Development of a Unit Commitment and Optimal Dispatch model used to evaluate the effect of variable Renewable Energy Sources on the power system

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Abstract

The growing problem of climate change has risen global concerns about the way of using natural resources and has brought several initiatives such as the EU 2030 targets towards the cleaner energy production and the emissions reduction. The high penetration of Renewable energy Sources (RES) is considered as a remedy to this issue. However the higher integration of RES to the system is a rather challenging task for it's different components. Therefore there is a growing need for the introduction of higher flexibility to the system as a countermeasure for the unpredictable and unstable RES generation.

In this report the flexibility potential coming from a portfolio of smart Domestic Hot Water Tanks (DHWT) is investigated. Their ability to provide Active Demand Response (ADR) in order to contribute to the more cost efficient electric system's operation is studied. These systems could allow to modify their electrical load pattern without affecting the final, thermal energy service they deliver, thanks to the thermal inertia of the system. The creation of a general model able to simulate the operation of DHWT is developed. This model is intended to be used in a unit commitment and power dispatch model in order to evaluate the contribution of Demand Side Management (DSM) into the higher RES integration. To accomplish this task first two detailed modeling approaches were followed. The first was was a Rule-Based Control (RBC) strategy able to simulate several thousands individual DHWT. This model was computationally efficient and allowed the simulation of 20000 tanks for 5 days with a sub-hourly operating time scale. The second analytical approach was a linear program (LP) that performed the same computation but for a decreased amount of tanks due to the high computational burden. In both models the ability of a centrally controlled (by an aggregator) portfolio to provide capacity and activation reserves are explored. The two approaches are compared in order to identify benefits and limitations. These models were the main guide towards the modeling of a Virtual Storage Plant (VSP) model. This model is able to follow and simulate the behavior of an increased number of DHWT without much detail. The assumptions made in the VSP model formulation are further explained. The ability of this model to perform in standard conditions and to participate in Demand Response operation are validated through the detailed models. This process lead to the creation of a VSP model that is able to simulate the behavior of a fleet of DHWT. The flexibility that can be offered along with the rate of RES penetration can be investigated by the integration of this model to Dispa-SET, a unit commitment and power dispatch model able to simulate the electric system.

Finally a part of this thesis is related to the improvement of the Dispa-SET simulations and the overall computed system's cost. This was performed by collecting yearly generation data available

at Entso-e's website from thousands of generation units in Europe. Afterwards several methods were developed in order to acquire important real-time values for the simulation parameters. These methods are tailor made and are explained in detail. To our knowledge this is the first attempt to collect and process real time generation data for European units.

Preface

This thesis is submitted to the Faculty of Applied Sciences in partial fulfillment of the requirements for acquiring an M.Sc. in Electro-mechanical Engineering at University of Liège.

The thesis contributes to the improvement of a unit commitment and economic dispatch model and investigates the flexibility potential that can be extracted by a portfolio of smart Domestic Hot Water Tanks.

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Contents

Chapter 1

Introduction

1.1 Context

In the past years, global attempts have been conducted against the climate change and the global warming. Starting from the Kyoto Protocol in December of 1997 several commitments regarding the reduction of Green house Gas (GhG) emissions were made[1]. At the Paris climate conference (COP21) in December 2015, 195 countries Parties to the UNFCCC adopted the first-ever universal, legally binding global climate deal and committed to assist developing countries towards this goal[2][3]. On a European level the policies for 2030 that expand those of 2020 state clearly among the GhG emissions reduction and the increase in energy efficiency, targets for 27% penetration of renewable energy sources (RES) [4]. The efficient integration of variable energy resources (VRE) in power systems has been addressed by the imminent need to switch into more eco-friendly power generation due to decisions made by energy policymakers around the world. Germany's decision to phase out nuclear plants [5] demonstrates the increased future need for renewable energy resources.

The forecast uncertainty and the variability of wind and solar energy are the main challenges towards the higher integration of renewable energy sources. In current energy systems, VRE constitute a small percentage of the energy mix and are handled similarly as the demand through corrective measures from conventional power production units. However this kind of remedies have certain limitations, based on cost inefficiencies. For instance, if the realization of the renewable generation output is different than the predicted value, conventional units should either be stand-by or start-up in order to adjust their output and balance the production and the demand. Thus, conventional units that operate part-loaded are kept as reserve or the production cost increases because of the additional start-up cost. These tactics are proved to be costly and inefficient in terms of social-welfare[6].

The operation of electric power systems relies on the fact that production and demand must be constantly matched. This balance is critical for the safe and secure operation of the power system and sets apart electricity from any other commodity. The frequency deviations that occur from a potential difference between demand and supply should be maintained in a small acceptable band. It has been established that in order to achieve efficient high penetration of VREs there is a need for increased flexibility to the system. The term flexibility in a power system refers to the ability of the system to adapt rapidly in the sudden changes of the demand or the variable energy resources under different conditions. Historically these changes were compensated by conventional power plants but it seems that these plants are progressively being removed of the dispatch as the VREs penetration increases. Although the use of storage in the form of batteries could be a possible countermeasure the high installation, operation and investment costs make such a solution prohibitive [6].

Therefore new strategies are needed to increase the flexibility of the different components of the power system. These strategies should exploit the potential of the system's components at it's fullest and investigate alternatives in order to decrease the needs for further flexibility. The available options to meet flexibility needs can be :

- **Generation** options that aim to make better use of the conventional units. Currently these units partially participate in providing flexibility or their ramping capacity [7] is not entirely used. The VER's output should also to be controlled (through curtailment) in an attempt to reduce the need for further flexibility on the system. The introduction of new products in the markets will give higher incentives to the generation facilities to procure flexibility resources and will direct their behavior towards a more efficient use of their capacities. Of great importance are the specific features of the different VREs. For instance, the integration of wind and solar generation should be spread in wide geographic range in order to decrease overall output fluctuation and deteriorate the flexibility needs. These specific characteristics of the renewable sources should be captured and incentivized by the market designation [6].

- **Demand-Side Management** options, where part of the demand is manipulated to procure flexibility. In many different cases the use of energy storage devices such as space and water heating systems (HVAC), electric vehicle charging and industrial activities that incorporate thermal inertia can serve as flexibility provision. Increasing the efficiency of consumption results in the release of valuable resources used to provide flexibility. A very important aspect of this type of reserve is the short response time needed. Although Demand side management (DSM) strategies are not new, they recently gained momentum due to technological advancements that allow the control and the quantification of the flexibility provided [8].

- **Network** options play a key role in the balancing of power variations due to the geographical spread and the transfer of flexibility resources. First the investment in new transmission capacity can facilitate the more efficient use of VREs and the balancing mechanisms. On the other hand the technological developments in the field of State Estimation allow the operators to acquire a better overview of the existing system. Thus, by dynamically assess the current network instead of making assumptions about the systems state, less resources should be deployed into the secure operation of the grid [6].

- **Markets and system operation** options are a set of adjustments that should result the more efficient integration of variable energy resources in the grid. The introduction of automated trading at sub hourly scale and the designation of flexibility products are changes that can lead towards the release of flexibility sources. Different pricing mechanisms can help so that the retail price reflects somehow the wholesale price, especially in order to incentivize large and small consumers to participate into the balancing process [8].

In general, it is important to state that the current flexibility potential should be further investigated before investing in other infrastructures. In many power systems these actions will allow the successful integration of the variable energy sources up to 70% [6].

1.2 Demand-Side Management: State of The Art

Several approaches have been explored in the literature in the attempt to capture the value and the necessity of Demand Side Management. In [8], the potential benefits of DSM in transmission and distribution networks are discussed together with the techniques that could be involved in such an implementation and the obstacles that should be overcome. The authors focus on the market infrastructure that should be developed and the incentives that should be given to the participants in order to achieve further development and utilization of the aforementioned techniques. A key element for the effective integration of Demand Side Response (DSR) according to [9, entso-e Policy Paper] is a price signal that stimulates the participation and the competition in reformed markets. In [10] the DSM is categorized according to the impact of the applied measures in the consumption into *Energy Efficiency (EE)*, *Time of Use (TOU)*, *Demand Response (DR)* and *Spinning Reserve (SR)* (see Figure 1.1). Different retail tariff schemes are proposed in the attempt to best trigger the participation of the demand in the balancing process. These are summarized as following [11]:

- *Time of Use rates (TOU)*: a pricing structure that is identical for everyday. During each day the level of prices fluctuates as a function of the average demand. Thus higher price levels are noticed during morning and evening hours. However prices may differ with respect to each season.
- *Critical peak pricing (CPP)*: similarly to the TOU the price is defined in blocks depending on the average daily demand but aims to penalize the demand's high peaks.
- *Real-time pricing (RTP)*: wholesale market prices are directly reflected to the end consumers. It is similar to the TOU structure but the price fluctuates changes for each hour or block of hours with respect to the system's price.

Various modeling approaches are used to best describe and evaluate the benefits of Demand Side Management. Among those the *Demand Shifting* and the representation of *Loads as Virtual Storage Power Plants*, will be explored deeper in the context of the present work. These categories are described as following [10]:

- *Demand Shifting*: processes that incorporate thermal inertia, diffusion inertia, mass transtport and logistics (i.e. scheduling etc.) can be shifted accordingly during a day to provide flexibility to the system. The quality of the processes must be ensured at all times and this constraint addresses the need for developing optimal strategies.

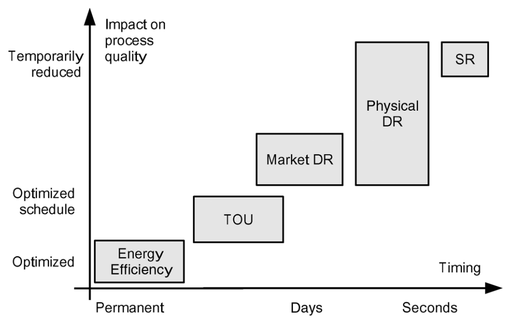


Figure 1.1: Categories of DSM [10].

- *Loads as Virtual Storage Power Plants*: the aggregation of many loads, storages and generators can lead to the notion of a VPP. The considered virtual plant can under various assumptions participate in the markets providing capacity reserves and activate according to it's bids. This approach introduces high stochasticity and thus the amount of the aggregated consumers and the way to control the VPP are crucial and of high significance.

1.2.1 Virtual Power Plant set up

In many studies a centralized control of the flexible-demand portfolio is simulated as a *Virtual Power Plant* (VPP). In [12] an aggregator that controls a VPP of flexible houses is able to track a given set point over time, by acceleration and postponement of its power consumption. The results indicate that the sensitivity of the amount shifted during a day is high with respect to the adopted temperature limits. Additionally, the authors demonstrate that a large amount of the demand can be postponed especially in cases of emergencies, concluding that the VPP can participate in reserve markets in order to offer security to the system. However the modeling approach assumes the comfort level to be captured only as a function of the temperature level, which is not entirely accurate.

Several articles consider an aggregated portfolio (VPP) that consists of either solely adjustable loads or a mix of generation units and loads. In [13] a set of flexible devices are modeled as batteries, bakeries and buckets, a taxonomy proposed in [14]. The approach chosen is not entirely realistic but enables the authors to evaluate the benefits of such a portfolio participating into the ancillary markets. High importance is given to the response times imposed by the Transmission System Operator (TSO). The aggregator first predicts the VPP's baseline and then bids to the markets for reserves. Finally the authors highlight the importance of the time that the aggregator has available to adjust his proposed day-ahead operational schedule in the intra-day market until the gate-closure.

The clustering of *Distributed Energy Resources* (DER) such as renewable energy sources (i.e. photo-voltaic, wind) and CHP units with thermal storage and DSR under a VPP set up is demonstrated in [15] , [16] and [17]. The main reason is the benefit that arises from the diversity in the generation of the different energy resources. In [15], the stochasticity of DER production is balanced by the storage and DSR components in an attempt to bid in the the day-ahead market for both energy and spinning reserve. The profits acquired by incorporating DSR strategies are significant. Similarly in [16] the authors conclude high economical potential and high degrees of freedom when DSR is included in the bidding strategy. They highlight the role a variable tariff structure to shift operations and to maximize profits. In a similar approach, a probabilistic price-based unit commitment model developed by [17] that is used for the dispatch of DER shows the sensitivity to the market price variations. In [18] a comparative study using the battery, bakery and bucket taxonomy of [14] investigates the potential profits of a VPP bidding in the danish markets day by day. The three types of flexibility units (battery, bakery and bucket) are used to simulate and model the aggregated realistic flexibility resources such as electric vehicles, heat pumps, HVAC and so on. Then the aggregator makes predictions on the market prices, bids his flexibility and collects revenues according to the realization of the market prices.

Increased interest is concentrated in the modeling and participation of *Thermostatically Controlled Loads* (TCL). The reason lies under the fact that these loads are simulated linearly and thus do not have big computational requirements. In [19] the aggregated flexibility of TCLs are modeled as a generalized battery model. The authors prove that a set of *homogeneous* loads behaves identically as a battery model. Then define the generalized model for a set of *heterogeneous* loads that is bounded upwards and downwards generalized battery models. Then they use this model to track a regulation signal through a priority stack based algorithm. A different approach places an aggregated fleet of *heterogeneous* TCLs in a multi-stage Stochastic Unit Commitment Model [20] in order to quantify the flexibility margins in Great Britain. Under the several case scenarios the authors highlight that the portfolio is able not only to decrease the system cost and the CO_2 emissions but also to provide large amounts of Frequency Response Reserves (FRR) especially in cases with large percentage of slow moving units such as nuclear and coal. Therefore they conclude that high penetrations of renewable energy resources and other inflexible technologies increase highly the value of smart controlled loads. An interesting definition of aggregated loads is presented by [21]. The DSR strategies of the decentralized approach are categorized in *Delay* (postpone their starting time), *Stop* (stop operation at any time) and *Rate* (continuously track). Due to the computational burden an aggregated model is first validated and then used to evaluate the participation of such a portfolio in *Frequency Containment Reserve* (FCR). These strategies are illustrated in Figure 1.2 and highlight a significant characteristic of DSM which is the rebound effect through energy conservation. The rebound effect is defined as the amount of energy that needs to be provided to the portfolio in order to recover to it's normal operation after participating in reserve provision. The authors highlight the long-run impact of the rebound effect in the frequency distribution and further FRR must be included.

1.2.2 Demand Shifting

The benefits of demand shifting are evaluated in a number of publications usually by embodying DSM simulations into unit commitment and economic dispatch models. The actual goal of demand shifting is to remove parts of the scheduled demand at its peaks resulting the system's cost reduction due to the fact that expensive peak load generators do not need to commit or produce less. This process is also referred as peak shaving. In [22], a simplistic economic dispatch model or in other words a merit-order model (MO) is used and different penetrations of DR were evaluated. Heat pumps coupled with domestic hot water tanks (DHWT) are used to provide DSM and the major outcome is the eventual cost reduction through demand shifting (see Figure 1.3). It is worth mentioning that the optimization problem is formulated as a Mixed Integer Linear

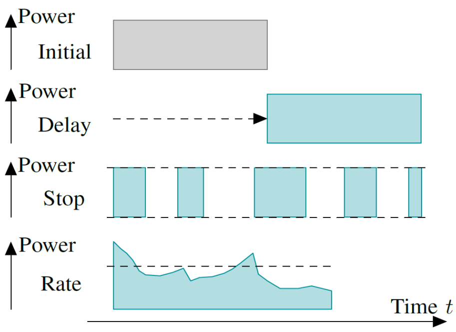


Figure 1.2: Control strategies of small loads [21].

Problem (MILP). The reason is that the heat pump is operating either in space heating mode or providing hot water to the DHWT. Thus there is a need for an integer to avert the charging of both simultaneously. Another critical conclusion is that the increase of DR participation decreased the individual benefits of each participant. However the increase in the temperature limits did not show any significant effect on the flexibility provided.

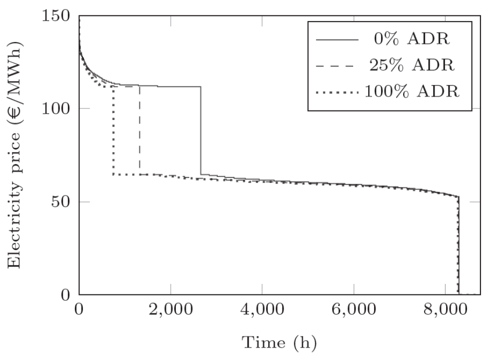


Figure 1.3: Price Duration curve under different DR penetration scenarios [22].

In [23] the authors take a step further and investigate the benefits of DSR by using a more detailed economic dispatch model that accounts for ramping constraints, start-up costs and CO_2 emissions of power generation units. The flexible demand is modeled as space heating and thermal storage and controlled by model predictive control (MPC). Then different price incentive scenarios are explored and comparisons upon the collected revenues (savings) are performed. Besides cost and emissions reduction, an important outcome was that besides cost and emissions reduction is that the maximum benefit in terms of participants' savings is attained when there is a centralized control that handles the consumption set point of each participant according to a price signal.

The role of the heat pumps in DSM strategies is investigated in [24] in an attempt to flatten the peak hours of demand. In this article the authors used detailed space heating models to shift the demand into off-peak hours and highlight the role of TES into controlling the inner temperature and prevent excessive cycling of the heat pump. Significant cost reductions were realized with the use of TOU tariff structure which highlights the need for a better suited retail tariff scheme. Similar approach was that of [25] where 50 households were detailed modeled in a two-stage stochastic Day-Ahead optimization problem. The authors assessed the flexibility potential while incorporating the stochasticity of the outdoor temperature, the hot water consumption and the imbalance prices. They stress that the marginal benefit from cost reduction and energy savings decreases as the flexibility increases , as already pointed out in [22].

Another critical aspect is the evaluation and the way to handle the rebound effect. In [26] a portfolio of 100 domestic heat pumps controlled by an aggregator was used to quantify the flexibility and the payback effect. The portfolio is used to track a reference signal and to resolve potential imbalances by deviating from its baseline predicted (see Figure 1.4). The study demonstrates how the payback effect is developed at both upwards and downwards activations. Moreover the authors highlight the dependence between the payback duration and the amplitude of each activation as well as the different flexibility potentials arising according to the season considered as illustrated in Figure 1.5.

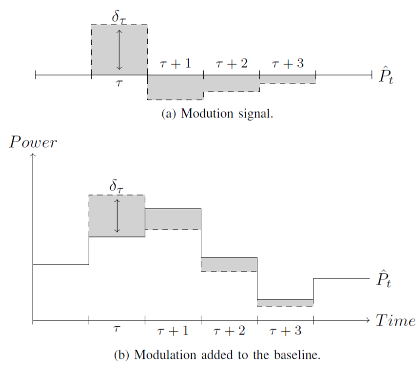


Figure 1.4: Signal tracking from heat pumps [26].

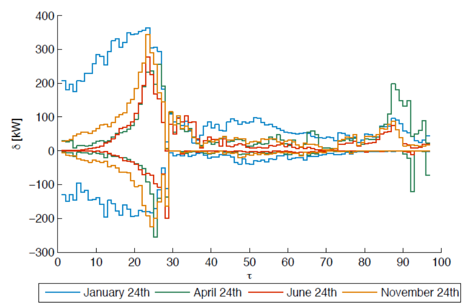


Figure 1.5: Seasonal dependence on activation flexibility [26].

In the effort of evaluating and recognizing which are the boundaries of DSM the modelers are faced against the compromise between detail and size of the problem. It was well stated by

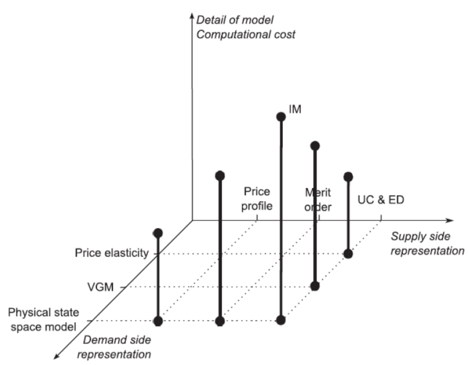


Figure 1.6: Comparison of complexity vs detail in modeling approaches [27].

[28], [27] and illustrated in Figure 1.6 that as the modeling attempt aproaches the physical state space model then the complexity rises. As a result the need to assess the impact of demand side management coming from a large amount of participants forces the community to make simplifications and assumptions in order to reduce the computational complexity. Thus in [28] the authors derived with a verified reduced order model (ROM) of domestic heat pumps and thermal energy storage. Thus a set of linear equations are used to simulate the behavior of clustered households. Then an aggregated model is used to even reduce the amount of the buildings assumed. The aggregated model performs as a worst case scenario for this large cluster of buildings that underestimates the flexibility potential as it was shown. Then an aggregated model is used to even reduce the amount of the buildings assumed. The aggregated model performs as a worst case scenario for this large cluster of buildings that underestimates the flexibility potential as it was shown. In [27] the authors are performing a comparison between the modeling techniques from both the demand and the supply side. Thus they use price elasticity and virtual generator models (demand side) and electricity price profiles and merit order models (supply side). They assess the obstacles in each case and conclude that there is a compromise to be made between an accurate and a large simulation. Finally it is worth mentioning that in [29] a real life project of DSM took place called LINEAR pilot. A small amount of households equipped with smart appliances was used to determine the economic viability of demand response but most importantly to analyze whether or not the domestic end users are willing to participate in such a major attempt. The results illustrated that the flexibility potential is highly asymmetric and he hot water buffers demonstrated the most stable behavior.

1.2.3 Agent-Based set up

The role and the outcomes of demand side management have been evaluated in literature also by agent-based techniques. Agents that interact in a system and aim to maximize their revenues are simulated. The optimal behavior of the overall system is ensured by maximizing the overall social welfare. In [30] this decentralized approach is used and the demand shifting potential is presented in a smart grid. The results are compared with a decentralized adaptive mechanism approach where each player acts through an iterative learning process. In this study the impact of the different tariff structures on the individual flexibility provider was also investigated. The authors concluded that DSM mechanism can contribute highly to reducing demand peaks and was proved by using evolutionary game theoretic techniques that smart-meters will eventually increase the agents' savings (see 1.8). In a similar manner the demand curve was flattened by using game theoretical techniques in [31]. First a day ahead optimization problem was solved and each agent assuming he could predict his overall energy demand would act to improve his position. This strategy is compared to Nash equilibrium computation results where each user updated his strategy iteratively to maximize his payoffs. In [32] end users act in a decentralized way and the authors suggest that the optimal solution of the system where agents share the same energy source can be accomplished (Nash equilibrium) given an appropriate tariff scheme (see Figure 1.7). The interactions between agents were identified in a distribution system in the study conducted in [33]. A testbed was developed in order to host the interaction models of each player (i.e.TSO, DSO, producer etc.) and each of them tries to solve its own optimization problem under the common goal to maximize the social welfare of the system. The flexibility potential is described generally by the chance of the balance responsible parties (BRP) to first calculate their baselines and in the second stage to bid or to offer flexibility in a common attempt to resolve imbalance. The interactions between each player are shown in Figure 1.9 and the total system's imbalance that was resolved is illustrated in Figure 1.10.

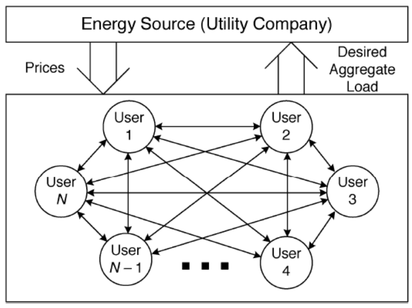


Figure 1.7: DSM strategies by autonomous users [32].

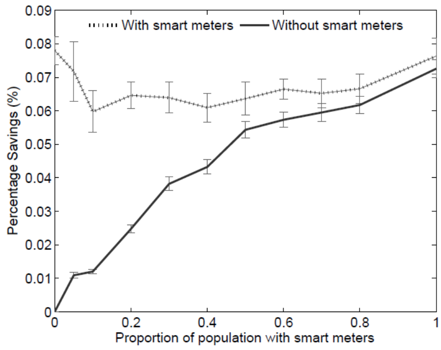


Figure 1.8: Impact of smart meters in savings from DSM[30].

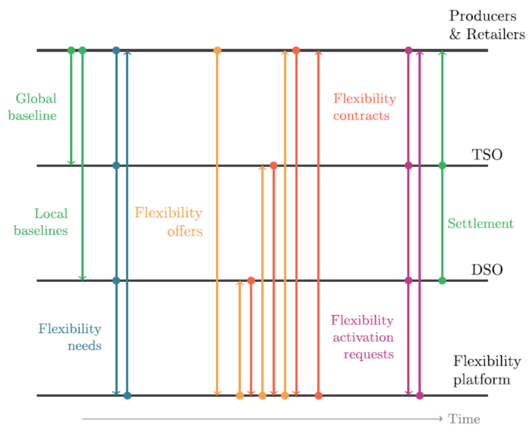


Figure 1.9: Interactions between players DSIMA [33].

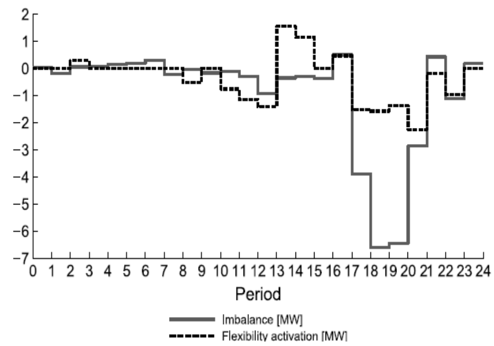


Figure 1.10: Imbalance of the system [33].

1.3 Objectives and Methodology

The present master's thesis focuses on the evaluation of flexibility resources within the Belgian power system, and in particular on the flexibility potential that could be exploited by the participation and the centralized control of the Belgian domestic hot water tanks (DHWT). The large number of tanks, the thermal storage characteristics, as well as the nature of the hot water consumption pattern are a key reason for this choice. An important aspect is that the modeling of a DHW tank is linear and similar to a generalized battery model.

