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***Abstract*— The increasing penetration of electric vehicles (EVs) in the mobility market and their significant impact on the power grids calls for new and "smart" approaches to the management of the charging process for these vehicles, aimed at maximizing the efficiency while respecting power budgets and minimizing costs. In this paper, we propose a robust model for optimal scheduling the charge power at sockets for a large EVs parking facility. We start by developing a nominal linear programming (LP) model for the smart charging problem and then observe that, in practice, key quantities such as electricity prices and the vehicles' energy demand are subject to uncertainty. We hence formulate a robust LP version of the problem, which provides charging plans that are resilient to uncertainties. The effectiveness of such model is analyzed by means of a-posteriori evaluations, where we test the candidate plan against scenarios and realizations of the uncertain data, using performance metrics such as the *regret* that allow for a fair comparison between different solutions (e.g., robust and nominal). The robust optimization model indeed handles uncertainties without drastically compromising performance, and offers a promising approach when deployed in real-time by means of a receding-horizon scheme.**

I. Introduction

With the increasing adoption of electric vehicles (EVs), it becomes crucial to develop innovative solutions for optimally managing their charging process. The number of EVs is expected to grow significantly in the near future [1], presenting new challenges for charging infrastructure. While many studies have focused on the impact of EVs on the power grid, using data-driven models to shift charging to off-peak hours and reduce grid overload [2], [3], efficient management of charging stations needs more attention.

Our approach focuses on optimizing charging stations through Smart Charging methods [4], some of which allow intelligent resource allocation and dynamic adjustment of charging schedules, improving operational efficiency and reducing costs [5]. Unlike vehicle-to-grid (V2G) systems, which has been proven to possibly shorten battery life [6], we focus on the more sustainable grid-to-vehicle (G2V) interaction.

Interest in Smart Charging optimization has been growing rapidly. Recent research has developed methods to reduce charging costs based on the state of charge (SoC) [7], as well as real-time management systems to identify optimal charging periods and minimize grid load [8], or also optimizing charger placement for long-distance EV travel by balancing congestion and charging time [9]. Furthermore, predictive models, such as the hybrid kernel density estimator, enable accurate forecasts of energy demand and charging duration [10]. Some works, like [11], rely on forecasted electricity prices to build a Model Predictive Control (MPC) framework that optimizes EV charging schedules while minimizing costs. The approach uses Lagrangian decomposition to allow decentralized decision-making, where each EV determines its charging profile based on real-time price updates. None of these works, however, directly deal with data and estimation uncertainty via a robust approach.

Robust smart charging for electric vehicles (EVs) has garnered significant attention in recent research, addressing challenges related to power management, economic costs, and system reliability under uncertain conditions. The focus has been on developing optimization models, stochastic programming approaches, bi-level models, adaptive robust optimization, and learning-based algorithms. Some papers in the very recent literature have tackled the problem of Smart Charging using a robust optimization approach.

The authors in [12] propose two models for robust power management using chance constraints to handle uncertainties: a mixed-integer nonlinear program (MINLP) and a simpler mixed-integer linear program (MILP). Their objective is to minimize economic and technical costs while adhering to load flow equations and EV charging constraints. In a related study, [13] focus on smart distribution networks for active and reactive power management using EVs. They employ Benders decomposition to convert the robust counterpart model into a max form, minimizing energy cost and voltage deviation subject to network and EV constraints.

A two-stage stochastic programming approach has been used by [14] to manage hybrid charging stations integrated with photovoltaic systems. Their model addresses uncertainties in photovoltaic generation, market prices, and load demand, comparing risk-neutral and risk-averse strategies. They find that robust optimization, despite increasing total expected costs by approximately 8.9%, significantly reduces scheduling risks.

The authors in [15] integrate L2-norm uncertainty into the charging cost function, ensuring resilience of their optimization model against cost fluctuations. This approach effectively allocates power to EVs, minimizing both charging costs and time, even under variable grid conditions.

