Optimal Scheduling of Demand-Responsive Services from Electric Vehicles in Distribution Grids

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Abstract - As the integration of Electric Vehicles (EVs) becomes increasingly prevalent, the optimization of grid operations becomes paramount. This thesis addresses the challenges and opportunities posed by the evolving energy landscape, focusing on the optimal scheduling and resource allocation in the point of view of the Distribution System Operator (DSO). Through mathematical modeling and algorithmic optimization with Mixed-Integer Nonlinear Programming (MINLP), this thesis analyzes two distinct approaches to the management of EVs considering both Unidirectional Vehicle-to-grid (V1G) and Vehicle-to-grid (V2G) capabilities. The first approach centers on the DSO's role in managing grid resources efficiently while considering the dynamic nature of renewable energies and EVs, showing some cost minimization through the use of V2G but increasing the computational time of the optimization compared to the V1G technology. In the second model, the focus shifts to the coordination between the DSO and multiple Electric Vehicle Aggregator (EVA), each with distinct objectives and constraints. This model provides a decentralized approach to the EV management problem with a significant reduction in its time of optimization, while guaranteeing grid stability and supplied demand. The use of an aggregator increases the flexibility of the DSO when it comes to handle increases in power demands, showing that the decentralization of resource management does not compromise the grid's functioning. In summary, this thesis contributes to the discourse on grid management strategies in the face of increasing EV penetration and integration with other resources such as renewable energies. The findings shed light on the complexities of energy management in modern and future grid systems and analyze optimal decision-making strategies for grid operators.

Keywords: Electric vehicle, Vehicle-to-Grid, Demand Response, Distribution Grid, Electric Vehicle Aggregators.

1 Introduction

The degradation of our planet, fueled by the mass consumption of fossil fuels [1], has lead to a rise in the adoption of renewable energy sources and alternative energy technologies. As one of the primary contributors to environmental harm, the transportation sector is undergoing a profound transformation, with Electric Vehicles (EV) emerging as a promising solution. A recent study conducted by Eurelectric [2] forecasts a dramatic increase in EV adoption, with projections suggesting that by 2030, Europe alone will boast a staggering fleet of 40 million EVs.

This exponential rise in EV adoption holds the promise of cleaner transportation, but it also presents a formidable challenge for the power grid. The substantial increase in electricity consumption, driven by the increase of EVs, is bound to pressure the grid infrastructure, leading to heightened power losses, voltage instability, peak power demands, and grid congestion [3]. To mitigate these challenges, it is imperative to implement intelligent charging and discharging strategies, encompassing both Unidirectional Vehicle-to-grid (V1G) and Vehicle-to-grid (V2G) services, alongside load management through demand response.

1.1 V1G and V2G - Smart Charging and Discharging

In normal charging, the EV starts to charge the moment it is plugged in at a constant rate. On the other hand, smart charging allows EV charging to be intelligently controlled, so it takes place when the electricity network has surplus capacity, or when there is reduced demand and electricity is cheaper. This process is denominated Unidirectional Vehicle-to-grid (V1G).

An EV can also provide energy to the power grid by discharging the battery, a process which is known as Vehicle-to-grid (V2G). Since most EVs are parked for long stretches of time [4], they can effectively perform both roles. Using intelligent scheduling of V2G means reshaping the load profile by charging the EV battery from the grid at the time when the demand is low and discharging the EV battery to the grid during peak hours [5].

EVs can contribute to Ancillary Services (AS) in power systems, the main ones considered being frequency regulation, Spinning Reserve (SR) and load levelling [6].

Load leveling, is a strategy employed to mitigate fluctuations in electrical load over a given period of time [7]. The EVs charge during off-peak demand periods to fill the valley of the curve, and discharge during times of high demand in order to feed power back to the grid and shave the peak of the load curve [8]. The primary objective of load leveling is to balance the supply and demand of electricity by redistributing loads across different time intervals, thereby reducing peak demand and ensuring more efficient utilization of resources within the electrical grid, such as renewables. EVs can work as backup batteries, storing the excess energy from renewables that would otherwise be wasted.

The ability to discharge energy back into the grid is not only favorable to the power systems, but also to the EV owners themselves, as it generates revenue for the sale of energy back to the grid [9].

However, it should also be considered that the use V2G does come with additional costs such as expenses of required equipment, advanced communications and smart metering, and the faster degradation of batteries [3].

2 Related work

Electric vehicle charging modeling involves factors such as electric vehicle battery properties, types of electric vehicles, travel time, mileage, charging properties and charging time.

In V1G, the scheduler tries to optimize the energy flow from the grid to the battery of the EV.

The authors of [10] consider a specific scenario for 55 distribution networks of The Netherlands, combining recent and future EV load profiles, concluding that controlled charging results in a significant reduction of overloaded network components compared to the uncontrolled charging, specially in the HV/MV transformer station level, followed by MV/LV transformers and MV cables.

In [11], orderly charging strategy is proposed using a multi-objective optimization model with a minimum peak-to-valley difference and minimum charging cost, setting as constraints the load limit, the EV charging time and the user demand. This model is then solved using weighted minimum modulus ideal point method, a method based on the Particle Swarm Optimization (PSO), that is also used in [12].

In [13], a normal probability distribution is used to estimate the time of arrival and departure of EV based on surveys of American vehicle users, a similar distribution to the one used in [11], but it does not consider the daily mileage of each EV, assuming that each EV takes the same time to finish charging.

