Published in Energy with doi: 10.1016/j.energy.2022.124219

A Stochastic-Interval Model for Optimal Scheduling of PV-assisted Multi-mode Charging Stations

Marcos Tostado-Véliz[1], Salah Kamel[2], Hany M. Hasanien[3], Paul Arévalo[1], Rania A. Turky[4], Francisco Jurado[1,*]

1. Department of Electrical Engineering, University of Jaén, 23700 Linares, Spain (e-mail: mtostado@ujaen.es (M.T.-V.), wpac0001@red.ujaen.es (P.A.), fjurado@ujaen.es (F.J.)).
2. Department of Electrical Engineering, Faculty of Engineering, Aswan University, Aswan 81542, Egypt (e-mail: skamel@aswu.edu.eg).
3. Electrical Power and Machines Department, Faculty of Engineering, Ain Shams University, Cairo 11517, Egypt (e-mail: hanyhasanien@ieee.org).
4. Electrical Engineering Department, Faculty of Engineering and Technology, Future University in Egypt, Cairo, Egypt (e-mail: Rania.turky@fue.edu.eg).

* Correspondence: fjurado@ujaen.es

Abstract. Nowadays, photovoltaic-assisted charging stations are becoming popular worldwide because its capacity to accommodate more clean energy, reduce carbon emissions, alleviate peak charging loads and provide wider charging infrastructures worldwide. When these infrastructures are operated locally, energy management becomes a challenge due to the large number and heterogeneity of uncertainties involved. This aspect is especially noticeable in the case of charging demand, which is difficult to predict. To address this issue, this paper develops a novel stochastic-interval model for optimal scheduling of multi-mode photovoltaic-assisted charging stations. The developed model uses interval formulation to model uncertainties from photovoltaic generation and energy price, while a comprehensive stochastic model is proposed for charging demand. The developed optimal scheduling model is solved using a developed iterative model, which avoids using interval arithmetic explicitly. This methodology encompasses two Mixed-integer linear programming problems and one Quadratic-programming problem, that can be efficiently addressed by conventional solvers, and allows adopting optimistic or pessimistic strategies. A case study is presented on a benchmark mid-size charging station to validate the developed model. As a sake of example, the system profit grows by 9% and decreases by 3% adopting optimistic and pessimistic point of view, respectively. Likewise, total PV generation increases by 150 kWh/day and reduces by 50 kWh/day. Similar conclusions are extracted for other parameters like monetary balances, PV peak power or satisfied EV demand.

Keywords. Photovoltaic; charging station; electric vehicle; renewable energy; interval optimization; robust optimization.

Nomenclature

Indexes (Sets)	
$t(\mathbb{T})$	Time
$s(\mathbb{S})$	Scenario
$r(\mathbb{R})$	Representative scenario
$j(\mathbb{J})$	Charging event
Ω_r	Cluster of the rth representative scenario
Ψ	Interval-based set of uncertainties
Superscripts	
$Grid, buy/sell$	Utility grid (buying/selling processes)
PV	Photovoltaic array
$BES, ch/dch$	Battery energy storage (charging/discharging processes)
$EV, F/SF$	Fast/semi-fast charging event
$\overline{(\cdot)}/\underline{(\cdot)}$	Maximum/minimum value
$\widehat{(\cdot)}$	Uncertainty
Subscripts	
det	Deterministic
opt/pes	Optimistic/pessimistic
Functions	
$[\cdot]$	Interval number
$E(\cdot)$	Expected value of uncertainties
$\mathrm{round}(\cdot)$	Rounds to the nearest integer
$\mathrm{rand}(\cdot)$	Yields a random number based on a probability function
$\mathrm{size}(\cdot)$	Yields the number of elements in a set or cluster
$\mathcal{F}$	Vehicle trip distribution
$\mathcal{N}(\mu, \sigma)$	Normal distribution with mean μ and standard deviation σ
Parameters	
R	Ramp limit (kW)
$\Delta\tau$	Time step (h)

η	Efficiency (p.u)
DOD	Depth-of-discharge (p.u)
π	Probability (p.u)
λ	Energy cost (\$/kWh)
κ	Operation & maintenance costs (\$/kWh)
Variables	
p	Power (kW)
u	Commitment status (Binary)
ε	Energy (kWh)

1 - Introduction

1.1 - Context & motivation

Decarbonization of the electricity sector is one of the main concerns for governmental entities. As a salient example, European Union members target of a 40% reduction of greenhouse gas emissions by 2030 and 80-95% reduction in 2050 [1, 2]. These ambitious goals suppose a challenge for current energy sectors, especially due to the prospective increase of electricity demand for the following decade [3]. These circumstances compromise the Paris agreement's goal of keeping global warming to well below 2 ºC [4]. In this context, photovoltaic (PV) generation will play a vital role, being one of the main renewable sources along wind and hydro energy. Actually, the total worldwide PV capacity exceeded 625 GW in 2019 with a yearly addition of 115 GW, thus observing an exponential grow in the last 10 years [5]. If this trend continues over the next 20 years, PV will provide 7208 TWh by 2040 [6].

PV finds its primary application in domestic installations, by means of rooftop arrays [7]. However, the installation of solar panels in electric vehicle (EV) charging stations has risen considerably in the last years [8]. PV-assisted charging stations (PVaCSs) bring multiple benefits for the operator or entity that manages it, e.g. it allows accommodating more clean energy, reducing carbon emissions, and alleviating peak charging loads [9]. Moreover, if battery energy storage (BES) systems are deployed in combination with PV modules, active participation in energy markets is enabled, thus allowing to buying and selling energy on pursuing improving the economy of the system [10]. Nevertheless, optimal coordination of on-site generation and storage assets with EV demand (which has a high stochastic behaviour) in PVaCSs supposes a formidable challenge, for which energy management tools and strategies are essential [8]. This paper tackles this issue.

1.2 - Literature review

In [11], an intelligent tool is developed for optimally charging electric vehicles in domestic installations, based on predicted profiles of PV generation and appliances consumption. Guo et al [12] developed a two-stage scheduling tool for PVaCSs, in which mixed-integer linear programming (MILP), stochastic modelling and model-predictive control (MPC) are combined to handle the uncertainty of renewable generation and EV demand. The reference [13] proposes an optimal planning model for storage sizing in fast charging stations. This framework uses a charging profile model based on the probability of daily mileage by which the expected EV demand is determined. Different day-ahead control strategies for distributed PV systems are presented in [14]. In this model, the vehicles in the fleet can be charged on different PVaCSs, while the power-sharing strategy among different agents is centrally decided. In [15], a home energy management system considering vehicle-to-home capability and PV generation is developed. The considered formulation incorporates sophisticated thermal models, which entails nonlinearities that are circumvented using a bio-inspired solver.

The reference [16] proposes a home energy management system that optimizes the reactive power flow at point of connection with the grid. To this end, the developed tool optimizes the charging pattern of a plug-in EV in presence of PV generation. Eldeeb et al [17] developed a multi-objective optimal scheduling tool for a grid-connected PVaCS, by which the BES state-of-health and economy are jointly maximized. A chance-constrained optimal scheduling model for a battery swapping station with on-site PV generation is presented in [18]. Likewise, an energy management strategy is presented in [19] for a business district with various charging stations. However, uncertainties from PV generation and EV demand are ignored in this model. In [20], a distributed energy management strategy for multiple PVaCSs is developed. This tool uses intensive data and deep-reinforced learning to manage with run-time and time-varying uncertain behaviour of consumers and generation.

Gupta et al [21] developed a collaborative framework for multiple aggregators in the presence of PVaCSs. Although the PV generation is considered deterministic, possible forecast errors and their effects on the final scheduling result are analysed. A comprehensive multi-energy model with charging stations is presented in [22]. The MILP formulation is suitable for energy management tools and encompasses electrical, gas and hydrogen sub-networks. In [23], an optimal design method is developed for fast charging stations. Optimal EV charging scheduling strategy is obtained as by-product. This way, the problem is formulated as a multi-objective optimization model and solved using a bio-inspired algorithm. The Ref. [24] presents a two-stage scheduling model for a grid-connected charging station with integrated hydrogen storage. In this formulation, uncertainties of demand, PV generation and energy price are incorporated via scenarios. A combined planning-operation MILP model for PVaCSs is presented in [25] in which uncertainties are not considered.

A MILP optimal electrification model for isolated dwellings is developed in [26]. In the proposed model, flexibility from smart appliances and vehicle-to-home features are considered to improve the accuracy of results and achieve better economy proficiency. The Ref. [27] presents an Information Gap Decision Theory (IGDT) based energy management tool for multi-energy microgrids integrated with various conversion technologies and intelligent parking lots. Osório et al [28] developed an optimal day-ahead scheduling model for EV aggregators supported by PV plants enabling the participation in energy markets. In [29], a Monte Carlo-based energy management tool for energy hubs integrated with PVaCSs is presented. In this model, reverse power flow from/to EV fleet is considered for supporting the operation of the multi-carrier system.

The article [30] develops a stochastic-based scheduling tool for DC nanogrids with integrated fast charging infrastructures.

