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A SMART ADAPTABLE CHARGING METHOD FOR ELECTRIC VEHICLES, CONSIDERING URGENT CHARGING DEMAND

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Electric vehicles (EVs) technologies and usage are increasing, contributing to planet pollution reduction. However, smart charging methods are needed, to avoid the surge of peak loads and increase the charging cost. This study proposes a smart charging method capable to transfer the EVs charging demand from rush hours to off-peak hours. An urgent charging scheme has been developed, using Particle Swarm Optimisation (PSO) algorithm. The results show that the proposed method supports the energy demands, which overcomes the increasing power demands of EVs.

Keywords: Electric Vehicles (EVs), Particle Swarm Optimisation (PSO), Urgent charging, and Charging optimization

1. Introduction

Electric vehicles (EVs) are considered economical and friendly to the environment [1]. They provide an alternative option, for achieving cleaner transportation systems [2]. The EVs allow almost zero carbon emissions [3] and can improve the transportation system's efficiency [4]. However, implementing EVs may face some challenges. For example, the EVs batteries could face a significant degradation in their charging. Further, the high cost of batteries is still a barrier towards EVs usage on a large scale [5][6]. The limitation of charging infrastructure is also considered a critical challenge [7][8]. Consequently, several research efforts have been carried out so far, focused on charging scheduling optimisation [9]. However, the existing research works have been mainly oriented to the supply side, aiming to shape the load from the peak-to-valley hours. On the user side, a specific charging demand of each EV has not been considered. In practice, the charging demands of EV users are different, and in some cases urgent charging is needed. To address this issue, a smart charging strategy for EVs with a fast-charging mode is required [10].

Several EV charging strategies have been proposed, based on decentralised or centralised approaches. For example, a decentralised valley-

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filling charging approach is developed in [11][12], aiming to redistribute load away from the grid system peak toward evening. Another decentralised method called “day-ahead pricing” is proposed in [13][14], trying to reduce the power load over the grid during peak hours, based on charging price.

In the centralised charging strategies, the EVs users have to share their charging information with an aggregator. Then, EVs could be scheduled for charging in a centralised way; this approach provides more flexible management and control in comparison to the decentralised method [15]. The works in [16][17] aimed to reduce energy consumption based also on a centralised method. The works in [18][19] studied how to integrate renewable energies for EVs charging in a centralised manner. The peak load reduction has been discussed in [20] and focused on scheduling the EVs users for charging in a centralised way; this could guarantee the use of a power supply through the off-peak hours.

Today, there is not yet a generally adopted method for efficient optimum charging scheduling. In addition, the urgent charging situation of some EVs has not been yet considered. Another issue is the computational complexity which can be significantly increased, especially when a high number of EVs is involved. This paper focused on finding an optimum charging method to reduce the total load, taking into account the urgent situation.

The main contributions of this study are:

1. A smart adaptable charging method was proposed, considering the urgent charging, and power load demand. The method can transfer the EV charging demand from rush hours to off-peak hours.
2. The Particle Swarm Optimisation (PSO) algorithm is investigated, to find the best charging urgency indicator. PSO algorithms have been used to find the optimum solution for similar problems [21].
3. Fast-charging and slow-charging modes are studied, to model the uncertainty of EVs charging needs. Monte Carlo Simulation with 1000000 random realisations is considered to simulate different EVs events and evaluate the system performance, under home charging and public charging schemes.

The results show the effectiveness of our proposed method with different charging modes selection for EVs. The method is able to support the energy demands by transferring the EVs charging load from rush hours to off-peak hours, which has the potential to overcome the increasing power demands. This paper is organised as follows. Section 2 presents the proposed system model. Section 3 presents the proposed adapted EVs charging method. Section 4 outlines the optimisation model. Section 5 adapts a PSO algorithm for our needs. Section 6 shortly describes the simulation model. Section 7 provides the results and discussion. Finally, this study is concluded in Section 8.

