A two-stage IGDT-stochastic model for optimal scheduling of energy communities with intelligent parking lots

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Abstract. The proliferation of green mobility will bring multiple benefits to the society; however, it may be counterproductive for power systems if its integration is not properly planned. In this context, Intelligent Parking Lots have emerged as a valuable paradigm for integration of electric vehicles into energy systems. This framework consists of a set of vehicles that are managed as a whole and makes possible to exploit them as large storage facilities through their vehicle-to-grid capability. This particular feature may be significantly advantageous for energy communities since they can exploit parking lots as collective storage systems. In this paper, a two-stage optimal scheduling framework has been developed for optimal scheduling of energy communities. The proposal uses a stochastic representation of the state-of-charge of the lots with the end of accounting for random behaviour of uncertainties. On the other hand, the uncertainty of the upstream energy market is dealt with Information Gap Decision theory, resulting in an original hybridization that allows to adopt a risk-averse strategy by the operator. The optimization problem is formulated as a Mixed-Integer Linear programming model that can be efficiently solved by average solvers. A case study is performed to validate the new proposal and analyse the role of Intelligent Parking Lots in energy communities. The results evidence the advantages that electric vehicles may bring to communities if they are optimally exploited, highlighting their capability to enhance the efficiency and economy of the system.

Keywords. Electric vehicle; Intelligent Parking lot; Energy community; Energy storage.

Nomenclature

Indexes (Sets)

$s(\mathbb{S})$	Scenario
$r(\mathbb{R})$	Representative scenario
v	Vehicle
$t(\mathbb{T})$	Time
$\boldsymbol{\Omega}_r$	Cluster of the r^{th} representative scenario
Φ	Decision variables (power, energy and commitment status)

Superscripts

$Grid, buy/sell$	Buying/selling exchanges with the utility grid
IPL	Intelligent parking lot
ch/dch	Charging/discharging mode
0	Initial
a/d	Arrival/departure
Pnd	Prosumers net demand
$(\overline{*})/(\underline{*})$	Maximum/minimum value

Functions

$\widetilde{\mathcal{N}}(\mu, \sigma, LB, UB)$	Truncated Gaussian distribution with mean μ, standard deviation σ, lower bound LB and upper bound UB
$\mathcal{F}$	Probability of daily trips
$E(*)$	Expected value of an uncertain parameter
$\text{size}(*)$	Number of elements within a set, vector, matrix or cluster
$[*]^{\intercal}$	Transpose operator

Parameters

NV	Number of vehicles that will park at the station throughout a day
C	Makes mention to the capacity of a vehicle or its initial state-of-charge when superscripted by 0 (kWh)
T	Total number of time slots that a vehicle will be plugged at the station or arrival/departure time when superscripted by a/d
$\mathbf{Q}$	Auxiliary matrix for modelling the vehicles' plugging status
π	Probability (pu)
λ	Energy price ($/kWh)
Δ^{Cost}	Marks the maximum deviation from the expected cost

Decision variables

p	Power (kW)
u	Commitment status (binary)
SOC	State-of-charge (kWh)
α	Uncertain radius for energy prices ($/kWh)

Linear representation of bi-linear terms (see Appendix)

$(\tilde{*})$	Grid-point of piecewise representation
δ	SOS1 variable (binary)
$\Delta\widetilde{\omega}$, Δy, Δz	Continuous auxiliary variables for representing deviation of variables from piecewise points

1 - Introduction

1.1 - Context & motivation

Greenhouse emissions and dependency of fossil fuels are two of major challenges that compromise the targets set in the EU 2050 Green Deal [1]. To achieve such ambitious targets, it is essential to facilitate the transition of the mobility sector towards a cleaner future. In this regard, considerable efforts have been made by national and local entities to promote the use of the electric vehicles (EVs) [2]. A clear effect of these policies is observed on the growing penetration of EVs worldwide, which increased by 41% in 2020 [3]. However, the massive penetration of EVs into the electricity sector may entail multiple issues if it is not properly planned [4]. In this regard, Intelligent Parking Lots (IPLs) have emerged as a valuable framework for optimal integration of EVs.

IPLs allow to cleverly manage a group of vehicles on pursuing a more efficient and clean operation of the entire system [5]; being beneficial for a variety of agents such as energy communities. This kind of systems (or sub-systems) are formed by a group of prosumers that share common interest and geographical area. This concept pursues the optimization of the resources available in the community, with the end of increasing the welfare of the group [6]. In this way, concepts like peer-to-peer (P2P) energy trading gain importance to exploit surplus renewable energy in rooftop photovoltaic (PV) panels, so that other prosumers can be benefited [7, 8]. In this context, IPLs may help to further increase the efficiency and economy of the community, which can exploit the set of EVs as a collective energy storage system. This principle undoubtedly helps to enhance the energy utilization and even could increase the economic profit by maximizing the exportable energy. Despite the apparent advantages of ILPs integration into energy communities, this topic has not been sufficiently studied so far. This paper aims to fill this gap.

1.2 - State of the art

Honarmand et al [9] developed an optimal scheduling tool for IPLs considering vehicle-to-grid capability of EVs. By this approach, vehicles can be partially discharged in order to fully exploit the features of onboard batteries, thus increasing the efficiency of the system. The scheduling tool accounts for comprehensive modelling of batteries and incorporates practical state-of-charge (SOC) constraints. A heuristic algorithm is used to determine the control actions of vehicles. The same authors extended the model in [10] by including PV units. In this case, stochastic programming was considered to model the uncertain PV generation, however, random behavior of EVs was not considered. The problem was formulated as a Mixed-Integer Linear programming (MILP) model which guarantees the achievement of the global optimum within a short execution time.

In [11], a MILP-based bi-objective optimization framework was developed for scheduling IPLs in the presence of demand response programs. This model uses the epsilon-constraint method for multi-objective optimization, showing the benefits of time-of-use rates in operation of EVs. Using this approach, the authors demonstrated that total emissions and operation cost can be reduced by 4% and 1.8%, respectively. The layout proposed in [12] incorporates hydrogen facilities in combination with IPLs. In this regard, the system can benefit of both storage technologies. To optimally operate the assets deployed into the grid, the authors developed a deterministic optimal scheduling model, which is solved using metaheuristic methods. The model in [13] also considers hydrogen storage facilitates to increase the efficiency of the system. In this case, renewable units are deployed to form a microgrid system, in which the different agents partake through demand response programs that enable a reduction of the energy cost by 2.46%. The uncertainty in the upstream energy price is modelled using interval optimization, however, other uncertainties such as unpredictable driving pattern are neglected.