1.3 - Paper contributions

Table 1 presents the taxonomy of the most relevant literature presented above. In the light of this study, various gaps have been detected related to energy management of PVaCSs:

Table 1 - Taxonomy of the related literature

Ref.	**Model**	**Uncertainties**	**EV demand**	**Charging mode**
[11, 16, 28]	MILP	Deterministic	Deterministic	Slow
[12]	MILP	Stochastic	MPC	Fast
[13]	MILP	--	Model-based	Fast
[14]	Heuristic	Deterministic	Deterministic	Slow
[15]	Metaheuristic	Deterministic	Deterministic	Slow
[17]	Nonlinear	Deterministic	Deterministic	Semi-Fast
[18]	Metaheuristic	Chance-constrained	Chance-constrained	Battery swapping
[19, 22]	MILP	Deterministic	Deterministic	Semi-fast Fast
[20]	Deep-learning	Deterministic	Deterministic	Fast
[21]	MILP + heuristic	Deterministic	Deterministic	Fast
[23]	Metaheuristic	Deterministic	Deterministic	Fast
[24, 30]	MILP	Stochastic	Stochastic	Fast
[25]	MILP	Deterministic	Deterministic	Fast
[26]	MILP	Stochastic	Stochastic	Slow
[27]	MILP	IGDT	Deterministic	--
[29]	MILP	Stochastic	Stochastic	--
Present	MILP-QP	Interval	Model-based Stochastic	Semi-fast Fast

- Some studied references present complex nonlinear formulations that require the use of metaheuristic techniques or specific solvers. This kind of tools are frequently computationally demanding, non-modular and do not endure the reachability of the global optimum [31], which limit their applicability.
- Most of the related previous studies use simple stochastic models for representing uncertainties (or even ignore them). However, this approach may be time-consuming [32]. Moreover, uncertainties modelling via scenarios require a priori

knowledge of distribution functions of uncertainties, which is not always available [33].

- In the majority of the studied models and formulations, only one charging mode is accounted, while multi-mode charging stations are rarely considered.

The present paper attempts to overcome the issues above. As seen in Table 1, this work presents the most completed model and many outstanding features that make it relevant and novel. In particular, the main contributions of this paper are listed below:

- Developing a multi-stage energy management tool for PVaCSs that combines MILP and quadratic programming (QP) formulations. This type of model is versatile being thus adaptable to different layouts. Moreover, they can be efficiently addressed using on-the-shelf solvers such as Matlab's embedding tools.
- Proposing a comprehensive stochastic model for EV charging demand considering semi-fast and fast charging modes, which allows to generate a large number of EV charging scenarios and thus treating this demand using stochastic programming.
- Developing a novel stochastic-interval formulation for PVaCSs scheduling. This methodology considers stochastic programming to model EV demand while other uncertainties are considered using interval formulation. In contrast to other interval-based energy management tools, the developed model uses the formulation proposed in [34], which avoids the use of interval arithmetic that may result computationally costly.

To validate the developed model, a case study is performed on a benchmark charging station involving fast and semi-fast chargers, as usually in public stations. In this regard, various results are provided and discussed to illustrate the usefulness of the developed approach.

In the rest of this paper. Section 2 overviews the system layout under study and explains the scheduling methodology. Section 3 presents the mathematical modelling. Section 4 develops a stochastic model for EV demand. Section 5 presents a solution methodology for the proposed model considering uncertainties. Section 6 presents a case study with the obtained results and their analysis. The paper is concluded with Section 7.

2 - Preliminaries

A conventional scheme of a PVaCS is pictorially represented in Fig. 1 which is similar to other layouts collected in the literature [12, 17]. The considered system is suited to serve both fast and semi-fast chargers, which are currently mature charging modes for a wide range of EVs [22]. The former focuses on the short-time park periods with the charging times of approximately 15 to 45 min. On the other hand, semi-fast charging may take various hours to be completed and it is normally devoted to long-time parking periods, typical of headquarters or commercial buildings. The charging station produces monetary revenues for the system, derived from charging costs that may be different for fast and semi-fast charging events.

It is considered that the station under study is connected to a utility grid. The PVaCS under study can freely purchase and sell energy to the utility grid, this way, the installation can exploit eventual surplus energy from PV to obtain a monetary revenue. The energy cost is assumed to be equal to the local marginal price at the point of connection to the grid, which is cleared in real-time energy markets. To enable a more efficient management and profitable participation in energy markets, a BES is deployed. The battery bank may be formed for any mature technology such as Li-ion or Lead-acid, but other storage devices could be considered without introducing major modifications in the model (e.g. hydrogen tanks).

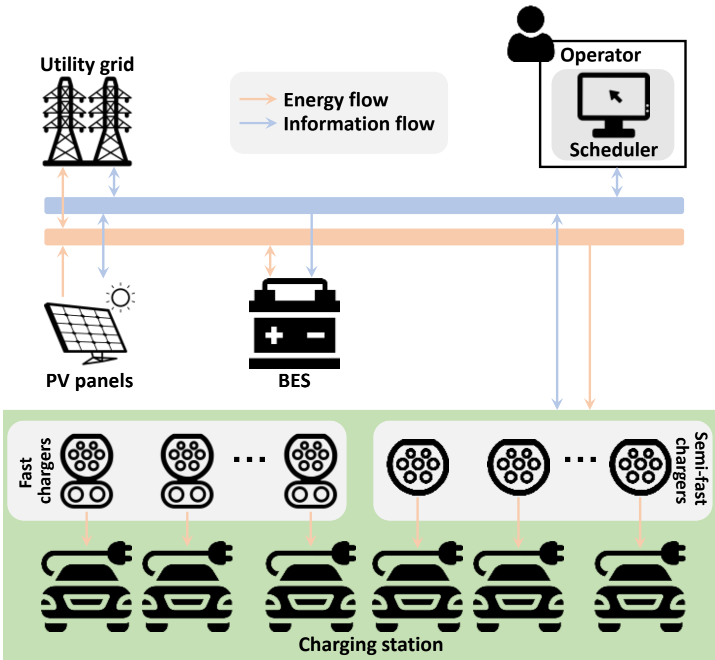

Fig. 1 - Scheme of the PVaCS under study

The operation of the different assets is day-ahead determined by an energy management tool, which is devoted on improving the economy of the system. In this paper, this role is assumed by the system operator, however, other agents may play this role or even being performed by multiple agents or in a decentralized way [35]. Sometime throughout the day *d-1*, the necessary forecasts are available with sufficient accuracy, which is a plausible assumption nowadays [36]. Along the expected value of the uncertainties, confidence intervals can be also forecasted, allowing to a more robust scheduling program (see Section 5). This information is then used by the scheduler to perform the optimal plan for the different on-site assets, which will be realized on day *d*.

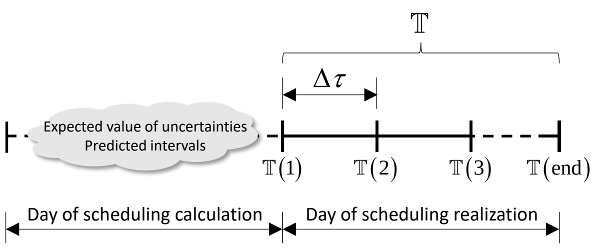

Fig. 2 - Timeline of the scheduling process

This paper assumes that the scheduling plan is day-ahead performed, as customary in energy management applications (e.g. see [16-18]). Nevertheless, the same principle could be extended to larger horizons if necessary. For example, an operator may be keen to plan the different assets for two, three or even more days. Nevertheless, this plan is usually updated with day-ahead horizon, when forecasts are available with more accurateness and, consequently, the results are more reliable. In this regard, the day-ahead scheduling could be even more refined in real-time, using proper fast algorithms [37]. However, this tool could be programmed as an independent module in combination with the proposed energy management scheme and therefore this topic is out of scope of this paper.

3 - Mathematical models

Throughout this section, the mathematical modelling of the different system components is presented. This formulation is incorporated into the optimal scheduling problem in the form of constraints or objective functions.

3.1 - Interval numbers

The interval arithmetic was firstly presented by Moore [38], and has been widely used in robust energy management tools [39]. This paradigm uses forecast information of uncertainties and their corresponding confidence intervals, which represent the range within the uncertain parameter may lie assuming possible forecast errors. This way, the uncertainties are represented by interval numbers, which are fully defined by their expected values and the predicted lower and upper margins. In this paper, the interval notation developed in [34], which is simple and avoids the use of interval arithmetic, has been used to model the energy price and PV generation. Given an arbitrary parameter a, its interval notation is defined by (1) and (2), while their upper and lower intervals can be calculated using (3) and (4), respectively.

$$[a] = \left[\underline{a}, \bar{a}\right] \tag{1}$$

$$[a] = \langle a | \underline{a} \leq a \leq \bar{a} \rangle \tag{2}$$

$$\Delta\bar{a} = \bar{a} - E(a) \tag{3}$$

$$\Delta\underline{a} = E(a) - \underline{a} \tag{4}$$

3.2 - Utility grid modelling

As commented, the PVaCS under study is connected to a local utility grid, from which can freely purchase and sell energy. The constraint (5) limits the instantaneous power that can be exchanged with the grid, while (6) makes the purchasing and selling processes complementary. Conventional thermal generators, which have a limited slow-response [40, 41], are assumed to be the principal generation technology at the upscale system. This circumstance is modelled by including ramp restrictions in (7).

$$p_{r|t}^{Grid,i} \leq u_t^{Grid,i} \cdot \overline{p}^{Grid};\ \forall r \in \mathbb{R} \wedge t \in \mathbb{T} \wedge i \in \{buy, sell\} \tag{5}$$

$$u_t^{Grid,buy} + u_t^{Grid,sell} \leq 1;\ \forall t \in \mathbb{T} \tag{6}$$

$$p_{r|t-1}^{Grid,buy} - R^{Grid} \leq p_{r|t}^{Grid,buy} \leq p_{r|t-1}^{Grid,buy} + R^{Grid};\ \forall r \in \mathbb{R} \wedge t \in \mathbb{T} \backslash t > 1 \tag{7}$$

3.3 - PV modelling

Potential PV generation is unpredictable due to it is mainly influenced by weather parameters. Nevertheless, the expected PV day-ahead potential can be forecasted with acceptable accuracy using conventional methods [36]. This feature motivates to use the interval notation to represent the potential PV generation with considerable confidence using (8).

$$p_{r|t}^{PV} \leq \overline{p}^{PV} \cdot [\hat{p}_t^{PV}];\ \forall r \in \mathbb{R} \wedge t \in \mathbb{T} \tag{8}$$

In fact, the constraint (8) limits the instantaneous PV generation to its forecasted value. Nonetheless, the predicted intervals are accounted as well when modelling the potential solar generation as an interval number.