In [14], a stochastic model of EVs charging loads is developed to analyze its impact on distribution power grid considering two types of vehicles: public transportation and private vehicles. Then, output data of a wind power/battery energy storage system and real-time pricing was used as to make better use of surplus wind power and save money on EV charging cost.

In [15], a dynamic multi-objective selection mechanism based on the power supply margin of distribution transformers is proposed to control the charging power of electric vehicles and initial charging time. For this, six optimization objectives are set, each one with its own objective function, regarding load peak, peak valley load difference, load fluctuation, sum of voltage offset in each node, power grid losses and charging cost.

In V2G, another level of complexity is added, with the scheduler trying not only to optimize the energy flow from the grid to the battery of the EV but also from the EV to the grid.

The authors of [9], [16] and [17] focus purely on the maximization of charging benefits for EV owners, considering similar constraints. [9] takes into account several constraints related to electricity price, battery capacity and state of charge, the objective of maximizing the benefits by charging the EV batteries when the price is low and discharging when the price is high. In [16], a day-ahead scheduling strategy for a fleet of EVs plugged-in to the grid is studied, which is then optimized using a deterministic linear programming formulation. The optimisation objective function used is similar to [11], but as it is implemented for V2G use, it allows negative power, representing the discharging of the EV to the grid.

With the goal of minimizing battery degradation, [18] proposes a battery anti-aging V2G behavior management method, based on Rain-flow Cycle Counting (RCC) algorithm. This anti-aging method aims to reduce the number of cycles and half cycles, thus increasing the lifespan of the batteries used in V2G applications.

In [19], the optimization of scheduling for both spinning reserve and user cost is studied, building a mathematical model to represent the spinning reserves taking into account EV mobility, but it does not take into account the peak-shaving capabilities of V2G. In [20], a model to provide frequency regulation services is proposed, adding a regulation request parameter assuming that the regulation services are zero-energy services. In [21], a V2G control strategy is studied to maintain the battery energy and provide frequency regulation done by droop control. When the frequency fluctuates above or below the set maximum frequency variation, additional power is discharged from the EV to the grid.

On the topic of how the management of EVs is done, several studies proposes the concept of EV fleet operators or Electric Vehicle Aggregator (EVA). The authors of [22] describe these entities as operators "that can exploit the flexibility potential of EVs, by participating in flexibility markets and by controlling both the time and the charging and discharging rate of connected EVs". The authors of [3] investigate the multifaceted roles of EVs within smart grids, focusing on how an EVA operates in conjunction with other types of operators. However, this study fails to achieve concrete numerical results of its benefits. On a different approach, [23] studies the use of a cooperative gaming model with real-time electricity price, where the Distribution System Operator (DSO), as the leader, regulates the load profiles, while an EVA, as the follower, schedules the EV charging and discharging behaviors according to the strategies of the grid operators. All in all, the research suggests that the implementation of EV aggregators can represent a critical component in the transition towards more sustainable and resilient grids with a high penetration of EVs.

3 Methodologies

To address these challenges, different models of grid management have emerged. This thesis explores two distinct deterministic models: one where the Distribution System Operator (DSO) assumes comprehensive control over all grid resources, and another where the DSO collaborates with EV aggregators for more efficient management.

3.1 Model 1: DSO

In the first model, the DSO assumes comprehensive control over all grid resources, encompassing loads, generators, storage systems, and EVs. This centralized approach empowers the DSO to orchestrate and optimize the entire distribution network's operation, ensuring efficiency, stability, and reliability. Under this model, the DSO leverages data from consumers and control algorithms to balance supply and demand, manage voltage levels, and enhance grid resilience. Additionally, it can facilitate the integration of renewable energy sources, such as solar power, by coordinating their output and storage. Two types of demand response for the loads are also considered, the first with continuous regulation and the other with discrete regulation. These programs are denominated reduce and cut DR, respectively.

This model will be studied considering both scenarios of EV capabilities, V1G and V2G, to analyze its impacts.

3.2 Model 2: DSO/EVA

In the second model, the DSO retains its role as the primary manager of grid resources, with the exception of EVs. In this scenario, EVs are managed by specialized entities known as Electric Vehicle Aggregator (EVA), which hold contracts with the DSO. These contracts are based on two critical factors: power and flexibility.

The EVA specifies a certain amount of power it requires from the grid on a daily basis. This power demand represents the minimum amount of electricity needed to meet the operational requirements of its EV fleet. This demand is essential to ensure that the EVA can fulfill its commitments to its customers, such as charging EVs within specified timeframes.

Beyond the fixed power demand, the EVA is granted a degree of flexibility in its power supply arrangements. Flexibility means that the EVA can receive less power than originally demanded, within predefined limits. This flexibility acknowledges the dynamic nature of grid operations and allows for adjustments in real-time. It provides the EVA with the capacity to adapt to unforeseen circumstances or grid constraints imposed by the DSO [24].

When the DSO fails to supply the full power demand specified by the EVA but remains within the flexibility bounds, an opportunity cost is applied. This cost operates on a sliding scale, meaning that it starts at a relatively low cost and increases with every hour the DSO falls short of supplying the full power demand. When it reaches the max amount of hours of unsupplied demand, the opportunity cost reaches its maximum value. This cost is designed to incentivize the DSO to meet the EVA's power demands promptly, making use of the flexibility offered. If the EVA cannot supply the power demand, even within the granted flexibility, a penalty cost is imposed.

