An Online Model for Scheduling Electric Vehicle Charging at Park-and-Ride Facilities for Flattening Solar Duck Curves

Raka Jovanovic and Sertac Bayhan
Qatar Environment and Energy Research Institute
Hamad bin Khalifa University
PO Box 5825, Doha
Qatar

Email: rjovanovic, sbayhan@hbku.edu.qa

I Safak Bayram
Department of Electronic and Electrical Engineering
University of Strathclyde
204 George St, Glasgow, 1XW
United Kingdom

Email: safak.bayram@strath.ac.uk

Abstract—**Electrical power systems with high solar generation experience a phenomena called "duck curve" which require conventional power generators to quickly ramp-up their output, thus resulting in financial losses. In this paper, we propose an online model (OLM) for scheduling the charging of electric vehicles (EV) located at park-and-ride facilities for flattening solar "duck curves". This model provides a significant improvement to existing ones for similar systems in the sense that the availability of information is related to the time period for which the optimization is done. In addition, a procedure for finding the schedules for EV charging that significantly decreases the ramping requirements is introduced. Proposed procedure includes a combination of a heuristic function and a neural network (NN) to make a decision on which EVs will be charged at each time period. The training of the NN is done based on optimal solutions for problem instances corresponding to the full information model (FIM). The computational experiments have been performed for instances reflecting different levels of solar generation and EV adoptions and prove highly promising. They show that the OLM manages to find schedules of similar quality as the FIM, while having some more desirable properties.**

I. INTRODUCTION

In the recent years there has been a strong push for increasing the use of renewable energy sources for electricity production, especially for solar generation. One of the main problems of a high level of solar electricity production is the imbalance between peak electricity demand and renewable energy production during afternoons, resulting in the "duck curve" issue which lead to financial losses [1], [2]. Moreover, to meet net-zero emission goals, there has been a growth in the rate of electric vehicles (EVs) adoption and it is expected that EVs will become a primary mode of ground transportation within a few decades. In parallel, a new direction of research, the exploration and optimisation of the potential EV demand flexibility to remedy ramping requirements, is becoming popular. In this paper, we present a scheduling framework to evaluate the potential of scheduling the charging of large groups of vehicles in a way that minimizes the ramping requirements of electric production systems.

The need for ramping up of electric production is a direct consequence of the "duck curve" phenomena . Here the term *ramping up* is used for the need to have a steep increase in electricity production in a short time period. The idea of scheduling energy usage of home appliances to achieve this goal has been extensively researched in the setting of demand response systems [3]. On the other hand, there has been only a limited research dedicated to this type of approach in the context of EV charging.

It is noteworthy that this type of scheduling is not suitable for fast chargers (50+ kW) due to relatively short service duration and the fact that EV demand may not align with the time of system ramping. On the other hand, EV scheduling can be efficiently incorporated to systems with slower level 2 (5-9 kW) chargers [4], [5] due to demand flexibility associated with long charging session. Part of the research on level 2 chargers is dedicated to the designing of convenient away-from-home charging infrastructure with a special focus on ones located at the workplace [6], [7], [8]. In the work of Tulpule et al., it has been shown that such systems can effectively incorporate the use of solar energy with a wide range of benefits [9]. Several papers have been published on the smart scheduling of EV charging at workplace parking lots and different benefits of such systems [10], [11], [12].

While there are many similarities between scheduling of home appliances and EV charging for lowering peak demand issues, there are also important differences. The primary distinguishing feature of EV scheduling is related to size and collective scale of loads and the duration of service times. Some examples of specifics of scheduling EV charging can be found in [13], [14], and [15]. Since the adoption of EVs is an ongoing process, there is still research dedicated to potential methods of incorporating such systems into the real world. In reference [16], it has been shown that inclusion of such systems, based on level 2 chargers, to park-and-ride systems (P-R) [17] is very promising to aid power system operations. The basic idea of P-R is making it easy to

park your vehicle and continue your commute using public transport. P-R systems are growing in popularity, since they decrease traffic congestion in metropolitan areas and have other positive effects[18], [19]. Another reason for considering P-R facilities is that there is a high interest in constructing new ones by local governments [20] to promote EV usage and the related projects can easily be adapted to include EV chargers. In [16], the potential of scheduling EV charging at P-Rs to decrease ramping up requirements is evaluated through finding upper bounds that such systems can achieve. This is done by defining a combinatorial optimization problem that models the scheduling problem and solves it based on a integer linear problem (ILP). For practical applications, this model has a major disadvantage as it requires all the relevant information such as the whole time period of scheduling as an input. Because of this, we call this model a full information one (FIM). In practice this is not practical, the relevant information becomes available only at specific time periods, making the problem an online one. This is a common property of systems for smart charging of EVs and some models have been designed to reflect this. [21], [22], [14], [13]

