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Flexibility from Batteries at End-User Level:

Implications for Distribution Grids

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Implications for Distribution Grids

By

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To my mother, Maria de la Concepción. To my father, Miguel Angel. To Antonio, Juana, Juan and Mercedes. This is for you.

Abstract

EU carbon emission targets related to climate change has set in motion a process of transition towards an environmentally clean and sustainable power system. A central focus on this process is the transition from fossil fuel based energy sources to clean Renewable Energy Sources (RES). However, the intermittency of RES (e.g. solar and wind) presents a formidable challenge to achieve a stable and reliable supply-demand balance in grid operations. To achieve high levels of RES deployment, increasing the power system flexibility will be central to accommodate large fluctuations in supply and to cope with peak demand. Prospects of electricity storage technologies have emerged as a potential key technology to manage high levels of RES in the power system.

Recent projections on the cost of electricity storage show a high decrease in the next five years ([1],[2], [3]). As the commercial maturity of batteries might become a reality within the next decade, many questions remain on the role of batteries in the power system, where batteries should be located? What capacity will be optimal? What kind of battery services are the most valuable? How do batteries contribute to the large deployment of distributed RES installations? Significant research has been done on estimating sizing and sitting of storage in power systems. Yet, most of this research treat storage capacity as continuous instead of discrete, i.e. allocating storage by percentages of a total allowed capacity, wherever necessary in the grid. Despite these previous studies have provided interesting contributions on the value of storage in the power system, many of them lack the modelling of power flows, technical limits, or voltage considerations.

This thesis focuses on battery flexibility in medium voltage grids. Specifically, how to define cost-effective strategies to deploy batteries in a medium voltage grid? What is the optimal battery location in a distribution grid? And how do the technical limits of the power grid influence the allocation of storage? To address these questions, an optimization model was developed to simulate half-hourly operational decisions for a distribution grid. The model is multi-period and includes: power flows, diverse technical consideration for different battery sizes, high RES penetration levels, time of use electricity prices (half-hour dynamic prices), load data of actual customers and battery costs. To decide on the battery location, the model employs binary variables to determine the investment and sitting of the battery in a distribution grid. That is, the model is a mixed integer linear program with multi-period features which provides an investment analysis for the cost-effective sitting of batteries in a time horizon of 10 years. The model is implemented to the IEEE 33 bus test system. Results show that in general battery location and size strategies are driven by multiple factors, which can be either fixed or dynamic, like thermal limits and power load consumption, respectively. Some relevant findings are: First, flexibility in terms of power arbitrage delivers costs reductions of around 4% when RES production is low, compared to a No-Batteries case. Moreover, when RES production is high, the reductions in total costs can ramp up to 12% below the No-Batteries case. Also, this model decides to al-

locate batteries only if they are economically feasible for a 10-year time horizon. These results indicate a potential revenue up to 2.1 million pounds (GBP) based on the investment in batteries. And they are based on battery cost prices from 2008, together with several optimistic projections for the next decade. Furthermore, depending on battery size, RES penetration, RES generation and technical limits, batteries tend to be located for buses at the entrance of branches with high loads. Likewise, line limits and voltage limits proved to be decisive in the election of buses and the number of batteries placed.

On one hand, results show that optimal allocation strategies depend on grid topology features and technical limits, on the other hand, they also have a high dependency on time-varying and unsteady factors (e.g. power generation and loads). The optimal location strategies tend to change and adapt to the dynamics of the system. Moreover, with the exception of the slack bus, every bus in the system turned out to be an optimal location, at least once. These results indicate that batteries might be useful in every bus of the distribution grid, but only if each battery is operated in coordination and cooperation with one another. These insights support the idea of designing local electricity markets. Based on a reflection of this work, we recommend a market design that retrieves day-ahead and intraday DSO-reports of the battery operations and the flexibility that is available in the distribution grid. And also a subsequent structure of market incentives and penalties that maximizes the value of flexibility while keeping non-optimal operations to a minimum.

In short, this thesis contributes with a novel modelling approach that can shed some lights on the optimal battery allocation problem for distribution grids. Moreover, it provides insights on how location affects the value of storage, how optimal locations are affected by multiple technical factors. And finally, it also provide some reflections on the need to collectively, cooperatively and coordinately operate the storage resources in the grid by considering market-based solutions.

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Chapter 1

Introduction, Motivation and Research Questions

1.1 Introduction

Climate change is a pressing global issue with transcendental consequences for the planet, the ecosystem and humankind. It is the result of decades of increasing green house gas emissions without much regard of the effects on the enviroment. Ergo, many nations have shaped their energy policy strategies so to transition between a carbon-based energy infrastructure, into a sustainable one. In this sense, the EU has committed to reduce their Greenhouse Gas (GHG) emissions up to 80% of 1990 levels by 2050. This ambitious goal will require that by 2020, the EU energy system consumes 20% of its energy from renewable sources [4]. If these goals are to be achieved, the share of RES in the power system has to increase substantially in the next decades. This transition is happening at a faster rate than expected in some parts of EU. For example, the penetration of RES in power grids is now large enough to supply the total demand of a small country, like Denmark, for a complete day [5]. Nevertheless, the principal challenge associated to renewable energy generation is the uncontrollable nature of the energy output, leaving the energy scheduling and demand supply at the mercy of uncertain wind and solar generation patterns.

The success in the implementation of this new energy infrastructure opens the door to new challenges, mainly, the ability of the future power system to maintain a stable supply-demand balance. The main question is, how to handle the lack or excess of energy generation? To address this technological challenge, many alternatives are being considered to integrate and balance RES. Due to its rapid decreasing costs, battery storage has emerged as a potential flexibility source to deal with RES. Batteries have experienced a rapid decrease on its cost, with some predictions noting that it will be a commercially viable technology by 2025 (costing around 200USD per kWh).

Storage deployment will be essential to reach a high level of RES supply in a future low carbon energy system. However, many questions surround the operations, deployment, value, services and benefits of battery technologies. For example, what type of battery? what size? where the battery should be located in the distribution grid? The use of batteries in the distribution grid has been investigated (in [6] [7] [8]), with promising results. It is also expected that the use of batteries would help to reducing power bottlenecks in distribution grids. From the end-user perspective, the use of batteries allows to leverage from more energy coming from RES and also to reduce the electricity expenses for prosumer households [6].

From the distribution grid perspective, batteries bring benefits but also challenges. The biggest challenge comes from battery costs, mostly because their fabrication is highly dependent on costly raw materials. Also, as a collateral consequence, the use of electrical batteries requires the use of Power Electronics (PE), meaning extra costs but also, higher harmonic pollution in the power system. Nevertheless, the prices of batteries, as any other technology, are expected to drop significantly according to [1], [2] and [3]. And the use of storage allows a higher use of renewable energy surpluses, that otherwise would have been wasted without batteries. Finally, the use of PE components gives the opportunity to provide reactive power control to the grid, which is already a highly desirable feature.

Since the large deployment of RES will likely be widespread in many distribution grids, and storage is vital to integrate RES, solving this questions and gaps in knowledge is critical. In this project, our goal is to try to resolve some of the key gaps presented here.

1.2 Motivation and problem statement

As noted before, the main concern of any power system is to assure the supply-demand balance, but now it will face the challenge of having intermittent sources as suppliers. To make this possible, it seems clear that battery storage could play an important role, but what is yet to be known is what kind of storage technology, and storage deployment strategy will offer the optimal solutions. Therefore, many research efforts have focused on the type of storage to use, the size of the storage, the distribution of the storage and its economical advantages/disadvantages.

In [6] a standard model of an average UK home was made to evaluate the value of the storage for different scenarios, involving wind energy leverage and water heating. There, it was found that even with some conservative assumptions, the combination of storage and wind could increase wind energy utilization up to 20% and lead to electricity costs reductions up to 15%. Yet, the paper uses a stylized model to represent the energy system that only considers the energy exchanges with no focus on the power flow, the internal home circuit, the battery dynamics, efficiency limitations, and so on. This approach reduces substantially the computational effort needed for simulation but also leads to slightly unrealistic results since the power flow math is key to describe practical problems.

In [7] its is shown how storage accounts for even more value when distributed generation units are present (as wind, solar, biomass, etc). Although, this study focus on a University Campus, which is a rather large user compared to a typical household.

In [8], a detailed battery model that allows real time control, is presented. Here, the results show that the battery losses can be reduced up to 30% just by considering the detailed model of the battery. This model was used to analyze the performance of a centralized predictive-control scheme, for distributed battery storage. However, a decentralized strategy was not covered.

Moreover, there are still many approaches to try and that are yet not found in the the literature. There are gaps to cover in the mentioned papers, for instance, could a more detailed grid model that contains power-flow features and other technical details, reach the same conclusions? Or, how optimal sizing and sitting for storage would affect these results? Also, how much of the storage value was underestimated due to simplifications? These questions are some of the many still unanswered in the literature.

In this project, we try to address similar questions but with strong focus on having a more detailed model to find the sizing and sitting of batteries in a distribution grid. In such a manner, it is our desire to retrieve valuable knowledge from our efforts and substantially contribute to take us one step forward in the construction of a sustainable, green and prosperous future, for generations to come.

1.3 Research Questions and Objectives

The objective of this thesis is to understand the role of battery storage in increasing the penetration of RES in distribution grids. It seems that sooner or later, more users might install, or increase the capacity of, their own storage. Yet, unplanned deployment of storage might not be the best scenario for DSO. User-own storage operated on a single-sided way, with its own objectives and with no cooperation with the rest of the system can lead to more congestion, voltage imbalance and low energy quality. On the other hand, stiff regulations for storage will prevent the full exploitation of storage value, leading to the under-utilization of RES and stagnation of the transition process. Both scenarios are unwanted and preventable. The first step to avoid them, consist on executing research that provides a deep understanding of the problem. With such groundwork established, DSOs will be able to design business models, policies and markets that benefit all players and the environment.

Ergo, this project's goal is to address some of the research gaps in the literature within battery location for distribution grids. Exciting answers may appear by looking for optimal and cost-effective strategies to deploy batteries while taking into account power flows. The complexity of such a study requires a breaking-down approach to tackle it appropriately. As a result, this thesis, was designed to: First, carry out these studies in a small and simple distribution system, to understand how the battery operates and how much value it adds. For this, we built our own python-based tool, which describes a linear optimization model that minimizes the operational costs for the DSO, considering power flows and other technical constraints. Second, to extend this model-software infrastructure to fit a larger IEEE 33-bus system, from which the most important and final remarks of this project will be extracted.

Research question

In this sense, the following research questions are devised as steps and orientation points to guide this investigation:

How to define cost-effective strategies to deploy batteries in a medium voltage grid?

Sub-questions:

1. What influences the battery location and sizing decisions in a distribution grid? What is the role of battery services for RES balancing and energy arbitrage in sitting/sizing decisions?

2. How do the technical limits of the power grid influence the allocation of storage?

3. From the DSO perspective, which are the implications of widespread battery storage deployment in the power grid?

Concerning these questions: First, it is expected that batteries will improve the performance of the system, mainly because batteries will schedule charging and discharging to store and discharge power whenever is the cheapest, optimizing the utilization of energy. Nevertheless, investment in batteries is taking time partially because batteries are expensive. Despite the recent and projected drop in prices, investing in batteries requires certainty over the return on investment. So, measuring how much savings batteries can provide in the long term is a straightforward way to find this out. Second, we know from the literature that when deploying batteries, there are optimal solutions and they depend on size as well as location. But, a remaining question is what makes certain buses optimal locations? And, for different circumstances, is there a familiar pattern among the optimal solution strategies?

Third, batteries are not only going to operate with the goal to achieve revenues but also, to make sure the grid operates under its security limits. Therefore, batteries will be subscribed to the same constraints as the system, and that raises the question of how these constraints will affect the solution. Are optimal locations determined solely by loads, generation and prices or, also by technical limitations? And fourth, with the drop in storage prices, improving battery technology and economical governmental incentives, the chances are that end-users quickly become prosumers and storage holders. That, combined to the increased presence of EVs and other flexibility options make possible the idea of flexibility markets, where these flexibility services will be traded among all the players involved, thus optimizing the resources available and increasing the economical and societal value of flexibility. That said, DSOs have to asses the impact of thousands of players stepping in and exchanging power with the grid or effectively disconnecting from the grid whatsoever, which are, so far, highly undesired scenarios. Then, which are the ramifications of these developments for the DSO ? what are the best strategies the DSO can take to adapt? These are some of the multiple inquiries yet to answer and it is the objective of this thesis project to solve them.

Thesis Structure

As an outline, the order of chapters goes as follows:

- Chapter 1: Motivations and Research Questions (this chapter).
- Chapter 2: The literature review is developed.
- Chapter 3: The problem formulation and definition of the small 3-bus example is carried out.
- Chapter4: The implementation of the optimization model to the IEEE 33-bus system and the main results.
- Chapter 5: A sensitivity analysis of the IEEE 33-bus system is carried out with discussion of the results.
- Chapter 6: Conclusions.

Chapter 2

Literature Review

As mentioned before, the ongoing integration of RES in power systems make essential the diversification of flexibility services. To provide this, demand side response, load shedding, curtailment, energy storage and other strategies are being discussed as potential options. Moreover, battery storage is on its way to become one of the key solutions to supply flexibility in the future grid, yet there still are many considerations to be taken before its fully implementation. One of the most important questions to be solved is how to optimally place and size storage; a problem that can be referred as Optimal Distributed Storage Placement (ODSP). To find answers for the ODSP, several studies with different angles of approaches have been carried out. This literature review presents an overview of relevant previous work in this field and discusses the different approaches to the problem, with a summary of the research gaps covered in this thesis shown at the end of the chapter in Figure 2.1.

2.1 Previous Approaches

Importance of Electricity Storage

This section covers related literature on why storage is so important and must be used. Literature shows consensus around the ideas that: first, in the near future there will be need for storage. Second, batteries are rather expensive, so benefits from them system will be achieved only if battery sizing and sitting is optimal. This optimal solutions have been shown to exist, and the methods to achieve them are various and different in approach.

As an example of the importance of storage, in [9] it is shown that the value of storage increases with tighter carbon emission policies. Also, that under strict carbon-emission limits, storage enables greater penetration of low-cost carbon-free resources and that longer duration storage increases the share of wind more than the share of solar. Concluding that, effective storage implementation will notably benefit the integration of RES

(Renewable Energy Sources) in the power grid. Furthermore, in [10] an infinite horizon average cost stochastic dynamic program to find the optimal sizing of energy storage towards RES integration. Results show that the optimal storage management policy has a simple dual threshold structure and that storage marginal value decreases with size. This study presents useful insights and suggests that the system will obtain the most benefit from storage when optimal sizing is in place.

Similarly, in [11] the impact of stochastic wind generation and DBS (distributed battery storage) in the distribution grid is studied. Stochastic wind generation and storage participation influenced an improvement of the voltage profile and also a significantly positive impact on the resistive losses and expected system cost. This study suggests a strong correlation between an improved power system performance, RES leverage and storage participation.

Storage Technologies

There are many storage technologies available, and they can be basically divided based on their capacity to provide energy services, or power services. For instance, storage installations based on Flywheel perform very good when providing 'power services', i.e, releasing or absorbing large amounts of power in little time. Whether batteries, are much better on providing energy services, i.e. absorbing, storing and releasing large amounts of energy for longer periods of time. Power services are fundamental to control frequency and maintain stability; energy services are vital to ensure grid balance in the long term.

Nevertheless, it was shown that the type of technology is not a compulsory constraint for the election of the storage, and that optimal sitting and sizing solutions can remain valid for a diverse portfolio of technologies. Likewise, in [12] storage sizing and siting is optimized for a a given portfolio of storage technologies in two cases, with fixed-function portfolio and with optimal-function portfolio. It was found that storage allocation depends not only in the network properties but also in the storage technology. For example, depending on the congestion in the grid and the storage technology mix, optimal solutions can be found where storage technologies perform both, energy and power services. Hence, storage allocation and sizing should not be strongly limited by the type of technology to be used.

Allocation Based on Topology Options

This section reviews papers regarding allocation options for storage. Storage can be allocated either in a centralized or a distributed way. Centralized approaches allows easier control from the TSO/DSO, but decentralized approach results in more renewable energy utilization and less congestion. To find which approach brings up the most advantage several papers have been done, as for example in [13] an interesting approach pro-centralized allocation have been done, proposing an interval model to quantitatively analyze and asses the impact boundaries of uncertainties on node voltages and further applying it to centralize storage optimal location. This model can accurately map the relationships between uncertainties and node voltages. Optimal solutions for centralized storage allocation can be found when these uncertainty-voltage relationships are taken into account. Also, in [14] a Multi Period OPF to optimize sizing and sitting of storage in LV grids is made, resulting in distributed allocation of storage as the best topology in comparison with centralized allocation. This is due mainly to the greater utilization of DG resources like PV or Wind.

The ODSP problem might be new, but similar problems have been studied before. The problem to optimally size and allocate distributed generation is rather similar to the ODSP and from there, relevant knowledge can be obtained. For instance, in [15] a review of the most relevant studies for DG sizing/placement is done, with an analysis of contributions of each study and evaluation of their advantages and disadvantages. There, it is shown that in the ODGP (Optimal distributed generation placement) problem, the strategies used are either Analytical, Numerical or Heuristical. For instance, in [16], [17] and [18] an heuristic, analytical and numerical approach were carried out respectively to solve the ODGP problem. Consequently, in the ODSP the trend is very similar and so far it can be observed the predominant abundance of heuristic methods, just like happened in the ODGP problem.

Sitting and Sizing Approaches

On the grounds of this, one interesting question to be asked is: *What are the optimal locations and capacities for storage in a power system?*. The way to answer that question depends on the objective desired and there can be many different objectives to aim for the optimization, like voltage control, minimal losses, maximum RES utilization, among others. This section reviews relevant sitting and sizing optimization approaches within the literature.

In the literature, the are three main approaches: First, to find the optimal size regardless of location. Second, to find optimal sitting and/or sizing by means of setting a global storage capacity and then allocate this capacity in a distributed manner among the nodes of the system. Then, when sizing is required, the size of each ESS is chosen based on the optimal percentage of the total capacity assigned to each node. Third, to find optimal sitting/sizing, first defining a given battery size and then changing the battery position on every simulation run, either manually or by means of heuristic approaches until all the available solutions are covered or a certain tolerance is fulfilled. The three methods are sub-categorized as 'Sole-Sizing', 'Optimal Capacity Allocation' and 'Try and Error Allocation' respectively.

Sole Sizing

The sole-sizing approach is not so common but it accounts for several works. For instance, the study made in [19] presents a model for determining the optimal size of an ESS in a microgrid (MG). An expansion planning problem is proposed to consider the investment cost of ESS, as well as operating cost of the MG. The numerical studies reveal that a larger storage system does not necessarily provide larger economical benefits. This study gives clear remarks regarding storage size and the need for finding models to optimize it.

Optimal Capacity Allocation

This is a very common approach, found in most of the literature, due to its easy implementation and somewhat low computational requirement. For example, in [20], show the influence of the local marginal prices (LMP) on the charging and discharging dynamics, finding that storage allocation and operation is driven by the incremental profit that an ESS installation can amass at a location for a given operating horizon. In such manner, this contribution consists in displaying how dynamic geographically-dependant pricing structure shape storage value, optimal size and optimal allocation. Furthermore, in [21] an unit commitment (UC) heuristic approach is proposed in 3 stages for a transmission network. It is demonstrated that the heuristic resulting from the decomposition used, does not cause a significant loss of optimality. The contribution of this method is to take into account both, the economic and the technical aspects of the sizing and sitting problem. This is a prudent approach knowing that energy storage feasibility will be dependent on both aspects. It is noteworthy to remember that this study considers only HV networks, leaving room for similar studies in MV/LV networks. As it can be noted, the complexity of the problem made the use of heuristic approaches very common, as in [22], where an optimal energy storage control algorithm is proposed to develop a heuristic procedure for energy storage placement and sizing.

Moreover, in [23] an optimal placement of storage is performed, within the full AC-OPF framework with both conventional and wind generation. Results show that changes in optimal storage siting congurations remain fairly consistent regardless of the generation mix and these outputs are robust to changes in total storage capacity and transmission line limits. Also, results might indicate that siting decisions made for the current (or planned) transmission grid may remain valid even if the generation portfolio or total storage capacity changes over time.

In [24] a compelling approach is made, where the optimal placement of storage is pursued. A continuous tree definition of a distribution radial grid with DistFlow model is used to locate the optimal locations and the value of storage in the system with the objective to minimize energy losses. There, it is shown that optimal storage locations tend to be at the ”leaves of the tree” (edges of the structure, away of the substations) and that the storage placement strategy allocates storage only after a certain threshold point in the grid is reached, from which storage is allocated in every node. Also, the value of storage increases from the substation towards these threshold points, and then it equalizes from those points onward everywhere in the grid. This suggests the existence of structural properties regarding storage allocation and value, that can be later studied in deep.

Also, in [25] it is proposed and discussed the use of the alternative direction method of multipliers in order to define an efficient algorithm capable to treat large-scale networks whilst finding an optimal solution. From the results it is noted how the proposed process is capable to allocate each ESS by distinguishing their influences on various network parameters. It can be concluded that the proposed process can be used by DNOs to evaluate the possible use of ESSs as a valid alternative to investments in grid reinforcement or massive telecom infrastructure for direct DG control.

Try and Error Allocation

This method is also common because it finds locations based on many simulations and less computational effort. The investigation done in[26] uses Optimal placement of the energy storage units within a deregulated power system to minimize its hourly social cost. A business model is developed to evaluate the economics of the storage system based on the energy time shift opportunity from wind generation. Results show that optimal storage distribution allows the effective utilization of the transmission capacity for wind power integration while satisfying the transmission constraints of the lines connected to the wind generating bus. The case studies demonstrate that distributed storage systems increase net arbitrage revenues. For the present overview, it is noted that this study makes a valuable contribution for ODSP but from the transmission level perspective, leaving room for similar research from LV and MV perspectives.

