+\sum_{n=1}^{N-1} H(l,n)\cdot\tilde{\theta}(n)\right) \le M\left(1-y_{l,b}^{low}\right) \tag{4.88}$$

$$-My_{l,b}^{low} \le \gamma_{b,l}^{low} \le My_{l,b}^{low} \tag{4.89}$$

$$-M\left(1-w_{j,b}^{up}\right) \le \left(\underset{\smile}{\tilde{g}}_{max}(j,b)-\sum_{s}\tilde{g}(j,b,s)\right) \le M\left(1-w_{j,b}^{up}\right) \tag{4.90}$$

$$-Mw_{j,b}^{up} \le \alpha_{j,b}^{up} \le Mw_{j,b}^{up} \tag{4.91}$$

$$-M\left(1-w_{j,b}^{low}\right) \le \sum_{s}\tilde{g}(j,b,s) \le M\left(1-w_{j,b}^{low}\right) \tag{4.92}$$

$$-Mw_{j,b}^{low} \le \alpha_{j,b}^{low} \le Mw_{j,b}^{low} \tag{4.93}$$

$$-M\left(1-v_{j,b,s}^{up}\right) \le \left(g_{max}(j,b,s)-\tilde{g}(j,b,s)\right) \le M\left(1-v_{j,b,s}^{up}\right) \tag{4.94}$$

$$-Mv_{j,b,s}^{up} \le \beta_{j,b,s}^{up} \le Mv_{j,b,s}^{up} \tag{4.95}$$

$$-M\left(1-v_{j,b,s}^{low}\right) \le \tilde{g}(j,b,s) \le M\left(1-v_{j,b,s}^{low}\right) \tag{4.96}$$

$$-Mv_{j,b,s}^{low} \le \beta_{j,b,s}^{low} \le Mv_{j,b,s}^{low} \tag{4.97}$$

$$-M\left(1-k_{j,b}^{up}\right) \le \left(g_{max}(j)-\underset{\smile}{\tilde{g}}_{max}(j,b)-\tilde{r}(j,b)\right) \le M\left(1-k_{j,b}^{up}\right) \tag{4.98}$$

$$-Mk_{j,b}^{up} \le \delta_{j,b}^{up} \le Mk_{j,b}^{up} \tag{4.99}$$

$$-M\left(1-k_{j,b}^{low}\right) \le \tilde{r}(j,b) \le M\left(1-k_{j,b}^{low}\right) \tag{4.100}$$

$$-Mk_{j,b}^{low} \le \delta_{j,b}^{low} \le Mk_{j,b}^{low} \tag{4.101}$$

$$-M\left(1-t_{j,b}^{up}\right) \le \left(\underset{\smile}{\tilde{g}}_{max}(j,b)-\tilde{r}(j,b)\right) \le M\left(1-t_{j,b}^{up}\right) \tag{4.102}$$

$$-Mt_{j,b}^{up} \le \zeta_{j,b}^{up} \le Mt_{j,b}^{up} \tag{4.103}$$

$$-M\left(1-t_{j,b}^{low}\right) \le \tilde{r}(j,b) \le M\left(1-t_{j,b}^{low}\right) \tag{4.104}$$

$$-Mt_{j,b}^{low} \le \zeta_{j,b}^{low} \le Mt_{j,b}^{low} \tag{4.105}$$

$$-M\left(1-u_{j,b}^{up}\right) \le \left(r_{max}(j)-\tilde{r}(j,b)\right) \le M\left(1-u_{j,b}^{up}\right) \tag{4.106}$$

$$-Mu_{j,b}^{up} \le \vartheta_{j,b}^{up} \le Mu_{j,b}^{up} \tag{4.107}$$

$$-M\left(1-u_{j,b}^{low}\right) \le \tilde{r}(j,b) \le M\left(1-u_{j,b}^{low}\right) \tag{4.108}$$

$$-Mu_{j,b}^{low} \le \vartheta_{j,b}^{low} \le Mu_{j,b}^{low} \tag{4.109}$$

$$-M\left(1-h_{j,b}^{up}\right) \le \left(\hat{d}_e(j,b)-\tilde{c}urt(j,b)\right) \le M\left(1-h_{j,b}^{up}\right) \tag{4.110}$$

$$-Mh_{j,b}^{up} \le \varepsilon_{j,b}^{up} \le Mh_{j,b}^{up} \tag{4.111}$$

$$-M\left(1-h_{j,b}^{low}\right) \le \tilde{c}urt(j,b) \le M\left(1-h_{j,b}^{low}\right) \tag{4.112}$$

$$-Mh_{j,b}^{low} \le \varepsilon_{j,b}^{low} \le Mh_{j,b}^{low} \tag{4.113}$$

where $y_{l,b}^{up}, y_{l,b}^{low}, v_{l,b}^{up}, v_{l,b}^{low}, w_{j,b}^{up}, w_{j,b}^{low}, k_{j,b}^{up}, k_{j,b}^{low}, t_{j,b}^{up}, t_{j,b}^{low}, u_{j,b}^{up}, u_{j,b}^{low}, h_{j,b}^{up}, h_{j,b}^{low} \in \{0,1\}$ are the binary variables. In this way, the complementary slackness conditions are now linear. However, the upper level objective function is not, yet. As can be seen in (4.114), the first and the second term on the right hand side of the objective function multiply variables by KKT multipliers of the lower level problem.

$$\max_{\underset{\smile}{\tilde{g}}_{max,j},\underset{\smile}{\tilde{c}}_j,\underset{\smile}{\tilde{P}}_{r,j},\tilde{z}_j} \Pi_t = E\left\{\begin{array}{l} \sum_b \sum_{j\in A} \sum_s \left(p_{el,b,j} - c(j,s)\right)\cdot \tilde{g}(j,b,s) + \\ +\sum_b \sum_{j\in A} p_{res,b,j} \cdot \tilde{r}(j,b) + \\ -\sum_b \sum_{j\in A} c_{fuel}(j)\cdot \left(g_{max}(j) - \sum_s \tilde{g}(j,b,s)\right) + \\ -\sum_{b>0} \sum_{j\in A} \hat{c}_{ramp}(j)\cdot \left|\sum_s \tilde{g}(j,b,s) - \sum_s \tilde{g}(j,b-1,s)\right| + \\ -\sum_{j\in B} c_{inv}(j)\cdot \tilde{z}(j) \end{array}\right\} \tag{4.114}$$

In other words, $p_{el,b,j} \cdot \tilde{g}(j,b,s)$ and $r_{res,b,j} \cdot \tilde{r}(j,b)$ are nonlinear. To linearise these terms, no more use of the complementary slackness conditions is made, in order not to add too many constraints to the problem. The stationarity conditions referring to the variables $\tilde{g}(j,b,s)$ and $\tilde{r}(j,b)$ are employed, instead. If (4.53) and (4.56) are multiplied by $\sum_s \tilde{g}(j,b,s)\ \ \forall j \in A$ and $\tilde{r}(j,b)\ \ \forall j \in A$, respectively, (4.115) and (4.116) are obtained.

$$\begin{aligned} &\sum_{j\in A}\left(-\underset{\smile}{\tilde{c}}(j,b)\right)\cdot \sum_s \tilde{g}(j,b,s) + \sum_{j\in A}\sum_n p_{el,b,n}\cdot m_g(j,n)\cdot \sum_s \tilde{g}(j,b,s) + \\ &+\sum_{j\in A}\left(-\alpha^{up}_{j,b} + \alpha^{low}_{j,b}\right)\cdot \sum_s \tilde{g}(j,b,s) + \sum_{j\in A}\sum_s \left(-\beta^{up}_{j,b,s} + \beta^{low}_{j,b,s}\right)\cdot \tilde{g}(j,b,s) = 0 \end{aligned} \tag{4.115}$$

$$\begin{aligned} &\sum_{j\in A}\left(-\underset{\smile}{\tilde{P}}_r(j,b)\right)\cdot \tilde{r}(j,b) + \sum_{j\in A}\sum_n p_{res,b,n}\cdot m_g(j,n)\cdot \tilde{r}(j,b) + \sum_{j\in A}\left(-\delta^{up}_{j,b} + \delta^{low}_{j,b}\right)\cdot \tilde{r}(j,b) + \\ &+\sum_{j\in A}\left(-\zeta^{up}_{j,b} + \zeta^{low}_{j,b}\right)\cdot \tilde{r}(j,b) + \sum_{j\in A}\left(-\vartheta^{up}_{j,b} + \vartheta^{low}_{j,b}\right)\cdot \tilde{r}(j,b) = 0 \end{aligned} \tag{4.116}$$

These can be simplified by means of some of the complementary slackness conditions. Specifically, introducing (4.69) to (4.72) in (4.115), and (4.73) to (4.78) in (4.116), the two following expressions are derived:

$$\begin{aligned} &\sum_{j\in A}\left(-\underset{\smile}{\tilde{c}}(j,b)\right)\cdot \sum_s \tilde{g}(j,b,s) + \sum_{j\in A}\sum_n p_{el,b,n}\cdot m_g(j,n)\cdot \sum_s \tilde{g}(j,b,s) + \\ &-\sum_{j\in A}\alpha^{up}_{j,b}\cdot \underset{\smile}{\tilde{g}}_{max}(j,b) - \sum_{j\in A}\sum_s \beta^{up}_{j,b,s}\cdot g_{max}(j,b,s) = 0 \end{aligned} \tag{4.117}$$

$$\begin{aligned} &\sum_{j\in A}\underset{\smile}{\tilde{P}}_r(j,b)\cdot \tilde{r}(j,b) + \sum_{j\in A}\sum_n p_{res,b,n}\cdot m_g(j,n)\cdot \tilde{r}(j,b) - \sum_{j\in A}\delta^{up}_{j,b}\left(g_{max} - \underset{\smile}{\tilde{g}}_{max}\right) + \\ &-\sum_{j\in A}\zeta^{up}_{j,b}\cdot \underset{\smile}{\tilde{g}}_{max} - \sum_{j\in A}\vartheta^{up}_{j,b}\cdot r_{max} = 0 \end{aligned} \tag{4.118}$$

The second term on the left-hand side of (4.117) corresponds to the first nonlinear term of the upper level objective function. Equivalently, the second term on the left-hand side of relation (4.118) is equivalent to the second term in the upper level objective function. Rearranging the two equations, these two terms can be written as functions of the other terms, which are linear:

$$
\begin{aligned}
&\sum_{j\in A}\sum_{n} p_{el,b,n}\cdot m_g(j,n)\cdot\sum_{s}\tilde{g}(j,b,s)= \\
&=\sum_{j\in A}\utilde{\tilde{c}}(j,b)\cdot\sum_{s}\tilde{g}(j,b,s)+\sum_{j\in A}\alpha_{j,b}^{up}\cdot\utilde{\tilde{g}}_{max}(j,b)+\sum_{j\in A}\sum_{s}\beta_{j,b,s}^{up}\cdot g_{max}(j,b,s)
\end{aligned}
\tag{4.119}
$$

$$
\begin{aligned}
&\sum_{j\in A}\sum_{n} p_{res,b,n}\cdot m_g(j,n)\cdot\tilde{r}(j,b)= \\
&=\sum_{j\in A}\utilde{\tilde{P}}_r(j,b)\cdot\tilde{r}(j,b)+\sum_{j\in A}\delta_{j,b}^{up}\left(g_{max}-\utilde{\tilde{g}}_{max}\right)+\sum_{j\in A}\zeta_{j,b}^{up}\cdot\utilde{\tilde{g}}_{max}+\sum_{j\in A}\vartheta_{j,b}^{up}\cdot r_{max}
\end{aligned}
\tag{4.120}
$$

The nonlinear terms in the upper level optimisation function can be replaced by the terms on the right-hand side of (4.119) and (4.120). Some of these are still not linear, because they multiply KKT multipliers by variables. However, the variables are not free variables, but decision variables (i.e. the bids of the companies). An approximation can be introduced, by which the decision variables are not continuous functions, but piecewise constant functions. In this way, the nonlinear terms become mixed-integer linear terms. Now, they can be replaced into the upper level objective function of the problem, and the final formulation is obtained. The resulting model is a MILP problem and its full structure is presented in Appendix B.

5.2. Outputs of the electricity market model

The model derived in the previous section contains elements normally pertaining to the short-term domain, such as the generation and reserve dispatch decisions, and elements pertaining to the long-term domain, such as the generation expansion decisions. However, the dispatch decisions in every demand block b, as well as the bids of the companies, should be seen not as punctual decisions in a single moment of one day, but as average decisions in that demand block throughout a larger time domain. The extension of the time domain depends on the duration chosen for each demand block. It may be imagined that each demand block sums up all the hours pertaining to a specific part of the day, throughout a year. In this way, the model results a mid-term model, which computes the average yearly equilibrium of the market. The generation and reserve by each generator, the energy and reserve capacity prices, the expansion decisions, the load curtailment are computed for every node of the network as yearly averages.

As anticipated, this is not a standard dispatch model. The welfare optimisation algorithm for computing the market clearing run every day by the electricity system operators corresponds to the sole lower level problem in the presented model. In the upper level problem, the novelty and the contribution of Game Theory are disclosed. The upper level problem is the profit maximisation of one company, and it indicates that a company makes decisions in its own interest before the market is cleared. The real equilibrium of the market shall be the one which maximises the profit of a company over all the possible decisions of the others. Therefore, it can be found only when one upper level problem is run for every company iteratively and all of them converge to a solution.

The model derived so far is one step into a long-range research activity. The further steps, not covered by this thesis, will be juxtaposing a number of these two-level problems, one for each company, and finally building the complete setting represented in Figure 37. Only then, the model will be ready to be applied. Once results are obtained, and the difference with respect to traditional dispatch models is clear, some elements may be synthesized in a simpler mathematical formulation, as it was for the power plant model. These could be added to energy system models, for Objective 3.2 of Section 3.5 to be pursued. It is clear from this picture that the further research steps, though long-term, will be more related to the application of proper solution algorithms and the setting of case studies. The core breakthrough research consisted in deriving the inmost two-level game between the electricity system operator and a single company, because it required elaborating a Game Theory view of the dynamics related to flexibility currently permeating the electricity market. Moreover, a big effort was put into making the developed mathematical formulation solvable with available solution algorithms.

6.
Energy system model

This chapter describes how Objective 3.1 of the modelling activity was pursued: *to develop models able to receive as inputs numerical values representing the costs and benefits of flexibility computed at a power plant scale and derive their impact at an energy system scale*. A full-fledged open source energy system model for the long-term planning, among the most employed in literature, was studied and modified for the scope: OSeMOSYS (the Open Source Energy Modelling System). Several activities concurred to pursuing the objective. First of all, the structure of the existing model was deeply studied, thanks to its open source nature. Afterwards, the achievements of a recently opened research mainstream investigating the introduction of short-term constraints into long-term energy planning models were looked into [183]. The author identified, aided by the existing literature, the unresolved questions of these recent developments. The possibility of providing the model with the capability of computing the costs of flexibility was one of them. Thereafter, the mathematical formulation of the global performance indices related to the flexible operation of power plants was introduced into the model: the fuel consumption at partial load, the cycling capability as a function of the configuration of the power plant, the cost of the starts. The formulations presented in Section 4.3 were deeply revisited, though, to adapt them to the structure of the existing model. A number of new parameters, variables, constraints had to be added to the original code.

In Section 6.1, the original structure of OSeMOSYS is first described, with the support of thd recent literature. Following, the derivation of the modified model is described: the author explains how the mathematical formulations developed in Section 4.3 were revisited and introduced into the model, supported by examples of the tests performed to check the functionality of the modifications. In Section 6.2, the outputs of the modified model and their relevance to the topic of this research are discussed.

Nomenclature

Symbols

$E, E_{full\ load}$	supplied energy at actual and full load
$\dot{E}$	power
FC, FC_{nom}	total fuel consumption, total fuel consumption assuming constant efficiency
k	additional fuel use

Indices

r	region
t	technology
l	time slice
f	fuel
m	mode of operation
e	emission
y	year

Subscripts

t time slice

6.1. An enhanced OSeMOSYS model for power plant flexibility

6.1.1. Original structure of OSeMOSYS

In the following sections, the electricity sector will be often referred to, since it is the object of this PhD dissertation. Therefore, examples referring to the electricity supply will be made, though OSeMOSYS is applicable to the study of any energy sector. When talking about a 'technology', the author will refer to the set of possible kinds of power plants, such as steam cycles, CCGTs, OCGTs, wind turbines, PV fields, etc. It is worth recall that in energy system models a technology does not represent individual power plants, but it sums up numerous individual power plants. Therefore, when referring to a technology, this is described in terms of global capacity (installed, spinning, retrofitted etc. capacity) and not in terms of units. The 'fuels' will be all the energy vectors implied in the electricity supply, such as primary resources to the power plants (natural gas, coal, oil, etc.), electricity, reserve capacity.

Before modifying the code of OSeMOSYS, preliminary activities had to be carried out. First of all, it was necessary to understand how the variables and parameters defined in the mathematical formulation of Section 4.3 could be linked to those in OSeMOSYS. According to the terminology commonly employed in energy system planning, a 'variable' indicates a quantity computed by the model, a 'parameter' identifies a user-defined numerical input. Secondly, a way to introduce the modifications with the least possible perturbation of the existing code had to be sought for. This was necessary for two main reasons:

- Limiting the number of new variables, parameters and constraint equations also limits the additional computational requirements of the modified model. This is fundamental in energy systems planning, since country-wide models with a time domain of three or four decades are usually run. The simulations could take up to days each and a number of simulations may be required. If some modification increases the computational time by 50%, the timeframe of entire research activities should be reconsidered.
- Every modification to the model aimed at adding new functionalities (such as the study of flexibility in the present case) should be stand-alone. In this way, it can be called in or out the main model as an add-in. This implies that the modification consists in a number of new constraint equations that can be dropped below the existing code, without changing any of the original equations.

The original model of OSeMOSYS is entirely reported in Appendix C as from the supporting information enclosed with [173]. In the following, the features which are useful to understand the modifications introduced by the author are described. The parameters and variables defined in OSeMOSYS are generically assigned values for each considered region, technology, time slice, fuel, mode of operation of the technology, pollutant, and year. Theses sets, for which the values are assigned, are indicated by indices in square brackets alongside the name of the parameter or the variable. The main sets and the relative indices are listed in Table 12.

Set	Index
Region	R
Technology	T
Time slice	L
Fuel	F
Mode of operation	M
Emission	E
Year	Y

Table 12. *Sets in OSeMOSYS.*

For instance, the parameter CapitalCost[r,t,y], representing the investment cost of a technology, is assigned a number for every Region, Technology and Year. In Table 13 and Table 14, the parameters and variables of OSeMOSYS recalled when deriving the code modifications from the mathematical formulations of Section 4.3 are listed and described.

Parameter	Description
CapacityFactor[r,t,l,y]	Maximum time a technology can operate in a time slice [fraction of hours of the year]
OperationalLife[r,t]	Useful life of a technology [years]
ResidualCapacity[r,t,y]	Capacity installed prior to the time domain of the study, still active at year y [GW]
InputActivityRatio[r,t,f,m,y]	Fuel input per unit production of a technology
OutputActivityRatio[r,t,f,m,y]	Fuel output per unit production of a technology (most times the output production coincides with the production, therefore the parameter is equal to 1). The ratio of the Output- to the InputActivityRatio is the energy efficiency.
CapitalCost[r,t,y]	Investment cost [M€/GW]
VariableCost[r,t,m,y]	Variable cost [M€/TWh]
CapacityOfOneTechnologyUnit[r,t,y]	Capacity of one new unit of a technology [GW] (if introduced, the model becomes mixed-integer)
REMinProductionTarget[r,y]	Minimum annual fraction of electricity generation from renewables in the whole system [fraction of total generation]
AnnualEmissionLimit[r,e,y]	Annual global limit for the emission of pollutant *e* [tonnes]
MinStableOperation[r,t,y]	Minimum Technical Load of a technology [fraction of the capacity on-grid]
MaxPrimReserveUp/Down[r,t,y]	Maximum primary upward/downward reserve of a technology, dictated by the maximum achievable ramping rate [fraction of the capacity on-grid]
MaxSecReserveUp/Down[r,t,y]	Maximum secondary upward/downward reserve of a technology, dictated by the maximum achievable ramping rate [fraction of the capacity on-grid]

Table 13. *Main parameters in OSeMOSYS.*

Variable	Description
NewCapacity[r,t,y]	New capacity of a technology installed in year y [GW]
AccumulatedNewCapacity[r,t,y]	Accumulated new capacity at year y [GW]
TotalCapacityAnnual[r,t,y]	Total capacity of a technology in the system in year y, summing the residual capacity and the accumulated new capacity [GW]
RateOfActivity[r,l,t,m,y]	Generation of technology t in mode of operation m
RateOfProductionByTechnology[r,l,t,f,y]	Production of fuel f by technology t [TWh] (similar to the rate of activity, but defined by fuel, not by mode of operation)
RateOfUseByTechnology[r,l,t,f,y]	Use of fuel f by technology t [TWh]
OnlineCapacity[r,t,l,y]	Part of the total installed capacity, which is on-line (active) in the time slice l [GW]

Table 14. *Main variables in OSeMOSYS.*

A focus on the relation between the variables TotalCapacityAnnual, OnlineCapacity and RateOfActivity is useful to understand how the original model deals with the supply of electricity and reserve capacity by each technology. The total available capacity of one technology at some year is represented by the variable TotalCapacityAnnual. In general, in a given time slice, part of this capacity may be temporarily off-line, because it has not been dispatched, while another part is spinning. The spinning capacity is named OnlineCapacity. Not all of this capacity generates electricity, because part of it is made available as upward primary and secondary reserve. That is, the spinning generators are, on average, operating at partial load, ready to ramp up when required by the system operator. If the total upward reserve capacity provided by the technology is subtracted from the OnlineCapacity, the maximum generating capacity a technology can provide in the time slice is obtained. It does not necessarily correspond to the actual generating capacity, yet. This could be less, precisely any value between the minimum stable operation and the maximum generating capacity. The actual generating capacity correspond to the variable RateOfActivity (defined in Table 14 and computed in energy units), divided by the duration of the time slice. The relations between all of these variables are synthesized in Figure 40, where the red-filled bar is the generating capacity, upper-bound by the maximum generating capacity and lower-bound by the MinStableOperation. These are discussed in depth in [174].

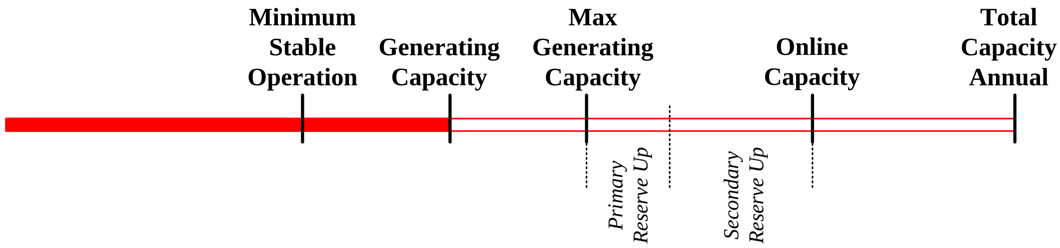

Figure 40. *Relation between the main variables related to the generation capacity.*

6.1.2. Derivation of the enhanced model

Studying the global structure of OSeMOSYS and the variables and parameters linked to the operation of the technologies helped the author identify how to modify the source code. In the following sections, the modifications introduced for the impact of flexibility to be taken into account are described one by one. These are the same ones presented in Section 4.3: the fuel consumption at partial load, the cycling performance as a function of the configuration of the power plant, the cost of the starts. Stemming from the mathematical formulations derived in Section 4.3, the code formulations are developed, and described in the following.

6.1.2.1. Fuel consumption at partial load

Let the mathematical formulation of this index be recalled:

$$FC = FC_{nom} + k \cdot \left(E_{full\ load} - E\right) \tag{6.1}$$

Where FC is the total fuel consumption at load E, FC_{nom} is the fuel consumption the technology would have at load E if its efficiency was constant and equal to the nominal efficiency, k is a constant which introduces a term of additional fuel consumption due to the efficiency decrease. The additional fuel consumption is represented by $k \cdot \left(E_{full\ load} - E\right)$, proportional to the load partialisation. Most of the quantities in (6.1) are already defined in OSeMOSYS as existing variables and parameters, and the formulation can be introduced with very little perturbation of the original code. The energy produced at full load, $E_{full\ load}$, can be computed as the product of the OnlineCapacity by the duration of the time slice. This last is actually represented by a pre-defined parameter for converting the power units into energy units, called CapacityToActivityUnit. The quantity E corresponds to the RateOfProductionByTechnology variable. A constraint equation is introduced, to name the difference $\left(E_{full\ load} - E\right)$:

$$\begin{aligned} &\forall_{r,t,l,y}\ \&\ f = \text{electricity}:\ \text{LoadPartialisation}_{r,t,l,y} = \text{OnlineCapacity}_{r,t,l,y} \cdot \\ &\cdot \text{CapacityToActivityUnit}_{r,t}\ \text{- RateOfProductionByTechnology}_{r,t,l,f,y} \end{aligned} \tag{6.2}$$

Now, k can be named AdditionalFuelUse, and declared for every Region, Technology, Fuel and Year (indices r, t, f, y). Therefore, the second term in the right hand side of (6.1) becomes:

$$k \cdot \left(E_{full\ load} - E\right) = \text{AdditionalFuelUse}_{r,t,f,y}\ \cdot\ \text{LoadPartialisation}_{r,t,l,y} \tag{6.3}$$

As anticipated, in the original formulation of OSeMOSYS the efficiency of a technology is assumed to be constant with the load. Therefore, $FC = FC_{nom}$. Using the variables defined in the code, FC corresponds to the variable RateOfUseByTechnology. The original formulation of the equation of the fuel consumption is:

$$\forall_{r,t,l,f,y}:\ \text{RateOfUseByTechnology}_{r,t,l,f,y} = \sum_{m} \text{RateOfUseByTechnologyByMode}_{r,t,l,f,m,y} \tag{6.4}$$

When the term of additional fuel consumption defined in (6.3) is added, (6.5) is obtained:

$$\begin{aligned} &\forall_{r,t,l,f,y}:\text{RateOfUseByTechnology}_{r,t,l,f,y} = \sum_{m} \text{RateOfUseByTechnologyByMode}_{r,t,l,f,m,y} + \\ &+ \text{AdditionalFuelUse}_{r,t,f,y} \cdot \text{LoadPartialisation}_{r,t,l,y} \end{aligned} \tag{6.5}$$

Overall, this modification to the source code of OSeMOSYS requires the definition of one new variable, one new parameter and one new constraint equation. Furthermore, one existing equation has to be modified.

6.1.2.2. Cycling capability as a function of the power plant configuration

Representing with a mathematical formulation the cycling performance of a power plant as a function of its configuration is a very complex task. The formulation cannot be developed independently from the model it is written for. For this reason, in Section 4.3 no mathematical formulation was presented, but only the rationale it should be based on. Traditionally, in electricity market and energy system models the configuration of the power plants is a fixed parameter, exogenously defined by the user. For the cycling performance to become a function of the configuration, this must be a variable, and the model must be able to compute it endogenously. According to what is meant by power plant configuration, this may be modelled as a continuous or discrete variable: if configuration means the opening of a by-pass valve, this will be continuous for instance from 0 (completely closed) to 1 (completely open); if configuration means the operation of the gas turbine in combined cycle or open cycle (with by-pass of the gases), this is a discrete variable. In the following, a formulation is presented, for allowing the model to choose the configuration from a discrete set of possibilities. The formulation is derived assuming the possibility to choose between two configurations, one less flexible and one more flexible. This is done without loss of generality, since the formulation can be easily adapted to more configurations. The operations to be carried out for such modification to the code to be successful shall be:

- To define in the data file of the user-defined inputs not one, but two versions of a technology, an old and a new version. The old version represents the original power plant, the new version the retrofitted one. The user defines a priori the characteristics of both versions, by assigning values to all the related parameters.
- To define in the source code of the model a set of constraints which allow it, at every time slice, to decommission part of the installed capacity of the old version and install at most a corresponding capacity of the new version.

The first point does not present any particular challenge. The user must only define one more technology in the data file. On the contrary, the second point is quite complex to realise. The new version of the technology is, in principle, a new technology, independent from the old version, for which the installed capacity and the dispatch shall be computed as for the other technologies. Constraints must be introduced, for this new technology to be linked to the old version. For instance, when a given capacity of the old version is retrofitted, it must be replaced by exactly the same capacity of the new version, no more and no less. Moreover, if some capacity of the old version is retrofitted ten years before its operational life ends, the new version which substitutes it cannot operate more than the remaining ten years. The following dissertation describes step-by-step how these limits and others were introduced. Examples are provided, for the meaning of every new constraint to be understood.

First of all, if the rationale of this modification implies that some capacity of the old version is withdrawn and replaced by the new version, an equation defining the withdrawn capacity must be introduced.

$$\forall_{r,t,y} : \text{AccumulatedWithdrawnCapacity}_{r,t,y} = \sum_{yy=0}^{y} \text{WithdrawnCapacity}_{r,t,yy} \qquad (6.6)$$

The expression defines the AccumulatedWithdrawnCapacity at year y as the sum of the capacity withdrawn every year before y. When some capacity is retrofitted, it is fictitiously represented with a corresponding capacity of the old version being withdrawn and a corresponding capacity of the new version being installed. The AccumulatedWithdrawnCapacity collects two contributions: the first one is the capacity fictitiously withdrawn because of retrofits; the second one is the capacity actually decommissioned in year y because it reaches the end of its operational life. This is also indicated by the parameter named ResidualCapacity, as described in Table 13. If, for instance, in year $y-1$ the ResidualCapacity equals 35 GW and in year y it equals 30 GW, it means that in year y 5 GW have been decommissioned. These 5 GW must be accounted also in the variable AccumulatedWithdrawnCapacity. Thereafter, the AccumulatedWithdrawnCapacity must be lower-bound by the accumulated ResidualCapacity. Two constraints are introduced to meet this purpose: one defines the AccumulatedRetiredCapacity in year y as the sum over the years of the ResidualCapacity; the other one states that the AccumulatedWithdrawnCapacity must be at least as much as the AccumulatedRetiredCapacity:

$$\begin{aligned}&\forall_{r,t,y}\ \&\ y \leq y_{max}-1: \text{AccumulatedRetiredCapacity}_{r,t,y} = \\ &= \sum_{yy=0}^{y}\left(\text{ResidualCapacity}_{r,t,yy}-\text{ResidualCapacity}_{r,t,yy+1}\right)\end{aligned} \tag{6.7}$$

$$\begin{aligned}&\forall_{r,t,y}\ \&\ y+1 \leq y_{max}: \\ &\text{AccumulatedWithdrawnCapacity}_{r,t,y+1} \geq \text{AccumulatedRetiredCapacity}_{r,t,y}\end{aligned} \tag{6.8}$$

In principle, the code should be allowed to retrofit both capacity already existing in the first year of the simulation and capacity newly installed in the following years. Let us assume that a simulation starts in 2015. In 2020 the model chooses to install some new capacity and in 2030 it becomes convenient to retrofit it; the code should be able to do this. For the moment, the author found no way to implement this possibility without deeply restructuring the code. Therefore, he deemed more convenient to make an approximation: the possibility of retrofitting newly installed capacity is not considered; only the capacity already existing in the first year of the simulation (defined by the ResidualCapacity) can be withdrawn and consequently retrofitted. In this case, a constraint must be introduced to ensure that no part of the new capacity installed during the years of the simulation is retrofitted. It is sufficient to impose that the WithdrawnCapacity in every year be less than or equal to the difference between the Total Installed Capacity and the AccumulatedNewCapacity in the previous year.

$$\forall_{r,t,y}: \text{WithdrawnCapacity}_{r,t,y+1} \leq \text{TotalCapacityAnnual}_{r,t,y} - \text{AccumulatedNewCapacity}_{r,t,y} \tag{6.9}$$

When this constraint is introduced, in case some capacity is decommissioned (i.e. the ResidualCapacity decreases), it is correctly taken from the power plants which were already existing at the first year of the simulation and reached the end of their operational life. These can be either of the old version, or of the new version, depending on whether they have been retrofitted or not. This case is shown in Figure 41. It represents a scenario where the request for flexible operation increases with the years, as is happening in Italy: the share of fluctuating renewable resources increases. The power not covered by the renewables can be supplied by old combined cycles, with worse cycling performance, higher cycling costs, but lower investment costs, or new combined cycles, with better cycling performance, lower cycling costs, but higher investment costs. The old combined cycles are due to be decommissioned according to the ResidualCapacity parameter. In order to match the demand for electricity, they must be replaced, either by old or new generation combined cycles. Before the old combined cycles end their life, however, they can be also retrofitted and turned into new generation combined cycles, with a cost corresponding to the sole cost of retrofits. The results are shown for some years of the whole time domain of the case study. On the right side of the figure, the reasons for the total installed capacity of the old or the new version to change are explained. In 2010, the first year of the simulation, only old combined cycles are present, by an amount of 35 GW.

	Residual capacity [GW]		Total Installed Capacity [GW]	
	Old	New/retrofitted	Old	New/retrofitted
2010	35		**24.176**	**10.824**
2011	35		24.176	10.824
2012	35		24.176	10.824
2013	35		**12.633**	**22.367**
2014	30		**7.633**	**22.367**
2015	30		7.633	22.367
2016	30		7.633	22.367
2017	30		7.633	22.367
2018	30		7.633	22.367
2019	30		7.633	22.378
2020	25		**2.699**	**27.993**
2021	25		**3.934**	**27.993**
2022	25		3.934	29.226
2023	25		3.934	29.802
2024	25		3.934	30.791
2025	25		3.934	31.269
2026	25		3.934	31.762
2027	10		**1.301**	**34.938**
2028	10		1.301	35.495

→ 2010: Of the 35 GW, 10.8 are retrofitted in the 1st year

→ 2013: More 11.5 GW are retrofitted

→ 2014: As requested by the residual capacity, 5 GW of the old version are withdrawn and not retrofitted

→ 2020: 5 GW of the old version are withdrawn and 0.066 newly instaled; 5.6 GW of the new version are newly installed

→ 2021: 1.23 GW of the old version are newly installed (so the accumulated new capacity from the 1st year becomes 1.3 GW)

→ 2027: Only 2.6 GW of the old version are withdrawn, because the other 1.3 GW are new. The rest is withdrawn from the retrofitted capacity. This increases just because more new capacity is installed

Figure 41. *Sample results when all the new constraints are correctly added to the source code.*

If the constraint (6.9) is not introduced, the model may show an odd behaviour: when some capacity is decommissioned, it is not only taken from the power plants at the end of their operational life, but also from newer ones. This makes no sense. Moreover, in order to comply with the constraint (6.8), which states that the AccumulatedWithdrawnCapacity is lower-bound by the AccumulatedRetiredCapacity, the model may choose to install new capacity and withdraw it right away. This is shown in Figure 42, where the same scenario as before is simulated, but constraint (6.9) is not introduced in the OSeMOSYS model.