In this paper, the basic model from [16] is extended to an online setting. We call this an online model (OLM). Further, a method for minimizing the ramping up requirements in the new setting is defined. It uses a greedy iterative approach to achieve this goal. An interesting novelty of the proposed method is that instead of defining a heuristic function, it uses a neural network to decide the amount of EV charging that will be conducted at each time period. The neural network is trained based on problem instances which have been solved using the FIM. The conducted computational experiments, show that the NN approach for the OLM, manages to provide solutions of almost the same quality as the FIM. In addition, as discussed in the next sections, the solutions found using for the OLM have some more desirable properties than the ones for the FIM.

The paper is organized as follows. In the following section the mathematical model for FIM is presented. In Section 3, details for the online version of the problem are given. The next section provides information about the proposed solution method for the OLM. In the following section details about the conducted computational experiments and their analysis are given.

II. FULL INFORMATION MODEL

In this section, an overview of the ideas from our previous work [16] for evaluating the potential of flattening the "duck curve" by exploiting EV demand flexibility. For the sake of completeness, in this section the mathematical model, in the form of an ILP, from [16] is presented.

This model contains the following assumptions. The scheduling of EVs is done for of a time window $\mathcal{T}$ which is divided into a set of periods $\{1, .., T\}$. This is done for a set of cars $C = \{1, .., M\}$, which visit the charging station at a P-R. It is assumed that the activation/deactivation of charging for each vehicle can be controlled. In relation, let use define a set of parameters that are known for the whole time window in the FIM:

- Parameter q_t corresponds to the base consumption minus the solar generation at each time period $t \in \mathcal{T}$.
- For each car $i \in C$ the arrival time a_i and departure time d_i are known.
- Each car $i \in C$ has a battery of capacity f_i and battery charge at arrival $0 \leq b_i^a \leq f_i$.
- A parameter for charger speed s is used to indicate how much a battery can be charged in one time period. It is assumed all the chargers at the facility are the same.

The model includes some natural constraints. For instance, each EV battery can only be charged until its full capacity. Each EV i must receive a minimal amount of charge r. Although a maximal allowed charge for the system can be given for each time period, for sake of simplicity in the used model is assumed that it is higher than the total charging potential of the charging station. The flattening of the "duck curve" can be understood as lowering the change in total energy consumption (sum of q_t and energy used for charging EVs) in successive time periods. An illustration of the FIP and solution can be seen in Fig 1.

Now, we present the ILP from [16] that formally describes the system of interest. Binary decision variables x_{it} are defined for $i \in C$ and $t \in \mathcal{T}$, which is set to one if EV i is charged at time t and zero otherwise. The goal of the FIP is to optimize the active periods for all the chargers, in essence making a charging schedule satisfying specific constraints. Let us define real variables b_{it}, for $i \in C$ and $t \in \mathcal{T}$, which indicate the state of the battery (level of charge) of car i at time t. In the ILP, instead of parameters for arrival (a_i) and departure times (d_i) for an EV i, a set of binary parameters v_{it}, for $i \in C$ and $t \in \mathcal{T}$, are used to indicate if EV i is at the charging station at time period t. Auxiliary variables h_t, defined for $t \in \mathcal{T}$, are used for the total power consumption of the charging station and based load q_t at some time period t. In relation let us define variables d_t for $t = 1 \ldots T - 1$, for storing the change in energy consumption, or in other words the absolute difference between h_t and h_{t+1}. Using this set of parameters and variables the necessary constrains can be defined using the following equations.