In [16] a bi-level model optimizes the design of EV

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charging stations with distributed energy resources. The upper level of the model determines the optimal configuration and pricing schemes, while the lower level captures EV owners' charging decisions. Transforming the bi-level robust optimization problem into a single-level one, they demonstrate how varying the uncertainty budget balances conservatism and optimality.

Price uncertainty in EV charging station scheduling is a key challenge addressed by [17]. They develop an algorithm to determine robust charging and discharging strategies, showing substantial improvements over deterministic methods. Later, in [18] they investigate an EV charging scheduling problem using an actor-critic learning-based algorithm. Their approach reduces charging costs and peak loads under uncertain future information about EVs, such as arrival and departure times and charging demand.

Finally, [19] proposes a bi-directional charging control strategy for public place EV-to-grid integration, using a two-stage distributed optimization model. They incorporate uncertainties in driver behavior and cluster EV users by behavioral patterns, showing significant energy cost savings in real-life simulations.

These studies collectively advance the understanding and implementation of robust smart charging strategies for EVs, balancing economic efficiency, system reliability, and integration with renewable energy sources. Following the line of research of these studies, in this work we develop a robust LP model for smart charging. The LP nature of the mathematical model is certainly an advantage with respect to MILP and SOCP problem formulations when it comes to handling large input data sets. Another interesting modification concerns the relaxation of the energy demand satisfaction constraint, which is directly linked to the addition of a second tradeoff term in the objective function. This term mathematically models the maximization of customer satisfaction alongside the minimization of the charging station's operating costs. We will see that our robust optimization model will manage to keep a high average satisfaction among EVs owners while not loosing much in operational costs.

In this paper, we also describe effective evaluation procedures for testing the "goodness" of a given solution (robust or not). The proposed a-posteriori evaluation analyzes objective value distribution, regret, and relative regret of a solution, allowing for a fair comparison among solutions obtained via different approaches, when input data are subject to uncertainty.

The structure of the paper is as follows. Section II presents the mathematical optimization model from the perspective of the charging station's manager. A robust formulation of the charging problem is given in Section III. Section V describes the simulations settings, implementation of the optimization model, and evaluation of the robust solution via a-posteriori tests. Conclusions are drawn in Section VI.

II. The Smart Charging model

We assume electricity is available from the power grid and purchased from the market. We denote by C_t the instantaneous power available from the grid (time dependence may be due to weather conditions, hydro availability and possible solar panel production), generating a total energy of δC_t during time interval $[t-1,t]$ of duration δ. Each charging socket has a fixed maximum power rating $\bar{p}$. It is implicitly assumed in the model that the total number of available sockets is larger than the number N of vehicles requesting charge at any given time, since anyways vehicles in excess of the sockets' number would not be allowed to enter the parking. Electric vehicle i arrives in the charging station at the discrete time instant a_i with an energy request $L_i \geq 0$, and leaves at d_i. Letting Y_{ti} denote the power allocated to the ith EV during time interval t (assumed to be constant within such interval), the model aims to optimally allocate the power Y_{ti} at all times t for all vehicles i. With the above definitions and letting π_t denote the energy price rate at t, we cast the nominal smart charging optimization problem over the time horizon $1 \leq t \leq T$ as

$$\begin{aligned}
\min_{Y,e} \quad & \sum_{t=1}^{T} \pi_t \left(\sum_{i:t\in[a_i,d_i]} \delta Y_{ti} \right) + \gamma \sum_{i=1}^{N} e_i \\
\text{s.t.} \quad & \sum_{t=a_i}^{d_i} \delta Y_{ti} \geq L_i - e_i, \quad \sum_{i=1}^{N} Y_{ti} \leq C_t, \\
& \qquad \forall i \in \{1,\dots,N\},\ \forall t \in \{1,\dots,T\} \\
& 0 \leq Y_{ti} \leq \bar{p}, \quad \forall i \in \{1,\dots,N\}, \forall t \in \{1,\dots,T\} \\
& e_i \geq 0, \quad \forall i \in \{1,\dots,N\}, \\
& Y_{ti} = 0 \quad \forall t \notin [a_i,d_i], \forall i \in \{1,\dots,N\}.
\end{aligned} \tag{1}$$

