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***Abstract*—The large Electric Vehicle (EV) fleet penetrations can provoke several grid impact issues if no EV smart-charging is implemented. However, many EV smart-charging works assume an accurate prediction of input data, such as the EV driving patterns, which are highly uncertain. This paper addresses the impact and potential management of several uncertainties related to EV smart charging, such as photovoltaic (PV) generation, load demand, arrival state-of-charge (SOC), requested energy, and arrival and departure time of the EVs. The application of different levels of uncertainty budgets is proposed to account for the gradual impact of every uncertainty on smart charging performance. Moreover, potential uncertainty management is investigated with the use of robust optimization (RO) in predictive receding-horizon EV smart charging under the worst-case uncertainty level, and the "price of robustness" is calculated. The results show that the EV driving uncertainties are more hazardous for the provided charging energy. In contrast, PV generation and load demand uncertainties have a significant impact mostly on the charging cost. Moreover, the price of robustness is very low for EV charging under every uncertainty case.**

***Index Terms*—EVs, PVs, uncertainties, uncertainty budget, robust optimization, receding horizon, smart charging, prediction**

I. Introduction

Increased and uncoordinated charging of electric vehicles (EVs) can provoke several negative impacts on future power grids. Therefore, multiple energy management systems (EMSs) have been developed to provide EV smart charging with minimum charging cost and minimum grid impact. Many EMSs treat EV charging as a static or dynamic scheduling problem, which assumes perfect prediction of various data inputs, such as in [1]. However, there are certain variables related to EV charging that cannot be perfectly predicted, such as the EV user driving patterns [2] or the intermittent PV generation [3]. In [1], the importance of the prediction errors in EV smart-charging was proved even under errors below 5%.

Receding horizon optimization (RHO) and model predictive control (MPC) is an uncertainty handling method that fragments the horizon into smaller parts and optimizes them in a rolling-window fashion upon certain re-optimization trigger events to correct forecasting errors [4]. Stochastic Optimization (SO) uses the probability density functions (PDFs) of the uncertain variables and performs multiple probabilistic scenarios; however, it is computationally expensive. On the contrary, Robust Optimization (RO) represents the uncertain variables with uncertainty sets, and considering only the worst-case scenario (upper or lower bound), it reduces the computational expense of the SO methods [5]. Finally, some works have combined methods such as RHO and RO to increase further the level of protection [6].

II. Literature Review & Contributions

Regarding receding-horizon smart charging systems can be found in [4], [7], [8]. The work in [7] used RHO for peak power minimization while EV charging. Moreover, an RHO approach was followed in [4] for solar forecasting error correction, which was used in the EV charging study case. Furthermore, the time anxiety property has been considered combined with RHO for EV smart charging in [8]. Moreover, regarding the impact of uncertainties on EV smart charging, the load forecasting error was investigated in [9] using two different charging strategies, but only concerning the operational costs. Additionally, the effect of the load forecasting error on EV smart charging performance was studied in [10] in case studies with different EV numbers. However, [9] & [10] did not compare the impact of different uncertainties in MPC smart charging systems. Regarding combinations of uncertainty handling methods, SO and RHO were combined in [11] & [12] to cope with multiple uncertainties regarding EV driving patterns, PV generation, and load demand. However, the impact and management of different uncertainty levels were not considered, and the computational burden of using SO could not be avoided. On the contrary, combinations of RO and RHO can be found in [13] & [6]. However, only PV generation and EV demand uncertainties were considered, respectively. Moreover, they did not incorporate characteristics of different EV fleets in their investigation.

Overall, this work evaluates and compares the impact and management of various uncertainties in receding-horizon EV smart charging, such as PV generation, load demand, arrival and departure time, arrival EV state-of-charge (SOC), and requested energy. In this regard, uncertainties have been represented by uncertainty budgets of different levels using RO

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to quantify their gradual impact on charging performance. Moreover, the use of RO in predictive receding-horizon smart charging systems is applied to further increase the level of uncertainty management by combining two uncertainty handling methods. Because this usually comes at the expense of higher cost, this cost increase (or "price of robustness") is calculated for method evaluation. Finally, this work considers the characteristics of different EV fleets at Home, Semi-Public, and Public chargers. Hence, the contributions of this paper can be summarized as follows:

1) Quantification and comparison of the impact of various uncertainties related to EV smart charging under different uncertainty levels (or budgets).