Cao et al [14] investigated the integration of hydrogen storage systems in IPLs. In this regard, a stochastic-based framework was developed, incorporating uncertainties from energy price and demand. In [15], the participation of IPLs in energy markets was explored. To this end, an optimal bidding strategy for IPLs integrating hydrogen storage was developed. The proposed framework is based on Mixed-Integer Nonlinear programming (MINLP) and Information Gap Decision Theory (IGDT) to model the uncertainty of market spot price, allowing to adopt different operational strategies; likewise, the authors in [16, 17] used interval formulation and robust optimization, respectively. In these references, the impact of demand response programs is also analyzed, allowing to reduce the overall operational cost by 4.4%.

Haghifam et al [18] developed a stochastic-based framework for optimal interaction between distribution operator and a set of local entities that own either renewable sources, storage systems or ILPs. The problem is formulated as a nonlinear bi-level optimization model that can be reduced to a one-level scheme by using optimality conditions and disjunctive tricks. In [19], the random behavior of EV owners is modelled by introducing penalties and awards constraints into the problem. It results in a nonlinear optimization framework that accounts for uncertainties of EV demand and is solved using Particle Swam Optimizer (PSO). Nosratabadi et al [20] developed a price-taker strategy for energy hubs encompassing an IPL and combined heat and power plants. In the model, a scenario-based approach is combined with a robust arrangement to consider the random behavior of vehicles and market energy price. However, the resulting problem is nonlinear and computationally costly. In [21], the optimal allocation of IPLs in a distribution network is addressed. To this end, a two-stage optimization problem is developed in which the optimal placement and operation are treated as separated problems. This formulation uses

IGDT to model the uncertain behavior of vehicles and renewable sources, however, the upstream price is considered deterministic.

In [22], a multi-objective model is proposed for optimal power allocation among vehicles with the aim of reducing the phase imbalance in the network. In this problem, uncertainties in prices and loads are considered via scenarios. Rajani and Kommula [23], combined evolutionary algorithms and neural networks to conduct energy management among EVs with network concerns. An improved second-order cone formulation was proposed in [24] for optimal coordination of electric vehicles connected to distribution networks. The optimization model was applied to a 33-bus distribution system, showing that large-scale EVs may have a negative impact on the network, if they are not properly managed. Finally, [25] proposed a multi-objective framework for optimal dispatching of vehicle fleets with the objective of reducing vehicles' cost and peak-to-valley ratio in the grid.

1.3 - Contributions

From the literature above it results clear that IPLs bring multiple advantages for power systems, however, their performance in energy communities has not been investigated so far. As seen in Table 1, the existing literature focuses on either sole operation of IPLs or the integration of such systems in microgrids. On the other hand, uncertainties involved in IPL operation have not been properly treated yet. In this regard, energy pricing and EV behavior present very different features. Indeed, while the energy pricing can be forecasted with acceptable accuracy [26], random behavior of EVs is hardly predictable [27, 28]. In this regard, while stochastic programming may be suitable to model EV demand, other approaches should be considered for energy pricing. This paper aims at filling these gaps. The main novelties of this work are listed below:

i. Developing a novel optimal scheduling framework for energy communities encompassing IPLs. The problem is formulated as a MILP, which ensures the reachability of the global optimum. Moreover, it is modular and efficiently tractable by commercial solvers [29].

ii. Proposing a scenario-based modelling to account for the uncertainty in EV behavior. The proposed approach models the characteristics of vehicles and their arrival and departure times. As a result, the available SOC in the IPL and the minimum energy required are obtained.

iii. To accommodate other uncertainties brought by energy prices, a novel hybrid stochastic-IGDT approach is developed, by which random EV's behavior is modelled via scenarios while an uncertainty-aware framework for IGDT-based modelling of energy prices is proposed.

iv. To make the developed model computationally tractable, a two-stage solution procedure is proposed. This novel scheme allows to easily schedule both IPLs and the rest of the community in a coordinated way while pursuing collective objectives with a limited information exchange.

Table 1 - Taxonomy of the related literature

Reference	Model	Uncertainties modelling	Uncertainties considered		System
			Pricing	EVs	
[9]	Heuristic	--	No	No	IPL
[10]	MILP	Stochastic	No	No	Microgrid
[11]	MILP	--	No	No	Microgrid
[12]	Metaheuristic	--	No	No	IPL
[13, 16]	MILP	Interval	Yes	No	Microgrid
[14]	MILP	Stochastic	Yes	Yes	Microgrid
[15]	MINLP	IGDT	Yes	No	IPL
[17]	MILP	Robust	Yes	No	Microgrid
[18]	MILP	Stochastic	Yes	No	Network
[19]	Metaheuristic	Penalties	No	Yes	IPL
[20]	MINLP	Stochastic	Yes	Yes	Energy Hub
[21]	MILP	IGDT	No	Yes	Network
[22]	MILP	Stochastic	Yes	No	Network
[23]	Metaheuristic	--	No	No	Network
[24]	Second-order	--	No	No	Network
[25]	MILP	--	No	No	Network
Present	MILP	Stochastic-IGDT	Yes	Yes	Energy community

To validate the developed approach and discern the advantages of IPL integration in energy communities, an energy community involving a set of prosumers and IPLs is used as case study. In the studied energy community, prosumers and IPLs can interact and exchange energy and also may exchange energy with an upstream grid.

In the rest of this paper, Section 2 describes the energy community layout and its scheduling framework. Section 3 develops a novel stochastic approach for modelling the random behavior of vehicles in IPLs. Section 4 presents the mathematical formulation and solution procedure of the scheduling problem. Section 5 presents a case study with results. The paper is concluded in Section 6.

2 - Background

This paper focuses on energy communities. Such paradigm gathers prosumers that can interact, exchanging energy through a suitable P2P mechanism [6]. In particular, this work is focused on cooperative energy communities, in which it is assumed that prosumers share their resources selflessly on pursuing the maximization of the total welfare (i.e. without obtaining a monetary counterpart) [30]. In this regard, IPLs can also partake in the community operation providing collective storage capacity by aggregating the individual storage capacity of the plugged vehicles [31]. In return, this agent requires energy supply from either prosumers or the utility grid for satisfying the requirements of its users. It is assumed that vehicles in IPLs are owned by individuals that may pose different interests. However, in this paper we focus on satisfying their charging requirements, ensuring that all the vehicles leaving the parking have their batteries fully charged. This service can be compensated through charging tariffs or other mechanisms established by the community [32].

Thereby, all the agents collectively partake taking advantage of each others. How the community operator compensates the participation of each user is out of scope of this paper, assuming that a fair mechanism is established that encourage the users to actively partake in the community operation. For further information about this topic, the reader is referred to [33], where compensation and tariff mechanisms are developed that account for individual participation of users. Fig. 1 shows a pictorial representation of the considered energy community. It is considered that prosumers and IPLs are managed by different operators, while a community operator governs the energy transactions among prosumers-vehicles-utility grid (in practise, these roles can be played by the same agent).

