Title:

Dynamic Resource Allocation for Parking Lot Electric Vehicle Recharging using Heuristic Fuzzy Particle Swarm Optimization Algorithm

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Abstract:

A parking lot (PL) dynamic resource allocation system for recharging electric vehicles (EVs) is introduced in this paper. For scheduling purposes, a day is divided into sequential timeslots. At the beginning of each timeslot, the dynamic system can determine an optimal charging schedule for that timeslot, as well as plan for subsequent timeslots. An EV may arrive at a PL with or without an appointment. Considering the variation in electricity prices during the day, the objective is to minimize the cost of electricity used to charge EVs by scheduling optimal electric quantities at the parking timeslots of each EV. The optimal solution satisfies the EV's charging rate limit and the PL's transformer limit. Based on particle swarm optimization (PSO), fuzzy systems and heuristics, this paper describes a heuristic fuzzy particle swarm optimization (PHFPSO) algorithm to solve the optimization problem. From the case studies, the results show the proposed dynamic resource allocation system has a significant improvement in satisfying charging requests and in reducing the electricity cost of the PL when compared with other scheduling mechanisms.

Keywords:

Electric Vehicle, parking lot, dynamic resource allocation, particle swarm optimization, fuzzy system, heuristics.

1. Introduction

Electric vehicles (EVs) typically charge at public parking lots (PLs) equipped with power outlets, which would take hours to fully recharge the battery. With the rapid growth of EV populations [1], it is essential to employ a resource allocation system to schedule the limited public PLs and satisfy the electric requirements for power infrastructures. The main limitations of EV PL systems include long charging times, uncertain parking periods, varied charging demands and transformer limits. Currently, most of the PLs manage the EV charging requests on a first-in-first-serve (FIFS) strategy.

The motivation for proposing a dynamic PL resource allocation system is given as follows. First, in some big cities where people mostly live in apartments and work in the urban areas, only a small proportion of EV owners can afford to install a private charging pile to recharge their EVs. Many other EV owners drive to some super-charging stations to recharge their vehicles while they run a few errands, typically within an hour. An alternative would be for EV owners to recharge their vehicles during parking in a public PL with specialized EV charging facilities. In this case, the vehicles are parked for a longer duration, from two or more hours. EV recharging can also take place in an office building PL while their owners go to work during daytime. Hence, it is essential for a PL to have a resource allocation system to manage the EV charging during parking.

Secondly, the PL should have a transformer limit due to the power grid and safety precautions. In this case, the PL should balance the allocated electric quantities in each timeslot to satisfy the transformer limit. Each timeslot is typically set as 30 minutes in this study. Also, considering the charging specifications, the allocated electric quantities cannot exceed the maximum charging rate of each EV. Hence, the PL should determine an optimal charging schedule that satisfies both the transformer limit and the charging rate limit.

Thirdly, most current commercial PLs use the FIFS scheduling mechanism to deal with the parking and charging requests from EVs. Due to the transformer limit, a PL with a FIFS mechanism cannot optimize the distribution of the charging resources to the vehicles, and some of the late arrival requests cannot be fulfilled. Hence, the PL should use some optimization schedule to take care of the charging requests.

Lastly, the PL providing a service to recharge the EVs has to buy a large amount of electricity from the power company. Knowing that many power companies provide a time-of-use price that varies at different times, the PL would aim to lower the cost by purchasing in a low-price period. Supposed the electricity is sold to the EV owners at a fixed price rate, the PL can make more revenue by determining an optimized strategy to allocate more electric supply during the low price period, and less amounts when the price is high.

The main contributions of this study are as follows. Firstly, a viable PL operation system is designed to manage the charging requests for vehicles that arrive with or without appointments. The dynamic system determines a charging schedule for the immediate timeslot. Secondly, the aim of the optimization model is defined to best satisfy the EV charging requests and minimizes the PL's electricity cost concurrently. Thirdly, a resource allocation model based on the proportion-based assignment method is proposed to improve the efficiency in generating the initial solutions for optimization. Lastly, a PHFPSO algorithm is proposed to solve the optimization problem with the use of the PSO algorithm, fuzzy systems and heuristics, and the results show that the PHFPSO can determine an optimized solution and outperform other algorithms.

The related work is described in Section 2. Section 3 introduces the operation model. The problem formulation is given in Section 4. In Section 5, the methodology for solving the optimization problem is presented. The simulation case studies are given in Section 6, and conclusions and future work complete this paper in Section 7.

2. Literature Review

Some approaches have been proposed in the literature to solve the EV charging problem for power grid and PLs, which include power grid coordination, charging station recommendation, PL planning, EV charging pricing, and charging schedule decision model.

In order to manage the potential high peak demand of EV charging at residential distribution areas, some demand response (DR) systems were studied in [2] – [7] for a smart grid. A hierarchical coordinated charging framework and a vehicle-to-grid (V2G) scenario were proposed in [8] and [9] to solve the optimization operation problem in a distribution system operator (DSO). Considering the benefit of a renewable energy source (RES) but with drawbacks such as the intermittent nature and uncontrollability, [10] – [13] proposed some optimization methods to manage a multi-energy system at a charging station. Besides that, an energy storage (ES) unit was used to minimize the impact of uncertainty and inaccurate prediction in [13] and [14].

Another approach is to determine the capacity and location of PLs in [15] – [17]. Starting with some candidate charging stations, [18] proposed a real-time charging station recommendation system for EV taxis. In [19], a coordinated bidding of ancillary services for V2G was proposed to maximize profits. Further studies determined the charging price so as to maximize the profit in [13] and [20].

A novel strategy allowing vehicle-to-vehicle (V2V) charging was proposed in [21]. It aimed to minimize the total cost, which included the electricity cost and the damage to the EV batteries due to extra charging cycles. The decision was determined using binary variables denoting the charging and discharging states of each EV. A small number of EVs were used to evaluate the performance, but the computational time was very high. [22] proposed a real-time charging scheme to coordinate EV charging decisions and to accommodate demand based on the electricity price and the demand curtailment request from the utility company. The objective was to maximize the number of EVs for charging at each scheduling period and to minimize the electricity bill. The schedule used a binary decision approach for determining the on-off strategy of each charging pole.

Differing from the binary decision approach, [23] proposed a PL management system to determine the optimal charging strategy for the EV charging in day-time. The objective was to minimize the charging cost of the station considering the electricity cost and a penalty cost if EV demand was not satisfied. In [24], authors also developed an optimal schedule for EV charging using a game-theoretic approach. However, the vehicle profiles they used overlapped for 30 time intervals and the charging demands were very low, so that the candidate solutions were easily found. In [25] and [26], some optimization intelligent-based algorithms were proposed for determining the charging schedule, and [27] designed new accelerated particle swarm optimization (APSO) algorithms to solve the same problem. The aim was to maximize the average State-of-Charge for all EVs at the next time step. However, in the optimization model, the decision was only for the EVs being charged in the next time step. Hence, this may not provide an optimized schedule without considering the whole parking period of the EVs.

Separated layers/scenarios/schemes was proposed to handle EVs with and without appointments in [28] – [30]. Two scenarios were proposed in [28] to determine a charging schedule considering the aggregator's revenue and customer demands and cost. The static charging scenario was for the known customers of the aggregator, while the dynamic charging scenario was for those customers who came and left without any advanced notice. The decision was fixed for these EVs in the static schedule. If a new customer comes without advanced notice, the determined schedule cannot be changed, even if a better solution exists. A PL management system for a centralized EVs recharging system was proposed in [29] for maximizing the PL revenue or maximizing the total number of EVs fulfilling their requirements. They defined a two-layer scheduling model to deal with regular and irregular EVs. They used an optimization algorithm to determine the schedule for the routine layer, and used the first-in-first-serve (FIFS) and earliest-deadline-first (EDF) mechanisms to deal with the irregular EVs. However, their optimization model can only deal with regular EVs but the FIFS and EDF are used to handle the irregular EVs, which may not lead to6 an optimal decision. [30] proposed a global optimal scheduling scheme and a locally optimal scheduling scheme for EV charging and discharging. The aim was to minimize the total cost of all EVs and the decision involved the charging and discharging power of each EV at each timeslot. A global and local scheduling scheme was defined to deal with the appointed and non-appointed EVs respectively. In their local optimization model, the power load may exceed the transformer limit.