2) Incorporation of RO in predictive horizons of receding-horizon smart-charging systems for uncertainty management enhancement and quantification of the price of robustness.

3) Comparison of the impact of different uncertainties and the related price of robustness in EV chargers of different characteristics (Home, Semi-Public, and Public chargers).

III. METHODOLOGY

A. Uncertainty Budget

The uncertainty set structure adopted in this paper is proposed by Bertsimas & Sim in [14]. In this regard, z_i^t denotes the "budget of uncertainty i for every t, which represents the considered uncertainty level and decides about the trade-off between robustness & conservatism. The uncertainty set is modeled in (1), where U^t the total order of uncertain variables i & $[\bar{u}_i^t$- $\hat{u}_i^t$, $\bar{u}_i^t$+$\hat{u}_i^t]$: the uncertainty set, where uncertain variable i takes values in. Notations $\tilde{}$, $\bar{}$ & $\hat{}$ represent the uncertain variable, forecasted variable's value & max deviation from forecasted value, respectively.

$$\begin{aligned} U^t = \{\tilde{u}_i^t \in R^n : u_i^t \in [\bar{u}_i^t - \hat{u}_i^t, \bar{u}_i^t + \hat{u}_i^t], \forall t \in T\} \rightarrow \\ \{\tilde{u}_i^t \in R^n : u^t = \bar{u}_i^t + z_i^t \hat{u}_i^t, -1 \leq z_i^t \leq 1, \forall t \in T\} \end{aligned} \tag{1}$$

B. EMS: Predictive Receding-Horizon (RH) EV Smart-Charging System under Uncertainties

1) EMS Model Explanation: The EMS is a mixed-integer linear programming (MILP) receding-horizon EV smart-charging model, based on the work in [15]. It represents a parking lot, which charges the EV fleets with an integrated PV park and minimum charging cost while it is also capable of importing/exporting power to the main grid. It integrates three different nodes at three different locations, named "Home", "Semi-public" & "Public" which encompass 3, 5 & 3 chargers, respectively, to consider EV fleets with different characteristics. In Fig. 1, typical uncontrolled charging events of EV fleets at the nodes of the three different locations are depicted for a 2-day duration. Charging at Home chargers usually lasts longer because of high requested energy, low arrival SOCs, and higher connection time. However, the frequency of EV arrivals is greatly lower than at Semi-public and Public chargers, typically 3-4 times per week. In comparison, Semi-public and Public chargers can have even 3 EV arrivals per day. The EMS follows a distributional approach, performing in-parallel optimizations at the different nodes. The concept of the receding-horizon EMS is depicted in Fig 2. The EMS uses an RHO of timestep $\delta T = 5min$, which triggers new re-optimizations whenever a new EV arrival is realized (t1). The optimization horizon is set in two different steps. Firstly, the EMS checks the EVs already connected to the EV chargers and sets the horizon until the latest EV departure (t2). The connected EVs represent the actual (certain) charging state of the EMS at the node. Secondly, the EMS predicts the future EV arrivals at all node chargers during this horizon and resets the optimization horizon until the latest EV departure, considering the predicted EVs (t3). This represents the predicted uncertain state of the EMS. Moreover, the EVs are only allowed to participate in EV smart-charging (SC EVs) when their SOC is above 20%. At the same time, the possibility of no participation is also incorporated (No-SC EVs). The rest of the EVs are not considered in the optimization horizon. Finally, the EMS is informed ahead of time about the PV generation, load demand, and EV driving patterns, such as arrival & departure time, arrival SOC, requested energy, EV specifications, etc.

