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Procedia Computer Science 16 (2013) 767 – 775

Procedia
Computer Science

Conference on Systems Engineering Research (CSER'13)
Eds.: C.J.J. Paredis, C. Bishop, D. Bodner, Georgia Institute of Technology, Atlanta, GA, March 19-22, 2013.

Real-time Scheduling Techniques for Electric Vehicle Charging in Support of Frequency Regulation

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Abstract

Apart from the potential to reduce emissions and reliance on petroleum, large-scale adoption of electric vehicles (EVs) presents an opportunity to provide electric energy storage (EES)-based ancillary services, e.g., smoothing intermittency due to renewable energy sources (RESs) and supporting grid-wide frequency stability. However, the potential benefits of EVs are accompanied by a number of challenges. Especially, the charging of EVs can impact the distribution grid because they consume a large amount of electrical energy and can exacerbate undesirable peaks in consumption. To mitigate such issues, in this paper, we present a concept of real-time scheduling (RTS) techniques for EV charging that minimizes impacts to the power grid and guarantees the satisfaction of individual consumer's charging requirements. Simulations using a model of RTS charging concept show its advantages compared to existing "valley-filling" techniques from the literature. For this initial proof of principle, the presented model assumes a centralized control scheme; the simulation environment for this scheme is the precursor to an *agent-based* concept for a decentralized scheme. The implications of this work to systems engineering are discussed.

Keywords: Electric Vehicle (EV); Electricity Distribution Grids; Frequency Regulation; Real-time Scheduling (RTS); Simulation; Smart Grid

1. Introduction

Apart from the potential to reduce greenhouse gas emissions and relieve reliance on petroleum [1], the large-scale adoption of electric vehicles (EVs) present an opportunity to provide electric energy storage (EES)-based ancillary services, e.g., smoothing intermittency due to renewable energy sources (RESs) and supporting grid-wide frequency stabilization. However, the potential benefits of EVs are accompanied by a large number of challenges. Especially, the charging of EVs has an impact on the distribution grid because they consume a large amount of electrical energy and can exacerbate undesirable peaks in power consumption [2]. Researchers from Oak Ridge National Laboratory indicate that most regions would need to build additional generation capacity to meet the added

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doi:10.1016/j.procs.2013.01.080

demand when charging EVs in the evening [3].

Many studies suggest that adopting a "smart" charging strategy can mitigate such issues. For example, scheduling EV charging so that aggregated EV power demand fills the overnight valley in power demand may reduce daily cycling of power plants and operational costs of utilities [5]. From the EV owners' point of view, the batteries of EVs have to be charged overnight so that the owners can drive off in the morning with fully charged batteries, which also gives opportunities for "smart" charging control. Reference [2] proposed a coordinated EV charging algorithm that minimizes the power losses and maximizes the grid load factor. In Reference [6], the relationships between feeder losses, load factor, and load variance were explored in the context of plug-in hybrid EV charging, from which three optimal charging algorithms were developed to minimize the impacts of EVs on the distribution network. These strategies are based on centralized control architectures, in which an aggregator collects the information and determines charging profiles of all EVs. Hence, they require complex communication infrastructure and higher computational capacity. References [7] and [8] proposed decentralized EV charging strategies, which optimize charging profiles through a day-ahead negotiation process between a utility and EVs based on the prediction of load profiles. The charging profiles obtained through the negotiation process are optimal in that they minimize total load variance, i.e., make load profiles flat by filling valleys of load curves. However, the decentralized "valley-filling" charging strategy has several technical limitations. First, it only deals with day-ahead negotiation of charging profiles based on the predicted load profiles that must be accurate enough to guarantee its optimality. Secondly, all EVs must participate in the negotiation simultaneously and their energy demand must be known to utilities beforehand. Most importantly, it does not consider that EV owners will control the timing of recharging, and their inclination will be to plug in when convenient, rather than when utilities would prefer.

In this paper, we first formulate a real-time scheduling problem for EV charging to tackle the technical limitations of the existing "valley-filling" charging scheme, while still providing the technical/economical benefits that the "valley-filling" strategy can offer. Second, we present a real-time scheduling concept for EV charging control, and show that initial simulations demonstrate the advantages of the real-time EV charging system over the existing "valley-filling" charging scheme.

