Dynamic electricity pricing for electric vehicles using stochastic programming

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ABSTRACT

Electric Vehicles (EVs) are an important source of uncertainty, due to their variable demand, departure time and location. In smart grids, the electricity demand can be controlled via Demand Response (DR) programs. Smart charging and vehicle-to-grid seem highly promising methods for EVs control. However, high capital costs remain a barrier to implementation. Meanwhile, incentive and price-based schemes that do not require high level of control can be implemented to influence the EVs' demand. Having effective tools to deal with the increasing level of uncertainty is increasingly important for players, such as energy aggregators. This paper formulates a stochastic model for day-ahead energy resource scheduling, integrated with the dynamic electricity pricing for EVs, to address the challenges brought by the demand and renewable sources uncertainty.

The two-stage stochastic programming approach is used to obtain the optimal electricity pricing for EVs. A realistic case study projected for 2030 is presented based on Zaragoza network. The results demonstrate that it is more effective than the deterministic model and that the optimal pricing is preferable. This study indicates that adequate DR schemes like the proposed one are promising to increase the customers' satisfaction in addition to improve the profitability of the energy aggregation business.

KEYWORDS: demand response; electric vehicles; energy resource scheduling; optimal pricing; smart grid; stochastic programming;

1. Introduction

Unlike conventional generation units, renewable sources are characterized by a high level of uncertainty and variability. Smart Grid (SG) should be highly flexible to accommodate large penetration of renewable energy and attenuate uncertainty. Increased flexibility of customers can contribute to achieve it, namely with controllable loads, i.e. non-critical loads that can be adjusted by the customer or by a third-party utility companies. Electric Vehicle (EV) can be a candidate for such applications. Nevertheless, in contrast to other types of loads, EVs can be connected to different locations, thus with higher degree of uncertainty [1]. Employing an advanced energy management model that takes into account these factors is quiet crucial for the efficient operation of smart grids. In fact, one of the top R&D needs identified by the department of energy in United States is to implement robust control and predictive models to deal with stochastic behavior and uncertainty [2].

Despite the extreme complexities imposed to the operation and planning tasks of power systems by the mass integration of EVs, it can also bring significant benefits [3–5]. One of the main concerns in power grids is the overloading of distribution transformers and voltage irregularities under simultaneous and uncontrolled charging [6]. To avoid huge investments, controlled charging or price-based mechanisms can be used to alleviate these concerns. Currently, some initiatives to avoid high peak demand have been started in the retailing sector. They consist in some special tariffs targeting the EV customers. Some of these initiatives devised by utility companies in Portugal, Spain and Germany are briefly described in this work. These business models seem functional and rapidly available in the short-term horizon, but they are very limited to attain the full potential of SG deployment. Therefore, immediate rethinking is urged and new business models must be developed to ensure the successful EVs' integration in the SG.

In this context, Demand Response (DR) has been shaped for EVs as a big opportunity that the power industry cannot miss. The DR programs can be classified in price-based DR, incentive-based DR, and emergency DR [4]. DR refers to "*changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized*" [7]. According to [8] vehicles are parked more than 90% of the time during a day, thus they can be available to serve as a storing device to the grid. Indeed, EVs represent additional loads which are well suited for DR participation as their demand can be shifted or reduced through incentive or price-based schemes. In addition, EVs charge and discharge can be controlled using optimization algorithms and control means, though these imply higher complexity and increased infrastructure costs.

1.1. Literature review

Several works regarding benefits of DR considering EVs have been explored in the recent literature. It is reported in [9] that EV loads are highly flexible, even while accommodating for highly uncertain individual travel needs. Moreover, grid problems can be entirely eliminated during DR periods when EV charging is properly coordinated. In fact, the increase of DERs and EVs will contribute to load unbalance in three-phase networks [10]. The work in [11] presents a multi-objective approach to optimally coordinate the charging of EVs, considering the energy costs under as well as grid losses under dynamic tariff environment. The approach is tested in unbalanced three-phase distribution system and the authors suggest that the method is quite efficient to obtain Pareto solutions. In [12], authors develop an optimal charging approach to minimize energy losses considering voltages and power losses. The method is tested in a stressed IEEE-31 bus system, and the results suggest that nodal voltages are more restricting than thermal rating constraints due to network radial configuration.

Regarding DR models approaches related to EVs, in [13], a game-based framework, Okeanos, is proposed to simulate EVs and households with the benefits of DR. The EVs and feed-in tariffs seems to decrease household electricity costs. In [14], authors claim that the electric heating systems, such as heat pumps, are a promising way to realize DR. An assessment is made to understand the benefits and interactions between consumers and producers using different degrees of model complexity. The work proposed in [15], develops a thermal and energy management of residential energy hubs. The DR program considers load shifting, load curtailing and flexible thermal loads. In [16], the unit commitment model includes DR (shifting and curtailment), EV and wind. The uncertainty in wind power is modeled using a fuzzy chance-constrained program. Recently in [8], EVs have been proposed for frequency control based on the travelling behavior in Great Britain. The simulation results show that the proposed strategy provides effective EV frequency response enabling more wind integration. In [17], a DR strategy to optimize EVs in parking lots, without violating grid operational limits is proposed. The strategy is based on prioritizing PEVs in order to determine the order in which they are charged. The priorities are assigned by a fuzzy expert system using PEV attributes, including the state of charge, battery capacity, charger rating, and departure time of the vehicle. Results of the analysis indicate that the proposed solution is able to serve more critical EVs. In [18], optimization model that considers EVs load-shifting and Vehicle-to-Grid (V2G) is proposed. Each agent maximizes its profit and acts on their own interest while a central SG operator validates the technical constraints. It is important to note that the study conducted in [19] suggests that V2G can increase the renewable utilization levels if adequate infrastructure is available. However, stationary storage is recognized to be more flexible than V2G. A decentralized DR approach for EVs is proposed in [20]. The goal is to minimize peak demand and shape the load profile. The results show evidence of achieving the same peak demand as without EVs for certain trip patterns as well accommodate a higher number of users in the grid. In [21], a decentralized framework to maximize the welfare of the EVs and profits of aggregator is proposed. The consumers minimize their costs in response to time-varying prices. Incentives are provided to mitigate potential overloads in the distribution system. Authors in [22] study the impact of DR interruptions on EVs charging, namely the customer satisfaction and propose an algorithm that improve the probability of achieving the desired state of charge and thus the increase customer satisfaction/comfort. In [23], several opportunities are identified for DR with EVs. A stochastic model for EV planning in DR programs and scheduling is presented. The risk and costs is evaluated and the results suggest that time-based DR is efficient to reduce costs for aggregators and system operator.

More specific DR programs shaped for EVs have been proposed in [3,4]. In [3], trip reduce and trip shifting of EVs are proposed as DR programs and integrated with the energy resource management scheduling optimization with the aim to minimize the aggregator costs. In [4], a fuel shifting DR program for EVs is developed as an additional alternative that the aggregator has to reduce operational costs. The fuel shifting program consists in replacing the electric energy by fossil fuels in plug-in hybrid electric vehicles daily trips, and the fuel discharge program consists in the use of their internal combustion engine to provide V2G services. In [24], authors propose a stochastic optimization to solve day-ahead scheduling of a SG. The model also outputs the optimal pricing of responsive loads, namely EVs. The consumers at each node are assumed to be the same type and are modeled as a single lumped load. Other kind of loads are assumed to be non-responsive.

Recently, in [25], a two-stage stochastic model is proposed to address the centralized ERM in hybrid AC/DC microgrids considering DGs, ESS and EVs. The possibility of DR is not considered in the referred work. The works presented in [26,27] address the day-ahead resource scheduling of a renewable-based virtual power plant. The work considers uncertainties in price, load demand and renewables but fails to consider the possibility of ESS, DR, EVs and V2G. A specific work regarding stochastic energy management using compressed air storage integrated with renewable generation is studied in [28]. In [29], authors provide a robust optimization for scheduling optimization considering uncertainties. These works demonstrates that it is possible to mitigate system uncertainties with adequate use of energy resources, namely ESS systems. However, they fail to consider EVs and its related uncertainties.

These works reveal some gaps that require additional attention and further work. Uncertainty on wind and solar generation are usually considered, while the variability of EVs and load demand is frequently overlooked. Furthermore, DR is not considered in most of the studied works considering some source of uncertainty and the presented case studies are relatively small in terms of optimization problem size. Moreover, specific DR programs for EVs in the context of aggregator energy management require further innovation.

1.2. Contributions

The motivation of establishing a stochastic modeling framework is associated with the increasing challenge of addressing the variability and uncertainty of renewable energy resources in smart distribution networks and microgrids [30]. These resources' share is significantly increasing and can constitute a large portion of the total generation portfolio in the near future. In this context, the entities related with the Energy Resources Management (ERM), such as energy aggregators [31], need adequate tools to deal with the increasing level of uncertainty.

This paper presents a stochastic programming approach for ERM in a smart distribution network, in the context of SG considering several forms of energy resources, including DR, namely optimal pricing for EVs and Direct Load Control (DLC) for regular loads. The proposed model formulates the uncertainty in regular load demand, wind and photovoltaic (PV) power, and EVs demand. The energy aggregator aims to maximize the expected profit and obtain the optimal pricing that ultimately influence the behavior of EVs customer, while managing Distributed Energy Resources (DER), including DG (e.g. Wind, PV, and biomass), EV, ESS, electricity supplier contracts, market transactions and DR. Thus, the proposed integrated energy management model with the several sources of uncertainty and considering optimal pricing is innovative in the literature. The literature review revealed that the very recent work (2016) proposed in [24] is similar to the idea presented here, but in this paper EVs are grouped into different customers classes, which enables to have an accurate and differentiated demand model. In addition, the DR in regular loads is not considered in [24], while in this work

DR program for regular loads is integrated. In the previous work, only the uncertainty in wind power output is considered by using the two-point estimate method, while other uncertainties are neglected.