The initial concept was to make use of the developed unit commitment and economic dispatch model the Dispa-SET Tool that was developed in the Joint Research Center [34]. This model is used to performed yearly simulations on the electric system of Belgium and is able to make projections for the different case scenarios of VRE penetration in the future. In this model, it is assumed that the system is controlled by a central operator with full information on the technical and economic data of the power plants, the demand and the transmission network. The model is formulated as a tight and compact mixed integer linear program (MILP) and aims to reduce the zone where the solver searches for the optimal solution. Tightness is represented by the gap, namely the distance between the integer solution and the relaxed solution whereas compactness refers to the amount of data to be processed by the solver. The model is implemented in GAMS [35] and PYOMO [36] and the process is described in the following graph (see Figure 1.11).

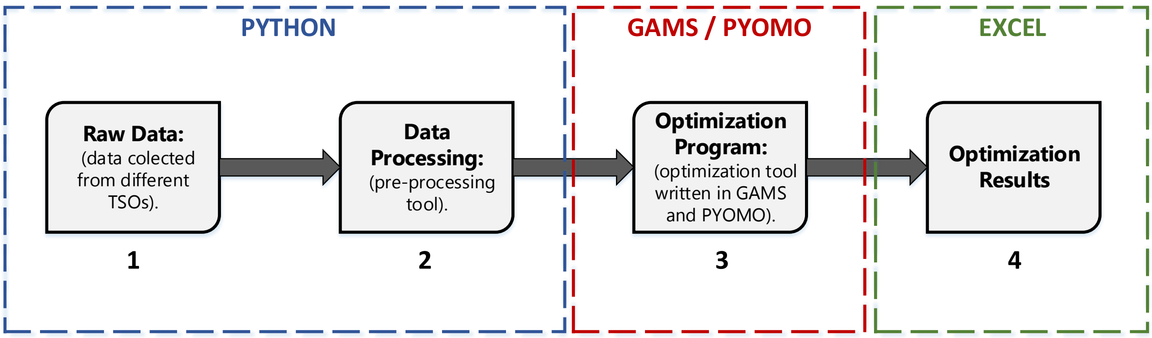


Figure 1.11: Flow chart of Dispa-SET

The procedure that is followed includes:

1. **Data collection and processing**: The data that will be used as input parameters for the problem formulation are first collected from many different sources.

2. **Preprocessing**: Afterwards these data are properly formulated by a preprocessing tool implemented in Python [37] in order to be delivered to the main optimization suite as inputs.

3. **Optimization program**: The main problem is thus formulated in GAMS and PYOMO and then handled to the solver. For this implementation CPLEX [38] is used.

4. **Post-processing/Results**: After solving the results are properly formulated and are available for evaluation.

That explained, a part of this thesis was first dedicated to improve the input parameters of the model. It is trivial to explain that if the data that are used as inputs are realistic the outcome of the simulations in terms of system cost and flexibility requirements will correspond better to reality. And what is a better source for this purpose than a platform which contains yearly generation data of all the European power plants. The mentioned platform is the entso-e Transparency Platform [39]. Entso-e Transparency Platform is a major project that aims to collect and publish electricity transportation, generation and consumption data and information on the pan-European power system. Acquiring this information and processing it accordingly gives to the model a strategic advance to better capture the benefits and the challenges of VRE integration in the European system. Thus a huge amount of data regarding the generation set points of the European generators was gathered, properly formulated and processed.

The next step was to introduce a Virtual Storage Plant (VSP) model into Dispa-SET (by analogy to a virtual power plant) in order to better evaluate the flexibility potential of the whole Belgian fleet of DHW tanks. The virtual storage unit is thought to operate similarly to the pump-storage plants that already existed in the Dispa-SET model and that captures the aggregation of all invidual decentralized storage units. The goal of this approach was to identify how such a unit could contribute to the overall cost reduction of the system and to the decrease of the cycling of units. With the introduction of RES at the system the operation of base-load units changed in order to prioritize the participation of renewables and as a consequence they performed significantly more start-ups and shut downs.

In order to model the Virtual Storage Plant a step back was taken. The operation of the DHW tanks was modeled in detail in order to recognize the overall challenges and to verify the behavior of such an aggregated model. Two different modeling approaches were carried out. The first was Rule Based Control (RBC) attempt to model in detail each particular tank with stochastic hot water consumption and identify through the temperature profiles and the power consumption profile how they could participate into the fulfillment of certain flexibility needs. The second attempt was an optimization model that was created to demonstrate how each individual consumer would act to first serve the hot water needs of the house and offer flexibility to the system. Both approaches take into account stochastic demand profiles for domestic hot water (DHW). The difference between these two models lies in the fact that the optimization algorithm acts as the best case scenario simulation since the future demand is known and allows optimizing the overall charging/discharging strategy (perfect foresight hypothesis). On the contrary, the RBC algorithm has no prediction option and thus serves as the worst case scenario.

These two disaggregated modeling approaches are further used to parametrize and validate the Virtual Storage Plant. Then this model was tested in a simple Merit Order dispatch program to identify if and how it acts according to the predefined and regulated flexibility provision. Finally it was meant to be incorporated into Dispa-SET in order to actually determine the benefits of such a unit.

The objectives of the present thesis are summarized as :

1. Improve the Dispa-SET input parameters to create more realistic simulations of VRE penetration scenarios.

2. Use a VSP model to identify through Dispa-SET the flexibility potential and the cost

effective integration of VRE

3. Determine which are the challenges and adjustments that must be taken into account regarding the future of the European Energy Markets.

1.4 Thesis Outline

The rest of the present thesis is organized as such:

- **Chapter 2**: The collection and process of generation data from Entso-e website is described. The methods that were developed in order to extract valuable prices for the simulation parameters are explained. Finally the results are discussed.
- **Chapter 3**: Two detailed modeling approaches are investigated in order to quantify and evaluate the flexibility potential that could be offered from a portfolio of centrally controlled DHWT. The challenges and limitations for the participation of this fleet to the reserves markets are discussed.
- **Chapter 4**: A Virtual Storage Plant model able to simulate a large number of DHWT is developed and its performance is validated through the previous detailed approaches. This model is able to participate in a unit commitment and economic dispatch model in order to evaluate the flexibility potential that could be offered to the system from a fleet of shiftable devices.
- **Chapter 5**: General remarks and conclusions.

Chapter 2

Collection And Process of Generation Data from Entso-e Transparency Platform

In this chapter, the extraction of yearly generation data of the European power producing units from the Transparency Platform [39]is performed. The data is then processed in order to obtain valuable information about the input parameters of the Dispa-SET model. The procedure that was carried out regarding the gathering of those data, the creation of a database out of them for the year 2015, the clustering of the power plants according to their technology and the methods that were developed in order to acquire significant values of the input parameters are described.

2.1 Motivation

As it was explained in the Introduction of this thesis the penetration of renewable energy sources (RES) will incorporate severe changes in the current structure of the power production system. The impact of RES on the operation of power plants has been thoroughly analyzed in the past decades, among others in the form of projections on the transition of the European system and the role of each generation technology in a green and RES dependent future.

In several European markets there is a percentage of power production resources that are self-scheduled. These include nuclear plants and other units and as it is guaranteed by the EU regulations renewable energy sources. The overall of self-scheduled production (priority-dispatch) is thus increasing and is going to further increase over the years due to the high RES penetration European targets. The overall generation of these units plus the minimum stable operation level of the committed plants is considerably similar to the total demand during off-peak periods [7]. A significant obstacle that arises is that more and more peak-load units operate in part-load or decommit and at several periods there is not enough ramping capacity.The phenomenon is demonstrated in Figure 2.1.

The outcomes of this effect can be summarized as following [40]:

- **Steep ramping needs**: in the attempt the generation level to meet the demand at all times there is an imminent need to fast ramp downwards before the midday and restore a big amount of capacity during the evening hours.
- **Oversupply risk**: if there is not enough ramping downwards capacity the generation level can exceed the demand during noon hours
- **Decreased frequency response**: there is less available on-line capacity to regulate frequency especiallyat periods with high RES penetration.

As a consequence the power plants that were initially designed to serve for base-load operation will progressively be used for cycling. As cycling is defined the change in operation either on/off starts usually referred also as hot, warm and cold starts, but also two-shifting load cycling that accounts for the on line up/downwards ramping ability [41]. In Figure 2.2 power plants that were used for base-load operation will not only have to reduce their outputs to minimum operating level but in some cases they should completely shut down. Then they will have to quickly recommit in order to serve in because of a possible deficit in the renewable energy production.

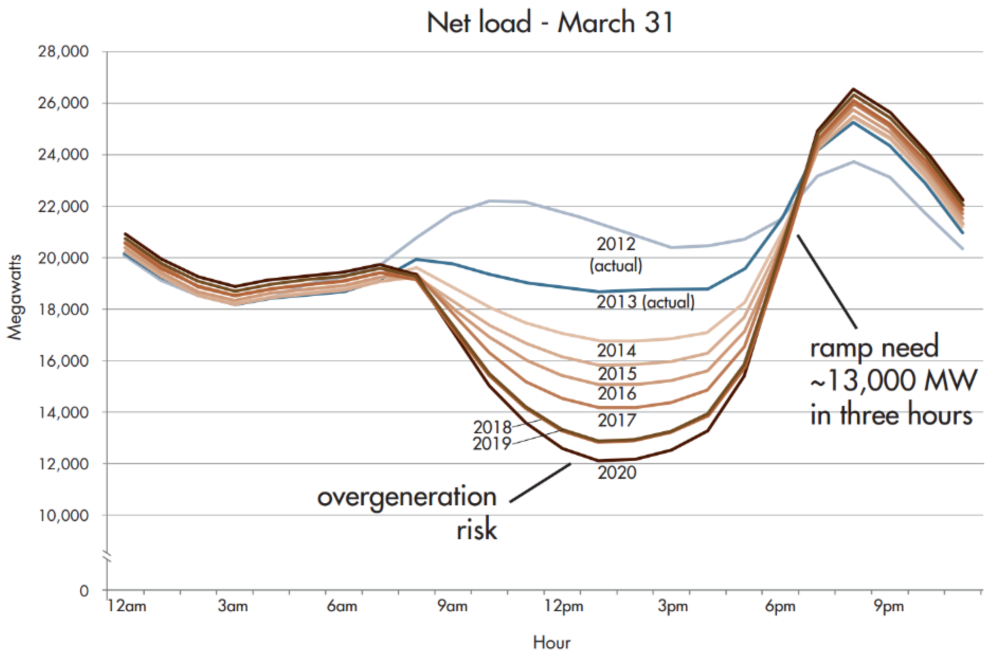


Figure 2.1: Overgeneration risk and steep ramping needs for typical day in 2020 [40]

Base-load plants such as nuclear or hard coal plants are able to participate in load following operation as it is shown in [42] , [43] and [44]. Because of the fact that rapid changes of power output cause fatigue to the mechanical parts and can raise chemistry issues, these units are not the major providers of ancillary services. The combined cycle units are the ones built and used for this purpose because of their fast response, the wide range of operation and the low emissions in comparison to the others, of course depending on the configuration. Power plants that are not designed for load following and are used for high cycling are exposed to high temperature and pressure rates and consequently to significant damages. Strong attention has been given to the effects of such operation on the long term costs associated with the maintenance of the plants. Thus the power plant Operation & Maintenance costs are strongly revised and new studies indicate new strategies for the assets optimization and management.

It has so far established that the business-as-usual practice regarding the operation of the conventional power plants is highly reconsidered. Changes in the way the plants are operated brings new issues that should be dealt. In this direction the current study focuses in the evaluation of available data to assess the capabilities of the different technologies and to investigate the potential flexibility needs of the future power system. Moreover the impact of these changes from the high penetration of RES in the total system cost should be quantified.

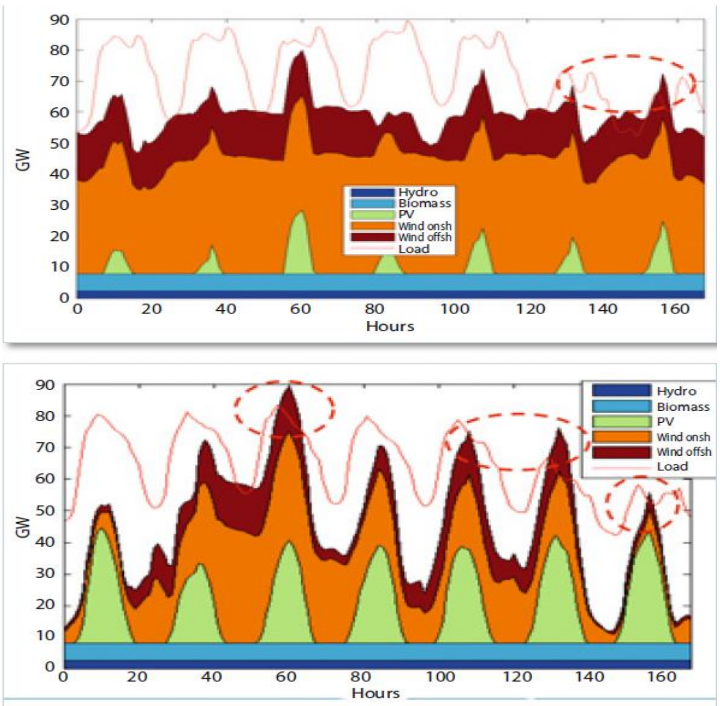


Figure 2.2: Power generation and demand projections for 2020 in Germany for a typical winter week (up) and a summer week (down) [45]

2.2 Gathering the Data

In accordance with the European Regulation 543/2013 the Entso-e Transparency Platform [46] is responsible for providing valuable information on transmission, generation, load and market related data from all the European interconnected system. These data are collected from TSOs, power exchanges and several other reliable sources in an attempt to enhance and promote a stable and continuously evolving European Electricity Markets foundation. The disclosure of such valuable information is a key element for further improvement of the system especially because it gives to the scientific community access to information that was too expensive or impossible to find so far. The possession of this information will give us better communication on how the system is operated and will contribute to the better analysis of future case scenarios. In this section the procedure that was carried out regarding the collection of the generation data is described.

2.2.1 Data extraction

For the extraction of the generation data from the Entso-e Transparency web site on has to first log in and then move to Generation and Actual Generation per Generation Unit. Then a table arises with the names of the power plants/units for each European country and the available selection of the date and time range (see Figure 2.3). The maximum range that can be demonstrated is for one day. Then the option of downloading the generation data under different file formats is available. The drawback of this process initially was that it would take huge effort to click for each one of the thousands power plants, and for each one of the 365 days of the year. The alternative that was found was that once the user had logged in he could insert a specific url to the browser's reception containing the time interval that in our case was the year 2015, the identification code of each unit (EIC) and the desirable output file format. Thus the downloading process became much more efficient. The only obstacle that was left was the acquiring of the identification code for each unit(EIC).

A first attempt to have access to this code was through the Installed Capacity per Production Unit table in the Transparency Platform. However this attempt was quickly abandoned as it was discovered that this table contained the capacities and the id codes (EIC) for the aggregation of several units. It was found that at this table Entso-e provides information about the production units. However the production units for a number of cases consist of several generation units. Therefore the EIC codes for the production units do not necessarily match the EIC codes of the production units. As it is illustrated in Figures 2.3 and 2.4 for instance the power plant Amercoeur 1 R TGV (with EIC code: 22WAMERCO000010Y) in this table consists of two generation units namely Amercoeur 1 R GT (with EIC code: 22WAMERCO000008L) and Amercoeur 1 R ST (with EIC code: 22WAMERCO000009J). Therefore the identification code (EIC) available in this table did not correspond to the one that were needed to download the generation data for each unit on the Actual Generation per Generation Unit table. The remedy to this was a script developed in Python [37] that was able to access the transparency website, log in automatically and then obtain the desired information through the source code of the Actual Generation per Generation Unit page. Thus a file for each country was created that contained the name and the type (i.e. nuclear, hard coal etc.) of each unit and it's identity code.

The next step was to visit the on line platform, log in and then perform an http request whose

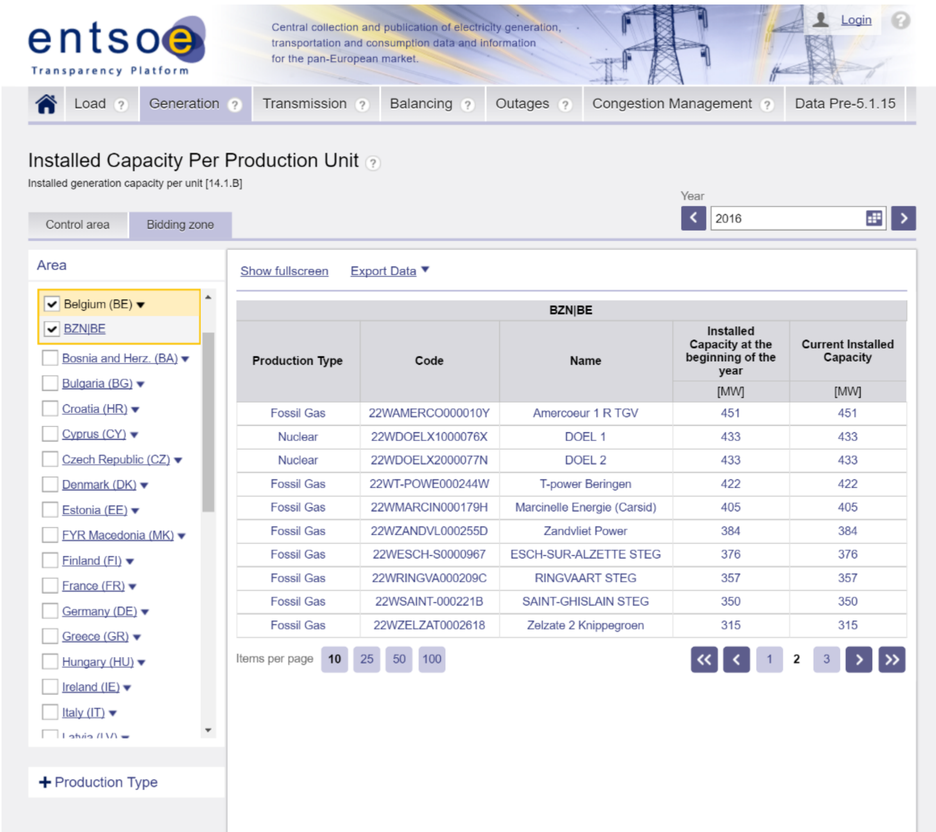


Figure 2.3: Installed Capacity per Production Unit table in Entso-e Transparency Platform [39]

parameters are adjusted to cover one full year of operation. This process was carried out by a Python [37] script. The script creates first the url address for all the units and logs in the platform. Then a repetitive loop assures that one by one the urls are inserted to the browser and waits until the downloading process for each one is finished. It worths mentioning that the downloading phase for all these units lasted nearly a week. The outcome of this procedure was the possession of roughly 1980 csv files that contained yearly generation data series. These archives were processed again by a Python [37] script in order to be properly named and encoded so they were prepared for the next step of the archive storage.

2.2.2 Definition of the power plants database

The data that were collected should be stored afterwards in a way that enables the quick and easy access. For this reason the storage of these data in an *SQLite* [47] database was decided. *SQLite* [47] is a compact library that enables the writing and reading directly to ordinary disk files and requires minimum memory usage. The creation of the final database is performed by *SQLAlchemy* [48], *a Python SQL Toolkit and Object Relational Mapper (ORM)*. The role of this ORM is to allow not only the creation of a collection of related tables but also the easy access through a set of commands that are related to complex data search. Moreover the philosophy

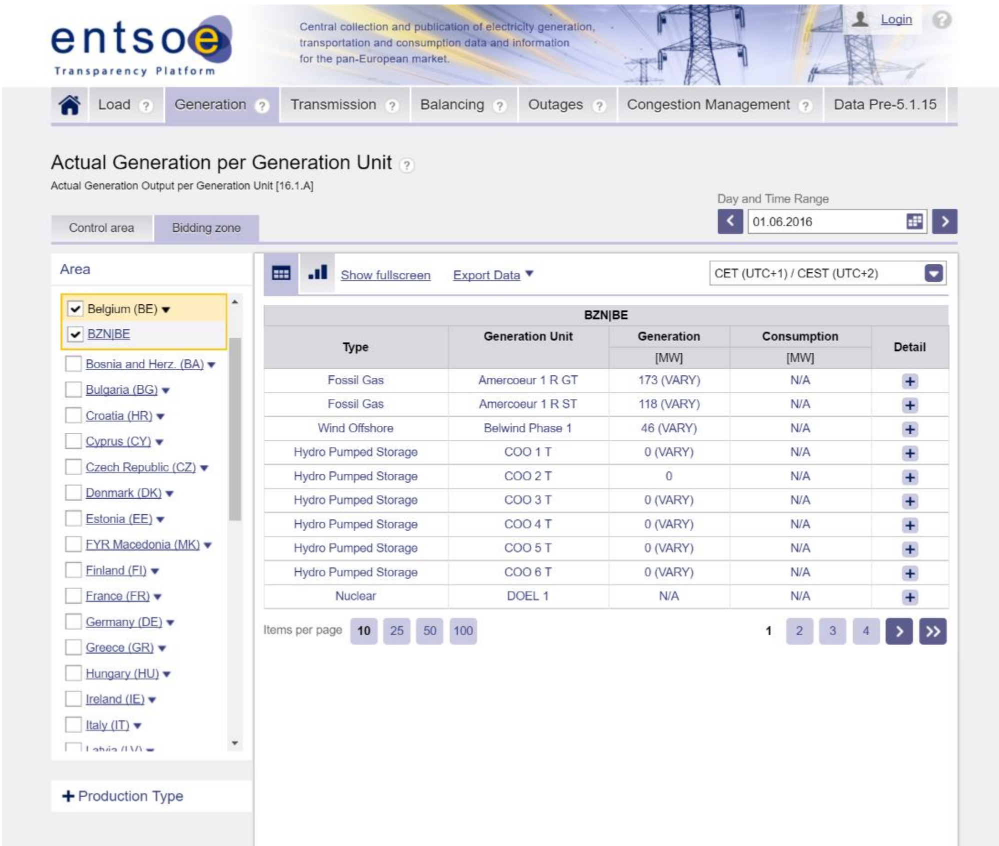


Figure 2.4: Actual Generation per Generation Unit table in Entso-e Transparency Platform [39]

that this suite is operating along with it's pythonic domain led to the utilization of this language.

The way the database is formated follows a tree structure and is presented in Figure 2.5. There are three tables that could be thought as hierarchical layers. The first contains the names of the countries that are included in the study. The names are "string" records that contain each country's acronym. The second layer is a table that includes the name, the type of technology, the identification code (EIC_Codes) for each unit and the country that the unit belongs to. The country name is used as a reference key to the unit records. The third layer contains the generation table, a big amount of records with the power output of each unit for every time stamp. The time stamp is provided in Central European Time (CET) and is recorded as an integer Unix Timestamp and translates to the seconds passed since the 1st of January 1970. The reason for that date transformation is that it enables the easier processing of the time step and the algebraic and logical operations. This table is linked to the previous one by a reference id of the unit table. The link between the tables is meant to facilitate the complex data search according to the users restrictions.

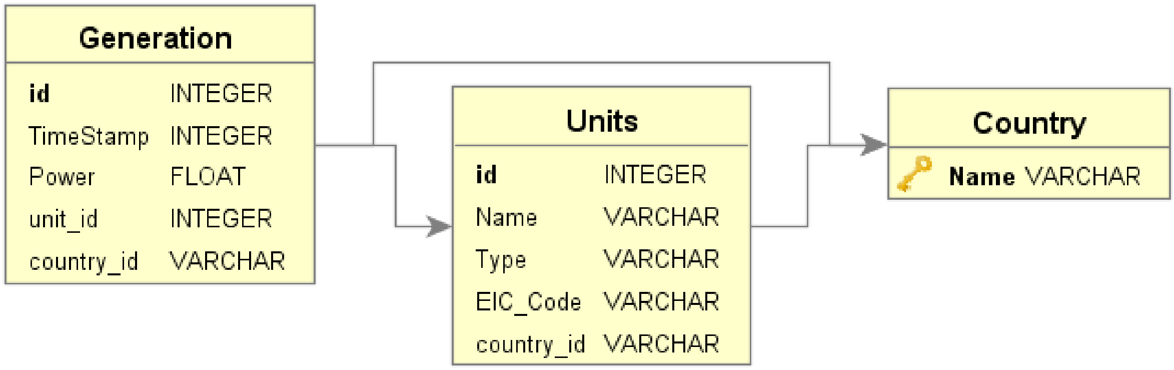


Figure 2.5: Database scheme as Entity Relation model.

2.3 Methods

In the following section the methods that were developed to process the large amount of data that were collected are explained. To our knowledge extracting technical and operational constraints from historical power plant generation data has never been performed before. A series of novel algorithms were therefore implemented in Python language to extract these characteristics. The results were put in an excel file for further processing. The methods that were developed first deal with the clustering of the power plants. Then the upwards and downwards ramping capacities or starting up and shutting down were investigated. The duration for which the units operated or remained inactive as well as the number of cycles are retrieved. Then in a further attempt to capture information regarding the time that is necessary for the units to reach 90% of their nameplate capacity and the minimum stable operation level tailor made algorithms were implemented.

