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ENERGY FORECAST MODELLING AND TOOLS:
a case study of The United Kingdom

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List of Figures

List of Tables

Abstract

The theme of energy forecasting is today a very sensitive topic. Until a few decades ago no one posed certain problems such as depletion of fossil resources and the degree of air pollution. Humanity is experiencing a time of great changes and, among these, energy supply is one of the most complicated aspects. In fact there are also other aspects connected to this theme, such as the unsustainability of an economy based on fossil fuels and the climate change in act. To address this issue each State is required to adopt an energy strategy that covers several years and not just the upcoming, in order to allow an appropriate transition towards greater sustainability. To this end, this work will attempt to provide an appropriate tool for accurate energy forecasting and, by creating different scenarios, it will try to analyze the possible actions to be considered, in order to achieve future goals aimed, for example, towards a more sustainable energy environment.
For the development of the thesis was therefore necessary to explore the theme of energy projections and the means used to conduct them, analyzing through the scientific literature their capabilities and limitations and choosing, finally, the most appropriate means for the goal set for this thesis.
The data collection has been a long and laborious task, necessary to obtain official data and validate the work of this thesis. The energy balance of the case study, the United Kingdom, is analyzed and then some scenarios have been built, which include a period between 2010 and 2040, based on official energy policies of the case study. Then the advantages of using the proposed instrument for energy prediction are highlighted, as well as the benefits of its use as an aid in policy planning strategies.

Keywords

Energy, energy forecast, energy policies, future strategies, leap, energy scenarios.

Sommario

Il tema delle previsioni energetiche è oggi un argomento molto delicato. Fino a pochi decenni fa nessuno si poneva certe problematiche quali l’esaurimento delle risorse di origine fossile e il grado di inquinamento atmosferico. L’umanità sta vivendo un’epoca di grandi cambiamenti e, tra questi, l’approvvigionamento energetico risulta uno degli aspetti più complicati a cui se ne collegano altri, quali l’insostenibilità di un’economia basata su fonti fossili e il cambiamento climatico in atto. Per affrontare tale argomento è necessario che ogni Stato adotti una strategia energetica che ricopra diversi anni e non solamente quelli imminenti, per poter permettere una fase di transizione adeguata verso una maggiore sostenibilità. A tal fine questo lavoro cercherà di fornire uno strumento alternativo per permettere una previsione energetica accurata e, tramite la creazione di diversi scenari, analizzare le possibili azioni da intraprendere per raggiungere obbiettivi futuri volti, per esempio, verso un ambiente energetico più sostenibile.
Per lo sviluppo della tesi è quindi stato necessario approfondire il tema delle previsioni energetiche ed i mezzi utilizzati per condurle, analizzandone nella letteratura scientifica le capacità ed i limiti e scegliendo, infine, il mezzo più appropriato per l’obbiettivo prefissato per questa tesi.
La raccolta dati si è rivelato un compito lungo e laborioso per poter ottenere dati ufficiali e validare il lavoro di questa tesi. E’ stato analizzato il bilancio energetico del caso studio, il Regno Unito, e si sono poi costruiti degli scenari, che comprendono un periodo tra il 2010 e il 2040, basati sulle politiche energetiche ufficiali del caso studio. Si evidenziano quindi i vantaggi nell’usare lo strumento proposto per la previsione energetica e come ausilio nella pianificazione delle strategie politiche.

Parole chiave

Energia, previsione energetica, politiche energetiche, strategie future, leap, scenari energetici.

Acronyms and Abbreviations

DUKES	Digest of United Kingdom Energy Statistics
EPA	US Environmental Protection Agency
GHG	Greenhouse Gas
HDI	Human Development Index
IEA	International Energy Agency
LEAP	Long range Energy Alternatives Planning system
OECD	Organization for Economic Co-operation and Development
UK	The United Kingdom
WEO	World Energy Outlook

1. Introduction

The present work analyzes the energy demand of a European country used as a case study, the United Kingdom, and presents a long-term forecast. More specifically, it describes the current energy account of the UK and forecasts the trend of its demand in the long-term, carefully examining current policies and creating energy scenarios based on these policies for the years between 2010 and 2040, through a software for energy projections. The objective of this thesis is to develop an alternative instrument for energy forecast, by analyzing the existing models in the scientific literature, and to apply it to a case study, consequently observing the effects of different kinds of energy management regarding the case study. An authority, for example, through the creation of different scenarios according to the chosen constraints, could compare the different results obtained, discuss strengths and weaknesses, and choose the energy strategy that best suits its needs, having an accurate energy forecasting. This is also important because of the recent climate conference in Paris, the COP21, in which several countries have made important commitments. In particular, the EU and its Member States have committed to a binding target of at least 40% domestic reduction in greenhouse gas emissions by 2030 compared to 1990, to be fulfilled jointly, as set out in the conclusions by the European Council of October 2014.
For the development of the thesis it was therefore necessary to examine the theme of energy forecasts and the means used to conduct them, analyzing the capabilities and limitations of each one and choosing, finally, the most appropriate for the case study. The software used for the analysis, LEAP, proved its usefulness and importance in energy forecast through the results and graphics given by its output. Its flexible hierarchical structure was essential to describe the different systems taken into account on several detailed levels and with different degrees of accuracy. The country chosen for the case study is one of the most industrialized and advanced and it was picked based on the ease in retrieving official data. In this way, a more accurate analysis was carried out, with the objective of making the results obtained more representative of reality.
The thesis is organized as follows: part 1 presents the theory about energy demand and energy forecast, in order to better understand the significance of this work and to introduce the reasons behind the choice of the tool used. Part 2 presents the tool used to conduct the study, the World Energy Outlook that inspired the baseline scenario, and the LEAP analysis of the case study. This analysis was conducted primarily through a hard work of gathering official energy data, in order to be able to product an accurate energy forecast. Hence, the first part of the work wants to provide the methodology and the inputs to carry out the analysis, which is developed in the second part.
All these aspects are presented in the following chapters on a detailed level.

Part 1

Capitolo 2 | Energy Demand

This chapter talks about energy demand: the first part presents an introduction to try to understand what this section is talking about. It continues by analyzing in more detail the energy demand through its economic foundations of energy demand, from theory to practice.

2.1 Understanding Energy Demand

Energy demand [1] is a derived demand that arises for satisfying some needs which are met through use of appliances. Hence, demand for energy then depends on the demand for energy services and the choice of energy using processes or devices. End-use service demand is affected by the cost of energy but also by other factors such as climatic conditions, affordability (or income of the decision-maker), preference for the end-use service, etc. Similarly, demand for end-use appliances depends on the relative prices of the appliances, relative cost of operation, availability of appliances, etc.

The dynamics of energy demand is influenced by the inertia of appliance stocks, which leads to limited flexibility. At any given time any consumer would possess a stock of some particular devices with specific operating characteristics (such as efficiency and costs). The stock cannot be changed immediately and therefore the response to any stimulation would come from behavioral changes (i.e. rate of use of the appliance, acceptance of lower levels of comforts, etc.) while using the same appliances. Over a longer period of time, consumers may find changing the stock of appliances remunerative. Similarly, new procurements would incorporate the characteristics preferred by consumers given the changes in the market conditions [1]. Therefore, in the short run the response is partial while the total response would be cumulate over time.

Energy demand analysis has attempted to capture these aspects in different ways: the traditional economists' approach relies on optimizing behavior within the neoclassical tradition of economics. Another approach follows the engineering tradition and criticizes the limitations of the optimizing and rational behavior assumed in the traditional analysis. Instead, they introduce other behavioral assumptions (such as "satisficing" approach in the sense of Herbert Simon [2] or evolutionary approach for technological change) and beliefs [3]. This divergence in the views has dominated the energy literature in the past and led to the emergence of two distinct traditions of energy analysis – namely the econometric approach and the engineering end-use approach.

2.2 Economic foundations of energy demand [4]

The factors driving energy demand differ across economic agents and sectors. Households consume energy to satisfy certain needs and they do so by allocating their income among various competing needs so as to obtain the greatest degree of satisfaction from total expenditure. Industries and commercial users demand energy as an input of production and their objective is to minimize the total cost of production. Therefore the motivation is not same for the households and the productive users of energy and any analysis of energy demand should treat these categories separately.

2.2.1 Household energy demand

The microeconomic basis for consumer energy demand relies on consumers' utility maximization principles. Such an analysis assumes that consumers know their preference sets and ordering of preferences. It also assumes that preference ordering can be represented by some utility function and that the consumer is a rational one in that it will always choose a most preferred bundle from the set of feasible alternatives. Following consumer theory [4], it is considered that an incremental increase in consumption of a good keeping consumption of other goods constant, increases the satisfaction level but this marginal utility (or increment) decreases as the quantity of consumption increases. Moreover, maximum utility achievable given the prices and income requires marginal rate of substitution to be equal to the economic rate of substitution. This in turn requires that the marginal utility per dollar paid for each good be the same. If the marginal utility per dollar is greater for good A than for good B, then transferring a dollar of expenditure from B to A will increase the total utility for the same expenditure. It follows that reduction in the relative price of good A will tend to increase the demand for good A and vice versa.

It follows the mathematical formulation of the problem:

Utility maximization and energy demand [4]
Consider that the utility function of a consumer can be written as

$$u = U(\mathrm{X1}, \mathrm{X2}, \mathrm{X3}, ..., \mathrm{Xn})$$

Eq. 1

Where Xn are the goods. The consumer has the budget constraint I:

$$I = p1X1 + p2X2 + ... + pnXn$$

Eq. 2

Where pn are the prices of Xn. For maximization of the utility subject to the budget constraint, set the Lagrange

$$L = U(X1, X2, X3, ..., Xn) - \lambda(I - (p1X1 + p2X2 + ... + pnXn))$$

Eq. 3

Setting partial derivatives of L with respect to X1, X2, X3,…, Xn and λ equal to zero, n+1 equations are obtained representing the necessary conditions for an interior maximum.

$$\frac{\delta L}{\delta X_1} = \frac{\delta U}{\delta X_1} - \lambda p_1 = 0$$

$$\frac{\delta L}{\delta X_2} = \frac{\delta U}{\delta X_2} - \lambda p_2 = 0$$

$$\frac{\delta L}{\delta X_n} = \frac{\delta U}{\delta X_n} - \lambda p_n = 0$$

$$\frac{\delta L}{\delta \lambda} = 1 + p_1 X_1 + p_2 X_2 + ... + p_n X_n = 0$$

Eq. 4

From above,

$$\left(\frac{\delta U}{\delta X_1}\right) / \left(\frac{\delta U}{\delta X_2}\right) = p_1 / p_2$$

Eq. 5

$$\lambda = \left(\frac{\delta U}{\delta X_1}\right) / p_1 = \left(\frac{\delta U}{\delta X_2}\right) / p_2 = ... = \left(\frac{\delta U}{\delta X_n}\right) / p_n$$

Eq. 6

Solving the necessary conditions yields demand functions in prices and income.

$$X_1 = d_1(p_1, p_2, ..., p_n, I)$$
$$X_2 = d_2(p_1, p_2, ..., p_n, I)$$
$$\vdots$$
$$X_n = d_n(p_1, p_2, ..., p_n, I)$$

Source: Bohi (1981)

An individual demand curve shows the relationship between the price of a good and the quantity of that good purchased, assuming that all other determinants of demand are held constant. The market demand function for a particular good is the sum of each individual's demand for that good. The market demand curve for the good is constructed from the demand function by varying the price of the good while holding all other determinants constant.

2.2.2 Industrial and commercial energy demand

In the case of industry and commercial sectors, energy is used as an input to produce an output (or outputs). The theory of the producers is used to determine energy demand in both sectors. Like households, producers face certain constraints:

a) The production process has its own technical limitations that specify the maximum output levels for a given combination of inputs.
b) The capacity of the plant at any given time is fixed and cannot be exceeded.
c) There may be constraints on the availability of certain inputs.

Production of any good is expanded until an additional increment of the good produced in the most efficient manner makes no further contribution to net revenue. Similarly, any factor of production will be increased until, other inputs remaining unchanged, an additional unit of the factor yields no additional net revenue. In order to minimize the cost of any given level of input, the firm should produce at that point for which the rate of technical substitution is equal to the ratio of the inputs' rental prices. The solution of the conditions leads to factor demand functions.

Cost minimization problem of the producer

Consider a firm with single output, which is produced with two inputs X1 and X2. The cost of production is given by

$$TC = c_1 X_1 + c_2 X_2$$

Eq. 7

Where cn are the costs of each inputs. This is subject to

$$St\ q_0 = f(X_1, X_2)$$

Eq. 8

The first order conditions for a constrained minimum are:

$$\delta L / \delta X_1 = c_1 - \lambda \delta f / \delta X_1 = 0$$
$$\delta L / \delta X_2 = c_2 - \lambda \delta f / \delta X_2 = 0$$

Eq. 9

From above,

$$c_1 / c_2 = (\delta f / \delta X_1) / (\delta f / \delta X_2) = RTS(X1 for X2)$$

Eq. 10

In order to minimize the cost of any given level of input, the firm should produce at that point for which the rate of technical substitution is equal to the ratio of the inputs' rental prices.
The solution of the conditions leads to factor demand functions.

2.2.3 Transport energy demand

For energy demand in the transport sector, three types of generic approaches are found:

a) Identity models
b) Structural models
c) The market-share model

The identity models consider the demand for a transport fuel to be equal to the product of vehicle utilization rate and total stock of vehicles. This can be expressed as

$$D_t = S_t \cdot R_t \cdot U_t$$

Eq. 11

where Dt is the demand for fuel at time t, St is the vehicle stock, Rt is the utilization rate (kilometers per year) and Ut is the unit energy consumption (litre per kilometer). The demand is estimated by estimating each component separately and the overall demand is obtained using the identity. Uri [5] provides an early example of application of this model econometrically. This identity is generally used in end-use models as well but applied as a disaggregated level.
The structural model on the other hand considers the demand for the transport services and derives the demand for energy related to those transport services as a derived demand. The demand for transport services is explained using the basic consumer theory assuming that profit maximizing firms choose the transport service to minimize costs of production (see par. Structural models of transport fuel demand). For given cost minimizing demands for transport services, the derived demand for specific fuels is developed.
The market-share model on the other hand considers the inter-fuel substitution possibilities. To ensure a consistent outcome, the demand is estimated using a set of simultaneous equation systems.
Clearly, the neo-classical foundation of the above theories of demand analysis assumes the completeness of markets and the participation of energy products in the market. Any energy that remains outside the market system is not covered. Accordingly, traditional energies which are collected by the users and for which no monetary transactions take place will not be covered by these theories. In addition, the external effects of energy use, to the extent they are not captured through the market pricing system, will not enter into the decision-making process, thereby providing incorrect resource allocation information and decisions. Informal economic activities will also not be included, thereby providing inaccurate information and forecasts.
Accordingly, the key assumptions imbedded in the theoretical foundation might be unrealistic in the context of developing countries. The co-existence of market and non-market based energy supplies introduces a complex decision-making which requires considering monetary and non-monetary transactions. The paragraph Rationale for traditional energy use in developing countries explains the necessity to incorporate traditional energy in energy demand modeling exercises in developing countries. Ignoring an important energy source from analysis due to data constraints or limitations of the analytical framework does not provide a realistic or correct picture.

2.2.3.1 Structural models of transport fuel demand [6]

The structural models generally determine the transport fuel demand using a two-stage process. In the first stage, the demand for transport services is related to the distance traveled by passengers (indicated by passenger-kilometers) and freight transport (indicated by ton-kilometers). For these two types of transport demand, the basic theories of consumer demand and producer demand are used.
For passenger demand, it is assumed that individuals maximize their utility through optimal selection of their goods and services operating within their budget constraint. The demand function is derived from the constrained optimization of the utility function. This yields the demand function of the following form:

$$PT = f(1, P_p, W, D)$$

Eq. 12

Where PT is the passenger transport demand function, I is the real income, Pp is the price of passenger transport, W is the price vector for other goods and services, D is a vector of other demographic variables.
For freight transport, let us assume that the industry using the transport services minimizes its cost. Let the cost function be denoted by:

$$C(\mathrm{P}_f, P_0, X, Q)$$

Eq. 13

Where Pf is the price for freight transport (per ton kilometer), Po – the price vector for other inputs, X is a vector of fixed factor quantities, Q is the level of output.
The cost minimizing demand for freight is obtained by differentiating the cost function with respect to Pf, which yields the demand equations of the following form:

$$FT = f2(Q, P_f, P_0, X)$$

Eq. 14

Given the demand for PT and FT, the demand for specific fuels is obtained assuming appropriate separability of functions. It is now considered that the utility or cost function contains the relevant passenger or freight demand, the price of the relevant fuels and other factor inputs or variables. The demand function for a specific fuel is obtained by differentiating Eq. 14 with respect to its price and takes the following form:

$$Demand = g(PT, FT, P)$$

Eq. 15

The two-stage econometric model for transport fuel demand is thus obtained.

Source: Brendt and Botero (1985)

2.2.3.2 Rationale for traditional energy use in developing countries [7]

Any energy use involves costs and resource allocation problems. Both traditional energies (TE: we use the term ‘traditional energies’ to ‘non-commercial energies’ to avoid any confusion arising out of monetisation or commercialisation of some of such fuels) which play a crucial role in the energy profile of the poor, and modern energies impose private and social costs. The private cost may be in monetary terms or in terms of time spent by the family members to collect the TEs. For collected TEs, the problem of valuation of the cost arises and the collected fuel is considered as free fuel by many, even perhaps by the poor themselves, as no monetary transactions are involved. However, depending on the quantity of collected fuel, its source and the type of labor used in the collection process, the private cost and social cost can be substantial. The social cost arises due to externalities arising from pollution and other socio-economic problems related to particular forms of energy use.

The entire decision-making process for use of any modern energy form (electricity, kerosene or LPG, or renewable energies) as opposed to any other form of traditional energies revolves around monetary transactions. Any commercial energy requires monetary exchanges and the decision to switch to commercial energies can be considered a three-stage decision-making process. First, the household has to decide whether to switch or not (i.e. switching decision). Second, it decides about the types of appliances to be used (i.e. appliance selection decision). In the third stage, consumption decision is made by deciding the usage pattern of each appliance (i.e. consumption decision).

While the costs do not always lend themselves to monetary-based accounting, the switching decision is largely determined by monetary factors: the amount and regularity of money income, alternative uses of money and willingness to spend part of the income to consume commercial energies as opposed to allocating the money to other competing needs. Appliance selection is affected by similar factors: cost of appliance, the monetary income variables described above and the availability of financing for appliance purchases through formal and informal credit markets. Finally, the consumption decision depends on, among others, family size, activities of the family members, availability of appliances and family income.

This framework of three-stage decision-making helps in analyzing the problem in a logical manner. The poor normally lack regular money income flows due to unemployment or part-employment, both of which sometimes produce in-kind payments as compensation. Moreover, they often participate in informal sector activities, where barter rather than monetized transactions prevail. It is rational for any household or individual to focus on private monetary costs rather than social and/or non-monetized costs due to the inherent subjectivity and complexity of the valuation problem. Moreover, any modern energy has to compete with other goods and services (including saving for the future) procured by the household for an allocation of monetary resources. Given above characteristics and constraints, it is quite logical for the poor to have a natural preference for the fuel that involves no or minimum money transactions. Reliance on firewood and other traditional energies used for cooking, which constitute the major source of energy demand by the poor, can be explained using this logic.

Source: Bhattacharyya (2006)

Bhattacharyya [8] further noted that “The application of economic theories that presuppose the existence of monetized markets and are concerned only with agents involved in such markets faces serious conceptual problems in dealing with economies that do not conform to such stereotypes. Serious conceptual difficulties and incompatibilities arise in the valuation of goods for which no tangible payment is made. For energy goods, the problem is further complicated by the fact that these are not goods for direct consumption but intended to derive certain end-use, which could be satisfied by a number of substitutes. Evaluating the contribution of these energies in monetary terms when some are acquired through non-money activities still rests problematic. Because non-money activities often occupy a far greater share than the monetized part in the rural energy of a developing economy, it is thus imperative that any and every economic indicator for these sectors and the whole economy should take into account both the monetized and the non-monetized sectors, as well as their mutual interaction".

While the theory is capable of capturing non-price variables in principle, the implementation in actual models would show how far this is captured. Similarly, the reliance on consumption data implies that only the satisfied demand is captured in the energy statistics. Using consumption and demand interchangeably implies that the non- manifested demand is not taken into consideration in practice. This again can introduce a bias in the analysis by providing an inaccurate picture in developing countries. Hence, the prescriptions based on standard economic theories can be misleading.

2.3 Energy demand modeling in practice [1]

In order to understand the mechanism of the model, this section presents a review of selected literature on energy demand forecasting with a view to take stock of the evolution in the knowledge and modeling preferences.

2.3.1 Aggregate energy demand forecasting

Aggregate energy demand generally refers to what is known as primary energy demand in energy accounting terminology and is normally obtained by combining the demand for various sectors and the energy needs for the transformation sector. Below it is presented two studies: one about primary energy demand forecasting and one sector or fuel-level aggregate studies. In the end-use tradition, the aggregated demand is obtained by summing demand at the disaggregated levels and accordingly, in methodological terms, there is nothing specific here. In contrast, in the econometric approach, some studies have focused on the aggregate demand only. In addition, there are some econometric studies which forecast energy demand by fuel or by sector but focus on the sectors or the fuels as a whole.

2.3.1.1 Primary energy demand forecasting

The aggregated studies were common using reduced form specifications because data and computing capacity was limited. Dahl (1994a) suggests that although models are found to test per capita energy and total energy consumption in the reduced form versions with or without dynamic elements, "aggregation can cause heteroscedasticity when the population varies across the sample." (See Difference between the total and per capita specifications of energy demand below for further explanation).

2.3.1.1.1 Difference between the total and per capita specifications of energy demand [9]

Consider a simple log-linear demand specification with price and income as dependent variables:

$$\ln Q = \alpha + \beta \ln P + \gamma \ln Y \qquad \text{Eq. 16}$$

where Q is the total energy demand, P is the price of energy and Y is the GDP of the country.

The per-capita specification can be written as:

$$\ln(Q/pop) = \delta + \varepsilon \ln(P) + \zeta \ln(Y/pop) \qquad \text{Eq. 17}$$

Where pop represents population. This equation can be rewritten as:

$$\ln Q = \delta + \varepsilon \ln(P) + \zeta \ln(Y) + (1-\zeta)\ln(pop) \qquad \text{Eq. 18}$$

Comparing Eq. 16 with Eq. 18, it becomes clear that the two specifications are equivalent, if the income elasticity is equal to 1. When the income elasticity is different from one, the two specifications are not equivalent because of the last term in Eq. 18. When ζ>1, the last term in Eq. 18 is negative and when ζ<1, the last term is positive. This would affect the income elasticity estimation and the forecast.

Source: Dahl (1994a)

Another study is presented by Westoby and Pearce [10] where they stablish a linear relationship between output and energy adjusted for calorific content or to study linear relationships between energy and income. Subsequently, more variables, including price, were included in the single equation models, so energy intensity has also been modeled in single equation form by linking it to price, fuel share and economic structure. The study finds that simple energy-output relationships break down during the periods of unstable energy prices and can provide robust forecasts even if these models are "cheap and transparent" and can still play a role in policy and planning decision-making processes. This view is echoed by Bohi and Zimmerman [11] who found that reduced form models produced comparable results as obtained from structural models and performed well. (See typical examples of single equation econometric models below).

2.3.1.1.2 Typical examples of single equation econometric models [10]

The following equations provide examples of specifications used in simple econometric analyses. E is energy consumption, Y is income (GDP), P is price, POP is population, EMP is employment of labour, a, b, c, d, e, f, - are coefficients to be determined through the estimation process, t is time period t while t-1 represents the time period before t.

a. Linear relation between energy and income (GDP)

$$E_t = a + bY_t$$

Eq. 19

This implies an (income) elasticity that tends asymptotically to unity as income increases. Note that b is not the elasticity in this specification, which has to be determined from the basic definition of elasticity (This turns out to be (1-a/E) and as E tends to infinity, the elasticity tends to 1).

b. Log-linear specification of income and energy

$$\ln E_t = \ln a + b \ln Y_t$$

Eq. 20

Here b represents the elasticity of demand, which is a constant by specification.

c. Linear relation between energy and price and income variables

$$E_t = a + bY_t + cP_t$$

Eq. 21

This is not a popular specification however.

d. Log-linear specification of income, price and energy

$$\ln E_t = \ln a + b \ln \mathrm{Y}_t + c \ln P_t$$

Eq. 22

As with model (b), the short-run price and income elasticities are directly obtained here.

e. Dynamic version of log-linear specification of energy with price and income variables

$$\ln E_t = \ln a + b \ln \mathrm{Y}_t + c \ln P_t + d \ln E_{t-1}$$

Eq. 23

The short run and long-run price and income elasticities are obtained here.

f. Log-linear model of price and other demographic variables

$$\ln E_t = \ln a + b \ln \mathrm{Y}_t + c \ln P_t + c \ln EMP_t + d \ln POP_t$$

Eq. 24

g. Log-linear model of energy, price, income, fuel share and economic structure variables

$$\ln E_t = \ln a + b \ln \mathrm{P}_t + c \ln \mathrm{Y}_t + d \ln F_t + e \ln S_t$$

Eq. 25

h. Dynamic version of the above model

$$\ln E_t = \ln a + b \ln \mathrm{P}_t + c \ln \mathrm{Y}_t + d \ln F_t + e \ln S_t + f \ln E_{t-1}$$

Eq. 26

i. Linear relation between per capita energy and income

$$\frac{E_t}{POP_t} = a + b \frac{Y_t}{POP_t}$$

Eq. 27

j. Log linear relation between per capita energy and income

$$\ln \frac{E_t}{POP_t} = \ln a + \ln b \frac{Y_t}{POP_t}$$

Eq. 28

k. Log-linear relation between energy intensity and other variables

$$\ln E_t / Y_t = \ln a + b \ln P_t + c \ln \mathrm{F}_t + d \ln S_t$$

Eq. 29

l. Dynamic version of log-linear energy intensity relation

$$\frac{\ln E_t}{Y_t} = \ln a + b \ln P_t + c \ln \mathrm{F}_t + d \ln S_t + e \ln E_{t-1} / Y_{t+1}$$

Eq. 30

Source: Westoby and Pearce (1984)

The main objective of these studies and others that it did not mentioned was to identify any statistically significant relationships between commonly known economic variables and aggregate energy demand even if they do not capture the spatial dimension or the traditional energies or technological diversity. Most of these studies find long-term price and income elasticities of energy demand does not play a significant role in influencing demand in developing countries where income drives the demand because in such cases may not be helpful. Further, these studies do not consider traditional energies, informal economic activities and being aggregated studies ignore rural-urban divide and technological diversities existing in developing countries. While such studies employ State-of-the-art econometric knowledge, the outcomes may prove to be of limited use for policy-making in developing countries.

2.3.1.2 Sector or fuel-level aggregate studies

Several studies focusing on specific fuels or specific sectors are found in the literature. For example, Suganthi and Jagadeesan [12] and more recently Iniyan et al [13] have reported aggregate demand models for India. The 1992 study considered three fuels (coal, oil and electricity) and presented estimations and forecasts for each fuel for 1995-96 and 2000-01. However, as this study used coal replacement equivalent as the unit of energy and the term was not adequately clarified, it was not possible to check how their forecast fared compared to the actual demand. Their 2006 study presents a system of three models for India for configuring energy systems for three years 2010-11, 2015-16 and 2020-21.

Since the 1990s, some studies analyzing specific fuel demand at the aggregate level have also used cointegration and error correction methods. For example, Chan and Lee [14] have analyzed coal demand in China using three alternative specifications, namely Engle-Granger's error correction model, Hendry's error correction model and Hendry's general-to-specific approach. Similarly, Moosa [15] analyses oil demand in developing countries to find the correct specification and importance of oil price in the demand relation.

Several studies do not allow a careful consideration of rural-urban dichotomy and often do not go beyond identifying the price and income elasticities as the drivers. The role of technology is hardly considered and structural change does not appear as a main concern. Given that all developing countries are aiming at breaking away from the past demand trend, attempts to find better or closer fit with the past data may not bear much importance for the future. There lies the problem with the econometric approach of demand analysis in the context of developing economies.

2.3.2 Energy demand forecasting at the sector level

The major energy consumers are the industry, transport, and residential sector. Now is presented how alternative approaches have attempted energy demand forecasting.

2.3.2.1 Industrial sector

2.3.2.1.1Econometric approach

Earlier studies of industrial energy demand, as Brendt and Wood [16], either focused on outputs solely and did not consider the influence of price on demand or failed to take inter-fuel and inter-factor substitution possibilities. They used trans-log cost function for analyzing industrial energy demand.

Translog cost function [17]

The translog cost function is considered to be the second order approximation of an arbitrary cost function. It is written in general form as follows:

$$\ln C = \propto_0 + \sum \propto_i \ln P_i + 0.5 \sum_i \sum_j \gamma_{ij} \ln P_i \ln P_j + \propto_Q \ln Q + 0.5 \gamma_{QQ} \left(\ln Q \right)^2 + \sum_i \gamma_{Qi} \ln Q \ln P_i$$

Eq. 30

where C = Total cost, Q is output, Pi are factor prices, i and j = factor inputs.

This cost function must satisfy certain properties:

- homogeneous of degree in prices;
- satisfy conditions corresponding to a well-behaved production function.
- Cost function is homothetic (separable function of output and factor prices) and homogeneous.

Accordingly, the following parameter restrictions have to be imposed:

$$\sum \propto_i = 1$$

Eq. 31

$$\gamma_{ij} = \gamma_{ji}, i \neq j$$

Eq. 32

$$\sum_i \gamma_{ij} = \sum_j \gamma_{ji}$$

Eq. 33

$$\sum_i \gamma_{Qi} = 0$$

Eq. 34

$$\gamma_{Qi} = 0 \qquad \gamma_{QQ} = 0$$

Eq. 35

The derived demand functions can be obtained from Shepherd's lemma

$$X_i = \delta C / \delta P_i$$

Eq. 36

Although these functions are non-linear in the unknown parameters, the factor cost shares $M_i = P_i X_i / C$ are linear in parameters.

$$M_i = \propto_i + \sum_j \gamma_{ij} \left(\ln P_j \right)$$ [for i = factor inputs, j = factor inputs, i # j

Eq. 37

These share equations are estimated to obtain the parameters. Only n-1 such equations need to be estimated as the shares must add to the first equation.
The own price elasticity of factor demand is obtained as follows:

$$E_{ii} = \delta \ln X_i / \delta \ln P_i$$

Eq. 38

$$X_i = \frac{C}{P_i} (\propto_i + \sum_j \gamma_{ij} \ln P_j$$

Eq. 39

$$\ln X_i = \ln C - \ln P_i + \ln \left(\propto_i + \sum_j \gamma_{ij} \ln P_j \right) = \ln C - \ln P_i + \ln M_i$$

Eq. 40

$$\frac{\delta \ln X_i}{\delta \ln P_i} = \frac{\delta \ln C}{\delta \ln P_i} - 1 + \frac{\gamma_{ii}}{M_i}$$

Eq. 41

$$E_{ii} = M_i + \frac{\gamma_{ii}}{M_i} - 1$$

Eq. 42

$$E_{ii} = \frac{M_i^2 - M_i + \gamma_{ii}}{M_i}$$

Eq. 43

The cross-price elasticity can be derived similarly as

$$E_{ii} = \frac{\gamma_{ii} + M_i M_j}{M_i}$$

Eq. 44

Allen partial elasticity of substitution is given by:

$$\sigma_{ij} = \frac{\gamma_{ii} + M_i M_j}{M_i M_j}$$

Eq. 45

Source: Pindyck (1979).

The disadvantages of this function include: local approximation of the demand that may not be plausible globally, loss of degrees of freedom, and complicated estimation techniques [18].
Parallel to the developments in the translog approach, the use of multinomial logit models became popular in the energy studies. The logit model is not derived from the utility maximization theory but derives its appeal from its interesting properties [17]:

- ○ it is relatively easy to estimate
- ○ it ensures that the outcomes are non-negative and add to one
- ○ as the share of a component becomes small, it requires increasingly large changes to make it smaller
- ○ Flexible for incorporating a dynamic structure

Logit model [17]
The logit model for fuel share, Si, can be written as:

$$\frac{Q_i}{Q_T} = S_i = \frac{\exp(f_i)}{\sum_{j=1}^{n} \exp(f_i)}$$

Eq. 46

Where Q_i is the quantity of fuel i, $Q_T = \sum Q_i$, and f is the function representing consumers preference choices.
The share equation for any two fuels can be written as

$$\log\left(\frac{Q_i}{Q_T}\right) = \log\left(\frac{S_i}{S_j}\right) = f_i - f_j$$

Eq. 47

As the sum of the shares adds up to one, only (n-1) equations need to be estimated simultaneously.
For estimation purposes, a specific functional form has to be chosen. This is often done arbitrarily and we use a linear specification of relative fuel pries, income and temperature as given below.

$$f_i = a_i + b_i \widetilde{P}_i + c_i Y + d_i T$$

Eq. 48

Where $\tilde{P}_i$ is (P_i / P_E) - ratio of price of fuel i to the aggregate fuel price, Y is income, T is the temperature. Substitution of *Eq. 3* in *Eq. 2* yields the equations to be estimated:

$$\log\left(\frac{S_i}{S_j}\right) = \left(a_i - a_n\right) + b_i \widetilde{P}_i - b_n \widetilde{P}_n + \left(c_i - c_n\right) Y + \left(d_i - d_n\right) T$$

Eq. 49

Where i = 1, 2, 3, …(n-1)

A dynamic version of the equation can be easily written by including the lagged shares in the functional form:

$$f_i = a_i + b_i \widetilde{P}_i + c_i Y + d_i S_{i,t-1}$$

Eq. 50

The equations for dynamic estimation in that case turns out as:

$$\log\left(\frac{S_i}{S_j}\right) = \left(a_i - a_n\right) + b_i \widetilde{P}_i - b_n \widetilde{P}_n + \left(c_i - c_n\right) Y + d_i S_{i,t-1} - d_n S_{n,t-1}$$

Eq. 51

Where i = 1, 2, 3, …, (n-1)

Source: Pindyck (1979)

With the cointegration revolution in the 1990s the trend changed to the reliance on single equations and this became a remarkable turning point in the econometric research when earlier methods were almost abandoned. These studies often adopted an aggregated analysis but used more advanced time-series data analysis techniques. That econometric analysis has been applied to the industrial energy demand of developing countries and their occurrences are rather limited and often restricted to more advanced developing countries with a large industrial base. Recent studies explain that the issues of structural change and technological improvements have not been sufficiently captured. This approach may not be suitable for many developing countries.

2.3.2.1.2 End-use approach

This approach to industrial energy demand, that depends by data availability, focuses on the disaggregated demand analysis and retains at least 2-digit level classification of industries following ISIC codes (International Standard of Industrial Classification) to take care of the diversity of industrial activities and fuel use. The method tries to capture the essential features of the production system through a detailed description of the technologies and practices prevalent in a region or country.
Various determinants of the end-use demand are then identified: the level of industrial activity (expressed as value added) is considered to be the main factor. Energy demand is estimated by linking the output from the industry to specific consumption or energy intensity as it can be seen in the figure below.

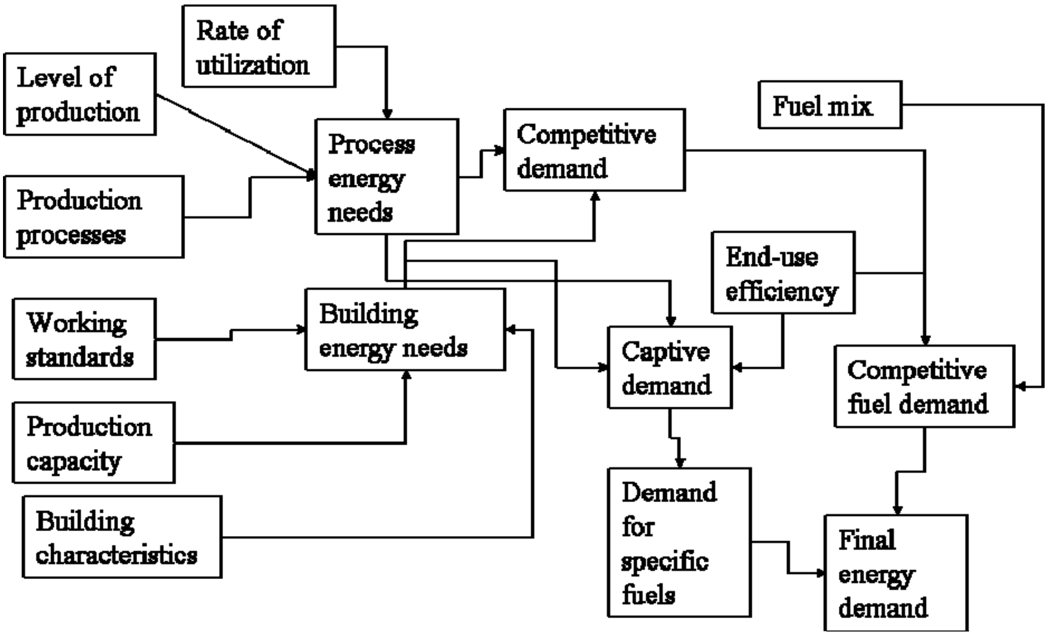


Figure 1: industrial energy demand estimation in end-use method [19]

In the next table are presented some examples of end-use engineering models with rich technological representation.