Regarding previous works, the major contributions of this paper are as follows:

1) proposing a two-stage stochastic model for SG considering uncertainty in wind, PV, EV integrated in the same model;
2) considering an energy aggregator characterized by heterogeneous management of energy resources, including EVs, individually or aggregated form;
3) considering DR program for regular demand in the two-stage stochastic model;
4) integrating optimal pricing for EVs for different customer groups, which are price-sensitive.

1.3. Organization of the paper

This paper is organized in seven main sections: after this introduction, section 2 presents a brief overview of the current status regarding EVs DR implementation and a few DR business models envisaged for the future SG, section 3 presents more details about the stochastic model approach that integrates the optimal pricing and describes the two-stage stochastic formulation, section 4 describes the case study, while the results and the discussion are presented in section 5. Finally, section 6 presents the conclusions and future works in this area.

2. EVs as a demand response resource

The advent of electric transportation replacing the petrol-fueled transportation, will carry significant changes in the current business model, e.g. the shifting of money and product transactions from petrol stations directly to the electricity supplier. In fact, EVs may add a significant portion of the household load demand, depending on the number of connected EVs and season of the year [20]. In this section some insights are provided regarding the initiatives launched by utility industries to handle the growing EVs' demand. These initiatives constitute means of DR to persuade the EV customers to charge their vehicles in specific periods of the day. Later in this section, some specific DR programs for EVs aligned with SG technologies are discussed.

2.1. DR initiatives for EVs

Currently, few initiatives are offered by the retailers to motivate the EV adoption and differentiate the EVs demand. One retailer company in Portugal offers a differentiated tariff for EV adoption. It consists in offering a 400 EUR discount to those who buy an EV from their partners [32]. The discount is applied for customers on a monthly basis, i.e. 40 EUR/month during a period of 10 months. The retailer claims that the discount is equivalent to 15.000 km. In addition to that discount, the same company launched a special time-of-use based tariff, for those who own an EV. It consists in a bi-tariff with 10% discount during the night (10 p.m. to 8a.m.)

for the daily option and 1% discount in the remaining periods. A weekly option[1] is also available. The discount rate is also applied to the basic monthly fee. In the case of the tri-tariff option the discount rate is 7% in the remaining periods. However, the tri-tariff is only available for contracts between 27.6 kVA and 41.4 kVA. The energy2move has not a single-tariff option. Instead, this retailer is motivating his customers to shift EV load to economic periods using bi-tariff (or tri-tariff) with some discount. The economic periods are mostly during the night.

In Spain an hourly pricing scheme is in place, which applies for all the Spanish territory regardless of the time-zone, known as voluntary price small consumer (PVPC). There are three types of tariffs: default, 2 periods and electric vehicle. Active energy invoicing term in €/kWh of PVPC for tariffs 2.0 A (default tariff), 2.0 DHA (2 periods tariff) and 2.0 DHS (EV), are established in section 2 a) of the Article 8 of the Royal Decree 216/2014. The royal decree states the calculation methodology of PVPC of electrical power and its legal and contracting system [33]. PVPC includes several terms, namely day-ahead market price, ancillary services, distribution and transmission tariff, capacity payment, interruptible service and operation, and maintenance fees.

Figure 1 shows the PVPC prices along an entire day (26th April 2016) for the three mentioned tariffs. Those prices do not include taxes. The prices range for each period can be seen in the *xx* axis; in green color the hours with prices lower or equal than 0.10 €/kWh, in yellow color for prices between 0.10 €/kWh and 0.15 €/kWh and in orange color for prices higher than 0.15 €/kWh (which did not happen in the considered day). For the 26th April 2016 most of the periods are in the green price range. The EV tariff is cheaper at night, namely between 0 a.m. and 12p.m.. The customers can freely choose PVPC. Retailers are not allowed to charge the customer higher prices than the PVPC in this mode [34].

Figure 1.

In Germany, despite high electricity prices (>0.25 €/kWh) for a typical household, some utilities are offering additional benefits for EV owners by proposing different tariffs. The e-mobility night tariff proposed by a German utility allows customers to charge their cars at lower rates during the night [35]. The same utility is studying an aggregator model for small generation and controllable loads. EVs, heat pumps, and overnight electric heating systems can all function as controllable consumption equipment [35]. This German utility believes that a household's power rate could be 30 percent lower when controllable consumption is correctly scheduled, and the cost of charging EV could drop by up to 200 EUR annually. Other retailers such are offering night tariff reductions for EV charging as well [36].

A few players in the retailing activity are introducing a variety of appealing schemes for the EVs end-users. However, it is fair to recognize that these schemes are based on discount rates and still very limited, not adequately adapted for the future SG. Nevertheless, the paradigm shift is occurring and eventually more advanced models have to be developed and implemented in practice. In the following section some innovative

[1] Bi-tariff low price periods:

Summer week cycle: Monday-Friday: 0h-7h; Saturday: 14h-20h and 22h-9h; Sunday: 24h.

Winter week cycle: Monday-Friday: 0h-7h; Saturday: 13h-18h30 and 22h-9h3; Sunday: 24h.

models are discussed, which could be increasingly viable with proper charging, communication and information technology infrastructure.

2.2. DR Business models

This subsection discusses some DR models shaped for EVs. These business models envisage a SG context, and therefore, smart metering and other important infrastructure is assumed to be in place. The presented programs include incentive-based programs – smart charging, V2G, trip shifting, trip reduced – and the proposed optimal pricing DR model (price-based).

1) Smart charging and vehicle-to-grid

EVs can provide power to the grid while they are connected to it, which is usually referred as V2G [37]. The control approach requires a control connection for communication with the grid operator and a meter sensor to indicate the battery state in each moment [38]. The Society of Automotive Engineers, known as SAE, establishes a series of requirements and specifications for communication between plug-in vehicles and the electric power grid, for energy transfer to and from the grid in the standard SAE J2847/1 " Communication for Smart Charging of Plug-in Electric Vehicles using Smart Energy Profile 2.0" [39]. The International Organization for Standardization (ISO) and the International Electrotechnical Commission (IEC) are also developing a similar series of standards known as ISO/IEC 15118 "Road vehicles -- Vehicle to grid communication interface" [40].

The smart charging and V2G approaches are effective types of DR resources use in the context of EV management. The EV charging can be effectively controlled while reducing operation costs and network problems, while still maintaining the comfort of the users. The drawback of V2G and smart charging is the high complexity and high capital costs of the infrastructure and the increase of power losses due to frequent charge and discharge cycles. Nevertheless, aggregators may convince users to shift from uncontrolled charging to smart charging by financial incentives and convenience of charging, e.g. with smart charging, the user could benefit from discounted flat tariffs

2) Fuel shifting

Fuel shifting is a special DR program [4], specifically proposed to target a particular kind of EVs, the Extended Range Electric Vehicles (EREV). These vehicles have an Internal Combustion Engine (ICE) that can charge the battery when a threshold limit is reached. This greatly increases the travelling range, while mitigating the user's range anxiety. The fuel shifting has 2 variants. One is to incentivize customers to leave the charging point (home/workplace) even if the minimum amount of state of charge was not satisfied (soft constraint). The customer in turn receives an incentive to cover the fuel costs that may be needed to cover the trips not satisfied by the electric energy supply. The grid in turn can mitigate and/or avoid network problems and costs and reduce the peak demand. The other variant of fuel shifting DR is that these cars can participate in V2G services, namely in extreme situations, and use the ICE more than intended.

3) Trip reduction

The trip reduction is an incentive-based DR program to provide the aggregator with a flexible resource, in which users can participate by agreeing to reduce the EVs' charge requirements as proposed in [3]. This program enables EVs' owners to get a financial incentive by agreeing to reduce their trip energy requirements and consequently the minimum battery level requirements. The participation of users in this DR program can be performed as follows: users should sign up to the DR trip reduce program and notify the aggregator about the maximum amount they are willing to reduce. With this information the aggregator runs a daily routine optimization. In the day-ahead, an initial optimization is made assuming that EVs with contracted DR program will participate. With the first-round optimization results, it is possible to identify the EVs that are scheduled to participate in the event and notify the respective users. Then, the notified users should confirm their participation within a defined time period. With the confirmation responses, the optimization program can perform a rescheduling with the updated information, fixing the users with confirmed participation and making the required adjustments. Users that do not confirm their participation within the requested time period are excluded from the DR event. A penalty scheme can be implemented for the EV users who confirmed the participation and withdraw it later.

4) Trip shifting

The trip shifting program is an incentive DR program similar to the trip reduce proposed in [3]. However, this DR program enables EVs' users to provide a list of flexible departure periods. This could be implemented in a similar way to the DR trip reduce program, i.e. the users sign up and setup their profiles and definitions by using an internet-based app. The DR program specifically enables the aggregator to shift EVs charging, which may help to reduce operational costs and alleviate network contingencies. The shifting is limited to the alternatives that users introduce, thus limiting the computational complexity of the optimization process. The users' participation in the DR shifting program would be similar to the process described for the trip reduce program. In face of the users positive replies to participate in the DR shifting event after being notified, the optimization program should perform a rescheduling with the updated information.

5) Proposed optimal pricing

The price-based DR strategy consists in defining the price that the EV owner pays to the aggregator, while ultimately changing his behavior. In this case it is assumed that the EV charging process cannot be controlled and consequently smart charging and V2G algorithms are not possible. The advantage of this approach is that it does not require an advanced and complex infrastructure, such as the previous DR programs. Therefore, the price is the relationship for indirectly controlling the timing and amount of charging. The proposed price-based DR assumes that there is a correlation between the quantity of charging and the price to be paid for it. Also, the decision-maker can describe the behavior of its customers and the correlation between the quantity that the owners of EVs usually charge and the price they pay. Figure 2 shows an overview of the proposed optimal pricing integrated with energy resource scheduling.

Figure 2.

The EVs can be classified according to several groups of consumers as suggested in Figure 2, which shows an example of price elasticity curves for five groups of EVs' consumers. A relative quantity of 1 means that the EV would charge whenever it would be possible, while a relative quantity of 0 means that the customer is not willing to charge at all. The represented data can be obtained using historical data or surveying consumers. The price is directly correlated with the quantity that the user is willing to charge. In this case, the worker group is willing to charge more than the shopper group even if the price is higher, whereas the bus fleet group is willing to pay and charge more than the other two groups due to its higher responsibilities towards third parties.

