Cooperative Control of Charging Stations for an EV Park with Stochastic Dynamic Programming

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***Abstract*—An increasing penetration of EVs and their charging impose challenges to the energy grid stability. As a consequence, an optimal management of EV charging in parking lots becomes essential. This work presents an approach of a cooperative control of charging stations based on a stochastic optimization model for the energy management of a group of charging stations . Uncertainties regarding the number of charging EVs at each time step are modelled using a Markovian process, while the probability mass function was generated using a Monte Carlo simulation. Furthermore, the concept prioritizes the exploitation of local renewable resources and energy storage for EV charging to the import of electrical energy from the grid. The stochastic optimization model was integrated into our own developed Stochastic Optimization Software Framework (SOFW), which deploys the application as Model Predictive Control (MPC) in the real-time scenario using dynamic programming. The cooperative control of charging stations presented in this work was evaluated succesfully with a variety of EV driving scenarios. The approach will be validated on the field in a car park of a DSO company including renewable generation and energy storage system.**

***Index Terms*—electric vehicle charging, dynamic programming, energy management, optimization methods, stochastic optimization framework**

I. Introduction

In recent years, ambitious environmental goals regarding reduction of CO_2 emissions, energy efficiency and sustainability gave rise to the integration of renewable energy sources and to an increasing number of electric vehicles [1]. However, the volatile character of renewable generation and the stochastic charging behaviour of electric vehicles account for significant challenges for the electrical grid. Here we propose a strategy to control the charging stations in a cooperative way and to integrate photovoltaics and energy storage systems in order to contribute to grid stability and to maximize RES exploitation. Cooperative in the sense of charging a number of EVs taking into consideration their initial SoC for charging preferences.

Our approach introduces three novelties: the first one is the deployment of Virtual Aggregated Capacity (VAC) into a stochastic optimization model for maximizing PV utilization for EV charging. It enables a flexible integration of an arbitrary number of additional EVs and chargers according to the requirements of the use case and, therefore, improves the scalability of the concept. Moreover, we included the stochasticity of EV charging by modeling uncertainties of the numbers of EVs plugged-in at the same time into the charging stations and including them into the stochastic optimization model. As a second novelty, our approach takes advantage of real-time information, of a stochastic optimization model as well as of PV prediction. It uses our own developed Stochastic Optimization Framework Software (SOFW) [2], which links real-time information from the system with the stochastic optimization model and returns the optimization results as setpoints for drivers controlling the charging stations. SOFW deploys a Model Predictive Control (MPC) system and applies stochastic dynamic programming to solve the stochastic optimization problem. As the control is performed in short time intervals including real-time information from the system, the error due to uncertainties incorporated by EVs and PV prediction is reduced. The third novelty corresponds to the disaggregation of the calculated power for the Virtual Energy Storage System (VESS) into the charging stations serving the EVs. The disaggregation strategy takes into account the actual SoC of the EVs connected to the charging stations and the maximal power that each charging station can offer, in order to distribute the calculated power between them. This approach privileges EVs with lower SoC at each calculation time.

Approaches in the literature focus on the management of the charging of one single EV [3] or on the aggregation of several EVs as for example in parking lots [4]–[6] . Jenkis (2017) proposes in [6] the aggregation and control methodology for a number of EVs, in order to manage them as a VESS. We used the concept of a VESS in our approach assuming a virtual aggregated capacity (VAC) and extended it for the optimal charging through stochastic dynamic programming. Other works include uncertainties related to EVs and link them into stochastic models. Some of them make use of Monte-Carlo simulations and Markov Models to model the uncertainties [7]–[9]. In our work, we used a Markov Process