Storage experiences at the Grid Level

In the literature, most of the storage sitting and sizing is done for transmission grids. For instance, in [27] a method for storage sizing and siting is developed for a transmission network, using heuristic approximations to find feasible but not necessarily optimal solutions. Here, three stages are defined, first the optimal locations are found. Second, the ESS are located accordingly and the optimal sizes for these locations are found. Third, simulations are an and a comparison is made with stage one. An example for MV grids is found in [28], where a methodology is proposed for optimally allocating ESS in distribution systems with a high penetration of wind energy. Results show that integrating ESS units for the proposed application is economically feasible when the least expensive ESS is used, although this approach does not take into account other ESS services that might lead to more promising results. In addition, there was no use of adequate variables (like binary, for instance) to allocate ESS optimally in that approach. What's more, there are many more examples of ODSP studies on transmission ([12]) and distribution ([6][13][15]) but there are not as many studies for MV or LV grids. One of the few is shown in [29], where a Model Predictive Control (MPC) strategy is used to create strategies for optimal storage placement and sizing in Low voltage grids. As longer prediction horizons lead to better storage placement but higher computational complexity, benders decomposition is used to reduce this complexity. With the aim to maximize PV utilization, and given that MPC exploits better the value of forecast information, it is found that the economic value of battery storage is higher when using MPC rather than heuristic storage control strategies. Nevertheless, most of the available publications on LV or MV have focus on brute force approaches or capacity allocation rather than proper ESS sitting.

2.2 Proposed Approach

Finally, it is important to know that all these approaches and strategies return meaningful and useful insights, but they also have weaknesses. In the sole-sizing approach, the allocation is assumed regardless of any optimality consideration. In the optimal capacity allocation the main disadvantage lies on the impossibility for the industry to size storage in accordance to any given percentage, at least not for the application intended. In the try-and-error approach, the disadvantage lies on the computational time it takes to change the battery in every node, and the infinite possibilities when considering a group of optimal batteries instead of just one. In this project, the aim is to find a midpoint between the two main approaches listed before, meaning that the intention is to allocate any number of pre-sized batteries in a system in order to optimize the objective function.

Binary Sitting

This objective can be achieved by means of binary variables used to allocate the batteries, an approach that has not been fully explored before in the field. Moreover, another goal in this project is to pursue a sensitivity analysis with the proposed sitting method for a distribution grid and thoroughly analyze the results. A summary of the main ideas and conclusions collected in this review can be seen in figure 2.1

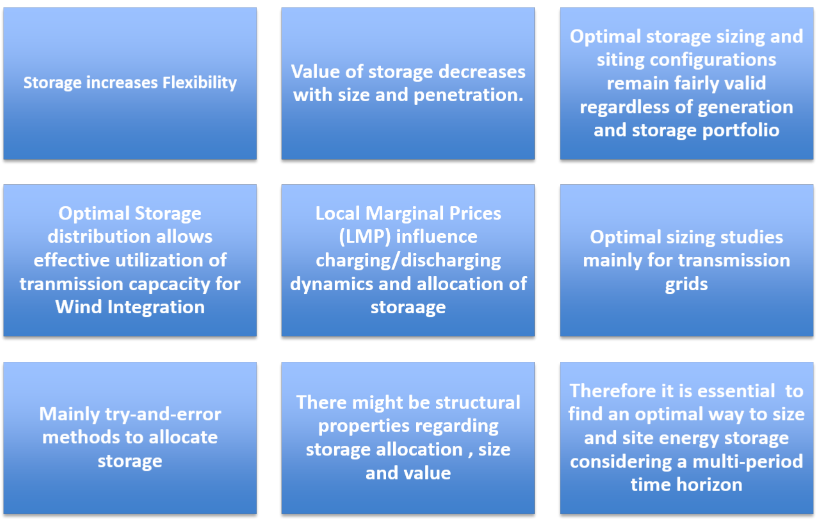


Figure 2.1: Summary

In this sense, it is the goal and the intended contribution of this work to formally define an analytical approach that optimally allocates pre-sized ESS with real capacities in a MV grid. With a solution method based on binary variables functioning as decision variables for locations, a local linearization for the power flow equations, local marginal dynamic prices, physical and economical constraints within a multi-period mixed integer linear programming problem. The results of this work will be thoroughly analyzed to shed some lights in the ODSP problem.

Chapter 3

Problem Formulation and Small Example

The thesis will employ the IEEE 33-bus system with some modifications to test the optimization algorithms for battery sitting decisions and operations. To initially understand the sitting problem and the operations of the battery in a multi-period setting, the first formulation will be done for a smaller system, comprised by just 3 buses. The insights and experiences attained with the 3 bus 'toy' system will be used to later tackle the 33 bus system. In this chapter, the theoretical and mathematical formulation of the toy problem are described in detail. For those purposes, the toy system was mathematically modeled at first with energy-based expressions and later the toy system was slightly modified and modeled with power flow expressions. All the modeling in this project is done using python-based optimization scripts. The details of both models are described in this chapter.

3.1 Energy-based Formulation

The toy problem scheme can be seen in Figure 3.1. The energy exchange with the grid results in costs or revenues for the system, as the import of energy produces a cost and the export produces a revenue. The goal of this optimization is to minimize the imported energy from the grid and to maximize the exported energy. The model formulation is a mixed integer non-linear integer problem with multi-period optimization features. The planning horizon is one day or one week.

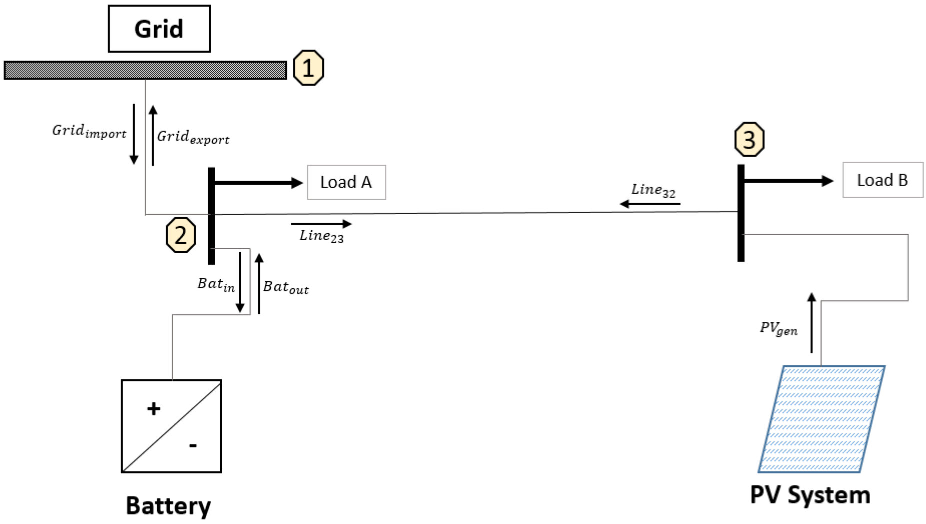


Figure 3.1: Toy System scheme 1

Toy Problem Components

Grid

The grid consist of the slack bus that will provide or absorb any imbalance in the system. All the energy imported from the grid will result in costs, and all the energy exported will result in revenues. The optimization function is designed such as to minimize imports and maximize exports.

PV System

The PV system is located at bus 3 and with the aid of the battery it provides the energy to the load when solar power is enough. When there is not enough solar power, the battery and the power coming from the line feed the load. The solar energy provided by this PV system is a dynamic parameter that will variate according to a deterministic forecast for a given scenario. This behavior will force the battery to schedule its charging and discharging operations according to the availability of solar energy and the needs of the load. It is defined as $P_{PV gen}(t)$.

Battery

The Battery stores PV energy surplus for later use. The optimization will be done period by period, resulting in a set with the optimal battery charging and discharging decisions. The battery charging and discharging dynamic depends upon the equation 3.8 which describes the relation between the state of charge (SoC) of the current period, the SoC of the previous period, the charging rate (Bat_{in}), discharging rate (Bat_{out}) and minimum state of charge (SoC_{min}). State of Charge is limited to the maximum battery capacity, as well as the charging and discharging rates are limited by physical constraints (3.9, 3.11 and 3.12 respectively). This equation is energy-wise, which is the reason why the time period t is multiplied by the power quantities.

$$SoC^{(t)} = SoC^{(t-1)} - Batt_{disch}^{(t)} * \frac{1}{\eta_{disch}} + Batt_{ch}^{(t)} * \eta_{ch} \tag{3.1}$$

$$SoC^{(t)} \leq Batt_{MaxCapacity} \tag{3.2}$$

$$SoC^{(t)} \geq SoC_{min} \tag{3.3}$$

$$Batt_{charge}^{(t)} \leq BatCh_{max} \tag{3.4}$$

$$Batt_{discharge}^{(t)} \leq BatDch_{max} \tag{3.5}$$

Line

The function of the line is to transfer the energy between buses. Hence, two variables will describe the line, one to represent the flow from node 2 to node 3 and one to represent the flow from node 3 to node 2.

$$Flow_{L23}^{(t)} \leq Line_{Limit} \tag{3.6}$$

$$Flow_{L32}^{(t)} \leq Line_{Limit} \tag{3.7}$$

$$\forall t \in T$$

Energy Balance Equations

Therefore, taking the above equations, the energy balance equations are derived for both nodes, as seen in Eq. 3.8 and 3.9.

For Node 2,

$$G_{import}^{(t)} + Flow_{L32}^{(t)} + Batt_{discharge}^{(t)} = G_{export}^{(t)} + Batt_{charge}^{(t)} + P_{LoadA}^{(t)} + Flow_{L23}^{(t)} \tag{3.8}$$

And Node 3,

$$P_{PVgen}^{(t)} + Flow_{L23}^{(t)} = P_{LoadB}^{(t)} + Flow_{L32}^{(t)} \tag{3.9}$$

$$\forall t \in T$$

Optimization Definition

Now the optimization function can be defined, with all the above equations as constraints. As aforementioned, the objective is to maximize the benefits from the energy exchange with the grid, as mathematically expressed in equation 3.10.

$$F_{opt} = Min \sum_{t=1}^{T} \left[Price_{Import}^{(t)} * G_{import}^{(t)} - Price_{Export}^{(t)} * G_{export}^{(t)} \right] \tag{3.10}$$

$s.t.$

$$SoC^{(t)} = SoC^{(t-1)} - Batt_{disch}^{(t)} * \frac{1}{\eta_{disch}} + Batt_{ch}^{(t)} * \eta_{ch} \tag{3.1}$$

$$SoC^{(t)} \leq Batt_{MaxCapacity} \tag{3.2}$$

$$SoC^{(t)} \geq SoC_{min} \tag{3.3}$$

$$Batt_{charge}^{(t)} \leq BatCh_{max} \tag{3.4}$$

$$Batt_{discharge}^{(t)} \leq BatDch_{max} \tag{3.5}$$

$$P_{Line_{23}^{(t)}} \leq Line_{Limit} \tag{3.6}$$

$$P_{Line_{32}^{(t)}} \leq Line_{Limit} \tag{3.7}$$

$$G_{import}^{(t)} + Flow_{L32}^{(t)} + Batt_{discharge}^{(t)} = G_{export}^{(t)} + Batt_{charge}^{(t)} + P_{LoadA}^{(t)} + Flow_{L23}^{(t)} \tag{3.8}$$

$$P_{PVgen}^{(t)} + Flow_{L23}^{(t)} = P_{LoadB}^{(t)} + Flow_{L32}^{(t)} \tag{3.9}$$

The expected outcome of this optimization is a set of multi-period variables that define the optimal schedule that the battery has to follow in order to maximize revenues from the energy exchange with the grid.

3.2 Power-Based Formulation

Here, the power flow equations of the system will be added to upgrade the previous problem formulation. Now, with the addition of power flow equations the problem evolves in complexity and the quantities have to be power-based instead of energy-based. To adapt the previous formulation to power flow considerations, several constraints will go through minor changes as it will be shown below. The power flow equations to be used are the classical power system's analysis equations described in the literature [30]. Also, as the IEE 3-bus system served as an inspiration and a source of data, the toy problem scheme went through some topology changes, which can be seen in Figure 3.2.

Table 3.1: Parameters used in Formulation

Parameter	Description	Units
t	Time Period of Simulation	Hours,Half-hours, Minutes
T	Time Horizon of Simulation	Hours,Half-hour, Minutes
η_{Ch}	Battery Charging Efficiency	%
η_{Disch}	Battery Discharging Efficiency	%
$Batt_{MaxCapacity}$	Battery Maximum Energy Capacity	kWh
SoC_{min}	Battery Minimum Allowed State of Charge	kWh
$Price_{Import}^{(t)}$	Price to pay for kWh imported from the grid	NOK/kWh
$Price_{Export}^{(t)}$	Price earned per kWh exported to the grid	NOK/kWh
$BattCh_{max}$	Battery Maximum Charging Rate	kWh
$BattDch_{max}$	Battery Maximum Discharging Rate	kWh
$Line_{Limit}$	Maximum Line Energy Thermal Limit	kWh
$P_{LoadA}^{(t)}$	Dynamic Load in Bus 1	kWh
$P_{LoadB}^{(t)}$	Dynamic Load in Bus 2	kWh
$P_{PVgen}^{(t)}$	Solar PV System Generated Power	kWh

Table 3.2: Variables used in the Formulation

Variable	Description	Units
$G_{import}^{(t)}$	Energy Import from the grid per period	kWh
$G_{export}^{(t)}$	Energy Export to the grid per period	kWh
$SoC^{(t)}$	State of Charge of the Battery for each period	kWh
$Batt_{charge}^{(t)}$	Battery Charging Energy per period	kWh
$Batt_{discharge}^{(t)}$	Battery Discharging Energy per period	kWh
$Flow_{L23}^{(t)}$	Line Energy Flow from node 2 to node 3 per period	kWh
$Flow_{L32}^{(t)}$	Line Energy Flow from node 3 to node 2 per period	kWh

Toy Problem Components

Bus 1

Bus 1 represents the slack bus. Here is where we exchange power with the grid, whether importing or exporting. P_1 is the net injected power in bus 1; P_{import} and P_{export} are the total imported and exported power between the system and the rest of the grid. When P_1 is positive, the system is importing power from the grid. When it is negative, the system is exporting power to the grid. P_{import} and P_{export} are both always positive and limited by the thermal limits of bus 1. Also, the reactive load required by the system will be supplied by the slack bus.

$$P_1^{(t)} = P_{import}^{(t)} - P_{export}^{(t)} \tag{3.10}$$

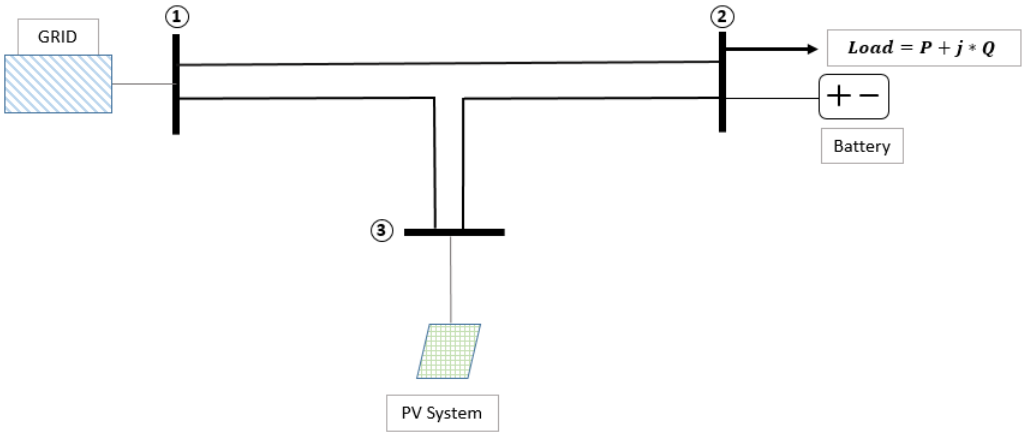


Figure 3.2: Toy System scheme 2

$$P_{min} \leq P_1^{(t)} \leq P_{Max} \tag{3.11}$$

$$Q_{min} \leq Q_1^{(t)} \leq Q_{max} \tag{3.12}$$

Bus 2

The battery is placed in this bus. Also, an active and a reactive load are located here. Thus, the total injected power in bus 2 is shown below. P_{ch} and P_{disch} represent the charging and discharging power flows coming in and out of the battery, respectively.

$$P_2^{(t)} = P_{disch}^{(t)} - P_{LoadB}^{(t)} - P_{ch}^{(t)} \tag{3.13}$$

$$Q_2^{(t)} = -Q_{Load}^{(t)} \tag{3.14}$$

Bus 3

Bus 3 has a PV system and a load. The total injected power equation is shown below. $P_{pv}^{(t)}$ is the power injected by the solar PV system at any given time. Zero reactive power generation or consumption is assumed in this bus.

$$P_3^{(t)} = P_{pv}^{(t)} - P_{LoadA}^{(t)} \tag{3.15}$$

$$Q_3^{(t)} = 0 \tag{3.16}$$

Battery

The battery is located at bus 2 and its modeling is described with the equation shown below. $SoC^{(t)}$ represents the state of charge of the battery and η_{ch}, η_{disch} represent the efficiencies of charge and discharge respectively.

$$SoC^{(t)} = SoC^{(t-1)} - P_{disch}^{(t)} * (t) * \frac{1}{\eta_{disch}} + P_{ch}^{(t)} * (t) * \eta_{ch} \tag{3.17}$$

$$SoC^{(t)} \leq Batt_{Capacity} \tag{3.18}$$

$$SoC^{(t)} \geq SoC_{min} \tag{3.19}$$

$$P_{ch}^{(t)} \leq P_{max}^{(ch)} \tag{3.20}$$

$$P_{disch}^{(t)} \leq P_{max}^{(disch)} \tag{3.21}$$

Power Flow

$$\mathrm{P}_i^{(t)} = \sum_{j=1}^{N} Y_{ij} \left[V_i^{(t)} * V_j^{(t)} \cos(\delta_i^{(t)}) * \cos(\delta_j^{(t)} + \theta_{ij}) + V_i^{(t)} * V_j^{(t)} \sin(\delta_i^{(t)}) * \sin(\delta_j^{(t)} + \theta_{ij}) \right] \tag{3.22}$$

$$\mathrm{Q}_i^{(t)} = \sum_{j=1}^{N} Y_{ij} \left[V_i^{(t)} * V_j^{(t)} * \sin(\delta_i^{(t)}) * \cos(\delta_j^{(t)} + \theta_{ij}) - V_i^{(t)} * V_j^{(t)} * \cos(\delta_i^{(t)}) * \sin(\delta_j^{(t)} + \theta_{ij}) \right] \tag{3.23}$$

Subject to voltage limitations,

$$V_{min} \leq V_1^{(t)} \leq V_{max} \tag{3.24}$$

$$V_{min} \leq V_2^{(t)} \leq V_{max} \tag{3.25}$$

$$V_{min} \leq V_3^{(t)} \leq V_{max} \tag{3.26}$$

Linearization of Power Flow Equations

Since the computational solving of the given equations can be quite demanding, it is common practice to approximate them into a linear form. Here, this is done using local linearization. In other words, using first order Taylor series. Hence, Taylor series mathematical expression can be seen in equation 3.27.

$$F(x) = \sum_{n=0}^{\infty} \frac{f^{(n)}(x_0)}{n!}(x - x_0) \tag{3.27}$$

$F(x)$:	The linear version of the original function
f :	The function to be linearized
n :	The order of the derivative
x :	The variable of the function f
x_0 :	The operational point of the linearization

Now, if we reshape the power flow equations 3.13 and 3.14, grouping a set of variables and making them linear, the result will look like equations 3.28 and 3.29,

$$P_i^{(t)} = \sum_{j=1}^{N} Y_{ij} \left[f_{ijA}^{(t)} + f_{ijB}^{(t)} \right] \tag{3.28}$$

$$Q_i^{(t)} = \sum_{j=1}^{N} Y_{ij} \left[g_{ijA}^{(t)} + g_{ijB}^{(t)} \right] \tag{3.29}$$

Where,

$$\begin{aligned} f_{ijA}^{(t)} &= V_i(t) * V_j^{(t)} * \cos(\delta_i^{(t)} * \cos(\delta_j^{(t)} + \theta_{ij}) \\ f_{ijB}^{(t)} &= V_i^{(t)} * V_j^{(t)} * \sin(\delta_i^{(t)} * \sin(\delta_j^{(t)} + \theta_{ij}) \\ g_{ijA}^{(t)} &= V_i^{(t)} * V_j^{(t)} * \sin(\delta_i^{(t)}) * \cos(\delta_j^{(t)} + \theta_{ij}) \\ g_{ijB}^{(t)} &= -V_i^{(t)} * V_j^{(t)} * \cos(\delta_i^{(t)}) * \sin(\delta_j^{(t)} + \theta_{ij}) \end{aligned}$$

Therefore, we want f_{1i}, f_{2i}, g_{1i} and g_{2i} to be linear around the working point x_0 which is represented by the following per unit values:

$$(V_{i0}, V_{j0}, \delta_{i0}, \delta_{j0}) = (1, 1, 0, 0)$$

If the method proposed is applied, each linear equation can be generally named h_m and its linearization is solved as follows:

$$\begin{aligned} h_m &= h(V_i, V_j, \delta_i, \delta_j) \\ h_{m0} &= h(V_{i0}, V_{j0}, \delta_{i0}, \delta_{j0}) \\ h_m &= h_{m0} + K_1(V_i - 1) + K_2(V_j - 1) + K_3(\delta_i) + K_4(\delta_j) \end{aligned}$$

