Advanced Scheduling Protocol for Electric Vehicle Home Charging with Time-of-Use Pricing

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Abstract— **In this paper, a scheduling protocol for electric vehicle (EV) home charging with time of use pricing is introduced. This work addresses the problem of EVs charging at home by adopting an appropriate charging process protocol over Power Line Communications (PLC). The scheduling protocol is aimed at minimizing peak loads on distribution feeders due to multiple EVs charging while using a time-of-use pricing policy. Energy efficiency and performance are both taken into account. An appropriate analytical formulation of the scheduling problem is given together with the proposed scheduling protocol. Simulations demonstrate the effectiveness of the proposed approach in minimizing peak loads while satisfying the defined constraints.**

Keywords- V2G, EV, scheduling, Smart Grid.

I. INTRODUCTION

The notion of connected vehicles is becoming a reality with new advances and standards for vehicle communications becoming ready for market. In parallel, communication capabilities are also expected to link smart Electric Vehicles (EVs) to the smart grid. However, EVs pose an enormous challenge. The more they are adopted and cluster for charging in areas and neighborhoods, the more they will pose a significant stress on the grid. This is because the charging of one electric car can add a demand equivalent of a new house [1], requiring for additional distribution capacity in areas beyond what was planned for. The problem is further exacerbated at peak loads. A recent study [2] showed that, for example, 16,000 electric cars in the City of Toronto would represent 86 MW of load if they were charged at the same time, for example at night or when the price of electricity is at its lowest. This load is the equivalent amount of energy used by an entire small city. If the same vehicles distributed their charging over a 12-hour period, the load would be reduced to 13 MW. It is evident then, that Vehicle-to-Grid (V2G) interoperation has to offer the capability to manage vehicles charging load wisely according to the overall power demand. Moreover, pricing policies should also be taken into account.

In this work, we consider the dynamic scheduling for EVs charging as a grid communication process, where PLC [1] is used to convey the desired functionality. We propose an optimal scheduling scheme for charging vehicles at home with varying prices, especially at night time, when the load of home EVs charging is expected to be high.

Our contributions are: 1) we present an analytical formulation of the scheduling problem that takes into account a number of constraints including a maximum neighbourhood charging capacity, a bounded scheduling time interval for charging, variable prices for charging at the given interval, and a random arrival of vehicles each requiring a maximum price threshold for charging at the end of the process; 2) we propose a scheduling mechanism that addresses the defined constraints; and 3) we perform simulations and demonstrate that the protocol and the mechanism can effectively schedule EVs charging operations within the defined constraints while considering realistic EV charging characteristics.

The remainder of the paper is organized as follows. Section 2 discusses the related work. In Section 3, we present the proposed scheduling model. We formulate and solve the electricity load scheduling problem with time-of-use pricing in Section 4. The simulation results are presented in Section 5, and the conclusions are drawn in Section 6.

II. RELATED WORK

Existing related work on V2G interface can be classified into two classes; new V2G protocols and standardization for EV and Electric Vehicle Supply Equipment (EVSE) communication, and Scheduling algorithms for EV charging processes. For the first class, a few works [4, 6] make a good summary of current standard protocols and related architectures for EV and grid interaction. In [5] the basic principles of standard V2G communication interfaces under specification at ISO/IEC are presented, with a focus on control communication but without a regard to administrative data, especially for V2G integration at home. In [7], the authors present a generic V2G information model allowing charge scheduling negotiations between EVs and grid operators. The work discusses a system model with theoretical consideration without treating a specific charging mode (slow, rapid or fast) as in realistic situations. In the second class of works, authors in [10,14] propose a decentralized charging control algorithm to schedule charging for large populations of EVs without considering EVSE characteristics such as plug in levels 1, 2 or

3 at home. The work in [9], presents smart energy control strategies for residential charging of EVs, aiming to flatten the overall load profile. However dynamic EV power loading situations were not studied, especially EVs random initial power distribution. Other works, such as [11], address the problem of scheduling and electric power management optimisation but not in the context of EVs charging.

In this work, we present a scheduling scheme that minimizes energy load peaks while taking into account constraints including maximum neighbourhood charging capacity, bounded scheduling time interval, variable prices for charging over time, and a random arrival of vehicles each requiring a maximum overall price threshold for charging. Furthermore, realistic EVSE characteristics were used.