Name of the model	Country of origin	Technology representation	Modelling approach
AMIGA	US	Explicit	Simulation
EERA	New Zeland	Unknown	Simulation
ENUSIM	UK	Explicit	Simulation
ENPEP	US	Explicit/stylistic	Simulation
MAED	Austria	Explicit	Simulation
MEDEE	France	Explicit	Simulation
LEAP	US	Explicit	Simulation

Table 1: energy end-use models for industrial energy demand analysis [20]

The end-use approach pays special attention to the technological aspect of the industrial sector. When a particular industry is being analyzed, the level of details is expected to be much greater compared to a study focusing on industry as part of an economy-wide analysis. This approach also allows the regional dimension to be taken into consideration and the analysis can be performed at the region-specific level. Additionally, the focus shifts to capturing structural changes, technological improvements and policy-induced effects rather than devoting entire effort to elasticity estimation or determining the correct specification. The skill requirement is often not too onerous and the data can be developed using expertise and judgments.

2.3.2.2 Trasport sector

2.3.2.2.1 Econometric approach

The single equation, reduced form of demand estimation either at the aggregate transport fuel level or for particular fuels (gasoline, diesel, etc.) remains the basic form of econometric analysis. Two common approaches used to estimate transport energy demand are the identity approach and the structural approach. Research from

as early as 1970s has recognized the importance of stock of cars, car utilization and the average car efficiency in the transport energy demand.
This is captured through the demand identity:

$$E = C * U * Eff$$

Eq. 51

Where E is the fuel demand, C is the stock of automobiles, U is the annual utilization rate (km/year), and Eff is the vehicle efficiency (l/km). The fuel demand is obtained as a product of the above three variables, each of which is estimated using a function of other explanatory variables. Accordingly, the demand is not obtained from the utility or cost functions or from the perspective of any optimization process [17]. The implementation of the above identity for estimation purposes can take alternative paths. It is presented two examples: one from Pindyck [17] and the other from Johansson and Schipper [21].

Transport energy demand model in Pindyck [17]
The study used the identity model for gasoline demand estimation. Three equations were used to determine stock of vehicles, while two other relations described the depreciation rate, transport volume and vehicle efficiency. The stock of vehicle is obtained from an accounting identify which reflects the depreciation of stock and addition of new vehicles to the stock. This is written as in *Eq. 1*:

$$STK_t = (1-r)\,STK_{t-1} + NR_t$$

Eq. 52

Where STK is the stock of automobiles, R is the depreciation of the stock and NR is new registrations. New registrations bring the stock to the desired stock level, where the desired stock is a function of explanatory variables such as car price (P_c), fuel price (P_f) and income. Per capita new registrations can be expressed as:

$$\frac{NR_t}{POP_t} = w\left(\frac{STK_t^*}{POP_t} - \frac{STK_{t-1}}{POP_{t-1}}\right) + r\,\frac{STK_{t-1}}{POP_{t-1}} + \lambda\,\frac{NR_{t-1}}{POP_{t-1}}$$

Eq. 53

Assuming STK* to be a linear function of P_i, P_f and Y, equation 2 can be rewritten as:

$$\frac{NR_t}{POP_t} = a_0 + a_1P_c + a_2P_f + a_3\frac{Y}{POP} - (w-r)\frac{STK_{t-1}}{POP_{t-1}} + \lambda\,\frac{NR_{t-1}}{POP_{t-1}}$$

Eq. 54

The depreciation rate r can be expected to increase with higher per capita income and fall with higher car prices. This can be captured through a linear function as given in equation 4.

$$r = b_{0+}\frac{b_1Y}{POP} + b_2P_c$$

Eq. 55

Equations 1, 3 and 4 define the stock of vehicles. The vehicle utilization is normally expressed in kilometers driven per year per car. It can be expected to depend positively on the per capita income but negatively on the price of fuel. This is captured through the log-linear relationship given in equation 5.

$$\ln(U_t) = c_0 + c_1\ln\left(\frac{Y}{POP}\right) + c_2\ln P_f + c_3\ln U_{t-1}$$

Eq. 55

The average fuel efficiency is expected to change with fuel price but with a lag. Another log-linear relationship, equation 6, captures this.

$$\ln\left(Eff_t\right) = d_0 + d_1 \ln P_f + d_2 \ln Eff_{t-1}$$

Eq. 55

Source: Pindyck (1979)

Johansson and Schipper [21] model
The fuel demand is defined as the product of three factors:

$$E = S * I * D$$

Eq. 56

Where S is the automobile stock per capita, I is fuel consumption per kilometer driven (or fuel intensity), and D is the distance travelled per year per car. The authors have chosen a recursive system approach where the variable D is estimated as a function of S and I and other variables, but I and S are estimated solely as functions of other variables. Moreover, they estimate all three demand components using log-linear relationships which are most widely used functional forms that yield constant elasticities and provide easy-to-interpret results. However, for tax and population density, semi-log specification was used to avoid the problems arising from near zero values. The following dynamic pooled model relationships were estimated:

for vehicle stock
$$\ln\left(S_{it}\right) = \alpha_0 + \alpha_1 \ln S_{i,t1} + \alpha_2 \ln P_{it} + \alpha_3 \ln Y_{it} + \alpha_4 T_i + \alpha_5 G_i + u_{it}$$

Eq. 57

for fuel intensity
$$\ln\left(I_{it}\right) = \beta_0 + \beta_1 \ln I_{i,t1} + \beta_2 \ln P_{it} + \beta_3 \ln Y_{it} + \beta_4 T_i + \beta_5 G_i + u_{it}$$

Eq. 58

for distance traveled
$$\ln\left(D_{it}\right) = \gamma_0 + \gamma_1 \ln D_{i,t1} + \gamma_2 \ln(P_{it} I_{it}) + \gamma_3 \ln Y_{it} + \gamma_4 T_i + \gamma_5 G_i + \gamma_6 \ln\left(S_{it}\right) + u_{it}$$

Eq. 59

Where P is the fuel price, Y is the income (GDP) G is the population density. The authors remark that the "distance traveled equation" is the most difficult to estimate because there are a large number of possible explanatory variables. The estimated relationships can be used to forecast future demand.

Source: Johansson and Schipper (1997)

Miklius et al (1986) provides an early example of a more common approach that is to rely on the market shares and forecast the demand ensuring consistency.

A simple model for transport fuel demand estimation [22]
Consider that two substitutable fuels diesel and gasoline are used for transport purposes. The market share approach is used to estimate the demand. The model has two components: first, the total fuel demand for transport is estimated; then, the demand for individual fuels is estimated using their market share. The total demand for diesel and gasoline is considered to be a function of weighted average price of fuels in real terms, real per capita GDP and the total consumption of both fuels in the previous year. The equation in log-linear form can be written as:

$$\ln TC = \alpha_0 + \alpha_1 \ln P + \alpha_2 \ln GDP + \alpha_3 \ln TC_{-1}$$

Eq. 60

where P = (DC/TC).DP + (GC/TC).GP, TC = total consumption of diesel and gasoline, P is the average price, GDP is the real per capita GDP, DC is the diesel consumption, GC is the gasoline consumption, DP is the price of diesel and GP is the price of gasoline. The market share of a fuel is assumed to be a function of its real price, the price of the substitute fuel, the per capita GDP and the share of the fuel in the previous year. The equation for gasoline can be written as follows:

$$\ln\left(\frac{GC}{TC}\right) = \beta_0 + \beta_1 \ln DP + \beta_2 \ln GP + \beta_3 \ln GDP + \beta_4 \ln\left(\frac{GC}{TC}\right)_{-1}$$

Eq. 61

As there are two fuels in this case, the total share has to be 100. The diesel share is thus obtained
DC/TC = 100 exp[– ln(GC/TC)]

Source: Miklius et al (1986)

Like industrial energy demand, recent econometric studies on transport demand forecasting have relied on cointegration and error correction models. These models focus on the technical properties of the time series and try to avoid misspecification of the models. But often these models are at an aggregated level and do not consider the efficiency or vehicle stocks explicitly. Most of these models focus on a particular fuel rather than considering the entire set of transport fuels or modes, thereby ignoring the substitution possibilities. Studies that consider demand at the aggregate level without considering the growth of transport vehicle stocks or the modes of transport cannot really capture the developing country features.

2.3.2.2.2 End-use approach

The end-use approach has focused on forecasting demand by capturing the diversity of transport modes, types of vehicles, efficiency and other drivers. The usual disaggregation of the transport sector is shown below [1]:

Need	Modes	Vehicles	Fuel use
Public passenger transport	Road	Taxis	Gasolene, Diesel, LPG, CNG
		Minibuses	Diesel, CNG
		Urban buses	Diesel, CNG
		Intercity buses	Diesel
		Others	Gasolene, Diesel, LPG, CNG
	Rail	Tramways, tube rails	Electric
		Light rails	Electric
		Commuter trains	Coal, Diesel, Elettric
		Intercity trains	Coal, Diesel, Elettric
	Dom air		Jet fuel
	Dom water		Fuel oil, Gasolene
Private passenger transport	Road	Motorcycles	
		Cars	
Freight transport	Road	Pick-ups	Diesel
		Light trucks	Diesel
		Heavy trucks	Diesel
	Rail		Coal, Diesel, Elettric
	Dom water	Barges, ships	Fuel oil, Gasolene

Table 2: disaggregation of the transport sector in end-use studies

In the transport sector, energy is mainly used for passenger transport and freight transport. The determinants of passenger transport demand are:

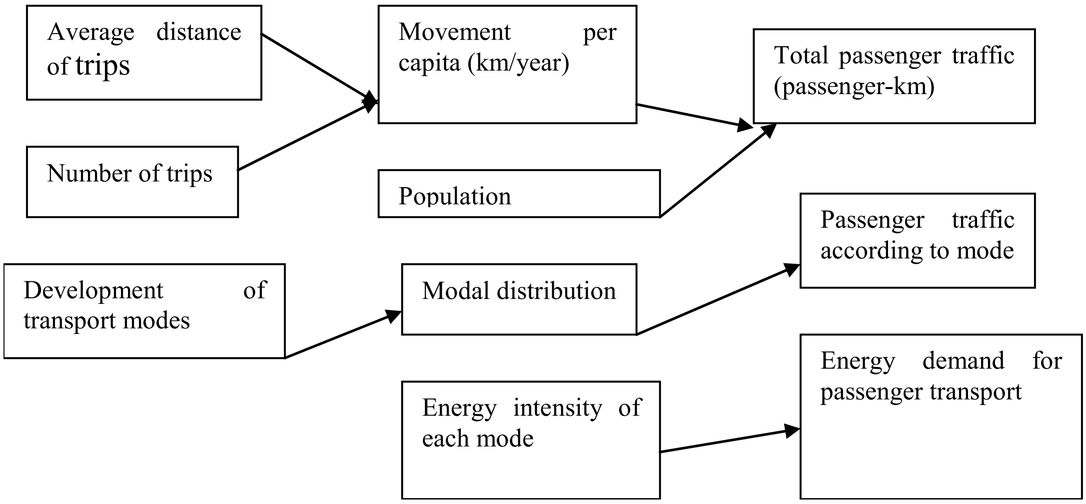


Figure 2: determinants of passenger transport demand

The development of transport modes and the modal distribution of a country are greatly affected by energy as well as general economic policy. The energy consumption per passenger-km varies greatly by mode of transformation and it per unit of driving (i.e. liters/km) is in principle a function of the power of the engine and of engine efficiency. The determinants of energy demand for freight transport are:

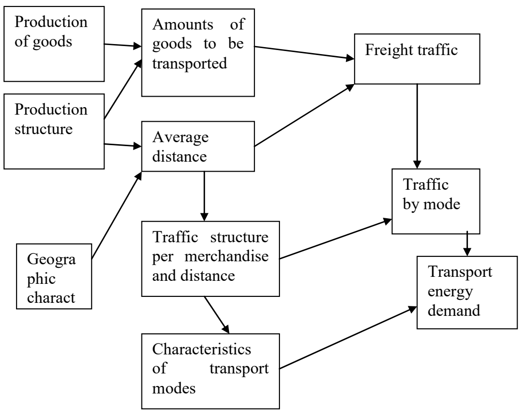


Figure 3: determinants of energy demand for freight transport

The end-use oriented studies of transport demand attempt to capture the fuel demand by considering individual components contributing to demand and accordingly, they tend to cover the relevant demand drivers for the developing countries. The disaggregated approach also allows a detailed representation of the vehicle stock, vehicle vintages, and changes in the fuel mix, modal mix and technologies, as well as rural-urban dichotomy. This method has been applied to the developing countries in the past but do not consider price-induced effects, the problem may not be acute due to inelastic demand of transport fuels.

2.3.2.3 Residential sector

2.3.2.3.1 Econometric approach

Residential energy demand studies have covered individual fuels (such as electricity, natural gas) or aggregate demand or the entire set of energies used. The reduced-form, single equation demand specifications are quire common for fuel-level analysis. The log-linear specification is most commonly used in such studies for the ease of estimation and simplicity. Although residential energy demand depends on the stock of energy-using appliances and other economic variables, in the short-run the demand is expected to be constrained by the existing capital stock, which in turn would influence the consumer response to any changes in the economic variables. To capture this aspect, some attempts were made to use two-stage demand analysis, one for the short-term and the other for the long-run. However, the data on appliance stocks is often poor and leads to problematic results. A large number of econometric studies exist for the developed countries, limited focus has been given on residential energy demand in developing countries and especially for rural areas. The main difficulty often faced by the residential and commercial sectors in analyzing energy demand is the availability of data, especially of end-use breakdowns of energy consumption. The single equation models or aggregated analysis do not capture the technological diversity and the spatial difference in energy demand. The problem can be worse where energy prices are controlled by the government because the econometric relations may not prove statistically significant or meaningful.

2.3.2.2.2 End-use models

Measuring residential activity is difficult because there are many different energy-using activities that take place in homes but no single measure. As there are different end-uses (e.g. space heating, water heating, lighting, electric appliances, etc.) and different appliances or applications within end-uses, the total energy demand is obtained by summing all applications in an end-use and then adding demand in all end-uses. Total energy consumption for space heating and air-conditioning of a country for a given year is determined by the average energy consumption per household and per building for those purposes, and the total number of households and buildings for that year. Similarly, energy demand for cooking is related to unit demand per household and number of households. The lighting requirement can be expressed as a function of household area, lighting requirement per unit area and the number of households. As the demand pattern in households vary with income level and geographical location (rural/ urban), better results are obtained by disaggregating the demand by income level and rural/ urban areas. The disaggregated approach to residential demand analysis allows better representation of the specific features of developing countries.

Capitolo 3 | Energy Forecast

The development of a State is closely related to its energy demand. It is therefore necessary to understand carefully the possible future energy scenarios based on different variables to make choices appropriate for future growth. Since the early 1970s, when energy caught the attention of policymakers in the aftermath of the first oil crisis, research on energy demand has vastly increased in order to overcome the limited understanding of the nature of energy demand and demand response due to the presence of the external shocks encountered at that time [17]. The lively debate between engineers and economists of that era led to important methodological developments that enriched the energy decision-making process as a whole, and a wide variety of models became available for analyzing and forecasting energy demand [18].
Energy demand forecasting is an essential component for energy planning, formulating strategies and recommending energy policies. It is a measurement and estimate of historic, current and projected patterns of energy supply and demand within an area that could be a restricted one as well as a State or a macro-region. It starts from a baseline forecast that illustrates what State energy use will look like in the absence of additional policies beyond what is already planned and consequently it is a reference case against which to measure the energy impacts of policy initiative or system shocks. Other possible scenarios are therefore introduced to analyze the consequences of adopting policies respect of the baseline case where they are not considered.
The task is challenging not only in developing countries where necessary data, appropriate models and required institutions are lacking, but also in industrialized countries in which these limitations are somewhat less serious. The limitation in the model structure or inappropriate assumptions often produce a deviation from what was expected so it is important to have as much data as possible to create a complex model can be very accurate. The main reasons [23] why the energy forecast are far from the actual demands could are that:
- inaccurate characterization of the behavior of economic agents (most models group consumers into a few representative agents to represent the "millions of decisions made by millions of individuals," and provide relatively stylized descriptions of their decision making);
- incomplete coverage of social and environmental impacts;
- lack of adequate technological detail;
- unrealistic economic assumptions such as fully employed and efficiently allocated resources, rational individuals, optimizing firms and perfectly functioning markets.

Furthermore is very important to consider the importance of developing countries in the world energy scene because their growth has become significant in recent decades.

3.1 Scope of energy forecast, steps and current analysis

Energy forecast are developed to [24]:
- Understand how energy, within the current policy and with the current energy situation, economic and social, how can be supplied and used. Through careful study, the energy forecast determines policies and investments in the energy sector.
- Estimate energy-related greenhouse gas and air pollution emissions
- Set specific targets with respect to energy usage, such as renewable energy or energy efficiency targets, policies and programs about climate change (for example EU 202020 plan)
- Identify specific sectors that could be targeted with policies and programs
- Analyze actions and measures that could help achieve targets and goals
- Predict alternative future energy profiles that can ensure the State can meet the needs of its residents and industries with clean, cost-effective strategies.

There are six steps involved in creating a baseline forecasting listed by EPA (US Environmental Protection Agency) [24]:

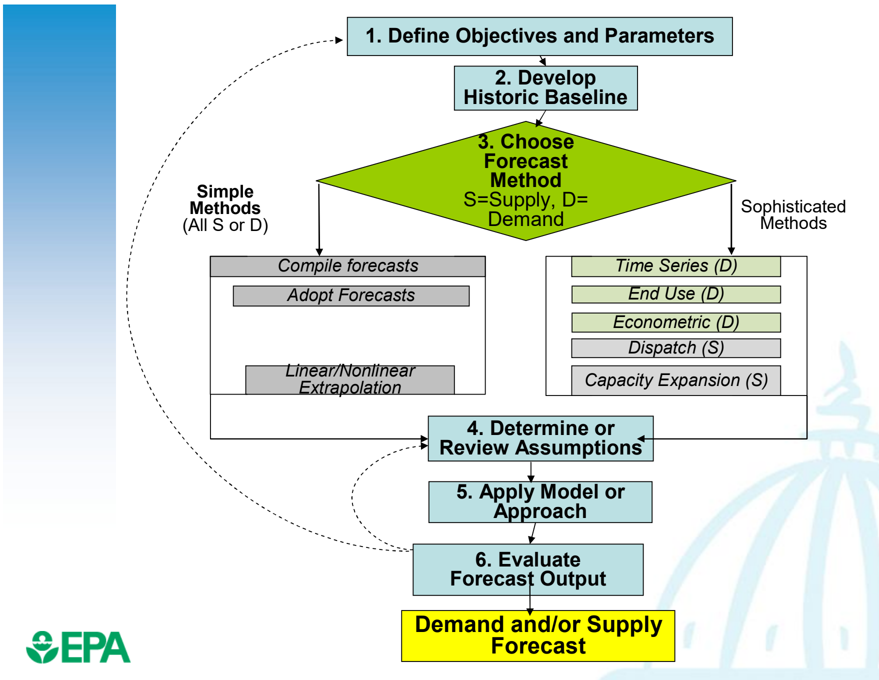


Figure 4: scheme of steps involved in creating a baseline forecasting listed by EPA

1. Define objective and constraints of the forecast

It is important for States to understand the objective behind developing an energy forecast. They should identify the use/purpose of the forecast (e.g. to obtain a general energy profile or conduct a detailed analysis) and consider several factors as they begin. At a minimum, States should:

• Determine if the forecast will be short-term or long-term and bottom-up or top-down
• Establish the level of rigor necessary
• Consider the availability of financial, labor and time resources to complete the forecast
• Verify the amount of energy data that they can readily acquire to develop the forecast

2. Compile historical energy consumption and generation data into a baseline profile

A comprehensive energy baseline profile includes consumption (demand) by sector and fuel and generation (supply) by fuel and/or technology. Energy consumption data is typically compiled by fuel type. A comprehensive baseline includes non-renewable and renewable fuels. Electricity can also be included as a fuel. Consumption data is often broken down by the sectors that consume the fuels, including commercial, residential, industrial, transportation and utility sectors. This top-down baseline helps a State understand the large and small consumers within a State and helps target sectors for policy interventions. Each sector can also be further disaggregated to show the types of consumption within. For example, if a State is interested in targeting residential sector demand, they may want to develop a bottom-up baseline that depicts the amount of residential consumption attributed to hot water heating or to appliances and cooling. This type of forecast would be very data intensive but would provide more information than an aggregated baseline that is useful if the State is interested in understanding trends and opportunities within a specific sector. Historic and forecast demand for energy is a product of the economic and weather conditions of the State as well as the types and efficiencies of end-use appliances and equipment. On the supply side, electricity generation data can also be categorized by fuel type and sector. A baseline energy forecast requires data about the types and amounts of fuel used to generate electricity. Electricity generation data typically includes electricity generation that has occurred within the State and electricity imported into or exported out of the State under contractual arrangements. It also accounts for transmission and distribution losses. If using a forecast to estimate a State's greenhouse gas or air pollution emissions, treatment of electricity imports and exports in a baseline is important to understand. Obtaining a clear emissions baseline that can be attributed to satisfying the electricity demand of a State requires an understanding of the amount of electricity consumption which is generated in-State, the amount imported from other places and the fuels used to generate either. For example, if a State generates and consumes all of its own

electricity which is produced using only hydropower, its emissions footprint will be quite different than a State that generates in-State electricity using only hydropower but imports electricity from a neighboring State that uses coal to generate its electricity. Understanding where and how all of a State's electricity is generated and consumed will provide a clear reference case for estimating emissions.
Regarding the United States, consumption and generation data can be obtained from several sources, including:
• utilities,
• public utility commissions,
• State energy offices,
• departments of transportation,
• independent system operators (ISOs),
• EPA's Emissions & Generation Resource Integrated Database (eGRID) model,
• DOE's Energy Information Administration (EIA) and
• North American Electric Reliability Corporation (NERC) among others.
In the following table it can be observed an example about possible data sources for BAU forecasts.

Sources	Elettricity		Netural Gas		Other Fuels	
	Historic	Forecast	Historic	Forecast	Historic	Forecast
Utilities; by service territory	x	x	x	x	x	x
Public Utility Commissions; also State Energy Offices for Other Fuels	x	x	x	x	x	x
Indipendent System Operators/RTOs	x	x				
North American Eletric Reliability Corporation (NERC) Electri-city Supply and Demand database	x	x				
EIA Electric Power Annual	x	x			x	
EPA Emission & Generation Resource Integrated Database eGRID	x					
EIA State Energy Data (SEDS)	x		x		x	
EIA Electric Sales, Revenue, and Price tables or EIA Annual Electric Utility data – EIA-861 data file	x					
EIAs Manufacturing Energy Consumption Survey (MECS); Commercial Buildings Energy Consumption Survey (CBECS); Residential En-ergy Consumption Survey (RECS) Consumption data	x		x		x	
EIA Annual Energy Outlook (AEO)	x	x	x	x	x	x
NREL						x

Table 3: sample energy data sources for BAU forecasts

3. Choose method to forecast the energy baseline
States can use basic or sophisticated modeling approaches to forecast their energy baseline and predict energy supply and demand based on the expectations of future population changes and economics. Basic methods may require the State to adopt others' assumptions about the projected population and the economy or compile and develop its own. These approaches are generally appropriate when conducting screening analyses or developing highly aggregated forecasts, when the amount of time or funding to support a forecast is limited, or when the time period of the forecast is short. More sophisticated models can be used for short-term or long-term analyses. They provide greater detail than the basic methods, can capture the complex interactions within the electricity and energy system, but may be data, time and labor intensive, lack transparency and require significant technical expertise.
Basic approaches for forecasting energy demand and supply generates high-level information about a State's

energy future without using rigorous, complicated, and sometimes costly software models. They include:

Methods	Advantages	Disadvantages	When to use
Compilation of individual forecasts by others	Easy to gather	May not be compatible; proprietary concerns; possible short horizons; may or may not provide information on construction requirements, fuel use, emissions, and costs.	High level, preliminary and quick analysis
Adoption of a complete forecast used by others	Easiest method	May not have the long-term outlook	High level, preliminary and quick analysis
Linear and/or Nonlinear Extrapolation of Baseline	Quick	May not capture impact of significant changes (e.g., plant retirements)	High level with simple escalation factors from history
	More robust data analysis	Possible errors in formulas, inaccurate representation of demand and supply	Knowledge in generation dispatch modeling by type of plant

Table 4: comparison of basic methods for forecasting energy demand and supply

Compilation of individual forecasts by others: generally, current energy plans from utilities, ISOs, and regulatory agencies will include a demand forecast that is reduced by estimated energy savings from energy efficiency programs. Likewise, the corresponding supply plan may include renewable energy sources, including combined heat and power plants, if significant. States can aggregate individual load forecasts, generation expansion plans, and energy efficiency program and renewable energy evaluations from state agencies, utilities, ISOs, local educational institutions, and special interest groups, such as interveners in rate cases. Compiling forecasts created by different entities can be challenging because they can vary significantly from each other in terms of underlying assumptions, proprietary concerns, data transparency (e.g., unit generation, costs), and time frame.
Adoption of a forecast used by others: in some states, an energy office, utility commission, revenue department, or academic organization may have prepared a suitable energy forecast. Also, utilities and ISOs may have available forecast plans. A regulatory filing requirement (e.g, Integrated Resource Plan) will provide a comprehensive long-term plan that includes impacts from energy efficiency, reliable demand response, if any, and existing renewable energy plans. However, there may be proprietary constraints to obtaining this information.
Linear/Non Linear Extrapolation involves spreadsheet analysis where historical demand growth rates and electricity production are extrapolated. The accuracy of this approach depends on the knowledge and experience of the analyst. An advantage to this approach is that it is easy to develop in a spreadsheet and use for preliminary forecasting. A disadvantage is that the exclusion of important variables beyond demand growth factors and electricity, such as weather, season, plant retirements or construction, operation or capital costs, emissions or macroeconomic growth, may result in an inaccurate forecast.

Regarding sophisticated forecast methods distinguish demand and supply separately:
• Demand Forecast
Once the historic baseline is developed, States can choose from three model types to develop a forecast:
- ○ Time Series-based Models use inputs that are based on historic patterns relative to time, and forecast future events based on known past events and patterns. Inputs require an analysis of historic patterns in demand for electricity. It's easy to use, fast and historical data are widely available by year, fuel and end use sector but the disadvantages are that data may relate to a historical baseline that may have undergone major structural changes, it is hard to reflect future structural changes even if they are anticipated and it cannot reflect supply-demand-price feedbacks.
- ○ End Use models develop the load profiles of customer types by analyzing the historical consumption of appliances and equipment and may use specific surveys from customers about future growth and

contraction. An advantage is that this approach uses a load profile for each customer class being served, providing a reasonable estimate of demand. A disadvantage is the time to collect the data and the cost to develop the data.
- ○ Econometric models provide a more complex and robust analysis that uses inputs for inflation, demographics, gross State product, consumer energy prices, gross/disposable income, housing starts, business starts/ failures, birth/death rates, surveys of business expansion plans, historical energy consumption, and other variables for structural changes and economic inputs. An advantage of using this method is that it creates a robust demand forecast consistent with a robust economic forecast. A disadvantage is the time and cost to prepare the inputs and review the results.

• Supply Forecast
The models are used for hourly, daily, monthly, short-term and long-term forecasting. Sophisticated supply forecasting models require large volumes of data on electricity production plants, transmission capabilities and a demand forecast. As with any model, the better the data, the better the results. There are two types of models:
- ○ Electricity Dispatch models simulate dynamic operation of the electric system, generally on a least-cost system dispatch.
- ○ Capacity Expansion or Planning models are designed to make decisions on how the electric system builds capacity to meet demand.

4. Develop or review assumptions
After choosing the forecasting approach or model type, the next steps are determining or reviewing the assumptions about population and economic variables, such as energy prices, productivity, gross State product, and the labor force upon which future projections of energy demand and supply depend. At this point in the process, it may also be necessary to "clean the data" or fill in any missing data gaps. If data points are missing for particular years, it may be necessary to interpolate the existing data to fill in gaps. This will minimize the likelihood of generating a strange forecast.

5. Apply the method
States can apply the selected model or approach to the historical baseline energy data based on the assumptions about future population, economic and energy expectations.

6. Evaluate forecast output
Once generated, it is important to evaluate the output to ensure that it makes sense and meets the original objectives.

3.2 Energy demand forecasting approach

There are a large variety of techniques used by different sets of users. For examples Werbos [25] presents the distinction between modeling approaches very succinctly: let us assume that we want to forecast population in the following year based on present year information. We write the following relationship:

$$POP(t+1) = c * POP(t)$$

Eq. 62

Where c is a constant and POP is the population, t is the time period. The obtaining of different "c" generates different models *[Werbos (1990)]*:
- c is obtained by asking the experts, the forecast is based on the judgmental approach.
- c is obtained through small-scale studies of controlled population, the model can be called an engineering model
- c is obtained by analyzing the time series of historical population, the model can be called an econometric model or a model estimated using the econometric approach

On the other hand Lipinsky [26] suggested a three dimensional categorization of demand forecasting models based on complexity (simple-complex), dynamics (static-dynamic) and uncertainty (deterministic – probabilistic). We will consider two broad categories for a simple classification: simple approaches and sophisticated approaches.

3.2.1 Simple approaches

The simple approaches are easy-to-use indicators that can provide a quick understanding. Four such simple indicators commonly used for forecasting are: growth rates, elasticities (especially income elasticity), specific or unit consumption and energy intensity. In addition, trend analysis that finds the growth trend by fitting a time trend line is also commonly used. All of these approaches rely on a single indicator and the forecast is informed by the assumed changes in the indicator during the forecast period. The attractiveness of these methods for any long-term work is rather low because of their weaknesses but is used for its simplicity. There are several examples of the use of the simple approaches: in two recent reports on energy policies of India and China, simple measures of GDP-elasticity and energy intensities have been used for demand forecasting for ten or more years. Some studies [e.g. in Armstrong [27], Craig et al [28], and Westoby and Pearce [10] argue that simple models can sometimes produce accurate results similar to those obtained from sophisticated ones. Many sophisticated models also retain simple techniques in some of their sub-components. For example, intensities or gdp-elasticities are commonly used in engineering-economic models while growth rates and elasticities are often used for forecasting independent variables in econometric approaches. In addition, these techniques can be used both at the aggregated and disaggregated levels. The virtue of simple models is that the skill and data requirement is low and such models are more tractable rather than the hidden assumptions of complex models [29]. This is further supported by Craig et al [28] who found that many long-term forecasts using sophisticated models for the USA produced inaccurate forecasts in the past. Armstrong [27] echoes the same view and States that "simple models can sometimes yield results as accurate as more complicated techniques." Simple methods can be applied for both commercial and traditional energies, can be used both in urban and rural areas and they could be used to include the effects of informal activities and unsatisfied demand. However, they neither explain the demand drivers, nor consider technologies specifically. They only rely on the value judgments of the modeler, wherein lies the problem. Further, these methods do not rely on any theoretical foundation and accordingly, they are ad-hoc approaches.

3.2.1.1 Simple approaches for energy demand forecasting [1]

Growth-rate based method

Let g be the growth rate in demand and D0 is the demand in year 0, then Dt can be obtained by

$$Dt = D_0 \left(1+g\right)^t$$

Eq. 63

Elasticity-based demand forecasting

Elasticity is generally defined as follows:

$$e_t = \frac{\left(\frac{\Delta EC_t}{EC_t}\right)}{\left(\Delta I_t / I_t\right)}$$

Eq. 64

where t is a period given, EC is energy consumption , I is the driving variable of energy consumption such as GDP, value-added, price, income etc., Δ is the change in the variable. In forecasting, output elasticity or income elasticity is commonly used. The change in energy demand can be estimated by assuming the percentage change in the output and the output elasticity. Normally, the elasticity is estimated from past data or gathered using judgment. The output change is taken from economic forecasts or planning documents.

Specific consumption method

Energy demand is given by the product of economic activity and unit consumption (or specific consumption) for the activity. This can be written as

$$E = A \times U$$

Eq. 65

Where A is level of activity (in physical terms), U is the energy requirement per unit of activity. These two factors are independently forecast and the product of the two gives the demand.

Ratio or intensity method

Energy intensity is defined as follows:

$EI=E/Q$

Where EI – energy intensity, E = energy demand , Q = output. This can be rearranged to forecast energy demand $E = EI \times Q$. Using the estimates for Q for the future and assumptions about future energy intensity, the future energy demand can be estimated.

3.2.2 Sophisticated approaches

Sophisticated models employ more advanced methodologies. Models can be classified such as top-down models, that tend to focus on an aggregated level of analysis, and bottom-up models, that identify the homogeneous activities or end-uses for which demand is forecast. Another classification relies on the modeling philosophy:

- econometric models are grounded in the economic theories and try to validate the economic rules empirically
- engineering-economy models (or end-use models) on the other hand attempt to establish accounting coherence using detailed engineering representation of the energy system
- combined or hybrid models attempt to reduce the methodological divergence between the econometric and engineering models by combining the features of the two traditions

3.2.2.1 Econometric models

This is a standard quantitative approach for economic analysis that establishes a relationship between the dependent variable and certain chosen independent variables by statistical analysis of historical data. The relationship so determined can then be used for forecasting simply by considering changes in the independent variables and determining their effect on the dependent variable.

This approach has the theoretical appeal because of its close link with the theory of consumers and the production theory. The set of potentially important variables to be tested in the model can be drawn from the appropriate theory and the influence of these factors is evaluated statistically. Normally the statistically relevant factors are considered and included in the estimated demand function. It is usual to test alternative functional forms to identify the most appropriate one but as the number of independent variables increases, the set of possible combinations increases exponentially, making the choice more difficult.

The degree of sophistication of econometric estimations varies widely: the single equation forms the basic level of analysis. The market share approach is also used in certain cases, especially for transport fuels. In such a case, the total demand is estimated jointly through one equation and the market share of each fuel is then estimated separately through another set of equations. More complex estimations based on "simultaneous equation expenditure share models" are also used. This approach has been applied to total aggregate energy demand as well as demand in individual sectors (industry, transport, residential, etc.). Even the econometric analysis has been applied to the entire energy system using the energy balance framework (e.g. Adams and Shachmurove, [30]).

Several studies have generally focused on the aggregated demand and considered a limited driver variables such as GDP and price, and do not capture the technological changes or other non-price related policies. Even the results from these sophisticated methods seem to depend on model specification and the strategies for data analysis. For limited sample sizes, these methods are unlikely to produce appropriate results. Consequently, simple OLS estimates still continue, perhaps in the belief that even if they are non-stationary, there exists a co-integration relationship so that the simple regression yields super-consistent results.

3.2.2.1.1 Sample of statistical and econometric models [31]

In this section is presented some sample of statistical and econometric models.

Autoregressive Model

Autoregressive (AR) models are useful when the value to be forecasted is correlated to the previous values in the time series. The AR model is:

$$Y_t = c + \varepsilon_t + \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + . \quad . \quad . \quad . + \varphi_p Y_{t-p}$$

Eq. 66

Where Y_t indicates the time series value at time t, Y_{t-1} indicates the value recorded at time t-i, φ represent the AR coefficients, c is a costant and ε_t a time-dependent normal random variable. Equation can be rewritten as:

$$Y_t = c + \varepsilon_t + \sum_{i=1}^{p} \varphi_i Y_{t-i}$$

Eq. 67

where p represents the number of previous time series values to be incorporated into the model. This variable p is known as AR model order.

Moving Average Model

Moving average (MA) models are constructed by calculating the running average of the error generated at each point of time. Generally, the average values are weighted. The moving average model has the form

$$Y_t = c + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + . \quad . \quad . + \theta_q \varepsilon_{t-q}$$

Eq. 68

Where Y_t is the forecasted value at time t, which is a weighted average of the error at previous instances of time. The θ values are the coefficients of the moving average terms. Equation can be rewritten as:

$$Y_t = c + \varepsilon_t + \sum_{j=1}^{q} \theta_j Y_{t-j}$$

Eq. 69

where q, representing the number of previous error terms in the model, is known as the MA model order.

Autoregressive and Moving Average Model

An autoregressive and moving average (ARMA) model combines both autoregressive and moving average terms. It is one of the most commonly used order, η_i is the parameter of the exogenous input at time i and ε_t is a time-dependent random value that represents model error.

Autoregressive Moving Average with Exogenous Input Model

The autoregressive moving average with exogenous input (ARMAX) model is an extension of the ARMA model. It is similar to the ARX model with the additional moving average terms. The ARMAX model is:

$$Y_t = c + \sum_{i=1}^{p} \varphi_i Y_{t-i} + \varepsilon_t + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \sum_{i=0}^{b} \eta_i d_{t-i}$$

Eq. 70

Where Y_t is the forecasted value at time t, c is a constant, p is the autoregressive orders, q is the moving average order, φ's are the autoregressive parameters, θ's are the moving average parameters, d is the exogenous inputs, b is the exogenous input order, ηi is the parameter of the exogenous input at time i and ε_t is random model error.