	Residual capacity [GW]		Total Installed Capacity [GW]	
	Old	New/retrofitted	Old	new/retrofitted
2025	25		0	35.175
2026	25		0	35.669
2027	10		**0**	**36.223**
2028	10		0	36.780
2029	10		0	37.901

→ 2027: From the analysis of the results, it is found in 2027 15 GW of the old version are installed and withdrawn right away, to comply with the reduction of residual capacity

Figure 42. *Sample results when (6.9) is not added to the source code.*

As said, the current formulation decouples a technology in two versions and approximates the retrofitting operation with a replacement of the old version by the new one. This causes one issue, related to the operational life of the technology. If some capacity reaches the end of life, it must be withdrawn. However, it may be the case that it has been retrofitted or not. If it has been retrofitted it appears as capacity of the new version, while, if it has not been retrofitted, it appears as the old version. A way must be found to take into account that, when some capacity is retrofitted into the new version, it has already spent part of its operational life. If no constraint is introduced to account for this, when some capacity is retrofitted, it is as if it became new again, and it restarts its operational life. This carries another consequence: when some capacity becomes old, the model finds it convenient to retrofit it, since its life restarts. To avoid this issue, the following approach can be adopted: the initial ResidualCapacity of the old version has to be withdrawn from both the old and the new version, and it has to be withdrawn when required so by the parameter. That is, if at year y the ResidualCapacity decreases from 25 to 10 GW, it means 15 must be decommissioned. All of them must be withdrawn in year y, either from the new or from the old version. A constraint can be introduced, stating that the difference between the TotalCapacityAnnual and the AccumulatedNewCapacity of the two versions together must equal the sum of their ResidualCapacity.

$$\begin{aligned}\forall_{r,y}\ \&\ t = \text{older},\ tt = \text{retrofitted:}\ & \left(\text{TotalCapacityAnnual}_{r,t,y} + \text{TotalCapacityAnnual}_{r,tt,y}\right) - \\ & \left(\text{AccumulatedNewCapacity}_{r,t,y} + \text{AccumulatedNewCapacity}_{r,tt,y}\right) \\ & = \left(\text{ResidualCapacity}_{r,t,y} + \text{ResidualCapacity}_{r,tt,y}\right)\end{aligned} \tag{6.10}$$

As said, if this constraint is not introduced, the capacity of the old version which should be shut down is retrofitted instead and it keeps operating as if it was new. This is shown in Figure 43. It refers to the same scenario as before, but constraint (6.10) is not introduced in the code of OSeMOSYS.

	Residual capacity [GW]		Total Installed Capacity [GW]	
	Old	New/retrofitted	Old	New/retrofitted
2010	35		24.182	10.818
2011	35		24.182	10.818
2012	35		24.182	10.818
2013	35		**12.094**	**22.906**
2014	30		12.094	22.906
2015	30		12.094	22.906

The capacity which should be decommissioned in 2014 is retrofitted in 2013, instead and it keeps operating as if it was new.

Figure 43. *Sample results when (6.10) is not added to the source code.*

As previously described, this scenario assumes that in the first year of the simulation only the old version of the technology is present in the system, i.e. the ResidualCapacity of the new version is zero. This is a simplification, adopted for the results to be more understandable. However, the current formulation holds also when the ResidualCapacity of the new version is not zero. The results are more complicated to understand. Such case is shown in Figure 44.

	ResidualCapacity [GW]		TotalCapacityAnnual [GW]		
	Old	New/retrofitted	Old	New/retrofitted	
2010	35	15	35.000	15.000	
2011	35	15	35.000	15.000	
2012	35	15	35.000	15.000	
2013	35	15	**21.664**	**28.336**	13.3 GW of the old version are retrofitted. This doesn't happen the years before, because the cost of retrofit is too high
2014	30	15	**16.664**	**28.336**	5 GW of the old version are decommissioned, according to the Residual Capacity
2015	30	15	16.664	28.336	
2016	30	15	16.664	28.336	
2017	30	15	16.664	28.336	
2018	30	10	**16.664**	**23.336**	5 GW of the new version are decommissioned, according to the Residual Capacity
2019	30	10	16.664	23.336	
2020	25	10	**11.664**	**23.336**	5 GW of the old version are decommissioned, according to the Residual Capacity
2021	25	10	11.664	23.336	
2022	25	10	11.664	23.336	
2023	25	10	12.536	23.336	
2024	25	10	12.536	24.565	
2025	25	10	12.536	25.614	
2026	25	5	12.536	26.096	
2027	10	5	**12.082**	**26.997**	11.7 GW of the old version are decommissioned and 11.2 newly installed (so the TotalCapacityAnnual globally decreases by little); the left 3.3 GW to decommission (it globally sums up to 15) are decommissioned from the new version, and 4.2 GW are newly installed.

Figure 44. *Sample results when all the constraints are correctly added to the source code and both versions of the technology have non-null ResidualCapacity.*

After defining the withdrawn capacity of the old version of the technology, the retrofitted capacity in the new version must be defined. As was done for the variable AccumulatedWithdrawn Capacity, the variable AccumulatedRetrofittedCapacity at year y is introduced, equalling the sum of the RetrofittedCapacity over the years until y:

$$\forall_{r,t,y} : \text{AccumulatedRetrofittedCapacity}_{r,t,y} = \sum_{yy=0}^{y} \text{RetrofittedCapacity}_{r,t,yy} \tag{6.11}$$

As described before, in order for the possibility of retrofitting capacity to be introduced, the model must be allowed every year to withdraw some capacity of the old version and replace it with a corresponding capacity of the new version. Therefore, a constraint is introduced, stating that in every year the RetrofittedCapacity of the new version must be less than or equal to the WithdrawnCapacity of the old version. It can be less, because the WithdrawnCapacity also accounts for the capacity which is permanently decommissioned.

$$\forall_{r,t,tt,y} : \left(\text{WithdrawnCapacity}_{r,t,y} - \text{RetrofittedCapacity}_{r,tt,y}\right) \cdot \text{RetrofitLink}_{r,t,tt} \geq 0 \tag{6.12}$$

In this formulation, a parameter named RetrofitLink is introduced. Its purpose is to make the inequality valid only for technologies which represent the old and the new version of the same technology. Therefore, it is equal to 1 in case this is verified, 0 otherwise. If the RetrofitLink was not added, it could happen that the RetrofittedCapacity of one technology is constrained by the WithdrawnCapacity of another technology it is not related to. This means that an old coal power plant could be retrofitted into a new nuclear power plant.

For all of these new constraints added to the original code of OSeMOSYS to be effective, two existing constraints must be modified. First of all, the constraint defining the TotalCapacityAnnual of a technology, i.e. the total capacity of a technology which is operative in some year, must be updated. In the original formulation, it states that the TotalCapacityAnnual at year y equals the sum of the ResidualCapacity and the Accumulated NewCapacity.

$$\forall_{r,t,y}: \text{TotalCapacityAnnual}_{r,t,y} = \text{ResidualCapacity}_{r,t,y} + \text{AccumulatedNewCapacity}_{r,t,y} \tag{6.13}$$

With the current modifications, the TotalCapacityAnnual of a technology also depends on the withdrawn and the retrofitted capacity. Specifically, the TotalCapacityAnnual is the sum of the ResidualCapacity, the AccumulatedNewCapacity and the AccumulatedRetrofittedCapacity, (capacity turned into this technology from an older version), less the AccumulatedWithdrawn Capacity.

$$\begin{aligned}\forall_{r,t,y}: \text{TotalCapacityAnnual}_{r,t,y} &= \text{ResidualCapacity}_{r,t,y_{min}} + \text{AccumulatedNewCapacity}_{r,t,y} + \\ &+ \text{AccumulatedRetrofittedCapacity}_{r,t,y} - \text{AccumulatedWithdrawnCapacity}_{r,t,y}\end{aligned} \tag{6.14}$$

Secondly, the constraint computing the investment cost of the technologies must be updated. In the original formulation, the investment cost was incurred only when new capacity was installed:

$$\forall_{r,t,y}: \text{CapitalInvestment}_{r,t,y} = \text{CapitalCost}_{r,t,y} \cdot \text{NewCapacity}_{r,t,y} \tag{6.15}$$

In the modified formulation, power plants can be either newly built or retrofitted from older power plants. Therefore, the investment cost must also include the cost for retrofits, in case any are carried out. A term is added to (6.15), consisting in the product of the annual RetrofittedCapacity by a parameter exogenously defined, the CostOfRetrofit. It is a cost specific to the capacity, expressed in M€/GW. Indicative values for this parameter can be retrieved from literature. Scarce information is publicly available, though, and it was all presented in Section 2.1 of PART II. Another way data are obtained is directly through power plant operators. However, in most of these cases the data are confidential, and they cannot be communicated. The updated formulation of (6.15) results:

$$\begin{aligned}&\forall_{r,t,y}: \text{CapitalInvestment}_{r,t,y} = \\ &= \text{CapitalCost}_{r,t,y} \cdot \text{NewCapacity}_{r,t,y} + \text{CostOfRetrofit}_{r,t,y} \cdot \text{RetrofittedCapacity}_{r,t,y}\end{aligned} \tag{6.16}$$

It is useful to sum up all the new and updated constraints that were necessary for this modification to the code to be effective.

New constraints

$$\forall_{r,t,y}: \text{AccumulatedWithdrawnCapacity}_{r,t,y} = \sum_{yy=0}^{y} \text{WithdrawnCapacity}_{r,t,yy} \tag{6.17}$$

$$\begin{aligned}&\forall_{r,t,y} \;\&\; y \le y_{max} - 1: \text{AccumulatedRetiredCapacity}_{r,t,y} = \\ &= \sum_{yy=0}^{y} \left(\text{ResidualCapacity}_{r,t,yy} - \text{ResidualCapacity}_{r,t,yy+1} \right)\end{aligned} \tag{6.18}$$

$$\begin{aligned}&\forall_{r,t,y} \;\&\; y+1 \le y_{max}: \\ &\text{AccumulatedWithdrawnCapacity}_{r,t,y+1} \ge \text{AccumulatedRetiredCapacity}_{r,t,y}\end{aligned} \tag{6.19}$$

$$\forall_{r,t,y}: \text{WithdrawnCapacity}_{r,t,y+1} \le \text{TotalCapacityAnnual}_{r,t,y} - \text{AccumulatedNewCapacity}_{r,t,y} \tag{6.20}$$

$$\forall_{r,y}\ \&\ t = \text{older},\ tt = \text{retrofitted: } \left(\text{TotalCapacityAnnual}_{r,t,y} + \text{TotalCapacityAnnual}_{r,tt,y}\right) - \left(\text{AccumulatedNewCapacity}_{r,t,y} + \text{AccumulatedNewCapacity}_{r,tt,y}\right) = \left(\text{ResidualCapacity}_{r,t,y} + \text{ResidualCapacity}_{r,tt,y}\right) \tag{6.21}$$

$$\forall_{r,t,y}: \text{AccumulatedRetrofittedCapacity}_{r,t,y} = \sum_{yy=0}^{y} \text{RetrofittedCapacity}_{r,t,yy} \tag{6.22}$$

$$\forall_{r,t,tt,y}: \left(\text{WithdrawnCapacity}_{r,t,y} - \text{RetrofittedCapacity}_{r,tt,y}\right) \cdot \text{RetrofitLink}_{r,t,tt} \geq 0 \tag{6.23}$$

Updated constraints

$$\forall_{r,t,y}: \text{TotalCapacityAnnual}_{r,t,y} = \text{ResidualCapacity}_{r,t,y_{min}} + \text{AccumulatedNewCapacity}_{r,t,y} + \text{AccumulatedRetrofittedCapacity}_{r,t,y} - \text{AccumulatedWithdrawnCapacity}_{r,t,y} \tag{6.24}$$

$$\forall_{r,t,y}: \text{CapitalInvestment}_{r,t,y} = = \text{CapitalCost}_{r,t,y} \cdot \text{NewCapacity}_{r,t,y} + \text{CostOfRetrofit}_{r,t,y} \cdot \text{RetrofittedCapacity}_{r,t,y} \tag{6.25}$$

The introduction of the cycling performance as a function of the power plant configuration into OSeMOSYS requires, in the end, the development of 7 new constraints and the update of 2 existing constraints. 5 new variables and 3 new parameters are introduced in the original model. This modification is deeper than the one for the consumption of fuel, and it is expected to affect more the computational time and memory.

6.1.2.3. Cost of the starts

According to the mathematical formulation developed in Section 4.3.3, the cost of the starts in a given time slice can be computed as:

$$C_{starts} = \sum_{day} \frac{c_{starts}}{2} \cdot \left|\dot{E}_t - \dot{E}_{t-1}\right| \tag{6.26}$$

(6.26) states that the daily cost of the starts is proportional to the difference in capacity online between consecutive time slices, through the proportionality constant $c_{starts}/2$. In the case of energy system models, $|\dot{E}_t - \dot{E}_{t-1}|$must be seen as the difference of global capacity online of a certain technology. For instance, if globally in Italy during the daytime 15 GW combined cycles are spinning and during the night 10 GW are, the difference of 5 GW represents the capacity which is on average cycled between day and night, i.e. the capacity which undergoes daily cycling. It was already explained how this formulation holds, whatever the duration of the time slices. The only items which must be redefined are $\sum_{day}\cdot$, which becomes the sum over less or more than one day, and $c_{starts}/2$. Therefore, this formulation is rather easily introduced into OSeMOSYS. First of all, the constant $c_{starts}/2$ is not present in the original code and has to be newly defined. A parameter is introduced, assigned to every region r and technology t. Since the term refers to individual downward or upward ramps, rather than to whole shut-down/start-up cycles, it is named CostOfRampsPerCapacity. It is specific to the capacity, and expressed for instance in M€/GW. The difference $|\dot{E}_t - \dot{E}_{t-1}|$ exactly corresponds to the difference in the OnlineCapacity between one time slice and the previous one:

$$\left|\dot{E}_t - \dot{E}_{t-1}\right| = \left|\text{OnlineCapacity}_{r,t,l,y} - \text{OnlineCapacity}_{r,t,l-1,y}\right| \tag{6.27}$$

The presence of the absolute value in (6.27), $\left|OnlineCapacity_{r,t,l,y} - OnlineCapacity_{r,t,l-1,y}\right|$ makes its introduction in OSeMOSYS tricky. The absolute value is necessary, because in principle the difference in the spinning capacity between one time slice and the previous one could be either positive or negative. However, introducing it in OSeMOSYS as-is would make the model mixed-integer and would slow down significantly the simulations. This issue can be by-passed by introducing a new variable, named DeltaOnlineCapacity, such as:

$$\begin{aligned}\forall_{r,t,y,l}:\ &\text{DeltaOnlineCapacity}_{r,t,l,y} \geq \text{OnlineCapacity}_{r,t,l,y} - \text{OnlineCapacity}_{r,t,l-1,y}\\ &\text{DeltaOnlineCapacity}_{r,t,l,y} \geq \text{OnlineCapacity}_{r,t,l-1,y} - \text{OnlineCapacity}_{r,t,l,y}\end{aligned} \tag{6.28}$$

These two inequalities exactly correspond to the formulation

$$\text{DeltaOnlineCapacity}_{r,t,l,y} = \left|\text{OnlineCapacity}_{r,t,l,y} - \text{OnlineCapacity}_{r,t,l-1,y}\right| \tag{6.29}$$

The reason is promptly demonstrated. If

$$\text{OnlineCapacity}_{r,t,l,y} > \text{OnlineCapacity}_{r,t,l-1,y} \tag{6.30}$$

the first inequality of (6.28) is positive, while the second one is negative. Then, the first inequality is constraining. On the contrary, if

$$\text{OnlineCapacity}_{r,t,l,y} < \text{OnlineCapacity}_{r,t,l-1,y} \tag{6.31}$$

the second inequality of (6.28) is positive and constraining. There is a reason why in (6.28) inequalities are employed, rather than equalities. Equalities should be usually avoided, since they increase the computational time. In this case, employing the inequality means that DeltaOnlineCapacity is not necessarily equal to the difference in OnlineCapacity between one time slice and the other. It may also be greater. However, if DeltaOnlineCapacity is multiplied by a cost, as it will be in this case, the model (whose objective function is a cost minimisation) ensures it is minimised, i.e. it ensures (6.28) holds strictly. Therefore, DeltaOnlineCapacity will always be equal to the difference in OnlineCapacity.

Some elements are still missing, for this formulation to be employable in OSeMOSYS. In (6.28), the difference between time slice l and time slice $l - 1$ is employed. However, two consecutive time slices may not refer to two time intervals periodically recurring one after the other. For instance, let us assume the time domain of a scenario is divided into 8 time slices, from 0 to 7, representing night and day of the four seasons. Specifically, 0 and 1 represent the night and day of winter, 2 and 3 the night and day of spring, and so on. It is clear that, though consecutive, time slices 1 and 2 do not refer to periods recursively following each other. That is, it is not significant to identify costs of the starts between days of winter and nights of spring. Therefore, the difference between the OnlineCapacity of these time slice must not be considered, when accounting for the cost of the starts. This can be done by introducing a parameter linking only the time slices for which a link is meaningful. This parameter can look as a square matrix, with as many rows and columns as the time slices. The cells referring to not linked time slices are assigned the value 0, the others 1. Referring, for instance, to the example just described, the shape of the matrix is the one of (6.32):

$$\begin{array}{c} \\ l0 \\ l1 \\ l2 \\ l3 \\ l4 \\ l5 \\ l6 \\ l7 \end{array} \begin{array}{c} \begin{array}{cccccccc} l0 & l1 & l2 & l3 & l4 & l5 & l6 & l7 \end{array} \\ \begin{pmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{pmatrix} \end{array} \tag{6.32}$$

As can be seen, only the time slices 0 and 1, 2 and 3, 4 and 5, 6 and 7 are linked in pairs. This parameter is already present in the original OSeMOSYS model, and it is named TimeSliceLinkTag, since it tags the desired time slices. When it is introduced, the formulation in (6.28) becomes:

$$\begin{aligned} \forall_{\text{r,t,y,l,ll}}: \text{DeltaOnlineCapacity}_{\text{r,t,l,y}} \geq & \left(\text{OnlineCapacity}_{\text{r,t,l,y}} - \text{OnlineCapacity}_{\text{r,t,ll,y}}\right) \\ & \cdot \text{TimeSliceLinkTag}_{\text{r,l,ll}} \end{aligned} \tag{6.33}$$

$$\begin{aligned} \forall_{\text{r,t,y,l,ll}}: \text{DeltaOnlineCapacity}_{\text{r,t,l,y}} \geq & \left(\text{OnlineCapacity}_{\text{r,t,ll,y}} - \text{OnlineCapacity}_{\text{r,t,l,y}}\right) \\ & \cdot \text{TimeSliceLinkTag}_{\text{r,l,ll}} \end{aligned} \tag{6.34}$$

At this point, the term $c_{starts}/2 \cdot |P_t - P_{t-1}|$ in (6.26) can be rewritten as:

$$\begin{aligned} \forall_{\text{r,t,y,l}}: \text{CostOfRamps}_{\text{r,t,l,y}} = & \text{CostOfRampsPerCapacity}_{\text{r,t}} / 2 \cdot 365 \cdot \text{YearSplit}_{\text{l,y}} \\ & \cdot \text{DeltaOnlineCapacity}_{\text{r,t,l,y}} \end{aligned} \tag{6.35}$$

Here, the additional items $/2 \cdot 365 \cdot YearSplit_{l,y}$ appear. The division by 2 is necessary because, by the shape of the matrix in (6.32), DeltaOnlineCapacity between consecutive time slices is taken into account twice. The multiplication by $365 \cdot YearSplit_{l,y}$ represents approximately the number of days in one time slice: 365 is the number of days in one year and $YearSplit_{l,y}$ is the ratio of the year occupied by the time slice. Let us consider, for instance, time slice 0, corresponding to winter daytime. The value of $365 \cdot YearSplit_{l,y}$ for this time slice corresponds to half the number of the days in winter. When multiplied by the cost of the ramps, the global cost for half the days in winter is computed. The same computation for the following time slice 1 gives the cost of the ramps for the remaining half of the days in winter. Introducing the number 365 slightly reduces the generality of the formulation, since it holds only when one day is split into more than one time slice. Though this is the case in far the majority of the applications, a way to make the formulation more general is being looked into.
Constraint (6.35) allows the costs of the ramps during one time slice to be computed. For the annual costs of the starts to be calculated, it is sufficient to sum CostOfRamps over all the time slices of the scenario:

$$\forall_{r,t,y}: \text{AnnualCostStarts}_{r,t,y} = \sum_{l}\text{CostOfRamps}_{r,t,l,y} \tag{6.36}$$

Once this item is computed for each technology, it is necessary to sum it up to the other annual operating costs of the technology. A constraint for computing the operating costs is already present in the original version of OSeMOSYS, stating that the variable OperatingCosts equals the sum of AnnualFixedOperaingCosts and the AnnualVariableOperatingCosts:

$$\begin{aligned}\forall_{r,t,y}: \text{OperatingCosts}_{r,t,y} = {} & \text{AnnualFixedOperatingCosts}_{r,t,y} \\ & + \text{AnnualVariableOperatingCosts}_{r,t,y}\end{aligned} \tag{6.37}$$

This constraint must be updated with the AnnualCostStarts:

$$\begin{aligned}\forall_{r,t,y}: \text{OperatingCosts}_{r,t,y} = {} & \text{AnnualFixedOperatingCosts}_{r,t,y} + \\ & + \text{AnnualVariableOperatingCosts}_{r,t,y} + \text{AnnualCostStarts}_{r,t,y}\end{aligned} \tag{6.38}$$

Also in this case it is useful to summarise the new and the modified constraints related to the code modification for the cost of the starts.

New constraints

$$\begin{aligned}\forall_{r,t,y,l,ll}: \text{DeltaOnlineCapacity}_{r,t,l,y} \geq {} & \left(\text{OnlineCapacity}_{r,t,l,y} - \text{OnlineCapacity}_{r,t,ll,y}\right) \\ & \cdot \text{TimeSliceLinkTag}_{r,l,ll}\end{aligned} \tag{6.39}$$

$$\begin{aligned}\forall_{r,t,y,l,ll}: \text{DeltaOnlineCapacity}_{r,t,l,y} \geq {} & \left(\text{OnlineCapacity}_{r,t,ll,y} - \text{OnlineCapacity}_{r,t,l,y}\right) \\ & \cdot \text{TimeSliceLinkTag}_{r,l,ll}\end{aligned} \tag{6.40}$$

$$\begin{aligned}\forall_{r,t,y,l}: \text{CostOfRamps}_{r,t,l,y} = {} & \text{CostOfRampsPerCapacity}_{r,t} / 2 \cdot 365 \cdot \text{YearSplit}_{l,y} \\ & \cdot \text{DeltaOnlineCapacity}_{r,t,l,y}\end{aligned} \tag{6.41}$$

$$\forall_{r,t,y}: \text{AnnualCostStarts}_{r,t,y} = \sum_{l}\text{CostOfRamps}_{r,t,l,y} \tag{6.42}$$

Updated constraints

$$\begin{aligned}\forall_{r,t,y}: \text{OperatingCosts}_{r,t,y} = {} & \text{AnnualFixedOperatingCosts}_{r,t,y} \\ & + \text{AnnualVariableOperatingCosts}_{r,t,y} + \text{AnnualCostStarts}_{r,t,y}\end{aligned} \tag{6.43}$$

In the end, the modification for introducing the cost of the starts in OSeMOSYS required the development of 4 new constraints and the update of one. 1 new parameter and 3 new variables had to be added.

6.1.2.4. Summary of the new features

The features of the three modifications to OSeMOSYS, in terms of new constraints, updated constraints, new variables and new parameters, are summarised in Table 15.

	New constraints	Updated constraints	New parameters	New variables
Fuel consumption	1	1	1	1
Cycling performance	7	2	3	5
Cost of the starts	4	1	1	3

Table 15. *Summary of the new features in the enhanced model of OSeMOSYS.*

The lightest modification is the one for the fuel consumption, while the heaviest is the one for the cycling performance. In all the three cases, existing constraints had to be updated, for the final costs of fuel, retrofits and starts to be summed up to the other cost items. This could not be avoided, while every other possible modification of existing constraints was.
The constraints presented in Subsections 6.1.2.1 to 6.1.2.3 were translated in GNU MathProg programming language, added to the original source code, and validated through several tests. The GNU MathProg implementation of the three sets of equations is presented in Appendix D.

6.2. Outputs of the energy system model

In this chapter, the derivation of an energy system model was illustrated, able to fulfil Objective 3.1 stated in PART II. The mathematical formulations for the fuel consumption as a function of the load, the cycling performance as a function of the power plant configuration, the cost of the starts were adapted and introduced in the open source energy system model OSeMOSYS.
These modifications allow the costs and benefits of flexibility computed at a power plant scale to be fed as inputs to the energy system model. Specifically:

- The fuel consumption as a function of the load is represented by the new parameter AdditionalFuelUse defined in (6.3). This can be computed for different power plant configurations through the efficiency curves.
- The configuration of the power plant and its cycling performance are introduced as discrete quantities, through the parameters characterising the old and the new version of a technology. These parameters may be the minimum technical load, the ramping rates, the efficiency. They correspond to the parameters MinStableOperation, MaxPrimReserveUp/Down, MaxSecReserveUp/Down, Input/OutputActivityRatio defined in Table 13, respectively.
- The costs of the starts are introduced through the term CostOfRampsPerCapacity in (6.35).

The inputs for the fuel consumption and the cycling performance can be obtained directly from thermodynamic models like the one developed in Section 4.1. The input for the cost of the starts comes from bottom-up or top-down models in literature like those analysed in Section 2.1.
When the inputs are fed into the modified energy system model, this becomes able to compute the impact of the flexible operation of fossil-fuel fired power plants on the system. As an introduction to the section of the applications, it is useful to understand what ‘impact’ means in terms of results of the model.
The main outputs of the energy system model are: the global present costs of the system (a country, a region) computed throughout a time domain of decades, the installed capacity of every technology every year, the energy and reserve capacity globally supplied by every technology in every time step. This energy mix changes, when the new sets of constraints are embedded in the source code of the model, keeping the scenario assumptions constant. The new constraints introduce new cost items, related to fuel consumption, retrofits and starts. The model chooses a different technology mix compared to when these items are not accounted for, because its

objective function is the minimisation of the system's cost: one expects that the technologies with higher fuel consumption or costs of the starts will be dispatched less, when flexibility scenarios are simulated. Both the original and the modified model can be employed by the policy makers to draw indications about the least cost pathways to meet given decarbonisation objectives. When the results of the two models differ, the policy indications should be based on the modified model, since it has a better resolution than the original model.

7.
Case studies

This chapter presents applications of the models described so far. The applications provide numerical examples of how the models fulfil the objectives stated at the end of PART II. Section 7.1 applies the power plant model to the computation of global and nodal performance indices for La Casella CCGT power plant. All of the case studies were developed in collaboration with Enel Production S.p.A. and they aim at providing indications for issues currently unsolved by the operators of La Casella. Moreover, the global performance indices provide the numerical inputs for the modified energy system model. Section 7.2 applies the modified OSeMOSYS model to test case scenarios. These are simplified scenarios aimed at showing if and how the new sets of constraints introduced in OSeMOSYS modify the predictions of the optimal long-term energy mix. Finally, Section 7.3 applies the modified OSeMOSYS model to a real case study: the long-term energy planning of Cyprus. This was carried out by the author during a collaboration with the division of Energy System Analysis of KTH Royal Institute of Technology, as part of a project with the Government of Cyprus and the European Commission. The interest of the Government of Cyprus is to assess the potential for increasing the share of renewables in the island. On the other side, the European Commission considers this case study a small scale representation of the whole European electricity network, since this could be modelled as a large-scale isolated system. These applications are meant to support the fulfilment of Objective 3.1, providing the energy system planners and policy makers with tools for assessing the impact of flexibility on the energy mix of countries and regions.
One last mention is made to the absence of an application of the electricity market model, able to support the fulfilment of Objective 3.2. As anticipated, the core of the research in these regards was elaborating a formulation to the dynamics of flexibility under a Game Theory point of view. This need was met. While elaborating the model, it emerged that a long-range research activity was necessary, to integrate Game Theory into energy system planning.

7.1. Power plant model: the costs of flexibility at La Casella CCGT

Three applications are presented in this section:

- *Computation of the fuel consumption*. This consists in the computation of the efficiency, as a function of the load and of the control logics employed at La Casella, and in the elaboration of curves for calculating the Indirect Specific Consumption of fuel.
- *Computation of the cycling performance*. The application focusses on the Minimum Environmental Load La Casella power plant may achieve with minor hardware modifications and new load control logics.
- *Computation of nodal performance indices and their interrelation*. The exergy destruction ratio of the most relevant components is computed, as a function of the load, and the interrelation between the exergy destruction of chosen heat exchangers in the HRSG is shown.

For all of these applications, it is clarified how the results are going to meet the needs of the operators. In addition, the link between the results of the first two applications, focussing on global indices, and the following energy system applications is highlighted.

7.1.1. Computation of the fuel consumption

The first sensible result of the thermodynamic model of La Casella power plant is the specific fuel consumption, or, equivalently, the net electric efficiency as a function of the load and the control logics of the power plant. These were described in Section 4.1.2. The trend of the efficiency is shown in Figure 45.

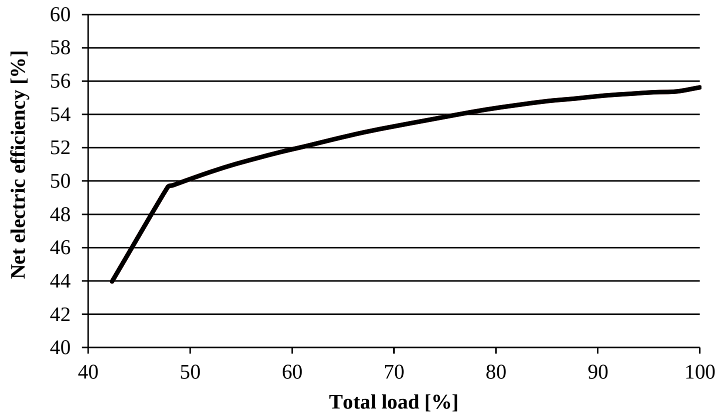

Figure 45. *Net electric efficiency of La Casella CCGT as a function of the total load.*

The full-load efficiency is 55.6%, which is on average for CCGTs built in the first 2000s [184]. It decreases slightly until 50% of the load, but then it drops sharply to 44% at the minimum load. This is due to the particular load control logic employed by the operators at the Minimum Environmental Load. As discussed before, the Minimum Environmental Load at La Casella CCGT is decreased from 190 to 170 MW thanks to the by-pass of intermediate pressure steam. The discontinuity slightly below 50% of the CCGT load corresponds to the point where valve V1 (Figure 28) starts opening and discharging steam. When intermediate pressure steam is by-passed to the condenser, the electric efficiency drops dramatically and the exergy destruction increases, because the intermediate pressure steam is at high temperature (around 540 °C). From this, it emerges how deeply the efficiency depends not only on the load, as expected, but mostly on the power plant control logics.

The trend of the efficiency as a function of the load and of the control logics is fundamental primarily for the power plant operators. Since the power plant is currently operating often at the minimum load, the operators are interested in studying solutions to reduce the efficiency drop and, therefore, the fuel expense at the minimum load.

Secondly, this index serves as input for energy system models: by means of (4.13), entering the obtained values of the maximum and minimum load and efficiency, the AdditionalFuelUse parameter for the technology representing state of the art CCGTs can be computed. This allows the impact of flexible operation on the fuel consumption to be assessed, through the modified OSeMOSYS code. Moreover, the Minimum Environmental Load in the model can be employed as MinStableOperation parameter for the CCGTs. Values of these parameters can be found in literature, but they are usually statistics-based, not model-based and they are not function of the control logics of the power plants.

More indications about the specific consumption of fuel can be drawn from the model and directly employed by the operators. The efficiency represented in Figure 45 refers to ISO conditions (environmental temperature 15 °C, pressure 1.013 bar, relative humidity 60%). However, in day-by-day operation, the operators have interest to monitor the real-time specific consumption of fuel, in order to monitor the operation costs. The specific consumption depends, besides the load, on the environmental conditions and the health of the components. Currently, the operators of La Casella estimate the specific consumption through the direct and the indirect methods described in Subsection 4.2.1.1. The results of the two methods are the Direct Specific Consumption (DSC) and the Indirect Specific Consumption (ISC). Their comparison allows diagnostic evaluations over the reliability of the measurement equipment and the degradation state of some components.

The reliability of the estimation of the ISC depends on the reliability of the correction curves for the corrected power and the specific consumption, as functions of a number of parameters. These curves were delivered to the operators by the manufacturers when the power plant was built. Since then, many modifications have been made to the power plant and the components experienced degradation. Therefore, there is a probability the correction curves are no more reliable and bias the estimation of the ISC. It is interest of the operators to recreate the correction curves through the model and compare these with the original ones. Moreover, the operators need to obtain correction curves for new parameters which may affect significantly the specific consumption, in order to improve the estimation of the ISC. This is strategic for them, since it provides them with the ability to self-compute the correction curves, without relying on information coming from the manufacturers.