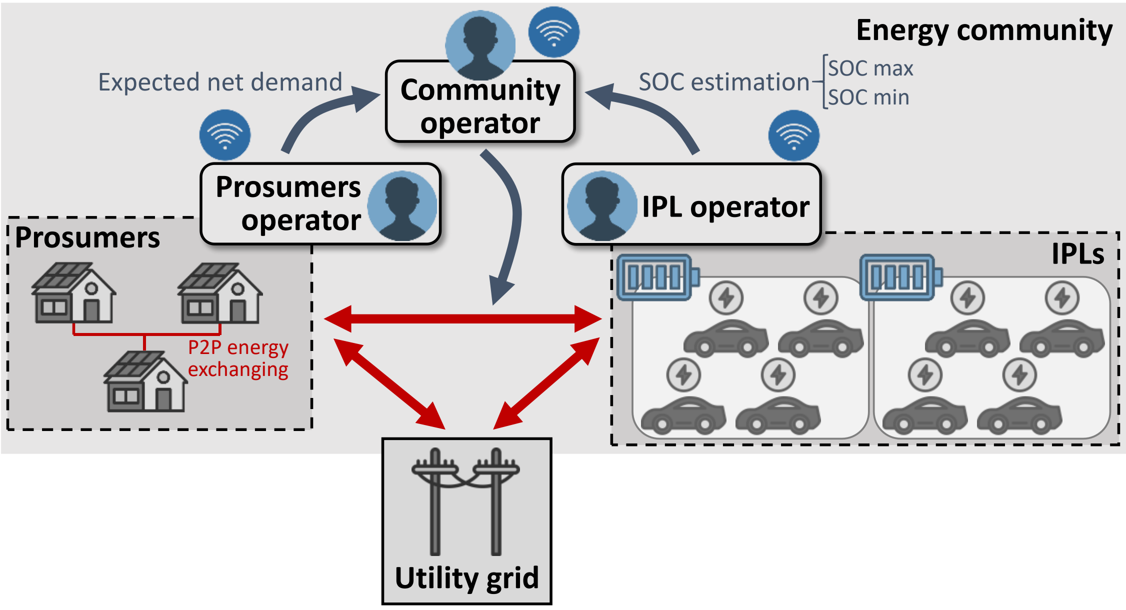

Fig. 1 - Pictorial representation of the community under study

Therefore, the prosumers operator focuses on scheduling the P2P transactions among prosumers. As result, the net demand of all dwellings is obtained, which is transferred to the community operator. On the other hand, the IPL operator estimates the maximum and minimum energy requirements for his users. Since this parameter is in essence unknown due to the random behaviour of EV users, it is modelled using a scenario-based approach described in Section 3. Thus, the IPLs are in essence considered as virtual storage facilities. This information is also sent to the community operator, who decides the P2P energy exchanging among the IPL and prosumers as well as the energy that must be purchased from the grid. Additionally, the community can sell energy to the utility grid in order to obtain a revenue. This scheduling routine is assumed to be performed daily, when energy pricing can be predicted with acceptable accuracy [26].

Nowadays, advanced communication infrastructures make possible bi-directional information exchange among agents, within a smart grid paradigm, such as depicted in Fig. 1 [34]. However, these schemes may be unaffordable due to privacy concerns [35]. In this sense, other simpler schemes can be assumed, for example, the community operator could play the role of the other operators and simplify the communication infrastructure. This is possible because of the cooperative essence of the community, in which all the participants pursue the same objectives.

3 - A model for SOC estimation of IPLs

As mentioned, the maximum and minimum SOC of IPLs is hardly predictable, because EV owners usually show random driving patterns [27]. In this sense, the SOC available in the IPL should be estimated. In this section, a stochastic-based approach is developed for modelling the energy status of the parking lot, which can be daily used by the IPL operator. Subsequent sections develop the mathematical formulation for stochastic representation of instantaneous SOC in IPLs.

3.1 - Characteristics of vehicles

Let us assume that a predefined number of vehicles will be plugged throughout a day. This parameter, denoted by NV, can be set on the basis of historical data [36]. However, each vehicle has a specific storage capacity, initial SOC and plugging time window. These characteristics are random and unknown; however, their bounds can be easily stated. For example, nowadays most of plug-in hybrid and battery EVs have a capacity between 10-60 kWh [37]. On the other hand, current fast and semi-fast chargers allow to get conventional vehicles fully charged within half an hour to a couple of hours [38]. These features allow to model the different parameters of each vehicle using truncated Gaussian distributions. Therefore, the characteristics of each vehicle that will be parked are determined by (1) and arranged in a vector form as (2).

$$x_{s|v} = \text{round}\left(\text{rand}\left(\widetilde{\mathcal{N}}(\mu_x, \sigma_x, LB_x, UB_x)\right)\right);\ \forall s \in \mathbb{S} \wedge v \in E(NV) \wedge x \in \{C, C^0, T\} \tag{1}$$

$$\boldsymbol{x}_s = \begin{bmatrix} x_{s|1} \\ \vdots \\ x_{s|E(NV)} \end{bmatrix}; \forall s \in \mathbb{S} \wedge x \in \{C, C^0, T\} \tag{2}$$

where x is, in general, an auxiliary index that may have different meanings (e.g. $x \in \{C, C^0, T\}$ in (1)). It is noteworthy that time lapse T may be longer than the actual charging time, which is usual in parking places at headquarters or industries. In these cases, the total plugged hours encompass charging periods combined with idle time slots. As seen in the nomenclature, some parameters can have different meaning depending on the superscript. A clear example is the time lapse T, which stands for the arrival time when superscripted by a.