The rest of the paper is organized as follows. In Section 2, we describe the formulation of a real-time scheduling problem for EV charging. The details of our proposed methodology are given in Section 3. Simulation studies demonstrating the feasibility of the proposed methodology and advantages over the existing "valley-filling" scheme are presented in Section 4, and conclusions and future work ideas are presented in Section 5.

2. Problem Formulation

Figure 1 illustrates the operating scenario of the EV charging system considered in this work. Although EVs could be charged at different places such as a company's parking deck, public charging stations, or home, the batteries of vehicles are assumed to be only charged at home in this paper. After coming back from work, an EV owner plugs his/her car in to the charging station connected to the outlet on the wall, and sets up charging preferences or requirements such as departure state of charge (SOC) and expected plug-out time. Then, the charging station sends the requirements and an activation request signal to the real-time EV charging scheduler located at a distribution substation. Based on requirements transmitted by many EVs, the real-time charging scheduler determines a feasible charging schedule and sends activation/deactivation signals back to the charging stations.

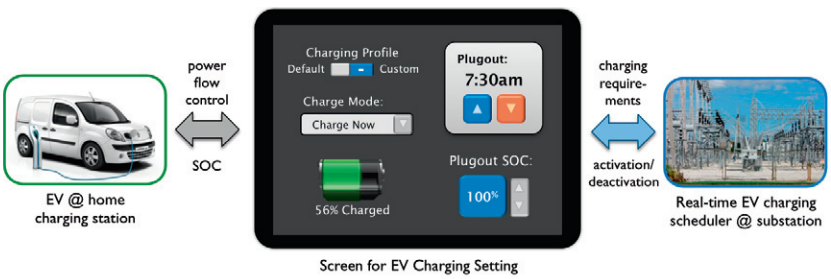

Fig. 1. Operating scenario of the proposed real-time EV charging system

Table 1. Timing characteristics of EV charging

Real-time system	EV charging system
Task, τ_i	Charging an EV
Period, T_i	N/A
Execution time, C_i	Charging time
Deadline, D_i	Plug-out time

The proposed real-time EV charging system can be viewed as an extension of the existing "valley-filling" charging strategy in that it can achieve the optimality of the "valley-filling" charging strategy in terms of minimizing total load variance (a utility's functional requirement), but, in addition, it also guarantees the satisfaction of EV owners' charging preferences/requirements, i.e., *complete charging* (consumers' functional requirements) *by when they want to plug out their cars* (consumers' timing constraints). Therefore, by definition, it can be thought of as a real-time system where timing constraints as well as functional requirements must be satisfied. According to [9], in order to apply a real-time scheduling technique to EV charging, it is required that the EV charging control system is represented as a real-time system, where a *task* or an *event* (τ_i) is modeled with timing parameters such as *period* (T_i), *execution time* (C_i), and *deadline* (D_i). The timing characteristics of the EV charging system are summarized in Table 1. It can be seen that the task, i.e., charging an EV, has all the timing parameters required to design or apply a real-time scheduling algorithm; however, there is no parameter directly related to the period (T_i) of a real-time task because in this paper only a daily EV charging scheduling is dealt with and thus the period needs not be necessarily considered. The *charging time* can be calculated based on plug-in/-out SOCs and the charging dynamics of batteries.

In general, a real-time system requires a real-time operating system that provides a real-time scheduling capability. A typical real-time system consists of a *waiting queue*, a *real-time scheduler*, and *processing queues* (or processors) as depicted in Fig. 2(a). Once a task or an event has arrived at the real-time system, it is first assigned to the waiting queue where the task is waiting to be released to the processing queue by the real-time scheduler. The real-time scheduling algorithm determines which task can be released based on a specific scheduling policy, for example, based on static- or dynamic-priorities in Earliest Deadline First (EDF) scheduling algorithm. Therefore, if each charging station can be viewed as a *processor* or *processing queue*, then an EV charging system can be represented as a *soft real-time system*[a] with variable number of heterogeneous, multiple processors as illustrated in Fig. 2(b) because power ratings of each charging station will be different and the number of charging stations that can be activated simultaneously will keep varying, depending on the available energy for EV charging. As a result, it can be concluded that real-time scheduling techniques are applicable to EV charging control problem, and enable the technical gaps of the "valley-filling" charging strategy to be filled.