III. SCHEDULING PROCESS

We present our proposed scheduling process. The scheduling process must operate under a set of constraints which correspond to realistic EV charging situations. We suppose that all homes are connected to an Advanced Metring Infrastructure (AMI) [8]. AMI Infrastructure typically refers to the measurement and collection systems that include meters at the customer site, networks between the customer and the Grid, and data reception and management systems at the Grid itself. We thus also assume that a charging communication service initialisation is established between smart grid and EVs via a two-way communication scheme every time an EV is plugged at home. We are interested in solving the following problem: Given a neighbourhood that is connected to a single local transformer of some finite capacity, and comprising a finite number N of electrically powered vehicles that are plugged in for charging during a bounded time interval, what is the optimal charging schedule for these vehicles given a set of defined constraints? We define the constraints as follows:

- The scheduling time interval is bounded (e.g., 12 hours duration, during night time).
- A maximum price is fixed and accepted by every vehicle during the charging process period. Every vehicle might accept a different maximum price.
- Pricing varies over time during the scheduling time interval, but different prices are known in advance to the scheduler.
- The initial charge prior to charge of each EV, denoted SoC, is random and can vary between 0% and 99%.
- The arrival time of each of the N vehicles at their charging stations is also random.
- Each vehicle requires a minimum charge value at the end of the scheduling process. This minimum value can be different for each vehicle.

Of course the problem above defined, and corresponding solutions, can be easily scaled to a set of neighbourhoods within a defined area. To solve this problem, we define the following system model:

We assume that the entire scheduling time interval is finite and is divided into T sub-intervals (for example 144 sub-intervals each of which has 5 min duration). The smart meter device determines the starting and finishing charging sub-intervals of each vehicle. The energy consumption scheduling vector of each vehicle n is defined as

$$x_n = \left[x_n^t\right]_{t=1..T} \tag{1}$$

where x_n^t is the amount of energy consumption of vehicle n during sub-interval t. Each vehicle n has its schedulable interval $[S_n;F_n]$ only during which it can be scheduled. In other words,

$$x_n^t = 0 \quad if \quad t \notin \left[S_n, F_n\right] \tag{2}$$

$L_n = F_n - S_n + 1$ is the length of this schedulable interval of vehicle n. We consider that each vehicle n has its maximum and minimum values for energy consumption, x_n^{max} and x_n^{min}, respectively, in each sub $-$ interval t, i.e.,

$$x_n^t \in \left[x_n^{min}, x_n^{max}\right], \quad \forall n, \quad t \in \left[S_n, F_n\right] \tag{3}$$

The price variation model is very important in such case study. In fact, in research works various time-differentiated pricing models have been proposed [14, 15]; real time pricing (RTP), day-ahead pricing (DAP), time-of-use pricing (TOUP), critical-peak pricing, inclining block rates (IBR), etc. Research findings [16, 15] indicated that compared to the other models, TOUP provides more incentives for customers to shift load to the less expensive hours. Thereby we use the TOUP model throughout this study. In TOUP model, the unit price for energy varies in each sub-interval t and it is denoted as γ_t. All γ_t ' s for the entire scheduling interval (i.e., $\forall t \in [1,T]$) are known to the scheduler in advance. According to these assumptions, the total energy cost for each vehicle is

$$E_T(x_n) = \sum_{t=1}^{T} \gamma_t x_n^t \tag{4}$$

Each vehicle n has its utility function $U_n^t(x_n^t)$ that represents its charging performance when it consumes x_n^t units of energy at sub-interval t. The energy consumption for each vehicle can be flexibly adjustable at each sub-interval and the vehicle charging performance depends only on the total energy consumption. In this context, each vehicle n has its total utility function $U_n(x_n)$, where x_n is its total energy consumption defined according to (1), (2) and (3) as

$$x_n = \sum_{t=S_n}^{F_n} x_n^t \tag{5}$$

The utility function is an increasing and strictly concave function [9, 13]. Moreover, for each vehicle n, the user has the following requirement:

$$U_n(x_n) \geq C_n, \quad \forall n = 1..N \tag{6}$$

This requirement indicates for vehicle n the total energy consumption should be higher than or equal to its minimum threshold C_n. We define a scheduling set X_{sched} that satisfies the last equation as

$$X_{sched} = \left\{ \begin{array}{l} x \mid x_n = \sum_{t=S_n}^{F_n} x_n^t, U_n(x_n) \geq C_n, \\ \forall n = 1..N \end{array} \right\} \tag{7}$$

Where $\quad x = [x_1, .. x_n, ..., x_N]$ (8)

IV. Power Load Scheduling

We consider a power load scheduling problem minimizing the total energy consumption [8, 9], which is formulated as

$$Minimize_x \left\{ \sum_{t=1}^{T} \gamma_t \sum_{n=1}^{N} x_n^t \right\} \tag{9}$$

Subject to $\quad x_n^{min} \leq x_n^t \leq x_n^{max}, \quad \forall n, \quad S_n \leq t \leq F_n$

Note that our formulation is valid when there is no constraint on the aggregate power demand to the grid.