3.2 - Arrival and departure times

The other uncertainties are the arrival and departure times of each vehicle. These times are related to the probability of daily trips. This probability has been well modelled in various reports and is freely available for some countries like U.S [39] (see Fig. 2). In essence, this function models the probability of a vehicle is driven each hour of the day. Intuitively, the probability of daily trips is directly related with the probability of arriving at the parking lot. This idea was already considered in other papers [27, 36], thus, the arrival time for each vehicle can be modelled using the probability of daily trips, as follows

$$T^a_{s|v} = \mathrm{round}\big(\mathrm{rand}(\mathcal{F})\big); \forall s \in \mathbb{S} \wedge v \in E(NV) \quad (3)$$

$$\mathbf{T}^a_s = \begin{bmatrix} T^a_{s|1} \\ \vdots \\ T^a_{s|E(NV)} \end{bmatrix}; \forall s \in \mathbb{S} \quad (4)$$

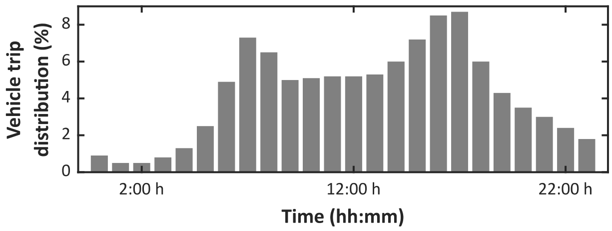

Fig. 2 - Probability of daily trips in U.S. (weekdays) [39]

Once the arrival time has been calculated for each vehicle in the fleet, the corresponding departure times can be easily obtained using (5).

$$\mathbf{T}_s^d = \mathbf{T}_s^a + \mathbf{T}_s; \forall s \in \mathbb{S} \tag{5}$$

Basically, (5) adds the total plugging time to the arrival time slot to calculate the departure time. Now, the matrix $\mathbf{Q}_s^a(v,t)$ and $\mathbf{Q}_s^d(v,t)$ can be constructed, for convenience. The vt^{th} element of the first one is equal to 1 if the v^{th} in the fleet arrives to the parking lot at time t, and 0 otherwise. While the second matrix is constructed similarly, but considering the departure times instead. Rigorously speaking, these matrixes are constructed according the following procedure.

$$\left.\begin{array}{l}\mathbf{Q}_s^a\left(v, \mathbf{T}_s^a(v)\right) = 1\\ \mathbf{Q}_s^d\left(v, \mathbf{T}_s^d(v)\right) = 1\end{array}\right\} \begin{array}{l}\text{all the other elements}\\ \text{equal to zero}\end{array}; \forall s \in \mathbb{S} \wedge v \in E(NV) \tag{6}$$

3.3 - SOC estimation

The IPL operator has to estimate the SOC bounds for the following scheduling window, which ensures that charging requirements of the users can be satisfied. This information is required by the community operator who determines the scheduling for the entire community. The minimum energy that must be stored in IPLs must be sufficient to ensure that all the vehicles that leave the park are fully charged. Thus, the minimum SOC can be calculated using the expression (7).

$$\underline{\mathrm{SOC}}_{s|t}^{IPL} = [\mathbf{Q}_s^d(:,t)]^{\intercal} \cdot \mathbf{C}_s;\ \forall s \in \mathbb{S} \wedge t \in \mathbb{T} \tag{7}$$

where $(:)$ is a Matlab-like operator that stands for all the elements in a row or column and the vector $\mathbf{C}_s = \left[C_1, C_2, \dots, C_{E(NV)}\right]^{\intercal}$; $\forall s \in \mathbb{S}$, so that, the product of $\mathbf{C}_s$ by $\mathbf{Q}_s^d(:,t)$

yields the total capacity of all the vehicles that leaves the parking at time t. Hence, the minimum SOC in the parking will be always higher than the total capacity of the vehicles that will be unplugged, ensuring the fully charging of all the vehicles at their departure times. By its formulation, (7) ensures that the total SOC of IPLs cannot be negative, since the vector $\mathbf{C}_s$ only contains elements higher than or equal to zero.

On the other hand, the maximum energy that can be stored in IPLs is determined by the capacity of the plugged vehicles, since storage capacity of the lots is limited by the actual capacity of vehicles. However, when a vehicle leaves the lot, its batteries are no longer available and consequently the storage capacity of the ILP is reduced. With these premises, the maximum energy that can be stored in IPLs can be calculated as follows

$$\overline{\mathrm{SOC}}_{s|t}^{IPL} = \overline{\mathrm{SOC}}_{s|t-1}^{IPL} + [\mathbf{Q}_s^a(:,t)]^\intercal \cdot \mathbf{C}_s - [\mathbf{Q}_s^d(:,t)]^\intercal \cdot \mathbf{C}_s;\ \forall s \in \mathbb{S} \wedge t \in \mathbb{T} \backslash t > 1 \qquad (8)$$

Indeed, (8) determines the maximum energy in IPLs at t as a function of the SOC at $t-1$ plus the capacity of the vehicles that arrive at t minus the capacity of the vehicles that leave the park at t.

3.4 - Data reduction

The developed stochastic approach requires to generate a large number of scenarios. This requirement may result in intractability issues, since the size of the optimization variables would be equal to the number of scenarios. To circumvent these problems, other references used clustering techniques [40, 41]. This kind of methods reduce the scenario space to a minimum set of representative profiles that can be considered an accurate representation of the whole set. There are many clustering techniques available in the literature [42]. In this paper, the k-medoids method has been used, due to its good overall features [43]. This technique groups the elements within a set into clusters. Then, a member of each cluster (called medoid), is considered a fair representation of all the members within the cluster. This technique allows to reduce the scenario-space to just 10-

15 samples without compromising the accuracy, usually [44]. Once the representative space is constructed, the probability of each representative scenario can be calculated, as follows.

$$\pi_r = \frac{\text{size}(\boldsymbol{\Omega}_r)}{\text{size}(\mathbb{S})}; \forall r \in \mathbb{R} \tag{9}$$

Indeed, (9) says that the probability of the r^{th} representative scenario is equal to the ratio between the number of members within its cluster and the total number of scenarios. Thus, a representative scenario is considered more probable if within its cluster there are many members. As a sake of example, is there is only one cluster (and therefore one medoid), its probability would be equal to 1 since, by definition, all the scenarios would be contained within that cluster. As a sake of example, Fig. 3 plots the maximum a minimum SOC estimations for two extreme values of the expected number of vehicles ($E(NV)$).

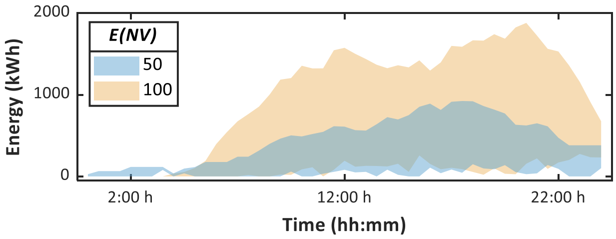

Fig. 3 - Examples of SOC bounds estimated using the developed stochastic modelling

The developed approach is summarized in the flowchart of Fig. 4. For scenario generation, a large number of samples must be considered (usually 1000-4000 scenarios are sufficient [45]), so that all the steps within the blue square in Fig. 4 have to be repeated for each scenario.