3.4 - BES modelling

In this paper, conventional battery bank model based on power exchanging with the grid is used [42, 43]. The constraint (9) upper bounds the instantaneous exchanged power to rated values while the charging and discharging processes are forced to be complementary by (10). The expression (11) models the instantaneous state-of-charge (SOC) of the BES, which lies within the nominal capacity and depth-of-discharge settings by imposing (12). Lastly, the initial and final SOC are fixed equal to the nominal capacity by (13) in order to complement the model (11) at $\mathbb{T}(1)$.

$$p_{r|t}^{BES,i} \leq u_t^{BES,i} \cdot \overline{p}^{BES};\ \forall r \in \mathbb{R} \wedge t \in \mathbb{T} \wedge i \in \{ch, dch\} \tag{9}$$

$$u_t^{BES,ch} + u_t^{BES,dch} \leq 1;\ \forall t \in \mathbb{T} \tag{10}$$

$$\varepsilon_{r|t}^{BES} = \varepsilon_{r|t-1}^{BES} + \Delta\tau \cdot \left(\eta^{BES} \cdot p_{r|t}^{BES,ch} - \frac{p_{r|t}^{BES,dch}}{\eta^{BES}}\right);\ \forall r \in \mathbb{R} \wedge t \in \mathbb{T} \backslash t > \mathbb{T}(1) \tag{11}$$

$$(1 - DOD) \cdot \overline{\varepsilon}^{BES} \leq \varepsilon_{r|t}^{BES} \leq \overline{\varepsilon}^{BES};\ \forall r \in \mathbb{R} \wedge t \in \mathbb{T} \tag{12}$$

$$\varepsilon_{r|\mathbb{T}(1)}^{BES} = \varepsilon_{r|\mathbb{T}(\mathrm{end})}^{BES} = \overline{\varepsilon}^{BES};\ \forall r \in \mathbb{R} \tag{13}$$

3.5 - Charging station modelling

The expected EV demand (which is represented via scenarios as detailed in Section 4) may be fully covered or not. This is due to a charging event may result no profitable for the system operation because, for example, eventual high energy cost or low PV generation. In this case, the operator may decide to totally or partially unsatisfied this expected demand, as said (14).

$$p_{r|t}^{EV,i} \leq \hat{p}_{r|t}^{EV,i};\ \forall r \in \mathbb{R} \wedge t \in \mathbb{T} \wedge i \in \{SF, F\} \tag{14}$$

3.6 - System balance

The expression (15) represents the instantaneous power balance in the grid under study, which must be complied anytime.

$$p_{r|t}^{Grid,buy} + p_{r|t}^{BES,dch} + p_{r|t}^{PV} = \sum_{i \in \{SF,F\}} \{p_{r|t}^{EV,i}\} + p_{r|t}^{Grid,sell} + p_{r|t}^{BES,ch};\ \forall r \in \mathbb{R} \wedge t \in \mathbb{T} \tag{15}$$

3.7 - System profit

It is assumed that the system operator aims at maximizing his own benefit. In this regard, the operator may obtain revenues from EV charging and energy selling, while the expenditures would be destined for operation and maintenance and energy purchasing. Thereby, the system profit is calculated by (16).

$$f = f^{EV} - f^{Grid} - f^{O\&M} \tag{16}$$

In the expression above, the first term is the monetary incomes obtained from EV charging. The second term is the monetary balance for purchasing-selling from the utility grid, in which the energy pricing is modelled using interval numbers. Whereas the last term in (16) accounts for the operation and maintenance costs. These terms are respectively defined in (17)-(19).

$$f^{EV} = \sum_{r\in\mathbb{R}}\left\{\pi_r \cdot \sum_{t\in\mathbb{T}}\left\{\Delta\tau \cdot \left(\lambda^{EV,SF} \cdot p_{r|t}^{EV,SF} + \lambda^{EV,F} \cdot p_{r|t}^{EV,F}\right)\right\}\right\} \tag{17}$$

$$f^{Grid} = \sum_{r\in\mathbb{R}}\left\{\pi_r \cdot \sum_{t\in\mathbb{T}}\left\{\Delta\tau \cdot \left(\left[\hat{\lambda}_t^{buy}\right] \cdot p_{r|t}^{Grid,buy} - \left[\hat{\lambda}_t^{sell}\right] \cdot p_{r|t}^{Grid,sell}\right)\right\}\right\} \tag{18}$$

$$f^{O\&M} = \sum_{r\in\mathbb{R}}\left\{\pi_r \cdot \sum_{t\in\mathbb{T}}\left\{\Delta\tau \cdot \left(\kappa^{BES} \cdot \sum_{i\in\{ch,dch\}}\left\{p_{r|t}^{BES,i}\right\}\right)\right\}\right\} \tag{19}$$

It is worth to note that the operation and maintenance costs have been considered as a linear function of the energy exchanged between the system and BES, which is a widely adopted assumption in the literature [42]. On the other hand, the maintenance costs of PV panels are not accounted, where these expenditures can be considered marginal compared with the purchasing energy costs, as explained in [44].

4 - Stochastic modelling of EV demand

While PV generation and energy price are treated as interval numbers, the EV demand is modelled via scenarios. This approach is considered more suitable for the EV charging profiles due to this aspect strongly depends on the high stochastic behaviour of drivers. To this end, a comprehensive stochastic modelling for fast and semi-fast charging profiles is developed in this section. The developed approach is summarized in the flowchart of Fig. 3 and is developed and explained below.

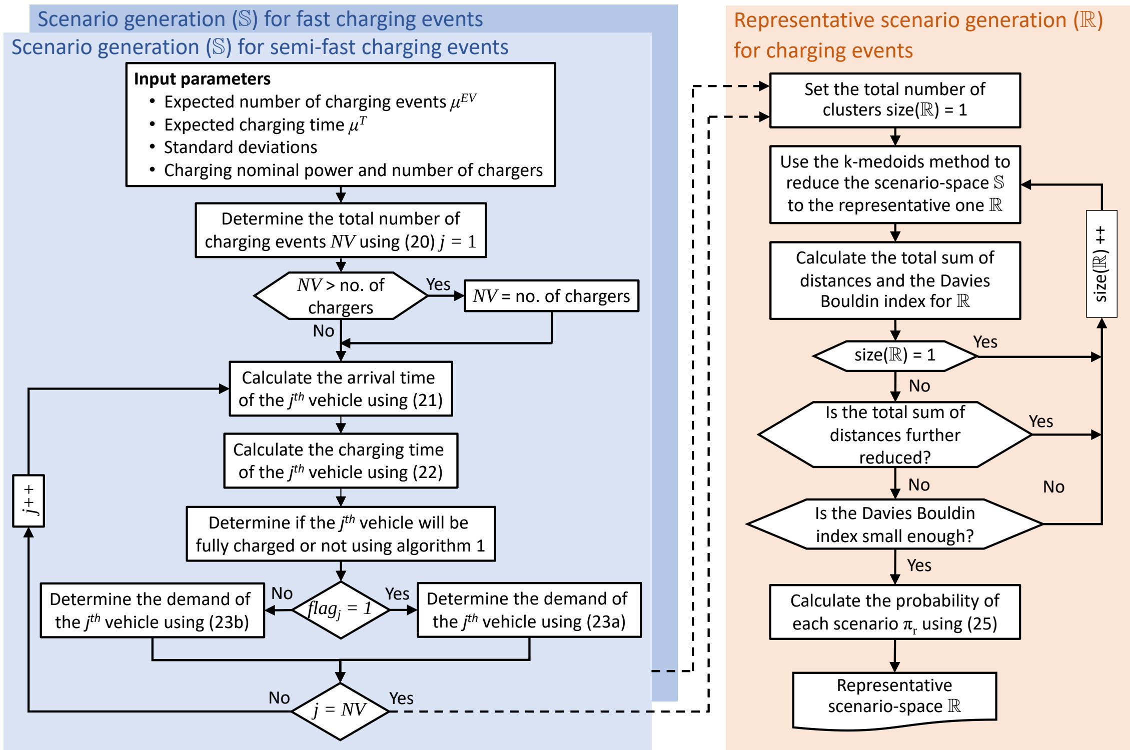

Fig. 3 - Flowchart of the developed stochastic approach for EV demand

The first aspect to consider is the expected number of charging events throughout the day. In this paper, it is assumed that this parameter can be modelled using a Gaussian distribution as follows

$$NV_s^i = \text{round}\left(\text{rand}\left(\mathcal{N}\left(\mu^{EV,i}, \sigma^{EV,i}\right)\right)\right);\ \forall s \in \mathbb{S} \wedge i \in \{SF, F\}, > 0 \tag{20}$$