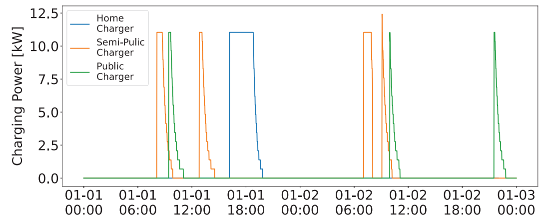

Fig. 1. Typical Uncontrolled Charging of EV fleets at Home, Semi-Public & Public Chargers (2 days)

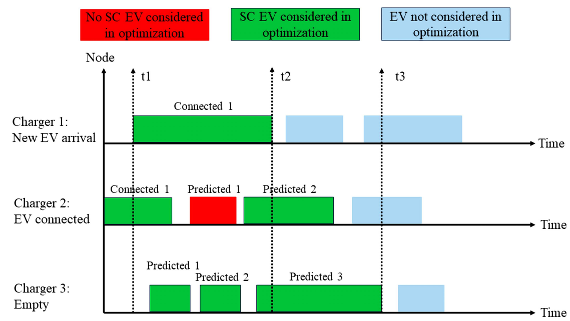

Fig. 2. Predictive Receding-Horizon EV charging EMS

$$\begin{aligned} \min C_n = \Delta t(\sum_{t=1}^{T}(P_{im}^{n,t} C_{buy}^t - P_{ex}^{n,t} C_{sell}^t)) \\ + \sum_{j=1}^{J}(B_a^{n,j} + d^{n,j} - B_d^{n,j}) C_{pen}^{n,j} \ \forall n, j, t \end{aligned} \tag{2}$$

$$\sum_{j=1}^{J}(\frac{P_{ch}^{n,j,t}}{h_{ch}^{n,j}}) + P_l^{n,t} - P_{PV}^{n,t} = P_{im}^{n,t} - P_{ex}^{n,t} \ \forall n, j, t \tag{3}$$

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$$B^{n,j,t} = B_a^{n,j} + \Delta t \sum_{T_a^{n,j}}^{t} (P_{ch}^{n,j} h_{ev}^{n,j}) \ \forall n,j,t \in [T_a^{n,j}, T_d^{n,j}] \tag{4}$$

$$P_{PV}^{n,t} \leq K_{PV}^{n,t} P_{PV_r}^{n} P_{PV_{fc}}^{n,t} h_{pv}^{n} \ \forall n,t \tag{5}$$

$$I_{ch}^{n,j,t} = \frac{P_{ch}^{n,j,t}}{V^{n,t}} \ \forall n,j,t \tag{6}$$

$$\sum_{j=1}^{J} \frac{P_{ch}^{n,j,t}}{h_{ch}^{n,j}} + P_l^{n,t} - P_{PV}^{n,t} \leq G_{in}^{n} \ \forall n,j,t \tag{7}$$

$$P_{PV}^{n,t} - P_l^{n,t} - \sum_{j=1}^{J} \frac{P_{ch}^{n,j,t}}{h_{ch}^{n,j}} \leq G_{out}^{n} \ \forall n,j,t \tag{8}$$

$$\begin{aligned} d^{n,j} \leq B_d^{n,j} - B_a^{n,j} &= (S_d^{n,j} - S_a^{n,j}) B_{max}^{n,j} \\ &= \Delta t \sum_{T_a^{n,j}}^{T_d^{n,j}} (P_{ch}^{n,j} h_{ev}^{n,j}) \ \forall n,j \end{aligned} \tag{9}$$

Equation (2) represents the objective function of the EMS, which aims to minimize the total cost for every horizon, where C_n, C_{buy}^t & C_{sell}^t denote the optimal charging cost of node n, the instantaneous buying and selling power price in [€] and $P_{ch}^{n,j}$, $P_{im}^{n,t}$ & $P_{ex}^{n,t}$ the EV charging power and the node imported & exported grid power in [kW]. The total cost depends on the costs and revenues by imported and exported power, respectively, and the penalty cost $C_{pen}^{n,j}$ paid to the EV owner for unfinished charging [$10€/1\%SOC$]. The unfinished charging gap is the difference between the sum of the arrival capacity $B_a^{n,j}$ and the requested energy $d^{n,j}$ from the departure capacity $B_d^{n,j}$ in [kWh].

