An Evaluation of Electric Vehicle Penetration under Demand Response in a Multi-Agent Based Simulation

Zhanle Wang, *Student Member, IEEE* and Raman Paranjape, *Member, IEEE*
Electronic Systems Engineering,
University of Regina, Regina, Canada
Raman.Paranjape@uregina.ca

Abstract—**This paper proposes an electric vehicle charging model and various control algorithms that are further incorporated into a multi-agent system [1] to evaluate impacts of electric vehicle penetration on the power system. Electric vehicles have become increasingly popular due to the high costs of the operation of gas / diesel powered vehicles and the potential to reduce CO_2 emission. In this work, we propose the electric vehicle charging model and associated control algorithms to aggregate the electric vehicle load. Simulation results show that uncontrolled charging of electric vehicles can jeopardize the stability of the power system. In a worst-case scenario this can lead to an increase of peak demand by 53.2%, while by using appropriate scheduled charging the electric vehicles can have no contribution to the peak demand. Furthermore, scheduled charging dramatically reduces the standard deviation of the residential load (by up to 51%). Therefore, the aggregation of electric vehicle demand under an appropriate demand response control strategy has the potential to dramatically improve the stability of the power system with virtually no negative impacts. The proposed electric vehicle charging model and the associated scheduling algorithm can be embedded into a home energy management system or a smart charger.**

Keywords—**Electric vehicle, demand response, dynamic pricing, smart grid, home energy management system, multi-agent system**

I. INTRODUCTION

Power generation and demand has three important characteristics [2]: 1) power generation must match exactly the power demand; 2) the electricity demand is highly variable with time of day and time of year; 3) electricity cannot be economically stored. These characteristics lead to many challenges in the efficient operation of any power system. In addition, the power system has to maintain maximum expected peak demand capacity across the aggregated load. As this peak demand occurs infrequently, power systems are inherently inefficient. For instance, 20% of power generation capacity exists to maintain peak demand which is used only 5% of the time [3].

There are three main types of Electric Vehicles (EV): Hybrid Electric Vehicles (HEV), Plug-in Hybrid Electric Vehicles (PHEV), and pure Battery Electric Vehicle (BEV) [4, 5]. While there are some important differences among these three types of the EVs, for the purposes of this study, which focuses on EV charging, we use the umbrella term of the EV to discuss all of these systems at once. According to the Navigant Research, there will be 35 million EVs on the road by 2022 across the world [6]. This large number of the EVs has the potential to significantly de-stabilize and reduce the efficiency of the current power system. However, this problem is eminently solvable by scheduling EV charging. There are a number of simplifying assumptions about most EVs that help in developing this scheduling solution. Most EVs will be plugged in for 10–15 hours a day while be driven only 1–2 hours a day [7]. This provides enormous potentials to control the EV charging. Furthermore, the aggregation of the scheduled charging can be integrated into the power system to provide frequency/voltage regulation, renewable power adoption and system optimization [5]. To accomplish this, it requires the application of Demand Response (DR) and various enabling technologies. DR is designed to reduce peak demand and encourage electric consumption when renewable energy is available in response to market price and/or power availability over time [8-10].

The U.S. Department of Energy classifies DR as having two options: price-based options and incentive-based options [9]. The price-based options and the incentive-based options are listed below and are primarily offered to residential customers [9].

- Time-of-use (TOU): a rate with different unit prices for usage during different blocks of time, usually defined for a 24 hour day.
- Real-time pricing (RTP): a rate in which the price typically fluctuates hourly reflecting changes in the wholesale price of electricity. Customers are typically notified of RTP prices on a day-ahead or hour-ahead basis.
- Critical Peak Pricing (CPP): a hybrid of the TOU and RTP design. The basic rate structure is TOU. A much higher CPP price is applied when the demand is very high or system supply is limited.
- Direct Load Control (DLC): a program in which the utility remotely switches off a customer's electrical equipment on short notice based on demand.

Since scheduling EV charging can not only eliminate the negative impacts of the bump of EV demand but also improve the stability of the power system, a number of schedule methodologies and their effectiveness are reviewed.

Clement-Nyns et al. [11] evaluate the impact of PHEVs on a residential distribution system. The distribution grid is represented by the IEEE 34-node test feeder [12]. This work quantifies the impact of uncontrolled and controlled PHEV charging by calculating power losses and voltage deviations among three levels of 10%, 20% and 30% of PHEV penetration. The PHEV charging is scheduled to minimize the power losses in the scenario of controlled charging. Quadratic programming and dynamic programming techniques are proposed to conduct this optimization problem. Simulation

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results show that the power losses are reduced by scheduling the PHEV charging.