where $e \doteq (e_1,\dots,e_N)$ and Y is the matrix with entries Y_{ti}. The minimization objective in problem (1) is a tradeoff between the energy costs and the customer (dis)satisfaction, where this latter component is measured in terms of the sum of deficit charges e_i, being e_i the amount of energy that the system fails to deliver to the i-th EV with respect to its desired charge level L_i ($e_i = 0$ for fully charged EVs). The tradeoff parameter $\gamma \geq 0$, having the interpretation of cost per unit energy not delivered to requesting customers, meausured in €/kWh, models the optimizer's preference: for $\gamma = 0$ the focus of the optimization is only on the energy cost minimization, while larger values of γ tilt the optimization focus towards customers' satisfaction. Problem (1) is a linear programming problem (LP). We next introduce a binary matrix A of dimensions $T \times N$ to represent the vehicles' arrival and departure times (a_i, d_i). Each element A_{ti} is set to 1 if time t falls within the interval $[a_i, d_i]$ for vehicle i, and 0 otherwise. This matrix enables us to condense the information about each vehicle's arrival and departure times in compact format. We can hence restate the optimization problem in the form

$$\begin{aligned}
\min_{Y,e} \quad & \pi^\top \delta Y \mathbf{1} + \gamma \mathbf{1}^\top e \\
\text{s.t.} \quad & \delta Y^\top \mathbf{1} \geq L - e, \\
& Y\mathbf{1} \leq C, \\
& Y \geq 0,\ Y \leq \bar{p}\mathbf{1},\ e \geq 0, \\
& Y_{ti} = 0\ \forall t, i : A_{ti} = 0,
\end{aligned} \tag{2}$$

where $\mathbf{1}$ denotes a vector or matrix of ones of suitable dimension, and $\pi = (\pi_1, \ldots, \pi_T)$ is the vector of energy prices. Here, $\delta Y \mathbf{1}$ contains the total energy consumption during the time intervals $[t-1, t]$, for $t = 1, \ldots, T$, and $\delta Y^\top \mathbf{1}$ contains the total overall energy supplied to each vehicle $i = 1, \ldots, N$.

III. Robust charging model

In model (2) the electricity rates π_t and the vehicles demands L_t are assumed to be given and known input data. In practice, however, electricity prices fluctuate not only with regular daily patterns (like high and low price periods) but also because of unexpected network conditions or real-time market situations. Similarly, we do not know precisely in advance how much energy each vehicle will need, which may become particularly critical during peak hours when higher demand may saturate the power capacity of the system. In this section we shall henceforth consider an uncertainty model on electricity price rates and vehicles' demands. Namely, we assume that prices at t are bounded within given intervals (assumed to be computable via estimation on suitable historical data sets) and subject to a rate constraint limiting their variability from one instant to the next, that is we assume $\pi \in \Pi$, where Π is the price uncertainty set defined by means of the conditions

$$\begin{aligned} &\pi_{t,\mathrm{lb}} \leq \pi_t \leq \pi_{t,\mathrm{ub}}, \quad \forall t = 1, \ldots, T, \\ &|\pi_{t+1} - \pi_t| \leq \epsilon, \quad \forall t = 1, \ldots, T, \end{aligned} \tag{3}$$

where ϵ is the given rate bound. Similarly, we assume for the demand vector that $L \in \mathcal{L}$, where $\mathcal{L}$ is an interval uncertainty set defined entry-wise by the inequalities

$$\underline{L}_i \leq L_i \leq \bar{L}_i, \quad i = 1, \ldots, N$$

where $\underline{L}_i = 0$ in many practical cases. The robust counterpart of problem (2) is then

$$\begin{aligned} \min_{Y,e} \max_{\pi \in \Pi} \quad & \pi^\top \delta Y \mathbf{1} + \gamma \mathbf{1}^\top e \\ \text{s.t.} \quad & \delta Y^\top \mathbf{1} \geq \max_{L \in \mathcal{L}} (L - e), \\ & Y \mathbf{1} \leq C, \\ & Y \geq 0, \ Y \leq \bar{p} \mathbf{1}, \ e \geq 0, \\ & Y_{ti} = 0 \ \forall t, i : A_{ti} = 0, \end{aligned} \tag{4}$$

(in case of vector arguments, the max or min operators are intended to be applied element-wise). The following proposition is easily derived.