$$b_{i,0} = b_i^a \qquad i = 1 \ldots M \qquad (1)$$

$$x_{it} \leq v_{it} \qquad i = 1 \ldots M, t = 1 \ldots T \qquad (2)$$

$$b_{it+1} = b_{it} + x_{it}s \qquad i = 1 \ldots M, t = 1 \ldots T - 1 \qquad (3)$$

$$b_{it} \leq f_i \qquad i = 1..M, t = 1 \ldots T \qquad (4)$$

$$b_{iT} \geq b_i^a + r \qquad i = 1 \ldots M \qquad (5)$$

$$q_t + \sum_{i \in M} x_{it}s = h_t \qquad t = 1 \ldots T \qquad (6)$$

$$d_t \leq h_t - h_{t+1} + Mg_t \qquad t = 1 \ldots T - 1 \qquad (7)$$

$$d_t \leq h_{t+1} - h_t + M(1 - g_t) \qquad t = 1 \ldots T - 1 \qquad (8)$$

$$d_t \geq h_t - h_{t+1} \qquad t = 1 \ldots T - 1 \qquad (9)$$

$$d_t \geq h_{t+1} - h_t \qquad t = 1 \ldots T - 1 \qquad (10)$$

	1	2	3	4	5	6	7	8	9
A(3,5)			x		x				
B(4,8)		x	x	x	x				
C(5,10)				x	x			x	x
D(3,6)		x	x	x					
E(3,5)					x				
F(3,6)		x	x	x					
G(3,5)								x	x
B+PV	13	10	9	8	8	14	15	13	12
B+PV+EV	13	13	13	12	12	14	15	15	14

(a) Full Information

	1	2	3	4	5	6	7	8	9
A(3,5)			x						
B(4,8)		x	x						
C(5,10)									
D(3,6)		x	x						
E(3,5)									
F(3,6)		x	x						
G(3,5)									
B+PV	13	10	9	8	8	14	15	13	12
B+PV+EV	13	13	13						

(b) Online

Fig. 1. Illustration for the FIM and the OLM. Different letters are used for separate EVs, the values in brackets indicate the initial battery charge and its maximal capacity. Columns are used for time periods. Orange cells indicate when a vehicle is at the P-R facility. The cells with an "x" indicate that an EV is charged at that time period. The bottom two rows provide the information for the base load and solar generation, and the same value with addition of energy used for charging EVS. In the OLM, the red rectangle indicates the active time period; the patterned cells indicate that the information is not available at the active time period.

$$o \geq d_t \qquad t = 1 \ldots T - 1 \qquad (11)$$

The constraint in (1) is used to set the initial value of the current battery charge to the state of the battery at arrival. Eq. (2) provides that an EV can be charged only at time periods when it is at the charging station. The constraint related to the change of battery charge of an EV, for one time period is given in (3). The constraints related to the maximal and minimal level of battery charge of an EV are given in (4) and (5), respectively. The total amount of power used by the charging station and the base load is specified in (6). The Eqs. (7)-(10) are used to set the values of variables to d_t to the absolute value of the difference between h_t of consecutive time periods in the standard way. In these equations, M is used for a sufficiently large number, and g_t are auxiliary values which indicate if $h_t > h_{t+1}$ is satisfied. The final constraint (11) is related to finding the maximal difference in power consumption between consecutive time periods.

There are two objectives of interest for evaluating the potential benefits of the proposed model. The first one is minimizing the change in power consumption between consecutive time periods, which corresponds to flattening of the "duck curve". This can be done by minimizing the value of o as in the following equation:

$$\text{minimize } o \qquad (12)$$

The second one is related to the benefits related to the charging station operator and drivers of EVs. To be more precise, the goal is to maximize the total amount of charge of all the EVs, as in the following equation.

$$\text{maximize } \sum_{t=1 \ldots T} h_t \qquad (13)$$

When finding the optimal solution for a problem instance, the first step is finding the minimal value of o. The second one, adds a constraint that sets o to that value and maximizes the value of eq. 13.

III. ONLINE MODEL

The practical application of scheduling of EV charging for flattening the "duck curve" is in essence an online problem. The model presented in the previous section assumes that all the relevant information for the EVs like arrival/departure times, battery size and state are available at the moment the optimization problem is solved. However, this is not the case in a real world application of such a system. To be more precise, at some time period t, only the information on EVs that are currently at the park-and-ride facility are known.

