A Load-Balancing Based Charging Management Mechanism for Electric Vehicles

Chenn-Jung Huang, Heng-Ming Chen, Kai-Wen Hu, Hsiu-Hui Liao, Han Wen Tsai, and Jui-Jiun Jian

***Abstract*—This work proposes an EV charging management mechanismand utilizes the scheduling systems for the charging stations to determine when to store electricity into batteries according to the real-time electricity price and charging requirement of EVs. A charging suggestion module is presented in this work to locate the most suitable charging station or battery exchange station for the EVs according to the available information in hand. When an EV cannot reach at any charging station due to the lack of electricity, a mobile charging vehicle management module is used to assisting the EV in finding a suitable mobile charging vehicle for recharging. The experimental results show that the proposed work can balance the loading of battery charging and exchange stations, and lower the load peak to make electricity cost down. Besides, the proposed charging suggestion module can decrease the driving distance of EVs for finding the charging stations and the waiting time wasted while charging. The mobile charging vehicle management module can effectively prevent EVs from halting on the road owing to running out of the electricity.**

***Index Terms*—Charging suggestion, preload, electric vehicle, load-balancing.**

I. Introduction

Electric vehicles (EVs) can be divided into two types, including electric motorcycles (EMs) and electric cars. Promoting EV industry has become the global trends, and each government does his utmost to propose the development strategies for EV industry. For example, Japan has announced that the EV market share will be up to 50% by 2050, and USA has declared to have one million EVs on the roads by 2015.

Although EVs have the advantage of carbon reduction, the cost of EVs and batteries, the short driving range, the long charging time, and the inconvenient deployment of charging stations are the reasons why EVs cannot be widely adopted for transportation. Therefore, if we want to popularize EVs, extensive establishment in charging stations and battery exchange stations is necessary. However, more charging and battery exchange stations may cause the overload and instability of power system. There are still lacks of the approaches to integrate the renewable energy to achieve load-balancing among charging stations and battery exchange stations and to decrease the power cost in those stations.

With the increasing number of EVs, a sudden high demand for electrical consumption usually happens. The instable charging requests may cause power cut due to excessive electrical consumption and even result in the damage of circuit system or electrical components in the local area. Besides, the timing and the location for charging are not fixed, and the major problem is that a new resource named as distributed energy resource (DER) such as solar power or wind energy should be discovered as soon as possible to relieve the load of electrical consumption.

In this work, a load-balancing based charging management mechanism for electric vehicles is proposed to tackle above-mentioned challenges. The goals of this work are to construct a power shortage warning mechanism, designing a charging recommendation system, make a charging reservation, and provide a seamless charging service via mobile charging vehicles. A series of experiments were performed and the experimental results exhibit the feasibility and practicality of our proposed work.

The remainder of this paper is organized as follows. The related work is presented in Section II. Section III presents the proposed mechanisms. The simulation results are given in Section IV. Conclusions and future work are presented in Section V.

II. Related Work

In the next few years, if the market share of EVs is increasing, the loading of power system may be affected. Besides, the influence on the overall power system for some charging stations providing quick charging service in the future was discussed in the literature [1]. Cao *et al.* addressed three kinds of methods to lower the influence on the power grid while charging for EVs, including vehicle to grid (V2G), the utilization of energy management equipment (EME), and the mechanism of electricity pricing [2]. V2G means that the EV discharges the remaining energy stored in the battery into the grid if necessary, and it also has near-zero harmonic distortion [3]. Masoum *et al.* [4] presented a smart load management system for plug-in EVs to tackle the problems that happen in distribution and residential networks with charging stations for peak demand shaving and power loss minimization. A smart energy control strategy based on quadratic programming for charging pluggable hybrid electrical vehicles (PHEVs) was presented by Mets *et al.* to minimize the peak load and smooth the overall electrical load [5]. Markel*et al.*[6]introduced a charging model for EVs according to real-time price information to minimize charging cost and maximize discharging profit.