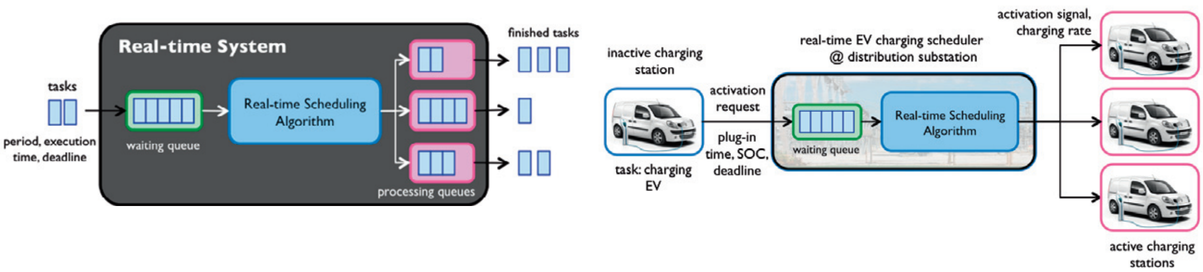

Fig. 2. Schematic representation of (a) generic real-time system, (b) EV charging system

[a] A soft real-time system is a real-time system in which performance is degraded but not destroyed by failure to meet response-time constraints [10].

Table 2. Possible EV charging modes

Mode	Description
1	Charge now
2	Charge when power is available
3	Charge when given electricity price is less than user-specified
4	Charge/supply (V2G)

3. Methodology

The schematic representation of the proposed method of real-time EV charging is presented in Fig. 3. As mentioned in Section 2, the EV charging system can be viewed as a soft real-time system with charging stations analogous to multiple processors, the number of which we must know before applying a real-time scheduling algorithm. Since each charging station can be viewed as a processor or processing queue, we can calculate the number of charging stations that can be simultaneously activated by dividing the difference between the day-ahead reference EV power demand and real-time non-EV power demand measurements, which can be utilized to refill the batteries of EVs, by the maximum charging rate as follows:

$$n_{\mathrm{PQ}}(\mathrm{t}) = (P_{\mathrm{ref}}(t) - P_{\mathrm{non\text{-}EV}}(t)) \,/\, r_{\max} \tag{1}$$

where n_{PQ} is the number of processing queues, i.e., charging stations, that can be activated simultaneously, P_{ref} is the day-ahead reference EV power demand, $P_{\mathrm{non\text{-}EV}}$ is the real-time non-EV power demand measurements, and $r_{\max}$ is the maximum charging rate.

The proposed algorithm can achieve the utility's functional requirement, that is, "valley-filling" by minimizing the deviation from the day-ahead reference EV power demand, which can be estimated using the existing day-ahead "valley-filling" charging strategy. Based on EV owners' requirements, the real-time EV charging scheduler dynamically assigns and updates the priorities of charging stations, depending on which it determines whether or not a charging station can be activated. For the purpose of incorporating frequency regulation using vehicle-to-grid (V2G) technology into the real-time EV charging system, the electricity price for V2G is also taken into account.

The most important task when developing a real-time EV charging system is to design or choose a real-time scheduling algorithm and dynamic-priority assignment policy. There are two categories for real-time scheduling for multiprocessor systems: partitioning algorithms and global scheduling algorithms [11]. By introducing different charging modes as summarized in Table 2, either partitioning or global scheduling algorithm, or both, i.e., a hybrid algorithm can be applied to the real-time EV charging system. Furthermore, the introduction of different charging modes, which are expected to be specified by EV owners when plugging in or contracted with utilities, will make the real-time EV charging system more realistic and also extendable to other design considerations such as the incorporation of V2G-based frequency regulation and the integration with demand response (DR) and home energy management system (HEMS).