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to model the uncertainty of how many EVs are plugged-in at the same time. In order to calculate the probability mass function, Monte Carlo simulations were conducted. Because SOFW has an internal repository where EV's connection to the charger data is stored, the probability mass function is updated with a defined frequency inside the platform becoming application specific. Furthermore, a number of optimization approaches deal with financial aspects for charging EVs, as for example the reduction of energy cost [7], [14]. Other works focus on grid stability avoiding the increase in peak consumption or reducing voltage instabilities [10]. In this regard, Choi uses model predictive control to optimize a strategy for charging EVs in a parking lot aiming at voltage stability and charging costs minimization [7]. Moreover, local renewable energy is also included in the research [11]. In this work, we aim at maximizing the utilization of renewable energy given by a PV working together with a ESS inside a car park while charging EVs of a DSO company. In this regard, we combined renewable generation with ESS taking also into consideration uncertainties brought by EVs plug-in time into a stochastic optimization model running inside a MPC software framework named SOFW. It allows the system to be deployed at the car park immediacies of the DSO company in the future. Finally, vehicle to grid (V2G) has been recently analyzed in a number of publications [5], [12], [14]. At the moment this work does not consider V2G.

II. Use Case specification

This chapter presents the use case tested within the framework of EU-funded Storage4Grid project with the objective of analyzing diverse control strategies for ESS and EV charging. The car park is owned by a DSO company located in Bolzano, Italy and consists of five charging stations serving five EVs owned by the company (Fig. 1).

The EVs are of the model Volkswagen E-up with 18.7 kWh individual battery capacities. The EVs are used randomly by the workers of the company. The connection time to the charging stations and the number of EVs connected differ continuously. The drivers as well as the driven distances can also change from day to day. Given these characteristics, creating a behavior model for the EV driving profile is not trivial. Three of the charging stations support slow charging with a maximal charging power of 7.4 kW and two of them support fast charging with a maximal charging power of 22 kW. In the future, the charging stations will be accessed using a software driver that interfaces the vendor's specific API. Consequently, a fine-grain monitoring and control of each one of them will be allowed. The car park is also composed of an Xolta building energy storage system BESS of the company Lithium Balance with a capacity of 70 kWh . Its maximal discharging power is 33 kW and its maximal charging power is 33 kW. Additionally, one PV installation with a maximal power of 50 kW supplies renewable energy for the whole system. One specific requirement of the use case is the usage of embedded devices for the control of the charging stations and the ESS at the car park. This requirement was established during the development of the project, enabling edge computing as the pilar of the site's control. For this reason, the platform Raspberry Pi 3 with Raspbian (Debian-based) as operating system was chosen as the alternative for reading the inputs of smart meters and for containing the software of the stochastic optimization framework (SOFW) presented in [2] and discussed in the next sections.

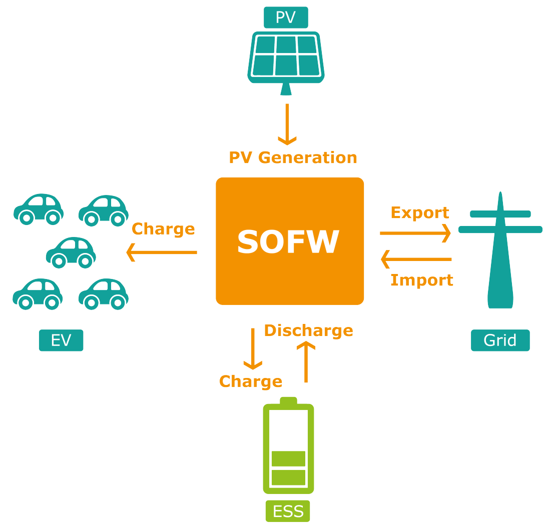

Fig. 1. Use case for cooperative EV charging.

III. Cooperative Control of Charging Stations - The Approach

Four steps will be presented in detail in the following subsections: 1) A Markov process was used for modelling the uncertainty; 2) The concept of virtual capacity was introduced to handle the cooperative approach of the control of several EV charging stations; 3) Equations for a stochastic optimization were developed and solved using dynamic programming; 4) The optimal power calculated in step 3 was disaggregated into the real system under study, i.e. into the single EVs connected to a specific charging station.