These two types of models have a significant difference in the way they are solved. For the FIM case, the complete schedule is calculated at once. On the other hand, in the more realistic OLM case, the decision on the scheduling is made iteratively at each time period t based on the available information. An illustration of the OLM can be seem in Fig. 1. In both models, the objective is the same, to minimize the level of change in the total load of the system. After an online problem is solved, all the information (over all the time periods) can be provided to the FIM and the optimal solution can be calculated using the presented ILP. It is important to point out that although the FIM cannot be directly applied in the real world, it can provide us with upper bounds for the level of "duck curve" flattening that can be achieved in this way.

Let us present the setting of the OLM and the corresponding online problem. The same notation is used as in the FIM. First, at each time period t, all the information for time periods 1 to t is assumed to be available. For each vehicle i at the time of arrival t, it is assumed that the battery state b_i^a, battery size f_i and departure time d_i are known. It is reasonable to assume that the driver of the EV provides the departure time at the time of arrival.

There are several important properties that can be calculated based on the known information from the previous time periods. The battery state b_{jt} of an EV j that has arrived at the station before time period t will be known based on its

initial state and the amount of charge it has received prior to time period t. Note that at each time period $t_p < t$ the number of EVs in the station is known along with the number of additional time periods an EV j will stay at the station. In addition, it is assumed that the base load q_t, at time period t, is known. For time periods prior to $t_p < t$, the base load q_{t_p}, number of EVs at the station V_{t_p} and the number that has been charged X_{t_p} are also known. These values can simply be calculated for time period t_p using the following equations.

$$V_t = \sum_{i \in C} v_{it} \tag{14}$$

$$X_t = \sum_{i \in C} x_{it} \tag{15}$$

IV. Solving the online problem

In this section, a method for solving the OLM is presented. To be more precise, a method for deciding which EVs that are currently at the P-R facility will be charged. Note that by iteratively applying such a method for all the time periods from 1 to T, a feasible solution for the FIM will also be generated. Such a method needs to provide the values x_{it} for time period t and $i \in C$ based on information available at time period t in a way that the maximal change in demand over all the time periods o is minimal. In addition, as in the case of FIM, the objective is to maximize the total amount of charge given in Eq. 13.

Although it is possible to define a heuristic function that decides which EVs will be charged at some time period $t \in \mathcal{T}$, or in other words specify all the values of x_{it} ($i \in C$), it may not be the best choice. There are several reasons for this. First, standard rule-of-thumb heuristics for online problems tend to be highly complex. The second issue is that such a method needs to incorporate some type of prediction for the future states of the system, which is often not precise.

To avoid these issues, in the proposed algorithm, the decision on which EVs will be charged and the values of x_{it} are divided into two subproblems. The first one is finding how many EVs X_t will be charged at time period t. In the following text, the notation h_n will be used for this function, potentially a heuristic one. The second one is selecting which EVs will be charged. In practice, this means that we wish to select X_t EVs for which $x_{i}t$ will be set to one. To achieve this a heuristic function h_s is defined. Result of h_s gives the indexes in C for which x_{it} will be set to 1, in a way that all the necessary constraints are satisfied. By doing so, in the decision function the part where prediction is highly needed, the number of EVs that will be charged, is separated from the one where this is less necessary, the specific vehicles that will be charged. In the proposed method the function h_s is defined as a standard "rule-of-thumb" heuristic. Instead of defining the heuristic h_n in the same way, a simple neural network (NN) is used. In the following text details on the heuristic h_s and the method for defining and training the NN for h_n are presented.
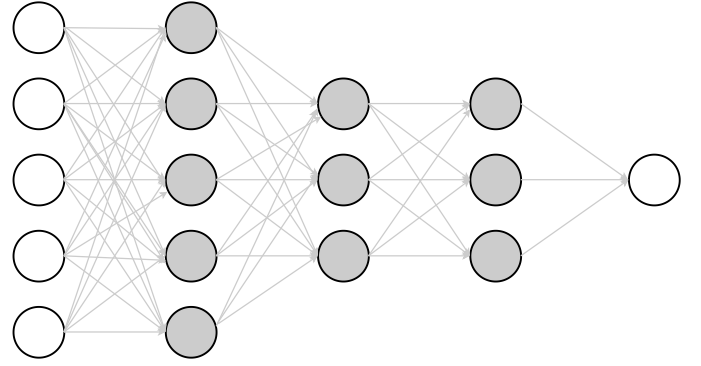

Fig. 2. Structure of the used NN. White is used for the input/output layers and grey for the hidden ones. All the layers are fully connected.