3. Stochastic Model

The energy scheduling problem is formulated as a two-stage stochastic model. Theoretical background on two-stage or multi-stage stochastic programming models can be found in [41]. The idea is to make the optimal decision on the day-ahead energy transactions in the first stage, while taking into account the possible real-time operations like the wind, solar power and EVs' uncertainty in the second stage. The objective is to maximize the expected profits and obtain the optimal pricing, while reducing the risk of the energy transactions for aggregator. With the proposed model, it is possible to obtain the amount of electricity to be purchased from the electricity suppliers, the market and the commitment of the dispatchable DG units over the next 24 hours. To achieve this, a scenario-based approach is used to model the underlying uncertainty. The uncertain production of wind and solar units and the variable demand are modeled as random variables. Different realizations are introduced for these variables as distinctive scenarios. The first-stage decisions of the stochastic model must fit and satisfy the constraints for every scenario, i.e. the variables without uncertainty do not change across the several scenarios. The first-stage decisions include the schedules of the dispatchable units, the EV pricing, and the market transactions, which must be met one day in advance.

To enable an efficient and effective, yet profitable operation, the aggregator needs to be equipped with adequate energy resource management tools, namely a scheduling optimization software. Figure 3 depicts the general overview of the energy transactions that the aggregator is able to perform in the decision-making problem under study.

Figure 3.

The aggregator can procure energy needs from several resources and the electricity market and makes revenue from reselling energy to its customers. In addition, it can use its own assets, e.g. storage units, to supply the load demand [42]**.** The energy aggregator establishes energy contracts with those who seek electricity supply, e.g. residential and industry customers. It is designated here as a bilateral contract, i.e. between the aggregator and the final end-user. In this case, it is assumed that the aggregator establishes a fixed price for fixed loads and a variable price for EVs charging. The fixed price is set independently for each consumer, based on single-tariffs. The EVs' charging price is variable and *unkown* for both parties before the energy scheduling optimization has been achieved by the aggregator. Nevertheless, the variable price is bounded between a minimum and maximum value agreed between both parties. The variable price must be released several hours in advance. Therefore, the 24-hour EV pricing is known for the EV customers in advance. The main idea is that the optimization software can perform the energy resource scheduling, while seeking an effective pricing approach that influences EVs' charging decision. The EV customers can freely choose the charging periods, e.g. low pricing periods, at their most convenience. An automated system may exist, such as an in-vehicle charging decision system or a home energy management system that is able to receive the aggregator prices by a web service and perform some local decision or optimization. Ultimately, the aggregator can indirectly shift the EVs charging decision to periods where it is best to charge the EVs while at the same time maximizing its profits and obtaining the best use of its contracts and assets, e.g. wind surplus energy. Unfortunately, there are some barriers that can compromise the quality of the energy resource management. A relevant issue discussed in this paper regards the sources of uncertainty that make the decision-making much more complicated from the optimization standpoint. Some discussion of these uncertainty sources is provided in the next subsection.

3.1. Data uncertainty

The presented ERM problem incorporates several sources of uncertainty, namely in the load demand, wind and solar generation forecasts. Moreover, the presence of EVs poses an additional source of uncertainty in the ERM problem, because trips and energy demand of EVs depend on the users' behavior, which is not easy to predict. Compared to conventional loads that are fixed at a specific bus in the power grid, the location of the EVs varies inevitably and highly depends on the users' trips. The aggregator requires knowing the timing of the trips and the associated expected energy consumption, as well as other parameters, such as battery size. This means that the drivers would need to notify the aggregator of their planned trips in advance, or eventually machine learning algorithms could be used to forecast driving needs [31].

The lack of realistic historical data is a barrier to actually build accurate case studies. Hence, most of the time, forecasts and associated errors are obtained based on previous experiences and used to simulate real-world behavior. The stochastic model is used assuming that a correct set of scenarios can be generated, considering future availability of such historical data. In fact, scenario generation is a broad topic that is beyond the scope of this work.

Dealing with a finite set of possible outcomes is the adopted way in decision-making problems under uncertainty, otherwise it would be impossible to solve the problem [43]. Continuous stochastic processes, such as the generation of the renewable units and the electricity demand, can be well approximated with discrete processes [43]. In stochastic programming models, the discrete processes are represented with finite set of realizations to represent the data uncertainty. Each realization of the stochastic process is known as a scenario. A probability of occurrence associated with each scenario can fully characterize the specifications of the stochastic process [43,44]. Sufficient number of scenarios should be generated to cover the most plausible realizations. Generally, it is required to generate a large number of scenarios to represent the stochastic process. This requirement can make the stochastic optimization problems computationally intractable [43]. Therefore, the scenario reduction techniques are then used to reduce the number of initial scenarios [43]. Scenario reduction techniques start with the large set of randomly generated scenarios. The large set is downsized to a small set trying to maintain the original probability distribution function. A good reduction has been obtained if the stochastic information has changed little after the reduction.

In this paper, Monte Carlo Simulation (MCS) is used for generating the required scenario set to represent the uncertainty, assuming that the source of uncertainties follows a normal distribution error. Another key assumption is that for the uncertain input we have a forecast given, and with the MCS approach several realizations for the forecast error is generated. MCS depends on repeated random sampling to compute the scenarios [45]. In this model, the MCS constructs the scenarios of hourly forecast errors based on probability distribution [44]. Although the MCS is used in this paper, the proposed model is compatible with other scenario construction techniques (probably far accurate) able to generate the required inputs. Different realizations of the random variables can be represented by arcs in a scenario tree. The sum of the probabilities of the generated scenarios is equal to 1.

3.2. Implementation assumptions

The proposed model is one-step forward towards an effective energy management of the SG resources. The optimization can be implemented in real-world cases once the main pillars of SG are developed, i.e., technology, policy and standards. It is assumed that the infrastructure and backbone has the following characteristics:

1) the smart distribution grid and microgrids are independent entities that are able to manage their own assets, and establish contracts with local DERs and other energy suppliers;
2) the advanced metering infrastructure to allow consumption data collection and monitoring in real-time;
3) also, there is communication capability to allow the broadcast of the electricity prices for the next 24 hours;
4) the control center can communicate with the local controllers of DERs and is equipped with an energy management system, in which the proposed model can be implemented;
5) the EVs customers are monitored and a price/demand model is kept and updated for different groups using machine learning techniques. New customers can be assigned to a group according to its preferences or characteristics;
6) the energy management system runs the two-stage stochastic optimization routine every 24 hours and has forecasting and scenario generation tools required to run the model;
7) the network conditions are monitored by the distribution system operator;

3.3. Objective function

The objective function (1), $\mathrm{E}\left(P_{Total}^{D+1}\right)$, which represents the expected profit for the day-ahead in monetary units (m.u.), is maximized over the scheduling horizon T (1), usually, hourly periods. The first term in (1) represents the expected revenue in the day-ahead operation and the second term represents the expected operation cost.

$$\text{Maximize} \quad E\left(P_{Total}^{D+1}\right) = E\left(R_{Total}^{D+1}\right) - E\left(C_{Total}^{D+1}\right) \tag{1}$$

The revenue is calculated as represented by (2). The first term corresponds to the revenue from the market sale. The second term represents the revenue from the energy billing with regular load customers, non-owned storage and EVs charging.

$$E\left(R_{Total}^{D+1}\right)=$$
$$\sum_{t=1}^{T}\left[\left(\sum_{M=1}^{N_M} P_{Sell(M,t)}\cdot MCP_{(M,t)}\right)\right]+\sum_{z=1}^{Z}\sum_{t=1}^{T}\left[\begin{pmatrix}\sum_{E=1}^{N_E} P_{Charge(E,t,z)}\cdot MP_{Charge(E,t)}+\\ \sum_{L=1}^{N_L} P_{Load(L,t,z)}\cdot MP_{Load(L,t)}+\\ \sum_{V=1}^{N_V} E_{EstimatedCharge(V,t,z)}\cdot T_{EVCharge(t)}+\\ \sum_{V=1}^{N_V}\left|\lambda_{ChargePenalty(V,t,z)}\right|\cdot 10\end{pmatrix}\cdot\pi(z)\right] \quad (2)$$

Where the indices are represented by: E is the index of ESSs; L is the index of loads; M is the index of market/energy buyer; t is the index of time periods; V is the index of EVs; z is the index of scenarios. The parameters used are: T is the number of periods; N_M is the number of energy markets; $MCP_{(M,t)}$ is the estimated market clearing price of market M in period t (m.u./kWh). In the second term the Z is the total number of scenarios; N_L is the number of loads; $MP_{Load(L,t)}$ is the price that load L pays for electricity supply in period t (m.u./kWh); N_E is the number of ESSs; N_V is the number of EVs; $MP_{Charge(E,t)}$ is the price that ESS E pays for charging the battery in period t (m.u./kWh), where price is 0 when ESS E is owned by the managing entity; and $\pi(z)$ is the probability assigned to the occurrence of scenario z (%). The variables in (2) are: $P_{Sell(M,t)}$ is the active power offer in market M in period t (kW); $P_{Charge(E,t,z)}$ is the active power charge of ESS E in period t in scenario z (kW); $P_{Load(L,t,z)}$ is the active power demand of load L in period t in scenario z (kW); $T_{EVcharge(t)}$ is the charging tariff of EV in period t; $E_{EstimatedCharge(V,t,z)}$ depends on $T_{EVcharge(t)}$ (see section 3.4) and corresponds to the active energy charge of EV V in period t in scenario z (kWh); $\lambda_{ChargePenalty(V,t,z)}$ is the penalty term for the charge of EV V in period t in scenario z (kWh) (see section 3.4).

