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EXECUTIVE SUMMARY OF THE THESIS

Development of a Comprehensive Technology Database for the design optimization of Aggregated Energy Systems with My-AESOPT

TESI MAGISTRALE IN ENERGY ENGINEERING – GREEN POWER SYSTEM (EEG)

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1. Introduction

There is an undeniable link between urban development, quality of life, and energy consumption. However, in light of the growing urgency of climate change, the increase in energy production must be accompanied by a transition toward cleaner systems that are less dependent on fossil fuels, with greater emphasis on energy efficiency and electrification. Among the solutions, the approach central to this thesis is that of Aggregated Energy Systems (AESs): broadly defined, an Aggregated Energy System (AES) constitutes a framework where diverse energy demands, technologies and vectors are integrated and simultaneously optimized. While the advantages of Aggregated Energy Systems are numerous, they come at the cost of increased system complexity, making traditional design approaches inadequate. For this reason, several optimization models have been developed to support system planning and operation under such complexity. This thesis focuses in particular on My-AESOPT, the tool proposed by Dipierro et al. [1], for the optimal investment planning of Aggregated Energy Systems. My-AESOPT is based on a Mixed-Integer Linear Programming (MILP) model, and the tool is designed to perform multi-step design optimization, allowing detailed and accurate representation of AES configurations in both the investment planning and operational phases. However, the reliability and validity of the results produced by My-AESOPT are strongly dependent on the quality of the input data. In this context, this thesis aims to provide a structured and reliable database to be used as input for My-AESOPT in the optimal investment planning of Aggregated Energy Systems. The resulting database is structured in two complementary formats. The first format presents technical and economic data for fixed system sizes, directly derived from manufacturers' specifications or academic sources. The second format adjusts and reworks these data to determine best-fit correlations (compatible with My-AESOPT MILP model) valid for energy systems with variable sizes.

2. Characteristics of Technology Databases

Although the databases include an extensive number of energy technologies, they can be classified into three main categories:

- **Dispatchable units:** these are energy technologies whose power output can be actively controlled, started, stopped, increased, or decreased by the user.
- **Non-dispatchable units:** these energy technologies have outputs that are primarily determined by uncontrollable factors, such as meteorological conditions.
- **Energy storage units:** these technologies absorb energy at one point in time, store it, and release it at a later time.

The energy technologies analyzed in this thesis, classified according to the categories introduced previously, are as follows:

- **Dispatchable units:** ICE CHP (internal combustion engines with cogeneration), SOFC CHP (solid oxide fuel cells with cogeneration), PEMFC CHP (proton exchange membrane fuel cells with cogeneration), natural gas condensing and non-condensing boilers, air–water heat pumps, large water–water heat pumps, geothermal heat pumps (using groundwater wells, borehole probes, or horizontal collectors), large alkaline electrolyzers, large PEM electrolyzers, wood chip boilers, pellet boilers, biomass ORCs (organic Rankine cycles), large absorption chillers (with water or high-pressure steam as the heat source), large compression chillers and large absorption chillers.
- **Non-dispatchable units:** monocrystalline PV panels, vertical-axis wind turbines (VAWTs), horizontal-axis wind turbines (HAWTs) at both utility and distributed scales, solar thermal panels (roof-mounted or open-air systems), and concentrated solar power (CSP) installations.
- **Energy storage units:** battery energy storage systems (BESSs), large thermal energy storage systems (TESs), hydrogen storage tanks, and hydrogen storage caverns.

3. Content of the Database

The fixed-size database includes the following parameters, divided in two different categories:

- **Technical data:** this includes unit size, input and output power at both minimum partial load and nominal operating points, hot ramp-up and ramp-down rates, start-up and shut-down times, fuel type, and lifetime. Only for energy storages, the C-rate parameter is also available.
- **Economic data:** this includes capital expenditure (CAPEX), variable operation and maintenance (O&M) costs, variable O&M costs including replacements, fixed O&M costs, and start-up costs.

All sources and references used to obtain this data are also documented in the database. For the variable-size database, some modifications have been introduced:

1. **Size range:** each energy unit is represented by a range of possible sizes.
2. **Part-load coefficients:** A set of coefficients (k_1, k_2, k_3 for each output) is included to accurately model part-load operation of energy units across the size range.
3. **Normalized power values:** Input and output power at minimum and nominal operating points are expressed as ratios relative to the unit's nominal input size.
4. **CAPEX correlations**: instead of the specific CAPEX, for each energy technology, and for each of its size ranges, a CAPEX correlation is presented.