The DERs, such as wind power, solar power, tidal power, and geothermal power is highly valued in recent years. Ipakchi presented a distributed management system that reflects the demand side to integrate renewable resources [7]. Lasseter provided micro-grid concepts and verified its advantage on the management of DERs [8].

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DOI: 10.7763/IJMO.2013.V3.270

Alamaniotis *et al.* proposed an evolutionary multi-objective optimization algorithm to predict a five-minute load [9], but the predicted time is too short to fit the need. Some literatures used wavelet neural networks to predict a short-term load forecasting [10] and [11], but this method introduces too much computation overhead and thus affects its feasibility. In this work, a fuzzy forecasting algorithm [12] is adopted to proceed the local load forecasting that will transfer the results to the charging and battery exchange for calculating the real-time pricing.

III. The Proposed Charging Management Mechanism for Electric Vehicles

The proposed load-balancing based charging management mechanism is composed by seven modules located at regional servers, upper-level regional servers, charging and battery exchange (C&BE) stations, and cell phones/On-Board Units (OBUs). The C&BE charging management module resides at each regional server can arrange the power preload schedules to achieve the load balancing among C&BE stations. That it, the C&BE charging management module administrates the electricity management and the calculation for electricity price related to all C&BE stations. This C&BE charging management module also collects the real-time driving information via OBUs or handheld GPS devices.

Based on the power preloading schedules, the up-to-date driving information, and the location information of available mobile charging vehicles and C&BE stations, the charging suggestion module located at each regional server can inform the drivers in advance if an EV needs charging. Notably, if the available mobile charging vehicles and C&BE stations are not located at the same region where the EV currently resides, a regional server at upper level will take over to plan an overall charging suggestion to decrease the loading of local servers at each region. The charging suggestion module can assist in determining if the remaining electricity of an EV is enough to arrive at the planned destination. Once the remaining electricity is not sufficient, we will locate the most suitable C&BE station for the EV.

After determining the most suitable C&BE station for the EV, dynamic path planning modules located at regional servers can be employed to find out the shortest path to the C&BE station. Notably, the dynamic path planning presented in this work utilizes A* algorithm to assist the deployment of a mobile charging vehicle and to plan an optimal path while executing the EV charging rescue task.

A. C&BE Charging Management Module

The C&BE charging management module consists of three components, namely power preload scheduling, real-time electricity price calculation, and charging demand prediction. The functionality of the power preload scheduling sub-module is to achieve the power load balancing and to integrate the distributed energy resources according to the prediction results of the charging demand of C&BE stations. The real-time electricity price calculation sub-module utilizes the power load prediction of C&BE stations and the charging demands of EVs to calculate the up-to-date electricity price. That is, when there is a higher electricity load or larger charging demands of EVs, the electricity price will be higher. Accordingly, some EV drivers might select some C&BE station with lower power load to avoid paying higher electricity price to the C&BE stations, although the drivers need to take a longer route to take the charging service.

1) Power preload scheduling

In order to minimize the operation cost of each C&BE Station and balancing the loading of each C&BE station, we use the following objective function to derive the electricity cost paid by each C&BE station,

$$\min C = \int_{t_0}^{t_N} M(t)P(t)\,dt \qquad (1)$$

where $M(t)$ and $P(t)$ represent the real-time electricity price and the total electricity the C&BE station received from the power company at time t, respectively. N denotes the number of time slices for each day which is determined by the power company; and t0 and tN represent the beginning and the end of time slices each day, respectively.

The power used by each C&BE station cannot surpasses the contacted capacity signed with the power company, Otherwise the extra power used by the C&BE station will be charged two to three times of the regular electricity price. To minimize the electricity cost given by Eq. (1), we first divide a day into N time sections. Due to the limitations of charging speed and capacity of a battery at a C&BE station, the capacity that can be charged into the battery can be expressed by,

$$P_{battery,i}(t) \geq E_{cv,i} + P_{DER,i}(t) \geq P(t_i) \qquad (2)$$

where $E_{cv,I}$ denotes the contracted capacity that a C&BE station signing with the power company at the ith time section during a day. $P(t)$stands for the total electricity that the station receives from the power company at time t, and $P_{DER,i}(t)$ represents the power generated by distributed energy resources governed by the C&BE station at the ith time section.