Proposition 1. *The robust problem (4) is equivalent to the LP*

$$\begin{aligned} \min_{Y,e} \quad & \bar{\pi}^\top \delta Y \mathbf{1} + \gamma \mathbf{1}^\top e \\ \textit{s.t.} \quad & \delta Y^\top \mathbf{1} \geq \bar{L} \mathbf{1} - e, \\ & Y \mathbf{1} \leq C, \\ & Y \geq 0, \ Y \leq \bar{p} \mathbf{1}, \ e \geq 0, \\ & Y_{ti} = 0 \ \forall t, i : A_{ti} = 0, \end{aligned} \tag{5}$$

where $\bar{\pi} = (\bar{\pi}_1, \ldots, \bar{\pi}_T)$, being $\bar{\pi}_1 = \pi_{1,\mathrm{up}}$, and

$$\bar{\pi}_{t+1} = \min(\bar{\pi}_t + \epsilon, \pi_{t+1,\mathrm{up}}), \quad t = 1, \ldots, T-1.$$

IV. A-posteriori performance evaluation

We next discuss how to numerically evaluate and validate the performance of a charging strategy against uncertain scenarios. The approach we describe next can be applied to any proposed charging schedule, which may come as an optimal solution of the robust problem (5), or as an optimal solution of a nominal problem instance, or yet from some other strategy. No matter the way in which a solution (i.e., a charging schedule Y) is obtained, our goal is to set up a test ground on which such solution can be tested and hence compared with other solutions. The main focus here, however, is on the comparison between the robust solution and the nominal solution. As typical with robust approaches, on the one hand the robust solution may tend to provide higher average objective values on nominal scenarios with respect to the nominal solution, due to its focus on extreme, worst-case events, but on the other hand the nominal solution may perform poorly on test scenarios that deviate substantially from nominal.

We assume that the charge scheduling problem has been solved by means of some approach (e.g., nominal, robust, mean field, etc.) and that we have a solution $Y \in \mathbb{R}^{T,N}$ that we want to validate by means of a-posteriori tests. For doing so, we assume to have also available a fresh batch of *test* scenarios $\mathcal{U} = \{u^{(1)}, \ldots, u^{(S)}\}$ of the uncertainties, in our context given by a sample $L^{(j)}$ of the demand vector and a sample $\pi^{(j)}$ of the price vector, that is $u^{(j)} = (L^{(j)}, \pi^{(j)})$. Given the candidate solution Y, for each scenario $j = 1, \ldots, S$ we compute the actual dissatisfaction vector

$$e^{(j)} \doteq L^{(j)} - \delta Y^\top \mathbf{1}$$

and hence the cost $c_j \doteq \delta \pi^{(j)\top} Y \mathbf{1}$ and the overall objective

$$o_j \doteq c_j + \gamma \mathbf{1}^\top e^{(j)}.$$

We also compute the optimal solution that we would have if we knew in advance the uncertainty scenario, that is we let o_j^* be the optimal value of problem (2) in which $L = L^{(j)}$ and $\pi = \pi^{(j)}$, and we let $Y_*^{(j)}$ be a corresponding optimal solution. The *regret* $r_j \doteq o_j - o_j^*$, see, e.g., [20], measures how much do we loose in terms of objective value, on occurrence of the jth scenario, by using the candidate solution Y instead of the solution $Y_*^{(j)}$ we would obtain if the scenario was known in hindsight. Normalizing with respect to o_j we obtain the *relative regret*

$$s_j \doteq \frac{o_j - o_j^*}{o_j^*}, \quad j = 1, \ldots, S.$$

Once the above quantities have been computed for all the test scenarios, we can construct several performance indicators that help us assess the quality of the solution Y under test, as done in the numerical simulations in Section V.