2. System model

This section provides the system model. The main goal is to find an efficient and smart EVs charging method that reduces the peak load of the power grid. Each EV driver has a specific charging demand. In the proposed charging method, the EVs drivers should share their charging request information with an aggregator, which will analyse it. This information represents the state of charge (SOC), arriving time, and estimated leaving time. The parameter SOC is essential for the stability and safety of the EVs batteries. Charging the EV battery before going down from 10% of its capacity and not more than 95% can increase the battery lifetime and achieve the safety requirements. The intelligent element is the system controller. Based on the collected information from the EVs, it decides upon the charging schedule to be applied. The obtained results for the EV driver are charging time, the energy required for all EVs batteries to be fully charged, and charging cost. Fig. 1 illustrates the architecture of the proposed charging scheduling system for EVs, considering also urgent charging demand.

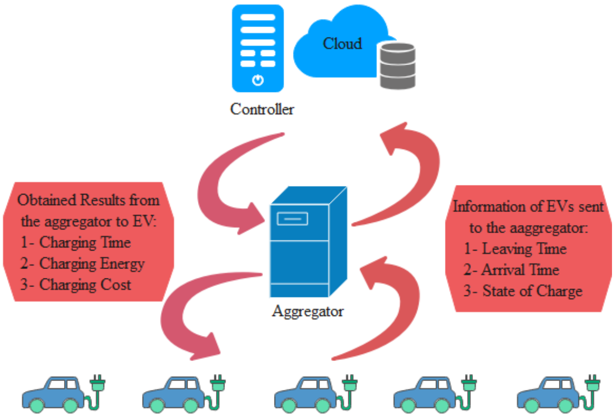

Fig. 1. Architecture of the proposed EVs charging system.

In this study, the charging urgency indicator could be also implemented, which can recognise the urgency of each EV demand. Therefore, a fast-charging mode for the EVs with urgent charging demand is applied, and a slow-charging mode is applied to the EVs that are scheduled as non-urgent charging demand. In a real implementation, the charging system could be supported, for instance, by a 5G dedicated slice where the slice tenant will include the aggregator and decision system (controller) and terminal users are the vehicles.

3. EVs charging scheme

The charging behaviour of the EV driver is considered in this study, which can be divided into two schemes: home charging and public charging. Typically, in the home charging scheme, the charging service for the EVs drivers would start from the evening instant of time when people are arriving at home until the next day morning instant when they leave to work. In the home charging scheme, the notation for arriving time is t_{1a} and for leaving time is t_{1l} . As seen in Fig. 2, we adopted the view from [22], where the data are generated randomly following a normal distribution in the Monte Carlo Simulation method. Then, the probability distribution function (PDF) for both arriving time and leaving time is defined in [22] as:

$$f(t_{1a}) = \begin{cases} \frac{1}{\sqrt{2\pi}\sigma_{1t_a}} exp\left(\frac{-(t_{1a}+24-\mu_{1t_a})^2}{2{\sigma_{1t_a}}^2}\right) & 0< t_{1a} \le \mu_{1t_a}-12 \\ \frac{1}{\sqrt{2\pi}\sigma_{1t_a}} exp\left(\frac{-(t_{1a}-\mu_{1t_a})^2}{2{\sigma_{1t_a}}^2}\right) & \mu_{1t_a}-12 < t_{1a} \le 24 \end{cases}$$
$$f(t_{1l}) = \begin{cases} \frac{1}{\sqrt{2\pi}\sigma_{1t_l}} exp\left(\frac{-(t_{1l}-\mu_{1t_l})^2}{2{\sigma_{1t_a}}^2}\right) & 0< t_{1l} \le \mu_{1t_l}+12 \\ \frac{1}{\sqrt{2\pi}\sigma_{1t_l}} exp\left(\frac{-(t_{1l}-24-\mu_{1t_l})^2}{2{\sigma_{1t_a}}^2}\right) & \mu_{1t_l}+12 < t_{1l} \le 24 \end{cases} \quad (1)$$

where parameters $\mu_{1t_a} = 18$, $\mu_{1t_l} = 8$, $\sigma_{1t_a} = 3.3$ and $\sigma_{1t_l} = 3.24$ [9]. In the public charging scheme, the charging service starts in the morning when the EVs drivers are arriving at work until the evening when they are leaving from the work. The arriving time t_{2a} and leaving time t_{2l} have also a normal distribution [22]. The expressions of the PDF are similar to those of formulas (1) but have other values for the mean value and standard deviation, i.e.: $\mu_{2t_a} = 8.5$, $\mu_{2t_l} = 17.5$, $\sigma_{2t_a} = 3.3$, and $\sigma_{2t_l} = 3.24$ [9].