2.3.1 Clustering of the plants

As it was mentioned before the Entso-e Transparency Platform makes available the generation data for each unit. In certain cases a number of generation units consist one power plant (production unit). For instance, a combined cycle CCGT plant comprises of two or more units' generation data series, the gas turbine and the steam turbine as demonstrated in Table 2.1. Another similar example is the one of COO, a hydro powered plant in Belgium. The web platform makes available the power output of the six units that it consists of. Therefore it was considered necessary to aggregate the information about those plants that could not be thought as self standing. On the other hand multiple units comprising a big hard coal fired plant such as Neurath in Germany presented in Table 2.2 should not be taken as the aggregation because it would be interesting to analyze one by one these units as they can operate independently. Thus it was decided that nuclear and fossil coal units would be considered separately. Fossil gas units and hydro powered units would be aggregated in case they were parts of a large production unit. It should be highlighted in this point that a valuable information in the final clustering would be the nameplate capacity of the plants. Thus a file containing all the units capacities and identification codes from Installed Capacity per Production Unit was used. This file was a guideline to separate and cluster the units.

Table 2.1: Generation units that constitute a CCGT production unit.

Production Unit	EIC	Type	Capacity (MW)
Amercoeur 1 R TGV	22WAMERCO000010Y	Fossil Gas	451
Generation Units	**EIC**		
Amercoeur 1 R GT	22WAMERCO000008L		
Amercoeur 1 R ST	22WAMERCO000009J		

Table 2.2: Generation units that constitute a coal production unit.

Production Unit	EIC	Type	Capacity (MW)
Neurath	11WD7NEUR-B-KW-B	Fossil Brown coal	4179
Generation Units	**EIC**		
Neurath A	11WD7NEUR2B–A-T		
Neurath B	11WD7NEUR1B–B-X		
Neurath C	11WD7NEUR1B–C-U		
Neurath D	11WD7NEUR1B–D-R		
Neurath E	11WD7NEUR1B–E-O		
Neurath F	11WD7NEUR1B–F-L		
Neurath G	11WD7NEUR1B–G-I		

Since no matching between generation and production units is proposed on the transparency platform, a specific algorithm was developed and presented in Algorithm 2.1. The clustering is performed in two stages. At first each name from this file is tested for compatibility with the database. If the name and the EIC code matches identically then the plant is registered as it is. Alternatively a more complex search is performed based on the name, the identification code and the type of the power plant and the units that are found to have a match rate of at least 95% are bundled in a list. The new plant is comprised of a number of generation units and this information is going to be used when the generation data are processed. The first stage is presented at lines 2-11 of Algorithm 2.1. Finally the rest of the plants that are not included or not matched through that process are processed in the second stage. The steps of this stage are presented at lines 12-18 of Algorithm 2.1. At this stage each of these units are compared with the others left from the previous stage. They certainly match with themselves and probably with others. An extra condition about the bundling of the units lies under the technology of each unit respectively. Because of the lack of information about the capacities of the second batch of units a check is done and the maximum operating point of their yearly generation data is considered as an approximate nameplate capacity. This process is finished when a new file that contains all the units properly aggregated. At this point it should be stated that the accuracy of this algorithm depends a lot on the way the units characteristics are given by Entso-e. The complexity of the algorithm is high and the implementation long but it is a first attempt to make a successful bundling of the units of nearly the whole European system.

Algorithm 2.1 Units Clustering

```
procedure bundleUnits
    for name in capacitiesFile do
        if name exists in database then
            write: Name Id Capacity
        else
            Fuzzy search through Name,ID,Type
            if matching rates>95% then
                write: [Names,Ids,Capacity]
            end if
        end if
    end for
    for units left in database do
        Fuzzy search through Name,ID,Type
        if matching rates>95% then
            Capacity=sum(max(unitsCapacities))
            write: [Names,Ids,Capacity]
        end if
    end for
end procedure
```

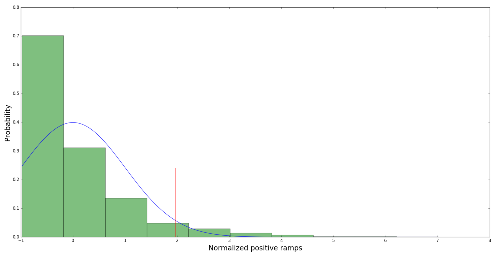
2.3.2 Upwards and Downwards Ramping

In this section the ramping capabilities of the plants are explored. As it is explained in previous section the ability of a unit to perform two-shifting load cycling plays a key role to the characterization of the unit as base load unit or load following unit. So far several studies have presented data regarding the ramping capacity of the plants but this is a first evaluation of the cycling ability of a large amount of operating power plants based on historical data provided by the units. Thus we can gain a realistic view on how the units actually performed during the past year. The method that was followed succeeds to identify all the upwards and downwards modulation of the generators set points. The algorithm that was developed is presented in Algorithm 2.2.

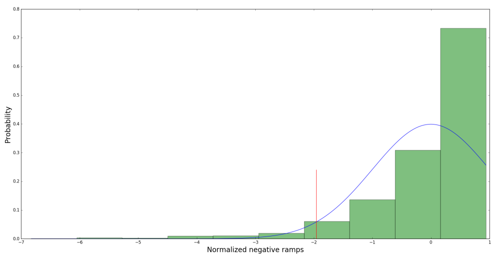
Algorithm 2.2 Ramps Upwards Downwards

```
procedure RampUpsDowns
    for unit in unitsCluster do
        for t=1 to N do
            if Power(t)! = 0 and Power(t + 1)! = 0 then
                Ramp=Power(t + 1) − Power(t)
            end if
        end for
        maxRampUp=max(normalDistribution(Ramp))
        maxRampDown=min(normalDistribution(Ramp))
    end for
end procedure
```

The algorithm takes into account the clustered units database that was created before as an input. For each plant the difference between the next and the current generation set point is accounted as ramping. The algorithm first makes sure that the next or the current time step the unit is not turned off. All the ramps are then categorized in positive and negative ramps. Then the filtering process demonstrated in Figure 2.6 takes place. The data are sampled, the mean and the standard deviation are computed. Assuming that the ramps are distributed under a normal distribution some of the extremes are discarded adopting a 95% level of confidence. Finally the values of this list are finally considered as the reference for the studied power plant. These outputs are expressed in a percentage of the unit's nameplate capacity per hour (%/hour).



(a) Upwards ramping capacity.



(b) Downwards ramping capacity.

Figure 2.6: Distributed ramping capacity and 95% confidence level.

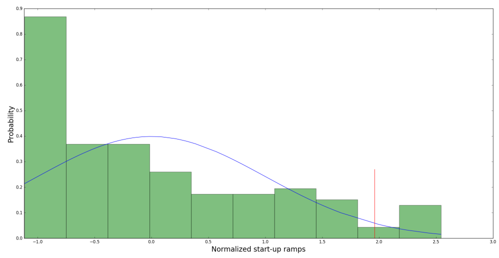
2.3.3 Start Up and Shut Down Ramping

The importance of the quick response of the power plants when needed to commit or decommit from the system was explained in section 2.1 through Figures 2.1 and 2.2. Especially in cases with high penetration of renewables, some of the traditional generation must be committed and decommitted during the same day. The speed at which a power plant can warm-up and start producing at its maximum capacity is therefore a key characteristic. It should be noted that in this work, we don't consider cold start-up (i.e. the time to warm-up the plant without any power generation) because this can't be seen in the historical data. We only consider the time required to perform a "warm start-up", i.e. the time required to reach full-load from the moment the plant starts producing. This ability is studied in this section. For this reason an algorithm was developed in order to detect the operational start ups and shut downs of the units and to define which was the maximum rate to perform them. The way to deal this kind of problem is rather simplistic but gives a realistic overview of the units performance regarding their ability to respond. The algorithm is implemented in Python and is demonstrated through pseudo-code in Algorithm 2.3.

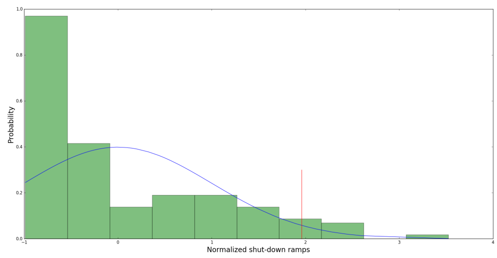
The presented algorithm takes as input the aggregated version of the units to better account for their cyclical capacities. Thus for each plant the yearly power production is scanned. When a start up or a shut down is detected it's size is registered. Then the results are filtered so that

Algorithm 2.3 Ramps On/Off

```
procedure RampOnOffs
    for unit in unitsCluster do
        for t=1 to N do
            if Power(t)! = 0 and Power(t − 1) > 0 then
                rampShutDown=Power(t − 1) − Power(t)
            else if Power(t)! = 0 and Power(t + 1) > 0 then
                rampStartUp=Power(t + 1) − Power(t)
            end if
        end for
        maxRampOn=max(normalDistribution(rampStartUp))
        maxRampOff=max(normalDistribution(rampShutDown))
    end for
end procedure
```



(a) Start-up ramping capacity.



(b) Shut-down ramping capacity.

Figure 2.7: Distributed ramping capacity and 95% confidence level.

the extreme cases are discarded. A normalized distribution is used for the filtering phase as it is illustrated in Figure 2.7. Thus we obtained the maximum rate for starting up or shutting down of every units. In some cases such as for the nuclear or the hard coal plants this information is extremely valuable because it is debatable if these units are able to respond quickly. The results are expressed in percentage of the unit's nameplate capacity per hour (%/hour).

2.3.4 Duration of Commitment and De-commitment

The amount of time that a plant remained active or inactive is a valuable information. It represents the physical characteristics of the units. When a generator starts up it should remain active for at least a certain amount of time. Respectively when a generator turns off it should remain off for a certain duration. It gives a rough overview of how each type of technology is handled by the operators as each power plant is operated in a manner that maximizes the revenues for the company. Thus for instance a nuclear plant usually operates at its nominal power for as long as possible. When a nuclear plant is shut down it is due to maintenance or security issues. On the contrast a fossil gas fired plant performs many cycles during one day as it is preferred to participate in load following operation. This information is thus valuable in the performance of projection using an unit commitment and economic dispatch model because the accuracy of the time needed for a unit to stay committed or de-committed enhances accuracy on the optimization outcomes. Therefore an algorithm to identify the minimum duration that the plants remained active and inactive was developed and is depicted in Algorithm 2.4.

Algorithm 2.4 Duration On/Off

```
procedure DurationOnOff
    for unit in unitsCluster do
        for t=1 to N do
            if Power(t)! = 0 and Power(t − 1) > 0 then
                timeShutDown=TimeStamp(t)
            else if Power(t)! = 0 and Power(t + 1) > 0 then
                timeStartUp=TimeStamp(t)
            end if
        end for
        numOfCycles=len(timeShutDown)
        for n=1 to numOfCycles do
            UpTimes=timeShutDown(n) − timeStartUp(n − 1)
            DownTimes=timeStartUp(n) − timeShutDown(n − 1)
        end for
        minDownTime=min(normalDistribution(DownTimes))
        minUpTime=min(normalDistribution(UpTimes))
    end for
end procedure
```

The presented algorithm takes as input the generation data of the clustered units. Then for each unit it detects the Unix Timestamp that the unit performed a start up and a shut down. The use of the Unix Timestamp facilitates the algebraic operations in order to extract the duration of each commitment status. The number of cycles that the unit performed is calculated as the number of times that the plant was shut down. Thus the durations are collected as the differences between the time stamps that correspond to start up and shut down respectively. The results are indicated in hours and the durations for nuclear units that are less than 5 hours are discarded.

2.3.5 Duration required for the plant to reach 90% of it's nameplate capacity

The ability of a power plant to engage quickly to the system in order to serve the demand especially when there are instabilities cause mainly by the renewable energy sources or the highly fluctuating demand can be evaluated by the amount of time necessary to reach almost the overall nameplate capacity. This size is used to characterize the units as slow or fast responding and it is expected to be higher for nuclear or coal units and low for fast CCGT units. A significant aspect of the activation process are the conditions under which the plants activate. It is considerably different when a generator performs a warm start up in comparison to a cold one as the latter will be significantly longer. The reason is that high temperature and pressure gradients can damage mechanical parts and lead to outages. It is obvious that when a plant is supposed to commit in real time operation, a sudden outage will cause a big unforeseen distortion to the system that has to be balanced under real time conditions. Therefore the time needed for plants to activate is studied in this section. A tailor made algorithm has been developed for this purpose and is illustrated in Algorithm 2.5.

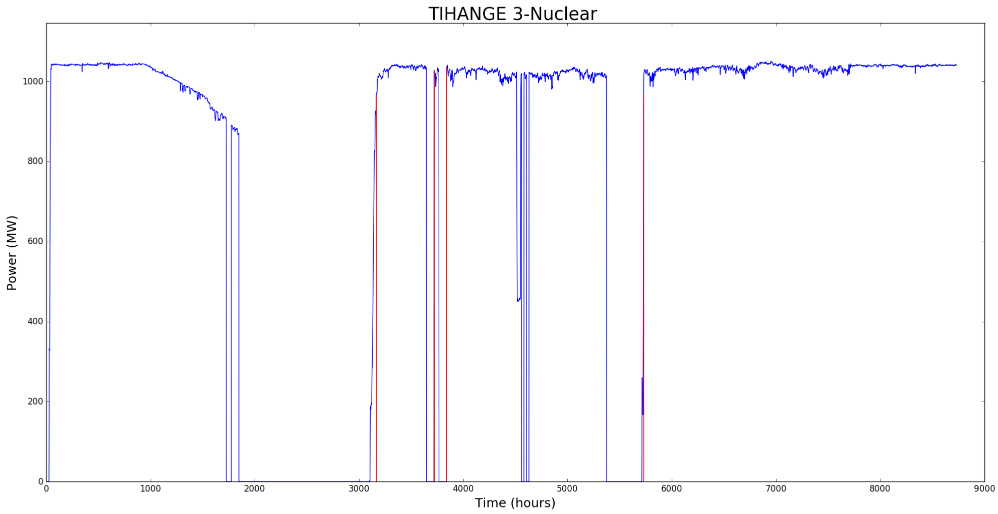
Algorithm 2.5 Duration required to reach 90% of nameplate capacity

```
procedure DurationFor90%
    for unit in unitsCluster do
        for t=1 to N do
            Locate a startUp
            if cold StartUp then
                for k=t to N do
                    find k at which Power = 90%P_N
                    duration=k − t
                end for
            end if
        end for
        minDuration=min(normalDistribution(duration))
    end for
end procedure
```

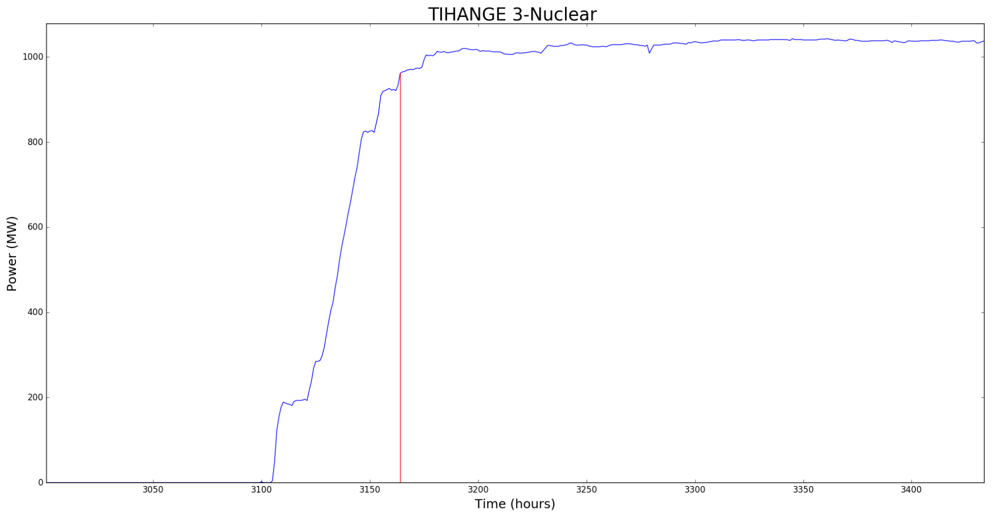
The algorithm presented here is designed to scan the entire yearly generation series of each power plant. Once it locates a start up it has to ensure that it was a cold start especially for nuclear plants and coal plants. A cold start is performed according to [41] when the unit does not operate for 48 to 120 hours. In this case a cold start was considered when the plant was inactive for more than 50 hours. Then the algorithm proceeds in order to identify the time stamp after the start up at which the power output was found to be 90%of the nominal capacity of the plant. It is important to state that the nominal capacity of the plants is either given dy the capacities file from the Entso-e's web site or calculated as the maximum power output of the unit or aggregated units that are investigated. Thus this method succeeds into identifying the amount of time needed for the power plants to reach approximately 90% of their installed capacity. Several representations of this method are demonstrated in Figure 2.9 for a coal plant and in Figure 2.8 for a nuclear plant.

2.3.6 Minimum Operating Load Detection

A supplementary capability to the flexibility provision of the power plants is referred as the minimum operating load. Several studies have investigated this ability of the power plants especially those that are slow and have increased start up costs like the coal plants. In [49] the authors test several scenarios where the penetration of RES is high and investigate the effect of the reduced minimum stable operation limit of coal plants. They show that if the minimum part load of coal units decreases to approximately 40% the RES curtailment is significantly reduced. This study demonstrated also that from the system's point of view the combination of high renewable penetration and lower part load limit decreased significantly the total cost and showed a somewhat linear correlation. What was not expected was that the flexible generators indicated

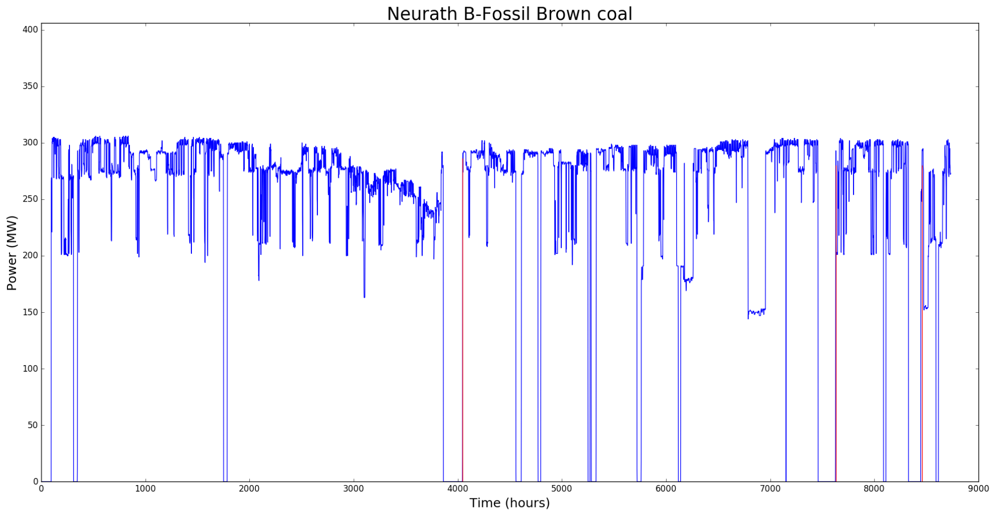


(a) Yearly generation data and cold start detection

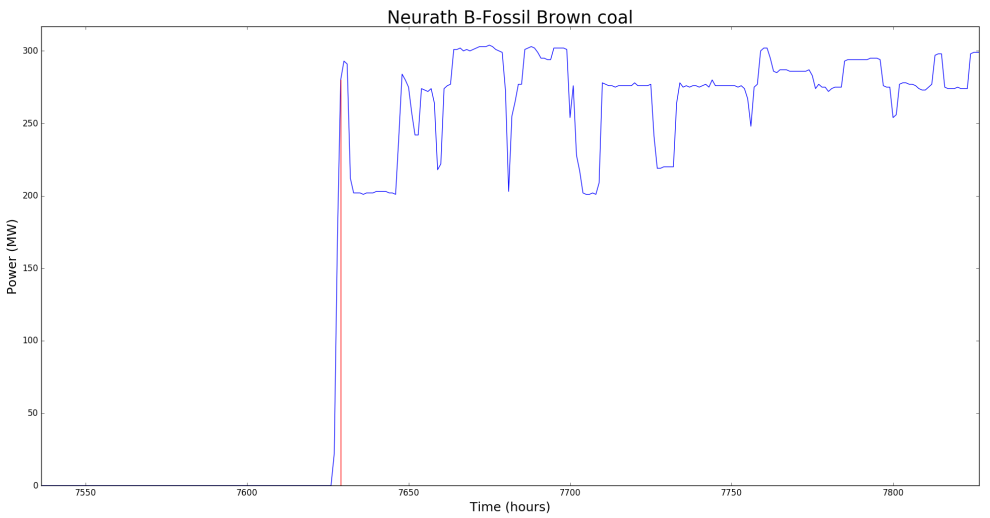


(b) Cold start and duration needed to reach 90% of nominal capacity

Figure 2.8: Duration required for a nuclear plant to reach 90% of it's nameplate capacity



(a) Yearly generation data and cold start detection



(b) Cold start and duration needed to reach 90% of nominal capacity

Figure 2.9: Duration required for a coal plant to reach 90% of it's nameplate capacity

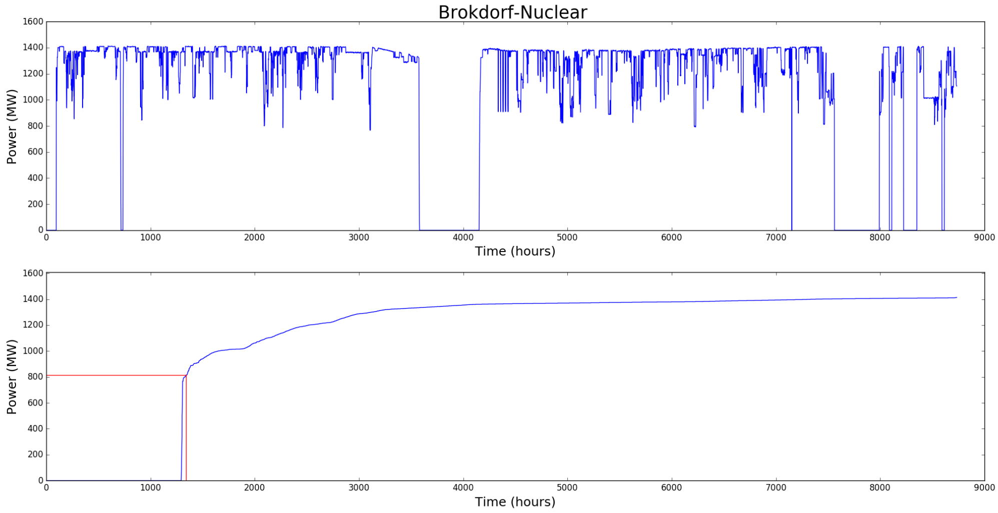
increased revenues due to the decrease in generation costs despite the reduced generation output. A similar study investigated the behavior of flexible coal plants with the addition of thermal energy storage (TES) as remedy to the instabilities introduced by the renewable energy sources [50]. The authors simulate in detail the operation of a coal plant with a retrofitted TES and they conclude that the unit was able to reach at 23% of it's nominal capacity. The goal of this study is to show that conventional units can indeed participate in a more flexible future and still will not get out of business because of the high start up costs in combination with the increased cycling that the system requires.

Thus the idea was to make use of the information from the generation data and try to investigate which is currently the minimum operating load of the plants. The results would give us an overview of what the generators have historically accomplished and how the operators used them to increase their revenues. The different part loads are expected to differ depending on the type of technology of each plant. For that reason a tailor made algorithm was built that is able to detect which is the minimum stable operation level.

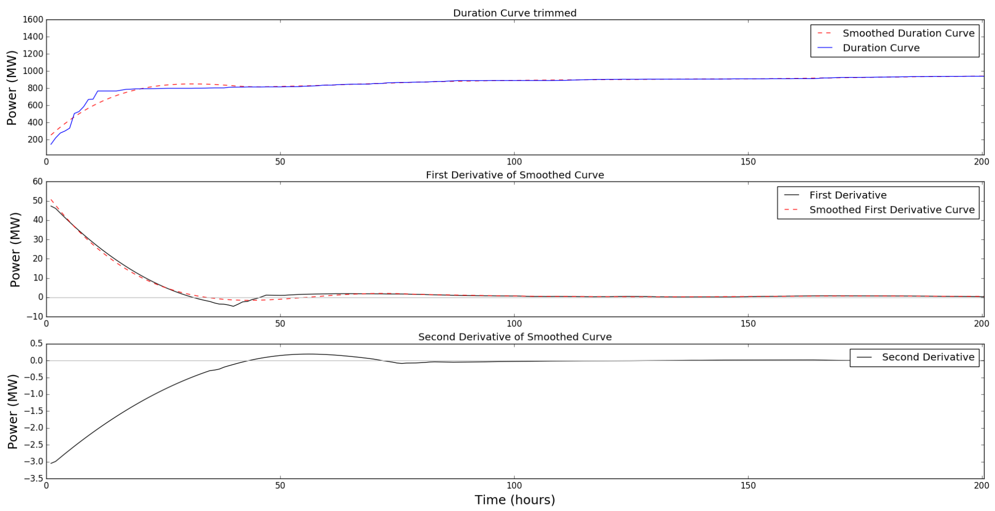
Algorithm 2.6 Minimum stable operation level

```
procedure PartLoadDetection
    for unit in unitsCluster do
        DurationCurve=sort(Power)
        DurationCurve=trim-zeros(DurationCurve)
        SmoothCurve=savgol-filter(DurationCurve)
        Derivative=gradient(SmoothCurve)
        SmoothDerivative=savgol-filter(Derivative)
        SecDerivative=gradient(SmoothDerivative)
        for t=1 to N do
            find t that Derivative= 0 or SecDerivative = 0
            partLoad=Power(t)
        end for
    end for
end procedure
```

The algorithm 2.6 demonstrates how the part load detection is performed. The main goal of this algorithm is to spot the "knee" of the generation Duration Curve (DC) as it is illustrated in the first part of Figures 2.11, 2.12 and 2.10. First the yearly generation data for each plant are sorted in order to create the generation Duration Curve. This curve shows for how long the plant operated at each output level. Afterwards all the zeros are removed. This assists the next process which is the smoothing of the DC. As can be seen the data contain several steps and taking the gradient of this curve would not be efficient. Thus it was first smoothed by using a *Savitzky-Golay* filter. This filter is used in order to remove the noise from the data and it is gradually fitting data with a low order polynomial by the method of least squares. Then the first derivative of the smoothed curve is calculated, smoothened in a similar manner and then differentiated to obtain the second derivative. Thus the part load is the power output at time t when the first derivative becomes zero. If that does not happen then the method resorts to the second derivative and identifies when it turns zero. The reason that we use the second derivative is because the first does not always become zero. If the part load can be detected then the first reaches a local minimum. It must be stated that in several cases the minimum operating level could not be calculated and these cases were discarded. The filtering and derivation of the curves were performed by *SciPy* [51] a scientific package embedded in python.