4. CAPEX correlations

The correlation adopted for CAPEX estimation follows a power-law formulation, which is common to all the technologies analyzed:

$$y = a \cdot x^{-k} \text{ with } k > 0$$

where the variable y represents the specific investment cost, expressed in €/kW, x denotes the nominal size of the technology in kW, k represents the positive scaling exponent returned by the script together with the coefficient a. To derive the specific CAPEX correlations, real data obtained from manufacturers, or, when unavailable, from academic sources, at fixed sizes are provided as input to a dedicated script: the same data that populates the fixed-size database was used for this purpose. The script returns a functional correlation that can be used to estimate CAPEX values for any system size within the applicable range. Two different fitting approaches are implemented and compared, as the performance of each method may vary depending on the characteristics and distribution of the input data: log–log linear regression (typically used when cost–capacity relationships closely follow a power-law behavior) and non-linear curve fitting (which can give better results when deviations from simple scaling laws are observed). The results obtained from both methods are compared against the original data points thanks to one of the features of the script, and the most appropriate correlation can be selected based on goodness-of-fit criteria and consistency with known cost points. Finally, the full script can be consulted in the GitHub repository .

5. Linearization of performance maps

In the variable-size sheet of the database, a set of coefficients (k_1, k_2, k_3) is provided for each applicable technology (or multiple sets where multiple size ranges are present for a single energy technology), which correspond to the linearized performance maps. These coefficients are introduced to accurately represent the part-load operation of energy units. The adopted formulation is based on the part-load model originally proposed by Lahdelma and Hakonen [2], combined with the operational strategy introduced by Yokoyama et al. [3], and applied by Zatti [4] in the context of part-load modeling for energy units within Aggregated Energy Systems. The approach relies on a key assumption: the nominal size of an energy unit can be treated as a continuous decision parameter. This assumption is justified by the wide range of commercially available technologies, which ensures that, in practical applications, a unit with a size very close (or equivalent) to the one determined by My-AESOPT can typically be identified on the market. The modeling of size effects and part-load performance for energy conversion units is therefore based on the coefficient set (k_1, k_2, k_3). These coefficients are determined through regression procedures and are subsequently used to linearize both the input (e.g., fuel consumption) and the useful outputs of the unit, such as, in the case of cogeneration technologies, both thermal and electrical power. The methodology introduced by Zatti [4] has been slightly adapted to meet the objectives of this thesis. For a cogeneration technology, which simultaneously produces both electricity and heat, the two outputs can be represented using linearized equations (1) as follows:

(1)

$$\begin{cases} P_{EE} = k_{1,EE} \cdot INPUT + k_{2,EE} \cdot XD_{EE} + k_{3,EE} \\ P_{TH} = k_{1,TH} \cdot INPUT + k_{2,TH} \cdot XD_{TH} + k_{3,TH} \end{cases}$$

where:

- $k_{1,EE}$, $k_{2,EE}$, $k_{3,EE}$ are the linear coefficients used to compute the electrical output.
- $k_{1,TH}$, $k_{2,TH}$, $k_{3,TH}$ are the linear coefficients used to compute the thermal output.
- INPUT represents the fuel consumed by the cogeneration unit, measured in kW.
- P_{EE} is the electrical power output of the cogeneration unit, measured in kW.
- P_{TH} is the thermal power output of the cogeneration unit, measured in kW.
- XD_{EE} and XD_{TH} are the nominal sizes of the cogeneration unit (referred respectively to electricity and heat), measured in kW.

These equations also illustrate why two separate sets of coefficients are required for cogeneration technologies, one for the electrical output and another for the thermal output. In contrast, for energy technologies that produce a single type of output only one set of coefficients and a single equation are necessary to model the input–output relationship accurately. By employing this linearized approach, it is possible to portray the part-load performance (which is controlled by the parameter INPUT) of the cogeneration unit while incorporating the influence of unit size, enabling My-AESOPT to optimize both design and operation accurately. The coefficient sets were determined using the least-squares method, applied to the input and output data of detailed energy unit models under both nominal and minimum (part-load) operating conditions, while making sure that P_{EE} and P_{TH} obtained with sets of coefficients do not introduce an error higher than 5% (with respect to the known points).

6. Fixed-size and Variable-size databases

Due to the extensive amount of information contained in the databases, their complete versions are reported in [5], where all the technical and economic parameters for the technologies considered are fully documented, along all the references.