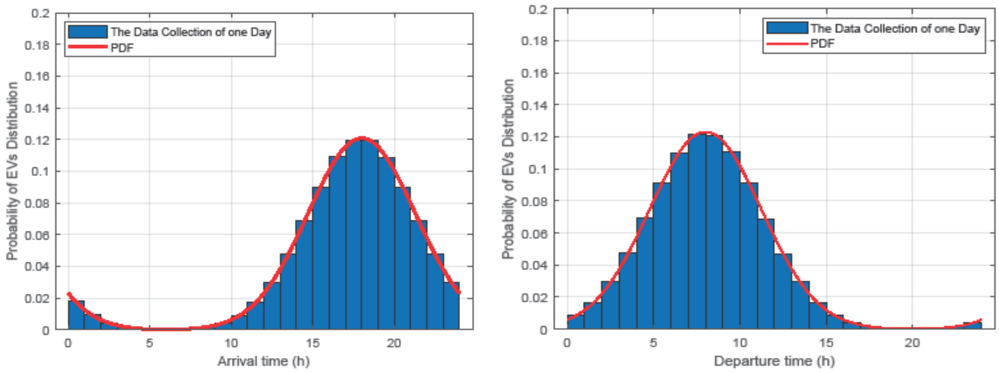

Fig. 2. Monte Carlo Simulation results of EVs behaviour considering a home charging scheme.

3.1. Time slot and urgent charging indicator for EVs

Typically, during the day, the charging time scheduled for EVs divided into time slots. This allows a discrete treatment of the charging process control.

This study considers that a whole day duration (24h) can be divided into j=96 time slots; each time slot is conveniently equal to 15 min. In this paper, we have considered the arriving time (t_i^a) and the leaving time (t_i^l) for each EV driver can be written as normalised values [22]:

$$J_i^a = \left\lfloor \frac{t_i^a}{\Delta T} \right\rfloor, \text{and } J_i^l = \left\lfloor \frac{t_i^l}{\Delta T} \right\rfloor \tag{2}$$

where the i is the index of EV so $i = 1, 2..., N$. The N denotes the number of EVs. The J_i^a and J_i^l represents the number of time slot when an EV is connected and disconnected from the power grid, respectively. The length of a time slot is given as ΔT. The time interval when an EV is connected to the power grid is given by subtracting the arriving time slot from the leaving time slot as [22]:

$$J_i^r = J_i^l - J_i^a, \tag{3}$$

where J_i^r denotes the remaining number of time slots, which allows i EV able to keep connected to the power grid. Besides, in these remaining time slots, the charging scheme and charging scheduling can be applied. To this end, the urgent charging indicator I_i is considered, which reveals the urgency of the demand for the EVs charging and can be written as [23]:

$$I_i = (J_i^r \times \Delta T) \times \mathcal{P}^{slow} \times \eta - \left(S_i^{min} - S_i^{max}\right) \times C^{bat} \tag{4}$$

where the $\mathcal{P}^{slow}$ is the power of the slow-charging mode for the EVs, and the η is the charging efficiency. The parameters S_i^{min} and S_i^{max} denote the minimum and the maximum value of SOC for i EV when its charging is stopped. The battery capacity is represented by the parameter C^{bat}. In this study, two charging modes are applied slow-charging and fast-charging. Selecting between these charging modes can be performed by the charging indicator, so that:

$$\mathcal{P}_i = \begin{cases} \mathcal{P}^{fast}, & I_i < 0 \\ \mathcal{P}^{slow}, & I_i \geq 0 \end{cases} \tag{5}$$

where the parameter $\mathcal{P}^{fast}$ represents the power of the fast-charging mode. As stated earlier, when the charging indicator $I_i < 0$, this implies that the charging is urgent for the i EV and the fast-charging mode will be selected. On the other hand, when the charging indicator is $I_i \geq 0$, it implies that the charging demand for the i EV is non-urgent, and the slow-charging mode will be selected.