Where:

$$\begin{aligned} K_1 &= \frac{\partial h}{\partial V_i}\Big|_{m=m_0} \\ K_2 &= \frac{\partial h}{\partial V_j}\Big|_{m=m_0} \\ K_3 &= \frac{\partial h}{\partial \delta_i}\Big|_{m=m_0} \\ K_4 &= \frac{\partial h}{\partial \delta_j}\Big|_{m=m_0} \end{aligned}$$

Hence, by applying the previous methodology we can linearize the power flow equations by linearizing the group of equations f_{1i}, f_{2i}, g_{1i} and g_{2i}, and the resulting equations are:

$$F_{ijA}^{(t)} = \cos\theta_{ij} + \cos\theta_{ij} * (V_i^{(t)} - 1) + \cos\theta_{ij} * (V_j^{(t)} - 1) - \sin\theta_{ij}^{(t)} * (\delta_j^{(t)}) \quad (3.30)$$

$$F_{ijB}^{(t)} = \sin\theta_{ij} * (\delta_i^{(t)}) \quad (3.31)$$

$$G_{ijA}^{(t)} = \cos\theta_{ij} * (\delta_i^{(t)}) \quad (3.32)$$

$$G_{ijB}^{(t)} = -\left[\sin\theta_{ij} + \sin\theta_{ij} * (V_i^{(t)} - 1) + \sin\theta_{ij} * (V_j^{(t)} - 1) + \cos\theta_{ij} * (\delta_j^{(t)})\right] \quad (3.33)$$

Therefore, the linear power flow equations will be:

$$P_i^{(t)} = \sum_{j=1}^{N} Y_{ij}\left[F_{ijA}^{(t)} + F_{ijB}^{(t)}\right] \quad (3.34)$$

$$Q_i^{(t)} = \sum_{j=1}^{N} Y_{ij}\left[G_{ijA}^{(t)} + G_{ijB}^{(t)}\right] \quad (3.35)$$

Which, result in the linearized form of the power flow equations:

$$\mathrm{P}_i^{(t)} = \sum_{j=1}^{N} Y_{ij}\left[\cos\theta_{ij} + \cos\theta_{ij} * (V_i^{(t)} - 1) + \cos\theta_{ij} * (V_j^{(t)} - 1) - \sin\theta_{ij} * (\delta_j^{(t)}) + \sin\theta_{ij} * (\delta_i^{(t)})\right] \quad (3.36)$$

$$\mathrm{Q}_i^{(t)} = \sum_{j=1}^{N} Y_{ij}\left[\cos\theta_{ij} * (\delta_i^{(t)}) - \cos\theta_{ij} * (\delta_j^{(t)}) - \sin\theta_{ij} - \sin\theta_{ij} * (V_i^{(t)} - 1) - \sin\theta_{ij} * (V_j^{(t)} - 1)\right] \quad (3.37)$$

Optimization Definition

Now, the objective function to be defined will maximize the benefit from the power exchange with the grid at bus 1. This means that the idea is to minimize power import and its resulting costs, and to maximize power export and its resulting revenues. In this sense, the objective function is presented in equation 3.38. This definition resembles the one given in the previous section, yet it is worthy to remember that the power flow now introduces new variables and parameters (like voltages and admittance angles) and that all the relevant output values and the given data are now defined as power and not energy. Moreover, all these power variables and parameters are given in per unit values, for simplification.

$$F_{opt} = Min \sum_{t=1}^{T}\left[P_{import}^{(t)} * price_{import}^{(t)} - P_{export}^{(t)} * price_{export}^{(t)}\right] \quad (3.38)$$

$s.t.$

$$P_1^{(t)} = P_{import}^{(t)} - P_{export}^{(t)} \quad (3.1)$$

$$P_{min} \leq P_1^{(t)} \leq P_{Max} \tag{3.2}$$

$$Q_{min} \leq Q_1^{(t)} \leq Q_{max} \tag{3.3}$$

$$P_2^{(t)} = P_{disch}^{(t)} - P_{LoadB}^{(t)} - P_{ch}^{(t)} \tag{3.4}$$

$$Q_2^{(t)} = -Q_{Load}^{(t)} \tag{3.5}$$

$$P_3^{(t)} = P_{pv}^{(t)} - P_{LoadA}^{(t)} \tag{3.6}$$

$$Q_3^{(t)} = 0 \tag{3.7}$$

$$SoC^{(t)} = SoC^{(t-1)} - P_{disch}^{(t)} * (t) * \frac{1}{\eta_{disch}} + P_{ch}^{(t)} * (t) * \eta_{ch} \tag{3.8}$$

$$SoC^{(t)} \leq Batt_{Capacity} \tag{3.9}$$

$$SoC^{(t)} \geq SoC_{min} \tag{3.10}$$

$$P_{ch}^{(t)} \leq P_{max}^{(ch)} \tag{3.11}$$

$$P_{disch}^{(t)} \leq P_{max}^{(disch)} \tag{3.12}$$

$$\mathrm{P}_i^{(t)} = \sum_{j=1}^{N} Y_{ij} \left[V_i^{(t)} * V_j^{(t)} \cos(\delta_i^{(t)}) * \cos(\delta_j^{(t)} + \theta_{ij}) + V_i^{(t)} * V_j^{(t)} \sin(\delta_i^{(t)}) * \sin(\delta_j^{(t)} + \theta_{ij}) \right] \tag{3.13}$$

$$\mathrm{Q}_i^{(t)} = \sum_{j=1}^{N} Y_{ij} \left[V_i^{(t)} * V_j^{(t)} * \sin(\delta_i^{(t)}) * \cos(\delta_j^{(t)} + \theta_{ij}) - V_i^{(t)} * V_j^{(t)} * \cos(\delta_i^{(t)}) * \sin(\delta_j^{(t)} + \theta_{ij}) \right] \tag{3.14}$$

$$V_{min} \leq V_1^{(t)} \leq V_{max} \tag{3.15}$$

$$V_{min} \leq V_2^{(t)} \leq V_{max} \tag{3.16}$$

$$V_{min} \leq V_3^{(t)} \leq V_{max} \tag{3.17}$$

In Figure 3.3 the operations for 24 days are given for the reference case, with and without battery. And in Figure 3.4 the total cost reduction is shown. Clearly, the battery is scheduling operations according to changes in price and thus enhancing the overall performance of the system. By smoothing RES surplus and exerting net arbitrage, it is reducing the operational costs of the system for about 25 %.

There are four major insights to recall from this chapter. First, breaking the problem into smaller challenges allows its modeling with very simple equations that can easily be upgraded to more complex, general versions. Second, a smaller version of the problem provides deeper understanding of where the boundaries of accuracy for the equations are, and what challenges might be encountered when modeling more complex systems. Third, the linearization of power flow equations and any non linear constraint is of paramount importance, since the computational effort to tackle non-linear equations is remarkably high and requires powerful hardware. Fourth, the dynamic correlation between prices, load profiles, generation profiles, topology and physical constraints is not easily observable in big systems. A bottom-up approach like this will increase the capacity to understand how these variables interact and influence the outcome. These insights will be applied in the next chapter, where a similar problem definition will be constructed for the IEEE 33 bus system, followed by results and further analysis.

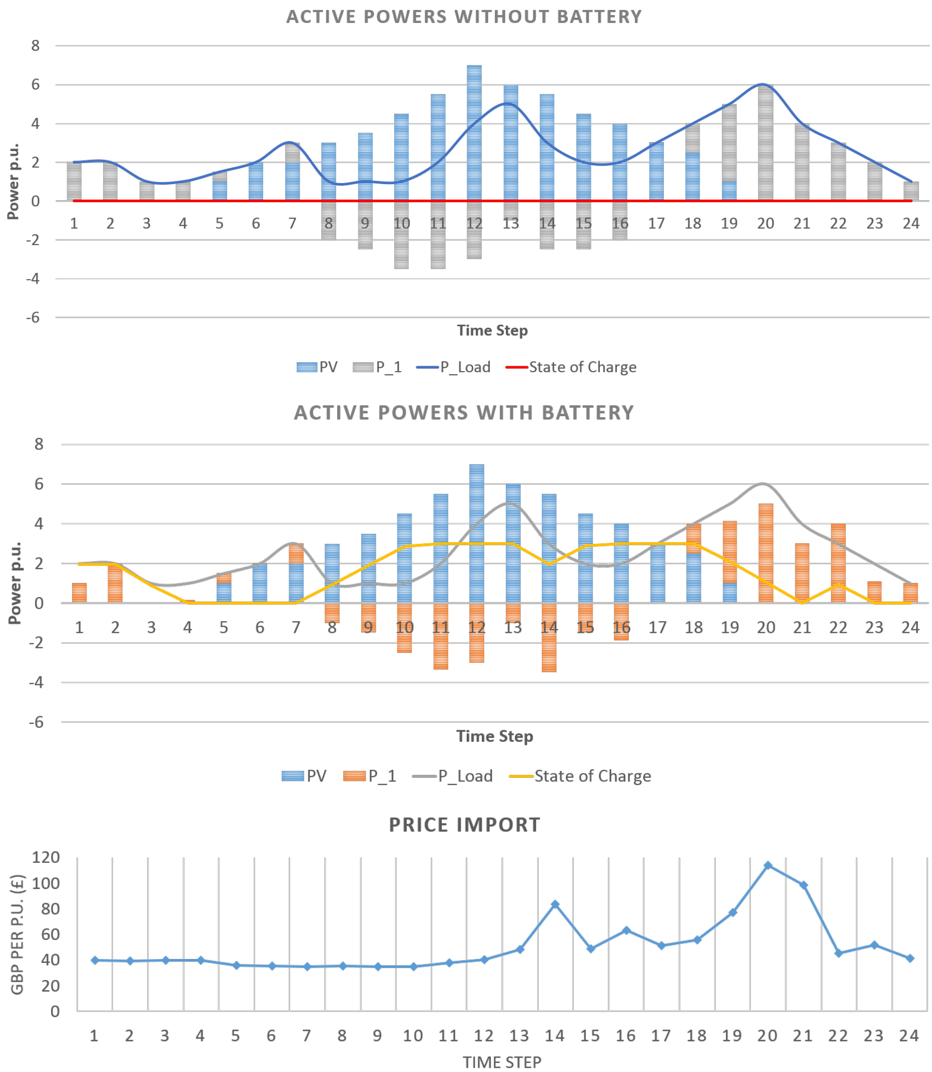


Figure 3.3: Operations for 24 hours

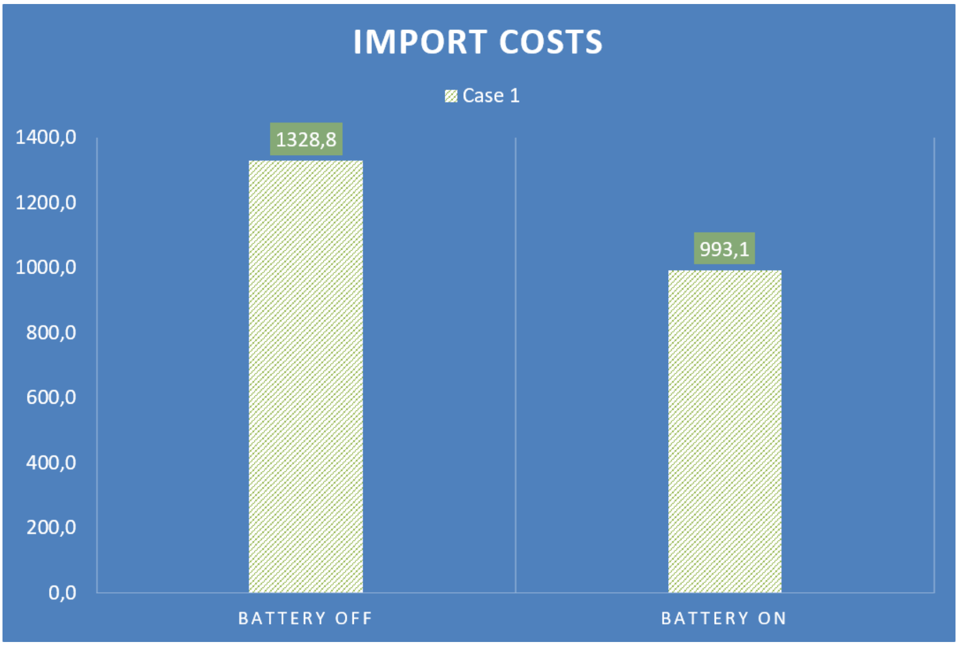


Figure 3.4: Operational Costs for both cases

Chapter 4

Implementation to IEEE 33-Bus System: Sitting Definition and Base Case

Using the procedures and lessons developed in the previous chapters, the model will be now upgraded to the IEEE 33 bus distribution system.

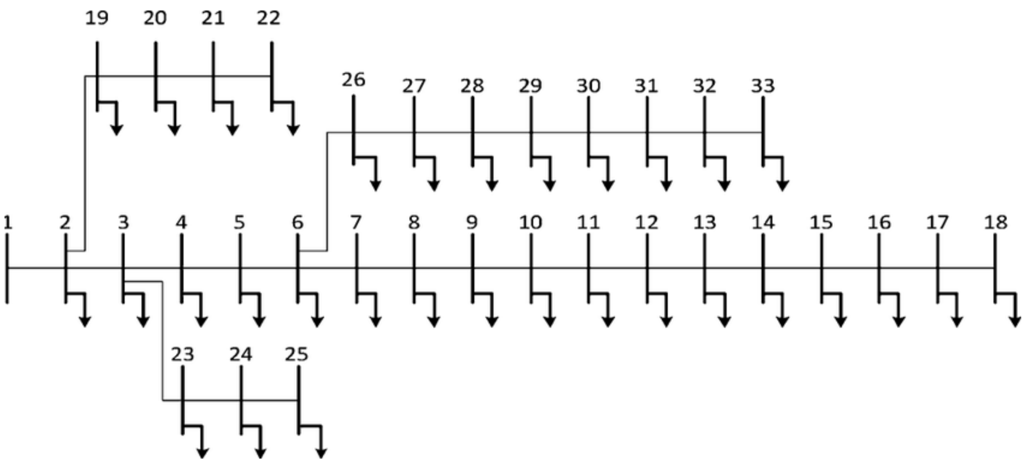


Figure 4.1: Distribution Power System scheme

4.1 Model: IEEE 33 bus system

The IEEE 33 bus system is well known in the literature and its topology can be seen in Figure 4.1. Some example studies using the same topology can be found in [31] and

[32]. In this implementation, bus one will represent the slack bus, which is connected to a strong grid. Then, renewable generation-like solar panels-, is added in different buses of the system. Finally, a tailored made python script is used to find the optimal buses where the installation of a ESS (energy storage system) will result in the largest revenues, taking into account economic and physical limits.

4.2 Mathematical Formulation

Power Flows

The system topology is described in the admittance matrix and the power flow is described using the classical equations shown below 4.1,4.2. This is for any system with any number of buses. As explained in previous chapters, a linearized version of the power flow equations is needed, and their derivation was shown in Chapter 3. In 4.3 and 4.4 the linearized versions used for the 33 bus system can be seen.

$$\mathrm{P}_i^{(t,i)} = \sum_{j=1}^{N} Y_{ij}\left[V_i^{(t,i)} * V_j^{(t,i)} \cos(\delta_i^{(t,i)}) * \cos(\delta_j^{(t,i)} + \theta_{ij}) + V_i^{(t,i)} * V_j^{(t,i)} \sin(\delta_i^{(t,i)}) * \sin(\delta_j^{(t,i)} + \theta_{ij})\right] \quad (4.1)$$

$$\mathrm{Q}_i^{(t,i)} = \sum_{j=1}^{N} Y_{ij}\left[V_i^{(t,i)} * V_j^{(t,i)} * \sin(\delta_i^{(t,i)}) * \cos(\delta_j^{(t,i)} + \theta_{ij}) - V_i^{(t,i)} * V_j^{(t,i)} * \cos(\delta_i^{(t,i)}) * \sin(\delta_j^{(t,i)} + \theta_{ij})\right] \quad (4.2)$$

Which, result in the linearized version of the power flow equations:

$$\mathrm{P}_i^{(t,i)} = \sum_{j=1}^{N} Y_{ij}\left[\cos\theta_{ij} + \cos\theta_{ij} * (V_i^{(t,i)} - 1) + \cos\theta_{ij} * (V_j^{(t,i)} - 1) - \sin\theta_{ij} * (\delta_j^{(t,i)}) + \sin\theta_{ij} * (\delta_i^{(t,i)})\right] \quad (4.3)$$

$$\mathrm{Q}_i^{(t,i)} = \sum_{j=1}^{N} Y_{ij}\left[\cos\theta_{ij} * (\delta_i^{(t,i)}) - \cos\theta_{ij} * (\delta_j^{(t,i)}) - \sin\theta_{ij} - \sin\theta_{ij} * (V_i^{(t,i)} - 1) - \sin\theta_{ij} * (V_j^{(t,i)} - 1)\right] \quad (4.4)$$

Power Net Injections

As the equations used in the script are automatized and able to model any system with any number of buses, the definition of power injection in all the buses is made by a general equation. This is done by defining matrix variables and parameters, that are initialized, indexed and/or computed in accordance with time steps, buses and even different scenarios. The general equations for power injection in all buses can be seen below.

$$P_i^{(t,i)} = P_{Gen}^{(t,i)} - P_{Load}^{(t,i)} + P_{RES}^{(t,i)} + P_{Battery}^{(t,i)} \quad (4.5)$$

$$Q_i^{(t,i)} = Q_{Gen}^{(t,i)} - Q_{Load}^{(t,i)} + Q_{RES}^{(t,i)} \quad (4.6)$$

Grid Connection

As in previous chapters, here the bus 1 represents the slack bus. The slack bus is connected to the strong grid, thus serving as reference and power support for the system. P_1 is the net injected power in bus 1; P_{import} and P_{export} are the total imported and exported power between the system and the grid. When P_1 is positive, the system is importing power from the grid, when it is negative, the system is exporting power to the grid. P_{import} and P_{export} are both always positive and limited by the thermal limits at bus 1. In addition, the system's reactive power requirement will be satisfied by the grid, thus they will be modelled as reactive generation at the slack bus. The equations describing this features are,

$$P_1^{(t)} = P_{import}^{(t)} - P_{export}^{(t)} \tag{4.7}$$

$$P_{min} \leq P_1^{(t)} \leq P_{Max} \tag{4.8}$$

$$Q_1^{(t)} = Q_{import}^{(t)} - Q_{export}^{(t)} \tag{4.9}$$

$$Q_{min} \leq Q_1^{(t)} \leq Q_{max} \tag{4.10}$$

Battery

The battery's modelling is described here. $SoC^{(t)}$ represents the state of charge of the battery and η_{ch}, η_{disch} represent the efficiencies of charge and discharge respectively. The batteries are theoretically allocated in every node, and it is the binary sitting variable the one that will result with the best nodes to install a battery. The equations that describe the battery are as follows:

$$SoC^{(t,i)} = SoC^{(t-1,i)} - P_{disch}^{(t,i)} * (t) * \frac{1}{\eta_{disch}} + P_{ch}^{(t,i)} * (t) * \eta_{ch} \tag{4.11}$$

$$SoC^{(t,i)} \leq Batt_{Capacity} \tag{4.12}$$

$$SoC^{(t,i)} \geq SoC_{min} \tag{4.13}$$

$$P_{Battery}^{(t,i)} = P_{disch}^{(t,i)} - P_{ch}^{(t,i)} \tag{4.14}$$

Battery Sitting

The sitting of the battery is done by using binary variables that will be multiplying the upper bounds of the charging and discharging variables of the battery. Thus, the power injection coming from the battery in each node will be zero in the nodes where the binary variable is zero, and will be non-zero where the optimal nodes (for battery sitting) happen to be. In this way, it is avoided the multiplication of the binary variable by another variable, increasing the computational effort and time of resolution.

$$P_{ch}^{(t,i)} \leq P_{max}^{(ch)} * B_{binary}^{(i)} \tag{4.15}$$

$$P_{disch}^{(t,i)} \leq P_{max}^{(disch)} * B_{binary}^{(i)} \tag{4.16}$$

The Sitting variable $b_{binary}^{(i)}$ is a binary vector indexed by buses and the optimization will assign ones (1) and zeros (0) respectively, for the optimal and non optimal locations for the batteries. Also, the total cost for batteries installed is computed by means of the following equation:

$$Cost_{Batteries} = \sum_{i=1}^{n} B_{binary}^{(i)} * Price_{Battery} \tag{4.17}$$

Bounds and Constraints

All the above equations are subject to a series of equations and limits that connect them one another. These limits are listed as follows.