In the following, as an example, the correction factors for the specific consumption and the power as functions of the ambient temperature and pressure are considered. A comparison is performed, between those delivered by the manufacturers and those extrapolated from the model. The operators compute the correction factors for the specific consumption f_η indirectly, since the manufacturers provide the curves in terms of efficiency. Since the following examples deal with the original curves, they refer to the efficiency, out of consistency. The curves of the correction factors delivered by the manufacturers are presented in (7.1) to (7.4):

$$\begin{aligned} f_{\eta,T_A} = & -7.8781E-11\cdot T_A^5 + 6.4314E-9\cdot T_A^4 - 1.3882E-7\cdot T_A^3 - 1.4224E-5\cdot T_A^2 + \\ & +4.4697E-4\cdot T_A + 9.9704E-1 \end{aligned} \tag{7.1}$$

$$f_{\eta,P_A} = -9.3201E-4\cdot P_A + 1.0008 \tag{7.2}$$

$$\begin{aligned} f_{\dot{E},T_A} = & \ 6.0563E-10\cdot T_A^5 - 7.9837E-8\cdot T_A^4 + 4.2946E-6\cdot T_A^3 - 1.2547E + \\ & -4\cdot T_A^2 - 2.6309E-3\cdot T_A + 1.0570 \end{aligned} \tag{7.3}$$

$$f_{\dot{E},P_A} = 9.9584E-1\cdot P - 9.0954E-3 \tag{7.4}$$

where f_{η,T_A}, f_{η,P_A}, $f_{\dot{E},T_A}$, $f_{\dot{E},P_A}$, are the correction factors for the efficiency as a function of the temperature, the efficiency as a function of the pressure, the power as a function of the temperature and the power as a function of the pressure, respectively. The temperature is expressed in °C, the pressure in bar. The model-based curves of the correction factors are obtained running parametric simulations with varying T_A and P_A, and collecting the results of the CCGT power and efficiency. They are presented in (7.5) to (7.8).

$$\begin{aligned} f_{\eta,T_A} = & -5.1977E-10\cdot T_A^5 + 6.9404E-8\cdot T_A^4 - 3.1964E-6\cdot T_A^3 + 4.8087E-5\cdot T_A^2 + \\ & +1.5003E-4\cdot T_A + 9.9445E-1 \end{aligned} \tag{7.5}$$

$$f_{\eta,P_A} = -1.8199E-2\cdot P_A + 1.0186 \tag{7.6}$$

$$f_{\dot{E},T_A} = -8.5506E-9 \cdot T_A^5 + 9.0967E-7 \cdot T_A^4 - 3.2458E-5 \cdot T_A^3 + \\ + 3.9704E-4 \cdot T_A^2 - 4.5739E-3 \cdot T + 1.0481 \quad (7.7)$$

$$f_{\dot{E},P_A} = 9.7389E-1 \cdot P - 1.3541E-2 \quad (7.8)$$

The percentage relative error between the correction factors computed through the model and those provided by the manufacturers, as a function of the ambient temperature and pressure is shown for some points in Figure 46 and Figure 47, respectively. It is computed as:

$$\text{Error \%} = \frac{f_{model} - f_{maunfacturer}}{f_{manufacturer}} \cdot 100 \quad (7.9)$$

where f is the value of the correction factor for either the power or the efficiency.

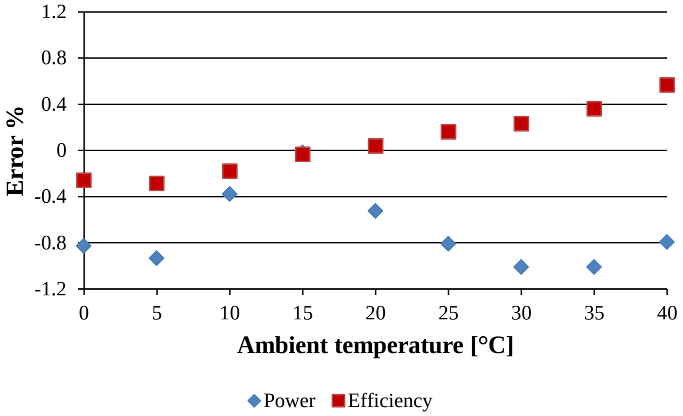

Figure 46. *Relative error between computed and released correction factors as a function of the temperature.*

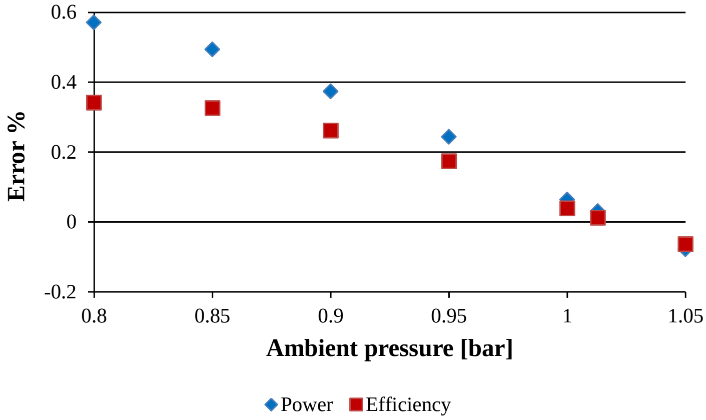

Figure 47. *Relative error between computed and released correction factors as a function of the pressure.*

In all the cases, the difference is null at the reference values of temperature and pressure, corresponding to the ISO conditions (15 °C and 1.013 bar). In these conditions, the correction factors are always equal to 1. For large ranges of different values of temperature and pressure, the difference lies below 1%. This indicates good agreement between the model and the original values provided by the manufacturers. The largest difference appears for the CCGT power, at temperatures different from 15 °C. It probably depends on the control logics at high ambient temperature. The curves of the manufacturers assume the de-superheaters of the high pressure steam start working already at 15 °C, because the steam is expected to reach 540 °C. On the contrary, in the model they start working at 25 °C, and this is confirmed by the operators. Though the errors are not big, this difference reveals the curves provided by the manufacturers are not up to date for the present control logics of the power plant, and they must be replaced by the model-based curves.

7.1.2. Computation of the cycling performance

In this application, the Minimum Environmental Load and the corresponding net electric efficiency are assumed as indices of the cycling performance of the CCGT. Currently, in the Italian electricity market, flexible operation also means operating most of the time at highly partial loads. Therefore, flexible fossil-fuel fired units able to reach lower minimum loads, possibly with higher efficiency, are likely to be dispatched more than the others. As described, the Minimum Environmental Load at La Casella power plant is constrained by the CO emissions. As the load of the gas turbine is decreased, these increase up to a maximum allowable value. The value is reached when the CCGT generates 190 MW. To further decrease the load, the load of the gas turbine is kept constant at 115 MW (the IGVs are almost completely closed), and intermediate pressure steam is by-passed to the condenser, through valve V1 in Figure 28. In this way, a Minimum Environmental Load of 170 MW is reached (42.3% of the nominal load). It is interest of the operators to find new power plant configurations and control logics, which allow them to reach the same Minimum Environmental Load with less steam by-pass. This would significantly reduce the efficiency drop at very low loads. To meet this scope, they proposed to employ air by-pass lines in the gas turbine. Three configurations are under study:

1. Using the air by-pass duct of the anti-acing system, already present in all the four groups of La Casella. The anti-acing system is a by-pass of hot air from the outlet to the inlet of the compressor, to avoid icing of the moisture at the suction during cold seasons. This line is sketched in Figure 48.

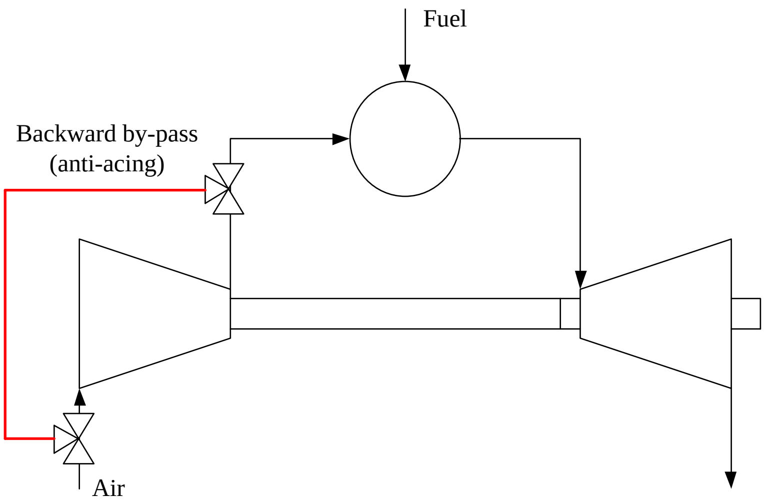

Figure 48. *Sketch of the backward by-pass duct.*

2. Using a by-pass duct from the compressor outlet to the turbine outlet (Figure 49). It is already installed on group 2 of La Casella CCGT.

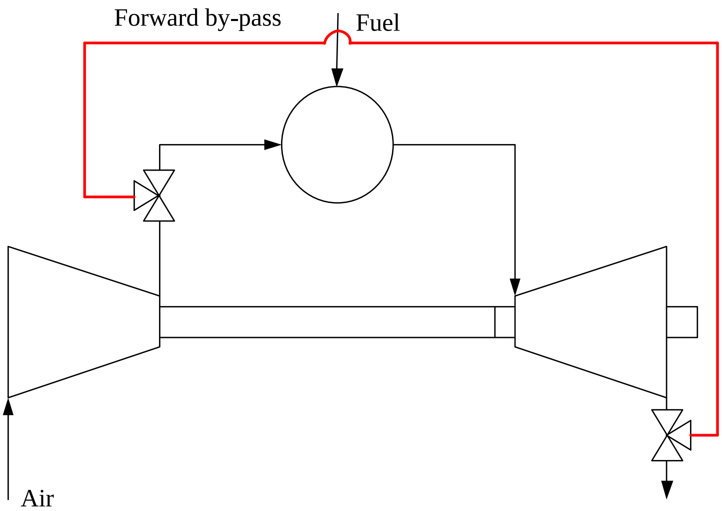

Figure 49. *Sketch of the forward by-pass duct.*

3. Combining the backward by-pass duct (anti-acing) to the compressor inlet and the forward one to the turbine outlet (Figure 50).

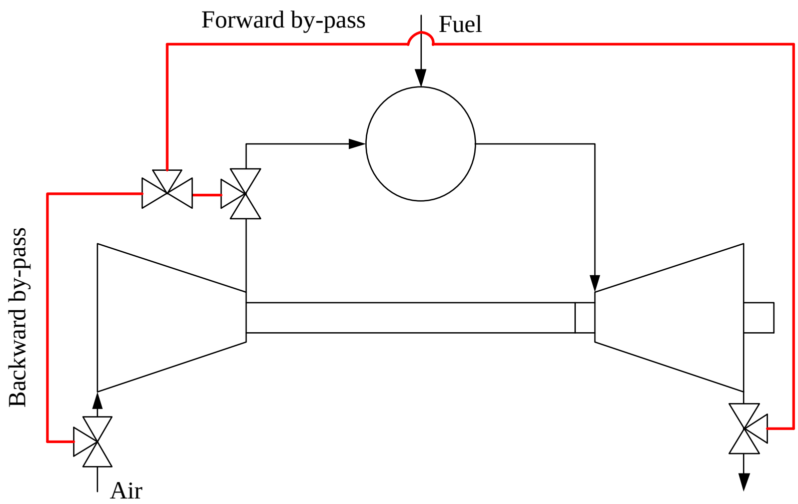

Figure 50. *Sketch of the combined by-pass ducts.*

These three configurations were designed in La Casella CCGT model, and simulations were run with different ratios of the air by-pass mass flows backward and forward. The aim of such study was to assess the performance of the power plant as a function of the air by-pass. The simulations were carried out with the following logic:

1. The CO emissions at the current Minimum Environmental Load are computed. The resulting value shall be the emission limit in any configuration. For computing the emissions, the Lefebvre semi-empirical correlation is employed [185]:

$$COEI = \alpha_{CO} \cdot \dot{m}_{CC} \cdot T_{CC} \cdot \exp\left(-\beta_{CO} \cdot T_{CC}\right) / \left[\left(V_C - V_{evap}\right) \cdot \left(\frac{\Delta P_{CC}}{P_{CC,in}} \right)^{0.5} \cdot P_{CC,in}{}^{2.5} \right] \qquad (7.10)$$

Here, COEI is the CO Emission Index $[g_{CO}/kg_{fuel}]$, α_{CO} and β_{CO} are two constants obtained by best-fitting the available emission data of the real combustor, $\dot{m}_{CC}$ is the air mass flow rate at the combustor inlet [kg/s], T_{CC} is the temperature in the primary zone of the combustion chamber [K], V_C and V_{evap} are the combustion volume and the fuel evaporation volume $[m^3]$, respectively, ΔP_{CC} is the pressure drop across the combustion chamber, $P_{CC,in}$ is the pressure at the inlet of the combustion chamber. In the computations, some adaptations and approximations were made, with respect to these quantities. Firstly, since the temperature of the primary zone cannot be computed with a lumped parameters model, the temperature at the outlet of the combustion chamber is assumed as T_{CC}. This approximation is conservative, with respect to the emissions, since the outlet temperature is lower than the primary zone temperature. Secondly, V_{evap} is zero for a gas-fired turbine. Eventually, V_C is unknown. Therefore, it was incorporated in the constant α_{CO}. The values of the CO emissions computed through the correlation were compared to values measured at the power plant. For the range of gas turbine loads of interest, the agreement between computed and measured values is very good, as shown in Figure 51.

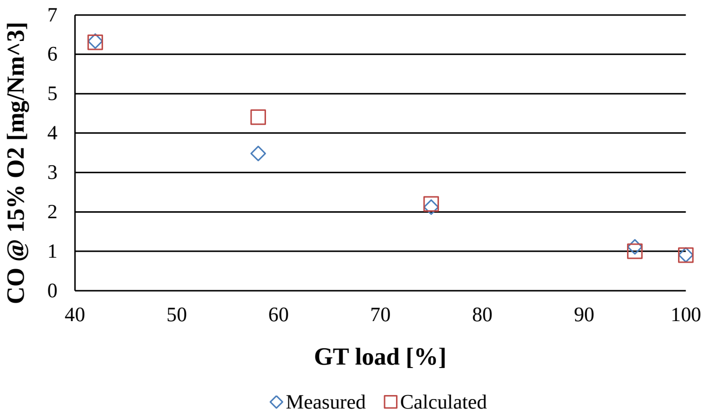

Figure 51. *Comparison between the measured and the calculated CO emissions.*

2. The load of the whole CCGT is kept constant and equal to 170 MW.
3. The backward or forward by-pass flow, as a ratio of the total flow exiting the compressor, is increased from 0% to 5%, in steps of 1%. Globally, combining all the ratios of the two by-pass flows, 36 cases are simulated.
4. For every case, the CO emissions are computed by means of the Lefebvre correlation.
5. If the emissions are higher than the limit computed in point 1, the aperture of the IGVs is regulated, until the emissions equal the limit again. The IGVs are employed to control the CO emissions, because they modify the air mass flow rate, thus the compressor outlet temperature and pressure, thus also T_{CC} and $P_{CC,in}$. The aperture which allows the emission limits to be met is found iteratively.

The 36 points resulting from the simulations at different backward and forward by-pass ratios are shown in Figure 52 and Figure 53, in terms of minimum load of the gas turbine and CCGT efficiency. At constant load of the CCGT, the load of the gas turbine decreases with both the backward and the forward by-pass ratio. This can be seen in Figure 52. This is due to the fact that the air flow to the combustion chamber decreases with increasing air by-pass. Without the possibility of by-passing air, the steam by-pass is needed to decrease the load of the CCGT. When the air by-pass is allowed, there is no more need of by-passing steam, since the load of the gas turbine can decrease, without increasing the CO emissions. For this reason, the steam by-pass decreases with increasing air by-pass flow, as noticed in Figure 54. At the limit, it becomes zero. The global efficiency increases with the backward by-pass, but it does not with the forward by-pass, as noticed in Figure 53. In this case, though the steam by-pass decreases and the efficiency of the HRSG increases, the compressed air is discharged at the turbine outlet, therefore the efficiency of the gas turbine decreases and counterbalance the other effect.

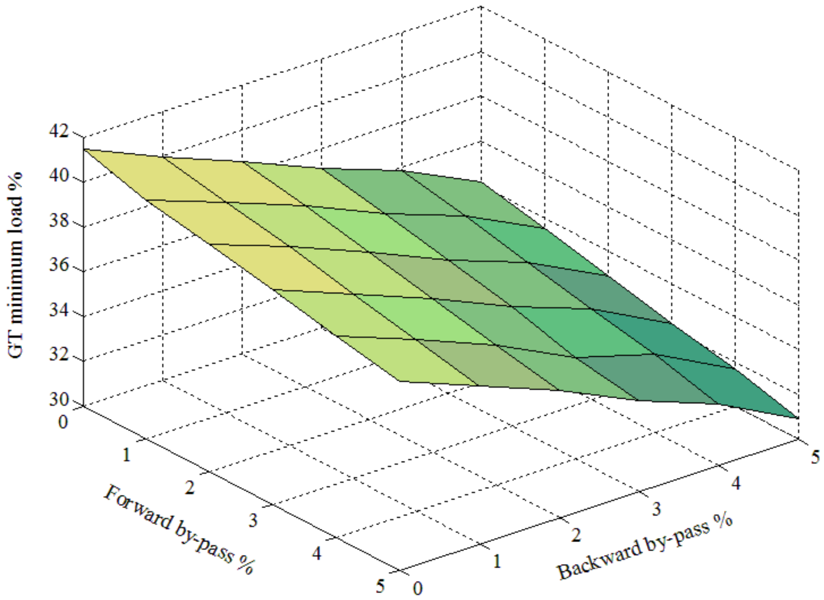

Figure 52. *GT Minimum Environmental Load as a function of the % by-pass on the backward and forward ducts.*

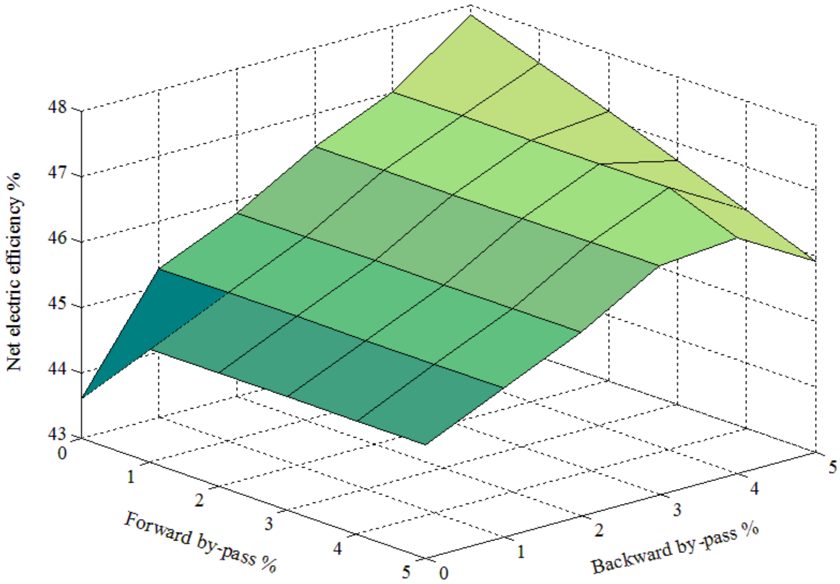

Figure 53. *Efficiency as a function of the % by-pass on the backward and forward ducts.*

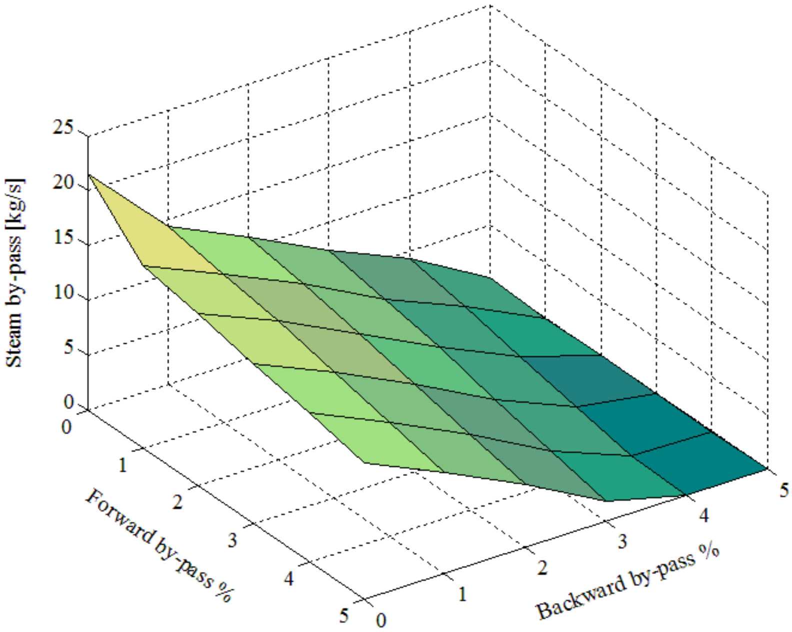

Figure 54. *Steam by-pass flow as a function of the % by-pass on the backward and forward ducts.*

All these evaluations are useful to both the power plant operators and the energy system planner. As regards the operators, if they know the efficiency gains at the minimum load when the by-pass lines are employed, they will communicate these numbers to the market division of the company. Here, the bidding strategies for all the power plants of the company are decided, based on optimisation algorithms which feed the performance of each power plant as input. If La Casella CCGT shows a better efficiency at the minimum load, it is likely to be dispatched more. As for the energy system planners, they may employ the values of the efficiency at the minimum load for computing the AdditionalFuelUse parameter in (6.3). The higher is the efficiency, the lower are the values of the parameter and, consequently, the costs of fuel for partial load operation. Since the energy system models like OSeMOSYS compute the least cost long-term energy mix, equipping CCGTs with by-pass systems like the ones illustrated may result in this technology gaining higher share in the optimal long-term energy mix. Such evaluation is made in Section 7.2.

7.1.3. Computation of nodal performance indices and their interrelation

In Section 4.2.2 the author described some of the most relevant nodal performance indices, for a CCGT in flexible operation. Among them, the exergy destruction ratio, $y_{D,k} = \dot{E}x_{des,k}/\dot{E}x_{fuel,tot}$, represents the ratio between the exergy destroyed by the component and the exergy of the fuel to the whole power plant. It allows all the components to be compared and ranked against their contribution to the global irreversibility of the cycle. In fact, they may be not comparable on the basis of the energy efficiency: for instance, while a compressor generically has a First Law of Thermodynamics efficiency lower than one and function of the load, a heat exchanger, if no heat loss is assumed, has a First Law efficiency equal to one in every condition. On the contrary, the exergy efficiency is lower than one and it may either decrease or increase at partial loads, depending on the average temperature difference between the cold and the hot stream. By means of the exergy destruction ratio, those components contributing most to the global irreversibility can be identified. When maintenance operations or hardware modifications for enhancing the efficiency of the power plant are planned, priority can be given to these components. In Table 16, the exergy destruction $\dot{E}x_{des,k}$, the exergy efficiency $\eta_{ex,k}$ and the exergy destruction ratio $y_{D,k}$ of the main components of La Casella CCGT at full load are shown. The components are sorted by $y_{D,k}$, from the highest to the lowest. The reader may refer to Figure 28 and the following description of the components, to recall their position and their function in La Casella power plant.

Component, k	$\dot{E}x_{des,k}$ **[MW]**	$\eta_{ex,k}$ **[%]**	$y_{D,k}$ **[%]**
Combustion chamber	168.74	81.99	23.38
Expander	36.09	94.01	5.00
Steam turbine	23.38	84.83	3.24
Compressor	14.79	94.79	2.05
Condenser	10.56	-	1.46
HP-EVA	7.99	86.74	1.11
LP-ECO	4.06	70.28	0.56
HP-SH1	3.80	85.51	0.53
HP-ECO2	2.34	89.12	0.32
IP-RH1	2.24	86.01	0.31
IP-EVA	1.91	87.89	0.26
LP-EVA	1.20	86.12	0.17
IP-RH2	1.12	91.24	0.15
HP-SH2	0.80	91.75	0.11
HP-ECO1+IP-ECO	0.80	86.57	0.11
IP-SH	0.41	83.48	0.06
LP-SH	0.31	68.36	0.04
System	291.90	55.62	40.44

Table 16. *Nodal outputs of La Casella case study.*

Notice that no exergy efficiency is defined for the condenser, since no useful product is defined for it, according to Figure 32 and Table 11. The first indication that can be drawn from the table is that a higher exergy destruction ratio does not necessarily correspond to a lower exergy efficiency. The exergy destruction ratio indicates how much the global efficiency of the system could be improved if the performance of the component was improved. The exergy efficiency indicates how much the performance of the component can be improved in itself. Therefore, the two indices may be employed as follows: first, the exergy destruction ratio is looked at, to identify which components are most worth caring about; afterwards, the exergy efficiency of these components is considered, to see how much their performance can be improved.

Looking at the exergy destruction ratio, all the components of the gas turbine are amongst those most affecting the whole cycle. Among them, the combustion chamber can be hardly improved, since the exergy destruction comes almost exclusively from the chemical reaction. On the contrary, the irreversibility in the compressor and the expander is mostly of aerodynamic nature. The causes may lie in the shape and the health state of the blades, or in fouling. In the first case, they are hardly removed with minor interventions, while in the second case they are avoidable with a better scheduling of the maintenance interventions.

Looking at the other components, the steam turbines and the condenser present a high contribution. However, this is not easily corrected with ordinary repair interventions.

As far as the heat exchangers are concerned, the high pressure evaporator, the low pressure economiser and the first high pressure superheater present the highest exergy destruction ratio. This contribution can be partly avoided, because also these components are subject to fouling, both on the steam and on the gas side. Therefore, again the washing interventions should focus mostly on these exchangers and should be accordingly planned.

The described performance indices refer to full load. A picture at full load is useful, because it is easily obtained with an on-design simulation. However, it might be the case that these indices vary by a significant amount between the nominal and the minimum load. Therefore, they must be computed also at lower loads. Simulations between the full and the Minimum Environmental Load, employing all the relevant control logics of La Casella CCGT, were performed, by steps of 5% of the load. Therefore, a quasi-stationary approach was chosen, and the results for every level of the load were obtained with steady-state approximation. In Figure 55, the values of the exergy destruction ratio as functions of the load are shown for the most relevant components.

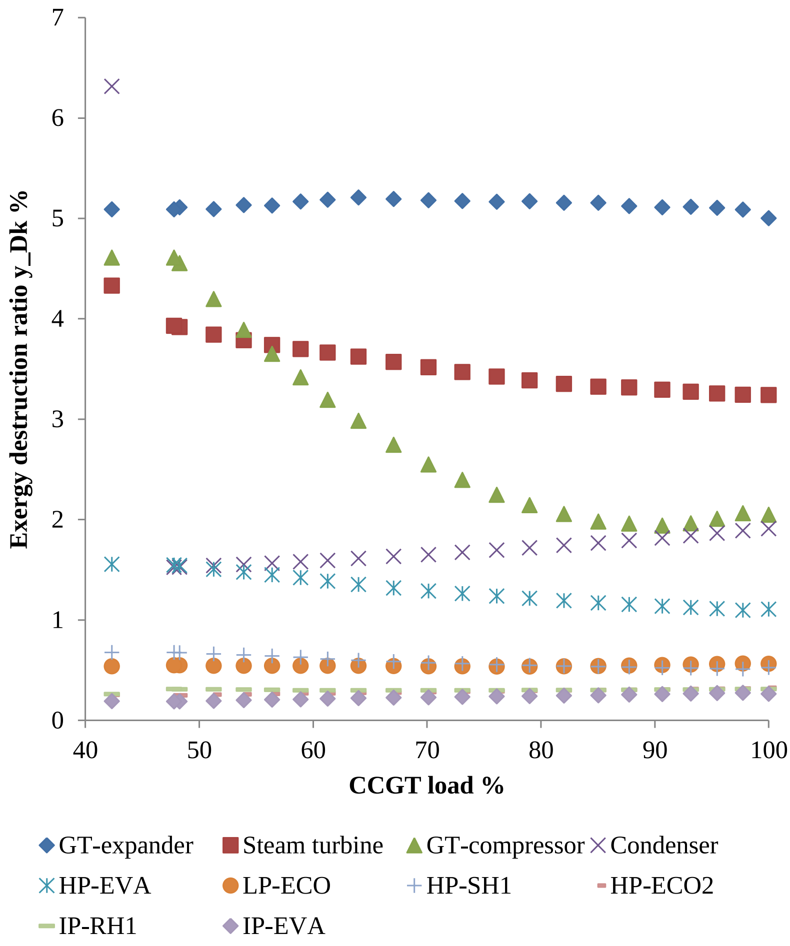

Figure 55. *Exergy destruction ratios in the HRSG as functions of the CCGT load.*

When the whole range of loads down to the Minimum Environmental Load is considered, the picture becomes more interesting. The deepest change is noticed in the compressor, for which y_D increases much. This is due to a significant drop in the efficiency of the machine, with decreasing load. At low loads, the compressor becomes much more an important source of exergy destruction for the power plant, indicating that it must be particularly cared about, if the power plant is expected to operate highly partialised. The second highest increase occurs in the ensemble of the steam turbines and in the high pressure evaporator. On the contrary, y_D remains almost constant for the low pressure economiser and decreases for the condenser. The trend of the exergy destruction ratio of the heat exchangers, included the condenser, is related to the trend of the temperature difference between the hot and the cold streams. This decreases as the load does, for the condenser, while it increases sensibly for the high pressure evaporator. Finally, the points close to the minimum load deserve particular attention. As described earlier, from 190 to 170 MW of the combined cycle, i.e. around 47.8% to 42.3% of the load, steam is by-passed, while the compressor works constantly at 115 MW. Therefore, the exergy destruction ratio of the compressor does not increase. The load of the steam turbine, on the contrary, decreases by a noticeable amount, because of the by-pass of intermediate pressure steam, therefore its exergy destruction increases steeply. Finally, the exergy destruction of the condenser increases to an outlier, because the intermediate pressure steam at high temperature is discharged directly to this component, and the corresponding exergy destruction is charged onto it.

As a final step of this evaluation, it is useful to study what influence the performance of a component may have on the performance of the others. This information should be collected for diagnostic purposes, in order to predict how the thermodynamic quantities through the power plant change, when something occurs on a component. As an example, the effect of a malfunction of the low pressure economiser on the power plant and the other heat exchangers was studied. The economiser exchanges thermal energy with the gases at low temperature, therefore it is particularly subject to fouling on the gas side. The fouling reduces the overall heat transfer coefficient, increases the temperature difference between the two streams, thus increases the exergy destruction across the component and, possibly, over other components. Fouling can be simulated in the model, by setting the value of a 'fouling factor' in the parameters of the low pressure economiser, such that:

$$\frac{1}{U\cdot S}=\frac{1}{(\eta_0 hS)_c}+R_w+\frac{R''_{f,h}}{(\eta_0 S)_h}+\frac{1}{(\eta_0 hS)_h} \tag{7.11}$$

In (7.11), $R''_{f,h}$ is the fouling factor on the side of the hot gases, U is the overall heat transfer coefficient, $1/(\eta_0 hS)_c$, R_w, $1/(\eta_0 hS)_h$ are the thermal resistances of the cold side, the wall, and the hot side, respectively, S are the exchange surfaces. From (7.11) it is deduced that, increasing $R''_{f,h}$, the overall heat transfer coefficient U is reduced. The influence of fouling on the gas-side of the LP-ECO of La Casella CCGT was studied. Three scenarios with increased fouling, i.e. decreased $U\cdot S$ were run. The effect on some relevant global and nodal performance indices and on the exergy destruction of other heat exchangers is shown in Table 17.

	Case 1	**Case 2**	**Case 3**
LP-ECO $(U\cdot S)$ [kW/K]	**1608.4**	**1489.7**	**861.6**
Global indices			
System net power [MW]	401.51	401.37	400.27
System net electric efficiency [%]	56.03	56.01	55.86
Nodal indices			
LP-ECO heat transfer [MW]	49.8	48.8	40.2
LP-ECO water outlet temperature [°C]	141.4	131.2	122.5
LP-SH flow rate [kg/s]	10.2	8.7	7.5
LP-ST inlet flow rate [kg/s]	103.8	102.2	101.0
LP-EVA pressure [bar]	4.3	4.1	3.9
LP-EVA ΔT [°C]	31.4	31.5	32.5
LP-EVA heat transfer [MW]	23.9	24.1	25.1
LP-SH heat transfer [MW]	2.1	2.0	1.6
LP-SH U [$\mathrm{W/m^2K}$]	16.2	16.0	13.9
LP-SH ΔT [°C]	120.0	118.7	105.8
IP-ECO heat transfer [MW]	3.17	3.19	3.33
HP-ECO1heat [MW]	11.9	12.0	12.6
IP-ECO ΔT [°C]	38.8	38.9	40.0
HP-ECO1 ΔT [°C]	38.5	38.70	39.8

Table 17. *Component results with different degrees of fouling on the LP-ECO.*

The impact of the fouling of the LP-ECO on the exergy destruction of the same component and others in the HRSG when the overall heat transfer coefficient is halved is shown in Figure 56.

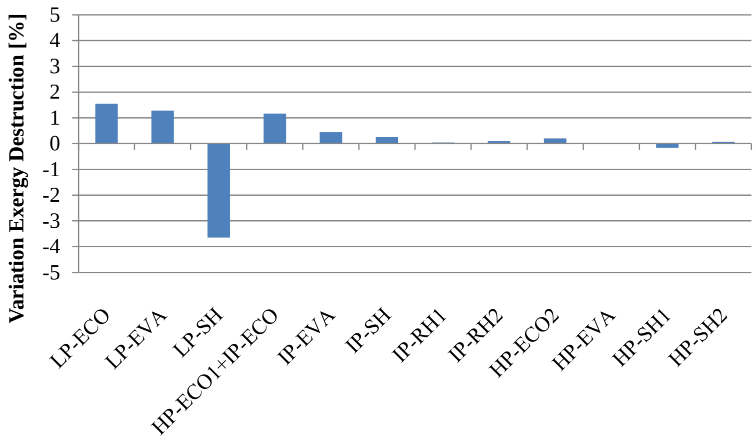

Figure 56. *Variation of the exergy destruction of components of the HRSG when the heat transfer coefficient of the LP-ECO is halved.*

From Table 17 it is inferred that neither the net electric power nor the efficiency vary significantly when the LP-ECO is subject to fouling. On the contrary, a number of effects can be detected on the individual components:

- The lower heat exchange coefficient causes the heat transferred across the LP-ECO to decrease and determines a lower LP-ECO outlet water temperature.
- The higher subcooling of the water exiting the LP-ECO causes an increased demand of low-pressure steam at the de-areator and a lower steam flow rate delivered to the LP-SH.
- The decreased steam flow rate implies a lower evaporation pressure because of the steam turbine characteristic. The LP-EVA therefore works with increased average temperature difference ΔT.
- Due to the reduced steam flow rate, the average temperature difference in the LP-SH decreases.
- The parallel exchangers IP-ECO and HP-ECO1 receive water from the feedwater pumps, which collect the saturated liquid from the LP-EVA. The lower evaporation pressure in the LP-EVA causes the temperature of the saturated water to decrease, therefore the average temperature difference in the parallel economisers increases and the heat they transfer increases.

