ARCHIVES OF ELECTRICAL ENGINEERING VOL. 67(3), pp. 641–654 (2018)

DOI 10.24425/123669

Dynamic electric vehicles charging load allocation strategy for residential area

YI WANG[1], XIU MA[1], FEIHONG WANG[1], XINGZHE HOU[2],
HONGLIANG SUN[2], KE ZHENG[1]

[1] *School of Communication and Information engineering*
Chong Qing University of Posts and Telecommunications
400065 Chongqing, China

[2] *Chong Qing Electric Power Research Institute*
400015 Chongqing, Chin
e-mail: wangyi81@cqupt.edu.cn

(Received: 04.01.2018, revised: 19.06.2018)

Abstract: A large amount of electric vehicles (EVs) charging load will bring significant impact to the power system. An appropriate resource allocation strategy is required for securing the power system safety and satisfying EVs charging demand. This paper proposed a power coordination allocation strategy of EVs' in distribution systems. The strategy divides the allocation into two stages. The first stage is based on scores assigned to EVs through an entropy method, whereas the second stage allocates energy according to EV's state of charge. The charging power is delivered in order to maximize EV users' satisfaction and fairness without violation of grid constraints. Simulation on a typical power-limited residential distribution network proves the effectiveness of the strategy. The analysis results indicate that compared with traditional methods, EVs, which have higher charging requirement and shorter available time will get more energy delivered than others. The root-mean-square-error (RMSE) and standard-deviation (SD) results prove the effectiveness of the methodology for improving the balance of power delivery.

Key words: electric vehicles, charging power management, allocation strategy, priority assessment

1. Introduction

As a clean energy carrier, electric vehicles (EVs) become an important way to deal with energy crisis and environmental problems which have been concerned widely in recent years [1, 2]. However, charging EVs imposes an additional load on the power grid [3]. Most of the existing public distribution networks have been built for many years, the power supply capacity is limited, and it costs significantly to expand the capacity. These negative factors are hindering EVs from entering the public distribution network. However, with the increasing popularity of electric vehicles, a large number of electric vehicle users will utilize the residential area-based public distribution system as the main stop and charging places, this will also lead to a great impact on the system, and then power resources will be in short supply. It will cause the distribution network and transformer overload, voltage drops and other electrical safety problems [4–7].

Renewable energy relieves the tension of power resources, but its intermittency may break the supply and demand balance of the power grid [8, 9]. Guiding electric vehicles to eliminate excess power in time is essential. Under the influence of peak and valley electricity price, electric vehicles are more inclined to charge under valley electricity price [10]. However, it may cause another peak load of the power grid. All the factors above could affect the formulation of charging strategies for electric vehicles.

With the support of the communication infrastructure [11], electric vehicles can be increased through wireless charging [12]. However, the construction of smart distribution residential area is not perfect, and the power supply capacity of some residential areas can't meet the charging demand of more electric vehicles [2, 13]. Thus current research mainly focuses on the orderly charging and the optimal scheduling to deal with the load impact of electric vehicles on the power grid. Literature [14] put forward two smart strategies with objective functions considering minimization of total daily cost and peak-to-average ratio respectively. The impact on PEV charging from an economic and technical was studied correspondingly. In [15], a methodology is proposed for moving numerous electric vehicles charging load to valley period using vehicle-to-grid (V2G) technology. However, as the total load increases, peak load shifting will no longer achieve the desired effect. Literature [16] put forward a scheduling strategy based on Time-of-use (TOU) power price, which suggests EVs charge during valley price periods and discharge in peak price time. The strategy considered both the power grid security and users' economic benefits, but it is subjected to car owners' personal schedule constraints, which limited its effectiveness.

A methodology for scheduling EV energy based on unit commitment practice is proposed in [17]. However, in reality, due to the stochastic nature of the EV owners' behavior, the optimization scheme based on forecast data cannot accurately provide a suitable solution for each user. A dynamic control strategy could adapt to the changing environment that need to be raised [18–20]. A method controlling the charging power of plug-in EVs is proposed in [21], a quality of service (QoS) aware admission control scheme is put forward to manage power, a vehicle owner who pays more gets a faster charging rate. In [22], a demand coordination method of plug-in EVs in distribution systems is proposed, and the methodology is based on the priority assigned to plug-in EVs through a fuzzy expert system. Vehicle owners which have shorter parking duration and higher required charging time can get better charging experience.