EV charging demand in a distribution system is also analyzed by Qian et al. [13] in four scenarios of uncontrolled domestic charging, uncontrolled off-peak domestic charging, “smart” domestic charging and uncontrolled public charging. The distribution system is modelled by a 38-bus distribution system [14]. Dynamic electricity tariffs such as TOU and real time pricing are introduced. The object is to minimize the charging cost.

Li et al. [15] consider EVs as resources of demand response to compensate for the generation of intermittent wind power. A hierarchical algorithm is used to coordinate EV charging and wind power generation. The first level schedules the conventional power plants and wind power output in the generation side. The EV charging is controlled in the second level to satisfy charging requirements. The third level also schedules EV charging but acts as ancillary services using electricity frequency as a feedback. Simulation results demonstrate that the proposed algorithm can improve the grid frequency stability and reduce the generation cost with charging up 99.5% of the EVs.

Xu et al. [16] examine EVs as both interruptible loads and distributed energy sources, based on which the well-being of the generation system is analyzed using the penetration of the EVs as a factor. The well-being of the generation system is defined as the probability of its health status as marginal or at risk. The concepts of interruptible loads and distributed energy sources are represented by an interruptible power capacity and a power capacity provided to the grid (V2G) respectively. Both these capacities can be use to mitigate the variations of power generation. Meanwhile, both the scenarios do not compromise the normal use of the EVs. This study concludes that the V2G scenario has better performance than the interruption scenario in terms of improving system well-being.

A Multi-Agent System (MAS) generally refers to a body of multiple autonomous agents that interact, cooperate, and negotiate with each other in order to satisfy their design objectives [17-19]. It provides a way of viewing the world in which an agent system can intuitively represent a real-world situation of interacting entities, and test how complex behaviors may occur [20]. Commonly accepted attributes of software agents are autonomy, social ability, reactivity, ability to learn and mobility (if using mobile agents) [21-23]. In order to execute, agents require an Agent Execution Environment (AEE). For instance, Java Agent DEvelopment Framework (JADE) provides an environment to develop agent systems compatible with FIPA protocols [24]. The TRlabs Execution Environment for Mobile Agents (TEEMA) was adopted as the platform in this work because of its availability and its familiarity to the authors [25, 26]. TEEMA provides standard libraries to support various types of operations for agents such as addressing, naming, messaging, mobility, security and logging [27, 28].

II. Electric Vehicle model

The power of the EVs depends on their charging characteristics and the driving patterns of their owners.

Similar to the work in [13], we choose GM EV1 Panasonic Lead Acid Battery as a prototype EV for this study. Fig. 1 shows State of Charge (SOC) and demand with charging time of this battery [29]. SOC is defined as Remain Capacity/Rated Capacity [5].

The EV charging demand depends on a charging point and an initial SOC. The function of demand (green dash line in Fig. 1) with respect to the charging points can be mathematically expressed as follows.

$$f(x)=\begin{cases}0.0043x+5.8 & 0<x<162\\ -0.0424(x-163)+0.5 & 162\le x<282\\ 1.5 & 282\le x<402\\ -0.0192(x-402)+1.5 & 402\le x\le 480\end{cases} \tag{1}$$

where $f(x)$ is the demand and x is the charging point in minutes.

The mathematical expression of SOC (blue solid line in Fig. 1) with respect to the charging points is simplified as follows.

$$soc(x)=\begin{cases}0.43x & 0<x<211\\ 0.036(x-211)+90.3 & 211\le x\le 480\end{cases} \tag{2}$$

where $soc(x)$ is the SOC in percentage and x is the charging point in minutes. Its inverse function is as follows.

$$x(soc)=\begin{cases}2.33soc & 0<soc<91\\ 27.78soc-2298.33 & 91\le soc\le 100\end{cases} \tag{3}$$