A. Dealing with the uncertainty

Since day-long data on individual driving profiles of EVs are not available, we modeled the uncertainty with a Markov model (Equation1) that describes the number of EVs being plugged-in and the probabilities of switching states by time.

$$p_{jk}(t) = P(x_{(t+1)} = k|x_t = j) \tag{1}$$

where j and k indicate the quantity of cars plugged-in in two successive time slots. Because historical data for calculating the probabilities for each state was not available, we performed a Monte-Carlo simulation to derive the probabilities to obtain the Markov model. Note that in the application this Markov model has been mapped to unique probability mass functions (PMF) for each time instant. The domain and range of the PMFs are number of driving cars that and the probability of being in this state respectively in the corresponding time instant. The probabilities are calculated from the results of the Monte-Carlo simulation by dividing the number of observed transitions from one state to another into the number of total transitions starting from the plugged-in state. Equation 2 shows this calculation.

$$p_{jk}(t) = \frac{n_{jk}(t)}{\sum_{m=1}^{M} n_{jm}(t)} \tag{2}$$

Moreover, it is necessary to calculate the electric vehicle consumption uncertainty, which is used to derive the mean energy consumption of EV when it is away from the charging station for a unit time. In this work we assume that the electric vehicle will solely be charged at the car park of the company. The away-state starts at the time when the electric vehicle is unplugged from the charging station and ends at the time when the electric vehicle is plugged-in back into the charging station. The SoC values of the electric vehicle's battery at the departure time and at the arriving time are measured through the charging station software and delivered to the SOFW via MQTT messages. In this form, equation 3 calculates the average energy consumption of an EVs daily trip E_{daily} according to the collected data. As already mentioned before, the collected data provides the mean departure $t^{departure}$ and arrival time $t^{arrival}$ of a single EV being charged at the car park. Similarly, state-of-charge levels of departing and arriving cars are recorded; and mean values $SOC^{departure}$ and $SOC^{arrival}$ are calculated. Consequently, this number is divided into the average trip period of an EV to calculate the mean unit-time energy consumption of one EV's away state $E_{unit-time}$. It is important to note that $t^{departure}$ and $t^{arrival}$ are entered into equation 4 as number of time steps regarding the optimization horizon.

$$E_{daily} = (SOC^{departure} - SOC^{arrival}) * E_{capacity} \tag{3}$$

$$P_{unit-time} = \frac{E_{daily}/\Delta T}{t^{arrival} - t^{departure}} \tag{4}$$

B. Virtual Aggregated Capacity

Due to the complexity of addressing all individual EV demands in the car park, we looked for a way to simplify the overall optimization problem. Each EV sets different energy consumption patterns that depend on the user driving behavior and on the driving's distance. For this reason, we decided to design the optimal charging policy according to the combined EV charging demands. We use in this paper an aggregation concept for EVs battery capacity, where the EV group is modelled as a virtual aggregated capacity (VAC), extending in this way the concept presented by Jenkins [6]. In fact, VAC represents a virtual battery providing a virtual energy capacity equals to the summation of each single EV battery capacity of the EVs belonging to the car park as represented in equation 5.

$$E_{VAC} = \sum_{n=1}^{i} E_{EV}^{n} \tag{5}$$

Consequently, the optimal charging policy will be defined according to the aggregated virtual capacity's needs and uncertainty.

C. Stochastic Dynamic Programming for VAC Charging

For the calculation of the optimal charging policy and because of the uncertainty brought by the plug-in time of the different EVs, we used Stochastic Dynamic Programming (SDP) as a solving method inside SOFW. Besides, due to the use of the VAC concept, some implications have to be taken into account for the modelling of the SDP problem. One of them is the disaggregation of the VAC explained later in this chapter. The second one corresponds to the abstract assumption that an EV could also be charged inside the VAC, even though it is not connected to a charging station. The last assumption helps us to simplify the modelling of the stochastic optimization problem without the need to define a state describing the position of individual EVs over time. In SDP, the variables that describe the system state are SoC of the stationary ESS and SoC of the VAC, as described in equation 6. The system can just switch between the combinations of these states. Moreover, the transition between SoC states of the stationary ESS are deterministic.