In order to manage an EVs' charging power resource in separate areas and optimize owners' charging experience, this paper studies the charging power of a single electric vehicle, presents a dynamic charging power allocation strategy for electric vehicles in the public distribution network area. The strategy utilizes the available charging power at present to fulfill users' needs without increasing the total power capacity of the distribution network. Each allocation will be divided into two stages, the first stage is based on priority, focusing on fairness between users; the second stage allocates all the remaining available power according to the state of charge (SOC), focusing on meeting the urgent needs of some particular users.

2. Power allocation in residential area

Generally, the charging of EVs can be classified into fast charging and slow charging. The power of slow charging is around 3.3 kW, and the power of fast charging rang from 10 kW to 50 kW [23]. The slow charging has little impact on the power grid and low installation cost, it is preferable in a residential area. However, it may pose a threat to the safety of the power grid with a large scale of EVs. Power allocation in residential area is indispensable.

2.1. Disordered allocation

There are mainly two charging ways for EVs in a public distribution area. In the first way, car owners use the existing plug-in device, whereas in other way, they use a charging pile built in a specific parking lot for EVs. Both ways belong to the category of disordered allocation, this type of allocation regards the EVs charging load as a regular load, which would not be regulated by the distribution system [24]. Keeping charging in a disordered type will threaten electricity safety when the EVs charging load is large enough to make total load of the district exceed the upper limit of power supply capacity, lead to tripping failure, power off or even causing fire disaster. Therefore, the disordered allocation is unreliable [25].

2.2. Queuing allocation

To avoid power overloading, a straightforward allocation strategy for EVs in a residential area applies a queuing mechanism [26]. Power grid monitors transformer capacity in real time, once electricity load reaches its upper limit, these EVs to be charged will have to wait in line, until a car finishes charging and releases enough energy space.

Queuing allocation could effectively avoid power overloading and can be implemented simply. However, queuing allocation did not consider user needs, when power load reaches its upper limit, car owners in queue have to wait for an uncertain time without any charging power supplied, this could be inconvenient for those who have emergency charging needs. Moreover, some users may arrive later than others, but they also have less time for charging, and it is possible for them not to start charging during their entire available time, which could be unfair and unreasonable.

3. Allocation strategy modeling

This paper proposes a dynamic Evs' charging load allocation strategy for a residential area, allocates the limited power resources to each EV connected to the power grid according to certain rules. The strategy divides the available power into two parts, participates in two stages respectively.

3.1. Information collection and processing

Before executing the allocation algorithm, we need to collect related information in advance (as shown in Table 1). The information can be obtained from a power consumption information collection system, smart electric meter and battery management system.

Table 1. Information needed to be collected

Name	**Description**
P	total power of public distribution network
$P_{0.t}$	regular load at time t
$P_{r.i}$	rated charging power of the i-th EV (EV_i)
$\mathrm{SOC}_{i.t}$	state of charge of EV_i at time t
$t_{\mathrm{hold}\,i}$	charged time of EV_i
$t_{\mathrm{plan}\,i}$	planning charge time of EV_i

Lithium-ion batteries are mainly used for the pure electric vehicles (such as private cars and pure electric buses) in the market currently [27]. The charge of the lithium-ion batteries usually adopts the constant current – constant voltage charging mode [28], the constant current charging is carried out with a standard current for a period of time, firstly, and when the battery voltage reaches the charging cut-off voltage, the lithium-ion batteries will be charged by the constant voltage.

In order to realize the distribution of power resources on demand in a dynamic real-time way, the proposed strategy sets maximum demand charging power for every EV involved in based on typical charging curve of lithium battery. The maximum demand charging power (P_e) was determined by EV battery rated charging power (P_r) and state of charge (SOC), when SOC approaches its maximum, P_e drops from P_r. The real-time maximum demand power can be obtained from the battery management systems (BMS).

By adding P_e to all EVs in the charge queue, we get total demand charge power at time t ($P_{\mathrm{sum}.t}$). According to the value between $P_{\mathrm{sum}.t}$ and total available charge power at time t ($P_{\mathrm{able}.t}$), current supply-demand relationship can be expressed as: $P_{\mathrm{able}.t} > P_{\mathrm{sum}.t}$, in this case, power resources are enough to support all EVs in the charge queue, they could get their P_e respectively. $P_{\mathrm{able}.t} \leq P_{\mathrm{sum}.t}$, in this case, power resources could not support every EV's P_e, the following two-stage allocation algorithm needs to be executed.