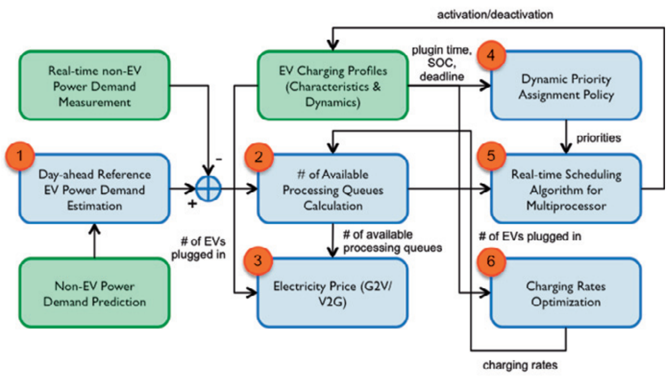

Fig. 3. Real-time scheduling for EV charging control

Table 3. Simulation settings

Parameter	Value
Number of EVs	100
Battery capacity	16 kWh
Maximum charging rate	3.3 kW
Charging efficiency	0.95
Charging window	0:00 – 17:00

In this work, a real-time scheduling algorithm is developed using the concept of the global scheduling algorithm and Earliest Deadline First (EDF) policy. A priority is dynamically assigned to each charging station and updated every 15 minutes, based on both 1) the amount of time to refill the battery and 2) the charging mode of the EV, and the real-time EV charging scheduler allows the charging station with the highest priority to be activated, no matter what charging mode it belongs to. The "*urgency*" taking account of the time to refill the battery is calculated as:

$$\gamma_n(t) = E_n(t) \,/\, (t_{\text{plugout}} - t) \tag{2}$$

where γ_n is the dynamic urgency, E_n is the energy necessary for charging, defined as $E_n = (s_{\text{plugout}} - s(t)) \times (\beta_n/\eta_n)$, β_n, battery capacity, s_{plugout}, plug-out SOC, $s(t)$, current SOC, η_n, charging efficiency, $t_{\text{plugout}}(n)$ is the plug-out time of the n-th EV, and t is the index of the current time slot. Therefore, combined with its charging mode, an EV with larger necessary energy (E_n) and shorter time-to-complete-charging ($t_{\text{plugout}} - t$) will have a higher priority.

By introducing different charging modes, the real-time EV charging system can facilitate V2G-based frequency regulation in its scheduling process because it determines a feasible schedule based on real-time non-EV power demand measurements. For instance, if EVs need to purchase power from the grid for up-regulation, the real-time EV charging system will increase the number of EVs that can be charged at the same time, or encourage EVs with charging modes 3 and 4 to start charging by reducing electricity price for charging. On the other hand, for down-regulation, the real-time EV charging system will increase electricity price to force some of EVs to postpone charging, or deactivate EVs with lower priorities or lower charging modes to reduce power consumption due to EV charging.

4. Simulation Studies

The purpose of simulation studies is to see the applicability of real-time scheduling techniques to EV charging control and to demonstrate that our proposed charging concept fills the technical gaps of the existing "valley-filling" charging scheme.

We used the average residential load profile in a service area of Southern California Edison from 20:00 on February 13th, 2011 to 19:00 on February 14th, 2011 as a non-EV base demand profile (see Fig. 4(a)) to compare the proposed real-time EV charging scheme with the one proposed in [8] as a benchmark. The parameter settings for simulation studies are summarized in Table 3. According to the typical charging characteristics of EVs in [13], we assumed that the battery capacity is 16 kWh, the maximum charging rate is 3.3 kW, and the charging efficiency is 0.95. Note that simulations are performed on a set of homogenous fleet of EVs, that is, the aforementioned characteristics are assumed to be the same for all EVs. The scheduling horizon, typically 24 hours, is divided into 96 time slots, each of 15 minutes, during which the charging rate of each EV is not changed. Based on the averaged non-EV power consumption, the number of EVs is assumed to be 100, representing 20% penetration level[a], according to which the non-EV base demand profile is appropriately scaled. In addition, the charging window is assumed to be 12:00AM to 5:00PM to achieve the flattened load shape of the "valley-filling" charging scheme.

[a] In 2010, the average annual electricity consumption for a U.S. residential utility customer was 11,496 kWh, an average of 958 kWh per month, and an average of 32 kWh per day [14].