A. Amount of Charging

In this subsection, the details on the method for selecting the number of vehicles that will be charged are provided. The full information version of the problem can easily be solved to optimality using the ILP presented in Section II. The idea of the proposed method is to exploit this fact, more precisely, the possibility of generating a large number of pairs, namely problem instance and optimal solution. From an optimal solution of the FIM, it is possible to observe the decision D_t, at some time period t in the FIM that leads to an optimal solution based on the information I_t available at that time. Such pairs (I_t, D_t) can be used as training data for a NN, which can later be used instead of the heuristic function h_n.

1) Neural Network Structure: In defining such a NN, it is essential to specify what the input and output parameters are. A straight forward definition of this NN would be to have D_t correspond to the decision which vehicles will be charged and the I_t to all the available information given in the definition of the problem. A significant disadvantage of this direct approach is that the NN becomes large due to the high number of input and output parameters which are connected to each of the EVs.

To avoid these issues, the NN is designed to only predict the number of EVs that are charged X_t, the output parameter; and use only the input parameters needed to efficiently calculated this value. Empirically, we have found found a list of suitable input parameters and the structure of such a neural network. The used parameters are the following:

- q_t is the base load at time period t for which the decision is being made.
- V_t is the number of vehicles that can potentially be charged at t.
- h_{t-1} is the total load as the sum of base load and load related to charging the EVs.
- X_{t-1} is the number of vehicles charged at time period $t-1$.
- V_{t-1} is the number of vehicles at the facility at time period $t-1$.

The structure of the NN can be seen in Fig 2. The activation function for the hidden layers was Relu and a linear one for the output layer. It should be noted that in our tests, there was

a wide range of NN structures (with the same set of input parameters) for which the performance was adequate.

2) Training: As previously stated, if an optimal solution for a FIM instance has been found, the decisions in the OLM, for that instance, that generate the optimal solution are known. More precisely, at some time period t, based on the solution of the FIM, the input values q_t, V_t, h_{t-1}, D_{t-1}, and V_{t-1} and the output X_t are known. All these values can be trivially calculated from the problem instance and the solution of the *FIM*.

If the relevant information about EVs, the solar production and base load are known for some time window (in our case one day), it is possible to find what would be the optimal scheduling. This fact is exploited in the method for training the NN in the following way. First, a set of problem instances is generated. Then, each one of them is solved using the ILP. These solutions are used to generate input/output pairs for the individual steps (decisions at specific time periods) of the OLM. This data is used to train the NN.

The training set (problem instances) has been generated based on real-world data in the same way as in [16], for which we give a short outline in the following text. The data used to generate the EV visits to the P-R facilities is related to the hourly utilization rate of P-R facilities taken from [17] and the behavior of passengers of metro services taken from [23]. In addition the battery sizes of the EVs have been generated based on EV sales data taken from [24] and corresponding battery sizes [25]. The information related to the total electric demand and solar energy production are adopted from [26].

Instances having 500 EVs visiting the P-R facility over a time period from 6:00 to 20:00 hours have been randomly generated. Each hour has been divided into 4 time periods. The generated instances had the same statistical properties as the used real-world data. Specific details on the method of generation and properties of the used data sets can be found in [16]. Separate training sets have been generated for different levels of EV and solar generation adaptation. In case of EVs, the adoption levels are related to the level of electric consumption used for charging EVs to the total one, and it was 2.5 %, 5% and 10 %. In case of PV production, the level of solar energy production is related to the total electric consumption (without EV charging) and it was 10%, 20% and 30% of the total load.