The first stage allocation relies on a priority level assigned to EVs. The priority determining can be considered as a multi-index comprehensive evaluation problem, involving $t_{\mathrm{hold}i}$, $t_{\mathrm{plan}i}$, $\mathrm{SOC}_{i.t}$. In order to evaluate the weight of each indicator objectively, an entropy method [29] is adopted to evaluate the priority level of each electric vehicle. The steps of the evaluation algorithm are as follows: the indicators need to be standardized firstly. Thus

$$Y_{ij} = \frac{X_{ij} - \min(X_i)}{\max(X_i) - \min(X_i)} \quad \text{or} \quad Y_{ij} = \frac{\max(X_i) - X_{ij}}{\max(X_i) - \min(X_i)}, \tag{1}$$

where: X_{ij} is the j-th index value of EV_i; Y_{ij} is the standardized index value, former one is a forward index, whereas latter one is the reverse index. In this paper, $t_{\mathrm{hold}i}$ is the forward index, $t_{\mathrm{plan}i}$ and $\mathrm{SOC}_{i.t}$ are the reverse indexes.

The information entropy of each index can be calculated as follows:

$$E_j = -\frac{1}{\ln n} \sum_{i=1}^{n} p_{ij} \ln p_{ij}, \tag{2}$$

where

$$p_{ij} = Y_{ij} \Big/ \sum_{i=1}^{n} Y_{ij} \,. \tag{3}$$

If $p_{ij} = 0$, then

$$\lim_{p_{ij} \to 0} p_{ij} \ln p_{ij} = 0. \tag{4}$$

E_j is the entropy of j-th index; n is the number of EVs.

The weight of index j is

$$W_j = \frac{1 - E_j}{k - \sum\limits_{j=1}^{k} E_j}\,, \tag{5}$$

where W_j is the weight of index j; k is the number of indexes.

Thus, the final score of EV_i is

$$Z_i = \sum_{j=1}^{k} W_j Y_{ij}\,, \tag{6}$$

where Z_i is the score assigned to EV_i, $\mathbf{Z} = \{Z_1, Z_2, \ldots, Z_i, \ldots, Z_n\}$.

The priority level of an electric vehicle is obtained by sorting $\mathbf{Z}$ in descending order. That is, if the score of EV_i equals $\max(\mathbf{Z})$, the EV_i priority level is 1; the score of EV_i equals $\min(\mathbf{Z})$, the EV_i priority level is n.

3.2. Two-stage allocation

The first stage allocation is illustrated as follows:

$$P_{g.i.t} = P_{\text{able}.t} * \frac{P_{e.i.t}}{P_{\text{sum}.t}}\,, \tag{7}$$

where i is the priority level decided by the size of Z_i in (6); $P_{g.i.t}$ is the charging power allocated for EV with priority i at time t; $P_{\text{able}.t}$ is the available charging power at time t, $P_{\text{able}.t} = P - P_{0.t}$. $P_{e.i.t}$ is the maximum demand charging power with priority i at time t.

The allocation starts from EV with $i = 1$, and $P_{\text{able}.t}$ updates itself after each allocation, thus, executing $P_{\text{able}.t} = P_{\text{able}.t} - P_{g.i.t}$, until all EVs are allocated. As the first stage allocation completes, part of $P_{\text{able}.t}$ will remain and will participate in the second stage allocation:

$$P_{g2.i.t} = P_{\text{able2}.t} * \frac{S_{\text{oc.}\max} - S_{\text{oc}.i.t}}{\sum\limits_{i=1}^{N} (S_{\text{oc.}\max} - S_{\text{oc}.i.t})}\,, \tag{8}$$

where $P_{g2.i.t}$ is the charging power allocated for the EV with priority i at time t; $P_{\text{able2}.t}$ is the remaining available charging power at time t after the first stage allocation; $S_{\text{oc.}\max}$ is the maximum SOC of the EV battery; N is the total number of EVs of the charging queue.

After calculating the $P_{g2.i.t}$, it is necessary to detect whether the total power of the two stage allocations exceeds the maximum charging power of the electric vehicle. If $P_{g.i.t} + P_{g2.i.t} > P_{e.i.t}$,

$P_{g2.i.t}$, it is adjusted as $P_{g.i.t} + P_{g2.i.t} = P_{e.i.t}$. The actual distribution power $P_{i.t}$ of an electric vehicle is the sum of two stages of the power allocation:

$$P_{i.t} = \begin{cases} P_{e.i.t}, & P_{g.i.t} + P_{g2.i.t} > P_{e.i.t} \\ P_{g.i.t} + P_{g2.i.t}, & P_{g.i.t} + P_{g2.i.t} \le P_{e.i.t} \end{cases} . \tag{9}$$

Thus, the allocation process of one time interval ends. The length of each time interval can be adjusted according to charging environment. The whole process of the allocation algorithm is shown in Fig. 1. The two-stage allocation can be explained in Fig. 2.

