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Optimal Operation Strategy for Electric Vehicles Charging Stations with Renewable Energy Integration

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Abstract. This paper proposes an aggregator for the optimal scheduling of a Electric Vehicle (EV) charging station. Assuming that the station charging can consume energy from the power grid and also from a renewable source at no cost, Day-Ahead and Real-Time strategies are developed for the station, considering uncertainty in the local renewable generation source. First, a scheduler decides the energy to buy in the day ahead market from the power grid considering a renewable source forecast and an EVs schedule. An autoregressive model developed from 5 years of historical solar radiation data is applied. In real time, a model predictive control strategy is designed to follow the scheduled power from the grid, compensating variations in renewable generation by exploiting flexibility in the EVs charging process. The resulting optimization problems are convex programming problems that can be solved efficiently. Simulation analysis show the effectiveness of the strategy in absorbing the variability of the renewable source, minimizing the deviations between the day ahead schedule and the actual real time consumption from the grid.

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Keywords: Energy Management, Renewable Integration, Electric Vehicles, Flexible Loads, Model Predictive Control.

1. INTRODUCTION

Renewable Energy Sources (RES) are increasing worldwide by an average of 2.8%/year [Energy U.S., 2017], leading to a potential imbalance between supply and demand in the electrical grid. The RES uncertainty has a significant impact on the scheduling of conventional generation [Nghitevelekwa and Bansal, 2018]. The main effects of the uncertainty appear both on power system operation and on the need for procuring sufficient reserve capacity to maintain acceptable levels of reliability and security [Pandurangan et al., 2012]. Then, a transformation to load response instead of generation response is needed, in which customers reduce their consumption [Vuelvas et al., 2018].

Several schemes to provide flexibility at the demand side have been proposed. Thermostatically Controlled Loads (TCL) are a potential source of flexibility, as shown in Hao et al. [2015] for a collection of TCLs. Nevertheless, also water booster pressure systems [Diaz et al., 2017], heat pumps [Papadaskalopoulos et al., 2013] and Electric Vehicles (EVs) [Pavić et al., 2015] have been previously studied to exploit their flexibility features.

In particular, EVs seams to be promising flexible loads to improve RES integration in the grid, smoothing the demand curves [Khemakhem et al., 2017], providing frequency regulation services [Wenzel et al., 2018], incrementing self-consumption [Giordano et al., 2018], reducing emissions and supporting green transport [Noel et al., 2018]. Typically, an aggregator coordinates EV battery charging. The EV flexibility to reduce the RES power fluctuations is quantified in Schuller et al. [2015].

A framework to exploit EV flexibility in a charging station is presented by Diaz-Londono et al. [2019], where the optimization of the EV charging profiles aims to minimize operation costs, while maximizing the flexibility capacity, to offer secondary frequency regulation services. The optimal charging scheduling problem formulated in Tang and Zhang [2017] considers estimated statistical information on the future EV arrival. In Su et al. [2014], a MPC-based power dispatch approach (based on the combination of updated current EV charging information with a short-term forecasting model) addresses the operational cost minimisation while accommodating the EV charging uncertainty. Interestingly, Halvgaard et al. [2012] highlights

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how, especially concerning uncertain parameters as electricity prices, energy demand and driving patterns, forecasts should always find a balance between long prediction horizons (implying a higher computation time) and how much money can be saved.

In the smart grid research area, MPC has found a number of applications to operation and control of distribution systems and microgrids with Distributed Energy Resources, especially when the effect of uncertainties has to be taken into account. One of the main concepts is to create predictions that take into account the uncertain information and then use them to optimize the microgrid operation for a given prediction horizon. Then, the decisions (e.g., the set points of dispatchable units) are applied only for a limited time period, and a rolling horizon scheme is used for updating the calculations, see for example, Palma-Behnke et al. [2013].

In this paper an optimal scheduling strategy for a EV Charging Station (EVCS) is proposed. Day-Ahead (DA) and Real-Time (RT) strategies are developed for the EVCS, considering the availability of a local renewable generation source. First, the DA controller is based on a renewable source forecast and on an EV schedule. This approach aims to define the electrical energy to be purchased from the grid for the next day. Second, the RT controller aims to follow the DA scheduled grid energy, taking into account the fluctuations of the actual renewable generation and EVs behaviour. Then, the strategy is responsible for deciding the injected power of each charger in the EVCS, either from the electrical grid or the renewable source, considering the EV owners' preferences. Moreover, these strategies consider a Photo-Voltaic (PV) generation source.