3.3 Mathematical Formulation

3.3.1 Objective Functions

For the first model, the objective function ($F1_{DSO/V2G}$) formulated represents the operation cost of all aggregated resources by the DSO, and is defined as:

$$
\begin{aligned}
F1_{DSO/V2G} = &\sum_{t=1}^{T}\Big(\sum_{GEN=1}^{N_{GEN}}(\lambda_{A(GEN,t)}+ \\
&\lambda_{B(GEN,t)}P_{GEN(GEN,t)}+ \\
&\lambda_{C(GEN,t)}P^2_{GEN(GEN,t)})+ \\
&\sum_{LOAD=1}^{N_{LOAD}}(\lambda_{LOAD_{Red}(LOAD,t)}P_{LOAD_{Red}(LOAD,t)}+ \\
&\lambda_{LOAD_{Cut}(LOAD,t)}P_{LOAD_{Cut}(LOAD,t)})+ \\
&\sum_{EV=1}^{N_{EV}}((\lambda_{EV_{dis}(EV,t)}+\lambda_{deg})P_{EV_{dis}(EV,t)})+ \\
&\sum_{ST=1}^{N_{ST}}\lambda_{ST_{dis}(ST,t)}P_{ST_{dis}(ST,t)}+ \\
&\sum_{GEN=1}^{N_{GEN}}\lambda_{GEN_{Exc}(GEN,t)}P_{GEN_{Exc}(GEN,t)}+ \\
&\sum_{LOAD=1}^{N_{LOAD}}\lambda_{LOAD_{Ens}(LOAD,t)}P_{LOAD_{Ens}(LOAD,t)}\Big)
\end{aligned}
\tag{1}
$$

The generators are expressed in a quadratic function where $P_{GEN(GEN,t)}$ represents the power generated by each generator and $\lambda_{A(GEN,t)}$, $\lambda_{B(GEN,t)}$ and $\lambda_{C(GEN,t)}$ are the coefficients used for their price. For the demand response of the loads, $P_{LOAD_{Red}(LOAD,t)}$ and $P_{LOAD_{Cut}(LOAD,t)}$ represent the power reduced and the power cut respectively, each one with their own price, represented by $\lambda_{LOAD_{Red}(LOAD,t)}$ and $\lambda_{LOAD_{Cut}(LOAD,t)}$. For EVs, $\lambda_{EV_{dis}(EV,t)}$ is used to represent the cost of discharging their batteries, followed by their respective power, $P_{EV_{dis}(EV,t)}$. The degradation cost of the batteries is represented with λ_{deg}. Similarly, the storage units are considered with $\lambda_{ST_{dis}(ST,t)}$ being their discharging price, and $P_{ST_{dis}(ST,t)}$ being their discharging power. It is important to note that the discharging of the EVs and storage units are considered expenses to the DSO, thus appearing in the objective function with a positive sign.

The DSO also has the responsibility of using all the energy generated by the DG units, hence having to pay a cost for the excess power that is not dispatched, represented by $\lambda_{GEN_{Exc}(GEN,t)}$ and $P_{GEN_{Exc}(GEN,t)}$. Another cost, denoted as $\lambda_{LOAD_{Ens}(LOAD,t)}$, is used in situations where the DSO encounters insufficient generation capacity to fulfill the entire power consumption of consumers. This cost serves as a mechanism to mitigate non-supplied demand represented by $P_{LOAD_{Ens}(LOAD,t)}$.

Equation 1 refers to the objective function of the DSO model considering V2G, as it allows the discharge of EV's batteries into the grid. If only V1G is considered, then the objective function changes, with the only difference being the variables $\lambda_{EV_{dis}(EV,t)}$ and $P_{EV_{dis}(EV,t)}$, relating to the discharging of EVs.

For the DSO/EVA model, two objective functions will have to be considered, one for the DSO and other for the EVA.

Considering that the DSO no longer has the responsibility to manage EV's charging and discharging schedule, the variables related to them disappear from its objective function, being replaced with the variables specifying the contracts with the EVAs.

$$
\begin{aligned}
F_{2_{DSO}} = & \sum_{t=1}^{T} \Big(\sum_{GEN=1}^{N_{GEN}} (\lambda_{A(GEN,t)} + \\
& \lambda_{B(GEN,t)} P_{GEN(GEN,t)} + \\
& \lambda_{C(GEN,t)} P^2_{GEN(GEN,t)}) + \\
& \sum_{LOAD=1}^{N_{LOAD}} (\lambda_{LOAD_{Red}(LOAD,t)} P_{LOAD_{Red}(LOAD,t)} + \\
& \lambda_{LOAD_{Cut}(LOAD,t)} P_{LOAD_{Cut}(LOAD,t)}) + \\
& \sum_{EVA=1}^{N_{EVA}} (\lambda_{OP(EVA,t)} (P_{EVA_{ChCont}(EVA,t)} + \\
& P_{EVA_{Dch}(EVA,t)}) + \\
& \lambda_{PEN(EVA,t)} P_{EVA_{ChNonCont}(EVA,t)}) + \\
& \sum_{ST=1}^{N_{ST}} \lambda_{ST_{dis}(ST,t)} P_{ST_{dis}(ST,t)} + \\
& \sum_{GEN=1}^{N_{GEN}} \lambda_{GEN_{Exc}(GEN,t)} P_{GEN_{Exc}(GEN,t)} + \\
& \sum_{LOAD=1}^{N_{LOAD}} \lambda_{LOAD_{Ens}(LOAD,t)} P_{LOAD_{Ens}(LOAD,t)} \Big)
\end{aligned}
\tag{2}
$$

As said contracts have two costs associated with them, $\lambda_{OP(EVA,t)}$ and $\lambda_{PEN(EVA,t)}$ are used to represent them, those being opportunity cost and penalty cost. The opportunity cost relates to the contracted power $P_{EVA_{ChCont}(EVA,t)}$, which is the power curtailment by the DSO, that respects the flexibility offered by the EVA. The penalty cost, on the other hand, relates to the non contracted power $P_{EVA_{ChNonCont}(EVA,t)}$, which is the unsupplied power that goes beyond the flexibility offered by the EVA.