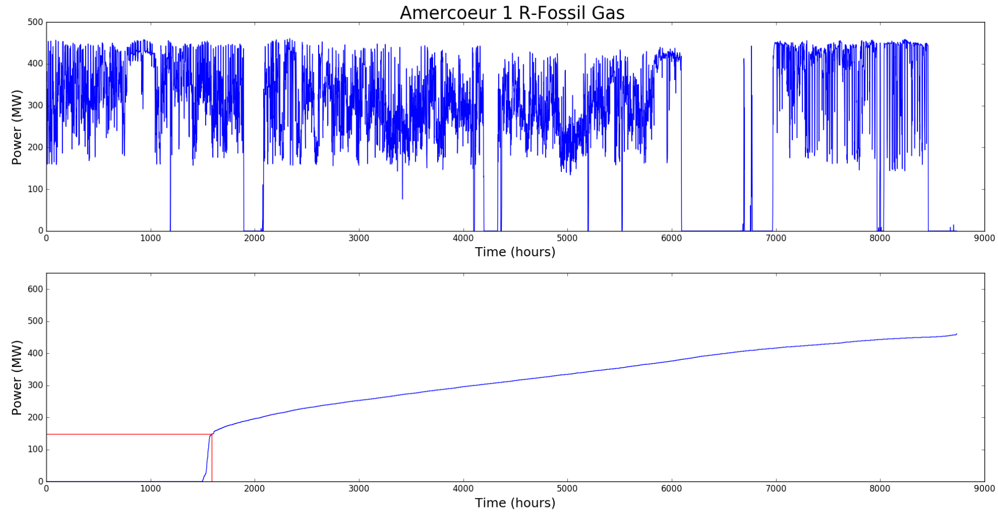


(a) Yearly generation data and Generation Duration Curve

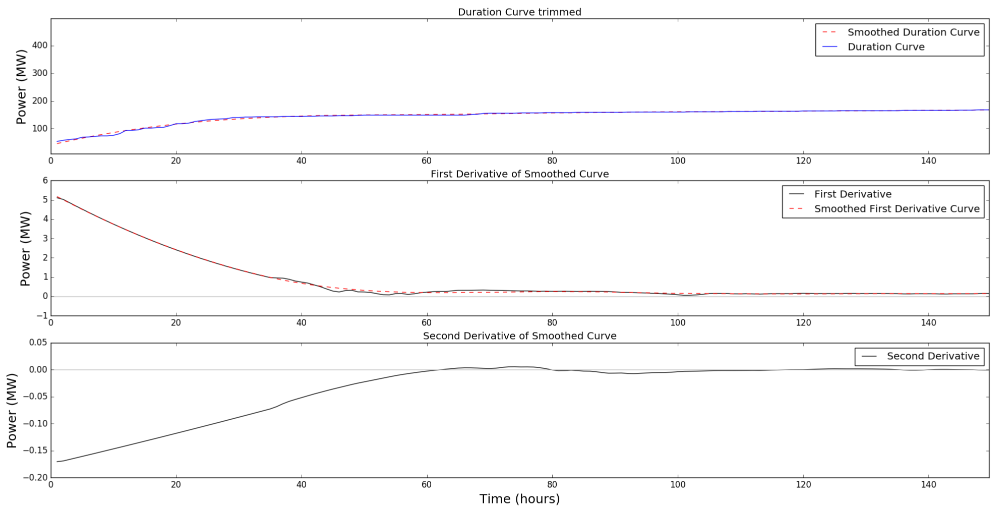


(b) Smoothened Duration Curves and derivatives

Figure 2.10: Minimum stable operating level detection for a nuclear plant



(a) Yearly generation data and Generation Duration Curve

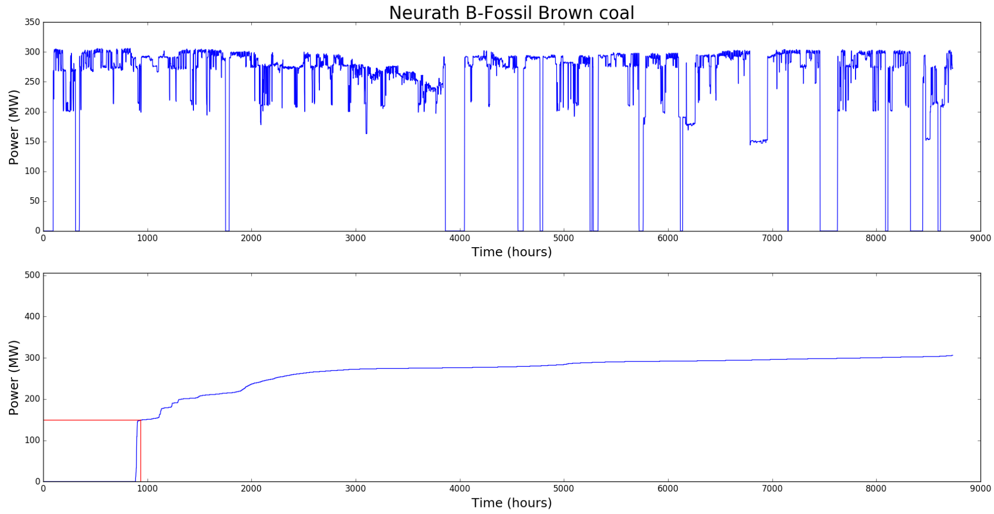


(b) Smoothened Duration Curves and derivatives

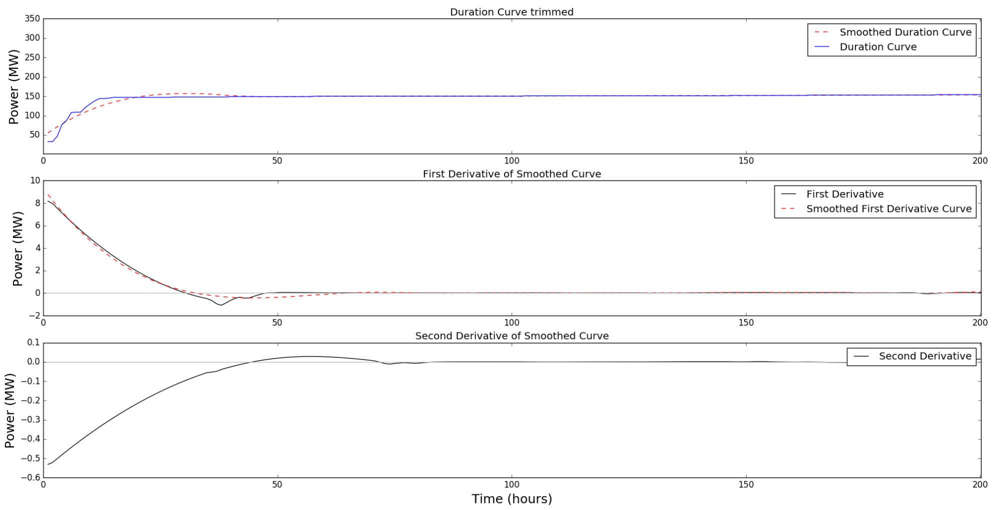
Figure 2.11: Minimum stable operating level detection for a CCGT plant

2.4 Results and Discussion

The results obtained by the implementation of the described methods are discussed in this section. Table 2.3 summarizes the average, the standard deviation and the median of the different parameters for the case of nuclear power plants. Nuclear units are slow units that are not capable to perform fast maneuvers. This is depicted by the low values of the ramping parameters. However they demonstrate in average the ability to reach approximately half of their installed capacity which indicates flexibility considering the dynamics of this type of generators. The consideration of the average value is not always a representative measure especially when dealing with a big number of differently operated units. Therefore the median is used to obtain a clearer picture of how the whole fleet behaved. For instance while the average minimum time that the



(a) Yearly generation data and Generation Duration Curve



(b) Smoothened Duration Curves and derivatives

Figure 2.12: Minimum stable operating level detection for a coal plant

nuclear plants were operating is high the median is significantly low. This can be interpreted in many ways. Several nuclear plants operated for many hours because their design is such and thus they increase the average while others were put in operation for a very short duration. Therefore the median differs significantly from the mean value. This is depicted also by the value of the standard deviation in the sample. On the contrary the duration that is demanded for a nuclear plant to reach 90% of it's nominal capacity is as expected in average 21 hours and agrees up to a certain extent to the median. The number of cycles is in average low as expected and the minimum stable load is around 60%.

A similar behavior was realized in general by the coal units. This type of power plants show low abilities in ramping due to the slow dynamics. The response of such a unit depends also on

Table 2.3: Results for Nuclear Plants

	maxRampDown (%/h)	maxRampUp (%/h)	maxRampShutDown (%/h)
Mean	24.18	15.10	94.60
STD	12.66	7.31	19.54
Median	21.28	14.72	99.04

	maxRampStartUp (%/h)	minDownTime (h)	minUpTime (h)
Mean	49.87	379.46	166.14
STD	44.42	1421.04	697.92
Median	28.02	6.00	6.00

	minDurationTo90% (h)	numOfCycles	partLoad (%)
Mean	21.48	22.00	62.06
STD	16.32	33.25	24.82
Median	16.00	7.00	56.94

the size of it but the numbers indicate higher ramping in start up processes than nuclear units in average at about 60%. Their ability to change their output in a quicker manner than the nuclear units is illustrated by the duration necessary to reach 90% of their nominal capacity that is significantly lower. Finally it can be seen that the high number of cycles is an index for the system requirements for the past year. Another significant result is that the coal plants operated part loaded in average at 47% of their capacity which shows the intension of their operators to keep them active even with a lower efficiency rather than shut them down.

Table 2.4: Results for Coal Plants

	maxRampDown (%/h)	maxRampUp (%/h)	maxRampShutDown (%/h)
Mean	29.46	23.73	77.51
STD	11.56	8.23	23.89
Median	28.30	22.98	87.04

	maxRampStartUp (%/h)	minDownTime (h)	minUpTime (h)
Mean	59.60	80.99	51.90
STD	31.35	485.99	330.25
Median	65.14	3.00	5.00

	minDurationTo90% (h)	numOfCycles	partLoad (%)
Mean	4.96	25.43	47.01
STD	9.37	26.37	14.31
Median	3.00	19.00	48.29

Finally the results for the gas power plants are demonstrated in Table 2.5. At this point it must be stated that the dynamics of the CCGT plants allow them to perform a wide range of operations depending on the way each company chooses to manage them. The abilities of these plants have a lot fewer limitations and are not depicted by the results in the following table. For instance the minimum duration needed for such a generator to reach 90% of it's nominal capacity is around 2 hours. Thus the resulted 3 hours indicates that these units are used for load following operation and thus in many scenarios it was not necessary to reach this output level. However the increased number of cycling in average around 50 is a clear index for the manner that these units are operated. A significant number obtained was the minimum stable operation level that was found in average around 45% and the median being 40%. This is a clear indication that these units are able to decrease a lot their level in order to facilitate the flexibility provision and will act as such in the future.

The methods and results provided in this section represent a first attempt to evaluate a big amount of generation data provided by the Entso-e Transparency Platform [39]. The main motivation for this research was the need to create more realistic projections for a clean energy future with more renewable energy sources integrated. The results obtained will improve the performance of simulations by using Dispa-SET an optimal dispatch tool that will evaluate the impact of high RES penetration in the current power system and will quantify the impact of it on the current fleet of power plants. Thus the collection and processing of the generation data contributes highly to the better understanding of the power plants operation and to the detection of the changes that will incur in the future and the role that each generation technology will play.

Table 2.5: Results for Fossil Gas Plants

	maxRampDown (%/h)	**maxRampUp (%/h)**	**maxRampShutDown (%/h)**
Mean	36.91	28.79	58.59
STD	19.11	15.86	28.82
Median	31.24	24.34	61.90

	maxRampStartUp (%/h)	**minDownTime (h)**	**minUpTime (h)**
Mean	36.87	71.61	30.18
STD	28.25	558.03	172.76
Median	30.32	2.00	2.00

	minDurationTo90% (h)	**numOfCycles**	**partLoad (%)**
Mean	6.61	49.64	45.89
STD	13.18	51.72	18.04
Median	3.00	35.00	40.37

CHAPTER 3

Quantification of the flexibility potential from Thermal Energy Storages

The present chapter describes the approaches followed in order to quantify the flexibility potential arising from the use of Domestic Hot Water Tanks (DHWT). First the role of Thermal Energy Storages (TES) is underlined as Demand Side Response (DSR). The thermodynamic modeling of the DHW tank is explained and used in two control strategies. A Rule Based Control strategy is used to simulate the power consumption of a fleet of tanks. This case will act as the worst case scenario because no forecast ability is considered. Afterwards the same case is formed as a Linear Program (LP) optimization problem. This scenario represents the best case as perfect prediction is assumed for the hot water consumption from the beginning of the simulation. In both cases the provision of several responses to the system's requirements are performed and the different strategies followed are evaluated. The goal of this approach is to identify in detail the behavior of a fleet of DHW tanks in certain circumstances. Thus would assist in the modeling of a big storage unit and it's interaction with the system.. A third and more realistic approach would be to use Model Predictive Control but the implementation would be time consuming and out of the limited time available for this thesis.

3.1 The role of Demand Side Management in Balancing Mechanisms

In order to ensure balance and stability of the system the Transmission System Operator (TSO) has established a balancing mechanism which provides power reserves used for the elimination of the imbalances that occur. These power reserves are provided by the grid users and are compensated by the Area Responsible Parties (ARPs) that caused the imbalances. These mechanisms also referred as ancillary services and specific markets are organized to cover this need. The TSO computes the optimal amount of ancillary services necessary to ensure stability to the grid and contracts both the *capacity reserves* and *activation reserves.* The participants are able to trade and be compensated for providing their *capacity* in $€/MW$/hour of availability. Then in case of *activation* depending on the direction (upwards or downwards) a settlement takes place. For upwards activation the TSO pays the participant the amount of modulation in the price that was requested. Alternatively the participant pays respectively an amount to the TSO in order to reduce it's output. Reserves were provided so far by conventional generators and big industrial loads that were contracted and adjusted their output per request in order to resolve the imbalances. With the development of advanced metering devices the *smart meters* the participation of distributed energy sources (DER) in ancillary services was enabled. The distributed energy resources comprise generation, storage and demand response units connected to the distribution system. Thus flexibility provided to the TSO can be the product of the aggregation of several grid users such as domestic loads.

This new type of ancillary services is provided under certain regulations imposed by the TSO in order to maintain the safe and secure operation of the system. In the case of capacity reserves a specific amount is required from the TSO at all times. Therefore the contracted capacity must be available at all times guaranteeing 100% availability by the aggregator. The metering equipment must be officially validated and necessary analysis about the grid impact of each participant's activation must be performed. The settlement process is validated through 15 min data provided by the aggregator. In the case of activation the contracted volume must be available 15 minutes after the request and further regulations regarding the timing and the duration of the activation are considered. For instance the activation requests are performed per quarter of an hour and should have maximum duration of two hours. The number of activations is also limited by the TSO (maximum of 40 per year, maximum of 8 per month).

This context is studied in the present modeling approach. The interactions between the different market players are illustrated in Figure 3.1. The aggregator sells capacity reserve either upwards or downwards to the system and gets compensated. This commitment must be fulfilled at all times. In case there is a balancing need the system sends a signal to the aggregator for upwards/downwards activation reserve in order to balance it's position. Then the aggregator would control his contracted capacity to provide this reserve. The Flexibility Request Party (FRP) is at a certain point *short* (deficit) or *long* (surplus) and requests for flexibility from the Flexibility Service Provider (FSP) in order to balance it's perimeter [52]. The imbalances that occur in case the retailer and the Flexibility Service Provider belong to a different Balance Responsible Party (BRP) are settled in the Hub. However this renumeration is out of scope for the present thesis. This kind of interaction is studied in the present modeling attempt where we assume first that the aggregator needs to contract a certain amount of capacity to the system. Afterwards he receives a power signal and is responsible to follow this signal by adjusting the consumption of it's portfolio. The financial interactions between the different market players are not considered in the present study because the goal is to integrate a charging/discharging strategy based on the fleet's physical requirements. We choose to form our problem as such because a big number of studies have dealt with this issue by evaluating the Demand Side Response potential by investigating different tariff structures. These studies have proven the need for financial incentives and thus we focus here on the physical aspect of flexibility provision.

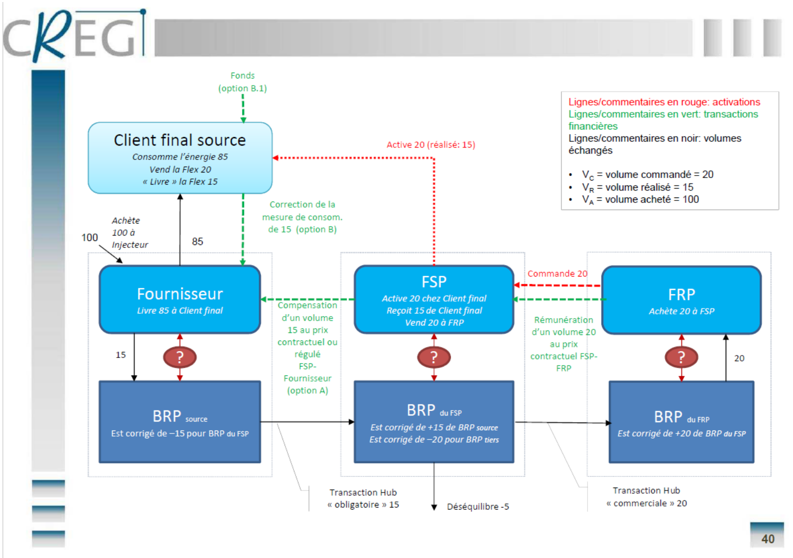


Figure 3.1: Interactions between the market players for flexibility provision. [52]

3.2 The role of Thermal Energy Storages (TES) in Demand Side Management (DSM)

Thermal Energy Storage technologies have drawn increased attention in the last decades and have become a powerful DSM tool especially because recent studies indicate that battery storage options are not yet financially profitable [53]. By taking advantage of the thermal inertia of those systems the user is able to store energy when the price is low and thus avoid the consumption of expensive energy while perfectly meeting his demand. TES are used to shift parts of the electrical loads to off-peak hours and enable the more efficient use of the existing generation capacity. TES technologies can be heating, cooling or vaporizing processes and they can be charged by consuming an amount of energy and discharge at a later time when this energy is consumed.

The impact of TES is usually studied in space heating applications. The coupling of a heat pump with a Domestic Hot Water Tank (DHWT) as a storage solution is investigated in numerous cases [24], [26],[28] in building applications as can be seen in Figure 3.2. Usually hot water buffers are considered stratified where the water forms layers with different temperature levels. This modeling is used to simulate the water's behavior when the hot water climbs on the top of the tank and the cold stays at the bottom. The water in-between evolves gradually and forms the thermocline. The shape of the tank as well as other constructional characteristics play a key role to the efficiency of the thermal storage. For high temperature applications such as space heating and domestic hot water provision costly insulation is necessary in order to increase the efficiency of the tank's performance.

In the present study the ability of smart Domestic Hot Water buffers to provide demand response to the system is considered. DHW tanks consuming electrical power will be used to evaluate the impact of DSM strategies to the total system cost. For this purpose the operation of DHW tank

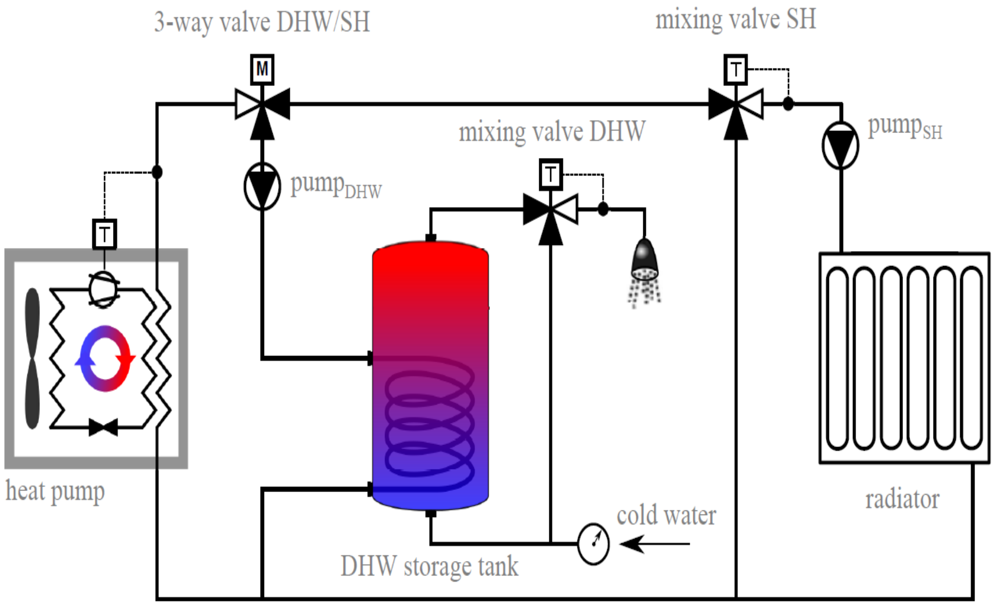
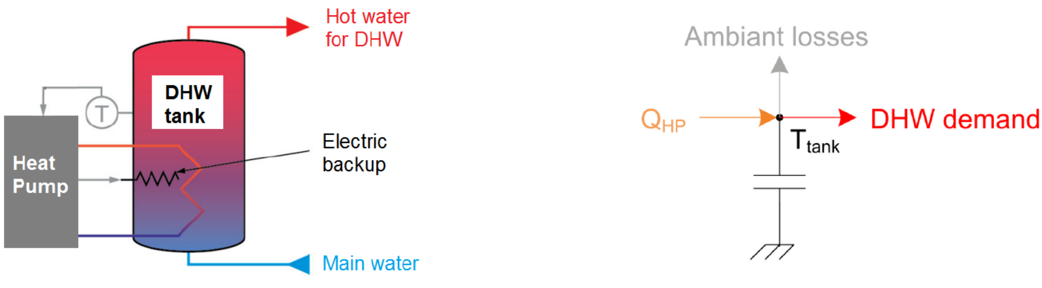


Figure 3.2: Heat pump coupled with DHWT [28]

is simulated in detail. Afterwards the aggregation of several thousands of tanks is performed and the results are analyzed. The ability of a fleet of tanks to perform peak shaving is examined in order to identify the limitations and the potential of such a strategy. For this study the modeling of the DHWT was done using a unified storage model without stratification. Although this approach tends to the reduce the accuracy, it was followed because it highly reduces the computational requirements as each node introduced increases the state-space order. Taking into account that the goal is to simulate thousands of tanks the resulting inaccuracies are not considered to be significant. The model that was used for the simulations is described in the following section.

3.3 Domestic Hot Water Tank model

The representation of the tank used in the context of this thesis is a unified model that assumes a perfectly uniform temperature profile across the whole tank. The main reason for this choice is the computational complexity that would arise when using a more detailed multi-node model for thousands of tanks. Therefore this compromise was done to surpass the computational limitations of the stratified tank model. The one-node representation of the tank is illustrated in Figure 3.3. As can be seen in Figure 3.3 b) the DHW tank is assumed to be a capacitor with one temperature node. The power inputs assumed will be the electric power coming from the heater. The power outputs consider are the ambient losses of the tank and the hot water consumption.



(a) Schematic **(b)** Electrical equivalent

Figure 3.3: Representation of unified (one-node) Domestic Hot Water tank. [11]

The energy balance across the homogeneous tank can be written as a first order differential equation (3.1). Euler integration yields Equation 3.2. Equation 3.2 is used to simulate the temperature evolution in a tank if the ambient temperature (T_{amb}) and the hot water consumption ($\dot{m}_w$) are given. The heat transfer coefficient (UA_{tank}) is calculated as a function of the tank's volume, the specific heat of water (c_w) is considered as $4187 J/kgK$ and the temperature of the intake of fresh water (T_{main}) is assumed to be 10 °C.

$$C_{tank}\frac{dT_{tank}}{dt} = P_{heater} - UA_{tank}(T_{tank} - T_{amb}) - \dot{m}_w c_w (T_{tank} - T_{main}) \tag{3.1}$$

$$T_{tank_t} = \frac{(\frac{C_{tank}}{\Delta t} - \frac{UA_{tank}}{2} - \dot{m}_w \frac{c_w}{2})T_{tank_{t-1}} + P_{heater} + UA_{tank}T_{amb} + \dot{m}_w c_w T_{main}}{\frac{C_{tank}}{\Delta t} + \dot{m}_w \frac{c_w}{2} + \frac{UA_{tank}}{2}} \tag{3.2}$$

The yearly hot water consumption for each household is assumed to be known and is created by the following stochastic process. In the context of this thesis 50 yearly typical hot water consumption profiles with a 15 min time step were used. Each profile represent the hot water that one occupant consumes and is constructed by a statistical process. The number of occupants for a household is considered as a statistical size that has an average of 3 and a standard deviation of 2. Thus in order to construct a yearly hot water consumption profile first the number of occupants is randomly chosen by the aforementioned method and then for each occupant one profile out of the 50 was chosen randomly. The household's overall consumption is thus the cumulative summation of the randomly picked profiles. This method aims to introduce stochasticity in the way the total consumption is formed. Towards this direction a more random procedure was selected. Instead of randomly picking one yearly profile out of the 50 prototypes a method was built in order to pick each day of the year randomly out of the 50 profiles. For instance to create the profile for one occupant each day was randomly selected by the 50 files. Again it should be stated that the reason for this approach is to introduce as much randomness as possible.

