sensei

D4.2 The drivers of the value of energy efficiency as an energy resource

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Smart Energy Services to Improve the Energy Efficiency of the European Building Stock

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Abbreviations and Acronyms

Acronym	Description
CVRMSE	Coefficient of Variation of the Root Mean Squared Error
ESCO	Energy Services Company
M&V	Measurement and Verification
OCC	One-Class Classification
ORDC	Operating Reserve Demand Curve
P4P	Pay for Performance
PCA	Principal Components Analysis
TSO	Transmission System Operator

Executive summary

This deliverable proposes a methodology to quantify the value of an energy efficiency improvement project, or a portfolio of such projects, as a power grid resource. The main assumption is that a retrofit project can be regarded as a grid resource if it helps in either phasing out old, polluting power plants that are only kept commissioned for the provision of capacity reserves or reducing curtailment of renewable-based power generation to improve the grid's hosting capacity for renewables.

Energy efficiency improvements in buildings may affect power consumption in two (2) ways:

(a) Decrease power consumption by improving the efficiency of a piece of electric equipment (such as the efficiency of an air cooling system) or reducing the total amount of work that must be performed by an existing piece of electric equipment (such as upgrading envelope insulation so that to reduce the cooling load);

(b) Increase power consumption due to fuel substitution, such as when an old oil-fuelled boiler is replaced by an electric heat pump.

The deliverable promotes the position that when energy efficiency projects lead to power consumption changes that persistently modify the power system's load shape in ways that harmonize with the system operator's goals, they should be regarded as a valuable grid resource. Quantifying and rewarding this value is a way to coordinate two energy policy aspects that are generally detached from each other: the medium-term planning for resource adequacy in the power system and the operation of public programmes that provide financial support to energy efficiency improvements in buildings.

The presented results suggest that it is possible and straightforward to define what an appropriate profile of power consumption changes should be and how the value of a retrofit project that contributes to such power consumption changes can be calculated. In addition, the proposed methodology is implemented using the same process and the same tools that power system operators use for capacity adequacy studies. Thisshowcases that the design of a program that compensates energy efficiency for its contribution to the grid does not need a radically new toolset, but rather a different way to treat energy efficiency; energy efficiency is not just a change in average yearly consumption, but has seasonal/temporal characteristics that may decrease or increase the total cost of the power system's operation. A *grid positive* energy retrofit project, i.e. one where the positive impacts for the grid outweigh the negative,

has value, and rewarding this value is a way to influence energy retrofit projects to implement measures that are better aligned with the needs and challenges that the power system faces towards decarbonization.

Pay for Performance (P4P) schemes can be utilized for rewarding energy retrofits to the extent that they lead to load shape changes that are beneficial for the grid's operation. The main premise of the P4P concept is simple: compensate an asset or a service according to its actual impact. Adopting P4P is necessary because all other alternatives for ensuring the power grid's reliability – capacity reserves and demand response – are compensated based on their performance. Treating energy efficiency on equal basis with the alternative options that system operators have at their disposal means that energy efficiency is rewarded based on actual rather than deemed impacts.

In the most general case, P4P is not meant to replace energy efficiency grants and subsidies; subsidizing the upfront investment costs is a strong driver for energy efficiency upgrades and, in particular, for deep retrofits. Instead, SENSEI promotes the idea of offering a premium to energy efficiency retrofit projects that can be regarded as valuable grid resources, and using P4P as the mechanism to provide this premium.

All the functionality that has been developed to enable the implementation of the proposed methodology has been open-sourced and can be accessed at https://github.com/hebes-io/eevalue.

1 Introduction

The ongoing EU goal for the decarbonisation of the power system means that decentralized and fluctuating solar- and wind-driven power generation substitutes more and more power from dispatchable, fossil-fuelled power plants. This results to increased variability of supply and to power system operators requiring more options to efficiently handle the stability and adequacy challenges of the power grid. While the most often suggested option is *demand flexibility*, i.e. the fast-responding adaptation of power consumption to the variable generation, the SENSEI project examines the role that *energy efficiency*, i.e. the persistent and maintained changes in power consumption compared to a baseline level, can play in a renewables-based electricity system.

Energy efficiency improvements may affect power consumption in two (2) ways:

(c) Decrease power consumption by improving the efficiency of a piece of electric equipment (such as the efficiency of an air cooling system) or reducing the total amount of work that must be performed by an existing piece of electric equipment (such as upgrading envelope insulation so that to reduce the cooling load);

(d) Increase power consumption due to fuel substitution, such as when an old oil-fuelled boiler is replaced by an electric heat pump.

Accordingly, energy efficiency improvements may reduce power demand during the hours when the probability of load loss is high and/or hours when persistent variability in the net load[1]leads to ramping events[2]. In both of these cases, energy efficiency can help phase out old, polluting power plants that are only kept commissioned for the provision of capacity reserves, as well as reduce the amount of new generation capacity that is needed to serve the future load growth. On the other hand, there are times when increased power demand may be actually beneficial, such as during periods of renewable power over-generation and curtailment. If energy efficiency interventions reduced power demand during those hours, the system needs for demand flexibility would increase.

Under this perspective, energy efficiency could be regarded by the power grid as a *load modifying resource*: although it is not dispatchable by the power or capacity market, energy

[1] Net load is the difference between the total system load and the electricity generation from renewable sources

[2] Defined as large changes in the magnitude of the net load lasting for a period of up to three (3) hours

efficiency is able to persistently modify the power system's load shape in ways that harmonize with the system operator's goals, such as peak shaving, increased hosting capacity for renewables, reducing steep upward and downward ramps, and reducing the overall costs of power procurement.

The study of Langevin et al. (2021)[3] has shown that implementing efficiency measures alongside flexibility measures can be of high value to grid operators so as to avoid future investments in generation capacity and relieve pressure on power storage deployments to support variable renewable energy integration. These results are aligned with the outcomes of the Southern California Edison (SCE) Preferred Resources Pilot[4], the primary objective of which was to determine whether locally deployed distributed energy resources can reliably serve the forecasted load growth. The main insight from the pilot was the need for a diverse mix of resource types to manage load growth, since no single resource type has all the performance characteristics to meet local and temporal grid needs.

In general, a load modifying resource would be most valuable if it could induce persistent changes in the power consumption profile that increase demand during some time periods and decrease demand during others, so that to better align with the daily/seasonal net load profile. This means that the value of an energy efficiency project for the power grid is highly dependent on the temporal profile of the power consumption changes that it induces: some aspects of a consumption profile change may increase the value of the project, such as when power demand decreases during periods of high probability of capacity deficit, while others decrease its value, such as when the probability of renewable generation curtailment is increased.

Accordingly, the value of an energy efficiency project for the power grid can be determined through a **composite indicator** that consolidates the different ways the project affects the grid. A project can be considered as *grid positive* if the positive impacts outweigh the negative. This deliverable proposes and demonstrates a **methodology** to estimate such an indicator. The proposed methodology is implemented using the same process and the same tools that system operators use for capacity adequacy studies. There are two (2) reasons for this

[3] Jared Langevin, Chioke B. Harris, AvenSatre-Meloy, Handi Chandra-Putra, Andrew Speake, Elaina Present, Rajendra Adhikari, Eric J.H. Wilson, Andrew J. Satchwell (2021) "US building energy efficiency and flexibility as an electric grid resource", Joule, Volume 5, Issue 8, pp. 2102-2128, https://doi.org/10.1016/j.joule.2021.06.002

[4] SCE Preferred Resources Pilot, Lessons Learned About DER Sourcing and Deployment, 2019

approach. The first reason is that the coordination between the needs of the power system and the incentives for energy efficiency improvements must take place during the medium-term planning for resource adequacy in the power system. The second reason is to showcase that the design of a program that compensates energy efficiency for its contribution to the grid does not need a radically new toolset, but can be done using the tools that power system operators already use for capacity adequacy planning.

2 Methodology

2.1 Energy efficiency and capacity adequacy

The identification of the capacity adequacy needs for the different EU Member State power systems is carried out by the respective Transmission System Operators (TSOs). These needs are quantified in the TSOs' capacity adequacy assessment studies that guide the national strategy for planning the introduction of new power plants and the decommissioning of old and polluting ones. The assessment of capacity adequacy evaluates two (2) main aspects:

a) Adequacy of *peak capacity*. The assessment evaluates the extent to which the sum of the expected available capacities is sufficient to meet the demand minus the expected generation from renewable sources.

b) Adequacy of *flexibility*. The assessment evaluates whether the existing capacity has the right technical characteristics to cope with the expected and unexpected variations in demand and renewable power generation. Flexibility can be distinguished into two (2) types:

   - *Slow flexibility*. According to the ELIA Adequacy and Flexibility Study for Belgium 2022-2032, "… slow flexibility represents the ability to deal with expected deviations in demand and generation based on information received between the day-ahead market (up to 36 hours before real-time) and the intra-day forecast received several hours before real-time".
   - *Fast flexibility*. Fast flexibility represents the ability to deal with unexpected power deviations in real time.

This deliverable aims at exploring the potential contribution of energy efficiency to the overall needs for peak capacity and slow flexibility of a power system.

Peak capacity

The *capacity margin* of a power system is the proportion by which the total available generation exceeds the demand at any given time period t:

$$Margin_t = \frac{G_t + VG_t}{L_t} \tag{2.1}$$

where:

G_t is the available capacity of all the dispatchable power generation plants at time t (MW)

VG_t is the variable power generation that is available at time t, i.e.the nameplate capacity multiplied by the respective capacity factor (MW)

L_t is the total load at time t (MW).

The assessment of the capacity adequacy focuses on the probability that the margin will become less than one under some conditions in the future. The capacity margin is not deterministic due to the variability in the demand and generation from renewable sources, as well as the forced outages of the dispatchable capacity. However, it does exhibit seasonal/temporal patterns.

The plot of Fig. 2.1 shows the yearly distribution of the lower 10% of the daily capacity margin values, whereas the plot of Fig. 2.2 depicts the average daily profile of the capacity margin in the Greek power system for the period 2018-2020.

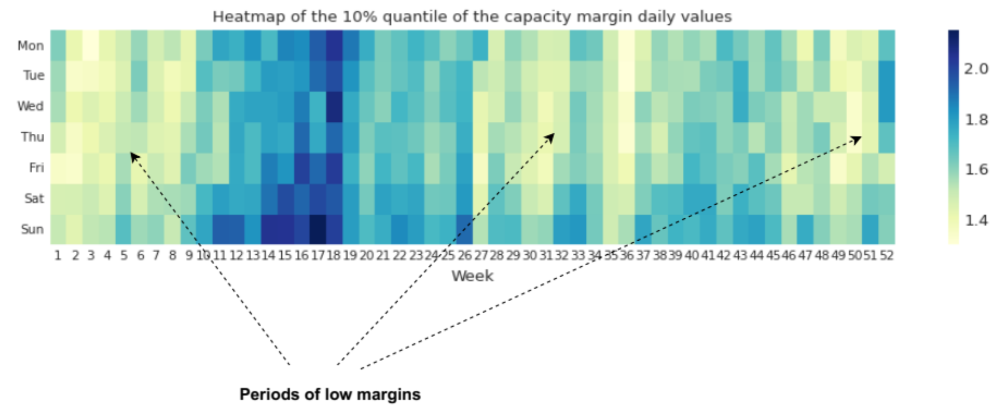

Figure 2.1– Yearly distribution of lower 10% of the daily capacity margin valuesfor 2018-2020

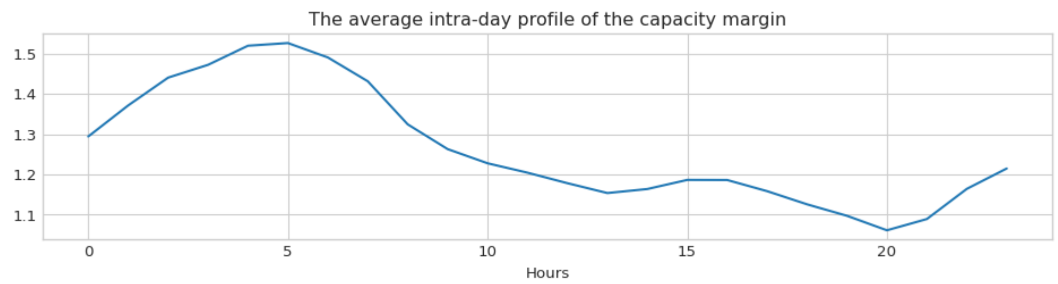

Figure 2.2– Average intra-day profile of the capacity margin for 2018-2020

Slow flexibility

The *ramp-up requirements* of a power system can be approximated as:

$$RU_t = \max\left[NL_t - \frac{\sum_{j=1}^{3} NL_{t+j}}{3}, 0\right] \tag{2.2}$$

where $NL_t$is the net load at time t (MW).

The plot in Fig. 2.3 shows the average intra-day ramp-up needs in the Greek power system for 2018-2020, where a temporal pattern is obvious.

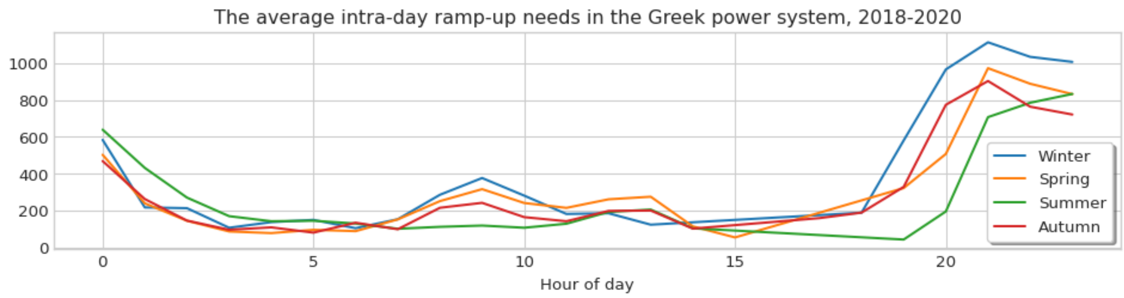

Figure 2.3– Average intra-day ramp-up needs in the Greek power system, 2018-2020

The existence of seasonal/temporal patterns is an argument in favour of considering energy efficiency support schemes as a way to reduce the needs for peaking or ramping capacity. In this case, the value of energy efficiency can be derived based on the capacity reserves that it can reliably displace. The value of these reserves can be quantified using the operating reserve demand curve (ORDC), which is calculated as:

$$V(R) = VOLL \times LOLP(R) \tag{2.3}$$

where:

R The reserve capacity that the system should carry before resorting to involuntary load shedding

$V(R)$ The value of the reserve capacity

$VOLL$ The value of lost load

$LOLP(R)$ The loss of load probability given the available amount of reserve capacity R

The loss of load probability (LOLP) at a given time period$t$ is derived as:

$$LOLP_t = Prob(G_t + VG_t + I_t - L_t < 0) \tag{2.4}$$

where:

I_t is the cross-border inflows at time t (MW).