The model above is considered plausible and practical since the probability distribution can be tuned on the basis of historical data or market studies. The developed approach considers the driver behaviour depicted in Fig. 4. By this model, it is assumed that the j^{th} vehicle that will charge at the station arrives at $q_{s|j}$, and will be charged during $T_{s|j}$ time intervals. These both parameters are actually uncertain. The arrival time is considered to be a function of the vehicle trip distribution. It means that the probability of a vehicle arrives at the station at time t will be proportional to the probability of a vehicle is driven at this time. This distribution is available for some countries like U.S. [45] (see Fig. 5), therefore, it can be used to determine the arrival time of the j^{th} according to (21), while the expected charging time will be calculated using a Gaussian distribution as in (22).

$$q_{s|j}^{i} = \text{round}(\text{rand}(\mathcal{F})); \boldsymbol{Q}_s^i = \left[q_{s|1}^i, q_{s|2}^i, \dots, q_{s|NV_s^i}^i\right], \forall s \in \mathbb{S} \wedge j \in \mathbb{J}^i \wedge i \in \{SF, F\} \quad (21)$$

$$T_{s|j} = \text{round}\left(\text{rand}\left(\mathcal{N}\left(\mu^{T,i}, \sigma^{T,i}\right)\right)\right); \forall s \in \mathbb{S} \wedge j \in \mathbb{J}^i \wedge i \in \{SF, F\}, > 0 \quad (22)$$

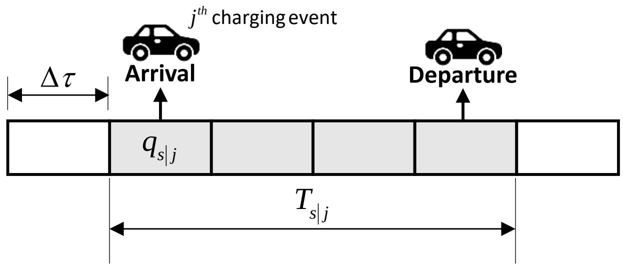

Fig. 4 - EV charging event modelling used in this paper

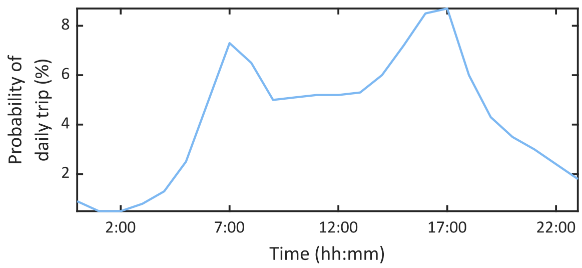

Fig. 5 - U.S. vehicle trip distribution [45]

The present approach also accounts for the total number of chargers available. This way, if the number of concurrent charging events at a determined time interval surpasses the number of chargers, it is assumed that the vehicle would leave the station without charging and therefore this event is lost. The charging profile is usually not constant during the whole charging event. This is due to some chargers limit the supplied power beyond a predefined SOC to avoid damaging the battery. Fig. 6 plots a typical charging profile and the piecewise representation used in this paper (Θ^{EV}). For each charging event, Algorithm 1 determines if the vehicle will be fully charged or not. This algorithm considers that the probability of a driver desires to get his vehicle fully charged at the departure time is fixed by the parameter $prob \leq 1$. Using this information, the algorithm determines for each j charging event in each s scenario, if the vehicle will be fully charged or not. After that, the expected EV demand of the *jth* charging event is calculated by (23a) in case of fully charging or (23b) otherwise. Lastly, the aggregated demand is calculated using (24). As a sake of example, Fig. 7 shows a daily EV demand profile generated by the developed approach.

$$\hat{p}^{EV,i}_{s|j|\boldsymbol{Q}_s(j):\boldsymbol{Q}_s(j)+T_{s|j}} = \overline{p}^{EV,i} \cdot \Theta^{EV,i}_{T_{s|j}:\mathrm{end}};\ \forall s \in \mathbb{S} \wedge t \in \mathbb{T} \wedge j \in \mathbb{J}^i \wedge i \in \{SF, F\} \tag{23a}$$

$$\hat{p}^{EV,i}_{s|j|\boldsymbol{Q}_s(j):\boldsymbol{Q}_s(j)+T_{s|j}} = \overline{p}^{EV,i} \cdot \boldsymbol{e}\left(T_{s|j}\right);\ \forall s \in \mathbb{S} \wedge t \in \mathbb{T} \wedge j \in \mathbb{J}^i \wedge i \in \{SF, F\} \tag{23b}$$

$$\hat{p}^{EV,i}_{s|t} = \sum_{j \in \mathbb{J}^i} \{\hat{p}^{EV,i}_{s|j|t}\};\forall s \in \mathbb{S} \wedge t \in \mathbb{T}\ \wedge i \in \{SF, F\} \tag{24}$$

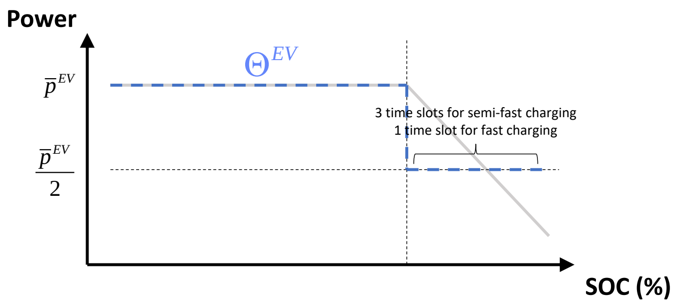

Fig. 6 - Typical EV charging profile (grey solid line) and the piecewise representation used in this paper (blue discontinuous line)

Algorithm 1: determination of fully or partially charging

1: Let NV_s and $prob$ (probability of fully charging)
2: **for** $j = 1{:}NV_s$ **do**
3: $\alpha_l = \mathrm{rand}\left(\mathcal{N}(1,0)\right)$
4: **if** $\alpha_j < prob$ **then**
5: $flag_j == 1$; *# Total charge*
6: **else**
7: $flag_j == 0$; *# Partial charge*
8: **end if**
9: **return** $flag_j$; $\forall j$

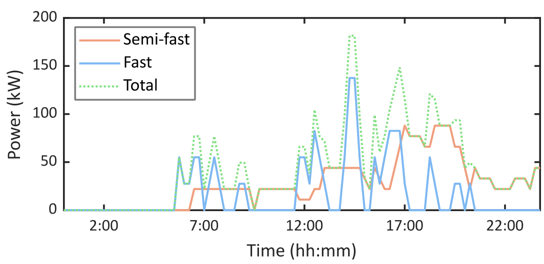

Fig. 7 - Example of daily EV demand generated by the developed approach

As pointed out in some references, the total number of scenarios to generate in stochastic models must be large (~1000 [46]). It normally entails a high computational burden that should be alleviated. To this end, multiple references use clustering techniques [47, 48]. In particular, the k-medoids method is used in this work because its good features [49]. To determine the optimal number of clusters, the algorithm presented in [26] has been used. This methodology uses some helpful indexes (the total sum of distances and the Davies Bouldin index) to iteratively set the most suitable number of clusters. This way, the scenario-space ($\mathbb{S}$) can be reduced to the representative scenario-space ($\mathbb{R}$), whose size is notably reduced. Finally, the probability of each representative scenario can be simply calculated by (25).

$$\pi_r = \frac{\text{size}(\Omega_r)}{\text{size}(\mathbb{S})}; \forall r \in \mathbb{R} \tag{25}$$

5 - The developed solution algorithm

This paper combines the interval formulation and stochastic modelling to represent the different uncertainties involved in the operation of the PVaCS described in Section 2. To solve the optimal scheduling problem associated with this model, an iterative algorithm has been developed, which is summarized by the flowchart in Fig. 8. This algorithm is inspired by [34] and avoids the use of interval arithmetic, which may result in large formulations and therefore high computational cost. The developed algorithm allows to consider optimistic and pessimistic point of views. In the former, it is assumed that uncertainties will impact positively on the economic profit, while the opposite trend will be observed if a pessimistic perspective is taken. For example, under an optimistic point of view, the PV generation will presumably take values at its upper predicted interval, thus the profit will increase. These both strategies can be assimilated to the risk-seeker and risk-averse perspectives described in [50]. This way, the obtained scheduling plan will be immune against possible deviations of the expected uncertain parameters. The iterative solution approach checks the convergence each iteration as follows

$$\frac{\left|f_k^{(2)}-f_k^{(3)}\right|}{f_k^{(3)}} \leq tol \tag{26}$$

where tol is the predefined convergence tolerance (0.1 in this paper), the superscripts indicate the stage and the subscript denotes the iteration counter. As seen in Fig. 8, the developed algorithm encompasses various stages which are described below.