Equations (3) & (4) dictate the node power balance and the SOC dynamics for every EV j connected to node n during parking time [$T_a^{n,j}$, $T_d^{n,j}$], where $P_{PV}^{n,t}$ & $P_l^{n,t}$ the PV generation and base load demand in [kW] and $B^{n,j,t}$ the instantaneous battery capacity in [kWh]. Moreover, (5) models the relation of the PV generation power with the forecasted PV power $P_{PV_{fc}}^{n,t}$, which depends on the rated PV power $P_{PV_r}^{n}$, equal in this work to 2.5kW and a scaling factor $K_{PV}^{n,t}$ assumed 1. Furthermore, (6) dictates the relation of the EV charging current $I_{ch}^{n,j,t}$ with the charging power and the node voltage $V^{n,t}$ assumed steady at 230V.

Equations (7) & (8) model the limits of the imported and exported power in kWs, where $G_{in}^n = 87kW$ & $G_{out}^n = 22kW$ the in and out grid power limits for node n, respectively. Moreover, (9) dictates the relation between the requested energy and the EV SOCs, where $S_a^{n,j}$ & $S_d^{n,j}$ the arrival and departure j EV SOC and $B_{max}^{n,j}$ its maximum battery capacity in [kWhs]. Finally, h_{pv}^n, $h_{ch}^{n,j}$ & $h_{ev}^{n,j}$ denote the efficiencies of the converters of the PV modules, chargers and EVs assumed equal to 1, 0.95 & 0.95, respectively.

2) PV Generation & Load Demand Uncertainties: The power balance (3) and grid limits constraints (7) & (8) dictate that a decrease in PV generation and/or increase in base load demand forces a higher imported or less exported power, that leads to increase of cost. Therefore, $z_{pv}^t < 0$ & $z_l^t > 0$ for $\forall t$ and PV generation and base load demand uncertainties are modeled as follows:

$$\tilde{P}_{PV_{fc}}^{n,t} = \bar{P}_{PV_{fc}}^{n,t} + z_{pv}^t \hat{P}_{PV_{fc}}^{n,t} : \ \hat{P}_{PV_{fc}}^{n,t} = \bar{P}_{PV_{fc}}^{n,t} \ \& \ z_{pv}^t < 0 \ \forall t \tag{10}$$

$$\tilde{P}_l^{n,t} = \bar{P}_l^{n,t} + z_l^t \hat{P}_l^{n,t} : \ \hat{P}_l^{n,t} = \bar{P}_l^{n,t} \ \& \ z_l^t > 0 \ \forall t \tag{11}$$

3) Arrival SOC & Requested Energy Uncertainties: The arrival SOC (and hence directly the arrival capacity) and the requested energy are two uncertainties integrated into the objective function (2), while they also affect (9). To model them with respective uncertainty sets, the robust counterpart of the objective function dictated by (12) must be considered.

$$\begin{aligned} \min C_n = \Delta t (&\sum_{t=1}^{T} (P_{im}^{n,t} C_{buy}^t - P_{ex}^{n,t} C_{sell}^t)) \\ + \max\{&\sum_{j=1}^{J} (B_a^{n,j} + \tilde{d^{n,j}} - B_d^{n,j}) C_{pen}^{n,j}\} \ \forall n,j,t \end{aligned} \tag{12}$$

The inner max of the robust counterpart is solved considering the first part of (9) and assuming that the departure capacity $B_d^{n,j}$ is certain under all conditions. Hence, the robust counterpart is substituted and solved by the model (13).

$$\begin{aligned} &\min \sum_{j=1}^{J} (-\tilde{B_a^{n,j}} - \tilde{d^{n,j}}) \ \& \\ -\tilde{d^{n,j}} - \tilde{B_a^{n,j}} \geq B_d^{n,j} &\rightarrow min(-\tilde{B_a^{n,j}} - \tilde{d^{n,j}}) \geq B_d^{n,j} \end{aligned} \tag{13}$$