4. Optimisation model

The main objective of this paper is to reduce the total load across the power grid considering different numbers of EVs. The total load of the power grid consists of the basic load and EV charging load. The EV charging load includes the fast-charging demand and the slow-charging demand of the EVs. To this end, the total load at the *j* time slot of the proposed charging method is written as:

$$\mathcal{P}_j^{T-C} = \mathcal{P}_j^{\text{basic}} + \sum_{i=1}^{N} x_{i,j}\mathcal{P}_i \qquad (6)$$

where $\mathcal{P}_j^{basic}$ represents the basic load of the power grid, and $\sum_{i=1}^{N} x_{i,j}\mathcal{P}_i$ is the total charging load of all the EVs including fast-charging and slow-charging demands. If *i* EV has an urgent charging demand, $\mathcal{P}_i$ is equal to $\mathcal{P}^{fast}$. On the other hand, if *i* EV has non-urgent charging demand, $\mathcal{P}_i$ is equal to $\mathcal{P}^{slow}$. To this end, PSO algorithm is proposed to find the optimum number of EVs that can be selected for charging to reduce the load. Therefore, the objective function of reducing the load of the power grid from rush hours to off-peak hours can be written as:

$$min\left[\mathcal{P}_{max}^{T-C} - \mathcal{P}_{min}^{T-C}\right] \qquad (7)$$

where $\mathcal{P}_{max}^{T-C}$ represent the maximum load demand and $\mathcal{P}_{min}^{T-C}$ represent the minimum load demand.

5. Proposed PSO algorithm

In the PSO algorithm, the fitness function denotes the objective function of the power load problem that needs to be addressed in this study. Swarm based method provided in [23], is exploited in this paper to formalise the fitness function. This proposed, the EV with an urgent demand needs to be charged with a fast-charging mode. This can be prioritised in the aggregator by setting a priority weight for that EV. To this end, the fitness function can be mathematically formulated as:

$$max_i \sum_{b=1}^{B} w_b \; f_b\,(i) = \; w_1\, C^{bat} + w_2\, S_i^{min} + w_3\, S_i^{max} \qquad (8)$$

where $f_b\,(i)$ denotes the performance criteria resulting by *i* particle in the search space, and w_b represents the weighting parameter that can be normalised to satisfy the power constraint, so that:

$$\sum_{b=1}^{B} w_b \; = 1 \qquad (9)$$

The search space in the proposed PSO algorithm involves all the feasible solutions, which can be chosen between S^{max} and S^{min}, so that:

$$D(i) = (S^{max}, S^{min}) \qquad (10)$$

The swarm size represents the number of particles inside the searching space. A large swarm size may reduce the number of iterations required to get the optimal value. However, the EVs number is chosen to be uniformly distributed within the swarm. A PSO is implemented by the controller, which has the ability to select the EV accordingly. To this end, in our proposal, each EV in the swarm has a position x_i, a velocity v_i, and the best position in the search space $p^t_{best,i}$, which represents the weight achieved by the objective function for the particle *i*. The largest value amongst all the personal best $p^t_{best,i}$ is known as the global best G_{best}, which denotes the EV obtained by the current iteration so that:

$$p^t_{best,i} = \begin{cases} p^t_{best,i} & if\ f(x^{t+1}_i) < p^t_{best,i} \\ x^{t+1}_i & if\ f(x^{t+1}_i) \geq p^t_{best,i} \end{cases} \tag{11}$$

$$G_{best} = max\{p^t_{best,i}\} \tag{12}$$

After updating the $p^t_{best,i}$ and G_{best} for particle *i* at iteration *t*, the position and the velocity of the particle will be updated accordingly as:

$$x^{t+1}_i = x^t_i + v^{t+1}_i \tag{13}$$

$$v^{t+1}_i = v^t_i + c_1 r^t_1 [p^t_{best,i} - x^t_i] + c_2 r^t_2 [G_{best} - x^t_i] \tag{14}$$