7. CAPEX correlations results

The resulting values of the parameters *a* and *k*, obtained through the method described previously, are presented (for a few examples) in Table 1 and are implemented in the variable-size database to easily obtain economic input data for My-AESOPT.

Energy unit	CAPEX correlations
ICE CHP	$y = 18729.721 * x^{(-0.401)}$ *(till 0.5 MW_el)* $y = 1908.689 * x^{(-0.065)}$ *(till 10 MW_el)*
NG BOILER (condensing)	$y = 4634.174 * x^{(-0.541)}$
PV panels	$y = 5142.023 * x^{(-0.162)}$

Table 1: CAPEX correlations.

As explained before, the built-in features of the script also present a direct confrontation between real points and the two CAPEX correlation obtained before, of which an example is reported in Figure 1, showing that the log–log linear regression correlation is the most accurate. Due to the extensive amount of energy technologies contained in the databases, the complete list of CAPEX correlations is reported in [5].

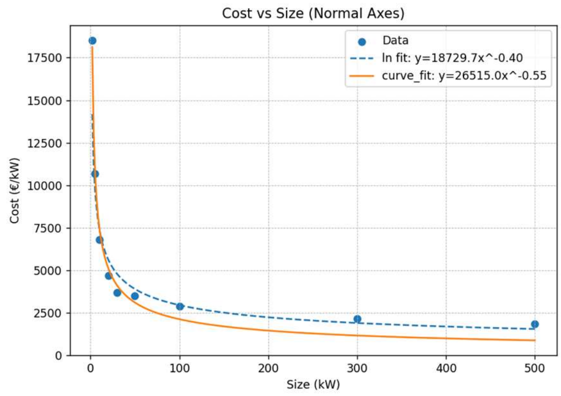


Figure 1: Analysis in linear space (correlation for ICE CHP with size below 500 kW_{el}).

8. Results for the linearization of performance maps

To assess the accuracy of the linearized performance maps derived using the methodology described above, Table 2 reports the corresponding average and maximum errors for one of the many energy technologies studied: natural gas condensing boilers.

Energy unit	Size range	Average and maximum error
NG boiler condensing	10 - 100 kW_{th}	0.5% (avg) 3% (max)
	100 - 500 kW_{th}	0.3% (avg) 3% (max)

Table 2: Error (percentage) introduced by the linearization of performance maps.

The reported errors are calculated by comparing the reference output values (at nominal and minimum part-load operation) with the corresponding values obtained using the linearized model based on the coefficients k_1, k_2, k_3. As highlighted by the results, the average errors are generally very low, confirming that the linearized approach maintains a high degree of accuracy across the size range considered. All coefficient sets, together with their corresponding error analyses, are reported in [5].

9. Application of the Technology Database to a case study

The technology database developed in the previous sections is now applied to a representative case study, modeled after a hospital located in Northern Italy. The optimization process must ensure that the final system configuration satisfies all the specified energy demands: electricity, heat, and cooling, continuously and reliably for every hour of the year. The hourly energy demands considered for this case study are summarized in Table 3.

	Peak [MW]	Total energy demand [MWh/y]
EE	5.00	25072
Heat	10.37	36014
Cooling	9.94	9360

Table 3: Energy demands.

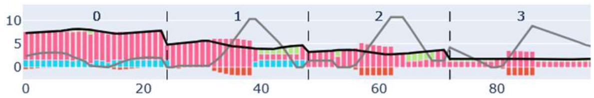
10. Optimal configuration

For this optimization scenario, a carbon tax equal to 92.2 €/ton$_{CO2}$ [6] has been applied to all energy technologies that produce direct CO_2 emissions during operation (ICE CHP, SOFC CHP, and both condensing and non-condensing natural gas boilers). This additional cost penalizes fossil-fuel-based technologies from an economic point of view. As shown in Table 4, the optimal configuration identified by My-AESOPT under this assumption includes the following technologies: natural gas non-condensing boilers, water-water heat pump for heating, ICE CHP, compression chillers, PV panels, thermal energy storage (TES) and battery energy storage system (BESS).

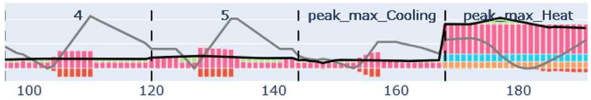
Energy Technology	Size [MW]	Size [MW]
NG non-condensing boilers	1.43	\
Water-Water Heat Pump (Heating)	6.18	\
ICEs CHP	1.36 (EE) 1.52 (Heat)	\
Compression chillers	7.47	2.47
PV panels	12.36	\
TESs	10.70 MWh	\
BESS (C-rate = 0.5)	7.69 MWh	\

Table 4: Optimal configuration.