For each pair, EV and solar generation adoption, a separate NN is trained. To be more precise, 1000 problem instances have been generated for each pair. Since each solved FIM instance provides 56 input-output pairs (14 hours scheduling window and each hour is divided into 4 time periods), a total 56000 such pairs are used for training the NN for each pair.

B. Vehicle selection

In this subsection, we give the details of the heuristic h_s used to selecting which N EVs will be charged at some time period t. The number of EVs that will be charged is calculated using the function h_n. In addition, for each EV i three values are provided based on the current time period t. The first one l_{it}

is the remaining time that the EV i will spend at the facility. The second parameter c_{it} is the amount of charge that the battery of EV can receive. The last parameter r_{it} is the total amount of charge that EV i has received before time period t. Let us define arrays R_t, C_t, and L_t that hold these values for all the vehicles i that can be charged at time period t. These are the EVs that are at the station and the battery is not fully charged at time period t. Note that the arrays R_t, C_t, and L_t are dependent on the time period t and the previous states of the system.

The heuristic function $hs(N, R_t, C_t, L_t)$ has output as an array $\hat{X}_t$ of binary values. As before, a value of $x_{it} = 1$ means that EV will be charged at time t, and the value of 0 the opposite. The idea of the heuristic is to set N values of elements of x_{it} to ones, for the vehicles whose charging is most desirable. There are two main factors for desirability. The first one is related to providing a minimal charge to a vehicle. The charging of a vehicle for which $r_{ti} < r$ is highly desirable, and for such vehicles the desirability is proportional to $r - r_{ti}$ and inversely proportional to the remaining time l_{it} at the station for that vehicle. This can be formalized using the following equation

$$charge(i, t) = \begin{cases} 0, & r_{it} \geq r \\ \frac{r - r_{it}}{l_{it}}, & r_{it} < r \end{cases} \qquad (16)$$

Note that in Eq. 16, only vehicles that can be charged will be considered, hence division by zero will not occur.

The second part is related to the available charging capacity of an EV battery. The goal is to maximize the potential charging in the future time periods. This can be achieved by preferring the charging of vehicles that have a high amount of available $c_i t$ and a low amount of remaining time l_{it}.

$$capacity(i, t) = \begin{cases} 0, & c_{it} = 0 \\ \frac{c_{it}}{l_{it}}, & c_{it} > 0 \end{cases} . \qquad (17)$$

Since providing the minimal charge to an EV is a hard constraint, it will be always preferred to charge a vehicle that has not received the minimal charge to one that did. The overall desirability o charging an EV i at time period t can be summarized using the following equation

$$Desirability(i, t) = M \cdot charge(i, t) + capacity(i, t). \qquad (18)$$

In Eq. (18), M is constant satisfying $M \gg 1$. The function *Desirability* simply states that the satisfying the minimal charge is of higher importance than remaining capacity of a battery for an EV. Using this function, we can specify the heuristic function h_s in the following way. It will set the value of x_{it} of N EVs, that can be charged at time period t, that have the highest values of $Desirability(i, t)$.

C. Implementation details

In this subsection, the details of applying the proposed OLM are given. The procedure can be divided into two parts. The first on is related to the training of the NN and the second one to the use of the heuristic functions. The training of the NN has the following steps:

- Collect data on related to EVs visiting the P-R facility, solar generation, and base load. In case only a small amount of such data is available, it is possible to generate it based on statistical properties.
- Use this data to generate FIM problem instances. Solve the instances using ILP.
- Transform FIM solutions to OLM format. More precisely, generate input/output pairs for each time period for each instance that will be used as training data.
- Normalize the training data.
- Train NN using the normalized data. The trained NN is later used as the function h_n

The second part of applying the OLM is specifying the application of the decision function for selecting EVs that will be charged over the time window of interest. As previously stated this is done iteratively over time periods 1 to T. This procedure is best understood through observing the pseudocode given in Algorithm 1.