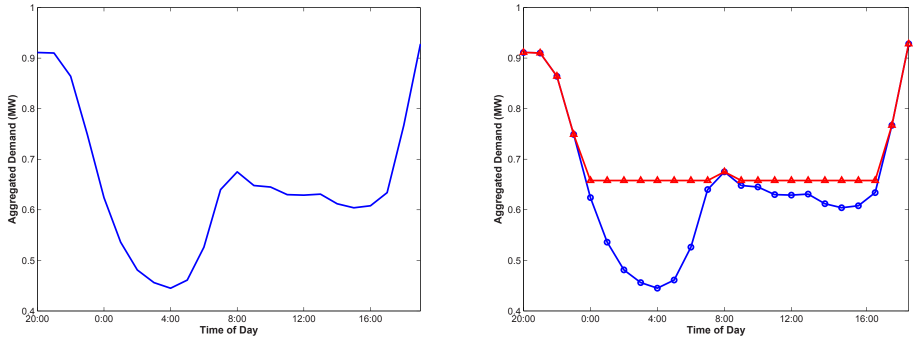

Fig. 4. (a) Base load profile (Source: Southern California Edison [12]), (b) ideal case of "valley-filling" charging scheme

In an ideal case where no EV owners' timing constraints (i.e., plug-in/-out time) are taken into account and all charging requirements (i.e., plug-out SOC) are assumed to be known to the utility beforehand, the "valley-filling" charging scheme proposed in [8] achieves the flat load curve as illustrated in Fig. 4(b). In this case, all EVs share the available power for EV charging, that is, every EV is being charged at the same rate, which is a Nash equilibrium that is converged through the day-ahead negotiation process and, as a result, can be approximately derived by dividing the available power by the total number of EVs in the network.

In order to take account of EV owners' charging requirements for EV charging control, we generated a set of EV charging profiles such as plug-in time, plug-out time, and SOC in a random fashion as shown in Fig. 5. We assume that the plug-in time is normally distributed around 6:00PM with standard deviation of 1 hour. Similarly, it is assumed that the plug-out time has a normal distribution with mean of 7:00AM and standard deviation of 1 hour, and the initial plug-in SOC is uniformly distributed between 10% and 30%. The charging modes as described in Table 2 are assumed to be uniformly distributed between 1 and 4.

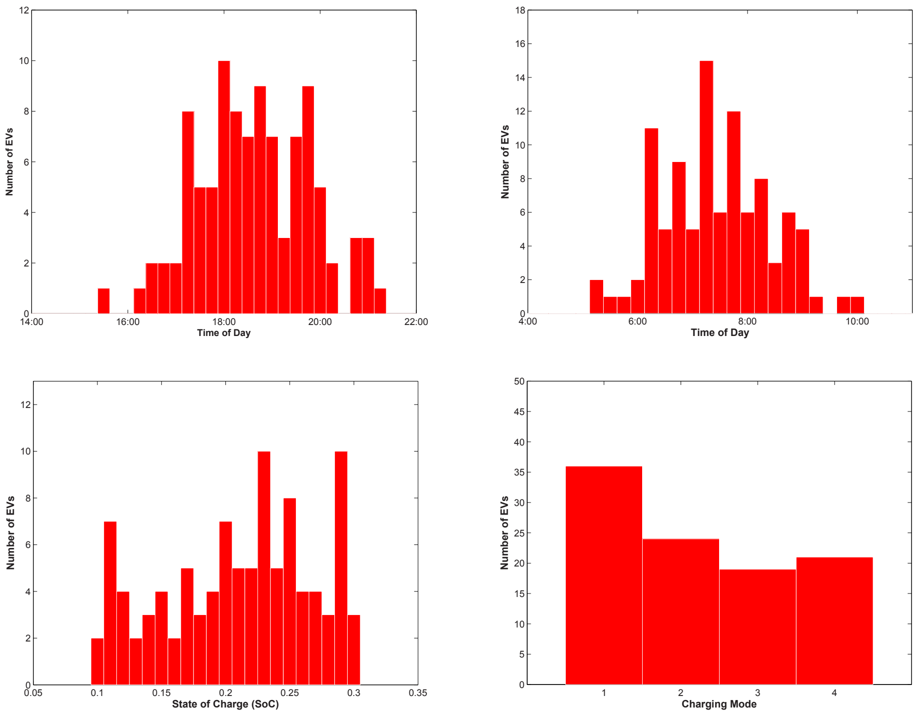

Fig. 5. EV charging profiles (a) plug-in time, (b) plug-out time, (c) plug-in state of charge (SOC), (d) charging mode