In this study, when the *i* EV is indicated as urgent, we select $x_{i,j}$ to be 1 in each arriving time slot. Besides, the EV with urgent charging demand can be charged from arriving time to leaving time. However, remaining charging an EV after its battery gets fully charged, may cause overcharging. In order to avoid overcharging in fast-charging mode, a power constraint has been set to limit the charging. This constraint should be lower than S^{max}_i. Furthermore, we select $x_{i,j}$ to be 0 when the *i* EV is disconnected from the power grid. The time slot when an EV stops charging is determined based on leaving time, so that the constraint for the EVs with urgent charging can be written as:

$$x_{i,j} = \begin{cases} 1, & if\ j = j^a_i, \dots j^{finish}_i \\ 0, & others, \end{cases} \tag{15}$$

where parameter j^{finish}_i represents the time slot when *i* EV stops charging, which is given as:

$$j^{finish}_i = min\left\{ j^l_i, \left\lfloor \frac{(S^{max}_i - S^{con}_i)C}{\mathcal{P}^{fast}\eta\Delta T} \right\rfloor + j^a_i \right\} \tag{16}$$

where S^{con}_i represents the SOC of an EV when is connected to the power grid, and $\frac{(S^{max}_i - S^{con}_i)C}{\mathcal{P}^{fast}\eta\Delta T}$ represents the charging time of an EV that should meet the maximum value of SOC:

$$S^{max}_i \geq S^l_i \geq S^{min}_i \tag{17}$$

Where the S_i^l represents the SOC of i EV when disconnected from the power grid. To ensure that a new charging peak load of the power grid in the proposed method do not appear, so a constraint for the power grid is given:

$$\mathcal{P}_{max}^{T-C} \leq \mathcal{P}_{max}^{T-uc(S_N^{max})} \tag{18}$$

where $\mathcal{P}_{max}^{T-uc(S_N^{max})}$ represents the maximum value of the total load in the normal charging that meets the constraint of maximum SOC for all EVs (S_N^{max}) over 96 time slots.

6. Simulation model

This section provides the simulation model and the evaluation of the proposed charging method. In this study, we used our personal laptop, equipped with MATLAB 2019, for the simulations and data analysis. Our computer system is an Intel Core i7 with 8GB of RAM, which is capable of handling the computational demands of the simulations. As for the cost of implementing the proposed solution, we only considered the cost of the necessary software licenses for the simulations. We generated the input data for our research using Monte Carlo simulation, which allowed us to simulate real EV charging behavior by generating a large number of samples with different probability distributions. The simulations were performed with a different number of EVs considered (e.g., 100 and 500) and in both home charging and public charging schemes. Based on the electricity usage presented in [24], Fig. 3 shows the average basic load of the regional power grid that is generated for one-day cycle.

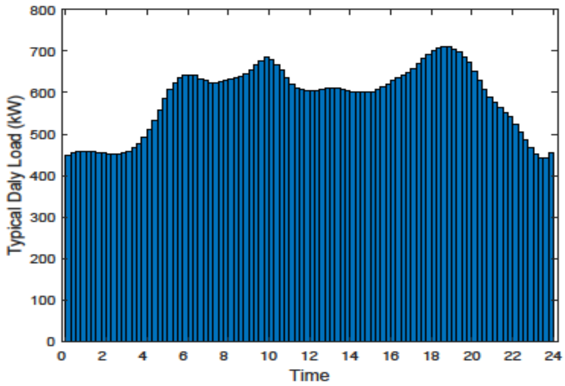

Fig. 3. The basic load of regional power grid for one day.

The basic load is used for benchmark comparison and the results show that the peak power happened at around 06:00 am, 10:00 am, and 18:00-20:00 pm. The highest load achieved is around 700 KW and the lowers recorded is around 450 KW. In this study, we consider the S_i^{con} value generated in uniform distribution, which is between (0.1-0.3), S_i^{min} between (0.4 - 0.6) and S_i^{max} between (0.8-1) as given in [24].

7. Results and discussion

In the home charging scheme, the charging service for EVs is available between 18:00 pm and 08:00 am. As illustrated earlier, we considered the one-day cycle divided by two half-days. Specifically, 12 hours is a period chosen to be the scheduling time of EV charging in the home charging scheme. Fig. 4 shows a plot of daily load as a function of time in one day comparing the proposed smart adaptable charging method with two methods of normal charging in the home charging scheme. In the normal charging process, the EVs start to charge at the arriving time until to reach the maximum SOC or until the leaving time. Noting that for each EV with urgent charging demand, the charging time for some EVs could be too short. As such, the normal (or uncoordinated) charging is not able to meet the requirement of minimum SOC for *i* EV in the urgent charging situation. Therefore, urgent charging is performed in the proposed charging method. In the proposed method, when the EVs are leaving the power grid, their SOC should be between the minimum and maximum SOC. The results show that the power load of charging demand in the proposed method is lower than that in the normal charging methods especially when the number of EVs is increased.