The rest of the paper is organized as follows: Section 2 describes how the EVCS operates taking into account the presence of a local renewable generation source. In Section 3, a PV generation model is presented, considering Bogotá (Colombia) whether conditions. In Section 4, the DA formulation is proposed. Section 5 introduces the RT strategy. In Section 6 case study is shown, along with the related numerical results. Finally, Section 7 contains the concluding remarks.

2. EVCS OPERATION WITH RES GENERATION

In this section, an operating model is presented for an EVCS considering power from the electrical grid and a PV source. The model is formed by two schedulers, one for the DA planning of energy procurement from the grid and another for the RT operation of the chargers. In both strategies, a solar radiation forecast is employed to calculate the RES production. The EVCS objective is to minimize the operation costs formed by two terms, i.e., i) the cost of acquiring energy in the DA market, and ii) the penalties charged by the System Operator (SO) if the DA scheduled energy profile is not properly followed.

Figure 1 shows the EVCS operation. A local PV source is available and bilateral communication with the SO is considered. It is assumed that the PV generator has a local monitoring system that informs the aggregator about the solar radiation G_{PV} and the ambient temperature T_{amb} in real time. This information is collected in w={G_{PV}, T_{amb}}. In addition, the communication between the aggregator and the SO aims to request the energy scheduled for the next day by the EVCS and this represents the DA scheduler output. The RT controller looks for minimizing the tracking error between the DA purchased power and the actual EVCS consumption, taking into account the uncertainty in solar radiation.

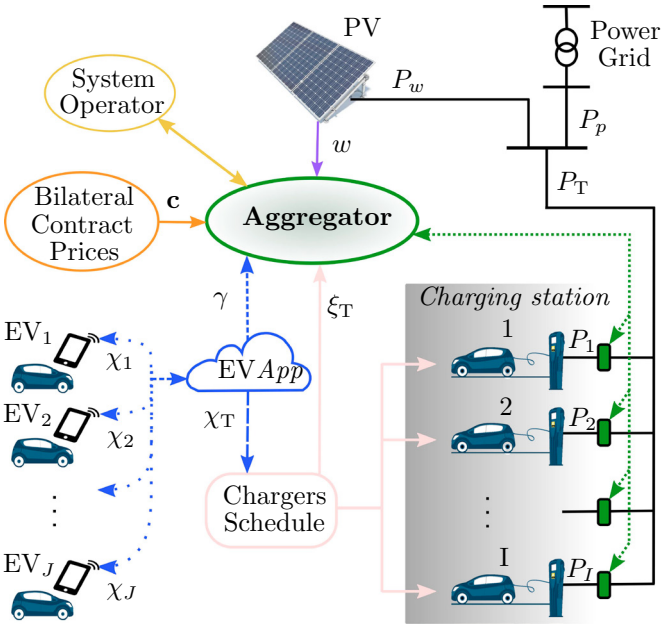

Figure 1. EVCS operation with PV generation.

The total power taken by the station P_T at time k, is composed of the grid power P_p and the RES one P_w, as:

$$P_{T,k} = P_{p,k} + P_{w,k}. \quad (1)$$

Therefore, the aggregator has three main elements:

- Solar radiation forecast.
- Day-ahead scheduler.
- Real-time MPC controller.

3. SOLAR RADIATION MODEL

In this section a forecast model is developed for the solar radiation in Bogotá, Colombia. The model is estimated considering five years of hourly solar radiation data. The data pre-processing and the model, are carried out in MATLAB® software. The model comprises two elements:

(1) a deterministic seasonal average radiation signal;
(2) a Nonlinear AutoRegressive (NAR) signal model.

The hourly measured solar radiation data of *Centro de alto rendimiento* in Bogotá, are evaluated. Five years of data (from 2011 to 2015) have been analysed, for a total of 8,760 samples per year. Considering that Bogotá has almost the same sunlight time along the year (from 6:00 to 18:00), the signal is evaluated for these 13 hours only.

The predicted radiation $\tilde{G}_{w,k}$ at hour k is expressed as:

$$\tilde{G}_{w,k} = \bar{G}_{w,k} + \hat{G}_{w,k}(\hat{G}_{w,k-1}, \hat{G}_{w,k-2}, \ldots, \hat{G}_{w,k-r}) \quad (2)$$

The first element of the predictor $\bar{G}_{w,k}$ is the mean value of the radiation at hour k in the 5 years dataset. Moreover,

to estimate the average radiation, seasonal variations are considered, dividing the data in four periods: a first dry season from December to February, a first rainy season from March to May, a second dry season from June to August and a second rainy season from September to November. It is found that the two dry seasons achieve higher peak radiations than the rainy ones, obtaining 614 W/m^2 for Dry 1 and 547 W/m^2 for Dry 2 at 12:00, while in the rainy ones, the peak is reached at 11:00.