2.1. Decision Methods

In the literature, different methods, such as decision strategies/mechanisms, linear programming (LP), mixed-integer linear programming (MILP), dynamic programming (DP), game theory and computational intelligent algorithms, are used to obtain solutions.

In most commercial PLs, some scheduling strategies/ mechanisms are used to manage the charging requests for EVs, such as FIFS and EDF. Accordingly, the FIFS and EDF mechanisms are widely used as the baseline scheduling method such as in [22] [23] [28] [29]. Some references, [6] [14] [15] [21] [22] [28] [29] [30], defined the problem as a linear optimization problem, which can be solved by mathematical methods such as LP and MILP. [6] and [28] used CPLEX to solve the LP problem. A dynamic programming method was implemented in [23] to determine the optimal charging strategy knowing the short-term future and long-term prediction information. In addition, game theory was used in [5] [7] [20] [24] to solve charging station pricing and charging scheduling problems.

Besides LP, MILP, DP and game theory methods, computational intelligent algorithms were also used in another approach to solve the optimization problems. In [26] – [28], estimation of distribution algorithm (EDA), particle swarm optimization (PSO) and interior point method (IPM) algorithms were implemented and compared in the simulation studies. In our study, an intelligent algorithm is proposed to solve the optimization problem with the use of the PSO algorithm, fuzzy systems and heuristics.

2.2. Comparisons with this paper

The decision in our paper are the electricity quantities allocated to all available timeslots of each EV, which are continuous variables that satisfy the constraints. On-off values were used as the decision variables, which means each EV can only be charged or not charged in a timeslot in [21] and [22]. This binary decision is a limitation of the problem setup and the result may not be refined. The solution given in [25] - [27] is only for one particular timeslot. In our model, the decision variables are determined by a proposed proportion-based assignment method to improve the efficiency in generating the initial solutions for optimization, and the proportion concept can ensure the fulfillment of the charging demands.

The proposed system can deal with EVs, no matter whether they come with or without appointments, in a single model. However, in [28] – [30], two separate systems were designed to make a schedule for the appointed and non-appointed EV, such as the static/ dynamic scenario in [28], regular/ irregular EVs in [29], and global/ local optimal scheme in [30]. In our work, the system can make an optimal charging schedule considering all types of EVs, which can help the system to determine a near global optimal solution.

Considering the influence of the charging load to the power grid, a transformer limit is defined in our paper to avoid the total power exceeding the demand limit, which is regarded as a vital consideration in the demand response strategy of [2] - [7]. Many papers (e.g. [21] – [30]) only used a constant transformer limit, which might be sufficient for determining a charging schedule. In our work, a varied value of the PL's transformer limit is used to evaluate the flexibility and performance of our system.

The vehicle-to-grid (V2G) model has been widely utilized in power grid coordination ([4] – [6], [9], [11] – [14]) and the charging station pricing model in [19]. However, in EV charge scheduling, most of the works ([21] – [29]) did not used the V2G model, considering the drawback of V2G, such as discharge damage to the battery, unfulfilled EV demand and the uncertain electricity selling price. We do not deny the positive influence of the V2G model to the power gird, but some further studies on V2G should be clarified before applying it into our model. Also, renewable energy sources, such as solar-based energy and energy storage units are not used in our model. The V2G, RES and ES models may be included in the next phase of our research.

In summary, our approach to tackling the EV charging scheduling problem are as follows. First, the decision is that continuous electric quantities are assigned to all EVs at each timeslot. Second, at the beginning of each timeslot, the dynamic system can determine an optimal charging schedule for that timeslot, as well as plan for subsequent timeslots. Thirdly, the drivers' charging demands will be satisfied when they leave the PL, which will minimize any negative effect on the drivers. Fourthly, the transformer limit is defined as the overall power constraint of the PL. We also vary the value of the power limit to compare its impact on the schedule result.

2.3. Particle Swarm Optimization (PSO) Algorithm

The particle swarm optimization (PSO) algorithm is a typical population-based search algorithm proposed by Kennedy and Eberhart in 1995 [31]. $X\in\mathbb{R}^{N\times M}$ is denoted a set of solutions with N candidate particles/solutions, and $V\in\mathbb{R}^{N\times M}$ is denoted a set of velocities for updating the solution set X in each iteration. Let n denotes the index of a particle in a solution set, and m is the index of the position in a solution. $X(n) \in\mathbb{R}^{M}$ is denoted as the solution of the n-th particle, which is constructed by a M-dimension vector for each position. Let $it\in\{1, 2, \ldots, IT\}$ be the index of iteration. At the it-th iteration, the set of solutions and velocities is denoted as X_{it} and V_{it} respectively. $P^{best}(n) \in\mathbb{R}^{M}$ denotes the personal best solution of the n-th particle. $G^{best}\in\mathbb{R}^{M}$ denotes the global best solution, whose objective value is better than the other solutions. P^{best} and G^{best} are updated at the end of each iteration.

In the original particle swarm optimization (OPSO) algorithm, at the it-th iteration, the velocity of the n-th particle $\boldsymbol{V_{it}}\ \boldsymbol{(n)}$ is updated by

$$\begin{aligned} V_{it}(n) = V_{it-1}(n) + c_1 \cdot Rand_1 \cdot [P^{best}(n) - X_{it-1}(n)] \\ + c_2 \cdot Rand_2 \cdot [G^{best} - X_{it-1}(n)], \end{aligned} \tag{1}$$

where c_1 and c_2 are defined as the personal acceleration coefficient and global acceleration coefficient respectively. $Rand_1$ and $Rand_2$ are different random numbers within the range of [0,1].

In order to improve the performance of the original PSO, Shi and Eberhart [32] proposed the inertia-weight PSO (IPSO) to adopt a linearly decreasing method for updating the inertia weight, and the revised velocity formula is given by

$$\begin{aligned} V_{it}(n) = w \cdot V_{it-1}(n) + c_1 \cdot Rand_1 \cdot [P^{best}(n) - X_{it-1}(n)] \\ + c_2 \cdot Rand_2 \cdot [G^{best} - X_{it-1}(n)], \end{aligned} \tag{2}$$

where w is defined as the inertia weight to adjust the velocity in the previous iteration. In the typical use of an IPSO algorithm, w decreases linearly from 0.9 to 0.4 as

$$w = 0.4 + (0.9 - 0.4) \cdot \frac{IT - it}{IT}, \tag{3}$$

where IT is the maximum number of iterations.

Clerc [33] proposed the construction PSO (CPSO) algorithm by using the constriction factor χ in the velocity updating equation by

$$\begin{aligned} V_{it}(n) = \chi \cdot (V_{it-1}(n) + c_1 \cdot Rand_1 \cdot [P^{best}(n) - X_{it-1}(n)]) \\ + c_2 \cdot Rand_2 \cdot [G^{best} - X_{it-1}(n)], \end{aligned} \tag{4}$$

where χ is obtained by the equation

$$\chi = \frac{2}{|\, 2 - \varphi - \sqrt{\varphi^2 - 4\varphi}\,|}, \tag{5}$$

and φ is determined by $\varphi = c_1 + c_2$.