Linear Regression Model

Linear regression (LR) models represent the relationship between a set of independent variables and a dependent variable. The dependent variable is correlated with each of the independent variables. The relationship is represented as:

$$Y_t = c + \alpha_1 x_1 + \alpha_2 x_2 + . \;\; . \;\; . + \alpha_n x_n$$

Eq. 71

Where Y_t is the dependent variable and $x_1, x_2,$, ... x_n are the independent variables. Each of these independent variables has a linear relationship with the dependent variable Y. The symbols $\alpha_1, \alpha_2, \alpha_n$ present the coefficients for respective independent variables and are known as the parameters of the linear regression model. Variable c represents a constant offset. Equation can be rewritten as:

$$Y_t = c + \alpha X_t$$

Eq. 72

Where $\alpha = [\alpha_1, \alpha_2, . . . \alpha_n]$

Eq. 73

3.2.2.2 End-use models

The end-use approach or engineering-economy approach (also known as the "bottom-up" approach) is another widely used energy demand forecasting tradition that focuses on end-uses or final needs at a disaggregated level. Bottom-up models offer such an alternative option for capturing different policy dimensions more closely. This method involves the following general steps [32]:

- Disaggregation of total energy demand into relevant homogenous end-use categories or modules;
- A systematic analysis of social, economic and technological factors to determine the long-term evolution and the identification of interrelationships;
- Organization of determinants into a hierarchical structure;
- Formalization of the structure in mathematical relationships;
- Snap-shot view of Reference year
    - Foundation of the forecasting exercise
    - All relevant data and mathematical relationships developed
    - Reference year is taken as the most recent year for which data is available
- Scenario design for the future;
- Quantitative forecasting using mathematical relations and scenarios;

These steps are presented in a visual form in figure below [1]:

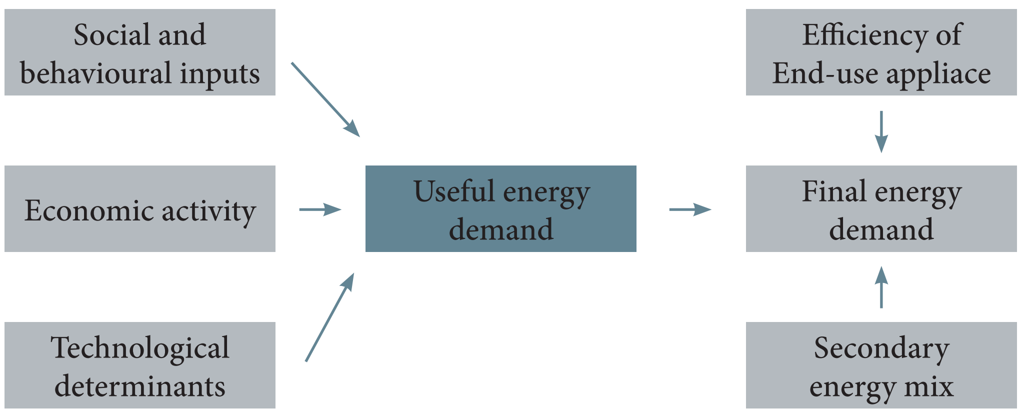


Figure 5: scheme of the end-use approach logic

A wide variety of models have been developed following this alternative approach but the models differ in terms of their level of disaggregation, technology representation, technology choice, model goal, and the level of macro-economic integration [3]. Generally end-use models either follow a simulation approach or an optimization goal, while the technology representation can be either explicit (where specific technologies are considered) or stylistic. The macro-economic linkage is often restricted to ad-hoc or judgmental use of key driver variables but some models are driven by a separate macro-model that captures the interaction with the macro-economy.

As most of the end-use models do not rely on the neo-classical economic paradigm, it brings a very different perspective on energy system analysis. These models are capable of capturing rural-urban divide and can include informal activities. They can also capture the diversity of actual processes and technologies of energy conversion and use, and accordingly do not need to rely on stylistic, aggregate and a single old representation of technologies. As these models do not rely only on past history or evolution, they can capture structural changes and new technological developments. In fact, this is one of the major strengths of this category of models. Through the formulation of different scenarios these models try to capture different development trajectories and the influences of policies on economic development. However, accounting-type end-use models suffer from their inability to capture price-induced effects alongside non-price policies, thereby reducing their effectiveness for certain policy analyses.

3.2.2.3 Input-output models

The input-output method provides a consistent framework of analysis and can capture the contribution of related activities through inter-industry linkages in the economy. Thus the input-output method is able to capture the direct energy demand as well as indirect energy demand through inter-industry transactions. This feature makes this method an interesting analytical tool.

The data requirements of basic input-output analysis are very demanding. The assumption of constant input-output coefficient which implies that the input and output changes are both strictly proportional and invariant over time is a restrictive assumption. These restrictions prohibit an analysis of inter-fuel substitution possibilities and allowance for substitution among non-energy inputs. The assumptions implied about relative prices remaining constant can be quite restrictive if relative prices were to vary significantly in practice. This may or may not be crucial, depending on the particular developing country. The static input-output models do not contain theory of investment behavior or treatment of technical change behavior.

Although this is a disaggregated approach, the details normally pertain to the industrial activities, while other actors or agents are normally represented by a single representative entity. Thus despite its detailed analytical structure, the rural-urban divide is hardly captured. Similarly, the technological diversity is difficult to capture within a given sector of activity. Moreover, as these tables are based on national accounting information, they exclude informal activities and non-monetary transactions. It is also difficult to use this approach for new demand or technologies as the input-output relations have to be established across sectors. However, price-induced policies are easily captured through these models.

3.2.2.4 Scenario approach

Scenarios refer to a “set of illustrative pathways” that indicate how “the future may unfold” [33]. They do not try to capture all possible eventualities but try to indicate how things could evolve. The strength of the scenario approach is its ability to capture structural changes explicitly by considering sudden or abrupt changes in the development paths. The actual level of disaggregation and inclusion of traditional energies and informal sector activities depend on model implementation. Theoretically it is possible to include these aspects but how much is actually done in reality cannot be generalized. Moreover, the development of plausible scenarios that could capture structural changes, emergence of new economic activities or disappearance of activities is not an easy task.

3.2.2.5 Hybrid approaches

This approach relies on a combination of two or more methods with the objective of exploring the future in a better way. The hybrid methods have emerged to overcome the specific limitations of individual approaches.

3.3 Energy demand forecast methods [34]

The mathematical modeling of the energy demand is necessary to engage the forecast problem and to equip the future scenarios of a country with the best models possible to program the right balance between supply and generation. It is impossible to build up an ‘exact’ physical model for the energy demand because of the large number of influence factors and their uncertainty. The quality of the demand forecast methods depends significantly on the availability of historical consumption data as well as on the knowledge about the main influence parameters on the energy consumption. These factors also determine the selection of the best suitable forecast tool. Generally, there is no ‘best’ method, therefore it is very important to proof the available energy data basis and the exact conditions for the application of the tool.

3.3.1 General modeling aspects

The quality of the forecast methods mainly depends on the available historical data as well as on the knowledge about the factors influencing the energy demand. The historical energy consumption data are divided into clusters depending on seasonal effects. Thus the modeling process must be specified for each cluster. Furthermore, the time horizon of the forecast determines the type of the applied method (from short-term to long-term forecast tools).
The figure below shows an overview of the most common used forecast methods which are described in this section.

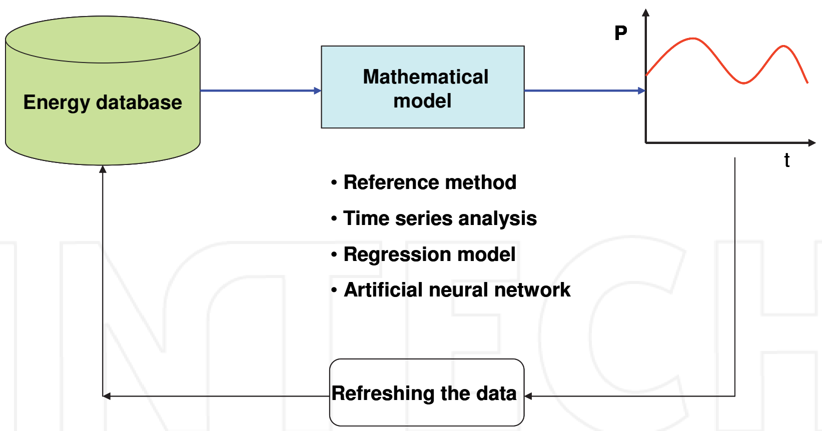


Figure 6: overview of the most common used forecast methods

3.3.2 Reference method

The pure reference method works without a mathematical model. The basic idea of this simple method is to find a situation in an energy data base of historical data that is similar to the one that has to be predicted. A set of explanatory variables is defined and similarity between situations is measured by these variables. The method will be described by an example: to calculate the heat or power demand for a Monday, with a mean predicted temperature of +5 deg C the algorithm is simply looking in a data base for another Monday with a mean temperature close to +5 deg C. Thus the historical consumption data for that day are used as the prediction. The advantage of the method is that it is simple to implement and the results are easily to be interpreted. However, the disadvantages are numerous. Although the implementation of the method seems to be straightforward, it becomes complicated if the number of criterions increases. If for instance hourly temperatures are used instead of daily mean temperature the measures of similarity are no longer so obvious. With an increasing number of explanatory variables, the probability to find no data set that is similar according to all criteria increases [35].
In practical applications the reference method is used in combination with some other adaptation criteria depending on the behavior of the energy consumption in the past. Additionally, the reference method is supported by a regression model describing the climate influence factors and time dependent energy consuming impacts caused by production factors in industrial enterprises. On the other side the knowledge of the energy consumption of selected historical reference days can improve the quality of model based methods.

3.3.3 Time series analysis

This method doesn't explain how the values of the variable being projected are determined. The variable to be predicted is purely expressed as a function of time, neglecting other influence factors. This function of time is obtained as the function that best explains the available data, and is observed to be most suitable for short-term projections. A time series is often the superposition of the following terms describing the energy demand as time dependent output y(t):

- Long-term trend variation (T)
- Cyclical variation (C)
- Seasonal variation (S)
- Irregular variation (R)

The trend variation T describes the gradual shifting of the time series, which is usually due to long term factors such as changes in population, technology, and economy. The cyclical component S represents multiyear cyclical movements in the economy. The periodic or seasonal variation in the time series is, in general, caused by the seasonal weather or by fixed seasonal events. The irregular component contains the residual of the time series if the trend, cyclical and seasonal components are removed from the time series. These terms can be combined to mixed time series model:

Additive model

$$y(t)=T(t)+S(t)+C(t)+R(t) \tag{Eq. 74}$$

Hybrid model

$$y(t)=T(t)*S(t)+R(t) \tag{Eq. 75}$$

In addition to the univariate time series analysis, autoregressive methods provide another modeling approach requiring only data on the previous modeled variable. Autoregressive models (AR) describe the actual output y_t by a linear combination of the previous time series y_{t-1}, y_{t-2}, . . . , y_{t-p} and of an actual impact at:

$$y_t = \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \ . \ \ . \ \ . {+}\varphi_p y_{t-p} + a_t \tag{Eq. 76}$$

The autoregressive coefficients have to be estimated on the basis of measurements. The time series method has the advantage of its simplicity and easy use. It is assumed that the pattern of the variable in the past will continue into the future. The main disadvantage of this approach lies in the fact that it ignores possible interaction of the variables. Furthermore, the climate impacts and other influence factors are neglected.

3.3.3.1 Machine Learning Techniques [31]

Machine learning techniques can be used for input selection and for learning the model dimension and parameters. It is possible to incorporate this to forecast a time series, with existing statistical and econometrics modeling techniques and to combine the results using an ensembler. Machine learning techniques are capable of translating domain knowledge and are able to provide equivalent accuracy in forecasting without having complete domain knowledge compared to the accuracy obtainable by having domain knowledge. Several machine solve classification problems, but they also can be applied to regression problems.

3.3.3.1.1 Ensemble Learning

Ensemble learning combines results from other learners to provide a summary of results. Majority voting treats each member (output from other machine learning techniques) equally and selects one output as a winner, that it is the output chosen by the majority of the members. The result is obtained once the outputs from all members are available.

While majority voting selects a single output, ensemble-regression uses the outputs from all of the component models in determining the final output. It non linearly transforms the component model outputs and learns weights for each of the transformed outputs. If component model outputs were not transformed, ensemble-regression would be equivalent to linear regression, where the component model outputs are independent variables, and the weights are regression parameters. Thus it combines the outputs from different modeling

techniques.
The figure below shows outputs from N forecasting techniques and they are combined using linear regression using a least square regression method

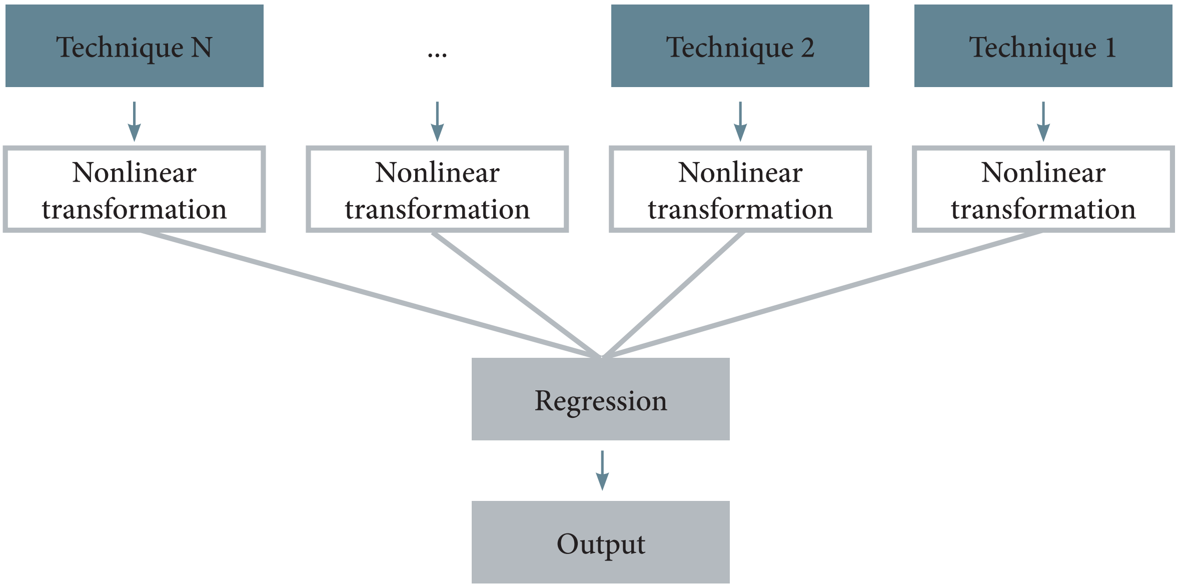


Figure 7: ensemble regression

3.3.3.1.2 Regression Tree

Regression tree is used for forecasting and it is a special form of a binary decision tree used for building non-linear regression models. A binary decision tree is a machine learning technique used for the classification, and a regression tree is used for regression. Like a binary decision tree, the decision nodes in a regression tree represent a decision based on the value of a given attribute. The leaves of the tree are learned using the forecasted values and there are fast and reliable algorithms available to learn the nodes and leaves.

3.3.3.1.3 Support Vector Regression

Support vector regression (SVR) is a nonlinear regression technique built on top of the support vector machine technology and it uses quadratic programming to find the optimized margins (i.e., the margin that fits the data most accurately). SVR is easily implemented through the support vector machine library and commonly used for energy demand forecasting. It is possible to select different kernel functions which allows modeling the nonlinearity. The target is to minimize:

$$\frac{1}{2}\|w\|^2 \qquad \textit{Eq. 77}$$

Subject to

$$\hat{y}_t = \left(w + \varphi\left(x\right)\right) + b \qquad \textit{Eq. 78}$$

$$y_t - (w + \varphi\left(x_i\right) - b < \epsilon \qquad \textit{Eq. 79}$$

$$(w + \varphi\left(x_i\right) + b - y_t < \epsilon \qquad \textit{Eq. 80}$$

where ε is the error boundary. This SVR is called ε-SVR. An example of that is showed in the figure below.

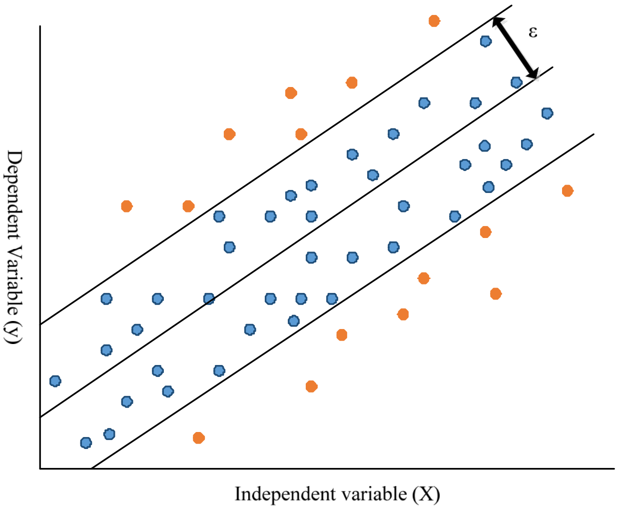


Figure 8: support vector regressions

3.3.4 Regression models

Regression models describe the causal relationship between one or more input variable(s) and the desired output as dependent variable by linear or nonlinear functions. In the simplest case the univariate linear regression model describes the relationship between one input variable x and the output variable y by the following formula:

$$y = f\left(x, a_0, a_1\right) = a_0 + a_1 x$$

Eq. 81

Thus geometrically interpreted a straight line describes the relationship between y and x. The shape of the straight line is determined by the so called regression parameters a0 and a1. For given measurements x_1, x_2, . . ., x_n and y_1, y_2, . . ., y_n of the variables x and y the parameters are calculated such that the mean quadratic distance between the measurements y_i (i=1, . . . ,n) and the model values $\hat{y}_i$ on the straight line is minimized. That means the following optimization problem is to be solved:

$$Q\left(a_0, a_1\right) = \sum_{i=1}^{n} (y_i - f\left(x_i, a_0, a_1\right))^2 \rightarrow Min_{a_1}^{a_0}$$

Eq. 82

The calculated regression parameters represent a so called least squares estimation of the fitting problem (Draper & Smith, 1998).
The regression model can be extended to a multivariate linear relationship where the output variable y is influenced by p inputs x_1, x_2, . . ., x_p:

$$y = f\left(x, a\right) = a_0 + a_1 x_1 + a_2 x_2 + \ldots a_p x_p$$

Eq. 83

We define the following notations:

$$y = \begin{bmatrix} y_1 \\ y_2 \\ . \\ y_n \end{bmatrix} a = \begin{bmatrix} a_1 \\ a_2 \\ . \\ a_n \end{bmatrix} \quad X = \begin{bmatrix} 1 & x_{11} & x_{1p} \\ 1 & x_{21} & x_{2p} \\ 1 & x_{n1} & x_{np} \end{bmatrix}$$

Eq. 84

where the vector y contains the measurements of the output variable, a represents the vector of the regression parameters, and the matrix X contains the measurements x_{ij} of the i^{th} observation of the input x_j. Thus the least squares estimation of the multivariate linear regression problem will be obtained by solving the minimization task:

$$Q\left(a_0, a_1, \ldots, a_p\right) = \sum_{i=1}^{nn} (y_i - a_0 - a_1 x_{i1} - a_2 x_{i2} - \ldots - -a_p x_{ip}))^2 = \left(y - Xa\right)^T \left(y - Xa\right) \rightarrow Min_{a_p}^{a_0}$$

Eq. 85

The least squares estimation of the regression parameter vector a represents the solution of the normal equation system referring to the minimization problem:

$$X^T Xa = X^T y$$

Eq. 86

Regarding the special structure of this linear system, adapted methods like Cholesky or Housholder procedures are available to solve $X^T Xa = X^T y$ using the symmetry of the coefficient matrix (Deuflhard & Hohmann, 2003). The model output can be described as

$$\hat{y} = X\hat{a}$$

Eq. 87

where the vector ŷ contains the model output values $\hat{y}_i$ (i=1, . . . , n) and a ˆ represents the vector of the estimated regression coefficients a_j (j=1, . . . , p) as the solution of $X^T Xa = X^T y$.
The results of the regression analysis must be proofed by a regression diagnostic. That means we have to answer the following questions:

- Does a linear relationship between the input variables x_1, x_2, . . . , x_p and the output y really exist?
- Which input variables are really relevant?
- Is the basic data set of measurements consistent or are there any “out breakers”?

With the help of the coefficient of determination B we can proof the linearity of the relationship.

$$B = 1 - \frac{\sum_{i=1}^{n} \left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{n} \left(y_i - \bar{y}\right)^2} = \frac{SSR}{SSY}$$

Eq. 88

where $\hat{y}_i$ represent the calculated model values given by $\hat{y} = X\hat{a}$ and y is the arithmetic mean value of the measured outputs y_i. B ranges from 0 to 1. Values of B in the near of 1 indicate, hat there exists a linear relationship between the regarded input and output. To identify the most significant input variables the modeling procedure must be repeated by leaving one of the variables from the model function within an iteration process. The coefficient of determination and the expression s^2 = SSR/(n-p-1) indicate the significance of the left variable. s^2 represents the estimated variance of the error distribution of the measured values of y. Finally the analysis of the individual residuals $r_i = y_i - \hat{y}_i$ gives some hints for the existence of “out breakers” in the basic data set.

Multivariate linear regressions are widely used in the field of energy demand forecast. They are simple to implement, fast, reliable and they provide information about the importance of each predictor variable and the uncertainty of the regression coefficients. Furthermore the results are relatively robust. Nonlinear regression models are also available for the forecast. But in this case the parameter estimation becomes more difficult. Furthermore the nonlinear character of the influence variable must be guaranteed. Regression based algorithms typically work in two steps: first the data are separated according to seasonal variables (e.g. calendar data) and then a regression on the continuous variables (meteorological data) is done. That means a regression analysis must be done for each seasonal cluster following the algorithm:

1. Analysis of the available energy data
2. Splitting the historical energy consumption data into seasonal clusters
3. Identifying the main meteorological factors on the energy demand
4. Regression analysis
5. Validation of the model
6. Integration of the sub models

3.3.4.1 A Simple Regression Model for Electrical Energy Forecasting [36]

In this section is presented a simple Regression Analysis (RA) based model for long-term forecasting of India's sector-wise electrical energy demand involving per capita GDP and Population. RA is a technique used for analysing the numerical data. The dependent variable y_i is a linear combination of the parameters, α, and the independent variables, y_i , which could be linear or nonlinear. The simple linear and multiple linear regressions are the two basic types of linear regression. For instance, in simple regression of N data points'modelling, there is one independent variable, x_i , and two parameters, α_0 and α_1 , which yield a straight line, called fitted regression line:

$$y_i = \alpha_0 + \alpha_i x_i + e_i \qquad i = 1, \ldots, N$$

Eq. 89

In multiple linear regressions, there are more than one independent variable or function of independent variables. For example, the preceding regression with x_i^2 term gives a parabola:

$$y_i = \alpha_0 + \alpha_1 x_i + \alpha_2 x_i^2 + e_i \qquad i = 1, \ldots, N$$

Eq. 90

Although the right-hand side expression is quadratic, it is still considered to be linear regression, as it involves linear parameters, α_0 , α_1 and α_2 .
In the general multiple RMs, there may be m independent variables:

$$y_i = \alpha_0 + \alpha_1 x_{1i} + \ldots + \alpha_m x_{mi}^2 + e_i \qquad i = 1, \ldots, N$$

Eq. 91

Where e_i is the error term, which represents the unexplained variation in the dependent variable and is treated as a random variable. In practice, the performance of Regression Models depends on the form of the data-generating process and its relation to the regression approach used. Typically, the best fit is evaluated by using the least squares method, although other criteria are also used.
After the overview of regression analysis, it can be moved to the objective: to develop a simple forecasting model for predicting the sector-wise electrical energy demand, unlike existing models of estimating the net energy demand, for the future years with least input data.
Per capita GDP and population are linked with the total energy consumption of any country and can be predicted. They are used as inputs in the long term forecasting model taken into account in this section, which fails to develop a tool for obtaining the required input data for the future years, thereby making the model incomplete. The proposed model comprises two regression models, the former one predicts the population and per capita GDP for a given future year and the later one estimates the sector wise energy demand by considering the

output of the former as input. It can be seen in the figure below.

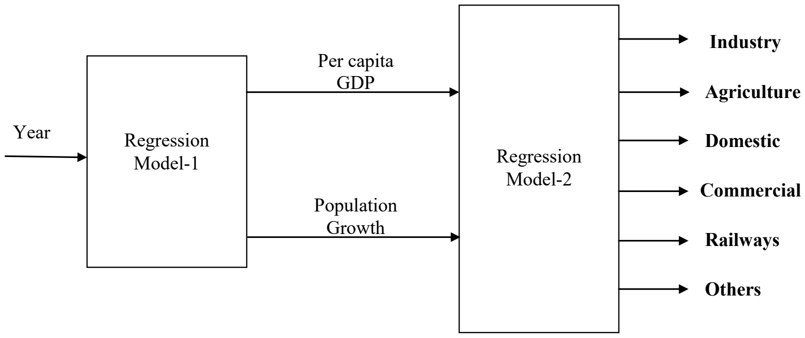


Figure 9: proposed forecasting model

The per capita GDP and the population data during the period of 1980-2012, are used to develop the model. The RA is applied to relate the year with per capita GDP and population growth. Then the per capita GDP and population growth are related with sector wise electrical energy demand through RA to construct RM-2. These two models are combined to form the proposed model. The proposed model receives the year of forecast as the input and predicts initially the population growth and per capita GDP, which are further processed to perform forecasting of sector-wise energy demand. The intermediate results in terms of per capita GDP and the population, offered by RM-1, for four different previous years are presented with the actual values in the following table.

Year		Intermediate Results/Data		Forecasted Electrical Energy (BkWh)						MAPE
		Per Capita GDP	Population (Millions)	Industry	Agriculture	Domestic	Commercial	Railways	Others	
1989	Actual	821.48	817.49	76.82	38.85	24.61	10.06	4.04	5.82	
	PM	847.74	817.55	80.71	44.03	25.47	10.43	3.87	6.81	7.80
1997	Actual	1285.94	962.38	104.17	84.02	55.27	17.52	6.53	12.64	
	PM	1298.55	958.70	100.71	80.54	56.72	16.64	6.51	13.20	3.31
2005	Actual	2190.27	1080.26	137.59	88.56	95.66	31.38	9.49	23.45	
	PM	2206.65	1086.40	147.93	95.59	96.34	33.71	9.82	23.63	4.64
2009	Actual	3103.73	1166.08	209.47	109.61	131.72	54.19	11.43	37.58	
	PM	3138.71	1158.59	226.92	112.03	136.16	53.76	11.98	36.31	3.82
Average of MAPE										4.89

Figure 10: results for previous years

The corresponding predictions of sector wise energy demand, obtained by RM-2, along with their mean absolute percent error (MAPE) are also included in the same table. The forecasted sector wise energy demand along with intermediate per capita GDP and population during the years 2013- 2025 are presented in the following table.

Year	Intermediate Results		Forecasted Electrical Energy (BkWh)					
	Per Capita GDP	Population (Millions)	Industry	Agriculture	Domestic	Commercial	Railways	Others
2013	5125.28	1209.75	313.98	149.00	200.76	86.42	16.19	47.89
2014	5690.23	1226.25	346.77	162.41	223.78	95.95	17.42	52.75
2015	6295.78	1248.56	381.04	178.13	249.46	106.02	18.78	57.94
2016	6938.99	1267.88	416.23	195.59	277.83	116.56	20.26	63.55
2017	7615.92	1287.75	452.06	214.25	309.42	127.70	21.81	69.51
2018	8321.45	1309.94	488.23	236.34	343.58	139.42	23.46	75.78
2019	9049.44	1330.69	524.08	260.31	380.58	151.60	25.22	82.09
2020	9792.53	1351.38	558.96	285.16	420.03	164.10	27.06	88.58
2021	10542.00	1372.50	592.39	314.00	461.56	177.11	28.90	94.96
2022	11287.82	1390.13	622.53	346.47	504.81	190.38	30.78	101.14
2023	12018.59	1406.69	649.42	380.28	549.05	204.05	32.62	106.63
2024	12721.35	1418.81	672.05	417.13	593.72	218.14	34.42	111.41
2025	13381.58	1431.25	689.50	457.66	637.76	232.55	36.11	114.97

Figure 11: results of the proposed model

The policy makers of the government as well as the energy utilities should take appropriate steps for construction of new power plants based on the electrical energy requirement by the year 2025.

3.3.5 Neural networks

Neural networks represent adaptive systems describing the relationship between input and output variables without explicit model functions. Neural networks are widely used in the field of energy demand forecast [37]. The basic elements of neural networks are the neurons, which are simple processing units linked to each other with directed and weighted connections. Depending on their algebraic sign and value the connections weights are inhibiting or enhancing the signal that is to be transferred. Depending on their function in the net, three types of neurons can be distinguished:

- The units which receive information from outside the net are called input neurons.
- The units which communicate information to the outside of the net are called output neurons.
- The remaining units are called hidden neurons because they only send and receive information from other neurons and thus are not visible from the outside.

The calculated output is processed by an activation function, and the final output is generated. The calculation taking place in a single neuron is:

$$y = f\left(b_0 + \sum_{i=1}^{n-1} w_i x_i\right)$$

Eq. 92

where x represents the input vector, y is the output, w is the weight vector, b_0 is the bias and f is the activation function. Most commonly, a sigmoid function is used as an activation function:

$$f(x) = \frac{1}{1+e^{-x}}$$

Eq. 93

To support nonlinearity, a neural network with more than one neuron is needed. Neural networks can have multiple layers, where each of the layers consists of one or more neurons. The neurons from one layer are connected to the adjacent layer neurons and a multilayer neural network contains an input layer, an output layer and one or more hidden layers, as suggested by figure below, where there is a multilayer artificial neural network.

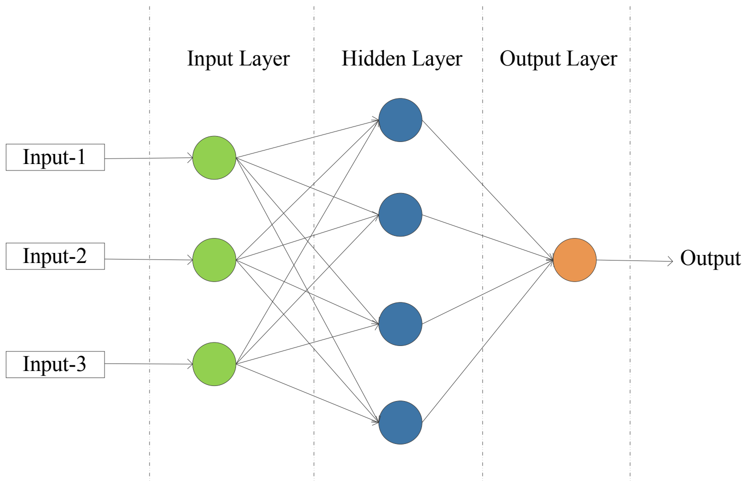


Figure 12: multilayer neural network

Generally a neural net consists of one input and one output layer, but it can have several hidden layers.

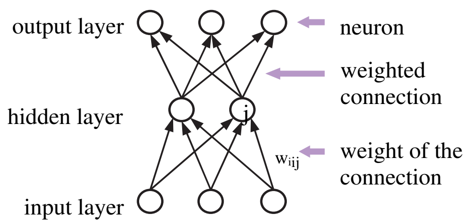


Figure 13: structure of a neural network

The pattern of the connection between the neurons is called the network topology. In the most common topology each neuron of a hidden layer is connected to all neurons of the preceding and the following layer. Additionally in so-called feedforward networks the signal is allowed to travel only in one direction from input to output.
To calculate its new output depending on the input coming from the preceding units (or from outside) a neuron uses three functions [38]:

- the inputs to the neuron j from the preceding units combined with the connection weights are accumulated to yield the net input.
- value is subsequently transformed by the activation function f_{act}, which also takes into account the previous activation value and the threshold θ_j (bias) of the neuron to yield the new activation value of the neuron.
- final output o_j can be expressed as a function of the new activation value of the neuron.

In most of the cases this function f_{out}, is not used so that the output of the neurons is identical to their activation values like in the figure below.

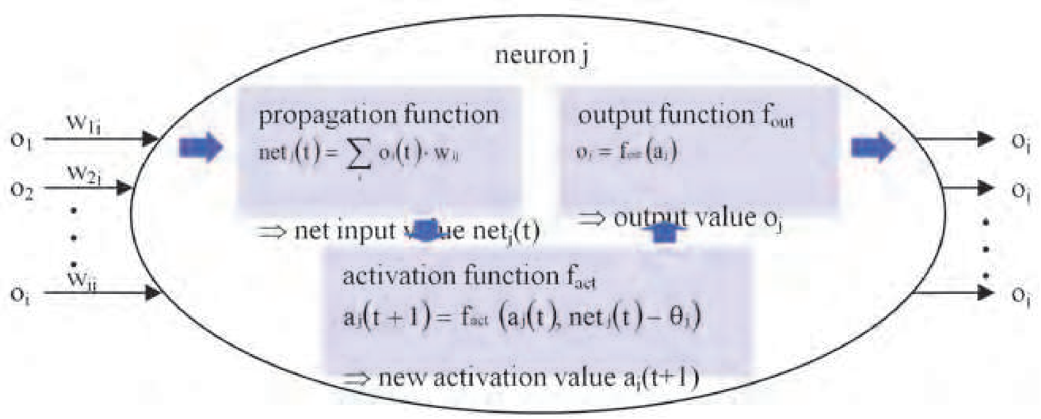


Figure 14: structure of a neuron

Three sigmoid (S-shaped) activation functions are usually applied: the logistic, hyperbolic tangent and limited sine function. The formulas of the functions are given by:

$$f_{log}(x) = \frac{1}{1+e^{-x}} \quad f_{tanh}(x) = \frac{e^{x}-e^{-x}}{e^{x}+e^{-x}} \quad f_{sin}(x) = \begin{cases} 1 & for\, x > \pi/2 \\ \sin(x) & for\, -\pi/2 \le x \le \pi/2 \\ -1 & for\, x \le \pi/2 \end{cases}$$

Eq. 94

A neural network has to be configured such that the application of a set of inputs produces the desired set of outputs. This is obtained by training, which involves modifying the connection weights. In supervised learning methods, after initializing the weights to random values, the error between the desired output and the actual output to a given input vector is used to determine the weight changes in the net. During training, input pattern after input pattern is presented to the network and weights are continually adapted until for any input the error drops to an acceptable low value and the network is not overfitted. In the case that a network has been adjusted too many times to the patterns of the training set, it may in consequence be unable to accurately calculate samples outside of the training set. Thus by overlearning the neural network loses its capability of generalization. One way to avoid overtraining is by using cross-validation. The sample set is split into a training set, a validation set and a test set. The connection weights are adjusted on the training set, and the generalization quality of the model is tested, every few iterations, on the validation set. When this performance starts to deteriorate, overlearning begins and the iterations are stopped. The test set is used to check the performance of the trained neural network [39]. The most widely used algorithm for supervised learning is the backpropagation rule where it trains the weights and the thresholds of feedforward networks with monotonic and everywhere differentiable activation functions.

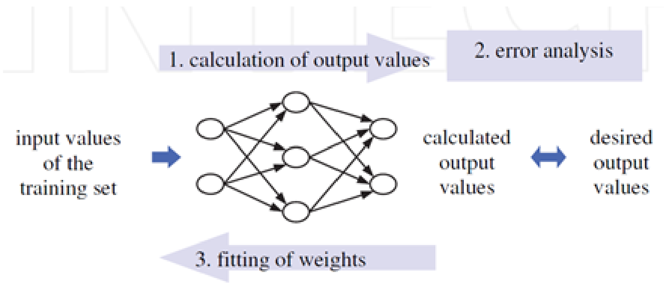


Figure 15: backpropagation learning rule

Mathematically, the backpropagation rule is a gradient descent method, applied on the error surface in a space defined by the weight matrix. The algorithm involves changing each weight by the partial derivative of the error surface with respect to the weight [40]. Typically, the error E of the network that is to be reduced is calculated by the sum of the squared individual errors for each pattern of the training set. This error depends on the connection weights:

$$E(W) = E(w_{11}, w_{12}, \ldots, w_{mn}) = \sum_p E_p \; with \; E_p = \frac{1}{2}\sum_j (t_{pj} - o_{pj})^2$$

Eq. 95

Where E_p is the error for one pattern p, t_{pj} is the desired output from the output neuron j and o_{pj} is the real output from this neuron. The gradient descent method has different drawbacks, which result from the fact that the method aims to find a global minimum with only information about a very limited part of the error surface. To allow a faster and more effective learning the so-called momentum term and the flat spot elimination are common extensions to the backpropagation method. The great disadvantage of neural networks is the large amount of computing time.

In order to use neural networks for the energy demand forecast the following algorithm must be realized:

1. Preliminary analysis of the main influence factors on the energy demand
2. Design of the topology of the Neural Network
3. Splitting the basic data into a training set, a validation set and a test set
4. Test and selection of the best suitable activation function
5. Application of the backpropagation learning rule with momentum term and flat spot elimination
6. Validation and comparison of the modeling results
7. Selection of the best suitable network

Part 2

Capitolo 4 | Energy analysis and projections

In this chapter it is begun to introduce what will be the objective of this thesis: the analysis of data and energy policies of a State, taken as a case study, and then proceed to future energy projections through the use of a specific tool, in our case LEAP. The chapter starts with the presentation of an example of analysis and energy projection, the World Energy Outlook, that contains the approach that has been followed for the creation of scenarios. It then goes on to describe LEAP and to emphasize the choice of the tool than other possible candidates, analyzing and comparing them.

4.1 World Energy Outlook [41]

The annual World Energy Outlook (WEO) is the International Energy Agency's flagship publication and it is now the world's most authoritative source of energy market analysis and projections, providing critical analytical insights into trends in energy demand and supply and what they mean for energy security, environmental protection and economic development.
The WEO projections are used by the public and private sector as a framework on which they can base their policy-making, planning and investment decisions and to identify what needs to be done to arrive at a supportable and sustainable energy future.
The WEO received numerous awards from governments and energy industry for its analytical excellence and it represents the leading source for medium to long-term energy market projections, extensive statistics, analysis and advice for both governments and the energy business. Using a Reference Scenario based on no change in current policies, it enables policy-makers to evaluate their current path.
This Outlook incorporates all the latest data and developments to produce a comprehensive and authoritative analysis of medium- and longer-term energy trends, with projections for the first time extended to 2040. It complements a full set of energy projections with strategic insights into their meaning for energy security, the economy and the environment.
The World Energy Outlook makes use of a scenario approach to examine future energy trends relying on the World Energy Model. For the Outlook 2014, detailed projections for three scenarios were modeled and presented: the New Policies Scenario, the Current Policies Scenario and the 450 Scenario. The scenarios differ with respect to what is assumed about future governments policies related to the energy sector.
The Current Policies Scenario embodies the effects of only those government policies and measures that had been enacted or adopted by mid-2014. The New Policies Scenario takes into account those policies and measures that countries are currently considering and are assumed to adopt and implement, taking account of technological and cost factors, the political context and market barriers. IEA use an often cautious method of the extent to which policy proposal will be implemented and it considers institutional, political and economic obstacles as well as, in some cases, a lack of detail in announced intentions and about how they will be implemented.
The 450 Scenario illustrates what it would take to achieve an energy trajectory consistent with limiting the long-term increase in average global temperature to 2°C by limiting the concentration of greenhouse gases in the atmosphere at a level above 450 parts per million(ppm) [11]. The basis of the 450 scenario is therefore different. Rather than being a projection influenced by policy actions, it deliberately selects a plausible energy pathway to achieve the objective of the GHG emissions reduction.