The second element of the predictor is a non-linear autoregressive signal model for the residual between the original data and the mean value resulting from the seasonal averages. An Artificial Neural Network (ANN) with one hidden layer and sigmoidal activation functions is used for modelling the residual dynamics. 70% of the data is used for estimation, while the last 30% is used for validation. It is found that the best performance is obtained with a predictor of order 13, i.e., employing the actual radiation data of the previous 13 hours. Figure 2 illustrates the behaviour of the model. It is shown the radiation between the day 1512 (20/2/2015) and 1527 (7/03/2015). Note that, there is a season change in 1520 (1/03/2015), from Dry 1 to Rainy 1.

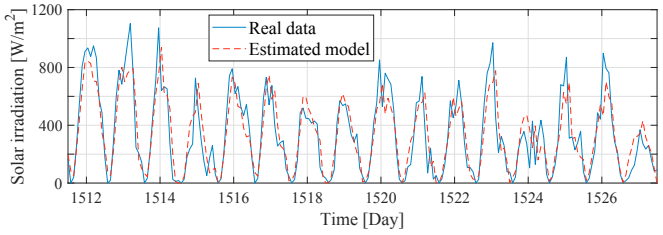

Figure 2. Sample predictor behaviour for one-step ahead forecast.

Considering the solar radiation model previously developed and the real-time ambient temperature data, the generated solar power is estimated [Tascikaraoglu et al., 2016],

$$P_{w,k} = \frac{G_{w,k}}{G_{STC}} P_{nom}(1 + \gamma_p \Delta T(T_k, G_{w,k})) \tag{3}$$

where, $G_{w,k}$ is the solar radiation (either real or predicted), G_{STC} is the solar radiation at Standard Test Conditions (STC) given by G_{STC}=1000W/m^2, P_{nom} is the nominal power of the PV plant, γ_p is the short circuit current thermal coefficient, and ΔT_k is the temperature deviation function, that depends of the ambient temperature, solar radiation and several parameters of the plant.

4. DAY-AHEAD FORMULATION

In this section it is presented the formulation of the DA strategy for planning the optimal energy purchase that the aggregator must perform in the market. The model looks for minimizing the operation costs of the EVCS facing uncertainty in the available PV source.

The station is formed by I chargers, whose power patterns must be programmed through the aggregator for the next day (β hours). Each day, the EVCS must serve J EVs, where for each EV j, its charging time spans from the arrival time a_j to the departure time d_j. In this work, arrival/departure times and State of Charge (SoC) are assumed deterministic parameters known one day in advance, in order to focus on handling uncertainty in the PV source. Previous analysis [Diaz et al., 2018b, Diaz-Londono et al., 2019], show that the application of a MPC strategy in the real time operation allows to mitigate the effect of EV behaviour uncertainties or generation disturbances [Diaz et al., 2018a].

Optimality refers to designing a charging profile plan that minimizes the costs of buying energy in the day-ahead market, guaranteeing for all the j=1, $\cdots$, J EV the minimum $\widetilde{SoC}_{j,d_j}$ at the departure time d_j and exploiting all the available PV energy. The operation time of the EVCS is divided into β discrete time intervals of length 1 hour. Each of them being a discrete time slot $k = 1, \ldots, \beta$, lasting a sampling time Δt in minutes.

The EVCS is modelled as a switched linear system, as proposed in [Diaz et al., 2018b]. A state variable x_i is defined for each charger, $i = 1, \ldots, I$ (Eq. (4)). When a vehicle is plugged in, the charger dynamics match the behaviour of an ideal accumulator. $\xi_{i,k}$ is a scheduling variable that indicates when an EV arrives or leaves a charger, causing jumps in the state variable, either from 0 to the arrival SoC $\widetilde{SoC}_{j,a_j}$, at each EV arrival, or from SoC_{j,d_j} to 0, at the EV departure.