The plot in Figure 2.4 depicts a stylizedORDC.

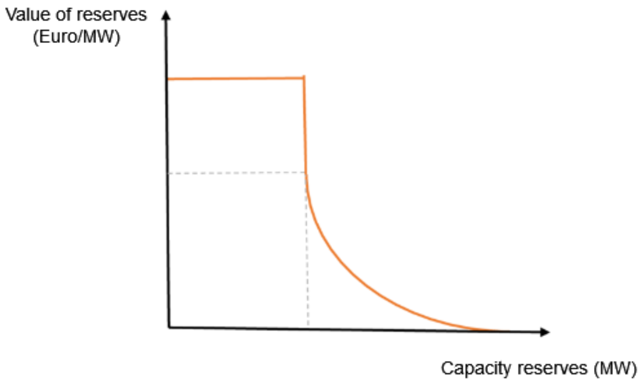

Figure 2.4– Stylized operating reserve demand curve

Based on the aforementioned, strategic load reductions at some hours of the year can be beneficial to the grid. However, this does not mean that load reductions are always beneficial. It should be expected, for instance, that load reductions are detrimental for the grid when they increase the probability of renewable generation curtailment. Accordingly, the value of an energy efficiency project for the power grid can be determined through a composite indicator that consolidates the different ways the project affects the grid. The proposed methodology offers a way to estimate such an indicator using the same process and the same tools that capacity adequacy studies use.

To this end, the quantitative analysis that is carried out utilizes a unit commitment model to identify the conditions under which energy efficiency improvements are most valuable for the power system and its operation. The details of the model are presented in Chapter 5. In this section, it is sufficient to note that the model:

- Simulates the state of a national power system given scenarios for future demand and supply;
- Identifies when conditions of missing capacity may arise;
- Allocates a limited amount of load modifying resources to the hours where largest impact on minimizing the overall system operation cost can be achieved.

2.2 The quantitative analysis workflow

The proposed quantitative modelling and analysis approach consists of the following six (6) stages:

1. **Preprocessing stage**. The preprocessing stage implements the clustering of the power plants based on their technology (such as combined cycle gas turbines or steam turbines) and primary fuel (such as natural gas, coal or water/hydro). The quantitative analysis that is proposed by this deliverable utilizes a unit commitment model to identify the conditions under which energy efficiency improvements are most valuable for the power system and its operation. To limit the computational cost of solving unit commitment problems, power plants are aggregated into a small number of clusters. Existing literature includes examples where clustered unit commitment formulations are applied to generation expansion planning and/or to integrating flexibility constraints in longer-term operational planning[5].

Furthermore, this stage performs Principal Components Analysis (PCA) on a data matrix that includes all hourly historical time series, and stores the principal components that explain up to 90% of the variability (this is a user-defined parameter and can be changed). The components are utilized during simulation to generate scenarios for all hourly time series (such as demand, wind and solar availability factors, maximum levels of power imports and exports, and so on).

2. **Back-testing stage**. The back-testing stage runs a simulation using historical data so as to compare actual and predicted results in terms of committed capacities per technology cluster. This helps evaluate how well the simulation model performs, as well as whether calibration to historical data is required.

3. **Calibration stage**. The calibration stage is a sequence of two (2) steps:

- The **1st step** identifies a function that predicts the *effective availability factor* of the hydropower resources. Although nominal availability data for hydropower plants can be found from the respective system operators' web sites, the corresponding capacity cannot be used in an unconstraint fashion, since reservoir water levels cannot be replenished at will. The effective availability factor of the hydropower resources is estimated as a function of their nominal availability factor and the value of water. The latter is quantified as the inverse of the ratio of the reservoirs' filling rate to their long-term average.
- The **2nd step** (optional) identifies a function that generates a *markup* to be added to the variable cost of each technology cluster given the power system's conditions. For such a

[5] Meus, J., Poncelet K.and Delarue E. (2018) "Applicability of a Clustered Unit Commitment Model in Power System Modeling," in IEEE Transactions on Power Systems, vol. 33, no. 2, pp. 2195-2204

function to make sense, it should be consistently related to factors that one would expect to define the power plants' bidding decisions: the levels of net load and available capacity in the system, and the value of water.

4. **Forward scenario simulation stage**. This stage creates forward scenarios for the parameters that define the state of the power system (such as demand, available generation capacity, etc.), runs the corresponding simulations, and stores both the scenarios and the results. By default, the model stores results on committed capacities per technology cluster, curtailment of renewable generation and lack of peak and ramping capacity.

5. **Replay scenario simulation stage**. This stage simulates the same scenarios that the previous stage (created and) simulated, but now adds storage and/or load modifying resources. The goal is to identify: (a) how to best utilize the available storage and/or load modifying resources, and (b) what these resources' impact is on the system's probability of capacity deficit and renewable power curtailment.

6. **Counterfactual comparison stage**. This stage compares the results of the two (2) previous steps to construct an indicator that associates storage capacity levels and/or load profile changes at specific hours of the year with reductions in capacity deficit and renewable power curtailment. This indicator defines the "grid friendliness" of an energy efficiency project given its pre- and post-retrofit power consumption profiles.

The whole workflow is summarised in Fig. 2.5 below.

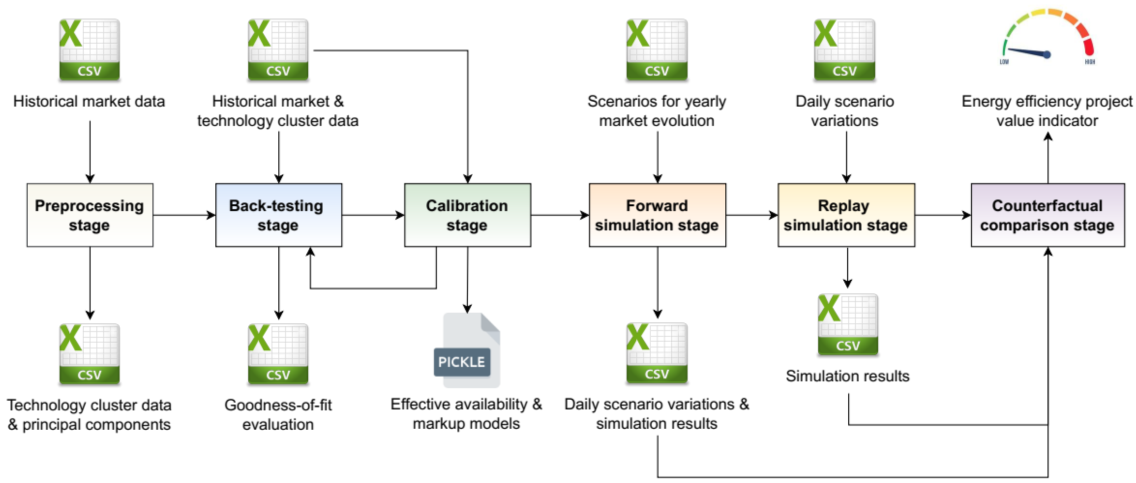

Figure 2.5– The modelling workflow

The details of each modelling step are presented in Chapter 5 as well. All the relevant functionality has been open-sourced and can be accessed at https://github.com/hebes-io/eevalue.

3 The Value of Energy Efficiency in the Greek Power System

3.1 Introduction

This chapter applies the methodology of Chapter 2 to the case of the Greek power system using data that is publicly available through the website of the Greek TSO (ADMIE)[6]. For the development of future scenarios, datafrom the Public Consultation[7] on Assumptions of the new National Resource Adequacy Assessment of the Greek system operator was utilized.

3.2 Overview of power capacity in Greece

The historical data that is used for calibration purposes include information from 2018 until the end of 2020. The power generation plants in the Greek power system during 2020 can be clustered as in Table 3.1:

Table 3.1 Clusters of power generation plants in the Greek power system

Parameters	Units	Cluster 1	Cluster 2	Cluster 3
N units	-	15	16	10
Technology	-	STUR	HDR	COMC
Fuel	-	LIG	WAT	GAS
Power capacity	MW	317.1	198.2	425.2
Minimum stable output	MW	150	0	94
Efficiency	%	0.36	1	0.55
CO_2 intensity	TCO_2/MWh	1.35	0	0.44
Minimum up time	hour	8	0	2
Minimum down time	hour	6	0	2
Ramp up rate	MW/hour	190	4,758	765
Ramp down rate	MW/hour	190	4,758	765
Ramp start-up rate	MW/hour	52.8	160	212
Ramping cost	EUR/MW	189	0	35

[6]https://www.admie.gr/en/market/market-statistics/detail-data
[7]https://www.admie.gr/en/node/124648 and https://www.admie.gr/sites/default/files/diaboyleyseis/diabouleusi-01-07-2021/Public%20Consultation%20on%20the%20assumptions%20of%20the%20new%20National%20Resource%20Adequacy%20Assessment%20of%20IPTO.pdf

On February22th of 2021, the Public Power Corporation (PPC) officially announced the retirement of the lignite fleet due to economic losses. According to a subsequent capacity adequacy study by the system operator, the capacity gap due to lignite phase out could compromise the system's stability until the beginning of 2023, when new power plants are expected to be operational. As a result, a Strategic Reserve scheme has been proposed so as to postpone the total phase-out of lignite.

Since energy efficiency has value for the grid mainly under conditions of capacity scarcity, the analysis carried out in this chapter focuses on the year 2025 assuming a phase-out of lignite happens until the end of 2024. In this way, the analysis aims to explore whether energy efficiency can help in phasing out lignite in the Greek power system.

In particular, the baseline scenario for entries and exits of conventional power plants is the following:

Table 3.2The baseline scenario for entries and exits of conventional power plants in Greek power system

Unit	Fuel	Capacity (MW)	Year
Entries			
New CCGT	Gas	825	2023
Ptolemaida V	Lignite	615	2023
Hydro with reservoir	Water	29	2025
Ptolemaida V	Gas	1000	2026
Hydro with reservoir	Water	160	2026
Hydro with reservoir	Water	83	2028
Exits			
Old lignite	Lignite	2,871	2024
Old natural gas	Gas	1,574.4	2034

Furthermore, the baseline scenario for the capacity for generation from renewable resources is:

Table 3.3The baseline scenario for renewable generation capacity expansion

Year	Wind (MW)	PV (MW)
2022	4246	4239
2023	4513	4934
2024	4813	5457
2025	5117	5885
2026	5393	6261

Year	Wind (MW)	PV (MW)
2027	5645	6612
2028	6022	6961
2029	6387	7184
2030	6619	7342
2031	6770	7436
2032	6883	7477
2033	6997	7519
2034	7111	7560
2035	7224	7601

3.3 Overview of power generation in Greece

The Greek power system is dominated by natural gas and renewables. The plot in Figure 3.1 shows the average daily profile of all generation, including net imports (Greece is net importer of electricity). Renewable generation (mainly solar) is dominant during noon hours, while hydropower is mainly used for filling the gap during evening hours when renewable generation decreases significantly.

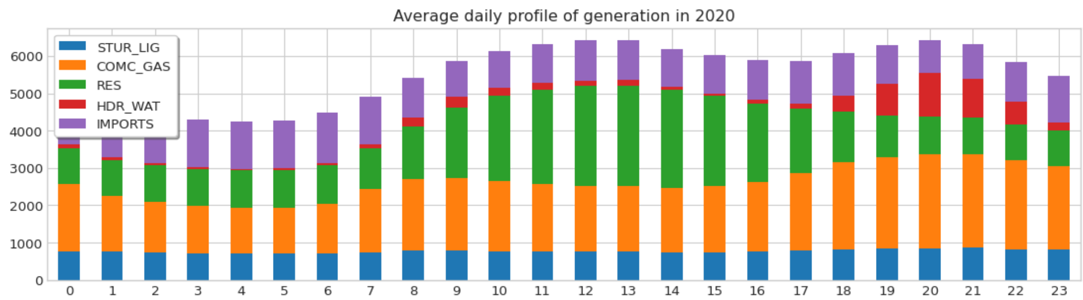

Figure 3.1– The average daily profile of all generation in the Greek power system

The plot in Figure 3.2 shows the average daily profile of the net load for the years 2018, 2019 and 2020 (upper panel) and the average profile of the one-hour-ahead changes in the net load (lower panel). The profiles show already a “duck-curve” shape: as demand increases and solar irradiation decreases during the evening hours, the available generation resources need to ramp up fast up to the demand peak that occurs at around 20:00.