After determining the velocity $V_{it}(n)$ of the n-th particle in the it-th iteration, the corresponding particle $X_{it}(n)$ is

$$X_{it} = X_{it-1} + V_{it}. \tag{6}$$

In this study, the OPSO, IPSO and CPSO algorithms are implemented and compared in Section 6.

2.4. Fuzzy Particle Swarm Optimization (FPSO) Algorithm

Fuzzy particle swarm optimization (FPSO), or fuzzy adaptive swarm optimization (FAPSO), was first introduced by Shi in 2001 [34]. A fuzzy system was designed to dynamically adapt the inertia weight *w* of the PSO with the use of normalized current best performance evaluation. [35] proposed a FAPSO to solve the biding strategy by determining the inertia weight dynamically. The normalized fitness value and the current inertia weight were used as the input variables, and the change in inertia weight was used as the output variable. [36] proposed the variance of the population fitness as the input of the fuzzy system with the use of two fuzzy rules and two membership functions. [37] used FAPSO to solve a power loss minimization problem in distribution systems. [38] proposed a FPSO algorithm to determine the inertia weight *w* and the learning factor (c_1 and c_2). A mutation fuzzy adaptive PSO algorithm was proposed in [39] to solve a multi-objective optimization problem.

[40] proposed a self-tuning algorithm PSO algorithm based on fuzzy logic. The fuzzy logic was used to calculate the best setting of inertia weight *w*, cognitive factor c_1 and social factor c_2. They used two linguistic variables, the distance from *g* and normalized fitness incremental factor, as the inputs of the fuzzy logic. The output variables were the inertia weight, cognitive factor and social factor corresponding to each particle in PSO algorithm. Three groups of fuzzy rules were defined in the fuzzy logic, and each group contained three rules to determine each fuzzy output variable respectively.

In this paper, we develop a fuzzy system to determine *w*, c_1 and c_2 in Section 5. The membership functions and fuzzy rules have been modified in our algorithm, and the performances have been compared with those in [40] in Section 6.

3. DYNAMIC RESOURCE ALLOCATION SYSTEM

3.1 Operation Model

In this section, we describe the dynamic operation model for determining the optimal charging schedule of EVs considering two types of EVs: EVs with appointments and EVs without appointment. Here, the EVs with appointments refer to those whose drivers have made appointments for reserving a parking space for charging before arrival. The drivers are encouraged to provide the expected arrival times, departure times and charging demands, so that the PL can make use of such information to predict the future demand and allocate proper charging facilities to the incoming EVs. On the other hand, the operation model also allows for drive-in EVs without appointments for drivers arriving for sudden meetings, shopping or short-time stay. The EVs' expected departure times and charging demands are also encouraged to be given when they arrive. Yet, in an actual operation, our model is also flexible to handle any EV which suddenly leaves the PL without notice. The model can also deal with EVs which made appointments but do not appear.

As shown in Fig.1, three types of information are used to determine the charging schedule for the immediate timeslot including the arrived EVs with appointments, the not-yet-arrived EVs with appointments and the arrived EVs without appointments. The arrived EVs (with and without appointments) can provide the expected departure times and charging demands, while the not-yet-arrived EVs with appointments should provide the expected arrival times, departure times and charging demands. Knowing the expected information, the PL can use the proposed resource allocation system to determine an optimized charging schedule for the immediate timeslot and the subsequent timeslots.

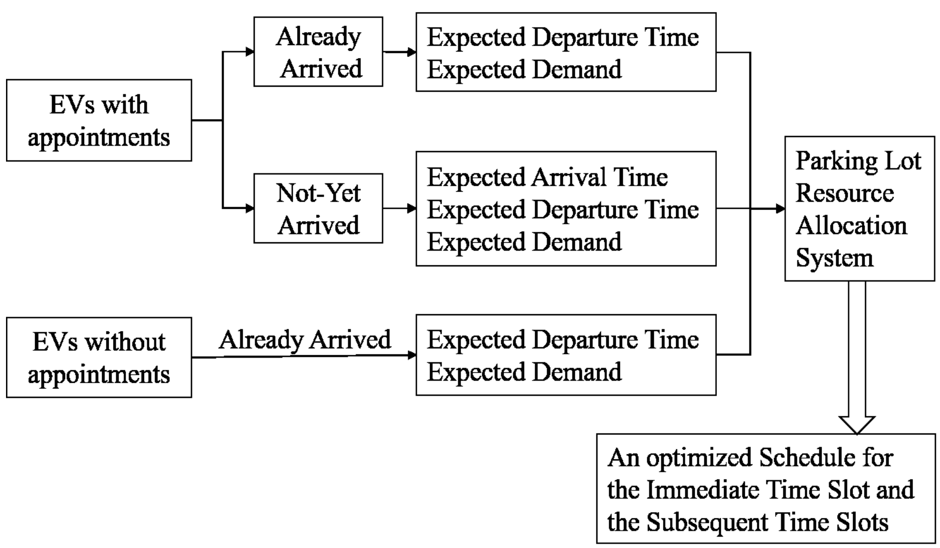

Fig. 1. Operation model of the dynamic resource allocation system.

Fig. 2 gives an example for determining an optimized charging schedule for timeslot t_3. A1, A2, …, A20 are the EVs with appointments, and B1, B2, …, B20 are the EVs without appointments. Within the 40 EVs, the EVs denoted as A1, A2, A3, A4, B1, B2 and B3 have arrived at the PL already. At the beginning of t_3, the system can make use of the information from the arrived EVs (A1, …, A4, B1, …, B3) and the EVs with appointments (A5, …, A20) to determine an optimized schedule for all the EVs in the immediate timeslot and the subsequent timeslots. Then, the schedule for the arrived EVs will be executed immediately. In this dynamic system, an optimized charging schedule can be determined at the beginning of each timeslot.

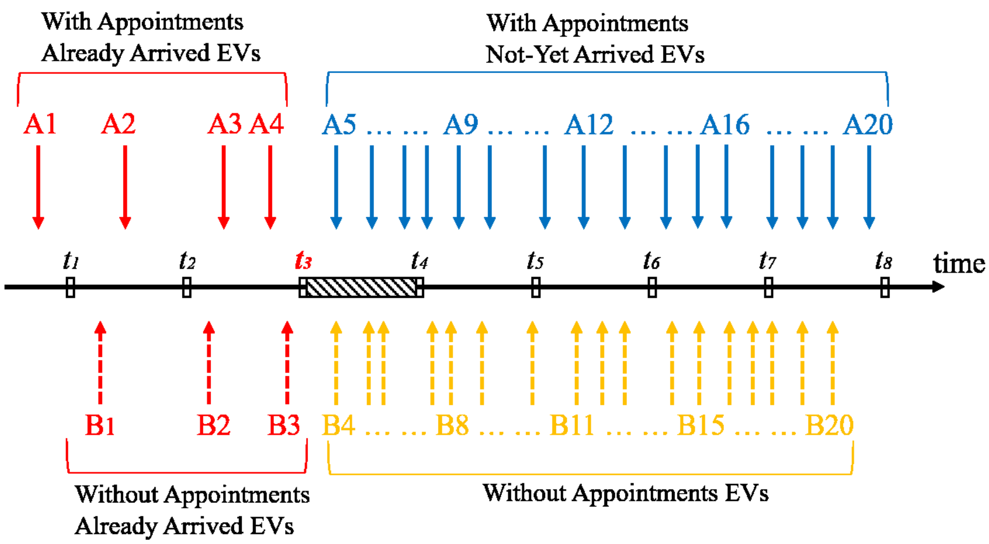

Fig. 2. Example of a schedule for timeslot t_3.

3.2 System Considerations

Based on the literature review, we propose a dynamic resource allocation for determining the charging schedule for the EVs. Some major considerations of the proposed system are presented.