$$s_{ESS}^{t} \rightarrow s_{ESS}^{t+1} \quad s_{VAC}^{t} \rightarrow s_{VAC}^{t+1} \tag{6}$$

The SoC of the stationary ESS is calculated by equation 7.

$$s_{ESS}^{t+1} = s_{ESS}^{t} + x_{ESS} * \frac{\Delta T}{E_{ESS}} \tag{7}$$

where E_{ESS} stands for energy capacity of the stationary ESS in kWh, x_{ESS} for the power inserted into or taken from the ESS in the next timestep and ΔT for the time interval between each optimization step. In contrast, the transition between SoC states of the VAC (s_{VAC}) are stochastic and depend on the consumed energy ($P_{cons}(t)$) during the time interval (ΔT). x_{EV} represents the power inserted into the Aggregated EV's Battery.

$$s_{VAC}^{t+1} = s_{VAC}^{t} + (x_{EV} - P_{cons}(t)) * \frac{\Delta T}{E_{VAC}} \tag{8}$$

Since SDP needs discretized state variables, s_{ESS}^{t} and s_{VAC}^{t} can take a finite number of values within the expected SoC range. This constraint limits the solution space for optimal action but converts the optimization problem into an integer problem, which can be solved by a mixed-integer linear solver such as CBC.

Moreover, our stochastic optimization model requires the energy consumption of the EVs while they are not plugged-in into the charging stations. For this calculation we modeled firstly the behavioral uncertainty as probability mass functions that represent the probability of number of cars driving at each time interval (Equation 9).

$$p(t) = \begin{vmatrix} p_0(t) \\ p_1(t) \\ p_n(t) \\ p_N(t) \end{vmatrix} \tag{9}$$

where $p_n(t)$ stands for n number of cars driving in the time interval t: Secondly, we modeled the energy consumption uncertainty, that corresponds to the energy consumption of the unplugged EVs, assuming an average consumption (see Eq. 10). The expected number of driving cars are multiplied with the mean unit-time power consumption of one EV's unplugged state in order to estimate the total consumption of the time interval t:

$$P_t^{exp} = P_{unit-time} * \sum_{n=0}^{N} n p_n(t) \tag{10}$$

Because SDP solves independently the combination of s_{ESS}^t and s_{VAC}^t states, the decision outputs for each optimization problem is a vector of PV output power (x_{PV}), power from the ESS (x_{ESS}), imported power from the grid (x_{Grid}) and power to the VAC (x_{VAC}). Besides, the optimization problem has to consider some constraints given by: x_{PV} which is limited by the weather conditions and which is constrained to the maximum PV forecast output power at each time interval (11); x_{EV} which is limited by the charger station maximal power $P_{evCh,max}^t$ and can receive a non-zero value solely when the EV is plugged-in (12); and the electric power balance represented by (13).

$$x_{PV} \leq P_{pv,max}^t \tag{11}$$

$$x_{EV} \leq P_{evCh,max}^t \tag{12}$$

$$x_{VAC} = x_{PV} + x_{ESS} + x_{Grid} \tag{13}$$

In principle, SDP solves an optimization function which incorporates the incurred immediate cost of a taken action and the future cost of a taken action. We assigned an incurred immediate cost of zero V^T at any state in final stage, which initiates the backward optimization calculation (Eq. 14).

$$V^T = 0 \forall s \in S \tag{14}$$

where s stands for a specific state combination of s_{ESS}^t and s_{VAC}^t, and S for all possible combinations.