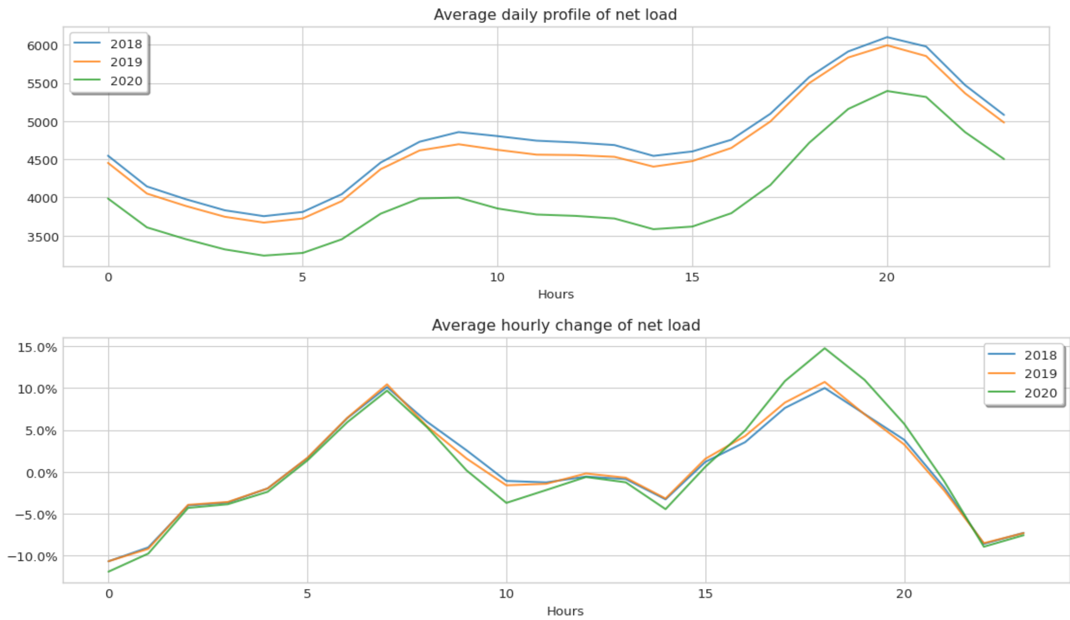

Figure 3.2– The average daily profile of the net load in the Greek power system

Finally, the plot in Figure 3.3 shows the relationship between the value of water (upper panel) and the committed capacity of hydropower generation (middle panel). It can be seen that significantly low water values can be associated with increased hydropower generation (green-coloured period). However, this may not be true when high levels of power imports are present (red-coloured period). It should be noted that negative values of net imports imply that imports exceed exports.

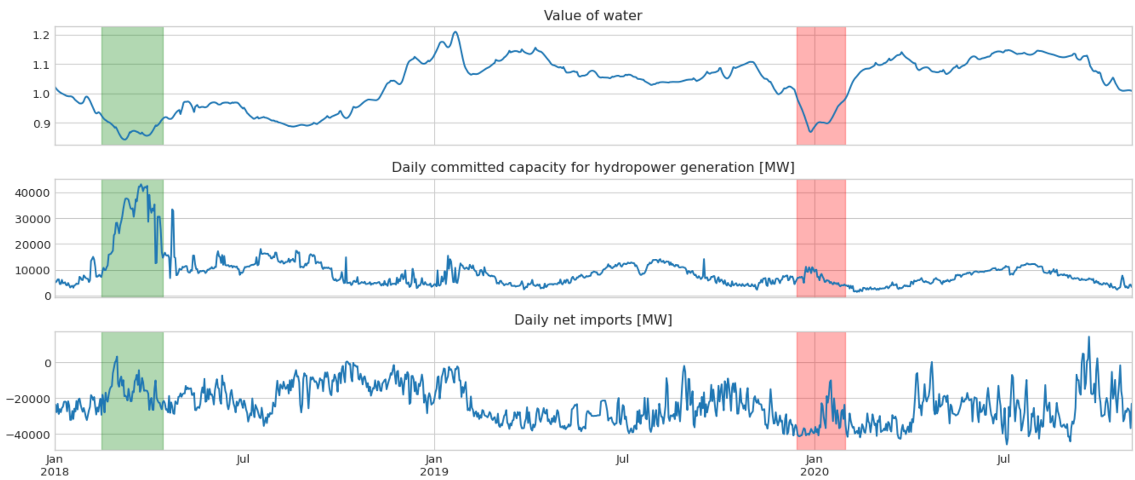

Figure 3.3– The relationship between value of water and committed capacity of hydropower generation

3.4 Scenarios for the future evolution of the Greek power system

According to the data from the aforementioned public consultation, two (2) demand evolution scenarios can be considered:

Table 3.4Scenarios the demand evolution

Year	Baseline (GWh)	Increased demand (GWh)
2022	51506	52146
2023	52674	53333
2024	52970	54144
2025	53711	55112
2026	53838	55768
2027	53957	56432
2028	55910	59033
2029	56728	60311
2030	57327	61117
2031	57952	61977
2032	58593	62742
2033	59236	63509
2034	59886	64282
2035	60543	65060

The consultation used the fuel and CO_2 prices that are considered in the ERAA 2021[8] and TYNDP 2022[9]reports by ENTSO-E, presented in Table 3.5:

Table 3.5Scenarios for fuel and carbon prices

		2022	2025	2030	2040
€ /GJ	Lignite	3.10	3.10	3.10	3.10
€ /GJ	Natural gas	5.17	5.57	6.23	6.90
€ /ton	CO_2 price	40	40	70	90

Given the available information so far (April 2022), the fuel and CO_2 prices for 2022 have been significantly underestimated. However, since the Greek power system is dominated by natural gas and renewables, this price underestimation does not fundamentally change the results.

[8]https://www.entsoe.eu/outlooks/eraa/

[9]https://2022.entsos-tyndp-scenarios.eu/

3.5 Simulation results without considering load modifying resources

For the forward simulation, the year 2025 was selected, so that to test the system under conditions of lignite-fuelled generation phase-out. In total, six hundred (600) yearly scenarios were evaluated.

The plot in Figure 3.4 shows the probability of demand exceeding supply in all simulated scenarios. A clear daily and yearly profile can be detected. The existence of a clear pattern suggests that there is scope for using energy efficiency as one of the tools for supporting the phase-out of lignite.

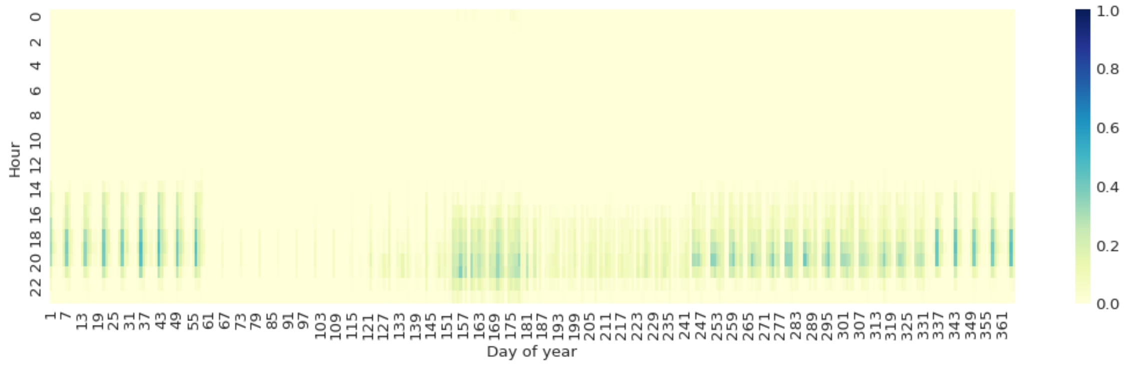

Figure 3.4– The probability of demand exceeding supply in all simulated scenarios

At the same time, the plot in Figure 3.5 offers a complementary view of the power system's needs. In particular, the plot shows the probability of renewable generation curtailment in all simulated scenarios. The plot indicates that there are specific hours and seasons during a year that demand reduction is not beneficial for the grid, since it increases the need for curtailment.

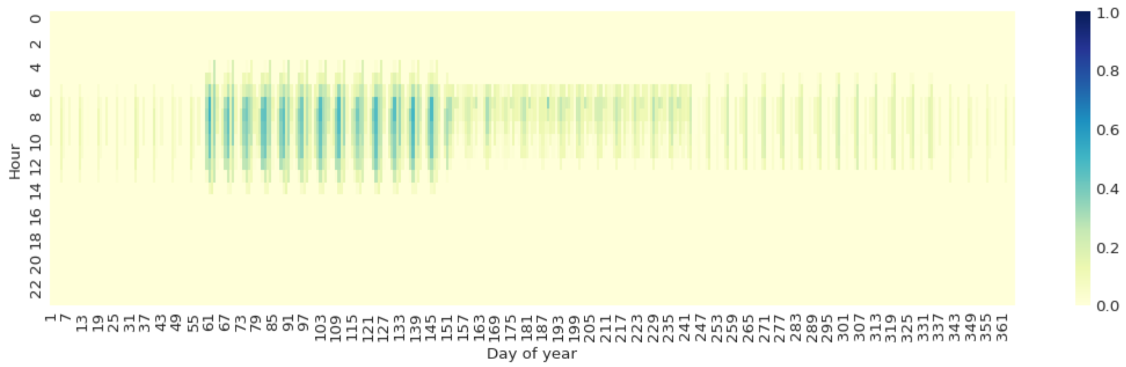

Figure 3.5– The probability of renewable generation curtailment in all simulated scenarios

Finally, the distribution of the missing capacity results over all the simulated scenarios can be used for determining the loss of load probability (LOLP) given different levels of additional capacity in the system (Figure 3.6).

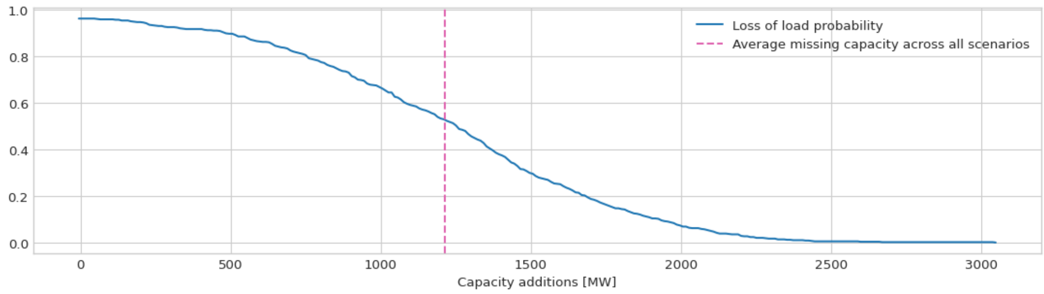

Figure 3.6– LOLP given different levels of additional capacity in the system

For the value of lost load, this deliverable uses the results from Giaccaria, Longo, Efthimiadis and Bouman (2018)[10] to choose a value of 20 €/kWh. Then, based on the (2.3) formula, the ORDC curve is calculated as in Figure 3.7 below.

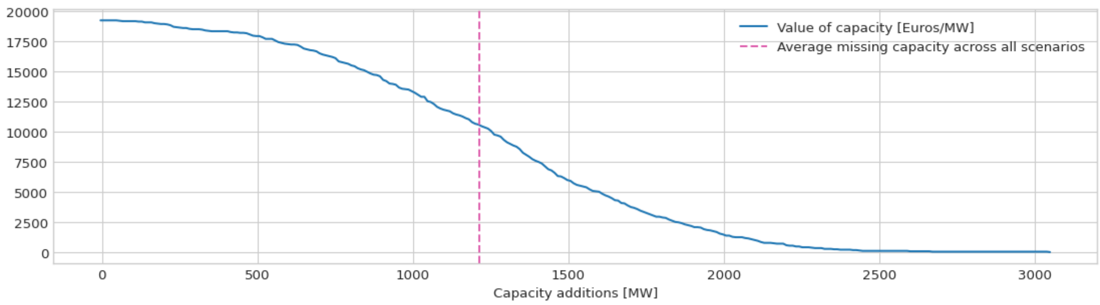

Figure 3.7– ORDC curve based on all simulated scenario results

3.6 Simulation results with load modifying resources available

Optimal allocation of load modifying resources would lead to persistent changes in the power consumption profile that increase demand during some time periods and decrease demand during others, so that to better align with the daily/seasonal net load profile (Figure 3.8). Accordingly, the methodology estimates separately the impact from reducing demand during specific hours of the year and the impact from increasing it.

[10]Giaccaria S., Longo A., EfthimiadisT. and Bouman T. (2018) "Societal appreciation of energy security, Volume 4: Value of Lost Load - Greece", Joint Research Center

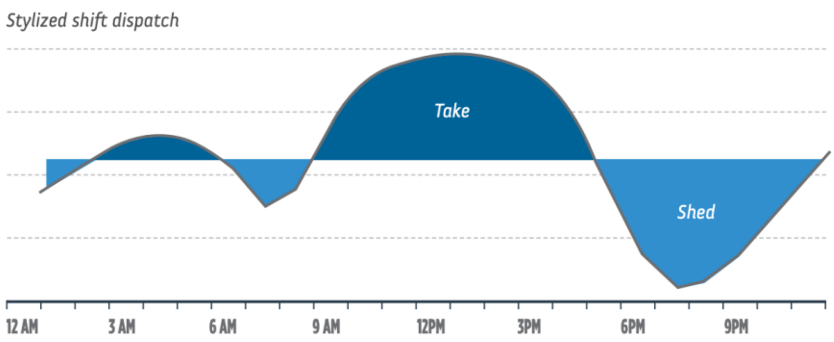

Figure 3.8: Optimal direction for load modification
(Source: Source: LBNL for the Load Shift Working Group)

3.6.1 Impact from load shedding resources

The impact from load shedding resources is estimated from the change in overall capacity deficit when they become available. To this end, the scenarios that were used by the forward simulation (Section 3.5) are replayed for a new simulation that has enabled load modifying resources, which are allowed to only reduce demand when it is optimal in terms of overall system operation cost. The total amount of the available load modifying resources remains always less than total missing capacity so that it is reasonable to assume a linear relationship between load reductions in each of the 8,760 hours of the year and the yearly reduction in missing capacity.

The resulting linear model is sparse, so most hours of the year have a zero coefficient. The plot in Figure 3.9 shows the model's coefficients for all hours of the year. The coefficients are positive, because reductions in load result in reductions in capacity deficit. For demonstration purposes, however, they have been negated so that is easier to recognize that they correspond to load reductions. The way to interpret the absolute value of the coefficients is that a retrofit project that reduces demand during a specific hour of the year displaces[11] reserve capacity (or, alternatively, reduces the need of additional capacity) that is equal to the demand reduction multiplied by the respective coefficient (x-axis of Figure 3.9).