Voltage Limits,

$$V_{min} \leq V_i^{(t,i)} \leq V_{max} \tag{4.18}$$

Slack bus Angle,

$$\delta_1^{(t)} = 0 \tag{4.19}$$

Line Current Limits,

$$(V_i^{(t,i)} - V_j^{(t,i)}) * Y_{ij} <= I_{i-j}^{Max} \tag{4.20}$$

4.3 Optimization Definition

Now, the objective function for the 33 bus system case will also seek to maximize the revenues of the power exchange, but now considering dynamic pricing per kW and the cost of every single battery. Ideally, the model will allocate from zero to n batteries in the system-being n the number of buses- so to maximize revenues and keep critical constraints like line and voltage limits under their respective bounds. In 4.21 the objective function definition, and the variables to minimize can be seen. There, the time factor F_{Time} accounts for the factors that have to be multiplied to the objective function when shorter time periods are run. This can happen for convenience purposes, due to the long computational times these simulations can take. In the other hand, the price factor F_P is necessary to scale up the power prices to a realistic value. This is because most of pricing data comes in terms of spot prices and these are not the real prices the consumer pays, i.e. a factor is needed. These quantities vary depending on data and time horizon and they will be specified when describing the study cases. Also, a factor for discount F_{Dis} was considered as first in order to account for interest rates, yet it was finally assumed to be equal to 1 for the studies presented in this project.

$$\mathrm{F}_{opt} = Min \sum_{t=1}^{T} \left[F_{Time} * \left(P_{import}^{(t,i)} * F_P * price_{Import}^{(t,i)} - P_{export}^{(t,i)} * price_{Export}^{(t,i)} \right) + Cost_{Batteries} \right] * F_{discount} \tag{4.21}$$

$s.t.$

$$\mathrm{P}_i^{(t,i)} = \sum_{j=1}^{N} Y_{ij} \left[V_i^{(t,i)} * V_j^{(t,i)} \cos(\delta_i^{(t,i)}) * \cos(\delta_j^{(t,i)} + \theta_{ij}) + V_i^{(t,i)} * V_j^{(t,i)} \sin(\delta_i^{(t,i)}) * \sin(\delta_j^{(t,i)} + \theta_{ij}) \right] \tag{4.1}$$

$$\mathrm{Q}_i^{(t,i)} = \sum_{j=1}^{N} Y_{ij} \left[V_i^{(t,i)} * V_j^{(t,i)} * \sin(\delta_i^{(t,i)}) * \cos(\delta_j^{(t,i)} + \theta_{ij}) - V_i^{(t,i)} * V_j^{(t,i)} * \cos(\delta_i^{(t,i)}) * \sin(\delta_j^{(t,i)} + \theta_{ij}) \right] \tag{4.2}$$

$$P_i^{(t,i)} = P_{Gen}^{(t,i)} - P_{Load}^{(t,i)} + P_{RES}^{(t,i)} + P_{Battery}^{(t,i)} \tag{4.3}$$

$$Q_i^{(t,i)} = Q_{Gen}^{(t,i)} - Q_{Load}^{(t,i)} + Q_{RES}^{(t,i)} \tag{4.4}$$

$$P_1^{(t)} = P_{import}^{(t)} - P_{export}^{(t)} \tag{4.5}$$

$$P_{min} \leq P_1^{(t)} \leq P_{Max} \tag{4.6}$$

$$Q_1^{(t)} = Q_{import}^{(t)} - Q_{export}^{(t)} \tag{4.7}$$

$$Q_{min} \leq Q_1^{(t)} \leq Q_{max} \tag{4.8}$$

$$SoC^{(t,i)} = SoC^{(t-1,i)} - P_{disch}^{(t,i)} * (t) * \frac{1}{\eta_{disch}} + P_{ch}^{(t,i)} * (t) * \eta_{ch} \tag{4.9}$$

$$SoC^{(t,i)} \leq Batt_{Capacity} \tag{4.10}$$

$$SoC^{(t,i)} \geq SoC_{min} \tag{4.11}$$

$$P_{Battery}^{(t,i)} = P_{disch}^{(t,i)} - P_{ch}^{(t,i)} \tag{4.12}$$

$$P_{ch}^{(t,i)} \leq P_{max}^{(ch)} * B_{binary}^{(i)} \tag{4.13}$$

$$P_{disch}^{(t,i)} \leq P_{max}^{(disch)} * b_{binary}^{(i)} \tag{4.14}$$

$$Cost_{Batteries} = \sum_{i=1}^{n} B_{binary}^{(i)} * Price_{Battery} \tag{4.15}$$

$$V_{min} \leq V_i^{(t,i)} \leq V_{max} \tag{4.16}$$

$$\delta_1^{(t)} = 0 \tag{4.17}$$

$$(V_i^{(t,i)} - V_j^{(t,i)}) * Y_{ij} <= I_{i-j}^{Max} \tag{4.18}$$

In general, the model will only allocate batteries *if* placing them is economically viable. Hence, any battery placed by this algorithm will be paying its own price by taking value of net arbitrage, RES surplus leverage, overall savings in operations, voltage support, etc. The way our objective function is designed, only the value of energy arbitrage and RES surplus services will be the main services to asses the value the battery has to increase savings. Nevertheless, voltage support plays a strong role in the location. As a matter of fact, if voltage limits are tighten to limits unbearable for the Base Case simulations (see next sections) then the allocation of batteries is "forced" upon the system to make it feasible. Yet, in this implementation we only asses the economical figures associated to net arbitrage and RES surplus smoothing.

4.4 Simulations

The given mathematical formulations define the model that was constructed in python for the purpose of this project. The model comprises three main bodies: the software infrastructure, the data and the output.

Software

The software infrastructure is simply the machinery that reads, process the data and delivers an intelligible output. The input of the software is basically made of 'xlxs', 'cvs' and 'raw data' files. The output consist on excel files with all the relevant outcomes contained.

The language of choice is python due to its straightforward and object-oriented syntaxis, its popularity in the industry and its open source features. The model is built using the framework and solving options offered by Pyomo, which is a collection of python packages tailored to simulate optimization models. The solver chosen is Gurobi, due to its powerful Mixed Integer Linear Programming (MILP for short) solving capacity, its generous student license and the numerous python examples that use Gurobi and that are available on the web.

Output

The python script has been designed to deliver all the results in excel files, where all the voltage, power, angle and other variables can be seen and placed in graphs. Also the locations of the battery, and the value of the objective function. In this way it is possible to compare the influence that each case makes in the sitting of batteries and what conclusions can be attained from it.

Data

The purpose of this study is to analyze where and how many batteries will be optimal for a power distribution system, and to achieve that it is necessary to test it in a system as real as possible. Hence, real data was used as input for the model. The necessary data was basically:

1. Load Power Consumption
2. Renewable Energy Production
3. Dynamic Electricity Prices

The load power consumption used is part of the *London Low Carbon Project* [33]. These data comprises kWh per half hour, which represents the power consumption of 5567 households in the greater London area, between November 2011 and February 2014. Around 4467 of these households were subject to a flat tariff of 14.228 pence/kWh, and the 1100 remaining went through an experimental three-level tariff structure that aimed to change consumer behavior. The objective of the London Low Carbon Project was to understand the response of consumers to dynamic pricing. In our case, the point is to find optimal solutions for systems where consumers have not changed their behavior yet. Hence the data was selected only among the households that paid a flat tariff. Additionally, the consumers were divided in three groups according to a prosperity classification index:

- Affluent: Highly prosperous families
- Comfortable: Middle Class families and young professionals
- Adversity:Financially struggling families and students

For this project only 33 out of these 4467 houses were picked, based on their yearly consumption and their prosperity group.

The Dynamic pricing structure data was initially retrieved from the former APX group website [34]. The reference price data (RPD) accounts for only over a third of the actual price consumers pay. Thus, the price had to be scaled up using a price factor $F_P = 3.70$ as defined in the objective function. Based on this assumption, we scaled up the spot prices to a real purchase value that in average is equivalent to the flat tariff paid by households in in London. This flat tariff is around 142.28 £/Mwh. The profile of the RPD spot price can be seen in Figure 4.2.

Wind power generation data depends on three main factors: wind speed, height of nacelle and swept area of blades. Wind speed data was taken from an UK meteorological Office from a climatological station near London and power output was calculated by fitting a polynomial curve, to the wind speeds and the output power curve for a wind turbine. A similar approach was taken in [6] and [7].

Similarly, solar power output depends mainly on solar irradiation, area of PV installation and tilt angle of panels. In this sense, global horizontal irradiation and temperature data can be retrieved from [35] and meteorological data can be downloaded from [36]. Very similar methodologies to extract wind and solar energy were taken in [37].

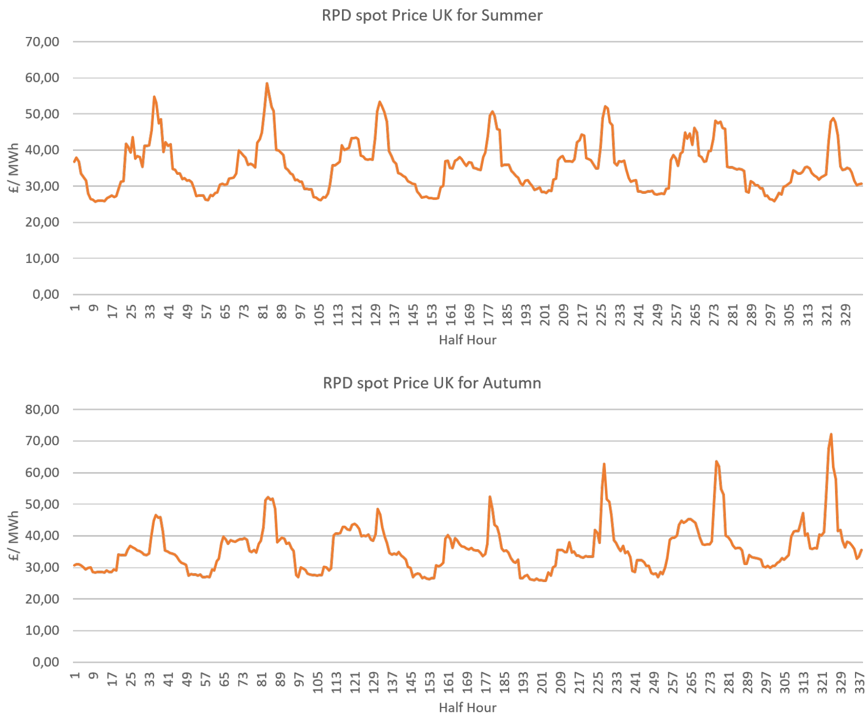


Figure 4.2: RPD spot price profile for the UK

4.5 Base case

Since batteries affect the distribution grid operational decisions and behavior, a control Case of the system without battery sitting is setup as the reference case. This control case is named *Base case* and It describes the elemental state of the grid. The Base Case delivers relevant quantities to contrast with the next cases. These next cases will be based on the Base case, so the data and assumptions elaborated here are valid in the following cases unless the opposite is explicitly expressed.

The base case was intended to be studied for a planning horizon of one year. Yet, a year of power consumption, wind production, solar production and spot prices data would contain millions of rows and several gigabytes of information. Even more data if we use an accuracy of half-an-hour time step, like we did in this project. This would result in more accuracy but also, more simulation time. The computational effort required to carry out a mixed integer multi-period optimization with such a vast amount of data pushes the computational hardware capabilities we have, and the scope of this thesis.

Thus, a series of simplifications had to be made to make the simulation feasible, but without affecting the one year time horizon. Specifically, our simulation works with two representative weeks, one week in summer and one in autumn. The weeks selected were July 13th-July 20th 2012 for summer and October 13th-October 20th 2012 for Autumn. After selecting the representative weeks, scaling up factors were added in the objective function to make the output figures equivalent to a year long simulation. In this case, the total 30 min time steps corresponding to a week are 337, so the optimization runs for 674 time steps. Experience has shown that despite these kind of reductions result in less accuracy, the behavior of the system remains fairly valid and since the analysis of the operations of the distribution grid is the objective of the study, this reductions will not affect our results. The main reasoning is to be able to perform numerous sensitivity analyses since taking a longer time horizon (e.g. four weeks) will create a long computational time. For example, in a PC laptop with 8 GB ram and Intel Core Haswell i7 processor, it might take up to 5 to 8 hours per case).

Battery

Although for the base case there will be no battery allocation, the following cases will do and they will use the battery as it is described here. In this sense, in table 4.1 the specifications of the battery are given. This is the same battery used in [37] but scaled up to a capacity of around 3 MW-h for our standard tests, which is equivalent to 250 batteries of the ones used there (1 per 4 households approx.). Coincidentally, the size obtained was almost equal to 3.5 Mwh, which is the hourly consumption of the system. The price per kW-h is based on several projections: One conservative projecting a price crossing the 200 USD (160 GBP) barrier by 2030 [1]. Another also published in 2017 projecting a price of 120 USD (90 GBP) for 2018 and 100 USD (75.5 GBP) by 2020 [2]. Recent reports inform a price of 160 GBP (200 USD) for late 2017 and early 2018 [3]. So the chosen standard price is very optimistic but they are in line with these cost projections..

Specification	**Value**	**Units**
Efficiency Charge	0.95	%
Efficiency Discharge	0.95	%
Battery Capacity	3	MWh
Battery Price per kWh	100	pounds per kWh
Battery Time of Discharge	4	hours

Table 4.1: Specifications of the Battery

Scenarios: high RES vs low RES

Furthermore, to perform interesting comparisons, two scenarios are built within each case. These scenarios are devised on the basis of the percentage of yearly load covered by RES.

So, the *High RES* scenario corresponds to a system in which 60% of the yearly energy demand is covered by RES. Similarly, the *Low RES* scenario corresponds to a system in which 30% of its energy demand is covered by RES.

RES distribution and profile

This does not mean that RES provide 60% of power at any given time. Rather, it means that from the total time horizon energy demand (10 years) of roughly 305 GWh, RES will provide approximately 183 GWh for one scenario and 91.5 GWh for the other. Also, out of the total energy produced by RES, 60% will come from solar PV and 40% from wind parks. This percentage are not based in any especial example, but they rather fit what was considered to be an interesting distribution of RES resources along the MV grid. In further cases the distribution of RES will be due to change in order to test its effects on the optimal locations result.

Moreover, Figure 4.4 shows the location of PV and Wind production on the system. This location strategy follows the logic of feeding different types of branches with different types of RES. A classification of the branches for this topology is shown in Figure 4.3.

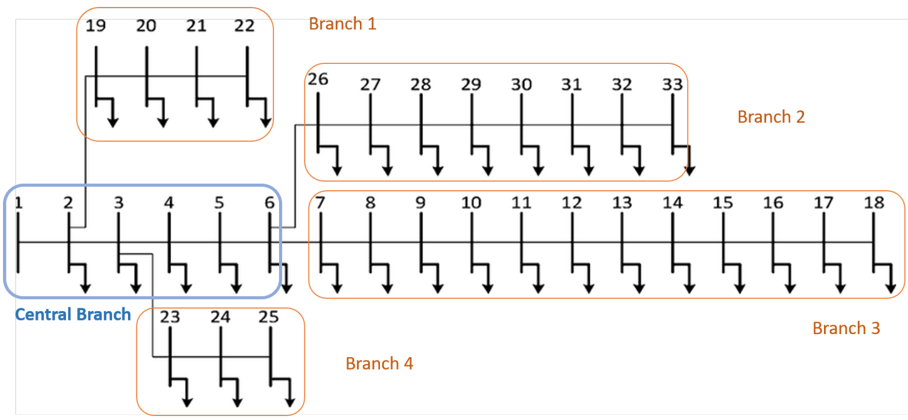


Figure 4.3: Scheme of branches

The branches 1, 2 3 and 4 are considered to be away from large substations and generation clusters. The households that these branches supply are in their majority prosumers with PV installations. The Central branch is considered to be the core of the distribution system and its closely located to large substation. Away from more urban areas, this branch is connected to wind energy production through buses 2, 3 and 6.

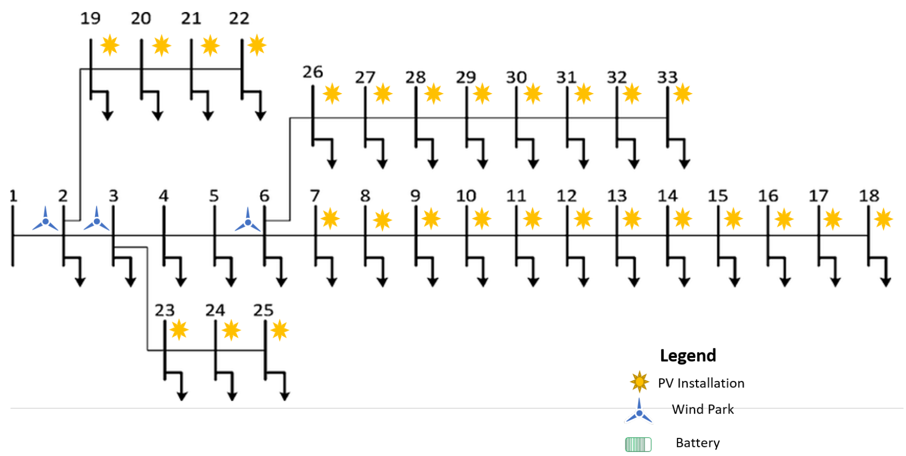


Figure 4.4: Distribution of RES in the grid

In Figures 4.5, 4.6, 4.7 and 4.8 the total power output profile of PV and Wind are shown for each representative week. This is the total power produced in the whole system for scenario High RES. For scenario Low RES the pattern is exactly the same but the amplitude is reduced 50%.

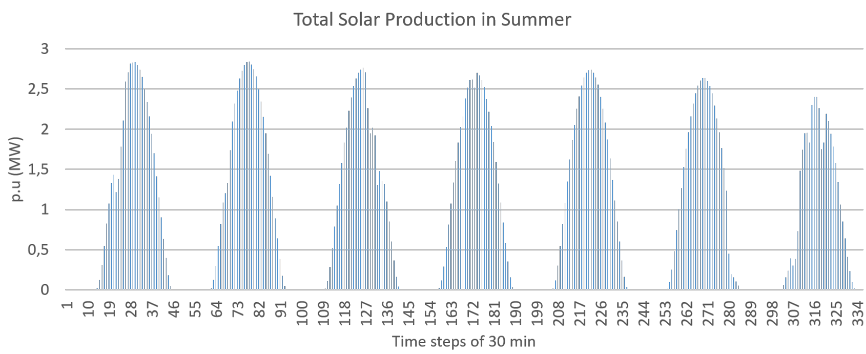


Figure 4.5: Total Solar power output for summer in scenario High RES

Load profile

The original load is in kWh per half hour so to simulate a distribution MV system this data was scaled up as if 1000 thousand consumers of the same kind were connected to each bus. This placed some challenges in the setting up and calibrating the system because these load profiles greatly differ from one another. So, to calibrate the system, each load profile was then multiplied by an additional percentage of consumers factor, to make some loads bigger than others and smooth as much as possible the overall load profile. In

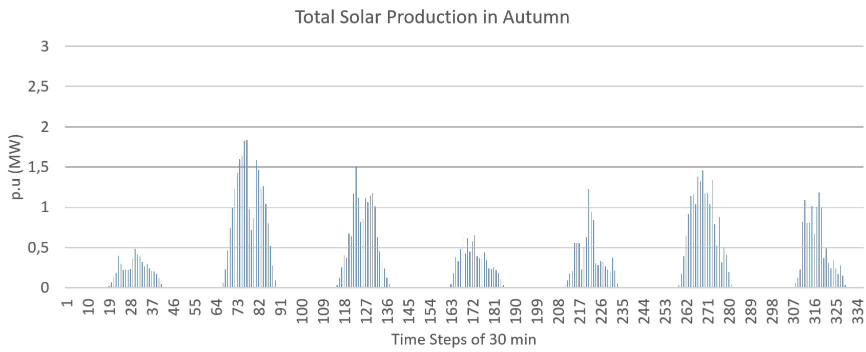


Figure 4.6: Total solar power output for autumn in scenario High RES

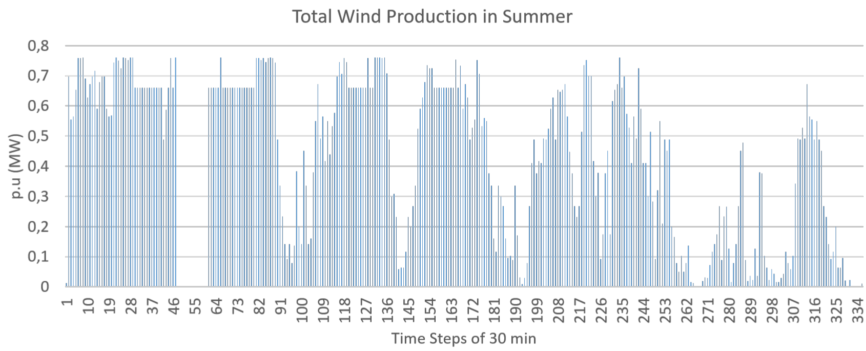


Figure 4.7: Total wind power output for summer in scenario High RES

total, a number of households with the same load profile was assumed in each bus; the numbers assumed are shown in table 4.3. In Figure 4.10 the consumer distribution can be graphically seen. In Figure 4.9 the load consumption of all buses in per unit (or for what it matters, in MWh per 30 min) can be seen for the two representative weeks. One can easily spot the load peak of bus 17, which will create a dip in voltage in this bus and adjacent buses. Before using RES to feed part of the load, many infeasibility problems were faced due to this unexpected and almost random load peaks. Voltage limits are constraint from 0.9 and 1.1 per unit, so when load peaks struck the system at the edge of the longest branch, the voltage drop was impossible to contain. Hence, reactive compensation had to be installed. As it will be seen in the sensitivity analysis in the next chapter, batteries made compensation unnecessary and in fact after the model was run with batteries there was no need for compensation anymore. Moreover, for these two representative weeks the total energy consumption is 1173 MWh. To assess the total load consumption for the whole investment analysis, the load has to be scale up accordingly: The factor used to scale up kWh per half hour data for 2 weeks to GWh for 10 years is: 2 for four weeks (original time horizon), 13 for 1 year, and 10 for 10 years. The final figures are shown in Table 4.2.

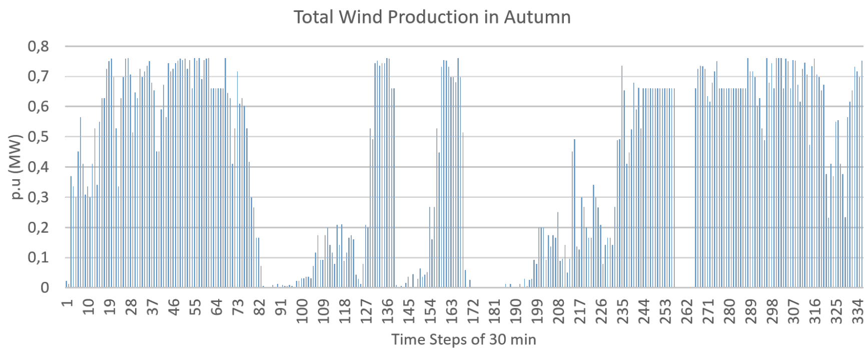


Figure 4.8: Total wind power output for autumn in scenario High RES

$$F_{Time} = 2 * 13 * 10$$

2 Weeks System's Energy Demand	Yearly Energy Demand	Total Energy Demand
1173 MWh	30.5 GWh	305 GWh

Table 4.2: Energy load demand scaling up figures

Hence, if the total energy demand for the time horizon is 305 GWh, then the average consumption for an hour will be around 3.5 MWh per hour, or 1.75 MWh per half hour. Thus, a power base of 1 MW was selected. Another interesting perspective to understand the load profile consist on the yearly load consumption per bus, which can be seen in Figure 4.11.