The EVAs will also have to have an objective function, as they also intend to minimize costs. As they're only responsible for the scheduling of EVs, their objective function will only have terms related to the charging and discharging of EVs, with $\lambda_{DSO_{supply}(t)}$ representing the cost of the power supplied by the DSO.

$$
\begin{aligned}
F_{2_{EVA}} = & \sum_{t=1}^{T} \sum_{EV=1}^{N_{EV}} ((\lambda_{EV_{dis}(EV,t)} + \lambda_{deg}) \\
& P_{EV_{dis}(EV,t)} - \lambda_{DSO_{supply}(t)} P_{EV_{ch}(EV,t)})
\end{aligned}
\tag{3}
$$

The opportunity and penalty costs are not taken into account in the objective function of the EVAs, as it is independent from the EVA choices.

3.3.2 Constraints

All the objective functions introduced previously have to submit to certain constraints to ensure that power and energy limits are not exceeded, as well as the proper functioning of the grid.

Starting with the DG units, the generators have to obey limits of maximum and minimum power.

The PV units have a fixed power generation constraint, meaning the active power generated will always have to be greater to the minimum allowed.

As for the reactive power, it is also subject to an upper limit.

Regarding the loads, the power that can be cut or reduced is subject to a maximum value. Also a constraint is added to be able calculate the amount of reactive power that the loads consume. For the storage units, the charging and discharging power rates are subject to an upper bound. As they cannot be simultaneously charging and discharging, a constraint is introduced to demonstrate this by using binary variables. As batteries have a limited capacity, the amount of energy in them that the model will consider will also have to be limited.

Similarly to the storage units, the EVs work as batteries, therefore needing constraints to limit battery capacity. The EV batteries need to always keep a certain amount of minimum energy, to avoid damage to the lifespan of the battery [25], but mainly to accommodate for the occasional need of the user for unplanned trips. The charging and discharging power rates are also subject to an upper bound, as well as a constraint to prevent the simultaneous charging and discharging.

When EVAs are also considered as entities with responsibilities on the grid, certain constraints will have to be established ensure grid efficiency and effectiveness. First, from the DSO perspective, it is necessary to include a constraint to limit the amount of contracted power $P_{EVA_{ChCont}(EVA,t)}$ and non contracted power $P_{EVA_{ChNonCont}(EVA,t)}$ that can be curtailed by the DSO. The power of EV discharge that the DSO can use at any period is also limited to EVA's capability to supply it. From the EVA perspective, the charge and discharge power is limited to a maximum value. When flexibility is used by the DSO, the EVAs need to reschedule their EV profiles, setting up new upper limits based on the power curtailed. Finally, a constraint is added to balance the overall power distribution in those hours where flexibility is used, allowing the EVA to choose his optimal balance between charging and discharging to meet power demands requested by the DSO.

Regarding the model of the network, obtaining the power flow and voltage magnitude in the distribution network busses and lines is necessary to guarantee reliability and safety in all the components that make up a network, from power lines to transformers and substations. It is also crucial to keep the voltage levels within an upper and lower limits, as well as the voltage angle. To ensure that the lines don´t overheat, a constraint is added to prevent them from reaching their thermal capacity.

These constraints are then used in conjunction with the objective functions described previously, to reach the optimal solution for the models proposed.

3.4 Optimization

To address the complex challenges inherent in the management of the distribution grid and decentralized energy resources, a robust optimization approach is essential. In this study, the Mixed-Integer Non-Linear Programming (MINLP) is employed to formulate and solve the deterministic optimization problem. The simulations were performed using MATLAB, while the optimization process was conducted using GAMS.

4 Case Study

The distribution grid under study comprises 37 buses, serving a total of 1908 consumers. The network is interconnected, with consumers connected to bus 1 (substation), which is the main entry point into the grid [26].

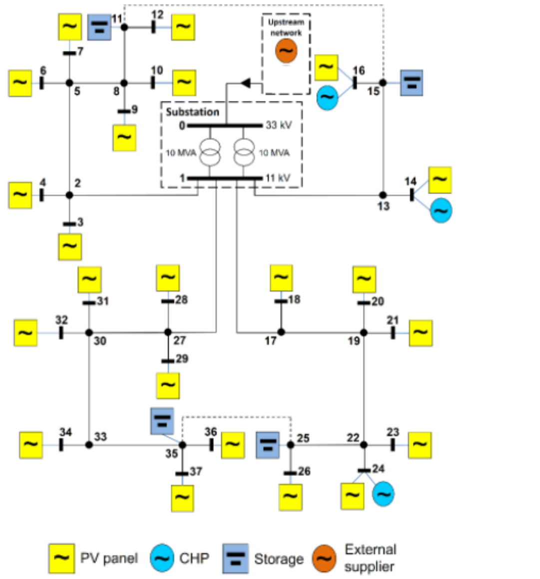

Figure 1: Distribution network proposed by [26] (adapted by [27]).