Among these effects, the variations of the average temperature differences across some heat exchangers are highlighted: the ΔT in the LP-EVA and in the parallel economisers increases, therefore the exergy destruction across them increases; on the contrary, the ΔT across the LP-SH decreases, and so does the exergy destruction. These effects are synthesized in Figure 56. For diagnostic purposes, it is important to notice that a malfunction on a component does not necessarily have only negative effects on the other components.

Figure 56 collects the information to fill in the first row of matrix (7.12), highlighted in bold characters. An equivalent matrix was introduced in Section 4.2.2.

$$\begin{pmatrix} \frac{\partial \dot{\mathbf{E}}_{\mathbf{D,1}}}{\partial \dot{\mathbf{E}}_{\mathbf{D,1}}} & \cdots & \frac{\partial \dot{\mathbf{E}}_{\mathbf{D,n}}}{\partial \dot{\mathbf{E}}_{\mathbf{D,1}}} \\ \vdots & \ddots & \vdots \\ \frac{\partial \dot{\mathrm{E}}_{\mathrm{D,1}}}{\partial \dot{\mathrm{E}}_{\mathrm{D,m}}} & \cdots & \frac{\partial \dot{\mathrm{E}}_{\mathrm{D,n}}}{\partial \dot{\mathrm{E}}_{\mathrm{D,m}}} \end{pmatrix} \tag{7.12}$$

If the same parametric simulations are performed on the other heat exchangers of the HRSG, a complete picture of the interrelations between all the components emerges. Since the model computes all the thermodynamic quantities at all the nodes in every simulation, the same matrix can be written for the temperatures, the exergy destruction ratios, the efficiencies, etc. The operators can use such matrices to overcome the limited knowledge they have about the interactions between the heat exchangers in the HRSG. For instance, when the temperature of the gases at the stack, which is measured, increases, the heat exchangers which are likely to cause such variation can be identified.

7.2. Energy system model: a test case study

This application aims at testing if and how the costs and benefits of the flexible operation of power plants may impact the least-cost long-term energy mix, in decarbonisation scenarios. The optimal energy mix computed with the original version of OSeMOSYS for a defined scenario is compared to the one computed for the same scenario with the modified version of OSeMOSYS, where the constraints derived in Section 6.1.2 are added. It is expected that the mix and the global cost in the two cases will be different. Generically, in the second case it happens that:

1. New cost items related to the additional fuel consumption at partial load, the cycling capability, and the cost of the starts appear in the objective function.
2. Since the objective function is the minimisation of the net present cost of the system, the model tries to minimise also these cost items, along with the other cost sources (investment, O&M, emissions).
3. The energy mix and the generation dispatch are computed in such way that also these costs are minimised, as opposed to what the original OSeMOSYS model computes.

In Section 7.2.1, the modifications for the cost of the starts and the fuel consumption are introduced, and the model is applied to a test scenario, simplified for the effect of the code modifications to be clear. In Section 7.2.2, the modification for the cycling performance is added to the previous two, and the model is applied to the same scenario, properly modified. In both cases, the values obtained from the thermodynamic model in Section 7.1 are employed, as numerical inputs for the efficiency of the CCGT technology, the newly defined AdditionalFuelUse parameter and the MinStableOperation parameter.

7.2.1. Introduction of the cost of the starts and the fuel consumption at partial load

It is convenient to apply the model to an ideal scenario, simple enough for the impact of the modifications on the energy technology and generation mix to be fully appreciated, but with realistic assumptions about the demand and the characteristics of the generation technologies. The main features of the scenario are described in Table 18.

Time domain	2013 to 2040
Time slices	8, day and night of each season
Electricity demand	297.3 TWh/year in 2013, then increasing at constant rate
Reserve capacity demand	485 MW in 2013, then increasing at constant rate
Renewable generation	11% of electricity generation in 2013, then linearly increasing
Taxations	30 €/ton CO_2, constant
Price of coal	12.5 €/MWh, constant
Price of gas	29 €/MWh, constant
Discount rate	5%

Table 18. *Main scenario assumptions for the test case study.*

A situation is assumed, where there is a given demand for electricity and reserve capacity, and a new electricity system must be designed to meet it. Before the first year of the simulation, no capacity of any technology is present. The time domain of the simulation covers the years from 2013 to 2040, like the scenarios of IEA. The year is split in 8 time slices, for day and night of every season: L0, L2, L4, L6 are the time slices for the days of winter, spring, summer, autumn, respectively; L1, L3, L5, L7 are the ones for the corresponding nights. The day lasts from 8 am to 8 pm, the night lasts from 8 pm to 8 am.

The demand for electricity in the first year of the simulation is equal to 297.3 TWh/year, corresponding to the final electricity demand in Italy in 2013 [21]. In the following years it is assumed to increase by 7% every year, which is the average expected increase rate for the OECD countries in years 2012 to 2040, according to the IEA Current Policies Scenario [11]. The demand for electricity is split between the time slices, according to a statistic study over the load curves in Italy in 2013 performed by the author. The demand for reserve capacity in 2013 is computed as the daily average of the demand for secondary reserve capacity in Italy in the same year [21]. It increases at the average rate recorded from 2011 to 2015.

It is assumed that the energy system planner imposes an increasing minimum share of renewables in the electricity generation. It is 11% in 2013 and it increases by 0.5% every year, up to 24.5% in 2040. Moreover, a carbon price of 30 €/ton for CO_2 emissions is enforced, constant through the time domain of the simulation. No other emission limit is imposed. The price of coal is 12.5 €/MWh, which is the median price across OECD countries in 2010, according to IEA [186]. As for gas, 32 €/MWh is assumed, close to the average of the wholesale price on the main European gas hubs in 2013 [22]. Both prices are assumed to be constant throughout the time domain. This assumption responds to the need of limiting as much as possible the variation of the boundary conditions along time, for the impact of the introduction of the code modifications to be clearer. The discount rate for the computation of the present costs is assumed to be 5%.

Eventually, two more hypotheses are made: the installation and the decommissioning of power plants are instantaneous; the installed capacity of the technologies is a continuous variable. This second hypothesis means that the new capacity is not installed in blocks or units of a certain capacity, as it is in reality. This would make the code mixed-integer, greatly increasing the computational time. The new capacity increases continuously, instead, as if it could be installed by very little amounts. When wide scenarios are analysed, this assumption is acceptable, since a global picture in terms of total capacity is needed, not information about the individual installations.

It is assumed the demand for electricity and reserve capacity can be met by only three technological options: wind turbines, representative of an intermittent renewable technology, coal-fired steam cycles and gas-fired CCGTs. Steam cycles and CCGTs can also supply reserve capacity, while wind turbines are not allowed to, since their generation is assumed to be nonprogrammable. The assumptions regarding the three technologies refer to [186], except for the ramping rates, which are retrieved from [187]. The Minimum Environmental Load is assumed as the minimum load that can be reached by the generators (corresponding to the MinStableOperation parameter in OSeMOSYS). The minimum efficiency and the unitary cost of the starts are the input parameters for the new formulations introduced into the code. The minimum efficiency of La Casella power plant is assumed as the minimum efficiency of the CCGTs. This implies that all the CCGTs are assumed to be equipped with a steam by-pass system for decreasing the Minimum Environmental Load to 42%. The minimum efficiency of the steam cycles is derived from [180,181]. Differently from the case of CCGTs, this number is generic and not depending on the control logics. However, a more specific figure can be fed as input, when as much detailed models of steam cycles are available. Finally, the unitary cost of the starts is derived from [33]. The technology data are listed in Table 19.

	Wind turbine	**Coal steam cycle**	**Gas CCGT**
Investment cost [€/kW]	1607	1460	730
Variable cost [€/MWh]	15	4.12	3.06
Design efficiency %	-	41.1%	57%
Availability %	26%	85%	85%
Lifetime [years]	25	40	30
Minimum load [% nominal]	0	45	42
Ramping rate [MW/min]	-	8	11
Minimum efficiency %	-	37%	43.6%
Unitary cost of the starts [€/MW]	-	150	55

Table 19. *Main cost and technology assumptions of the test case study scenario.*

Notice that, for the wind turbines, no efficiency is indicated, since it is assumed the environment is a thermodynamic reservoir of wind power. The availability of the wind source is constrained by means of the Availability parameter, which upper-binds the annual wind generation. The ramping rate of the wind turbines is not indicated, because they are assumed not to contribute to the capacity reserve provision.

In Figure 57, the annual generation by every technology in the described scenario is shown, as computed with the original version of OSeMOSYS, i.e. without any of the modifications derived in Section 6.1.2.

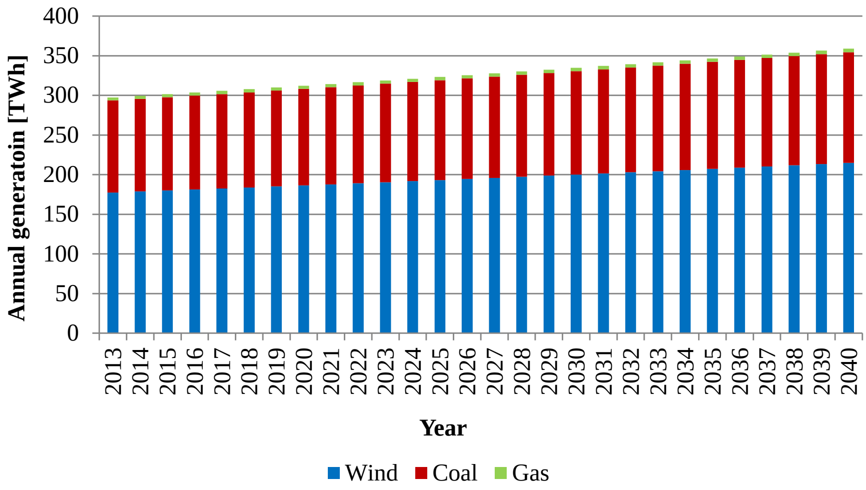

Figure 57. *Annual generation with the original OSeMOSYS code.*

Under the assumptions reported above, the least cost generation mix from 2013 to 2040 relies almost exclusively on wind and coal-fired steam cycles. As for wind, it shares no more than the minimum generation imposed as a constraint, because its capital and variable costs are both higher than those of the other two technologies. As for coal, it results more convenient than gas due to the price of the fuel. In the end, gas supplies a very little share of the electricity generation. In Figure 58, the annual generation in one sample year, 2018, is shown, divided per time slice. It can be seen wind provides the base-load generation, while steam cycles provide the daily cycling generation. This result relies on the assumption that a certain amount of wind source is always available, during the day and during the night.

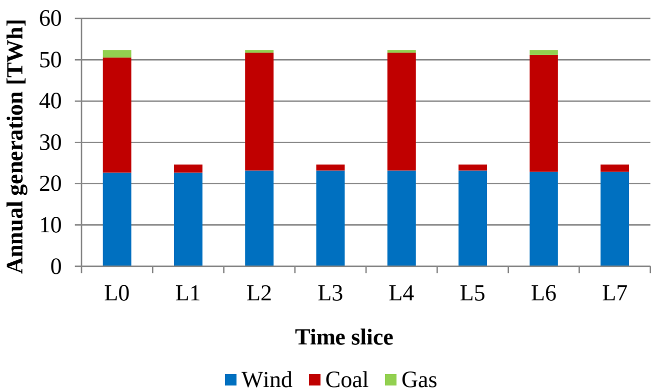

Figure 58. *Annual generation by time slice in one sample year with the original OSeMOSYS code.*

In Figure 59, the annual reserve capacity is reported, as computed under the same conditions as the generation. It is reported in energy units, since it is the product of the reserve capacity supplied every time slice by the duration of the time slice, i.e. the time the capacity is made available.

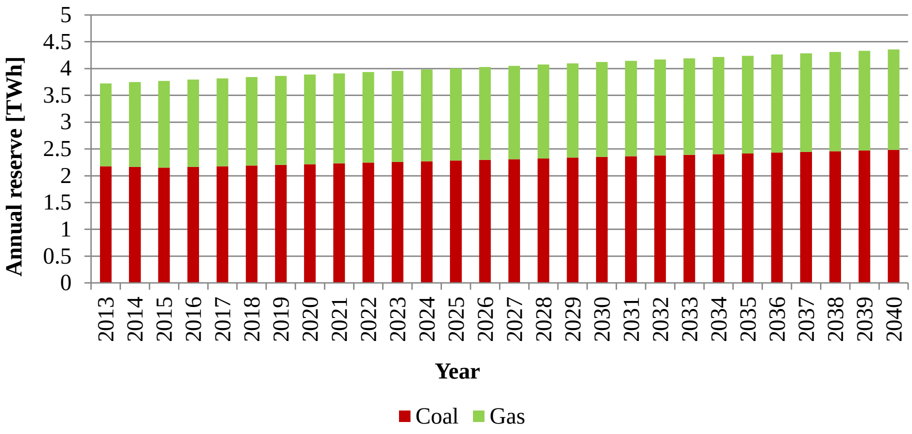

Figure 59. *Annual reserve with the original OSeMOSYS code.*

Interestingly, the little capacity of gas-fired CCGTs which is online and generates a small amount of electricity is employed to meet the reserve capacity demand. Gas and coal-fired power plants equally share the provision of reserve, more or less. As mentioned earlier, wind does not account for any reserve, because it is not allowed to, by assumption. Splitting the provision of reserve capacity between the time slices, a pattern appears where CCGTs provide reserve during daytime, steam cycles provide reserve during the nighttime.

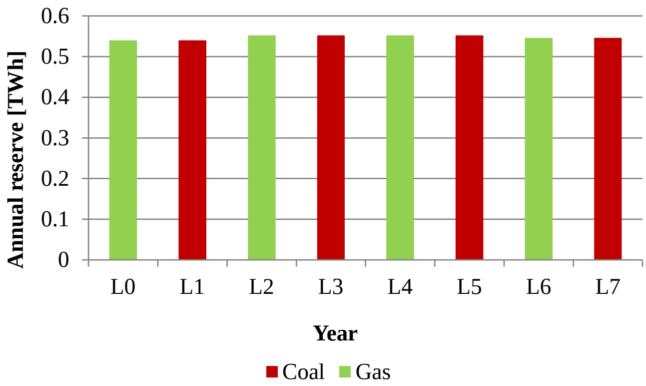

Figure 60. Annual reserve by time slice in one sample year with the original OSeMOSYS code.

Figure 61 presents the annual generation when OSeMOSYS is modified by introduction of the constraints for computing the cost of the starts and applied to the same scenario. In this case, the annual electricity globally supplied does not change, since the demand to be met is the same and it is fixed by the scenario assumptions. On the contrary, the share of the different technologies for meeting this demand at the least cost does change: the gas-fired CCGTs now share a significant amount of the annual generation, in place of the coal-fired steam cycles.

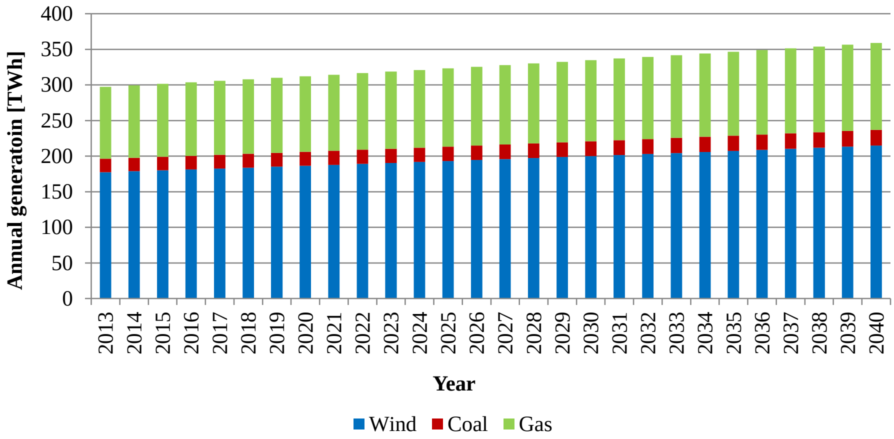

Figure 61. *Annual generation when the cost of the starts is introduced.*

The reason lies in the different cost function of the model. In the previous cases the main cost source in the operation of the technologies was the fuel. Since the cost of the fuel is much lower for coal-fired steam cycles, they were largely preferred over gas-fired CCGTs. In the present case, also the starts become a significant cost source. Since these are much higher for steam cycles than for CCGTs, the steam cycles become less convenient. This is clearer when the annual generation is split between the time slices (Figure 62). As opposed to the previous case, now CCGTs provide the cycling capability, because it would be far more expensive to provide it with steam cycles. The global present cost of the system slightly increases, when the cost of the starts is taken into account. However, the cost increase is little, because it was assumed the system is created ex novo, so all the investments are included. These are much higher, in absolute terms, than the costs of the starts.

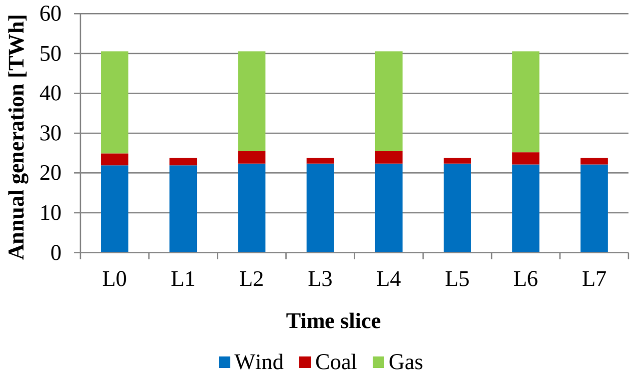

Figure 62. *Annual generation in one sample year when the cost of the starts is introduced.*

Different results are obtained when the second code modification is introduced in the OSeMOSYS source code and added to the cost of the starts: the fuel consumption as a function of the load. In this case, the mix for the electricity generation does not change noticeably, compared to what shown in Figure 62. This happens because the power plants undergo daily cycling, operating close to full load during the day, and being shut down during the night. The costs for the operation at partial load are negligible compared to the costs of the starts. However, a difference with the previous case, where only the cost of the starts was introduced, can be noticed in the provision of capacity reserve. Though the demand for reserve capacity is not significant, supplying upward capacity reserve implies operating lower than the full load. The cost of fuel from the efficiency decay of CCGT part-load operation is higher than that of coal-fired steam cycles, because the efficiency decreases more for CCGTs and because gas is much more expensive than coal. For this reason, when the cost of fuel at partial load operation is introduced, the reserve capacity is provided only by coal-fired steam cycles, as shown in Figure 63.

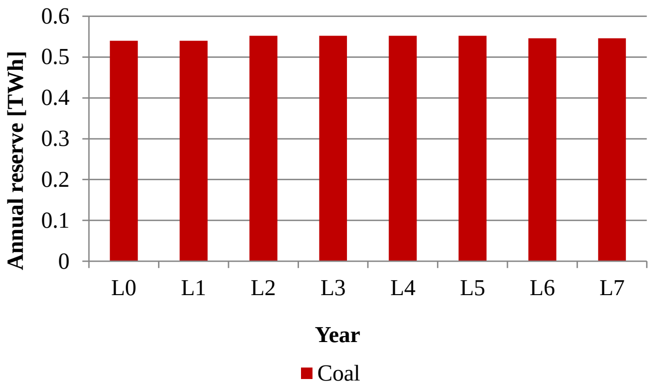

Figure 63. *Annual reserve in one sample year when the fuel consumption at partial load is introduced.*

One last point is worth mentioning. A sensitivity analysis highlighted that the impact of each modification on the results of the simulations is highly sensitive to the costs assumptions of the scenario, particularly to the cost of the fuels and the carbon price. For instance, with a higher price of the natural gas, equal to 35 €/MWh, introducing the cost of the starts does not change the share of electricity generation with respect to the base case, i.e. coal-fired steam cycles keep providing most of the generation. On the contrary, if in addition to the price of natural gas also the carbon price is increased (for instance to 50 €/tonne), introducing the cost of the starts has fairly the same effect as shown in Figure 61.

This means that with different real applications the developed modifications may be relevant or not, and several applications will be needed to have a clear picture of whether they are worth adding to the source code, with additional computational effort. The case study developed in Section 7.3 moves a first step in this direction.

Different is the case of the modification related to the cycling capability as a function of the power plant configuration, for which an application is shown in the next section. Though it might not cause the global cost of the system to change significantly, it will always be worth introducing in the model, to understand whether any of the existing power plants or group of power plants are worth retrofitting or not.

7.2.2. Introduction of the cycling capability as a function of the power plant configuration

Now the case is considered, where the code modifications for representing the cycling capability as a function of the power plant configuration are introduced. In this case, it is assumed that the CCGTs can change their configuration through minor retrofits, and their cycling capability depends on the configuration. For the impact of this modification to be assessed, some new assumptions must be introduced in the scenario, in addition to those of the scenario previously assumed. First of all, in 2013, the first year of the simulation, some capacity of CCGTs must be already in place. It is supposed that 30 GW CCGTs are present in 2013, which were installed in the decades before. Therefore, they end their lifetime during the time domain of the study and they are gradually decommissioned. In 2013 30 GW CCGTs are operating, at the end of 2017 10 GW are decommissioned, at the end of 2028 10 more are, and at the end of 2035 the last 10 GW are decommissioned. This trend is shown in Figure 64.

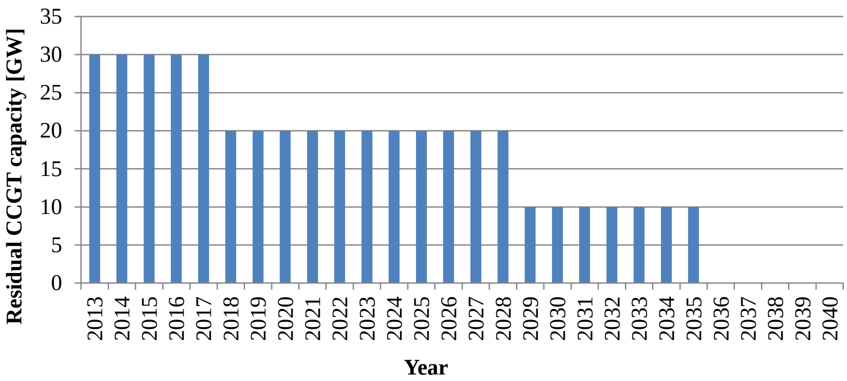

Figure 64. *Assumed ResidualCapacity for the CCGT technology.*

According to the rationale of the code modification for the cycling capability, in addition to this ‘old’ version of the CCGT technology, a ‘new’ one is introduced, with different performance. Specifically, the two indices which distinguish the performance of the old and the new CCGTs are the efficiency at the minimum technical load (assumed to be the Minimum Environmental Load) and the unitary cost of the starts. Their values are given in Table 20.

	Old – Gas CCGT	**New – Gas CCGT**
Minimum efficiency %	43.6	47.9
Unitary cost of the starts [€/MW]	55	44

Table 20. *Additional assumptions for the introduction of the modification for the cycling capability.*

First of all, it is assumed the new CCGTs have a different logic for lowering the Minimum Environmental Load to 42%. While the old ones are all equipped with steam by-pass as currently is La Casella power plant, the new ones are equipped with a by-pass duct of the compressed air to the compressor inlet. The efficiency of the new CCGTs at the minimum load is therefore 47.9%, corresponding to 5% air by-pass to the compressor inlet, as computed in Section 7.1.2 through the thermodynamic model. Secondly, the new CCGTs have lower costs of the starts, corresponding to the costs experienced by new flexible units, according to [33]. It is assumed the reduction of these costs comes from minor retrofits actually under study at La Casella power plant.

The model is allowed to either install new capacity of the old and the new version, or to retrofit capacity from the old into the new version. In the first case, the whole investment cost is borne, in the second case only the cost for updating one version into the other. This last is represented in the parameter CostOfRetrofit, defined in Section 6.1.2. For simplicity, it is assumed that the difference between the investment cost of the new and the old CCGTs equals the cost of the retrofits. It must be said this might overestimate the cost of new CCGT units, because no scale factor is considered. The summation of the retrofit costs estimated by the manufacturers for carrying out a number of key flexibility retrofits at La Casella CCGT is assumed as the value of the parameter CostOfRetrofit, in 2015. Before then (2013 and 2014), the cost is much higher, assuming that

retrofits are hardly realisable. After 2015, the cost linearly decreases throughout the time domain, since a learning curve for the retrofits is assumed. The cost is in the order of few M€/GW.
Since in this case the existence of different CCGT configurations for flexible operation is represented by the possibility of retrofitting installed power plants, it is useful to show how the installed capacity varies through the time domain, more than the generation. In Figure 65, the annual installed capacity of the four technologies, Wind turbines, Coal-fired steam cycles, Old Gas-fired CCGTs, New Gas-fired CCGTs, is shown, in the case where the original OSeMOSYS model is applied to the scenario.

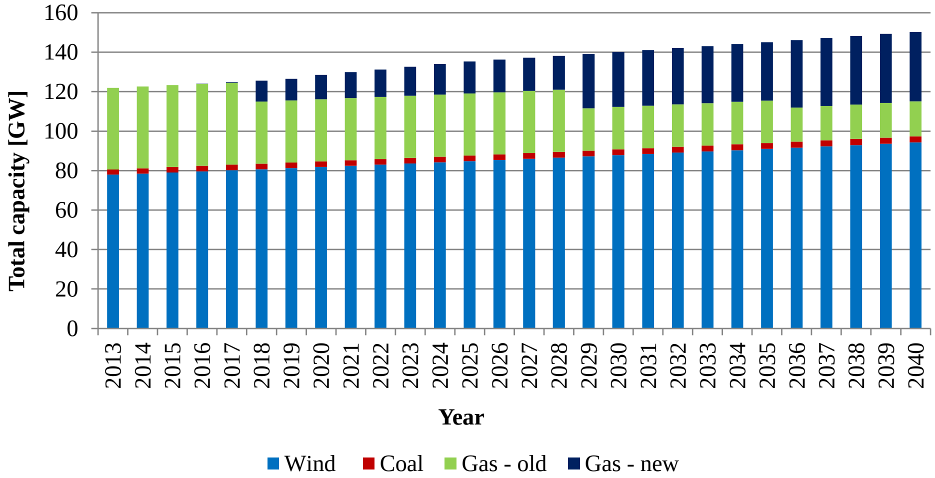

Figure 65. *Total capacity in the modified scenario, with the original OSeMOSYS code.*

The figure is easily explained in this case. The global installed capacity increases in the years, since both the electricity and the reserve capacity demand do. The global increase is due to increase of the capacity of both wind turbines and gas-fired CCGTs. To compensate for the decommissioning of old CCGTs in the end of 2017, 2028, 2035, a corresponding capacity of new CCGTs is installed. The situation becomes more dynamic when the code is allowed to retrofit old CCGTs, by introduction of the code modifications developed by the author. The results in terms of installed capacity are shown in Figure 66.

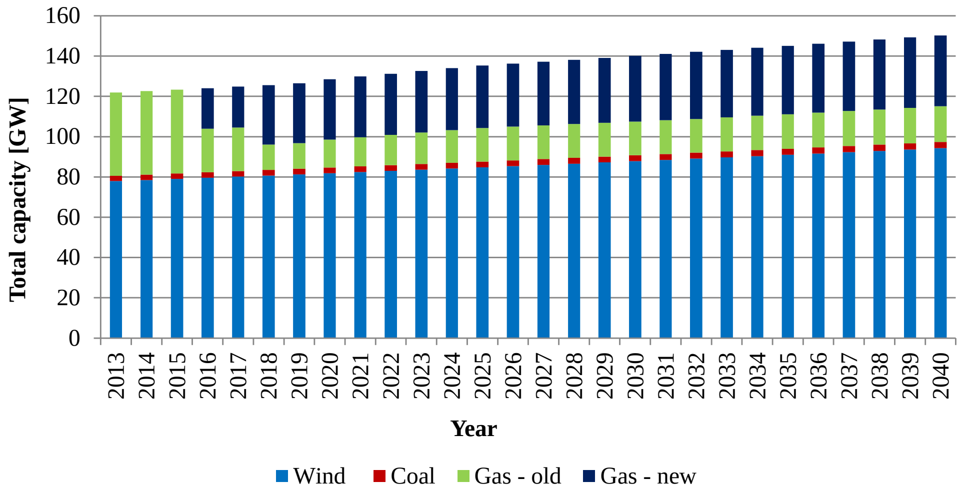

Figure 66. *Total capacity in the modified scenario, when the cycling capability is introduced.*

In this case, as soon as it becomes convenient, in 2015, a consistent part of the old CCGTs is retrofitted. This is evident in the sharp reduction of the green area and the corresponding increase of the dark blue area in 2015. Then, according to the scenario, in 2017 another part of the old CCGTs is decommissioned, and it is replaced by a corresponding capacity of new CCGTs. Finally, as before, in 2028 and 2035 more CCGTs are decommissioned. However, it cannot be understood from Figure 66 whether old or retrofitted units are decommissioned, since they are replaced right away by new units. Notice that, in 2028 and 2035, the capacity to be decommissioned can be withdrawn from both the old and the new CCGTs, because among the new CCGTs some were retrofitted from the old ones, and they may have reached the end of life. So, in order to understand whether old or retrofitted CCGT units are decommissioned in 2028 and 20235, the total installed capacity of the old and new CCGTs must be analysed year by year, as in Figure 67.

	Residual Capacity [GW]		Total capacity [GW]		
	Gas - old	Gas - new	Gas - old	Gas - new	
2013	30		41.328	0	
2014	30		41.487	0	
2015	30		41.631	0	
2016	30		**21.631**	**20.181**	20 GW are retrofitted and 0.181 GW of new CCGTs installed
2017	30		21.631	20.347	
2018	20		**12.592**	**29.554**	10 GW old CCGTs are decommissioned, but 0.961 GW installed; 9.207 GW new CCGTs are installed
2019	20		12.771	29.761	
2020	20		13.943	29.969	
2021	20		14.486	30.179	
2022	20		15.036	30.390	
2023	20		15.593	30.603	
2024	20		16.158	30.817	
2025	20		16.604	31.033	
2026	20		16.722	31.250	
2027	20		16.759	31.551	
2028	20		16.759	31.891	
2029	10		**16.759**	**32.234**	10 GW new CCGTs are decommissioned, from those retrofitted before, but 10.342 GW are installed
2030	10		16.759	32.579	
2031	10		16.759	32.927	
2032	10		16.759	33.277	
2033	10		16.878	33.509	
2034	10		16.999	33.744	
2035	10		17.120	33.980	
2036	0		**17.242**	**34.218**	10 GW new CCGTs are decommissioned, from those retrofitted before, but 10.238 GW are installed
2037	0		17.366	34.458	
2038	0		17.490	34.699	
2039	0		17.615	34.942	
2040	0		17.741	35.186	

Figure 67. *Numerical results of the total capacity year by year.*

7.3. Energy system model: the long-term energy planning of Cyprus

In this section, the application of the original and the modified OSeMOSYS model to a real scenario is presented. The aim of this application is different from the aim of the previous one. In the present case, a Government employs the energy system model to plan, with a cost minimisation perspective, the optimal future energy mix under a number of constraints, dictated by the national policies already in place. When the simulations are carried out with the original model, a certain mix of fossil-fuel fired, renewable, storage technologies is obtained. This is the mix which the country should have in the future, for the costs of the system to be minimised, while complying with the national policies. In order to drive the energy system towards this mix, the Government may have to put in place some financial and legislative measures. When the mix is attained, the energy strategy objectives of the Government shall be considered fulfilled. However, a number of assumptions are present, both in the model and in the scenario, which may undermine the reliability of the predictions. One of them is that the costs of flexible operation are neglected. If the predictions are unreliable, in the future the country may experience unpredicted shifts of the energy mix from the one deemed optimal, and additional costs. Removing some of the assumptions may make the estimations more reliable and partly avoid unpredicted costs and outcomes. The present application has this aim. The OSeMOSYS model, as modified in Section 6.1.2, is applied to the energy system planning of Cyprus. The application was developed at the division of Energy System Analysis of KTH Royal Institute of Technology, in the framework of a

project with the Government of Cyprus and the European Commission. The Government of Cyprus is interested in assessing which technology mix will allow a very high generation from renewables, without compromising the stability of the grid. The power system of Cyprus is completely isolated from those of the neighbouring countries. Therefore, the TSO of Cyprus has expressed concerns that the integration of high shares of variable renewable energy technologies will increase substantially the vulnerability of the system to blackouts, unless properly supported by storage and other flexible generation options. OSeMOSYS, enhanced with the code modifications presented in Chapter 6, and informed through the inputs from the power plant model, may provide indications about the optimal long-term energy mix of the country: the share of storage and flexible power plants is computed, which allows high penetration of renewables and guarantees the adequacy of the system. The European Commission, on the other side, considers this study a small scale sample of how the European electricity grid should be planned. Cyprus is an island, therefore the networking with neighbouring countries is limited and the energy mix must meet particularly demanding requirements of energetic independence. Stepping back to the Climate and Energy Package and to the Roadmap 2050, one of the drivers for a new energy policy in Europe is the need for a greater independence.
In Section 7.3.1, the features of the scenario are described, while in Section 7.3.2 the results are presented.

7.3.1. Scenario settings

The main features of the scenario for the energy system planning of Cyprus are listed in Table 21 and described in the following.

Time domain	2013 to 2040
Time slices	63: 7 seasons, 9 subdivisions per season
Energy demand	Projections from [188]
Reserve capacity demand	Endogenously computed by the model, based on indications from TSO
Renewable generation	No constraint
Fuel prices	Projections from [189] and indications from Government
Taxations	Carbon tax increasing from 6.6 to 103.3 €/ton
Discount rate	6%

Table 21. *Main scenario assumptions for the Cyprus case study.*

In order to capture the load variability in as much detail as possible, the year is split into 7 seasons, based on recorded generation data in 2012 [190]. Two day types are also identified, workday and weekend. The workday is broken down into 6 time slices, while the weekend is divided into 3 time slices, for a total of 9 time slice per week. Since the time slices for each of the 7 seasons are 9, the total number of time slices is 63. As far as the demand for energy is concerned, again only the demand for electricity is considered. It is split among five sectors: agriculture, services, industry, residential, transport. The annual projections made by Zachariadis et al. at the Cyprus University of Technology for the electricity demand in the years 2013 to 2040, are referred to [188]. They are reported in Figure 68.

