Scheduling Protocol with Load Managementfor EV Charging

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Abstract— **In the next few years, as the number of EVswill become important, the smart grid will be solicited to satisfy high power demands. To deal with this problem, efficient power charge scheduling techniquesare required. In this paper, a scheduling protocol with a load management technique is introduced. The scheduling protocol is aimed first at minimizing peak loads due to multiple EVs charging at home while using pricing policies. Second, it aims at coordinating charging and discharging processes to achieve cost optimization and improve grid stability. An analytical formulation is given for the scheduling problem with a load management strategy. The simulation results showed the effectiveness of the proposed approach in minimizing peak loads, optimization cost and improving grid stability while satisfying the defined constraints.**

Keywords- V2G; EV; scheduling; smart grid; load management.

I. INTRODUCTION

With the new advances in battery capacities and electric powertrains Electric Vehicles (EVs) are becoming increasingly popular [4, 5]. So much so that, that the load introduced by EV charging operations is expected to be one of the most challenging issues for demand response systems in the smart grid. Efficient energy management for EVs supply will, in fact, become a key aspect to tackle in the smart grid. For this end, advanced scheduling algorithms seen as a part of Vehicle-to-Grid (V2G) interaction [1, 2, 3], are necessary. Integrated into the smart grid, these algorithms target objectives such as grid stabilization by reducing power fluctuations through a judicious control of the charging procedure of vehicles. Since the load due to charging numerous EVs puts a significant strain on the grid network, future V2G interface has to offer a capability to manage EVs charging load wisely according to power demand. For residential load management in general, the smart grid typically will use three types of strategies[8,10]:1) reducing peaksby disabling low priority loads when necessary, 2) shifting peaks by moving some loads past peak times occurrences; and 3) valley filling strategies which schedule low priority loads at times where the cost of energy is lower or at its lowest. Recently researches in [7, 9, 13] proposed a decentralized charging control algorithm to schedule charging for large populations of EVs in public power supply locations or at home without considering Electric Vehicle Supply Equipment (EVSE) characteristics such as plug in level 1, 2 or 3. The work in [8] presents smart energy control strategies for residential charging of EVs, aiming to minimize peak loads and flatten the overall load profile. However, dynamic EV power loading situations were not studied, especially EVs random initial power distribution. Other works, such as [10], address the problem of scheduling and electric power management optimisation but not in the context of EVs charging.

The work [17] proposes a communication –based PHEV load management scheme between the smart grid utility and the distribution system based on wireless mesh networks (WMN) to control the charging of PHEV batteries. This scheme does not address any spatiotemporal EV specification such as the charging/ discharging plug-in socket at home or at public supply station. Moreover, this scheme does not focused the EV charging or discharging scheduling problem and it does not take into account the EV priority for charging or discharging service to improve the EV satisfaction level. The electricity price variation is out of the scope of this work. The work [18] is focused on smart buildings and PHEVs. It proposes a multi-agent control system to integrate PHEV with buildings. The scheduling of EV charging is out of the scope of this proposed scheme which does not take into account the EV satisfaction when PHEVs need to be charged. This paper considers the PHEV as energy storage system for buildings only. The dynamic scheduling protocol for EVs charging at home introduced in [16], aims at minimizing peak loads at distribution feeders due to multiple EVs charging while using a time-of-use pricing (TOUP) [15]. The work presents several advantages; satisfying each EV charging demand under TOUP constraints and lowering peak loads. Nevertheless, this charging protocol has no mechanism that guarantees grid stability at peak loads when EVs number is high. Also, it does ensure neither a load fluctuation reduction nor a regulation service procedure.