Voltage profile

In Figures 4.12 the voltage profiles of all buses are shown, for scenario high RES. This figure shows the voltage behavior for each representative week as a snapshot of the behavior of voltages.

Scenario High RES

Clearly, there are two main disturbances in the voltage profiles, occurring around time step 200 in each chart respectively. These voltage alterations are related to the two large load peaks in bus 17 during those same periods. Similarly, no major difference between the three voltage profiles is observed.

Operational costs

In short, operational costs are the result of the objective function. As observed in Table 4.5, the costs increase for Scenario Low RES. This is logical since in Scenario Low RES the

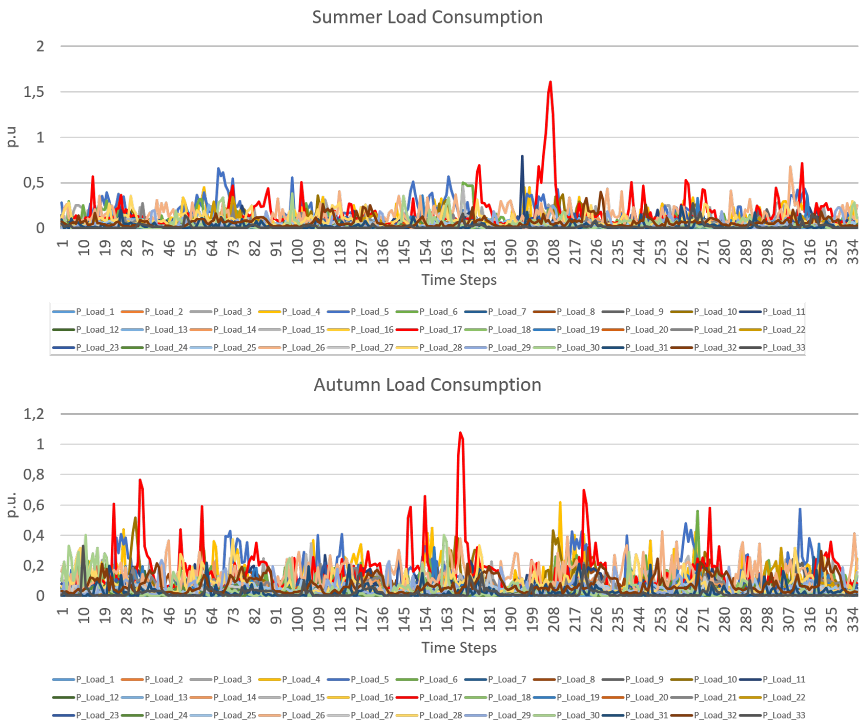


Figure 4.9: Load profiles

PV and Wind supply for up to a third of the total energy. Thus, operational costs increase due to greater electricity imports.

Line limits

The line thermal limits are the values that constraint the power flows to be higher than what is thermally possible. It is basically a security limit. Yet, since it constraint the amount of power that can flow to or from a bus, it is a *key* constraint that influence the sitting in high degree. For instance, the impossibility to transport power from certain buses of the system due to line restrictions will definitely define where the optimal locations to place the battery will be. After all, one of the purposes of the battery is to leverage of surplus of RES, and the line thermal limits is one of the first reasons for curtailment of RES.

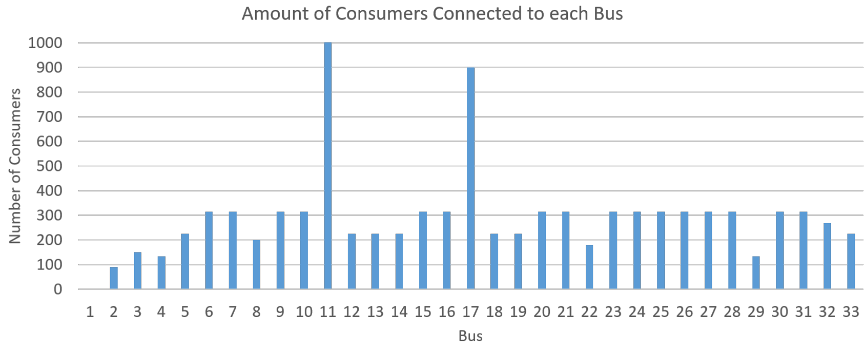


Figure 4.10: Amount of consumers connected to each bus

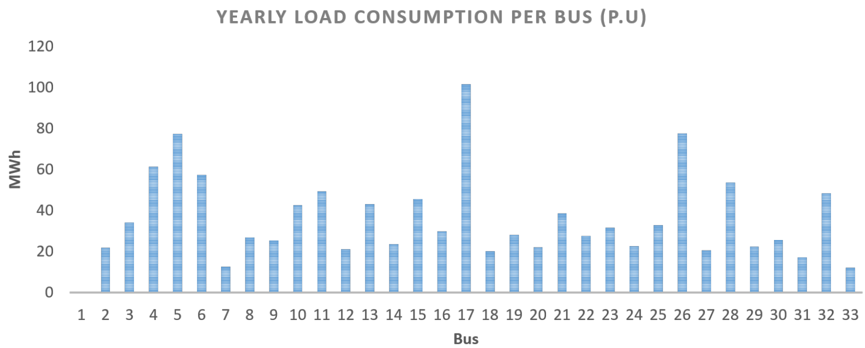


Figure 4.11: Yearly load consumption per bus

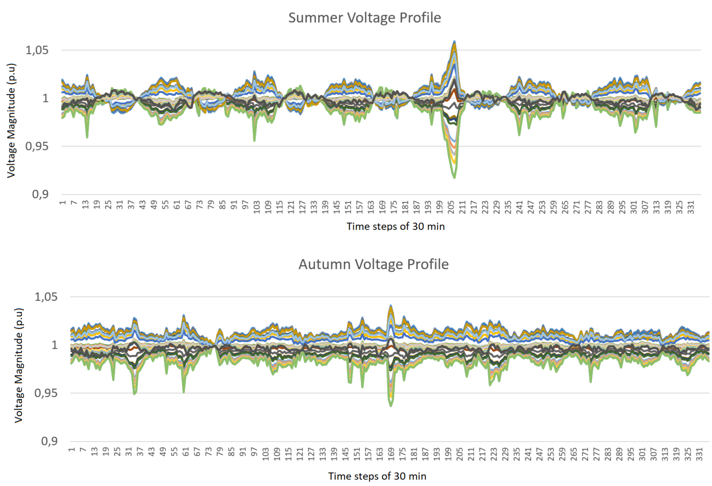


Figure 4.12: Voltage profiles for representative week in summer and autumn

Consumers Connected to each Bus
0
90
150
135
225
315
315
200
315
315
1350
225
225
225
315
315
900
225
225
315
315
180
315
315
315
315
315
315
135
315
315
270
225

Table 4.3: Number of consumers connected to each bus

Bus	Prosperity Group	Yearly Consumption (MWh)
2	*Affluent*	21.85
3	*Affluent*	34
4	*Affluent*	61.24
5	*Affluent*	77.38
6	*Affluent*	57.20
7	*Affluent*	12.68
8	*Affluent*	26.87
9	*Affluent*	25.39
10	*Comfortable*	42.46
11	*Conformable*	49.38
12	*Comfortable*	2117
13	*Comfortable*	43.04
14	*Comfortable*	23.69
15	*Comfortable*	45.56
16	*Comfortable*	29.80
17	*Adversity*	101.53
18	*Adversity*	19.96
19	*Adversity*	28.11
20	*Adversity*	22.19
21	*Adversity*	38.61
22	*Adversity*	27.63
23	*Adversity*	31.46
24	*Adversity*	22.49
25	*Adversity*	32.74
26	*Adversity*	77.43
27	*Adversity*	20.52
28	*Adversity*	53.43
29	*Adversity*	22.32
30	*Adversity*	25.49
31	*Comfortable*	17.05
32	*Comfortable*	48.41
33	*Affluent*	12.11

Table 4.4: Yearly consumption of each bus

Scenario	Total Operational Costs (GBP)
Scenario High RES	17,850,341
Scenario Low RES	27,451,314

Table 4.5: Operational costs for the two scenarios

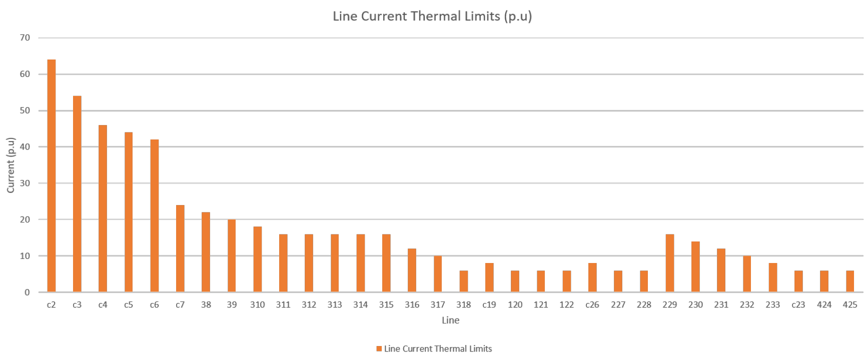


Figure 4.13: Line current thermal limits in p.u

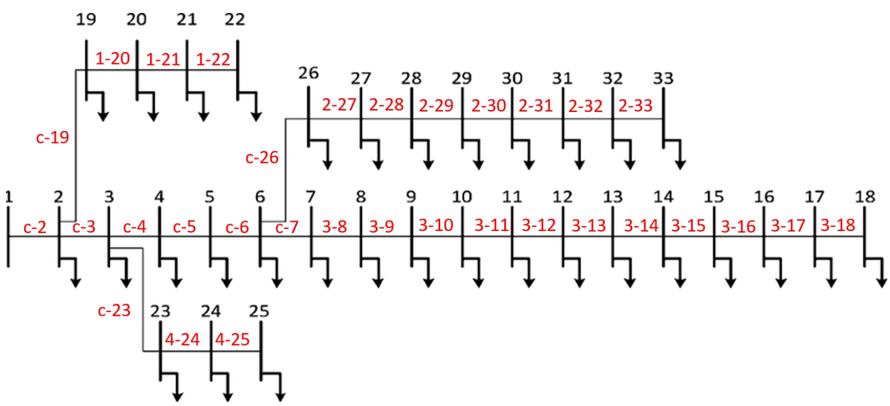


Figure 4.14: Topology of the system with the code names of each line

Line	***Current limit (p.u)***
c2	64
c3	54
c4	46
c5	44
c6	42
c7	24
38	22
39	20
310	18
311	16
312	16
313	16
314	16
315	16
316	12
317	10
318	6
c19	8
120	6
121	6
122	6
c26	8
227	6
228	6
229	16
230	14
231	12
232	10
233	8
c23	6
424	6
425	6

Table 4.6: Line current limits

Chapter 5

Sensitivity Analysis, Results and Discussions

Storage has to be steadily integrated into the grid in the most cost-effective way possible. This will involve broad and thorough studies for every single case. There probably are general properties and patterns governing the sitting and operation of storage in power grids, and it is the objective of this chapter to unwind some of these attributes. Hopefully that will provide insights on how to deploy storage and how the DSO can benefit from.

A sensitivity analysis was studied to the base case to test how the model solved the problem of storage sitting when different conditions arose. In this way, we can challenge the model's ability to site batteries under changing scenarios and consequently reveal any existing pattern among different scenarios. For this purpose, we have designed several cases whose results will be presented and analyzed in the following sections. Each case is built upon the Base Case described in the previous chapter, and any relevant difference will be explicitly pointed out.

Also, it is noteworthy to remark that this model has -reasonable-limitations. It is built upon certain assumptions and approximations that have an impact on accuracy. Besides, the number of studies necessary to achieve absolute conclusions will require a length of time unpractical for the scope of this work. Nevertheless, the model is reasonably accurate and despite the computational limitations encountered, it worked very well on simulating the dynamic behavior of power systems, considering many of its complexities.

5.1 Case 1

This Case is the base case but with the binary sitting activated. We find the optimal points to allocate batteries in the system for different battery sizes, i.e., the rest of the parameters are kept the same. To this end, we use batteries of 1, 2, 3, and 4 MWh for each scenario.

Scenario High RES

In Figure 5.1 The four outcomes for each battery capacity size can be seen. For 1 MWh there are 19 batteries all spread over the grid, with battery presence at every edge of each branch. Whereas for bigger capacities, the number of batteries tends to be reduced and allocated more scattered. As seen in Chapter 4, there are buses where lines with high capacity arrive and lines with much lower capacity leave. We termed these buses as *threshold buses* and they usualy appear at the border of the central branch with the outer branches (1,2,3 and 4). These threshold points are important because there is a *valve* effect for the power flows in these buses. It seems that batteries tend to be optimally allocated in these buses, like in buses 3, 6, 23, 15 and 29. We have observed optimal storage locations to ”oscillate” around these buses in several studies, as we will see in the following sections.

Also, it can be seen that as we increase the size, the batteries allocate where they can extract the most surplus power possible, and perform services to the system where the line limits make it more difficult. For example, for 1 MWh there are batteries in all branches, for 2 MWh, central branch and branch four are empty, and instead, the batteries are placed in branches 1, 2 and 3. For 3 MWh branch, 1 and two are empty and substituted by branch 4, in the threshold bus 23. In central branch, the number of batteries remains relatively the same. Since for 4 MWh example, the price per battery is higher, and these batteries are located at fewer but strategic buses. Like the battery placed at threshold bus 6, where not only line limits change but also there is wind production. The rest of the batteries tend to be located towards the edged of the other branches; this is perhaps due to the voltage/line limits and complications that batteries help to alleviate.

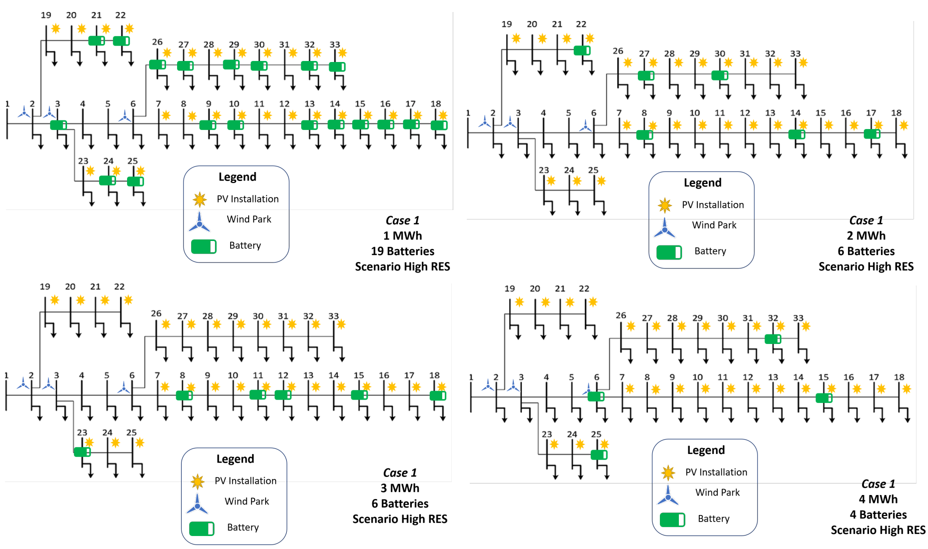


Figure 5.1: Optimal Locations for each battery size in High RES scenario.

Scenario Low RES

In Figure 5.2 the four outcomes for each battery capacity size can be seen. For 3 MWh and 4 MWh, the trend observed in the High RES scenario seems to appear again. On the other hand, for 2 MWh no batteries are allocated. This is rather interesting since the cost is not the limitation, as we can see for lower and higher capacities. The reason for that result is difficult to trace since, as we know, there are multiple factors playing part on the final outcome. But it does tell us to what extent the ideal size of the battery depends on every system, thus not just any battery can fit the requirements of a power system. Storage is a *discrete* resource, which means it cannot be considered as ”fluid” or ”continuous” as fuel is, for example. Therefore, considering the deployment of storage in units, like it is done here with binary variables, provides a more genuine result. The increased number of batteries for low RES scenario may be the result of the fact that less RES production means higher operational costs, which are comparatively much higher than allocating 10 or more batteries. That result speaks for the ample value that storage brings to the system.

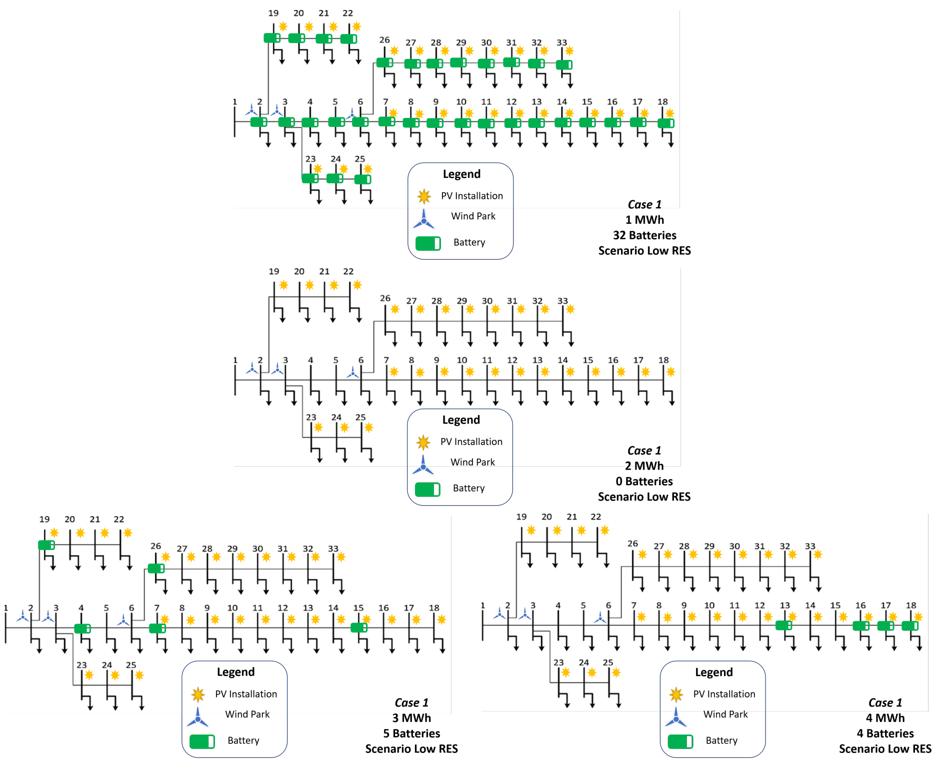
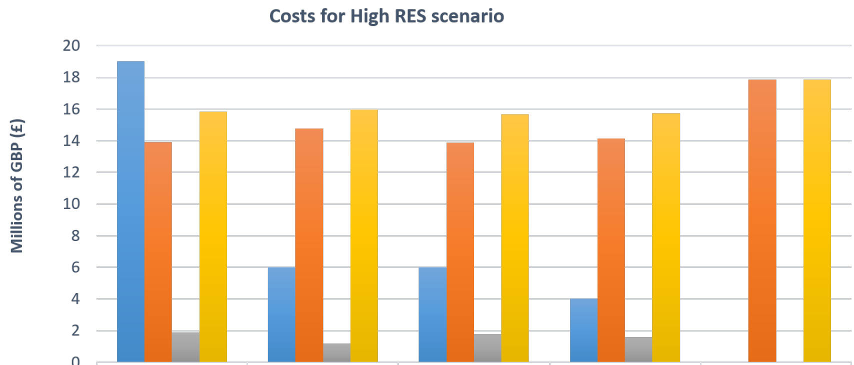


Figure 5.2: Optimal Locations for each battery size in Low RES scenario.

Objective function outcomes

In Figures 5.3 and 5.4 the output of the objective function computations is shown for every capacity of battery in both scenarios. Operational costs are the costs of the optimization function, i.e., the expenditures related to the import and export of energy. Storage costs account for the number of pounds invested in all the batteries of the system. Total Costs is simply the sum of operational and storage costs. And finally, the number of batteries shows how many batteries were used, so to make visible that the number of batteries can change sharply without increasing too much the overall storage costs.