Algorithm 1 Pseudocode for the online method

   $t = 1$
   repeat
      Calculate $q_t, V_t, h_{t-1}, X_{t-1}$ and V_{t-1}
      $X_t = h_n(q_t, V_t, h_{t-1}, X_{t-1}, V_{t-1})$
      $\hat{X}_t = hs(X_t, R_t, C_t, L_t)$
      Update problem state based on $\hat{X}_t$
      $t = t + 1$
   until $t = T$

In Algorithm 1, each iteration represents the procedure for one time period. At each of them, the first step is calculating the parameters of the system known at time period t, in exact $q_t, V_t, T_{t-1}, X_{t-1}$ and V_{t-1}. These value are used to decide the number of EVs that will be charged using function h_n which uses the previosly trained NN. The next step, is calculating the specific vehicles that will be charged, and stored in $\hat{X}_t$, based on function heuristic function h_s. The values of $\hat{X}_t$ are used to update the system parameters. This procedure is repeated for all the consequential time periods until the end of the time window for which the scheduling is done.

V. Results

In [16], the positive effects of scheduling the charging of EVs at P-R facilities for flattening "duck curves" have been evaluated. To be more precise, computational experiments show that the optimal solutions for the FIM can decrease ramping requirements (difference between minimal and maximal load) between 3 % and 25%, depending on the level of adoption of EVs and solar generation. Due to this, the main objective of the conducted computational experiments is to show the potential of keeping such positive effects in case of a more realistic online setting. The properties of solutions acquired using the OLM are compared to the optimal ones for the corresponding FIM. The OLM has been evaluated for settings in which the total electric consumption need for EV charging corresponds to 2.5%, 5%, and 10% of the base load.

In addition, several levels of solar generation are considered, more precisely settings where 10%, 20%, and 30% of the base load (excluding EV charging) is satisfied in this way. It should be noted that the generated problem instances are different than the ones used to train the NNs.

In our computational experiments, the behavior of FIM and OLM has been compared over a hundred problem instances for each pair solar generation and EV adoption. From our analysis, there is no significant difference between the behavior of the methods on different instance of the same type. Because of this, we have used illustrative examples on specific problem instances for each pair solar generation and EV adoption, see Fig. 3. In these figures, we show the sum of base load, EV charging and solar generation over the entire time window on which the scheduling is conducted.

It can be observed that the OLM manages to maintain the positive effects of the FIM for all the levels of EV adoption. The total load curve, is smoother for the OLM than for the FIM. This is important since this is a more desirable behavior for electric distribution systems, and in a sense the OLM produces better results than the FIM. It is expected that this improvement comes from some deficiencies of the ILP used for the FIM. Note that this data is used for generating the data for training the NN for the OLM. This model focuses on minimizing the maximal difference of total load between two consecutive time periods while maximizing sum of the total load. It does not take into account that it is preferable to minimize the total sum of differences. Consequently, this results in adding some small peaks in the demand curve that maximizes the energy use. It is very interesting that the trained NN, manages to "abstract" the positive requirement of having a smooth total load. In a sense the "fine tuning" done by the ILP is considered as "noise" by the NN.

Although the OLM has a very good overall performance, in case of some test instances, it would increase the maximal change of the total load for consecutive time periods, even when compared with the base load summed with PV. This type of behavior was rare and would not occur if the difference was observed over a larger time window (time period on a distance greater than 1). The total ramping up requirements for the OLM had a neglectable increase when compared to FIM, which was the most important parameter for evaluating the new model.