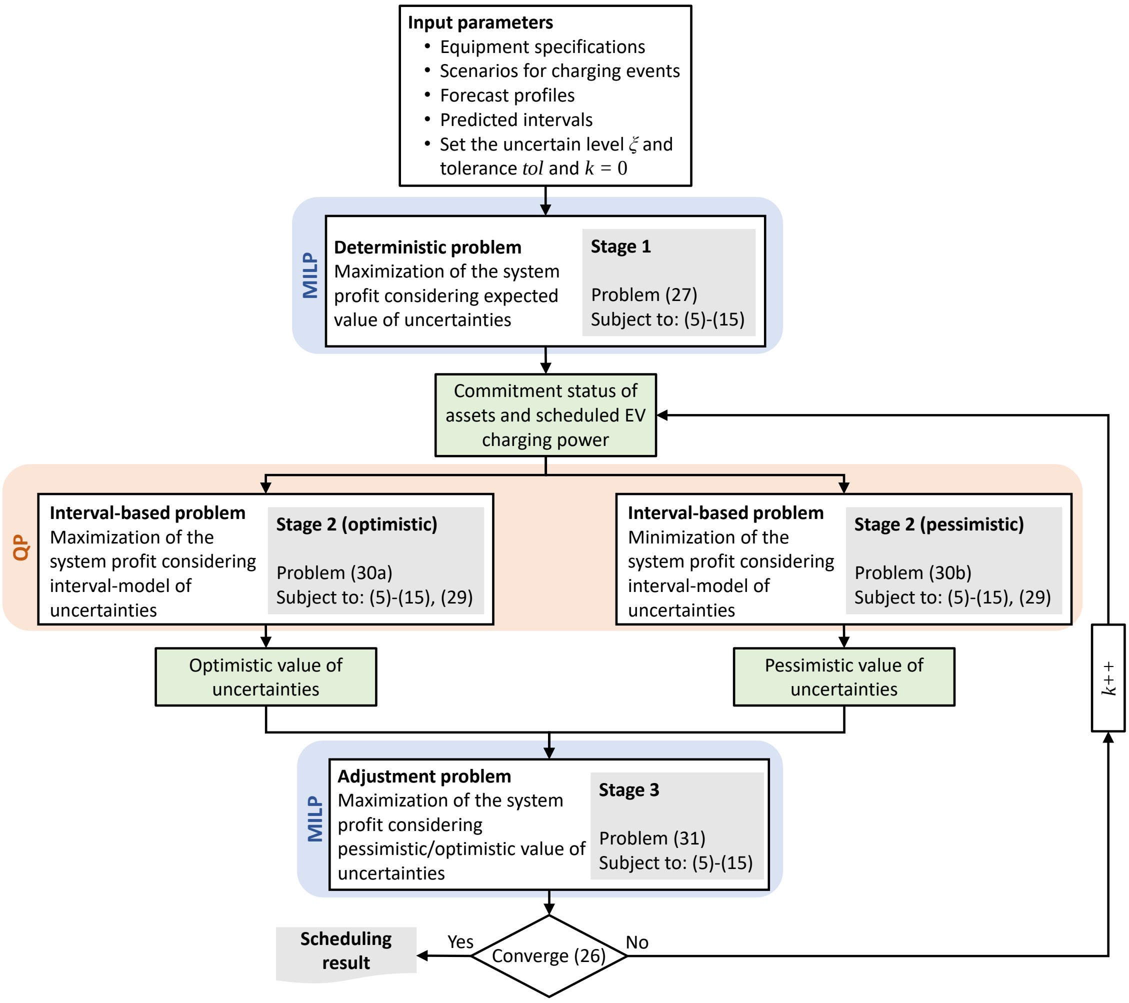

Fig. 8 - Flowchart of the developed solution procedure

5.1 - Stage 1: deterministic problem

The first stage corresponds to the conventional deterministic problem in which the profit is maximized assuming the expected value of the uncertainties. As a result of this problem, the commitment status of assets and satisfied EV demand are obtained.

Therefore, the Stage 1 of the developed methodology can be formally established as follows

$$\boldsymbol{u}_{det}, \boldsymbol{P}_{det}^{EV,i} \rightarrow \underset{\boldsymbol{x},\boldsymbol{u}}{\operatorname{argmax}} f\left(E(\boldsymbol{\Psi})\right); i \in \{SF, F\} \tag{27}$$

Subject to: (4)-(14)

where

$$\boldsymbol{P}_{det}^{EV,i} = \begin{bmatrix} p_{\mathbb{R}(1)|\mathbb{T}(1)}^{EV,i} & \cdots & p_{\mathbb{R}(1)|\mathbb{T}(\mathrm{end})}^{EV,i} \\ \vdots & \ddots & \vdots \\ p_{\mathbb{R}(\mathrm{end})|\mathbb{T}(1)}^{EV,i} & \cdots & p_{\mathbb{R}(\mathrm{end})|\mathbb{T}(\mathrm{end})}^{EV,i} \end{bmatrix}; i \in \{SF, F\} \tag{28}$$

5.2 - Stage 2: uncertain-related problem

This stage focuses on determining the extreme value of the interval-based uncertainties, for which the results obtained at Stage 1 are feasible yet. In this regard, the PV generation and energy pricing are considered variables of the problem, and allowed to vary within the corresponding predicted intervals, as said (29).

$$E(\hat{a}_t) - \xi \cdot \Delta\underline{a}_t \leq [\hat{a}_t] \leq E(\hat{a}_t) + \xi \cdot \Delta\overline{a}_t;\ \forall t \in \mathbb{T} \wedge\ \hat{a} \in \boldsymbol{\Psi} \tag{29}$$

where $\xi \in [0,1]$ is the so-called uncertain level that allows to set the degree of robustness of the problem. Indeed, if $\xi = 1$, the uncertainties can take any value within their predicted intervals. This way, the problem is more uncertain-oriented. In contrast, if $\xi = 0$, the uncertainties will take their expected values and therefore the problem becomes deterministic.

As commented, the Stage 2 aims at seeking the extreme value of the uncertainties for which the deterministic result is still feasible. Therefore, the formulation of this stage will change depending on the adopted perspective. In the optimistic case, the uncertainties are assumed to vary so that the profit is maximized, while under a pessimistic perspective the uncertainties negatively impact on the monetary revenues. Therefore, this stage can be formulated by (30).

$$\boldsymbol{\Psi}_{opt} \rightarrow \underset{\boldsymbol{x},\boldsymbol{\Psi}}{\operatorname{argmax}} f\left(\boldsymbol{u}_{det}, \boldsymbol{P}_{det}^{EV,i}\right);\ i \in \{SF, F\} \tag{30a}$$

$$\boldsymbol{\Psi}_{pes} \rightarrow \underset{\boldsymbol{x},\boldsymbol{\Psi}}{\operatorname{argmin}} f\left(\boldsymbol{u}_{det}, \boldsymbol{P}_{det}^{EV,i}\right);\ i \in \{SF, F\} \tag{30b}$$

Subject to: (4)-(14), (29)

5.3 - Stage 3: adjustment problem

Finally, the commitment status and satisfied EV demand are adjusted according the extreme values of uncertainties obtained at the previous stage. Therefore, this problem is posed as a deterministic model, but considering the optimistic or pessimistic uncertain profiles instead of the expected ones. Following this idea, the mathematical formulation of the Stage 3 is given by

$$\boldsymbol{u}_{det}, \boldsymbol{P}_{det}^{EV,i} \rightarrow \underset{\boldsymbol{x},\boldsymbol{u}}{\operatorname{argmax}} f\left(E(\boldsymbol{\Psi}_l)\right); i \in \{SF, F\}, l = opt \vee pes \tag{31}$$

Subject to: (4)-(14)

6 - Case study

This section presents a case study based on the PVaCS layout described in Section 2. The developed solution procedure involves two MILP problems and one QP, which have been coded under Matlab R2019a and solved using Gurobi [51]. All simulations have been performed on an Intel® Core™ i5-9400F, 2.90 GHz, 8.00 GB RAM, over a 24 hours horizon.

Time resolution (denoted by $\Delta\tau$) is a critical aspect as it determines the computational burden and accuracy of the scheduling tool. Normally, this parameter should be fixed by the operator in order to obtain a trade-off between these two aspects. For the scope of this paper, the charging events are by far the fastest processes that must be captured by the time step. Hence, this parameter should be fixed short enough to accurately represent the charging events. Currently, fast chargers are able to charge an average vehicle in 15-30 minutes [22]. In consequence, it seems reasonable to set the time step in 15 minutes in order to be able to capture fast charging events. Preliminary experiments carried out by the authors revealed good performance, taking 5-10 minutes to be completed, on average. Nevertheless, shorter time intervals may be used without any problem, using the same formulation and principles described in previous sections.

6.1 - Input data

For the different simulations performed, real data have been considered as expected profiles for PV generation and energy pricing, which are plotted in Fig. 9 along their predicted intervals. In particular, the expected PV generation has been built according to weather data observed at Madrid (Spain) on July 19, 2016 [52], assuming a PV array of 150 kW rated power. On the other hand, purchasing and selling energy prices correspond to real-time pricing at the PJM FE Ohio system on July 1 and 9, 2019, respectively [53]. The EV demand has been constructed according the model described in Section 3. A medium-size multi-mode station has been considered. Table 2 collects the data of the charging infrastructures. With this data, 1000 scenarios were constructed, which were further reduced to 13 using the reduction technique described in [26] and summarized in Fig. 3. The other relevant data referred to different system components are collected in Table 3.