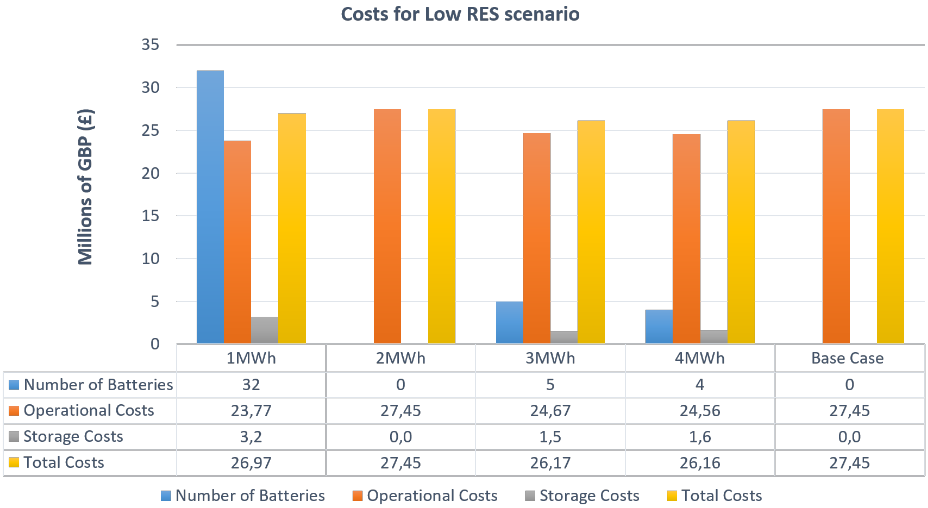
	1MWh	2MWh	3MWh	4MWh	Base Case
Number of Batteries	19	6	6	4	0
Operational Costs	13,92	14,76	13,87	14,13	17,85
Storage Costs	1,9	1,2	1,8	1,6	0,0
Total Costs	15,82	15,96	15,67	15,73	17,85

Figure 5.3: Objective Function Results for Scenario High RES

The pattern-filled bars correspond to the lowest total costs for each scenario. So to say the "optimal" sizes found for each scenario. Interesting enough, for a higher share of RES the optimal size of battery turned out to be 3 MWh, whereas, for half of that share, the optimal size is 4 MWh. This can be seen more clearly in figures 5.5 and 5.6. There, it is shown for each scenario the cost savings that each battery size provides, as a percentage of the Base case. The savings achieved for the high RES scenario are remarkably superior to the case of Low RES, and this is consistent with previous findings in the literature [7].

Discussion

Wrapping up and elaborating on the analysis made before, we have identified some trends and interesting outcomes from Case 1. First, regarding size, it seems that the optimal size depends on the system topology, the RES share and the price per kWh. Although, we observed that the system does well when the size of the battery is 1 MWh, which is a third of the standard battery size. Also, the smaller the size of the battery is, the less its allocation becomes relevant for the algorithm as it simply allocates batteries in all or almost



	1MWh	2MWh	3MWh	4MWh	Base Case
Number of Batteries	32	0	5	4	0
Operational Costs	23,77	27,45	24,67	24,56	27,45
Storage Costs	3,2	0,0	1,5	1,6	0,0
Total Costs	26,97	27,45	26,17	26,16	27,45

Figure 5.4: Objective Function Results for Scenario High RES

all buses. It seems that, as the batteries become smaller, the optimal allocation strategy comprises spreading the batteries all over the grid. The same happens in both scenarios. Despite these battery sizes where not the optimal sizes for each case, they did surprisingly good while providing the system with the *higher* total installed storage capacity, for both cases. The higher the total installed capacity is, the higher the flexibility of the system is; i.e., the ability to leverage from RES surplus, to perform congestion management, to carry out net arbitrage, to enforce voltage and power limits, etc.

Second, regarding location, it seems that as the battery capacity increased the number of batteries became less and their places more influenced by technical factors. One factor that that appears to alter the location of batteries is the size of the loads. As the battery size is higher and fewer batteries are affordable, the sites tend to switch to branch three which is the longest and more prone to voltage disruptions. Moreover, the most significant load is located on bus 17, and the vast majority of solar production is also distributed along branch number 3. All this plays a role in the deployment of the batteries, and from the results, we see that the best solution located 3 MWh-batteries mostly along branch number 3. Moreover, for all of our studies, it did not matter how cheap or small in size the battery was, there was never a battery located on the slack bus. At the slack bus, despite being the source of all power import, there is no load. This result gives a hint on how important the size and location of loads are for the optimization model.

Third, there is also another highly important factor: technical limits. As mentioned before, voltage violations can quickly occur at the edges of long branches. Batteries and curtailment (which is also activated but it remains in zero for all studies) can prevent voltage violations. So, the locations are also profoundly influenced by the technical limits governing the system. Line limits for example, which are shown in Figure 4.13, dras-

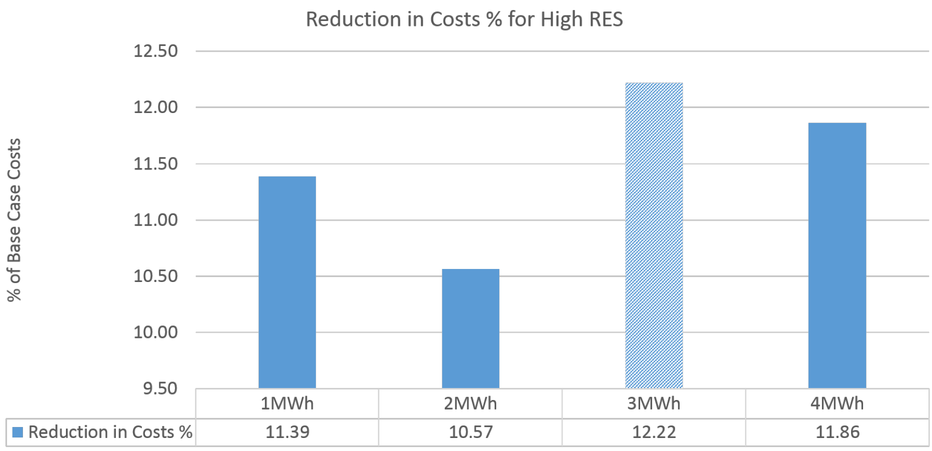


Figure 5.5: Reduction in Costs compared to Base Case for Scenario High RES

tically change as one approaches the edges of the system. Line limits decrease because there are fewer buses to feed as we approach the end of branches (except for bus 26, where a ”funnel” phenomenon takes place). Since some of the most significant loads, both in energy and power requirements, are located at the edges or around the edges of the system (17, 28 32 for instance), some optimal locations seem to be perfect to prevent sudden voltage drops due to peak demands, which always result in stress for the system and higher losses. Additionally, this can also happen in the opposite direction, where high peaks of power generated by PV resources along the 4 outer branches can sum up and overload the lines. In the view of all this, it is not surprising that for the optimal solution (3 MWh) batteries are allocated along the branch with both the highest load and the top PV production. An exciting example comes from Scenario High RES, with 4MWh batteries: One of the four batteries is placed at bus 6, which is a threshold point where the line limits of both branch two and branch three change abruptly. And also, a point of Wind production, thus a *prosumer* bus. Hence, this battery can serve as a buffer that stores energy from multiple immediate sources and then provides power to the constrained branches when generation or demand peaks occur.

Therefore, some recognizable behaviors seemed to appear. First, the higher the share of RES the more value batteries can add. Second, the smaller the battery size is, the easier it is to distribute storage all over the grid while creating quite good costs reductions. Third, the bigger the battery size is, the fewer batteries that can be affordable, thus making the ideal locations to be in the whereabouts of the most significant loads, RES production clusters and the changes in line limits.

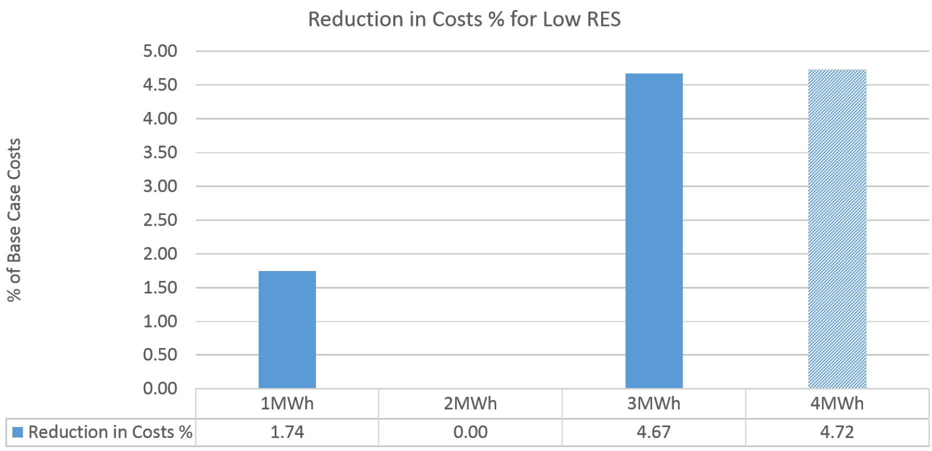


Figure 5.6: Reduction in Costs compared to Base Case for Scenario Low RES

5.2 Case 2

In Case 2 the penetration of RES is reduced, leaving the total amount of power generated by RES the same. So, there are fewer generation facilities but the ones remaining produce more so that 60% or 30% of the total load is supplied by RES depending on the scenario. The purpose of doing that, to measure how much the location of distributed RES affect the potential locations of batteries. The results will be compared to equivalent results for 3 MWh batteries in Case 1.

Scenario High RES

In Figure 5.7 The four outcomes for each battery capacity size can be seen. It can be seen that the reduction in solar penetration results in fewer batteries allocated compared to the 3 MWh results in case 1. As for a reduction in wind penetration, the result is the opposite; more batteries are allocated.

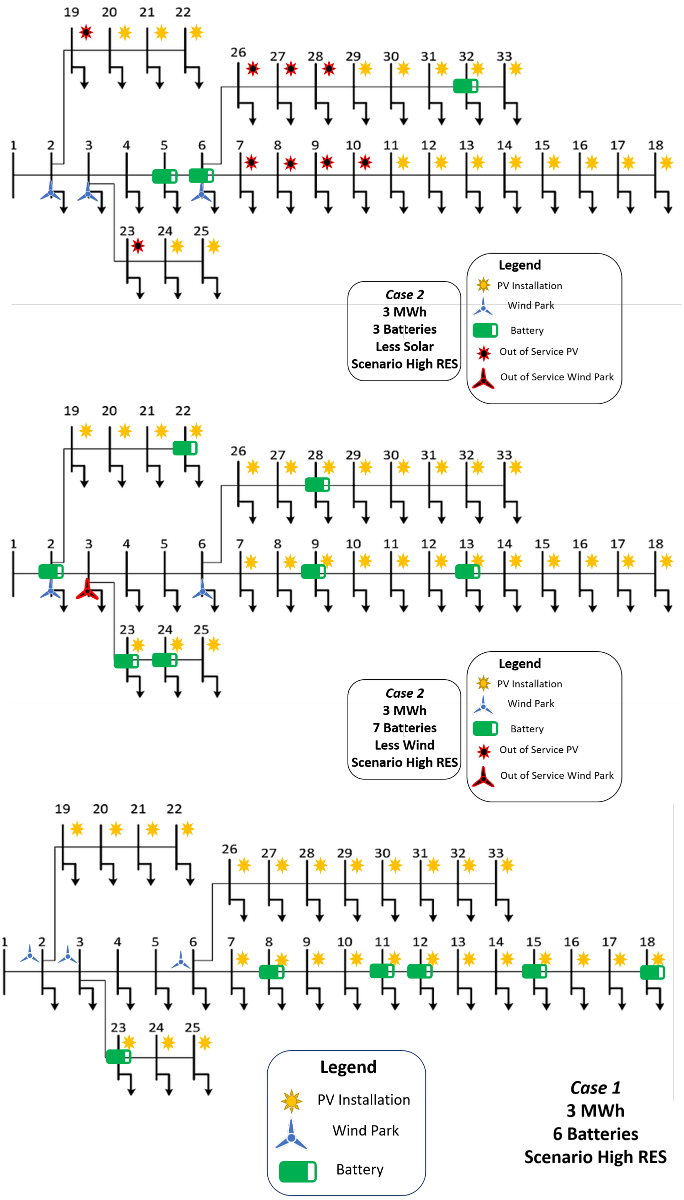


Figure 5.7: Optimal Locations of batteries

Scenario Low RES

In Figure 5.8 The four outcomes for each battery capacity size can be seen. In this case, there are more batteries allocated in the system when the less solar scenario is tested. These batteries are allocated along branches 1 2 and 3, with the support of two batteries in the threshold point in bus 6 and bus 5. For less wind, there are also more batteries, and they are allocated correspondingly. It seems that the algorithm is trying to reinforce the branches in the best possible way, locating the batteries wherever necessary.

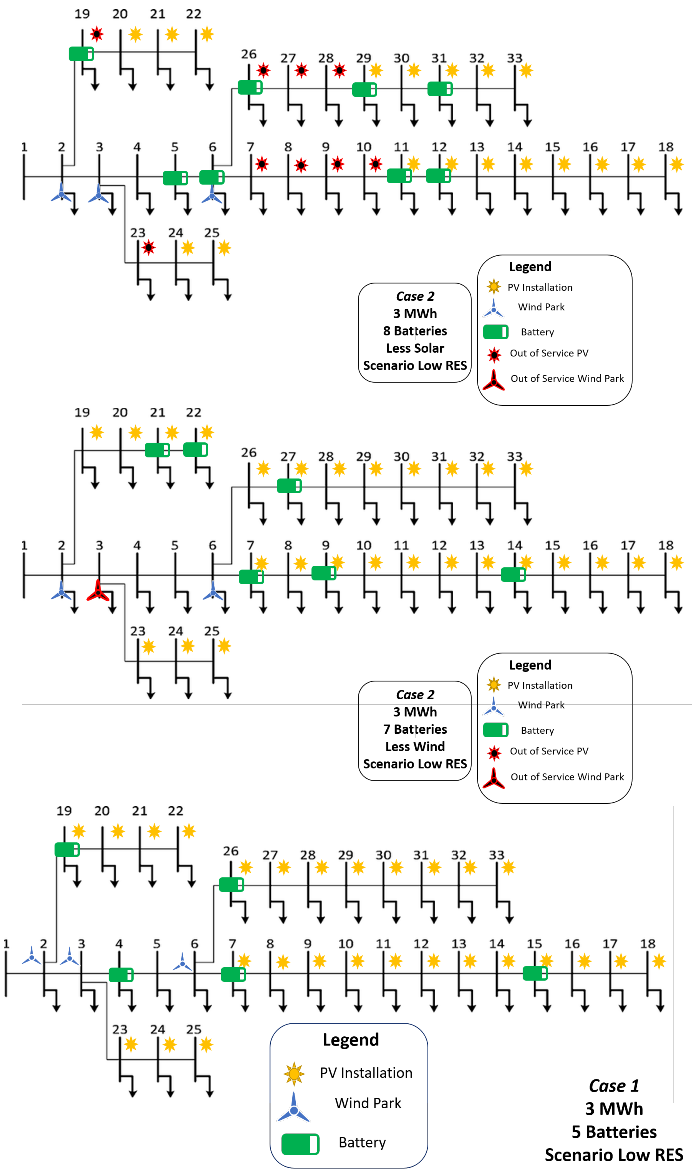
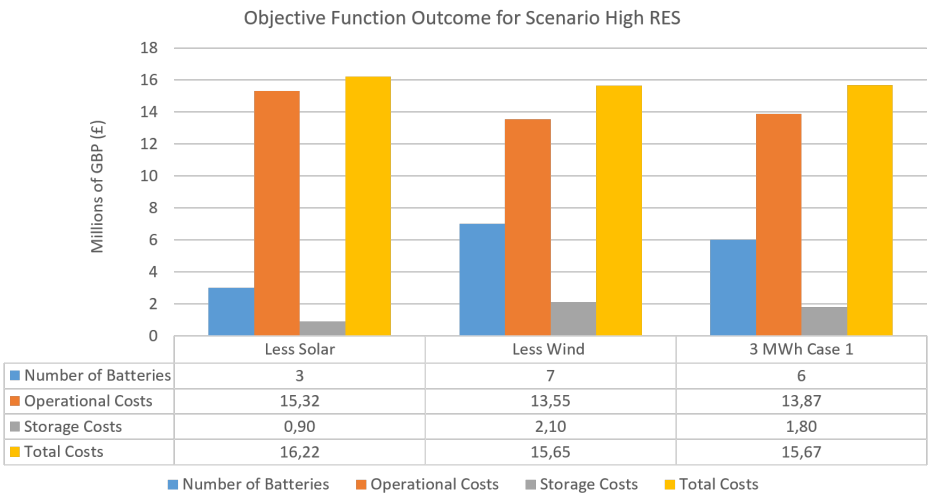


Figure 5.8: Optimal Locations of batteries

Objective Function Outcomes

The total, operational and storage costs for Case 2 in its both scenarios can be seen as follows. In Figure 5.9 the costs for the reference case and less wind case are almost the same. The operational and the total costs rise for the less solar example, though. In Figure 5.10 the same results are shown for the low RES scenario. Apparently, for both less wind and less solar, more batteries were allocated, and fewer costs were achieved.



	Less Solar	Less Wind	3 MWh Case 1
Number of Batteries	3	7	6
Operational Costs	15,32	13,55	13,87
Storage Costs	0,90	2,10	1,80
Total Costs	16,22	15,65	15,67

Figure 5.9: Objective Function Results of Case 2, High RES

The result for less solar in High RES scenario results compelling. The software is using fewer batteries than in the reference case, and the operational costs are higher than the reference case. Of course, this makes sense because for High RES scenario the dependency of the system on the renewable production is higher. Hence, any changes in the distribution of the RES will instantly impact the overall behavior of the system.

Discussion

What is more interesting about the results of this case is the disparity of battery numbers between less solar for Scenario High RES and Scenario Low RES. For less wind, the results show that more batteries are distributed all over the system. This strategy is probably trying to benefit as much as possible from the PV installations that remain untouched and that account for 60% of the total RES output.

For less solar another phenomenon takes place. The solar production is now intensified and concentrated on fewer buses. Then, comparatively big batteries can be allocated in threshold buses and high load buses, to provide net arbitrage services. For the low RES scenario, the result is the opposite: More batteries are allocated in a distributed manner but keeping batteries in buses 5 and 6. It seems like when the share of RES is high, its

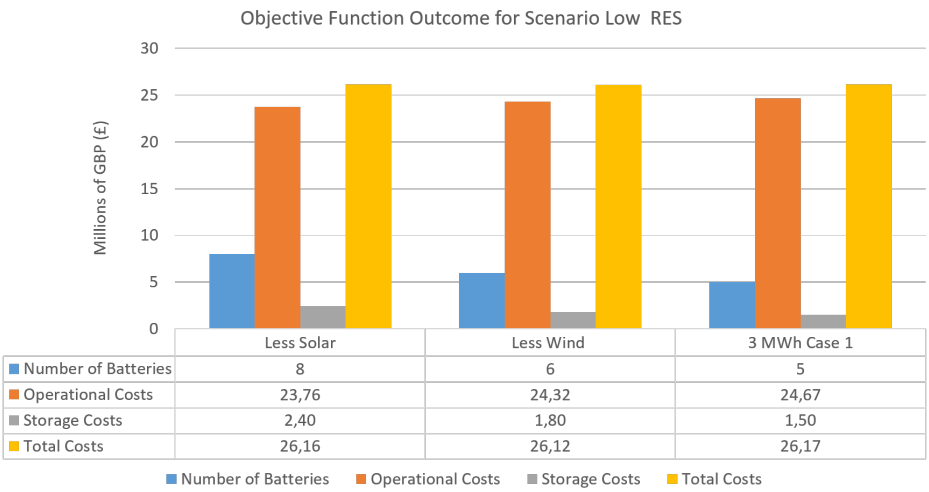


Figure 5.10: Objective Function Results of Case 2, Low RES

concentration in some buses increases the operational cost, and reduces the value of using batteries. So the more distributed generation is, the more value storage has and perhaps, the more batteries that become economically feasible.

Another interesting outcome is that the trend seen in case 1 is followed here as well. Batteries, in case 2 more than case 1. Tend to have an optimal location in large load buses, RES production buses, threshold buses or, a combination of the these three like in bus 6.

5.3 Case 3

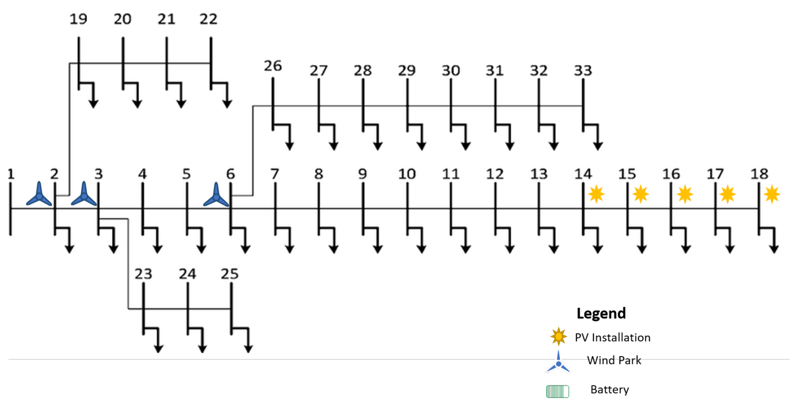


Figure 5.11: Schematics of Case 3

To further investigate the behavior of optimal allocation, Case 3 proposes to allocate all PV generation in only five buses, as observed in Figure 5.11. For only Scenario High RES and the same distribution of wind resources, the simulations were run for 1 MWh and 4 MWh. Location results are shown in Figure 5.12 and objective function results are shown in Figure 5.13. A battery with 1 MWh achieved the higher cost reduction with 20 MWh installed all over the system.