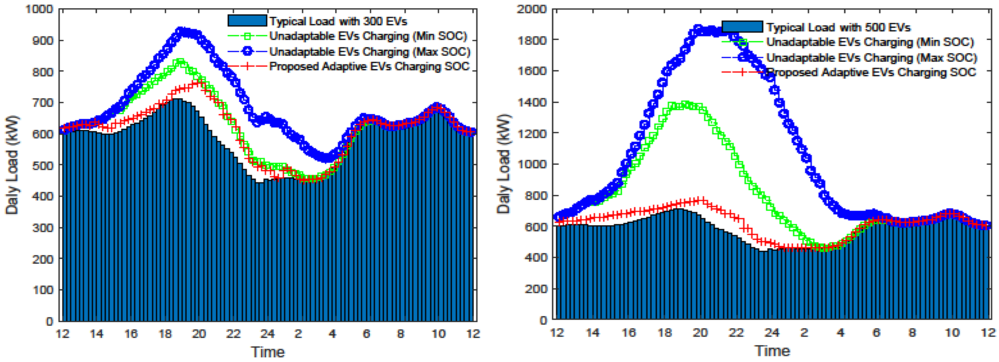

Fig. 4. Plots of daily load as a function of time comparing the proposed charging method and the normal charging in home-charging for 100 EVs and 500 EVs.

In-public charging scheme, the charging service for the EVs is available between 08:30 am and 05.30 pm. Fig. 5 shows plots of daily load as a function of time comparing the proposed smart adaptable charging method with two normal charging methods in the public charging scheme. When the number of EVs is increased the peak load happens at 06:00 am, 10:00 am, and 20:00 pm. The basic load in public charging can only be filled by a few EVs. This is because most of the EVs are charged during off-peak hours. However, urgent charging is

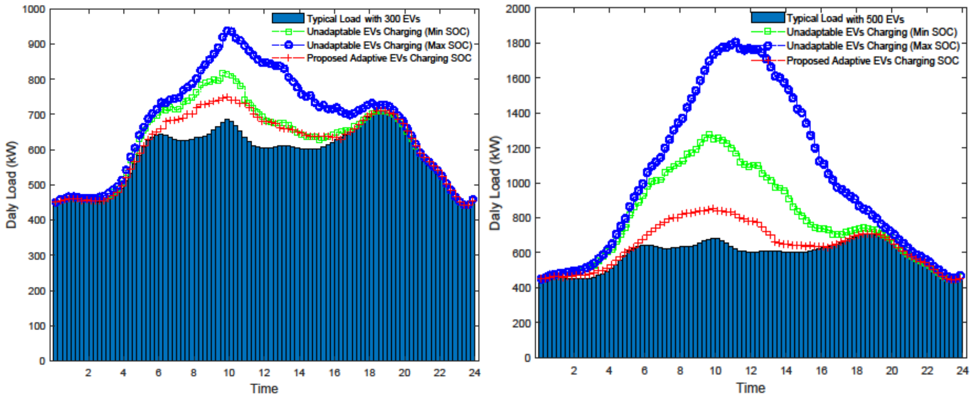

Fig. 5. Plots of daily load as a function of time comparing the proposed adapted charging method and the normal charging in public-charging for 100 EVs and 500 EVs.

considered in the proposed method. The results show that the power of EVs demand in the proposed method is significantly lower than that method of normal charging especially when the number of EVs is increased.

Fig. 6 shows results comparing the proposed charging method and two methods of normal charging, respectively, over different charging stations. In these figures, we have selected a very large number of EVs and a small number of charging stations to investigate the variation in the probability of selecting a charging station between the two charging schemes. Clearly, unlike normal charging, the results show that the proposed charging method provides an equal probability of charging overall the charging stations. Specifically, an almost equal number of EVs are using the charging station in the proposed method. This is clearly illustrating the fair comparison between different methods.