The objective function used in this work tries to maximize the energy consumption of the PV (Eq. 15). In this equation, the last term is the expected future cost of a taken decision, which depends on the actual state to be reached by taking the decision x.

$$\begin{aligned} min \quad & (x_{PV_{forecast}} - x_{PV}) + W_d * L(s_{VAC}^{t+1} < 0 \mid x) + \\ & + \sum_{w=1}^{W} \xi_t^w * v_{t+1} * (s_{t+1}) \end{aligned} \tag{15}$$

In equation 15, EV charging is motivated through the second term in the objective function. However, the objective function also allows to reach some physically infeasible results of VAC such as the following inequality :

$$s_{VAC}^{t+1} < 0 \tag{16}$$

In reality, this is compensated by charging car at another station. Hypothetical negative SoC is compensated by adding extra cost to the objective function according to the likelihood of reaching negative end state s_{VAC}^{t+1} with the decision x. In this case, W_d is the penalty factor. Optimal cost of starting from this initial state equals to the value of the objective function when the optimal decision is taken.

$$\begin{aligned} V^t(s_{ESS}^t, s_{VAC}^t) = (x_{PV_{forecast}} - x_{PV}) + \\ + W_d L(s_{VAC}^{t+1} < 0 \mid x^*) + \sum_{w=1}^{W} \xi_t^w v_{(t+1)} s_{(t+1)} \end{aligned} \tag{17}$$

D. Disaggregation of VAC Charging into Plugged-in EVs

As already mentioned, the SDP problem is solved taken into consideration a virtual battery. It means that the values of the power calculated to be delivered by the charging stations via SDP have to be disaggregated into each single charging station to which the EVs are plugged-in. In this case, the control action has to include the number of EVs plugged-in into the charging stations and their respective SoC level. Consequently, we calculate the depth-of-discharge (DoD_n), which defines the depleted portion of the battery capacity of EV n (Eq.18). Moreover, the total DoD_{Tot} of the plugged-in EVs is calculated (Eq.19).

$$DoD_n = 1 - SoC_n \tag{18}$$

$$DoD_{Tot} = \sum_n DoD_n \tag{19}$$

Thus, we prioritize the charging of the EV with the lowest SoC. Therefore, the power to be delivered to the virtual battery is disaggregated following equation 20.

$$P_{ch,n} = x_{VAC}^{t=0} \frac{DoD_n}{DoD_{Tot}} \tag{20}$$

The disaggregation approach is limited by the maximal power that the charging stations can deliver. If the calculated power to be delivered to the EVs by the charging stations is bigger than the allowed maximal power of the charging stations, the surplus calculated power is discarded.

IV. SOFW Framework

The architecture of SOFW was already presented in a previous work [2]. The main objective of the framework is to help users to deploy stochastic optimization models into real-time applications such as the use case presented in this paper. In this way, users can enter custom stochastic optimization models, register inputs and outputs that are automatically mapped to the parameters and variables of the optimization model, and send commands for starting, stopping or getting the status of the framework. For this goal, SOFW presents a RESTful Application Programming Interface (API), which works through HTTP communication.

Because the use case presented in this project is a real-time use case, SOFW uses MQTT Communication Protocol for obtaining data from smart meters located at the ESS, at the output of the PV and at the grid connection point. A dedicated software package reads in real-time the smart meters measurements and publishes them into the respective MQTT topics using a standardized SenML data format. The published values correspond to the ESS SoC, the PV output power and the grid input and output power. Similarly, information from the charging stations of the car park is read into SOFW. This information include the plug-in/unplug time, EV id and initial SoC of the respective EV.

While defining the SDP states resolution, SOFW allows the user to define a minimum and maximum value for the state variables and the time step size. In this way, s^t_{ESS} and s^t_{VAC} states were registered. Because of the flexibility for defining the granularity of the states, SOFW allows testing different SDP state granularities. However, finer resolution increases the number of single optimization steps [13].

For defining uncertainties, we registered mean and standard deviation of the plug-in and of the unplug time of the EVs. The plug-in time used in this work is $7:19h \pm 0:46h$ and the unplug time is $18:45h \pm 1:18h$. SOFW performs internally Monte-Carlo simulations and builds automatically the probability mass function used for Stochastic Dynamic Programming (SDP).