Finaly, the expected cost is represented by (3). The first term corresponds to the cost with the energy acquisition from external suppliers, dispatchable DG, and market purchase. The second term considers the cost with intermittent generation, DR, storage, non-supplied demand (NSD) and generation excess (GCP).

$$
E\left(C_{Total}^{D+1}\right)= \sum_{t=1}^{T}\left[\begin{pmatrix} \sum_{S=1}^{N_S} P_{Supplier(S,t)} \cdot c_{Supplier(S,t)} + \\ \sum_{I\in\Omega_{DG}^{d}} P_{DG(I,t)} \cdot c_{DG(I,t)} + \\ \sum_{M=1}^{N_M} P_{Purchase(M,t)} \cdot MCP_{(M,t)} \end{pmatrix}\right] + \sum_{z=1}^{Z}\sum_{t=1}^{T}\left[\begin{pmatrix} \sum_{I\in\Omega_{DG}^{nd}} P_{DG(I,t,z)} \cdot c_{DG(I,t)} + \\ \sum_{L=1}^{N_L} P_{LoadDR(L,t,z)} \cdot c_{LoadDR(L,t)} + \\ \sum_{E=1}^{N_E} P_{Discharge(E,t,z)} \cdot c_{Discharge(E,t)} + \\ \sum_{L=1}^{N_L} P_{NSD(L,t,z)} \cdot c_{NSD(L,t)} + \\ \sum_{I=1}^{N_{DG}} P_{GCP(I,t,z)} \cdot c_{GCP(I,t)} \end{pmatrix}\cdot\pi(z)\right] \tag{3}
$$

Where the sets are: Ω_{DG}^{d} is a set of dispatchable DG units; Ω_{DG}^{nd} is a set of non-dispatchable DG units. In addition to the indices used by (2), there are: I is the index of DG units; S is the index of external suppliers. The parameters are: in the first term, N_S is the number of external electricity suppliers; and $C_{Supplier(S,t)}$ is the costs of the energy supplier S in period t (m.u./kWh) and $C_{DG(I,t)}$ is the generation cost of DG unit I in period t (m.u./kWh); In the second term, $C_{LoadDR(L,t)}$ is the load reduction (DR) cost of load L in period t (m.u./kWh); $C_{Discharge(E,t)}$ is the discharging cost of ESS E in period t (m.u./kWh); $C_{NSD(L,t)}$ is the non-supplied demand (NSD) cost of load L in period t (m.u./kWh); N_{DG} is the number of DG units; and$C_{CGP(I,t)}$ is the curtailment cost of DG unit I in period t (m.u./kWh); and $P_{DG(I,t,z)}$ is the forecasted non-dispatchable DG unit I in period t in scenario z (kW). The variables of (3) are. $P_{Supplier(S,t)}$ is the active power scheduled for external supplier S in period t (kW); $P_{DG(I,t)}$ is the active power generation of DG unit I in period t (kW); $P_{Purchase(M,t)}$ is the active power bid in market M in period t (kW); $P_{LoadDR(L,t,z)}$ is the active power reduction of load L in period t in scenario z (kW); $P_{Discharge(E,t,z)}$ is the active power discharge of ESS E in period t in scenario z (kW); $P_{CGP(I,t,z)}$ is the generation curtailment power of DG unit I in period t in scenario z (kW); and $P_{NSD(L,t,z)}$ is the active power of NSD of load L in period t in scenario z (kW).

The scheduling horizon covers 24 hours, and the decision-making is done for the next day. The first-stage variables correspond to the dispatchable and controllable DG units, external suppliers, market bids and market offers. The objective function includes a multiplication of two decision variables, namely $T_{EVCharge(t)}$ and $E_{EstimatedCharge(V,t)}$, i.e. a nonlinear function. In addition, the absolute value of a penalty term, $\lambda_{ChargePenalty(V)}$, is added to the objective function and multiplied by 10.

3.4. Stochastic model constraints

The constraints incorporate the multi-period equations for considering predicted demand, technical limits of ESSs, balance and capacity in each period, dispatchable DG capacity and supplier's limits. In addition, the DR (direct load control) is considered in the constraints, namely the maximum amount of power reduction of each load. It is important to note that some of the constraints spread across all scenarios, like the energy balance equation. However, there are few constraints that are not dependent on the variation of the scenarios, e.g. the dispatchable generation.

1) Energy balance constraint

The balance constraint (2) is included in the proposed model. The amount of generated energy should equal the amount of consumed energy at every instant *t*. The stochastic balance constraint will validate if the first stage variables can match the load balance among the different scenarios *z* as follows:

$$\begin{aligned}
&\sum_{I\in\Omega_{DG}^{d}} P_{DG(I,t)} + \sum_{S=1}^{N_S} P_{Supplier(S,t)} + \\
&\sum_{I\in\Omega_{DG}^{nd}} \left(P_{DG(I,t,z)} - P_{GCP(I,t,z)} \right) + \\
&\sum_{L=1}^{N_L} \left(P_{NSD(L,t,z)} + P_{Load\,DR(L,t,z)} - P_{Load(L,t,z)} \right) + \\
&\sum_{E=1}^{N_E} \left(P_{Discharge(E,t,z)} - P_{Charge(E,t,z)} \right) + \\
&\sum_{V=1}^{N_V} E_{EstimatedCharge(V,t,z)} + \\
&\sum_{M=1}^{N_M} \left(P_{Purchase(M,t)} - P_{Sell(M,t)} \right) = 0 \;\; \forall t, \mathrm{z}
\end{aligned} \tag{4}$$

2) Generation

A binary variable is used to represent the commitment status of dispatchable DG units. A value of 1 means that the unit is connected. Maximum and minimum limits for active power in each period *t* can be formulated as:

$$X_{DG(I,t)} \cdot P_{DGMinLimit(I,t)} \le P_{DG(I,t)} \le X_{DG(I,t)} \cdot P_{DGMaxLimit(I,t)} \qquad \forall t, \forall I \in \Omega_{DG}^{d} \tag{5}$$

$$P_{DG(I,t,z)} = P_{DGScenario(I,t,z)} \qquad \forall t, \forall I \in \Omega_{DG}^{nd}, \forall z \tag{6}$$

where

Variables

$X_{DG(I,t)}$	binary variable of state of DG unit *I* in period *t*

Parameters

$P_{DGScenario(I,t,z)}$	forecasted non-dispatchable DG unit *I* in period *t* in scenario *z* (kW)
$P_{DGMinLimit(I,t)}$	minimum active power of dispatchable DG unit *I* in period *t* (kW)
$P_{DGMaxLimit(I,t)}$	maximum active power of dispatchable DG unit *I* in period *t* (kW)

The upstream supplier maximum limit in each period *t* regarding active power and reactive power can be formulated as:

$$X_{\text{Supplier}(S,t)} \cdot P_{SMinLimit(S,t)} \le P_{Supplier(S,t)} \le X_{\text{Supplier}(S,t)} \cdot P_{SMaxLimit(S,t)} \qquad \forall t, \forall S \tag{7}$$

where

Variables

$X_{Supplier(S,t))}$	binary variable of choosing supplier S in period t

Parameters

$P_{SMinLimit(S,t)}$	minimum active power of supplier S in period t (kW)
$P_{SMMaxLimit(S,t)}$	maximum active power of supplier S in period t (kW)

3) Energy storage systems

The constraints for the ESS (batteries) are described below. The ESS charge and discharge cannot be simultaneous. Therefore, two binary variables guarantee this condition for each ESS:

$$X_{ESS(E,t,z)} + Y_{ESS(E,t,z)} \le 1 \qquad \forall t, \forall E, \forall z \tag{8}$$

where

Variables

$X_{ESS(E,t,z)}$	binary variable representing discharging state of ESS E in period t in scenario z
$Y_{ESS(E,t,z)}$	binary variable representing charging state of ESS E in period t in scenario z

The maximum battery balance for each ESS can be formulated as:

$$\begin{aligned} &E_{Stored(E,t,z)} = E_{Stored(E,t-1,z)} + \\ &\eta_{c(E)} \cdot P_{Charge(E,t,z)} \cdot \Delta t - \frac{1}{\eta_{d(E)}} \cdot P_{Discharge(E,t,z)} \cdot \Delta t \qquad \forall t, \forall E, \forall z \end{aligned} \tag{9}$$

where

Variables

$E_{Stored(E,t,z))}$	energy stored in ESS E in period t in scenario z (kWh)

Parameters

$\eta_{c(E)}$	charging efficiency of ESS E (%)
$\eta_{d(E)}$	discharging efficiency of ESS E (%)

The maximum discharge limit for each ESS can be represented by:

$$P_{Discharge(E,t,z)} \le P_{DischargeLimit(E,t,z)} \cdot X_{ESS(E,t)} \qquad \forall t, \forall E \tag{10}$$

where

Parameters

$P_{DischargeLimit(E,t,z)}$	maximum active discharge rate of ESS E in period t in scenario z (kW)

The maximum charge limit for each ESS can be represented by:

$$P_{Charge(E,t,z)} \leq P_{ChargeLimit(E,t,z)} \cdot Y_{ESS(E,t,z)} \qquad \forall t, \forall E, \forall z \tag{11}$$

where

Parameters

$P_{ChargeLimit(E,t,z)}$ maximum active charge rate of ESS E in period t in scenario z (kW)

The maximum battery capacity limit for each ESS can be represented by:

$$E_{Stored(E,t,z)} \leq E_{BatCap(E)} \qquad \forall t, \forall E, \forall z \tag{12}$$

where

Parameters

$E_{BatCap(E)}$ maximum energy stored allowed by ESS E (kWh)

Minimum stored energy to be guaranteed at the end of period t can be represented by:

$$E_{Stored(E,t,z)} \geq E_{MinCharge(E,t,z)} \quad \forall t, \forall E, \forall z \tag{13}$$

where

Parameters

$E_{MinCharge(E,t,z)}$ minimum energy stored required in ESS E in period t in scenario z (kWh)