3.2.1. EV's charging demand.

The fulfillment of the EV's charging demand is a vital constraint in our model, which is different from most other research on scheduling problems. Instead of charging at a residential location, most public PLs and charging stations are located in office buildings or shopping malls. In this case, the drivers usually leave the PL for some other purposes, such as working or shopping, instead of waiting in the vehicle. When they come back to pick up the EV, they expect it to be fully recharged, which would allow for long driving mileage. In this model, all the EV drivers' charging demands are fulfilled when they depart the PL, which maximizes the satisfaction of EV drivers.

3.2.2. Transformer limit

The transformer limit is defined as the maximum capacity/ power supply of the PL, which restricts the power load exceeding the requirement of the grid. In most of the demand response literature [2] – [14], the power load of EV charging is regarded as an important influence of the power grid, which may cause potential transformer overload, feeder congestion and undue circuit faults [2]. In the EV charging schedule literature [21] – [30], the maximum charging power load or transformer limit is defined as a constraint to limit the total power of a PL. In this paper, the transformer limit is considered as an important constraint to the PL. The transformer limit determines the maximum number of EVs that the PL can serve. For example, if the transformer limit of a PL is 100 kW and the charging rate of an EV is 9.6 kW, only 10 EVs can be recharging at the same time. In this study, the transformer limit will be varied to evaluate the performance, which was not undertaken in previous research.

3.2.3. Insufficient charging poles

An insufficient number of charging poles is considered as the major reason for queueing. In the proposed system, the drawback of insufficient poles can be avoided as follows. First, rather than a constant maximum charging rate, the rate of each charging pole can be a continuous value between 0 and the maximum rate. Within a timeslot, the scheduling system can recharge more EVs to fulfill their requests. Secondly, with the use of a lower charging rate, the number of charging poles can be increased given a constant transformer limit. Lastly, the EV drivers can make an advanced appointment to the PL to reserve a charging space to avoid queuing.

3.2.4. Unaccepted charging request

Due to the transformer limit, it is possible that the PL cannot determine a feasible solution when a new charging request comes, which is regarded as an unaccepted charging request. In this case, the EV driver can reduce the charging demand or prolong the stay period to satisfy the PL's constraints. In addition, the drivers are encouraged to make advanced notice before arrival. It has been shown in Section 6.4 that the appointments from EV drivers can help the PL to make a general schedule and reduce the total cost. Hence, the appointment process not only helps the EV drivers to reserve a charging space in advance, but also help the PL to reduce its electricity cost. In future work, we will work out a new algorithm to suggest a lower charging request or a later departure time if the current request is not accepted by the PL.

3.2.5. V2G model

In our paper, the vehicle to grid (V2G) model is not considered as revenue generating due to the following reasons. Firstly, the discharge damage of EV batteries could be a potential cost to EV owners, and they may not agree to sell the electricity to grid even if some discount and benefits are given. Secondly, the arrival time and departure time of EV drivers should be more flexible. For example, if an EV departs earlier than the expected departure time, its desired SOC may not be fulfilled if it is in a discharging process. Thirdly, the electricity energy loss during the transmission cannot be avoided, which would be a potential cost to the PL. Fourthly, the additional facilities to transmit the electricity to grid and the operation expense would also be an extra cost to the PL. Lastly, the bidding strategy with the electricity markets and the cooperation model between the PL and the power company should be further investigated, and currently is an uncertain factor to the V2G model.

3.3 Optimal solution

In the proposed system, the solution is the charging schedule for all the EVs in the immediate and the subsequent timeslots. Compared with the schedule determined by the FIFS or EDF mechanisms, the proposed method can use a lower electricity cost to serve the EVs, and can accommodate more charging requests, which is shown in the case studies. The solution contains $numE \times numT$ dimensions/ variables, where $numE$ is the number of EVs and $numT$ is the number of timeslots. For each variable, the charging decision is a continuous value between zero and the charging rate limit. Hence, it is impossible to search for all possibilities without using some intelligent algorithms.

As shown in Section 2.1, many methods can be used to solve the optimization problem. In this paper, PSO algorithms along with the fuzzy systems and heuristics are used to find a better solution for the following reasons. First, the algorithms are universal for solving the problem, and do not need to format the problem as linear and mixed-integer models. Secondly, we define some constraints to satisfy the charging demands, the transformer limit and the charging rate limit, and the proposed algorithm is suitable to search for solutions. Lastly, the algorithm can be implemented in MATLAB without using any toolbox or embedded solver. Hence, the program can be easily migrated to any platform.

It is notable that the optimal solution denotes the best solution that the algorithm has found so far, which does not guarantee that the solution is the final/global optimal solution.

3.4 Benefits for EV drivers

The dual parking and charging process in our system is similar to the current parking in a public PL. In the proposed model, given a constant transformer limit, the PL can provide more charging poles, so that there would be more parking spaces with charging facilities. The appointment process can help EV drivers to reserve a space in advance, which means that they do not need to queue up for charging. When the departure time and charging demand of an EV is known, the system can fully recharge its battery before leaving the PL.

3.5 Benefits for parking lot

We have developed a dynamic resource allocation system for the PL for serving the incoming EVs, which has some significant benefits for PL. First and foremost, the system can help the PL to minimize the cost of buying electricity from the power grid, so that its profit can be increased. Second, the system is based on an intelligent algorithm/software, which do not need to reconstruct the utility and equipment of the PL. Third, the proposed system allows the EV drivers to make advanced appointments to reserve a parking and charging outlet. Hence, EV drivers can avoid queuing up for recharging and the PL can make use of advanced information to determine an optimal charging schedule. Lastly, the system does not exceed the transformer limit of the grid, and the charging schedule is a continuous electric quantity assigned to each EV at each timeslot. Hence, the PL can employ more charging outlets/poles to satisfy more EVs.

4. Problem Formulation

This section is to formulate the optimization model for determining a solution at the beginning of a single timeslot. In the dynamic model, this computation process can be repeated at the beginning of each timeslot after updating the EV arrival information and charging statues of the arrived vehicles.

The notation of variables is shown in Table 1.

Table 1
Notation

	Descriptions
Sets:	
E	Set of EVs with index i
T	Set of timeslots with index t
Parameters:	
τ	Timeslot unit
arr_i	Arrival timeslot of EV i
dep_i	Departure timeslot of EV i
dem_i	Charging demand capacity EV i
A_i^t	Availability of EV i at timeslot t
$numE$	Number of EVs
$numT$	Number of timeslots
$numV$	Number of variables in a solution
EP_t	Electricity price at timeslot t
$limC$	Limit of charging rate in a timeslot
$limT_t$	Limit of transformer capacity in timeslot t
M_i^t	Average electricity amount of EV i assigned to timeslot t
P_i^t	Proportion of EV i's demand assigned to timeslot t
Decision Variables:	
X	Solution Vector
x_i^t	Proportion of EV i's demand to timeslot t
C_i^t	Allocated capacity of EV i to timeslot t
TC_t	Total capacity of parking lot in the timeslot t

4.1. EV profile

We define each timeslot τ as 30 minutes, and each EV arrives at the PL at known arrival timeslot arr_i, departure timeslot dep_i and charging demand of electricity dem_i. We assume the EV arrives right before arr_i and departs right after dep_i, which means that the EV charging process occurs between arr_i and dep_i. We also assume each EV will be fully recharged with the demand capacity dem_i when it departs the PL. A_i^t denotes the availability of EV i at timeslot t, and A_i^t is defined as in

$$A_i^t = \begin{cases} 1 & arr_i \le t \le dep_i \\ 0 & \text{otherwise} \end{cases} \quad \forall i \in E \quad . \tag{7}$$

EP_t denotes the electricity price at timeslot t, which varies at different timeslots, such as off-peak, mid-peak and on-peak.