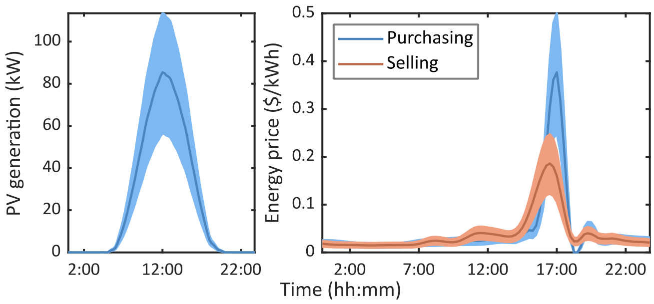

Fig. 9 - Expected PV generation (left) and energy pricing (right) along their predicted intervals

Table 2 - Data of the charging station and EV scenarios

Charging mode	**Fast**	**Semi-fast**
λ^{EV}	0.5 $/kWh	0.2 $/kWh
μ^{EV}	30	15
σ^{EV}	5	2
μ^{T}	30 min	3 hours
σ^{T}	1	1
Rated power	55 kW	22 kW
No. of chargers	10	5

Table 3 - Simulation parameters [42]

Parameter	**Value**
$\overline{p}^{Grid}/R^{Grid}/\overline{p}^{BES}$	100/50/25 kW
$\overline{\varepsilon}^{BES}$	100 kWh
DOD	0.7 pu
η^{BES}	0.98 pu
κ^{BES}	2.35 $/MWh

6.2 - Results and discussion

In this subsection, various results are presented considering the data collected in the previous section. The simulations are presented for various uncertain levels (ξ) in general, with illustrative purposes. To validate the scheduling tool, Fig. 10 plots the scheduling result under deterministic conditions. As observed, EV demand is completely satisfied during morning and evening, when low energy prices and high PV generation make attractive to purchase energy from the grid and sell it to vehicles. During these hours, batteries are also partially discharged in order to increase the energy available. During midday, high PV potential and low EV demand enable the possibility of selling energy to the grid. This process is however not attractive at 17:00 h despite selling prices achieve their maximum during this hour. This is because it is more profitable to use the energy to charge vehicles. In this regard, the high demand for EVs puts the limits of the station, so that it is unable to produce a surplus energy that may be delivered to the grid. Finally, the last hours of the day are devoted on charging the batteries and covering the low EV demand during night. It is also noteworthy that EV demand is only partially covered about

17:00h. At this hour, the purchasing price reaches its maximum and, in addition, PV generation is falling down. These circumstances force to acquire energy from the grid at high price to satisfy the EV demand, which results few attractive economically.

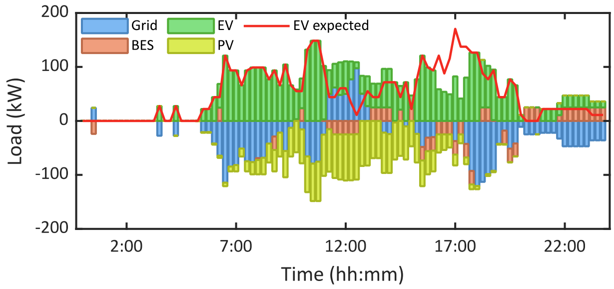

Fig. 10 - Scheduling result under deterministic conditions (negative values mean to-station (generation) flows)

To discern the role of uncertainties and how the new proposal handle with, Fig. 11 plots the expected system profit under different point of views. As seen, the obtained results follow a logic trend. Hence, the expected profit grows by 9% with the uncertain level when an optimistic strategy is taken, while the opposite behavior was observed under a pessimistic perspective, thus reducing the expected profit by 3% compared with the deterministic case. These results are logic since, under an optimistic point of view, the uncertainties took values that favor the increment of the monetary revenues. This is more clearly observed in Fig. 12, where the potential PV generation is plotted for various cases. As seen, the PV potential is assumed to be higher than the expected profile when an optimistic point of view is adopted. In contrast, the developed methodology adopts a risk-seeker strategy when a pessimistic point of view is considered, assuming that the PV potential will be lower than the forecasted value, which is negatively reflected in the system profit, as observed in Fig. 11.

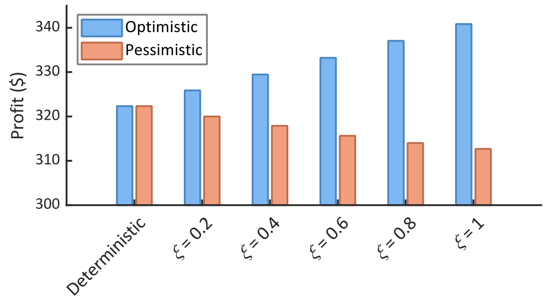

Fig. 11 - Expected profit for uncertain levels

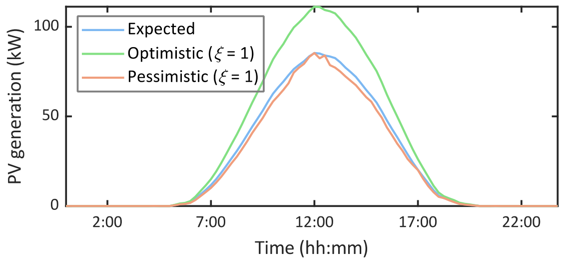

Fig. 12 - Assumed extreme values of potential PV generation under different point of views

Logically, the lower PV potential, the lower PV generation, as observed in Fig. 13 where the actual PV contribution is shown in different cases. From this figure, it can be observed that when a pessimistic perspective is assumed, the PV generation is reduced by ~50 kWh/day. In contrast, if an optimistic position is adopted, the expected PV contribution is assumed to increase by ~150 kWh/day. Similar behavior can be observed in the energy price, as depicted in Fig. 14, where the average energy pricing is plotted for different cases. As observed, under an optimistic strategy, the average selling price is incremented with the uncertain level while the purchasing price falls down. As in the case of the PV generation, the opposite trends were observed under a pessimistic perspective. Indeed, these extreme values of the uncertainties have a positive or negative effect on the economy of the system when optimistic or pessimistic perspectives are adopted, respectively. This result was expected since, under a pessimistic strategy, the scheduling tool becomes risk-averse and seeks a result immune against uncertainties, whereas the algorithm becomes risk-seeker under an optimistic point of view.

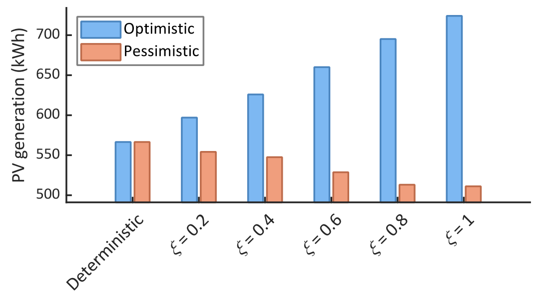

Fig. 13 - Total PV generation for different cases

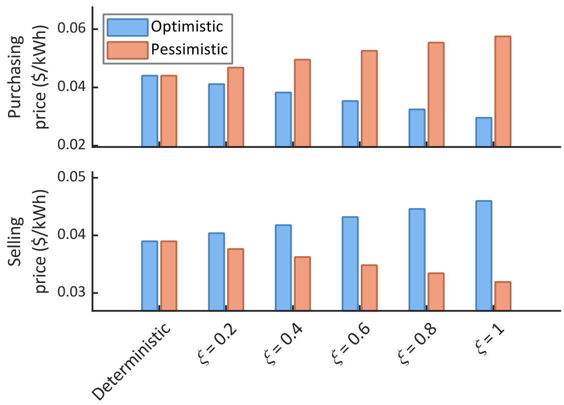

Fig. 14 - Average purchasing and selling prices for different cases

As expected, the energy price has a direct impact on the total energy exchanged with the grid. Fig. 15 shows the total expenditures/revenues obtained from energy exchanging with the utility grid for different cases. As seen in this figure, the total expenditures grow with the uncertain level when a pessimistic perspective is adopted. This circumstance is reflected in lower monetary revenues, as explained above. In contrast, the system obtains a notably profit from energy selling under an optimistic point of view. Actually, monetary incomes from energy selling could be increased by 70% adopting an optimistic strategy. Under both strategies, expenditures and revenues, followed different trends, as expected. The energy exporting character of the studied system is better observable in Fig. 16, where the hourly PV generation and energy sold are plotted when both pessimistic and optimistic strategies are adopted. As seen, the system is able to sell much more energy when the scheduling tool takes an optimistic character. This is undoubtedly propitiated by a larger PV generation that occasionally produces a surplus energy which can be sold to the grid to obtain a monetary revenue. In fact, PV peak power is expected to be about 125 kW with an optimistic point of view, while the peak solar power did not reach 100 kW with a pessimistic strategy.