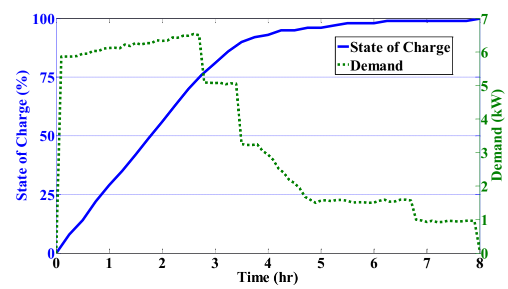
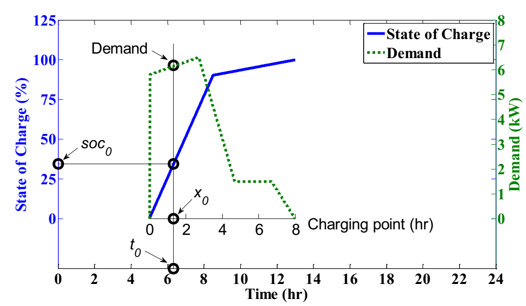


Fig. 1. State of Charge and Demand of GM EV1 Panasonic Lead Acid Battery

The initial charging point x_0 can be found by substituting the initial SOC (soc_0) to Equation (3). This is presented in Fig. 2.



* t_0 is initial charging time

Fig. 2. Individual EV charging in a day

The initial SOC can be assumed as normally distributed, as shown in Equation (4).

$$f(soc_0,\mu,\sigma)=\frac{1}{\sigma\sqrt{2\pi}}e^{-\frac{(soc_0-\mu)^2}{2\sigma^2}} \tag{4}$$

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where μ is the average of soc_0 and σ is the standard deviation. The available EV travel range is proportional to its SOC [29]; therefore, μ can be calculated by the following.

$$\mu = \frac{Range - DVM}{Range} \tag{5}$$

where *Range* is the available driving range of a fully charged vehicle. *DVM* is average daily vehicle miles, which means the average driving miles per vehicle per day.

The fully charged GM EV1 can be driven up to 90 miles [29], so the value of *Range* is 90 miles. The average daily vehicle travelling miles (DVM) was 32.73 miles in the year of 2001 [30]. Because people use vehicles more frequently since 2001, we assume that the average value becomes 35 miles. Consequently, if the EVs are fully charged after recharging, the average initial SOC is approximate 60%, which is calculated as follows.

$$\mu = \frac{Range - DVM}{Range} = \frac{90-35}{90} \approx 60\% \tag{6}$$

By substituting μ (0.6) and σ (assumed to be 10%) into Equation (4), the standard normal distribution of SOC_0 is found.

The individual EV charging demand is defined as follows.

$$P(t, x, soc_0) = f(x-t) \quad x_0 \le x \le 480 \tag{7}$$

where t is charging time (0 ~ 1440-minute) in a day, x is the charging point and soc_0 is the initial SOC. x_0 is the initial charging point, which is calculated by substituting soc_0 to Equation (3) as $x_0 = x(soc_0)$.

III. AGGREGATING ALGORITHMS

The charging aggregation of EV profiles is formulated as follows.

$$P_a(t, x, soc_0) = \sum_{i=1}^{k} P_i(t_i, x_i, soc_{0i}) \tag{8}$$

where $P_a(t)$ is the aggregation of EV demand and P_i is defined by Equation (7). i is the # of a specific EV and k is the number of the EVs in the system. t_i, x_i and soc_{0i} is the charging time, the charging point and the initial SOC of the i^{th} EV respectively.

The EVs are assumed to be exclusively charged at home.

A. Uncontrolled charging

Fig. 3 shows the probability of the home-arrival-time [31]. There are no DR options in this situation, in other words, people do not have incentive to shift EV loads; therefore, people plug-in and charge the EVs immediately after arriving home. The probability distribution of initial charging time (t_0) is the same as the one of home arrival time.

As expected the probability density of home arrival time is mostly like a normal distribution. To characterize this observation, we sample 2000 times of this probability density, which is enough to determine this distribution, where the probabilities of the range from 0hr to 10hr are taken out as errors. The average value is 17hr. The standard deviation is 2.8 hours. This probability density of home-arrival-time is formalized as follows.

$$g_1(t, \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(t-\mu)^2}{2\sigma^2}} \tag{9}$$

where $g_1(t, \mu, \sigma)$ is the probability density of home arrival time in a day. μ is the average value (17hr) and σ is the standard deviation (2.8 hours).