	Current Policies Sce-nario	New Policies Scenario	450 Scenario
Definitions	Government policies that had been enacted or adopted by mid- 2014 continue un-chan-ged	Existing policies are maintai-ned and recently announced commit-ments and plans, includ-ing those yet to be for-mally adopted, are im-plemented in a cautious manner	Policies are adopted that put the world on a path-way that is consistent with having around a 50% chance of limiting the global increase in av-erage temperature to 2°C in the long term, com-pared with pre-industrial levels
Objectives	Provide a baseline that shows how energy markets would involve if underlying trends in energy demand and supply are not changed	To provide a benchmark to assess the potential achieve-ments (and limitations) of re-cent developments in energy and climate policy	To demonstrate a plausible path to achieve the climate target

Table 5: definitions and objectives of WEO scenarios

4.1.1 WEO Model

The WEM is a simulation model covering energy supply, energy transformation and energy demand. The majority of the end-use sectors use stock models to characterise the energy infrastructure. In addition, energy-related CO2 emissions and investments related to energy developments are specified. Though the general model is built up as a simulation model, specific costs play an important role in determining the share of technologies in satisfying an energy service demand. In different parts of the model, Logit and Weibull functions are used to determine the share of technologies based upon their specific costs. This includes investment costs, operating and maintenance costs, fuel costs and in some cases costs for emitting CO2.

The main exogenous assumptions concern economic growth, demographics and technological developments. Electricity consumption and electricity prices dynamically link the final energy demand and transformation sector. Consumption of the main oil products is modelled individually in each end-use sector and the refinery model links the demand for individual products to the different types of oil. Demand for primary energy serves as input for the supply modules. Complete energy balances are compiled at a regional level and the CO2 emissions of each region are then calculated using derived CO2 factors. The time horizon of the model goes out to 2040 with annual steps in between. The model is each year recalibrated to the latest available data point (for WEO-2014, this is typically 2012 although 2013 data is included where available).

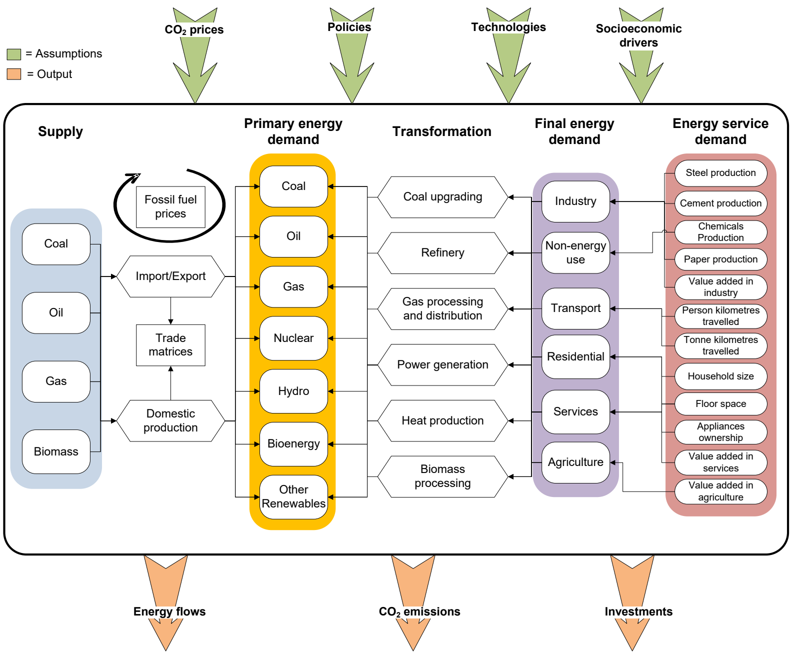


Figure 16: schematic representation of the World Energy Model 2014, showing input and output for each category

Demand side drivers, such as steel production in industry or household size in dwellings, are estimated econometrically based on historical data and on socioeconomic drivers. All end-use sector modules base their projections on the existing stock of energy infrastructure. This includes the number of vehicles in transport, production capacity in industry, and floor space area in buildings. The various energy service demands are specifically modelled, in the residential sector e.g. into space heating, water heating, cooking, lighting, appliances, space cooling. To take into account expected changes in structure, policy or technology, a wide range of technologies are integrated in the model that can satisfy each specific energy service. Respecting the efficiency level of all end-use technologies gives the final energy demand for each sector and sub-sector (Figure 2). Simulations are carried out on an annual basis. The WEM is implemented in Vensim (www.vensim.com), but makes use of a wider range of software tools.

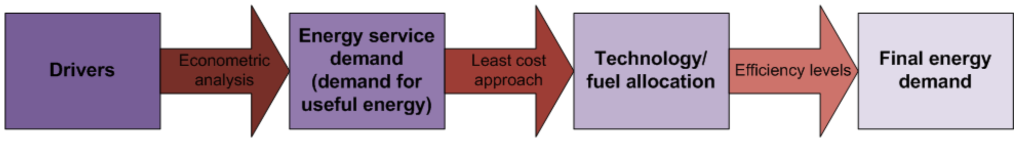


Figure 17: general structure of demand modules

The same macroeconomic and demographic assumptions are used in all the scenarios, unless otherwise specified. The projections are based on the average retail prices of each fuel used in final uses, power generation and other transformation sectors. These end-use prices are derived from projected international prices of fossil fuels and subsidy/tax levels.

Population assumptions

Rates of population growth for each WEM region are based on the medium-fertility variant projections contained in the United Nations Population Division report (UNDP, 2013). In WEO-2014, world population is projected to grow by 0.9% per year on average, from 7.0 billion in 2011 to 9.0 billion in 2040. Population growth slows over the projection period, in line with trends of the last three decades: from 1.0% per year in 2012-2025 to 0.8% in 2025-2040 (Table 2). Population expanded by 1.6% from 1980 to 2012.

Estimates of the rural/urban split for each region have been taken from UNDP (2012). This database provides percentage of population residing in urban areas by country in 5 yearly intervals to 2050. By combining this data2 with the UN population projections an estimate of the rural/urban split may be calculated. In 2012, slightly more than half of the world population was estimated to be living in urban areas. This is expected to rise to 64% by 2040.

	Population growth (compound annual average)			Population (million)		Urbanisation rate (%)	
	2012-25	2025-40	2012-40	2012	2040	2012	2040
OECD	**0.5%**	**0.3%**	**0.4%**	**1258**	**1403**	**80%**	**86%**
Americas	0.8%	0.6%	0.7%	488	594	82%	87%
United States	0.8%	0.6%	0.7%	318	383	83%	88%
Europe	0.3%	0.2%	0.2%	566	604	75%	82%
Asia Oceania	0.1%	-0.1%	0.0%	205	205	89%	94%
Japan	-0.2%	-0.5%	-0.4%	128	115	92%	97%
Non-OECD	**1.1%**	**0.8%**	**1.0%**	**5783**	**7601**	**47%**	**60%**
E. Europe/Eurasia	0.0%	-0.3%	-0.2%	341	326	63%	69%
Russia	-0.3%	-0.5%	-0.4%	144	127	74%	80%
Asia	0.8%	0.4%	0.6%	3678	4382	42%	58%
China	0.4%	-0.1%	0.1%	1358	1416	52%	74%
India	1.1%	0.7%	0.8%	1237	1566	32%	46%
Middle East	1.7%	1.1%	1.4%	213	313	68%	74%
Africa	2.4%	2.1%	2.2%	1083	1998	40%	52%
Latin America	1.0%	0.6%	0.8%	468	581	79%	85%
Brazil	0.7%	0.4%	0.5%	199	229	85%	90%
World	**1.0%**	**0.8%**	**0.9%**	**7042**	**9004**	**53%**	**64%**
European Union	0.1%	0.0%	0.1%	507	516	74%	81%

Table 6: population growth by region [41]

4.1.2 Macroeconomic assumptions

Economic growth assumptions for the short to medium term are based largely on those prepared by the OECD, IMF and World Bank. Over the long term, growth in each WEM region is assumed to converge to an annual long-term rate. This is dependent on demographic and productivity trends, macroeconomic conditions and the pace of technological change.

In WEO-2014 world GDP (expressed in year-2013 dollars at purchasing power parity [PPP] terms) is expected to grow on average by 3.3% per year over the projection period (Table 3). That rate is similar to the last two decades (3.3% in 1990-2012). Growth is assumed to drop from 3.7% in 2012-2020 to 3.6% in 2020-2030 and 3.0% in 2030-2040. India and Africa are expected to grow faster than all other regions, followed by China and the Brazil. The economies of many regions are expected to shift away from energy-intensive heavy manufacturing towards lighter industries and services, though the pace of this process, which is well advanced in the OECD and some emerging economies, varies. Industrial production growth over the next decades is going to come mainly from countries outside the OECD.

	1990-2012	2012-20	2020-30	2030-40	2012-40
OECD	**2.2%**	**2.2%**	**2.0%**	**1.7%**	**1.9%**
Americas	2.6%	2.6%	2.2%	2.0%	2.1%
United States	2.5%	2.6%	2.0%	1.9%	1.9%
Europe	1.9%	1.7%	1.9%	1.6%	1.7%
Asia Oceania	1.9%	1.9%	1.8%	1.3%	1.5%
Japan	0.9%	1.1%	1.1%	0.8%	0.9%
Non-OECD	**4.9%**	**5.3%**	**4.9%**	**3.7%**	**4.3%**
E. Europe/Eurasia	0.8%	2.8%	3.5%	2.7%	3.1%
Russia	0.7%	2.2%	3.5%	2.5%	3.0%
Asia	7.5%	6.3%	5.4%	3.9%	4.7%
China	9.9%	6.9%	5.3%	3.2%	4.2%
India	6.5%	6.2%	6.6%	5.3%	5.9%
Middle East	4.4%	3.7%	3.9%	3.3%	3.6%
Africa	4.0%	5.1%	4.8%	4.4%	4.6%
Latin America	3.4%	3.1%	3.5%	3.0%	3.2%
Brazil	2.9%	2.9%	4.0%	3.3%	3.6%
World	**3.3%**	**3.7%**	**3.6%**	**3.0%**	**3.3%**
European Union	1.7%	1.6%	1.8%	1.5%	1.7%

Note: Calculated based on GDP expressed in year-2012 dollars in PPP terms.

Table 7: real GDP growth by region (compound average annual growth rates) [41]

4.2 Choice of the tool to conduct the study

The software chosen to conduct this study is LEAP, a model based on the end-use approach (described in paragraph 3.2.2.2). The method used by this software is the Time Series Analysis described in paragraph 3.3.3. The purpose of this thesis is to be able to analyze all energy aspects of a case study to analyze energy futures with current policies and produce a plausible optimization on the same data. Beyond a remarkable collection specific data, the innovation that reveals this work is to have a reliable basis from which to build all possible scenarios of interest, to be able to analyze the effectiveness or not of certain corrective actions in area of interest. With the skills to adapt to any geographic level, to cover both demand and supply side using an end-use approach, to analyze at a disaggregated level (where the level of disaggregation can be decided by users), to develop a consistent storyline of the possible paths of energy system evolution, LEAP model has been chosen among the models based on the end-use approach. A brief summary of LEAP characteristics is shown in the following table:

Type	Purpose	Approach	Geographical coverage	Activity coverage
Bottom-up	Energy system analysis	Accounting	Flexible	Demand and supply sec-tors
Level of dis-aggre-gation	Technology coverage	Data need	Skill	Versatility
Industry, tran-sport, house-hold and service	Both conventional and renewable	Historical, so-cio-economic, techno-logical and other information	Medium	High general model
Portability to another coun-try	Documentation	Capability to analy-ze price-induced policies	Capability to analyze non-price policies	Rural energy
Easy	Excellent	Does not exist	High	Can be included

Table 8: brief summary of LEAP characteristics

4.2.1 Integrated models

4.2.1.1 Description of the tool used: LEAP software

LEAP [42], the Long range Energy Alternatives Planning System, is a widely-used software tool for energy policy analysis and climate change mitigation assessment developed at the Stockholm Environment Institute. It has been adopted by thousands of organizations in more than 190 countries worldwide. LEAP is an integrated modeling tool that can be used to track energy consumption, production and resource extraction in all sectors of an economy. It can be used to account for both energy sector and non-energy sector greenhouse gas emission sources and sinks.

It is a flexible modeling environment that allows building specific applications suited to particular problems at various geographical levels (cities, State, country, region or global). As an integrated energy planning model LEAP covers both the demand and supply sides of the energy system. The model follows the accounting framework approach to generate a consistent view of energy demand (and supply) based on the physical description of the energy system. It also relies on the scenario approach to develop a consistent storyline of the possible paths of energy system evolution. Thus for the demand forecasting, the model does not optimize or simulate the market shares but analyses the implications of possible alternative market shares on the demand.

The demand analysis, following the end-use approach, is carried out as follows [43]:

- The analysis is carried out at a disaggregated level, where the level of disaggregation can be decided by the users.
- The disaggregated structure of energy consumption is organized as a “hierarchical tree”, where the total or overall activity is presented at the top level and the lowest level reflects the fuels and devices used.
- The socio-economic drivers of energy demand are identified and developed.
- The product of activity and the energy intensity determines the demand at the disaggregated level. The model allows alternative options:
    - at the end-use level, useful energy can be considered to forecast the demand.
    - Stock analysis allows the possibility of capturing the evolution of the stock of appliances/ devices or capital equipment and the device energy intensity.
    - For the transport sector, the fuel efficiency of the vehicle stock and distance traveled can be used to determine the demand.

The demand relationships are indicated below [43]:

- Final energy analysis: E = A x I, where A = activity level, I = final energy intensity.
- Useful energy analysis: E = A x (U/η), where U = useful energy intensity, η = efficiency.
- Stock analysis: E = S x D, where S = stock and D = device intensity.
- Transport analysis: E = S x (M/Fe), where M = vehicle miles and Fe = fuel economy.

The model can be run independently on a stand alone mode and can be used for specific sector analysis or for analyzing the energy system of a given geographic region.

The supply-side of the model does not try to find the least cost solution or system configuration as in the optimisation model but uses accounting and simulation approaches to provide answers to "what-if" type of analysis under alternative possible development scenarios. This spreadsheet like tool is flexible enough to consider various data requirements and supports some econometric and simulation features in addition to basic energy accounting framework.

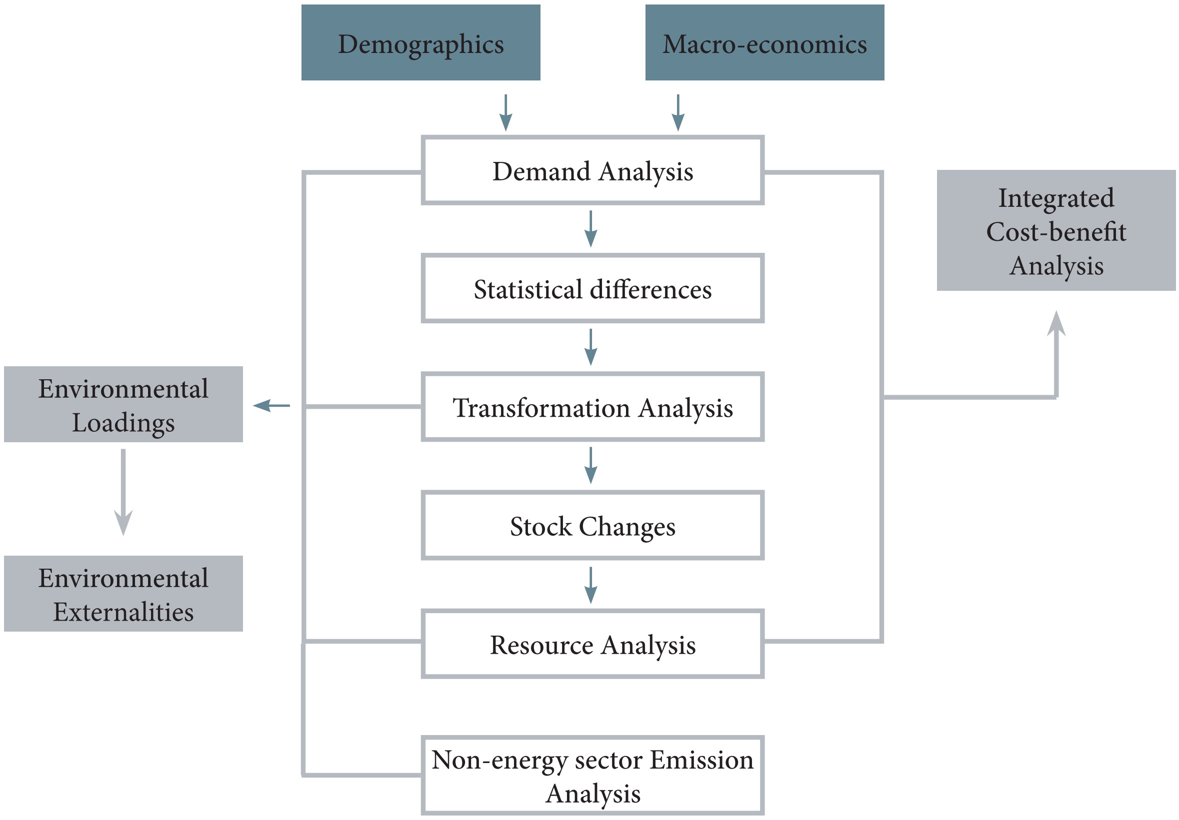


Figure 18: LEAP framework [43]

LEAP is not a model of a particular energy system, but rather a tool that can be used to create models of different energy systems, where each requires its own unique data structures. It supports a wide range of different modeling methodologies: on the demand side these range from bottom-up, end-use accounting techniques to top-down macroeconomic modeling. LEAP also includes a range of optional specialized methodologies including stock-turnover modeling for areas such as transport planning. On the supply side, LEAP provides a range of accounting and simulation methodologies that are powerful enough for modeling electric sector generation and capacity expansion planning, but which are also sufficiently flexible and transparent to allow LEAP to easily incorporate data and results from other more specialized models. LEAP's modeling capabilities operate at two basic conceptual levels. At one level, LEAP's built-in calculations handle all of the "non controversial" energy, emissions and cost-benefit accounting calculations. At the second level, users enter spreadsheet-like expressions that can be used to specify time-varying data or to create a wide variety of sophisticated multi-variable models, thus enabling econometric and simulation approaches to be embedded within LEAP's overall accounting framework. The newest versions of LEAP also support optimization modeling that allow the construction of least cost models of electric system capacity expansion and dispatch, potentially under various constraints such as limits of CO2 or local air pollution.

LEAP is intended as a medium to long-term modeling tool. Most of its calculations occur on an annual time-step, and the time horizon can extend for an unlimited number of years. Studies typically include both a historical period known as the Current Accounts, in which the model is run to test its ability to replicate known statistical data, as well as multiple forward looking scenarios. Typically, most studies use a forecast period of between 20 and 50 years.

LEAP is designed around the concept of long-range scenario analysis. Scenarios are self-consistent storylines of how an energy system might evolve over time. Using LEAP, policy analysts can create and then evaluate alternative scenarios by comparing their energy requirements, their social costs and benefits and their environmental impacts. The LEAP Scenario Manager can be used to describe individual policy measures which can then be combined in different combinations and permutations into alternative integrated scenarios. This approach allows policy makers to assess the marginal impact of an individual policy as well as the interactions that occur when multiple policies and measures are combined.

4.2.1.1.1 LEAP and the optimization [42]

LEAP includes the capability to automatically calculate least cost capacity expansion and dispatch of supply side transformation modules. This capability works through integration with the Open Source Energy Modeling System (OSeMOSYS) which has been developed by a coalition of organizations including the Royal Technical University (KTH) in Sweden, SEI, the International Atomic Energy Agency (IAEA), and the UK Energy Research Center. OSeMOSYS in turn depends on the GNU Linear Programming Kit (GLPK), a software toolkit intended for solving large scale linear programming problems by means of the revised simplex method. Both OSeMOSYS and GLPK are open source and freely distributed tools. Both are included as part of LEAP's standard installation and both are fully integrated into LEAP's user interface. No additional software is needed to use optimization in LEAP.
Optimization can be used to calculate the least-cost expansion and dispatch of power plants for an electric system, where optimal is defined as the energy system with the lowest total net present value of the social costs of the system over the entire period of calculation (from the base year through to the end year). In calculating the optimal system LEAP takes into account all of the relevant costs and benefits incurred in the system including:

- The capital costs for building new processes.
- The salvage values (or decommissioning costs) for decommissioning processes
- The fixed and variable operating and maintenance costs
- The fuel costs
- The environmental externality values (i.e. pollution damage or abatement costs).

A least cost system can optionally be calculated subject to a number of user specified constraints including maximum annual levels of emissions for any given pollutant (CO_2, SO_x, NO_x, PM_{10}, etc.) and minimum or maximum capacities for certain plant types. For example, an expansion pathway for an energy system could be calculated that met a minimum renewable portfolio standard (RPS) whilst also staying within a target for reducing greenhouse gas (GHG) emission.

4.2.1.2 POLES

The POLES (Prospective Outlook on Long-term Energy Systems) model is a recursive, disaggregated global model of energy analysis and simulation. It covers both the demand and the supply sides of the energy systems and has been used for long-term energy policy analysis by the European Union and the French government. The model captures the entire energy system and it has four main modules: final energy demand, new and renewable energy technologies, conventional energy transformation system and fossil fuel supply.
The demand is analyzed at a disaggregated level in each country or region following the bottom-up approach. The model is disaggregated into five sectors (industry, transport, residential, service and agriculture) to ensure homogeneous levels of activities. To capture the importance of the industrial sector and the transport sector, industry is further disaggregated in four groups, namely steel, chemical, non-metallic minerals and other industries, while four modes of transport, namely road, rail, air and water are considered. The demand is analysed using a disaggregated end-use approach in which demand is broken down into homogeneous groups to allow for separate treatment of energy intensive and non-intensive uses.
The general structure of the POLES model is:

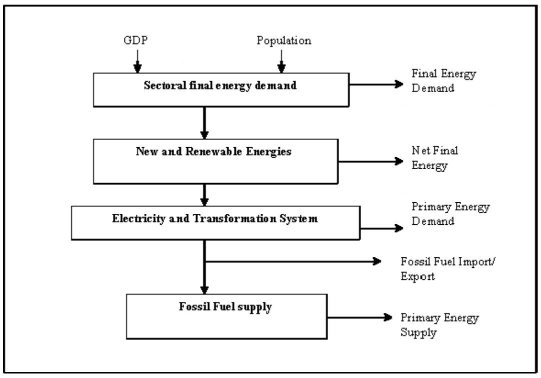


Figure 19: POLES model structure [44]

The model uses a polynomial lag structure of variable duration to capture stock adjustment process and dissipation of reaction to exogenous shocks:

$$\log\left(FC\right) = Re_s\_FC + \log(FC_{-1} + \left(-ES\right) * \left(\log\left(\frac{AP}{AP_{-1}}\right) * 0.67 + og\left(\frac{AP_{-1}}{AP_{-2}}\right) * 0.33\right) +$$

$$-\sum_{I=-1}^{-DP} f\left(EL * DI, I\right) * \log\left(\frac{AP_{I-1}}{AP_{I-2}}\right) + EY * \log\left(\frac{ACT}{ACT_{-1}}\right) + \log\left(1 + \frac{TR}{100}\right)$$

Where
FC – final energy consumption,
AP – average price of energy,
ES – short-term price elasticity of energy demand,
EL – long-term price elasticity of energy demand,
EY – income elasticity of demand,
ACT – activity variable,
F(EL, DI, I) – function capturing long term price effect, where DI is price asymmetry effect,
DP – duration of long-term price effect,
TR – autonomous technological trend, and
the subscripts indicate the lag periods.
Although the demand model is deeply rooted in the accounting framework and follows the bottom-up approach, unlike other end-use models, the POLES model has a few special features to whom can be considered a hybrid model:
• it generates the what on a yearly basis, as opposed to a snapshot picture at the end of a forecasting period;
• incorporates the price variable as a demand driver and thus can analyse the effects price and tax influences on demand;
• uses econometric-style relationships that are quite different from other standard end-use models.

4.2.2 Country-specific models

4.2.2.1 NEMS

The National Energy Modeling System (NEMS) was designed and primarily used by the US Department of Energy for preparing the Annual Energy Outlook. It is a model of energy-economy interaction that is used to analyze the functioning of the energy market under alternative growth and policy scenarios. The model uses a time horizon of about 25 years.
The model employs a technologically rich representation of the energy sector and covers the spatial differences in energy use in the US. The demand-side is disaggregated into four sectors, namely industry, transport, residential and commercial but both industry and transport are further disaggregated to capture the specific

features of energy intensive users and alternative modes of transport. This is a hybrid model because it uses the details found in engineering-economic models but retains the behavioural analysis found in topdown models. The model structure is presented in the next figure:

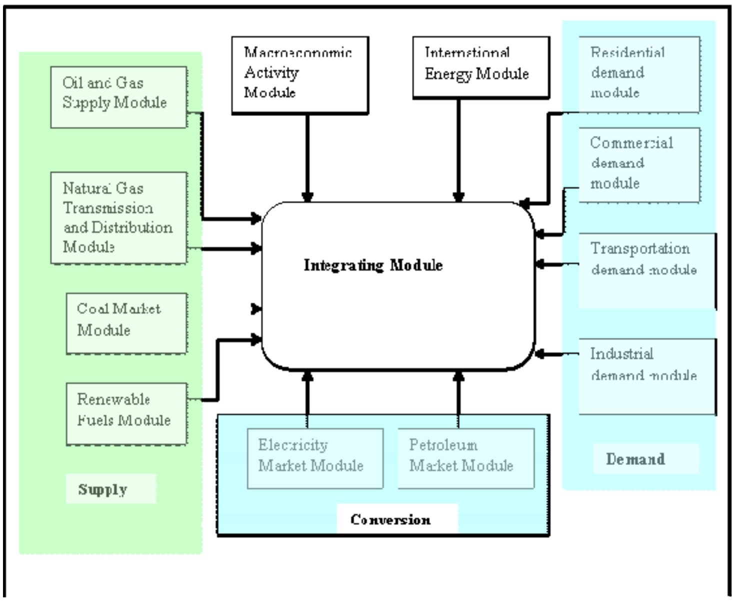


Figure 20: NEMS model structure [45]

The model is fairly detailed and explicitly represents the economic decision making at various levels (production, consumption, etc.) as well as technologies. The demand analysis component is divided into four modules (residential, commercial, industrial and transport) and each module captures the diversity at the regional level to a great extent.

Energy activity	Categories	Regions
Residential demand	Sixteen end-use services Three housing types Thirty–four end–use technologies	Nine Census divisions
Commercial demand	Ten end–use services Eleven building types Ten distributed generation technologies Sixty–four end-use technologies	Nine Census divisions
Industrial demand	Seven energy–intensive industries Eight non–energy–intensive industries Cogeneration	Four Census regions, shared to nine Census divisions
Transportation demand	Six car sizes Six light truck sizes Sixty–three conventional fuel-saving technologies for light–duty vehicles Gasoline, diesel, and thirteen alternative–fuel vehicle technologies for light-duty vehicles Twenty vintages for light-duty vehicles Narrow and wide–body aircraft Six advanced aircraft technologies Medium and heavy freight trucks Thirty–seven advanced freight truck technologies	Nine Census divisions

Table 9: demand representation in NEMS [45]

The residential demand module forecasts energy demand using a structural model based on housing stock and the appliance stock. It is driven by economic and demographic factors, structural effects, technology, and market effects. The commercial sector demand module projects energy demand in the commercial sector by taking into account building and non-building demand. It also captures the appliance stock and technological advancements and their effects on energy demand for three major fuels, namely electricity, natural gas and distillate oil. The industrial demand module projects energy demand in the industrial sector using a hybrid approach: it uses the technological representation found in the end-use method and incorporates the behavioral aspects of a top-down approach. The transport demand module projects the fuel demand in the transport sector by mode and includes alternative energy demand. A disaggregated approach is used in demand forecasting where personal car usage, light truck, freight transport, air transport and miscellaneous transport are considered separately.
The use of NEMS has remained confined to government agencies and a limited number of research laboratories because of the model's reliance on costly proprietary software packages and complex model design.

4.2.2.2 ERASME
ERASME is a short-term energy model that is used by the European Commission for quarterly forecasting of energy demand at the Community level (Deimeizis [46]). It also has a supply-side forecasting and the model produces the forecasts of energy balance. The results of the model feed into the Short-Term Energy Outlook of the Commission. The model contains 55 behavioral relations and a large number of identities capturing the European energy system. The model uses the data obtained from the Statistical Office of the Community and the equations are re-estimated twice a year.
The logic of the model's demand side is that final energy prices are considered to be a function of international oil prices, coal import prices, exchange rate, changes in the fiscal regime and seasonal factors. Energy demand by fuel is considered to a function of exogenous macro and sectoral variables (such as GDP, private consumption, industrial production, etc.) and real energy prices.

4.2.3 Generic energy forecasting models

4.2.3.1 MAED
MAED (Model for Analysis of Energy Demand) is a widely used bottom-up model for forecasting medium to long-term energy demand. The earlier versions of the model were built around a pre-defined set of economic activities and end-uses. The model follows the end-use demand forecasting steps typical for an engineering-economy model and it relies on the systematic development of consistent scenarios for the demand forecasts where the socio-economic and technological factors are explicitly taken into consideration. The demand is first calculated in useful energy form and the final demand is derived taking market penetration and end-use efficiency into consideration. The model does not use pricing and elasticity information for the inter-fuel substitution as is common in the econometric tradition. The energy demand is aggregated into four sectors (industry, transport, households, service) and it is essentially determined by relating the activity level of an economic activity to the energy intensity. The demand is first determined at the disaggregated level and then added up using a consistent accounting framework to arrive at the overall final demand.

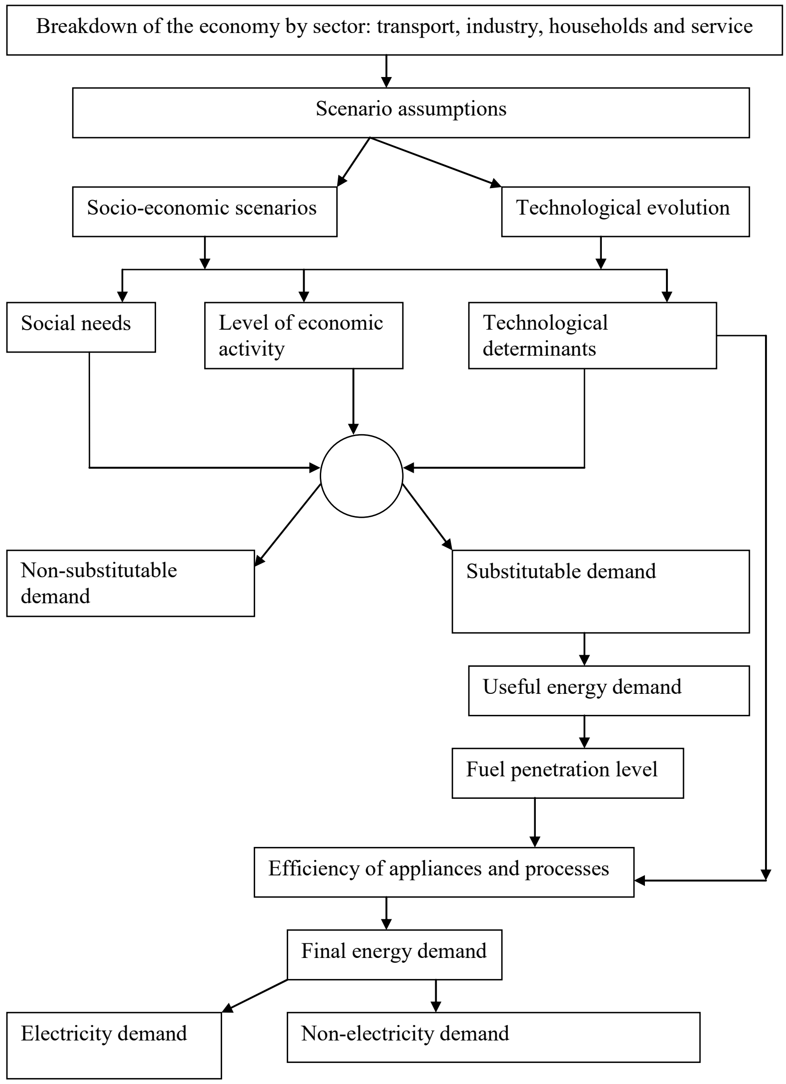


Figure 21: MAED framework of analysis [32]

The MAED model described above is essentially derived from the MEDEE model. The main difference between MAED and MEDEE is that MAED was based on an earlier version of MEDEE which has been further developed by IAEA into its present form, while MEDEE remains the model of the original authors and is supported by their energy consulting firm ENERDATA. Thus the modeling approach remains the same but the development of the two products has taken different paths in the recent times.

4.2.4 Comparison of selected energy demand models

In this section is presented a table to review the main features of the of the models seen and some observation from scientific literature.

Criteria	Kuwait model	DTI	ERASME	NEMS	MAED/ MEDEE	LEAP	POLES
Type	Top-down	Top-Down	Top-down	Hybrid	Bottom-up	Bottom-up	Hybrid
Purpose	Energy demand forecasting	Energy system analysis	Energy demand forecasting	Energy market analysis	Energy demand forecasting	Energy system analysis	Energy market analysis
Approach	Econometric	Econometric	Econometric	Econometric with rich technology representation	Accounting	Accounting	Accounting with econometric-style equations
Geographical coverage	National	National	Regional level but aggregated	National	Flexible	Flexible	Global
Activity coverage	Main end-use sectors	Demand and supply sectors	Main demand and supply sectors	Supply and demand sectors	Demand sectors	Demand and supply sectors	Demand and supply sectors
Level of disaggregation	Industry, residential, transport, commercial and others	Domestic, transport, service and industry	?	Industry, residential, commercial and transport	Industry, transport, household and service	Industry, transport, household and service	Industry, transport, household, service and agriculture
Technology coverage	Conventional	Both renewable and conventional	?	Both conventional and renewable	Both conventional and renewable	Both conventional and renewable	Both conventional and renewable
Data need	Time series data for econometric estimation	Time series data and technology data	Time series data for econometric estimation	Time series data, technology data, survey and census data	Data and survey/ estimates for base year information and estimation parameters	Historical, socio-economic, technological and other information	Time series, socio-economic data, technological data and survey/ estimates for various parameters
Skill requirement	High for econometric estimation	High for econometric analysis	High econometric analysis	High for running a complex model	Low	Medium	High for running a global model
Versatility	Low – country specific	Low – country specific	Low – region specific	Low – country specific	High – general model	High-general model	Low – specific global model
Portability to another country	Difficult	Difficult	Difficult	Difficult	Easy	Easy	Difficult
Documentation	Limited	Limited	Limited	Excellent	Excellent	Excellent	Poor
Capability to analyse price-induced policies	High	High	High	High	Does not exist	Does not exist	High
Capability to analyse non-price policies	Low	Good	Low	Good	High	High	High
Rural energy	Not covered separately	Not covered separately	Not covered separately	Included through geographical coverage	Can be included	Can be included	Not covered specifically

Table 10: comparison of energy demand forecasting models

The scientific literature agrees on the following observations from the comparison:

- Large national or global models are purpose-built and require considerable skills and lack versatility, irrespective of modeling approach used (econometric or hybrid). They also lack transferability or transportability. As a consequence, these models tend to be used by a limited number of dedicated user groups and are not accessible to wider users.
- Only MAED/ MEDEE and LEAP have the generic capabilities to be used in a wider context.
- While econometric models can be used for price-based policy analyses, many such models lack the capability to capture non-price based policies. Moreover, being aggregated demand models, they fail to capture the technological diversity and possibilities adequately.
- On the contrary, end-use models do not capture price signals and price-based policy analysis cannot be captured. Moreover, the issue of consistency with the macro-economic performance of the country or region is not verified in these models. However, their rich scenario capabilities allow them to consider non-price policies and structural changes in detail.
- Data requirement is generally a major issue for any demand model. All varieties of models require large data inputs and can pose problems for developing countries. However, simple end-use models can be developed with limited information and LEAP intends to introduce such a limited data version model for developing countries.
- Rural energy demand tends to be more difficult to capture through econometric models but end-use models can include them if relevant. Hybrid models can also include them if they use geographically differentiated information.

Capitolo 5 | Case Study: United Kingdom

In this chapter is presented the case study of this thesis, The United Kingdom. This is the heart of this work, where, through the software tool LEAP, the current energy situation of the UK is analyzed and then the future energy context is forecasted. The choice fell on this State, which belongs to the sphere of the industrialized countries, for the possibility of finding complex official data with greater ease and accuracy. In the first part the general context is presented, then energy forecast and scenario analysis is performed.