This problem can be decomposed into sub-problems each of which corresponding to each vehicle n. For each vehicle n, we have to solve the following problem:

$$Minimize_{x_n} \left\{ \sum_{t=1}^{T} \gamma_t x_n^t \right\} \tag{10}$$

subject to $\quad x_n = \sum_{t=S_n}^{F_n} x_n^t$ (11)

and $\quad U_n(x_n) \geq C_n$ (12)

The above problem is a convex optimization problem [13]. To solve this problem, standard algorithms for convex optimization should be used [12]. Since the utility function is strictly increasing [9, 13], it has an inverse function. As a result, the first and second constraints can be rewritten as

$$\sum_{t=S_n}^{F_n} x_n^t \geq U_n^{-1}(C_n) \tag{13}$$

Moreover, to minimize the cost, the amount of energy consumption has to be minimized while satisfying the constraints. The inequality (13) should be satisfied with equality and the problem posed by equations (10, 11, 12) subject to equation (3), is reformulated as

$$Minimize_{x_n} \left\{ \sum_{t=1}^{T} \gamma_t x_n^t \right\} \tag{14}$$

subject to $\quad \sum_{t=S_n}^{F_n} x_n^t = U_n^{-1}(C_n)$ (15)

To solve (14), we use the following optimisation algorithm.

1. Put the unit prices for sub-intervals $[S_n; F_n]$ in an increasing order as :

$$\gamma_{(1)} \leq \gamma_{(2)} \leq, ..., \leq \gamma_{(L_n)}$$

given a mapping function f between t and t' such that $\gamma_{(t')} = \gamma_{f(t)}$ and $\gamma_{(t)} = \gamma_{f^{-1}(t')}$

Begin by initialization of counter p :

2. Let $p = 1$ and $Z = U_n^{-1}(C_n)$

Procedure {

3. Assign $x_n^p = min\{Z, x_n^{max}\}$ and $Z = Z - x_n^p$

incrementation of counter p

4. Let $p = p + 1$ }

Repeat this Procedure until $Z \leq x_n^{max}$

5. Assign $x_n^p = max\{Z, x_n^{min}\}$

From the algorithm description, it is clear that its implementation requires low computation cost. Figure 1 summarizes the interactions between the smart Grid and EVs for the dynamic scheduling process. The Grid begins by broadcasting the price profile $\gamma_1, \gamma_2 ..., \gamma_T$ to all connected EVs through their EVSEs. As a response, each EV send its charging interval, the maximum and minimum power demand as given by eq.(2) and eq.(3). After compiling all input data from EVs, the smart Grid send for each EV its energy consumption scheduling vector.

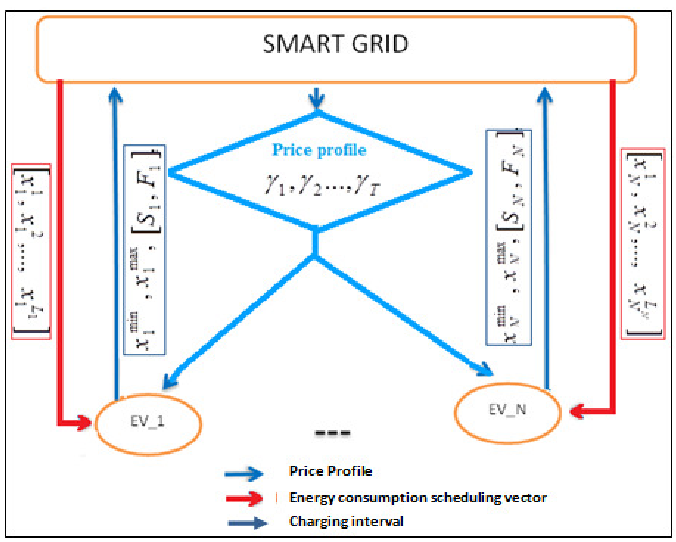

Figure 1: Schematic view of information flow patterns between the Smart Grid and EVs when considering our charging algorithm.