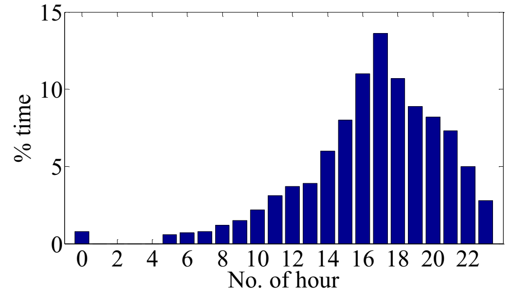

Fig. 3. Probability density of home arrival time

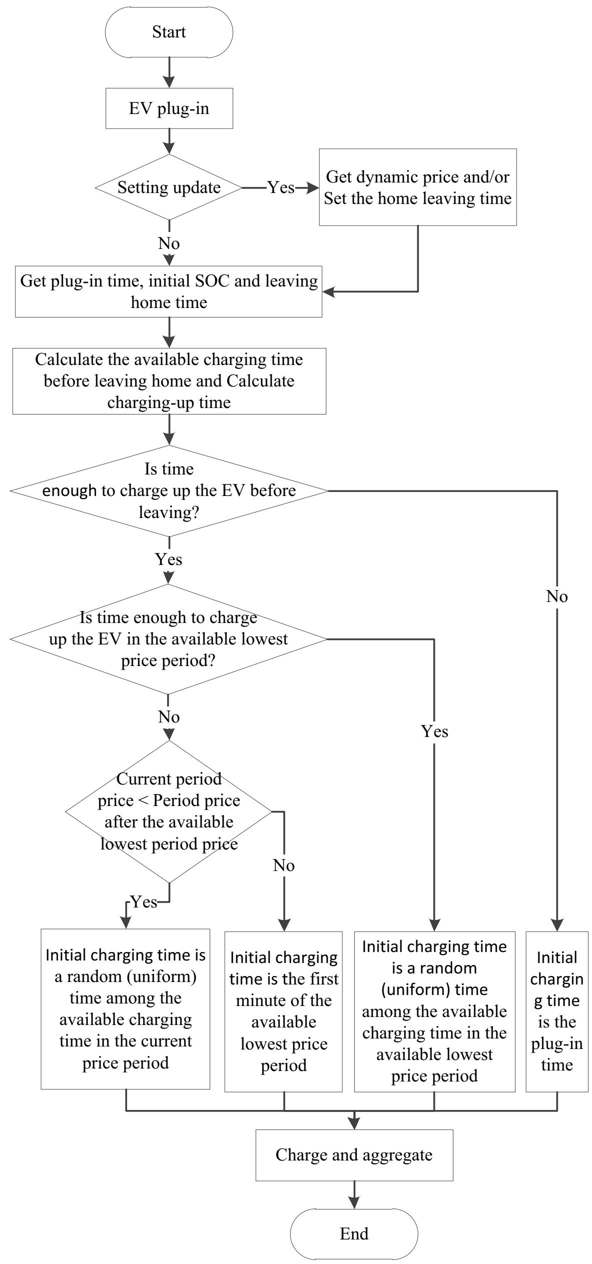

Fig. 4. Scheduling algorithm

B. Scheduled charging under the TOU

The TOU is one of the mechanisms to encourage people to change their electricity consumption pattern. For instance, in Ontario, Canada, the price is 7.9 ¢/kWh, 11.2 ¢/kWh and 13.5 ¢/kWh in the off-peak period, the mid-peak period and peak period respectively [32]. It is reasonable to expect that higher prices will discourage people to charge the EVs while lower prices will encourage people to do so.

In a smart home, a home Energy Management System (EMS) or a smart charger intelligently controls the EV charging to minimize the house holders' expenses [33]. The objective function to evaluate this is as follows.

$$min(\sum_{t_0}^{t_1} P(t)M(t)) \quad t_0 \le t < t_1 \tag{10}$$

where *P(t)* is the EV demand and *M(t)* is the electricity price. t_0 is the initial charging time and t_1 is the time of leaving home, which is assumed as a normal distribution with a average value of 7hr and a standard deviation of 1 hour.

Fig. 4 shows the scheduling algorithm. This algorithm can be embedded into a home energy management system or a smart charger.

IV. Evaluation of EV penetration

A. Experimental configurations

Simulations are designed to evaluate the impacts of EV penetration in two scenarios:

1: Uncontrolled charging
2: Scheduled charging

The first scenario is designed as a reference to evaluate the impacts of uncontrolled EV charging on the power system. The second scenario predicts the influence of the TOU.