4) Electric vehicle tariff

To formulate the price-based model, new constraints are developed in this subsection. The aggregator may need to limit the bounds of the tariff price in order to keep it appealing to the consumer. Therefore, the maximum tariff price is defined as follows:

$$T_{EVCharge(t)} \leq T_{EVChargeMaxLimit} \qquad \forall t \tag{14}$$

where the following represent

parameters

$T_{EVChargeMaxLimit}$ maximum EV charge tariff (m.u./kWh)

and variables:

$T_{EVCharge(t)}$ EV charge tariff price in period t (m.u./kWh)

The minimum price of the tariff is defined as follows:

$$T_{EVCharge(t)} \geq T_{EVChargeMinLimit} \qquad \forall t, \forall V \tag{15}$$

where the following represent

parameters:

$T_{EVChargeMinLimit}$ minimum EV charge tariff (m.u./kWh)

5) Electric vehicle demand

The charge demand of a given vehicle in period t depends on the price $T_{EVCharge(t)}$ and the coefficients of elasticity. These coefficients depend on the group, that the EV customer belongs.

$$E_{EstimatedCharge(V,t)} = \left(\kappa_{LinearA(V)} + T_{EVCharge(t)} \cdot \kappa_{LinearB(V)}\right) \cdot P_{ChargeMaxLimit(V,t)} \cdot \Delta t \quad \forall t, \forall V \tag{16}$$

where the following represent

parameters:

$\kappa_{LinearA(V)}$	fixed coefficient of linear elasticity equation for EV V
$\kappa_{LinearB(V)}$	linear coefficient of elasticity equation for EV V
$P_{ChargeMaxLimit(V,t)}$	maximum charge limit of vehicle V in period t (kW)

and variables:

$E_{EstimatedCharge(V,t)}$	estimated charge of EV V in period t based on elasticity equation (kWh)

The quadratic relantionship between the price and the quantity can be employed instead of the linear approximation (17) as follows:

$$E_{EstimatedCharge(V,t)} = \begin{pmatrix} \kappa_{QuadA(V)} + \\ T_{EVCharge(t)} \cdot \kappa_{QuadB(V)} + \\ \left(T_{EVCharge(t)}\right)^2 \cdot \kappa_{QuadC(V)} \end{pmatrix} \cdot P_{ChargeMaxLimit(V,t)} \cdot \Delta t \quad \forall t, \forall V \tag{17}$$

where the following represent

parameters:

$\kappa_{QuadA(V)}$	fixed coefficient of elasticity equation for EV V
$\kappa_{QuadB(V)}$	linear coefficient of quadratic elasticity equation for EV V
$\kappa_{QuadC(V)}$	quadratic coefficient of elasticity equation for EV V

The demand charge of the vehicle V in period t should be equal to the forecasted trip demand, i.e. the necessary amount of energy to accomplish a given trip before departure. The penalty term, $\lambda_{ChargePenalty(V)}$, is positive if the charge is higher than the demand of the expected trips and negative if the charge is insufficient. The optimization tries to find the value that match estimated charge with the forecasted demand without incurring in these penalties. However, this is quite hard to solve as the estimated demand also depends on the price, $T_{EVCharge(t)}$, that the EVs' owners pay (price/demand model), and the goal is to obtain the optimal hourly price that satisfies all EV customers' needs (18), while maximizing the profit function (1).

$$E_{EstimatedCharge(V,t,z)} = E_{ForecastedDemand(V,t,z)} + \lambda_{ChargePenalty(V,t,z)} \quad \forall V, \forall t, \forall z \tag{18}$$

where the following represent

parameters:

$E_{ForecastedDemand(V,t,z)}$	forecasted amount of charge demand of EV V in period t in scenario z (kWh)

and variables:

$\lambda_{ChargePenalty(V,t,z)}$	charge penalty of EV V in period t in scenario z (kWh)

6) Demand response

Load demand response program, namely the direct load control program, can be formulated as:

$$P_{LoadDR(L,t,z)} \leq P_{LoadDRMaxLimit(L,t,z)} \qquad \forall t, \forall L, \forall z \tag{19}$$

where

Parameters

$P_{LoadDRMaxLimit(L,t,z)}$ maximum limit of active power reduction of load L in period t in scenario z (kW)

7) Market

The market offers and bids are constrained by (20-24), namely maximum and minimum energy sale and purchase, respectively. A market bid cannot coexist with a market offer (sale) at the same time in the same marketplace (24).

$$P_{Sell(M,t)} \leq P_{MarketOfferMax(M,t)} \cdot X_{Market(M,t)} \qquad \forall t, \forall M \tag{20}$$

$$P_{Sell(M,t)} \geq P_{MarketOfferMin(M,t)} \cdot X_{Market(M,t)} \qquad \forall t, \forall M \tag{21}$$

$$P_{Purchase(M,t)} \leq P_{MarketPurchaseMax(M,t)} \cdot Y_{Market(M,t)} \qquad \forall t, \forall M \tag{22}$$

$$P_{Purchase(M,t)} \geq P_{MarketPurchaseMin(M,t)} \cdot Y_{Market(M,t)} \qquad \forall t, \forall M \tag{23}$$

$$X_{Market(M,t)} + Y_{Market(M,t)} \leq 1 \tag{24}$$

where

Parameters

$P_{MarketOfferMax(M,t)}$ maximum energy sale allowed in market M in period t (kW)

$P_{MarketOfferMin(M,t)}$ minimum energy sale allowed in market M in period t (kW)

$P_{MarketPurchaseMax(M,t)}$ maximum energy purchase allowed in market M in period t (kW)

$P_{MarketPurchaseMin(M,t)}$ minimum energy purchase allowed in market M in period t (kW)

$X_{Market(M,t)}$ binary variable that represents an offer in market M in period t

$Y_{Market(M,t)}$ binary variable that represents a bid in market M in period t

3.5. Implementation algorithm and metrics

The formulated model is a Mixed Integer Nonlinear Programming (MINLP), due to the presence of both continuous and integer variables and nonlinear objective function. The MINLP is implemented in TOMLAB [46], which is an advanced optimization toolbox for MATLAB [47], using KNITRO solver.

To measure the advantage of using stochastic programming, some metrics are implemented. The Expected value of Perfect Information (EVPI) for maximization problems, described by (25), represents the quantity that the decision maker would need to pay to obtain perfect information about the future. $z^{\mathrm{S}*}$ is the optimal value of the original stochastic objective function, and $z^{\mathrm{P}*}$ denotes the optimal value of the same problem after relaxing the nonanticipativity of the decisions. This problem is known as the wait-and-see problem. In wait-and-see problem, all variables are defined as scenario-dependent [43]**.** The Value of Stochastic Solution (VSS), defined by (26), represents the economic advantage of using stochastic programming over a deterministic model. A deterministic problem should be solved first to obtain $z^{\mathrm{D}*}$. In this deterministic problem, the uncertain parameters in the original two-stage problem are replaced with their expected values. Another stochastic problem is developed by replacing the first stage decision variables of the original problem with the optimal values obtained from solving the deterministic problem. z^{D*} is the optimal objective function of this modified problem [43]. For more information about the quality metrics of the stochastic programming problems, the reader can refer to [43].

$$\mathrm{EVPI} = z^{P*} - z^{S*} \tag{25}$$

where

z^{P*}	profit of the wait-and-see solution (P stands for perfect information)
z^{S*}	profit of the stochastic solution

$$\mathrm{VSS} = z^{S*} - z^{D*} \tag{26}$$

where

z^{D*}	profit of the modified stochastic problem
z^{S*}	profit of stochastic solution

4. Case study

The developed DR optimization model is tested using a case study based on a real distribution network with 201 buses, in Zaragoza, Spain [48]. The original data is slightly modified with regard to the production and consumption targets of 2030. Therefore, a high penetration of DG units is considered, corresponding to about 70% of the installed capacity in the considered network, according to what is expected in 2030 [49]. Regarding DG, the cogeneration installed capacity represents 33%, the photovoltaic represents about 30%, wind represents 22 %, small hydro represents 11%, and biomass represents 4%. Moreover, an approximate number of 1300 EVs has been estimated in the corresponding grid, taking into account the expected penetration rate (14%), in the fleet size of Spain for 2030 [50]. The mentioned penetration rate (14%) is the recommended value to understand the effects of the mass integration of EVs in the different applications, according to [50]. The EVs' scenarios are initially generated using the tool provided by [51], taking into account these parameters. The generated scenario is assumed to be the initial forecast of the EVs demand.

In this case study, the energy aggregator is able to manage 118 DG units, the energy bought from external supplier, 6 ESS[2] units (the charging and discharging efficiency considered for the ESS units is 90%), 1300 EVs[3], 168 loads aggregated by bus and 89 aggregated consumers with DR programs (direct load control). It is assumed that the aggregator manages the customers in the area, using the proposed stochastic model, with the aim to maximize the total expected profits. Table 1 shows the energy data and respective prices. The information

[2] ESS units are assumed to be advanced utility-scale storage units of 1 MWh capacity each.

[3] 1300 EVs are aggregated in 100 equivalent units to reduce computational burden.

of price is depicted in monetary units per kWh (m.u./kWh)[4] and the capacity in MW. The prices have been designed according to [52].

Table 1.

The scenario-based approach requires to have scenarios that catch the representative uncertainty in the underlying data. A higher number of sampling scenarios translates to a higher degree of uncertainty representativeness. To demonstrate the application of the stochastic model, 50 scenarios for each source of uncertainty have been generated using MCS sampling. More scenarios could have been generated but at a cost of higher computational demand. Uncertainty in renewable-based generation, EVs and load demand is considered. The initial forecast is assumed to have an error followed by a normal distribution for each of the different sources of uncertainty. The standard deviation is assumed to be as follows: 15% for the EVs demand (σ_{EVs}); 10% for the load demand σ_{load}; and 15% for the renewable-based demand $\sigma_{renewable}$.