[11] On average, across all simulated scenarios

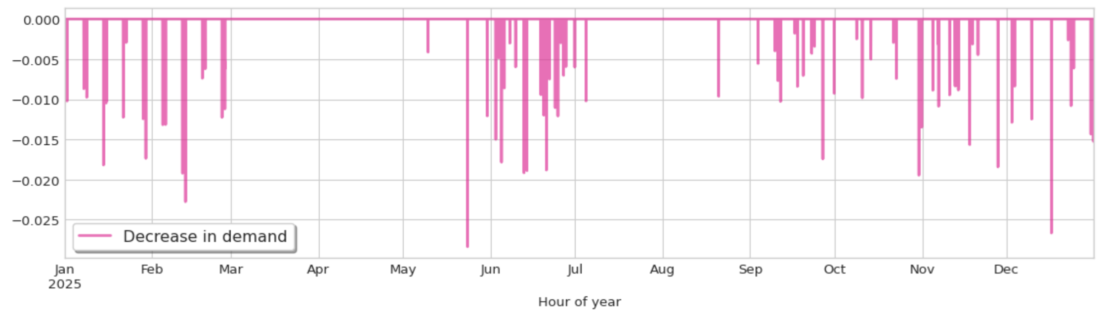

Figure 3.9– Impact coefficients of strategic load shedding

At this point, a series of simple thought experiments is needed so that to better define what the coefficients actually represent:

- Suppose that a power system is missing 1MW of capacity. If in all scenarios, this amount of capacity is missing during one specific hour of the year, an energy efficiency project that reduces load by 1MW at that hour is equivalent to having 1 MW of extra capacity available for every hour of the year.
- Suppose that a power system is missing 1MW of capacity. If in all scenarios, this amount of capacity is missing during two specific hours of the year, an energy efficiency project that reduces load by 1MW at only one of these hours has zero impact on the need for additional capacity.
- Suppose that a power system is missing 1MW of capacity at different hours of the year. If there is a portfolio of energy retrofit projects with enough diversity to include, on aggregate, load reductions at all those hours, the coefficients of Figure 3.9 provide a way to calculate the contribution of each project to the portfolio's ability to displace capacity.

In order to highlight what type of load changes the coefficients dictate, Figure 3.10 presents the total achievable impact per season of the year. Indicatively, a project that reduces load by 1 MW during all 19:00 hours of winter displaces on average 0.2 MW of extra capacity (that should have been available for the whole year).

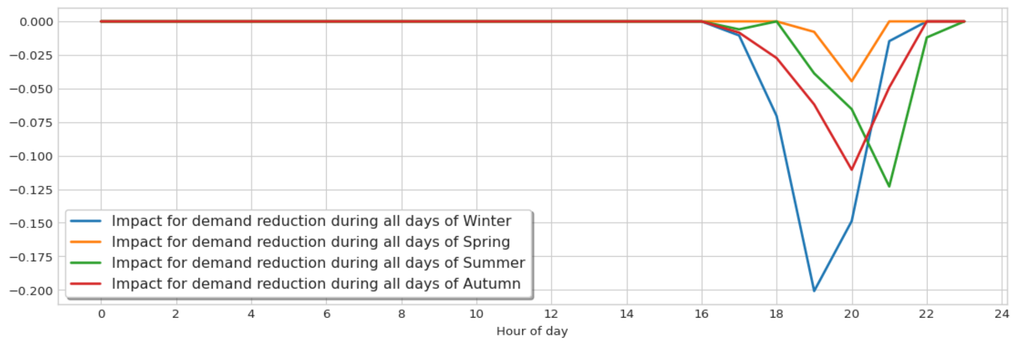

Figure 3.10– Total achievable impact per season of the year for strategic load reduction

This is the first step towards building an indicator for the value of an energy efficiency project from the perspective of the grid: the coefficients map to displaced capacity, and, displacing capacity is equivalent to shifting the ORDC curve of Figure 3.7 to the left. The resulting reduction in the capacity value reflects the value of the project.

As an example, the plots in Figure 3.11 show the pre- and post retrofit power consumption of a hypothetical office building where a package of envelope improvements and heating system upgrade has been installed. The data comes from the dataset that accompanies the work of Langevin et al. (2021)[12].

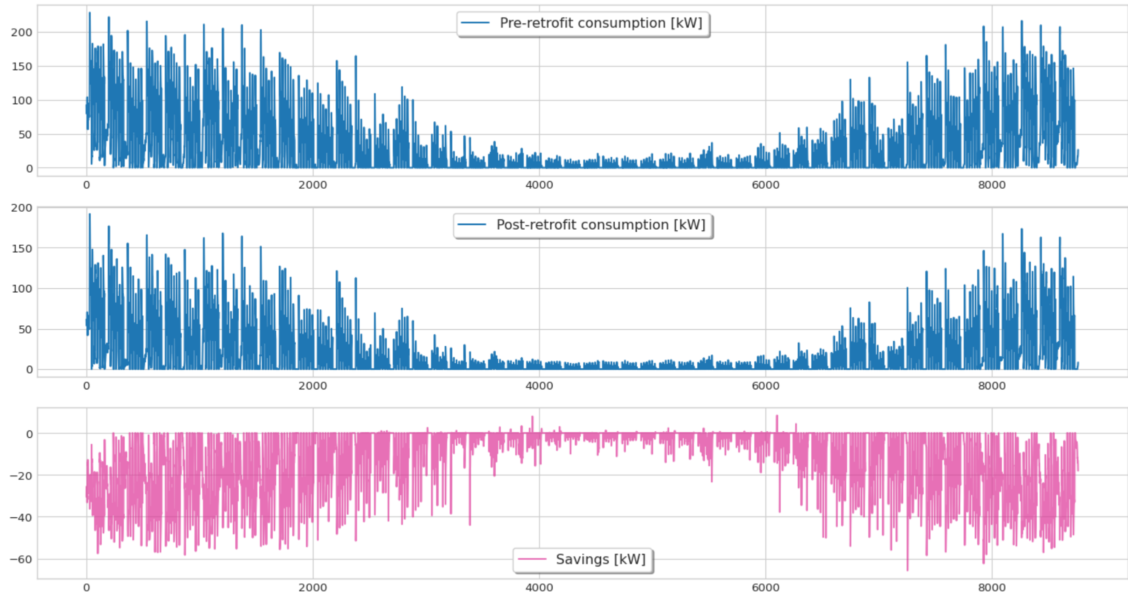

Figure 3.11– Pre- and post retrofit power consumption of a hypothetical office building

The first step to calculate the value of this project is to multiply the impact coefficients with the savings in the corresponding hours of the year. The result is the time series of Figure 3.12. Then, the time series is summed to calculate the equivalent amount of displaced capacity over the year; in this case, it is 10.7 kW. Finally, the displaced capacity amount is multiplied by the capacity value provided by the ORDC curve of Figure 3.7, which would lead to a total value of the project that is equal to €107/year.

[12] Jared Langevin, Chioke B. Harris, AvenSatre-Meloy, Handi Chandra-Putra, Andrew Speake, Elaina Present, Rajendra Adhikari, Eric J.H. Wilson, Andrew J. Satchwell (2021) "US building energy efficiency and flexibility as an electric grid resource", Joule, Volume 5, Issue 8, pp. 2102-2128

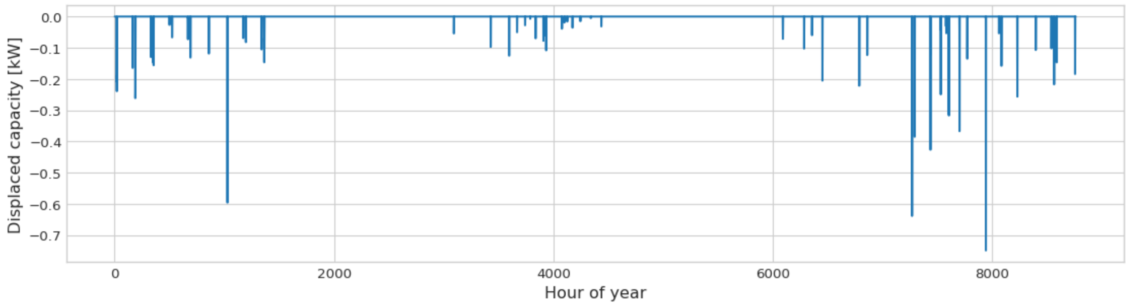

Figure 3.12– Contribution in capacity displacement by hypothetical energy retrofit project

In order to demonstrate how the timing of the savings affects their value, Figure 3.13 presents the average savings by the hypothetical energy retrofit project during all months of winter. One can imagine a case were the building was a residential one, and the savings took place in the evening instead of the morning. This can be easily realized by going through all days of the year and swapping the savings during the 05:00-07:00 interval for the savings during the 18:00-20:00 interval, and vice versa (Figure 3.14).

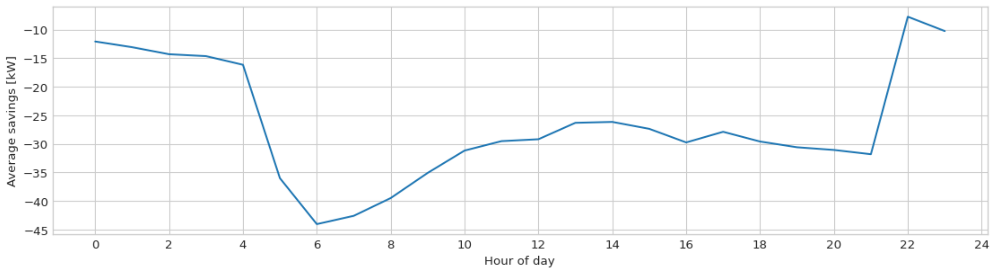

Figure 3.13– Average savings by hypothetical energy retrofit project during all months of winter

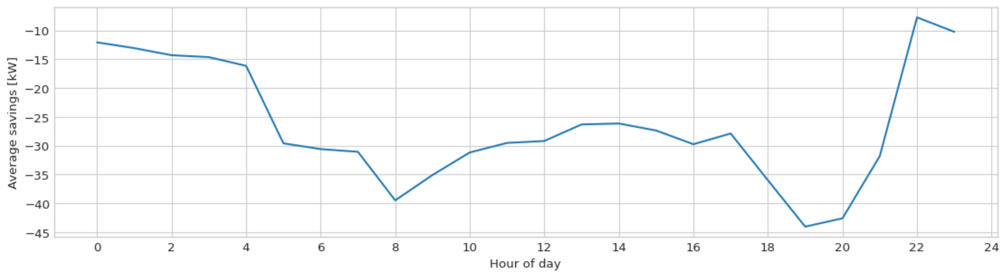

Figure 3.14– Average savings by hypothetical energy retrofit project after swap

In this case, the contribution of the project is presented in Figure 3.15, while the total value almost doubles to €217.7/year.

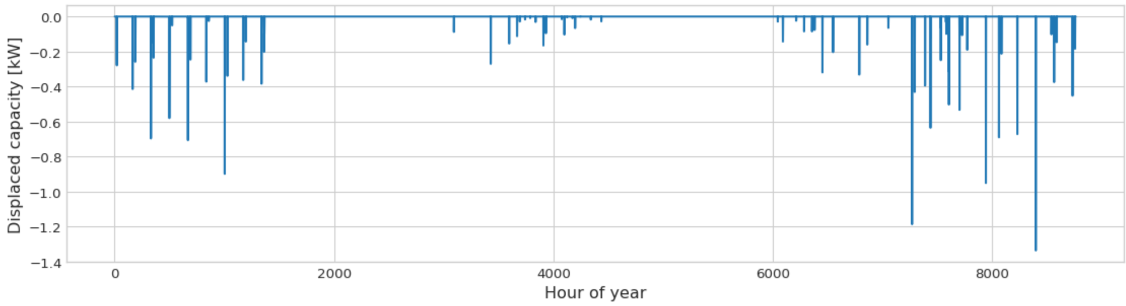

Figure 3.15– Contribution in capacity displacement by hypothetical energy retrofit project after swap

3.6.2 Impact from load increasing resources

The impact from load increasing resources is estimated from the change in overall curtailment of renewable generation. To this end, the scenarios that were used by the forward simulation are replayed for a new simulation that has enabled load modifying resources, which are allowed to only increase demand when it is optimal in terms of overall system operation cost. The coefficients are negative because increases in demand reduce the average curtailment of renewable generation. For demonstration purposes, however, they have been negated so that is easier to recognize that they correspond to load increases (Figure 3.16).

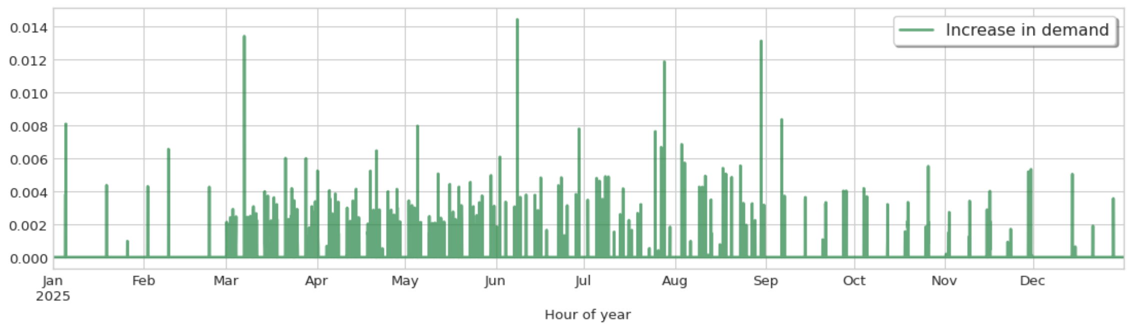

Figure 3.16– Impact coefficients of strategic load growth

In order to highlight what type of load changes the coefficients dictate, Figure 3.17 presents the total achievable impact per season of the year. In particular, the plot shows much many MWs of curtailment a 1-MW increase in demand can achieve on average (i.e. across all simulated scenarios) for different hours of the day.

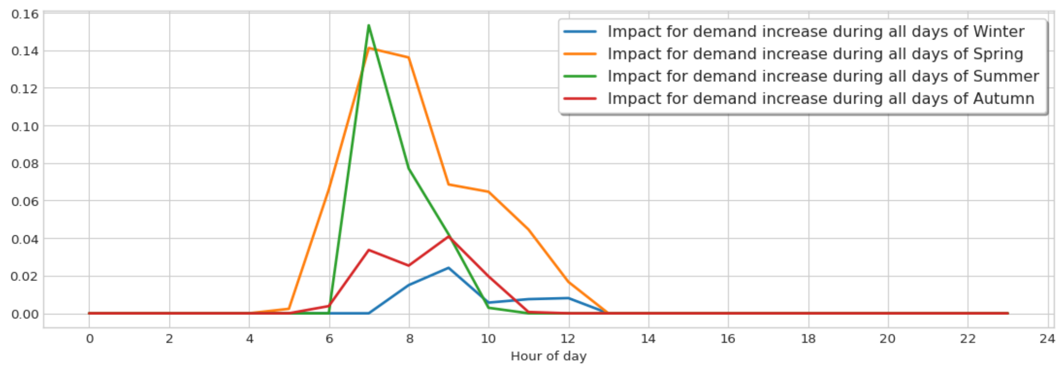

Figure 3.17– Total achievable impact per season of the year for strategic load growth

The end result is as set of coefficients that can be applied sequentially on the consumption changes of a retrofit project. Consumption changes that decrease demand generate value when they correspond to hours when capacity deficit will be mitigated, and decrease value when they correspond to hours of high renewable generation curtailment.