$$x_{i,k+1} = \begin{cases} x_{i,k} + \Delta t\,(P_{p,i,k} + P_{w,i,k}) & \text{if} \quad a_j < k < d_j \\ SoC_{j,a_j} & \text{if} \quad k = a_j \\ 0 & \text{if} \quad \xi_{i,k}{=}0 \vee k{=}d_j \end{cases} \tag{4}$$

The optimal scheduling problem is defined as,

$$\min_{P_{p,i,k},\ P_{w,i,k}} \quad \Delta t \sum_{k=0}^{\beta-1} \left(c_k \sum_{i=1}^{I} P_{p,i,k} \right) \tag{5a}$$

s.t.

$$\text{Eq. (4)} \tag{5b}$$

$$\widetilde{SoC}_{j,d_j} \leq x_{i,d_j} \leq x_{i,\max} \tag{5c}$$

$$\sum_{k=0}^{\Delta k-1} \sum_{i=1}^{I} P_{w,i,k} \leq \widetilde{P}_{w,k} \tag{5d}$$

$$P_{p,i,k} + P_{w,i,k} \leq P_{i,\max} \tag{5e}$$

$$0 \leq P_{p,i,k} \leq P_{i,\max} \tag{5f}$$

$$0 \leq P_{w,i,k} \leq P_{i,\max} \tag{5g}$$

$$0 \leq x_{i,k} \leq x_{i,\max} \tag{5h}$$

$$\forall\ k = 1, 2, \ldots, \beta, \quad i = 1, 2, \ldots, I,$$

In this strategy, each charger has two decision variables at each time step, i.e., the power extracted to the grid $P_{p,i,k}$ and the power extracted to the PV source $P_{w,i,k}$. The cost function considers the price for the grid power $P_{p,i,k}$, with known time-varying costs c_k, while, the renewable power $P_{w,i,k}$ is dispatched with zero cost.

The constraint in Eq. (5b) sets the dynamic behaviour of the EVCS. Eq. (5c) sets the minimum state of charge of any EV at its departure time. Eq. (5d) limits the available PV power to the prediction $\widetilde{P}_{w,k}$ (see Section 3) updated every hour. Eq. (5e) fixes the maximum power that any EV

can receive. Eqs. (5f) and (5g) restrict solutions to positive power flows (no V2G capability) and upper limits to each source, respectively. Eq. (5h) avoids overcharging events. Note that the aggregator faces a Linear programming (LP) convex problem. Feasibility is guaranteed if each EV remains at the station for a time longer then the minimum charging time at full power.

Problem (5) is an open-loop optimal control problem that allows finding the power grid power to purchase in a DA market to minimize the operation costs considering the PV generation forecast. Given an optimal solution $P^*_{p,i,k}$, the power to buy is:

$$P_{p,DA,k} = \sum_{i=1}^{I} P^*_{p,i,k}. \tag{6}$$

5. REAL-TIME FORMULATION

In this section a Real-Time (RT) controller is proposed to handle the uncertainty in PV generation. The aim of the RT dispatch is to deliver a proper grid power $P_{p,i,k}$ at each time slot to each charger, while following the DA power scheduling sequence $P_{p,DA,k}$. A MPC strategy is adopted to achieve this goal exploiting the flexibility of EVs in their charging trajectories. At each time sample the power injected by each charger is adjusted to compensate the fluctuations of the PV power $P_{w,i,k}$, while guaranteeing for each EV_j the minimum $\widetilde{SoC}_{j,d_j}$ at the departure time d_j.

At each sample time the EVCS deals with the following optimal control problem,

$$\min_{P_{p,i,k},\ P_{w,i,k}} \ \Delta t \sum_{k=0}^{H-1} \left(\phi_k \left(\sum_{i=1}^{I} P_{p,i,k} - P_{p,DA,k} \right)^2 \right) \tag{7a}$$

$$\text{s.t. Eq. (4), Eq. (5c), Eq. (5d), Eq. (5e),}$$
$$\text{Eq. (5f), Eq. (5g) and Eq. (5h)} \tag{7b}$$

The cost function in Eq. (7a) aims to minimize the deviations between the scheduled DA grid power $P_{p,DA,k}$ and the power effectively extracted from the grid for an horizon of H samples. The error is penalized by a price sequence ϕ_k.

The aggregator has the same two decision variables $P_{p,i,k}$ and $P_{w,i,k}$ used in the DA problem. The constraints are the same as in problem described in Eq. (5). However, the PV generation forecast $\widetilde{P}_{w,k}$, is recalculated every sample for the next H intervals, assuming that the solar radiation for the current sample is precisely known.