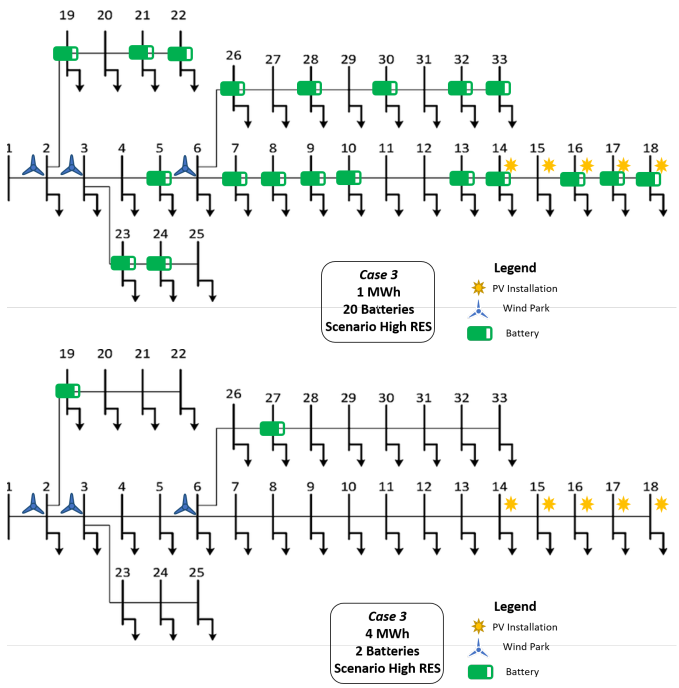


Figure 5.12: Optimal Locations of batteries for Case 3

Discussion

The objective of Case 3 was to cluster most PV generation to a handful of buses and test how much battery sitting locations are affected by this. On a broader sense, it was expected to have batteries located as close as possible to big clusters of generation, like trying to store the most surplus possible. Instead, we see batteries scattered over the system and not necessarily where generation is taking place. For 1 MWh there were 20 batteries allocated in all the branches, with special emphasis in the third branch where the solar PV is generated but also with multiple numbers in branch 2 and almost all the buses of branch 1 and 4. Whereas for 4 MWh, there are no batteries allocated at any point where RES generation is taken place; nor even in the same branch. This result is interesting because if we check the output results, we can spot that the total costs for 1 MWh were lower but not dramatically lower than for 4 MWh. In Short, two big batteries managed to find an optimal solution while located away from generation.

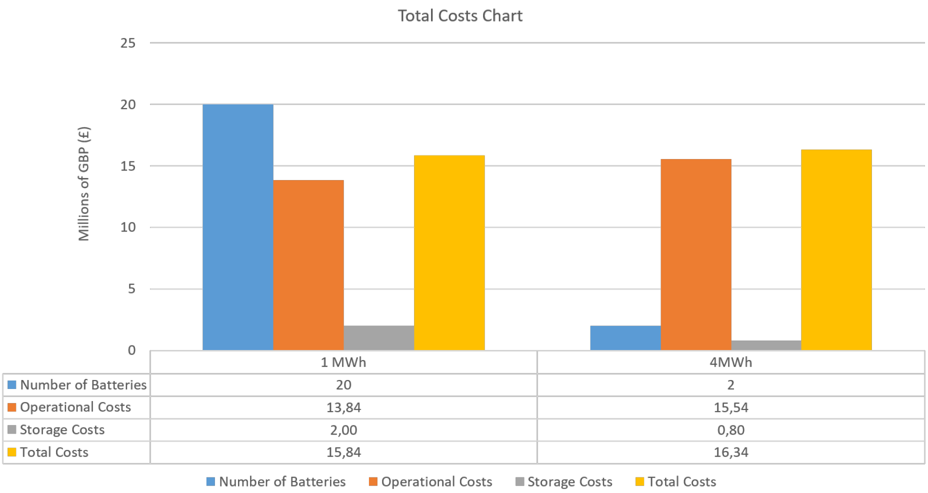


Figure 5.13: Objective Function Results Case 3

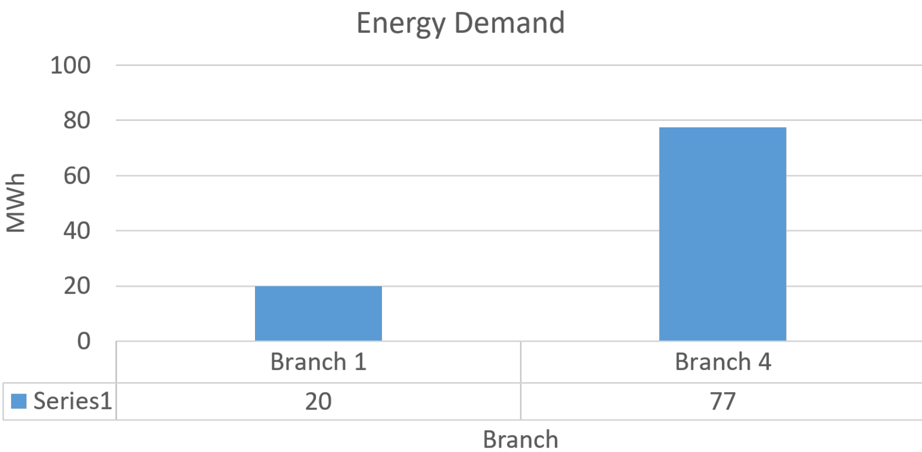


Figure 5.14: Energy Demand for Branches 1 and 4

Moreover, in the 4 MWh case, batteries are located on buses 19 and 27. But why not in buses 23, at branch 4? Previously, we have seen the optimization software to have a ”preference” for branch one over branch three, why is that? In Figure 5.14 the energy demand of these two branches can be seen. In Figure 5.15 the power demand of the same branches can be seen. The energy demand of Branch 1 is higher but comparatively not so much bigger than the demand in Branch 4. Nevertheless, the power demand of Branch 1 reaches peaks of consumption of more than double of the ones in Branch 4. Hence, the allocation of big batteries in bus 19 is probably because this power demand behavior will stress the limits of the system.

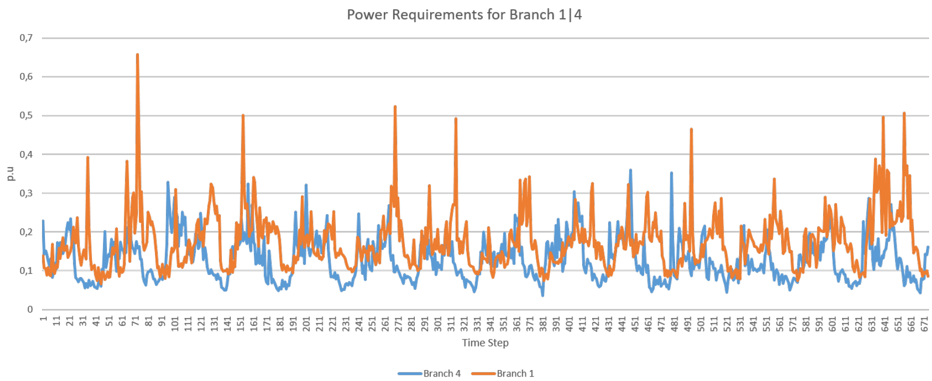


Figure 5.15: Power Demand for Branches 1 and 4

Also, for branch two a similar scenario takes place. The battery is located on bus 27, which has not a significant load connected but it is located next to some of the biggest loads after Load 17, as we can see in Figure 4.11. And also, as we can see in Figure 4.13, the thermal limits of line 6-26 (Central-26), 26-27, and 27-28 are among the lowest of the system, despite the following lines in the branch have higher limits. Thus, there is a ”funnel” effected in these lines and buses 26, 27 and 28 are also threshold points. Hence, it is probable that the location of batteries in these two buses would alleviate the system enough to make it profitable. Otherwise, no batteries would have been placed.

5.4 Case 4

In Case 4 the price of the battery was increased, from 100 £/kWh to 200 £/kWh. The RES penetration is as base case Scenario High, so the only difference lies in the price of the battery. First, a battery capacity of 1 MWh was set, and then the price was changed. Starting in 400 £/kWh and then going down, no batteries were allocated for 400, 300, and 200. If the size of the battery is decreased, 32 batteries of 500 kWh are allocated for 200 £/kWh, and 32 batteries of 250 kWh are allocated for 300 £/kWh.

The most relevant allocation results are shown in Figure 5.16 and the objective function results are shown in Figure 5.17. Also, the cost reduction from the Base Case (in percentage) is shown in Figure 5.18. Current Lithium-Ion based batteries have reached a price of approximately 160 £/kWh (200 USD) according to reports released in late 2017 [3]. Hence, the price for which sitting of 1 MWh batteries begins to be profitable, is the current market price of batteries.

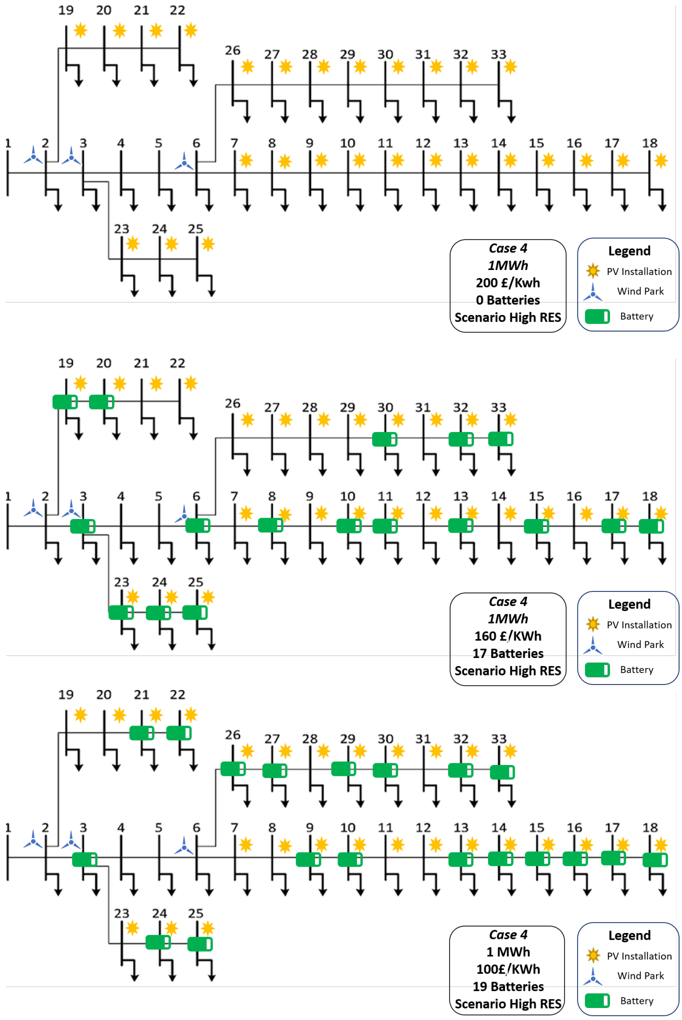


Figure 5.16: Location Results for Case 4

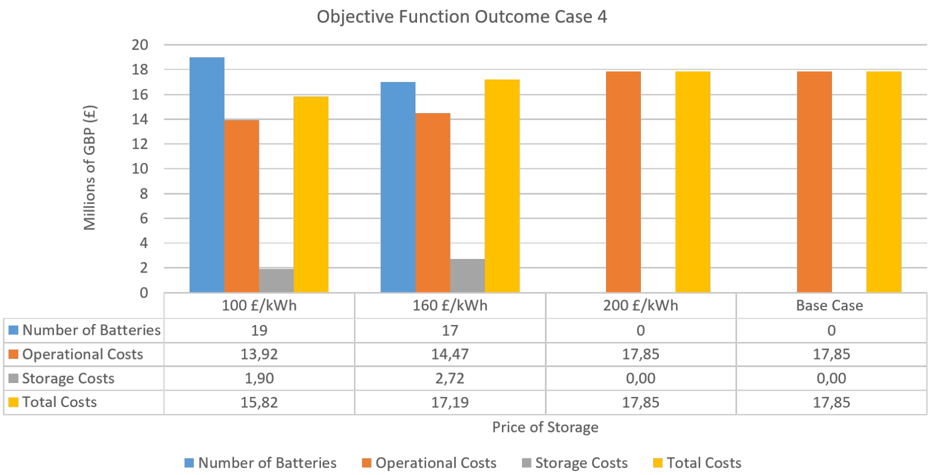


Figure 5.17: Objective Function Results Case 4

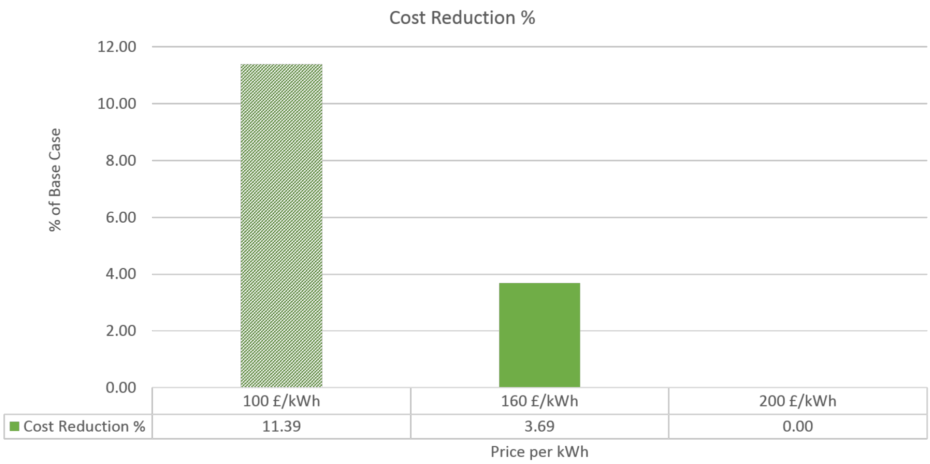


Figure 5.18: Cost Reduction for Case 4

Discussion

Regarding locations, a similar and repetitive trend is recognizable here. The battery size is the same for all studies, but the price changes. For 100 and 160 pounds, almost the same amount of batteries are placed (19 and 19 respectively). And it can be seen that the buses of these batteries change, but the overall strategy remains: Batteries in all the branches, at least one battery in the core (central branch), high concentration of batteries in branch 3 and batteries located in almost the same key buses: 17, 32 for example. There is one key learning here, and it is that the specific locations the software decides for batteries in every simulation, depend on a wide variety of factors and change constantly, so the optimal strategies may also change with the circumstances. The *overall strategy* of sitting seems to remain and its based on common sense: Large loads (like in 17), the edges of branches (like in 18, 33, 25, etc), threshold buses (like 26, 19, 23) and ”Hub” buses where production and load from different branches meet (like bus 6). The optimal locations *tend* to be around these type of buses.

Regarding price, it is very promising to see that for current prices the system is showing 17 1MWh-batteries as an optimal solution. And for even higher prices like 200 or 300 £/kWh, smaller batteries comprise a feasible option. If we check Figure 5.18, it might be arguable that there is no profitability on placing batteries in the long term if the reductions are only about four % after ten years. Yet, this investment analysis is not measuring and considering other benefits of storage that would increase the reduction costs even more. For instance, congestion management, voltage control, reserve storage services, etc. And what's more, battery prices are going down and will continue to go down. Therefore, despite the limitations and assumptions that had to be made, these results seem to be quite relevant, and their insights can provide much value for the ODSP.

5.5 Case 5

In recent years we have seen quick developments in the field of renewable energy, battery storage, and smart grids. The current trend indicates a deeper integration of RES, and thus, a deeper integration of storage. Companies like Tesla now offer household energy storage solutions, that are already under use and that can make substantial parts of the grid effectively disconnected. At least for long periods of time. This is especially a challenge for DSOs because it changes the game rules. On this sense, Case 5 is a compilation of several simulations done with different approaches, aiming to assess the implications of widespread use of storage at end-user level and which are the best scenarios for the DSO under these circumstances.

Capacity Allocation case

Assuming the aforementioned, widespread use of storage at every point of the system, e.g. no binary sitting, this case intents to find out how the capacity should be distributed along the system to provide the highest profits possible to the DSO. This was realized running for 674 periods, at 100 £/kWh and with a maximum capacity of 10MWh per bus.

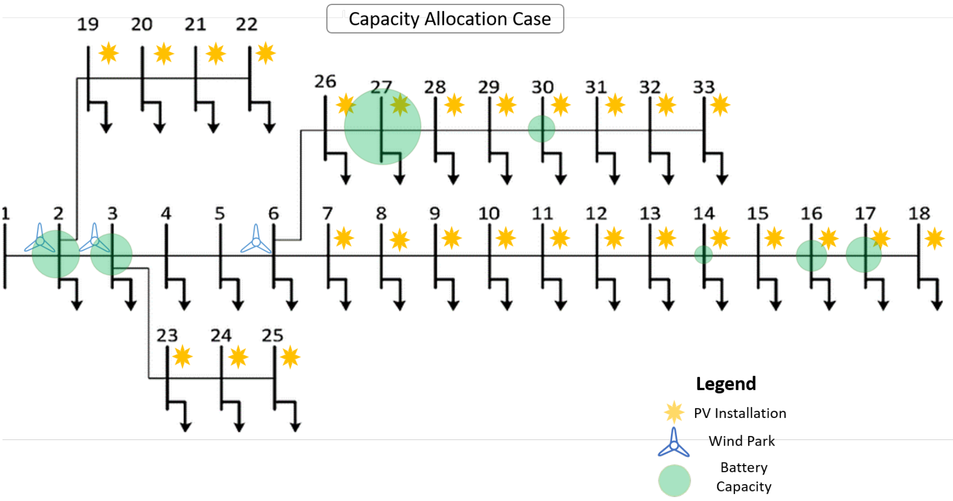


Figure 5.19: Capacity Allocation Results

Bus	Capacity (MWh)
2	2.98
3	2.78
14	0.80
16	1.99
17	2.11
27	5.53
30	1.34
Total	**17.54**

Table 5.1: Capacity allocated per bus

Power Rate case

The system may require sometimes to obtain power rather than energy services, e.g. the capacity of batteries has less importance compared to the power rate of the battery. This is especially true for loads that are small in energy terms but might reach high peaks from time to time. This happens often and might result in oversizing of batteries just to provide power services. Therefore, in this case the power rates have been changed to provide quicker responses compared to the base case. That is done by changing the total discharge/charge time of the battery, from the standard 4 hours down to 1 hour. To avoid long computational times, the study was done for 100 periods and the results are shown as follows.

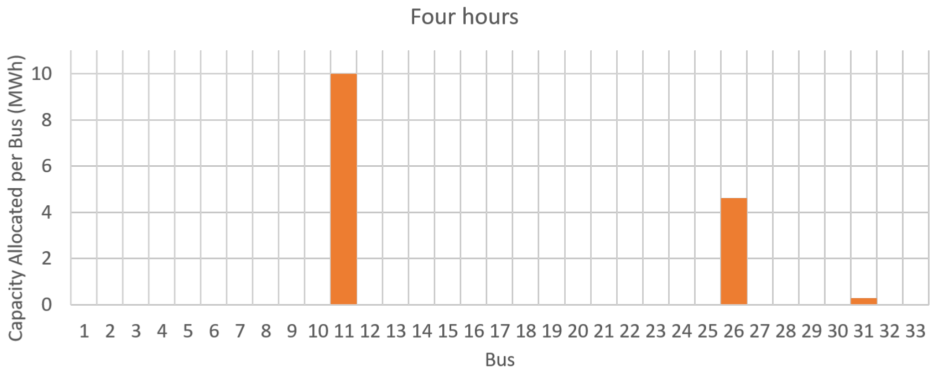


Figure 5.20: Capacity Allocation Results for 4 hours (standard) discharge time

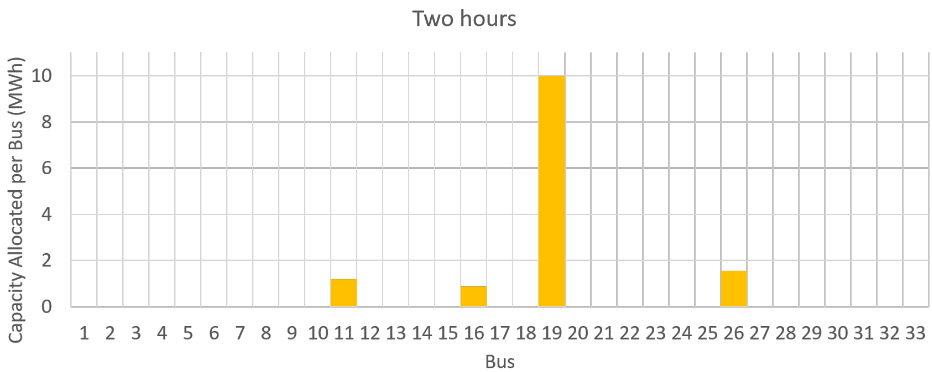


Figure 5.21: Capacity Allocation Results 2 hours of discharge time

Integer Sitting case

As seen and mentioned before, the capacity of storage is not a malleable resource that can be distributed so easily. Henceforth, this case makes use of very small battery sizes, of about 0.1 MWh, so to ”granulate” the storage capacity and observe how the system allocates it. To make it a sort of sizing simulation, the binary variable that results in the sitting decisions was replaced by an integer variable. This means that the python tool can allocate as many batteries as desired in any part of the grid. Additionally, a high price of 200 £/kWh was set to challenge the solution further (For this price, no battery was allocated in any of the previous studies).