In this work, we propose a dynamic scheduling protocol for EVs charging with a Load Management (LM) technique with the aim of overcoming the shortcomings of the approaches mentioned above. The scheduling protocolintegrates a load management technique with a valley filling strategy. This allows the grid to alleviate the load at peak periodswhile letting EVs take advantage of lower power prices. The scheme also lets EVs provide the grid with some of their stored power when power demand is high and power prices can be twice as high as those of off-peak hours. Moreover, since some EVs may have diverse applicationdescriptions (e.g. emergency vehicle, security vehicle, etc.)while using the same charging service,the priority of each EV application is an important parameter to consider in the load scheduling process. Therefore the proposed scheme is an optimized scheduling process integrating an LM technique with varying prices, which takes into account the individual EVs charging priority information during the plug-in phase for charge scheduling. This information is also exploited by the smart grid to take advantage, when necessary, of the power charge stored in batteries of EVs with low charging priority.

Our contributions are: 1) we present formulation of the scheduling problem with load management that takes into account variable prices for charging at a given scheduling interval, with a random arrival of vehicles acceptingeach some maximum price for charging, 2) we propose a scheduling mechanism that addresses the defined constraints with an LM technique using a valley filling strategy to improve grid stability and 3) we show with simulation studies using realistic EV charging characteristics that the LM technique achieves a good performance in terms of EVs charging cost optimisation and grid stability.

The remainder of the paper is organized as follows. In Section 2, we present the proposed scheduling model and we formulate and solve the electricity load scheduling problem with time-of-use pricing. The LM extension of the charging protocol is presented in the Sections 3. The performance evaluation of our scheduling algorithm and LM technique in terms of load cost optimisation and grid stability are presented in Section 4. Finally, Section 5 concludes the paper.

II. LOAD MANAGEMENT SCHEME

We suppose that all homes are equipped by an Advanced Metring Infrastructure (AMI), and we assume that a charging service communication initialisation has already been established between the smart grid and all EVs involved in the scheduling process. Without loss of generality, we suppose that the scheduling time interval is bounded (e.g., night time between 6pm and 6am).We also suppose that each vehicle has accepted some maxium charging price for the charging service and the initial charge of each vehicle prior to plug is random between 0% to 99 %. The arrival time of each of the vehicles at their charging stations is also supposed random. Table-1 contains the definitions of variables used in the paper.

We first consider a power load scheduling problem as in [16] minimizing the total price of energy consumptionwhen there is no constraint on the aggregate power demand to the grid. This problem is formulated as

$$Minimize_{x} \left\{ \sum_{t=1}^{T} \gamma_t \sum_{n=1}^{N} x_n^t \right\} \quad (1)$$

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

Where T is the number of sub $-$ intervals of the entire scheduling time interval (e.g., at night), γ_t denotes TOUP model unit price for energy consumption in sub-interval t of T, x_n^t is the amount of energy consumption of vehicle n during interval t, N is the total number of EVs and $[S_n; F_n]$ is the schedulable interval for EV n

Table-1 Summary of notations

T	Number of number of sub intervals of scheduling time interval
N	Number of vehicles
γ_t	unit price for energy consumption in sub-interval t
x_n^t	Energy consumption of vehicle n during interval t
x_n	Total energy consumption of vehicle n during the scheduling time interval
${}^{LM}x_n$	Total energy consumption of vehicle n during the scheduling time interval when LM is used
P_Level_Ref	Price reference level used in LM technique
x_n^{min}	The minimum power fixed by each EV in the beginning of plug-in phase
x_n^{max}	The maximum power fixed by each EV in the beginning of plug-in phase
S_n	Start of schedulable interval for EV n
F_n	End of schedulable interval for EV n
$U_n(x_n)$	Utility function for vehicle n
C_n	Minimum energy consumption threshold for vehicle n
$\gamma_{\min}$	Minimum price of energy during the scheduling time interval
$\gamma_{\max}$	Maximum price of energy during the scheduled time interval
λ	Constant between 0 and 1
P_load	EVs electric power before the load management technique
P_load^{LM}	EV electric power after the load management technique

This problem can be decomposed into the following Nsub-problems for each vehicle$n$:

$$Minimize_{x_n} \left\{ \sum_{t=1}^{T} \gamma_t x_n^t \right\} \quad (2)$$

Subjectto $x_n = \sum_{t=S_n}^{F_n} x_n^t$ (3)

and $U_n(x_n) \ge C_n$ (4)

where $U_n(x_n)$ is the utility functionfor vehicle n, and C_n itstotal energy consumption minimum threshold .