Moreover, assuming a certain departure capacity $B_d^{n,j}$, the uncertain requested energy $\tilde{d^{n,j}}$ can be calculated by the uncertain arrival capacity and hence the arrival SOC $\tilde{S}_a^{n,j}$. Therefore, the uncertainties of arrival SOC and requested energy are modeled in (14), where $z_{soc}^{n,j}$ is the budget of arrival SOC uncertainty.

$$\begin{aligned} \tilde{S}_a^{n,j} = \bar{S}_a^{n,j} - z_{soc}^{n,j} \hat{S}_a^{n,j} : \ \hat{S}_a^{n,j} = \bar{S}_a^{n,j} \ \& \ z_{soc}^{n,j} > 0 \\ \& \ \tilde{d}^{n,j} = (\bar{S}_d^{n,j} - \tilde{S}_a^{n,j}) B_{max}^{n,j} \ \forall n,j \end{aligned} \tag{14}$$

4) Arrival & Departure Time Uncertainties: Considering certain arrival and departure capacities, the second part of (9) dictates that a lower parking time $T_d^{n,j} - T_a^{n,j}$ will force the EMS to charge with higher charging power. Therefore, treating the two uncertainties of arrival and departure time as one, the uncertain parking time $(T_d^{n,j} \tilde{-} T_a^{n,j})$ is dictated by (15), where $z_{pt}^{n,j}$ is the budget of parking time uncertainty.

$$\begin{aligned} (T_d^{n,j} \tilde{-} T_a^{n,j}) = (T_d^{n,j} \bar{-} T_a^{n,j}) + z_{pt}^{n,j} (T_d^{n,j} \hat{-} T_a^{n,j}) : \\ (T_d^{n,j} \hat{-} T_a^{n,j}) = (T_d^{n,j} \bar{-} T_a^{n,j}) \ \& \ z_{pt}^{n,j} < 0 \ \forall n,i \end{aligned} \tag{15}$$

Overall, the model is summarized as follows:

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- Decision Variables: $P_{ch}^{n,j,t}$, $P_{ex}^{n,t}$, $P_{im}^{n,t}$, $B^{n,j,t}$, $S^{n,j,t}$, $P_{PV}^{n,t}$ & $I_{ch}^{n,j,t}$
- Pre-decided Variables: C_{buy}^{t}, C_{sell}^{t}, $P_{l}^{n,t}$, $P_{PV_{fc}}^{n,t}$, $V^{n,t}$ & $z_i^t, \hat{u}_i^t \; \forall \; U^i$
- Parameters: $C_{pen}^{n,j}$, $B_a^{n,j}$, $B_{max}^{n,j}$, $S_a^{n,j}$, $d^{n,j}$, G_{in}^{n}, G_{out}^{n}, $T_a^{n,j}$, $T_d^{n,j}$, $P_{PV_r}^{n}$, $K_{PV}^{n,t}$, h_{pv}^{n}, $h_{ch}^{n,j}$ & $h_{ev}^{n,j}$

IV. Description of Case Studies & Scenarios

As already explained, the horizon of the EMS has two features, named "reaction" and "prediction" parts: actual and predicted charging state in Fig. 2. The PV park owner, grid operator, and EV drivers have notified the EMS in advance about the respective forecasts for PV generation, load demand, and driving patterns. In this regard, the reaction part is related to the currently connected EVs and the actual charging state since the EMS is certain about the actual values of the considered uncertainties. On the contrary, the prediction part is related to incorporating the future predicted charging state, in which the considered variables remain uncertain. Using these two features, the following scenarios are considered:

1) Ideal Scenario: No uncertainty sets are used and the uncertain variables are represented by their forecasted values in both the actual and predicted charging state.