Bus 1 is equipped with two transformers, each with a capacity of 10 MVA, There are ten external suppliers considered, each one with a maximum power generation of 2000kW. For the PV panels, a probability forecast [28] was used to obtain power output throughout the day. Three CHP units are also considered. In terms of storage, there are four storage systems are strategically placed at the end of each main feeder.

The load profile encompass 22 consumers with diverse consumption patterns. The total power of the loads corresponds to 370,6MW.

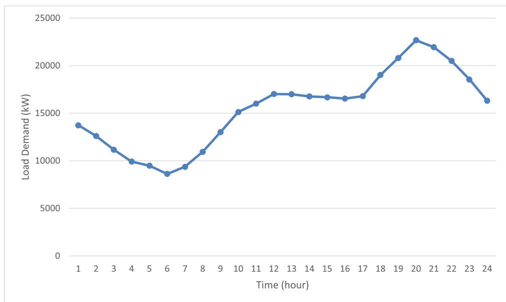

Figure 2: Total load demand

Two different DR services considered for the loads, reduce loads and cut loads, providing flexibility in managing consumption during peak periods. These programs have a limited amount of power that can be used.

A fleet of 500 EVs, collectively possessing an energy capacity of 7.7 MW, is considered in this dataset.

For the distribution network shown in figure 1, four EVAs are considered, each one responsible for managing the EVs in each one of the feeders. Figure 3 illustrates the distribution of EVAs across the network's feeders, highlighting their spatial distribution and coverage.

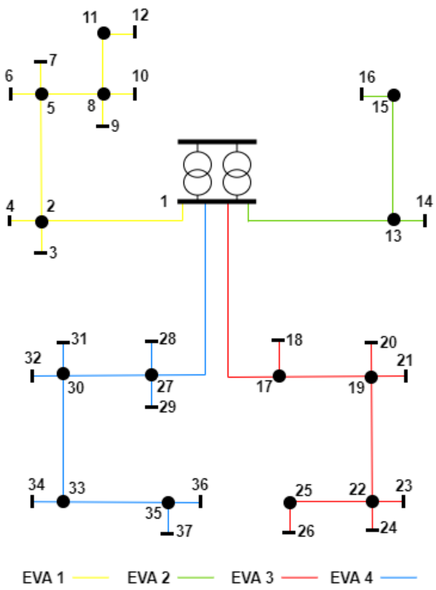

Figure 3: Distribution of the busses per EVA

The opportunity cost escalates for each hour the contract is activated, culminating at 10 hours, the guaranteed hours outlined in all EVA contracts, going from 0.17 m.u./kW to 0.30 m.u./kW.

Furthermore, in scenarios where the DSO cannot meet the energy demands beyond the flexibility of 5% offered by the EVAs, a penalty cost of 1 m.u./kW is incurred.

5 Results

5.1 Model 1 - DSO

When considering only V1G, the power scheduling of figure 4 was obtain. The line in black represents the total demand of the network, including the loads, storage charge and EV charge.

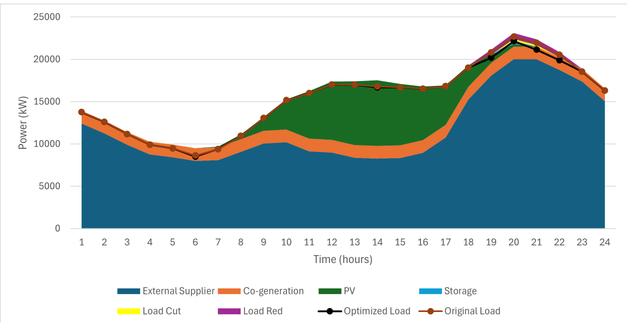

Figure 4: Power scheduling for Model 1 considering only V1G

By analyzing the graph, the types of generators used at the different periods of the day can be identified. Through periods 1 to 7, only external suppliers and CHP were used to supply energy. As the price of the external suppliers increases with every additional 2MW used, the DSO chooses to use them until they reach a higher price than the CHP power. When they do, the CHP power supplies the remaining demand. Starting from period 8, the PV power becomes available. The DSO chooses to use all the PV power available, as it represents a renewable energy source with a cheaper price than the additional external suppliers.

From period 18 onwards, the PV generation starts to fade away, as the night time starts to come. Coincidentally, the demand profile also starts to increase reaching its peak at period 20.

The DR program were activated, reducing the power demand in about 3 MWh between periods 19 and 22. As for the storage, their discharge supplies around 400 kWh to the grid,

The DSO avoided charging the EVs during peak hours where the load demand was higher. Instead opted to charge the EVs at periods with lower demand and excess PV power, between period 3 and 8, as well as between 11 and 16.

In terms of cost, the MINLP optimization reached an optimal solution of 23 396 m.u. as the total cost for the DSO. The optimization took 109 seconds to reach a solution.

Considering the use of V2G capabilities in the EVs, the power scheduling shown in figure 5 was obtained.

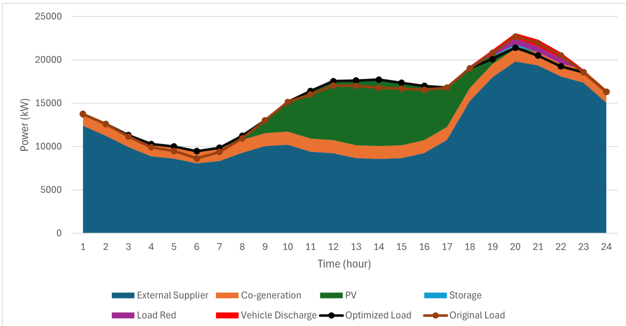

Figure 5: Power scheduling for Model 1 considering V2G

Allowing the EVs to supply energy back into the grid, gives the DSO a new tool to use during times of peak demand. Such use of the EVs discharge is seen in this model's power distribution. The DSO opted for using power stored in EVs between periods 19 and 22 to supply the power demanded in those hours, as the power from the generators available did not meet the total demand. EVs discharge was used in conjunction with storage discharge and demand response programs to meet the system total power demand.