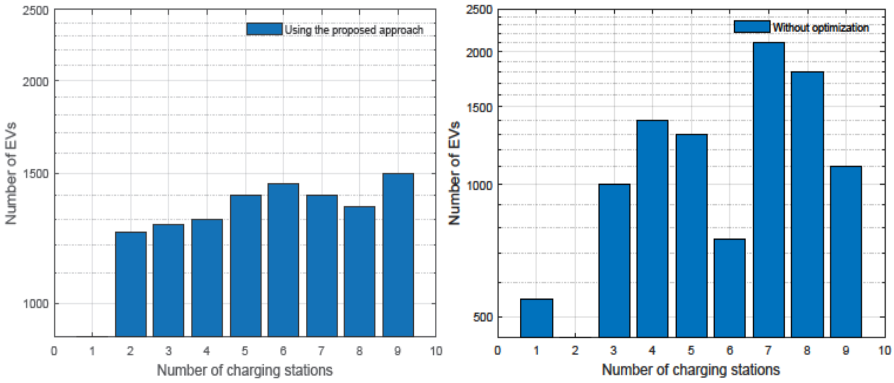

Fig. 6. EVs at charging stations with normal charging and using a proposed method.

Fig. 7 shows the results of comparing the load difference between the normal charging methods and the proposed charging method. The results demonstrate the effectiveness of the proposed method in reducing the total load in comparison to the normal charging methods. The difference is significantly increased when the number of EVs is increased.

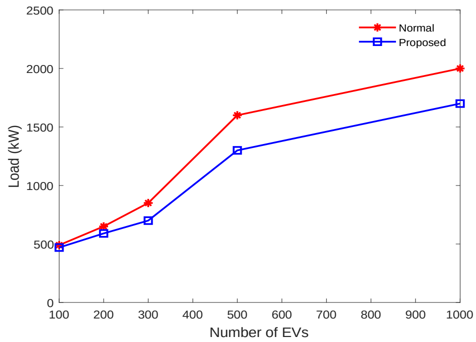

Fig. 7. Comparing load difference of normal charging method and proposed method.

8. Conclusions

A smart charging method for EVs has been proposed. The urgent charging demand of each EV, and the total load demand have been considered. Besides, a PSO algorithm has been invested to find the best charging urgency indicator. This study evaluated the system performance by considering a different number of EVs and two charging schemes namely home and public charging. The results showed that the proposed charging method reduced the load efficiently by transferring the EVs power demand from rush hours to off-peak hours.

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R E F E R E N C E S

[1]. *R. Miao, H. Wenjie, P. Donghao, G. Xiyao, L. Zefeng, Z. Jie, J. Zhibin*, Research on lease and sale of electric vehicles based on value engineering, Int. J. Prod. Res., **vol. 54**, pp. 5361–5380, 2016.

[2]. *A. Teixeira, D. Da Silva, L. MacHado Neto, A. Diniz, and J. Sodré*, A review on electric vehicles and their interaction with smart grids: The case of Brazil, Clean Technol. Environ. Policy, **vol. 17**, pp. 841–857, 2015.

[3]. *A. Gopal, W. Park, M. Witt, and A. Phadke*, Hybrid- and battery-electric vehicles offer low-cost climate benefits in China, Transp. Res. Part D Transp. Environ., **vol. 62**, pp. 362–371, 2018.

[4]. *M. Kumar and S. Revankar*, Development scheme and key technology of an electric vehicle: An overview, Renew. Sustain. Energy Rev., **vol. 70**, no. December, pp. 1266–1285, 2017.

[5]. *J. Domínguez-Navarro, R. Dufo-López, J. Yusta-Loyo, J. Artal-Sevil, and J. Bernal-Agustín*, Design of an electric vehicle fast-charging station with integration of renewable energy and