2) Impact of Uncertainty Scenario: The uncertain variables are represented by the worst-case bound of their uncertainty sets (depending on the decided uncertainty budget) in the actual charging state and their forecasted values in the predicted charging state. In this scenario, the EMS relies on the forecasted information about its charging decision-making and does not protect charging against uncertainties. Three different uncertainty budgets z_i have been considered for this scenario to analyze the gradual impact of the uncertainties: 5%, 15%, and 25%, which represent a low, medium, and high level of uncertainty, respectively. The impact of uncertainties is evaluated by:

- Charging Performance: the amount of the total EV requested energy that was not provided to the EVs (called unfinished charging gap)
- Total Cost: the total cost of the EMS operation. It must be noted that if the total charging cost results negative, the number represents revenues-earnings for the EMS

3) Price of Robustness Scenario: The uncertain variables are represented by the worst-case bound of their uncertainty sets in the predicted charging state using RO and their forecasted values in the current charging state. In this scenario, the robustness of the current decision-making is enhanced since the EMS will consider potential future uncertainties. While a higher charging performance is expected, an increase in the total charging cost can also be seen. This is because the EMS decreases the charging cost optimality at the expense of charging robustness. This increase in the charging cost is called the "Price of Robustness" and is quantified for this scenario validation. This scenario has been validated for the worst-case uncertainty budget $z_i = 25\%$.

It must be noted that for PV generation and load demand uncertainties, a maximum period of 1h has also been considered for separating the actual and predicted states since they are not directly connected with the two states. Hence, a perfect forecast for the next 1 hour has been assumed. Finally, the case studies are summarized in TABLE I.

TABLE I
Case Studies of EV Smart Charging.

Nodes	Uncertainties	Levels	Scenarios	Evaluation
Home	PV Generation	5%	Ideal	Charging Performance
Semi-Public	Load Demand	15%	Impact of Uncertainty	Total Cost
Public	Arrival SOC	25%	Price Robustness	
	Parking Time			

V. Results & Discussion

A. EMS model: Ideal Scenario

In Fig. 3, the ideal EV charging scenario and the energy prices are depicted for the Home and Public Nodes for a 2-day duration where all uncertainty levels are set to zero. Most PV generation is exported to the main grid because it overlaps with the high energy prices. Moreover, EV charging is mostly performed during low energy prices between 20:00-03:00. Furthermore, load demand is covered by PV generation when there is availability; otherwise, power is imported from the main grid. Finally, the different characteristics of the incoming EV fleets at the chargers of the different nodes, seen in Fig. 2, can also be seen here. The EV charging sessions at the Home node usually last longer due to the longer parking periods and higher charging power levels due to the higher requested energy. On the contrary, the EV charging sessions at the Public node are frequent and last for a shorter period of time.

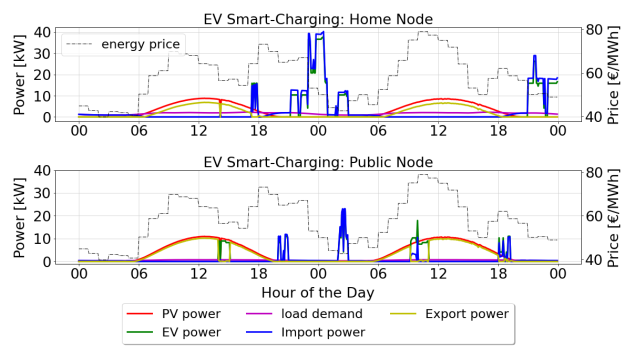

Fig. 3. Ideal Case for Home and Public nodes (2 days duration).

B. Impact of Uncertainties

The impact of the investigated uncertainties is summarized in Figs. 4 & 5. In both Figs, the ideal case is accounted as a benchmark case of 0% uncertainty, which is characterized by a total cost and unfinished charging gap compared to whom all other uncertainty cases are compared. The impact of the uncertainties on the unfinished EV charging gap (upper figures) and charging cost (lower figures) for all three nodes