It is possible to add more coefficient layers to this approach for indicator development, such as coefficient layers that increase the value of a project if it reduces the needed amount of electricity storage/demand flexibility in the system, and/or layers that decrease a project's value when the utilization of some power generation plants decreases:

Effect of change in demand profile	**Impacts on grid**
Reduction of probability of capacity deficit	⊕
Reduction of needed amount of electricity storage (proxy for flexibility)	⊕
Increase of renewable generation curtailment	⊖
Reduction of utilization factor of technology clusters that are not in phase-out stage	⊖

The last point is important because, in many cases, capacity markets and strategic reserve schemes exist so that to support generation capacity that is necessary but cannot be profitable due to its low utilization factor in the power market. If an energy efficiency project or portfolio of such projects further reduces the utilization factor of a group of power plants (without completely displacing them), it actually increases the total cost of the power system's operation.

4 Linking Energy Efficiency to the Power Grid's Needs

4.1 Pay-for-Performance schemes

Pay for Performance (P4P) schemes can be utilized for rewarding energy retrofits to the extent that they lead to load shape changes that are beneficial for the grid's operation. The main premise of the P4P concept is simple: compensate an asset or a service according to its actual impact. For the specific case of energy efficiency, a P4P scheme is a scheme where an entity with a mandate to support energy efficiency does so by compensating real, post-retrofit results instead of deemed ones estimated before the implementation of the retrofits.

In the most general case, P4P is not meant to replace energy efficiency grants and subsidies; subsidizing the upfront investment costs is a strong driver for energy efficiency upgrades and, in particular, for deep retrofits. Instead, SENSEI promotes the idea of offering a premium to energy efficiency retrofit projects that can be regarded as valuable load modifiers, and using P4P as the mechanism to provide this premium. An overview of the proposed scheme is presented in Figure 4.1 below.

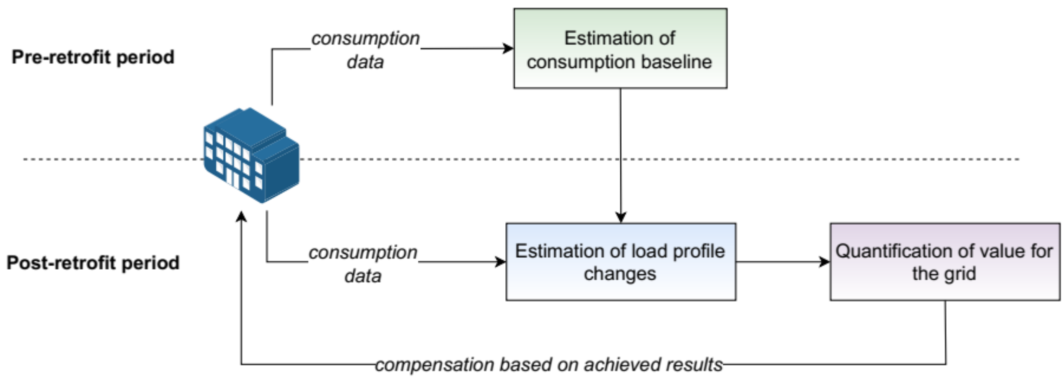

Figure 4.1– P4P scheme to compensate energy efficiency retrofits

A P4P scheme can steer energy efficiency improvements into a direction that is beneficial for the grid without interfering with the daily operation of the power markets:

- It operates outside of the power and capacity market. This is important because power system operators cannot directly compensate the energy efficiency measures and cannot directly monitor their performance;
- It is based on target load shapes that change gradually according to the evolving conditions of the grid. In this sense, it provides consumers with a consistent signal

which steers the energy efficiency measures towards high peak periods or periods when ramping reserves are systematically required, instead of providing a variable signal which incentivizes measures that increase demand flexibility (like demand response does);

- It incentivizes decisions with a persistent effect on the daily and seasonal profile of power consumption, such as equipment upgrades, installation of control technologies and building envelope improvements.

In principle, a P4P program can offer compensation rates that are higher than the value for the grid if, for instance, the rates are otherwise not enough to incentivize the right energy efficiency measures. In this case, however, underperformance should be linked to negative compensation. One way to structure such a scheme is by requiring ESCOs to participate by providing performance guarantees to the *program facilitator*. A P4P program facilitator is a third party that is responsible for the execution of a P4P program on behalf of the corresponding program owner (the public entity that offers the premium).The facilitator also provides measurement and verification (M&V) services to both the program owner and the involved building owners. Performance guarantees would level the playfield between dispatchable capacity resources that are subject to penalties for non-compliance and the resources participating in a P4P program. This approach is depicted in Fig. 4.2.

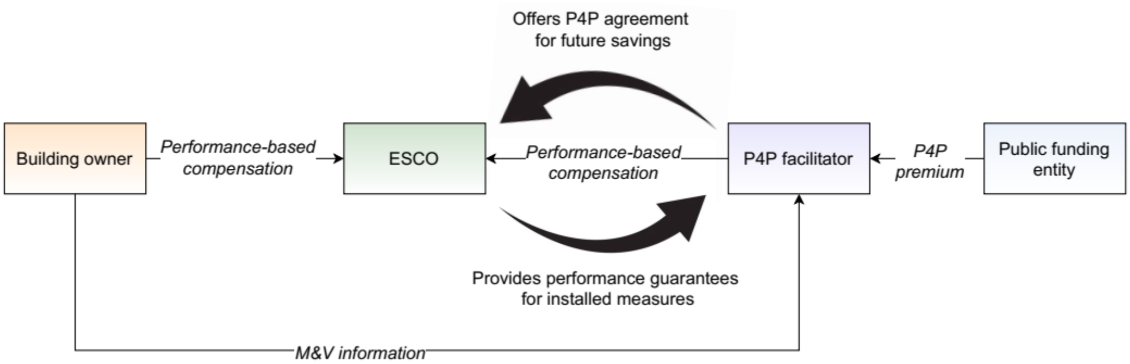

Figure 4.2– Mitigating the risk of underperformance through ESCO performance guarantees

4.2 The interplay between energy efficiency and demand response

A P4P scheme, as described in the previous section, is complementary to tertiary reserves, such as the R3 product from the Belgian system operator ELIA. In support of this argument, the plot in Figure4.3 shows the daily distribution of the upward tertiary reserve capacity activations in the Belgian power system for the years 2020 and 2021. The curve that corresponds to the 95% quantile of the hourly values highlights clearly the periods during which power consumption reductions would reduce the needed amount of upward capacity reserves. Since a consistent pattern is evident in the activations, energy efficiency improvements that target the hours of the pattern should be valuable for the grid.

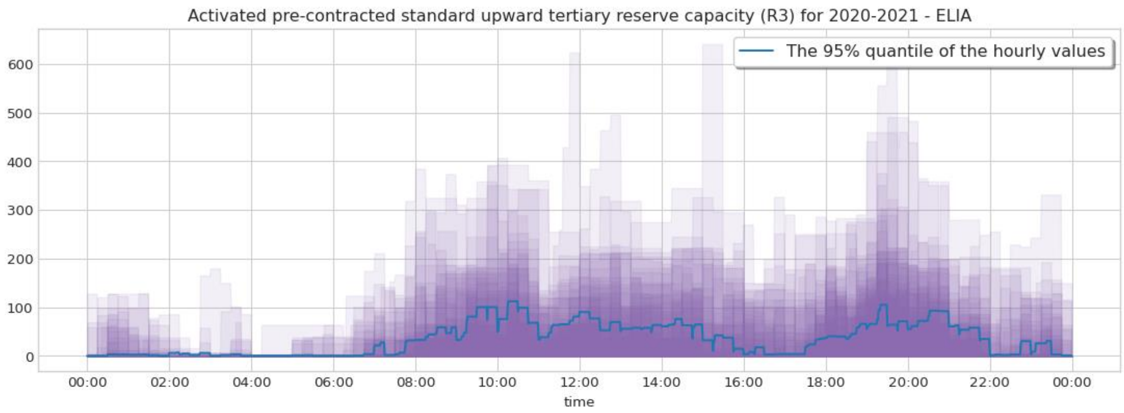

Figure 4.3 – Daily distribution of upward tertiary reserve capacity needs in the Belgian power system

The use of P4P makes it possible to coordinate the need for tertiary reserves with the supply of load modifying resources from energy efficiency. Conceptually, this can be achieved if demand response and load modifying resources share the same funding source: load modifying resources are compensated for the demand response resources that they replace, and if load modifying resources underperform, demand response can cover the gap (Fig. 4.4).

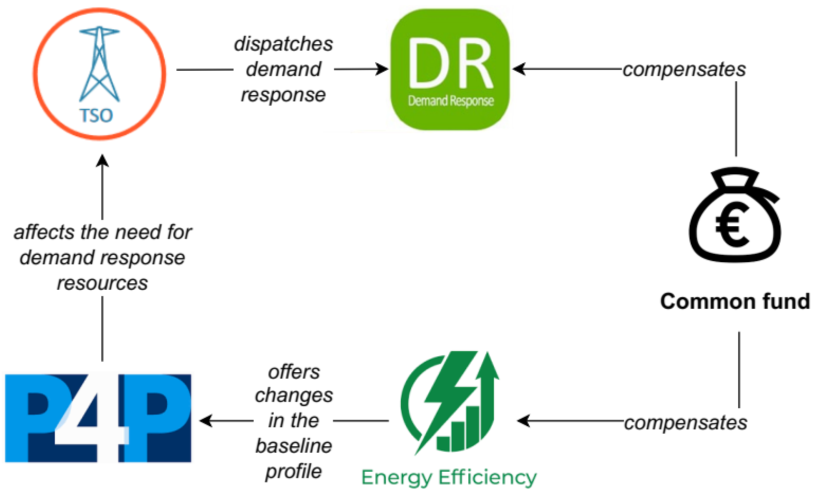

Figure 4.4– Coordination of financial flows between demand response and P4P of energy efficiency

5 The power market modelling approach

5.1 The unit commitment model

The structure of the utilized unit commitment model is largely based on the Linear Programming (LP) formulation of the Dispa-SET model that has been developed within the Joint Research Centre of the European Commission[13]. The mathematical details of the model are presented next.

5.1.1 Sets

All the model's parameters and variables are indexed using one or more of the following sets:

Name	Description
$\boldsymbol{h}$	Hours
$\boldsymbol{cl}$	Clusters of generation units. Each cluster is homogeneous in terms of the technology and the primary fuel of the included power plants.
$\boldsymbol{t}$	Power generation technologies.
$\boldsymbol{f}$	Fuel types.
$\boldsymbol{mk}$	Markets (day-ahead, secondary reserve up, secondary reserve down).

5.1.2 Parameters

The parameters of the model include:

Name	Index	Units	Description
$\boldsymbol{AF}$	(cl, h)	%	Availability factor: percentage of the total nominal capacity of cluster cl that is available at hour h
$\boldsymbol{CommittedInitial}$	cl	-	Number of units initially committed per cluster
$\boldsymbol{CostRampUp}$	cl	EUR/MW	Ramping up cost of cluster cl
$\boldsymbol{CostRampDown}$	cl	EUR/MW	Ramping down cost of cluster cl
$\boldsymbol{Demand}$	(mk, h)	MW	Hourly demand per market

[13]Quoilin, S., Hidalgo Gonzalez, I., and Zucker, A. (2017) "Modelling Future EU Power Systems Under High Shares of Renewables: The Dispa-SET 2.1 open-source models," Publications Office of the European Union

Name	Index	Units	Description
$\boldsymbol{Efficiency}$	cl	%	Power plant efficiency
$\boldsymbol{EmissionRate}$	cl	$tonCO_2/MWh$	Emission rate of CO_2 from cluster cl
$\boldsymbol{Fuel}$	(cl, f)	-	Fuel type. Binary: 1 if cluster cl uses fuel f otherwise 0
$\boldsymbol{FuelPrice}$	(f, h)	EUR/MWh	Fuel price
$\boldsymbol{Markup}$	(cl, h)	EUR/MWh	Markup that is added to the variable cost of each cluster.
$\boldsymbol{Nunits}$	cl	-	Number of units inside cluster cl
$\boldsymbol{PermitPrice}$	h	$EUR/tonCO_2$	CO_2 emission permit price
$\boldsymbol{PowerCapacity}$	cl	MW	Nominal capacity of each unit in cluster cl
$\boldsymbol{PowerInitial}$	cl	MW	Power output of cluster cl before initial simulation period
$\boldsymbol{PowerMinStable}$	cl	MW	Minimum power output for stable operation of cluster cl
$\boldsymbol{RampDownMax}$	cl	MW/h	Ramp down limit of cluster cl
$\boldsymbol{RampUpMax}$	cl	MW/h	Ramp up limit of cluster cl
$\boldsymbol{RampStartUpMax}$	cl	MW/h	Start-up ramp limit of cluster cl
$\boldsymbol{RampShutDownMax}$	cl	MW/h	Shut-down ramp limit of cluster cl
$\boldsymbol{Reserve}$	t	-	Binary: If 1, technology t provides reserve services
$\boldsymbol{StorageCapacity}$	-	MWh	Nominal storage capacity installed
$\boldsymbol{StorageChargingCap}$	-	MW	Maximum charging capacity of storage
$\boldsymbol{StorageCycleCost}$	-	EUR	The cost of a full (charge-discharge) cycle of power storage
$\boldsymbol{StorageFinalMin}$	-	MWh	Minimum storage level at the end of the simulation period
$\boldsymbol{StorageInitial}$	-	MWh	Storage level before initial simulation period
$\boldsymbol{StorageMinimum}$	-	MWh	Minimum storage level
$\boldsymbol{StoChargeEff}$	-	%	Storage charging efficiency
$\boldsymbol{StoDischargeEff}$	-	%	Storage discharging efficiency
$\boldsymbol{Technology}$	(cl, t)	-	Binary: If 1, cl belongs to t
$\boldsymbol{TDM}$	cl	h	Minimum down time of cluster cl
$\boldsymbol{TUM}$	cl	h	Minimum up time of cluster cl
$\boldsymbol{VOLL}$	-	EUR/MWh	Value of lost load