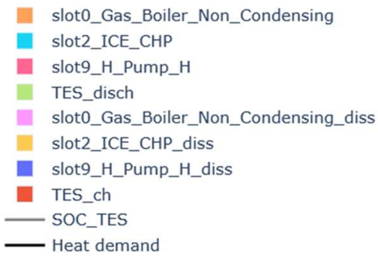
Due to the carbon tax the system presents a greater reliance on electricity as the main energy vector, with a low dependence on natural gas. The heat power balance is presented in Figure 2, and it shows the major role of the water-water heat pump, which guarantees a high percentage of the heat required by the hospital. The internal combustion engine and the natural gas boiler are only active when the heat demand is high and cannot be fully covered by the heat pump.



(a) Heat Power Balance (typical days 0, 1, 2, 3).



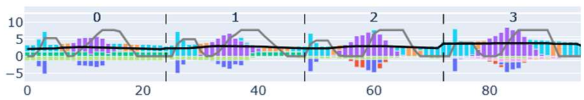
(b) Heat Power Balance (typical days 4, 5, peak cooling day, peak heat day).



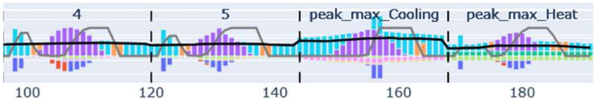
(c) Legend.

Figure 2: Heat Power Balance.

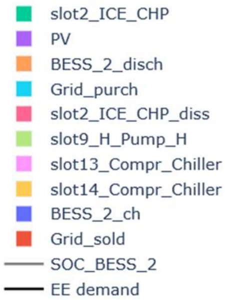
The system greater reliance on electricity over natural gas is confirmed by the electrical power balance, which is presented in Figure 3.



(a) Electrical Power Balance (typical days 0, 1, 2, 3).



(b) Electrical Power Balance (typical days 4, 5, peak cooling day, peak heat day).



(c) Legend.

Figure 3: Electrical Power Balance.

The electricity demand is mostly guaranteed by the PV panels and the grid (for which an emission factor is also considered), while the battery enables temporal shifting of electrical energy, improving the utilization of locally generated electricity. Part of the electricity produced is also sold to the grid (usually when PV panels are active and the demand for electricity is low) or used by the compression chillers to guarantee the cooling demand.

11. Comparison between the optimal configuration and reference configuration

It is particularly meaningful to compare the optimal configuration in terms of CO_2 emissions and Net Present Cost (NPC) with a reference configuration, for which no carbon tax is applied. The reference configuration presents different energy units, which are presented in Table 5.

Energy Technology	Size [MW]	Size [MW]
NG non-condensing boilers	3.95	\
NG condensing boilers	5 x 0.50	0.50
ICEs CHP	2.45 (EE) 2.67 (Heat)	\
Compression chillers	7.47	2.47
PV panels	12.36	\
TESs	12.07 MWh	\

Table 5: Reference configuration.

In the absence of a carbon tax, fossil-fuel-based technologies for electricity and heat production become more economically attractive. Although they are characterized by higher operational costs due to fuel consumption, their relatively low capital investment costs make them more competitive than alternative solutions such as heat pumps for thermal production. The comparison between the two different configurations is highlighted in Table 6.

Configuration	CO_2 Emissions [kton/y]	NPC [M€]
Reference	12.01	74.387
Optimal	6.29	79.526

Table 6: CO_2 Emissions and NPC comparison.

This outcome highlights a key result of the optimization process: a substantial reduction in environmental impact can be achieved with a relatively limited increase in overall system cost. The modest rise in NPC reflects the higher investment in low-emission technologies (such as heat pumps and electrical storage) and the reduced reliance on fossil-fuel-based generation. These results demonstrate the capability of My-AESOPT to identify balanced solutions that significantly reduce emissions without imposing disproportionate economic penalties, supporting the feasibility of decarbonization strategies in complex energy systems.

12. Conclusions

This work aimed to develop and implement a comprehensive technology database to support the optimization process performed by My-AESOPT for Aggregated Energy Systems (AES). The application of the database to the case study returned promising results, demonstrating that significant reductions in AES CO_2 emissions can be achieved with only a marginal increase in investment costs, thanks to the optimization capabilities of My-AESOPT. The consistency of the results also supports the validity and reliability of the input data adopted for the analysis.

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13. Acknowledgements

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