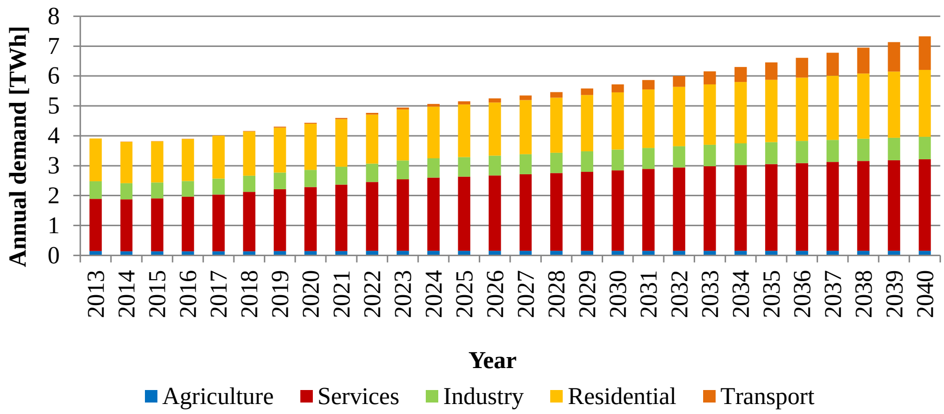

Figure 68. *Energy demand projections for the Cyprus case study.*

On the contrary, no projections are made for the reserve capacity demand. According to the indications of the TSO of Cyprus, the demand for secondary reserve capacity must consist of a base of 60 MW plus 10% of the active capacity from solar and 50% from wind, and it must be provided within 5 minutes upon request. No clear information was obtained about the primary reserve, instead. Therefore, only the demand for secondary reserve capacity is taken into account in the present scenario. The code of OSeMOSYS is modified, and it is allowed to compute endogenously the need for secondary capacity reserve. The modification here introduced is case-specific, but its generalisation would mark a big step forward in energy system modelling. Therefore, it will be object of further research.

In Cyprus several primary energy resources are available for meeting the demand for electricity, either endogenous or from imports. As regards the renewable sources, besides hydro, wind and solar, biomass is present, from which biogas can be produced, but only in limited quantities. As far as fossil fuels are concerned, at present the island relies on the importation of diesel and heavy fuel oil with high sulphur content. In the future, due to environmental policies, the need may arise for importing fuel oil with low sulphur content. These fuels are currently employed for the supply of energy in all sectors. However, according to the national plans, in 2023 the domestic production of natural gas will be started. It is expected to replace diesel and heavy fuel oil, since it is less polluting and it guarantees energy independence. The model is allowed to deploy all of these conventional and renewable sources, since the time they are expected to become available (e.g. 2023 for the natural gas), and by no more than their maximum potential. The prices of the fossil fuels are derived from the projections by IEA [189], and adjusted with information specific to Cyprus. The trend of the prices is reported in Figure 69.

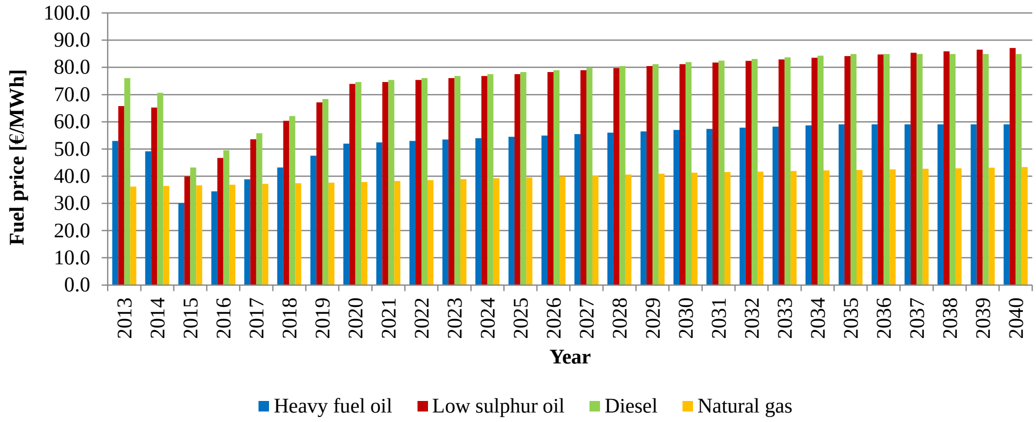

Figure 69. *Projections of the fuel prices for the Cyprus case study.*

No limit for the emissions is directly imposed, but a carbon tax, increasing through the time domain, as in Figure 70.

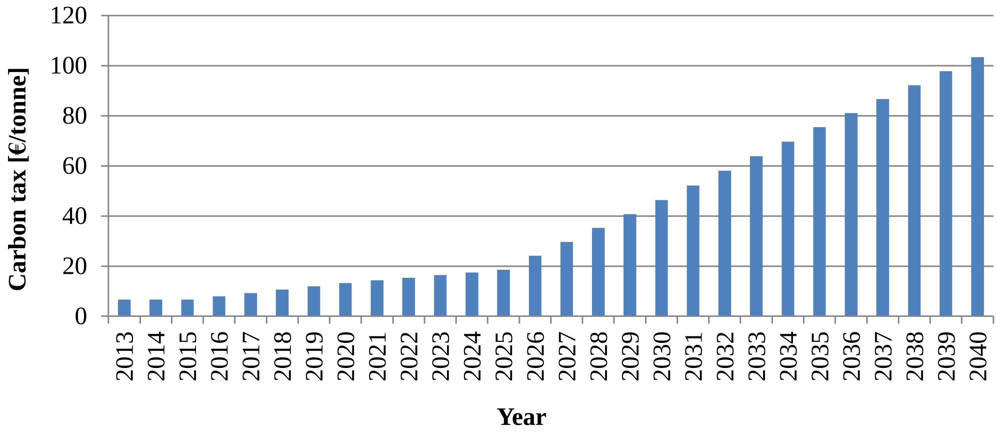

Figure 70. *Projections of the carbon price for the Cyprus case study.*

The tax increases sharply from 2026 on, due to a strong intensification of the environmental constraints.
Eventually, a discount rate of 6% is assumed, as recommended by the Ministry of Finance of Cyprus.

7.3.1.1. Current status of the energy system

Presently, the electricity demand in Cyprus is almost only met with fossil-fuel fired technologies, with a smaller contribution from biogas, transmission- and distribution-connected wind turbines and distribution-connected PV. The reserve capacity is supplied by the fossil-fuel fired units. The main characteristics of the current installations are given in Table 22. All of them were provided by the TSO of Cyprus.

Name	Type of unit	Capacity [MW]	Fuel	End of life
Vasilikos CCGT	CCGT	432	Diesel/natural gas	After 2040
Vasilikos ST	Steam turbine	372	Fuel oil/natural gas	2038
Vasilikos GT	Gas turbine	32	Diesel	After 2040
Dhekelia ST	Steam turbine	348	Fuel oil	2027
Dhekelia ICE	ICE	102	Fuel oil	2034
Moni GT	Gas turbine	138	Diesel	After 2040
-	Biogas	8.8	Biomass	After 2040
-	Distribution PV	16.4		2032
-	Transmission wind	144.3		After 2040
-	Distribution wind	2.4		2035

Table 22. *Current status of the energy system of Cyprus.*

The total installed capacity of these technologies amounted to 1596 MW in 2013. The Vasilikos, Dhekelia and Moni units are large power plants supplying electricity to the transmission grid. Among the existing renewable energy technologies, only the transmission-connected wind covers the same role. On the contrary, the remaining wind turbines, the distributed PV and the biogas facilities supply electricity to the distribution grid or directly feed consumers in the five end-use sectors: agriculture, services, industry, residential, transport.

7.3.1.2. Future technology assumptions

With increasing demand for electricity, new power plants will be needed. The candidate units for generation capacity expansion are:

- *Fossil-fuel fired technologies*: gas-fired CCGTs, steam turbines fired on fuel oil with low sulphur content, ICEs (Internal Combustion Engines) fired on fuel oil with low sulphur content, either equipped with DeNOx system or not.
- *Renewable energy technologies*: biogas, transmission-connected wind, and distributed PV units like the one already existing; solar CSP (Concentrated Solar Power) power plants connected to the transmission grid, PV connected to the transmission grid.
- *Storage technologies*: flow batteries connected to the transmission grid, Li-Ion batteries connected to the distribution grid and PHS.

As far as the renewable energy technologies are concerned, the Government has already planned to realise a number of projects: a 50 MW CSP field will start operation in 2018; new transmission-connected wind turbines will start generating in 2015 and 2016; new biogas facilities enter operation in 2013 (though by little amount). It is worth pointing out that few degrees of freedom are left to the model for choosing whether to install renewable energy technologies or not: for most of them, strict limits are imposed by the investments already planned by the Government, and the model is not let free to invest less or more than what planned. The only technologies for which no upper limit is imposed in the investments are the solar PV, CSP and the wind turbines connected to the transmission grid. As the penetration of the renewables increases, the demand for reserve capacity does. The model is allowed to meet the demand for reserve by means of fossil-fuel fired units, or by installing storage capacity.

As regards storage, the model can choose from technologies actually available in Cyprus: flow batteries, for storage at the transmission scale, Li-Ion batteries, for storage at the distribution scale. These last shall feed the residential and services sectors in times of peak. No upper limit is set for the installed capacity of these technologies. It is also assumed that in 2021 a PHS plant, for which a feasibility assessment is currently in process, will become operative. However, no more investment is planned in PHS capacity.

The detailed cost and operation assumptions about the candidate units for generation capacity expansion were provided by the TSO of Cyprus, along with the data about the existing units.

7.3.2. Results and discussion

OSeMOSYS is applied to the scenario described in Section 7.3.1. As for the test case study, both the original code of OSeMOSYS and the modified code are applied to the described scenario. In this second case, however, only the modifications related to the fuel consumption at partial load and to the cost of the starts are embedded in the code, because no scenario was considered in the project, where any of the existing power plants could be retrofitted. The data provided by the TSO were employed for computing the parameter AdditionalFuelUse for the first modification, while no data were available for the CostOfRampsPerCapacity parameter for the second modification. Thereafter, numerical values of the costs of the starts from [33] were employed, as for the test case study. The results of the base and modified models are compared, to assess if and how the energy technology and generation mix changes, when a high resolution model is employed. In Figure 71, the total installed capacity in Cyprus from 2013 to 2040 is presented, relative to the simulation with the original code of OSeMOSYS.

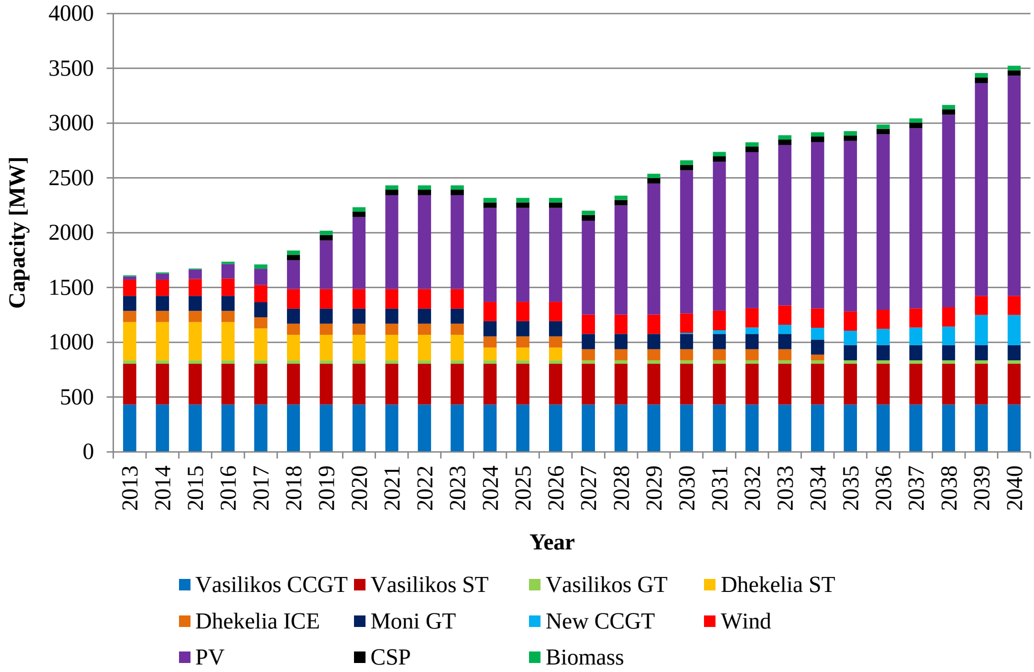

Figure 71. *Results of total capacity in Cyprus from 2013 to 2040 with the original OSeMOSYS code.*

Through the years, the installed capacity of the old fossil-fuel fired units decreases, due to the decommissioning of Dhekelia units. From 2030, new gas-fired CCGTs are installed, up to 274 MW in 2040. No new thermal units of other type are deemed convenient. The renewable capacity increases strongly and gains the highest share in the installed capacity already around 2030. This increase is almost only due to PV, in particular the installations connected to the transmission grid. In 2017 and 2018, an increase in the installed capacity of biomass-fired power plants and CSP is noticed, respectively, but it is limited to what planned by the Government. In the case of biomass-fired power plants, this happens because no more investments are allowed; in the case of CSP, instead, it happens because the model does not deem economically optimal to install more CSP capacity than the minimum planned by the government. In Figure 72, the installed storage capacity is shown.

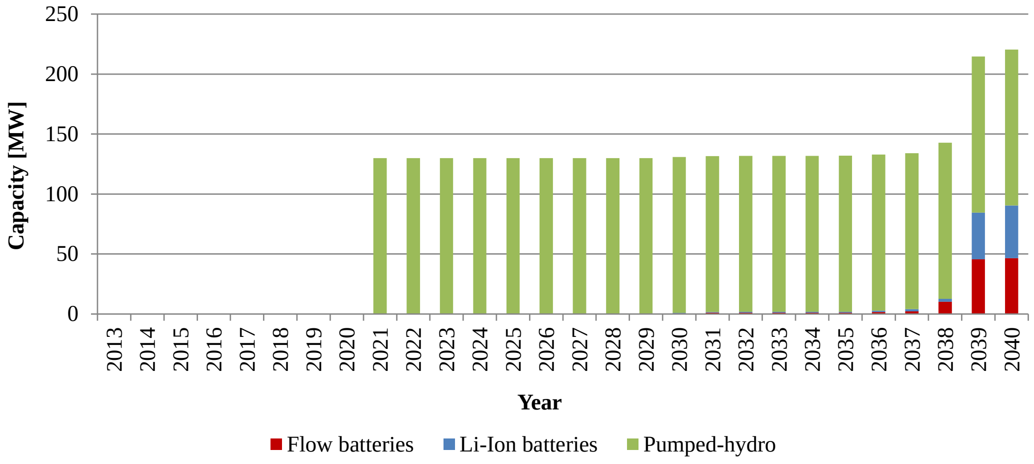

Figure 72. *Results of storage capacity in Cyprus from 2013 to 2040 with the original OSeMOSYS code.*

130 MW of pumped-hydro storage are introduced in 2021, by assumption, according to the plans of the Government. No degree of freedom is left for installing more, as mentioned before, therefore no more capacity is introduced in the following years. On the contrary, there is no limit over the capacity of flow or Li-Ion batteries, but the economic optimisation finds it convenient to install them only in the two last years of the time domain, due to the necessity of balancing the much higher share of intermittent renewables.

In Figure 73 and Figure 74, the annual generation and the reserve capacity, again computed with the original OSeMOSYS code, are presented. Only the shares of reserve capacity provided of the technologies connected to the transmission grid are shown, since only these may change in case the costs of flexible operation of large power plants are taken into account. Moreover, not all the technologies supplying electricity also supply reserve capacity. Therefore, in Figure 74, only the technologies with a positive contribution to transmission-connected reserve are included. Again, the reserve capacity is in energy units, since it represents the capacity made available in each time slice, multiplied by the time it is made available (the duration of the time slices).

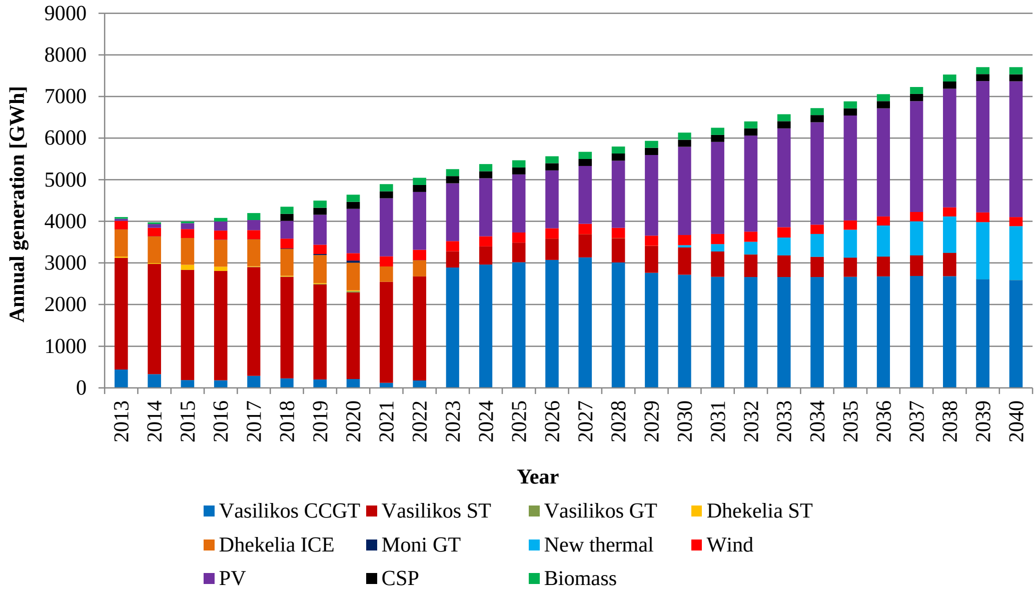

Figure 73. *Results of annual generation with the original OSeMOSYS code.*

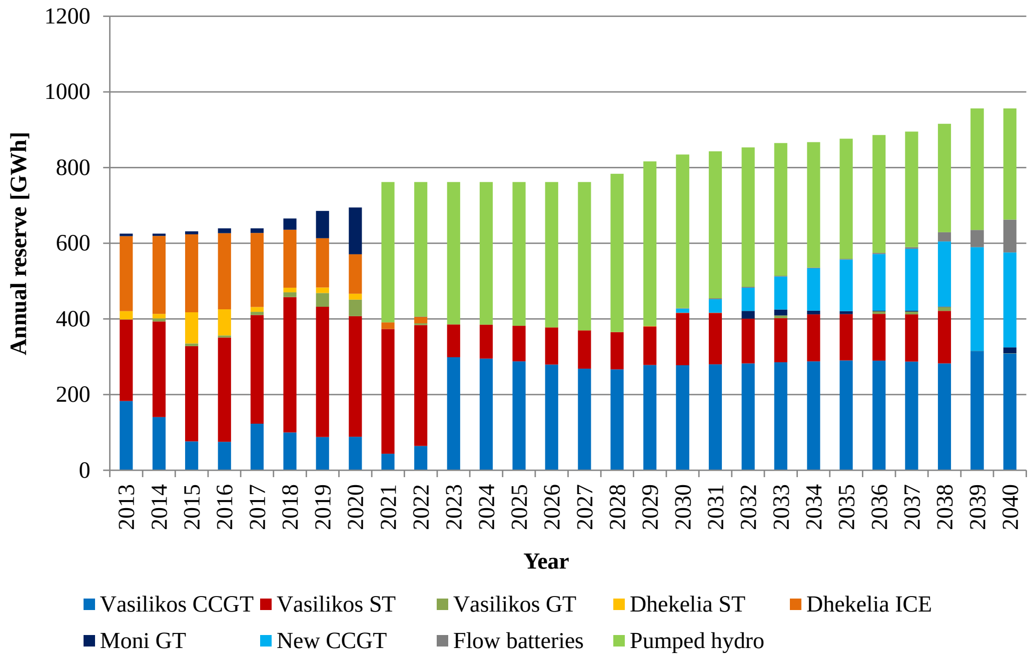

Figure 74. *Results of annual reserve with the original OSeMOSYS code.*

The global generation follows the trend of the global demand, since these two must match. Nonetheless, the shares change deeply through the time domain of the study, depending on the availability of fuels. In 2023, when the domestic production of natural gas starts, Vasilikos CCGT starts generating much more, while the steam turbine reduces its share by a corresponding amount. This happens because, as soon as natural gas becomes available, the fuel of both Vasilikos CCGT and Vasilikos ST is switched from diesel to gas: the CCGT becomes more efficient when fuelled with gas, the ST does not, because the gas is burnt in the heater anyway. The second major change

is the steep increase of the PV generation, mostly the one connected to the transmission grid. Finally, from 2031 on, new CCGTs must start generating, to cover the remaining part of the load.
As far as the reserve supply is concerned, it increases throughout the time domain, as expected: the demand for reserve capacity increases as the generation from wind and/or PV does. All the fossil-fuel fired technologies are able to supply reserve capacity, so they do contribute, as long as they are in operation. The biggest change in the shares of supplied reserve capacity appears in 2021, when PHS becomes available. PHS becomes the technology most contributing to the supply of reserve capacity: it stores energy during low-load times and it releases it during peak times and when the renewables cannot generate. The flow batteries contribute to the provision of reserve only in the very last years of the simulation.
When the code modification related to the fuel consumption at partial load is introduced in OSeMOSYS, the technologies for which no limits are imposed by the plans of the Government moderately change their share in the installed capacity. A decrease in the capacity of new CCGTs to be installed is noticed, from 274 MW in 2040 to 260 MW. A consistent capacity of distribution connected solar PV installations appears in the last two years of the time domain, reaching more than 100 MW. In line with such increased flexibility of the transmission and distribution network, higher capacity of both flow and Li-Ion batteries is installed in the last years. This proves that when the long-term plans of the Government do not constrain the energy technology mix, a high resolution energy model may give different indications than a lower resolution one, implying changes in the investments.
The global generation mix does not change significantly, while the supply of reserve capacity does, as shown in Figure 75. Once again, the results are presented in energy units, with the same rationale as before.

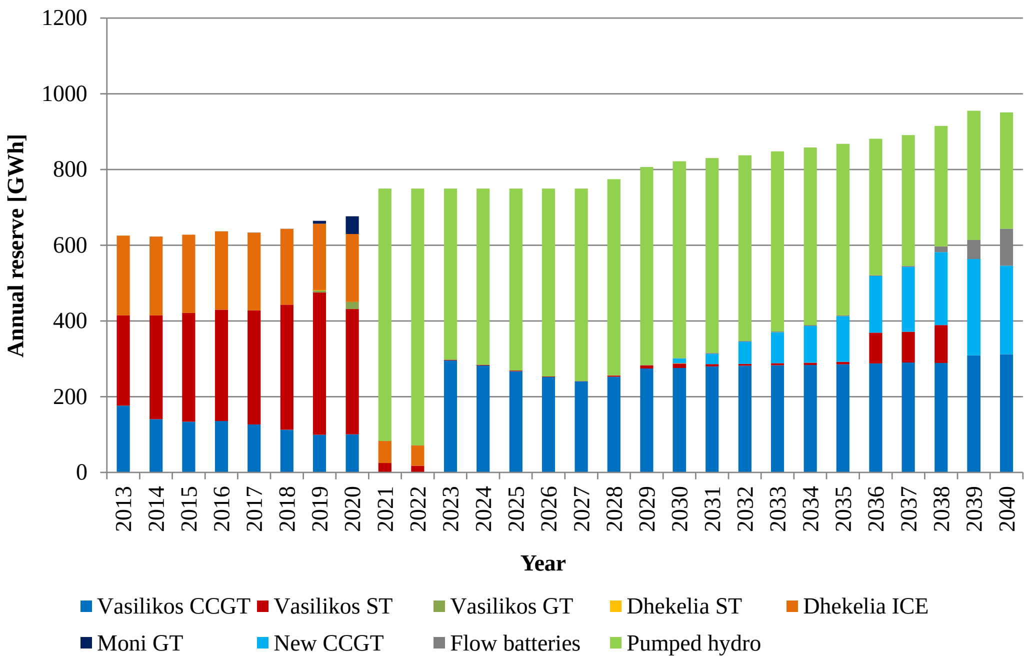

Figure 75. *Results of annual reserve when the cycling capability is introduced.*

The global demand for reserve capacity does not change, since the generation from wind and PV is almost the same. On the contrary, the shares do. In the first years of the time domain Dhekelia ICE is called to provide more reserve, replacing Moni GT. This is due to the major efficiency drop of

Moni GT in partial load operation, notwithstanding its capacity to reach very low loads. Since 2021, when the pumped-hydro storage becomes available, it gains a higher share than in the previous case, because it also replaces Vasilikos ST. The low efficiency of the steam turbine at partial load makes it economically less convenient for supplying reserve capacity than PHS. In the simulation with the original model this effect cannot be noticed, because the efficiency does not decrease with the load. The share of the CCGTs in the provision of reserve does not change significantly.

When the modification for computing the cost of the starts is added, the installed capacity, the electricity generation and the provision of reserve capacity do not change significantly with respect to the case where only the fuel consumption at partial load is introduced. This may be due to the fact that the scenario assumptions leave too few degrees of freedom to the model, for limiting the cycling costs. The global cost does not change significantly in relative terms, either, because the costs of the starts represent a small part of the whole operation and investment costs of the grid. Nonetheless, more than 12 M€ of start costs are experienced throughout the time domain by Vasilikos CCGT, GT and SC and Moni GT. This figure is significant in absolute terms.

This application provides a full scale representation of how the code modifications developed during this research for increasing the resolution of energy system models may impact the results of long-term scenarios. In line with the results of the test case study, the introduction of the modification for computing the fuel consumption at partial load impacts mostly the shares in the provision of reserve capacity. The fossil-fuel fired units with the worst efficiency at partial load are unlikely to provide reserve capacity, because this would imply operating at partial load, with higher fuel consumption, therefore higher operation costs. This has no impact on the investment decisions by the Governments, but informs them about which power plants should be supporting the adequacy of the grid in a welfare maximisation perspective, in scenarios with high penetration of renewables. This may orient the long-term policies of the Governments. The same information can be shared by the companies, and drive their investment decisions as well.

In addition, differently from the test case study, the introduction of this modification also impacts the shares of installed capacity of the technologies for which no strict constraints are imposed by the plans of the Government.

The introduction of the modification for computing the cost of the starts does not add any significant deviation of the predicted trends of installed capacity, generation and reserve capacity provision, with respect to the first modification. This marks a significant difference with respect to the test case study, where the introduction of the modification caused the share in the generation to change deeply. The difference may be partly due to the cost assumptions for the technologies and the fuels: the test case study has already highlighted that the impact of introducing the cost of the starts is highly sensitive to the cost assumptions. However, surely one more cause is the low number of degrees of freedom that were left to the model in computing the best technology and generation mix in the Cyprus case study. Taking into account the numerous plans of the Government constrained the installed capacity and the investments for most of the technologies.

Nonetheless, introducing the modification for computing the cost of the starts allowed the quantification of their global impact over the system, which amounts to 12 M€ throughout the time domain of the study. Again in a welfare maximisation perspective, this cost item must be charged by the Government onto the expenses for increasing the flexibility of the electricity supply, and weighed against the benefits.

PART IV - Conclusions

The key achievement of this research was the demonstration that the economic and technological challenges faced by the operators when running their power plants under flexible profiles are a concern also for the players of electricity markets and for energy system planners. Any information about the costs of the flexible operation of power plants and the technological possibilities the operators have for limiting these costs is not redundant for the companies or the system planners, because these costs and decisions do impact the electricity market and the energy system. When the companies and the planners are able to quantify this impact they may gain a competitive advantage for their long-term objectives to be better pursued.
The concept that the long-term energy and decarbonisation policies and the market outcomes somehow depend on issues occurring at the scale of individual power plants is not new to policy makers, nor to the Governments themselves. Nonetheless, their response to this issue seems not to be based on a deep analysis and prediction of the costs and benefits of flexible electricity supply. It is commonly known that the adequacy of the electricity systems in Europe is not at risk, at present, but there is high uncertainty on whether it might be in the near future. Some Governments believe it could, and they consequently plan investments in capacity markets, for supporting the provision of reserve capacity by fossil-fuel fired power plants and paying them back the costs of flexible operation. Other Governments believe it will not. In this case the capacity markets would only distort the electricity markets, because the adequacy of the grid can be guaranteed just by allowing the electricity markets to be fully competitive.
It is opinion of the author that this lack of a univocal view has one of its causes in an informational gap about the very definition of flexibility and its expected impact over different scales of the decision making in the energy supply system. The present research proposed an approach for filling this gap. Given the multi-faceted nature of the issue dealt with in this research, the author found it convenient to structure this section as a chapter, and to lead the reader through the relevance and contributions of each part of the thesis.

Relevance and contributions in PART II

This part addressed the need of providing a definition of flexibility. The extensive literature review about the current impact of flexibility was meant to show that the lack of a univocal policy for supporting the adequacy of the electricity grid in flexible supply scenarios could be due to the complexity of shaping the issue of flexibility. Power plant operators, companies and energy system planners give it different definitions, because it impacts the power plant, the electricity market and the energy system scales in different ways. By impact, the author means all the costs caused by the flexible operation of power plants at these three scales and the reactions the costs induce. The consequence of such fragmented perspective is that all the available data about the impact of flexibility at the three scales are scattered around in literature, in a number of independent studies for international agencies or industrial reports. No specific field of the scientific research is dedicated to flexibility, so that none of these studies references the others and no database exists which condenses and elaborates the information. The work of the author contributed to condense and elaborate the existing information, and it moved one step in the direction of shaping flexibility as a unique multi-dimensional characteristic of electricity systems. It originates with the flexible operation of power plants, but it causes chain effects also at the electricity market and the energy system scales. The costs, the actions and the reactions at each of these scales impact the others, because they interact dynamically. One way to prove and quantify this multi-dimensional nature is to develop mathematical models of the three scales.

Relevance and contributions in PART III

This part represented the modelling core of the research. Its main achievement is the development of three models for computing the impact of the flexible operation at the power plant, electricity market and energy system scales. In the following paragraphs, the author finds it convenient to detail the outputs of each model he developed, and how they contribute to proving and quantifying the impact of flexibility at the three scales.

Power plant model

The author addressed the modelling needs at the power plant scale by developing an off-design thermodynamic model of a fossil-fuel fired power plant. The model was set up through a widely employed lumped parameters simulation environment, where every component is a node, and it can be modelled in detail, as if it was a stand-alone black box. In this way, it was possible to model all the relevant off-design and load control logics of the power plant, and obtain a highly reliable representation of its performance in a number of operation scenarios.
As far as the thermodynamic representation of the cycle is concerned, this model represents no methodological advancement, compared to those existing in literature. The original contribution lies in the fact this model condenses several characteristics which single models in literature do not present. In this way it constitutes a bridge between the scientific research and the industrial practice, and it allows evaluations about the feasibility, the costs and the benefits of asset modifications and control logics to enhance the cycling capability of a power plant. Specifically, these characteristics are:

- It represents an existing and operating power plant, not a new one. Therefore, it does not allow for design optimisation, but only for the study of those asset modifications and new control logics which can be actually implemented in the operating power plant. The degrees of freedom for enhancing the cycling capability of the power plant are much less than in the design phase, well representing the limited decision space that the operators have in reality.
- It is set up in a simulation environment, whose setting and interface are similar to those employed in the control rooms of the power plants. The model in the simulation environment is modular enough for individual components to be modified, removed and added, and for control logics to be easily updated. Wide sets of simulations considering a number of operation scenarios can be run with limited computational time and effort. All of these features make the model directly employable by the power plant operators. Therefore, the analyses about the costs of flexibility and the possible ways to avoid them can be carried out jointly with the operators, abating possible barriers between scientific research and industrial practice.
- The model was developed with the support and expertise of power plant operators, and it represents an existing CCGT in the North of Italy. The collaboration with operators of the power industry while setting up the model and the test of different simulation environments allowed the author to find the right compromise between a detailed representation of all the relevant control logics, and limited computational requirements.

The reader may observe that setting the model based on an existing power plant is a loss of generality. However, a model including all the relevant control logics of a power plant in detail must be associated to a real case. Moreover, it indeed presents a certain degree of generality:

- First of all, the CCGTs of late installation have similar plant layouts.
- Secondly, even when the configuration or the control logics must be changed, the simulation environment is modular enough for the changes to be performed promptly.

The output of the model is, like for every other, a number of global and nodal performance indices based on the First and on the Second Law of Thermodynamics. The ones proposed as key indicators of the off-design performance of the power plant are largely known and employed in literature. Nonetheless, in the present case, they are specifically provided as functions of the sole employable load and off-design control logics of a power plant.

In conclusion, the core feature of the thermodynamic model is its connection to the industrial practice, in order for it to provide a representation of the costs of flexibility and the possible reactions of the operators, when real operating power plants are considered.

Following the development of the thermodynamic model, the power plant modelling phase also consisted in the development of mathematical formulations for global performance indices of the power plant. These formulations are functional relations, for computing global performance indices as continuous or discrete functions of the load and the control logics. They are the key contribution of this research, providing the physical link between the power plant, electricity market and energy system scales, and an objective, mathematical definition for the multi-dimensional nature of flexibility.

It is promptly explained how these links between the scales work. In electricity market and energy system models, the operation profiles of the generators (in terms of electricity generation or reserve capacity provision, for instance) are usually computed, as functions of a number of scenario assumptions. When the equations developed by the author are included in such models, the global performance indices of the generators are computed in turn, as functions of the operation profiles. Summing up these indices for all the generators in a region, the global operation costs are derived, including the costs of flexibility

The reader might argue that avoiding this step and directly joining the power plant, electricity market and energy system models together would be much more rigorous. Indeed, this would unreasonably increase the computational requirements: the companies and the energy planners do not need all the features of a thermodynamic model to be represented in their models, but only its relevant outputs.

Electricity market model

The second output of the modelling activity of this research was the development of a Game Theory model of the electricity market, consisting in a two-level nonlinear stochastic program. Its relevance lies in its capability of computing endogenously the reactions of the generation companies to the requirement for power plant flexibility. In addition to other models in literature, it condenses features of markets characterised by high penetration of renewable energy sources and by the need for flexible electricity supply: the demand and supply of reserve capacity, the possibility for the companies to present the market operator offers of both quantity and price, the operation costs related to the starts and to the increased fuel consumption at partial load. Specifically, these last two cost items are introduced by means of the mathematical formulations developed in the power plant modelling phase. Therefore, they represent the link between the power plant and the electricity market scale.