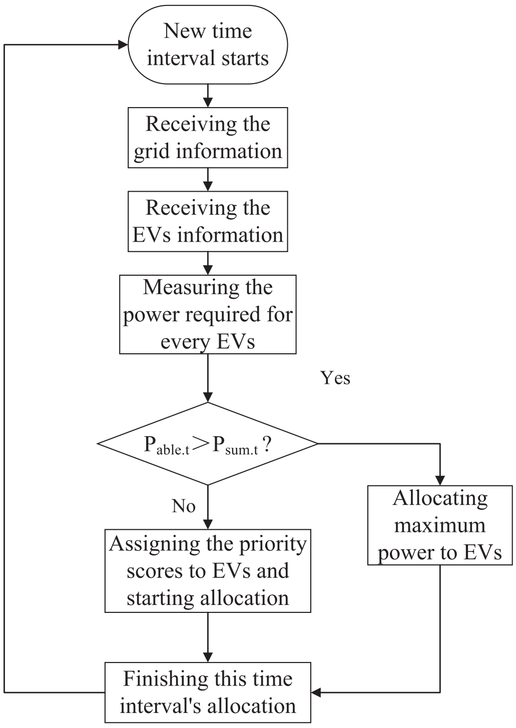

Fig. 1. Flow chart of power allocation algorithm

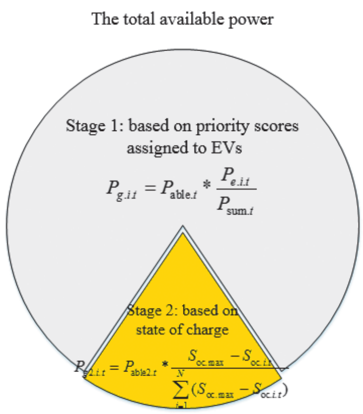

Fig. 2. Waveforms of the source currents before symmetrisation

4. Case study

To evaluate the proposed strategy, two cases were examined. The first case is five EVs charging data from a parking lot, and the second case is a more practical illustration of a residential area. All the charging power delivered by devices is considered adjustable. Both cases are modeled in a MATLAB software environment, where the length of simulation time is set for one day, and one hour for each time interval correspondingly.

4.1. Residential distribution network

The residential distribution network studied here is the IEEE 34-node test feeder [30] as shown in Fig. 3. In the test system, node 1 is connected to the grid, and the other 33 nodes are connected with a residential load. It is assumed that each house has an electric vehicle. There are some nodes, which will have EV charging randomly.

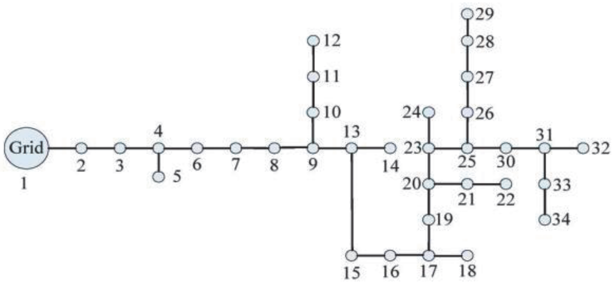

Fig. 3. IEEE 34-node test feeder [30]

4.2. Case study involving five EVs

In order to analyze the effect of priority on the SOC of electric vehicle, the traditional queuing allocation method and the two stage allocation method proposed in this paper are compared under the same scene. It is assumed that the five EVs charging information during a peak period are shown in Table 2. It is assumed that due to an energy capacity limit, only three EVs can be simultaneously charged in the parking lot. The entropy method is adopted as follows:

Table 2. Five EVs charging information at a time interval

	$t_{\text{hold}\,i}$ / min	$t_{\text{plan}\,i}$ / min	SOC $i(t)$ / %
EV1	180	270	58
EV2	90	360	42
EV3	0	360	21
EV4	0	60	23
EV5	60	180	30

Table 3 shows the results of indicators standardization using (1):

Table 3. Indicators standardization

	$t_{\text{hold } i}$	$t_{\text{plan } i}$	SOC $i(t)$
EV1	1	0.3	0
EV2	0.5	0	0.43
EV3	0	0	1
EV4	0	1	0.95
EV5	0.33	0.6	0.76

Table 4 indicates the entropy and weight of each index using (2) (5):

Table 4. Entropy and weight of each index

	$t_{\text{hold } i}$	$t_{\text{plan } i}$	SOC $i(t)$
E_j	0.62	0.62	0.83
W_j	0.41	0.41	0.18

Finally, the scores assigned to five EVs are shown in Table 5 using (6):

Table 5. Results of priority score

	Score	**Priority level**
EV1	0.53	2
EV2	0.28	4
EV3	0.18	5
EV4	0.58	1
EV5	0.52	3

Fig. 4 and Fig. 5 indicate the SOC trend on a traditional queuing allocation and the proposed two-stage allocation, respectively. It is assumed that these five EVs have the same battery capacities and charger ratings.