The above problem is a convex optimization problem [12]. To solve this problem, standard algorithms for convex optimization problems should be used [11]. We suppose that the utility function is strictly increasing and has an inverse function. As a result, first and second constraints can be rewritten as

$$\sum_{t=S_n}^{F_n} x_n^t \geq U_n^{-1}(C_n) \quad (5)$$

The inequality (5) should be satisfied with equality and the problem posed by equations (1, 2, 3) subject to equation (4), is reformulated as

$$Minimize_{x_n}\left\{\sum_{t=1}^{T}\gamma_t x_n^t\right\} \quad (6)$$

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

To solve equation (6), we use algorithm I.

Algorithm I. scheduling algorithm

Input: price profile, sub-intervals [S,F], p=0, utility function(U), EVs priority, Reference level

$\gamma_{i=1..T}$ /*Price Profile*/

Output: x_n /*EV energy consumption of vehicle *n**/

1. Smartgrid broadcasts price profile/*All EVs receive $\gamma_{i=1..T}$ */
2. Record price profile in an increasing order $\gamma_1 < \gamma_2 < \ldots < \gamma_T$
3. Let p=1 and Z=U^{-1} (C_n)
4. Assign $x_n^p = min\{Z, x_n^{max}\}$ and $Z = Z - x_n^p$
5. Let $p = p+1$
6. Repeat until $Z \leq x_n^{max}$ and assign $x_n^p = max\{Z, x_n^{min}\}$

/*Smart grid return to each EV its power consumption x_n */

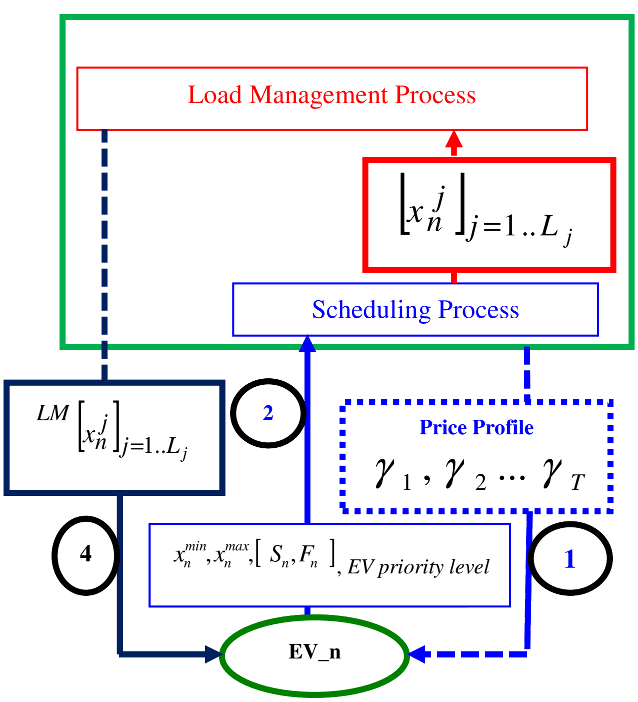

Figure 1: Schematic view of information flow between the Smart Grid and EVs for the LM technique in Algorithm II.

As a second stage of the optimisation problem, we propose an LM technique, illustrated in Fig.1, which takes advantage of low energy cost periods to improve grid stabilization. Home EV load shape adjustment can be done by many strategies, such as peak reduction, peak shifting or valley shifting. The objective is to flatten the consumption curve as much as possible not only to perform EVs cost optimization but also to improve grid stability.

Our proposed LM technique is based on the idea of using individual EVs charging priority to both exploit the charge stored in the batteries of EVs of low priority at peak periods, and to shift their load to periods of less demand. The individual information of EVs charging priority can be communicated by EVs to the smart grid in the beginning of plug-in.