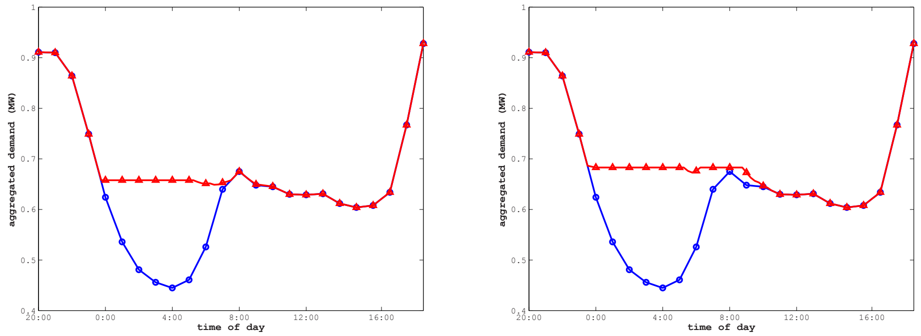

Fig. 6. Load profile (blue circle: base, red triangle: base + EV) (a) valley-filling charging scheme, (b) proposed real-time charging scheme

If timing constraints are taken into account, then the “valley-filling” scheme does not guarantee its optimality as illustrated in Fig. 6(a). Since the optimal charging profiles are generated such that the shape of the load profile is flattened out all over the charging window and all EVs share available power at the same time, all EVs start charging simultaneously at the beginning of the charging window, i.e., 12:00AM, and finish charging at the end of the charging window, i.e., 5:00PM. Therefore, if many EVs are plugged out from charging stations earlier than the scheduled a day before, then its optimality is no longer guaranteed. On the other hand, since the real-time charging scheme generates charging schedules based on the timing constraints of EV owners as well as instantaneous available power, it can alleviate the deviation from the ideal power demand curve resulting in Fig. 6(b). Note that the “valley-filling” scheme (Fig. 6(a)) adjusts charging rates, which is the same for all EVs, while the number of EVs being charged simultaneously at the maximum rate is controlled in the “real-time” charging scheme (Fig. 6(b)).

The difference between the “valley-filling” and “real-time” EV charging schemes can be seen more obviously in Fig. 7. For the “valley-filling” case (Fig. 7(a)), since all EVs are charging at the same time at the same charging rate, none of EVs are fully charged to their desired departure SOC’s when EVs are plugged out; however, all EVs are evenly charged compared with the “real-time” case (Fig. 7(b)). On the other hand, the “real-time” charging scheme fully charges the batteries of EVs with higher charging modes (1: highest, 4: lowest) and shorter time to full charge while many EVs with lower charging modes and longer time to full charge miss their deadlines, in other words, are not fully charged when plugged out. Out of 100 EVs, 23 EVs missed their deadlines, i.e., were not fully charged, and most of them have charging mode 4, the lowest charging mode.

We also run Monte Carlo simulations with various sets of EV profiles, and Table 4 summarizes the simulation results such as the number of EVs missing their deadlines, sample total load variances for optimality measure, and guarantee ratios of the “valley-filling” and “real-time” charging schemes, which is defined as the ratio of the number of EVs satisfying their deadlines to the total number of EVs.