We next allocate the power from suitable distributed energy resources to each C&BE station by considering the distance between distributed energy resources and each C&BE station as follows,

$$\min\,(d(X_i, X_j)) \qquad (3)$$

where X_i and X_j denote the jth C&BE station that demands power and the jth distributed energy resource, respectively. Each C&BE station will demand power from the nearest distributed energy source, if the power of the requested source not enough to meet the demands of the C&BE station, the C&BE station will search the next nearest distributed power source to provide power until the demand of the C&BE station has been met or until all distributed power sources have been checked.

2) Real-time electricity price calculation for C&BEstations

This module takes into consideration the cost of electricity and the cost of batteries to produce dynamic prices to let C&BE stations earn higher profits and lower down electricity price paid by the customers. Meanwhile, the strategy of dynamic pricing can guide the customers to use C&BE station with lower load by keeping the electricity price positively correlated with power load.

3) Charging demand prediction

This module predicts how much power a C&BE station discharges during a period of time. We first obtain some information of a vehicle, such as current position, remaining power, speed, and route plans, etc. We then predict the charge demand of an EV by,

$$P_{request}=P_{total}-(P_o-\frac{d}{V}\times c) \tag{4}$$

$$\text{Subject to} P_o-\frac{d}{V}\times c>0 \tag{5}$$

B. Charging Suggestion Module

This module mainly assists an EV to determine the location to charge or exchange the battery. Based on the remaining electricity and the driving speed of an EV, the charging suggestion module will search the C&BE station or mobile charging vehicle that is close to the user's planned navigation path with lowest electricity price. However, if the user's requirement is to save the waiting time for charging service, this module will find out the suitable C&BE station or mobile charging vehicle where the EV can get charged immediately or exchange the battery that has been fully charged to minimize the waiting time. Notably, our proposed hierarchical architecture can deal with the case that the suggested charging station located at another region. In other words, the local regional server that the EV resides at will request the upper-level regional server to give the charging suggestion if no C&BE stations and mobile charging vehicle are available at the same region that the EV resides at.

We first compute the electricity that an EV consumes before arriving at the *i*th C&BE station as follows,

$$P_i=\frac{X_i}{V_i}\times S_i \tag{6}$$

whereX_i denotes the distance of the EV to the *i*th C&BE station, V_i represents the speed of the EV, and S_i is the electricity that the EV consumes per hour. Notably, S_i and V_i are strongly correlated. That is, the electricity that the EV consumes increases as the EV drives faster.

C. Mobile Charging Vehicle Management Module

To avoid the situation that an EV halts on the road due to the exhaustion of the battery power, this module deploys mobile charging vehicles in the areas where there is no charging station nearby or there are much higher demands of charging for EVs. Meanwhile, we present a charging mechanism to make the deployment of mobile charging vehicles more feasible for real-world applications.

1) Deployment of mobile charging vehicles

In this study, the deployment of mobile charging vehicles (CVs) must beat the locations where no charging stations are nearby or the demands for charging rescues for EVs are higher. Therefore, the purpose of the deployment of mobile CVs is to determine the locations of mobile CVs, which can support the regions lacking of C&BE stations or the regions that the rescue request of EVs are frequent. Although the deployment of the mobile base stations has been operated for many years and the deployment techniques for mobile base stations have been mature enough. The mobile base stations need to know in advance the number of users at each deployment locations and the mobile base station must assign channels to customer once she/he enters the communication range of the base station. However, the situation is different in dealing with the deployment optimization problem of mobile CVs. It can be observed that not every EV will ask for the charging service from mobile CVs. Besides, a mobile base station does not need to worry about the adequacy of power, where as the mobile CV does. That's why the method of optimizing the deployment of the mobile CVs is proposed in this work.