The EV model and the algorithms are incorporated into a multi-agent system, in which the main stakeholders are modeled by software agents including Conventional Home Agents, Smart Home Agents, and a Utility Agent [1]. The Utility Agent is not used in this study since generation cost is not observed in this work. A number of EVs are assigned to the Conventional Home Agents and the Smart Home Agents based on a penetration level.

2000 Conventional Homes Agents and 2000 Smart Home Agents are configured to the Scenario #1 and the Scenarios #2 respectively. The smart home agent is equipped a home EMS. Each scenario evaluates overall household electricity load with three levels of EV penetration: 10%, 20% and 30%, which represents 200, 400 and 600 house holders owning the EVs respectively.

The price is 7.5 ¢/kWh in the off-peak period from 0:00 to 6:00 and the hour of 23:00. The price is 11.2 ¢/kWh in the mid-peak period from 7:00 to 16:00. In the peak period from 17:00 to 22:00, the price is 13.5 ¢/kWh. This TOU is modified from the announced prices of Ontario Energy Board [32].

The observations include:

- Peak demand
- Comparable standard deviation

The peak demand is the maximum value of the load profile and the comparable standard deviation refers to the standard deviation over the average value of the load profile. This makes the standard deviation comparable since it eliminates impacts of increase of total demand with improvement of penetration levels.

B. Simulation results

A set of two-day simulations were conducted since the charging time cross two days. The simulation results of the second day are presented.

1) Scenario #1: uncontrolled charging

The impact of uncontrolled EV load in the three levels of penetration is shown in Fig. 5. The peak demand and the comparable standard deviation without EV penetration was 2.20 mW and 0.53 (blue areas in Fig. 5) [1]. The peak demand with 10%, 20% and 30% of EV penetration was 2.56 mW, 2.98 mW and 3.37 mW respectively. The comparable standard deviation was also increased to 0.57, 0.61 and 0.65 respectively.

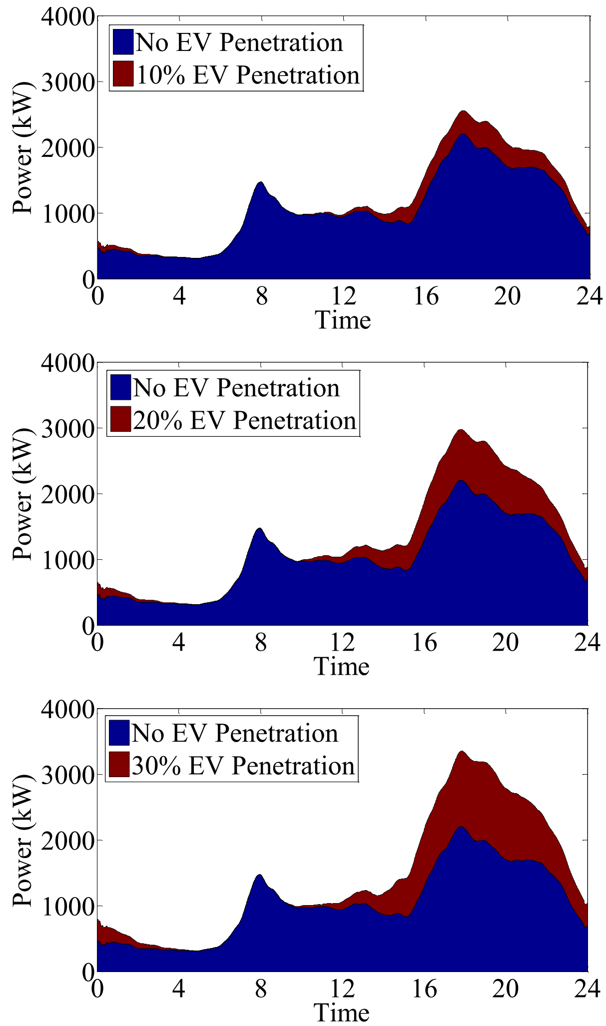

Fig. 5. Aggregation of 2000 Conventional Home Agents with uncontrolled EV penetration

2) Scenario #2: Scheduled charging

The peak demand was 2.20 mW among all the levels of penetration. The comparable standard deviations with different levels of penetration were 0.37 (10%), 0.28 (20%) and 0.26 (30%).