At each sample time, the aggregator recalculates the optimal injected power considering the updated PV generation forecast, obtaining sequences $P^*_{p,i,k}$ and $P^*_{w,i,k}$ for the next H intervals. However, the chargers follow this power signals only during the $k-th$ interval. Then, the EVs' SoC and radiation information are updated and the optimal charging profile is obtained again, leading to a closed-loop operation.

6. CASE STUDY

In this case study, a simulation campaign is set up considering the EVCS *El Salitre* located in Bogotá, Colombia. It has 13 chargers (n=13) and a potential to implement a PV plant of 50 kW (P_{nom}=50 kW). A set of Kia Soul EVs® is considered with SoC_{max}=30 kWh. The level 2 (semifast) charging power is selected for the chargers, i.e., P_{max}=8 kW. The number of EV charging requests to be handled is equal to 34. All chargers are scheduled for charging up to four EVs during one day.

For the DA scheduler one day (β=24 h) is considered. For the RT (MPC strategy) the sample time is Δt=10 min and the prediction horizon is H=7 h (42-time steps). Hourly solar radiation data of *Centro de alto rendimiento* in Bogotá are used for forecasting the PV production with the generation model developed in Section 3. In order to simulate high frequency variations in solar radiation, the actual solar radiation is generated as the sum of the radiation in the available dataset plus a random Gaussian component with zero mean and standard deviation 90W/m^2. Note that this high frequency signal is not used in the predictor design and operation.

The energy price sequence c_k corresponds to real data taken from the Colombian stock market for one particular day. It is shown in Fig. 3. The penalization energy price ϕ_k is assumed as the same time-variant energy cost c_k.

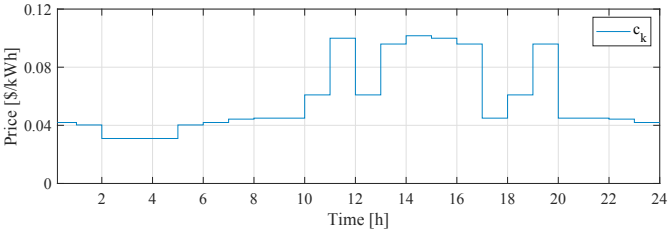

Figure 3. Energy price sequence.

Figure 4 depicts the amount of EVs arriving at the station (red line) and the number of EVs connected (dashed-blue line) at each time slot. For example, at 8:00 all chargers have an EV connected.

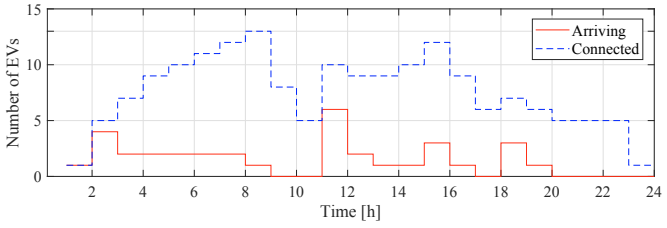

Figure 4. EVs arrival and EVs connected to the EVCS.

In Figure 5, the maximum power available in the PV plant is presented in green, the predicted solar power in DA is shown in red and the RT dispatched solar power is depicted in blue. Notice that not always all the available PV power was injected to the EVs, for example, at 12:00 the injected PV power is lower than the available one. Table 1 present the estimated, consumed and available PV production.

In Figure 6, the requested grid power is shown. It can be seen that the power used by the EVCS closely follows

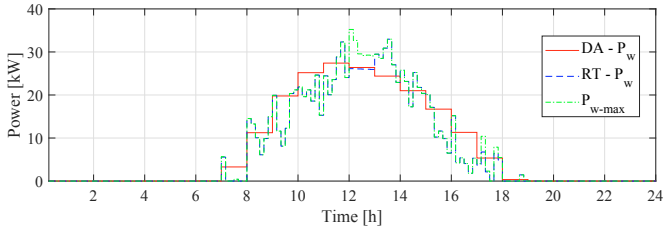

Figure 5. Forecast and delivered PV power trajectories.

the power acquired in the day ahead market. The root mean squared error between the power P_p purchased in DA and the power consumed in RT is 7.37 kW, obtaining a maximum error of 17.9 kW at 16:50, when there is a large deviation between the predicted and actual PV power. In fact, 514 kWh are purchased in DA, with a cost of 152$. However, the consumed grid energy in RT deviates 5.9% (32 kWh) from the DA. This produces a consumption of 546 kWh, generating a penalization cost of 15$. In Table 1, the energy and cost of the DA and RT are reported.