4.2. Solution

In this model, the electric quantity stands for the energy charged to the EV battery, and the solution is to have the electric quantities allocated to all available timeslots for each incoming EV. Hence, the number of variables $numV$ is derived based on

$$numV = \sum_{t \in T} \sum_{i \in E} A_i^t \tag{8}$$

The solution is denoted as

$X = \{x_1^{arr_1}, ,..., x_1^{dep_1}, x_2^{arr_2}, ..., x_2^{dep_2}, ..., x_i^t, ..., x_{numE}^{arr_{numE}}, ..., x_{numE}^{dep_{numE}}\}$, which is a set of allocated electricity proportions corresponding to the available timeslots. In vector X, the number of variables is $numV$, and x_i^t denotes the proportion of EV i's demand assigned to the timeslot t.

4.3. Objective function

The objective of this model is to minimize the cost of buying electricity by the PL from the power grid, considering the varying electricity price at different timeslots.

$$\text{minimize} \quad \sum_{i=1}^{numE} \sum_{t=arr_i}^{dep_i} x_i^t \cdot dem_i \cdot EP_t \tag{9}$$

s.t.:

$$0 \le x_i^t \le 1 \quad \forall i \in E, \forall t \in T \tag{10}$$

$$\sum_{t=arr_i}^{dep_i} x_i^t = 1 \quad \forall i \in E \tag{11}$$

$$C_i^t = x_i^t \cdot dem_i \quad \forall t \in [arr_i, dep_i], \forall i \in E \tag{12}$$

$$TC_t = \sum_{i \in E} C_i^t \quad \forall t \in T \tag{13}$$

$$C_i^t \le limC \quad \forall i \in E, \forall t \in T \tag{14}$$

$$TC_c \le limT_t \quad \forall t \in T \tag{15}$$

Here, the minimum cost of electricity can be achieved by allocating more charging demands to the timeslots in which the electricity price is low.

4.4. Constraints

Constraint (10) indicates that the proportion of the charging demand should be a non-negative value. Constraint (11) shows that the sum of the allocated proportions to any EV equals 1. This means the charging demands by EVs are fully satisfied during the parking periods. Equation (12) defines the electric quantity allocated to EV i in the timeslot t, and (13) determines the required capacity of the PL at timeslot t by summarizing the individual allocated capacities of each EV. Considering an EV's charging rate limit, constraint (14) states that the allocated capacity for any EV at any timeslot should be within the defined charging rate $limC$. Constraint (15) indicates that the total capacity in timeslot t should not exceed the maximum transformer capacity limit $limT_t$.

5. Methodology

Here, the complexities for determining the optimal schedule are summarized as follows. Firstly, the number of variables in the decision vector is large, and the values of the variables are real numbers. Secondly, due to the transformer limit and charging rate limit in the timeslots, the decision model needs to check constraints (14) and (15) after obtaining candidate schedules. Lastly, due to the various electricity prices during the time period, it is essential to apply the optimization operation to minimize the PL's cost.

The number of iterations is denoted by *numI*. The population size is *numP*. The dimension of the decision solution is *numV*, which is derived by the attributes of the EVs. We also denote *numRep* as the number of repeats for the algorithm in evaluating the performance.

The flowchart of the proposed heuristic fuzzy particle swarm optimization (PHFPSO) algorithm is given in Fig. 3. Firstly, the proportion-based assignment (PBA) method is designed to determine the initial population of candidate solutions for the following optimization algorithm. In each optimization iteration, the particle swarm optimization (PSO) algorithm is used to obtain better solutions. Then, a fuzzy system is deployed to determine the three crucial coefficient of PSO algorithms, inertia weight w, personal acceleration coefficient c_1 and global acceleration coefficient c_2. Lastly, the heuristics are used to improve the solutions. The PSO algorithm, fuzzy system and heuristics will be executed in each iteration. When it reaches the end of iteration, the solution with the best objective value will be assigned as the optimal solution.

In this section, the PBA method is presented in Section 5.1. The proposed fuzzy system is introduced in Section 5.2, which includes the definition of the fuzzy variables, membership functions, fuzzy rules and defuzzification functions. In Section 5.3, the heuristics for improving the solutions is illustrated. Lastly, the baseline algorithms for evaluating the PHFPSO algorithm are given in Section 5.4.

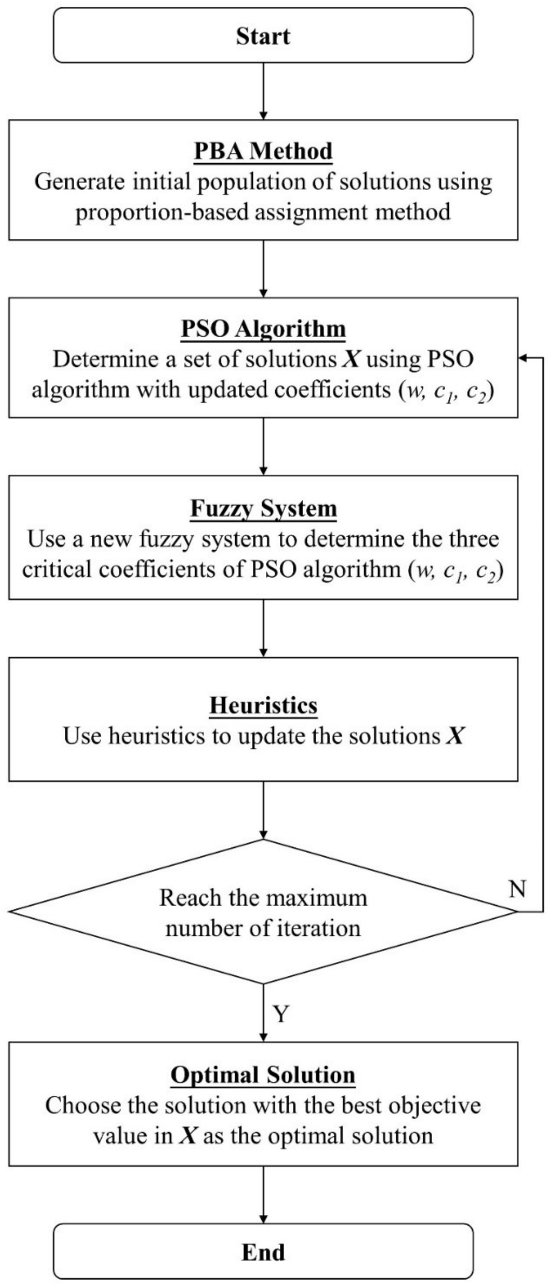

Fig. 3. Flowchart of the PHFPSO algorithm

5.1.Proportion-Based Assignment (PBA Method)

As shown in Section 4.2, the solution contains the allocated electric quantity proportion for each EV's demand. The use of proportion makes sure that the EVs' demands are satisfied. In the evolutionary algorithm, the initial population is usually generated randomly. In this paper, a proportion-based assignment method is proposed to improve the efficiency for generating the initial population. The detailed pseudo-code of the PBA method is shown in Algorithm 1, and the basic steps are as follows.

First, the charging demand of each EV is assigned to its available timeslots by an average quantity. Let M_i^t be the average electricity amount of EV i assigned to timeslot t, which is derived by

$$M_i^t = \frac{dem_i}{dep_i - arr_i + 1}. \tag{16}$$

Then, TC_t is denoted as the total electric quantity at timeslot t, which is determined by

$$TC_t = \sum_{i=1}^{numE} M_i^t. \tag{17}$$

The arrival time, charging demand and stay time are different for each EV, and hence the electricity demand for each timeslot could vary a lot. The following is used to calculate the proportion value P_i^t for allocating an EV's charging demand at timeslot t by

$$P_i^t = 1 - \left(TC_t \Big/ \sum_{t=arr_i}^{dep_i} TC_t \right). \tag{18}$$

For each EV i, the proportions P_i^t are adjusted by random variation, and then scaled to the solution x_i^t.