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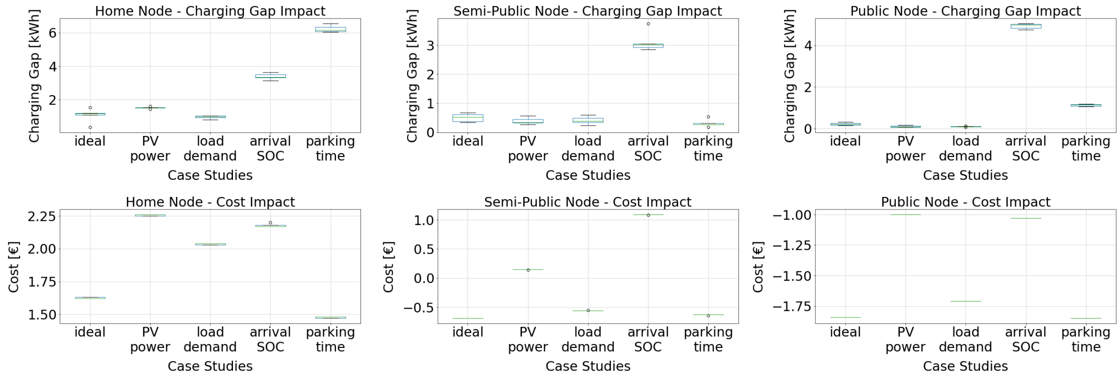

Fig. 4. Charging Gap and Cost Impact of every uncertainty case per Node for 10 iterations for 25% uncertainty level.

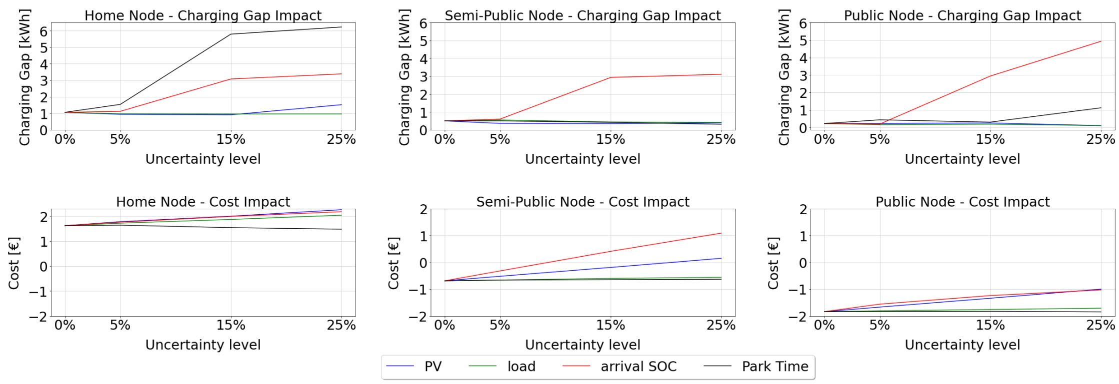

Fig. 5. Average Node Charging Gap and Cost for all uncertainties and uncertainty levels

is summarized in Fig. 4 compared to the ideal scenario for a 25% uncertainty level. It must be noted that a negative node cost means final revenues for the node due to exported power to the grid. PV generation and load demand uncertainties do not have a notable impact on the charging performance of the EVs, while they mostly affect the charging cost. That is because, on the one hand, the load demand excess is covered with higher imported grid power. On the other hand, the PV generation shortage leads either to an exported power decrease or an imported power increase for EV charging. Moreover, the daily PV generation is higher than the base load consumption; hence, the impact of PV generation uncertainty affects much higher the total node cost, leading to an average 37% cost increase for the Home node and a 43% revenue decrease for the Public node. Additionally, the load demand of the Semi-public and Public nodes is lower than that of the Home node, and hence, load demand uncertainty has a greater impact on the Home node cost (25% increase). Parking time uncertainty has a notable impact only on the EV charging performance and mostly on the Home node reaching a more than 6kWh unfinished charging gap. This can be justified by the characteristics of the different EV fleets at the nodes. The parking periods at Semi-public and Public nodes are usually very low, for example, in the range of 1-2 hours; therefore, a 25% uncertainty is translated on the range of minutes. Hence, also due to the low requested energy at these nodes, the uncertainty is less impactful. Finally, arrival SOC is considered the worst uncertainty due to its impact on both metrics. Firstly, it greatly increases the charging cost to similar levels as PV power uncertainty because of the higher EV requested energy at all nodes. Secondly, it increases the unfinished charging gap to an average of 3.7kWh, 3kWh, and 4.8kWh, representing a 4x, 6x, and 24x increase for Home, Semi-public, and Public nodes, respectively.