3.4 Rule-Based Control model

In this section the development of a rule-based control is described. The main target of this method is first the simulation of power requirements of a fleet of tanks, to formulate the so-called *baseline*. Afterwards the power consumption of this portfolio will deviate from the calculated *baseline* in order to respond to a modulation signal. Thus the deviation from the baseline either upwards or downwards defines the terms *off-take* and *injection* [26]. In this thesis we assume that there is an entity that centrally controls the fleet of tanks (aggregator) when there is a modulation signal. Otherwise the tanks are acting autonomously. It should be stated as a reminder that this type of control acts in no way preventively and respond to a disturbance after it happens. In our case the disturbance would be a decrease of the tank's temperature due to ambient losses or hot water consumption.

3.4.1 Baseline computation

For the formulation of the DHWT fleet's baseline what we seek to create is a transformation of the hot water consumption into electrical power or energy consumption. For this reason a rule based model was created. The nature of such control strategy entails no means of prediction. The control acts only after an incident that violates an imposed constraint, has occurred. In our case the variable we try to control is the tank's temperature. The way to adjust the temperature is through the provision of power via the electrical heater. We assume a number of tanks N and a simulation period of n_{days}. The necessary data for the hot water consumption of each household are obtained by the process described above and the simulation time step considered is fifteen minutes ($\Delta t = 900sec$). Finally the ambient temperature is considered as constant because it was assumed that the tank is usually at a basement with generally constant temperature $T_{amb} = 15$ ℃.

The method that was followed is presented in Algorithm 3.1. First the initial conditions for all tanks are set. The temperature at time step zero is set as a random number to enhance stochasticity in the simulation of the fleet. Then the method loops in time and for each tank the condition regarding it's previous temperature is checked. If previous temperature is lower than a set-point then power is given by the heater. Otherwise no power is given. At each step the temperature is upgraded using the function $DHWT$. This function represents the equation 3.2 and takes as inputs the power from the electrical heater, the temperature level at the previous step and the hot water consumption. Thus the whole period is simulated for all the tanks.

It is important at this point to state the way the power from the heater is calculated. We assume that the maximum power output of each heater is $P_{heater_{max}} = 4kW$ and that the heater can switch on and off multiple times during the time step. Thus we solve the linear equation 3.2 and find which power output will result in the temperature set point plus a dead-band of $\Delta T = 5$℃. Thus at each time step the power consumption is defined as $P = max(4kW, P_{T=T_{set}+\Delta T})$. Finally the command setBounds(t) is performed at each step and it is used to determine the minimum and the maximum amount of power that the portfolio can or should accept. It is mostly used when the fleet is participating in reserve provision. The maximum amount of power that the fleet can receive is defined as the minimum between the summation of the $P_{max} = 4kW$ of the individual tanks and the summation of the power that the tanks can receive in order to reach the constraint of $T_{max} = 95$℃. This technical constraint is imposed for the safe operation of the tank in order to avoid evaporation. In other words the upper power limit is at each step defined as $P = min(sum(P_{heater_{max}}), sum(P_{T=95}))$. The minimum amount of power that the fleet needs to consume is derives as the summation of the individual power that each tank needs to maintain it's temperature level at $T_{min} = 45$°C. This constraint is imposed in order to maintain comfort levels of the users. However it was noticed that for several cases due to the increased hot water consumption in combination with the ambient losses the temperature decreases below the limit $T_{min} = 45$°C. This issue arises for two reasons. The inaccuracy of the one-node model along with the non preventive a posteriori actions of the specific control type result this undesired behavior. This approach though can be considered realistic as sometimes the increased demand can lead to significant temperature drops in the tanks.

Algorithm 3.1 Rule Based Control-Baseline computation

procedure BASELINERBC(N, n_{days})
  $T_{tank_0} = randnum(45, 70)$
  for $t = 1$ to n_{days} **do**
    setBounds(t)
    for $tank = 1$ to N **do**
      if $T_{tank_{t-1}} < T_{set}$ **then**
        $P_{heater} = P$
      else
        $P_{heater} = 0$
      end if
      $T_{tank_t} = DHWT(P_{heater}, T_{tank_{t-1}}, \dot{m}_w)$
    end for
  end for
end procedure

The results of the presented algorithm are illustrated in the following graphs. The evolution of the temperature, power and hot water consumption is shown in Figure 3.4. As can be clearly seen the control keeps the temperature close to the predefined set-point but at some points there is a further decrease of the temperature due to the increased hot water demand and the nature of this control strategy. The power consumption of a portfolio that is comprised of 10000 tanks is demonstrated in Figure 3.5. As can be seen, the energy demand profile presents two peaks during the day, one in the morning and one in the evening. The evening is characterized by a reduced amplitude compared to the morning one. Another significant fact is the repeated pattern for each day except the weekends. In Figure 3.5 the upper and lower limit of the power consumption for each step is shown as boundaries. The power between the consumption (black line) and the upper limit (green line) could be thought as the capacity for downwards reserve that an aggregator that controls this portfolio of tanks could contract. Similarly the distance between the consumption (black line) and the lower limit (red line) would be the downwards capacity reserve.

3.4.2 Demand Response

In this section the ability of this fleet to participate in Demand Side Response is evaluated. The goal of the current modeling approach is to investigate the physical limits that a portfolio of DHW tanks has and to develop strategies for the charging and discharging while providing flexibility to the system. Thus we assume that the system has several requirements and the fleet that is

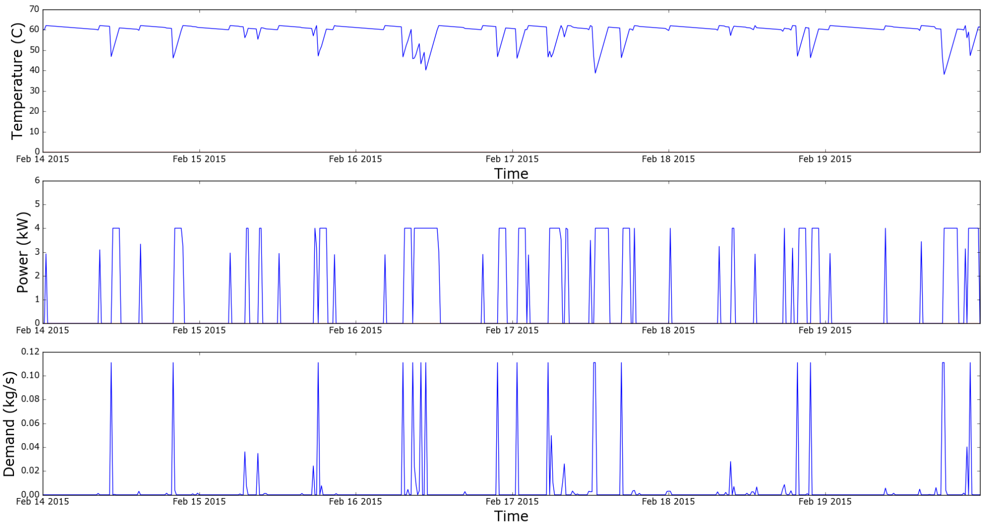


Figure 3.4: Temperature, power and hot water consumption profiles for a DHWT under rule-based control.

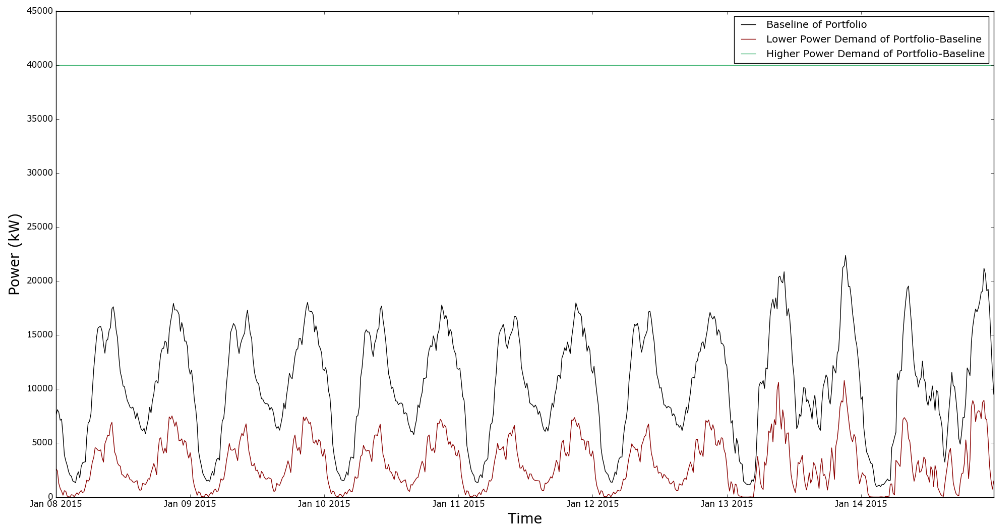


Figure 3.5: Baseline calculated for 10000 tanks and upper/lower power limits.

centrally controlled by an entity (the aggregator) tries to fulfill them by respecting the physical and thermal constraints as they were presented in the previous section ($T_{max} = 95$℃,$T_{min} = 45$℃).The aggregator contracts capacity reserves to the system as explained in section 3.1 and in case there is an activation signal the aggregator follows this request by controlling it's portfolio.

Algorithm 3.2 presents the way the demand is assumed to respond to an external signal from the system. To simulate this kind of control a Priority Stack based algorithm is use in case of reserve provision. Thus each tank consumes power according to Algorithm 3.1. When the

Algorithm 3.2 Rule Based Control-Demand Response

```
procedure DemandResponseRBC(N, n_days, baseline)
    T_tank_0 = randnum(45, 70)
    Define flexSignal
    for t = 1 to n_days do
        setBounds(t)
        if flexSignal(t) = 0  then
            for tank = 1 to N do
                if T_tank_{t-1} < T_set then
                    P_heater = P
                else
                    P_heater = 0
                end if
            end for
        else
            PowerAvailable = baseline(t) + flexSignal(t)
            MaxLevel = sum(UpLimit_tank(t))
            MinLevel = sum(DownLimit_tank(t))
            if PowerAvailable > MaxLevel then
                PowerAvailable = MaxLevel
            end if
            if PowerAvailable < MinLevel then
                PowerAvailable = MinLevel
            end if
            sortTanks(T_tank_{t-1})
            while PowerAvailable > 0 do
                if PowerAvailable > 4kW then
                    P_heater = 4kW
                else
                    P_heater = PowerAvailable
                end if
                PowerAvailable = PowerAvailable − P_heater
            end while
        end if
        T_tank_t = DHWT(P_heater, T_tank_{t-1}, ṁ_w)
    end for
end procedure
```

aggregator receives an activation signal upwards/downwards the tanks are sorted according to the temperature level in the previous step and each one receives an amount of power. The power that is available to be distributed to the tanks is considered as the previously computed baseline plus the system's signal which can be negative (upwards reserve) or positive (downwards reserve). However the power that is available for the tanks at each time step is bounded by the upper and lower limit that is computed at the beginning of each step. The process to calculate the bounds is described earlier and is a measure to avoid extreme increase or decrease of the temperature level in the tanks. Therefore in case the power that is assigned to the tanks is more (less) than the maximum (minimum) allowed power limit then the maximum (minimum) power is consumed. The priority stack based algorithm is considered to be a fair manner to distribute the available power because the tank with the lowest temperature is receiving power first. Finally the power that was decided in case of normal operation or demand response is assigned to each tank and the next step's temperature is calculated taking into account the previous temperature level and the hot water consumption.

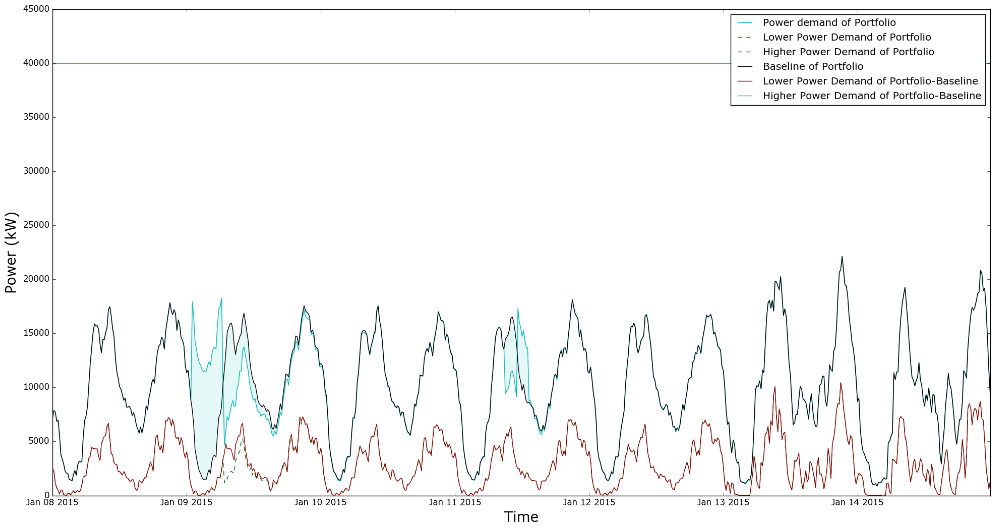
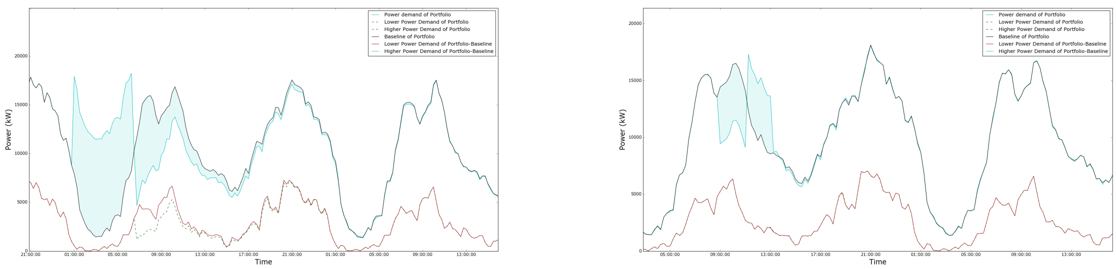


Figure 3.6: Demand response to flexibility signals of 10000 tanks.

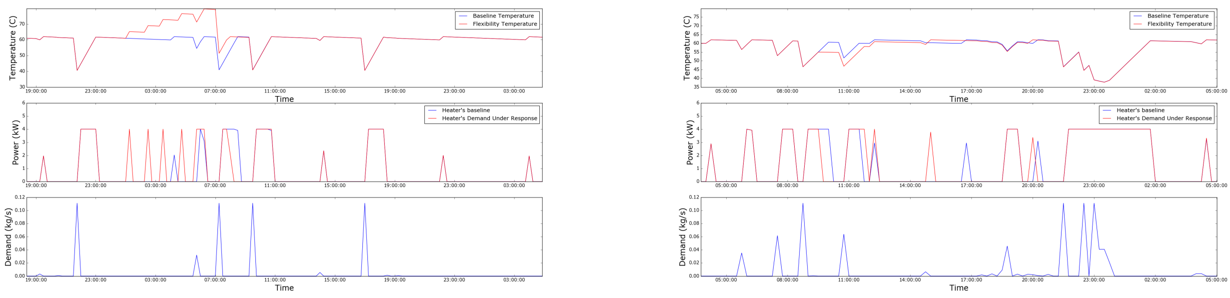


(a) Upwards activation reserve provision

(b) Downwards activation reserve provision

Figure 3.7: Valley-filling and peak-shaving with demand response.

The impact of an activation signal to a portfolio of 10000 hot water tanks is evaluated in Figure 3.6. The power consumption for a week is investigated and two signals one for downwards and one for upwards are provided. In the first part the fleet is asked to increase it's consumption by 10MW for about four consecutive hours. Afterwards an upward activation of 5MW is requested for two hours. The choice of time is not random but it was done in order to demonstrate that the tanks can change their consumption pattern and maintain the same level of service to the users. Therefore an increased consumption during early morning hours or a decreased consumption during peak hours would have the desirable effects for the system as illustrated in 3.7. The *rebound effect* is demonstrated by Figure 3.6. As can be seen when the fleet of tanks is requested to increase (decrease) it's consumption for a period it will need to consume less (more) for the next period. In [26] the authors highlighted the impact of the payback horizon to the activation reserve capacity. They concluded that the longer the horizon is the higher the flexibility activation can potentially be. In this case we notice that slight deviations from the



(a) Upwards activation reserve provision

(b) Downwards activation reserve provision

Figure 3.8: Comparison between baseline and flexibility temperature, power and hot water consumption profiles for 1 DHWT.

baseline occur even days after the activation and that the available margins are affected only by the state of charge (SoC) of the tanks. In the case of rule-based control though the constraining of the payback horizon is not possible. It is in the nature of this type of control to face an event only after it has occurred based on several conditions. It can be also observed in Figure 3.7(a) the lower bound has been reduced. This occurs because of the reduced need of the fleet for power after an upwards modulation from it's baseline.

The effect of the modulation into the DHW tank's evolution of temperature is demonstrated in Figure 3.8. In the case of downwards activation (3.8(a)) an increased temperature level is noticed and by making use of the thermal inertia of the tank there will not be need for charging at a later time step. For the case of upwards activation (3.8(b)) the tanks postpone the charging phase. We should highlight at this point the importance of the ambient losses that have a significant role especially for high temperatures. Therefore the amount of energy that is consumed in the event of a modulation signal differs from the energy retrieved at the rebound phase and this difference is attached to heat losses.

The computational complexity of the RBC implementation was not extremely high. Thus the problem was solved for about 20000 individual tanks in about ten minutes. The algorithm was highly parallelized at time steps that there was no activation signal. Each tank's profile was handled in parallel and when an upwards or a downwards modulation was requested the priority stack algorithm was serially performing the computations for each tank as explained. The parallelization enabled the fast calculations of several thousands of tanks. However the limitation of such an implementation was introduced by memory. Therefore incorporating more tanks was not possible due to memory limitations but valuable conclusions were extracted by the increased number of tanks and reasonable time that this algorithm allowed.

3.5 Optimal Control model

In the following section the development of an optimal control model in order to simulate the behavior of a portfolio of flexible domestic hot water tanks is described. A linear optimization program (LP) is formed and solved first to compute the baseline and afterwards the response to a system's signal. The outcome of this modeling approach can be considered as the best case scenario because the control is assumed to have perfect knowledge of the several parameters beforehand. This is the main difference between this type of control and the Rule-based control. Thus the aggregator that controls this fleet possesses an accurate forecast of the hot water consumption of each household. The hot water consumption is computed in the same way described in section 3.3. The problem is formulated in two stages. In the first stage the baseline of the portfolio along with the individual temperature and power profiles is computed. Afterwards a new problem is solved in order to evaluate the flexibility that can be offered by the consumers both for capacity and activation reserves.

3.5.1 Baseline computation

For the computation of the power consumption of the whole fleet of hot water tanks a linear optimization is formulated. The objective of this model is to minimize the total consumer's cost while maintaining the individual tank's temperature between the predefined limits. Similarly to the previous model each tank is modeled as an one-node capacity model with homogeneous temperature. Ambient losses and hot water consumption are considered the factors that drain energy from the tank. The formulation of the model is described by equations 3.3 - 3.6.

$$\min_{P,\epsilon} \sum_{t \in T c \in C} P_{c_t} \pi_t dt + VOLH \epsilon_{c_t} \tag{3.3}$$

subject to:

$$T_{c_t} = f(P_{c_t}, T_{c_{t-1}}, \dot{m}_{c_t}) \qquad \forall t \in T, \forall c \in C \tag{3.4}$$

$$T_{min} - \epsilon_{c_t} \leq T_{c_t} \leq T_{max} + \epsilon_{c_t} \qquad \forall t \in T, \forall c \in C \tag{3.5}$$

$$0 \leq P_{c_t} \leq P_{max} \qquad \forall t \in T, \forall c \in C \tag{3.6}$$

The objective presented in Equation 3.3 is to minimize the total cumulative operating cost of all the fleet and to restrict the deviations (ϵ_{c_t}) (upwards or downwards) from the predefined comfort limits except in certain cases which is necessary. Thus a constant parameter with a high value is used to penalize these deviations $VOLH$ - value of lost heat. It is a term that is used to reflect the discomfort of several periods during the simulation when the hot water consumption is high and the tank's temperature is significantly low. Equation 3.4 is the state-space formulation of the differential equation 3.1 and is used to describe the transitions of each tank at each time step. The term T_{c_t}, represents the temperature of each tank c at each time step t of the simulation's period. The temperature variable is constrained to be between an upper and a lower limit which are defined to ensure the supply of hot water at equation 3.5 and the variables ϵ_{c_t} are used to relax this constraint in case the hot water consumption is too large. The electric power supplied by the heater is denoted as P_{c_t} and is bounded (equation 3.6) to be nonnegative and less than $4kW$ which is the maximum assumed output of the heater. The time step for the simulations is fifteen minutes ($\Delta t = 900sec$) and the optimization horizon is 7 days. Due to memory restrictions which will be discussed later in this document the number of tanks that can be simulated are around one thousand.

The temperature power and hot water consumption profiles for a weekly simulation of a household are presented in Figure 3.9. As far are the temperature level is concerned the limits are set to $T_{min} = 55$ ℃,$T_{max} = 65$℃. The strategy of the optimal control is maintaining the temperature of the tank at a minimum level to minimize the losses and the power consumption. When a high consumption is foreseen the control is increases (charging) the temperature of the tank in order to end up at the end again at the minimum level. At time steps with extreme consumption the

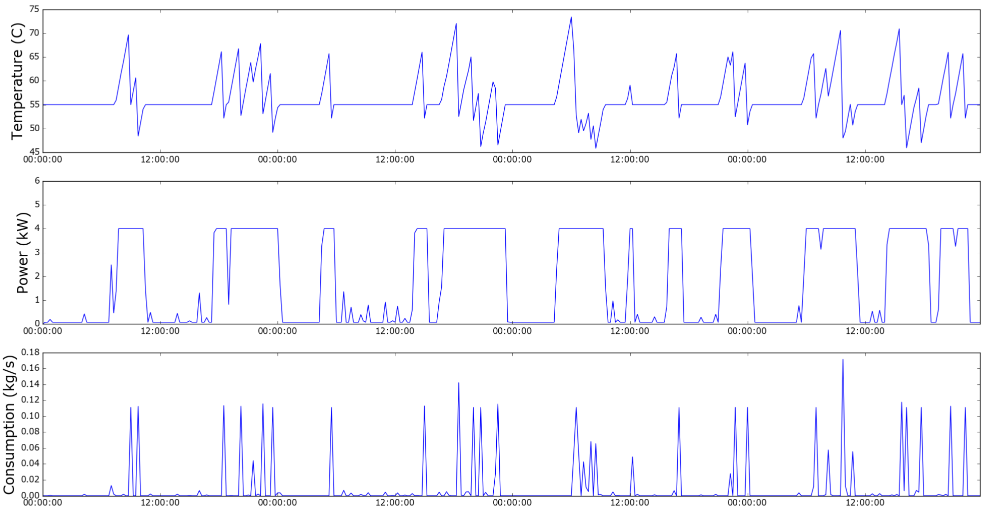


Figure 3.9: Temperature, power and hot water consumption profiles of one DHWT under optimal control.

control uses the relaxation of the temperature limits. Thus we can notice that at several steps the temperature exceeds the upper or lower limits that were predefined. The behavior of the control is affected also by the maximum power output which is set to $P_{max} = 4kW$.

The baseline of a portfolio that is comprised of 1000 tanks is illustrated in Figure 3.10. The fleet's power consumption has two peaks during the morning and the evening. Thus the optimal control strategy acts predictively and charges the tank before the hot water consumption is realized. The difference between this type of control and the rule-based is the time step of the reaction. At Figure 3.10 the different reaction time between the baseline of optimal and the rule-based control is illustrated. The power levels appear to be similar for the two approaches however the rule-based approach will react to the presence of hot water consumption only after it occurs because there is no prediction happening.

3.5.2 Demand Response

In order to evaluate the abilities of a centrally controlled fleet to provide reserves a second stage of optimal control was investigated. In this model the previously computed baseline is considered and the portfolio is responsible to track a signal. The system requests from the portfolio to follow an activation signal and modulate from it's baseline either *upwards* or *downwards*. The potential and the cost at which such a fleet is able to provide capacity reserve is investigated. The interactions between the aggregator and the system's participants are considered as described in section 3.4.2. For this purpose a linear program (LP) was developed and solved. The model simulates a portfolio of DHW tanks and the control that the aggregator would hypothetically adopt if he had full prediction of the fleet's hot water consumption and their normal power demand, their baseline. The problem is formulated as described in equations (3.7) - (3.19).