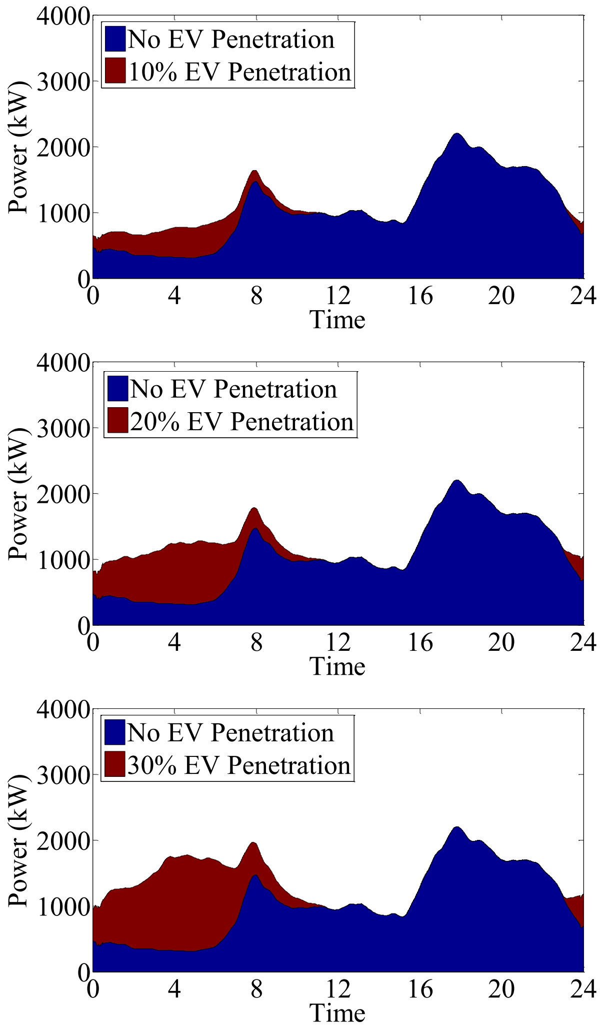

Fig. 6. Aggregation of 2000 Smart Home with EV penetration under TOU

V. Discussion

The observations of the simulation results include the peak demand and the comparable standard deviation. A lower value of the peak demand and of the standard deviation is more valuable since lower values represent higher stability of the power system.

Table I summarizes these observations. In the first scenario, the EV penetration in all levels of raises the peak demand and the comparable standard deviation. In the 30% penetration level, the peak demand is increased by 53.2%. The comparable standard deviation increases by 22.6%.

The second scenario evaluates the impacts of introducing the dynamic tariff of the TOU. This scenario requires various technologies such as the smart meter and the home EMS/the smart EV charger. Since people wants to minimize their expense, they recharge their EVs when the electricity price is lower or the off-peak demand period; therefore the penetration of EVs does not contribute to the peak demand. The comparable standard deviation is dramatically reduced. Furthermore, the higher level of EV penetration the lower comparable standard deviation is shown.

Table I. Comparison of the observations among three scenarios

Observations Scenarios\Levels		Peak Demand (mW)	Comparable Standard Deviation
No penetration		2.20	0.53
#1	10%	2.56	0.57
	20%	2.98	0.61
	30%	3.37	0.65
#2	10%	2.20	0.37
	20%	2.20	0.28
	30%	2.20	0.26

VI. Conclusions

The significant entry of EVs into the main stream of automobile based transportation provides both challenges and opportunities and will be an essential component of the future power system or "smart grid". The challenges are the demand surge which comes from the electricity demand of EV charging. However, the batteries within these vehicles provide a huge power storage capability that can be used to regulate power systems; absorb the variation of renewable resources (e.g., wind power and solar power); and provide quick response to sudden peak demand. Scheduling EV charging not only addresses these challenges but also creates the opportunities to improve the stability of the power system.

This study proposes the EV model that simulates EV charging profiles and the algorithms that predict the aggregation of EV charging, which are further incorporated into the multi-agent system. The first simulation is used to quantify the impact of the uncontrolled EV penetration as references in the three levels of 10%, 20% and 30%. The simulation results show that the uncontrolled EV charging would jeopardize the power system by increasing the peak demand (e.g., by 53.2% in the level 30% of EV penetration). The second simulation evaluates the scheduled EV penetration. The scheduled EV load greatly improves the stability of the power system.

The proposed model and the algorithms can also be incorporated into other systems in the simulation environment to evaluate the EV penetration under various types of DR. The study can be extended into distributed power systems to evaluate the impact of EV penetration on specific feeders.

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