The use of methods and tools from the domain of Game Theory is not new to electricity market modellers, but it is for those who deal with power plant and energy system analysis. Therefore, it

is worthwhile summarising why the author considered it relevant for his study of flexibility. In line with the general scope of this research to propose a new perspective for the electricity supply planning under flexibility constraints, Game Theory introduces a new perspective in the modelling of electricity markets. It does not bring in any new mathematical concept or solution algorithm, but it offers a valid framework for turning the interactions between players of the market into well-known mathematical constructs. By Game Theory model, the author means a model able to endogenously compute the best decisions of the company as functions of the decisions of the competitors and the market outcomes. A traditional dispatch optimisation model prevents this computation, because it focusses on the phase which follows the decisions of the companies, where these are fed as inputs (i.e. price and quantity bids).
Though this difference already emerges from the structure of the new model developed by the author, no quantification was provided for it, because the model has not been applied, yet. The application will be a development of this research work.

Energy system model

The third and last output of the modelling activity in this research was the elaboration of an energy system model, able to compute the impact of power plant flexibility on the long-term energy planning. This implied the modification of an existing open source model, for it to take into account the costs of flexibility when computing the least cost energy technology and generation mix.
The work of the author was in this case facilitated by a significant pioneer work previously carried out in literature, for introducing short-term constraints like the provision of reserve into long-term energy system models. Nonetheless, the development of formulations for assessing the impact of flexibility is new to the field, and it represents an original contribution of this research. The author modified the energy system model introducing the equations he developed for computing global performance indices of the power plants as functions of the load and the off-design control logics. These represent the link between the power plant and the energy system scale and they complete the mathematical shaping of the multi-dimensional nature of flexibility.
The applications of the modified model to a test case study and to the energy planning of Cyprus allow some general conclusions about the relevance of the work carried out by the author.
The results of the test case study show that all the developed code modifications may impact, in different ways and to different extent, the cost optimal long-term energy technology and generation mix.

- The code modification for the cycling capability as a function of the power plant configuration may be considered the most significant development: it will always be useful, either to energy system planner or to companies, for understanding whether a given unit or a technological option is economically worth retrofitting, independently from its impact on the global system cost.
- The second most significant code modification results the one for computing the cost of the starts. Under specific assumptions it may cause the generation mix to completely shift from one technology to another.
- The code modification for introducing the fuel consumption at partial load apparently has the least effect on the investment decisions of the Governments. It seems to affect only the shares of the technologies in the provision of capacity reserve. In this case, the projections provided by the modified energy system model would be useful to the companies, to predict whether their fleet will share generation or reserve in the long-term welfare-maximisation plans of the Government. On the contrary, this code modification

may not be worth employing by the Governments, whose investment and policy decisions should not be affected.

However, these results are highly sensitive to the cost assumptions of the scenario. Therefore, a number of applications will be needed to have a picture of the effective relevance of each code modification to real-life situations.

The first application was made in this research and it relates to the energy system planning of Cyprus. Under the scenario assumptions agreed with the Government and the Transmission System Operator, the introduction of the cost of the starts seemed to show no effect. On the contrary, the introduction of the fuel consumption at partial load confirmed the results of the test case study, regarding the shares of reserve capacity provision. It even showed that performing the long-term planning with the higher resolution modified model may have a moderate impact on the investment decisions of the Government.

However, it is hard to discern whether the limited impact of the costs of flexibility on the investment decisions resulting from this case study may be a general conclusion, or a case-specific conclusion depending on the scenario assumptions. In this case study, all the plans of the Government to 2040 were taken into account, but this left few degrees of freedom to the model, for determining the optimal energy mix. It may be convenient to elaborate scenarios where only some key long-term plans are taken into account. In this way, if the model computes a technology mix which is different from the one envisaged by the Government, this may indicate that some of the long-term policies are not pursuing cost minimisation objectives and they need to be updated.

In conclusion, the code modifications developed by the author do show an impact of power plant flexibility on the energy system planning. To what extent this impact is relevant for the investment decisions of the Governments, for the portfolio decisions of the companies, or just as a general policy indication, it must be discussed upon the results of several different applications.

Final remarks

The most peculiar aspect of the study of flexibility emerged during the modelling activity. The development of models at different scales required the author to dive into deeply different scientific domains. The performance analysis of power plants pertains to systems engineering and Thermodynamics, the study of the interactions between players of the electricity markets is best fitted by Game Theory, while energy systems modelling requires principles of Macroeconomics. Most representative of this variety was the complexity of defining a unique nomenclature for all the three developed models: the author tried to recall in each model the names employed in the other models for indices, variables and parameters, but he also had to comply with the nomenclature usually employed in each discipline.

This all helped the author understand that the first informational barriers to be abated for an objective and comprehensive work to be carried out were those in who writes.

PART V - Appendices

Appendix A - Validation of the CCGT off-design model

Variable	Real	Model	Δ
CCGT net electric efficiency %	55.8	55.9	0.1%
CCGT net electric power [MW]	377.8	378.3	0.1%
Steam turbine net electric power [MW]	120.6	121.9	1.0%
Gas turbine net electric power [MW]	264.2	262.7	-0.6%
T at compressor outlet [°C]	403.5	400.0	-3.5 °C
P at compressor outlet [bar]	17.7	17.5	-0.2 bar
Mass flow rate at compressor inlet [kg/s]	661.5	656.8	-4.7 kg/s
T at gas turbine outlet [°C]	560.5	566.3	5.8 °C
T gases at stack [°C]	88.3	85.5	-2.8 °C
T, P, mass flow rate at HP-ST inlet [°C, bar, kg/s]	514.7	518.5	3.8 °C
	81.6	82.9	1.3 bar
	69.8	70.4	0.6 kg/s
T, P, mass flow rate at IP-ST inlet [°C, bar, kg/s]	515.4	519.7	4.3 °C
	12.4	12.5	0.1 bar
	84.6	85.3	0.8 kg/s
T, P, mass flow rate at LP-ST inlet [°C, bar, kg/s]	335.5	338.3	2.8 °C
	3.4	3.4	0.0 bar
	97.8	97.7	-0.1 kg/s

Table 23. *Comparison of the real data and the model outputs at 89.4% aperture of the IGVs.*

Variable	Real	Model	Δ
CCGT electric efficiency %	54.3	54.5	0.4%
CCGT net electric power [MW]	309.0	310.2	0.4%
Steam turbine net electric power [MW]	103.0	105.0	2.0%
Gas turbine net electric power [MW]	212.4	210.6	-0.9%
T at compressor outlet [°C]	380.1	373.4	-6.7 °C
P at compressor outlet [bar]	15.3	15.0	-0.3 bar
Mass flow rate at compressor inlet [kg/s]	580.2	573.5	-6.7 kg/s
T at gas turbine outlet [°C]	552.0	561.6	9.6 °C
T gases at stack [°C]	87.1	83.6	-3.5 °C
T, P, mass flow rate at HP-ST inlet [°C, bar, kg/s]	513.0	520.5	7.5 °C
	71.2	72.9	1.7 bar
	60.6	61.6	1.0 kg/s
T, P, mass flow rate at IP-ST inlet [°C, bar, kg/s]	510.1	518.8	8.7 °C
	10.7	10.8	0.1 bar
	72.9	74.0	1.1 kg/s
T, P, mass flow rate at LP-ST inlet [°C, bar, kg/s]	331.8	337.6	5.8 °C
	2.9	2.9	0.0 bar
	83.9	84.3	0.3 kg/s

Table 24. *Comparison of the real data and the model outputs at 58.7% aperture of the IGVs.*

Variable	Real	Model	Δ
CCGT electric efficiency %	52.3	52.7	0.8%
CCGT net electric power [MW]	247.2	249.2	0.8%
Steam turbine net electric power [MW]	90.1	93.3	3.5%
Gas turbine net electric power [MW]	163.1	160.6	-1.6%
T at compressor outlet [°C]	361.2	363.5	2.3 °C
P at compressor outlet [bar]	13.0	12.7	-0.2 bar
Mass flow rate at compressor inlet [kg/s]	494.6	489.9	-4.7 kg/s
T at gas turbine outlet [°C]	561.2	572.8	11.6 °C
T gases at stack [°C]	84.3	80.8	-3.5 °C
T, P, mass flow rate at HP-ST inlet [°C, bar, kg/s]	521.9	533.7	11.8 °C
	63.9	66.0	2.1 bar
	53.8	55.1	1.3 kg/s
T, P, mass flow rate at IP-ST inlet [°C, bar, kg/s]	517.5	529.8	12.3 °C
	9.4	9.5	0.2 bar
	63.4	65.0	1.6 kg/s
T, P, mass flow rate at LP-ST inlet [°C, bar, kg/s]	336.4	346.3	9.9 °C
	2.5	2.5	0.1 bar
	72.4	73.0	0.6 kg/s

Table 25. *Comparison of the real data and the model outputs at 30.2% aperture of the IGVs.*

Appendix B - Extended form of the electricity market model

B.1. Reduction to one-level nonlinear problem

$$\max_{\underset{\smile}{\tilde{g}}_{max,j},\underset{\smile}{\tilde{c}}_j,\underset{\smile}{\tilde{P}}_{r,j},\tilde{z}_j} \Pi_t = E\left\{\begin{aligned}
&\sum_b \sum_{j\in A} \sum_s \left(p_{el,b,j} - c(j,s)\right)\cdot \tilde{g}(j,b,s) + \\
&+\sum_b \sum_{j\in A} p_{res,b,j} \cdot \tilde{r}(j,b) + \\
&-\sum_b \sum_{j\in A} c_{fuel}(j)\cdot\left(g_{max}(j) - \sum_s \tilde{g}(j,b,s)\right) + \\
&-\sum_{b>0} \sum_{j\in A} \hat{c}_{ramp}(j)\cdot\left|\sum_s \tilde{g}(j,b,s) - \sum_s \tilde{g}(j,b-1,s)\right| + \\
&-\sum_{j\in B} c_{inv}(j)\cdot \tilde{z}(j)
\end{aligned}\right\}$$

s.t.

$$0 \le \underset{\smile}{\tilde{g}}_{max}(j,b) \le g_{max}(j) \qquad j = 1,\dots,N_A$$

$$0 \le \underset{\smile}{\tilde{g}}_{max}(j,b) \le \tilde{z}(j)\cdot g_{max}(j) \qquad j = 1,\dots,N_B$$

$$f\left(\tilde{z}(j) = k\right) = x(j)^k \left(1 - x(j)\right)^{1-k} \qquad k \in \{0,1\}$$

$$-\underset{\smile}{\tilde{c}}(j,b) + \sum_n p_{el,b,n}\cdot m_g(j,n) - \alpha^{up}_{j,b} + \alpha^{low}_{j,b} - \beta^{up}_{j,b,s} + \beta^{low}_{j,b,s} = 0 \qquad j = 1,\dots,N_G$$

$$-\sum_k p_{el,b,n}\cdot B(k,n) - \sum_l \gamma^{up}_{l,b}\cdot H(l,n) + \sum_l \gamma^{low}_{l,b}\cdot H(l,n) = 0 \qquad n = 1,\dots,N\text{-}1$$

$$-P_{curt} + \sum_n p_{el,b,n}\cdot m_d(j,n) - \varepsilon^{up}_{j,b} + \varepsilon^{low}_{j,b} = 0 \qquad j = 1,\dots,N_D$$

$$-\underset{\smile}{\tilde{P}}_r(j,b) + \sum_n p_{res,b,n}\cdot m_g(j,n) - \delta^{up}_{j,b} + \delta^{low}_{j,b} - \zeta^{up}_{j,b} + \zeta^{low}_{j,b} - \vartheta^{up}_{j,b} + \vartheta^{low}_{j,b} = 0 \qquad j = 1,\dots,N_G$$

$$0 \le \sum_s \tilde{g}(j,b,s) \le \underset{\smile}{\tilde{g}}_{max}(j,b) \qquad j = 1,\dots,N_G$$

$$0 \le \tilde{g}(j,b,s) \le g_{max}(j,b,s) \qquad j = 1,\dots,N_G$$

$$\sum_{j=1}^{N-1} B(n,j)\cdot\tilde{\theta}(j) = \sum_{j\in G}\sum_s \tilde{g}(j,b,s)\cdot m_g(j,n) +$$

$$+\sum_{j\in D} \tilde{c}urt(j,b)\cdot m_d(j,n) - \sum_{j\in D} \hat{d}_e(j,b)\cdot m_d(j,n) \qquad n = 1,\dots,N$$

$$\sum_{j\in G} \tilde{r}(j,b)\cdot m_g(j,n) = \sum_{j\in D} \hat{d}_r(j,b)\cdot m_d(j,n) \qquad n = 1,\dots,N$$

$$-F(l) \le \sum_{n=1}^{N-1} H(l,n)\cdot\tilde{\theta}(n) \le F(l) \qquad l = 1,\dots,L$$

$$0 \le \tilde{r}(j,b) \le g_{max}(j) - \underset{\smile}{\tilde{g}}_{max}(j,b) \qquad j = 1,\dots,N_G$$

$$0 \le \tilde{r}(j,b) \le \underset{\smile}{\tilde{g}}_{max}(j,b) \qquad j = 1,\dots,N_G$$

$$0 \le \tilde{r}(j,b) \le r_{max}(j) \qquad j = 1,\dots,N_G$$

$$0 \le \tilde{c}urt(j,b) \le \hat{d}_e(j,b) \qquad j = 1,\dots,N_D$$

$$\alpha_{j,b} \geq 0, \beta_{j,b,s} \geq 0, \gamma_{j,b}^{up} \geq 0, \gamma_{j,b}^{low} \geq 0, \delta_{j,b}^{up} \geq 0, \delta_{j,b}^{low} \geq 0,$$

$$\zeta_{j,b}^{up} \geq 0, \zeta_{j,b}^{low} \geq 0, \vartheta_{j,b}^{up} \geq 0, \vartheta_{j,b}^{low} \geq 0, \varepsilon_{j,b}^{up} \geq 0, \varepsilon_{j,b}^{low} \geq 0$$

$$\gamma_{l,b}^{up} \cdot \left(F(l) - \sum_n H(l,n) \cdot \tilde{\theta}(n) \right) = 0$$

$$\gamma_{l,b}^{low} \cdot \left(F(l) + \sum_n H(l,n) \cdot \tilde{\theta}(n) \right) = 0$$

$$\alpha_{j,b}^{up} \cdot \left(\underset{\smile}{\tilde{g}}_{max}(j,b) - \sum_s \tilde{g}(j,b,s) \right) = 0$$

$$\alpha_{j,b}^{low} \cdot \sum_s \tilde{g}(j,b,s) = 0$$

$$\beta_{j,b,s}^{up} \cdot \left(g_{max}(j,b,s) - \tilde{g}(j,b,s) \right) = 0$$

$$\beta_{j,b,s}^{low} \cdot \tilde{g}(j,b,s) = 0$$

$$\delta_{j,b}^{up} \cdot \left(g_{max}(j) - \underset{\smile}{\tilde{g}}_{max}(j,b) - \tilde{r}(j,b) \right) = 0$$

$$\delta_{j,b}^{low} \cdot \tilde{r}(j,b) = 0$$

$$\zeta_{j,b}^{up} \left(\underset{\smile}{\tilde{g}}_{max}(j,b) - \tilde{r}(j,b) \right) = 0$$

$$\zeta_{j,b}^{low} \tilde{r}(j,b) = 0$$

$$\vartheta_{j,b}^{up} \left(r_{max}(j) - \tilde{r}(j,b) \right) = 0$$

$$\vartheta_{j,b}^{low} \tilde{r}(j,b) = 0$$

$$\varepsilon_{j,b}^{up} \cdot \left(\hat{d}_e(j,b) - \tilde{c}urt(j,b) \right) = 0$$

$$\varepsilon_{j,b}^{low} \cdot \tilde{c}urt(j,b) = 0$$

B.2. Final structure of the model

$$\max_{\underset{\smile}{\tilde{g}}_{max,j}, \underset{\smile}{\tilde{c}}_j, \underset{\smile}{\tilde{P}}_{r,j}, \tilde{z}_j} \Pi_t = E \left\{ \begin{array}{l} \sum_b \left(\begin{array}{l} \sum_{j \in A} \left(-c(j,s) + \underset{\smile}{\tilde{c}}(j,b) \right) \cdot \sum_s \tilde{g}(j,b,s) \\ + \sum_{j \in A} \alpha_{j,b}^{up} \cdot \underset{\smile}{\tilde{g}}_{max}(j,b) + \sum_{j \in A} \sum_s \beta_{j,b,s}^{up} \cdot g_{max}(j,b,s) \end{array} \right) + \\ + \sum_b \left(\sum_{j \in A} \underset{\smile}{\tilde{P}}_r(j,b) \cdot \tilde{r}(j,b) + \sum_{j \in A} \delta_{j,b}^{up} \left(g_{max} - \underset{\smile}{\tilde{g}}_{max} \right) + \sum_{j \in A} \zeta_{j,b}^{up} \cdot \underset{\smile}{\tilde{g}}_{max} + \sum_{j \in A} \vartheta_{j,b}^{up} \cdot r_{max} \right) + \\ - \sum_b \sum_{j \in A} c_{fuel}(j) \cdot \left(g_{max}(j) - \sum_s \tilde{g}(j,b,s) \right) + \\ - \sum_{b > 0} \sum_{j \in A} \hat{c}_{ramp}(j) \cdot \left| \sum_s \tilde{g}(j,b,s) - \sum_s \tilde{g}(j,b-1,s) \right| + \\ - \sum_{j \in B} c_{inv}(j) \cdot \tilde{z}(j) \end{array} \right\}$$

s.t. $\quad 0 \leq \underset{\smile}{\tilde{g}}_{max}(j,b) \leq g_{max}(j) \qquad j = 1, \ldots, N_A$

$$0 \le \underset{\smile}{\tilde{g}}_{max}(j,b) \le \tilde{z}(j) \cdot g_{max}(j) \qquad j = 1,\ldots,N_B$$

$$f(\tilde{z}(j) = k) = x(j)^k (1 - x(j))^{1-k} \qquad k \in \{0,1\}$$

$$-\underset{\smile}{\tilde{c}}(j,b) + \sum_n p_{el,b,n} \cdot m_g(j,n) - \alpha_{j,b}^{up} + \alpha_{j,b}^{low} - \beta_{j,b,s}^{up} + \beta_{j,b,s}^{low} = 0 \quad j = 1,\ldots,N_G$$

$$-\sum_k p_{el,b,n} \cdot B(k,n) - \sum_l \gamma_{l,b}^{up} \cdot H(l,n) + \sum_l \gamma_{l,b}^{low} \cdot H(l,n) = 0 \quad n = 1,\ldots,N\text{-}1$$

$$-P_{curt} + \sum_n p_{el,b,n} \cdot m_d(j,n) - \varepsilon_{j,b}^{up} + \varepsilon_{j,b}^{low} = 0 \quad j = 1,\ldots,N_D$$

$$-\underset{\smile}{\tilde{P}}_r(j,b) + \sum_n p_{res,b,n} \cdot m_g(j,n) - \delta_{j,b}^{up} + \delta_{j,b}^{low} - \zeta_{j,b}^{up} + \zeta_{j,b}^{low} - \vartheta_{j,b}^{up} + \vartheta_{j,b}^{low} = 0 \quad j = 1,\ldots,N_G$$

$$0 \le \sum_s \tilde{g}(j,b,s) \le \underset{\smile}{\tilde{g}}_{max}(j,b) \quad j = 1,\ldots,N_G$$

$$0 \le \tilde{g}(j,b,s) \le g_{max}(j,b,s) \quad j = 1,\ldots,N_G$$

$$\sum_{j=1}^{N-1} B(n,j) \cdot \tilde{\theta}(j) = \sum_{j \in G} \sum_s \tilde{g}(j,b,s) \cdot m_g(j,n) +$$

$$+\sum_{j \in D} \tilde{c}urt(j,b) \cdot m_d(j,n) - \sum_{j \in D} \hat{d}_e(j,b) \cdot m_d(j,n) \quad n = 1,\ldots,N$$

$$\sum_{j \in G} \tilde{r}(j,b) \cdot m_g(j,n) = \sum_{j \in D} \hat{d}_r(j,b) \cdot m_d(j,n) \quad n = 1,\ldots,N$$

$$-F(l) \le \sum_{n=1}^{N-1} H(l,n) \cdot \tilde{\theta}(n) \le F(l) \quad l = 1,\ldots,L$$

$$0 \le \tilde{r}(j,b) \le g_{max}(j) - \underset{\smile}{\tilde{g}}_{max}(j,b) \qquad j = 1,\ldots,N_G$$

$$0 \le \tilde{r}(j,b) \le \underset{\smile}{\tilde{g}}_{max}(j,b) \qquad j = 1,\ldots,N_G$$

$$0 \le \tilde{r}(j,b) \le r_{max}(j) \qquad j = 1,\ldots,N_G$$

$$0 \le \tilde{c}urt(j,b) \le \hat{d}_e(j,b) \qquad j = 1,\ldots,N_D$$

$$\alpha_{j,b} \ge 0, \beta_{j,b,s} \ge 0, \gamma_{j,b}^{up} \ge 0, \gamma_{j,b}^{low} \ge 0, \delta_{j,b}^{up} \ge 0, \delta_{j,b}^{low} \ge 0,$$

$$\zeta_{j,b}^{up} \ge 0, \zeta_{j,b}^{low} \ge 0, \vartheta_{j,b}^{up} \ge 0, \vartheta_{j,b}^{low} \ge 0, \varepsilon_{j,b}^{up} \ge 0, \varepsilon_{j,b}^{low} \ge 0$$

$$-M(1 - y_{l,b}^{up}) \le \left(F(l) - \sum_{n=1}^{N-1} H(l,n) \cdot \tilde{\theta}(n) \right) \le M(1 - y_{l,b}^{up})$$

$$-My_{l,b}^{up} \le \gamma_{b,l}^{up} \le My_{l,b}^{up}$$

$$-M(1 - y_{l,b}^{low}) \le \left(F(l) + \sum_{n=1}^{N-1} H(l,n) \cdot \tilde{\theta}(n) \right) \le M(1 - y_{l,b}^{low})$$

$$-My_{l,b}^{low} \le \gamma_{b,l}^{low} \le My_{l,b}^{low}$$

$$-M(1 - w_{j,b}^{up}) \le \left(\underset{\smile}{\tilde{g}}_{max}(j,b) - \sum_s \tilde{g}(j,b,s) \right) \le M(1 - w_{j,b}^{up})$$

$$-Mw_{j,b}^{up} \le \alpha_{j,b}^{up} \le Mw_{j,b}^{up}$$

$$-M(1 - w_{j,b}^{low}) \le \sum_s \tilde{g}(j,b,s) \le M(1 - w_{j,b}^{low})$$

$$-Mw_{j,b}^{low} \le \alpha_{j,b}^{low} \le Mw_{j,b}^{low}$$

$$-M(1 - v_{j,b,s}^{up}) \le (g_{max}(j,b,s) - \tilde{g}(j,b,s)) \le M(1 - v_{j,b,s}^{up})$$

$$-Mv_{j,b,s}^{up} \le \beta_{j,b,s}^{up} \le Mv_{j,b,s}^{up}$$

$$-M\left(1-v_{j,b,s}^{low}\right) \le \tilde{g}\left(j,b,s\right) \le M\left(1-v_{j,b,s}^{low}\right)$$

$$-Mv_{j,b,s}^{low} \le \beta_{j,b,s}^{low} \le Mv_{j,b,s}^{low}$$

$$-M\left(1-k_{j,b}^{up}\right) \le \left(g_{max}\left(j\right)-\sum_{s}\tilde{g}\left(j,b,s\right)-\tilde{r}\left(j,b\right)\right) \le M\left(1-k_{j,b}^{up}\right)$$

$$-Mk_{j,b}^{up} \le \delta_{j,b}^{up} \le Mk_{j,b}^{up}$$

$$-M\left(1-k_{j,b}^{low}\right) \le \tilde{r}\left(j,b\right) \le M\left(1-k_{j,b}^{low}\right)$$

$$-Mk_{j,b}^{low} \le \delta_{j,b}^{low} \le Mk_{j,b}^{low}$$

$$-M\left(1-t_{j,b}^{up}\right) \le \left(\underset{\smile}{\tilde{g}}_{max}\left(j\right)-\tilde{r}\left(j,b\right)\right) \le M\left(1-t_{j,b}^{up}\right)$$

$$-Mt_{j,b}^{up} \le \zeta_{j,b}^{up} \le Mt_{j,b}^{up}$$

$$-M\left(1-t_{j,b}^{low}\right) \le \tilde{r}\left(j,b\right) \le M\left(1-t_{j,b}^{low}\right)$$

$$-Mt_{j,b}^{low} \le \zeta_{j,b}^{low} \le Mt_{j,b}^{low}$$

$$-M\left(1-u_{j,b}^{up}\right) \le \left(r_{max}\left(j\right)-\tilde{r}\left(j,b\right)\right) \le M\left(1-u_{j,b}^{up}\right)$$

$$-Mu_{j,b}^{up} \le \vartheta_{j,b}^{up} \le Mu_{j,b}^{up}$$

$$-M\left(1-u_{j,b}^{low}\right) \le \tilde{r}\left(j,b\right) \le M\left(1-u_{j,b}^{low}\right)$$

$$-Mu_{j,b}^{low} \le \vartheta_{j,b}^{low} \le Mu_{j,b}^{low}$$

$$-M\left(1-h_{j,b}^{up}\right) \le \left(\hat{d}_{e}\left(j,b\right)-\tilde{c}urt\left(j,b\right)\right) \le M\left(1-h_{j,b}^{up}\right)$$

$$-Mh_{j,b}^{up} \le \varepsilon_{j,b}^{up} \le Mh_{j,b}^{up}$$

$$-M\left(1-h_{j,b}^{low}\right) \le \tilde{c}urt\left(j,b\right) \le M\left(1-h_{j,b}^{low}\right)$$

$$-Mh_{j,b}^{low} \le \varepsilon_{j,b}^{low} \le Mh_{j,b}^{low}$$

Appendix C - OSeMOSYS

```
# Model Definition #
```

```
# SETS #

set YEAR;
set TECHNOLOGY;
set TIMESLICE;
set FUEL;
set EMISSION;
set MODE_OF_OPERATION;
set REGION;
set SEASON;
set DAYTYPE;
set DAILYTIMEBRACKET;
set FLEXIBLEDEMANDTYPE;
set STORAGE;
```

```
# PARAMETERS #
```

```
# Global #

param YearSplit{y in YEAR,l in TIMESLICE};
param DiscountRate{t in TECHNOLOGY, r in REGION};
param DaySplit{y in YEAR, lh in DAILYTIMEBRACKET};
param Conversionls{ls in SEASON, l in TIMESLICE};
param Conversionld{ld in DAYTYPE, l in TIMESLICE};
param Conversionlh{lh in DAILYTIMEBRACKET, l in TIMESLICE};
param DaysInDayType{y in YEAR, ls in SEASON, ld in DAYTYPE};
param TradeRoute{y in YEAR, f in FUEL, r in REGION, rr in REGION};
```

```
# Demand #

param SpecifiedAnnualDemand{y in YEAR,f in FUEL, r in REGION};
param SpecifiedDemandProfile{y in YEAR, l in TIMESLICE, f in FUEL, r in REGION};
param AccumulatedAnnualDemand{y in YEAR, f in FUEL, r in REGION};
```

```
# Performance #

param CapacityToActivityUnit{t in TECHNOLOGY, r in REGION};
param TechWithCapacityNeededToMeetPeakTS{t in TECHNOLOGY, r in REGION};
param CapacityFactor{y in YEAR, t in TECHNOLOGY, l in TIMESLICE, r in REGION};
param AvailabilityFactor{y in YEAR, t in TECHNOLOGY, r in REGION};
param OperationalLife{t in TECHNOLOGY, r in REGION};
param ResidualCapacity{y in YEAR, t in TECHNOLOGY, r in REGION};
```

param InputActivityRatio{y in YEAR, t in TECHNOLOGY, f in FUEL, m in MODE_OF_OPERATION, r in REGION};
param OutputActivityRatio{y in YEAR, t in TECHNOLOGY, f in FUEL, m in MODE_OF_OPERATION, r in REGION};

Technology Costs

param CapitalCost{y in YEAR, t in TECHNOLOGY, r in REGION};
param VariableCost{y in YEAR, t in TECHNOLOGY, m in MODE_OF_OPERATION, r in REGION};
param FixedCost{y in YEAR, t in TECHNOLOGY, r in REGION};

Storage

param TechnologyToStorage{t in TECHNOLOGY, m in MODE_OF_OPERATION, s in STORAGE, r in REGION};
param TechnologyFromStorage{t in TECHNOLOGY, m in MODE_OF_OPERATION, s in STORAGE, r in REGION};
param StorageLevelStart{s in STORAGE, r in REGION};
param StorageMaxChargeRate{s in STORAGE, r in REGION};
param StorageMaxDischargeRate{s in STORAGE, r in REGION};
param MinStorageCharge{s in STORAGE, y in YEAR, r in REGION};
param OperationalLifeStorage{s in STORAGE, r in REGION};
param CapitalCostStorage{s in STORAGE, y in YEAR, r in REGION};
param DiscountRateStorage{s in STORAGE, r in REGION};
param ResidualStorageCapacity{s in STORAGE, y in YEAR, r in REGION};

Capacity Constraints

param CapacityOfOneTechnologyUnit{y in YEAR, t in TECHNOLOGY, r in REGION};
param TotalAnnualMaxCapacity{y in YEAR, t in TECHNOLOGY, r in REGION};
param TotalAnnualMinCapacity{y in YEAR, t in TECHNOLOGY, r in REGION};

Investment Constraints

param TotalAnnualMaxCapacityInvestment{y in YEAR, t in TECHNOLOGY, r in REGION};
param TotalAnnualMinCapacityInvestment{y in YEAR, t in TECHNOLOGY, r in REGION};

Activity Constraints

param TotalTechnologyAnnualActivityUpperLimit{y in YEAR, t in TECHNOLOGY, r in REGION};
param TotalTechnologyAnnualActivityLowerLimit{y in YEAR, t in TECHNOLOGY, r in REGION};
param TotalTechnologyModelPeriodActivityUpperLimit{t in TECHNOLOGY, r in REGION};
param TotalTechnologyModelPeriodActivityLowerLimit{t in TECHNOLOGY, r in REGION};

```
# Reserve Margin #
```

param ReserveMarginTagTechnology{y in YEAR,t in TECHNOLOGY, r in REGION};
param ReserveMarginTagFuel{y in YEAR,f in FUEL, r in REGION};
param ReserveMargin{y in YEAR, r in REGION};

```
# RE Generation Target #
```

param RETagTechnology{y in YEAR,t in TECHNOLOGY, r in REGION};
param RETagFuel{y in YEAR,f in FUEL, r in REGION};
param REMinProductionTarget{y in YEAR, r in REGION};

```
# Emissions & Penalties #
```

param EmissionActivityRatio{y in YEAR, t in TECHNOLOGY, e in EMISSION, m in MODE_OF_OPERATION, r in REGION};
param EmissionsPenalty{y in YEAR, e in EMISSION, r in REGION};
param AnnualExogenousEmission{y in YEAR, e in EMISSION, r in REGION};
param AnnualEmissionLimit{y in YEAR, e in EMISSION, r in REGION};
param ModelPeriodExogenousEmission{e in EMISSION, r in REGION};
param ModelPeriodEmissionLimit{e in EMISSION, r in REGION};

```
# Wind Capacity Credit #
```

param ElectricityForTransmissionTag{f in FUEL, r in REGION};
param WindTechnologyTag{t in TECHNOLOGY, r in REGION};
param PeakElectricityDemandEntered{y in YEAR, r in REGION};
param WindDispersionCoefficient{y in YEAR, r in REGION};
param ReliabilityConventionalPlants{y in YEAR, r in REGION};
param WindCapacityCreditSwitch;

```
# Operating Reserve #
```

param PrimReserveUpCapacityDemand{y in YEAR, l in TIMESLICE, r in REGION};
param SecReserveUpCapacityDemand{y in YEAR, l in TIMESLICE, r in REGION};
param PrimReserveDownCapacityDemand{y in YEAR, l in TIMESLICE, r in REGION};
param SecReserveDownCapacityDemand{y in YEAR, l in TIMESLICE, r in REGION};
param MinStableOperation{y in YEAR, t in TECHNOLOGY, r in REGION};
param MaxPrimReserveUp{y in YEAR, t in TECHNOLOGY, r in REGION};
param MaxSecReserveUp{y in YEAR, t in TECHNOLOGY, r in REGION};
param MaxPrimReserveDown{y in YEAR, t in TECHNOLOGY, r in REGION};
param MaxSecReserveDown{y in YEAR, t in TECHNOLOGY, r in REGION};
param MinSecReserveUpOnline{y in YEAR, r in REGION};
param MinPrimReserveUpOnline{y in YEAR, r in REGION};
param TimeSliceLinkTag{l in TIMESLICE, ll in TIMESLICE, r in REGION};
param MaxOnlineCapReduction{y in YEAR, t in TECHNOLOGY, r in REGION};

```
param MaxGenerationReduction{y in YEAR, t in TECHNOLOGY, r in REGION};
```

MODEL VARIABLES

Demand

```
var RateOfDemand{y in YEAR,l in TIMESLICE, f in FUEL, r in REGION}>= 0;
var Demand{y in YEAR,l in TIMESLICE, f in FUEL, r in REGION}>= 0;
```

Storage

```
var RateOfStorageCharge{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in
  DAILYTIMEBRACKET, r in REGION};
var RateOfStorageDischarge{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in
  DAILYTIMEBRACKET, r in REGION};
var NetChargeWithinYear{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in
  DAILYTIMEBRACKET, r in REGION};
var NetChargeWithinDay{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in
  DAILYTIMEBRACKET, r in REGION};
var StorageLevelYearStart{s in STORAGE, y in YEAR, r in REGION} >=0;
var StorageLevelYearFinish{s in STORAGE, y in YEAR, r in REGION} >=0;
var StorageLevelSeasonStart{s in STORAGE, y in YEAR, ls in SEASON, r in REGION} >=0;
var StorageLevelDayTypeStart{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, r in
  REGION} >=0;
var StorageLevelDayTypeFinish{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, r
  in REGION} >=0;
var StorageLowerLimit{s in STORAGE, y in YEAR, r in REGION}>=0;
var StorageUpperLimit{s in STORAGE, y in YEAR, r in REGION} >=0;
var AccumulatedNewStorageCapacity{s in STORAGE, y in YEAR, r in REGION} >=0;
var NewStorageCapacity{s in STORAGE, y in YEAR, r in REGION} >=0;
var CapitalInvestmentStorage{s in STORAGE, y in YEAR, r in REGION} >=0;
var DiscountedCapitalInvestmentStorage{s in STORAGE, y in YEAR, r in REGION} >=0;
var SalvageValueStorage{s in STORAGE, y in YEAR, r in REGION} >=0;
var DiscountedSalvageValueStorage{s in STORAGE, y in YEAR, r in REGION} >=0;
var TotalDiscountedStorageCost{s in STORAGE, y in YEAR, r in REGION} >=0;
```