Algorithm 1 Proportion-Based Assignment Method

Input: EVs list **E**, number of EVs *numE*; number of variables *numV*, number of population *numP*;

Output: A set of populations/solutions **P** ;

Calculate the maximum time slots in $\boldsymbol{E}$ as T_{max} ;
for $i = 1$ to *numE* **do**
    $ave_i = dem_i / (dep_i - arr_i + 1)$;
    for $t = arr_i$ to dep_i **do**
        $al_{it} = ave_i$;
    end for
end for
for $t = 1$ to T_{max} **do**
    $TC_t = \sum_{i=1}^{numE} C_i^t$;
end for
while $numP' \geq numP$ **do**
    P' = *null* ;
    for $i = 1$ to *numE* **do**
        $T = arr_i$ to dep_i;
        for $t = arr_i$ to dep_i **do**
            $P_i^t = 1 - \left(TC_t / \sum_{t=arr_i}^{dep_i} TC_t \right)$
        end for
        calculate the minimum value in P_i^T as P^{min} ;
        for $t = arr_i$ to dep_i **do**
            $x_i^t = P_i^t + P^{min} - 2 \times P^{min} \times rand(1);$
        end for
        scale x_i^T to range [0,1];
        insert x_i^T to **P'**;
    end for
    if check(**P'**) $\neq$ -1 **then**
        insert **P'** to **P**;
    end if
    calculate the size of **P'** as *numP'* ;
end while
return P

5.2. Fuzzy System for Determining the PSO coefficients

In the proposed heuristic fuzzy particle swarm optimization (PHFPSO) algorithm, a new fuzzy system is used to determine the three critical coefficients of the PSO algorithm in equation (1). The pseudo-code of the fuzzy PSO algorithm is shown in Algorithm 2. The equation of velocity is revised:

$$
\begin{aligned}
V(it,iP) = {} & w(it,iP)\times V(it-1,iP) \\
& + c_1(it,iP)\times Rand_1 \times [P^{best}(it-1,iP) - X(it,iP)] \\
& + c_2(it,iP)\times Rand_2 \times [G^{best}(it-1) - X(it,iP)].
\end{aligned} \tag{19}
$$

Here, $w(it,iP)$, $c_1(it,iP)$ and $c_2(it,iP)$ denote the inertia weight, personal acceleration coefficient and global acceleration coefficient at the *it*-th iteration corresponding to the *iP*-th particles. At the end of each iteration, the coefficients are updated according to the proposed fuzzy system.

In this new fuzzy system, we use two input fuzzy variables, δ and ϕ. The Euclidean distance δ between the particle X and the global best G is calculated by

$$\delta(X) = \|X - G\| = \sqrt{\sum_{i=1}^{numV}(X_i - G_i)^2} . \tag{20}$$

The normalized fitness incremental factor ϕ is used to measure the improvement between the current iteration to the previous iteration of particle X, which is calculated by

$$\phi(X) = \frac{f(X(t)) - f(X(t-1))}{F_{worst}} \cdot \frac{\|X(t) - X(t-1)\|}{\delta_{\max}} , \tag{21}$$

where $f(X)$ is the objective value obtained by the solution X, F_{worst} is the worst objective value and $\delta_{\max}$ is the maximum distance between any two solutions. The first part is used to calculate the improvement of the objective between the current and previous iterations, and the second part is to calculate the Euclidean distance between the current and previous iterations.

The input fuzzy variable δ is defined in three fuzzy sets, Low, Medium and High with associated membership functions, and the input fuzzy variable ϕ is defined in another three fuzzy sets of linguistic values (Better, Unvaried and Worse) with the associated membership function. The fuzzy sets and corresponding associated membership functions are shown in Fig. 4. The output variables are defined in three different fuzzy sets of linguistic values in Table 2.

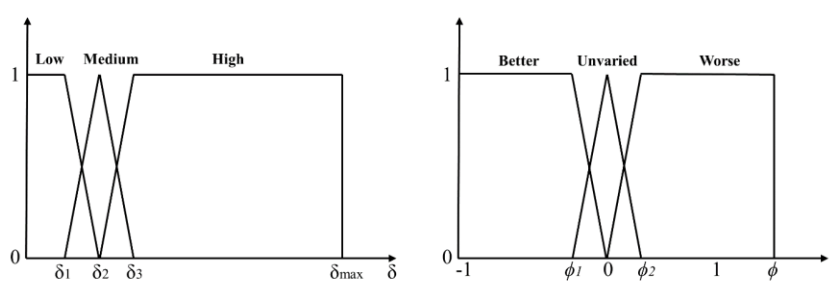

Fig. 4. Membership functions for the Euclidean distance δ and normalized fitness incremental factor ϕ

Table 2
Output Fuzzy Variables

Linguistic Value	Output Value		
	Inertia Weight w	Personal Coefficient c_1	Global Coefficient c_2
Low	0.3	0.1	0.1
Medium	0.5	1.5	1.5
High	1.0	3.0	3.0

As shown in Table 3, nine fuzzy IF/THEN rules are defined with two input variables, and each input variable contains three different linguistic values. The linguistic variables are connected using the OR operator in the fuzzy rules. In this proposed fuzzy system, all rules having the same output variable are selected as the candidate rules, then the final output variable is determined by the weighted average of the individual output of the candidate rules.

Table 3
Fuzzy Rules

Rule	*Rule Definition*
1	IF (δ IS Low OR ϕ IS Worse) THEN w IS Low
2	IF (δ IS Medium OR ϕ IS Unvaried) THEN w IS Medium
3	IF (δ IS High OR ϕ IS Better) THEN w IS High
4	IF δ IS High THEN c_1 IS Low
5	IF (δ IS Low OR δ IS Medium OR ϕ IS Worse OR ϕ IS Unvaried) THEN c_1 IS Medium
6	IF ϕ IS Better THEN c_1 IS High
7	IF ϕ IS Better THEN c_2 IS Low
8	IF (δ IS Low OR δ IS Medium OR ϕ IS Unvaried) THEN c_2 IS Medium
9	IF (δ IS High OR ϕ IS Worse) THEN c_2 IS High

The defuzzification function for determine the three coefficient is given by

$$w=\frac{0.3\times\delta_{Low}+0.5\times\delta_{Medium}+\delta_{High}+0.3\times\phi_{Wrose}+0.5\times\phi_{Unvaried}+\phi_{Better}}{\delta_{Low}+\delta_{Medium}+\delta_{High}+\phi_{Wrose}+\phi_{Unvaried}+\phi_{Better}} \tag{22}$$

$$c_1=\frac{1.5\times\delta_{Low}+1.5\times\delta_{Medium}+0.1\times\delta_{High}+1.5\times\phi_{Wrose}+1.5\times\phi_{Unvaried}+3\times\phi_{Better}}{\delta_{Low}+\delta_{Medium}+\delta_{High}+\phi_{Wrose}+\phi_{Unvaried}+\phi_{Better}} \tag{23}$$

$$c_2=\frac{1.5\times\delta_{Low}+1.5\times\delta_{Medium}+3\times\delta_{High}+3\times\phi_{Wrose}+1.5\times\phi_{Unvaried}+0.1\times\phi_{Better}}{\delta_{Low}+\delta_{Medium}+\delta_{High}+\phi_{Wrose}+\phi_{Unvaried}+\phi_{Better}} \tag{24}$$

In this PHFPSO algorithm, the number of populations *numP* is given by

$$numP=\left\lfloor 10+2\sqrt{numV}\right\rfloor \quad , \tag{25}$$

, as proposed by Hansen et. al [41].