V. Test Scenario and Results

We tested the control approach by simulating different EV drive scenarios for 24 hours. For easy presentation of results, we chose one hour as the size of one time step and 24 steps as optimization horizon. In the test scenarios we partitioned each time step into several sub-problems, each of which represents a unique state combination for ESS and VAC. The ESS' and the VAC's SoC state domains are discretized by 10% (in the range 20-100%) and by 2.5% (in the range 0-100%), respectively. Thus, the resulting SDP problem consists of 8856 sub-problems. Within this work we computed the optimization problems by running the open source optimization solver CBC [15] with Intel(R) Xeon(R) CPU E5-2420 v2 @ 2.20GHz processor. The average computation time for SDP in this setup has been recorded as 904 seconds. Note that the potential performance enhancement through parallel processing is not in the scope of this paper as it will be in focus later on.

At the beginning of each hour a new instance of SDP is constructed inside SOFW with the updated real-time parameters and forecasts. After solving the complete problem, the optimal decision that corresponds to the real SoC values of ESS and VAC is implemented according to the disaggregation principle introduced in Chapter III.D. Note that SOFW is able to calculate the real SoC of VAC precisely only when all EVs are connected. Otherwise the VAC's SoC is calculated under the assumption that a car would drive 10km at each hour, hence it depletes the energy stored in VAC by 1.17 kWh.

Simulated test scenarios are presented in the columns of Table I. In the basic scenario each EV leaves the charging station at 8:00am and returns at 7:00pm (scenario S0). The remaining scenarios are variants of the basic scenario where a different number of EVs leave earlier than expected but always return at 7:00pm. Charging processes start at 00:00am with 20% SoC in vehicle batteries and 40% in ESS.

TABLE I
Test Scenarios - Departure times

Car ID	*S0*	*S1*	*S2*	*S3*	*S4*	*S5*
carA	08:00	06:00	06:00	06:00	06:00	06:00
carB	08:00	08:00	06:00	06:00	06:00	06:00
carC	08:00	08:00	08:00	06:00	06:00	06:00
carD	08:00	08:00	08:00	08:00	06:00	06:00
carE	08:00	08:00	08:00	08:00	08:00	06:00

As most of the charging process takes place in the periods where PV generation is low, the EV charging power is supplied by import from the electricity grid. Conversely, the PV power is fed to the grid during the peak generation hours. Fig. 2 shows the imported/exported power (positive/negative sign) by the charging park in Scenario S0.

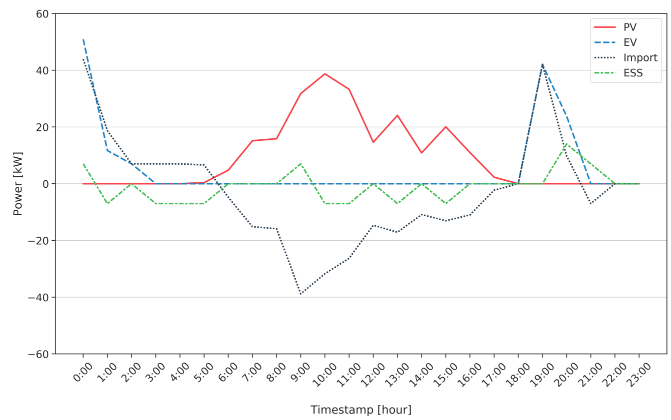

Fig. 2. Net power exchange with the grid.

A summary of the comparison between the scenarios is presented in Table II. The SoC of EV batteries throughout the day correlated with their departure times. In scenario S0 cars A,B, and C left the car park with 90.7% SoC, whereas cars D and E were fully charged by the fast chargers. Thus, SoC of VAC was 94.4% at departure in the morning and 25.6% at arrival in the evening. On the other hand in scenario S5, fast charged cars returned with 18.7% SoC in vehicle batteries, while the others had only 9.4% SoC. Although the SoC values of EVs A-C seem critical, the collected data of the company shows that arrival later than 7pm is a very unlikely scenario. Simulation results show that vehicles are able to complete their daily trips without needing mid-day charging even in the most extreme scenario. Results also show that the implemented control assured full utilization of 222.9 kWh PV generation potential in each scenario.