5.1 The general context

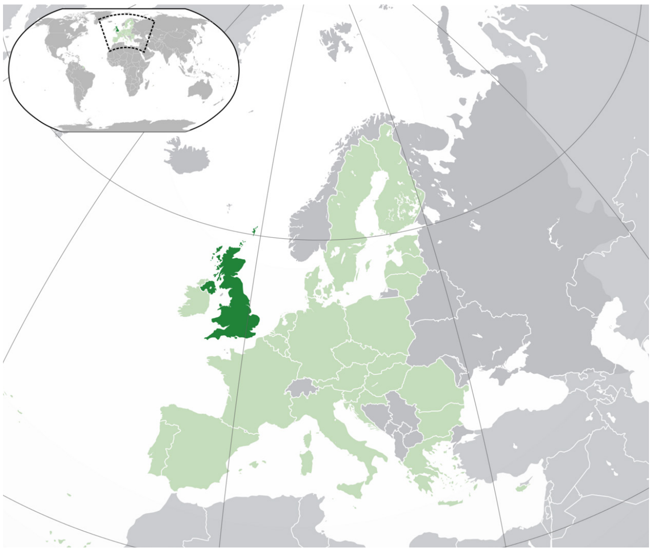


Figure 22: Great Britain [47]

The United Kingdom [47] of Great Britain and Northern Ireland, commonly known as the United Kingdom (UK) or Britain, is a sovereign State in Europe. The country has an area of 93,800 square miles (243,000 km2), making it the 80th-largest sovereign State in the world and the 11th-largest in Europe. This State is the 22nd-most populous country, with an estimated 64.5 million inhabitants. It is a constitutional monarchy with a parliamentary system of governance.

The UK is a developed country and has the world's fifth-largest economy by nominal GDP and tenth-largest economy by purchasing power parity. It is considered to have a high-income economy and is categorised as very high in the Human Development Index, currently ranking 14th in the world.

The United Kingdom's HDI value [48] for 2014 is 0.907— which put the country in the very high human development category—positioning it at 14 out of 188 countries and territories. Between 1980 and 2014, the country's HDI value increased from 0.738 to 0.907, an increase of 22.9 percent or an average annual increase of about 0.61 percent. The table below reviews the United Kingdom's progress in each of the HDI indicators. Between 1980 and 2014, The UK's life expectancy at birth increased by 7.2 years, mean years of schooling increased by 5.6 years and expected years of schooling increased by 3.3 years. Its GNI per capita increased by about 92.7 percent between 1980 and 2014.

	Life expectancy at birth	Expected years of schooling	Mean years of schooling	GNI per capita (2011 PPP$)	HDI value
1980	73.5	12.9	7.5	20,381	0.738
1985	74.6	13.2	7.7	22,570	0.753
1990	75.6	13.6	7.9	26,310	0.773
1995	76.6	14.9	11.4	28,255	0.837
2000	77.7	16.1	11.6	32,732	0.865
2005	79.0	16.6	12.2	37,518	0.890
2010	80.1	16.8	13.1	36,641	0.906
2011	80.2	16.2	13.1	36,973	0.901
2012	80.4	16.2	13.1	36,425	0.901
2013	80.5	16.2	13.1	36,576	0.902
2014	80.7	16.2	13.1	39,267	0.907

Table 11: life expectancy at birth, expected years of schooling, mean years of schooling, GNI, HDI in Britain [47]

The figure below shows the contribution of each component index to the United Kingdom's HDI since 1980.

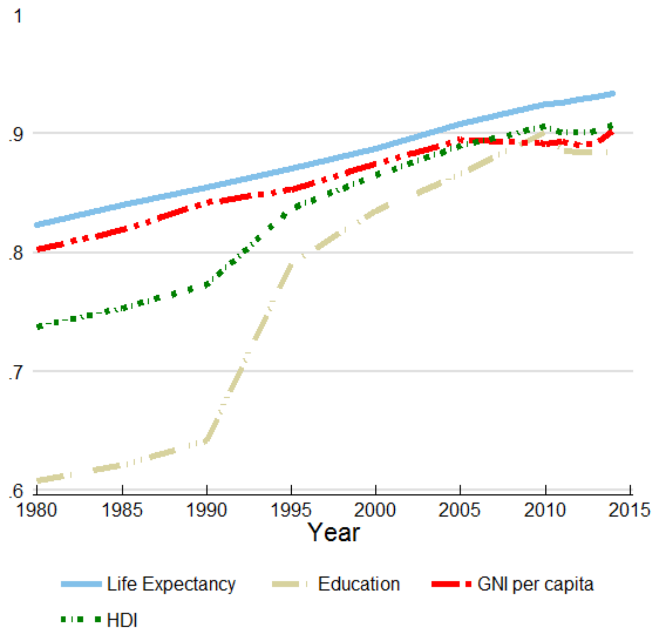


Figure 23: contribution of Life Expectancy, Education and GNI per capita to the United Kingdom's HDI since 1980

5.2 Analysis of the current state

The analysis of the UK case study in Leap begins from the productive structure's construction of the two main sections, Demand of Energy and Transformation. After that the Resources section is built with the data of production, import, export and cost. Each of these categories is explained and analyzed in the next chapters. The initial hard work to get along the results expressed in this thesis started from collecting official data with which fill all subcategories of the main branches, making a more accurate analysis possible. On this point it is correct

to spend some words: collect so much accurate data, both about consumption and energy transformations and about the policies implemented and being implemented, was a demanding activity.
The base year chosen is 2010 for reasons of data accuracy. In the first part of the analysis, in addition to showing the UK productive structure, all the data collected and their related sources are described.
Appendix 1 illustrates the policies adopted or planned by United Kingdom that determined the trends of the "current policies" scenario, from which were built optimized scenarios, treated after the current policies' analysis.
The analysis of the case study will be carried out by describing the scenarios created through the LEAP's results, with graphs and tables. The results of the program include energy data and the emissions of the case study, analyzed in depth between 2010 and 2040. Some charts may not arrive until 2040 because of the difficulty of being able to accurately predict the results until that date.
The main scenario, from which they are born after all the other optimized, is the Current Policies. This is loosely based on the scenario of the New Policies Scenario of the World Energy Outlook, described in paragraph 4.1. The Current Policies used in this paper takes into account both the policies implemented until 2014 as well as those that have only been announced (as of 2014) but will definitely be implemented shortly afterwards.
The scenarios created, inherited from Current Policies, are the following three:
• Optimize CP, which optimizes the Current Policies from a purely economic point of view.
• Carbon Tax opt30, which adds to the optimization of a £ 30 fee on the use of coal as a fuel in power generation.
• Carbon Tax opt40, which adds to the optimization of a £ 40 fee on the use of coal as a fuel in power generation

5.2.1 Input data and resources: the "Current Accounts"

In this section it will be described the data entered in the base year, 2010. A hierarchical structure is used to create and organize data under four major categories:
• Key Assumptions: under which independent variables are imposed and used to "drive" the calculations.
• Demand: under which the disaggregated structure of the energy demand analysis is created.
• Transformation: it simulates the conversion and transportation of energy forms from primary resources and imported fuels to the point of final fuel consumption.
• Resources: they include the production of indigenous resources and the import and export of secondary fuels.

In the figure 24 the productive structure for the case of the UK is divided into the categories described above. In the Key Assumptions a list of all constant was created to allow to attribute some calculations to these reference points.

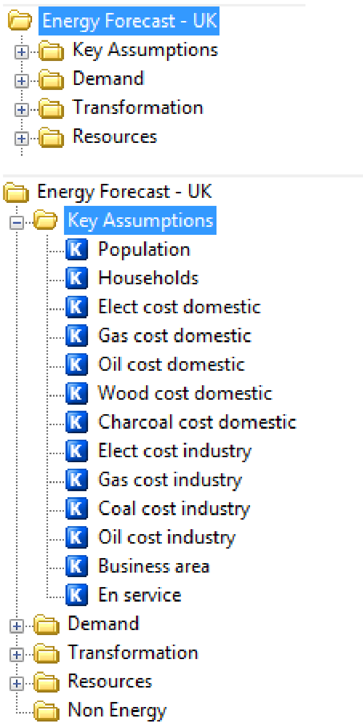


Figure 24: LEAP productive structure

5.2.1.1 Demand

The Demand is structured through the consumption's analysis of Households, Industry, Service, Transport and Energy Transformation.

5.2.1.1.1 Households

The households data are taken directly from the UK government website [49] and they are based on research by Department of Energy and Climate Change and Market Transformation Programme and analysis by Cambridge Architectural Research Ltd. The analyzed areas are visible in the tree diagram in the figure 25 and include in consumption of light, cold appliances, wet appliances, consumer electronics, home computing, cooking, space heating and water. The first five categories contain a list of the main electrical uses. As for cooking, space heating and water uses, it was decided to list the technologies related to energy consumption. This due to the fact that, unlike the previous categories, these uses don't involve only electric energy.
In the following pie diagram (figure 26) the categories described are showed, proportional to their energy consumption.

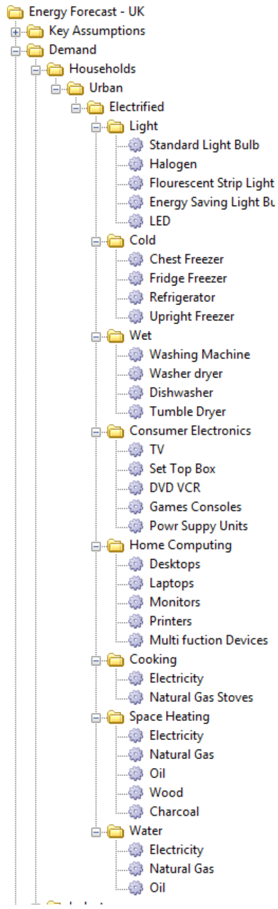


Figure 25: households structure

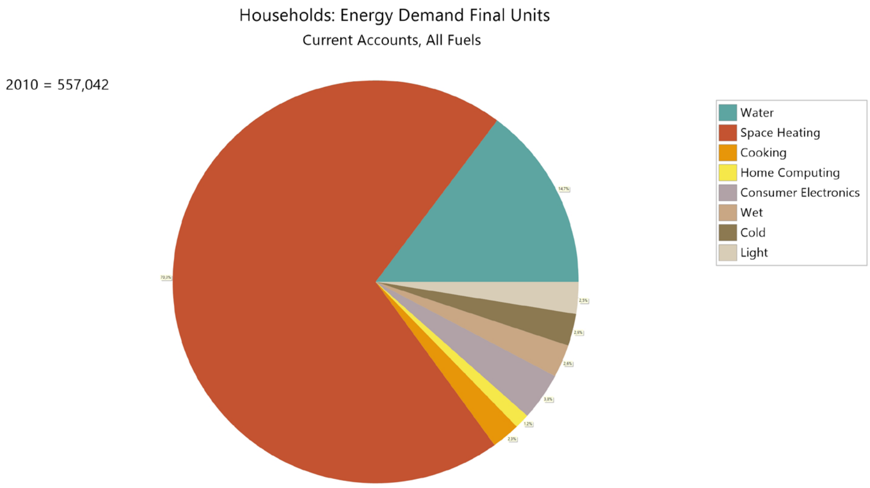


Figure 26: household energy demand, current accounts

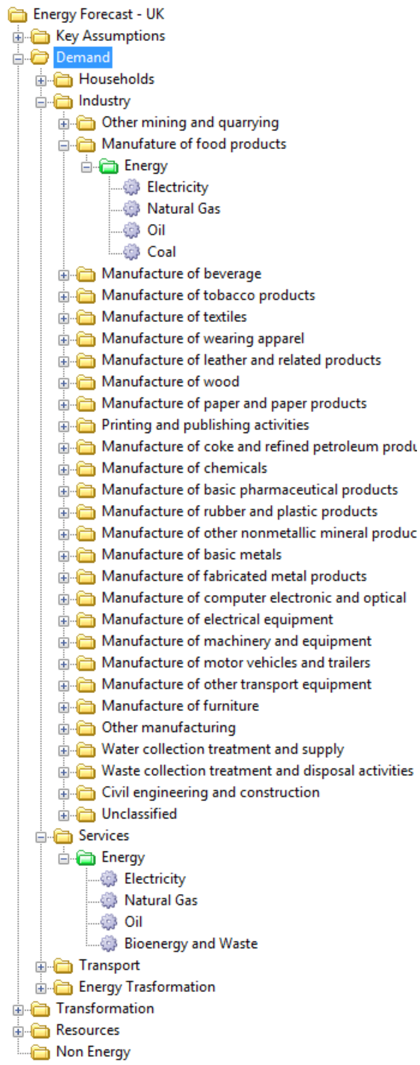
Consumption derived from the space heating and the use of hot water is greater, because are the categories with the highest energy demand.

5.2.1.1.2 Industrial Sector and Services

For each industry the energy consumption was analyzed between the four most used fuels: electricity, natural gas, oil and coal. The figure 27 shows all industries analyzed and then the category of services.

Even Industrial energy consumption data are taken directly from the UK government website [49] and exactly from Department of Energy and Climate Change. The industrial energy analysis was done based on the economic value added by energy intensive industries in United Kingdom. According to The World Bank [50] data, industries contributed to 22% of UK 2010 total GDP PPP which resulted to a total added value of 505,01 billion USD. Each sector of the following table presents the values of final energy intensity.

In the figure 28, the proportional consumption of all industrial sectors referred to 2010 is shown. It may be noted that the industrial sectors that consume most energy are the manufacture of coke and refined petroleum products, the manufacture of chemicals, the manufacture of non-metallic mineral products, the manufacture of food products, the manufacture of basic metals and the manufacture of rubber and plastic product.



Unit: Terawatt-hours

Figure 27: industry and services structure

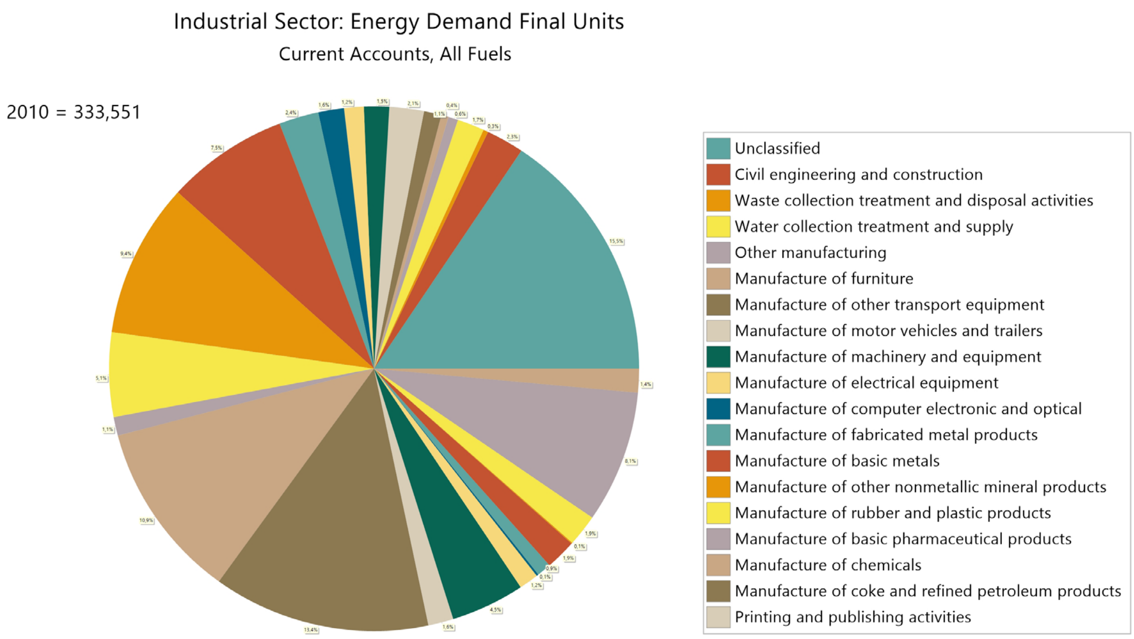


Figure 28: industrial sector energy demand final units, current accounts

Industrial final energy consumption

SIC(2007) codes	Description	Coal	Gas oil	Fuel oil	Oil	Burning oil	Natural gas	Electricity	Total	TOE/US $	Elec	Gas	Oil	Coal	Wood	LPG
		Thousand tonnes of oil equivalent (ktoe)									Fuel share %					
08	Other mining and quarrying	0	122	37	159	-	117	138	414	0,00000082	0,332747	0,28213	0,385122	0		
10	Manufacture of food products	24	49	78	127	-	1.377	790	2.318	0,00000459	0,340658	0,594119	0,054806	0,010416		
11	Manufacture of beverages	6	12	19	30	-	330	189	556	0,00000110	0,340659	0,59412	0,054806	0,010415		
12	Manufacture of tobacco products	0	0	0	0	-	7	12	19	0,00000004	0,6244	0,3756	0	0		
13	Manufacture of textiles	36	27	0	27	-	304	170	537	0,00000106	0,316271	0,566556	0,049389	0,067783		
14	Manufacture of wearing apparel	10	20	0	20	-	144	74	249	0,00000049	0,297757	0,579097	0,081229	0,041917		
15	Manufacture of leather and related products	0	0	0	0	-	18	18	36	0,00000007	0,505523	0,494449	0	0		
16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	0	13	2	14	-	104	224	342	0,00000068	0,654205	0,303953	0,041842	0		
17	Manufacture of paper and paper products	71	29	0	29	-	594	606	1.300	0,00000257	0,466611	0,456631	0,022142	0,054616		
18	Printing and publishing of recorded media and other publishing activities	0	4	0	4	-	106	335	446	0,00000088	0,752601	0,238727	0,008675	0		
19	Manufacture of coke and refined petroleum products	824	0	543	543	-	209	466	3.832	0,00000759	0,121614	0,054433	0,141683	0,68227		
20	Manufacture of chemicals and chemical products	46	158	125	282	-	1.360	1.437	3.126	0,00000619	0,459766	0,435186	0,090377	0,014671		
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations	5	16	13	29	-	142	150	326	0,00000064	0,459765	0,435185	0,090379	0,014672		
22	Manufacture of rubber and plastic products	311	11	2	13	-	238	913	1.474	0,00000292	0,619224	0,1615	0,008672	0,210603		
23	Manufacture of other non-metallic mineral products	702	40	0	40	-	1.479	487	2.708	0,00000536	0,179819	0,546201	0,014839	0,259142		
24	Manufacture of basic metals	61	0	4	4	-	686	909	2.147	0,00000425	0,423197	0,319565	0,001953	0,25427		
25	Manufacture of fabricated metal products, except machinery and equipment	9	0	0	0	-	298	393	701	0,00000139	0,561398	0,425675	0	0,012757		
26	Manufacture of computer, electronic and optical products	3	0	0	0	-	101	351	455	0,00000090	0,770789	0,222093	0	0,007063		
27	Manufacture of electrical equipment	0	0	0	0	-	126	222	347	0,00000069	0,638344	0,361567	0	0		
28	Manufacture of machinery and equipment n.e.c.	0	0	0	0	-	179	265	444	0,00000088	0,595535	0,403821	0	0		
29	Manufacture of motor vehicles, trailers and semi-trailers	36	64	8	72	-	215	287	610	0,00000121	0,47136	0,352308	0,117674	0,058659		
30	Manufacture of other transport equipment	0	38	15	53	-	89	167	309	0,00000061	0,540218	0,287926	0,171857	0		
31	Manufacture of furniture	0	2	0	2	-	40	85	128	0,00000025	0,669662	0,312327	0,015337	0		
32	Other manufacturing	0	3	0	3	-	54	115	172	0,00000034	0,669657	0,312325	0,015337	0		
36	Water collection, treatment and supply	0	3	0	3	-	15	458	477	0,00000094	0,960627	0,032458	0,006182	0		
38	Waste collection, treatment and disposal activities; materials recovery	0	23	0	23	-	11	52	86	0,00000017	0,607072	0,125382	0,263325	0		
42	Civil engineering/construction	3	125	28	153	-	369	139	665	0,00000132	0,209534	0,555307	0,23048	0,004681		
	Unclassified	0	1.427	246	3.314	1.641	2	0	4.456	0,00000882	0	0,000482	0,743622	0,012238	0,100659	0,142998
Total	Industrial consumption	2.147	2.185	1.121	4.945	1.641	8.715	9.453	28.680							

Table 12: industrial final energy consumption

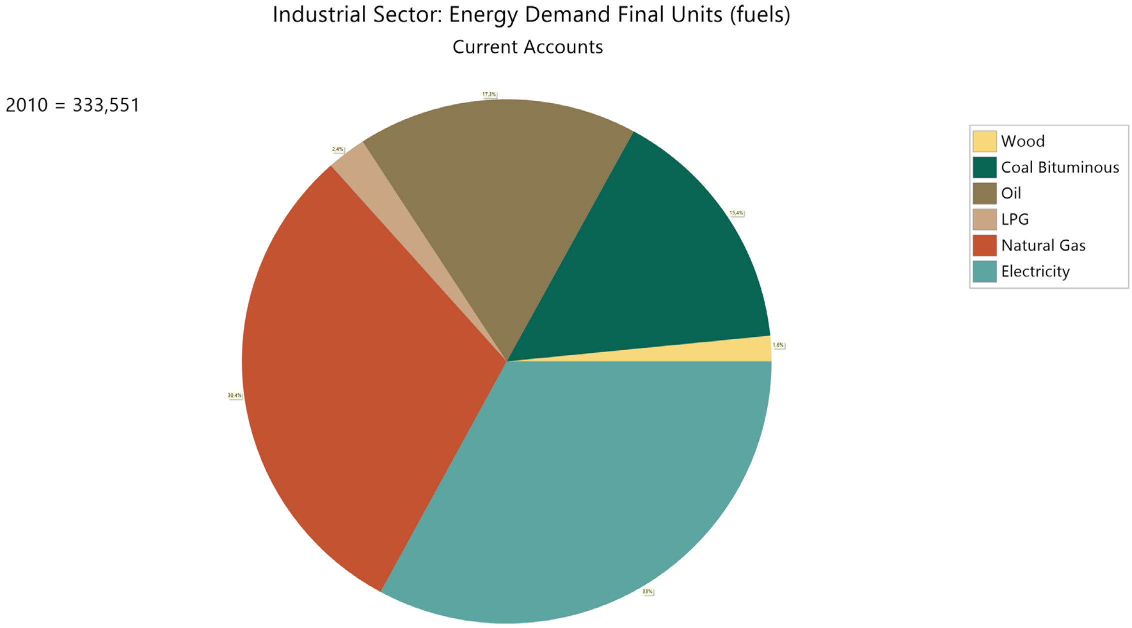


Figure 29: industrial sector energy demand final units, current accounts, divided by fuels

Regarding fuels, figure 29 shows the share of energy consumption of the industrial sector by type of fuel. It can be noticed that approximatively 60% of the overall consumption refers to fossil fuels.

The service sector energy analysis was done based on the floor area. For a given 207746 square meter [51] of services space in UK it is considered the total energy consumed. As for the industrial sector, it has been used the mechanism of calculating the energy intensity, this time based on floor area [Tonnes of oil equivalent/square meters]. The source data derive from Digest of UK Energy Statistics Annex, created by Department of Energy and Climate Change, available from the government web site [49]. Here the most widely used fuels are natural gas and electricity (figure 30).

Unit: Terawatt-hours

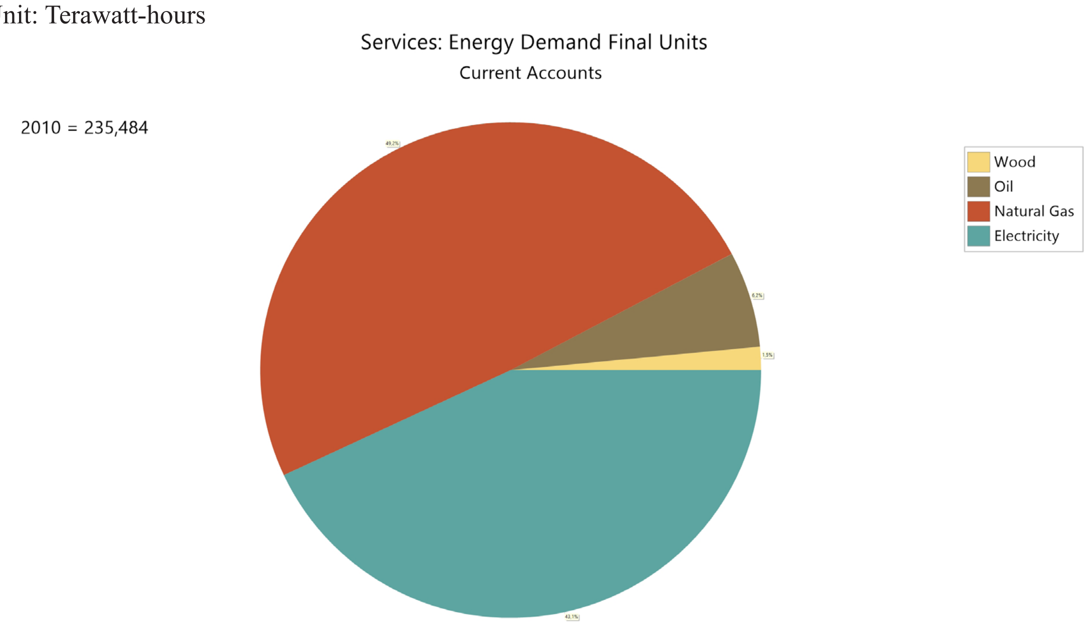


Figure 30: services sector energy demand final units, current accounts

5.2.1.1.3 Transport and Energy Trasformation

In this section four large areas were divided: Road, Rail, Water and Air. In the section of road, the distinction was made between energy used to transport people and freight (figure 31).

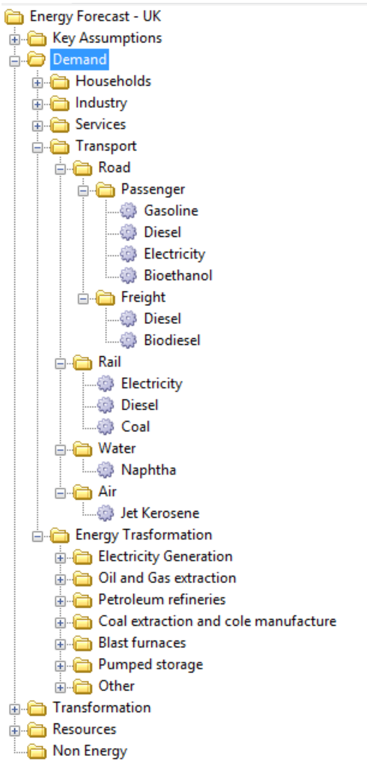


Figure 31: transport and energy transformation tree

Regarding the transport sector, data result more accurate if taken from analysis of data supplied by AEA Energy and Environment [49]. It may be noted from the following diagrams that the greatest amount of energy is consumed on the road section and, consequently, the most widely used fuel in the United Kingdom are diesel and gasoline (figure 32-33).

Unit: Terawatt-hours

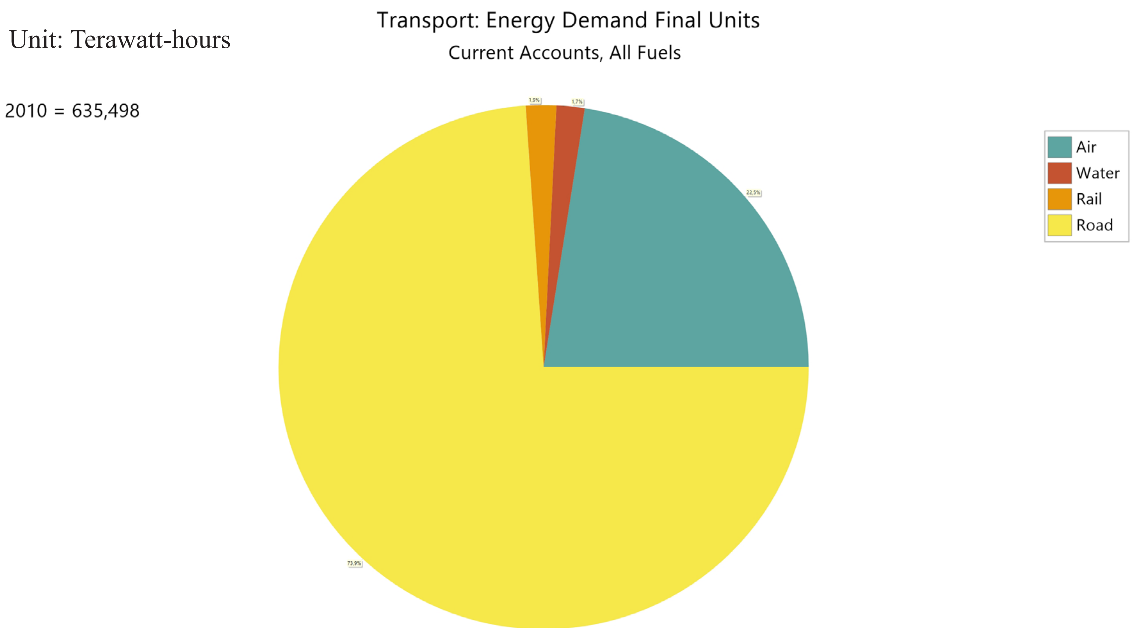


Figure 32: transport energy demand final units, current accounts

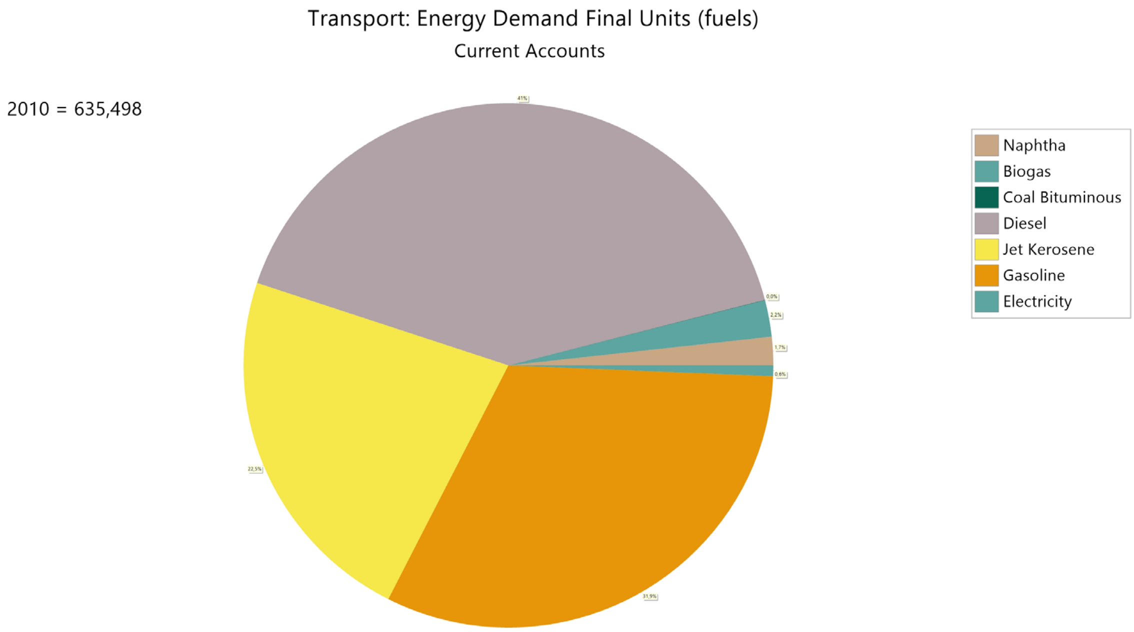


Figure 33: transport energy demand final units, current accounts, divided by fuels

Energy transformation data are taken from Digest of United Kingdom Energy Statistics, a National Statistics publication by Department of Energy and Climate Change [52]. This sector includes all energy consumption of the industry transformation that normally is not considered but is right to include because it represents a good part of consumption.

Unit: Terawatt-hours

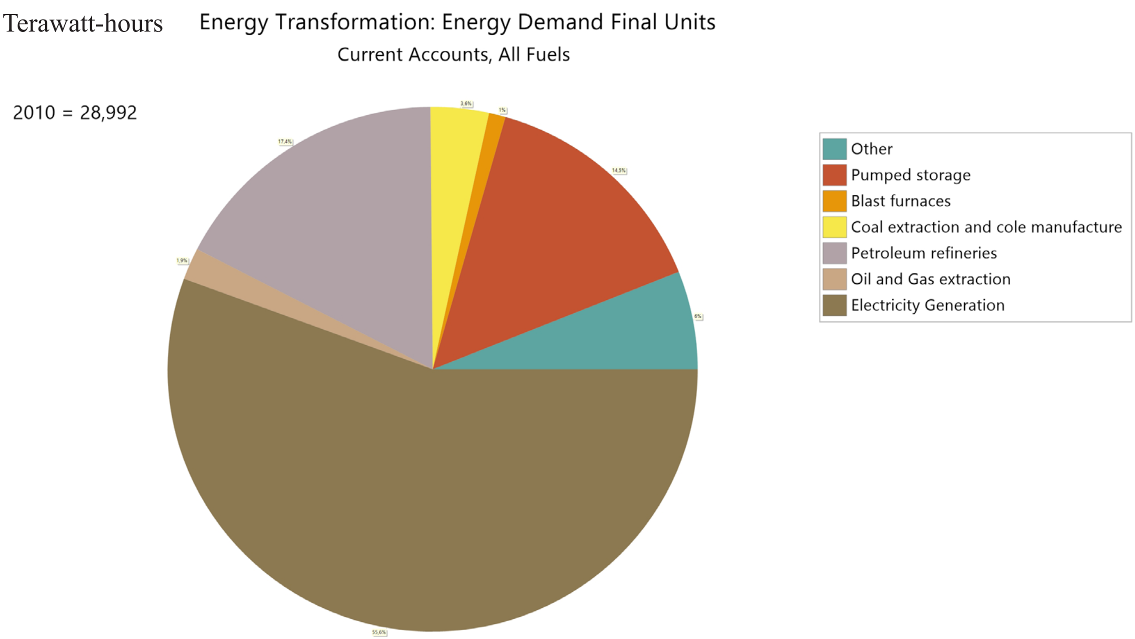


Figure 34: energy transformation demand final units, current accounts

5.2.1.2 Transformation

Transformation sector includes transmission, production, conversion and distribution of energy. This sector includes (see figure 36) the transmission and distribution losses, the processes of electric generation, the oil refinement, the coal mining product and the charcoal production. It is important to have a fair idea of all energy flows in the UK energy supply. In the next Sankey diagram the intertwining of all flows can be observed.

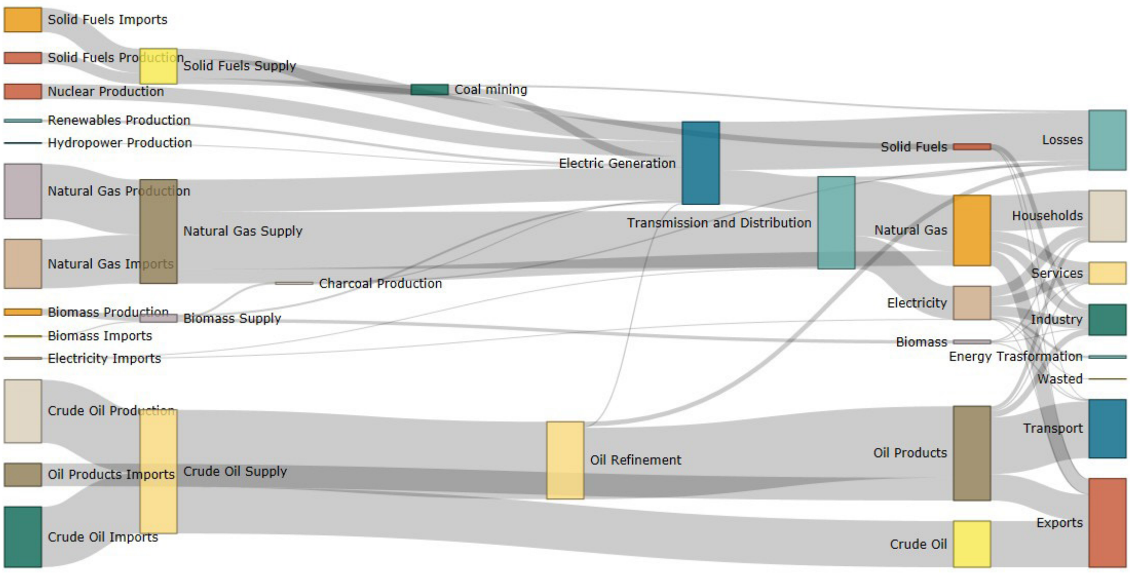


Figure 35: Sankey diagram for UK energy, current policies

On the left, all resources from which to derive energy are shown, while on the right all end-uses already described in the section of the energy demand (5.2.1.1) are presented. The path of the flows report all transformations that raw materials undergo before arriving to end-use. The division between imports and exports is also put in evidence.

The technical losses are due to energy dissipated in the conductors and equipment used for transmission, transformation, sub- transmission and distribution of power. The commercial losses are caused by pilferage, defective meters, and errors in meter reading and in estimating unmetered supply of energy. The information about T&D loses is taken from Data World Bank [50].

Concerning Oil Refinement, Coal Mining and Charcoal production , data are taken from DUKES [52].

5.2.1.2.1 Electricity Generation

The generation data are taken from Digest of United Kingdom Energy Statistics [52]. The electricity generation in UK is generally done by the traditional fossil fuels coal and gas, but there is significant portion wind, hydro and biomass capacity installed. Generation by nuclear plant represents a significant percentage. In the figure 37 the share percentage of the current capacity installed is shown and in the figure 38 the production of electricity is presented.