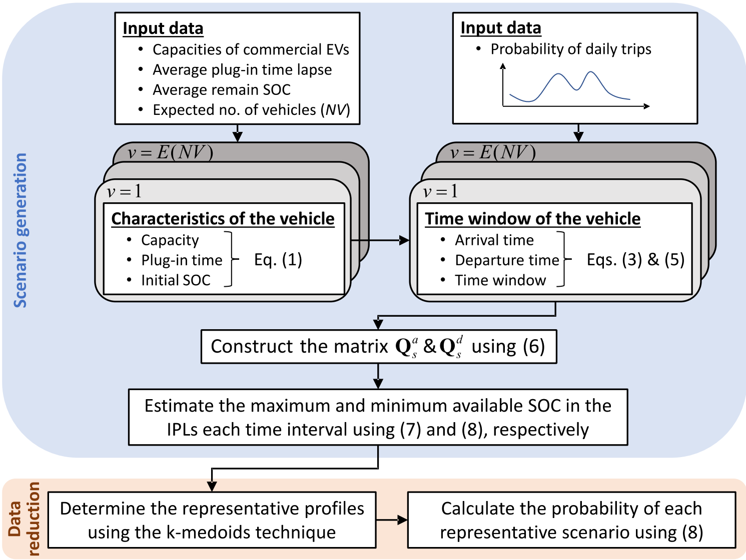

Fig. 4 - Flowchart for SOC estimation using stochastic modelling

4 - Mathematical solution procedure

In the following subsections, the mathematical modelling of the scheduling problem for the community is presented. In this paper, different uncertain models are used for SOC estimation in IPLs and upstream energy price. The former is modelled via scenarios, following the procedure described in the previous section, while the latter is managed using IGDT. Thus, the resulting problem is an original hybridization between stochastic programming and IGDT modelling. IGDT is a non-probabilistic method that has been used in multiple optimization problems [46]. Its main foundation is sketched in Fig. 5 and basically consists of modelling the uncertainties by its predicted value and a so-called uncertain radius that represents the deviation from the expected profile. Thus, the higher the value of the radius, the more uncertainty aware the scheduling result is. The resulting problem is divided into two stages. At first stage, the problem is solved assuming the expected energy price, so that the unique uncertainties involved are the scenarios generated for IPLs. At second stage, the IGDT modelling is incorporated to accommodate the uncertainties in the energy price.

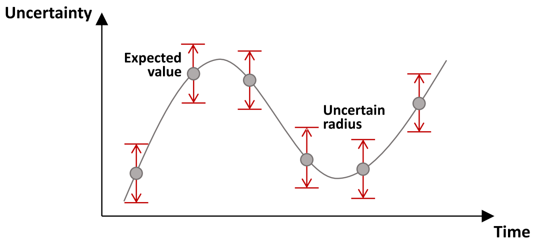

Fig. 5 - Basic foundation of IGDT modelling

4.1 - Assumptions

In the operation of the studied community, three agents are involved. The prosumers operator aims at scheduling the P2P energy exchange among prosumers. The scope of this paper is far away from modelling and studying this kind of energy transactions. Thus, it is simply assumed that instantaneous net demand of prosumers has been already calculated, as result of minimizing the energy that prosumers must acquire from the community or the utility grid. This scheduling problem is not covered in this paper and the reader is referred to the rich literature for further information [30, 47-50]. On the other hand, degradation of on-board batteries is not considered in (10) because the following reasons:

- Bi-directional power flows from on-board batteries can be compensated by operators through advanced charging tariffs [32], which are not considered in this paper. Other charging points available in public or private infrastructures may offer free-of-charge services for which the vehicle-to-grid service might serve to compensate the charging service.
- Users can partake in battery rental businesses offered by manufacturers, by which the battery can be replaced after an agreed period [51]. In addition, batteries can be involved in a second-use program by which the entire community can be benefited when batteries are degraded to a point that are useless for mobility [52, 53].

- Degradation costs are normally marginal compared to energy prices [36]. Moreover, its inclusion may complicate the problem, as these costs are normally a quadratic function of the energy exchanged.
- The present scheduling mechanism aims at encouraging the usage of on-board batteries, assuming that this service can be compensated in different ways, as previously mentioned.

4.2 - First stage

At first stage, expected values for buying and selling prices are assumed. In this way, the total operation cost of the community can be expressed as follows

$$Cost = \sum_{r\in\mathbb{R}}\{\pi_r \cdot \sum_{t\in\mathbb{T}}\{E(\lambda_t^{Grid,buy}) \cdot p_{s|t}^{Grid,buy} - E(\lambda_t^{Grid,sell}) \cdot p_{s|t}^{Grid,sell}\}\} \quad (10)$$

In (10), both expenditures by energy imported and revenues by energy selling are considered. The community operator aims at satisfying the demand at minimum cost, therefore, this stage can be formulated as the following minimization problem.

$$E(Cost) = \min_{\Phi} Cost \quad (11)$$

Subject to:

$$p_{r|t}^{IPL,dch} + p_{r|t}^{Grid,buy} = p_{r|t}^{IPL,ch} + p_{r|t}^{Grid,sell} + p_t^{Pnd}; \forall r \in \mathbb{R} \wedge t \in \mathbb{T} \quad (12)$$

$$p_{r|t}^{Grid,x} \leq u_t^{Grid,x} \cdot \overline{p}^{Grid}; \forall r \in \mathbb{R} \wedge t \in \mathbb{T} \wedge x \in \{buy, sell\} \quad (13)$$

$$u_t^{Grid,buy} + u_t^{Grid,sell} \leq 1; \forall t \in \mathbb{T} \quad (14)$$

$$p_{r|t}^{IPL,x} \leq u_t^{IPL,x} \cdot \overline{p}^{IPL}; \forall r \in \mathbb{R} \wedge t \in \mathbb{T} \wedge x \in \{ch, dch\} \quad (15)$$

$$u_t^{IPL,ch} + u_t^{IPl,dch} \leq 1; \forall t \in \mathbb{T} \quad (16)$$

$$\mathrm{SOC}_{r|t}^{IPL} = \mathrm{SOC}_{r|t-1}^{IPL} + [\mathbf{Q}_s^a(:,t)]^\intercal \cdot \mathbf{C}_r^0 - \underline{\mathrm{SOC}}_{r|t-1}^{IPL} + \Delta\tau \cdot \left(\eta^{IPL} \cdot p_{r|t}^{IPL,ch} - \frac{p_{r|t}^{IPL,dch}}{\eta^{IPL}}\right); \ \forall r \in \mathbb{R} \wedge t \in \mathbb{T} \backslash t > 1 \quad (17)$$

$$\underline{\mathrm{SOC}}_{r|t}^{IPL} \leq \mathrm{SOC}_{r|t}^{IPL} \leq \overline{\mathrm{SOC}}_{r|t}^{IPL}; \forall r \in \mathbb{R} \wedge t \in \mathbb{T} \tag{18}$$

$$\mathrm{SOC}_{r|1}^{IPL} = [\mathbf{Q}_r^a(:,1)]^\intercal \cdot \mathbf{C}_r^0;\ \forall r \in \mathbb{R} \tag{19}$$

As a result of this stage, the expected operational cost is obtained, since it is calculated assuming expected energy prices. Eq. (12) is the power balance of the community. In this expression it is assumed that prosumers net demand is positive if the dwellings need to acquire energy from the community, and negative if there is an excess of PV generation that can be exported. On the other hand, (13) and (14) avoid the simultaneous purchases and sales with the upscale grid, since only $u_t^{Grid,buy}$ or $u_t^{Grid,sell}$ can take 1 at the same time, as said (14). Likewise, the set of constraints (15) and (16) avoid the simultaneous charging-discharging of IPLs, so that the community cannot export and deliver energy to the IPLs at the same time.