The DR program used was decreased, reducing the power demand in about 2.5 MW between periods 19 and 22. As for the storage units, their discharge supplied the same 400 kWh.

The EVs charge pattern retain the same time periods as previously, but to accommodate the discharge into the grid, a higher power was used to charge their batteries. A total of 6.2 MW were used to charge the 500 EVs. The V2G starts to be implemented at period 20, discharging a total of 2.2 MW into the grid.

In terms of cost, the MINLP optimization reached an optimal solution of 23 350 m.u. as the total cost for the DSO, a small reduction of cost compared to the V1G model due to the less DR programs activated, less use of storage energy and less need for external suppliers during peak hours. On the other hand, the MINLP optimization took 996 seconds to reach a solution.

5.2 Model 2 - DSO + EVA

The second model proposed in this study depicts two different entities with management privileges in the grid. In order to analyze the dynamic nature of these contracts, the model was simulated to obtain the scheduling for 10 days. For the first day, it is considered that no flexibility has been used yet.

The EVAs start by making their EV management considering the EV constraints, resulting in the power scheduling depicted in Figure 6.

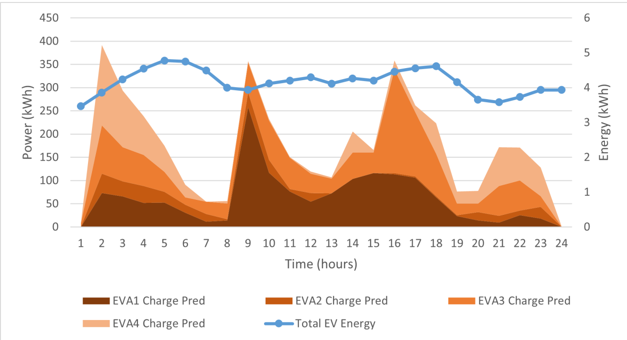

Figure 6: EV charge profile on the first EVA scheduling

The EVAs need to ensure that the EVs have enough energy for their next trip, without violating the minimum energy requirement. As EVs change busses throughout the day, the EVA that is responsible for their charging also changes.

Considering this first optimization by the EVAs, the DSO then makes its power scheduling for 10 days to accommodate the EV power demand, alongside the management of the other resources, such as loads and generation. Figure 7 represents the evolution of flexibility used by the DSO.

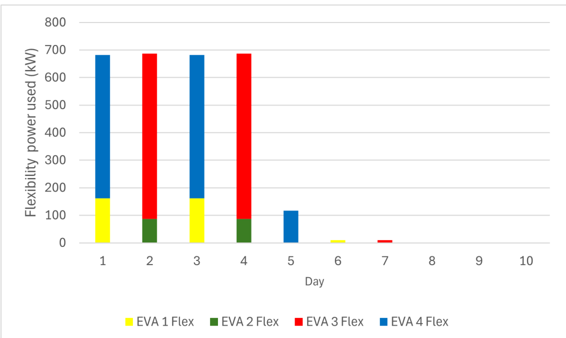

Figure 7: EVA flexibility used throughout the days simulated

As the opportunity cost starts off low, the DSO chooses to use the flexibility on day 1, using about 690 kWh of the flexibility offered by the EVAs between periods 20 and 21.

The opportunity cost starts off the same for all EVAs, meaning whatever flexibility it chooses to activate, it will imply the same cost. On day 1, it activates the power curtailment offered by EVA 1 and EVA 4. The rest of the demand in those peak hours is reached with storage discharge (400 kWh), as well as the activation of the DR programs (about 2.5 MWh), all in between these periods of high demand. This results in a total cost of optimization of 23 518 m.u. for the DSO.

As EVA 1 and EVA 4 had their power supply curtailed, they need to adapt to these restrictions imposed by the DSO, meaning a new optimization must take place.

To meet the power constraints imposed, EVA 1 decides to discharge the EV batteries on the periods where those constraints were flexibility was used. As EVs need to meet their minimum energy requirements, additional power needs to used for their charging throughout the day, increasing the power demand in the other periods where flexibility was not used. This makes charging power used increase to 2.3 MWh, from the original 1.5 MWh. Its total cost of optimization also increases.

EVA 4 reschedules its charging profile, considering the restrictions imposed on period 20 and 21, similarly to EVA 1. The cost of optimization also increases, with a total charging power of 2.4 MWh and a discharge power of 400 kWh during those periods of curtailment.

EVA 2 and EVA 3 did not suffer any power curtailment, so their original scheduling does not need to be updated.

Moving on to day 2, the DSO decides to activate the same amount of flexibility as in day 1, but this time on EVA 2 and EVA 3. This is due to the fact that the opportunity cost increased on the EVAs previously used. The power scheduling is the same as in Figure **??**, with the same amount of storage and DR programs used, on the same periods, resulting in a total cost of 23 402 for the DSO, just as in day 1.

The new optimizations increase the cost for EVA 2 and EVA 3 , while representing a total EV charging power of 570 kWh and 2.8 MWh, respectively. To meet the DSO restriction, EVA 2 discharged 55 kWh, while EVA 3 discharged 517 kWh.