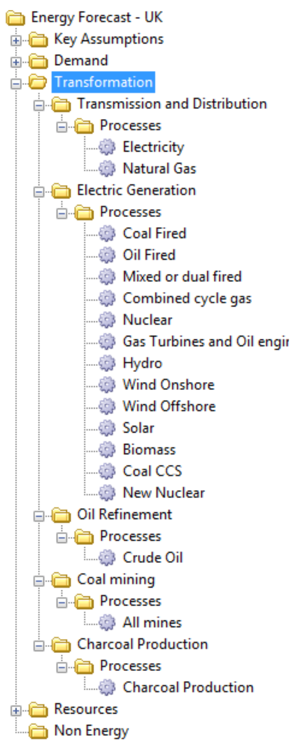


Figure 36; transformation structure

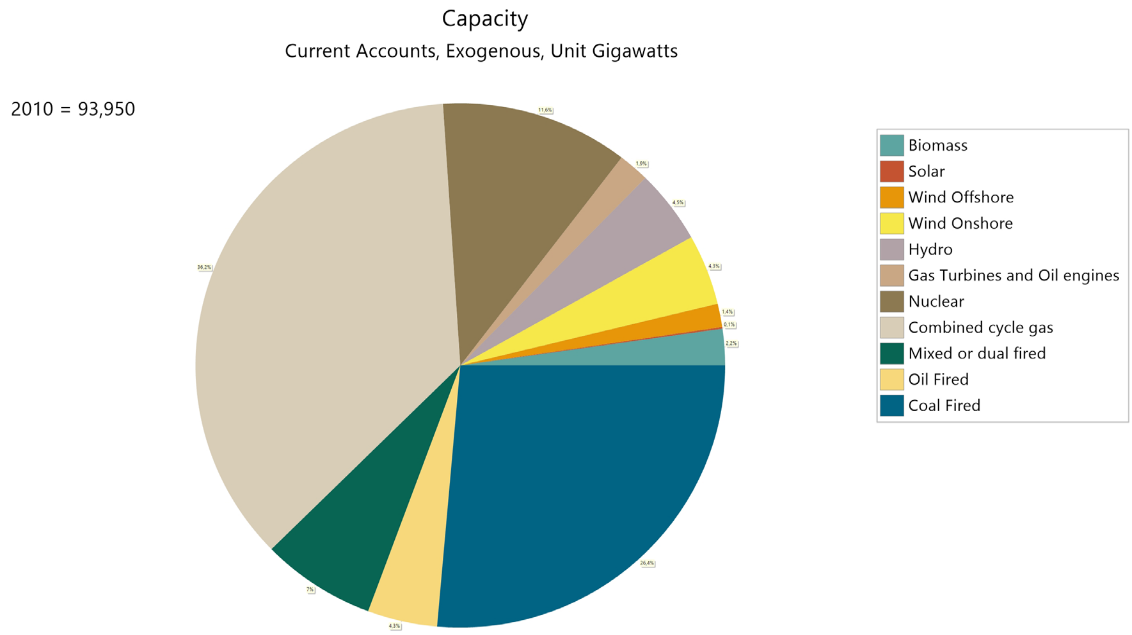


Figure 37: capacity of electric generation, current accounts, divide by processes

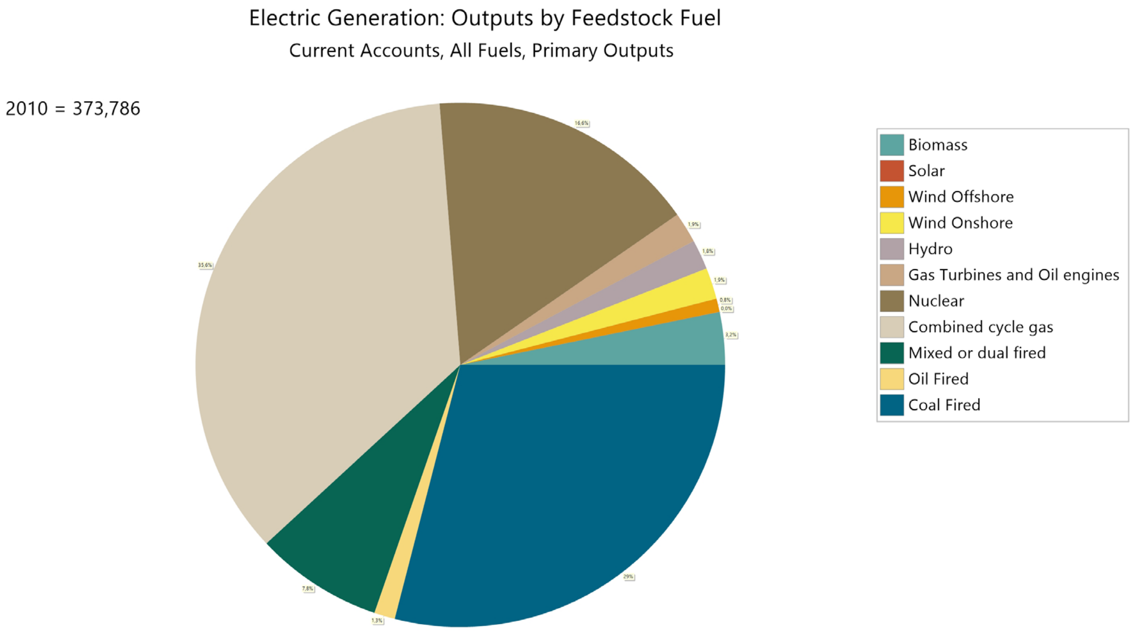


Figure 38: electric generation, current accounts, divide by processes

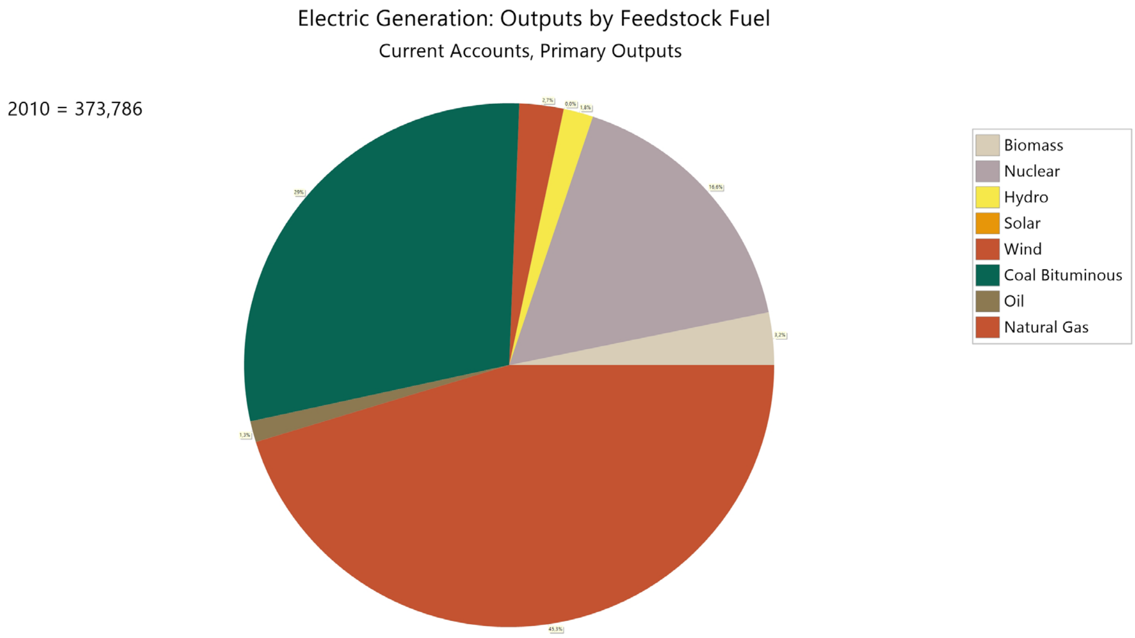


Figure 39: electric generation, current accounts, divide by fuel

In figure 39 can be noticed that approximatively 75% of the overall production of electric refers to fossil fuels. The efficiency of every plant is the following, taken from DUKES [52]:

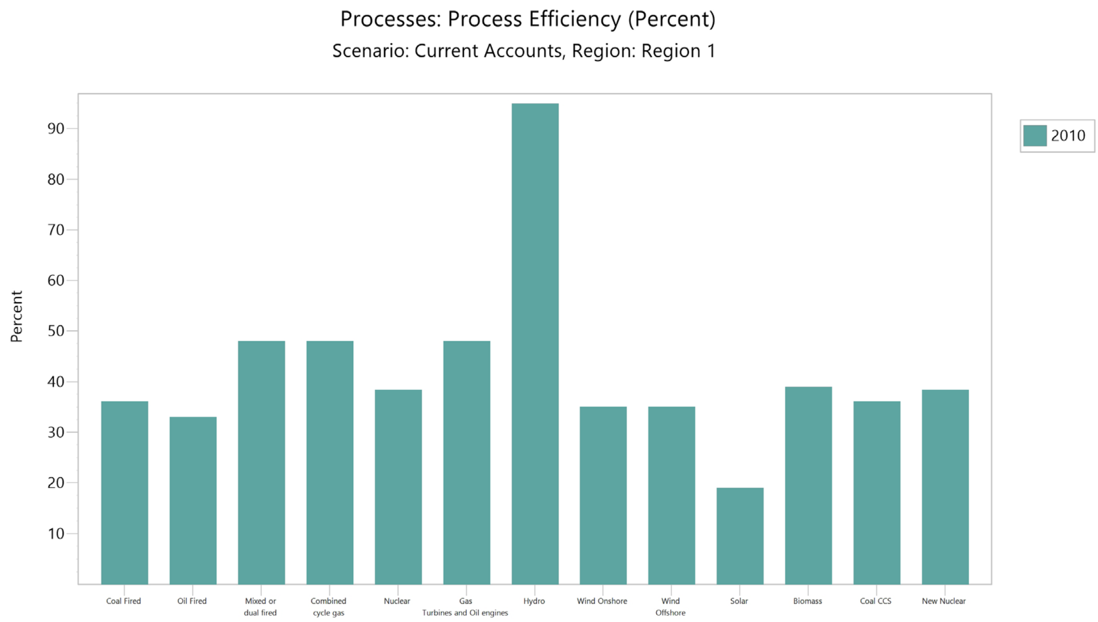


Figure 40: processes efficiency

It is also needed to specify the performance of the system load, which describes how the electric load varies every year. The division of the year was made into four parts, as in the DUKES data, and has specified the energy load for each quarter [52].

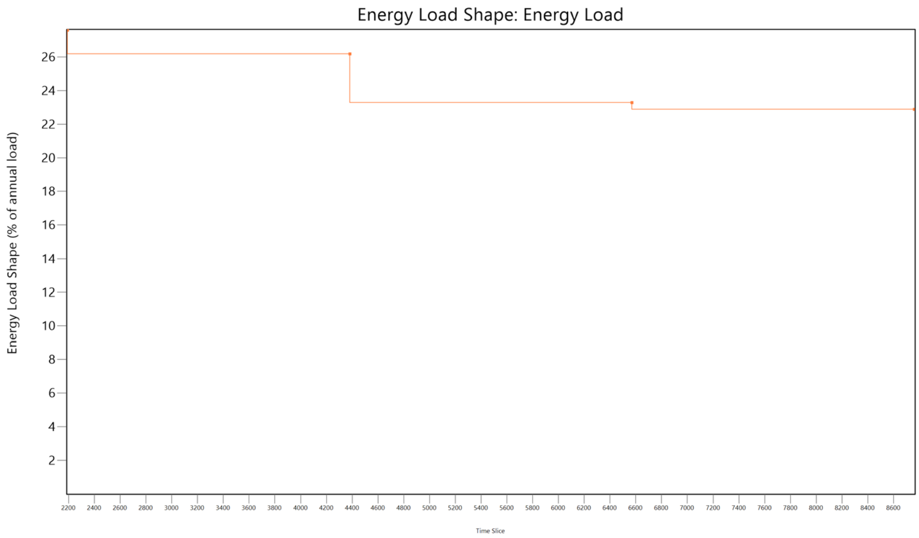


Figure 41: energy load shape

Concerning the costs, the data are taken from Department of Energy and Climate Change website [49] and from the E.I.A. [45].

	Plant Characteristics		Plant Costs (2010$)			
	Nominal Capacity (MW)	Heat Rate (Btu/kWh)	Overnight Capital Cost ($/kW)	Fixed O&M Cost ($/kW-yr)	Variable O&M Cost ($/MWh)	NEMS Input
Coal						
Single Unit Advanced PC	650	8.800	$3.246	$37,80	$4,47	N
Dual Unit Advanced PC	1.300	8.800	$2.934	$31,18	$4,47	Y
Single Unit Advanced PC with CCS	650	12.000	$5.227	$80,53	$9,51	Y
Dual Unit Advanced PC with CCS	1.300	12.000	$4.724	$66,43	$9,51	N
Single Unit IGCC	600	8.700	$4.400	$62,25	$7,22	N
Dual Unit IGCC	1.200	8.700	$3.784	$51,39	$7,22	Y
Single Unit IGCC with CCS	520	10.700	$6.599	$72,83	$8,45	N
Natural Gas						
Conventional CC	620	7.050	$917	$13,17	$3,60	Y
Advanced CC	400	6.430	$1.023	$15,37	$3,27	Y
Advanced CC with CCS	340	7.525	$2.095	$31,79	$6,78	Y
Conventional CT	85	10.850	$973	$7,34	$15,45	Y
Advanced CT	210	9.750	$676	$7,04	$10,37	Y
Fuel Cells	10	9.500	$7.108	$0,00	$43,00	Y
Uranium						
Dual Unit Nuclear	2.234	N/A	$5.530	$93,28	$2,14	Y
Biomass						
Biomass CC	20	12.350	$8.180	$356,07	$17,49	N
Biomass BFB	50	13.500	$4.114	$105,63	$5,26	Y
Wind						
Onshore Wind	100	N/A	$2.213	$39,55	$0,00	Y
Offshore Wind	400	N/A	$6.230	$74,00	$0,00	Y
Solar						
Solar Thermal	100	N/A	$5.067	$67,26	$0,00	Y
Photovoltaic	20	N/A	$4.183	$27,75	$0,00	N
Photovoltaic	150	N/A	$3.873	$24,69	$0,00	Y
Geothermal						
Geothermal – Dual Flash	50	N/A	$6.243	$132,00	$0,00	N
Geothermal – Binary	50	N/A	$4.362	$100,00	$0,00	N
Municipal Solid Waste						
Municipal Solid Waste	50	18.000	$8.312	$392,82	$8,75	N
Hydroelectric						
Conventional Hydroelectric	500	N/A	$2.936	$14,13	$0,00	N
Pumped Storage	250	N/A	$5.288	$18,00	$0,00	N

Table 13: plant characteristics and costs

5.2.1.3 Resources assessment

The data resources are taken from the IEA (international energy agency) website [41], primary and secondary. The costs are also taken from EIA publication [45]. In the diagrams it can be noticed the import-export flows refer to 2010.

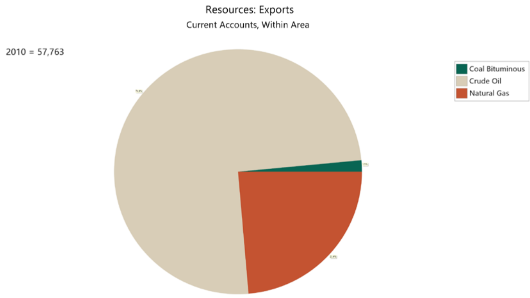


Figure 42: resources exports, current accounts

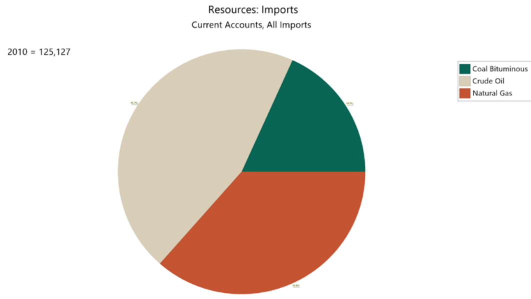


Figure 43: resources imports, current accounts

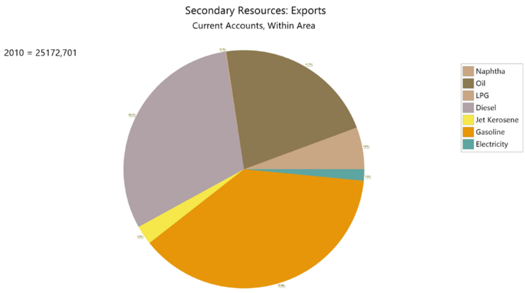


Figure 44: secondary resources exports, current accounts

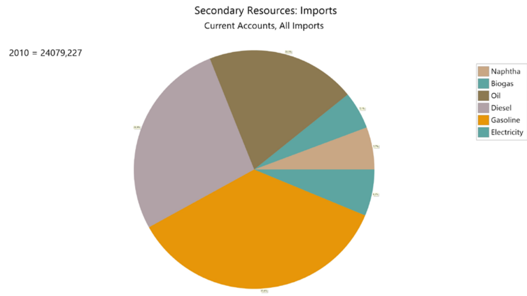


Figure 45: secondary resources imports, current accounts

In Figures 42 and 43 the commercial exchange of primary resources can be observed. The graphs show that the trade balance leans towards a predominance of imports of coal, natural gas and oil. Figures 44 and 45 show that secondary resources, including gasoline and diesel, are almost equal in the trade balance between exports and imports. This implies that domestic consumptions are satisfied by refineries, for the case study.

5.2.2 The "Current Policies" Scenario

The analysis starts from the baseline scenario, called "current policies". Here we have analyzed the policies undertaken and planned in recent years for UK, entering into every sector the possible effects that such actions should take in the future.

The Current Policies Scenario is based on those government policies and implementing measures that had been formally adopted as of mid-2014. The policies adopted can be found on UK government website [49] and on policy database of WEO [53]. The documents consulted are the following:

- Low carbon Transition Plan - 2008-09 [54]
- Renewable Energy Strategy - 2009 [55]
- Renewable Transport Fuels Obligation - 2009 [56]
- Energy White Paper - 2011 [57]
- UK 2012 Policies [58]
- WEO 2014 [41]
- Updated energy and emissions projections 2014 [59]

To see the description of the various policies refer to Appendix 1.

5.2.2.1 Demand of Energy

Energy demand includes all domestic consumption due to Households, Industrial sector, Service sector, Transport sector and all the energy needed for the Transformation sector.

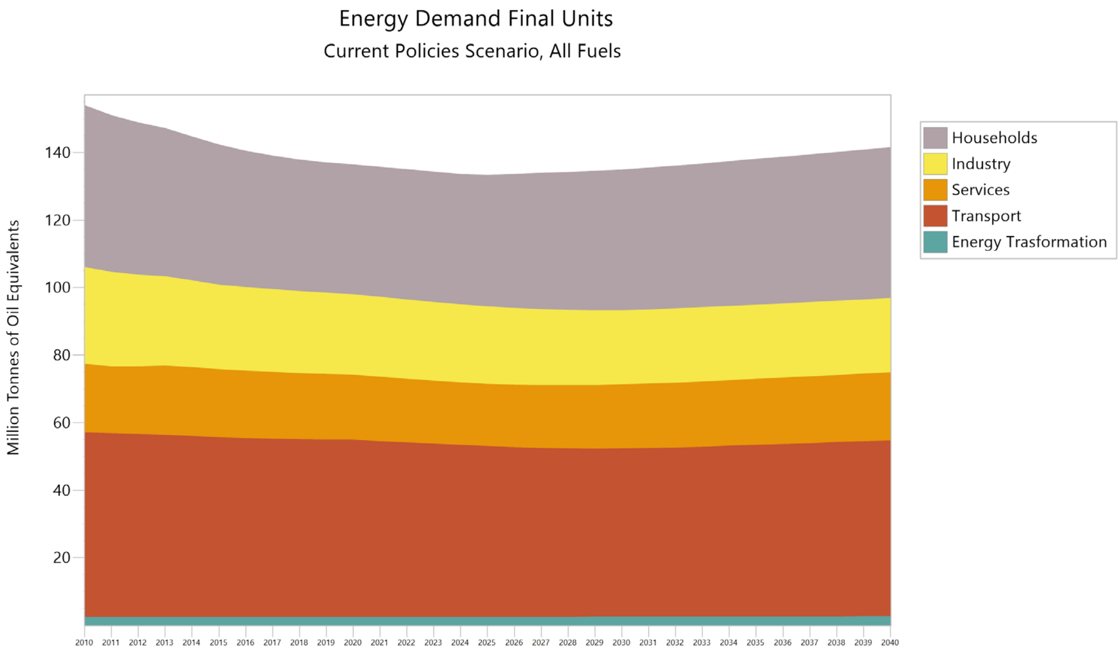


Figure 46: energy demand final units, current policies scenario, divide by sector

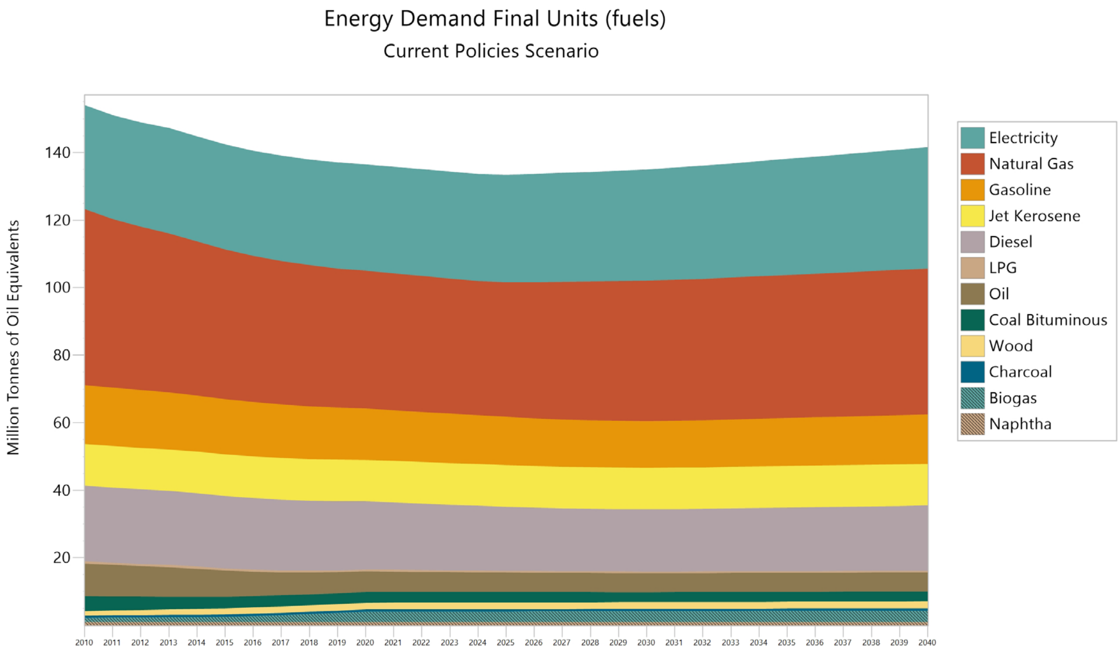


Figure 47: energy demand final units, current policies scenario, divide by fuel

From these graphs, the performance of UK's internal energy consumption between 2010 and 2040 can be easily observed: the effects of actions on energy efficiency yield, despite a population growth of 0.75% per annum, resulted in a lower consumption until year 2025, when consumption starts increasing steadily. This is because many objectives, shared with the European Union, seek to produce concrete results by 2020, but also because the policies, with a demographic growth and an increase in consumption, become insufficient after a certain date. Some objectives for 2020 for example are, regarding households, the reduction of consumption for the

space heating, while, for the transport sector, the reduction of car emissions from 130 g/km in 2013 to 95 g/km. The performance of the various sectors and the fuels used can also be seen. These data could be used to focus attention on other goals. It can also be seen that the areas that use more energy are those of Transports and Households. Policies' effects on these areas are also evident. On this matter, the most decisive policies are contained in "Energy White Paper" [57] and in "UK 2012 Policies" [58]. The effects of energy efficiency are noticed in all sectors excluding the small part related to Energy Trasformation and in a less invasive way in Services. Although developments graphics are descendants, the Households sector is showing the best effects of the policies undertaken, especially in the early years.
The performance of the various sectors and the fuels used can also be seen, data that could be used to focus attention on other goals. The areas that use more energy can be observed, Transport and Households, and the policies' effects on them. About this the most decisive policies are contained in '' Energy White Paper 'and in' "UK 2012 Policies". The effects of energy efficiency are noticed in all sectors excluding the small part related to Energy Trasformation and in a less invasive way in Services. Although developments graphics are descendants, the Households sector is showing the best effects of the policies undertaken, especially in the early years.

5.2.2.1.1 Households

The number of households continually increases over the years, from approximately 26.5 million to almost 33 million in 2040. That suggests consumers, and therefore consumption, is expected to increase, especially in the absence of suitable energy policies.

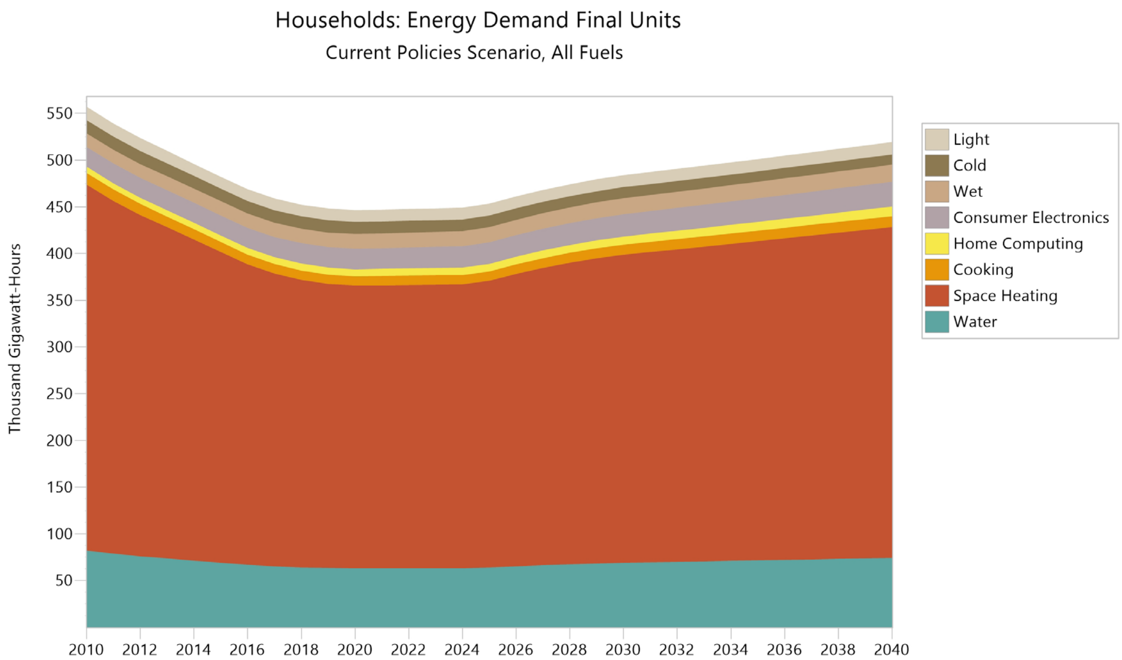


Figure 48: households energy demand final units, current policies scenario, divide by sector

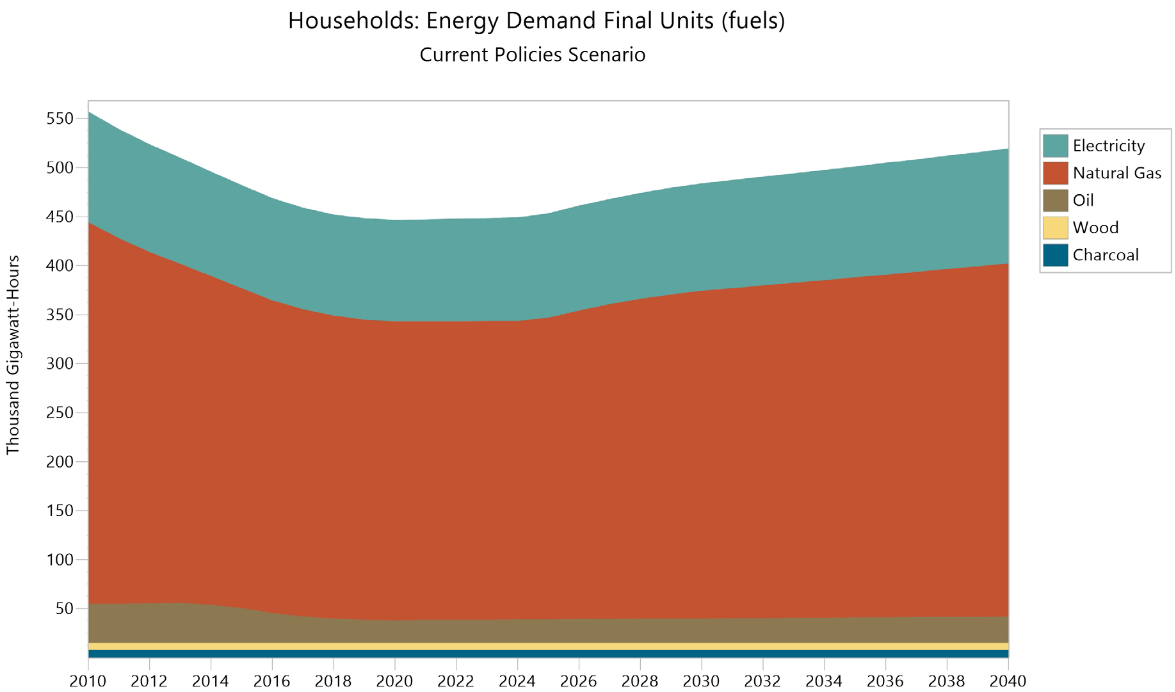


Figure 49: households energy demand final units, current policies scenario, divide by fuel

The largest consumption in this area is due to the space heating and water. The graphs show how the consumption due to the space heating is subjected over the years to a considerable reduction, only to follow an increasing trend after 2025. This is due to the special attention to the space heating and domestic hot water usage, as explained in the previous section. The attention to these two aspects of consumption is due to the fact that they are the sectors that have the largest consumption, but also to the fact that they are the areas that show the greatest potential for increasing energy efficiency. The most used fuel is natural gas, due precisely to the large amount of energy needed for heating, followed by electricity.
The next list analyzes in detail all the consumption items of households over the coming years:

• Lightening
The progressive replacement of standard light bulb, more expensive in terms of energy, with lamps that consume less. The process lasted a few years and it can not fully appreciate in the graph because the life of the bulbs is usually a few years. The LED lamps, the best in terms of energy, beginning to appear but with the current cost data it can not predict a large diffusion.

• Cold appliances
Despite the progressive increase of households, consumption of cold appliances are set to fall due to the attention placed on the policies for appliances with low energy cost.

• Wet, Consumer Electronics, Home Computing
The trend of this consumption results in growing because of the increase in households and access to technological solutions to be part of a growing number of people.

• Cooking
For cooking logically the households are mostly using gas and electric stoves. The graph shows a reduction in consumption for energy efficiency research. Efforts are maximum in the first period of the analysis and then decrease over time for the progressive increase of the households and population

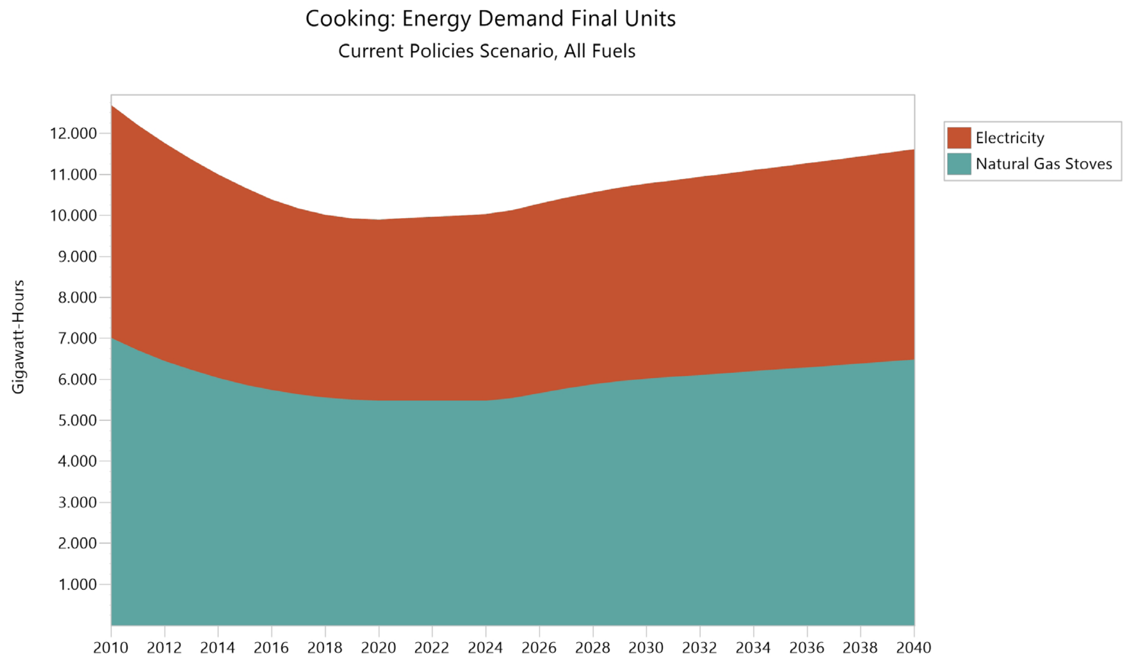


Figure 50: cooking energy demand final units, current policies scenario, divide by fuel

• Space and water heating

The great work policy is concentrated on the energy efficiency of space and water heating because are aspects where energy expenditure is greater. As for cooking, efforts are maximum in the first period of the analysis and then decrease over time, after 2025. The more fuel used is undoubtedly the natural gas, followed by the electricity.

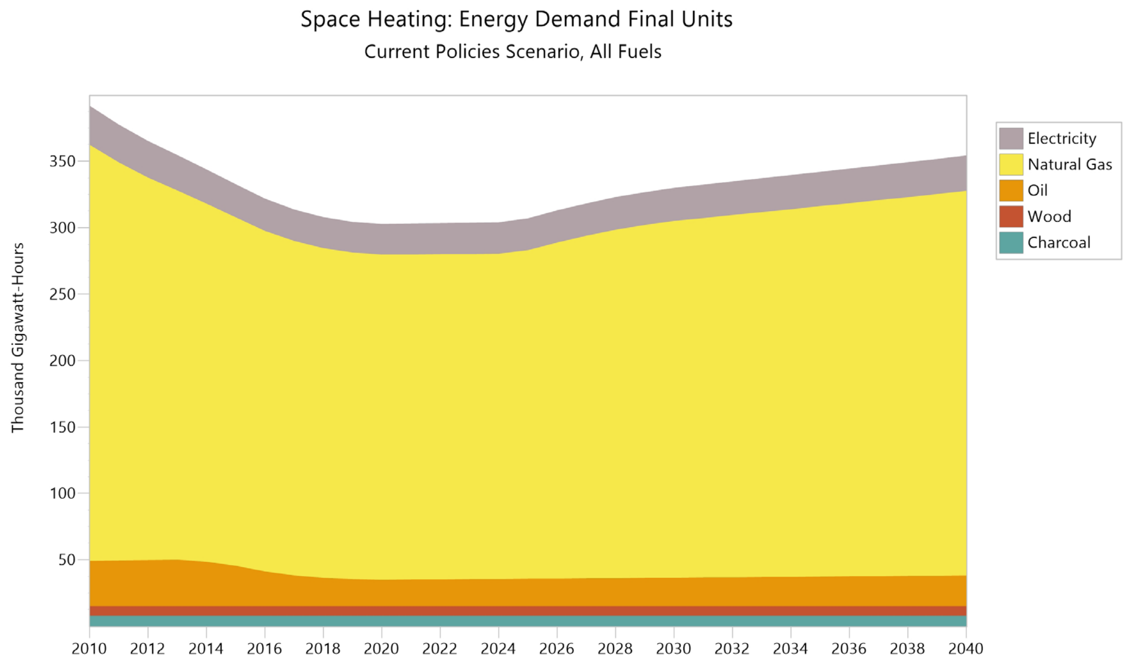


Figure 51: space heating energy demand final units, current policies scenario, divide by fuel

5.2.2.1.2 Industrial sector

The industrial energy analysis was done based on the economic value added by energy intensive industries in United Kingdom. According to The World Bank [50] data, industries contributed to 22% of UK 2010 total GDP PPP which resulted to a total added value of 505,01 billion USD. This added value is growing in the early years of the analysis around 0.5% due to the recent financial crisis. Subsequently it settles around the growth of 2%. As presented in the following graphs, the industrial sector has been the subject of aggressive policies, which promote a reduction of the use of primary energy from fossil fuels and a strong increase in energy efficiency. Initially, as an effect of these aggressive policies, the reduction of consumption should be about 15%. Afterwards, the reduction becomes less effective and by 2030 the reduction is about 25% compared to 2010.