Equation (17) models the instantaneous SOC of IPLs, which is a function of the SOC at the previous time step, the initial SOC of the vehicles that arrive to the parking, the capacity of the vehicles that leave the lot besides the energy exchange with the community or the upscale grid. In this regard, (17) should not be confused with the SOC bounds, which are given in (18) and calculated in (7) and (8). Thereby, (17) models the instantaneous energy in IPLs that is immediately available for operators. Thus, the set of constraints (17) and (18) ensures that sufficient energy is always available in the parking to satisfy the requirements of users. In other words, all the vehicles that leave the park at time t have their on-board batteries fully charged, as ensured by (18). Finally, the initial SOC of the IPL is given by (19), which models the initial SOC of the vehicles that arrive to the parking at the beginning of the time horizon.

4.3 - Second stage

IGDT modelling is incorporated at second stage to account for uncertain energy prices. It is assumed that upstream purchasing and selling prices are determined by spot energy markets. However, the community has no capacity to directly partake in the market and therefore it must adopt a price-taker strategy [54].

IGDT allows to model the uncertainties by their corresponding uncertain radiuses (denoted by the α's), which are taken as optimization variables. Thus, uncertainties are allowed to vary according their radiuses, in contrast to deterministic problems. In practise, risk-averse and risk-seeker strategies can be adopted [55]. In this paper, a risk-averse strategy has been taken, thus, the uncertainties are assumed to vary in a pessimistic way. Thus, the following constraints model the deviation of uncertainties using their corresponding radiuses.

$$\begin{cases} \lambda_t^{Grid,buy} \geq \left(1+\alpha^{Grid,buy}\right) \cdot E\left(\lambda_t^{Grid,buy}\right) \\ \lambda_t^{Grid,sell} \leq \left(1-\alpha^{Grid,sell}\right) \cdot E\left(\lambda_t^{Grid,sell}\right) \end{cases} ; \forall t \in \mathbb{T} \tag{20}$$

Assuming that uncertainties may deviate from their predicted profiles leads to a more robust scheduling result. However, this result is only accessible at expense of incrementing the expected operating cost [56]. In this paper, it is assumed that the operator is only willing to increment the expenditures beyond a limit, represented by the parameter Δ^{Cost}. Thus, the constraint (21) limits the total cost by assumable bounds.

$$Cost\left(\Phi, \alpha^{Grid,buy}, \alpha^{Grid,sell}, \lambda_t^{Grid,buy}, \lambda_t^{Grid,sell}\right) \leq \left(1+\Delta^{Cost}\right) \cdot E(Cost) \tag{21}$$

Incorporating the constraints above, the second stage (22) is run yielding a robust-oriented result determined by the bound Δ^{Cost}.

$$\max_{\substack{\Phi, \alpha^{Grid,buy}, \alpha^{Grid,sell} \\ \lambda_t^{Grid,buy}, \lambda_t^{Grid,sell}}} \frac{\alpha^{Grid,buy} + \alpha^{Grid,sell}}{2} \tag{22}$$

Subject to: (12)-(21)

Note that the second stage of the developed procedure only needs information about the expected cost obtained in (11), so that the new proposal requires very limited information exchange between stages, simplifying its codification and implementation.

It is noteworthy that when declaring the energy price a decision variable, two bilinear terms appear in (11). To keep the model in MILP formulation, advanced piecewise representations are adopted to linearize these terms (see Appendix).

5 - Case study

This section presents a case study on a benchmark community, similar to that described in Section 2. The developed MILP optimization model is coded in Matlab R2020b and the optimization problem is solved using Gurobi [57], which currently offers free license for research and academic purposes. The experiments performed by the authors were run on an Intel® CoreTM i7-10700 K CPU 3.80 GHz 3.79 GHz personal computer taking a 24-hour time horizon with 30 minutes time resolution. The simulations consumed 5-10 minutes on average, which is considered acceptable for energy management tools [58]. Moreover, the MILP structure of the problem ensures its good scalability for larger problems involving more variables and constraints [59].

5.1 - Input data

One of the particular features of the developed scheduling tool is the scarce information needed to be performed. In fact, only net demand and SOC estimation are required by the community operator. As commented, the community operator can assume the role of the other agents, thus limiting the information exchanges. The expected net demand for the prosumers is plotted in Fig. 6 together with the expected purchasing and selling prices. The real demand at La Palma Island Spain on May 3, 2016 [60] has been considered to model the prosumers demand. A 300 kWp PV potential is assumed to be available, encompassing collective and customer-owned PV panels. Then, using the model described in [61] and the weather parameters observed at Virgin Islands (U.S.) on May 3, 2016 [62], the PV generation is estimated. On the other hand, the energy prices correspond to real data observed in the PJM FE Ohio on July 1 and 9, 2019 [63] for the purchasing and selling prices, respectively. Since the considered community assumes a price-taker strategy, upstream prices are fixed disregarding the status of the community. In this way, purchasing and selling prices may follow a different pattern from renewable generation in the community.

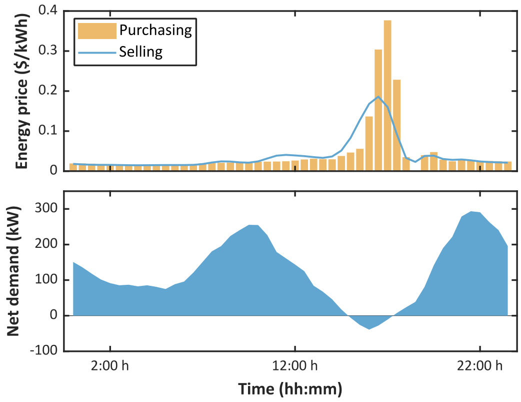

Fig. 6 - Expected energy prices (top) and net demand (bottom)

On the other hand, Table 2 collects the parameters used in the distribution functions for creating the scenarios for SOC estimation in IPLs. As commented previously, these parameters have been set on the basis of average commercial battery and plug-in hybrid vehicles, as well as usual characteristics of semi-fast and fast chargers. With this information, 1000 scenarios were generated, which were reduced to 10 representative scenarios using the k-medoids technique. Finally, the utility grid and IPLs can exchange up to 300 kW.