The average impact of the uncertainties for the intermediate uncertainty levels of 5% and 15% for the unfinished charging gap (upper figures) and charging cost (lower figures) is summarized in Fig. 5. The impact on the cost increases linearly for all the nodes for all uncertainties with higher slopes observed for the arrival SOC and PV generation uncertainties. A similar slope is also seen for the parking time at the Home node. Regarding the charging performance, the 5% uncertainty level has a low impact for all nodes. However, a 15% arrival SOC uncertainty level increases the unfinished charging gap to approximately 3kWh for all nodes (15x higher for the Public node). Moreover, a 15% parking time uncertainty level is even more impactful for the Home node, increasing the charging gap to 6kWh, 200% higher than the related increase by the arrival SOC. Finally, an impact saturation is seen for most cases after the 15% uncertainty level.

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C. Price of Robustness

In Fig. 6, the price of robustness is quantified for all uncertainties and nodes considering the worst-case scenario of 25% uncertainty level to investigate the trade-off between protection and cost of robust optimization. By considering the worst-case scenario of the uncertainties with RO in the prediction part of the horizon, the EMS can charge the currently connected EVs earlier to protect charging against uncertainties. However, this reduces the total unfinished charging gap and not the total cost. Therefore, the charging may be performed under higher energy prices and the charging cost can increase. It can be seen that for all three nodes and all uncertainties, the cost increase remains below 3% with only the exception of the parking time uncertainty at the Home node that reaches up to 4.4%. Since PV generation and load demand uncertainties do not affect the charging gap of the EVs (Figs. 4,5), considering the worst-case scenario of these uncertainties in the prediction part of the horizon is not recommended since it inflicts an unnecessary cost on EV charging. This cost is deemed unnecessary for PV generation and load demand because it does not protect the charging performance against future uncertainty events and simultaneously increases the current total cost of the EMS. On the contrary, this is recommended for the arrival SOC and parking time uncertainties due to their high impact on charging performance and low price of robustness.

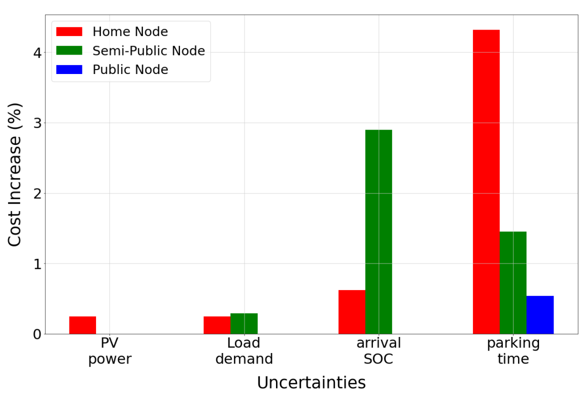

Fig. 6. Price of Robustness (% cost increase) for uncertainty management.

VI. Conclusion & Future Work

This work investigated the impact and the potential management of several uncertainties related to EV smart charging. Firsty, the impact of every uncertainty was quantified under different considered increasing uncertainty sets concerning the charging performance and total cost of receding-horizon EMSs. Secondly, combining two uncertainty methods was proposed, considering uncertainties with uncertainty sets using RO in the prediction part of the charging receding horizon. Finally, the price of robustness was quantified. The PV generation and load demand uncertainties affected the total charging cost increase linearly during increasing uncertainty levels. On the contrary, parking time uncertainty was found to be more hazardous for the EV charging performance. Finally, arrival SOC uncertainty had a significant impact on both evaluation metrics and has been considered the worst uncertainty for EV charging. The price of robustness was found to be very low in all cases, reaching a 4.4% cost increase at the most.

The main limitation of this work is the consideration of every uncertainty individually. However, uncertainties in EV smart charging can also have a simultaneous effect on the EMS performance, which can be exponentially increased in combination. Therefore, it is recommended for future work.

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