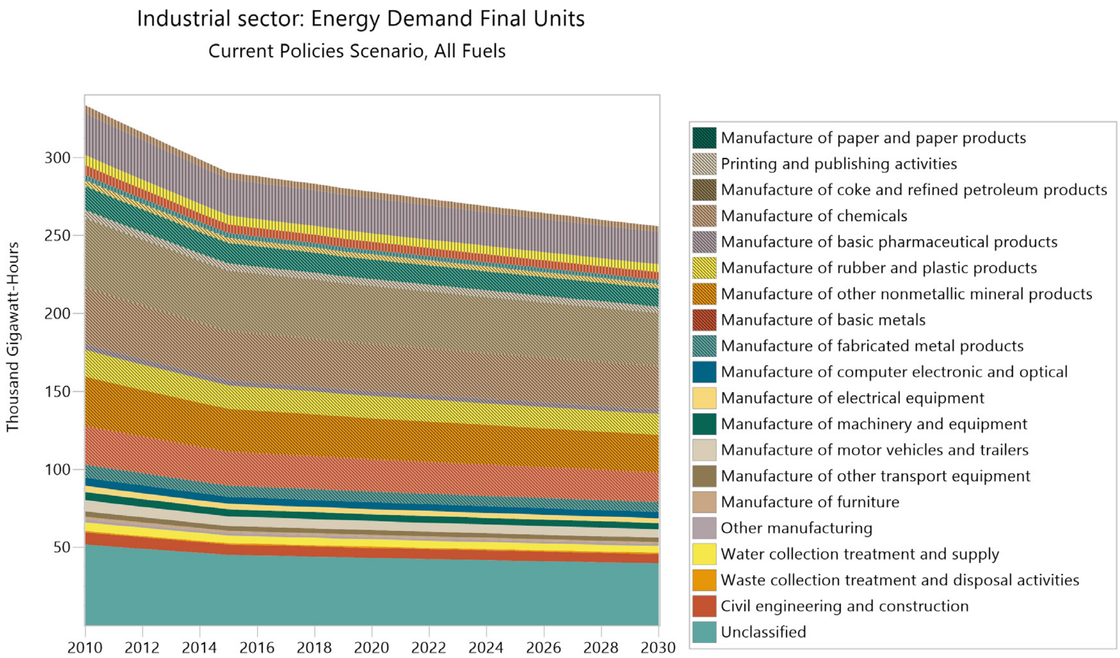


Figure 52: industrial energy demand final units, current policies scenario, divide by sector

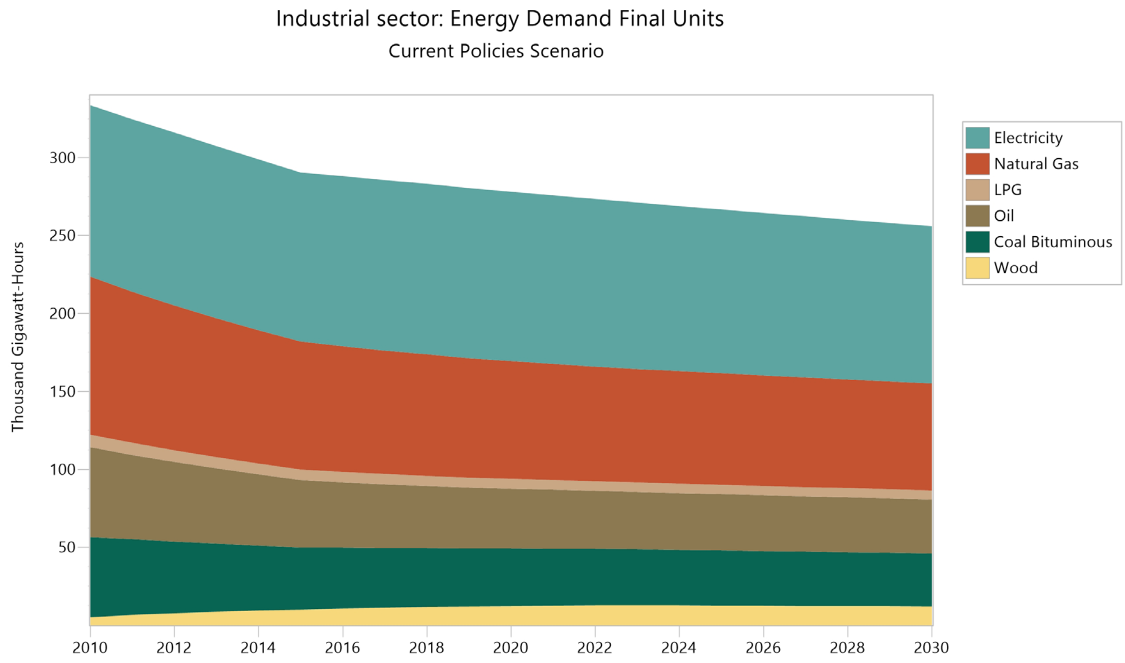


Figure 53: industrial energy demand final units, current policies scenario, divide by fuel

It was chosen as the date range 2010-2030 because there are not available enough data to go beyond this time. The industrial sectors that consume the most energy are the manufacture of coke and refined petroleum products, the manufacture of chemicals, the manufacture of non-metallic mineral products, the manufacture of food products, the manufacture of basic metals and the manufacture of rubber and plastic product.

As regards the use of fuels in the following graphics it can be noted how the utilization percentage changes over the years. In particular, it decreases the use of natural gas, oil and coal dropped respectively by 30.4%, 17.3%, 15.4% to 26.8%, 13.6%, 13.2% in 2030. Increase the percentage of the use of electricity, whose generation will be discussed in the transformation sector, from 33% to 39,4%.

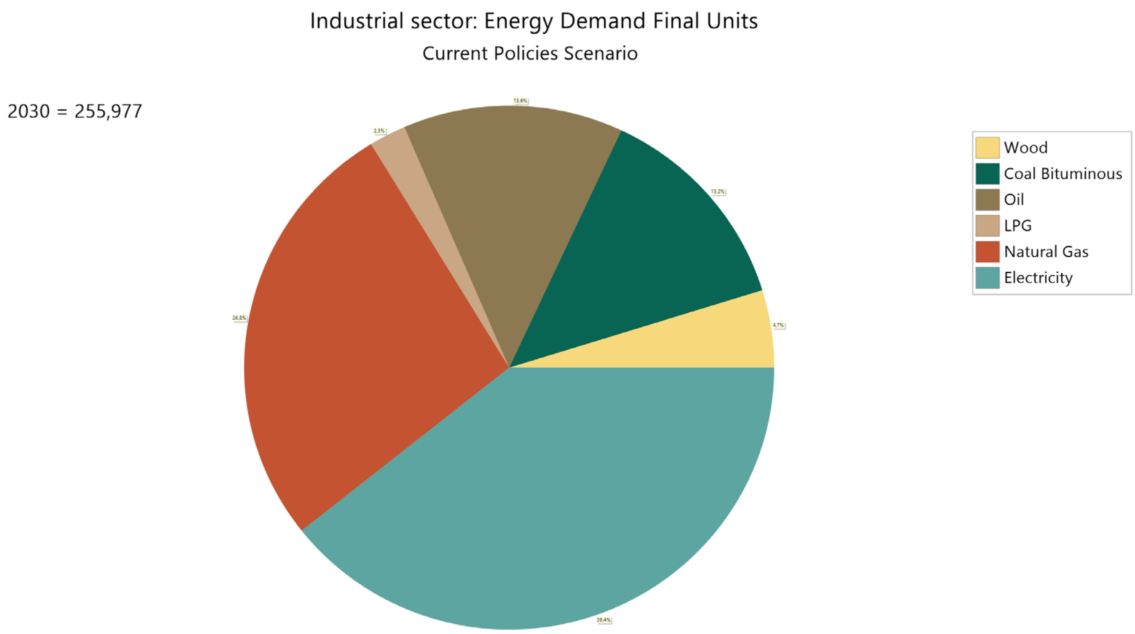


Figure 54: industrial energy demand final units, current policies scenario, divide by fuel, 2030

5.2.2.1.3 Services

The growth of the Services is around 0.7% per annum which it is similar to the growth of the population. The first part of the graph shows an adjustment due to the consequences of the global crisis. In the second there is a decrease in energy use until 2025, when the trend started to rise. At the same time the percentage of electricity use grows instead of natural gas and oil.

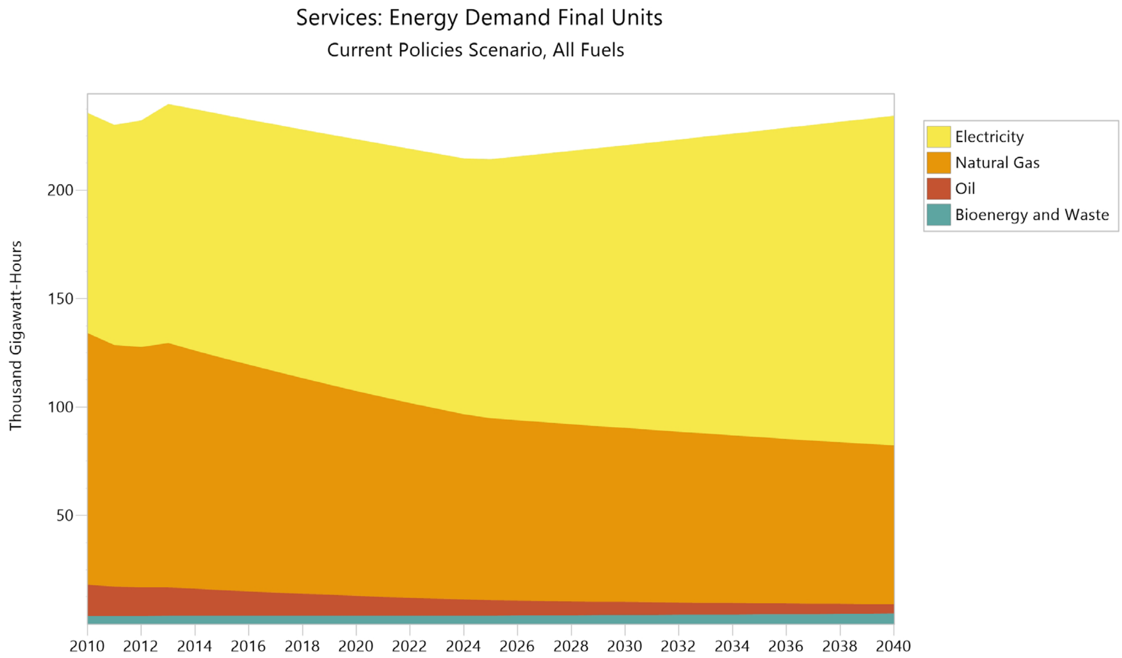


Figure 55: services energy demand final units, current policies scenario, divide by fuel

5.2.2.1.4 Transport

The transport sector in the UK sees a preponderance for the road transport of passengers and freight. Consequently the use of gasoline and diesel is significant.

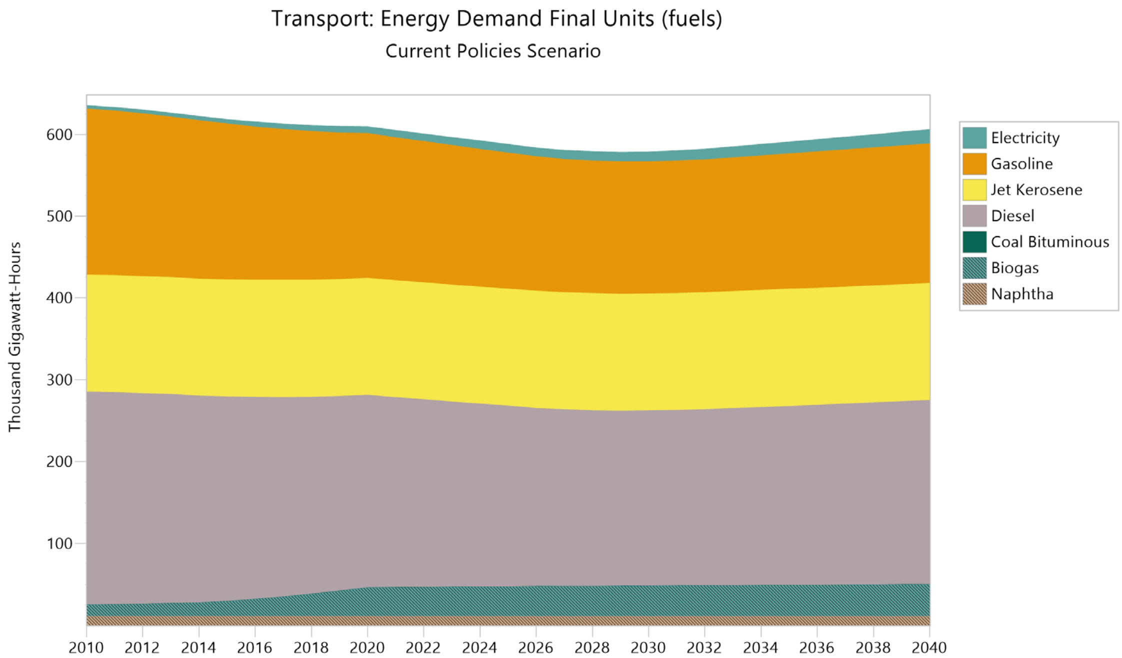


Figure 56: transport energy demand final units, current policies scenario, divide by fuel

Policies in place, like seek to minimize emissions despite the number of road passengers increases every year due to steady population growth.

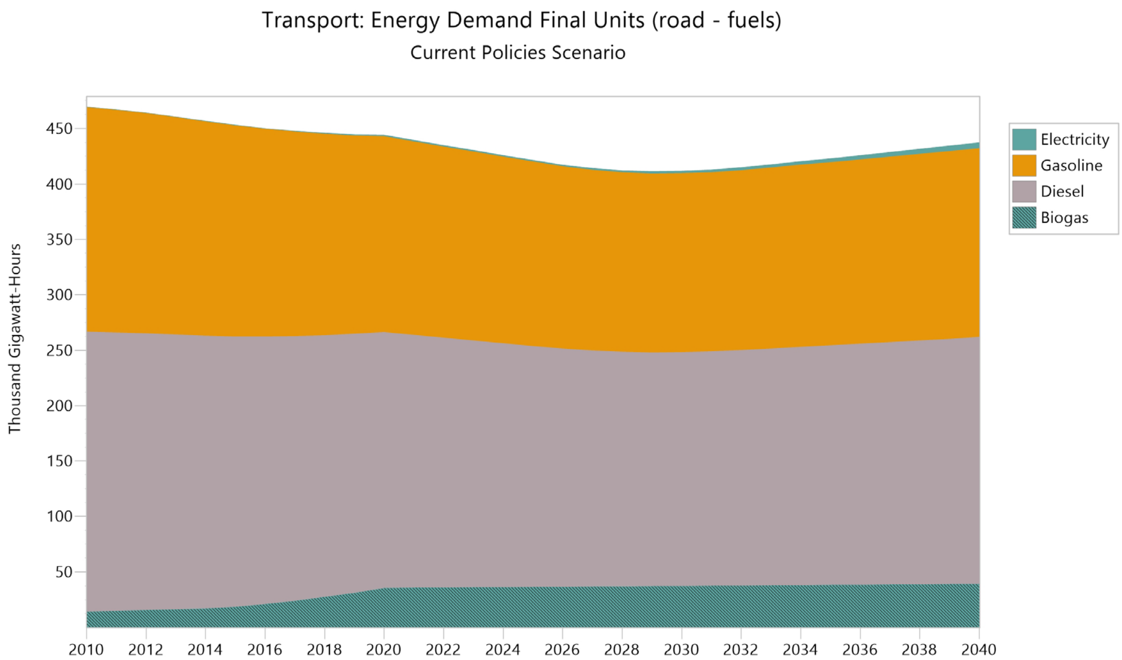


Figure 57: road transport energy demand final units, current policies scenario, divide by fuel

Use of Gasoline and Diesel will diminish over the years but current efforts do not appear to produce significant results. Also around 2028 consumption will rise again, a sign that the current policies are insufficient for long-term projects. Appears on the scene the use of biofuel vehicles that are encouraged and seen a strong growth until 2020 before stabilizing after that.

The increase of efficiency in the sector of road transport is a delicate and complex issue. Only strong actions aimed at revolutionizing it, such as the introduction of electric vehicles, would bring lasting positive effects. In Figures 56 and 57 the increase in the use of electricity in transport can be observed, but such an increase is still too low, in particular on road which is the dominant sector. The electricity in transport is increased in rail, as shown in figure 58.

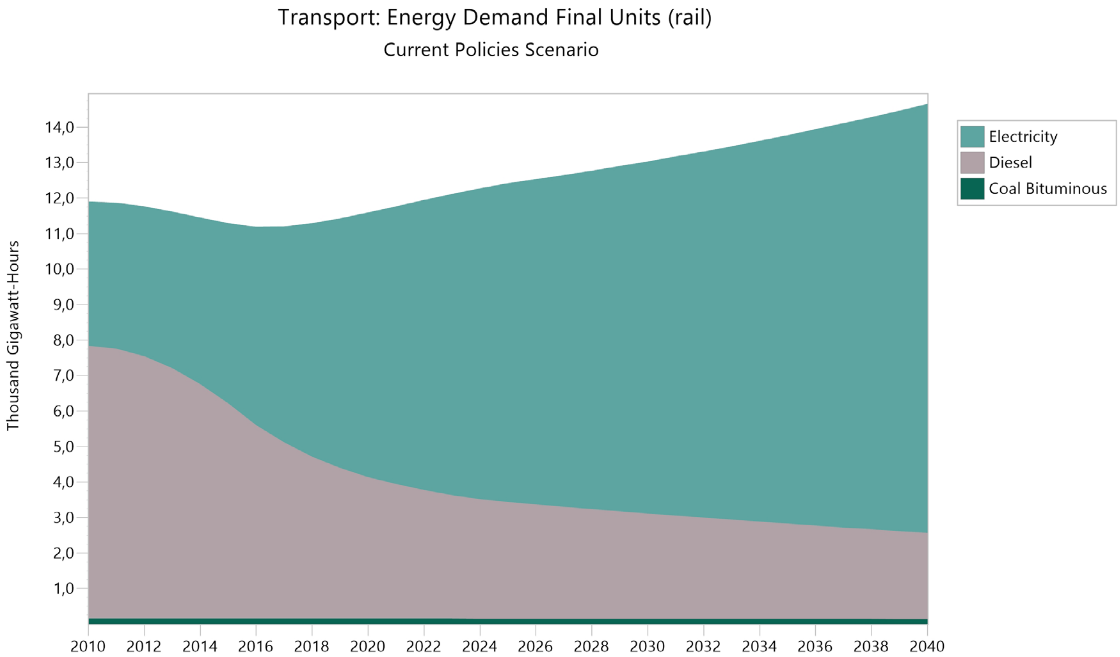


Figure 58: rail transport energy demand final units, current policies scenario, divide by fuel

The railway sector is subject to a major modernization through the introduction of the power lines on the rail network in order to replace old and polluting diesel locomotives. The growth trend in consumption is a sign of encouragement in the use of the rail network instead of the road network.

5.2.2.1.5 Energy Transformation

This sector includes all energy consumption in the industry transformation that usually is not considered but it represents a good part of consumption.

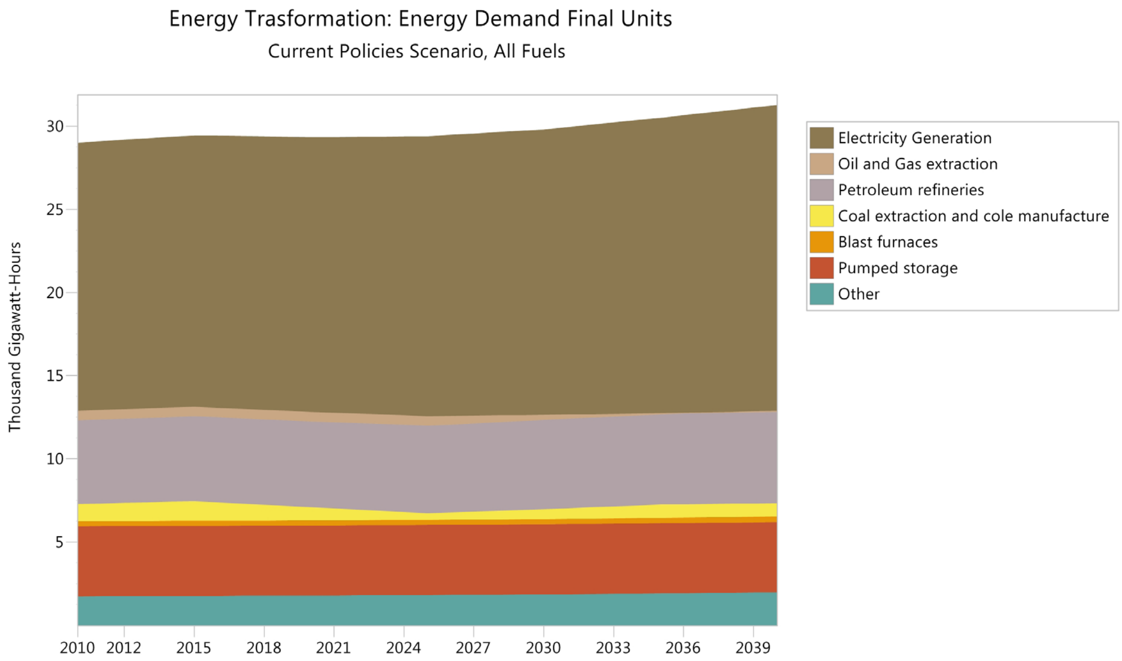


Figure 59: energy trasformation demand final units, current policies scenario, divide by sector

The consumption for electricity generation are uphill because it increases over the years analyzed while oil and gas extraction decreased for the reduction of extractions.

5.2.2.2 Transformation

The sector that was the most impacted by the energy policies is the production of electricity. The Low Carbon Transition Plan [54], Renewable Energy Strategy [55] and the Energy White Paper [57] seek to establish the foundations for an energy development less dependent on fossil fuels. The main objectives are the production of 30% of electricity from renewable sources by 2020, the reduction of 22% in CO_2 emissions by 2020, a reduction of 10% in fossil fuel demand, the closure of old nuclear plants, for 18 GW, by 2018 in favor of new plants, for 20 GW of power, and the introduction of 2025 carbon capture storage (CCS) to reduce by 90% the emissions, by 2025. The logic behind this is based on the increase in efficiency and a growth in power production based on renewables, promoting their use and penalizing the consumption of fossil fuels.

5.2.2.2.1 Electric Generation

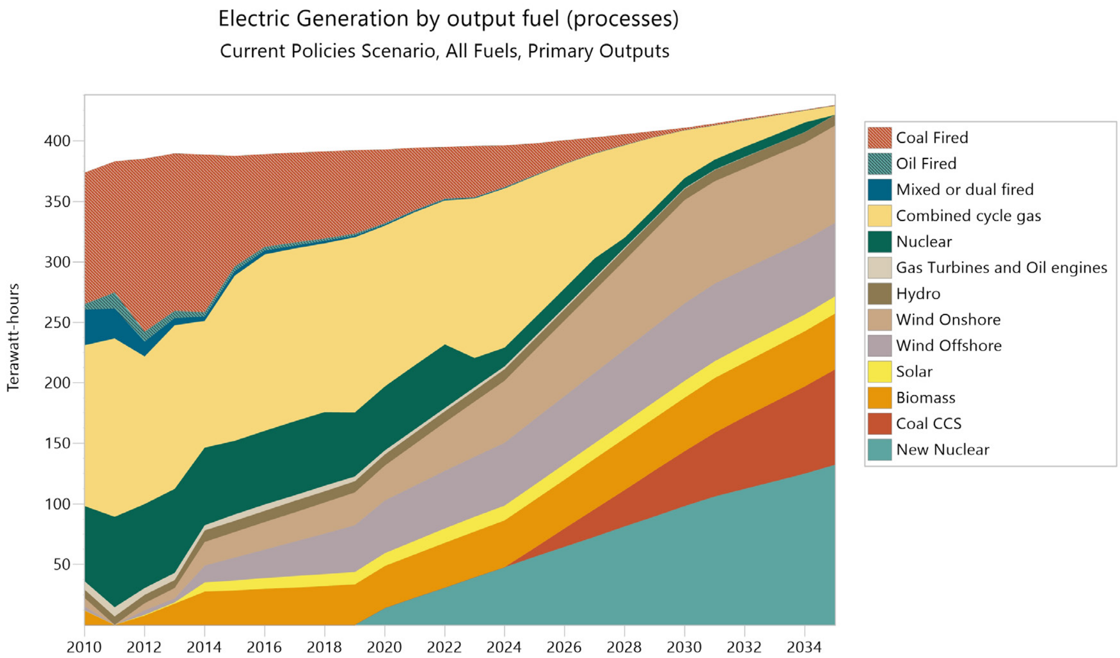


Figure 60: electric generation by output fuel, current policies, divide by processes

The electric generation over the years analyzed changes considerably, as can be seen from the graph. Policies analyzed in Appendix 1 provide a substantial reduction in the use of fossil fuel plants. Initially this concerns the coal plants that are gradually decreased without open new ones. Simultaneously with the promotion of renewable energy, particularly wind energy, power generation becomes less and less dependent on fossil fuels. From 2018-20 are also put into operation a number of new nuclear power plants currently under construction that will generate by 2035 about 30% of the total energy. From 2025 began to produce energy the first coal carbon capture storage plant that should not release CO_2 into the air and will have an increasingly important. As far as the renewable sources, wind power plants are those having a major evolution. Initially the aim is on wind energy offshore but is gradually achieved and exceeded by wind onshore: together is expected that in 2035 will produce about 35% of total power. Too few, however, benefits from solar energy than the UK does not see a great evolution. The role of energy produced from biomass grows in the early years to settle back down generation values stable.

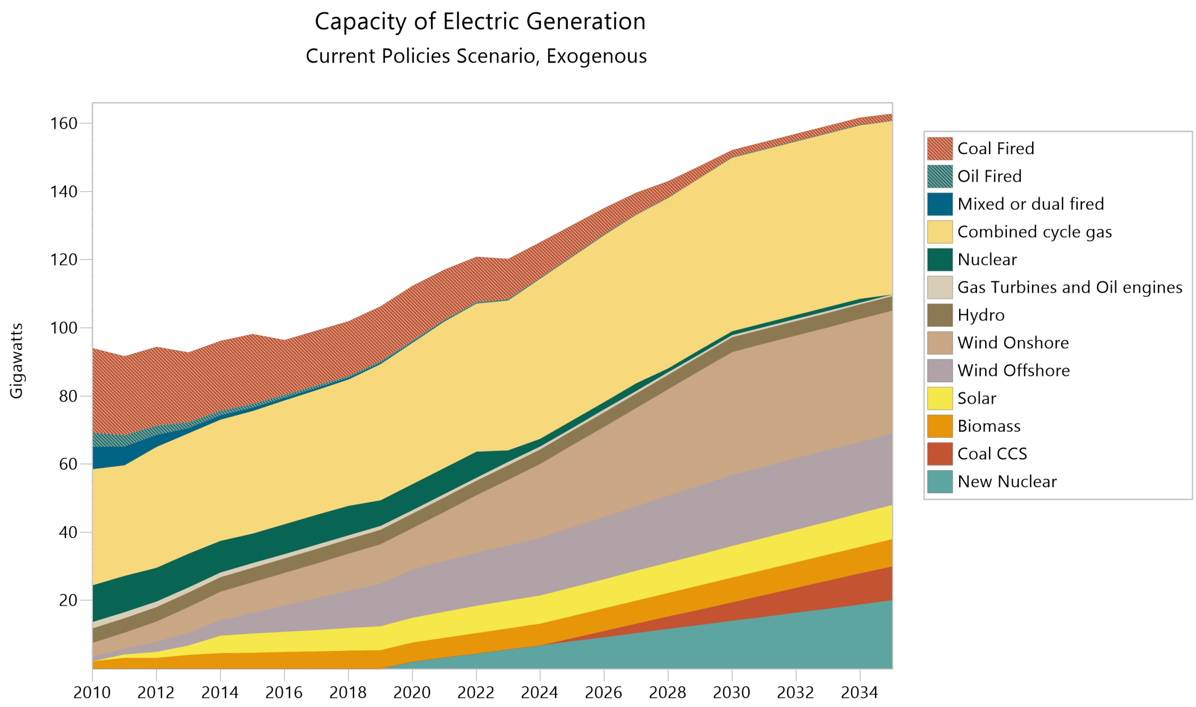


Figure 61: capacity of electric generation, current policies, divide by processes

The electricity generation capacity, as already said, varies considerably over the years. It 'important to note that the largest installed capacity in 2035 is made up of about 45% of renewable energy, but energy being aleatory and not programmable need to be supported by gas plants, nuclear power plants and CCS.

The electricity generation capacity, as already said, varies considerably over the years. It's important to note that the largest installed capacity in 2035 is made up of about 45% of renewable energy, which is characterized by being aleatory and not programmable, therefore leading to the need of being supported by gas plants, nuclear power plants and CCS. From 2010 to 2035 the majority of plants put into operation for are based on wind. In the years between 2015 and 2020 the installed wind power plants are mostly offshore. From 2020 the onshore plants have a considerable increase and outweigh the offshore's for installed capacity. The solar power plants have a first significant increase in the first 5-year period. Afterwards, however, the United Kingdom prefers to focus on wind energy, which at that latitude is much more efficient than solar. From 2018 new nuclear plants start operating, replacing the old ones that are dismissed. The only fossil fuel plants that survive are those based on gas, which have the ability to switch on and off in a very short time, providing electricity to mend the issue of scarcity of production from aleatory renewables sources. The other plants based on fossil fuels, such as coal, are gradually abandoned and not rebuilt. From 2025, however, carbon capture storage plants star operating. These type of plants, although with coal, don't produce emissions.

5.2.2.2.2 Oil refinement and Coal mining

The production of the products of refinery undergoes a reduction over the years, especially for the smaller demand for gasoline and diesel. This will happen if it be come into circulation vehicles with less environmental impact.

As for oil refinement, in the analysis on the power generation, coal, very polluting, is gradually abandoned in favor of less polluting technologies. From 2025 the request grows again for the entry into operation of the plant carbon capture storage.

5.2.2.3 Environmental impact

Below are presented graphs of the environmental effects from pollutants. In the first chart are shown all the effects in order to realize the relationship between pollutants. Then analyzes the major polluting and source of the greatest environmental problems.

In Figure 62 the strong impact of CO_2 compared to other pollutants can be noticed. However, this impact decreases over the years, initially significantly and then becomes stable. This happens because they are not yet planning important actions after 2030.

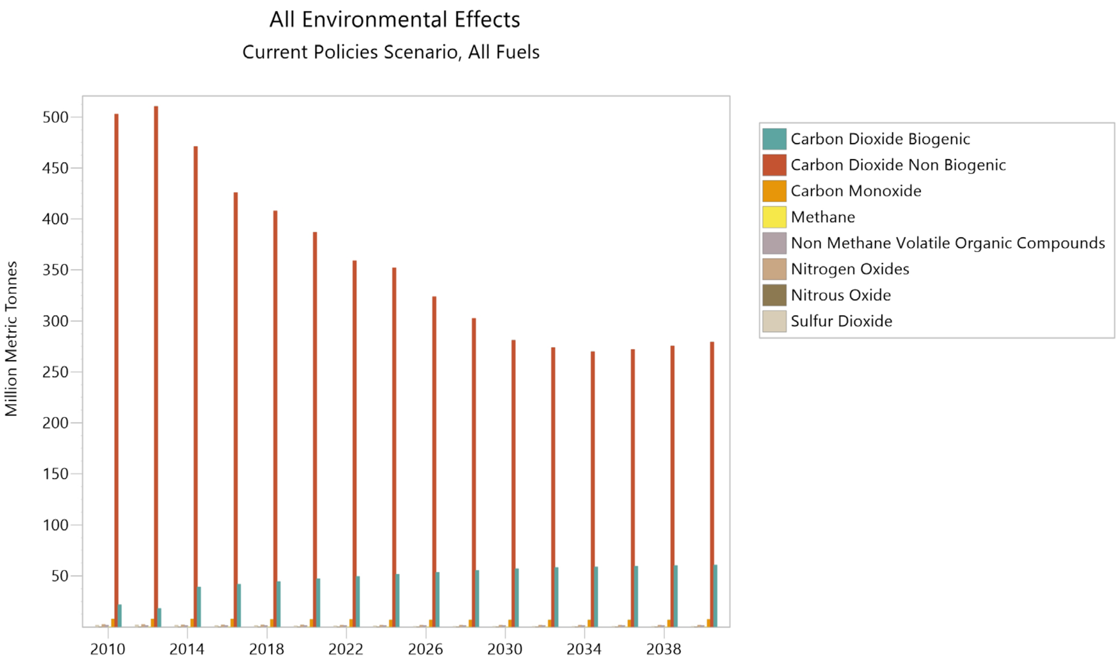


Figure 62: all environmental effects, grouped by year

In figure 63 and 64 the difference of the actions explained in the preceding paragraphs from the demand and the trasformation can be observed. In the area of demand there is a drop in the CO2 emissions, but it is in the transformation sector that have remarkable results. This is because the attention of the UK government on energy focuses more on the aspect of power generation to reduce emissions, with energy efficiency and use of renewable sources.

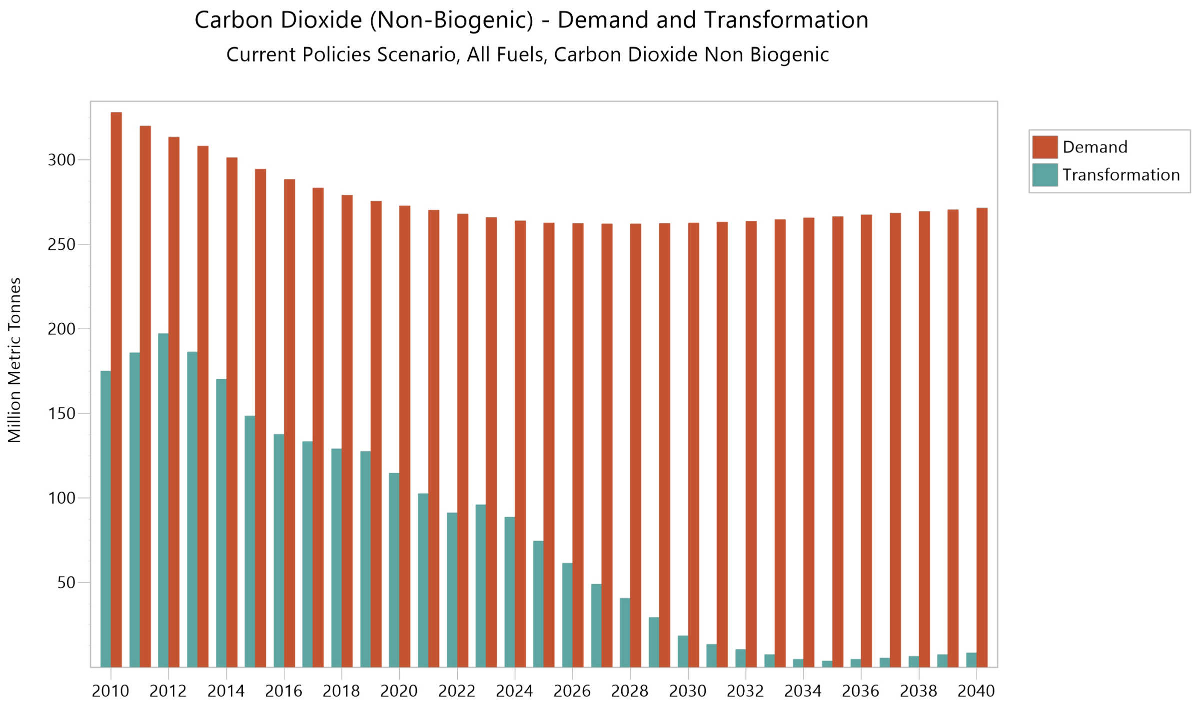


Figure 63: carbon dioxide (non-biogenic) from demand and trasformation, current policies

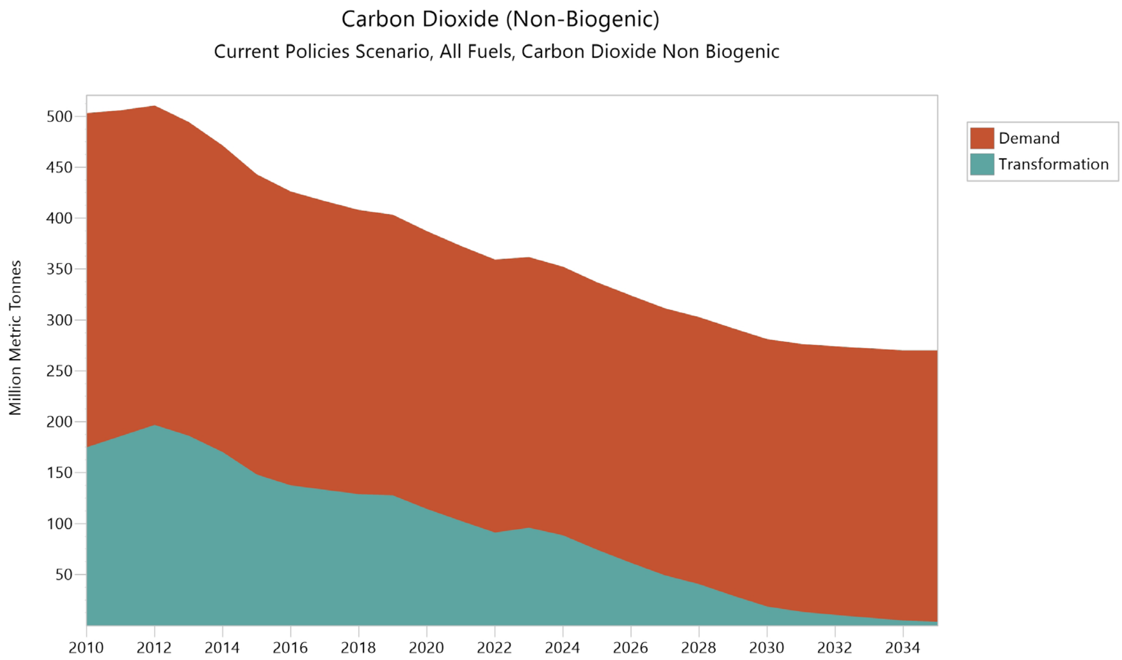


Figure 64: carbon dioxide (non-biogenic), current policies, divide by origin

In Figure 65 the demand is divided between the four main sectors. In this way, emissions by category can be observed. The transport sector results to be one that produces more CO2 emissions and, although these emissions decrease, them are still significant. The category of households presents an initial decrease and then even return to rise. This trend could produce a starting point from which to take corrective actions. The industry and the services have CO2 emissions decrease.