V. Numerical simulations

We next describe the simulation setup we developed for testing the performance of our smart charging methodology. We considered a time horizon $H = 24$ hr and a sample interval $\delta = 5$ min, resulting in $T = 288$ discrete time intervals. We let $N = 100$ vehicles and, for each vehicle i we generated an arrival time a_i according to a Beta(α, β) distribution and rescaled the result by T. After tuning, we let $\beta = 12$, $\alpha = 5.52$, which results in the arrival distribution having a peak at around 7am, which is a typical pattern of charging stations close to universities or workplaces. Then, we generated the vehicle's departure time d_i by adding to the arrival time a Normal random parking duration with mean 6 hr and standard deviation of 1 hr. With the described procedure we generated an instance of the $T \times N$ occupancy matrix A, whose columns we further ordered according to the vehicles' times of arrival. Also, for each vehicle i, we generate a sample of the corresponding demand L_i as $L_i = w\bar{L}_i$, where w is some number sampled in $[0, 1]$ and $\bar{L}_i \doteq \bar{p}(d_i - a_i)$ represents the demand upper bound that we use in the robust model. Nominal electricity prices π_t, $t = 1, \ldots, T$, have been obtained from publicly available hourly data from Italy [21], averaged over 456 days from 01-Jan-2023 to 31-Mar-2024 included, and then resampled at the required δ rate. From this real historical price data we also determined the upper and lower price bounds and maximum slew rate ϵ that describe the price uncertainty set in (3).

A. The FIFS baseline solution

For the purpose of comparison and further motivation of the smart charging approach, we define the first-in-first-served (FIFS) approach to charging as the standard method by which vehicles access the charging slots in their order of arrival and get charged without interruption until when they either complete their charge (i.e., the demand L_i is met) or depart. Vehicles arriving when the overall power capacity C_t has been reached must wait for some of the vehicles in charge to finish their service in order to see the power capacity restored and start their charging. Such a baseline approach defines a charging schedule matrix $Y_{\text{fifs}} \in \mathbb{R}^{T,N}$ and a dissatisfaction vector $e_{\text{fifs}} \in \mathbb{R}^N$ that are clearly suboptimal for the nominal optimal charging problem (2).

For illustration, we generated an instance of the A matrix as described above, and we let the demands be set as $L_i \leftarrow \bar{L}_i/4$. We used nominal electricity prices π_t, $t = 1, \ldots, T$, set maximum plant capacity $C_t = 1.13$ MW at all t and $\bar{p} = 22kW$, as it is in the most common charging ports in Europe [22]; we solved (2) with $\gamma = 0.157$ €/kWh (which corresponds to the maximum of the price profile over time), thus obtaining a nominal optimal charging schedule Y^* and corresponding dissatisfaction e^*. Figure 1 shows a comparison between the optimal schedule and the FIFS schedule Y_{fifs} and dissatisfaction e_{fifs}. In this example, the total dissatisfaction with both methods is zero, meaning that in both cases all vehicles receive their full demanded charge. The total charging cost, however, is 391€ for the FIFS method and 343€ for the smart method, resulting approximately in a 14% overall cost reduction; Figure 2 shows more precisely that the mean cost rate per EV under the smart method is always lower or equal than the cost rate under the FIFS, for each of the $N = 100$ EVs. As clear from the bottom panel of Figure 1, the smart approach achieves such saving by optimally shifting in time the charging tasks towards the valleys of the energy price.