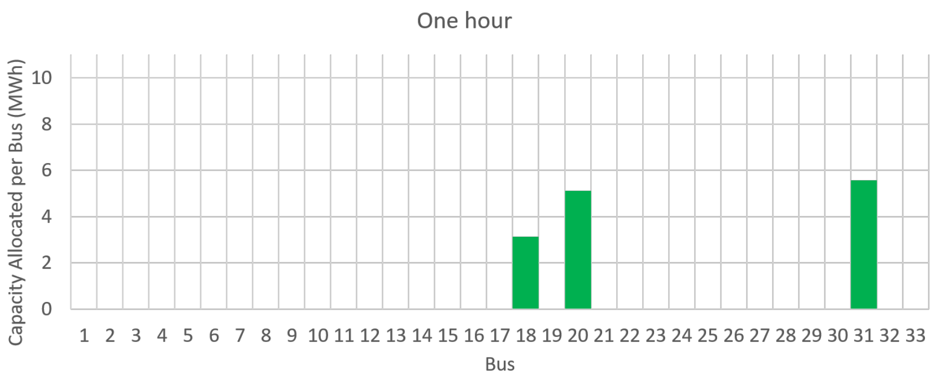


Figure 5.22: Capacity Allocation Results for 1 hour discharge time

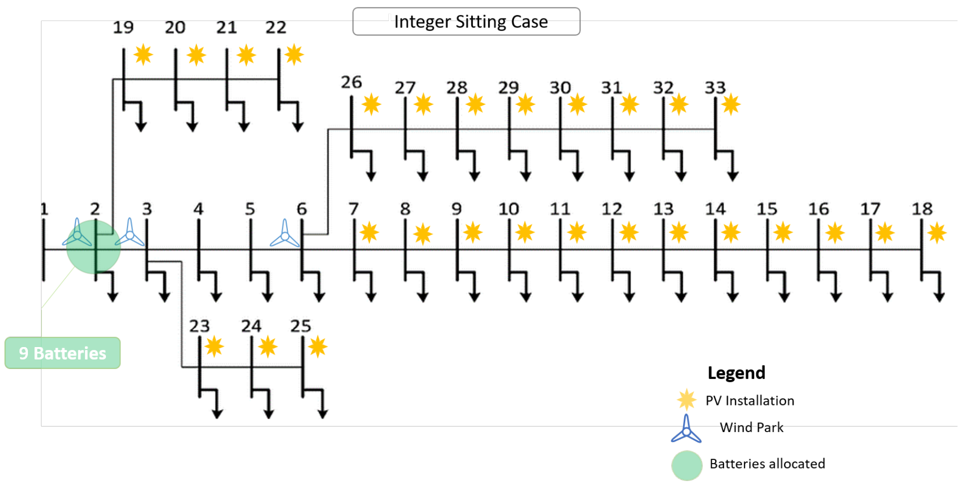


Figure 5.23: Batteries allocated using integer variables

Discussion

Regarding Capacity Allocation

In Figure 5.19 it is noted that the optimal capacity in most of the buses turned out to be zero. Whereas in only 7 buses the capacity was non-zero. The exact values where capacity was no zero can be seen in Table 5.1. Interesting enough, the system allocates batteries of more than 5 MWh when there is no binary sitting. Also, it allocates two considerable amounts of storage in buses 27, 2 and 3. Overall, the total capacity allocated in the system is 17.54 MWh.

These results show that even when the capacity is treated as a fluid resource, the python tool clusters the capacity in pretty much the same areas as before: buffer and threshold buses, with some capacity at the end of highly demanding branches. This is contrary to what might be expected: allocation of storage as spread out as possible. Therefore, despite previous results show that spread out allocation of storage can result in optimal solutions, it is not necessarily the most optimal in all cases.

Regarding Power Rate

As it can be seen in Figures 5.20, 5.21 and 5.22, the faster the battery can be discharged/charged-thus, the higher the power rate- the lower the optimal capacities allocated are. Another perspective of this phenomenon can be seen in Figure 5.24, where it is shown, for each power rate case, the percentage of the total storage allocated that falls in one of the 5 ranges of battery size shown in the horizontal axis. For example, for the 4 hours discharge time we can see that most of the capacity is allocated using sizes ranging from 8 to 10 MWh. Whereas for a discharge time of 1 hour, 77.3 % of the total capacity is allocated with sizes ranging from 4 MWh to 6 MWh. Moreover, in Figure 5.25 the total installed storage capacity is shown, with the golden trend line decreasing as we decrease the discharging time. That is a sign that the fastest the battery can deliver the energy, the smaller the needed batteries have to be. Therefore, it seems that the optimal distributed storage capacity is being in the system is determined-at least in part- by the need of power services throughout the system. So in short, the higher the power capacity the battery can provide, the smaller the energy capacity the battery has to have.

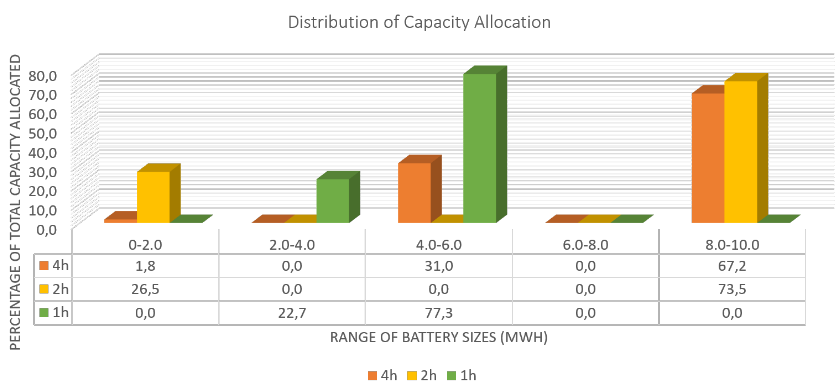


Figure 5.24

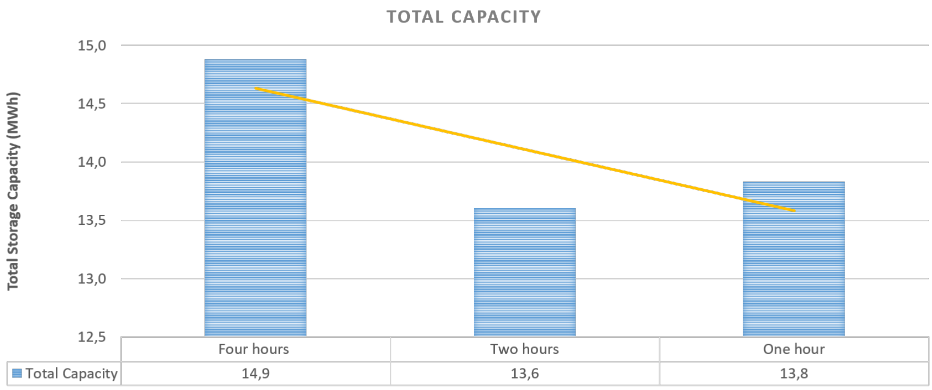


Figure 5.25

Regarding Integer Sitting

As shown in Figure 5.23, even when using outdated, expensive battery prices with very small maximum capacities per battery (0.1 MWh), the tool finds profitable strategies. In this case, the strategy is to allocate 9 batteries in bus 2, making up to 0.9 MWh in total. This gives a crucial view on which buses are the most important in the system. Bus number 2 has renewable generation and loads in situ (Prosumer bus), it connects the main grid to the distribution system (Hub bus) and it is located between lines with sharply different thermal limits (Threshold bus).

Chapter 6

Conclusions

6.1 Concluding remarks

The Optimal Distributed Storage Placement problem a relatively not much explored area of research. As seen in the literature, there are gaps concerning many areas. For instance, there are not many studies where storage placement has been formulated as a mathematical optimization. Also, not many studies made a thorough analysis of the influence of technical limits on the sitting problem. We need to cover these gaps if we intend to accelerate the transition to a sustainable economy; a process currently under socio-economic pressure to speed up. For that transition to take place, intermittent RES sources will have to become the norm rather than the exception, which in conjunction to a deregulation of the electricity market, will transform storage into a key technology to achieve power balance. Therefore, the objective of this project is to cover these gaps by carrying out an investment analysis of cost-effective battery placement for an MV grid, considering power flows, technical limits, dynamic pricing as well as consumption, generation, and batteries real data. Results show that batteries can indeed optimize the performance of the system and that their location and size greatly affect how optimal these solutions turn out to be. Also, it shows that the optimal locations are highly susceptible to dynamic changes in the system, like power and generation profiles.

From the results, it seems that the optimal size for each system highly depends on many inter-related parameters and variables, like technical limits, power demand, energy demand, voltage limitations, and battery's power rates, to name a few. All of these play a role, and the extent of their singular influence on the location decision is hard to measure. Yet we see that the smaller the battery becomes, the easier it is to place it cost-effectively. This then makes storage affordable even for higher prices. A good reference for what means "big" or "small" in this context is according to our standard battery capacity of 3 MWh which is close to the hourly average consumption of the system, which is around 3.5 MWh. Therefore, despite the optimal size changes from case to case and from scenario to scenario, a size of a third of the total hourly system consumption seemed to have worked very well for different prices, RES share and RES penetration. That makes sense since the smaller the capacity of the battery, the more ”freedom” the python tool has to allocate them in any way convenient. In Fact, smaller sizes, like 500 kWh, 250 kWh and 100 kWh (Case 5) did quite good for comparatively high prices, as shown in Case 4 and Case 5.

Even though battery with sizes of 3 or 4 MWh turned out to be more difficult to allocate, they provided the optimal solutions for both scenarios in Case 1. That confirms many previous findings in the literature, where there is a stark argument pledging for optimal allocation in contrast to random, or equal distribution. However, the optimal locations and sizes obtained in Case 1 depend not only on static system features like topology, but also on dynamic features, like load and generation profiles. Among others, these factors are:

- Location of High Energy and High Power Loads
- Line Thermal Limits
- Penetration of RES
- Battery properties (Capacity, Power Rates, etc)

As for the type of buses, there are several types of buses, or groups of buses, where batteries seemed to perform optimally for numerous scenarios and conditions. These buses can be outlined as:

- *Threshold buses*: Buses connected or close to lines where thermal limits change, especially if this lines constraint branches where large loads or considerable generation lies, thus complicating its supply. Batteries in these buses help to provide the power while reducing congestion and help to prevent voltage violations in constraint branches.
- *Large-Load buses*: As expected, batteries can be of much utility at buses where large loads are located. As a matter of fact, in the results of cases 1 to 4, we found that buses 17 and 18 were optimal locations for a total of 7 times each. Although in general almost all buses appeared as optimal solutions at least twice, except for bus one, *where there is no load*.
- *Prosumer Buses*: On these buses there is load and generation. It is understandable that batteries are useful here, and it is not a surprising result given that it has been mentioned before in the literature provided in chapter 1.
- *Hub* buses where multiple line connections, RES production, and high power consumption make network arbitrage more effective.
- *Dead-End buses*: These buses are nothing but the ones located at the end or close to the end of branches, where batteries are of utmost utility to keep technical limits under check. Especially regarding voltage limits.

Strategies that allocated batteries *around* these buses were the most successful, thus giving the impression that the optimal strategies comprise an approach of allocating storage in optimal ”areas” rather than optimal buses, but to affirm so more research needs to be done, for several topologies with higher number of buses. Nevertheless, the best solution will always depend on the specific circumstances of the system and we have seen that when these circumstances change, the optimal locations change. Hence, we recommend making an extensive analysis of where these group of buses are located to give an initial idea on what might be the best deployment strategies for a given system.

Furthermore, flexibility regarding power arbitrage and RES surplus leverage was proven to have a decisive effect on overall costs. Every case where a battery was allocated had a lower total operational cost than the base case. This effect was clearly shown in the objective function outputs for all cases. For instance, in Case 1 Scenario High RES, there was a reduction in costs of 12.21 % of the Base case using six 3 MWh-batteries. Whereas for the same case, but in the Low RES scenario the reduction in costs with five batteries of the same size was of about 4.67 % only. That is precisely the result of the intervention of storage in the system and the leverage it provides for RES utilization. Also, with sufficiently small batteries or at a sufficiently low price of storage, allocation of batteries decrease the system total costs, as seen in Case 4 where for 160 £/kWh (current prices for 2018 [3]) allocating 17 batteries of 1 MWh each reduced total costs up to 3.68 %. What's more, our studies did not consider the economic revenues associated with congestion management or reserve storage services for purposes of control and stability. It is entirely possible that if considered, the reduction in costs would have dropped even more.

Moreover, Case 5 showed that either by allocated capacity or sitting smaller batteries, a handful of buses (of maybe 21% of the total buses for the Capacity Allocation Case) can be enough to provide an optimal solution. It also showed that just by changing the power rate capacity of batteries, the optimal locations changed sharply and the size of the batteries used, decreased. Moreover, with current drop in prices, more efficient technologies, and the advent of EVs, the trend seems to be one of an extended use of storage in the system, both in industrial and user level. If we bridge those results with the previous 4 cases and combined that with the observable trend for the following years, we can draw some conclusions and recommendations for the DSO, which are listed and explained in the next section.

Conclusions

From the presented studies, we can draw the following conclusions:

- We found that yes, the location of storage highly influences the revenues based on a DSO perspective. And that these locations are influenced by fixed properties like line limits, voltage limits, stability, topology, among others. But, these locations are under even more influence of dynamic, constantly changing factors like load profile, weather forecast, energy and power consumption, battery's specifications, and more.
- We observed drastic changes on the solution just by changing battery specifications or load profiles, for instance. Therefore, optimal locations for storage do not tend

to be fixed over long periods of time, but rather tend to change with the changing dynamics of the grid. Furthermore, it seems that all the buses in the system are going to be part of an optimal solution at some point, depending on the grid dynamics.

- Consequently, planned deployment of storage only in some ”optimal” buses (like prosumer, hub, large-load and threshold buses), might achieve good results but will not be the best solution overall.

- When allocating capacity it was found that the sizes of the battery was, in large part, influenced by the need to provide high rates of power to strategic loads. When batteries with higher power limits were used, the resulting capacities decreased in size. Although, the total installed capacity remained similar.

Recommendations

Based on the exposed analysis and conclusions, and with the intend to achieve a smooth energy transition, where RES are finally integrated in the economy, consumers can benefit and participate in the flexibility market and traditional system operators like DSOs can still make a business model, we provide the following recommendations:

- The DSO has to be involved in the flexibility market design. Not only to establish the fixed technical regulations that will rule the market, but also to design the market such as it encourages battery operations in locations found optimal by the DSO. The process to do this can be described as an optimization study, to find the optimal locations for battery operations in the distribution grid. With day-ahead forecast of load and generation, technical limits and information about the storage capacity installed throughout the system, the DSO can develop a day ahead analysis to determine which will be the optimal buses to perform energy arbitrage, RES surplus, or any other desired service. With an array of the resulting hierarchy-arranged of buses, graded on the basis of profitability, the DSO can set a structure of incentives and penalties to favour and/or discourage storage operations where they are considered convenient. In this way, the needs of the DSO can be made financially visible without incurring in stiff regulations that will deprive everyone, of the societal benefits of storage and RES combination. That of course, will play a role in the market clearance and in market prices, thus financially determining how to operate and maximize the benefits of the flexibility resources available in the market.

- Also, given that the DSO optimal locations are highly influenced by the need of power services and that residential end-user level batteries are not precisely the most efficient to provide power services, perhaps the DSO can perform optimal storage location and size planning studies for long horizons and invest, or encourage power producers to invest, in power-service storage allocated in the best possible locations. Those best possible locations probably being within one or several of the categories stated before: Prosumer buses, Large-Load Buses, Hub Buses and Threshold buses. This will avoid the need to use expensive polluting energy sources, prevent costly grid expansions, maximize RES utilization, reduce long term operational costs for the DSO, improve the grid’s power stability and provide a portfolio of flexibility resources the DSO (or any other party) can trade in the upcoming flexibility market. These Power-assisting storage units provide a compulsory flexibility service that the DSO has to be able to deliver to guarantee not only profit, but also stability. Therefore the DSO can charge the users to finance these investments, and can also profit from them in the long term.

- As well, the DSO can encourage the investment on storage at end user level in the short term, given that under the current prices it is profitable and beneficial for both the DSO and the end users. As we have seen, the optimal location of batteries depend on a wide variety of factors and they hardly remain the same when these factors change. Hence, these investments should start allocating storage in the locations best suitable for whatever the main goal of the DSO is at the beginning: Congestion Management, Losses minimization, RES maximization, etc, but with a plan to deploy storage as spread as possible. A business case on how to do this in a way that benefits all the players is a good proposition for future work.

Overall, this research was intended to find useful insights for the DSOs that might be facing challenges to integrate RES and storage in their systems. We hope the results, insights, analyses and recommendations are beneficial for Distribution System Operators.

Limitations and Future Work

To study ”the battery allocation” phenomena in Power Systems means to study a very complex problem. The amount of data and computational power that have to be done to make these simulations without simplifications is something we leave for supercomputers or for the elaboration of detail solution methods. Hence, to be able to gain some insights on the ODSP problem without having had a sophisticated solution method, some assumptions had to be made. The most relevant assumptions made in this work are associated with:

- Linearization of Power Flow Equations
- Reduction of Time Horizon down to two representative weeks. Therefore, the use of time factors to scale up the magnitude of costs to resemble the figures of a ten-year investment analysis.
- No degradation model for the battery.
- Load and RES profiles were considered to be deterministic instead of stochastic.

Even after implementing these assumptions, the computational efforts were still challenging. For instance, before the reduction of the time horizon, the four weeks of simulation lasted for about 8.5 hours. Moreover, on average, the simulation times oscillated around an hour. In the appendix, Figure 6.1 shows a wrapping up of simulation times for each shown case, and in Figure 6.2 the total simulation time is shown. In short, if we find a mistake in data and we have to re-run all simulations, it will take 15.5 hours just to run these 4 cases. Ergo, the number of cases and scenarios to simulate are sharply limited by computational times. Also, the time horizon we could simulate was constraint by this. Regarding future work, some recommendations are made as follows:

- Address the problem with more sophisticated methods to deal with the non-linearity of power flow equations so that less compromise between feasibility and accuracy has to be made.
- To simulate the problem for longer time horizons without the use of scaling up factors and other assumptions aimed to reduce computational time. For this, it might be necessary the use of more powerful hardware, more advanced methods, and more efficient software design.
- A similar approach but with the use of stochastic data will provide great understanding on how to develop the actual tools that will be used in the practice.
- A similar approach containing a detailed battery model that includes degradation features.
- Regarding the best strategies that the DSO can take, there is need for further research on how to design flexibility markets in a way that justly satisfies the needs of all players and maximizes the societal value of the resources available.
- Also, as we understand it, the value of storage rest upon the assumption that it will be operated in a collective manner, i.e. the operation of every battery will take into account the location and capacities of each of the other batteries installed in the system. This is more a requirement than an assumption, and its materialization needs extensive research. For instance, more research is needed on the policies that governments and DSOs can design to promote and finance the installation of storage at end-user level, and the creation of a common platform to operate efficiently this resource. A cloud-based solution is one plausible alternative, but more investigation has to be made on this topic.
- Moreover, assuming the flexibility market will seek the optimization of the resources available, more research is needed to determine which optimization objectives deliver the best results. Whether these objectives are maximizing the use of RES, minimizing losses, managing congestion, etc; research on the advantages and disadvantages of each objective, is required to clarify which type of optimal operation fits best our societal and economical needs.

Finally, we are very optimistic that the combined implementation of the approaches covered in the literature, the ones in this very project and the ones listed on future work, will strengthen the know-how of energy storage deployment and take us one step closer to a sustainable, clean and environmentally friendly economy.

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Appendix

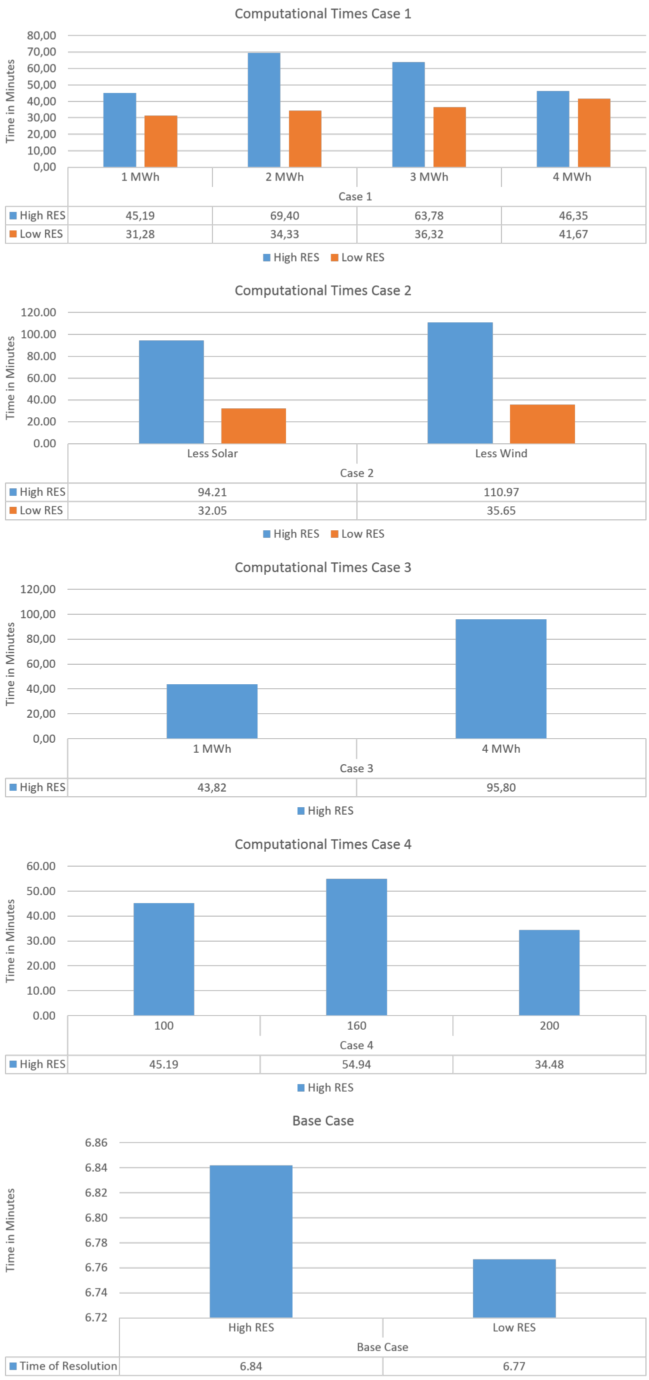

Figure 6.1: Simulation Times for the project

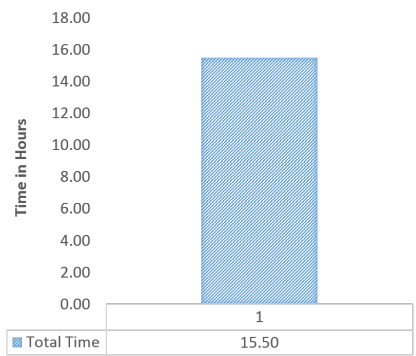

Figure 6.2: Total Simulation Times of the Project