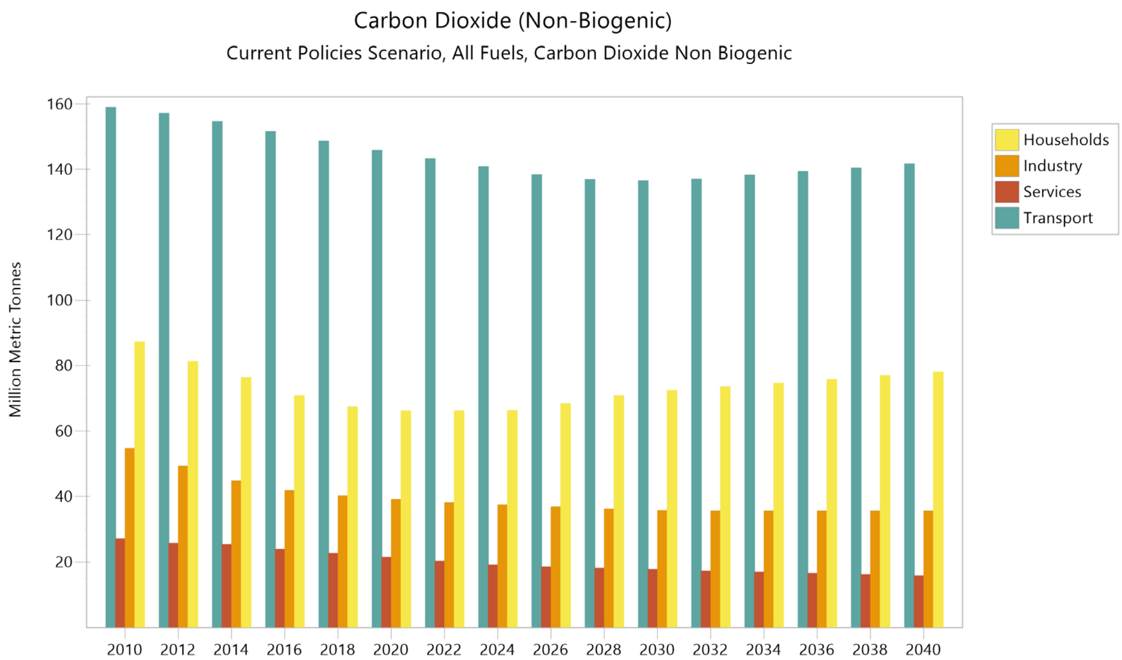
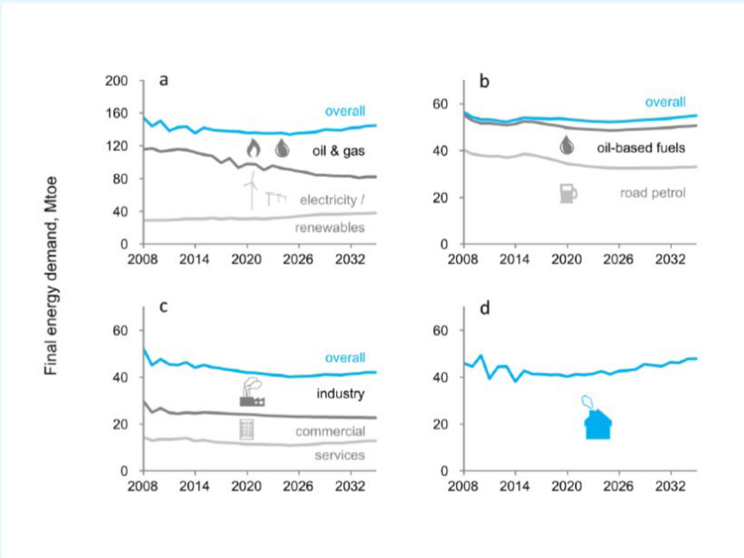


Figure 65: carbon dioxide (non-biogenic), current policies, divide by demand sector

5.2.2.4 Validation of results

Although free information on future energy projections are relatively few, in this section the results obtained by comparison with the annual "Updated energy and emissions projections", a document of the Department of Energy and Climate Change (DECC) that update annually the estimates of demand, power generation and emissions of United Kingdom, want briefly to validate the work.
As for the energy demand, it can be compared the following charts:



a) Summary of demand by fuel type. The figure shows the overall shift from final demand from oil and gas to electricity and renewables. b) Final energy demand by transport. *Dark grey* all oil-based fuels. *Light grey* road petrol. Demand for oil-based fuels for transport declines slightly due to substitution with biofuels. c) Final energy demand by industry, services and agriculture. *Dark grey* industry only. *Light grey* commercial services only. Final energy demand in industry, services and agriculture declines by 6% by 2035. d) Domestic final energy demand. Increasing household numbers drive projected domestic final energy demand higher in 2035 than currently.

Figure 66: grouped charts of final energy demand by DECC

If the results obtained in LEAP are compared, it is observed that the trends and the data are very similar:

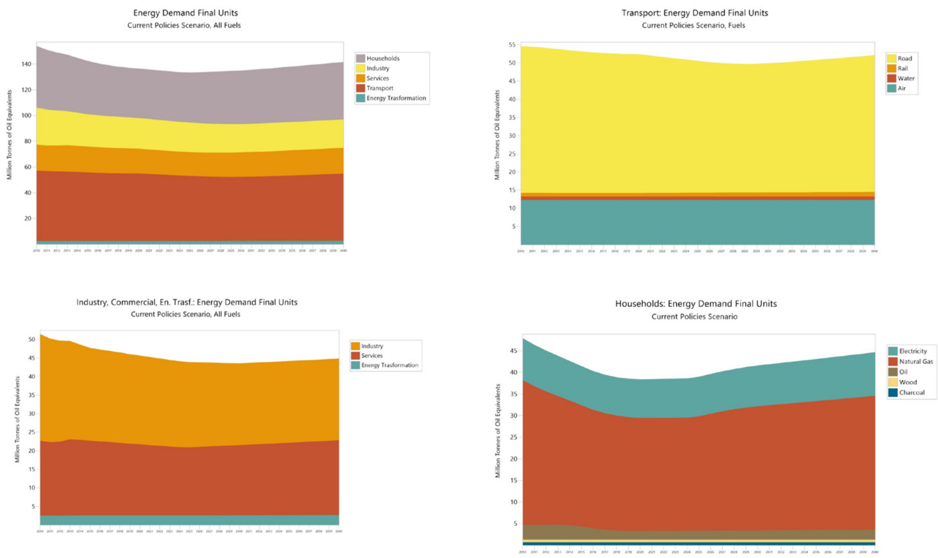


Figure 67: grouped charts of final energy demand by "Current Policies Scenario"

As for electricity generation it is observed slight differences but the trends are also very similar overall.

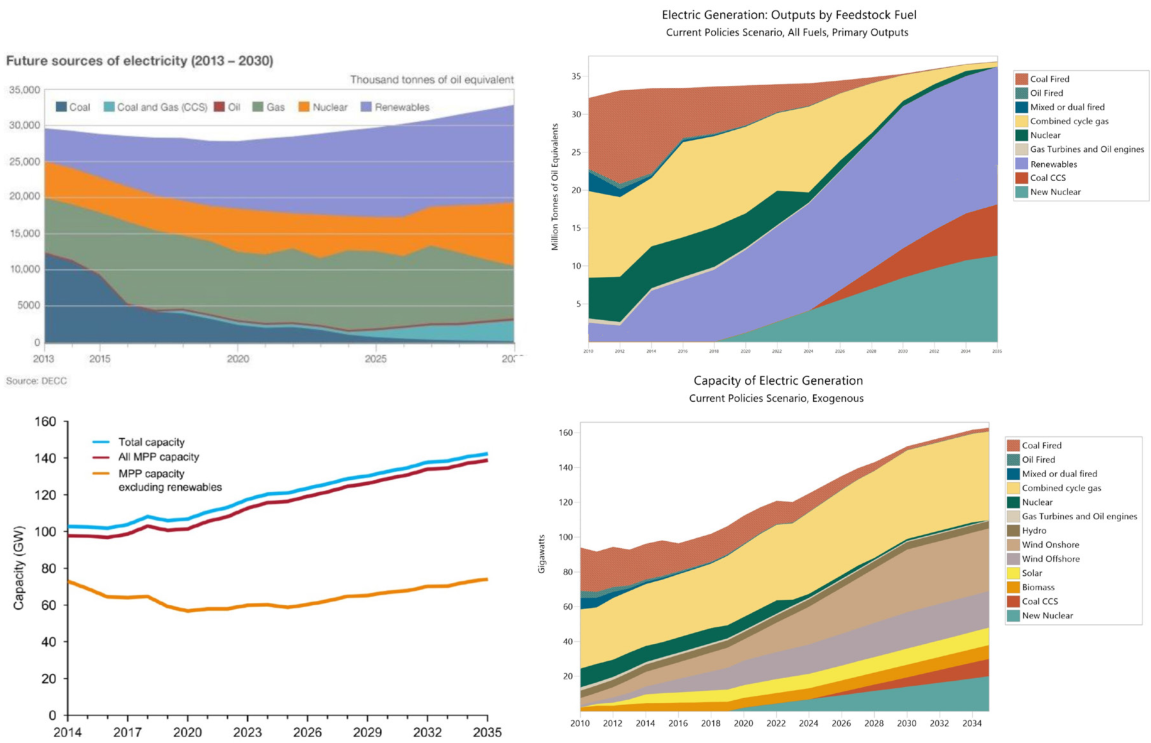


Figure 68: comparison of electric generation and capacity in UK, between DECC and “Current Policies Scenario”

In the following charts it can be observed the trends on emissions. The output provided by LEAP is definitely more positive than the British government estimates, but the trend is still confirmed.

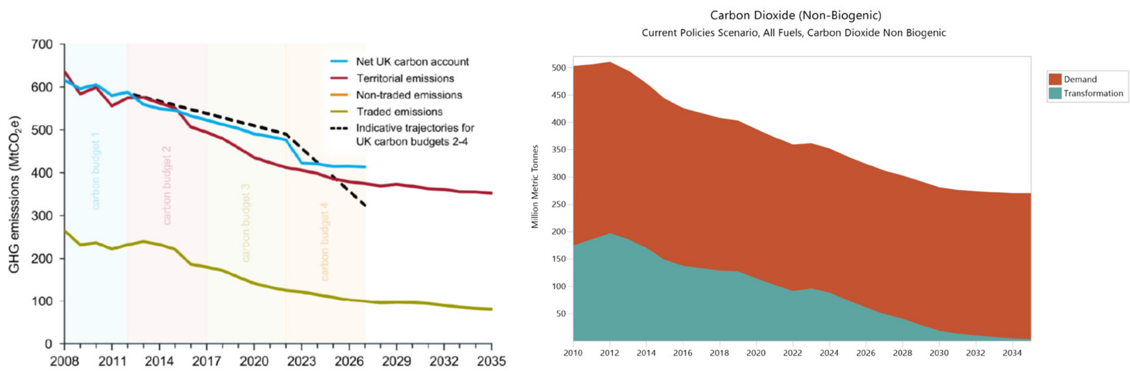


Figure 69: comparison of GHG emissions in UK, between DECC and “Current Policies Scenario”

The results obtained from the model are therefore in line with government reports, thus validating the work conducted.

5.3 The optimized scenarios

In the analysis carried out in leap three more scenarios were created.

The first scenario, called “Optimize CP scenario”, is inherited directly from “current policies” and is taking advantage of an optimization algorithms LEAP based on data cost included. LEAP, thus, creates an alternative scenario, taking into account the guidelines inherited, where it finds the balance with the costs of various generation systems.

The other scenarios, called “Carbon Tax opt30” and “Carbon Tax opt40”, are inherited from “current policies” and they are based on the same optimization process of scenario “Optimize CP scenario,” but taking into account a tax on the use of fossil fuels in the production of electricity. The fee, therefore, interests coal, gas, oil and as the scenarios' name suggests, it is calculated by putting £ 30 or £ 40 per tonne of CO2 produced in the 2020, raising the tax steadily. Then tax increases further until 2030. The production data of CO2 per kWh were taken from the following table [45], considering the value of one pound equal to 1.56 dollars:

		Fuel			
		Coal	Natural Gas	Oil	
tonn per MWh		0,939	0,5488	0,8165	
$/MWh	46,8 (30£/MWh)	43,9452	25,68384	38,2122	2020
$/MWh	62,4 (40£/MWh)	58,5936	34,24512	50,9496	
$/MWh	109,2	102,5388	59,92896	89,1618	2030
$/MWh	140,4	131,8356	77,05152	114,6366	

Table 14: added costs from carbon tax for carbon tax scenarios

The following graphic shows different electric generations in the three new scenarios. In order to observe the differences was again added the generation graph of the "current policies".

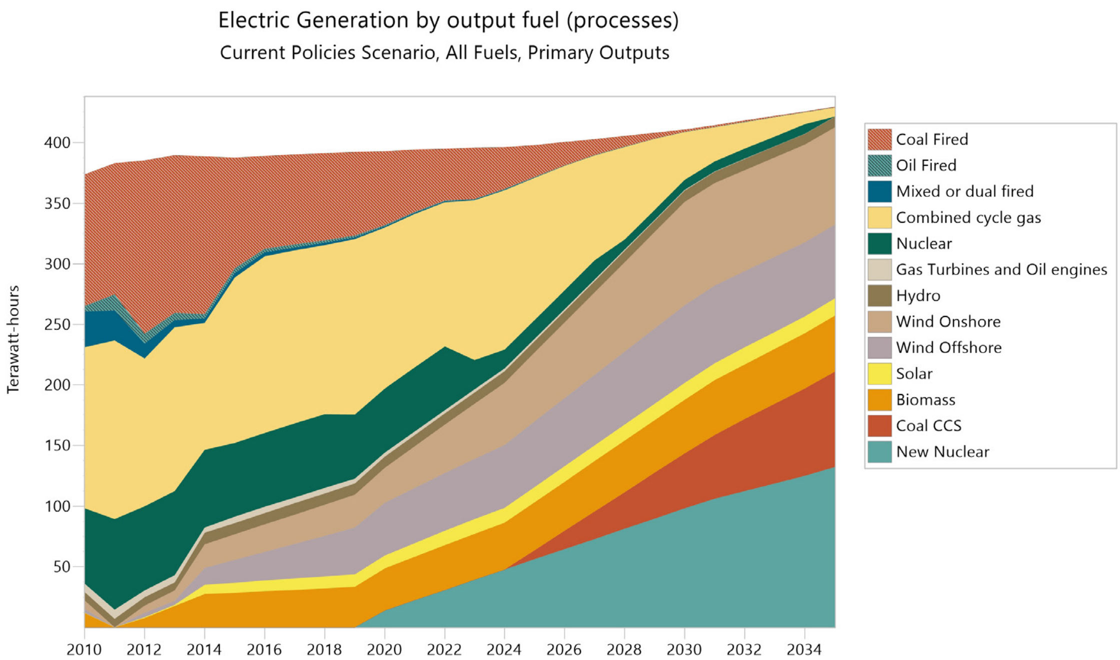


Figure 70: electric generation by output fuel, current policies, divide by processes

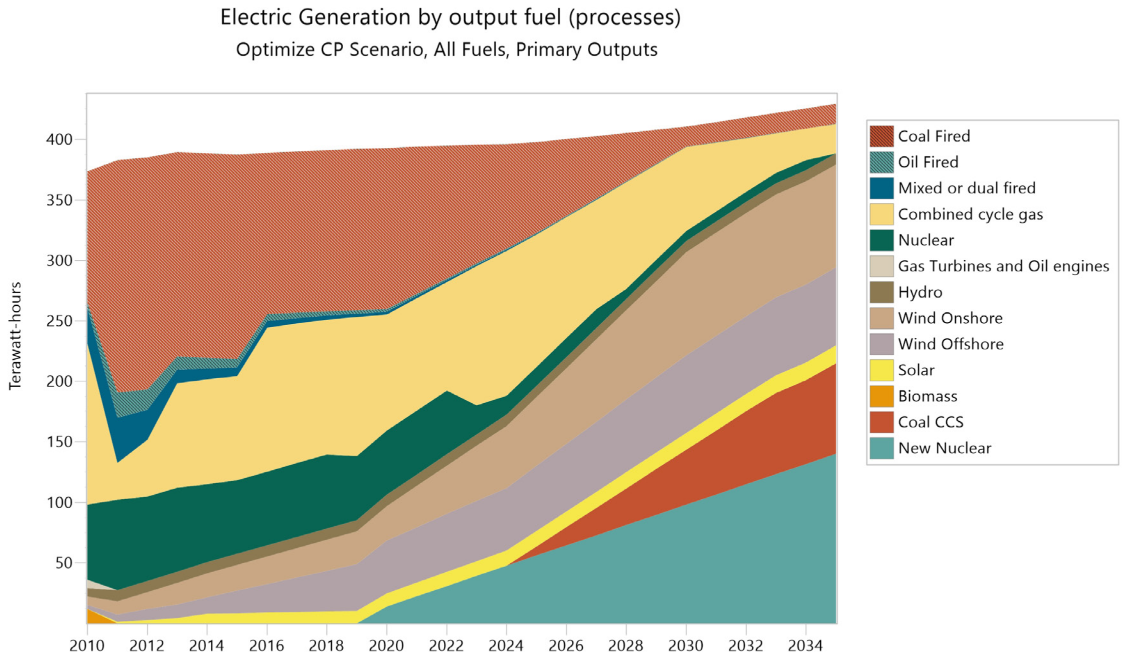


Figure 71: electric generation by output fuel, optimize CP scenario, divide by processes

In the optimized scenario become obvious that the generation through coal plants is preferred than the other, and the program tries to use every megawatt of installed capacity. This is because electricity generation through coal is cheaper than the other and the cost / benefit ratio it's better. The generation through gas plants decreases, because it's more expensive but necessary, while disappears the generation through biomass plants.

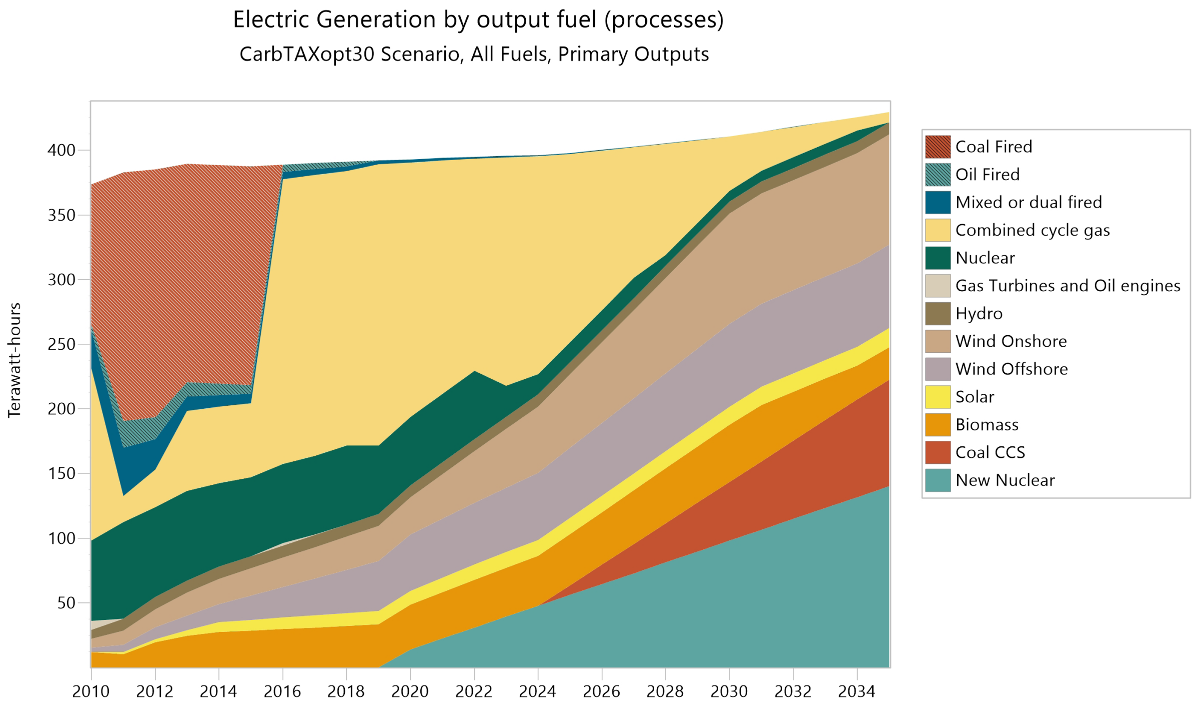


Figure 72: electric generation by output fuel, carbTAXopt30 scenario, divide by processes

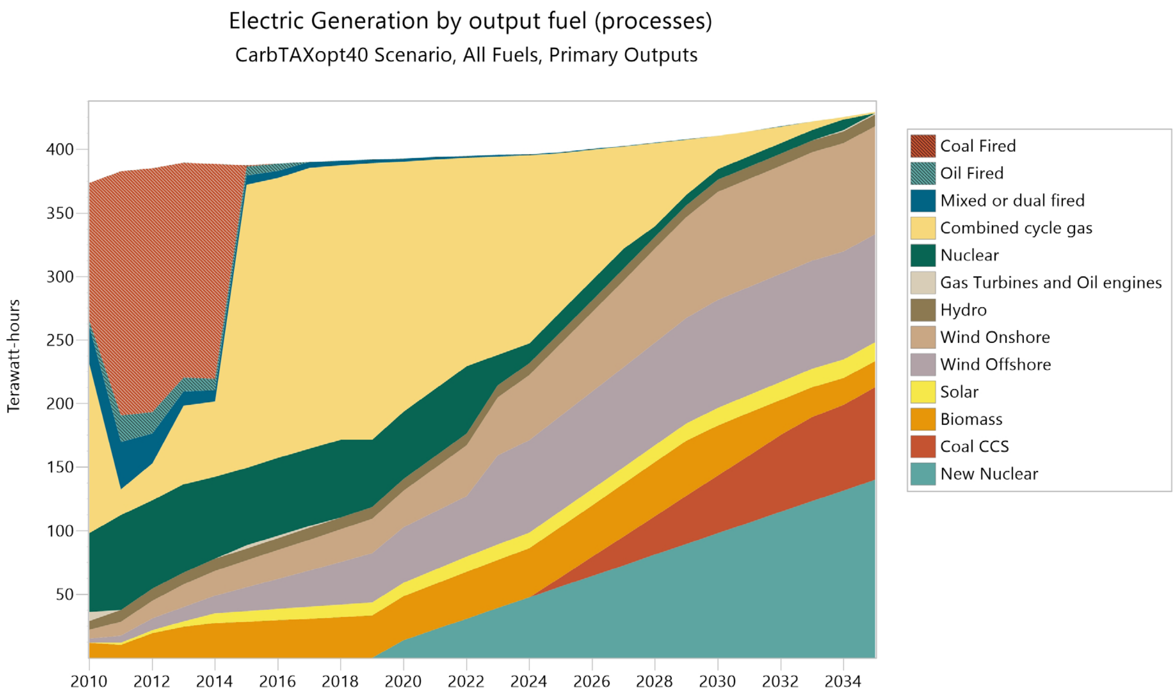


Figure 73: electric generation by output fuel, carbTAXopt40 scenario, divide by processes

As for the scenarios with the carbon tax can be observed that as soon as the costs become not convenient the generation through coal is cut cleanly. The plants that make up for the lack of coal plants generation are those gas plants which, although they are powered by fossil fuels, emit fewer pollutants in the air, and above all less CO2 than other fossil fuel plants. Obviously a break so sharply it is impossible to apply in practice but the graphs give an idea of the time that is necessary to take different decisions than for example as programmed. The change in the CO2 emissions of the different scenarios can be observed.

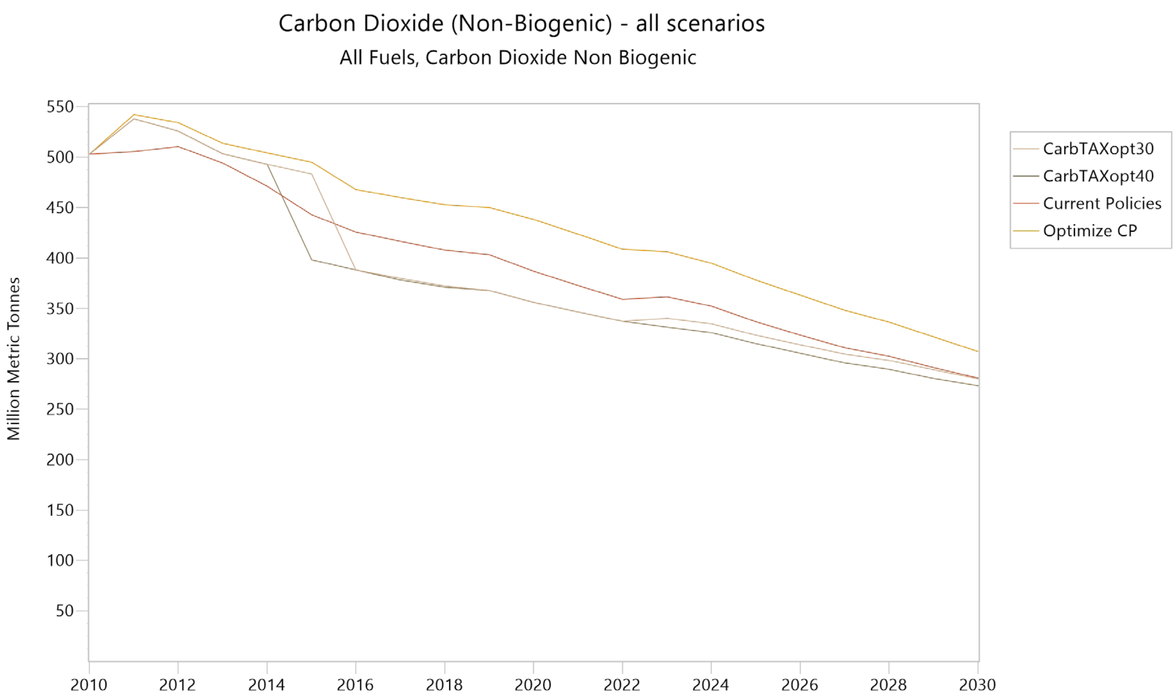


Figure 74: carbon dioxide (non-biogenic), divide by scenario

The scenario “Optimize CP” even increases emissions than the “Current Policies” because the economic aspect is considered, while the scenarios with Carbon Tax require major economic investment but decrease emissions significantly.

Cumulative Costs & Benefits: 2010-2040. Relative to Scenario: Current Policies. Discounted at 5,0% to year 2010. Units: Million 2010 U.S. Dollar	Current Policies	Optimize CP	CarbTAXopt30	CarbTAXopt40
Transformation	-	-10.590,8	53.383,5	69.763,5
Electric Generation	-	-10.590,8	53.383,5	69.763,5
GHG Savings (Mill Tonnes CO2e)	-	-1.001,6	188,7	383,3

Table 15: cumulative cost&benefits relative to current policies scenario

The table shows the values of the cost compared to the scenario “current policies”. Obviously the costs change substantially in the transformation and consequently the required resources. “Optimize CP” scenario has accordingly lower costs than the “current policies”, while scenarios with the carbon tax obviously have higher costs. As regards the emissions, the situation is reversed: scenario “Optimize CP” emits significantly more than the “Current Policies”, while scenarios with carbon tax have definitely positive results.
The following table shows the costs relative to KWh produced.

Cumulative KWh 2010-2040	74.118.354,506 MKWh

	Net Present Value relative to Current Policies Scenario	Additional cost to KWh produced
Optimize CP	45432,9 M$	0,0006130 $/Kwh
CarbTAXopt30	96814,9 M$	0,0013062 $/Kwh
CarbTAXopt40	109112,1 M$	0,0014721 $/Kwh

Table 16: Additional cost to KWh produced

The data concerning the “Optimize CP” scenario is positive because it shows an increase in the import of fossil fuels, especially coal and gas. These resources are for the most part imported and therefore have a cost. Regarding the scenarios with the carbon tax, the cost per kilowatt increases especially due to the higher cost required by power generation, whose production mainly depends on the renewable energies.

Capitolo 6 | Conclusion

The thesis presents an accurate work about energy forecasting related to the case study. The LEAP instrument was used to structure the complex energy apparatus of the United Kingdom. The tree structure created well represents the demand side and the transformation side, while analyzing the resources involved as well. The analysis of the results and the software output graphics give a clear idea of the direction towards which the energy policies considered will push. Such an analysis could be used as the starting point on which to base the creation of other future scenario, depending on the objectives that arise.

For the study, in part 1 a literature research on the theme of energy forecast has been conducted, in order to evaluate the methodology and the appropriate tools to apply for the context. The positive aspects and limits of LEAP have also been highlighted. The collection of official data, a hard work carried out for a long time, has been crucial to make the study as accurate as possible: without reliable data, forecasts could be very far from reality.

The usefulness of the software LEAP in the energy analysis was evident, especially in its ability to structure the complex energy context of a country and to create different energy scenarios, according to the chosen constraints. The scenarios created were: the "Current Policies" scenario, based both on current energy policies and on those policies that are now being implemented, loosely inspired by the New Policies Scenario of the WEO; the "Optimize CP", a scenario derived from the "Current Policies" scenario, to which an economic optimization was applied, and scenarios based on a carbon tax, "Carbon Tax opt30 " and "Carbon Tax opt40 ", which allowed to observe the evolution of the side transformation in case of clear choices about fossil fuels.

The results obtained in the baseline scenario, the "Current Policies" (built by analyzing various energy policies fully explained in Appendix 1), validated by comparison with government reports, clearly the future of the energy sector, both from the demand side point of view and transformation side. The United Kingdom's commitment to reduce its emissions and to target an energy future less dependent on fossil fuels is evident. The use of the optimization function on the basic scenario led to the '' Optimize CP" scenario, characterized by the same energy demand of all the other scenarios and by a modified transformation side, based on economic convenience. In particular, the production of electricity, while respecting the constraints of retirement of fossil fuels based power plants and the growth of power generation capacity from renewables, has changed in favor of plants that guaranteed a lower cost of production, that is fossil fuel plants, increasing the emissions. In the other two scenarios, that introduced the so-called carbon tax, and in fact increasing the cost of electricity generation from coal, the optimization led to a general increase in production costs but at the same time also to a substantial reduction in greenhouse gas emissions. The use of these scenarios has brought a clear example of how, once created the foundation, different energy futures can be built, according to various constraints chosen, obtaining an accurate prediction of energy analysis.

Through this work, an appropriate and efficient instrument for energy forecast was therefore developed. This new tool allowed to observe the effects of different kinds of energy management for a case study, through the use of different scenarios.

Capitolo 7 | Appendix 1

The Current Policies Scenario is based on those government policies and implementing measures that had been formally adopted as of mid-2014. The policies adopted can be found on UK government website [49] and on policy database of WEO [53]. The documents consulted are the following:
• Low carbon Transition Plan - 2008-09 [54]
• Renewable Energy Strategy - 2009 [55]
• Renewable Transport Fuels Obligation - 2009 [56]
• Energy White Paper - 2011 [57]
• UK 2012 Policies [58]
• WEO 2014 [41]
• Updated energy and emissions projections 2014 [59]

A.1 Low carbon Transition Plan

The UK Low Carbon Transition Plan [54] was a white paper outlining how the British economy will be transformed to ensure the UK meets its emission reduction targets, secures its energy supplies for the future, maximises the economic opportunities for jobs, skills and investment as well as ensuring policies are fair to protect the most vulnerable in society. It set out the then government's long-term strategy to radically cut the nation's carbon emissions by 2020 - 18% from 2008 levels (over one third from 1990 levels) and meet its first three carbon budgets. It Is not a statement of current Government policy.

A.2 Renewable Energy Strategy

The UK Renewable Energy Strategy 2009 [55] is a white paper outlining how the UK will meet its legally-binding target to ensure 15% of energy comes from renewable energy sources by 2020. Under the 2008 Climate Change Act, the UK must meet legally binding carbon "budgets", committing the UK to cuts its emissions by 34% by 2020 and 80% by 2050. The Strategy comprises three primary 2020 targets:

• Over 30% of electricity to be generated from renewable energy sources, mostly from wind power, with biomass, hydro, wave and tidal power playing important roles;
• 12% of heat to be generated from renewable energy sources, from a large range of sources (biomass, biogas, solar, heat pumps);
• 10% of transport energy to come from renewable energy sources.
• The key measures to achieve the targets are:
• An expansion and extension of the Renewables Obligation, requiring energy suppliers to sell larger amounts of renewable energy. New measures to increase financial support for offshore wind will also be considered.
• Introducing payment schemes to support the production of renewable heat and small-scale clean electricity generation by households, industry, businesses and communities.
• New guaranteed payments will be provided through feed-in tariff schemes from 2010 onwards, and a Renewable Heat Incentive from 2011 onwards. Before the schemes take effect, GBP 45 million in grants have been committed.
• The Renewable Transport Fuel Obligation will be amended or replaced, taking into account sustainability issues, to ensure transport fuels contain a rising amount of renewable biofuels.

The Strategy also creates an Office for Renewable Energy Deployment (ORED) within the Department of Energy & Climate Change (DECC) to take forward the commitments outlined in the Strategy.
In addition, the Strategy sets out areas for action in four areas.

1. The first aims to improve planning processes to be swifter and more strategic.
2. The second for measures to strengthen the UKs renewable energy industry, including through greater investment and work with the financial sector.

3. The third targets improvements and investments in the electricity grid, including improved grid access, more strategic investments (including in an offshore grid and a smarter grid).
4. Finally, the government outlines commitments for sustainable bioenergy development and use. This will act on the supply-side (woods management, energy crops, use of waste), focus on better sustainability criteria, and measures to facilitate use of biofuels and innovative bioenergy (for example, better fuel quality standards, injection of biogas into the grid, capacity of road and transport for greater biofuel use).

The Strategy also commits to using part of GBP 405 million of funding for key emerging technologies for renewable energy technologies, such as wave and tidal generation, offshore wind, and advanced biofuels. The government estimates that the Strategy will provide cumulative savings of 755 MtCO2 between now and 2030, 535 MtCO2 of which will help the UK meet EU Emissions Trading System (EU-ETS) caps, and 220 MtCO2 will provide additional CO2 reductions. Within the additional savings, 73 MtCO2 will be saved over the third carbon budget period (2018 - 2022) and deliver about a sixth of the abatement needed to meet this third budget.

A.3 Renewable Transport Fuels Obligation

In November 2005 the Government announced it would introduce a Renewable Transport Fuel Obligation [56] (RTFO) - a long term mechanism requiring transport fuel suppliers to ensure a set percentage of their sales are from a renewable source. The Obligation also requires suppliers to publicly report on the carbon savings and sustainable production of biofuels supplied. Non-complying suppliers will pay a penalty.
Backed by tradable offset certificates - Renewable Transport Fuel Certificates (RTFCs), the Obligation programm aligns with the EU Directive 2003/30/EC on the promotion of biofuels and renewable fuels for transport.

Fuel obligation levels

	2008/2009	2009/2010	2010/2011	2011/2012	2012/2013	2013/2014
Obligation levels for renewable transport	2.50%	3.25%	3.50%	4%	4.50%	4.75%

Table 17: fuel obligation levels

A.4 Energy White Paper

The UK White Paper [57] presents the overall reform of the UK electricity system, aiming at designing a smart, flexible and responsive electricity system that provides for secure, low-carbon and affordable electricity supply. The UK power system needs to tackle 5 main challenges, namely:

• Supply security, as old and polluting generation plants are bound to close (20GW by 2020) and as the system needs to adapt to higher levels of intermittent (wind) and inflexible generation (nuclear).
• The need for electricity mix decarbonisation to reach 2020 RE targets -15% of primary energy needs from RE.
• The increase in generation capacity to meet rising demand (transport sector electrification needs) in parallel with energy savings and efficiency practices.
• Great need for cost-efficient investments to avoid high increases in cost of electricity, considering that carbon price and environmental policies are likely to lead to higher bills in the future.

The government has identified several key tools, central to the reform strategy, that would allow for the transition to a decarbonised energy system to happen, namely:

- The Feed in tariffs with Contract for Difference, expected to start by 2014, will provide a clear, stable and predictable revenue stream for investors. None of the tariff adjustments are retroactive.
- The Carbon Price Floor, expected to be in force by 2013, would guarantee a fair price on carbon and provide a stronger incentive to encourage investment in low carbon generation.
- The Emission Performance Standard (EPS) expected to be in force by 2013, equivalent to 450g CO2/kWh at baseload, to limit the amount of carbon new fossil-fuel power plants can emit.

Engaging with energy consumers to reduce demand will also become a priority both in the electricity and the heating sectors, where the Green deal will help to reduce cost and carbon emissions in buildings, with smart electricity and gas meters. On the short term, the market design reform shall allow for a smooth transition and investments to continue. Therefore, the existing Renewables Obligation will continue for existing projects supported by the scheme (principle of no retrospective change) and new ones until March 31st 2017. Between 2011 and 2017 new renewable energy generators will have a one-off choice between Renewable obligation support of feed-in tariff. The reform will also be included in the devolution process at the national scale.

A.5 UK 2012 Policies

This is United Kingdom review by Energy policies IEA Countries [58]. It is available on IEA website, in the publication section [58].

A.6 WEO 2014

The annual World Energy Outlook (WEO) [41] is now the world's most authoritative source of energy market analysis and projections, providing critical analytical insights into trends in energy demand and supply and what they mean for energy security, environmental protection and economic development.
The WEO projections are used by the public and private sector as a framework on which they can base their policy-making, planning and investment decisions and to identify what needs to be done to arrive at a supportable and sustainable energy future.

A.7 Updated energy and emissions projections 2014

The Department of Energy and Climate Change (DECC) updates projections of energy demand, supply and greenhouse gas (GHG) emissions annually [59]. These projections are an important way of assessing whether current and planned policies are consistent with achieving UK carbon budgets in future years. This publication is available from Department of Energy and Climate change, in the UK government website [49].

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