The stochastic model presented in section 3 is used to solve the presented case study. Determining the optimal day-ahead EV pricing implies knowing the reaction to price of the EV customers. In this case study, 5 distinct EV customers' groups are assumed and empirically classified: bus fleet, taxi, salesman, worker and shopper groups. Each group has distinct characteristics as shown in Figure 4, where bus fleets are less sensitive to price variation. The data has been assumed for demonstration purposes as currently no such data is available. In a real-world situation and with sufficient data, the aggregator could maintain a historic file to understand the behavior of its customers towards different prices and perform some surveys to obtain a more reliable model.

Figure 4.

Figure 5 depicts the distribution of the 1300 EVs, e.g. 64% of them belong to worker group. In parentheses the estimated trip demand of each group is presented. Although, only 3% of EVs are bus fleets, their trip demand represents more than 20% of the total. The worker group represents more than 40% of the total estimated trip demand.

Figure 5.

The trip demand forecast of the considered 1300 EVs customers can be seen in Figure 6. The uncertainty is catch by the MCS for 50 scenarios and the variation is represented in the figure by a bold line. For instance, in period 18 the demand forecast varies between 0.95 MWh and 1.26 MWh, according to the scenario generation. The initial state of the charge of EV battery is of stochastic nature.

Figure 6.

Figure 7 shows the box plot regarding the variation catch by MCS, which corresponds to about 1 MWh of uncertain variation. All of these data serves as inputs for the developed stochastic energy resource model.

Figure 7.

[4] The monetary unit corresponds to $ (dollar) in this case study.

5. Results and Discussion

The proposed two-stage stochastic model is applied to the described case study. In addition, the counterpart deterministic model is assessed to evaluate the performance of the proposed stochastic model. The dimension of the optimization problem is 1,294,152 variables with 373,488 constraints in the stochastic version. The deterministic counterpart formulation only uses 26,424 variables with 7,919 constraints.

5.1. Deterministic solution

Figures 8 present the deterministic energy resource scheduling. The total scheduled energy resources is 251.22 MWh. Concerning the total external supplier acquisition, the amount is 126.13 MWh (dark blue in the figure), while the controllable generation (dispatchable) is 75.86 MWh (light pink). The non-controllable generation (dark grey) is 19.03 MWh. The total storage discharge is 6.00 MWh (yellow), while the total scheduled DR is 6.81 MWh (orange). The total market purchase is 17.39 MWh (light blue).

Figure 8.

Figure 9 presents the deterministic consumption scheduling. The optimal solution for the market sale is 4.52 MWh (in light blue), storage charge is 7.41 MWh (yellow), and the expected vehicle charge is 26.43 MWh (light green). The NSD is not verified in this solution. However, the deterministic solution does not takes into account the uncertainty underlying in the problem inputs. Therefore, the given deterministic solution may easily not be optimal if these forecasts are not accurate.

Figure 9.

To understand how two-stage stochastic programming can improve the decision-making, a comparison is made by considering a reasonable accuracy error in the underlying uncertain parameters (forecasts) as discussed in section 4. Hence, the solution obtained in the stochastic programming is analyzed and compared with the deterministic counterpart next.

5.2. Stochastic solution comparison

Before analyzing the obtained EV tariff, the energy scheduling decision variables are compared. Figure 10 shows the temporal variation of the stochastic solution compared with the deterministic, namely regarding the first-stage decision variables, except for the EV tariff variables (analyzed later). It can be seen in Figure 10 that the most part of the decision's variations occur in the earlier periods of the energy scheduling, namely in the market sale, purchase and controllable DG variables. In fact, the highest variation occur in the market purchase in period 9, i.e. 52% market purchase reduction when compared with the deterministic solution. In addition, it can be seen that positive variations occur in market sale (+20% in period 4) and also positive variations in controllable DG variables (despite slightly negative in period 3 and 24). Finally, very few variations are registered with the external supplier variables. In this case NSD is not registered either.

Figure 10.

Table 2 depicts the aggregated sum of controllable DG, external supplier energy acquisition, market sales and market purchases for the deterministic and stochastic solution. Hence, it can be seen that the variations are relatively small from this perspective (aggregated sum).

Table 2.

Table 2 shows that the stochastic solution prefers to increase market sale by 2% while reducing market purchase by 3% in comparison with the deterministic approach. The total controllable DG is increased by 1%, while there is insignificant variation in the total scheduling of the external supplier.

The following analysis focus in the comparison of the obtained EV tariff in both approaches. Figure 11 shows the resulting tariff in m.u./kWh for solutions obtained with the deterministic (black line) and stochastic model optimization (green line). In the figure, the resulting tariff is rounded to the second decimal. Analyzing the obtained solutions, it is possible to see that the differences between both methods are considerably small. The maximum difference in the obtained tariff is 0.01 m.u./kWh. The differences happen in periods 1, 10, 12, 15 and 23. There are 3 periods (1, 10, 23) where the stochastic solution presents a higher price than the deterministic solution and 2 periods otherwise (12, 15).

Figure 11.

Figure 12 depicts the EV tariff (light transparent green) obtained in the stochastic solution compared with the amount of expected EV charging by group. The different groups are represented by different colors, where it can be seen that the worker group represents a significant part of the expected charging (69%). The bus fleet group is also significant (10%) but its presence is more concentrated in certain periods, e.g. 1-2, 10, 14-16 and 20. Moreover, it can be identified that the demand/price model is being followed as more demand is expected when the prices are low and lower demand when prices are higher.

Figure 12.

5.3. Advantages of the stochastic solution

Table 3 depicts VSS and EVPI metrics that demonstrate the advantage of the two-stage stochastic programming over the deterministic counterpart for this case. The Z^{D^*} was obtained by running the deterministic model with the average scenario and then locking the first-stage variables in the two-stage stochastic programming with the result of the first deterministic optimization. The expected profit of the stochastic solution (Z^{S^*}) was 5120 m.u., against 4824 m.u. in Z^{D}. Consequently, the VSS is 296 m.u., while the EVPI is 170 m.u. in this case. The EVPI means how much the aggregator would be willing to pay to have perfect information (utopian idea). The execution time of the stochastic solution was 3680s, while the deterministic counterpart was 7s. This computational time increase is mainly attributed to problem dimensionality and its nonlinearity, namely because of over 1 million variables in the stochastic model. In fact, the curse of dimensionality poses a hard limitation in the number of scenarios it is possible to deal under reasonable time and available computer resources.

Table 3.

Although, the VSS indicated that the stochastic solution was better in the long-term than the deterministic counterpart, i.e. an advantage of 296 m.u. or 6%, the differences realized in the solutions were not very noticeable as initially presumed. Even so, the most noticeable difference verified in the solutions was in the market transactions, namely market purchases, where the stochastic solution was 3% more conservative than the deterministic solution, i.e. less 520 kWh market purchases. Even though, these small differences translate into a more profitable solution in the long-term. A daily difference of 296 m.u. could potentially represent more than 108,000 m.u./year in savings.

5.4. Results under different EV pricing scheme

Table 4 depicts the expected operation performance under different EVs pricing schemes. The proposed EV pricing scheme (optimal pricing) is compared with several fixed price schemes using the previously discussed EV price/demand model.

Table 4.

The implemented EV fixed pricing schemes vary from 0.15 m.u./kWh to 0.19 m.u./kWh for comparison with the optimal pricing. It can be seen that that the expected profit increases when the fixed price increases as well. However, the expected revenue decreases, and eventually, the profit would start to decrease. The EVs revenue represents the EVs' owner bill, i.e. what they pay for EVs charging. In other words, the EVs are willing to charge more at lower prices and far less at higher prices. The EV revenue does not seem to increase as the EV price increases. At lower prices the expected profit seems to be significantly lower and the $\sum|\lambda_{ChargePenalty(V)}|$ penalties are also higher, due to high increase of EV demand. The ideal situation would be when $\sum|\lambda_{ChargePenalty(V)}|$ is 0 where the customers would be satisfied. The case where this is more likely to happen is with the proposed dynamic pricing approach. In addition to a relatively high profit, the EVs demand is satisfied at reduced energy costs (lowest EV revenue). At a fixed price of 0.19 m.u./kWh the expected profit could be higher, i.e. 5247 m.u., than in the proposed dynamic pricing. However, there is a higher level of penalties, including potentially unrealized EVs demand, while customers pay much more for less energy, thus potentially leading to customers' dissatisfaction.

5.5. Limitations

A few limitations in the current proposal have been identified, which could be improved in future works. The major limitation in the current model is the computational burden, namely when a high number of scenarios (higher accuracy of uncertainty representation) is desired. Nevertheless, the nonlinearity of the problem may be mitigated by using metaheuristics and decomposition-based approaches. Moreover, the results strongly depend on the accuracy of the price/demand model, which can be difficult to obtain as specific data regarding customers' preferences and behavior are needed. In the future, better use and techniques in the field of big data may provide easy answers to this.

6. Conclusions and future work

With mass integration of EVs in a near future, a significant part of the consumers' electric bill will be due to mobility. In fact, EVs may increase costs related to infrastructure supply and energy without appropriate actions. Therefore, sophisticated demand response models are crucial to leverage power grid efficiency and postpone high investment costs in generation and transmission infrastructure. The currently proposed tariffs by the energy providers to tackle the envisaged problem consist in fixed time of use strategies, which are limited to attain the full SG potential. The dynamic environment of a SG calls for better exploitation of its resources, namely maximizing renewables use and improve consumer participation.

This paper discusses the DR models for EVs and proposes a price-based strategy to deal with a large number of EVs in the grid. These DR programs are shaped for EVs and can be offered by energy providers in their business models, which can take full advantage of the upcoming opportunities. In addition to the large number of EVs, these utilities face a growing number of other DERs. These resources must be considered in the ERM problem, which require sophisticated software tools that can handle its complexity, consider the involved uncertainty, and achieve an effective and efficient operation. Therefore, this paper presents a new stochastic model that considers several sources of uncertainty, including the variability of the load demand, intermittency of wind and PV generation and stochastic demand of EVs, while considering the optimal dynamic pricing (DR) for EVs. These features have been considered in the same optimization model. The results suggest that the two-stage stochastic programming approach can provide a better result for the aggregator, i.e. a higher profit (more 6%) than the deterministic counterpart approach, which considers only the average scenario. However, the current computational burden of the stochastic solution (>1 hour) is incomparable to the deterministic approach (7 s). This issue may be mitigated in a near future as technology evolves. The integrated optimal pricing scheduling demonstrates to improve the profits of the aggregator while satisfying the expected EV customers' requirements in comparison with the regular flat price schemes, which do not influence user's behavior. The users' satisfaction is conveniently exploited, by minimizing the unrealized trips and the unwanted charges the objective function. Indeed, the results show that the proposed approach is the most suitable one to match the users' needs and the energy price, thus contributing to the highest satisfaction.