V. SIMULATIONS

We evaluated the performance of the scheduling algorithm through simulations. We used Matlab to perform the simulations, and we adopted the following function as a utility function for vehicles [7]:

$$U(x) = \log(x+1) \tag{16}$$

We performed simulation sets with two scenarios; the first one having 50 EVs plugged in to their respective level 1[17] EVSEs at the scheduling start, and the second scenario having 100 EVs. Level 1 equipment is the one expected to be installed in homes as part of the AMI. The scheduling period was considered 12hours with subintervals of 5mn. We assumed the neighborhood transformer can allow a simultaneous load of 100 EVs. We compared in simulation the performance of our scheduling algorithm with the un-scheduled case. Figures 2 and 3 show example random distributions of plugged in EVs in the scheduling period for scenarios 1 and 2.

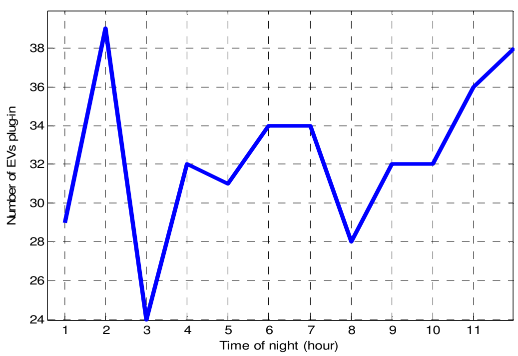

Figure 2: Random distribution of connected EVs in the scheduling period (First Scenario).

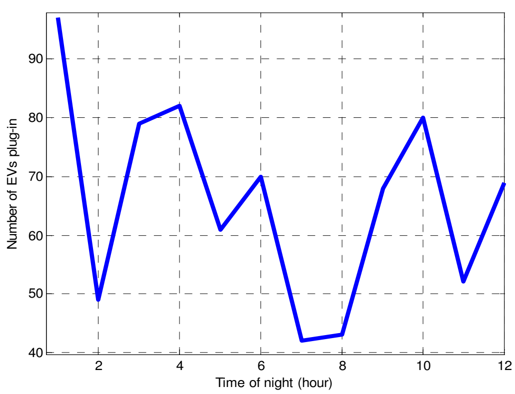

Figure 3: Random distribution of connected EVs in the scheduling period (Second Scenario)

At the end of the charging period, all vehicles should be satisfied. We rank vehicles based on their initial SoC. We start the charging process for EVs which have the least charge (x_n). Parameters for each vehicle are generated randomly as follows:

- starting time (S_n): with a uniform distribution between sub-intervals of the night period;
- finishing time (F_n): with a uniform distribution between sub-intervals S_n of the of the night period;
- maximum power consumption (x_n^{max}): with a uniform distribution between 0 and 100 percent of charge ;
- $\gamma_{(t)}$ is generated according to the TOUP model.
- threshold (C_n): with a uniform distribution between 0 and $L_n \times U_n(x_n^{max})$.

We study the power consumption of our algorithm compared with the unscheduled case with the variation of the electricity price over night time. In the unscheduled case, we assume that the charging process of each EV starts at the first sub-interval in its schedulable interval, i.e., sub-interval S_n, and no active control of EVs charging is present (once an EV is connected, the charging process commences until the corresponding maximum value of the charging price is attained, or charging is completed). We assume that EVs always consume energy with their maximum power limit until the performance threshold is satisfied. Figures 4 and 5 show examples of the charging process operations scheduled for 50 and 100 vehicles respectively. Figures 6 and 7 show the average power consumption for simulation sets for scenarios 1 and 2 respectively.

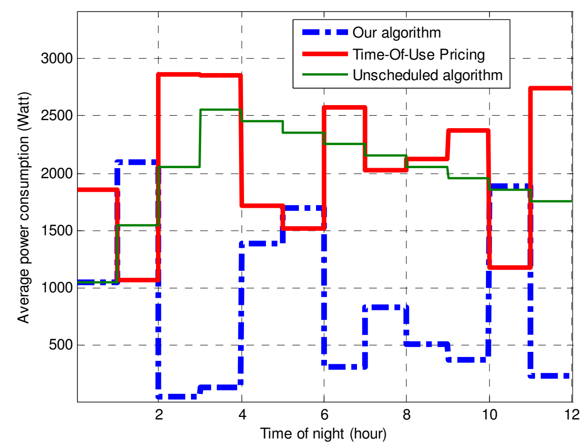

Figure 4: Average power consumption comparison between our algorithm and the unscheduled case (simulation for 50 EV)