Table 2 - Parameters of probability functions for SOC estimation

Characteristic	**Mean**	**Standard deviation**	**Range**
Capacity	25 kWh	20 kWh	[10,60] kWh
Plug-in time	4 hours	2 hours	[0.5,8] hours
Initial SOC	40 %	10 %	[20,60] %

5.2 - Results: first stage

At first stage, the SOC estimation of IPLs is the unique concerned uncertainty. As mentioned, this parameter is modelled using scenarios and stochastic programming. Table 3 collects some relevant indicators obtained at this stage considering different number of expected vehicles in IPLs ($E(NV)$). As seen, the minimum cost is obtained when 50 vehicles are expected to be parked throughout a day. In this case, the high number of vehicles allow to exploit them as a collective storage system optimally, thus maximizing the energy sold to the grid. Indeed, when the number of vehicles is minimum, the energy discharged from IPLs is reduced by 40%, limiting the capability to sell energy to the grid. This aspect is especially relevant since it compensates the energy that must be purchased for charging the vehicles. In contrast, if the number of vehicles is maximum ($E(NV) = 100$), the total operation cost and energy imported from the grid increase by 48% and 15%, respectively. This is due to the total number of vehicles exceeds the optimal capacity of IPLs, which work under stressful conditions in order to satisfy the charging events. This result evidences the necessity of optimally planning this kind of systems, which will be addressed in future works.

Table 3 - Results obtained at first stage

Result	$\boldsymbol{E(NV)}$		
	10	**50**	**100**
Total cost ($)	48.2	33.4	64.2
Energy bought (kWh)	3528.4	4721.1	5563.3
Energy sold (kWh)	243.3	536.3	471.4
IPL energy charged (kWh)	533.0	1634.2	2487.9
IPL energy discharged (kWh)	302.9	504.4	450.9

Observing the results reported in Table 3, it is evident that most of energy sold to the grid is directly exported from IPLs. This is better appreciated in Fig. 7, where the scheduling program is plotted for different number of expected vehicles. As seen, IPLs are only discharged about 17:00 h, when the selling price reaches its maximum, exporting power directly to the upstream grid. It is also worth noting that surplus energy from domestic users is not sold to the grid, since it is available when the selling price is low. Under this situation, the scheduling program prefers transferring the available surplus renewable energy to IPLs, which reduce their energy imported from the grid. On the other hand, when $E(NV) = 100$, the imported power frequently achieves its upper bound (300 kW), with the end of ensuring the minimum SOC necessary in IPLs. This circumstance hinders the capability of selling energy to the grid, reducing the monetary revenues. Finally, Fig. 8 shows the SOC in IPLs. As expected, the higher number of vehicles the higher margin to operate the IPLs as a collective storage system. This result evidences that reduced monetary revenues in case of $E(NV) = 100$ are not due to the number of vehicles but for the limited capacity of IPLs.

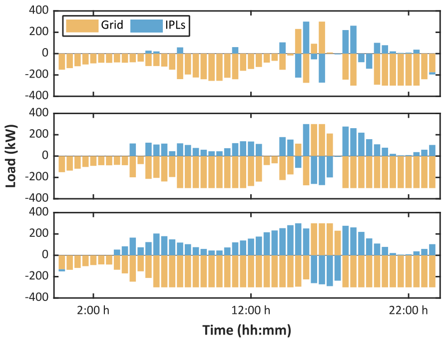

Fig. 7. Scheduling result obtained at first stage with 10 (top), 50 (middle) and 100 (bottom) vehicles. Negative powers mean ‘to-the-community’ energy flow

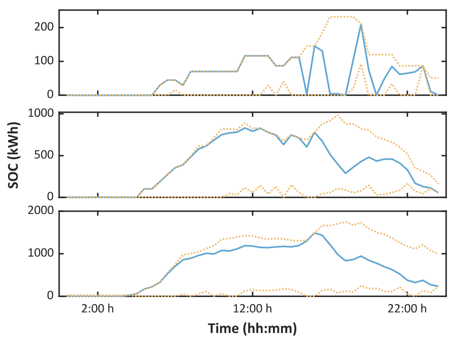

Fig. 8. Actual SOC of IPLs (blue line) and upper and lower bounds (yellow dotted lines) with 10 (top), 50 (middle) and 100 (bottom) vehicles

5.3 - Results: IGDT case

Next, the second stage is analysed, in which the energy pricing is modelled using IGDT. This modelling allows to set the parameter Δ^{Cost}, which represents the limit up to the expected cost can be incremented in order to consider deviation of energy pricing from expected values. Fig. 9 shows the total operating cost in various scenarios. As expected, the higher value of Δ^{Cost} implies the higher operating cost. Nevertheless, the highest expenditures were obtained with $E(NV) = 100$ since, as previously commented, the limited capacity of IPLs hinders the possibility of increasing the monetary revenues obtained by e.g. selling energy to the grid. Obviously, the higher expenditures are due to unfavourable upstream pricing conditions. In this regard, Table 4 reports the average purchasing and selling prices in various scenarios. As observed, while the selling price is inversely proportional to the value of Δ^{Cost}, the purchasing price is not affected by this parameter. This is due to the selling price has a more notably impact on total expenditures compared to the purchasing cost. In this sense, the scheduling mechanism focuses on the most damaging uncertainty, thus considering a reduced selling price, as observed in Fig. 10.