Future proposals may include obtaining more than one tariff for each of the different groups, including other kinds of load demand, such as residential, commercial and industrial loads. This may improve the operational results and the increase the flexibility of the current proposal. In addition, the idea could be tested under an agent-based simulation platform with several energy aggregators offering their services to several customers in a market competitive environment. In this platform it would be possible to refine the developed model and further understand its advantages and benefits to the involved players, including the consumers, whose active role could be explored.

Acknowledgements

The present work was done and funded in the scope of the following projects: EUREKA - ITEA2 Project SEAS with project number 12004; UID/EEA/00760/2013, and SFRH/BD/87809/2012 funded by FEDER Funds through COMPETE program and by National Funds through FCT.

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Figure Captions:

Fig. 1. Active energy invoicing price in Spain using PVPC (10-11-2016) [34].

Fig. 2. Integrated energy resource scheduling with the proposed optimal pricing

Fig. 3. Energy aggregator transactions and customer’s contracts: EVs contract a variable price term

Fig. 4. Considered price/demand model of the 5 EV groups

Fig. 5. EVs group distribution and trip demand forecast by group in parentheses

Fig. 6. Electric vehicles trip demand forecast: 50 scenarios in MCS simulation (σ_{EVs} =15%)

Fig. 7. Uncertainty in the initial state of charge of the EVs (σ_{EVs} =15%)

Fig. 8. Energy resource scheduling in the deterministic model

Fig. 9. Consumption scheduling in the deterministic model

Fig. 10. Variation of decision variables for the deterministic and stochastic solution

Fig. 11. Comparison of the proposed EV pricing solution between the deterministic and stochastic model

Fig. 12. EV tariff vs expected EV charging by group (average) of the stochastic solution

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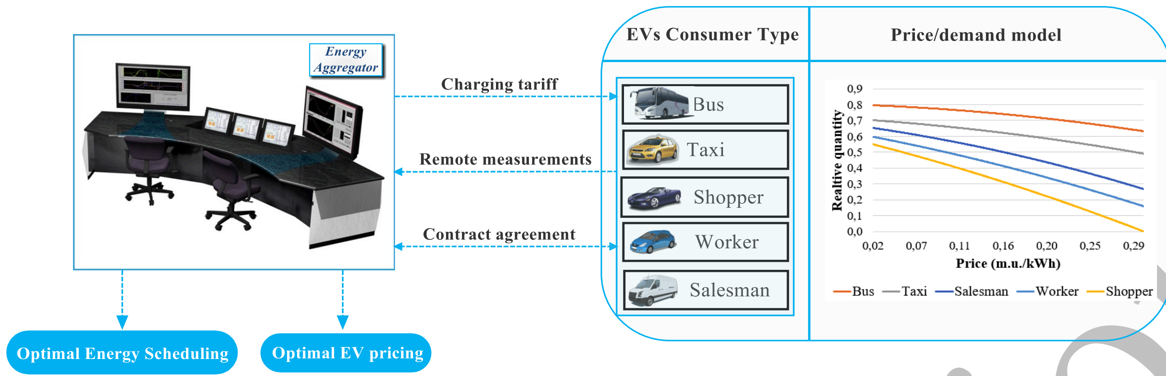

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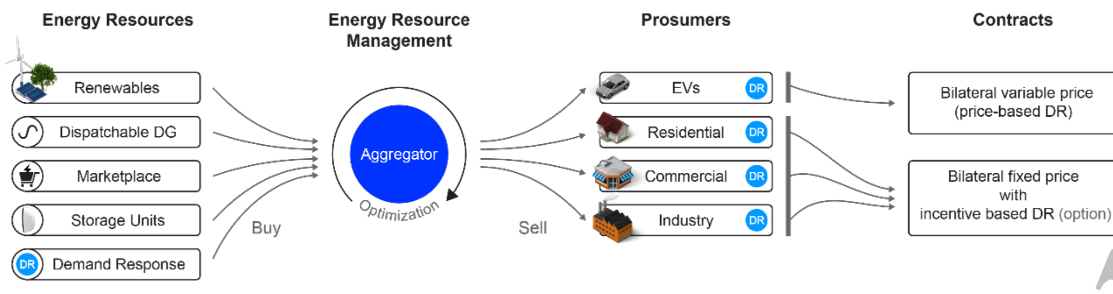

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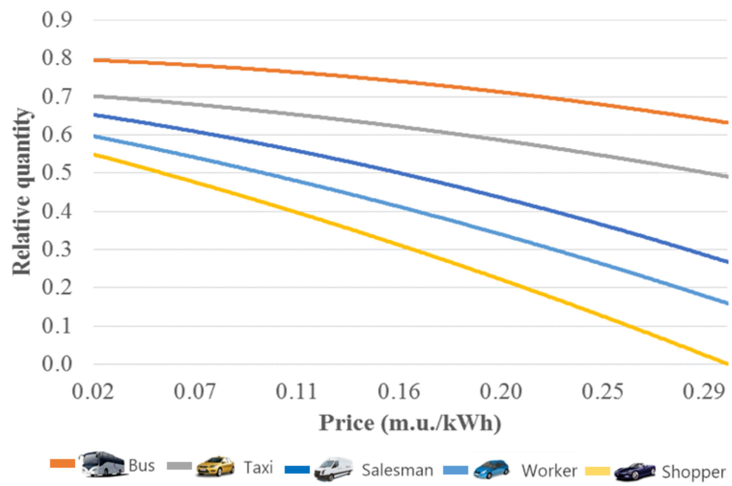

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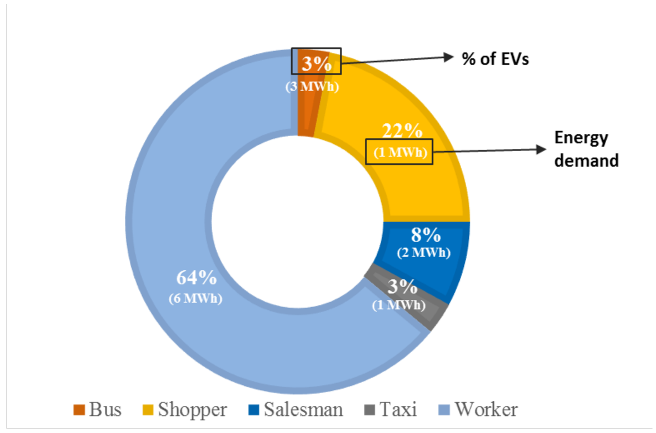

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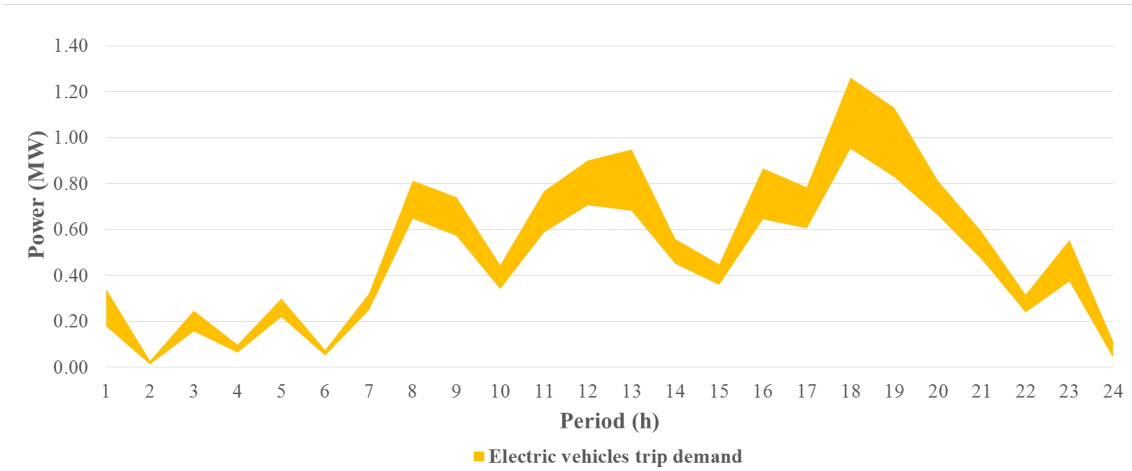

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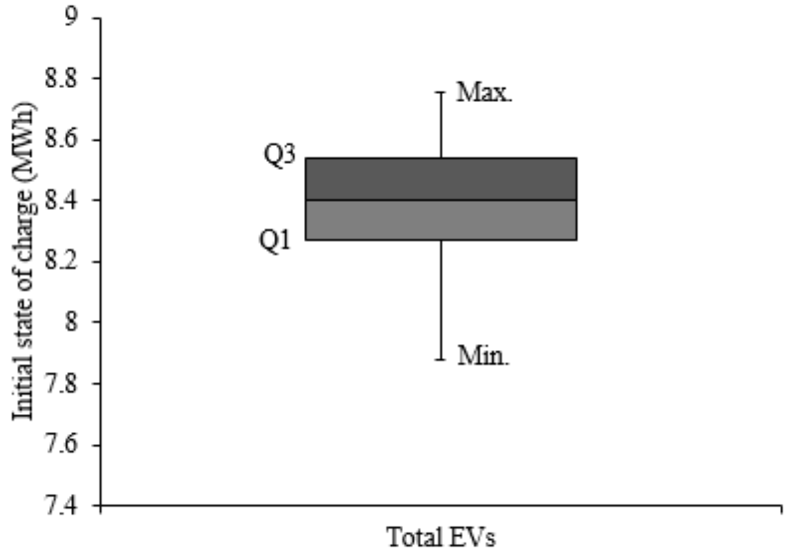