As shown in Fig. 4, EV2 with 75% initial SOC arrives first and plugs. EV3 and EV5 sequentially arrive and start charging. EV1 and EV4 have to wait for charging as they finally arrive. In Fig. 5, EVs get charged without waiting due to real-time energy adjustment. EV4 is assigned a high-level priority, so its charging resources are guaranteed, whereas EV3's charging power is relatively limited because of its low priority. Due to the existence of the maximum demand power, EV2 gets lower energy as its battery is about to full.

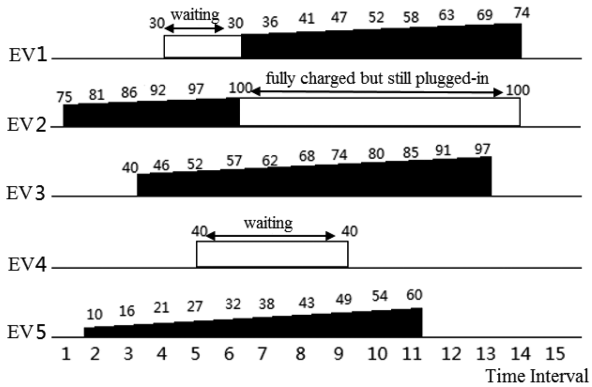

Fig. 4. SOC (%) trend based on queueing allocation solution

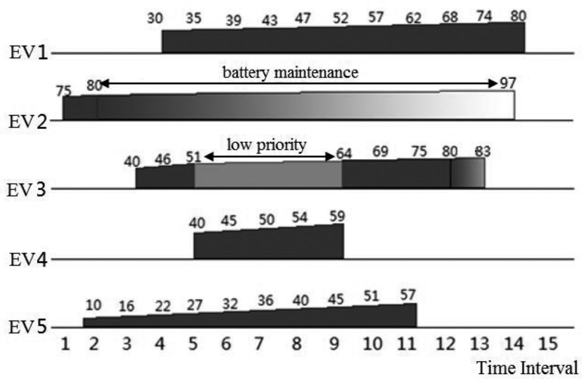

Fig. 5. SOC (%) trend based on the proposed two-stage allocation solution

4.3. Case study involving a residential area

The second case study involves a residential area where transformer's maximum active power output is 1009 kW [31]. Disordered allocation, queuing allocation and the proposed two-stage allocation are all implemented in the case. For convenience, it is assumed that EVs involved have a common specification, the battery capacity is 60 kWh and the rated charging power is 30 kW. The number of charging EVs at each time period is shown in Fig. 6. The probability density distribution of charging data is listed in Table 6. It is assumed to follow uniform distribution. Fig. 7 indicates system loading of a day in three allocation ways. Here the proposed two-stage allocation's time interval is set to 1 h.

The total daily load and the maximum overload rate of the four modes are shown in Table 7.

As illustrated in Fig. 7 and Table 7, in disordered allocation, EVs start charging as soon as they plug-in the system, regardless of the power grid constraints. As can be noted, significant overloading occurs in the scheme, which will lead to a serious threat to the safety of electricity within the area. The disordered allocation, as a result, is infeasible. In addition, both queuing and

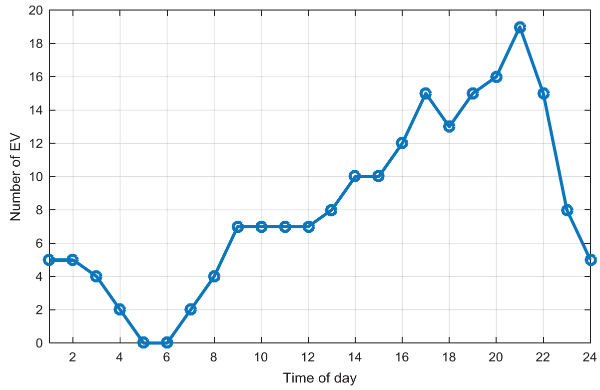

Fig. 6. The number of EVs charging at each time period in residential area

Table 6. Probability density distribution of charging datas

	SOC$_{i.t}$	$t_{\text{plan } i}$ **/ min**	$t_{\text{hold } i}$ **/ min**
EV	U(20, 45)	U(30, 120)	U(20, 30)