Algorithm 2 Fuzzy Particle Swarm Optimization Algorithm

parameters
numP: number of particles in the PSO population
nunIT: number of iterations

generate an initial population of particles using ***PBA*** method
P←{ ***X***(0,1), ***X***(0,2), …, ***X***(0,numP-1), ***X***(0,numP) }
generate an initial velocity of each particle
V←{ ***V***(0,1), ***V***(0,2), …, ***V***(0,numP-1), ***V***(0,numP) }
calculate the scores of all particles from ***P***
set the particle with highest score as $\boldsymbol{P^{best}}$ and $\boldsymbol{G^{best}}$
for each iteration *it* less than *numIT* **do**
    calculate the scores of each solution from ***P***
    for each particle *iP* less than *numP* **do**
        F_{worst} ← the worst objective value
        δ_{max} ← the maximum distance between any two solutions
        $\delta(it,iP)=\sqrt{\sum_{i=1}^{numV}(X(it,iP)-G^{best})}$
        $\phi(it,iP)=\frac{f(X(it,iP))-X(it-1,iP)}{F_{worst}}\times\frac{\sqrt{\sum_{i=1}^{numV}(X(it,iP)-X(it-1,iP))}}{\delta_{\max}}$
        $\delta_1=0.12\times\delta_{max}$; $\delta_2=0.14\times\delta_{max}$; $\delta_3=0.16\times\delta_{max}$
        if $\delta(it, iP)\le\delta_2$ **then**
            $\delta_{Low}=\min(\frac{\delta(it,iP)-\delta_2}{\delta_1-\delta_2},1)$

$$\delta_{Medium} = \max(\frac{\delta(it,iP)-\delta_1}{\delta_2-\delta_1},0)$$

$$\delta_{High} = 0$$

else

$$\delta_{Low} = 0$$

$$\delta_{Medium} = \max(\frac{\delta(it,iP)-\delta_3}{\delta_2-\delta_3},0)$$

$$\delta_{High} = \min(\frac{\delta(it,iP)-\delta_2}{\delta_3-\delta_2},1)$$

end if

if $\phi(it, iP) \le 0$ **then**

$$\phi_{Worse} = 0$$

$$\phi_{Unvaried} = \max(1-\frac{\phi(it,iP)}{\phi_1},0)$$

$$\phi_{Better} = \min(\frac{\phi(it,iP)}{\phi_1},1)$$

else

$$\phi_{Worse} = \min(\frac{\phi(it,iP)}{\phi_2},1)$$

$$\phi_{Unvaried} = \max(1-\frac{\phi(it,iP)}{\phi_2},0)$$

$$\phi_{Better} = 0$$

end if

$$w = \frac{0.3\times\delta_{Low}+0.5\times\delta_{Medium}+\delta_{High}+0.3\times\phi_{Wrose}+0.5\times\phi_{Unvaried}+\phi_{Better}}{\delta_{Low}+\delta_{Medium}+\delta_{High}+\phi_{Wrose}+\phi_{Unvaried}+\phi_{Better}}$$

$$c_1 = \frac{1.5\times\delta_{Low}+1.5\times\delta_{Medium}+0.1\times\delta_{High}+1.5\times\phi_{Wrose}+1.5\times\phi_{Unvaried}+3\times\phi_{Better}}{\delta_{Low}+\delta_{Medium}+\delta_{High}+\phi_{Wrose}+\phi_{Unvaried}+\phi_{Better}}$$

$$c_2 = \frac{1.5\times\delta_{Low}+1.5\times\delta_{Medium}+3\times\delta_{High}+3\times\phi_{Wrose}+1.5\times\phi_{Unvaried}+0.1\times\phi_{Better}}{\delta_{Low}+\delta_{Medium}+\delta_{High}+\phi_{Wrose}+\phi_{Unvaried}+\phi_{Better}}$$

$$\begin{aligned} V(it,iP) = {} & w\times V(it-1,iP)+c_1\times Rand_1\times(P^{best}(it-1,iP)-X(it,iP)) \\ & +c_2\times Rand_2\times(G^{best}(it-1)-X(it,iP)) \end{aligned}$$

$$X(it,iP) = X(it-1,iP)+V(it-1,iP)$$

if the objective value of *X(it, iP)* is smaller than that of ***P***^{best} **then**

$$P^{best} = X(it,iP)$$

end if

if the objective value of *X(it, iP)* is smaller than that of **G**$^{\mathbf{best}}$ **then**

$$G^{best} = X(it,iP)$$

end if

end for

end for

$X \leftarrow G^{best}$

5.3.Heuristics

In the previous section, the fuzzy PSO algorithm can obtain an optimal solution of the scheduling problem. Here, further heuristics are employed in the final PHFPSO algorithm to explore solutions with a better objective value. Heuristics have been used in many applications including distribution system planning [42], clock skew scheduling [43], distribution substation planning [44] and sensor localization [45].

As shown in Algorithm 3, the proposed heuristics are used to reduce the cost of solution X when a particle is updated. Based on a given solution X, the total capacity in the timeslot t is determined as TC_t. The transformer limit margin m_t is defined as $m_t = limT_t - TC_t$, which indicates the remaining electric quantity. Let w_t denote the weighting to time t. A higher weighting is assigned to a low cost period. Then, the weighted margin wm_t of timeslot t is derived by $wm_t = w_t \times m_t$. A higher weighted margin is obtained if the timeslot has further remaining capacity and the electricity price is lower. A modification step on electric quantity is defined as σ.

The detailed steps in the heuristic process are given as follows. An EV index is randomly chosen, and two available timeslots are chosen as $t1$ and $t2$. If the electricity price $EP_{t1} > EP_{t2}$ and the weighted margin $wm_{t1} < wm_{t2}$, a candidate solution is determined by moving σ from $t1$ to $t2$ because the electricity price in $t2$ is lower and the weighted margin in $t2$ is higher. If the candidate solution satisfies the transformer limit and charging rate limit, the solution X will be updated. Lastly, the margin m_t and weight wm_t will be calculated according to the updated solution.

Algorithm 3 Heuristics

Input: A solution X determined by the PSO algorithm at each iteration

Output: A improved solution X'

Total capacity assigned to timeslot t

for timeslot t less than $numT$ **do**

    $TC_t \leftarrow$ total capacity assigned to timeslot t

    $m_t \leftarrow limT_t - TC_t$

    $w_t \leftarrow EP_0 - EP_t$

    $wm_t \leftarrow w_t \times m_t$

end for

while a candidate solution is obtained or reach the end of searching

    $t1, t2 \leftarrow$ randomly choose two timeslots

    if $EP_{t1} > EP_{t2}$ **and** $wm_{t1} < \mathrm{wm}_{t2}$

        tmpX $\leftarrow$ move electric quantity (by σ) from $t1$ to $t2$

```
        end if
        if tmpX satisfy the constraints
            X' ← tmpX
        end if
    end while
    return X'
```

5.4.Baseline Algorithms

In this paper, we evaluate the performance of our proposed heuristic fuzzy PSO (PHFPSO) algorithm with basic scheduling mechanisms and six versions of PSO algorithm.

- FIFS, EDF: the first-in-first-serve (FIFS) and earliest-deadline-first (EDF) mechanisms use the basic rules to deal with the incoming charging requests without any optimization algorithm.
- RS: the random search (RS) is to choose the best schedule from 100 candidate solutions.
- OPSO, IPSO, CPSO: in Section 2.3, three basic PSO algorithms are introduced with difference velocity function, so that the original PSO (OPSO), inertia-weight PSO (IPSO), construction PSO (CPSO) algorithms are implemented as baseline algorithms.
- OFPSO: the fuzzy PSO algorithm introduced in Section 2.4 is implemented as the original fuzzy PSO (OFPSO) algorithm, which is used to compare with our proposed fuzzy PSO algorithm.
- PFPSO: we have designed a new fuzzy system to determine the three coefficients of PSO algorithm in Section 5.2, which is denoted as proposed fuzzy PSO (PFPSO) algorithm.
- PHFPSO: after deploying the heuristics (in Section 5.3) to the PFPSO algorithm, the proposed heuristic fuzzy PSO (PHFPSO) algorithm is designed as the finalized algorithm.