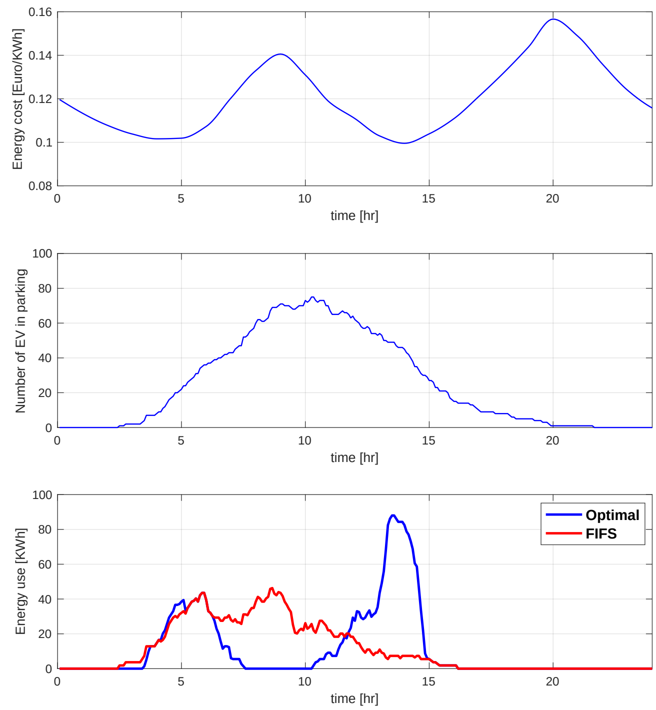

Fig. 1: Top panel: nominal price profile. Mid panel: parking occupancy. Bottom panel: overall energy consumption per period for the smart approach (blue) and the FIFS approach (red).

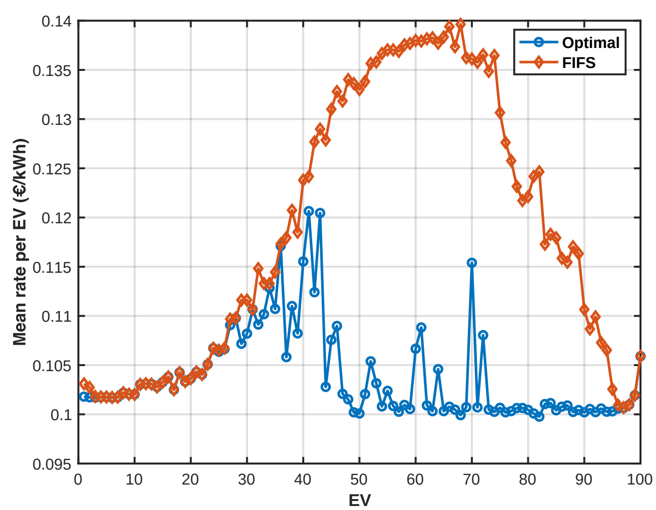

Fig. 2: Mean charging cost rates for the FIFS and the smart approach. EVs are numbered in the arrival order.

B. Performance of nominal vs. robust model

We next evaluate and compare the performance of the nominal optimal and robust optimal charging methods, following the approach outlined in Section IV. To this end, we created A as described at the beginning of this section. Uncertainty scenarios $\mathcal{U} = \{u^{(1)}, \ldots, u^{(S)}\}$, where $u^{(j)} = (\pi^{(j)}, L^{(j)})$, are generated by a mixing distribution whereby with probability $p \in [0, 1]$ scenario j is randomly generated by sampling a price vector $\pi^{(j)}$ uniformly at random between the lower and upper bounds $\pi_{\rm lb}$, $\pi_{\rm ub}$[1] and demand vectors are generated uniformly in the hyperrectangle $[0, \bar{L}]$; and with probability $1 - p$ scenario j is randomly generated as

$$\pi^{(j)} = \omega_j \pi_{\rm ub} + (1 - \omega_j)\pi_{\rm lb}, \quad L^{(j)} = w_j \bar{L},$$

where ω_j, w_j are uniform random numbers in $[0, 1]$. This latter part of the mixture distribution insures that scenarios visit boundary regions of the uncertainty set that would otherwise be visited with exceedingly low probability by using only the first part of the mixture distribution. We selected in the simulation $p = 0.2$ for the mixture probability. The L value used in the nominal model (2) is taken midway from the maximum, i.e., $L_i = \bar{L}_i/2$, $i = 1, \dots, N$. The maximum plant capacity was set again at $C_t = 1.13$ MW at all t, $\bar{p} = 22kW$ and γ was set at $\max(\bar{\pi}) = 0.2258$.