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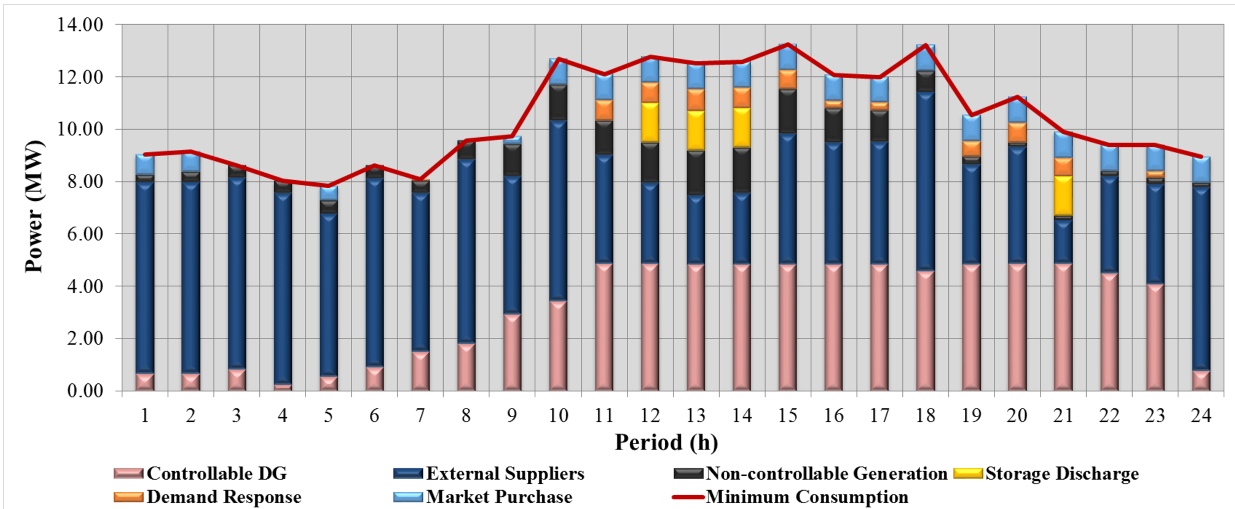


Fig. 8. Energy resource scheduling in the deterministic model

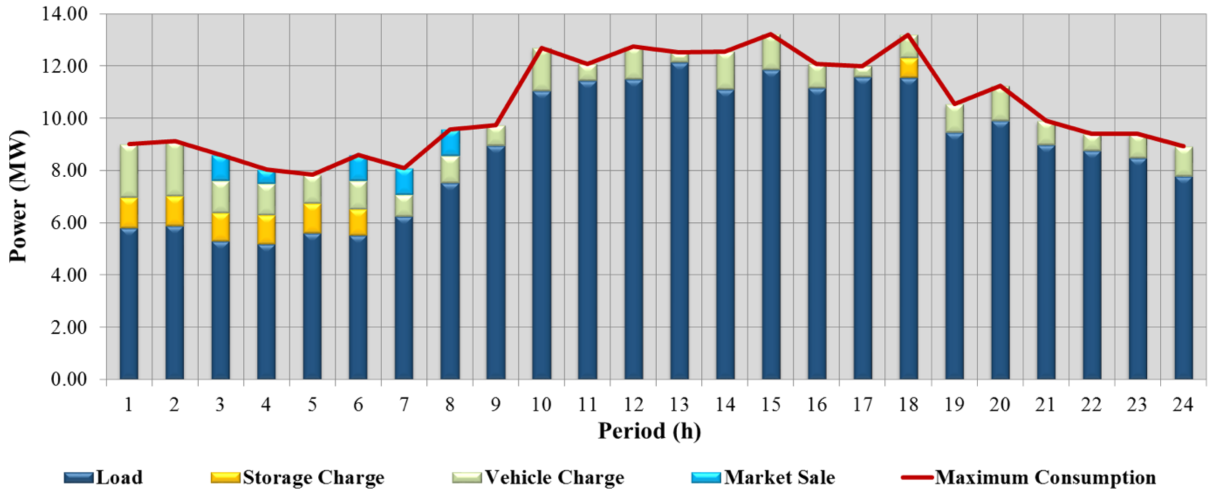
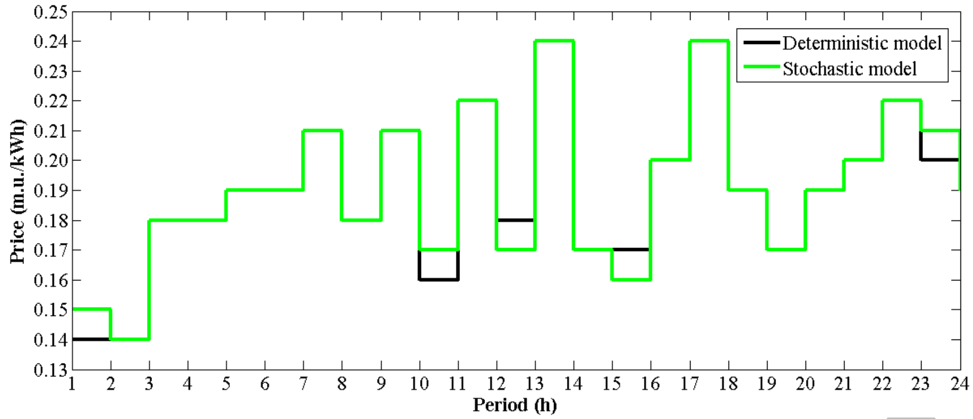


Fig. 9. Consumption scheduling in the deterministic model

Fig. 10. Variation of decision variables for the deterministic and stochastic solution



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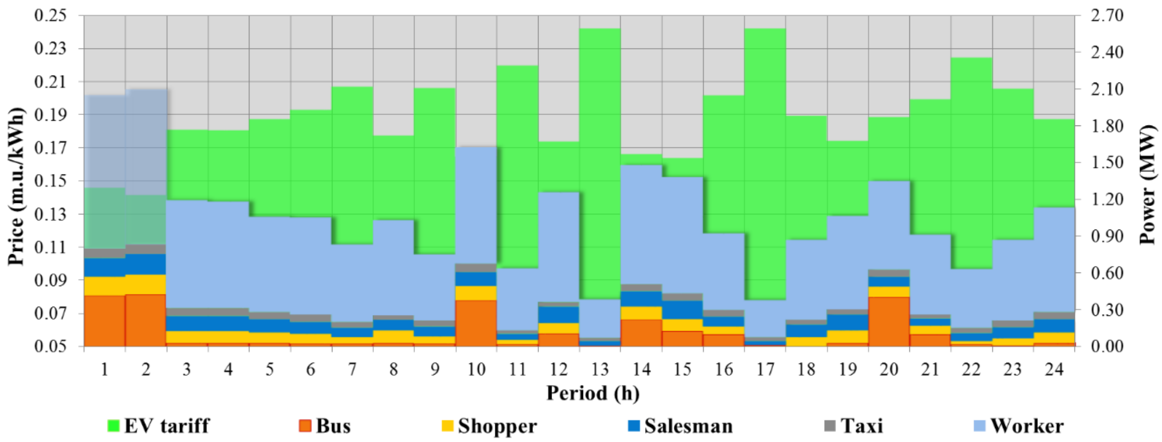

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Table Captions:

Table 1. Zaragoza 2030 scenario characterization

Table 2. Comparison of results between deterministic and stochastic solution

Table 3. Advantage of stochastic programming approach

Table 4. Expected operation performance under different pricing schemes

Table 1. Zaragoza 2030 scenario characterization

Energy resources		Prices (m.u./kWh)	Capacity/forecast (MW)	Units #
		min – max	min – max	
Biomass		0.15 – 0.15	0.00 – 0.52	1
CHP		0.10 – 0.12	0.00 – 4.00	4
Small Hydro		0.13 – 0.13	0.12 – 0.35	1
Photovoltaic		0.20 – 0.20	0.00 – 1.70	82
Wind		0.12 – 0.12	0.07 – 0.94	30
External Supplier		0.09 – 0.20	0.00 – 7.30	1
Storage	Charge	0.12 – 0.12	0.00 – 1.50	6
	Discharge	0.18 – 0.18	0.00 – 1.50	
Electric Vehicle	Charge	Decision variable	0.00 – 6.94	1300
Demand Response	Direct load control (reduce)	0.11 – 0.17	0.35 – 0.85	89
Load		0.09 – 0.15	5.04 – 12.38	168
Market		0.08 – 0.13	0.00 – 1.00	1

Table 2. Comparison of results between deterministic and stochastic solution

	Deterministic (Z^{P^*})	**Stochastic (Z^{S^*})**	**Variation (%)**
Controllable DG (MWh)	75.86	76.36	1
External supplier (MWh)	126.13	126.04	0
Market sale (MWh)	4.52	4.62	2
Market purchase (MWh)	17.39	16.87	-3

Table 3. Advantage of stochastic programming approach

Indicator		Value
Z^{S*} (m.u.)		5120
Z^{D*} (m.u.)		4824
VSS (m.u.)		296 (6%)
EVPI (m.u.)		170 (3%)
Execution time (s)	Z^{S*}	3680
	Z^{D*}	7

Table 4. Expected operation performance under different pricing schemes

EV pricing scheme	Expected profit (m.u.)	Expected EVs revenue (m.u.)	Unrealized EVs forecast (MWh)	$\sum \lvert \lambda_{ChargePenalty(V)} \rvert$
Optimal pricing	5120	4743	0.02	1.6
Fixed: 0.15 m.u./kWh	4325	5665	0.00	36.6
Fixed: 0.16 m.u./kWh	4643	5570	0.00	26.35
Fixed: 0.17 m.u./kWh	4903	5416	0.00	16.4
Fixed: 0.18 m.u./kWh	5105	5203	0.10	7.4
Fixed: 0.19 m.u./kWh	5247	4931	0.32	4.6