storage systems, Int. J. Electr. Power Energy Syst., **vol. 105**, no. July, pp. 46–58, 2019.
[6]. *L. Zhen, Z. Xu, C. Ma, and L. Xiao*, Hybrid electric vehicle routing problem with mode selection, Int. J. Prod. Res., **vol. 58**, no. 2, pp. 562–576, 2020.
[7]. *K. Benabdelaziz and M. Maaroufi*, Battery dynamic energy model for use in electric vehicle simulation, Proc. 2016 Int. Renew. Sustain. Energy Conf. IRSEC 2016, pp. 927–932, 2017.
[8]. *Y. Zhao, P. Liu, Z. Wang, L. Zhang, and J. Hong*, Fault and defect diagnosis of battery for electric vehicles based on big data analysis methods, Appl. Energy, **vol. 207**, pp. 354–362, 2017.
[9]. *Y. Luo, T. Zhu, S. Wan, S. Zhang, and K. Li*, Optimal charging scheduling for large-scale EV (electric vehicle) deployment based on the interaction of the smart-grid and intelligent-transport systems, Energy, **vol. 97**, pp. 359–368, 2016.
[10]. *K. Qian, C. Zhou, M. Allan, and Y. Yuan*, Modeling of load demand due to EV battery charging in distribution systems, IEEE Trans. Power Syst., **vol. 26**, no. 2, pp. 802–810, 2011.
[11]. *K. Zhan, Z. Hu, Y. Song, N. Lu, Z. Xu, and L. Jia*, A probability transition matrix based decentralized electric vehicle charging method for load valley filling, Electr. Power Syst. Res., **vol. 125**, pp. 1–7, 2015.
[12]. *K. Zhang, L. Xu, M. Ouyang, H. Wang, L. Lu, J. Li, Z. Li*, Optimal decentralized valley-filling charging strategy for electric vehicles, Energy Convers. Manag., **vol. 78**, pp. 537–550, 2014.
[13]. *D. Liu and B. Xiao*, Exploring the development of electric vehicles under policy incentives: A scenario-based system dynamics model, Energy Policy, **vol. 120**, no. April, pp. 8–23, 2018.
[14]. *T. Zhang, H. Pota, C. Chu, and R. Gadh*, Real-time renewable energy incentive system for electric vehicles using prioritization and cryptocurrency, Appl. Energy, **vol. 226**, no. June, pp. 582–594, 2018.
[15]. *K. Zhou, L. Cheng, L. Wen, X. Lu, and T. Ding*, A coordinated charging scheduling method for electric vehicles considering different charging demands, Energy, **vol. 213**, p. 118882, 2020.
[16]. *A. Di Giorgio and F. Liberati*, Near real time load shifting control for residential electricity prosumers under designed and market indexed pricing models, Appl. Energy, **vol. 128**, pp. 119–132, 2014.
[17]. *D. Oliveira, A. Zambroni De Souza, and L. Delboni*, Optimal plug-in hybrid electric vehicles recharge in distribution power systems, Electr. Power Syst. Res., **vol. 98**, pp. 77–85, 2013.
[18]. *A. El-Zonkoly*, Intelligent energy management of optimally located renewable energy systems incorporating PHEV, Energy Convers. Manag., **vol. 84**, pp. 427–435, 2014.
[19]. *F. Fazelpour, M. Vafaeipour, O. Rahbari, and M. A. Rosen*, Intelligent optimization to integrate a plug-in hybrid electric vehicle smart parking lot with renewable energy resources and enhance grid characteristics, Energy Convers. Manag., **vol. 77**, pp. 250–261, 2014.
[20]. *L. Jian, X. Zhu, Z. Shao, S. Niu, and C. C. Chan*, A scenario of vehicle-to-grid implementation and its double-layer optimal charging strategy for minimizing load variance within regional smart grids, Energy Convers. Manag., **vol. 78**, pp. 508–517, 2014.
[21]. *J. Yang, L. He, and S. Fu*, An improved PSO-based charging strategy of electric vehicles in electrical distribution grid, Appl. Energy, **vol. 128**, pp. 82–92, 2014.
[22]. *Y. Zheng, Y. Shang, Z. Shao, and L. Jian*, A novel real-time scheduling strategy with near-linear complexity for integrating large-scale electric vehicles into smart grid, Appl. Energy, **vol. 217**, no. February, pp. 1–13, 2018.
[23]. *Y. del Valle, G. Venayagamoorthy, S. Mohagheghi, J. Hernandez, and R. Harley*, Particle swarm optimization: Basic concepts, variants and applications in power systems, IEEE Trans. Evol. Comput., **vol. 12**, no. 2, pp. 171–195, 2008.
[24]. *L. Jian, Y. Zheng, and Z. Shao*, High efficient valley-filling strategy for centralized coordinated charging of large-scale electric vehicles, Appl. Energy, **vol. 186**, pp. 46–55, 2017.