At the end of day 2, the opportunity cost are the same all EVAs, so the process repeats. As the cost is higher now, the total cost of optimization for the DSO increases.

By day 5, the opportunity cost reached a value high enough that the DSO has better alternatives to meet the demand at those peak hours, such as the activation of DR programs with discrete regulation. This makes the use of flexibility decrease, only needing to activate it in EVA 4. The further increase in use, makes the flexibility less and less attractive for DSO, forcing it not to rely on power curtailment on EV charging to meet high power demands in peak hours and compromising the energy requirements of the EV batteries.

By day 8, no flexibility is activated, thus not requiring the EVAs to change their initial charging profile. This comes at a cost for the DSO, as now it needs more expensive options to reach the demand in those peak hours.

6 Conclusion

Through the exploration of two distinct models, this thesis aims to provide valuable insights into the complex dynamics of EV-grid integration. These models help analyze possible solutions to accommodate the rising number EVs without compromising the proper functioning of an energy grid.

In Model 1, the role of the DSO is studied as a centralized control entity. The simulation analyses both types of technologies suggested in recent studies, them being the use of smart charging and smart discharging (V1G and V2G). It revealed the promising advantages that the use of EV batteries to supply energy back into the grid can have in terms of energy allocation from renewable energies, diminishing the use of other programs to curtail power from other consumers, allowing for a reduction in terms of cost of operation for the DSO when compared to the smart charging solution, at the cost of increased complexity and time to schedule the day ahead power supply

In Model 2, where control is decentralized to EV aggregators that hold contracts with the operator, the results underscored the importance of distributed optimization strategies and the potential for increased flexibility and resilience in EV-grid interactions. The aggregators add a level of flexibility through their contracted power that allow the grid to more easily adapt to sudden increases in load demand or power curtailment. It takes computational burden from the operator, allowing it to make the optimization problem much simpler and quicker.

Both models provided good results and served as good demonstration of how the EVs can impact the distribution grid and how they can be used in the future as a cornerstone of demand responsive services to accommodate the current expansion of networks.

Although the results were good, some other areas can be explored in future to further evaluate the role of EVs in power networks, like the use of other optimization algorithms to increase the computational times, implementation of a stochastic problem to assess the reliability of the formulations studied and application of the EV aggregator methodology in a bigger network with a bigger penetration of EVs.

References

[1] Donald J. Wuebbles and Atul K. Jain. "Concerns about climate change and the role of fossil fuel use". In: *Fuel Processing Technology* 71.1 (2001). Fuel science in the year 2000: Where do we stand and where do we go from here?, pp. 99–119. ISSN: 0378-3820. DOI: https://doi.org/10.1016/S0378-3820(01)00139-4. URL: https://www.sciencedirect.com/science/article/pii/S0378382001001394.

[2] *Power Sector Accelerating E-mobility*. 2022. URL: https://www.eurelectric.org/media/5704/power_sector_accelerating_e-mobility-2022_eyeurelectric_report-2022-030-0059-01-e.pdf.

[3] Junjie Hu et al. "Electric vehicle fleet management in smart grids: A review of services, optimization and control aspects". In: *Renewable and Sustainable Energy Reviews* 56 (2016), pp. 1207–1226. ISSN: 1364-0321. DOI: https://doi.org/10.1016/j.rser.2015.12.014. URL: https://www.sciencedirect.com/science/article/pii/S1364032115013970.

[4] Weifeng Zhong et al. "On Stability and Robustness of Demand Response in V2G Mobile Energy Networks". In: *IEEE Transactions on Smart Grid* 9.4 (2018), pp. 3203–3212. DOI: 10.1109/TSG.2016.2629378.

[5] Chengke Zhou et al. "Modeling of the Cost of EV Battery Wear Due to V2G Application in Power Systems". In: *IEEE Transactions on Energy Conversion* 26.4 (2011), pp. 1041–1050. DOI: 10.1109/TEC.2011.2159977.

[6] Siyamak Sarabi et al. "The feasibility of the ancillary services for Vehicle-to-grid technology". In: *11th International Conference on the European Energy Market (EEM14)*. 2014, pp. 1–5. DOI: 10.1109/EEM.2014.6861251.

[7] Bowen Zhou et al. "The impact of electric vehicle uncertainties on load levelling in the UK". In: *2017 IEEE Power Energy Society General Meeting*. 2017, pp. 1–5. DOI: 10.1109/PESGM.2017.8274727.

[8] Christos S. Ioakimidis et al. "Peak shaving and valley filling of power consumption profile in non-residential buildings using an electric vehicle parking lot". In: *Energy* 148 (2018), pp. 148–158. ISSN: 0360-5442. DOI: https://doi.org/10.1016/j.energy.2018.01.128. URL: https://www.sciencedirect.com/science/article/pii/S0360544218301567.

[9] Khouloud Wali, Rayhane Koubaa, and Lotfi Krichen. "Cost benefit smart charging schedule for V2G applications". In: *2019 16th International Multi-Conference on Systems, Signals Devices (SSD)*. 2019, pp. 34–39. DOI: 10.1109/SSD.2019.8893171.

[10] Remco A. Verzijlbergh et al. "Network Impacts and Cost Savings of Controlled EV Charging". In: *IEEE Transactions on Smart Grid* 3.3 (2012), pp. 1203–1212. DOI: 10.1109/TSG.2012.2190307.