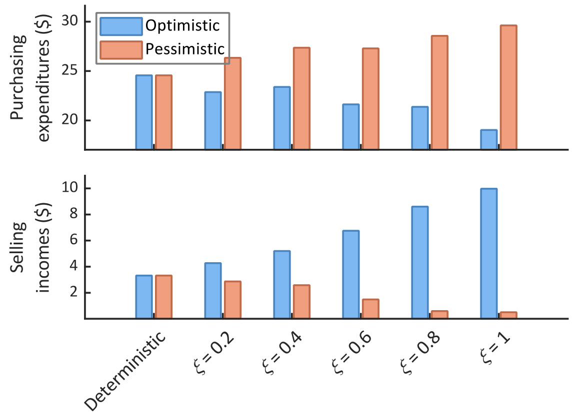

Fig. 15 - Total expenditures and revenues obtained from energy exchanging with the utility grid

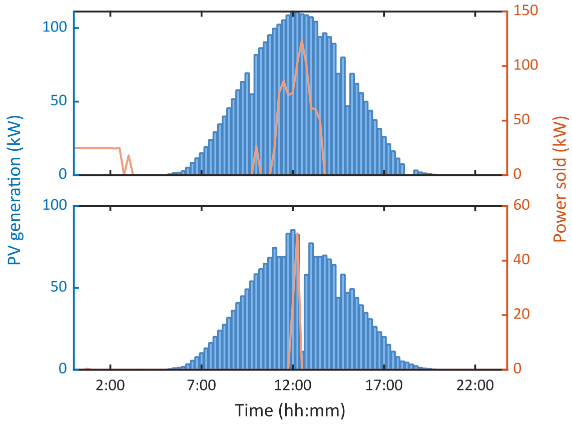

Fig. 16 - Hourly PV generation and energy sold under optimistic (top) and pessimistic (bottom) point of views with $\xi = 1$

Lastly, it is interesting to analyze how the different strategies affect the satisfied EV demand. As commented, the developed model considers that EV demand may be partially unsatisfied if it results economically not attractive. In Fig. 17, the expected monetary revenues obtained from EV charging are plotted for different cases. As seen in this figure, charging incomes grow with the uncertain level under an optimistic point of view and decrease with a pessimistic strategy. It means that, under a pessimistic point of view, more charging events are only partially satisfied. This is due to low PV generation and high energy prices make the charging business not attractive during some particular hours of the day. On the face of this situation, the developed scheduling tool determined that it is more profitable rejecting the charging event than satisfying it.

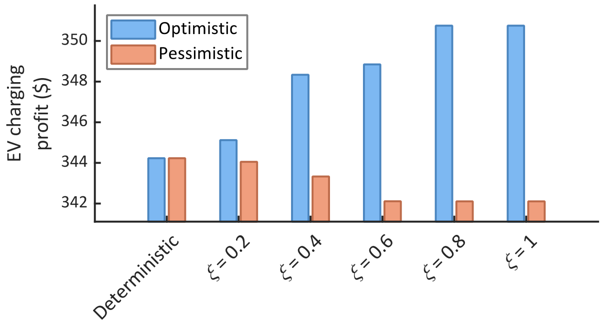

Fig. 17 - Monetary revenues from EV charging for different cases

7 - Conclusions and future works

In this paper, a novel stochastic-interval model for multi-mode PVaCSs has been developed. The new proposal uses an interval formulation to model the uncertainties brought by PV generation and energy price, while a comprehensive stochastic model was developed to represent the uncertain behaviour of EV demand. An iterative procedure has been proposed to solve the optimal scheduling problem under pessimistic or optimistic strategies. This methodology encompasses the various stages that imply two MILP problems and one QP problem, that can be efficiently solved using standard software.

A case study was presented to show the effectiveness of the developed tool. To this end, the results have been analysed for various uncertain levels and strategies. The results obtained were totally logic, thus validating the developed scheduling tool. As a sake of example, the system profit grew by 9% and decreased by 3% adopting optimistic and pessimistic point of view, respectively. Likewise, total PV generation increased by 150 kWh/day and reduced by 50 kWh/day. Similar conclusions were drawn for other parameters such as monetary balances, PV peak power or satisfied EV demand.

Ongoing works are focused on applying similar formulations to other related problems like home energy management tools. Moreover, it is projected to analyse the interaction of PVaCSs with other system agents, for which the developed model may be useful.

Acknowledgements

The icons used in this paper were developed by AmethystDesign, Freepik and fjstudio from www.flaticon.com.

References

[1] European Commission. Stepping up Europe’s 2030 climate ambition Investing in a climate-neutral future for the benefit of our people. COM/2020/562 final, 2020.

[2] R.T. Pietzcker, S. Osorio, R. Rodrigues. Tightening EU ETS targets in line with the European Green Deal: Impacts on the decarbonization of the EU power sector. *Applied Energy* 2021; 293: 116914. https://doi.org/10.1016/j.apenergy.2021.116914.

[3] International Energy Agency. World Energy Outlook 2021. Online, available at: https://www.iea.org/reports/world-energy-outlook-2021, (accessed on Jan. 21, 2022).

[4] European Commission. A Clean Planet for all: A European long-term strategic vision for a prosperous, modern, competitive and climate neutral economy. COM(2018) 773, 2018.

[5] A. Jäeger-Waldau. PV Status Report 2019. EUR 29938 EN, Publications Office of the European Union, Luxembourg, 2019. https://doi.org/10.2760/329862.

[6] A. Jäeger-Waldau. Snapshot of Photovoltaics-February 2020. *Energies* 2020; 13: 930. https://doi.org/10.3390/en13040930.

[7] R. Khezri, A. Mahmoudi, H. Aki. Optimal planning of solar photovoltaic and battery storage systems for grid-connected residential sector: Review, challenges and new perspectives. *Renewable & Sustainable Energy Reviews* 2022; 153: 111763. https://doi.org/10.1016/j.rser.2021.111763.

[8] Y. Guo, J. Xiong, S. Xu, W. Su. Two-Stage Economic Operation of Microgrid-Like Electric Vehicle Parking Deck. *IEEE Transactions on Smart Grid* 2016; 7(3): 1703-12. https://doi.org/10.1109/TSG.2015.2424912.

[9] Q. Chen et al. Dynamic Price Vector Formation Model-Based Automatic Demand Response Strategy for PV-Assisted EV Charging Stations. *IEEE Transactions on Smart Grid* 2017; 8(6): 2903-15. https://doi.org/10.1109/TSG.2017.2693121.

[10] A. Saez-de-Ibarra et al. Management Strategy for Market Participation of Photovoltaic Power Plants Including Storage Systems. *IEEE Transactions on Industry Applications* 2016; 52(5): 4292-303. https://doi.org/10.1109/TIA.2016.2585090.

[11] Y. Wi, J. Lee, S. Joo. Electric vehicle charging method for smart homes/buildings with a photovoltaic system. *IEEE Transactions on Consumer Electronics* 2013; 59(2): 323-8. https://doi.org/10.1109/TCE.2013.6531113.

[12] Y. Guo, J. Xiong, S. Xu, W. Su. Two-Stage Economic Operation of Microgrid-Like Electric Vehicle Parking Deck. *IEEE Transactions on Smart Grid* 2016; 7(3): 1703-12. https://doi.org/10.1109/TSG.2015.2424912.

[13] S. Negarestani, M. Fotuhi-Firuzabad, M. Rastegar, A. Rajabi-Ghahnavieh. Optimal Sizing of Storage System in a Fast Charging Station for Plug-in Hybrid Electric Vehicles. *IEEE Transactions on Transportation Electrification* 2016; 2(4): 443-53. https://doi.org/10.1109/TTE.2016.2559165.

[14] Q. Zhong, Y. Sun, L. Peng. A Novel Control Strategy on Multiple-Mode Application of Electric Vehicle in Distributed Photovoltaic Systems. *Complexity* 2018; 2018: 1640395. https://doi.org/10.1155/2018/1640395.

[15] F. Luo, G. Ranzi, W. Kong, Z.Y. Dong, F. Wang. Coordinated residential energy resource scheduling with vehicle-to-home and high photovoltaic penetrations. *IET Renewable Power Generation* 2018; 12(6): 625-32. https://doi.org/10.1049/iet-rpg.2017.0485.

[16] S. Golshannavaz. Cooperation of electric vehicle and energy storage in reactive power compensation: An optimal home energy management system considering PV presence. *Sustainable Cities & Society* 2018; 39: 317-25. https://doi.org/10.1016/j.scs.2018.02.018.

[17] H.H. Eldeeb, S. Faddel, O.A. Mohammed. Multi-Objective Optimization Technique for the Operation of Grid tied PV Powered EV Charging Station. *Electric Power Systems Research* 2018; 164: 201-11. https://doi.org/10.1016/j.epsr.2018.08.004.

[18] H. Liu, Y. Zhang, S. Ge, C. Gu, F. Li. Day-Ahead Scheduling for an Electric Vehicle PV-Based Battery Swapping Station Considering the Dual Uncertainties. *IEEE Access* 2019; 7: 115625-36. https://doi.org/10.1109/ACCESS.2019.2935774.

[19] Y. Liu, J. Yang, Y. Wang, Y. Chai, J. Xu. Electric Vehicle Charging and Batteries Swapping Management Strategy with Photovoltaic Generation in Business Districts. *Electric Power Components & Systems* 2019; 47(9-10): 889902. https://doi.org/10.1080/15325008.2019.1627609.