The LM technique uses the notion of price reference level denoted *P_Level_Ref* , as defined in (7), which is used to determine when to switch between the charging and the discharging process for EVs with low priority.

$$\text{P\_Level\_Ref} = (\gamma_{\max} - \gamma_{\min}) * \lambda + \gamma_{\min} \quad (7)$$

Where $\lambda \in [0,1]$ is a constant chosen by the smart grid and ,

$\gamma_{\min} = \min\{\gamma_{i=1..T}\}$ and $\gamma_{\max} = \max\{\gamma_{i=1..T}\}$

Thereafter, the algorithm II is performed by the grid.

Algorithm II. LM algorithm

Input: price profile, sub-intervals [S,F],p=0, utility function(U), EVs_priority, EVs_priority_list, Reference level

Output: ${}^{LM}x_n$, /* EV energy consumption */

P_load^{LM} /* grid power load */

1. **If** (EV priority level is high) or (price<=P_level_ Ref)
   Call Algorithm I
   ${}^{LM}x_n = x_n$; $P\_load^{LM} = P\_load$
2. **else** /*EVs sell their power to grid /*Stop charging EVs*/
3. $P\_load^{LM} = P\_load + x_n^t$
4. EV_priority =high
5. Update EV_priority_List./*Smart grid updates EVs state*/
6. Goto**1**

Figure 1 shows the exchange of information between the grid and each EV during the real-time operation. The value calculate in (7) is used as a reference level to switch between the following cases: if the price is under the reference level, all EVs will be charged if they are not full already and if the price is above the reference level, only EVs with high priority level will be charged and the others EVs (with low priority level) will be discharged if they are not empty already.

Figure 2 shows that the grid begins by broadcasting the price profile $\gamma_1, \gamma_2 ..., \gamma_T$ (TOUP) to all connected EVs. As a response to the grid, each EV sends its loading interval, the maximum and minimum power demand as given by eq.(2) and eq.(3). After compiling all inputs data from EVs, the smart grid send for each EV its energy consumption scheduling vector.

III. Simulation Results

In this section, simulation results and discussion are presented to illustrate the performance of the LM scheduling algorithm. We used MATLAB to perform the simulations. We adopted the following function as a utility function for vehicles [7]:

$$U(x) = \log(x+1) \quad (8)$$

The price variation model is very important in such case study. In fact, in many works, various time-differentiated pricing models have been proposed [13, 14]: real-time pricing (RTP), day-ahead pricing (DAP), time-of-use pricing (TOUP), critical-peak pricing, Inclining block rates (IBR), etc. Research findings [15] indicated that compared to others models, TOUP provides more incentives for customers to shift load to the less expensive hours. Thereby, we used the TOUP model throughout the study.

In the simulations, a number of vehicles (100-1000) plugged in via EV charging equipment Level1. The duration of the charging period is 12 hours. Constant λ value was chosen to be 0,7. After the end of the overall charging time duration, all vehicles needed to be satisfied. The parameters for each vehicle where generated randomly as follows:

- Starting time (S_n): generated with a uniform distribution between sub-intervals 1 and 12.
- The finishing time (F_n): generated with a uniform distribution between sub-intervals S_n and 12;
- Maximum power consumption (x_n^{max}): generated with a uniform distribution between 0 and 100 percent of charge ;
- The threshold (C_n): generated with a uniform distribution between 0 and $(F_n - S_n) \times U_n(x_n^{max})$.
- Pricing $\gamma_{(t)}$: generated according to the TOUP model.

We compared the results of algorithm I (scheduling for energy cost minimisation) with those of algorithm II (scheduling with load management). We assumed that an EV always consumes the energy with its maximum power limit until its performance threshold is satisfied. We also assumed that all EVs communicate their charging priority level on plugging-in to smart grid. Two EV groups were considered: the first group included EVs with high level charging priority which had to be charged even if the price was high. The second groupwas composed by EVs with low level charging priority. Those vehicles could be charged on the same basis as those with high priority only at the lower price periods. Theycould also sell their stored power when the price becomes high. Thereby, they can save money when they consume and sell power, respectively, at low and high price times.