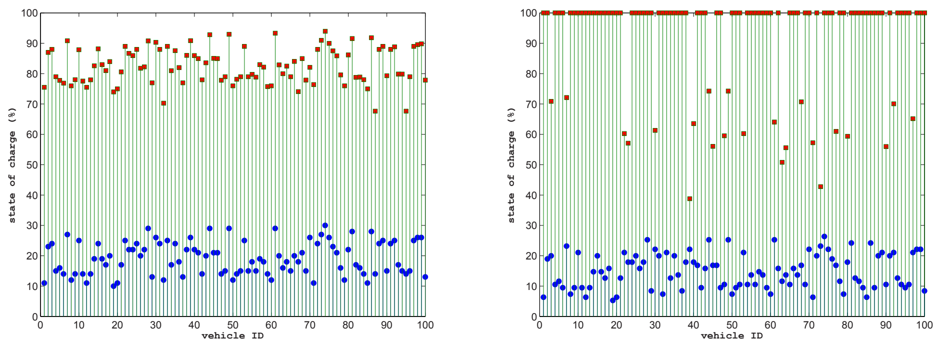

Fig. 7. State of charge (blue circle: plug-in SOC, red rectangle: plug-out SOC) (a) valley-filling charging scheme, (b) proposed real-time charging scheme

Table 4. Summary of Monte Carlo simulation runs

	Valley-filling	Real-time
# of EVs missing deadlines	100	33.2
Sample total load variance	2.43×10^{-5}	9.00×10^{-5}
Guarantee ratio	0%	66.8%
Averaged plug-out SOC	82.9%	91.5%

It can be concluded from Table 4 that if EV owners' charging requirements, esp. timing constraints, are considered, the proposed real-time EV charging scheme can fill the technical gaps of the existing "valley-filling" scheme in that it can achieve a flat load curve (similar sample variance of total load) with higher satisfaction of EV owners' charging requirements (higher guarantee ratio) even though there is still room for improvement.

5. Conclusions

In this paper, we formulated EV charging control as a real-time scheduling problem, proposed a concept for a real-time EV charging system, and showed initial results from a simulation platform used to characterize the behavior of the concept. It is demonstrated through simulations that the proposed charging scheme provides not only the benefits of the "valley-filling" charging scheme but also fills its technical gaps since it takes account of timing constraints of EV owners as well as functional requirements when generating a charging schedule. Furthermore, the proposed models and simulation platform made for this study can provide an EV charging system *design environment* for various purposes due to its modularity. For example, it can be utilized for the quantitative evaluation of a variety of existing real-time scheduling algorithms whereby the most suitable algorithm for EV charging control can be identified; and, it can also allow an economic analysis of various pricing policies for V2G-based services within the real-time EV charging control framework.

It is observed from simulation studies that there are many possibilities for improvement of the "real-time" EV charging scheme. First, using a different real-time scheduling policy will improve the performance of the proposed charging scheme. For this work, a global scheduling algorithm was developed which prioritizes all EVs based on their charging modes and urgencies as in Eq. (2); however, it keeps EVs with lower priorities from being charged, which can be avoided by assigning processing queues to each charging mode proportionally to the number of EVs with the same mode, i.e., partitioning algorithm, or a hybrid of global and partitioning algorithms.

Second, for the proof of concepts herein, it is assumed that EVs can be charged only at the maximum charging rate, which causes the number of EVs being charged simultaneously to be minimum (refer to Eq. (1)). Therefore, if charging rates can be appropriately controlled so as to maximize the number of EVs that can be charged simultaneously while maintaining its optimality, i.e., a flat load curve, it is expected that the guarantee ratio of the proposed charging scheme will be improved.

Finally, the work presented serves as the first step towards more complex decentralized system-of-systems modeling and simulation. The real-time EV charging system proposed in this paper was implemented as a centralized control system in that the real-time scheduler determines charging schedules of all EVs and set electricity price based on set price pre-specified by EV owners to encourage EVs to follow the schedules. However, in a potentially realistic future scenario, charging schedules could also be subject to the interactions with other system components such as home energy management system (HEMS). Therefore, it is the interest of the authors to extend the current centralized scheme (and the supporting modeling and simulation environment) into a decentralized one. It is hypothesized that this can be done by using an *agent-based* approach to modeling hierarchical real-time scheduling for EV charging and HEMS, which each would be modeled as differently motivated systems in a system-of-systems. In summary, the modeling and simulation discussed in this paper has been used for a preliminary proof-of-concept for applying RTS concepts to vehicle charging and can now be used for scheduling algorithm design. In addition, the environment serves as a starting point for exploring how to capture (and design given) the behavior of a Smart Grid system-of-systems. This more comprehensive problem will most likely motivate a broader set of systems engineering research.

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