In a flexible DHWT portfolio the aggregator seeks to maximize it's profits from providing reserves

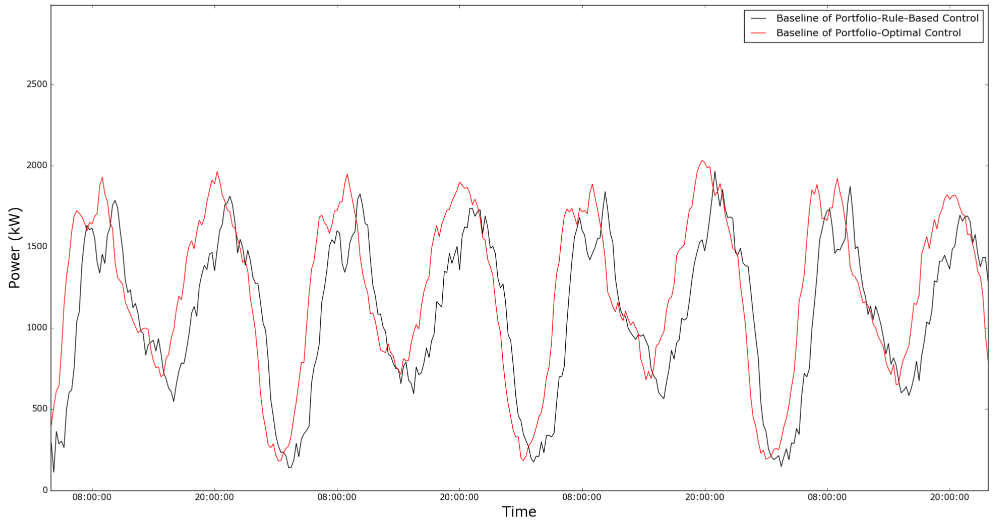


Figure 3.10: Optimal and rule-based control baselines (1000 tanks).

to the system while simultaneously minimizing the overall power consumption of the fleet. This strategy is described by equation 3.7 where the revenues from upwards (I_{ct}^{+}) and downwards (I_{ct}^{-}) capacity reserves offered by each tank minus the expenses from the power consumed are maximized. The Value of Lost Heat ($VOLH$) is a large ficed parameter that is used in this formulation to penalize the deviations (ϵ_{ct}) from the predefined comfort limits. Equations 3.8 and 3.9 are used to calculate the transition at the next state of each tank in case there is an activation signal (S^{+}, S^{-}). Thus the temperature at the next time step is computed by the baseline power of each heater and the individual activation signal ($S_{c,t}^{+}, S_{c,t}^{-}$), the hot water consumption and the previous temperature level. The way to distribute optimally the activation signals either upwards or downwards is denoted by equations 3.18 and 3.19. In case there is a flexibility activation signal the temperature upper and lower limits are given by equation 3.10 and these limits are given as in section 3.4.2, $T_{Flex_{min}} = 45$ ℃, $T_{Flex_{max}} = 95$℃. Otherwise the limits are those defined also for the baseline computation $T_{min} = 55$ ℃,$T_{max} = 65$℃. The variable ϵ_{ct} is used to relax the temperature constraint in case there is an increased hot water demand. The transition of each individual tank in time is given as in the baseline computation by equation 3.11. The constraints defined in equations 3.15 and 3.17 are used to describe the limits for each of the power variables. Thus the power that can be consumed for upwards activation, capacity reserve and consumption is bounded by the upper power limit of the electric heater which is assumed to be $P_{max} = 4kW$. For the downwards reserves the amount that can be offered at each step is limited by the power consumed by the heater. The available amount for the capacity allocation both for upwards and downwards is also defined by the margin between the temperature at each time step and the minimum and maximum limits. Thus equations 3.14 and 3.16 add extra limitations to the offered capacity (I^{+}, I^{-}).

In order to proceed into the computations there was a need to choose values for the price of the electricity and the capacity reserves. Therefore the value for the parameter π_t is selected to be the retail price of electricity at Belgium (0.211€$/kWh$). The prices for the renumeration of the capacity reserves denoted as π_t^{+} and π_t^{-} are considered equal. The value was chosen to be 3.14€$/MW/hour$ of availability, according to the price that the TSO of Belgium has published for tertiary reserve dynamic profile (R3-DP) [54]. At this point it should be stated that the *day-night tariff* is not considered in the current formulation because it was though to be out of scope. The use of *day-night tariff* results in charging the tanks during the night hours as expected. It was not chosen because it would just influence the shape of the baseline at certain time steps and that was not relevant to what the present thesis is investigating. The role of more dynamic pricing schemes that definitely influence the behavior of the loads has been explored in section 1.2 and is also out of scope in the current formulation. However it is shown that the role of the compensation prices for capacity reserves is significant and is examined in the present section.

$$\max_{P,\epsilon,I^+,I^-} \sum_{t\in T c\in C} (I^+_{ct}\pi^+_t + I^-_{ct}\pi^-_t - P_{ct}\pi_t)dt - VOLH\epsilon_{ct} \tag{3.7}$$

subject to:

$$\text{If } S^+ > 0\text{: } T_{ct} = f(P_{base,c,t} + S^+_{c,t}, T_{ct-1}, \dot{m}_{ct}) \qquad \forall t \in T, \forall c \in C \tag{3.8}$$

$$\text{Else If } S^- > 0\text{: } T_{ct} = f(P_{base,c,t} - S^-_{c,t}, T_{ct-1}, \dot{m}_{ct}) \qquad \forall t \in T, \forall c \in C \tag{3.9}$$

$$T_{Flex_{min}} \le T_{ct} \le T_{Flex_{max}} \qquad \forall t \in T, \forall c \in C \tag{3.10}$$

$$\text{Else: } T_{ct} = f(P_{c,t}, T_{ct-1}, \dot{m}_{ct}) \qquad \forall t \in T, \forall c \in C \tag{3.11}$$

$$T_{min} - \epsilon_{ct} \le T_{ct} \le T_{max} - \epsilon_{ct} \qquad \forall t \in T, \forall c \in C \tag{3.12}$$

$$0 \le P_{ct} \le P_{max} \qquad \forall t \in T, \forall c \in C \tag{3.13}$$

$$T_{Flex_{max}} \ge f(P_{c,t} + I^+_{ct}, T_{ct-1}, \dot{m}_{ct}) \qquad \forall t \in T, \forall c \in C \tag{3.14}$$

$$0 \le I^+_{ct} + P_{ct} + S^+_{c,t} \le P_{max} \qquad \forall t \in T, \forall c \in C \tag{3.15}$$

$$T_{Flex_{min}} \le f(P_{c,t} - I^-_{ct}, T_{ct-1}, \dot{m}_{ct}) \qquad \forall t \in T, \forall c \in C \tag{3.16}$$

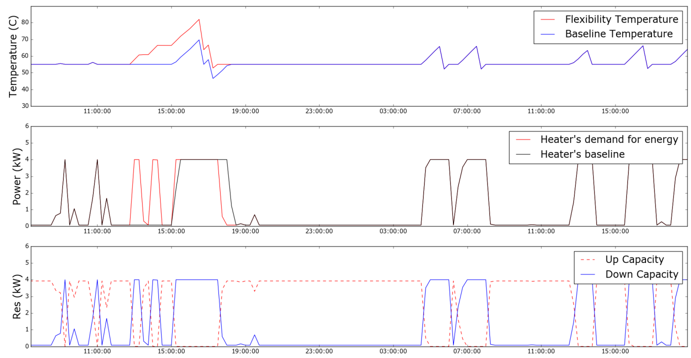
$$0 \le I^-_{ct} + S^-_{c,t} \le P_{ct} \qquad \forall t \in T, \forall c \in C \tag{3.17}$$

$$\sum_{t\in T c\in C} S^+_{c,t} = S^+ \tag{3.18}$$

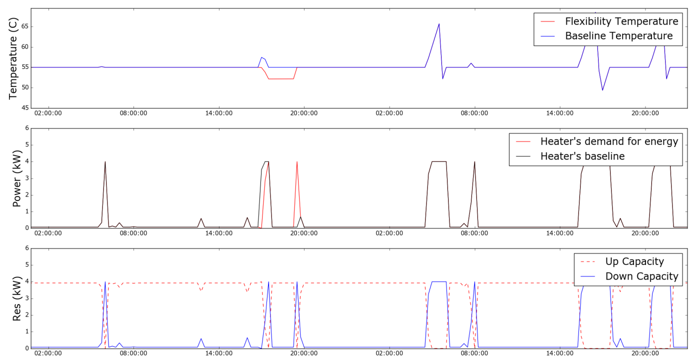
$$\sum_{t\in T c\in C} S^-_{c,t} = S^- \tag{3.19}$$

The simulations performed considered several scenarios where the response of the portfolio to provide either capacity or activation of the reserves is evaluated. Due to the increased complexity of the computation it was not feasible again to simulate a large number of consumers participating in this service. However we are able to get a good impression on the aggregated behavior of a portfolio. Furthermore this detailed modeling approach gives the ability to deduct the physical behavior of each tank and allows to quantify and evaluate the *rebound effect* in such a set-up.

The response of a DHW tank to flexibility activation signals and the provision of capacity reserves are illustrated in Figure 3.11. In the case of an upwards activation the tanks are requested to consume more and their temperature is increasing while the permitted limits have increased. In this case the tank will reduce it's consumption before and after the activation so that the total amount of energy received will be approximately the same. Thus the load has been shifted by the control and the rebound effect takes place. The only defect is the existence of thermal losses where energy is rejected to the ambiance. In a similar way when downwards reserve activation is requested the tank reduces at a given point it's output. Thus the temperature that is allowed to reach lower flexible limits decreases. In the same manner energy is needed either before or after this operation to better allocate this disturbance. The significant difference between this type of control and the rule-based one is that the *rebound effect* is suitably distributed before and after the activation signal due to the full knowledge that it possesses. The capacity reserve potential is also presented in Figure 3.11 and as can be seen the two types of reserve contradict. Important notice is that at the points where the temperature reaches maximum or minimum levels the available reserve capacity is reduced or eliminated. For this reason the number of tanks deployed plays a key role into providing stable capacity reserve.



(a) Upwards activation.



(b) Downwards activation.

Figure 3.11: Baseline and flexible temperature profiles,power consumption and capacity reserve provision from a DHWT.

The impact on the power consumption of 300 DHW tanks is demonstrated in Figure 3.12. Initially an increase in the overall consumption is requested and the adjustment of the power needs is such that the tanks fulfill this request. The rebound effect as it was expected is spread before and after the reserve operation. In a similar manner the second signal is a request for the fleet to decrease it's consumption. The compensation for this disturbance appears to be quite sharp and the reason for that is the high difference between the flexibility and the normal-operation lower temperature limits. Thus a big number of heaters are immediately fully activated to bring back the temperature to it's predefined limits. These phenomena are also illustrated with better resolution in Figure 3.13 (a) and (b). It is important to note the upper and lower portfolio demand as it gives an insight to the amount of capacity reserves that an aggregator would be able to sell at the balancing markets. The number of the DHW tanks participating is significantly small in this implementation mainly due to the computational complexity and the high need for memory resources in comparison to the RBC implementation. However we are able to obtain a clear view about the dynamics and the potentials incorporated with the participation of DHW tanks into providing flexibility to the system.

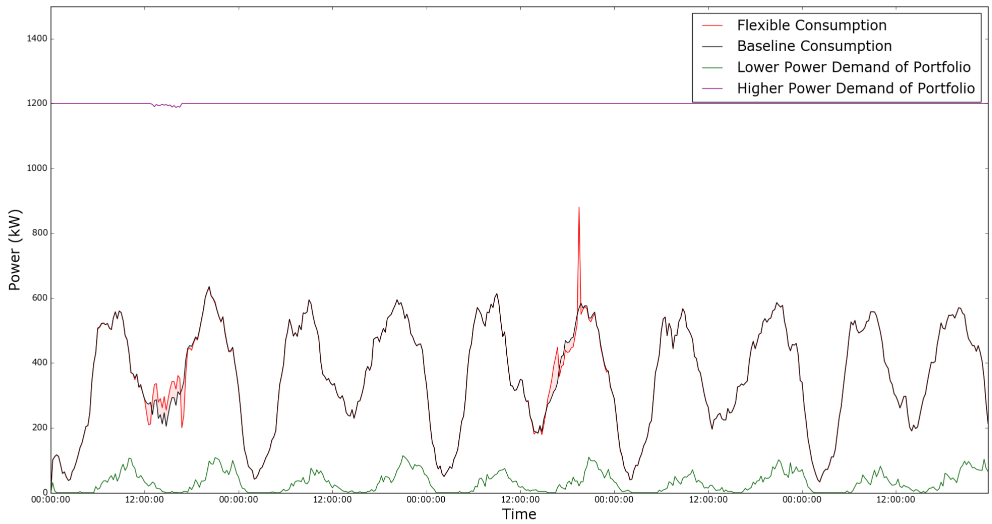
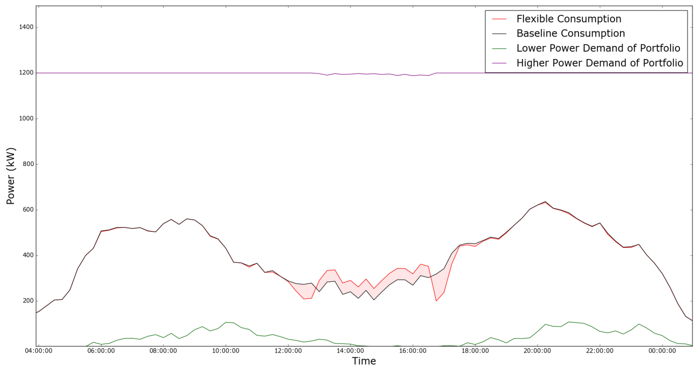


Figure 3.12: Optimal Demand Response to flexibility signals from 300 tanks.

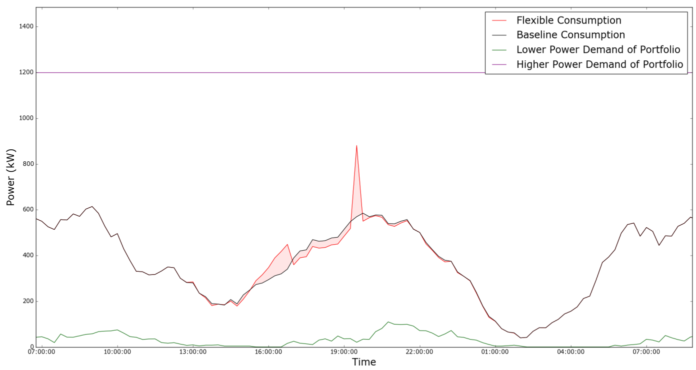
The current optimal formulation allows us to evaluate what would be the different strategies that a portfolio of smart DHW tanks would follow in order to provide steady capacity reserves. If an aggregator would participate in the balancing markets he would like to be able to select a strategy that maximizes his revenues and simultaneously minimizes the amount of energy consumed from the fleet. Another valuable information would be the cost at which he would be able to offer this product and which factors affect this cost. Thus we use the previous model but this time we explicitly state through a constraint the amount of capacity (upwards or downwards) that should be kept at each time step. Then we plot the *shadow price* of this constraint in order to evaluate the cost incorporated with such a reserve procurement. The shadow price is computed as the dual variable of this constraint,it indicates the marginal cost for maintaining this amount of reserve and it is expressed in $€/kWh$.

For instance in Figure 3.14 a portfolio of 300 tanks is used to provide 200kW of downwards capacity reserve is illustrated. The portfolio is binded to consume at least 200kW of power at each time step and the adjusted power consumption is depicted in Figure 3.14(a). We see that the load is shifted to the valley and because of the fact that the tanks are charged a short period of peak shaving occurs systematically. Another observation is that the marginal cost for providing this reserve increases at the valleys when it was not necessary to consume this amount of power (Figure 3.14(b)).

A similar impact is realized by the provision of 700kW of upwards capacity reserve. In 3.15(a) the power consumption becomes flat in order to reserve the predefined amount of power for the system's disposal. Thus the necessary power to charge the tanks is obtained earlier. This operation comes with a certain cost. We can see in 3.15(b) that a cost is observed only when the power consumption is upper limited. This functionality is rather expected because at these



(a) Upwards activation reserve provision

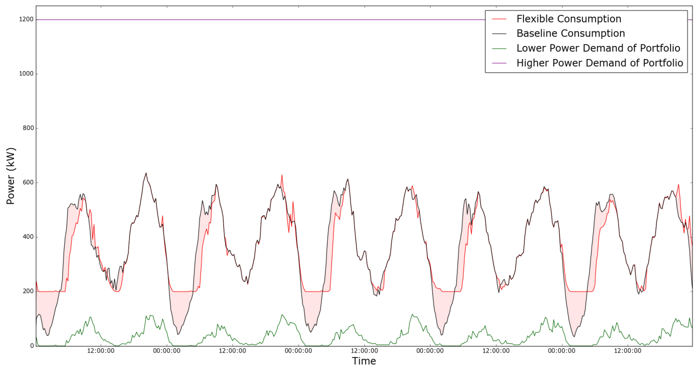


(b) Downwards activation reserve provision

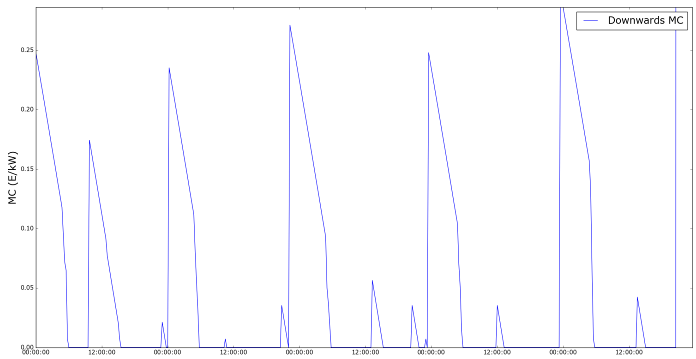
Figure 3.13: Valley-filling and peak-shaving with optimal demand response.

time steps power that was meant to be used for charging is kept for reserve. It is also important to note that there is more capacity available for upwards rather than for downwards modulation and that fact is also depicted to the significant difference of the marginal costs. However the cost is shown to be highly dependent on the available capacity and thus the size of the portfolio.

As it was described in section 3.1 the main purpose of the aggregator is to offer capacity reserve services to the system and in case there is an imbalance his portfolio should adjust it's output to track the system's signal. This behavior is simulated with the assistance of the current formulation in order to define which is the impact of such an operation to a fleet of tanks. Therefore the aggregator is responsible to provide 200kW of downwards and 650kW of upwards capacity reserve to the system. At some predefined steps the portfolio is requested to modulate from it's baseline and consume more (upwards activation) or consume less (downwards activation). The output of a simulated period of one week is illustrated at Figure 3.16. Indeed the portfolio maintains its power consumption above 200kW and below 550kW at all times. It is reminded that the maximum power consumption for a tank is 4kW and thus the maximum for a fleet of 300 tanks is 1200kW. Besides the capacity that the aggregator can offer the fleet follows two activation signals. The upwards modulation takes place after 12:00 until 16:00 at the first day as depicted at Figure 3.17 (a). The downwards modulation occurs from 17:00 until 19:00 of the third day. It is quite interesting that the rebound effect in this case is completely different than what it was for the exact same signals in Figure 3.13. The reason is that the rebound has



(a) Downwards capacity reserve provision

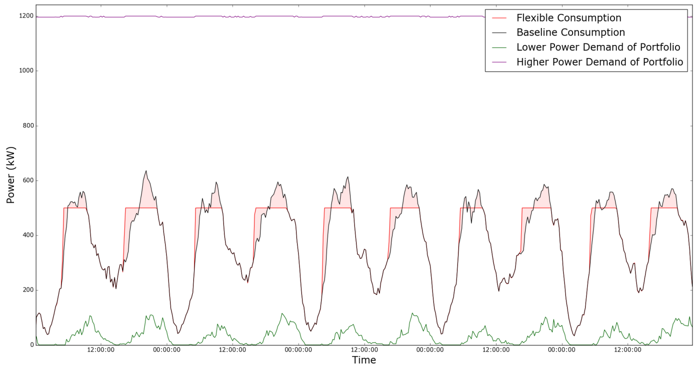


(b) Downwards capacity reserve Marginal Cost

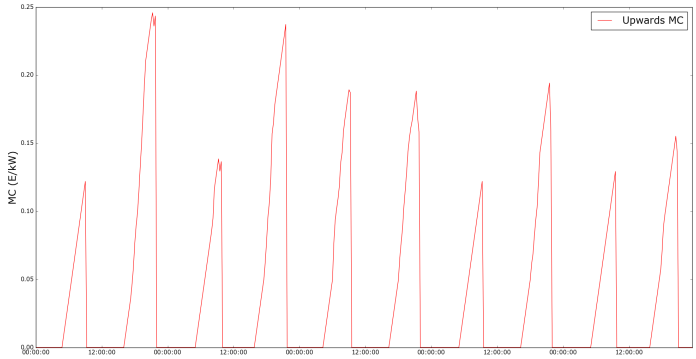
Figure 3.14: Constant 200kW downwards reserve provision.

moved especially in the case of the downwards activation before the modulation because of the strict limits imposed by the capacity reserve constraints. Thus the rebound effect is also highly adjusted due to the need to procure capacity at all times. The impact that this strategy on the temperature and profiles of the tanks is indicated at Figure 3.18. It is observed that the charging and discharging phases have been shifted to serve the flexibility requirements and the hot water demand. Finally it must be highlighted that a cost reduction of around 7% at the final cost was found. This means that even with the existing low price of renumeration for capacity reserve the aggregator of a flexible portfolio can benefit financially while there is no comfort or other violation for the final user. Of course this study is roughly an approximation of the reality and it's aim is to evaluate the flexibility potential of a centrally controlled fleet of DHW tanks. Thus the financial benefits are not explored in detail but a projection of what could be the final outcome was made.

At this point it should be stated that both optimization problems were written in PYOMO [55] and solved by CPLEX [38]. The computational complexity is enhanced in both cases, especially in the demand response algrithm where it was able to simulate only 300 households. The memory restrictions that occurred are mainly due to the increased amount of data used and the high resolution (15 min) that was used. Finally PYOMO as optimization suite and Python as a language in general are not considered to be memory efficient. However they were chosen for their wide use and their efficient interface.



(a) Upwards capacity reserve provision



(b) Upwards capacity reserve Marginal Cost

Figure 3.15: Constant 700kW upwards reserve provision.

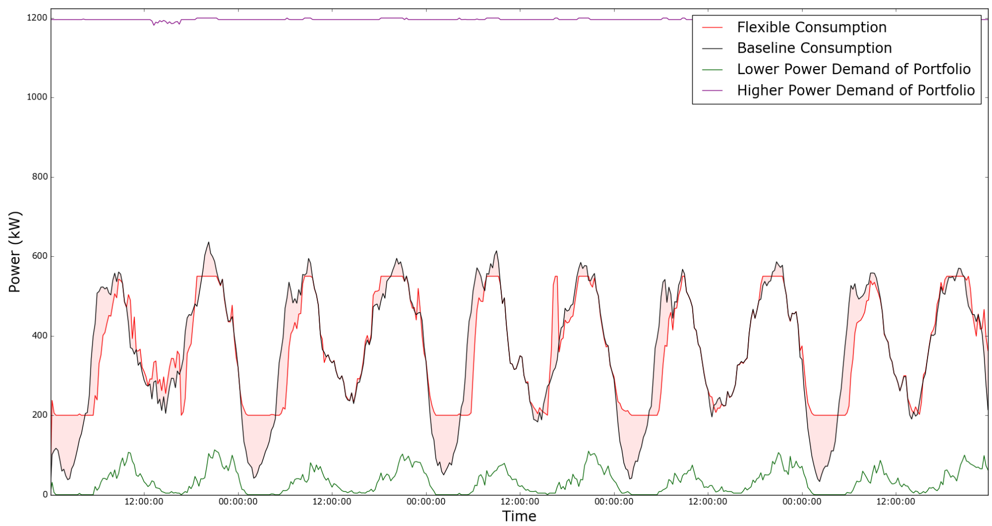
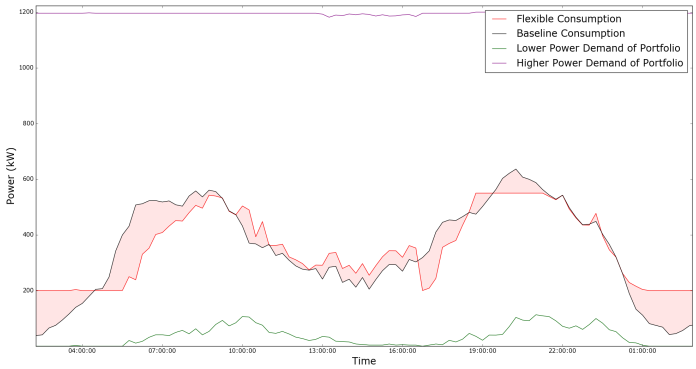
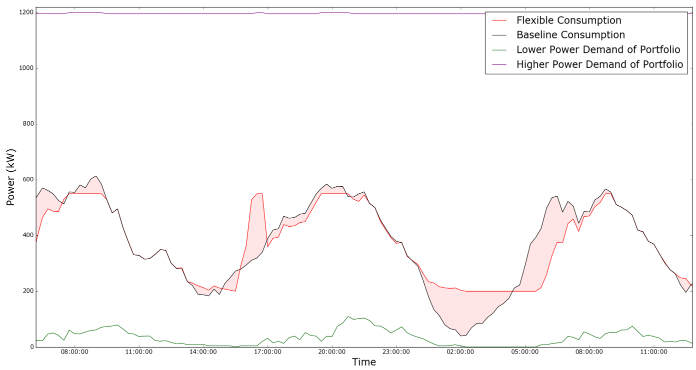


Figure 3.16: Constant capacity and activation reserves provision from 300 DHWTanks.



(a) Upwards activation reserve provision.



(b) Downwards activation reserve provision.

Figure 3.17: Capacity and activation reserves provision from 300 DHWTanks.