Simulations were run 50 times and we took the average power consumption at each sub-interval. We supposed we had 50 homes (for scenario 1) and 500 homes (for scenario 2) each of which had two EVs plugged in. The transformer needed to be maintained at an acceptable operating limit, and thus could allow a simultaneous loading of 100 EVs (for scenario 1) and 1000 EVs (for scenario 2).

Figure 2 shows an exampleof random distributionsof EVs charging and discharging considering TOUP price model. The continuous (blue) curve in this figure presents the number of EVs that consume power and the dashed (red) curve indicates the number of EVs that sell load to the grid. It is clear that the process of selling the power to the smart grid starts when the price becomes high and only EVs with low charging priority are solicited for power at that time.

The outcomes of our charging algorithm without the LM technique (algorithm I) and with the LM technique (algorithm II) considering TOUP model correspond, respectively, to the dashed (blue) and continuous (red) curve in Fig. 3. We observe from this figure that the average power consumption is still sensitive to the price variation. It is shown that with the LM charging algorithm, the grid manages more efficiently the power distribution using TOUP variation compared to the outcome of algorithm I without the LM technique. We also observe that the LM strategy consumes relatively more power when the electricity price is relatively low and provides electricity to grid via an EV discharging process applied to EVs with low priority level charging.

Table 2 summarises the results obtained in Fig. 3. As illustrated in the table, it is clear that the extended scheduling LM technique can improve the average load by more than 15% compared to the outcome of our scheduling algorithm without LM. These results show that such an LM algorithm is indeed beneficial to EV owners and utility companies. EV owners achieve important cost savings when buying electricity with low price and selling it at high price.

Table 2: Comparison of PowerConsumption with and without LM (100 EVs, TOUP model)

	Maximum load (kW)	Minimum load (kW)	Average load(kW)
Without LM	47.647	0	20.539
With LM	47.647	6.851	24.423

Thereafter we studied the influence of the number of EVs on the performance of the LM chargingalgorithm. We considered a scenario where the number of EVs is 1000. We show an example of random distribution ofthe number of high priority plug-in EVs in each time period in Fig. 4.

The outcome of our algorithm without and with the LM technique considering TOUP model with 1000 EVs corresponds respectively to the dashed (blue) and continuous (red) curve in Fig. 5. In addition to the remarks described in the first scenario of 100 EVs, we observe from Fig. 6 that the performance of the LM chargingalgorithm is significantly higher compared with our charging algorithm without the LM technique.

Table 3 summarizes the observation obtained from Fig.7. As illustrated in the table, it is clear that when increasing the number of EVs, the scheduling algorithm with the LM technique can improve the average load with a saving rate more than 75% by increasing the average load compared to the outcome of the algorithm without our LM technique.

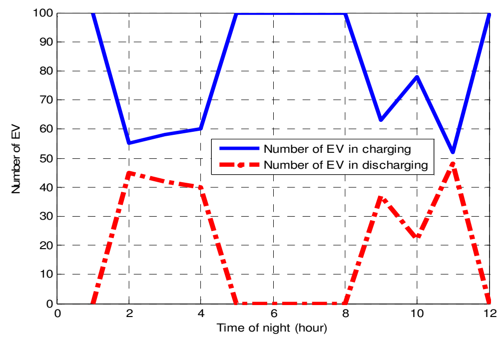

Figure 2: A random distribution of EVs during the charging and discharging process