Capacity Variables

```
var NumberOfNewTechnologyUnits{y in YEAR, t in TECHNOLOGY, r in REGION} >=
  0,integer;
var NewCapacity{y in YEAR, t in TECHNOLOGY, r in REGION} >= 0;
var AccumulatedNewCapacity{y in YEAR, t in TECHNOLOGY, r in REGION} >= 0;
var TotalCapacityAnnual{y in YEAR, t in TECHNOLOGY, r in REGION}>= 0;
```

Activity Variables

```
var RateOfActivity{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, m in
  MODE_OF_OPERATION, r in REGION} >= 0;
var RateOfTotalActivity{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, r in REGION} >=
  0;
var TotalTechnologyAnnualActivity{y in YEAR, t in TECHNOLOGY, r in REGION} >= 0;
var TotalAnnualTechnologyActivityByMode{y in YEAR, t in TECHNOLOGY,m in
  MODE_OF_OPERATION,r in REGION}>=0;
var RateOfProductionByTechnologyByMode{y in YEAR, l in TIMESLICE, t in
  TECHNOLOGY,m in MODE_OF_OPERATION,f in FUEL,r in REGION}>= 0;
var RateOfProductionByTechnology{y in YEAR, l in TIMESLICE, t in TECHNOLOGY,f in
  FUEL, r in REGION}>= 0;
var ProductionByTechnology{y in YEAR, l in TIMESLICE, t in TECHNOLOGY,f in FUEL, r in
  REGION}>= 0;
var ProductionByTechnologyAnnual{y in YEAR, t in TECHNOLOGY, f in FUEL, r in
  REGION}>= 0;
var RateOfProduction{y in YEAR, l in TIMESLICE, f in FUEL, r in REGION} >= 0;
var Production{y in YEAR, l in TIMESLICE, f in FUEL, r in REGION} >= 0;
var RateOfUseByTechnologyByMode{y in YEAR, l in TIMESLICE, t in TECHNOLOGY,m in
  MODE_OF_OPERATION,f in FUEL,r in REGION}>= 0;
var RateOfUseByTechnology{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, f in FUEL, r in
  REGION} >= 0;
var UseByTechnologyAnnual{y in YEAR, t in TECHNOLOGY,f in FUEL, r in REGION}>= 0;
var RateOfUse{y in YEAR, l in TIMESLICE, f in FUEL, r in REGION}>= 0;
var UseByTechnology{y in YEAR, l in TIMESLICE, t in TECHNOLOGY,f in FUEL, r in
  REGION}>= 0;
var Use{y in YEAR, l in TIMESLICE, f in FUEL, r in REGION}>= 0;
var Trade{y in YEAR, l in TIMESLICE, f in FUEL, r in REGION, rr in REGION};
var TradeAnnual{y in YEAR, f in FUEL, r in REGION, rr in REGION};
var ProductionAnnual{y in YEAR, f in FUEL, r in REGION}>= 0;
var UseAnnual{y in YEAR, f in FUEL, r in REGION}>= 0;

# Costing Variables #

var CapitalInvestment{y in YEAR, t in TECHNOLOGY, r in REGION}>= 0;
var DiscountedCapitalInvestment{y in YEAR, t in TECHNOLOGY, r in REGION}>= 0;
var SalvageValue{y in YEAR, t in TECHNOLOGY, r in REGION}>= 0;
var DiscountedSalvageValue{y in YEAR, t in TECHNOLOGY, r in REGION}>= 0;
var OperatingCost{y in YEAR, t in TECHNOLOGY, r in REGION};
var DiscountedOperatingCost{y in YEAR, t in TECHNOLOGY, r in REGION};
var AnnualVariableOperatingCost{y in YEAR,t in TECHNOLOGY, r in REGION};
var AnnualFixedOperatingCost{y in YEAR,t in TECHNOLOGY, r in REGION};
var TotalDiscountedCostByTechnology{y in YEAR, t in TECHNOLOGY, r in REGION};
var TotalDiscountedCost{y in YEAR, r in REGION}>= 0;
var ModelPeriodCostByRegion {r in REGION} >= 0;

# Reserve Margin #

var TotalCapacityInReserveMargin{y in YEAR, f in FUEL, r in REGION}>= 0;
```

```
var DemandNeedingReserveMargin{y in YEAR,l in TIMESLICE, f in FUEL, r in REGION}>= 0;
```

RE Gen Target

```
var TotalREProductionAnnual{y in YEAR, r in REGION};
var RETotalDemandOfTargetFuelAnnual{y in YEAR, r in REGION};
var TotalTechnologyModelPeriodActivity{t in TECHNOLOGY, r in REGION};
```

Emissions

```
var AnnualTechnologyEmissionByMode{y in YEAR, t in TECHNOLOGY, e in EMISSION, m in
  MODE_OF_OPERATION, r in REGION}>= 0;
var AnnualTechnologyEmission{y in YEAR, t in TECHNOLOGY, e in EMISSION, r in
  REGION}>= 0;
var AnnualTechnologyEmissionPenaltyByEmission{y in YEAR, t in TECHNOLOGY, e in
  EMISSION, r in REGION}>= 0;
var AnnualTechnologyEmissionsPenalty{y in YEAR, t in TECHNOLOGY, r in REGION}>= 0;
var DiscountedTechnologyEmissionsPenalty{y in YEAR, t in TECHNOLOGY, r in REGION}>=
  0;
var AnnualEmissions{y in YEAR, e in EMISSION, r in REGION}>= 0;
var ModelPeriodEmissions{e in EMISSION, r in REGION}>= 0;
```

Wind Capacity Credit

```
var PeakElectricityDemandCalculated{y in YEAR, r in REGION} >= 0;
var WindPenetration{y in YEAR, r in REGION} >= 0;
var WindCapacityCreditCalculated{y in YEAR, r in REGION} >= 0;
var Segment1Tag {y in YEAR, r in REGION} binary;
var Segment2Tag {y in YEAR, r in REGION} binary;
var Segment3Tag {y in YEAR, r in REGION} binary;
var Segment4Tag {y in YEAR, r in REGION} binary;
var Segment5Tag {y in YEAR, r in REGION} binary;
var Segment6Tag {y in YEAR, r in REGION} binary;
var Segment1Fraction {y in YEAR, r in REGION} >=0 <=1;
var Segment2Fraction {y in YEAR, r in REGION} >=0 <=1;
var Segment3Fraction {y in YEAR, r in REGION} >=0 <=1;
var Segment4Fraction {y in YEAR, r in REGION} >=0 <=1;
var Segment5Fraction {y in YEAR, r in REGION} >=0 <=1;
var Segment6Fraction {y in YEAR, r in REGION} >=0 <=1;
var WindAverageCapacityFactor{y in YEAR, r in REGION} >= 0;
var WindCapacityCreditEntered{y in YEAR, r in REGION};
```

Operating Reserve

```
var PrimReserveDownByTechnology{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, r in
  REGION} >= 0;
var SecReserveDownByTechnology{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, r in
  REGION} >= 0;
```

```
var SecReserveUpOnline{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, r in REGION}
  >=0;
var PrimReserveUpOnline{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, r in REGION}
  >=0;
var OnlineCapacity{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, r in REGION};

# OBJECTIVE FUNCTION #

minimize cost: sum{y in YEAR, r in REGION} TotalDiscountedCost[y,r];

# CONSTRAINTS#

# Demand #

s.t. EQ_SpecifiedDemand{y in YEAR,l in TIMESLICE, f in FUEL, r in REGION}:
  SpecifiedAnnualDemand[y,f,r]*SpecifiedDemandProfile[y,l,f,r] / YearSplit[y,l] =
  RateOfDemand[y,l,f,r];

# Capacity Adequacy A #

s.t. CAa1_TotalNewCapacity{y in YEAR, t in TECHNOLOGY, r in
  REGION}:AccumulatedNewCapacity[y,t,r] = sum{yy in YEAR: y-yy < OperationalLife[t,r] &&
  y-yy>=0} if CapacityOfOneTechnologyUnit[y,t,r]=0 then NewCapacity[yy,t,r] else
  CapacityOfOneTechnologyUnit[yy,t,r]*NumberOfNewTechnologyUnits[yy,t,r];
s.t. CAa2_TotalAnnualCapacity{y in YEAR, t in TECHNOLOGY, r in REGION}:
  AccumulatedNewCapacity[y,t,r]+ ResidualCapacity[y,t,r] = TotalCapacityAnnual[y,t,r];
s.t. CAa3_TotalActivityOfEachTechnology{y in YEAR, t in TECHNOLOGY, l in TIMESLICE,r
  in REGION}: sum{m in MODE_OF_OPERATION} RateOfActivity[y,l,t,m,r] =
  RateOfTotalActivity[y,l,t,r];
s.t. CAa4_Constraint_Capacity{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, r in
  REGION: TechWithCapacityNeededToMeetPeakTS[t,r]<>0}: RateOfTotalActivity[y,l,t,r] <=
  TotalCapacityAnnual[y,t,r]*CapacityFactor[y,t,l,r]*CapacityToActivityUnit[t,r];

# Capacity Adequacy B #

s.t. CAb1_PlannedMaintenance{y in YEAR, t in TECHNOLOGY, r in REGION}: sum{l in
  TIMESLICE} RateOfTotalActivity[y,l,t,r]*YearSplit[y,l] <= sum{l in TIMESLICE}
  (TotalCapacityAnnual[y,t,r]*CapacityFactor[y,t,l,r]*YearSplit[y,l])*
  AvailabilityFactor[y,t,r]*CapacityToActivityUnit[t,r];

# Energy Balance A #

s.t. EBa1_RateOfFuelProduction1{y in YEAR, l in TIMESLICE, f in FUEL, t in
  TECHNOLOGY, m in MODE_OF_OPERATION, r in REGION: OutputActivityRatio[y,t,f,m,r]
  <>0}: RateOfActivity[y,l,t,m,r]*OutputActivityRatio[y,t,f,m,r] =
  RateOfProductionByTechnologyByMode[y,l,t,m,f,r];
```

```
s.t. EBa2_RateOfFuelProduction2{y in YEAR, l in TIMESLICE, f in FUEL, t in
  TECHNOLOGY, r in REGION}: sum{m in MODE_OF_OPERATION:
  OutputActivityRatio[y,t,f,m,r] <>0} RateOfProductionByTechnologyByMode[y,l,t,m,f,r] =
  RateOfProductionByTechnology[y,l,t,f,r] ;
s.t. EBa3_RateOfFuelProduction3{y in YEAR, l in TIMESLICE, f in FUEL, r in REGION}:
  sum{t in TECHNOLOGY} RateOfProductionByTechnology[y,l,t,f,r] =
  RateOfProduction[y,l,f,r];
s.t. EBa4_RateOfFuelUse1{y in YEAR, l in TIMESLICE, f in FUEL, t in TECHNOLOGY, m in
  MODE_OF_OPERATION, r in REGION:InputActivityRatio[y,t,f,m,r]<>0}:
  RateOfActivity[y,l,t,m,r]*InputActivityRatio[y,t,f,m,r] =
  RateOfUseByTechnologyByMode[y,l,t,m,f,r];
s.t. EBa5_RateOfFuelUse2{y in YEAR, l in TIMESLICE, f in FUEL, t in TECHNOLOGY, r in
  REGION}: sum{m in MODE_OF_OPERATION:InputActivityRatio[y,t,f,m,r]<>0}
  RateOfUseByTechnologyByMode[y,l,t,m,f,r] = RateOfUseByTechnology[y,l,t,f,r];
s.t. EBa6_RateOfFuelUse3{y in YEAR, l in TIMESLICE, f in FUEL, r in REGION}: sum{t in
  TECHNOLOGY} RateOfUseByTechnology[y,l,t,f,r] = RateOfUse[y,l,f,r];
s.t. EBa7_EnergyBalanceEachTS1{y in YEAR,l in TIMESLICE, f in FUEL, r in REGION}:
  RateOfProduction[y,l,f,r]*YearSplit[y,l] = Production[y,l,f,r];
s.t. EBa8_EnergyBalanceEachTS2{y in YEAR,l in TIMESLICE, f in FUEL, r in REGION}:
  RateOfUse[y,l,f,r]*YearSplit[y,l] = Use[y,l,f,r];
s.t. EBa9_EnergyBalanceEachTS3{y in YEAR,l in TIMESLICE, f in FUEL, r in REGION}:
  RateOfDemand[y,l,f,r]*YearSplit[y,l] = Demand[y,l,f,r];
s.t. EBa10_EnergyBalanceEachTS4{y in YEAR,l in TIMESLICE, f in FUEL, r in REGION, rr in
  REGION}: Trade[y,l,f,r,rr] = -Trade[y,l,f,rr,r];
s.t. EBa11_EnergyBalanceEachTS5{y in YEAR,l in TIMESLICE, f in FUEL, r in REGION}:
  Production[y,l,f,r] >= Demand[y,l,f,r] + Use[y,l,f,r] + sum{rr in REGION}
  Trade[y,l,f,r,rr]*TradeRoute[y,f,r,rr];
```

Energy Balance B

```
s.t. EBb1_EnergyBalanceEachYear1{y in YEAR, f in FUEL, r in REGION}: sum{l in
  TIMESLICE} Production[y,l,f,r] = ProductionAnnual[y,f,r];
s.t. EBb2_EnergyBalanceEachYear2{y in YEAR, f in FUEL, r in REGION}: sum{l in
  TIMESLICE} Use[y,l,f,r] = UseAnnual[y,f,r];
s.t. EBb3_EnergyBalanceEachYear3{y in YEAR, f in FUEL, r in REGION, rr in REGION}:
  sum{l in TIMESLICE} Trade[y,l,f,r,rr] = TradeAnnual[y,f,r,rr];
s.t. EBb4_EnergyBalanceEachYear4{y in YEAR, f in FUEL, r in REGION}:
  ProductionAnnual[y,f,r] >= UseAnnual[y,f,r] + sum{rr in REGION}
  TradeAnnual[y,f,r,rr]*TradeRoute[y,f,r,rr] + AccumulatedAnnualDemand[y,f,r];
```

Accounting Technology Production/Use

```
s.t. Acc1_FuelProductionByTechnology{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, f in
  FUEL, r in REGION}: RateOfProductionByTechnology[y,l,t,f,r] * YearSplit[y,l] =
  ProductionByTechnology[y,l,t,f,r];
s.t. Acc2_FuelUseByTechnology{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, f in FUEL,
  r in REGION}: RateOfUseByTechnology[y,l,t,f,r] * YearSplit[y,l] = UseByTechnology[y,l,t,f,r];
```

```
s.t. Acc3_AverageAnnualRateOfActivity{y in YEAR,t in TECHNOLOGY, m in
  MODE_OF_OPERATION, r in REGION}: sum{l in TIMESLICE}
  RateOfActivity[y,l,t,m,r]*YearSplit[y,l] = TotalAnnualTechnologyActivityByMode[y,t,m,r];
s.t. Acc4_ModelPeriodCostByRegion{r in REGION}:sum{y in YEAR}TotalDiscountedCost[y,r]
  = ModelPeriodCostByRegion[r];

# Storage Equations #

s.t. S1_RateOfStorageCharge{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in
    DAILYTIMEBRACKET, r in REGION}: sum{t in TECHNOLOGY, m in
    MODE_OF_OPERATION, l in TIMESLICE:TechnologyToStorage[t,m,s,r]>0}
    RateOfActivity[y,l,t,m,r] * TechnologyToStorage[t,m,s,r] * Conversionls[ls,l] *
    Conversionld[ld,l] * Conversionlh[lh,l] = RateOfStorageCharge[s,y,ls,ld,lh,r];
s.t. S2_RateOfStorageDischarge{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh
    in DAILYTIMEBRACKET, r in REGION}: sum{t in TECHNOLOGY, m in
    MODE_OF_OPERATION, l in TIMESLICE:TechnologyFromStorage[t,m,s,r]>0}
    RateOfActivity[y,l,t,m,r] * TechnologyFromStorage[t,m,s,r] * Conversionls[ls,l] *
    Conversionld[ld,l] * Conversionlh[lh,l] = RateOfStorageDischarge[s,y,ls,ld,lh,r];
s.t. S3_NetChargeWithinYear{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in
    DAILYTIMEBRACKET, r in REGION}: sum{l in
    TIMESLICE:Conversionls[ls,l]>0&&Conversionld[ld,l]>0&&Conversionlh[lh,l]>0}
    (RateOfStorageCharge[s,y,ls,ld,lh,r] - RateOfStorageDischarge[s,y,ls,ld,lh,r]) * YearSplit[y,l]
    * Conversionls[ls,l] * Conversionld[ld,l] * Conversionlh[lh,l] =
    NetChargeWithinYear[s,y,ls,ld,lh,r];
s.t. S4_NetChargeWithinDay{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in
    DAILYTIMEBRACKET, r in REGION}: (RateOfStorageCharge[s,y,ls,ld,lh,r] -
    RateOfStorageDischarge[s,y,ls,ld,lh,r]) * DaySplit[y,lh] = NetChargeWithinDay[s,y,ls,ld,lh,r];
s.t. S5_and_S6_StorageLevelYearStart{s in STORAGE, y in YEAR, r in REGION}:
     if y = min{yy in YEAR} min(yy) then StorageLevelStart[s,r]
    else StorageLevelYearStart[s,y-1,r] + sum{ls in SEASON, ld in DAYTYPE, lh in
    DAILYTIMEBRACKET} NetChargeWithinYear[s,y-1,ls,ld,lh,r]
    = StorageLevelYearStart[s,y,r];
s.t. S7_and_S8_StorageLevelYearFinish{s in STORAGE, y in YEAR, r in REGION}:
    if y < max{yy in YEAR} max(yy) then StorageLevelYearStart[s,y+1,r]
    else StorageLevelYearStart[s,y,r] + sum{ls in SEASON, ld in DAYTYPE, lh in
    DAILYTIMEBRACKET} NetChargeWithinYear[s,y,ls,ld,lh,r]
    = StorageLevelYearFinish[s,y,r];
s.t. S9_and_S10_StorageLevelSeasonStart{s in STORAGE, y in YEAR, ls in SEASON, r in
    REGION}:
    if ls = min{lsls in SEASON} min(lsls) then StorageLevelYearStart[s,y,r]
    else StorageLevelSeasonStart[s,y,ls-1,r] + sum{ld in DAYTYPE, lh in
    DAILYTIMEBRACKET} NetChargeWithinYear[s,y,ls-1,ld,lh,r]
    = StorageLevelSeasonStart[s,y,ls,r];
s.t. S11_and_S12_StorageLevelDayTypeStart{s in STORAGE, y in YEAR, ls in SEASON, ld in
    DAYTYPE, r in REGION}:
    if ld = min{ldld in DAYTYPE} min(ldld) then StorageLevelSeasonStart[s,y,ls,r]
    else StorageLevelDayTypeStart[s,y,ls,ld-1,r] + sum{lh in DAILYTIMEBRACKET}
```

NetChargeWithinDay[s,y,ls,ld-1,lh,r] * DaysInDayType[y,ls,ld-1]
= StorageLevelDayTypeStart[s,y,ls,ld,r];
s.t. S13_and_S14_and_S15_StorageLevelDayTypeFinish{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, r in REGION}:
if ls = max{lsls in SEASON} max(lsls) && ld = max{ldld in DAYTYPE} max(ldld) then StorageLevelYearFinish[s,y,r]
else if ld = max{ldld in DAYTYPE} max(ldld) then StorageLevelSeasonStart[s,y,ls+1,r]
else StorageLevelDayTypeFinish[s,y,ls,ld+1,r] - sum{lh in DAILYTIMEBRACKET} NetChargeWithinDay[s,y,ls,ld+1,lh,r] * DaysInDayType[y,ls,ld+1]
= StorageLevelDayTypeFinish[s,y,ls,ld,r];

Storage Constraints

---

s.t.
SC1_LowerLimit_BeginningOfDailyTimeBracketOfFirstInstanceOfDayTypeInFirstWeekConstraint{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in DAILYTIMEBRACKET, r in REGION}: 0 <= (StorageLevelDayTypeStart[s,y,ls,ld,r]+sum{lhlh in DAILYTIMEBRACKET:lh-lhlh>0} NetChargeWithinDay[s,y,ls,ld,lhlh,r])-StorageLowerLimit[s,y,r];
s.t.
SC1_UpperLimit_BeginningOfDailyTimeBracketOfFirstInstanceOfDayTypeInFirstWeekConstraint{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in DAILYTIMEBRACKET, r in REGION}: (StorageLevelDayTypeStart[s,y,ls,ld,r]+sum{lhlh in DAILYTIMEBRACKET:lh-lhlh>0} NetChargeWithinDay[s,y,ls,ld,lhlh,r])-StorageUpperLimit[s,y,r] <= 0;
s.t.
SC2_LowerLimit_EndOfDailyTimeBracketOfLastInstanceOfDayTypeInFirstWeekConstraint{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in DAILYTIMEBRACKET, r in REGION}: 0 <= if ld > min{ldld in DAYTYPE} min(ldld) then (StorageLevelDayTypeStart[s,y,ls,ld,r]-sum{lhlh in DAILYTIMEBRACKET:lh-lhlh<0} NetChargeWithinDay[s,y,ls,ld-1,lhlh,r])-StorageLowerLimit[s,y,r];
s.t.
SC2_UpperLimit_EndOfDailyTimeBracketOfLastInstanceOfDayTypeInFirstWeekConstraint{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in DAILYTIMEBRACKET, r in REGION}: if ld > min{ldld in DAYTYPE} min(ldld) then (StorageLevelDayTypeStart[s,y,ls,ld,r]-sum{lhlh in DAILYTIMEBRACKET:lh-lhlh<0} NetChargeWithinDay[s,y,ls,ld-1,lhlh,r])-StorageUpperLimit[s,y,r] <= 0;
s.t.
SC3_LowerLimit_EndOfDailyTimeBracketOfLastInstanceOfDayTypeInLastWeekConstraint{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in DAILYTIMEBRACKET, r in REGION}: 0 <= (StorageLevelDayTypeFinish[s,y,ls,ld,r] - sum{lhlh in DAILYTIMEBRACKET:lh-lhlh<0} NetChargeWithinDay[s,y,ls,ld,lhlh,r])-StorageLowerLimit[s,y,r];
s.t.
SC3_UpperLimit_EndOfDailyTimeBracketOfLastInstanceOfDayTypeInLastWeekConstraint{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in DAILYTIMEBRACKET, r in REGION}: (StorageLevelDayTypeFinish[s,y,ls,ld,r] - sum{lhlh in

DAILYTIMEBRACKET:lh-lhlh<0} NetChargeWithinDay[s,y,ls,ld,lhlh,r])-StorageUpperLimit[s,y,r] <= 0;

s.t. SC4_LowerLimit_BeginningOfDailyTimeBracketOfFirstInstanceOfDayTypeInLastWeekConstraint{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in DAILYTIMEBRACKET, r in REGION}: 0 <= if ld > min{ldld in DAYTYPE} min(ldld) then (StorageLevelDayTypeFinish[s,y,ls,ld-1,r]+sum{lhlh in DAILYTIMEBRACKET:lh-lhlh>0} NetChargeWithinDay[s,y,ls,ld,lhlh,r])-StorageLowerLimit[s,y,r];

s.t. SC4_UpperLimit_BeginningOfDailyTimeBracketOfFirstInstanceOfDayTypeInLastWeekConstraint{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in DAILYTIMEBRACKET, r in REGION}: if ld > min{ldld in DAYTYPE} min(ldld) then (StorageLevelDayTypeFinish[s,y,ls,ld-1,r]+sum{lhlh in DAILYTIMEBRACKET:lh-lhlh>0} NetChargeWithinDay[s,y,ls,ld,lhlh,r])-StorageUpperLimit[s,y,r] <= 0;

s.t. SC5_MaxChargeConstraint{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in DAILYTIMEBRACKET, r in REGION}: RateOfStorageCharge[s,y,ls,ld,lh,r] <= StorageMaxChargeRate[s,r];

s.t. SC6_MaxDischargeConstraint{s in STORAGE, y in YEAR, ls in SEASON, ld in DAYTYPE, lh in DAILYTIMEBRACKET, r in REGION}: RateOfStorageDischarge[s,y,ls,ld,lh,r] <= StorageMaxDischargeRate[s,r];

Storage Investments

s.t. SI1_StorageUpperLimit{s in STORAGE, y in YEAR, r in REGION}: AccumulatedNewStorageCapacity[s,y,r]+ResidualStorageCapacity[s,y,r] = StorageUpperLimit[s,y,r];

s.t. SI2_StorageLowerLimit{s in STORAGE, y in YEAR, r in REGION}: MinStorageCharge[s,y,r]*StorageUpperLimit[s,y,r] = StorageLowerLimit[s,y,r];

s.t. SI3_TotalNewStorage{s in STORAGE, y in YEAR, r in REGION}: sum{yy in YEAR: y-yy < OperationalLifeStorage[s,r] && y-yy>=0} NewStorageCapacity[s,yy,r]=AccumulatedNewStorageCapacity[s,y,r];

s.t. SI4_UndiscountedCapitalInvestmentStorage{s in STORAGE, y in YEAR, r in REGION}: CapitalCostStorage[s,y,r] * NewStorageCapacity[s,y,r] = CapitalInvestmentStorage[s,y,r];

s.t. SI5_DiscountingCapitalInvestmentStorage{s in STORAGE, y in YEAR, r in REGION}: CapitalInvestmentStorage[s,y,r]/((1+DiscountRateStorage[s,r])^(y-min{yy in YEAR} min(yy))) = DiscountedCapitalInvestmentStorage[s,y,r];

s.t. SI6_SalvageValueStorageAtEndOfPeriod1{s in STORAGE, y in YEAR, r in REGION: (y+OperationalLifeStorage[s,r]-1) <= (max{yy in YEAR} max(yy))}: 0 = SalvageValueStorage[s,y,r];

s.t. SI7_SalvageValueStorageAtEndOfPeriod2{s in STORAGE, y in YEAR, r in REGION: (y+OperationalLifeStorage[s,r]-1) > (max{yy in YEAR} max(yy)) && DiscountRate[s,r]=0}: CapitalInvestmentStorage[s,y,r]*(1-(max{yy in YEAR} max(yy) - y+1)/OperationalLifeStorage[s,r]) = SalvageValueStorage[s,y,r];

s.t. SI8_SalvageValueStorageAtEndOfPeriod3{s in STORAGE, y in YEAR, r in REGION: (y+OperationalLifeStorage[s,r]-1) > (max{yy in YEAR} max(yy)) && DiscountRateStorage[s,r]>0}: CapitalInvestmentStorage[s,y,r]*(1-(((1+DiscountRateStorage[s,r])^(max{yy in YEAR} max(yy) - y+1)-

1)/((1+DiscountRateStorage[s,r])^OperationalLifeStorage[s,r]-1))) = SalvageValueStorage[s,y,r];
s.t. SI9_SalvageValueStorageDiscountedToStartYear{s in STORAGE, y in YEAR, r in REGION}: SalvageValueStorage[s,y,r]/((1+DiscountRateStorage[s,r])^(max{yy in YEAR} max(yy)-min{yy in YEAR} min(yy)+1)) = DiscountedSalvageValueStorage[s,y,r];
s.t. SI10_TotalDiscountedCostByStorage{s in STORAGE, y in YEAR, r in REGION}: DiscountedCapitalInvestmentStorage[s,y,r]-DiscountedSalvageValueStorage[s,y,r] = TotalDiscountedStorageCost[s,y,r];

Capital Costs

s.t. CC1_UndiscountedCapitalInvestment{y in YEAR, t in TECHNOLOGY, r in REGION}: CapitalCost[y,t,r] * NewCapacity[y,t,r] = CapitalInvestment[y,t,r];
s.t. CC2_DiscountingCapitalInvestment{y in YEAR, t in TECHNOLOGY, r in REGION}: CapitalInvestment[y,t,r]/((1+DiscountRate[t,r])^(y-min{yy in YEAR} min(yy))) = DiscountedCapitalInvestment[y,t,r];

Salvage Value

s.t. SV2rev_SalvageValueAtEndOfPeriod2{y in YEAR, t in TECHNOLOGY, r in REGION: (y + OperationalLife[t,r]-1) > (max{yy in YEAR} max(yy))}: SalvageValue[y,t,r] = CapitalCost[y,t,r]*NewCapacity[y,t,r]*(1-(max{yy in YEAR} max(yy) - y+1)/OperationalLife[t,r]);
s.t. SV3_SalvageValueAtEndOfPeriod3{y in YEAR, t in TECHNOLOGY, r in REGION: (y + OperationalLife[t,r]-1) <= (max{yy in YEAR} max(yy))}: SalvageValue[y,t,r] = 0;
s.t. SV4_SalvageValueDiscountedToStartYear{y in YEAR, t in TECHNOLOGY, r in REGION}: DiscountedSalvageValue[y,t,r] = SalvageValue[y,t,r]/((1+DiscountRate[t,r])^(1+max{yy in YEAR} max(yy)-min{yy in YEAR} min(yy)));

Operating Costs

s.t. OC1_OperatingCostsVariable{y in YEAR,l in TIMESLICE, t in TECHNOLOGY, r in REGION}: sum{m in MODE_OF_OPERATION} TotalAnnualTechnologyActivityByMode[y,t,m,r]*VariableCost[y,t,m,r] = AnnualVariableOperatingCost[y,t,r];
s.t. OC2_OperatingCostsFixedAnnual{y in YEAR,t in TECHNOLOGY, r in REGION}: TotalCapacityAnnual[y,t,r]*FixedCost[y,t,r] = AnnualFixedOperatingCost[y,t,r];
s.t. OC3_OperatingCostsTotalAnnual{y in YEAR,t in TECHNOLOGY,r in REGION}: AnnualFixedOperatingCost[y,t,r]+AnnualVariableOperatingCost[y,t,r] = OperatingCost[y,t,r];
s.t. OC4_DiscountedOperatingCostsTotalAnnual{y in YEAR, t in TECHNOLOGY, r in REGION}: OperatingCost[y,t,r]/((1+DiscountRate[t,r])^(y-min{yy in YEAR} min(yy)+0.5)) = DiscountedOperatingCost[y,t,r];

Total Discounted Costs

s.t. TDC1_TotalDiscountedCostByTechnology{y in YEAR, t in TECHNOLOGY, r in REGION}: DiscountedOperatingCost[y,t,r]+DiscountedCapitalInvestment[y,t,r]+DiscountedTechnologyEmissionsPenalty[y,t,r]-DiscountedSalvageValue[y,t,r]+sum{l in TIMESLICE}

(SecReserveDownByTechnology[y,l,t,r]+PrimReserveDownByTechnology[y,l,t,r])*(-0.00001) = TotalDiscountedCostByTechnology[y,t,r];
s.t. TDC2_TotalDiscountedCost{y in YEAR, r in REGION}: sum{t in TECHNOLOGY} TotalDiscountedCostByTechnology[y,t,r]+sum{s in STORAGE} TotalDiscountedStorageCost[s,y,r] = TotalDiscountedCost[y,r];

Total Capacity Constraints

s.t. TCC1_TotalAnnualMaxCapacityConstraint{y in YEAR, t in TECHNOLOGY,r in REGION}: TotalCapacityAnnual[y,t,r] <= TotalAnnualMaxCapacity[y,t,r];
s.t. TCC2_TotalAnnualMinCapacityConstraint{y in YEAR, t in TECHNOLOGY,r in REGION: TotalAnnualMinCapacity[y,t,r]>0}: TotalCapacityAnnual[y,t,r] >= TotalAnnualMinCapacity[y,t,r];

New Capacity Constraints

s.t. NCC1_TotalAnnualMaxNewCapacityConstraint{y in YEAR, t in TECHNOLOGY, r in REGION}: NewCapacity[y,t,r] <= TotalAnnualMaxCapacityInvestment[y,t,r];
s.t. NCC2_TotalAnnualMinNewCapacityConstraint{y in YEAR, t in TECHNOLOGY, r in REGION: TotalAnnualMinCapacityInvestment[y,t,r]>0}: NewCapacity[y,t,r] >= TotalAnnualMinCapacityInvestment[y,t,r];

Annual Activity Constraints

s.t. AAC1_TotalAnnualTechnologyActivity{y in YEAR, t in TECHNOLOGY, r in REGION}: sum{l in TIMESLICE} RateOfTotalActivity[y,l,t,r]*YearSplit[y,l] = TotalTechnologyAnnualActivity[y,t,r];
s.t. AAC2_TotalAnnualTechnologyActivityUpperLimit{y in YEAR, t in TECHNOLOGY, r in REGION}: TotalTechnologyAnnualActivity[y,t,r] <= TotalTechnologyAnnualActivityUpperLimit[y,t,r] ;
s.t. AAC3_TotalAnnualTechnologyActivityLowerLimit{y in YEAR, t in TECHNOLOGY, r in REGION: TotalTechnologyAnnualActivityLowerLimit[y,t,r]>0}: TotalTechnologyAnnualActivity[y,t,r] >= TotalTechnologyAnnualActivityLowerLimit[y,t,r] ;

Total Activity Constraints

s.t. TAC1_TotalModelHorizonTechnologyActivity{t in TECHNOLOGY, r in REGION}: sum{y in YEAR} TotalTechnologyAnnualActivity[y,t,r] = TotalTechnologyModelPeriodActivity[t,r];
s.t. TAC2_TotalModelHorizonTechnologyActivityUpperLimit{y in YEAR, t in TECHNOLOGY, r in REGION}: TotalTechnologyModelPeriodActivity[t,r] <= TotalTechnologyModelPeriodActivityUpperLimit[t,r] ;
s.t. TAC3_TotalModelHorizenTechnologyActivityLowerLimit{y in YEAR, t in TECHNOLOGY, r in REGION: TotalTechnologyModelPeriodActivityLowerLimit[t,r]>0}: TotalTechnologyModelPeriodActivity[t,r] >= TotalTechnologyModelPeriodActivityLowerLimit[t,r] ;