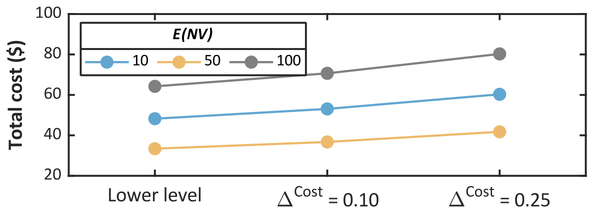

Fig. 9 - Total operating cost in various scenarios

Table 4 - Average upstream prices in various scenarios

Pricing		**1st stage**	$\Delta^{Cost} = \mathbf{0.10}$	$\Delta^{Cost} = \mathbf{0.25}$
Purchasing	$E(NV) = 10$	0.044 $/kWh	0.044 $/kWh	0.044 $/kWh
	$E(NV) = 50$	0.044 $/kWh	0.044 $/kWh	0.044 $/kWh
	$E(NV) = 100$	0.044 $/kWh	0.044 $/kWh	0.044 $/kWh
Selling	$E(NV) = 10$	0.039 $/kWh	0.025 $/kWh	0.017 $/kWh
	$E(NV) = 50$	0.039 $/kWh	0.034 $/kWh	0.032 $/kWh
	$E(NV) = 100$	0.039 $/kWh	0.032 $/kWh	0.028 $/kWh

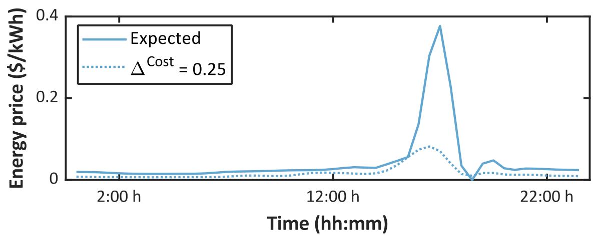

Fig. 10 - Expected and assumed selling price using IGDT ($E(NV) = 10$)

The pessimistic selling price considered with IGDT modelling makes the exporting process less attractive from economical point of view. This evidence is clearly appreciated in Fig. 11, where the total energy sold is plotted for various scenarios. As seen, the total energy sold to the grid decreases with higher values of Δ^{Cost}, which is expected since, as observed in Table 4, the selling price is assumed to be lower than expected values, making less attractive selling energy to the grid. The sharpest decrease is observed with $E(NV) = 100$, when the sold energy is reduced by 40%. This is due to, the low number of vehicles further limits the storage capacity of the community, thus hindering the possibility of selling power. The results in Fig. 11 are related to the energy discharged from IPLs, as appreciated in Fig. 12. This result demonstrates that the capability of the community for selling energy is related to the total amount of energy that can be discharged from vehicles. Thereby, those cases in which the vehicle-to-grid feature cannot be further exploited supposes a more pessimistic and unfavourable scenario for community operation.

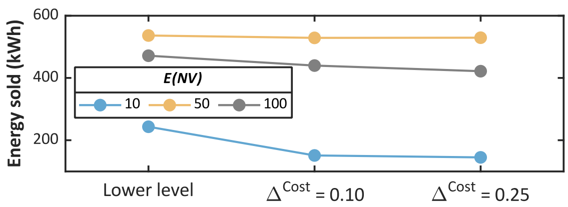

Fig. 11 - Total energy sold to the grid in various scenarios

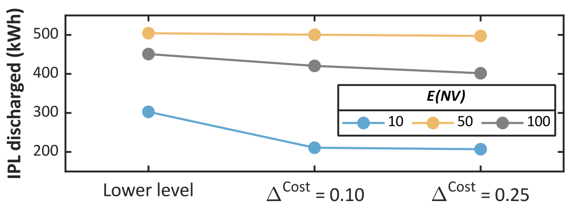

Fig. 12 - Total energy discharged from IPLs in various scenarios

6 - Conclusions and future works

A novel scheduling tool for energy communities encompassing IPLs has been presented. The new proposal is based on a two-stage procedure, in which a novel hybrid stochastic-IGDT model has been developed to manage with multiple uncertainties. In this regard, a novel stochastic-based modelling has been developed for SOC estimation in

IPLs, while the uncertain upstream energy prices are treated using IGDT. The resulting problem is a MILP, which is efficiently solvable by average machines and software.

The developed method has been validated through extensive simulations, using a benchmark energy community involving prosumers and IPLs. The obtained results highlighted the role of IPLs in energy communities, usually improving the economy of the system. However, it is evident that IPLs should be optimally planned since a large number of charging points may lead to stressful operating conditions. Actually, the expected total operating cost was incremented by 40% when the expected number of vehicles increased from 50 to 100. On the other hand, the total energy exported was the main factor influencing on monetary balance of communities, thus highlighting the importance of these frameworks as virtual generators in future energy systems.

Future works should focus on developing planning tools for IPLs, especially when they are integrated in upscale systems as energy communities.

Appendix. Linearization of bi-linear terms

In the developed mathematical modelling, a set of nonlinear terms appear when the energy price is multiplied by the imported/exported power in (10). To preserve the MILP structure of the problem, advanced piecewise representations have been used to linearize those bi-linear terms. In particular, the formulation denoted by 'nf4l' in [64] has been used because of its good overall characteristics. Let us consider the product of the continuous variables ω and y. Then, the grid-point partitioning of the domain of ω can be declared, as follows

$$\omega \approx \langle \widetilde{\omega}_i \rangle; \forall i \in \{0,1,\dots,n\} \tag{A1}$$

The partitioning above allows to represent the variable ω by its approximated piecewise partition, which is constructed by introducing the continuous variable $\Delta\widetilde{\omega}$ and the constraints (A2)-(A4):

$$m_i = \widetilde{\omega}_i - \widetilde{\omega}_{i-1}; \forall i \in \{0,1,\dots,n\} \tag{A2}$$
$$\omega = \sum_{i=1}^{i=n}\{\delta_i \cdot \widetilde{\omega}_{i-1} + \Delta\widetilde{\omega}_i\} \tag{A3}$$
$$0 \le \Delta\widetilde{\omega}_i \le m_i \cdot \delta_i;\ \forall i \in \{0,1,\dots,n\} \tag{A4}$$

where δ is a SOS1 variable. Likewise, the variable y can be represented by the limits of its domain and the continuous variable Δy, as follows

$$y = \underline{y} + \sum_{i=1}^{i=n}\{\Delta y_i\} \tag{A5}$$
$$0 \le \Delta y_i \le \left(\overline{y} - \underline{y}\right) \cdot \delta_i;\ \forall i \in \{0,1,\dots,n\} \tag{A6}$$

Finally, the bi-linear term can be replaced by the dummy variable z, which is calculated using (A7). This model needs to declare the continuous variable Δz, that represents the deviation of the variable z with respect its bounds, as said (A8)-(A10).

$$z = \underline{y} \cdot \omega + \sum_{i=1}^{i=n}\{\widetilde{\omega}_{i-1} \cdot \Delta y_i\} + \Delta z \tag{A7}$$
$$\Delta z \ge \sum_{i=1}^{i=n}\{m_i \cdot \Delta y_i\} + \left(\overline{y} - \underline{y}\right) \cdot \sum_{i=1}^{i=n}\{\Delta\widetilde{\omega}_i - m_i \cdot \delta_i\} \tag{A8}$$
$$\Delta z \le \left(\overline{y} - \underline{y}\right) \cdot \sum_{i=1}^{i=n}\{\Delta\widetilde{\omega}_i\} \tag{A9}$$
$$\Delta z \le \sum_{i=1}^{i=n}\{m_i \cdot \delta_i\} \tag{A10}$$

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