VI. Conclusion

In this paper, a new model for evaluating the potential of using EV scheduling for flattening the solar "duck curve" has been proposed. The focus of the model was on systems of this type that can be applied at P-R facilities. Compared to existing ones for similar systems, it has a significant advantage that the information related to the underlying optimization problem becomes available as it would be in a real-world application. To be more precise, the model is an online one in the sense that the availability of information is related to the time period for which the optimization is done. In this way the new model simulates the passage of time.
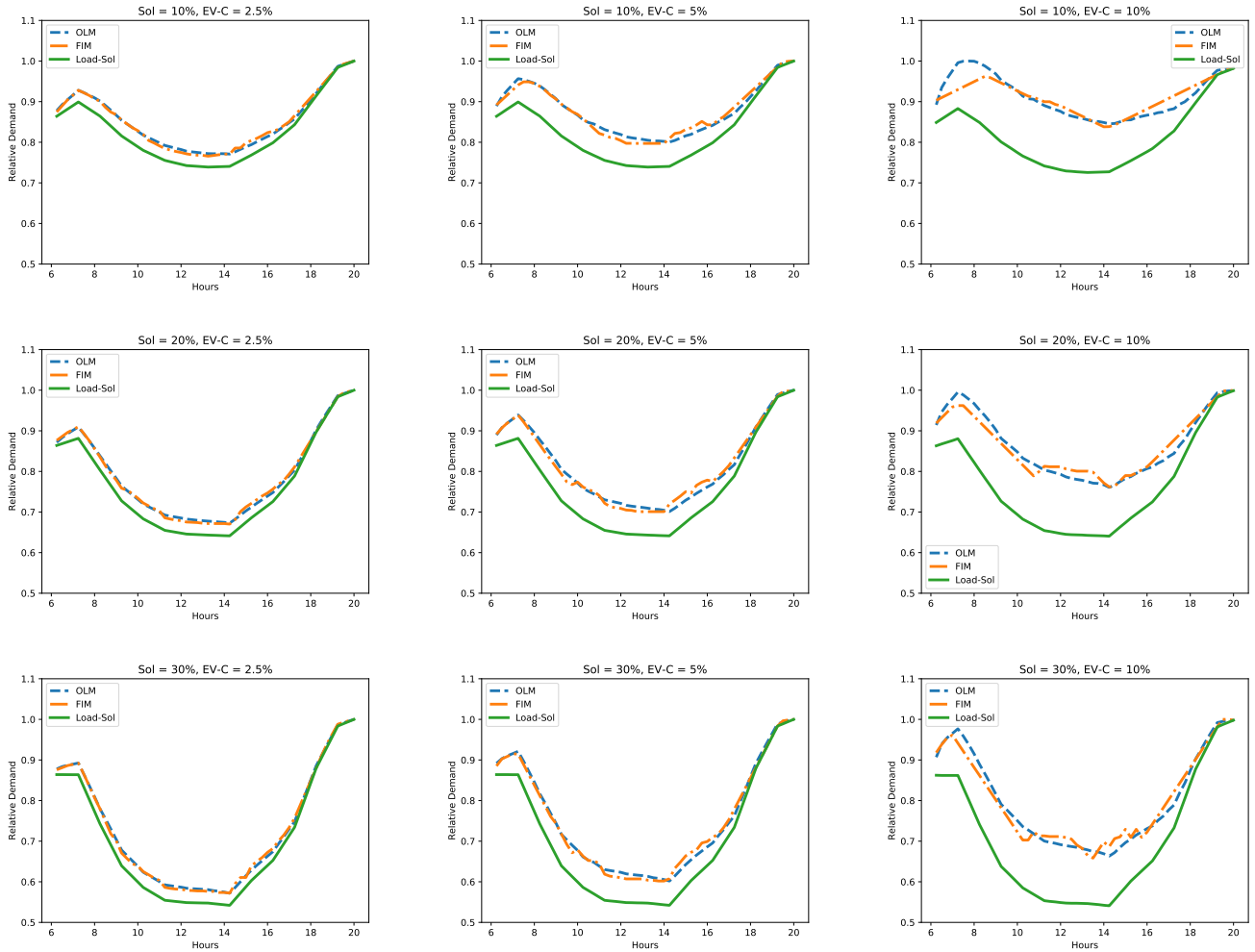
Fig. 3. Comparison of the normalized values required generation of electricity for different levels of solar production with different levels of consumption related to charging of EVs. The notation $Load - Sol$ is used for the case there is not EV charging, and $EV - C/Sol$ to indicate the part of the load that is related to EV charging/Solar generation. FIM and OLM are used for the values corresponding to the full information and the online models, respectively.

In addition to defining the model, a solution methods has been designed. It consist in using a combination of a heuristic function and neural network to make a decision on which EVs will be charged at each time period. The training of the NN is done using optimal solutions for problem instances, which can be potentially acquired using data collection, using an ILP. The conducted computational experiments indicate that the use of this type of decision method in the online model provides schedules that are near to the upper bounds for improvement provided by the previously developed full information model. One interesting aspect of the schedules found by the proposed method is that they even have some advantages to the previously developed FIM.

In the future, we plan to adapt this model to other charging systems for EVs. Some promising adaptations can be for office charging and charging of fleets of vehicles.

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