[11] Xiaoxi Huang et al. "The Impact of Electric Vehicle Development on Grid Load Power and Electricity Consumption". In: *2019 12th International Conference on Intelligent Computation Technology and Automation (ICICTA)*. 2019, pp. 158–161. DOI: 10.1109/ICICTA49267.2019.00041.

[12] Mengjiao Zou et al. "Optimization Model of Electric Vehicles Charging and Discharging Strategy Considering the Safe Operation of Distribution Network". In: *World Electric Vehicle Journal* 13.7 (2022). ISSN: 2032-6653. DOI: 10.3390/wevj13070117. URL: https://www.mdpi.com/2032-6653/13/7/117.

[13] Sulabh Sachan and Nadia Adnan. "Stochastic charging of electric vehicles in smart power distribution grids". In: *Sustainable Cities and Society* 40 (2018), pp. 91–100. ISSN: 2210-6707. DOI: https://doi.org/10.1016/j.scs.2018.03.031. URL: https://www.sciencedirect.com/science/article/pii/S221067071830338X.

[14] Yin Yao, Wenzhong Gao, and Yan Li. "Optimization of PHEV charging schedule for load peak shaving". In: *2014 IEEE Conference and Expo Transportation Electrification Asia-Pacific (ITEC Asia-Pacific)*. 2014, pp. 1–6. DOI: 10.1109/ITEC-AP.2014.6940718.

[15] WanJun Yin, ZhengFeng Ming, and Tao Wen. “Scheduling strategy of electric vehicle charging considering different requirements of grid and users”. In: *Energy* 232 (2021), p. 121118. ISSN: 0360-5442. DOI: https://doi.org/10.1016/j.energy.2021.121118. URL: https://www.sciencedirect.com/science/article/pii/S0360544221013669.

[16] Sid-Ali Amamra et al. “Optimal Day Ahead Scheduling for Plug-in Electric Vehicles in an Industrial Microgrid Based on V2G System”. In: *2019 23rd International Conference on Mechatronics Technology (ICMT)*. 2019, pp. 1–5. DOI: 10.1109/ICMECT.2019.8932121.

[17] Yee-Ting Chai et al. “An Optimal Charging and Discharging Schedule to Maximize Revenue for Electrical Vehicle”. In: *2019 IEEE Conference on Sustainable Utilization and Development in Engineering and Technologies (CSUDET)*. 2019, pp. 240–245. DOI: 10.1109/CSUDET47057.2019.9214678.

[18] Shuangqi Li et al. “Optimization of Bi-Directional V2G Behavior With Active Battery Anti-Aging Scheduling”. In: *IEEE Access* 8 (2020), pp. 11186–11196. DOI: 10.1109/ACCESS.2020.2964699.

[19] Wenping Zhang et al. “Optimal Scheduling of Spinning Reserve and User Cost in Vehicle-to-Grid (V2G) Systems”. In: *2018 IEEE Energy Conversion Congress and Exposition (ECCE)*. 2018, pp. 1058–1064. DOI: 10.1109/ECCE.2018.8558391.

[20] Xiangyu Chen et al. “Online Scheduling for Hierarchical Vehicle-to-Grid System: Design, Formulation, and Algorithm”. In: *IEEE Transactions on Vehicular Technology* 68.2 (2019), pp. 1302–1317. DOI: 10.1109/TVT.2018.2887087.

[21] Huachun Han et al. “Autonomous frequency regulation control of V2G(Vehicle-to-grid) system”. In: *2017 29th Chinese Control And Decision Conference (CCDC)*. 2017, pp. 5826–5829. DOI: 10.1109/CCDC.2017.7978208.

[22] Konstantinos D. Afentoulis et al. “Smart charging business model framework for electric vehicle aggregators”. In: *Applied Energy* 328 (2022), p. 120179. ISSN: 0306-2619. DOI: https://doi.org/10.1016/j.apenergy.2022.120179. URL: https://www.sciencedirect.com/science/article/pii/S0306261922014362.

[23] Siyang Sun et al. “A Scheduling Strategy of Vehicle-2-Grid based on Stackelberg Gaming Model”. In: *2021 IEEE 5th Conference on Energy Internet and Energy System Integration (EI2)*. 2021, pp. 1850–1853. DOI: 10.1109/EI252483.2021.9713447.

[24] Dongxiang Yan, Chengbin Ma, and Yue Chen. “Distributed Coordination of Charging Stations Considering Aggregate EV Power Flexibility”. In: *IEEE Transactions on Sustainable Energy* 14.1 (2023), pp. 356–370. DOI: 10.1109/TSTE.2022.3213173.

[25] Mahammad A. Hannan et al. “State-of-the-Art and Energy Management System of Lithium-Ion Batteries in Electric Vehicle Applications: Issues and Recommendations”. In: *IEEE Access* 6 (2018), pp. 19362–19378. DOI: 10.1109/ACCESS.2018.2817655.

[26] R.N. Allan et al. “A reliability test system for educational purposes-basic distribution system data and results”. In: *IEEE Transactions on Power Systems* 6.2 (1991), pp. 813–820. DOI: 10.1109/59.76730.

[27] Tiago Sousa. “Vehicle-to-grid Integration for Optimal Resource Scheduling in the Smart Grid Context”. In: 2017.

[28] Pierre Pinson et al. “From probabilistic forecasts to statistical scenarios of short-term wind power production”. In: *Wind Energy* 12.1 (2009), pp. 51–62. DOI: https://doi.org/10.1002/we.284. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/we.284. URL: https://onlinelibrary.wiley.com/doi/abs/10.1002/we.284.