2) Assignment of mobile CVs

This module is used to assign mobile CVs to the locations to meet the EVs asking for charging so as to achieve the seamless charging support. Kiam [13] proposed a taxi dispatch system that optimizes the taxi resource to reduce the waiting time for customers and to increase the efficiency of the taxi dispatch task. We refer its way of distribution to make the assignment decision of mobile CVs. However, we modified the algorithm in accordance with the characteristics of mobile CVs and EVs. For example, once EVs face the shortage of electricity, the location where mobile CVs and EVs will meet should be the place that the EVs can arrive at.

IV. Simulation Results

We ran a series of simulations to verify the feasibility and effectiveness of our proposed EV charging management mechanism. The simulation time lasted for one day, and each region had its own local server, which was governed by an upper-level regional server. The battery power consumption of EVs under constant speed is listed in Table I, and the charging speed referred to the relationship between the charging power and charging time for a lithium battery used by EVs. Each C&BE station have its own backup battery which can store excess electricity or pre-load the electricity needed in the next time period. All the battery capacity at each C&BE station was set as 200 kW, and the charging cost was US$ 0.00009852 per kilowatt-hour.

TABLE I: Battery Power Consumption of EVs Under Constant Speed.

	Battery Capacity (kW/hr)	Maximum Mileage (50km/hr)	Maximum Speed (km/hr)
Electric vehicle	30	160 km	93
Electric motorcycle	0.5	35 km	50
Mobile charging vehicle	200	800 km	80

The first part of the simulations was to examine the performance of the proposed preload scheduling algorithm (PLS), whose main purpose is to balance the loading among C&BE stations. The PLS was compared to the method without using PLS algorithm (NAN) and a recently presented Smart Load Management (SLM) algorithm in the literature [14]. The number of the C&B Estations was set as

450 and the performance metrics is load-balancing outcome.

Fig. 1 represents the comparison of the load of C&BE stations among PLS, SLM, and NAN. We can observe that the curve of NAN had an obvious peak load at 9:00 and 19:00. This peak made contracted electricity bills rise and increase the risk of electricity consumption exceeding the contracted capacity. Our proposed PLS not only had charging demand forecasting mechanism but also considered the schedule of the contracted capacity and time-of-use tariff. Meanwhile, PLS can control the amount of charged and discharged electricity during each period of time and take use of distributed energy resources timely for the battery charging at C&BE stations to meet charging requirements of EVs. Accordingly, the highest peak load of PLS was lower than that of SLM and NAN. Besides lowering the peak load, our proposed PLS can reduce electricity cost and achieve load balancing as well. In the simulations, we assumed that the electricity during the period of 8:00 and 23:00 is more expensive than the rest of the time period during a day. Thus, our PLS method avoided charging for C&BE stations during the period of 8:00 and 23:00 to lower the electricity cost. Notably, if the load is still too high during some time period, PLS would release the battery power to avoid drawing too much power from the power company in that period because electricity price of the power company is higher.

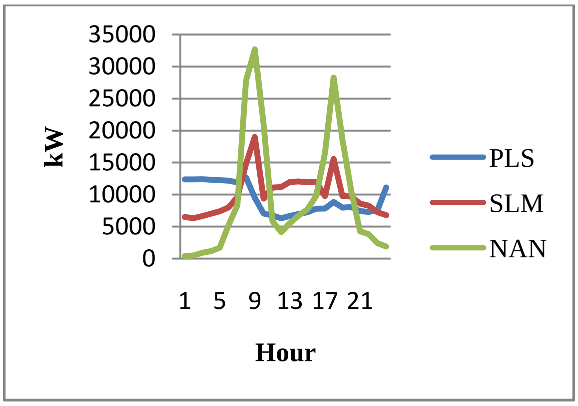

Fig. 1. Power load comparison of PLS, SLM, and NAN.