3.6 Conclusions

In this chapter an attempt to identify and quantify the flexibility potential that could be extracted by a fleet of DHW tanks was made. Two modeling approaches were carried out. Both are based in the computation of a power baseline that the fleet of tanks would consume and the deviation from it to procure flexibility. The first used a rule-based control strategy while the second was formulated as a linear optimization problem. The main difference between the two modeling approaches was the lack of prediction in the case of RBC. On the contrary the optimal control acts upon full knowledge of the future and thus the reaction was proven to be at different time steps but quite similar concerning its amplitude. Due to the increased computational burden because of memory limitations only a certain number of tanks was possible to be simulated. The results were quite indicative of how such a flexible portfolio would operate to provide flexibility services. It was shown in both cases that an aggregation of DHWTanks can be considered as a flexible buffer, capable to track an activation signal by making use of the thermal inertia of the tanks and the diversity of the hot water consumption. It was also shown that the fleet was able to participate to the capacity reserve markets. The cost attached to this operation is further explored.It was observed that there is an fluctuation is providing capacity reserves depending on the current state. For instance it was found that it was more expensive to offer downwards (upwards) capacity at times when the overall consumption is low (high) or the mean temperature is low(high). Thus a

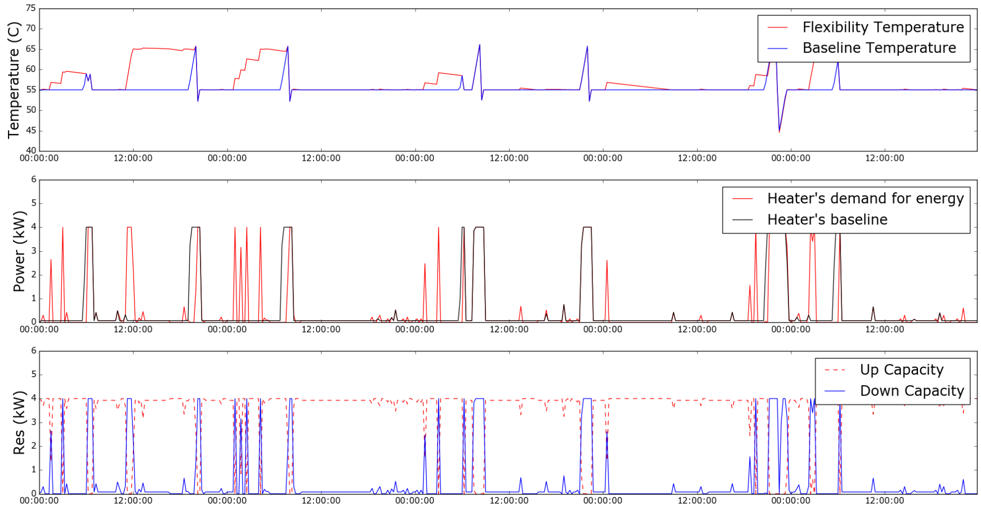


Figure 3.18: Temperature, power consumption and capacity reserves profiles from a flexible DHWT.

general remark is that providing upwards capacity or flexibility is easier and more cost-efficient as demonstrated in the current formulation. Finally the simultaneous provision of capacity and activation reserves was performed. The results indicate that the aggregator would be able to procure the contracted amounts of flexibility and fulfill the requirements for thermal demand. It was shown that a cost reduction of 7% is achievable taking in account the current prices for reserves. However this result should only be considered as an indication because no elaborate tariff scheme was assumed.

Chapter 4

Virtual Storage Plant model

In this chapter the development of a Virtual Storage Plant (VSP) model as a way to generalize the behavior of a large amount of DHWT is described. The main goal of this modeling approach is to identify the flexibility potential that could be offered to the system by a fleet of DHW tanks without modeling each tank in detail in order to reduce the computational effort, To accomplish this goal first the model is created and then validated through the validation process. The model performance is validated based on the results obtained with the detailed modeling approach presented in Chapter 3. The VSP model is able to predict the behavior of the DHW tank fleet within 10% error. The final objective of the development of the VSP is the future integration to the Dispa-SET [34].

4.1 Description of the VSP model

The notion of a Virtual Storage Plant is used to describe the behavior of many individual tanks. It is modeled similarly to a conventional pump storage plant. However the name virtual refers to the disaggregated form that in reality exists. Thus it is assumed that by centrally controlling a fleet of individual DHW tanks a virtual plant can be formed. This plant has the ability to be part of the system as a conventional plant. The power consumption of this plant is modified and it's ability to participate in *load-shifting* strategies is evaluated. However the main criteria for its successful operation is to ensure that the demand for hot water is fulfilled at all times identically. This constraint is perfectly aligned to the comfort constraints that were imposed in the previous chapter.

The modeling approach that was carried out was motivated by the final goal which has been the incorporation of this VSP model to the Dispa-SET. Therefore the fleet of tanks is described by a battery model like the one used to describe the hydro pump storage plants in Dispa-SET [34]. However the VSP model differs from the typical battery model because of the fact that the tanks are not able to inject power to the system but they allow the postponement of consuming which is equivalent to a negative production. Alternatively the virtual storage plant is strategically charging (consuming power) in order to fulfill the demand in hot water and provide flexibility to the system.

The mathematical formulation of the VSP model is described in Equations 4.1 - 4.5. The decision variables are presented in Table 4.2 and relate to the amount of power consumed at each time step to the VSP (StorageInput$_h$) and the state of charge of the VSP at each time step (StorageLevel$_h$). In the current formulation the time step is one hour ($\Delta t = 1 hour$). The list of parameters that are used to describe the various characteristics of the problem are presented in Table 4.1. The objective function denoted in Equation 4.1 is such that it minimizes the overall amount of power needed to serve the consumption of hot water. The amount of energy that can be stored has a low limit that is imposed by Equation 4.2 and an upper one that is imposed by the overall capacity in Equation 4.3. In Equation 4.4 the charging phase is limited by the level of charge of the unit. Finally the energy that is stored at each time step is given by the energy stored in the previous time step net of charges and discharges as denoted in Equation 4.5.

Table 4.1: List of parameters.

Name	**Description**	**Units**
StorageCapacity	Storage capacity	[MWh]
StorageChargingCapacity	Maximum charging capacity	[MW]
StorageChargingEfficiency	Charging efficiency	[%]
StorageInflow$_h$	Storage inflows (potential energy)	[MWh]
StorageOutflow$_h$	Storage outflows	[MWh]
StorageInitial	Storage level before initial period	[MWh]
StorageMinimum	Minimum storage level	[MWh]
HeatLosses	Ambient Losses as a percentage of the storage level	[%]
ReferenceCapacity	Reference capacity representing the ambiance	[MWh]

Table 4.2: List of decision variables.

Name	**Description**	**Units**
StorageInput$_h$	Charging input for storage units	[MWh]
StorageLevel$_h$	Storage level of charge	[MWh]

$$\text{minimize} \sum_{h \in H} StorageInput_h \tag{4.1}$$

$$StorageMinimum \leq StorageLevel_h \tag{4.2}$$

$$StorageLevel_h \leq StorageCapacity \tag{4.3}$$

$$\begin{aligned}&StorageInput_h \cdot StorageChargingEfficiency - StorageOutflow_h\\&+StorageInflow_h \leq StorageCapacity - StorageLevel_h\end{aligned} \tag{4.4}$$

$$\begin{aligned}&h = 1:\\&StorageInitial + StorageInflow_h\\&+StorageInput_h \cdot StorageChargingEfficiency\\&= StorageLevel_h + StorageOutflow_h\\&h > 1:\\&StorageLevel_{h-1} + StorageInflow_h\\&+StorageInput_h \cdot StorageChargingEfficiency\\&= StorageLevel_h + StorageOutflow_h + HeatLosses * (StorageLevel_h - ReferenceCapacity)\end{aligned} \tag{4.5}$$

It can be observed that this modeling approach is quite similar to a battery model that has no ability to discharge. However the VSP model differentiates from a conventional storage plant in the way that several parameters are defined. In a normal storage unit, parameters $StorageOutflow_h, StorageInflow_h$ represent the energy that is taken or given to the plant, in other words the leakages and the gains of the unit. In the current formulation no gains are assumed because there is not any physical process that adds energy to the tanks similarly to the way river flow adds energy to a hydro storage plant. The parameter $StorageOutflow_h$ it was chosen to be time-dependent and to represent the hot water consumption. Thus this parameter is computed as shown in Equation 4.6 and constitutes the energy equivalent of supplying hot water of $T_{Dem} = 50$ °C, to the households. The consumption of hot water $\dot{M}_h$ is assumed to be the cumulative consumption of all the individual consumption of the DHW tanks as described in section 3.3 and the temperature at which the cold water enters the tanks is denoted as $T_{ref_{VSP}} = 10$°C. In practice the output of this representation is a curve as steep as the term $\dot{M}_h$. For this reason a filter was used in order to smoothen the curve in order to approximate the output of the baseline of the optimal control model of section 3.5.1 without any ambient losses. The outcome is presented in Figure 4.1.

$$StorageOutflow_h = \dot{M}_h \cdot C_p \cdot (T_{Dem} - T_{ref_{VSP}}) \tag{4.6}$$

The ambient losses are linearly related to the temperature of an individual tank as explained in section 3.3. Therefore in the VSP modeling the heat losses are assumed to be a linear function of the state of charge (SoC) as denoted in Equation 4.7. A constant coefficient ($HeatLosses$) is used in order to represent the percentage of the energy level that is consumed in ambient losses and is computed in Equation 4.8. A correction parameter ($ReferenceCapacity$) states that the heat losses occur due to the temperature difference between the tank and the ambiance. This way of handling losses allows to the optimization algorithm to retain the state of charge at the lowest possible level in order to ensure minimum heat losses.

$$\begin{aligned} Losses_h &= HeatLosses \cdot (StorageLevel_h - ReferenceCapacity) & (4.7)\\ HeatLosses &= \frac{UA_{VSP}(T_{VSP} - T_{ref_{VSP}})}{M \cdot C_p \cdot (T_{VSP} - T_{ref_{VSP}})} = \frac{UA_{VSP}}{M \cdot C_p} & (4.8)\\ ReferenceCapacity &= M \cdot C_p \cdot (T_{amb} - T_{ref_{VSP}}) & (4.9) \end{aligned}$$

The minimum capacity that the VSP unit is able to store is given by Equation 4.10. It represents the minimum amount of energy that should be consumed by the fleet of DHW tanks in order to maintain the minimum temperature level. $StorageCapacity$ indicates the total energy that can be stored to the storage plant of DHW tanks. The maximum capacity is given by Equation 4.11. The parameter that defines the initial state of charge for each simulation period ($StorageInitial$) is modeled as presented in Equation 4.12. The initial temperature is considered to be $T_{init} = 55$°C, but this is an arbitrary assumption which does not affect the computations.

$$\begin{aligned} StorageMinimum &= M \cdot C_p \cdot (T_{min} - T_{ref_{VSP}}) & (4.10)\\ StorageCapacity &= M \cdot C_p \cdot (T_{max} - T_{ref_{VSP}}) & (4.11)\\ StorageInitial &= M \cdot C_p \cdot (T_{init} - T_{ref_{VSP}}) & (4.12) \end{aligned}$$

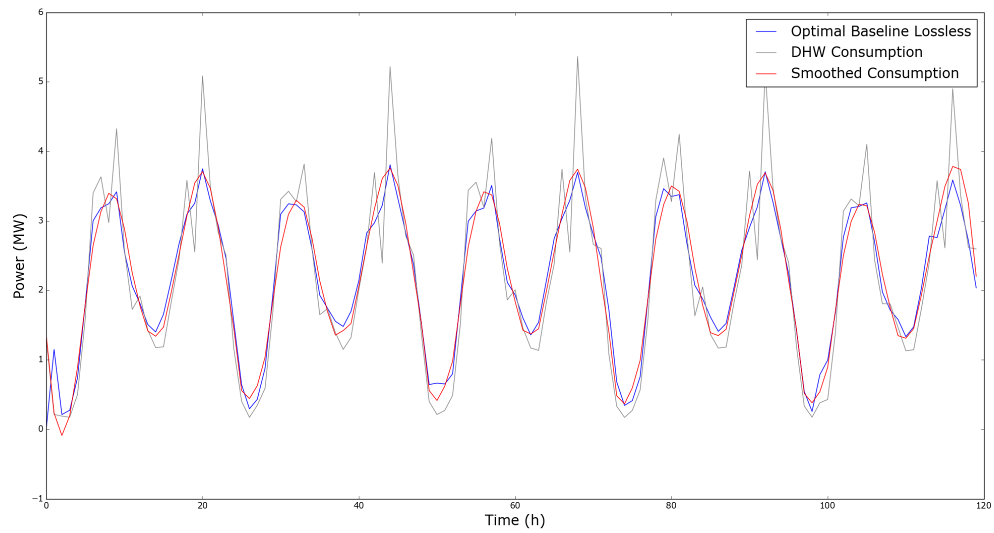


Figure 4.1: Comparison between optimal baseline and consumption computed by equation 4.6 (2000 tanks).

The modeling of the virtual storage plant was performed in PYOMO [55], an optimization suite embedded in Python and solved by CPLEX [38]. The computational burden is minimum due to the light representation of the processes. The low computational effort was a prerequisite for this modeling approach as it was intended to be incorporated into Dispa-SET, a large optimization problem. Therefore the VSP model is light enough to perform efficiently in such an environment.

4.2 Validation of the VSP model

This section presents the validation of the VSP model that was defined in the previous section. The ability of the VSP model to describe the physical processes that were defined in chapter 3 is evaluated. The simulation output of the VSP is compared to the other two modeling approaches and the results are discussed. The expected result for the VSP model is to be able to describe the operation of several thousands of DHW tanks in a predefined accuracy range. The validation process was performed for 2000 and 3000 domestic hot water tanks and the steps that were followed are summarized as:

1. The optimal baseline program (section 3.5.1) for 2000 and 3000 tanks without considering any heat losses is executed in oder to identify the mean temperature T_{mean}. Thus the power consumption of the disaggregated portfolio is computed without incorporating losses.
2. The computed lossless power consumption is compared to the one calculated by Equation 4.6 in order to identify the parameter $StorageOutflow_h$. In this equation the parameter the parameter T_{Dem} takes the value of the mean temperature (T_{mean}) that was calculated in the previous step. The mean temperature is set to $T_{Dem} = 48.6$ °C. The output of this step is shown in Figure 4.1
3. The optimal control program is executed while considering ambient losses. The hot water consumption for each tank is the the same for this run. After this step the baseline consumption of the portfolio of either 2000 or 3000 tanks is acquired.
4. The rule based control model is executed in order to compute the baseline as described in section 3.4.1. The hot water consumption for each DHWT is again considered the same as in step 1.
5. The VSP model is executed by considering the overall hot water consumption as the summation of the individual DHW consumption. The results are then compared to the disaggregated cases.

In Figures 4.2 and 4.5 the power consumption and the state of charge of the VSP that represents 2000 and 3000 tanks are illustrated respectively. The graphs compare in the first and second plot the mean temperature as computed by the optimal-control algorithm and the state of charge of the VSP. It can be observed that in both cases the optimization solver keeps the SoC at minimum in order to prevent high heat losses. However in the disaggregated cases the small temperature fluctuation is visible whereas in the VSP case there is no fluctuation in the SoC. This fact indicates that the VSP model is not able to capture with high accuracy the dynamics of the system. At the initial steps of the simulation both models are discharging. The third plot in Figures 4.2 and 4.5 demonstrates the way that the VSP is consuming power (charging). It can be seen that the rate of consumption is identical to the DHW demand augmented by the heat losses. This is the reason for the offset that can be observed in the charging curve.

Figures 4.3 and 4.6 compare the consumption patterns of the VSP model and the optimal-control algorithm. The two curves demonstrate high resemblance and the VSP charging is not only able to perform the same shape but the same amplitude for both the case of 2000 and 3000 DHWT. However several differences are noticed due to the different nature of the two approaches. The rooted mean squared error (RMSE) is used as an indication of the accuracy and is found to be

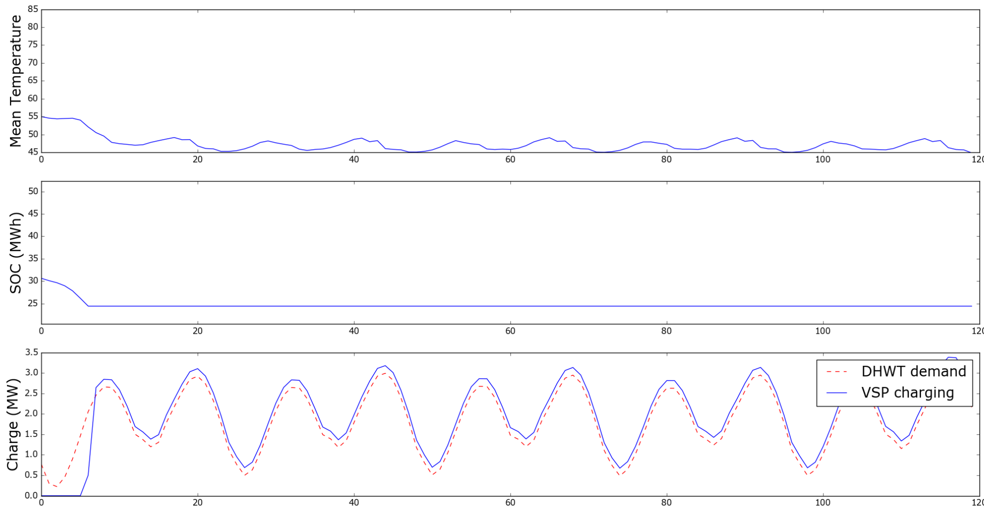


Figure 4.2: VSP state of charge and consumption (2000 tanks).

$0.3MW$ for the case of 2000 DHWT and $0.6MW$ for 3000 DHWT. The energy that is consumed in the current optimization horizon that was 5 days presented a difference of $2MWh$ and $3MWh$ in the cases of 2000 and 3000 DHWT respectively between the VSP and the optimal-control. It was observed that the error is less than 10% and the number of tanks is slightly increasing the error.

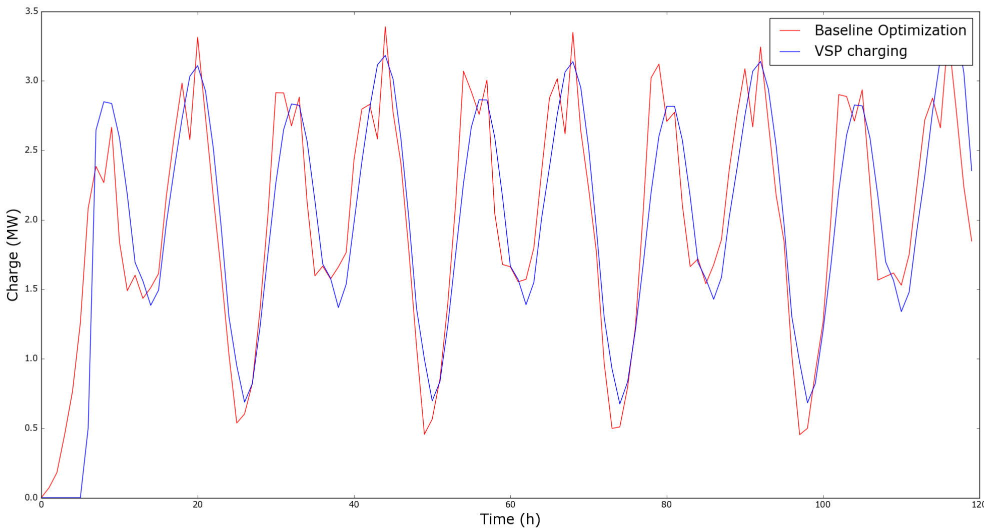


Figure 4.3: Comparison between optimal baseline and VSP consumption (2000 tanks).

Similar results were obtained by the comparison of the VSP model to the RBC model. The consumption profiles for 2000 and 3000 DHWT are presented in Figures 4.4 and 4.7. In this case there is a slightly higher divergence between the VSP and the RBC model due to the different

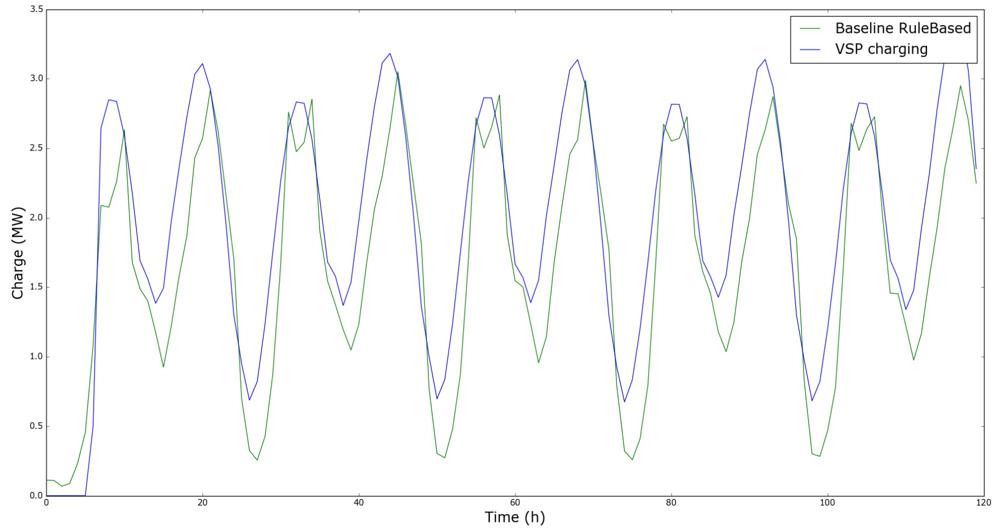


Figure 4.4: Comparison between rule-based baseline and VSP consumption (2000 tanks).

nature of these two modeling approaches. The RBC presents a general shift in time due to the lack of prediction of the hot water consumption. However the magnitude along with the pattern of the curve shows compliance between the two. The RMSE is computed to be 0.37 MW and 0.65 MW for simulating 2000 and 3000 DHWT respectively. The energy consumed by the RBC is $2MWh$ and $4MWh$ less than what the VSP consumed which indicates that the two approaches do not diverge highly.

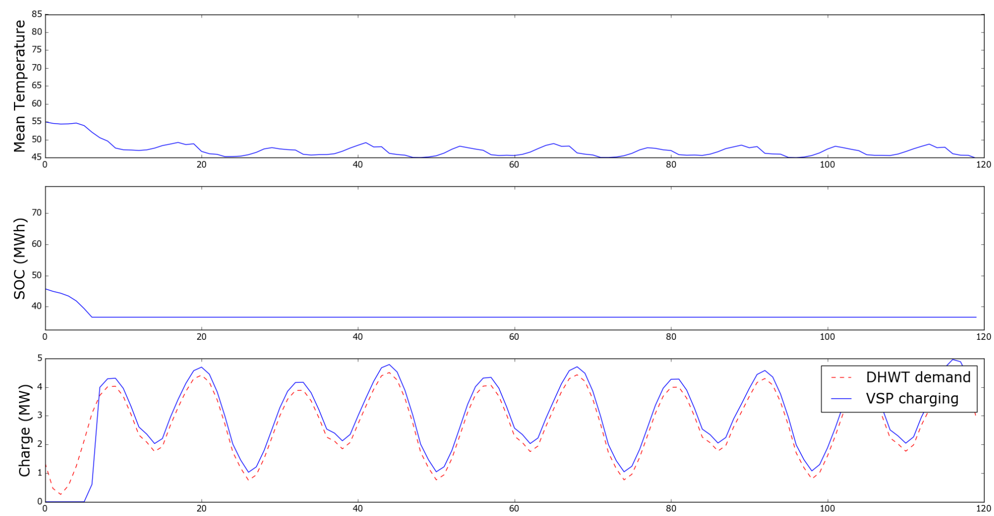


Figure 4.5: VSP state of charge and consumption (3000 tanks).

It is concluded that the Virtual Storage Plant model is able to describe the operation of a large number of DHW tanks under a certain accuracy range. It was shown that the power consumption

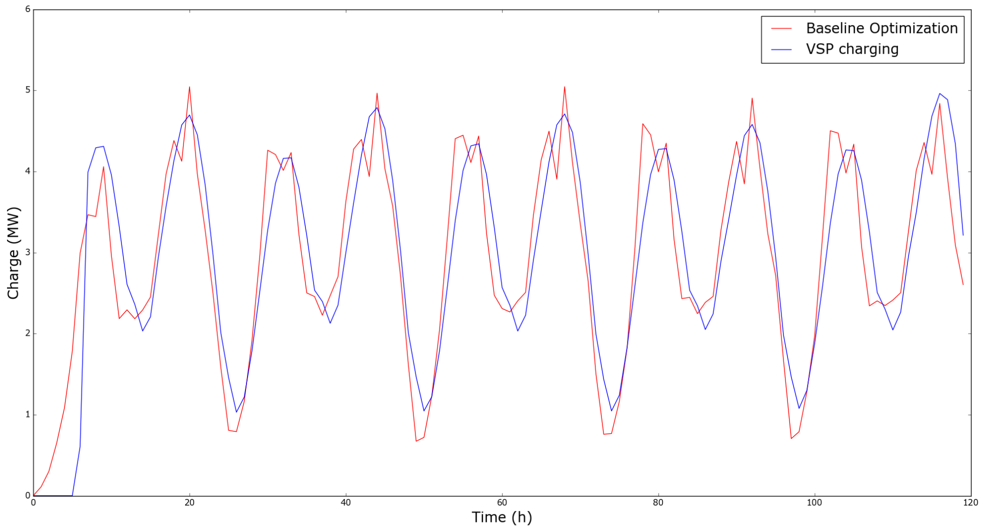


Figure 4.6: Comparison between optimal baseline and VSP consumption (3000 tanks).