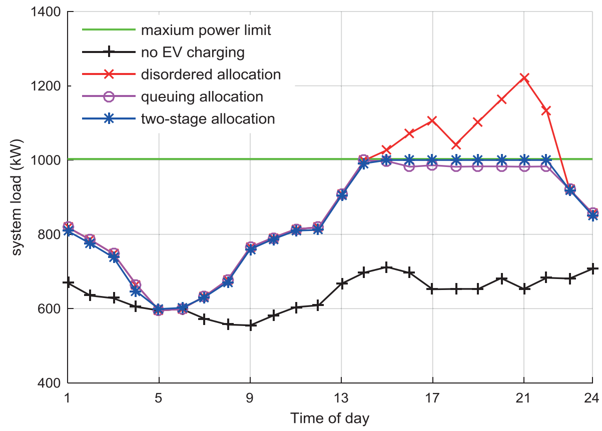

Fig. 7. Simulation results of the system loading

the proposed two-stage allocation are able to avoid the grid overloading, moreover, they almost have the same trend and total load. Compared with the queuing allocation, electric vehicles absorb all available resources with the proposed two-stage allocation. It shows that the proposed allocation method can effectively use available resources for electric vehicles.

At 16:00 pm, the available load is 304 kW under the limitation of the distribution network capacity and twelve electric vehicles are being charged. The cell grid cannot support all electric vehicles to charge with maximum demand power. According to the data distribution in Table 6,

Table 7. Comparison of load conditions in four ways

	No EV	Disordered	Queuing	Two-stage
Total daily load (MW)	15.346	21.264	20.274	20.308
Max. overloading	0	122.2%	0	0

the two-stage allocation algorithm has been operated for 1000 times with twelve electric vehicles. Fig. 8 shows the relationship between the priority z and the power difference $\Delta P(z)$. The abscissa is the priority level, 1 indicates highest priority. The ordinate is the average value of the difference between the demand power and the actual distribution charging power of the charging vehicles corresponding to each priority:

$$\Delta P(z) = \frac{\sum\limits_{k=1}^{1000} P_{e.z.k} - P_{z.k}}{1000}, \tag{10}$$

where k means the simulation time; $P_{e.z.k}$ and $P_{z.k}$ are the maximum demand power and actual distribution power of the electric vehicle with the priority of z ($z = 1, 2, \ldots, 12$) in K-th simulation, respectively.

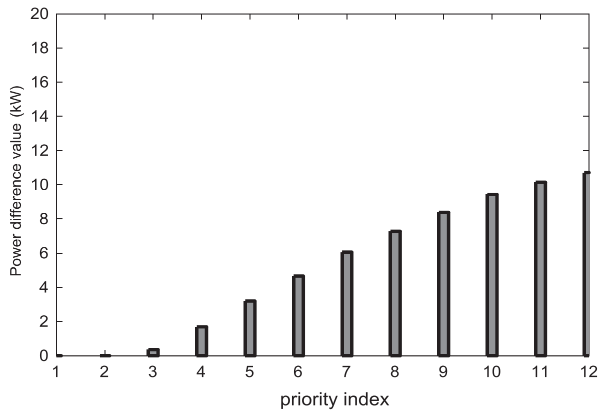

Fig. 8. The relation schema between priority and demand power difference

The priority level reflects the charging urgency of an electric vehicle. The higher priority of the electric vehicle, the higher charging urgency it is, and the distribution power should be closer to the maximum demand power correspondingly. In Fig. 8, it can be seen that the two-stage allocation presents an inverse relationship between the priority and the power difference. As a result, the proposed allocation method uses the priority level to determine the allocated power, and to improve fairness among EV owners.

In order to evaluate EV owners' satisfaction and fairness, both the queuing and proposed two-stage allocations are compared by calculating the root-mean-square-error (RMSE) and standard-deviation (SD) between the delivered power and the required power. RMSE is typically used to measure the differences between values predicted by a model and the values actually observed, whereas SD represents the confidence or significance of the analysis [32]. The combination of the RMSE and SD reflects the overall satisfaction of EV user's needs. Thus

$$RMSE_{\text{pow}} = \sqrt{\frac{\sum\limits_{i=1}^{n} d_i^2}{n}}, \tag{11}$$

$$SD_{\text{pow}} = \sqrt{\frac{\sum\limits_{i=1}^{n} (d_i - \mu)^2}{n}}, \tag{12}$$

where $RMSE_{\text{pow}}$ is the root-mean-square-error between the required power and the delivered power among n vehicles; n is the number of EVs; d_i is the difference between the delivered and the required power of the i-th EV. SD_{pow} is the standard-deviation between the required power and the delivered power among n vehicles; μ is the mean of power difference.