The second part of the simulations was to confirm the performance of the proposed charging suggestion module. The proposed EV charging management mechanism using the charging suggestion module was compared with that without using the charging suggestion module. The simulation environment is as follows. When the battery electricity of an EV is less than 30%, the EV would search the nearest C&BE station for charging. If the EV cannot arrive at any C&BE station due to the lack of electricity, the charging suggestion module would assign a mobile charging vehicle to rescue the EV. The number of electric cars and electric motorcycles were 81429 and 114286, respectively, and the number of C&BE stations were 450.

Table II lists the independent sample t-test results for the charging price with/without using the proposed charging suggestion module, assuming α=0.05 as the significance level. It can be observed that the mean and the standard deviation using the charging suggestion module were both less than the ones without using the charging suggestion module, and the one-tailed significance (p-value) is smaller than α as well. This experimental result revealed that our proposed method can effectively lower the electricity price.

TABLE II: COMPARISON OF THE CHARGING PRICE.

	Number of observations	Mean (dollar/watt-hour)	Standard deviation
Without charging suggestion module	57350	5.1942	5.2668
With charging suggestion module	63601	4.0221	2.8251
	t	Degrees of freedom	Sig. (one tailed)
Without charging suggestion module With charging suggestion module	95.177	85761.422	0.000

The last part of the simulations was to examine of effectiveness of the proposed mobile charging vehicle management module. We assumed that the number of EVs and mobile charging vehicles are 264286 and 36 per day, respectively. Four combinations of different number of C&BE stations, including 400, 900, 1400, and 2600, were simulated to compare the successful ratio of rescues applied with the deployment of mobile charging vehicles.

Table III shows the comparison between the one used in the proposed mobile charging vehicle management module and the compared target, random deployment, in terms of different number of C& BE stations. While the number of C&BE stations was 400 or 900, which indicates that the C&BE stations were distributed sparsely, we can observe the proposed mobile charging vehicle management module can effectively improve the successful ration of rescues. It can be inferred that more EVs had less possibility to halton the road owing to running out of electricity, and therefore it would increase users' satisfaction for mobile charging service. However, while the number of C&BE stations was over 1400, which means the C&BE stations intensively distributed, the successful ratio of recues for the proposed mobile charging vehicle management module is similar with that of the random deployment. This is because when C&BE stations were distributed more intensively, the EVs can easily reach the nearby C&BE stations. Therefore, the successful ratios of rescues for these two approaches have insignificant difference.

TABLE III: COMPARISON OF SUCCESSFUL RATIO OF RESCUES.

Number of C&BE stations	Successful ratio of rescues	
	Mobile charging vehicle management module	Random deployment
400	41%	21%
900	88%	92%
1400	93%	98%
2600	93%	100%

V. CONCLUSION

The rapid establishment of the C&BE stations for EVs may lead to the significant increase of the peak load, the contracted capacity, and the basic electricity charge. In our work, the proposed load-balancing EV charging management mechanism not only provides a seamless charging service for EVs, but also enhances the quality of electricity supply of the charging stations, maintains the regional power grid stability, and achieves load-balancing. This work also integrates and optimizes the use of distributed energy, and thus lower the operation costs and maximizes the profits of C&BE stations. There are three core modules in this work. A C&BE charging management module is used to manage the power preload scheduling and predict charging demand effectively and thus lower the peak of load successfully and decrease the cost of electricity for the C&BE stations. An EV charging recommendation module is employed to find the most suitable C&BE station for EVs. Besides, a mobile charging vehicle management module is used to search the C&BE station or mobile charging vehicle that is close to the planned navigation path of the EV with lowest electricity price. Comparing our proposed work with the latest frameworks in the literature, the simulation results show that our mechanism achieves better performance in terms of not only relieving the peak load of C&BE stations, but also lowering the electricity cost.

ACKNOWLEDGMENT

The authors would like to thank the National Science Council of the Republic of China, Taiwan for financially supporting this research under contract numbers NSC 99-2511-S-259-008-MY3 and 101-2622-E-259-001-CC3 for financially supporting this research.

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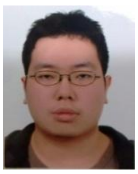

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