Reserve Margin Constraint

```
s.t. RM1_ReserveMargin_TechologiesIncluded_In_Activity_Units{y in YEAR, f in FUEL, r in
  REGION}: sum {t in TECHNOLOGY, m in MODE_OF_OPERATION:
  OutputActivityRatio[y,t,f,m,r] <>0}
  TotalCapacityAnnual[y,t,r]*ReserveMarginTagTechnology[y,t,r]*CapacityToActivityUnit[t,r] =
  TotalCapacityInReserveMargin[y,f,r];
s.t. RM2_ReserveMargin_FuelsIncluded{y in YEAR, l in TIMESLICE, f in FUEL, r in
  REGION}: RateOfProduction[y,l,f,r]*ReserveMarginTagFuel[y,f,r] =
  DemandNeedingReserveMargin[y,l,f,r];
s.t. RM3_ReserveMargin_Constraint{y in YEAR, l in TIMESLICE, f in FUEL, r in REGION}:
  DemandNeedingReserveMargin[y,l,f,r]*ReserveMargin[y,r] <=
  TotalCapacityInReserveMargin[y,f,r];
```

RE Production Target

```
s.t. RE1_FuelProductionByTechnologyAnnual{y in YEAR, t in TECHNOLOGY, f in FUEL, r in
  REGION}: sum{l in TIMESLICE} ProductionByTechnology[y,l,t,f,r] =
  ProductionByTechnologyAnnual[y,t,f,r];
s.t. RE2_TechIncluded{y in YEAR, r in REGION}: sum{t in TECHNOLOGY, f in FUEL}
  ProductionByTechnologyAnnual[y,t,f,r]*RETagTechnology[y,t,r] =
  TotalREProductionAnnual[y,r];
s.t. RE3_FuelIncluded{y in YEAR, r in REGION}: sum{l in TIMESLICE, f in FUEL}
  RateOfDemand[y,l,f,r]*YearSplit[y,l]*RETagFuel[y,f,r] =
  RETotalDemandOfTargetFuelAnnual[y,r];
s.t. RE4_EnergyConstraint{y in YEAR, r in
  REGION}:REMinProductionTarget[y,r]*RETotalDemandOfTargetFuelAnnual[y,r] <=
  TotalREProductionAnnual[y,r];
s.t. RE5_FuelUseByTechnologyAnnual{y in YEAR, t in TECHNOLOGY, f in FUEL, r in
  REGION}: sum{l in TIMESLICE} RateOfUseByTechnology[y,l,t,f,r]*YearSplit[y,l] =
  UseByTechnologyAnnual[y,t,f,r];
```

Emissions Accounting

```
s.t. E1_AnnualEmissionProductionByMode{y in YEAR, t in TECHNOLOGY, e in EMISSION, m
  in MODE_OF_OPERATION, r in REGION:EmissionActivityRatio[y,t,e,m,r]<>0}:
  EmissionActivityRatio[y,t,e,m,r]*TotalAnnualTechnologyActivityByMode[y,t,m,r]=AnnualTec
  hnologyEmissionByMode[y,t,e,m,r];
s.t. E2_AnnualEmissionProduction{y in YEAR, t in TECHNOLOGY, e in EMISSION, r in
  REGION}: sum{m in MODE_OF_OPERATION}
  AnnualTechnologyEmissionByMode[y,t,e,m,r] = AnnualTechnologyEmission[y,t,e,r];
s.t. E3_EmissionsPenaltyByTechAndEmission{y in YEAR, t in TECHNOLOGY, e in
  EMISSION, r in REGION}: AnnualTechnologyEmission[y,t,e,r]*EmissionsPenalty[y,e,r] =
  AnnualTechnologyEmissionPenaltyByEmission[y,t,e,r];
s.t. E4_EmissionsPenaltyByTechnology{y in YEAR, t in TECHNOLOGY, r in REGION}: sum{e
  in EMISSION} AnnualTechnologyEmissionPenaltyByEmission[y,t,e,r] =
  AnnualTechnologyEmissionsPenalty[y,t,r];
```

s.t. E5_DiscountedEmissionsPenaltyByTechnology{y in YEAR, t in TECHNOLOGY, r in REGION}: AnnualTechnologyEmissionsPenalty[y,t,r]/((1+DiscountRate[t,r])^(y-min{yy in YEAR} min(yy)+0.5)) = DiscountedTechnologyEmissionsPenalty[y,t,r];
s.t. E6_EmissionsAccounting1{y in YEAR, e in EMISSION, r in REGION}: sum{t in TECHNOLOGY} AnnualTechnologyEmission[y,t,e,r] = AnnualEmissions[y,e,r];
s.t. E7_EmissionsAccounting2{e in EMISSION, r in REGION}: sum{y in YEAR} AnnualEmissions[y,e,r] = ModelPeriodEmissions[e,r] - ModelPeriodExogenousEmission[e,r];
s.t. E8_AnnualEmissionsLimit{y in YEAR, e in EMISSION, r in REGION}: AnnualEmissions[y,e,r]+AnnualExogenousEmission[y,e,r] <= AnnualEmissionLimit[y,e,r];
s.t. E9_ModelPeriodEmissionsLimit{e in EMISSION, r in REGION}: ModelPeriodEmissions[e,r] <= ModelPeriodEmissionLimit[e,r] ;

Wind Capacity Credit

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s.t. WCC1_PeakDemand{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, f in FUEL, r in REGION: SpecifiedDemandProfile[y,l,f,r] / YearSplit[y,l] >= max{ll in TIMESLICE} max(SpecifiedDemandProfile[y,ll,f,r] / YearSplit[y,ll]) && ElectricityForTransmissionTag[f,r]=1 && WindTechnologyTag[t,r]=1}: (RateOfDemand[y,l,f,r] + RateOfUse[y,l,f,r])/CapacityToActivityUnit[t,r] = PeakElectricityDemandCalculated[y,r];
s.t. WCC2_WindPenetration{y in YEAR, t in TECHNOLOGY, r in REGION: WindTechnologyTag[t,r]=1}: TotalCapacityAnnual[y,t,r]/PeakElectricityDemandEntered[y,r] = WindPenetration[y,r];
s.t. WCC3_WindAverageCapacityFactor{y in YEAR, t in TECHNOLOGY, r in REGION: WindTechnologyTag[t,r]=1}: sum{l in TIMESLICE} CapacityFactor[y,t,l,r]*YearSplit[y,l] = WindAverageCapacityFactor[y,r];
s.t. WCC4_WindCapacityCreditEntered{y in YEAR,t in TECHNOLOGY, r in REGION: WindTechnologyTag[t,r]=1}: ReserveMarginTagTechnology[y,t,r] = WindCapacityCreditEntered[y,r];
s.t. WCC5_SegmentSelection{y in YEAR, r in REGION: WindCapacityCreditSwitch=1}: Segment1Tag[y,r] + Segment2Tag[y,r] + Segment3Tag[y,r] + Segment4Tag[y,r] + Segment5Tag[y,r] + Segment6Tag[y,r] = 1;
s.t. WCC6a_SegmentFraction1{y in YEAR, r in REGION: WindCapacityCreditSwitch=1}: Segment1Fraction[y,r] <= Segment1Tag[y,r];
s.t. WCC6b_SegmentFraction2{y in YEAR, r in REGION: WindCapacityCreditSwitch=1}: Segment2Fraction[y,r] <= Segment2Tag[y,r];
s.t. WCC6c_SegmentFraction3{y in YEAR, r in REGION: WindCapacityCreditSwitch=1}: Segment3Fraction[y,r] <= Segment3Tag[y,r];
s.t. WCC6d_SegmentFraction4{y in YEAR, r in REGION: WindCapacityCreditSwitch=1}: Segment4Fraction[y,r] <= Segment4Tag[y,r];
s.t. WCC6e_SegmentFraction5{y in YEAR, r in REGION: WindCapacityCreditSwitch=1}: Segment5Fraction[y,r] <= Segment5Tag[y,r];
s.t. WCC6f_SegmentFraction6{y in YEAR, r in REGION: WindCapacityCreditSwitch=1}: Segment6Fraction[y,r] <= Segment6Tag[y,r];
s.t. WCC7_WindPenetrationSegment{y in YEAR, r in REGION: WindCapacityCreditSwitch=1}:
(Segment1Fraction[y,r]*1 + Segment2Tag[y,r]*1 + Segment2Fraction[y,r]*4 + Segment3Tag[y,r]*5 + Segment3Fraction[y,r]*5 + Segment4Tag[y,r]*10 + Segment4Fraction[y,r]*10 + Segment5Tag[y,r]*20 + Segment5Fraction[y,r]*15 + Segment6Tag[y,r]*35 + Segment6Fraction[y,r]*965)/100 = WindPenetration[y,r];

s.t. WCC8_WindCapacityCredit{y in YEAR, r in REGION: WindCapacityCreditSwitch=1}:
1/100*((Segment1Tag[y,r] + Segment2Tag[y,r])*32.8/(0.306 + WindDispersionCoefficient[y,r])*sum{l in TIMESLICE, t in TECHNOLOGY: WindTechnologyTag[t,r]>0} CapacityFactor[y,t,l,r]*YearSplit[y,l]/ ReliabilityConventionalPlants[y,r]*(1+3.26*WindDispersionCoefficient[y,r]) + Segment2Fraction[y,r]* (32.8/(0.306 + WindDispersionCoefficient[y,r])*sum{l in TIMESLICE, t in TECHNOLOGY: WindTechnologyTag[t,r]>0} CapacityFactor[y,t,l,r]*YearSplit[y,l]/ReliabilityConventionalPlants[y,r]* (3.26*WindDispersionCoefficient[y,r]*(exp(-0.1077*(0.306+WindDispersionCoefficient[y,r])*(5-1))-1))) + Segment3Tag[y,r]*(32.8/(0.306 + WindDispersionCoefficient[y,r])*sum{l in TIMESLICE, t in TECHNOLOGY: WindTechnologyTag[t,r]>0} CapacityFactor[y,t,l,r]*YearSplit[y,l]/ ReliabilityConventionalPlants[y,r]* (1+3.26*WindDispersionCoefficient[y,r]*exp(-0.1077*(0.306+ WindDispersionCoefficient[y,r])*(5-1)))) + Segment3Fraction[y,r] *(32.8/(0.306 + WindDispersionCoefficient[y,r])*sum{l in TIMESLICE, t in TECHNOLOGY: WindTechnologyTag[t,r]> 0} CapacityFactor[y,t,l,r]*YearSplit[y,l]/ ReliabilityConventionalPlants[y,r]*(3.26* WindDispersionCoefficient[y,r]*(exp(-0.1077*(0.306+ WindDispersionCoefficient[y,r])*(10-1))-exp(-0.1077*(0.306+WindDispersionCoefficient[y,r])*(5-1))))) + Segment4Tag[y,r]*(32.8/(0.306 + WindDispersionCoefficient[y,r])*sum{l in TIMESLICE, t in TECHNOLOGY: WindTechnologyTag[t,r]> 0} CapacityFactor[y,t,l,r]*YearSplit[y,l]/ReliabilityConventionalPlants[y,r]* (1+3.26* WindDispersionCoefficient[y,r]*exp(-0.1077*(0.306+WindDispersionCoefficient[y,r])*(10-1)))) + Segment4Fraction[y,r]*(32.8/(0.306 + WindDispersionCoefficient[y,r])*sum{l in TIMESLICE, t in TECHNOLOGY: WindTechnologyTag[t,r]>0} CapacityFactor[y,t,l,r]*YearSplit[y,l]/ ReliabilityConventionalPlants[y,r]*(3.26*WindDispersionCoefficient[y,r]*(exp(-0.1077*(0.306+ WindDispersionCoefficient[y,r])*(20-1))-exp(-0.1077*(0.306+WindDispersionCoefficient[y,r])*(10-1))))) + Segment5Tag[y,r]*(32.8/(0.306 + WindDispersionCoefficient[y,r])*sum{l in TIMESLICE, t in TECHNOLOGY: WindTechnologyTag[t,r]>0} CapacityFactor[y,t,l,r]*YearSplit[y,l]/ReliabilityConventionalPlants[y,r]*(1+3.26* WindDispersionCoefficient[y,r]*exp(-0.1077*(0.306+WindDispersionCoefficient[y,r])*(20-1)))) + Segment5Fraction[y,r]*(32.8/(0.306 + WindDispersionCoefficient[y,r])*sum{l in TIMESLICE, t in TECHNOLOGY: WindTechnologyTag[t,r]> 0} CapacityFactor[y,t,l,r]*YearSplit[y,l]/ ReliabilityConventionalPlants[y,r]*(3.26* WindDispersionCoefficient[y,r]*(exp(-0.1077*(0.306+ WindDispersionCoefficient[y,r])*(35-1))-exp(-0.1077*(0.306+WindDispersionCoefficient[y,r])*(20-1))))) + Segment6Tag[y,r]*(32.8/(0.306 + WindDispersionCoefficient[y,r])*sum{l in TIMESLICE, t in TECHNOLOGY: WindTechnologyTag[t,r]> 0} CapacityFactor[y,t,l,r]*YearSplit[y,l]/ReliabilityConventionalPlants[y,r]* (1+3.26* WindDispersionCoefficient[y,r]*exp(-0.1077*(0.306+WindDispersionCoefficient[y,r])*(35-1)))) = WindCapacityCreditCalculated[y,r];

Meeting Operating Reserve Demands

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s.t. R1_PrimDemandUp{y in YEAR, l in TIMESLICE, f in FUEL, r in REGION: f = "PrimReserveUp"}: sum{t in TECHNOLOGY}

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  RateOfProductionByTechnology[y,l,t,f,r]/CapacityToActivityUnit[t,r] >=
  PrimReserveUpCapacityDemand[y,l,r];
s.t. R2_SecDemandUp{y in YEAR, l in TIMESLICE, f in FUEL, r in REGION: f =
  "SecReserveUp"}: sum{t in TECHNOLOGY}
  RateOfProductionByTechnology[y,l,t,f,r]/CapacityToActivityUnit[t,r] >=
  SecReserveUpCapacityDemand[y,l,r];
s.t. R3_PrimDemandDown{y in YEAR, l in TIMESLICE, r in REGION}: {t in TECHNOLOGY}
  PrimReserveDownByTechnology[y,l,t,r]/CapacityToActivityUnit[t,r] >=
  PrimReserveDownCapacityDemand[y,l,r];
s.t. R4_SecDemandDown{y in YEAR, l in TIMESLICE, r in REGION}: {t in TECHNOLOGY}
  SecReserveDownByTechnology[y,l,t,r]/CapacityToActivityUnit[t,r] >=
  SecReserveDownCapacityDemand[y,l,r];

# Considering Ramping Characteristics #
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s.t. R5_MaxOnlineCapacity{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, r in
  REGION}:OnlineCapacity[y,l,t,r] <= TotalCapacityAnnual[y,t,r]*CapacityFactor[y,t,l,r];
s.t. R6_MaxPrimCapacityDown{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, r in
  REGION}: PrimReserveDownByTechnology[y,l,t,r] <=
  OnlineCapacity[y,l,t,r]*MaxPrimReserveDown[y,t,r]*CapacityToActivityUnit[t,r];
s.t. R7_MaxSecCapacityDown{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, r in
  REGION}: SecReserveDownByTechnology[y,l,t,r] <=
  OnlineCapacity[y,l,t,r]*MaxSecReserveDown[y,t,r]*CapacityToActivityUnit[t,r];
s.t. R8_MaxPrimCapacityUp{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, f in FUEL, r in
  REGION: f = "PrimReserveUp" && MaxPrimReserveDown[y,t,r] >= MinStableOperation[y,t,r]
  && MaxPrimReserveUp[y,t,r] >= MinStableOperation[y,t,r] && MaxSecReserveDown[y,t,r]
  >= MinStableOperation[y,t,r] && MaxSecReserveUp[y,t,r] >=
  MinStableOperation[y,t,r]}:RateOfProductionByTechnology[y,l,t,f,r] <=
  TotalCapacityAnnual[y,t,r]*CapacityFactor[y,t,l,r]*MaxPrimReserveUp[y,t,r]*CapacityToActivi
  tyUnit[t,r];
s.t. R9_MaxSecCapacityUp{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, f in FUEL, r in
  REGION: f = "SecReserveUp" && MaxSecReserveDown[y,t,r] >= MinStableOperation[y,t,r]
  && MaxSecReserveUp[y,t,r] >= MinStableOperation[y,t,r]}:
  RateOfProductionByTechnology[y,l,t,f,r] <=
  TotalCapacityAnnual[y,t,r]*CapacityFactor[y,t,l,r]*MaxSecReserveUp[y,t,r]*CapacityToActivit
  yUnit[t,r];
s.t. R10_MinElecGeneration1{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, f in FUEL, r in
  REGION: ElectricityForTransmissionTag[f,r]=1 && MaxSecReserveDown[y,t,r] >=
  MinStableOperation[y,t,r] && MaxSecReserveUp[y,t,r] >= MinStableOperation[y,t,r] &&
  (MaxPrimReserveDown[y,t,r]>0 || MaxPrimReserveUp[y,t,r]>0 || MaxSecReserveDown[y,t,r]>0
  || MaxSecReserveUp[y,t,r]>0)}: PrimReserveDownByTechnology[y,l,t,r] +
  SecReserveDownByTechnology[y,l,t,r] <= RateOfProductionByTechnology[y,l,t,f,r];
s.t. R11_MinOnlineCapacity{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, f in FUEL, r in
  REGION: ElectricityForTransmissionTag[f,r]=1 && MaxPrimReserveDown[y,t,r] >=
  MinStableOperation[y,t,r] && MaxPrimReserveUp[y,t,r] >= MinStableOperation[y,t,r] &&
  MaxSecReserveDown[y,t,r] >= MinStableOperation[y,t,r] && MaxSecReserveUp[y,t,r] >=
  MinStableOperation[y,t,r]}: RateOfProductionByTechnology[y,l,t,f,r] <=
  OnlineCapacity[y,l,t,r]*CapacityToActivityUnit[t,r];
```

```
s.t. R12_MinElecGeneration2{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, f in FUEL, r in
  REGION: ElectricityForTransmissionTag[f,r]=1 && MaxSecReserveDown[y,t,r] >=
  MinStableOperation[y,t,r] && MaxSecReserveUp[y,t,r] >= MinStableOperation[y,t,r]}:
  OnlineCapacity[y,l,t,r]*MinStableOperation[y,t,r]*CapacityToActivityUnit[t,r] <=
  RateOfProductionByTechnology[y,l,t,f,r];
s.t. R13_MaxPrimCapacityUp{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, f in FUEL, r
  in REGION: f = "PrimReserveUp" && (MaxPrimReserveDown[y,t,r] <
  MinStableOperation[y,t,r] || MaxPrimReserveUp[y,t,r] < MinStableOperation[y,t,r])}:
  RateOfProductionByTechnology[y,l,t,f,r] <=
  OnlineCapacity[y,l,t,r]*MaxPrimReserveUp[y,t,r]*CapacityToActivityUnit[t,r];
s.t. R14_MaxSecCapacityUp{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, f in FUEL, r in
  REGION: f = "SecReserveUp" && (MaxPrimReserveDown[y,t,r] < MinStableOperation[y,t,r] ||
  MaxPrimReserveUp[y,t,r] < MinStableOperation[y,t,r]) && (MaxSecReserveDown[y,t,r] <
  MinStableOperation[y,t,r] || MaxSecReserveUp[y,t,r] <
  MinStableOperation[y,t,r])}:RateOfProductionByTechnology[y,l,t,f,r] <=
  OnlineCapacity[y,l,t,r]*MaxSecReserveUp[y,t,r]*CapacityToActivityUnit[t,r];
s.t. R15_MinElecGeneration{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, f in FUEL, r in
  REGION: ElectricityForTransmissionTag[f,r]=1 && (MaxPrimReserveDown[y,t,r] <
  MinStableOperation[y,t,r] || MaxPrimReserveUp[y,t,r] < MinStableOperation[y,t,r]) &&
  (MaxSecReserveDown[y,t,r] < MinStableOperation[y,t,r] || MaxSecReserveUp[y,t,r] <
  MinStableOperation[y,t,r]) && (MaxPrimReserveDown[y,t,r]>0 || MaxPrimReserveUp[y,t,r]>0
  || MaxSecReserveDown[y,t,r]>0 || MaxSecReserveUp[y,t,r]>0)}:
  OnlineCapacity[y,l,t,r]*MinStableOperation[y,t,r]*CapacityToActivityUnit[t,r] +
  PrimReserveDownByTechnology[y,l,t,r] + SecReserveDownByTechnology[y,l,t,r] <=
  RateOfProductionByTechnology[y,l,t,f,r];
s.t. R16_MinOnlineCapacity{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, f in FUEL, ff in
  FUEL, fff in FUEL, r in REGION: ff = "PrimReserveUp" && fff = "SecReserveUp" &&
  ElectricityForTransmissionTag[f,r]=1 && (MaxPrimReserveDown[y,t,r] <
  MinStableOperation[y,t,r] || MaxPrimReserveUp[y,t,r] < MinStableOperation[y,t,r]) &&
  (MaxSecReserveDown[y,t,r] < MinStableOperation[y,t,r] || MaxSecReserveUp[y,t,r] <
  MinStableOperation[y,t,r])}: RateOfProductionByTechnology[y,l,t,f,r] +
  RateOfProductionByTechnology[y,l,t,ff,r] + RateOfProductionByTechnology[y,l,t,fff,r] <=
  OnlineCapacity[y,l,t,r]*CapacityToActivityUnit[t,r];
s.t. R17_MinOnlineCapacity{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, f in FUEL, ff in
  FUEL, r in REGION: ff = "PrimReserveUp" && ElectricityForTransmissionTag[f,r]=1 &&
  (MaxPrimReserveDown[y,t,r] < MinStableOperation[y,t,r] || MaxPrimReserveUp[y,t,r] <
  MinStableOperation[y,t,r]) && MaxSecReserveDown[y,t,r] >= MinStableOperation[y,t,r] &&
  MaxSecReserveUp[y,t,r] >= MinStableOperation[y,t,r] && (MaxPrimReserveDown[y,t,r]>0 ||
  MaxSecReserveDown[y,t,r]>0 || MaxPrimReserveUp[y,t,r]>0 || MaxSecReserveUp[y,t,r]>0)}:
  RateOfProductionByTechnology[y,l,t,f,r] + RateOfProductionByTechnology[y,l,t,ff,r] <=
  OnlineCapacity[y,l,t,r]*CapacityToActivityUnit[t,r];
s.t. R18_MinElecGeneration{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, f in FUEL, r in
  REGION: ElectricityForTransmissionTag[f,r]=1 && (MaxPrimReserveDown[y,t,r] <
  MinStableOperation[y,t,r] || MaxPrimReserveUp[y,t,r] < MinStableOperation[y,t,r]) &&
  MaxSecReserveDown[y,t,r] >= MinStableOperation[y,t,r] && MaxSecReserveUp[y,t,r] >=
  MinStableOperation[y,t,r] && MaxPrimReserveDown[y,t,r] >
  0}:PrimReserveDownByTechnology[y,l,t,r]*(MinStableOperation[y,t,r] +
```

MaxPrimReserveDown[y,t,r])/MaxPrimReserveDown[y,t,r] + SecReserveDownByTechnology[y,l,t,r] <= RateOfProductionByTechnology[y,l,t,f,r];

Minimum online upward reserve calculations

s.t. R19_MinPrimReserveUpOnline{y in YEAR, l in TIMESLICE, r in REGION}: PrimReserveUpCapacityDemand[y,l,r]*MinPrimReserveUpOnline[y,r] <= sum{t in TECHNOLOGY} PrimReserveUpOnline[y,l,t,r];
s.t. R20_MinSecReserveUpOnline{y in YEAR, l in TIMESLICE, r in REGION}: SecReserveUpCapacityDemand[y,l,r]*MinSecReserveUpOnline[y,r] <= sum{t in TECHNOLOGY} SecReserveUpOnline[y,l,t,r];
s.t. R21_MaxPrimReserveUpOnline1{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, f in FUEL, r in REGION: f = "PrimReserveUp" && (MaxPrimReserveDown[y,t,r] < MinStableOperation[y,t,r] || MaxPrimReserveUp[y,t,r] < MinStableOperation[y,t,r])}: RateOfProductionByTechnology[y,l,t,f,r]/CapacityToActivityUnit[t,r] = PrimReserveUpOnline[y,l,t,r];
s.t. R22_MaxSecReserveUpOnline1{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, f in FUEL, r in REGION: f = "SecReserveUp" && (MaxSecReserveDown[y,t,r] < MinStableOperation[y,t,r] || MaxSecReserveUp[y,t,r] < MinStableOperation[y,t,r])}: RateOfProductionByTechnology[y,l,t,f,r]/CapacityToActivityUnit[t,r] = SecReserveUpOnline[y,l,t,r];
s.t. R23_MaxPrimReserveUpOnline1{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, f in FUEL, r in REGION: f = "PrimReserveUp" && (MaxPrimReserveDown[y,t,r] >= MinStableOperation[y,t,r] && MaxPrimReserveUp[y,t,r] >= MinStableOperation[y,t,r])}: RateOfProductionByTechnology[y,l,t,f,r]/CapacityToActivityUnit[t,r] >= PrimReserveUpOnline[y,l,t,r];
s.t. R24_MaxSecReserveUpOnline1{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, f in FUEL, r in REGION: f = "SecReserveUp" && (MaxSecReserveDown[y,t,r] >= MinStableOperation[y,t,r] && MaxSecReserveUp[y,t,r] >= MinStableOperation[y,t,r])}: RateOfProductionByTechnology[y,l,t,f,r]/CapacityToActivityUnit[t,r] >= SecReserveUpOnline[y,l,t,r];
s.t. R25_MaxReserveUpOnline{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, f in FUEL, r in REGION: ElectricityForTransmissionTag[f,r]=1 && (MaxPrimReserveDown[y,t,r] >= MinStableOperation[y,t,r] && MaxPrimReserveUp[y,t,r] >= MinStableOperation[y,t,r] || MaxSecReserveDown[y,t,r] >= MinStableOperation[y,t,r] && MaxSecReserveUp[y,t,r] >= MinStableOperation[y,t,r])}: OnlineCapacity[y,l,t,r] - RateOfProductionByTechnology[y,l,t,f,r]/CapacityToActivityUnit[t,r] >= PrimReserveUpOnline[y,l,t,r] + SecReserveUpOnline[y,l,t,r];
s.t. R26_MaxPrimReserveUpOnline2{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, r in REGION: MaxPrimReserveDown[y,t,r] >= MinStableOperation[y,t,r] && MaxPrimReserveUp[y,t,r] >= MinStableOperation[y,t,r]}: OnlineCapacity[y,l,t,r]*MaxPrimReserveUp[y,t,r] >= PrimReserveUpOnline[y,l,t,r];
s.t. R27_MaxSecReserveUpOnline2{y in YEAR, l in TIMESLICE, t in TECHNOLOGY, r in REGION: MaxSecReserveDown[y,t,r] >= MinStableOperation[y,t,r] && MaxSecReserveUp[y,t,r] >= MinStableOperation[y,t,r]}: OnlineCapacity[y,l,t,r]*MaxSecReserveUp[y,t,r] >= SecReserveUpOnline[y,l,t,r];

Maximum changes in online capacity and generation

```
s.t. R28_MaxCycling{y in YEAR, l in TIMESLICE, ll in TIMESLICE, t in TECHNOLOGY, f in
  FUEL, r in REGION: ElectricityForTransmissionTag[f,r]=1 && TimeSliceLinkTag[l,ll,r]<>0}:
  OnlineCapacity[y,ll,t,r]*(1-MaxOnlineCapReduction[y,t,r])*TimeSliceLinkTag[l,ll,r] <=
  OnlineCapacity[y,l,t,r];
s.t. R29_MaxGenerationChange{y in YEAR, l in TIMESLICE, ll in TIMESLICE, t in
  TECHNOLOGY, f in FUEL, r in REGION: ElectricityForTransmissionTag[f,r]=1 &&
  TimeSliceLinkTag[l,ll,r]<>0}: (RateOfProductionByTechnology[y,ll,t,f,r] -
  OnlineCapacity[y,ll,t,r]*MaxGenerationReduction[y,t,r]*CapacityToActivityUnit[t,r])*TimeSlic
  eLinkTag[l,ll,r] <= RateOfProductionByTechnology[y,l,t,f,r];
```

```
solve;
end;
```

Appendix D - GNU MathProg formulation of the modifications to OSeMOSYS

D.1. Fuel consumption at partial load

New constraints:
s.t. R30_PartialLoad{r in REGION, t in TECHNOLOGY, l in TIMESLICE, f in FUEL, y in YEAR: ElectricityForTransmissionTag[r,f]=1 }: OnlineCapacity[r,t,l,y]* CapacityToActivityUnit[r,t] - RateOfProductionByTechnology[r,t,l,f,y] = LoadPartialisation[r,t,l,y];

Updated constraints:
s.t. EBa5_RateOfFuelUse2{r in REGION, t in TECHNOLOGY, l in TIMESLICE, f in FUEL, y in YEAR}: sum{m in MODE_OF_OPERATION: InputActivityRatio[r,t,f,m,y]<>0} RateOfUseByTechnologyByMode[r,t,l,f,m,y] + LoadPartialisation[r,t,l,y]* AdditionalFuelUse[r,t,f,y] = RateOfUseByTechnology[r,t,l,f,y];

D.2. Cycling performance as a function of the power plant configuration

New constraints:
s.t. CAa5_Accumulated_Withdrawn_Capacity{r in REGION, t in TECHNOLOGY, y in YEAR}: AccumulatedWithdrawnCapacity[r,t,y]= sum{yy in YEAR: y-yy>=0} WithdrawnCapacity[r,t,yy];
s.t. CAa6_AccumulatedRetiredCapacity{r in REGION, t in TECHNOLOGY, y in YEAR}: AccumulatedRetiredCapacity[r,t,y] = sum{yy in YEAR: y-yy>=0 && (yy +1)<= (max{yyy in YEAR} max(yyy))}(ResidualCapacity[r,t,yy] - if ResidualCapacity[r,t,yy+1] <=ResidualCapacity[r,t,yy] then ResidualCapacity[r,t,yy+1] else ResidualCapacity[r,t,yy]);
s.t. CAa7_Accumulated_Withdrawn_Capacity2{r in REGION, t in TECHNOLOGY, tt in TECHNOLOGY, y in YEAR: (y+1) <= (max{yy in YEAR}max(yy))}: AccumulatedWithdrawnCapacity[r,t,y+1] >= AccumulatedRetiredCapacity[r,t,y];
s.t. CAa8_Withdrawn_Capacity{r in REGION, t in TECHNOLOGY, y in YEAR: (y+1) <= (max{yy in YEAR}max(yy))}: WithdrawnCapacity[r,t,y+1] <= TotalCapacityAnnual[r,t,y]- AccumulatedNewCapacity[r,t,y];
s.t. CAa9_Balance_old_retrofitted{r in REGION, t in TECHNOLOGY, tt in TECHNOLOGY, y in YEAR: RetrofitLink[r,t,tt]=1}: TotalCapacityAnnual[r,t,y] + TotalCapacityAnnual[r,tt,y] - AccumulatedNewCapacity[r,t,y] - AccumulatedNewCapacity[r,tt,y] = ResidualCapacity[r,t,y]+ResidualCapacity[r,tt,y];
s.t. CAa10_AccumulatedRetrofittedCapacity{r in REGION, t in TECHNOLOGY, tt in TECHNOLOGY, y in YEAR}: AccumulatedRetrofittedCapacity[r,t,y] = sum{yy in YEAR: y-yy>=0 && (y-(min{yyy in YEAR}min(yyy)))<=OperationalLife[r,t]}RetrofittedCapacity[r,t,yy];
s.t. CAa11_RetrofittedCapacity{r in REGION, t in TECHNOLOGY, tt in TECHNOLOGY, y in YEAR}: (WithdrawnCapacity[r,t,y]-RetrofittedCapacity[r,tt,y])*RetrofitLink[r,t,tt]>=0;

Updated constraints:

s.t. CAa2_TotalAnnualCapacity{r in REGION, t in TECHNOLOGY, y in YEAR}: AccumulatedNewCapacity[r,t,y]+ ResidualCapacity[r,t,min{yy in YEAR}min(yy)] - AccumulatedWithdrawnCapacity[r,t,y]+AccumulatedRetrofittedCapacity[r,t,y] = TotalCapacityAnnual[r,t,y];
s.t. CC1_UndiscountedCapitalInvestment{r in REGION, t in TECHNOLOGY, y in YEAR}: CapitalCost[r,t,y] * NewCapacity[r,t,y] + CostOfRetrofit[r,t,y]*RetrofittedCapacity[r,t,y] = CapitalInvestment[r,t,y];

D.3. Cost of the starts

New constraints:
s.t. OC5_DeltaOnlineCapacity1{r in REGION, t in TECHNOLOGY, l in TIMESLICE, ll in TIMESLICE, y in YEAR: TimeSliceLinkTag[r,l,ll]<>0}: DeltaOnlineCapacity[r,t,l,y] >= (OnlineCapacity[r,t,l,y]-OnlineCapacity[r,t,ll,y])*TimeSliceLinkTag[r,l,ll];
s.t. OC6_DeltaOnlineCapacity2{r in REGION, t in TECHNOLOGY, l in TIMESLICE, ll in TIMESLICE, y in YEAR: TimeSliceLinkTag[r,l,ll]<>0}: DeltaOnlineCapacity[r,t,l,y] >= (OnlineCapacity[r,t,ll,y]-OnlineCapacity[r,t,l,y])*TimeSliceLinkTag[r,l,ll];
s.t. OC7_CostOfRamps{ r in REGION, t in TECHNOLOGY, l in TIMESLICE, ll in TIMESLICE, y in YEAR}: CostOfRamps[r,t,l,y] = DeltaOnlineCapacity[r,t,l,y]* CostOfRampsPerCapacity[r,t] /2*365* YearSplit[l,y];
s.t. OC8_AnnualCostStarts{r in REGION, t in TECHNOLOGY, y in YEAR}:sum{l in TIMESLICE}CostOfRamps[r,t,l,y]=AnnualCostStarts[r,t,y];

Updated constraints:
s.t. OC3_OperatingCostsTotalAnnual{r in REGION, t in TECHNOLOGY, y in YEAR}: AnnualFixedOperatingCost[r,t,y]+AnnualVariableOperatingCost[r,t,y]+AnnualCostStarts[r,t,y] = OperatingCost[r,t,y];

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