With the above data, we solved the nominal model (2) and the robust model (5), obtaining the solutions $(Y_{\rm nom}, e_{\rm nom})$ and $(Y_{\rm rob}, e_{\rm rob})$, respectively. Each of these two solutions is then tested against a number $S = 5000$ of sampled random scenarios of prices and demand, generated as previously described. Following the approach discussed in Section IV, for each scenario j we computed the actual dissatisfaction vectors $e^{(j)}_{\rm nom} \doteq L^{(j)} - \delta Y^{\top}_{\rm nom}\mathbf{1}$, $e^{(j)}_{\rm rob} \doteq L^{(j)} - \delta Y^{\top}_{\rm rob}\mathbf{1}$, energy costs $c^{(j)}_{\rm nom} \doteq \delta\pi^{(j)\top} Y_{\rm nom}\mathbf{1}$, $c^{(j)}_{\rm rob} \doteq \delta\pi^{(j)\top} Y_{\rm rob}\mathbf{1}$, objective values $o^{(j)}_{\rm nom} \doteq c^{(j)}_{\rm nom} + \gamma\mathbf{1}^{\top} e^{(j)}_{\rm nom}$, $o^{(j)}_{\rm rob} \doteq c^{(j)}_{\rm rob} + \gamma\mathbf{1}^{\top} e^{(j)}_{\rm rob}$, and relative regrets $s^{(j)}_{\rm nom}$, $s^{(j)}_{\rm rob}$. Notice that the $e^{(j)}_{\rm nom}$, $e^{(j)}_{\rm rob}$ vectors may now contain both positive or negative values. Positive values refer to proper dissatisfactions, since they represent an amount of energy that the charging schedule failed to deliver to a vehicle. Contrary, negative values reflect the situation when the charging schedule happens to surpass the energy demand of a vehicle; this surplus energy is hence saved and subtracted to the cost.

Figure 3 shows a scatter plot of the two components of the optimization objective function, for the nominal and the robust solutions, on the scenarios. Specifically, the sum of the coordinates of each blue (resp., green) point in the plot corresponds to a value of the objective function $o^{(j)}_{\rm nom}$ (resp., $o^{(j)}_{\rm rob}$). As expected, the robust model generates higher charging costs on average, since it strives to cover most of the energy demand scenarios. This results in typical *negative* dissatisfaction and thus in significant objective value reductions in typical scenarios. Figure 4 shows histograms of the objective values for the the nominal and robust solutions on the uncertainty scenarios: the robust solution performs better that the nominal one, both on average and on the extreme, worst-case, scenarios. In particular, the average objective value for the nominal solution resulted to be 773.54, while the average objective value for the robust solution resulted to be 366.35, corresponding to a 52.64% average reduction. Finally, Figure 5 shows boxplots of the relative regrets $s^{(j)}_{\rm rob}$, $s^{(j)}_{\rm nom}$ for the robust and the nominal solutions, respectively.

[1]Enforcement of the slew rate constraint is obtained by rejection (and regeneration) of the samples that do not respect it.

In these boxplots, the 50% of the values are contained within the upper and lower bounds of the central boxes, with the median value as central line. The lower is the relative regret, the better the solution performs on actual scenarios, and we observe again that the robust model outperforms the nominal one both in terms of average performance and performance on extreme events.