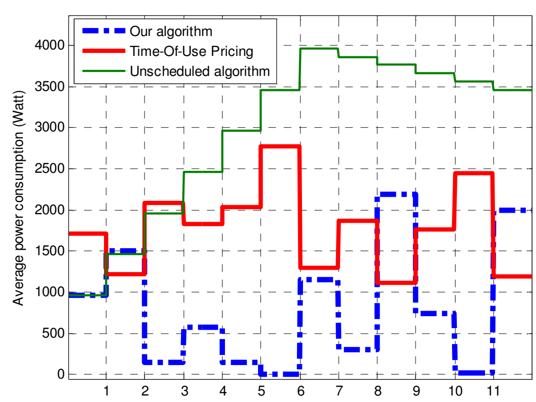

Figure 5: Average power consumption comparison between our algorithm and the unscheduled case (simulation for 100 EV)

In Figures 4 and 5 the results of our algorithm correspond to the blue dashed curve. We observe that the average power consumption is sensitive to the price variation. This shows that with using the proposed scheduling, the grid changes power consumption using TOUP variation. The figures also clearly show that the algorithm follows inversely TOUP variation in order to optimize the individual power consumption for each EV. Additionally, we observe that, compared to the unscheduled case, our algorithm consumes relatively more power when the electricity price is low and relatively less power when the electricity price is high.

Table 1 highlights the peak power consumption for our algorithm and the unscheduled one as shown in Figures 6 and 7 corresponding to scenario 1 and 2 respectively. As illustrated in Table 1, it is clear that our algorithm can reduce the peak power consumption by more than 22% for the least loaded scenario (50 EVs), and by more than 42% for the second scenario (100 EVs).

Table 1: Comparison of peak electricity with unscheduled case

	Unscheduled algorithm (KW)	Our algorithm(KW)	Saving rates (%)
Scenario1 50 EV	2700	2100	22,22 %
Scenario2 100 EV	3900	2250	42.30

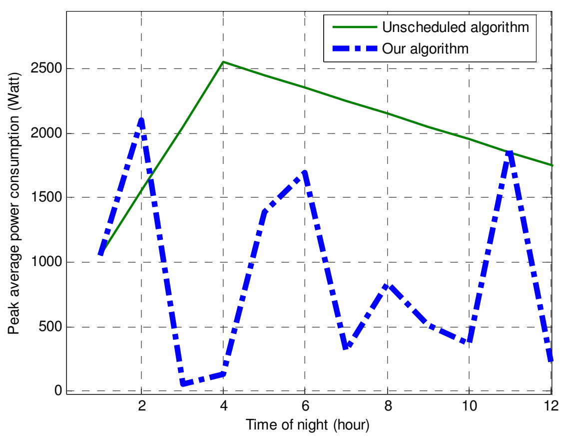

Figure 6: Peak aaverage power consumption comparison between our algorithm and unscheduled algorithm (simulation for 50 EV)

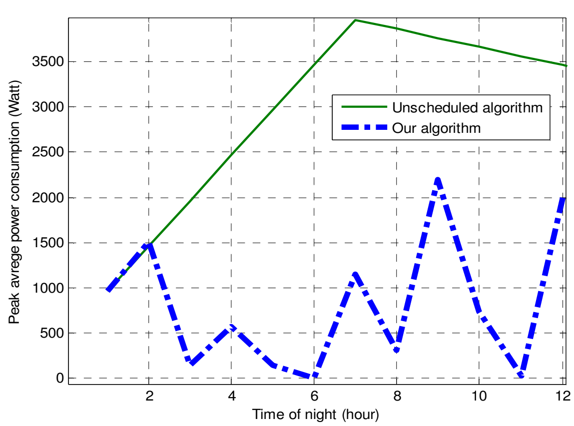

Figure 7: Peak average power consumption comparison between our algorithm and unscheduled algorithm (simulation for 100 EV)

VI. CONCLUSIONS

In this paper, we formulated a dynamic scheduling algorithm for EVs charging at home with TOUP, and analysed it through simulations considering different EV load scenarios. Two principal objectives were taken into account in the algorithm. First, satisfying each EV charging demand under TOUP constraints and second, lowering peak loads. Simulations that considered realistic EV home station charging models showed that the proposed scheduling algorithm manages the charging process in an efficient way under the defined constraints. Future work will be targeted at including load balancing techniques among neighbouring transformers while considering similar constraints.

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