[20] M. Shin, D.-H. Choi, J. Kim. Cooperative Management for PV/ESS-Enabled Electric Vehicle Charging Stations: A Multiagent Deep Reinforcement Learning Approach. *IEEE Transactions on Industrial Informatics* 2020; 16(5): 3493-503. https://doi.org/10.1109/TII.2019.2944183.

[21] V. Gupta, S.R. Konda, R. Kumar, B.K. Panigrahi. Collaborative multi-aggregator electric vehicle charge scheduling with PV-assisted charging stations under variable solar profiles. *IET Smart Grid* 2020; 3(3): 287-99. https://doi.org/10.1049/iet-stg.2019.0088.

[22] M. Tostado-Véliz, P. Arévalo, F. Jurado. A comprehensive electrical-gas-hydrogen Microgrid model for energy management applications. *Energy Conversion & Management* 2021; 228: 113726. https://doi.org/10.1016/j.enconman.2020.113726.

[23] B. Sun. A multi-objective optimization model for fast electric vehicle charging stations with wind, PV power and energy storage. *Journal of Cleaner Production* 2021; 288: 125564. https://doi.org/10.1016/j.jclepro.2020.125564.

[24] A. Akbari-Dibavar, V.S. Tabar, S.G. Zadeh, R. Nourollahi. Two-stage robust energy management of a hybrid charging station integrated with the photovoltaic system. *International Journal of Hydrogen Energy* 2021; 46(24): 12701-14. https://doi.org/10.1016/j.ijhydene.2021.01.127.

[25] L.F. Nishimwe, S.-G. Yoon. Combined Optimal Planning and Operation of a Fast EV-Charging Station Integrated with Solar PV and ESS. *Energies* 2021; 14: 3152. https://doi.org/10.3390/en14113152.

[26] M. Tostado-Véliz, R.S. León-Japa, F. Jurado. Optimal Electrification of Off-grid Smart Homes Considering Flexible Demand and Vehicle-to-Home Capabilities. *Applied Energy* 2021; 298: 117184. https://doi.org/10.1016/j.apenergy.2021.117184.

[27] A. Mansour-Saatloo et al. Multi-objective IGDT-based scheduling of low-carbon multi-energy microgrids integrated with hydrogen refueling stations and electric vehicle parking lots. *Sustainable Cities & Society* 2021; 74: 103197. https://doi.org/10.1016/j.scs.2021.103197.

[28] G.J. Osório et al. Modeling an electric vehicle parking lot with solar rooftop participating in the reserve market and in ancillary services provision. *Journal of Cleaner Production* 2021; 318: 128503. https://doi.org/10.1016/j.jclepro.2021.128503.

[29] A.R. Jordehi, M.S. Javadi, J.P.S. Catalão. Day-ahead scheduling of energy hubs with parking lots for electric vehicles considering uncertainties. *Energy* 2021; 229: 120709. https://doi.org/10.1016/j.energy.2021.120709.

[30] S.A. Habeeb et al. DC Nanogrids for Integration of Demand Response and Electric Vehicle Charging Infrastructures: Appraisal, Optimal Scheduling and Analysis. *Electronics* 2021; 10: 2484. https://doi.org/10.3390/electronics10202484.
[31] M. Gough et al. Operation of a Technical Virtual Power Plant Considering Diverse Distributed Energy Resources. *IEEE Transactions on Industry Applications*; Early access. https://doi.org/10.1109/TIA.2022.3143479.
[32] M. Tostado-Véliz, S. Gurung, F. Jurado. Efficient Solution of Many-objective Home Energy Management Systems. *International Journal of Electrical Power & Energy Systems* 2022; 136: 107666. https://doi.org/10.1016/j.ijepes.2021.107666.
[33] M. Shafie-Khah, P. Siano. A Stochastic Home Energy Management System Considering Satisfaction Cost and Response Fatigue. *IEEE Transactions on Industrial Informatics* 2018; 14(2): 629-38. https://doi.org/10.1109/TII.2017.2728803.
[34] M. Tostado-Véliz, S. Kamel, H.M. Hasanien, R.A. Turky, F. Jurado. A mixed-integer-linear-logical programming interval-based model for optimal scheduling of isolated microgrids with green hydrogen-based storage considering demand response. *Journal of Energy Storage* 2022; 48: 10428. https://doi.org/10.1016/j.est.2022.104028.
[35] M. Mehdinejad, H. Shayanfar, B. Mohammadi-Ivatloo. Peer-to-peer decentralized energy trading framework for retailers and prosumers. *Applied Energy* 2022; 308: 118310. https://doi.org/10.1016/j.apenergy.2021.118310.
[36] A.R. Jordehi, M.S. Javadi, M. Shafie-khah, J.P.S. Catalão. Information gap decision theory (IGDT)-based robust scheduling of combined cooling, heat and power energy hubs. *Energy* 2021; 231: 120918. https://doi.org/10.1016/j.energy.2021.120918.
[37] V.S. Tabar, S. Ghassemzadeh, S. Tohidi. Energy management in hybrid microgrid with considering multiple power market and real time demand response. *Energy* 2019; 174: 10-23. https://doi.org/10.1016/j.energy.2019.01.136.
[38] R.E. Moore. Methods and applications of interval analysis. Philadelphia, PA, U.S.: SIAM, 1979.
[39] N. Nasiri et al. Interval optimization-based scheduling of interlinked power, gas, heat, and hydrogen systems. *IET Renewable Power Generation* 2021; 15(2): 1214-26. https://doi.org/10.1049/rpg2.12101.
[40] Y. Zhou, Q. Zhai, W. Yuan, J. Wu. Capacity expansion planning for wind power and energy storage considering hourly robust transmission constrained unit commitment. *Applied Energy* 2021; 302: 117570. https://doi.org/10.1016/j.apenergy.2021.117570.
[41] S.J.S. Gao, G. Pan, Y. Liu, C. Wu, S. Wang. Congestion-aware robust security constrained unit commitment model for AC-DC grids. *Applied Energy* 2021; 304: 117392. https://doi.org/10.1016/j.apenergy.2021.117392.
[42] M. Tostado-Véliz, P. Arévalo, F. Jurado. An optimization framework for planning wayside and on-board hybrid storage systems for tramway applications. *Journal of Energy Storage* 2021; 43: 103207. https://doi.org/10.1016/j.est.2021.103207.
[43] M. Lotfi et al. Coordinating energy management systems in smart cities with electric vehicles. *Applied Energy* 2022; 307: 118241. https://doi.org/10.1016/j.apenergy.2021.118241.
[44] N.G. Paterakis, O. Erdinç, A.G. Bakirtzis, J.P.S. Catalão. Optimal Household Appliances Scheduling Under Day-Ahead Pricing and Load-Shaping Demand Response Strategies. *IEEE Transactions on Industrial Informatics* 2015; 11(6): 1509-19. https://doi.org/10.1109/TII.2015.2438534.
[45] S. Negarestani, M. Fotuhi-Firuzabad, M. Rastegar, A. Rajabi-Ghahnavieh. Optimal Sizing of Storage System in a Fast Charging Station for Plug-in Hybrid Electric Vehicles. *IEEE Transactions on Transportation Electrification* 2016; 2(4): 443-53. https://doi.org/10.1109/TTE.2016.2559165.
[46] H. Rashidizadeh-Kermani, M. Vahedipour-Dahraie, A. Anvari-Moghaddam, J.M. Guerrero. A stochastic bi-level decision-making framework for a load-serving entity in day-ahead and balancing markets. *International Transactions on Electrical Energy Systems* 2019; 29(11): e12109. https://doi.org/10.1002/2050-7038.12109.

[47] A.R. Jordehi. Economic dispatch in grid-connected and heat network-connected CHP microgrids with storage systems and responsive loads considering reliability and uncertainties. *Energy* 2021; 73: 103101. https://doi.org/10.1016/j.scs.2021.103101.
[48] M. Mansour-Lakouraj, H. Niaz, J.J. Liu, P. Siano, A. Anvari-Moghaddam. Optimal risk-constrained stochastic scheduling of microgrids with hydrogen vehicles in real-time and day-ahead markets. *Journal of Cleaner Production* 2021; 318: 128452. https://doi.org/10.1016/j.jclepro.2021.128452.
[49] E.S. Pinto, L.M. Serra, A. Lázaro. Evaluation of methods to select representative days for the optimization of polygeneration systems. *Renewable Energy* 2020; 151: 488-502. https://doi.org/10.1016/j.renene.2019.11.048.
[50] M. Daneshvar, B. Mohammadi-Ivatloo, K. Zare, S. Asadi, A. Anvari-Moghaddam. A Novel Operational Model for Interconnected Microgrids Participation in Transactive Energy Market: A Hybrid IGDT/Stochastic Approach. *IEEE Transactions on Industrial Informatics* 2021; 17(6): 4025-35. https://doi.org/10.1109/TII.2020.3012446.
[51] Gurobi Optimization L.L.C. Gurobi Optimizer Reference Manual, 2021. Online, available at: https://www.gurobi.com, (accessed Jan. 31, 2022).
[52] European Commission. Photovoltaic Geographical Information System. Online, available at: https://re.jrc.ec.europa.eu/pvg_tools/en/tools.html, (accessed Jan. 11, 2022).
[53] Engie. Historical data reports. Online, available at: https://www.engieresources.com/historical-data#reports_anchor, (accessed Jan. 11, 2022).