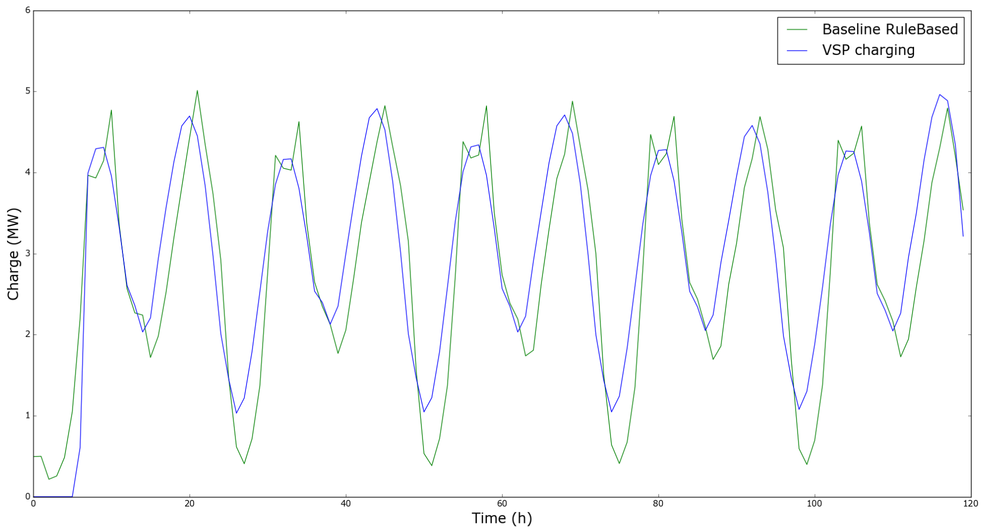


Figure 4.7: Comparison between rule-based baseline and VSP consumption (3000 tanks).

of the aggregated portfolio of DHW tanks simulated by the VSP model had the same shape and amplitude as the disaggregated detailed models developed in chapter 3. However as it was expected the VSP model fails to capture in detail part of the system's dynamics related to the SoC-temperature and the power consumption. The small deviations of the mean temperature in the detailed formulation are not depicted in the VSP model because of the imperfect knowledge regarding the upper limit of the charging power. The consumption of power for charging in demonstrates the same inaccuracy issues due to the same reason. Higher accuracy could be achieved if there was sufficient knowledge about how many tanks are experiencing the overall hot water consumption at each time step. Thus the upper limit of the power allowed to be consumed would deviate and the dynamics of the system would be much better captured.

4.3 Participation of the Virtual Storage Plant in a simple economic dispatch model

The participation of the Virtual Storage Plant model into Dispa-SET would contribute highly towards the identification and quantification of the flexibility that could be offered by a smart portfolio of DHWT to the system under the sight of the higher RES penetration. Therefore the next step towards the full integration of the VSP model into Dispa-SET was the incorporation of the VSP into a simple economic dispatch model. A merit-order model was used and the VSP formulation was compared to the detailed optimal-control model in order to validate the behavior of the VSP under Demand Side Management strategies. The ability of the VSP to participate in load-shifting strategies as efficiently as the optimal-control model that was described in section 3.5.2 is investigated.

4.3.1 Merit-order model

The merit-order model that was used is the simplest form of an economic dispatch problem. Several conventional units with different operating costs were considered. These units had a maximum operating point and no other constraints such as ramping constraints were assumed. A cyclical constant demand represents the power consumption of the system. The units are responsible to supply enough power for the demand and the smart portfolio of DHW tanks. The mathematical formulation of the problem is described by Equations 4.13 - 4.17. The problem is formulated and solved as a linear problem (LP).

The objective function of the problem presented in Equation 4.13 minimizes the overall system cost. This analysis does not include real data about the prices. It is a tool to identify and to validate the behavior of the VSP model in a dispatch model. Thus the costs are set in an ascending order. The power output of each unit is such that the day-ahead balance between production and consumption is satisfied at all times. The DA balance for the VSP model is formed as shown in Equation 4.14. The power output of the units must be such that satisfies the constantly fluctuating demand ($Demand_h$) and the charging of the virtual storage plant. The rest of the VSP model is used as described in Equations 4.2 - 4.12. Thus there is an interaction between what the VSP is requested to do in terms of charging and what it can do limited by the operational. For instance it is not possible to consume more power than the maximum allowed power until the SoC reaches it's maximum capacity as indicated by Equation 4.4. Similarly the DA balance for the detailed optimal-control model is described by Equation 4.15. In this problem the same principles are applied. The power output of the units are such that the balance between the supply and the demand is ensured at all times. The individual tanks are strategically charging through the power given by the units under the variable $OptCharge_h$. This amount of power is then distributed to each one of the DHW tanks by Equation 4.16. There is also in this case an interaction between the amount of power that is requested and the amount that can be consumed by the tanks. The constraints that describe the operation of the DHW tanks under optimal control are given in section 3.5.1 by Equations 3.4 - 3.6. Finally the maximum power output of each unit is given by Equation 4.17. This constraint enables the smart portfolio of tanks to change it's charging pattern in order to minimize the total operating cost.

$$\underset{Power}{\text{minimize}} \sum_{u \in U, h \in H} unitsCost_u \cdot Power_{u,h} \tag{4.13}$$

subject to:

$$\text{VSP:} \sum_{u \in U} Power_{u,h} = Demand_h + StorageInput_h \qquad \forall h \in H \tag{4.14}$$

$$\text{Optimal:} \sum_{u \in U} Power_{u,h} = Demand_h + OptCharge_h \qquad \forall h \in H \tag{4.15}$$

$$\sum_{t \in T} P_{heater_{t,h}} = OptCharge_h \qquad \forall h \in H \tag{4.16}$$

$$Power_{u,h} \leq MaxPower_u \qquad \forall u \in U, \forall h \in H \tag{4.17}$$

The demand that is used as non-shiftable is described by Equation 4.18. It is assumed to be fluctuating around a constant level with a constant amplitude and a constant frequency. This a simplified assumption in order to simulate the demand modulations and to illustrate the possibilities for *valley-filling* and *peak-shaving* from the VSP.

$$Demand_h = Const + A \cdot \sin \frac{\pi \cdot h}{12} \qquad \forall h \in (0, n_{hours}) \tag{4.18}$$

4.3.2 Validation Results and Discussion

For the validation of the ability of the VSP to perform as desired in DSM strategies a merit-order model was used. The VSP and the optimal-control models are compared in order to identify the differences and the inaccuracies between the two approaches. In favor of simplicity without loss of generality it is assumed that are three generation units participating with a maximum output level of $MaxPower_u = 10MW$. The constant part of the demand is set to $Const = 10MW$ and it's amplitude is set to $A = 7MW$. Both modeling approaches simulate 3000 consumers. The overall demand is assumed to be the summation of the sinusoidal demand described in Equation 4.18 and the consumption computed as baseline in both cases. For the VSP model it is the power consumption as calculated in section 4.2 and for the optimal control as computed in 3.5.1. As expected, results show that both models are storing energy when the constant demand is low whereas when the demand is high they consume the least possible power in order to reduce the overall system cost.

The ability of both models to strategically charge is demonstrated in Figures 4.9 and 4.10. The new demand curve (red line) differentiates in comparison to the case without DSR strategy (black line). Both approaches are performing valley-filling and peak-shaving in order to reduce the system's cost. Thus both storages are charging when the baseline demand (black line) is lower than 10MW at the maximum available power and the total demand reaches the level of 10 MW which is the maximum output of the cheapest unit. Thus energy is stored in the most efficient way. As it is illustrated in Figure 4.8 the state of charge of the VSP and the mean temperature of the tanks is increasing at this period in a similar way. The stored energy results then in a period where there is no need for further charging. Thus the overall demand (red line) is slightly lower than in the baseline case without DSR (black line). Thus effective peak-shaving occurs. It can be observed that load-shifting is performed from the periods with high demand to periods with low demand. It is rather intuitive to state that the load-shifting happens due to the available cheap power during the off-peak hours.

Although it is demonstrated that both models are capable to capture the flexibility potential in such a merit-order model further reasoning should be made about the ability of the VSP model to perform as well as the detailed optimal-control model. It is demonstrated in Figure 4.8 that the mean temperature (first plot) of the disaggregated model is evolving similarly to the state of charge of the VSP model (second plot). It can be seen that the SoC and the temperature end up always at the minimum level. This is due to the increased heat losses that occur.

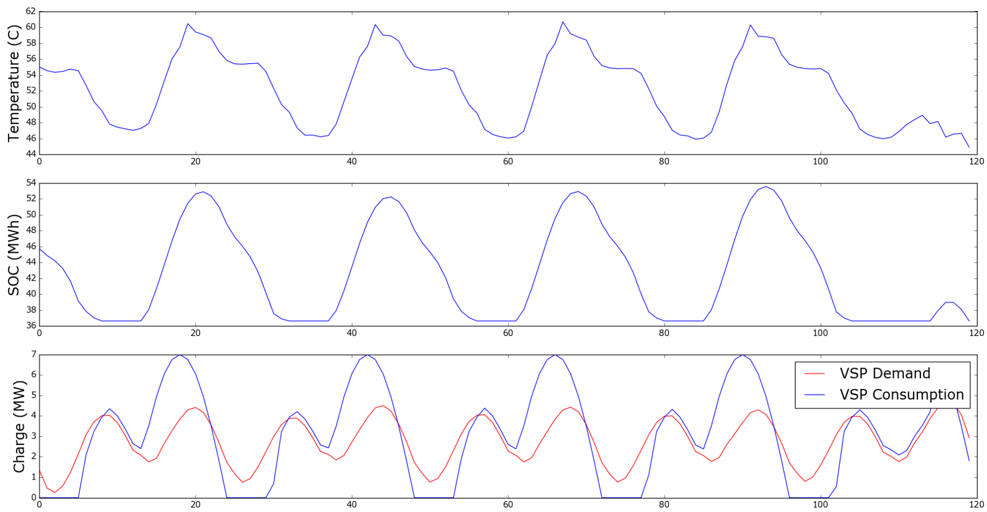


Figure 4.8: VSP state of charge and power consumption profile, mean tanks temperature (3000 tanks).

The charging pattern is identical in the two approaches. However the VSP model fails to track the discharging phase entirely. The VSP model leads to immediate charging and discharging, which can be observed in Figure 4.9. When the overall demand reaches the level of 10 MW the VSP is charging immediately whereas the optimal-control model presents a short latency. The same behavior is noticed in the discharging phase. The VSP overall demand follows precisely the constant demand and no charging occurs until the SoC reaches minimum. On the contrary the optimal control seems to better distribute the energy that is stored. Thus the charging start later than the VSP and the discharge phase is allocated over the whole peak. A significant indication of this is the charging of the optimal control that never reaches zero.

In Figure 4.11 the comparison of the charging strategies reveal a similar shape and pattern. At charging phases the amplitude of the consumption is indicated by the available margin between the constant demand and the maximum output level of the cheapest available unit. Thus the two curves are identical. The way the two models handle the discharging phases slightly differs. It can be observed that the VSP is more steep and turns into radical action not to charge at all. The optimal control on the contrary is constantly charging even at very low levels compared to it's baseline. The root mean squared error is found to be 0.78 MW. The energy that is consumed by the VSP during the simulation period of 5 days was 8 MWh less than that consumed by the

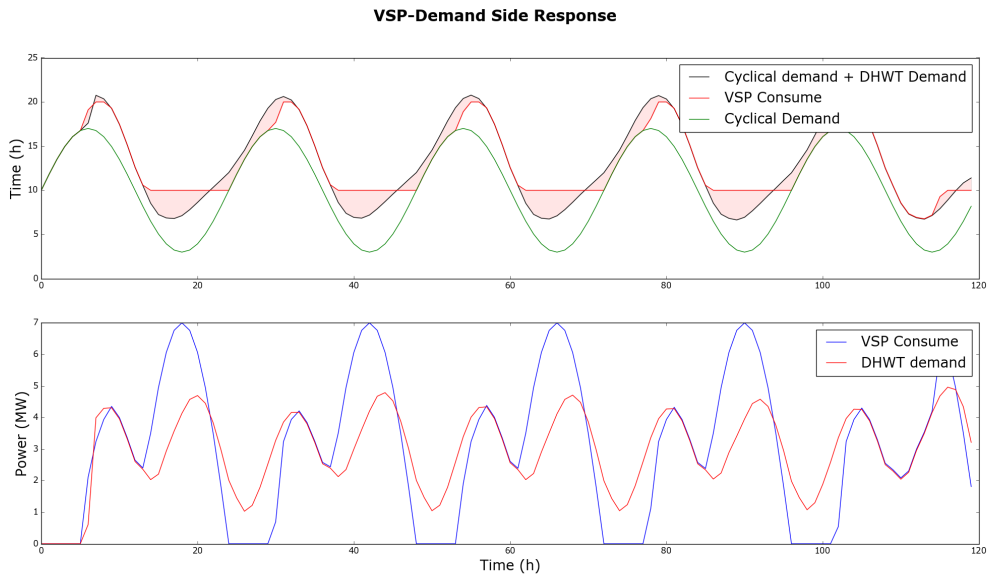


Figure 4.9: VSP valley-filling and peak-shaving.

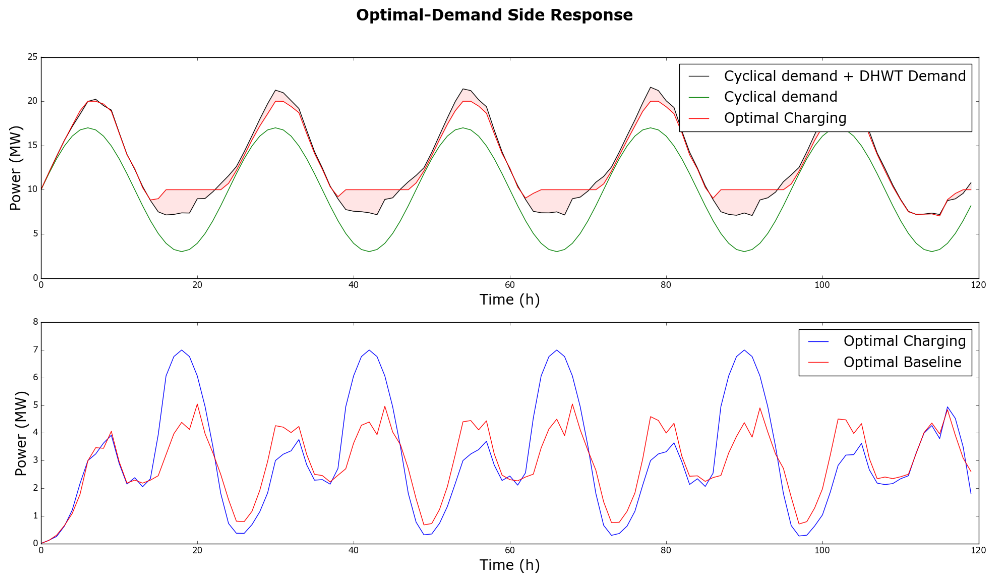


Figure 4.10: Optimal control valley-filling and peak-shaving.

optimal- control model.

In general it can be observed that although the VSP model is not able to track and reproduce the exact same behavior as the disaggregated model, it is able to simulate it up to a satisfying extent. The lack of information about the detail of the process in the case of the VSP model results in partial loss of the system's dynamics. This was expected as the original intension was to remove the computational burden of the detailed optimal-control model. Finally it was shown that it is possible with a general and much lighter representation to simulate with a satisfying accuracy the behavior of several thousands of DHW tanks. It should be noted that the same tests were performed by considering 2000 tanks and the results obtained were quite similar. It was also observed during the tests that the VSP tends to perform better than the optimal case which seems to have limitations concerning the rate of either charging or discharging. This leads into consideration about imposing further power constraints for the power consumption of the VSP. For instance, if the demand fluctuated in maximum amplitude the optimal would respond at a later step than the VSP and would consume slightly less than what the VSP would.

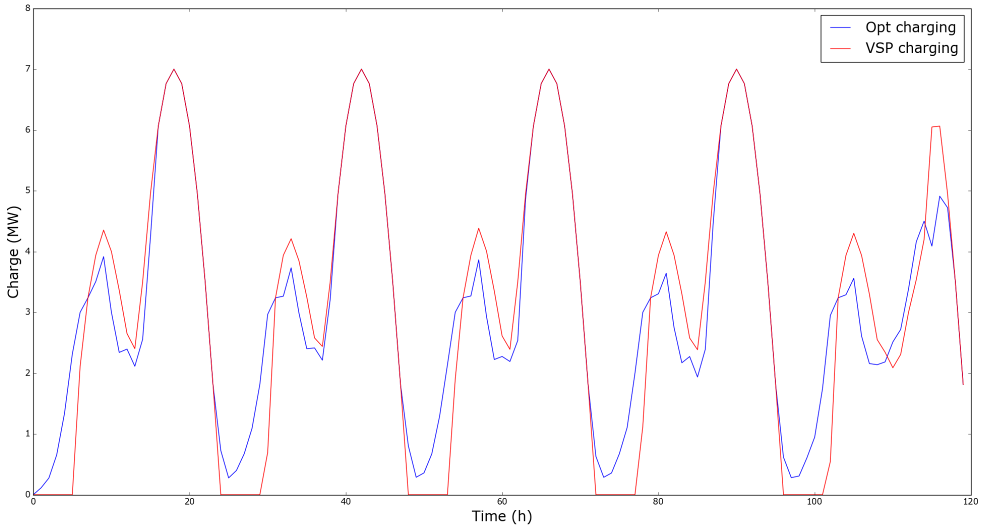


Figure 4.11: Comparison between optimal-control and VSP DSR.

4.4 Conclusions

In the present chapter the development of a Virtual Storage Plant model is performed. This modeling approach intends to simulate the shiftable demand of smart DHW tanks in a virtual plant set-up. Thus assuming that the portfolio of tanks is centrally controlled and that their consumption is handled in a way at first to supply hot water to the households and afterwards to offer flexibility to the system. During the development of the model several attempts were performed and finally the VSP model proved to be more realistic when simulating it's operation as a plant that is able only to charge. No discharging of power to the system is thus assumed. The ability of the VSP model to initially operate as the disaggregated fleet of tanks was validated. Afterwards the participation of this VSP and the optimally controlled portfolio of tanks in a simple dispatch algorithm was considered in order to validate the performance of this model in Demand Side Management strategies. The conclusions drawn by this investigation can be summarized as follows:

- Modeling the ambient losses in the VSP model as a linear function of the state of charge succeeds in capturing the behavior of the DHWT model regarding the heat losses. Indeed the detailed optimization tries to maintain the temperature level as low as possible in order to decrease the amount of energy wasted to the ambiance. This is the main difference between thermal storages and other forms of storage (batteries). Moreover, making the simplification regarding the energy demand to cover the hot water consumption in Equation

4.6 and the smoothening of this curve produced a really good approximation of what is computed by the detailed optimal-control model. Thus the VSP model is found to perform extremely well into describing the behavior of the fleet of DHWT in standard operation (non-DSR).

- Comparing the two models in DSM strategies proved that the VSP model is able to simulate the operation of a portfolio of DHWT in load-shifting. Indeed it was shown that both models were charging strategically in order to reduce the overall system cost. The charging phase took place when power was available from the cheap generator. Then the stored energy was used to reduce the overall demand at periods when the more expensive generator was producing.

- Merit order models can be used as a proxy for the evaluation of the VSP model. While no operational constraints are not taken into account, nor all costs, they allow to approximate the solution of the integrated model in about 1/60th of the calculation time. However the results should not be over-interpreted due to the lack of several operational constraints.

- The VSP model was found after the validations to be able to approximate the operation of the flexible DHWT but presented several inaccuracies due to its weakness to track the dynamics of the system. The general approach fails at several points to follow the behavior of the detailed model. Thus it is a good tool to make generalized projections and to realize expectations about the operation of the tanks.

- Further constraints regarding the power consumption of the VSP should be investigated in order to make it more realistic and similar to the detailed model. For instance the VSP at each time step has the capacity and the volume of the aggregation of DHWT and experiences the hot water consumption of a certain number of them. The big difference is that the individual tanks have a limited capacity available. Due to the way that the VSP is formulated the assumption is made that the tanks can share power resources which is not accurate and creates loss of the detail.

  In the VSP model by the way it is

  formulated we assume that for the hot water consumption of one tank there is available power from another that has no consumption at this time step.

Finally it can be concluded that the present modeling approach of a VSP was found to be able to simulate a fleet of DHWT serving flexibility to the system by their ability to charge strategically. A centralized control is assumed by the aggregator who is responsible to offer capacity and activation reserve to the system. The VSP model is able to capture the benefits that the aggregator would have by participating in the reserves market offering this flexibility. The participation of this model into an economic dispatch and unit-commitment model such as Dispa-SET rather than a simple merit-order model would give a clear overview of the benefits arising from DSM strategies to the system. Moreover projections and estimations about the impact that the high penetration of RES would introduce to the system can be performed. The implementation of simulations regarding the higher RES integration in combination with DSM contribute highly to the identification of the future system cost and the challenges that DSM would have to front. Therefore the integration of this model to a Unit-Commitment and Economic Dispatch model is suggested as future work along withe the improvement of the current VSP model.

Chapter 5

Conclusions

In the general context of global warming and climate change the need for cleaner and more efficient energy production is becoming more and more imminent. The higher integration of RES is considered to be the remedy to this issue from energy policy makers. However the instabilities and uncertainties deployed with the high penetration of RES to the electrical system introduce challenges and obstacles. Therefore the need for flexibility has been highlighted in this thesis and in the literature. This thesis studies the current flexibility offered by the conventional production units and the flexibility potential arising from the utilization of smart devices. The role of *Demand Side Management* is critical towards the secure and safe integration of Variable Energy Sources. Thus the participation of a large share of Domestic Hot Water Tanks in the Active Demand Response and ancillary services provision is broadly discussed.

The collection and processing of generation data available at Entso-e website has been performed. Several methods have been developed for the extraction of critical values. These values are intended to be used in Dispa-SET a unit commitment and power dispatch model in order to produce more realistic projections under various scenarios. The improvement of these parameters will introduce higher levels of accuracy due to the fact that the values are coming from real-time data. The inclusion of real-time values in a dispatch model will reveal the adequacy and the capacity of the present power system to integrate higher rates of VRE. It was shown that the ramping capacities of the plants and the minimum stable operation output are crucial for the secure operation of the system. The part-load that was detected for many of those plants especially coal and CCGT units was lower than the one considered in previous simulations. The increased cycling and the high ramping capacities of CCGT plants are confirmed. However the available data were given in hourly time scale and thus the accuracy could be reduced especially when dealing with ramping values. The development of more elaborate methods for the extraction of other important values as well as the improvement of the ones currently developed is suggested. Furthermore, the assessment of the performance of individual units should be considered. The grouping of units based on its type of technology reduces the extraction of useful conclusions about each unit characteristics. It should be stated that this is to our knowledge the first attempt that deals with real generation data from production units. Further investigation should consider higher resolution for accomplishing higher accuracy.

The evaluation and quantification of the flexibility that a portfolio of smart Domestic Hot Water Tanks can offer to the system is investigated in the present thesis. Moreover their ability to participate in reserves (capacity and activation) markets is evaluated. The aggregator, an entity that contracts the individual tanks is responsible to centrally control their operation and respond to the system's need for flexibility while supplying the thermal needs of the households. Two detailed modeling approaches were developed in order to assess the portfolio's capabilities. A rule-based control strategy is used as a first attempt and the computation is divided in two parts. First the baseline consumption is computed. Afterwards a priority stack based algorithm is used and the portfolio is simulated in Active Demand Response. The main characteristic of this method is the lack of prediction. However the results indicate high efficiency in providing both activation and capacity reserves. This method computationally light and is able to simulate the detailed operation of 20000 tanks for five days with a fifteen minutes time step. High parallelism is used to reduce the overall computations time (about ten minutes) and the main problem is memory deficit. The rules that were used were mainly considering the temperature level of the tank, however other system price rules can also be used. An optimal control strategy is then used to identify the flexibility potential of the smart DHWT. The problem is divided in two stages, the baseline consumption computation and the reserves provision. This strategy entails full prediction and the results indicate a shift of the power consumption in time compared to the outcome of the rule-based control strategy. The optimal control is used to simulate the behavior of an aggregator that offers capacity and activation reserves to the markets. It was demonstrated that the costs for providing these reserves depend highly on the current state of the portfolio. For instance, it is more expensive to offer downwards capacity reserves when the consumption is at its lowest. It was also conducted that the operation of such a fleet can be more costly efficient when participating in reserves market. A cost reduction of 7% was found. However the pricing context that was used was not precise. Therefore the participation of such a model in an agent-based set up that simulates the market players interactions could be more indicative about the cost reduction in the DHWT operation and the potential benefits of the aggregator. Finally due to memory restrictions 300 tanks were simulated with a fifteen minutes time step. The computational burden arising from the model's nature and the optimization suite that was used limited the number of tanks that could be simulated.

Finally a Virtual Storage Plant model was developed similar to the hydro storage model used in Dispa-SET and other dispatch models. This VSP model is used to simulate a large number of smart devices such as the DHWT participating in DSM operation. The notion of VSP is similar to a virtual generator but the storage plant is only able to strategically consume energy from the system. The modeling assumptions are further discussed and the heat losses are introduced as a linear function of the state of charge. The model is then validated both in standard and reserves provision operation. For the validation process the models developed in chapter 3 are used. It is shown that the model is able to follow the disaggregated cases with a good accuracy and the overall is not greater than 10%. For the Active Demand Response provision validation a merit-order model was used with fictional generators and sinusoidal demand. It was demonstrated that the VSP was able to perform *valley-filling* and *peak-shaving* in a similar manner to the optimal control model. However the VSP was found to be less sensitive than the disaggregated case due to the lack of detail, which was rather expected. The goal of this modeling approach was to create a light model that was able to simulate the flexibility potential coming from electrical heating devises. Then its participation into Dispa-SET would be performed in order to analyze the higher rate of RES penetration that could be accomplished by introducing higher flexibility to the system.

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