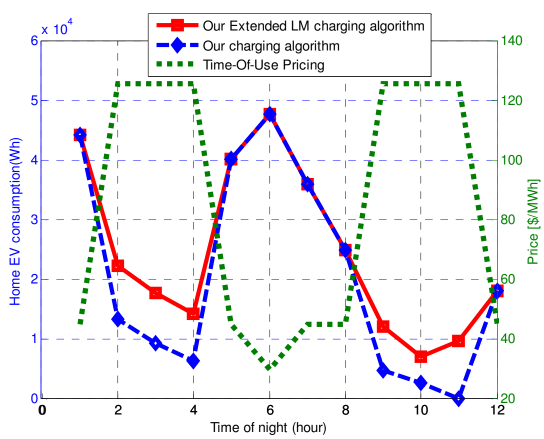

Figure 3: EVs average consumption (100 EVs)

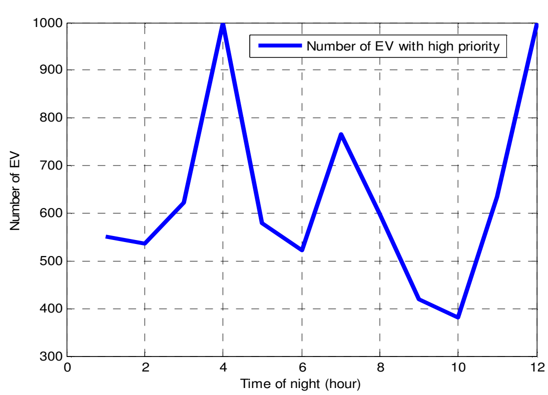

Figure 4: Random distribution of EVs during the charging process

Table 3: Comparison of Power Consumption with and without LM (1000 EVs, TOUP model)

	Maximum load (MW)	Minimum load (MW)	Average load(MW)
Without LM	0.513	0	0.212
With LM	3.267	0.461	2.132

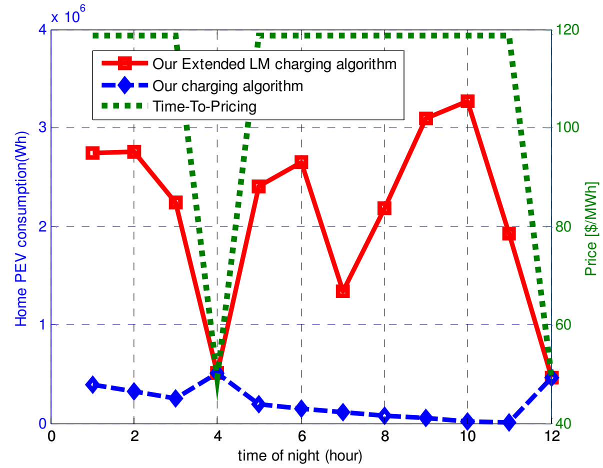

Figure 5: EVs average consumption (1000EVs)

IV. CONCLUSIONS

In this paper, we proposed a dynamic scheduling algorithm for EVs charging at home with LM considering a TOUP price model. Two principal constraints were taken into account in the scheduling algorithm: 1) satisfying individual EVs charging demands under-price constraint and 2) judiciously managing the energy load by shifting the load of low priority vehicles, out of peak loading periods. Numeric results for realistic EV characteristics and home station charging models (socket level 1) showed that the proposed scheduling algorithm manages the charging process in an efficient way. It satisfies EVs demand constraints at a low price, and enhances grid stability. The algorithm can help the smart grid to better manage EVs charging at peak loading periods, while compensating power fluctuations and improving grid stabilization. Moreover, simulation results showed that coordinating the charging and discharging process of EVs can reduce the cost of EV ownership to consumers by saving money when EVs consume energy with low prices while selling it with high price during peak hours. In addition, simulationsshowed that by increasing the number of plug-in EVs, the performance of the LM schedulingalgorithm increases. The LM charging algorithm requires low computation capability and could be used with additional constraints.

As future work, we plan to extend our proposed LM scheduling algorithm to perform load balancing between neighbour transformers to improve the maximum number of satisfied EVs during the charging period with a minimum charging cost constraint.Moreover, the multiple EV priority level impact on grid stability and EV satisfaction level can be seen as a significant issueto improve our proposed model.

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