Obviously, when the power resources are sufficient to satisfy all EVs' charging requirement, there is $RMSE_{\text{pow}} = SD_{\text{pow}} = 0$ for both the queuing and two-stage allocation (assume that there is no charging loss, thus $d_i = 0$). Therefore, only the 6 peak hours' data are picked up for comparison.

Table 8. RMSE and SD calculation results in both schemes

	Time period	**16–17**	**17–18**	**18–19**	**19–20**	**20–21**	**21–22**
RMSE	**Queuing**	11.77	8.66	11.77	16.04	15.49	14.41
	Two-stage	6.49	5.42	6.29	8.93	8.72	8.20
SD	**Queuing**	10.82	8.29	10.82	13.55	13.27	12.64
	Two-stage	4.51	4.14	4.15	4.90	4.91	5.31

Table 8 demonstrates the RMSE and SD values for residential area at peak hours. Compared with the queuing allocation, the proposed two-stage allocation has lower RMSE and SD values, performs more robustly for serving EV owners. Overall, the proposed two-stage allocation outperforms the queuing allocation in delivering energy balanced and stable energy.

5. Conclusions

This paper proposed an electric vehicles charging load allocation strategy for residential area that enables a grid system to dynamically adjust EV charging power in order to optimize energy utilization. The strategy was divided into two stages. The first stage allocation was based on priority which determines the order EVs get charged, whereas the second stage serves EVs according to their state of charge.

Case studies were simulated for a typical residential area with different allocation methods. Simulation results indicates that compared to traditional ways of allocation, the proposed strategy outperforms in delivering energy effectively and safely. Furthermore, the root-mean-square-error (RMSE) and standard-deviation (SD) results prove the effectiveness of the methodology for improving the stability and balance of the charging process. However, there is still a need to find a way to guide EV owner's charging behavior, a demand response mechanism should be a future extension of this study.

Acknowledgements

This work was supported by the National Key Technology Support Program (2015BAG10B00), Natural Science Foundation of Chong Qing cstc2016jcyjA0214.

References

[1] Smith M., *Batteries versus biomass as a transport solution*, Nature, vol. 457, no. 7231, p. 785 (2009).

[2] Deb S., Tammi K., Kalita K., Mahanta P., *Review of recent trends in charging infrastructure planning for electric vehicles*, WIREs Energy Environ (2018), DOI: 10.1002/wene.306.

[3] Saber A.Y., Venayagamoorthy G.K., *Plug-in vehicles and renewable energy sources for cost and emission reductions*, IEEE Transactions on Industrial Electronics, vol. 58, no. 4, pp. 1229–1238 (2011).

[4] Lopes J.A.P., Soares F.J., Almeida P.M.R., *Integration of electric vehicles in the electric power system*, Proceedings of the IEEE, vol. 99, no. 1, pp. 168–183 (2010).

[5] Fernandez L.P., Roman T.G.S., Cossent R., *Assessment of the impact of plug-in electric vehicles on distribution network*, IEEE Transactions on Power Systems, vol. 26, no. 1, pp. 206–213 (2011).

[6] Dow L., Marshall M., Xu L., Agüero J.R., Willis H.L., *A novel approach for evaluating the impact of electric vehicles on the power distribution system*, Power and Energy Society General Meeting, pp. 1–6 (2010).

[7] Hu J., Morais H., Sousa T., Lind M., *Electric vehicle fleet management in smart grids: A review of services, optimization and control aspects*, Renewable and Sustainable Energy Reviews, vol. 56, pp. 1207–1226 (2016).

[8] Bhatti A.R., Salam Z., Abdul M.J.B., Yee K.P., *A comprehensive overview of electric vehicle charging using renewable energy*, International Journal of Power Electronics and Drive Systems, vol. 7, no. 1, pp. 114 (2016).

[9] Luo C., Huang Y.F., Gupta V., *Stochastic Dynamic Pricing for EV Charging Stations With Renewable Integration and Energy Storage*, IEEE Transactions on Smart Grid, vol. 9, no. 2, pp. 1494–1505 (2018).

[10] Su H., Liang Z., *Orderly charging control based on peak-valley electricity tariffs for household electric vehicles of residential quarter*, Electric Power Automation Equipment, vol. 35, no. 6, pp. 17–22 (2015).

[11] Echols A., Mukherjee S., Mickelsen M., *Communication Infrastructure for Dynamic Wireless Charging of Electric Vehicles*, Wireless Communications and NETWORKING Conference, IEEE, pp. 1–6 (2017).

[12] Maglaras L.A., Topalis F.V., Maglaras, A.L., *Cooperative approaches for dymanic wireless charging of Electric Vehicles in a smart city*, Energy Conference, IEEE, pp. 1365–1369 (2014).