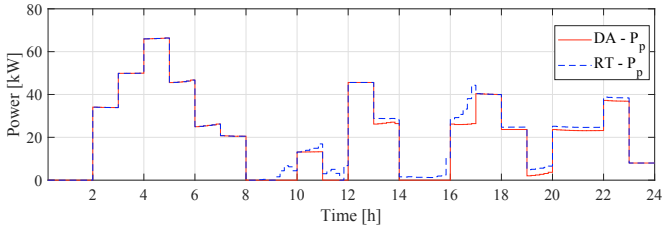

Figure 6. Day-Ahead and Real-Time grid power trajectories P_P.

Table 1. Energy and cost for the Day-Ahead schedule and Real-Time controller.

Step	Energy [kWh]	Cost [$]
DA	514 (Grid purchased)	152
	192 (PV estimated)	N.A.
RT	546 (Grid consumed)	15 (Penalization)
	173 (PV consumed)	N.A.
	179 (PV available)	N.A.

Note that the deviations between DA and RT grid power are much lower than the forecast errors of the predictor that is employed to design the day ahead schedule, meaning that the MPC strategy is able to reduce the effect of the uncertainty, distributing the power between the EVs in real time, exploiting the flexibility in the charging process. In fact, when the power curves of a single charger are observed, the deviation between the DA and RT power signals is larger. Indeed, Figure 7 shows the trajectories of the predicted DA and the actual RT power to charge the four EVs. Both trajectories respect the constraint on the departure SoC. In Figure 8 the trajectories of the EV SoC are reported, illustrating that the requested final SoC is achieved with very different power profiles.

7. CONCLUSIONS

In this paper a strategy to operate an electric vehicles charging station has been proposed, when a photovoltaic source is available, considering uncertainty the available renewable power. The strategy is formed by a Day-Ahead scheduler (DA) and a Real-Time (RT) controller. The

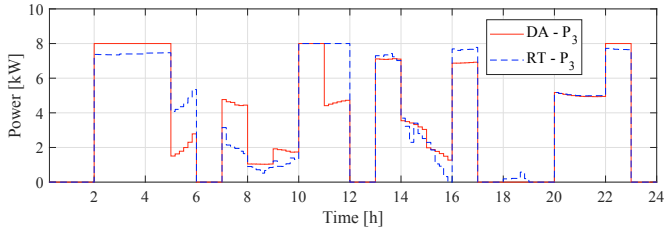

Figure 7. Day-Ahead and Real-Time power trajectories $P_{3,k}$ in charger 3.

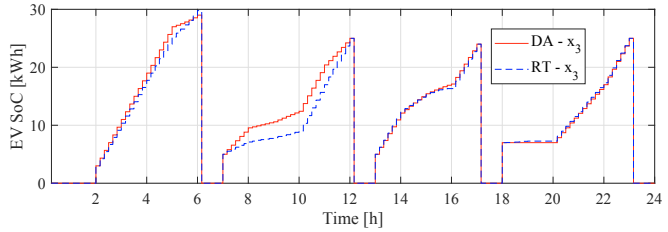

Figure 8. Charger 3 SoC $x_{3,k}$.

DA strategy aims to minimize the operation cost by optimally exploiting the renewable source, while the RT strategy looks for minimizing the error on following the DA schedule, considering the variability of the solar radiation.

A PV generation model is developed using five-year data of solar radiation in Bogotá, Colombia. A deterministic seasonal average model plus a non-linear autoregressive signal model are used to predict the solar radiation with acceptable precision. A linear state-space model with switching behaviour is used to model the charger dynamics while it serves several EVs. A linear programming problem is formulated to solve the optimal scheduling of each charger in day-ahead, while a quadratic programming problem is proposed for the real-time operation, minimizing operation costs and satisfying constraints on charging power limits, final state of charge and solar energy availability. The real time scheduling is used to build a MPC control strategy that acts in closed-loop, updating the schedule at each sample time, when new solar radiation information is available.

Simulation results using real solar radiation data and EV characteristics, show that the strategy is able to produce a minimum cost day ahead energy provision that later (in real time) is followed with a deviation of less than 5.9%, considering real-time fluctuations of solar radiation. The MPC strategy exploits the flexibility of the EV charging curve to absorb the solar radiation variability in order to minimize the penalties caused by any deviation from the day ahead scheduled power.

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