In addition, the presence of some parameters depends on whether the model is used for calibration to historical data, back-testing or forward scenario modelling:

Name	Index	Units	Description	Added during
$\boldsymbol{AF_{Solar}}$	h	%	Availability factor of installed solar PV power capacity	Forward simulation
$\boldsymbol{AF_{Wind}}$	h	%	Availability factor of installed wind power capacity	Forward simulation
$\boldsymbol{CostCurtailment}$	-	EUR/MWh	Cost of renewable energy generation curtailment	Forward simulation
$\boldsymbol{ExportsMax}$	h	MW	Upper bound for power exports	Forward simulation
$\boldsymbol{ImportsMax}$	h	MW	Upper bound for power imports	Forward simulation
$\boldsymbol{LoadShapeMax}$	-	MW	Maximum amount of load modifying resources	Forward simulation
$\boldsymbol{NetImports}$	h	MW	Hourly net power imports	Back-testing, Calibration
$\boldsymbol{Power_{RES}}$	h	MW	Hourly power generation from renewable sources	Back-testing, Calibration
$\boldsymbol{SolarCapacity}$	h	MW	Nominal solar power capacity installed	Forward simulation
$\boldsymbol{WindCapacity}$	h	MW	Nominal wind power capacity installed	Forward simulation

5.1.3 Variables

The decision variables of the model include:

Name	Index	Units	Description
$\boldsymbol{Commited}$	(cl, h)	-	Number of units of cluster cl committed at hour h (takes values from 0 to $Nunits[cl]$)
$\boldsymbol{CostRampUpH}$	(cl, h)	EUR	Realised cost of ramping up cluster cl at hour h
$\boldsymbol{CostRampDownH}$	(cl, h)	EUR	Realised cost of ramping down cluster cl at hour h
$\boldsymbol{CostVariable}$	(cl, h)	EUR/MW	Variable cost of cluster cl operating at hour h
$\boldsymbol{LL_{MaxPower}}$	h	MW	Deficit in terms of maximum power at hour h
$\boldsymbol{LL_{MinPower}}$	h	MW	Power exceeding the demand at hour h
$\boldsymbol{LL_{RD}}$	(cl, h)	MW	Deficit in terms of ramping down capacity for cluster cl at hour h
$\boldsymbol{LL_{RU}}$	(cl, h)	MW	Deficit in terms of ramping up capacity for cluster cl at hour h

Name	Index	Units	Description
$\boldsymbol{LL_{2U}}$	h	MW	Deficit in reserve up at hour h
$\boldsymbol{LL_{2D}}$	h	MW	Deficit in reserve down at hour h
$\boldsymbol{Power}$	(cl, h)	MW	Power output of cluster cl at hour h
$\boldsymbol{Reserve_{2U}}$	(cl, h)	MW	Spinning reserve up provided by cluster cl at hour h
$\boldsymbol{Reserve_{2D}}$	(cl, h)	MW	Spinning reserve down provided by cluster cl at hour h
$\boldsymbol{StartUp}$	(cl, h)	-	Number of units in cluster cl started at hour h (takes values from 0 to $Nunits[cl]$)
$\boldsymbol{ShutDown}$	(cl, h)	-	Number of units in cluster cl shutting down at hour h (takes values from 0 to $Nunits[cl]$)
$\boldsymbol{StorageInput}$	h	MWh	Charging input o fall storage units at hour h
$\boldsymbol{StorageLevel}$	h	MWh	Storage level of charge at hour h
$\boldsymbol{StorageOutput}$	h	MWh	Discharging output of all storage units at hour h
$\boldsymbol{SystemCost}$	h	EUR	Hourly total system cost

In addition, the following variables are added for forward simulations:

Name	Index	Units	Description
$\boldsymbol{CurtailedPower}$	h	MW	Curtailed renewable energy generation at hour h
$\boldsymbol{Exports}$	h	MW	Power exports at hour h
$\boldsymbol{Imports}$	h	MW	Power imports at hour h
$\boldsymbol{LoadMod_D}$	h	MW	Negative difference from the baseline at hour h
$\boldsymbol{LoadMod_U}$	h	MW	Positive difference from the baseline at hour h
$\boldsymbol{NetImports}$	h	MW	Hourly net power imports
$\boldsymbol{Power_{RES}}$	h	MW	Power consumed from renewables at hour h

All the decision variables except $NetImports$ are non-negative real numbers; $NetImports$ is a real number.

5.1.4 Constraints

The number of start-ups and shut-downs at each time step is computed as:

$$Commited_{cl,h} - Commited_{cl,h-1} = StartUp_{cl,h} - ShutDown_{cl,h} \tag{5.1}$$

The operation of the generation units is limited by the amount of time each unit has been running or stopped; once a unit is started up, it cannot be shut down immediately, and if the unit is shut down, it cannot be started immediately:

$$
\begin{aligned}
Commited_{cl,h} &\geq \sum_{i=0}^{TUM[cl]} StartUp_{cl,h-i} \qquad \forall h > TUM[cl] \\
Nunits[cl] - Commited_{cl,h} &\geq \sum_{i=0}^{TDM[cl]} ShutDown_{cl,h-i} \qquad \forall h > TDM[cl]
\end{aligned}
\tag{5.2}
$$

Each unit is characterized by a maximum ramp up and ramp down capability. The following constraints ensure that each cluster operates within its ramping limits while also accounting for start-up and shut-down events:

$$
\begin{aligned}
Power_{cl,h} - Power_{cl,h-1} \leq\ & \left(Commited_{cl,h} - StartUp_{cl,h}\right) \cdot RampUpMax_{cl} \\
& + StartUp_{cl,h} \cdot RampStartUpMax_{cl} \\
& - ShutDown_{cl,h-i} \cdot PowerMinStable_{cl} \cdot AF_{cl,h} \\
& + LL_{RU_{cl,h}} \\
Power_{cl,h-1} - Power_{cl,h} \leq\ & \left(Commited_{cl,h} - ShutDown_{cl,h}\right) \cdot RampDownMax_{cl} \\
& + ShutDown_{cl,h} \cdot RampShutDownMax_{cl} \\
& - StartUp_{cl,h} \cdot PowerMinStable_{cl} \cdot AF_{cl,h} \\
& + LL_{RD_{cl,h}}
\end{aligned}
\tag{5.3}
$$

Ramping costs are defined by the following equations:

$$
\begin{aligned}
CostRampUpH_{cl,h} &\geq CostRampUp_{cl} \cdot \left(Power_{cl,h} - Power_{cl,h-1}\right) \\
CostRampDownH_{cl,h} &\geq CostRampDown_{cl} \cdot \left(Power_{cl,h-1} - Power_{cl,h}\right)
\end{aligned}
\tag{5.4}
$$

The upward secondary reserve (2U) can only be covered by spinning units and is limited by the capacity margin between current and maximum power output:

$$
\begin{aligned}
& Reserve_{2U_{cl,h}} \leq \\
& PowerCapacity_{cl} \cdot AF_{cl,h} \cdot Commited_{cl,h} - Power_{cl,h}
\end{aligned}
\tag{5.5}
$$

The downward secondary reserve (2D) is limited by the different between current power output and minimum power output for stable operation, with an additional term to take into account the downward reserve capability of storage units:

$$Reserve_{2D_{cl,h}} \leq Power_{cl,h} \\ - PowerMinStable_{cl} \cdot AF_{cl,h} \cdot Commited_{cl,h} \\ + StorageChargingCap - StorageInput_h \tag{5.6}$$

The minimum power output of a cluster is determined by its minimum stable generation level if it is committed:

$$Power_{cl,h} \geq \; PowerMinStable_{cl} \cdot AF_{cl,h} \cdot Commited_{cl,h} \tag{5.7}$$

In addition, the power output is limited by the available capacity, if the cluster is committed:

$$Power_{cl,h} \leq \; PowerCapacity_{cl} \cdot AF_{cl,h} \cdot Commited_{cl,h} \tag{5.8}$$

Each hour, the sum of the power produced by all the generation clusters, the power generated by renewables, the discharging output of the storage units, and the power injected from net imports[14]is equal to the demand in the day-ahead market, plus the power consumed for energy storage charging, adjusted by the impact of the load modifying resources (applicable only for forward simulations).

$$\sum_{cl} \left(Power_{cl,h}\right) + Power_{RES_h} + StorageOutput_h - NetImports_h = \\ Demand_{DA,h} + \; StorageInput_h + LoadMod_{U_h} - LoadMod_{D_h} \\ - LL_{MaxPower_h} + LL_{MinPower_h} \tag{5.9}$$

The secondary reserve demand should be fulfilled at all times as well:

$$Demand_{2U,h} \leq \sum_{cl,t} \left(Reserve_{2U_{cl,h}} \cdot Technology_{cl,t} \cdot Reserve_t\right) \; + LL_{2U_h} \\ Demand_{2D,h} \leq \sum_{cl,t} \left(Reserve_{2D_{cl,h}} \cdot Technology_{cl,t} \cdot Reserve_t\right) \; + LL_{2D_h} \tag{5.10}$$

Storage level must be above a minimum and below storage capacity:

$$StorageMinimum \leq StorageLevel_h \leq StorageCapacity \tag{5.11}$$

[14]Net imports are negative if imports are larger than exports.

Storage charging is bounded by the maximum capacity:

$$StorageInput_h \leq StorageChargingCap \tag{5.12}$$

Storage discharging is limited by the level of charge, and storage charging is limited by the remaining storage capacity:

$$\begin{gathered} StorageOutput_h \leq StoDischargeEff \cdot StorageLevel_h \\ StoChargeEff \cdot StorageInput_h \leq StorageCapacity - StorageLevel_h \end{gathered} \tag{5.13}$$

The power stored in a given period is given by the power stored in the previous period, net of charges and discharges:

$$\begin{gathered} StorageLevel_{h-1} + StoChargeEff \cdot StorageInput_h = \\ StorageLevel_h + \frac{StorageOutput_h}{StoDischargeEff} \end{gathered} \tag{5.14}$$

A minimum storage level constraint is required for the last hour of the optimisation, since otherwise the model would systematically tend to empty the storage level:

$$StorageLevel_N \geq StorageFinalMin \tag{5.15}$$

The amount of RES curtailment during a given hour is defined by:

$$\begin{aligned} &SolarCapacity \cdot AF_{Solar_h} + WindCapacity \cdot AF_{Wind_h} \\ &\quad = Power_{RES_h} + CurtailedPower_h \end{aligned} \tag{5.16}$$

The amount of power imports cannot exceed the upper bound:

$$Imports_h \leq ImportsMax_h \tag{5.17}$$

The amount of power exports cannot exceed the upper bound:

$$Exports_h \leq ExportsMax_h \tag{5.18}$$

Imports and exports define the net imports:

$$NetImports_h = Exports_h - Imports_h \tag{5.19}$$

The amount of the load modifying resources is limited:

$$\sum_h LoadMod_{U_h} + \sum_h LoadMod_{D_h} \leq MaxLoadShaping \tag{5.20}$$

The total number of cycles is calculated as:

$$Cycles = \frac{\sum_h StorageInput_h + \sum_h StorageOutput_h}{2 \cdot StorageCapacity} \tag{5.21}$$

The variable cost of each cluster is calculated as:

$$\begin{aligned} CostVariable_{cl,h} = Markup_{cl,h} + \sum_f \left(\frac{Fuel_{cl,f} \cdot FuelPrice_f}{Efficiency_{cl}} \right) \\ + EmissionRate_{cl} \cdot PermitPrice \end{aligned} \tag{5.22}$$

Finally, the goal of the optimization problem is to minimize the sum of the system cost:

$$\begin{aligned} \min \Bigg[& \sum_{cl,h} \left(CostVariable_{cl,h} \cdot Power_{cl,h} \right) \\ & + \sum_{cl,h} \left(CostRampUpH_{cl,h} + CostRampDownH_{cl,h} \right) \\ & + \sum_h \left(CostCurtailment \cdot CurtailedPower_h \right) \\ & + StorageCycleCost \cdot Cycles \\ & + VOLL \cdot \sum_h \left(LL_{MaxPower_h} + LL_{MinPower_h} \right) \\ & + 0.8 \cdot VOLL \cdot \sum_h \left(LL_{2U_h} + LL_{2D_h} \right) \\ & + 0.7 \cdot VOLL \cdot \sum_{cl,h} \left(LL_{RU_{cl,h}} + LL_{RD_{cl,h}} \right) \Bigg] \end{aligned} \tag{5.23}$$

5.2 The details of the preprocessing stage

5.2.1 Creation of clusters

The clustering of the plants is carried out based on their technology and primary fuel. As a result, each cluster includes a unique technology and fuel combination. The corresponding parameters are derived as follows:

$\boldsymbol{AF}$	The AF parameter corresponds to the availability factor of each cluster. Since the relevant data is publicly available through the websites of the corresponding system operators, we model the availability factors using the historical availability data divided by the nominal capacity of each cluster, instead of using the plants' equivalent forced outage rates.

$\boldsymbol{CostRampUp}$

The $CostRampUp$ parameter corresponds to the ramping up costs of each cluster. Start-up costs are included into the ramping up costs as:

$$CostRampUp_{cl} = \frac{\sum_j \left(P_{j,max} \times CostRampUp_j\right)}{\sum_j P_{j,max}} + \frac{\sum_j CostStartUp_j}{\sum_j P_{j,max}}$$

for all j units in the cluster.

$P_{j,max}$ is the nominal capacity of the j unit.

Shut-down costs are included into the ramping down costs similarly to the ramping up case

$\boldsymbol{CostRampDown}$

The $CostRampDown$ parameter corresponds to the ramping down costs of each cluster. Shut-down costs are included into the ramping down costs as:

$$CostRampDown_{cl} = \frac{\sum_j \left(P_{j,max} \times CostRampDown_j\right)}{\sum_j P_{j,max}} + \frac{\sum_j CostShutDown_j}{\sum_j P_{j,max}}$$

for all j units in the cluster.