[13] Clement-Nyns K., Haesen E., Driesen J., *The impact of charging plug-in hybrid electric vehicles on a residential distribution grid*, IEEE Transactions on Power Systems, vol. 25, no. 1, pp. 371–380 (2010).

[14] Mehta R., Srinivasan D., Khambadkone A.M., Yang J., Trivedi A., *Smart charging strategies for optimal integration of plug-in electric vehicles within existing distribution system infrastructure*, IEEE Transactions on Smart Grid, vol. 9, no. 1, pp. 299–312 (2018).

[15] Guille C., Gross G., *Design of a Conceptual Framework for the V2G Implementation*, Energy 2030 Conference 2008, Energy IEEE, pp. 1–3 (2008).

[16] Chen L., Zhang H., *Orderly discharging strategy for electric vehicles at workplace based on time-of-use price*, Mathematical Problems in Engineering, vol. 2016, no. 15, pp. 1–7 (2016).

[17] Saber A.Y., Venayagamoorthy G.K., *Resource scheduling under uncertainty in a smart grid with renewables and plug-in vehicles*, Systems Journal IEEE, vol. 6, no. 1, pp. 103–109 (2012).

[18] Singh M., Thirugnanam K., Kumar P., Kar I., *Real-time coordination of electric vehicles to support the grid at the distribution substation level*, IEEE Systems Journal, vol. 9, no. 3, pp. 1000–1010 (2013).

[19] Deilami S., Masoum A.S., Moses P.S., Masoum M.A.S., *Real-time coordination of plug-in electric vehicle charging in smart grids to minimize power losses and improve voltage profile*, IEEE Transactions on Smart Grid, vol. 2, no. 3, pp. 456–467 (2011).

[20] Khayyam H., Ranjbarzadeh H., Marano V., *Intelligent control of vehicle to grid power*, Journal of Power Sources, vol. 201, no. 3, pp. 1–9 (2012).

[21] Erol-Kantarci M., Sarker J.H., Mouftah H.T., *Quality of service in Plug-in Electric Vehicle charging infrastructure*, Electric Vehicle Conference, pp. 1–5 (2012).

[22] Akhavan-Rezai E., Shaaban M.F., El-Saadany E.F., Karray F., *Online intelligent demand management of plug-in electric vehicles in future smart parking lots*, IEEE Systems Journal, vol. 10, no. 2, pp. 483–494 (2016).

[23] Jian L., Zheng Y., Xiao X., *Optimal scheduling for vehicle-to-grid operation with stochastic connection of plug-in electric vehicles to smart grid*, Applied Energy, vol. 146, pp. 150–161 (2015).

[24] Hartmann N., Özdemir E.D., *Impact of different utilization scenarios of electric vehicles on the german grid in 2030*, Journal of Power Sources, vol. 196, no. 4, pp. 2311–2318 (2011).

[25] Morais H., Sousa T., Vale Z., Faria P., *Evaluation of the electric vehicle impact in the power demand curve in a smart grid environment*, Energy Conversion & Management, vol. 82, no. 4, pp. 268–282 (2014).

[26] Huang J., Gupta V., Huang Y.F., *Scheduling algorithms for PHEV charging in shared parking lots*, American Control Conference, vol. 50, pp. 276–281 (2012).

[27] Zhang X., Mi C.C., Yin C., *Active-charging based powertrain control in series hybrid electric vehicles for efficiency improvement and battery lifetime extension*, Journal of Power Sources, vol. 245, no. 1, pp. 292–300 (2014).

[28] Fernández I.J., Calvillo C.F., Sánchez-Miralles A., Boal J., *Capacity fade and aging models for electric batteries and optimal charging strategy for electric vehicles*, Energy, vol. 60, no. 60, pp. 35–43 (2013).

[29] Coifman R.R., Wickerhauser M.V., *Entropy-based algorithms for best basis selection*, IEEE Transactions on Information Theory, vol. 38, no. 2, pp. 713–718 (1992).

[30] Kersting W.H., *Radial distribution test feeders*, IEEE Transactions on Power Systems, vol. 6, no. 3, pp. 908–912 (1991).

[31] Wang S., Yang S., *A Coordinated Charging Control Strategy for Electric Vehicles Charging Load in Residential Area*, Automation of Electric Power Systems, vol. 40, no. 4, pp. 71–77 (2016).

[32] Akhavan-Rezai E., Shaaban M.F., El-Saadany E.F., *Online Intelligent Demand Management of Plug-In Electric Vehicles in Future Smart Parking Lots*, IEEE Systems Journal, vol. 10, no. 2, pp. 483–494 (2016).