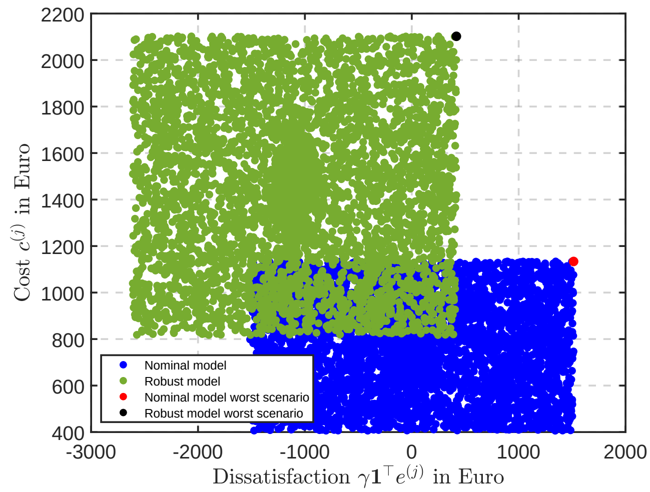

Fig. 3: Scatter plot comparison between Nominal and Robust solutions.

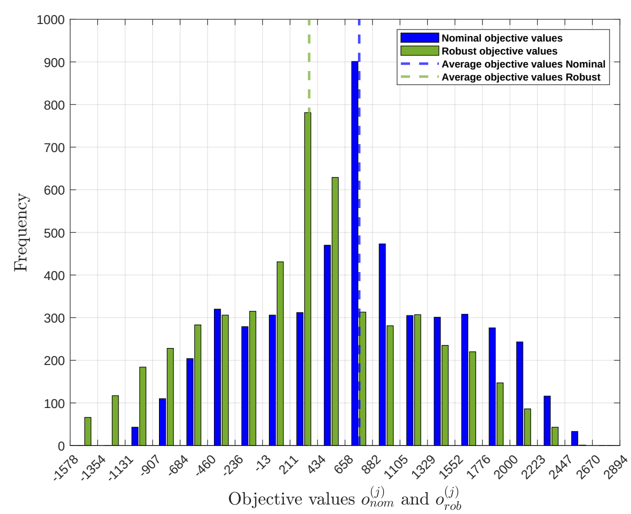

Fig. 4: Histogram of objective values.

VI. Conclusions

Smart charging via optimal scheduling of the charging power has the potential of substantially improving over standard heuristics, such as the first-in-first-served approach, reducing operating costs by exploiting fluctuations of the energy price while maintaining customer satisfaction, as discussed in Section V-A. As realistic interval uncertainties (e.g., on prices and vehicles' energy demands) are introduced in the model, we considered a robust version of the smart charging problem that can still be cast as an efficiently solvable LP. Section V-B then reports the results of a-posteriori randomized tests on the robust and the nominal solutions, showing that, despite conservatism, the robust

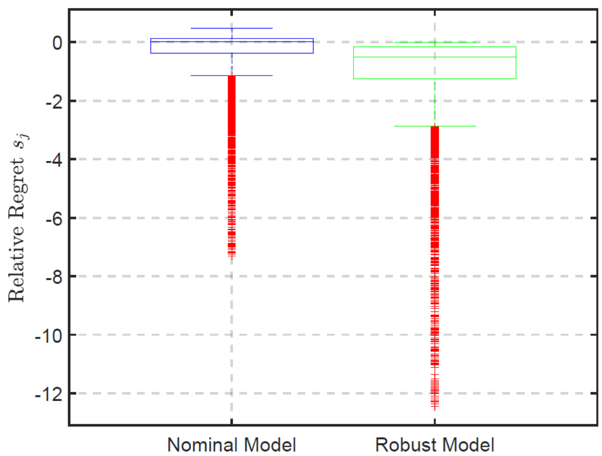

Fig. 5: Boxplot of relative regret.

approach yields superior validation performance both on average and near-worst-case scenarios.

The results reported in this work, albeit promising, are still preliminary: realistic implementation of a robust smart charging method should require real-time solution of the optimization problem repeatedly over a sliding time horizon, using updated estimated quantities (e.g., demands, departure times, prices) at each optimization step. Our ongoing research efforts are in fact directed towards consideration of such more complex setting, including dynamic estimation and updating of predictions, solution over sliding horizon, and implementation of the first-step decision in the style of model predictive control.

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