$\boldsymbol{Nunits}$

The $Nunits$ parameter of each cluster corresponds to the number of plants that have been assigned to this cluster.

$\boldsymbol{PowerCapacity}$

The $PowerCapacity$ parameter of a cluster is the average nominal capacity, i.e.

$$\frac{\sum_j P_{j,max}}{Nunits}$$

for all j units in the cluster.

$\boldsymbol{PowerMinStable}$ The $PowerMinStable$ parameter of a cluster is the minimum of all the minima power outputs of the units in the cluster, i.e.

$$\min(P_{j,min})$$

$\boldsymbol{RampDownMax}$, $\boldsymbol{RampUpMax}$, $\boldsymbol{RampStartUpMax}$, $\boldsymbol{RampShutDownMax}$, $\boldsymbol{TDM}$, $\boldsymbol{TUM}$ The ramp up and down limits are computed as a weighted averaged, e.g.:

$$RDM_{cl} = \frac{\sum_j (P_{j,max} \times RDM_j)}{\sum_j P_{j,max}}$$

for all j units in the cluster.

The same applies to the minimum up/down times.

The $Demand_{DA}$ parameter corresponds to the total load that is used as an input to the day-ahead scheduling. Following the approach that the Dispa-SET model has adopted, the demand for secondary reserves – if not available as historical data –is defined as a function of the maximum expected load for each day:

$$Demand_{2U,h} = \sqrt{10 \cdot \max_h(Demand_{DA,h}) + 150^2} - 150$$
$$Demand_{2D,h} = 0.5 \cdot Demand_{2U,h} \tag{5.24}$$

5.2.2 Dimensionality reduction of hourly time series through PCA

All hourly historical data is arranged into a table with a structure similar to the one in Figure 5.1. Then, PCA is applied so that to reduce the number of columns (>140) to a small number of new ones (<10) that are linear combinations of the original. This will be useful for the simulation of forward scenarios later on.

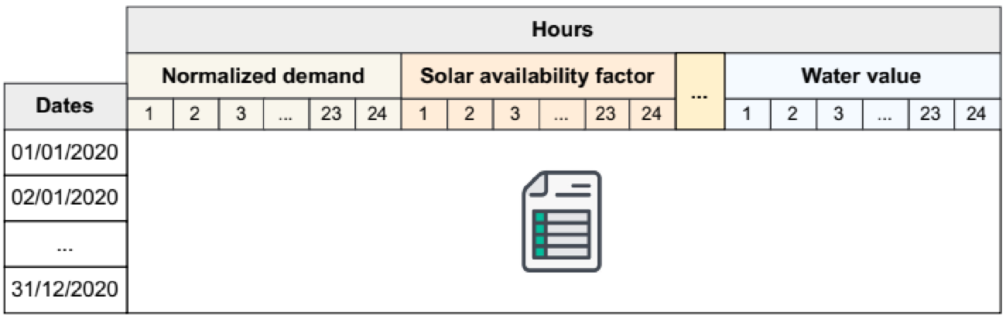

Figure 5.1– The input to the PCA analysis step

One way to evaluate the impact due to the PCA compression is to compare the characteristics of the power demand between: (a) the actual dataset and (b) a dataset where all the daily demand profiles have been derived by inverting the PCA transformation. The plot of Fig. 5.2 shows the distribution of the total daily demand in the Greek power system for 2019-2020; the upper panel corresponds to the actual dataset, while the lower panel to the one with the reconstructed data.

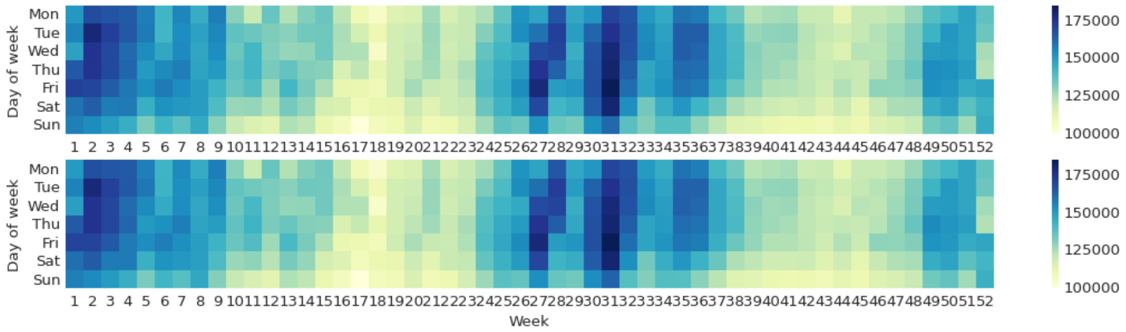

Figure 5.2– Distribution of the total daily demand in the Greek power system for 2019-2020

Similarly, the plot of Fig. 5.3 shows the distribution of the hourly demand in the Greek power system for 2019-2020; the upper panel corresponds to the actual dataset, while the lower panel to the one with the reconstructed data.

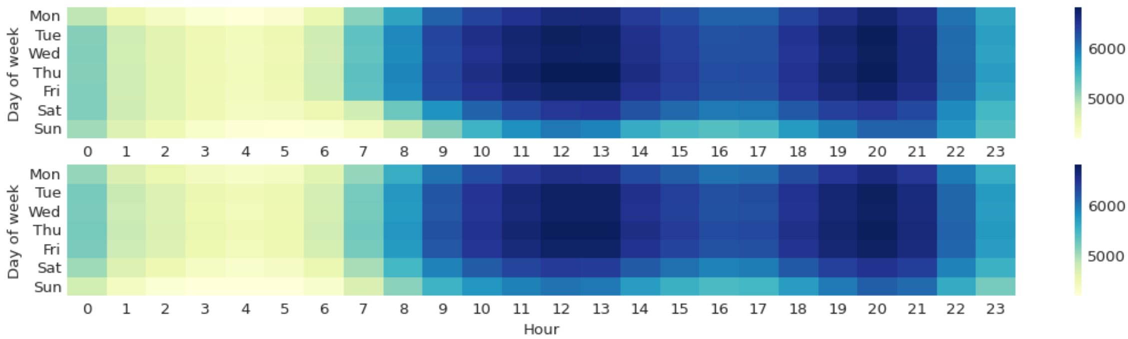

Figure 5.3– Distribution of the hourly demand in the Greek power system for 2019-2020

5.3 The details of the back-testing stage

The back-testing stage runs a simulation using historical data and compares the actual and predicted results in terms of the committed capacities per technology cluster. The main function of this stage is to evaluate how well the simulation model performs. The metric that is used for the evaluation is the coefficient of variation of the root mean squared error (CVRMSE). The CVRMSE provides a quantification of the typical size of the error relative to the mean of the observations. The CVRMSE is calculated by:

$$\text{CV(RMSE)} = \frac{1}{\bar{y}} \times \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} \times 100(\%) \quad (5.25)$$

where:

n The number of observations

$\bar{y}$ The mean value of the observed data.

y_i The actual value of the i^{th} observation ($i = 1,2, \ldots, n$)

$\hat{y}_i$ The estimation for the i^{th} observation's value.

The plot in Fig. 5.4 shows the actual and predicted committed capacity for natural gas-fuelled plants in the Greek power system – aggregated to daily sums so that it is easier to compare between the two time series (CVRMSE is 56%).

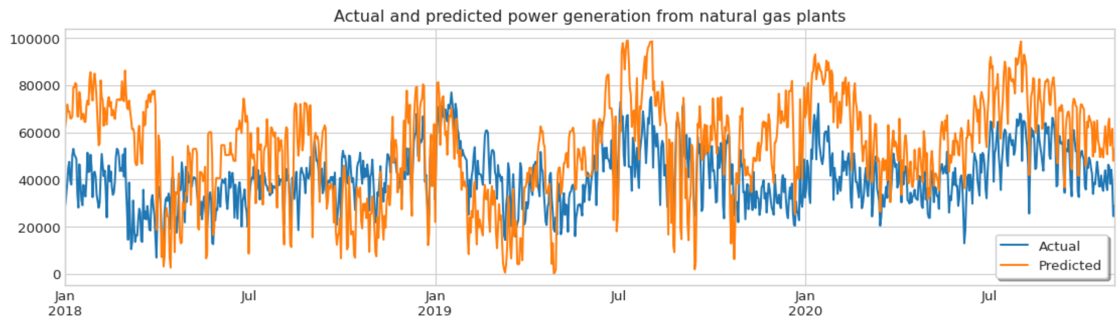

Figure 5.4– Actual and predicted power generation from natural gas plants before calibration

In contrast, the plot in Fig. 5.5 shows the actual and predicted committed capacity for hydropower plants in the Greek power system with a CVRMSE of 368%. In this case, calibration is definitely needed because the utilized model assumes that there are not limitations in replenishing the reservoir levels. As a general rule, if a model includes hydropower capacity, calibration is required so that to estimate an effective availability factor for the hydropower generation.

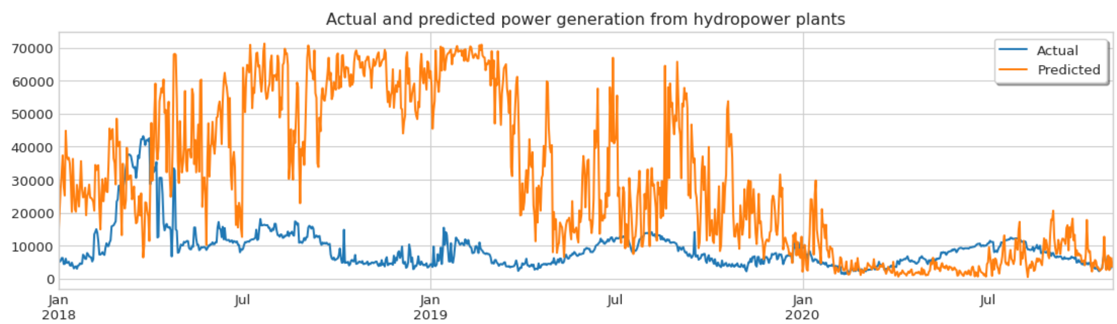

Figure 5.5– Actual and predicted power generation from hydropower plants before calibration

5.4 The details of the calibration stage

The calibration stage consists of two (2) steps. The first step learns the effective availability factor for hydropower generation through the following process (Figure 5.6):

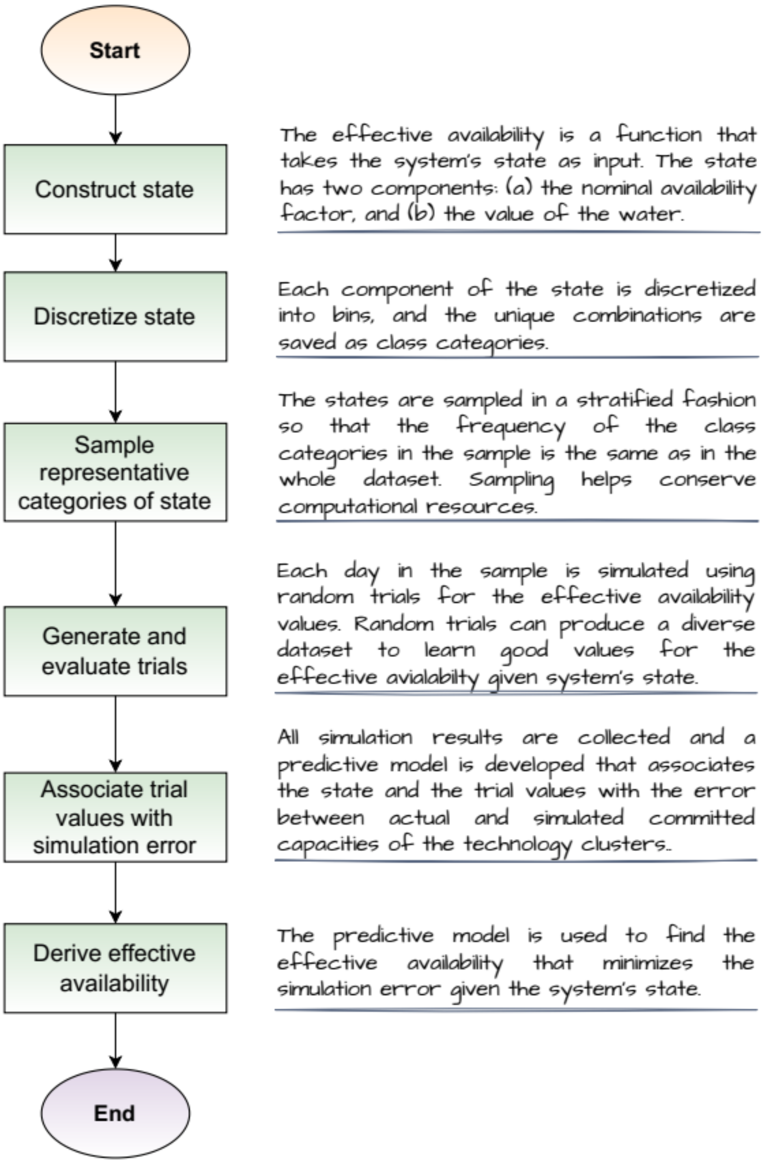

Figure 5.6– The process for learning the effective availability factor for hydropower generation

The second step, which is optional, learns a markup function for each technology cluster. The relevant process is the same as the one for learning the effective availability factor for hydropower generation, with three (3) differences:

(a) The state of the markup function is composed of: (a) the margin of the system, quantified as the net load divided by the total available capacity in the system, and (b) the value of water.

(b) Each day in the sample is simulated using random trials for the markup values.

(c) During the last step, the predictive model is used to find the markup values that minimize the simulation error given the system state.

The results after the calibration are presented in Fig. 5.7 (CVRMSE of 62%), Fig. 5.8 (CVRMSE of 72%) and Fig. 5.9 (CVRMSE of 108%).