In order to evaluate the impact of poor estimation of driving profiles on the results, we developed a scenario that our behaviour model could never estimate. In this scenario all the cars leave the charging park for short trips multiple times during the day. Table III shows the position of each car in the so-called 'Multiple trip scenario'.

Although EVs were charged mostly in early hours similarly to the one trip scenarios, EVs that performed multiple trips

TABLE II
TEST SCENARIOS - RESULTS

Indicator	***S0***	***S1***	***S2***	***S3***	***S4***	***S5***
Import kWh	142.1	142.1	184.1	165.4	206.5	168.2
Export kWh	208.5	206.2	248.7	224.9	273.9	224.8
PV Gen kWh	222.9	222.9	222.9	222.9	222.9	222.9
VAC SoC 08:00am	94.4	94.4	91.3	86.7	84.4	81.9
VAC SoC 07:00pm	25.6	25.6	22.4	18.1	15.6	13.1

TABLE III
MULTIPLE TRIP SCENARIO

Period	***A***	***B***	***C***	***D***	***E***
00:00-05:00	CS1	CS2	CS3	CS4	CS5
05:00-07:00	CS1	CS2	CS3	—	CS5
07:00-08:00	CS1	—	—	—	CS5
08:00-09:00	—	CS2	—	—	—
09:00-11:00	—	CS2	CS3	CS4	—
11:00-12:00	CS1	CS2	—	—	—
12:00-13:00	—	—	—	—	CS5
13:00-14:00	—	—	—	CS4	—
14:00-15:00	—	—	—	—	—
15:00-16:00	—	—	CS3	—	CS5
16:00-17:00	—	—	CS3	—	—
17:00-19:00	—	—	—	—	—
19:00-00:00	CS1	CS2	CS3	CS4	CS5

found the opportunity to recharge their batteries during the day thanks to the additional time at the charging stations. Simulation results show that SoC in VAC is 62.7% at 7pm, which is significantly higher than that of the basic scenario, 25.6%. Results also show that full utilization of PV potential goal is achieved in this case too. Charging demand due to the multiple recharging events is 12 kWh higher than the Scenario 0. This increase is mostly compensated by the discharge from ESS without causing significant increase (only 4kWh) in imported power from the grid. In conclusion, unlikely scenarios are also manageable by this control approach without decreasing the performance of the energy management.

VI. CONCLUSIONS

In this work we used the software framework SOFW that deploys an stochastic optimization model as MPC in real-time applications. For solving the stochastic optimization model, SOFW used SDP linking the CBC solver. The results using different driving scenarios of the five EVs of the car park demonstrated the suitability of the stochastic optimization model for calculating the optimal charging power to be fed into the EVs. In all scenarios the EV's battery had enough energy to accomplish their driving routines. The results are good as they show that the implemented control assured full utilization of the power generated by the local renewable source and contributed indirectly to grid stability. This was achieved despite the assumption of the driven distance within an hour (10km) being probably too high and hence leading to too high charging needs.

The VAC concept proved to be suitable in terms of simplifying the modelling of the stochastic system and allowing flexibility for adding more charging stations and EVs in the real scenario without changing the stochastic optimization model.

The objective of maximizing the PV generation consumption was also achieved. Nevertheless, we observed power peaks in the grid when all EVs arrived at the same time. This particular undesired effect will be studied in the future work trying to penalize the power import from the grid.

The results showed a high mean calculation time of 904s using the computer described in Chapter V. Therefore, performance enhancement through parallelisation will be further implemented. We believe that it is possible to achieve a 15 min control at the test site.

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