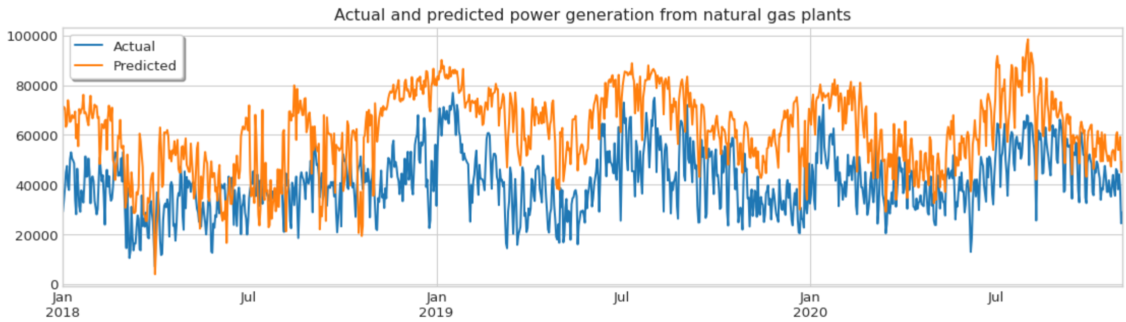

Figure 5.7– Actual and predicted power generation from natural gas plants after calibration

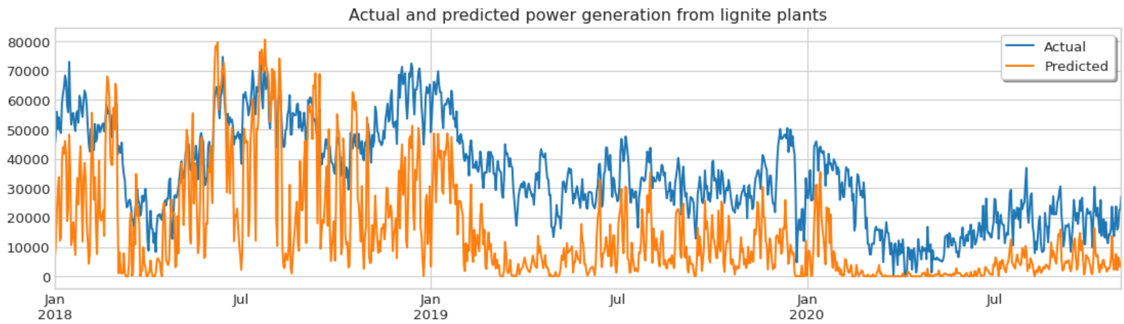

Figure 5.8– Actual and predicted power generation from lignite plants after calibration

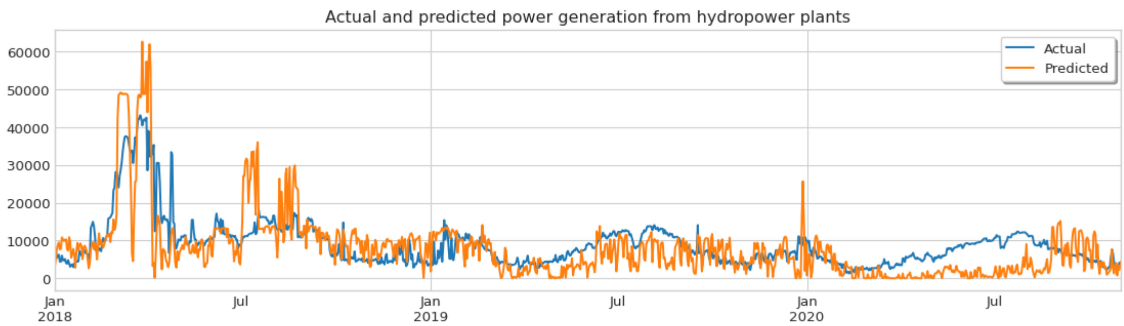

Figure 5.9– Actual and predicted power generation from hydropower plants after calibration

5.5 The details of the forward scenario simulation stage

Scenarios are generated and run using two (2) loops, one nested into the other. The outer loop provides yearly variation and concerns demand and capacity levels, as well as fuel and

CO_2prices. The inner loop provides daily and intra-daily variation, and concerns demand profiles, availability factors for dispatchable capacity, solar and wind, the value of the water for hydropower generators, as well as the markup values (Figure 5.10).

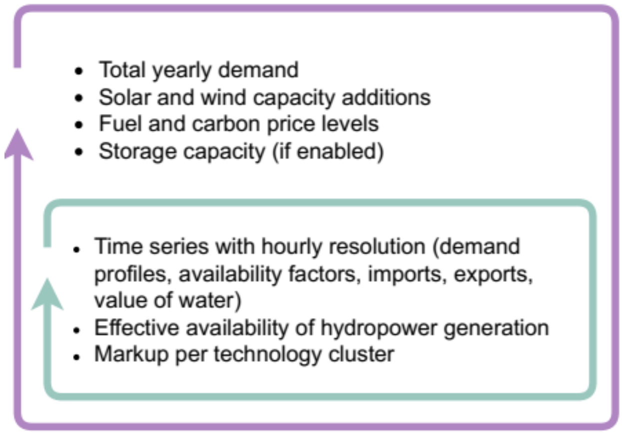

Figure 5.10– The nested loops of scenario generation and simulation

Forward scenario data at yearly level, such as total demand, or capacity levels for solar, wind and each technology cluster, are taken from input files and, if a multiplying coefficient has been provided, stochasticity is added by uniformly sampling a value for the coefficient between 1 and the provided coefficient's value.

To generate scenarios for hourly time series, the simulation functionality first samples from the principal components (estimated during the preprocessing stage) and, then, reconstructs the time series. The sampling methodology makes sure that samples are drawn from same groups of data (same season, same month and/or same day of week).

The provided functionality simulates yearly scenarios, i.e. 8,760 hours. However, the scenario generation and simulation process runs in line with another process that aims to predict if the scenario data for any given day are really informative. In this context, scenario data is informative if there is a non neglectable probability that one of the following variables will not be zero:

Name	**Units**	**Description**
$\boldsymbol{CurtailedPower}$	MW	Curtailed renewable energy generation at hour h
$\boldsymbol{LL_{MaxPower}}$	MW	Deficit in terms of maximum power at hour h (i.e. shortage)
$\boldsymbol{LL_{MinPower}}$	MW	Power exceeding the demand at hour h (i.e. oversupply)
$\boldsymbol{LL_{RD}}$	MW	Deficit in terms of ramping down capacity at hour h
$\boldsymbol{LL_{RU}}$	MW	Deficit in terms of ramping up capacity at hour h

Name	Units	Description
LL_{2U}	MW	Deficit in secondary reserve up at hour h
LL_{2D}	MW	Deficit in secondary reserve down at hour h

Initially, all scenario combinations are considered informative, and full-year scenario data is simulated. As the underlying classification model learns to distinguish between informative and uninformative combinations, some days are excluded from the full year scenario data, and as this process continues, the number of scenarios to actually simulate becomes smaller and smaller. This significantly reduces the computational resources that are needed for evaluation scenarios.

The underlying classification model performs One-Class Classification (OCC). OCC is a special case of classification, where the data that is used during training is considered to belong to a single "normal" class. The goal of OCC is to learn to distinguish between normal data and novelty data (unusual observations).The inputs to the classification model are the sampled principal components – and this is the main reason for estimating the principal components in the first place. This process is summarized in Figure 5.11.

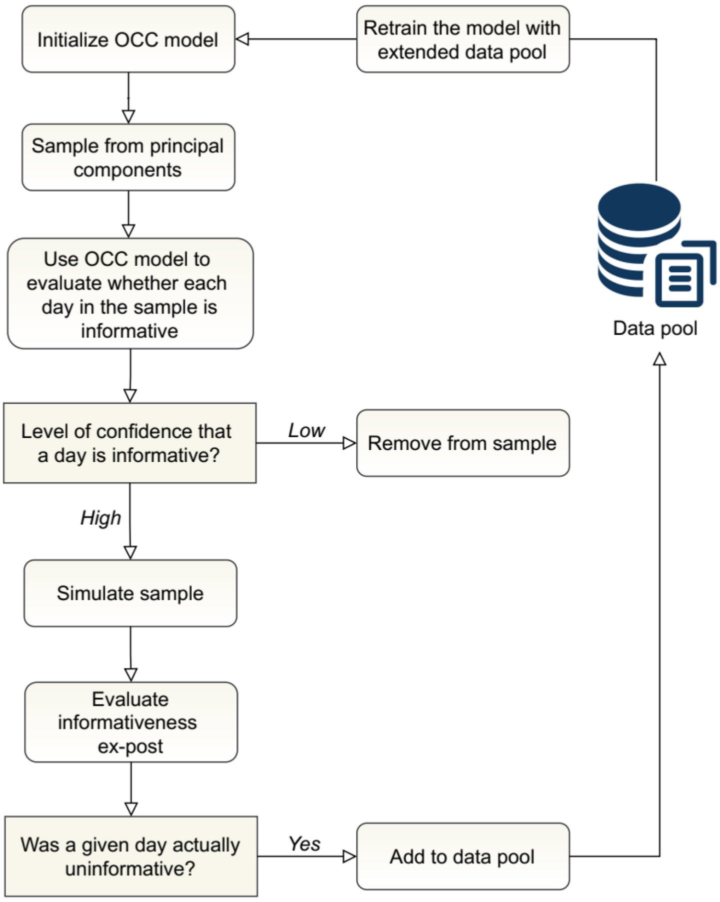

Figure 5.11– The scenario reduction approach

5.6 The details of the replay scenario simulation stage

The replay simulation stage re-runs the scenarios that were generated during the previous stage (forward simulation stage) with storage and/or load modifying resources activated. This acts as a what-if simulation process that explores how the results of the forward simulation stage would change if storage and/or load modifying resources were available to the power system. As an example, the diagram in Figure 5.12 describes the reply concept when the goal is to quantify the impact from enabling load modifying resources that can only reduce demand when it is optimal to do so.

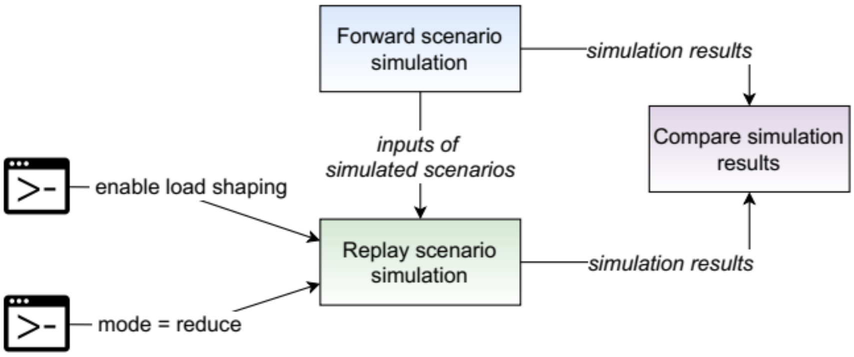

Figure 5.12– The process of learning the impact of load shedding resources

5.7 The details of the counterfactual comparison stage

The counterfactual comparison stage learns a sparse linear model between load changes during each hour of the year and the corresponding impact in terms of reducing capacity deficit (in MW) or curtailed generation (in MWh). The linear model is estimated using an L1 prior as regularizer (commonly referred to as LASSO regression). Finally, the model's coefficients are divided by their sum, so that their sum is equal to one.

6 Conclusions

The deliverable presented a methodology for quantifying the value of an energy retrofit project for the power grid. This value is estimated through a composite indicator that consolidates the different ways a retrofit project affects the grid. A project can be considered as grid positive if the positive impacts outweigh the negative.

The methodology was applied on the Greek power system so as to explore the potential contribution of energy efficiency in phasing out old, polluting lignite plants that are kept commissioned only for ensuring the system's reliability. Data suggests that phasing out lignite and installing more capacity for renewables leads to a non neglectable probability of over-generation during some hours of the day and lack of adequate capacity during others. Although storage can level out such capacity peaks and valleys, the contribution of energy efficiency should also be taken into consideration given its multiple benefits for consumers.

If the goal is to decrease CO_2 emissions and/or reliance on imported fossil fuels, the power system needs to utilize in the best possible way all the resources that can be available, including energy efficiency. In addition, rewarding energy efficiency as a grid resource is a way to expand the way energy efficiency is perceived by consumers: from the notion of improving a building to reduce the energy bill to improving a building so that to help transform the national energy system into a more sustainable and resilient version.

The overall conclusion of the deliverable is that energy efficiency can be valuable for the power grid when its impact is aligned with persistent needs of the grid that reflect the regularity and seasonality of power demand at the aggregated level. The proposed methodology quantifies this value using the same process and the same tools that system operators use for capacity adequacy studies. There are two (2) reasons for this approach:

(a) The coordination between the needs of the power system and the incentives for energy efficiency improvements must take place during the medium-term planning for resource adequacy in the power system.

(b) To showcase that the design of a program that compensates energy efficiency for its contribution to the grid does not need a radically new toolset, but can be done using the tools that power system operators already use.

The proposed methodology builds upon a unit commitment model that is largely based on the formulation of the Dispa-SET model that has been developed within the Joint Research Centre of the European Commission. However, any commitment model can be used to replicate the methodology. Furthermore, the deliverable proposes ways to address some computational difficulties that power system modelling commonly faces. In particular, the deliverable offers:

- A quantitative approach for model calibration. Calibrating a model on historical data is an important step before a practitioner is able to trust its results. The deliverable offers a way to use the historical data so that what the model learns is consistent and generalizable.
- A quantitative approach for scenario number reduction. Since the simulation of a large number of yearly scenarios is computationally intensive, the utilised model learns to distinguish between informative and uninformative scenario combinations so that more and more days are excluded from the full year scenario data. This significantly reduces the computational resources that are needed for the scenario evaluation.

All the functionality that has been developed to enable the implementation of the proposed methodology has been open-sourced and can be accessed at https://github.com/hebes-io/eevalue.

Although the calculation of the indicator is straightforward, the adoption of the proposed approach requires a retrofit project aggregation process in place. A project aggregator would bring together a variety of projects with synergistic effects on the buildings' consumption profiles so that the resulting portfolio can capture as much as possible of the value potential that energy efficiency has as a grid resource.

In addition, the aggregator would be responsible for the reliability of the provided load shape changes; as the variability in the load shape changes increases, their value decreases, and, in the limit case, high variability could mean zero value. The aggregator would control how projects are added or removed from a portfolio so that to maintain its reliability and consistency.