6. Simulation Studies

A series of simulation studies have been conducted for evaluating the performance of the dynamic scheduling system and the proposed algorithm. In the first part (Section 6.1 and 6.2), we show two static examples to compare the performance of the algorithms described in Section 5.4. In the second part (Section 6.3 and 6.4), we simulate the operation of the dynamic scheduling system over the entire period with ten timeslots. At the beginning of each timeslot, the system would be executed to determine an optimized charging schedule for the immediate timeslot with the minimum electricity cost. The schedule for the subsequent timeslots is also available but the schedule would be revised at the beginning of the next timeslot when the system is again executed. Two simulation examples are presented to evaluate the case of EVs that arrive with and without appointments. In the evaluation of the dynamic scheduling system, the performance determined by the new PHFPSO algorithm are compared with other scheduling methods.

The timeslot unit is defined as 30 minutes. We used the Nissan Leaf model 2017 [46] as the electric vehicle, which is equipped with a 30 kWh lithium-ion battery with 107 mile traveling distance. We assumed the PL uses SAE J1772 as its standard EV connector [47], whose charging power can reach 19.20 kW with the use of the AC Level 2 mode. The limited charging rate *limC* in a timeslot is 9.60 kW. We define a dynamic electricity price pattern EP_t as shown in Table 4, which denotes the electricity price at timeslot t. Hence, the varied electricity price affects the expenditure in buying electricity from the power company. The electricity price is defined in USD per kWh, and the price is used in all simulation studies.

Table 4
Electricity Price at Timeslot ($/kWh)

t	1	2	3	4	5	6	7	8	9	10
EP	0.1	0.2	0.4	0.2	0.1	0.1	0.2	0.4	0.2	0.1

The simulation results were computed by MATLAB R2016b on a PC with Intel Core i5-4570 CPU @3.20GHZ 3.20GHz, 8GB RAM and 64-bit Windows 10 Enterprise.

6.1. Simple Example with 20 EVs

In this section, a simple numerical example is illustrated to explain the proposed model. We used 20 EVs (Table 5) to determine a charging schedule for the first timeslot. The parking profile included the arrival timeslot, departure timeslot and the charging capacity demand of each EV. The first 18 EVs made the appointments, and the last two EVs arrived at the PL without appointments. The transformer limit was set to 60 kW, and the charging rate limit was set to 9.6 kW. The number of solutions in the initial population was set to 28 as determined by (25), and number of iterations was 50.

Table 5
EV Parking Profile

EV id i	arr_i	dep_i	dem_i	EV id i	arr_i	dep_i	dem_i
1	1	3	18	11	3	8	26
2	3	5	15	12	2	6	17
3	1	5	25	13	5	8	15
4	2	4	18	14	4	8	16
5	2	3	15	15	3	7	14
6	6	10	22	16	5	8	12
7	7	8	14	17	4	7	16
8	8	10	16	18	5	9	19
9	7	8	10	19[a]	1	10	28
10	6	9	20	20[a]	1	5	16

[a]EV comes without appointment.

Table 6 shows an optimal schedule determined by the proposed PHFPSO algorithm with the total electricity cost of 53.766. For example, the EV1 stays at the PL from timeslot 1 to 3. The optimal schedule will only assign capacity to the first two timeslots because their electricity prices are low. The EV19 will stay at the PL for all ten timeslots, and its charging schedule includes the first and last timeslot due to the low electricity price, while no capacity is assigned to timeslot 2, 3, 4 and 8.

The total electric quantity in the ten timeslots are 38.25, 41.78, 5.41, 46.23, 59.91, 60.00, 42.54, 4.90, 24.18 and 28.80. The most expensive electricity price is at timeslot 3 and 8, which is the reason why the total quantity in timeslot 3 and 8 are lower than the others. Also, the electric quantity assigned to timeslots 5 and 6 is higher than others because the electricity price is low.

Table 6
An Optimal Schedule for 20 EVs

	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
EV1	**9.53**	8.47	0	-	-	-	-	-	-	-
EV2	-	-	0	7.61	7.39	-	-	-	-	-
EV3	**9.55**	5.85	0	0	9.60	-	-	-	-	-
EV4	-	9.25	0	8.75	-	-	-	-	-	-
EV5	-	9.60	5.40	-	-	-	-	-	-	-
EV6	-	-	-	-	-	7.46	0	0	4.94	9.60
EV7	-	-	-	-	-	-	9.55	4.45	-	-
EV8	-	-	-	-	-	-	-	0	6.40	9.60
EV9	-	-	-	-	-	-	9.55	0.45	-	-
EV10	-	-	-	-	-	9.55	7.90	0	2.55	-
EV11	-	-	0	3.44	8.89	8.40	5.27	0	-	-
EV12	-	8.62	0	4.26	0	4.12	-	-	-	-
EV13	-	-	-	-	7.67	7.33	0	0	-	-
EV14	-	-	-	8.29	3.98	0	3.73	0	-	-
EV15	-	-	0	0	4.95	9.00	0.05	-	-	-
EV16	-	-	-	-	8.64	3.36	0	0	-	-
EV17	-	-	-	7.45	8.55	0	0	-	-	-
EV18	-	-	-	-	0	7.32	6.43	0	5.25	-
EV19	**9.60**	0	0	0	0.24	3.46	0.06	0	5.04	9.60
EV20	**9.57**	0	0	6.43	0	-	-	-	-	-

The objective values obtained by PHFPSO, PFPSO, OFPSO, CPSO, IPSO and OPSO are 53.7660, 54.3166, 54.5614, 58.5152, 56.5936 and 59.4461 respectively, and the results determined by RS, FIFS and EDF are 70.10, 73.52 and 73.69. The results show that the performance of the PSO algorithms are significantly better than random search, FIFS and EDF scheduling mechanisms. Within the performances of the PSO algorithms, the proposed PHFPSO algorithm achieves the minimum electricity cost, and the performances by PFPSO and OFPSO are comparable.

6.2. Evaluation of Algorithms with 100 EVs

A dataset of 100 EVs was simulated to evaluate the performance, and an optimized schedule was obtained. The arrival and departure times were randomly assigned within the ten timeslots, and the charging demand of each EV was randomly set to an integer value between 4 and 8 kWh. The constraints of charging rate limit and transformer limit remained to be 9.6 kW and 500 kW respectively. In this 100 EV dataset, the number of variables in the solution was 485. The size of initial population was set to 54 as determined by (25), and the number of iteration was set to 50. In order to avoid the fluctuation of the performances, we repeated the algorithms for 20 times, then the statistical results were illustrated for comparison.

Table 7 and Fig. 5 compare the performance obtained by different versions of PSO algorithms. After repeating the algorithms for 20 times, the best, worst, mean, median and standard deviation of the objective value are calculated. It is clear that the proposed algorithm (PHFPSO) outperforms other algorithms on all the merits on the objective value and the standard variation is slightly higher than CPSO and OPSO. Hence, the PHFPSO algorithm is shown to be an effective method to solve the scheduling problem.

Table 7
Performances Comparison with 100 EVs

	Best	Worst	Mean	Median	S.D
OPSO	641.0	652.9	645.3	644.8	2.79
IPSO	626.5	647.4	635.9	636.3	5.09
CPSO	641.9	649.2	645.8	645.5	**2.15**
OFPSO	594.6	618.6	605.5	606.9	7.12
PFPSO	580.9	600.2	591.4	592.9	5.78
PHFPSO	**546.1**	**559.3**	**552.1**	**551.4**	3.35

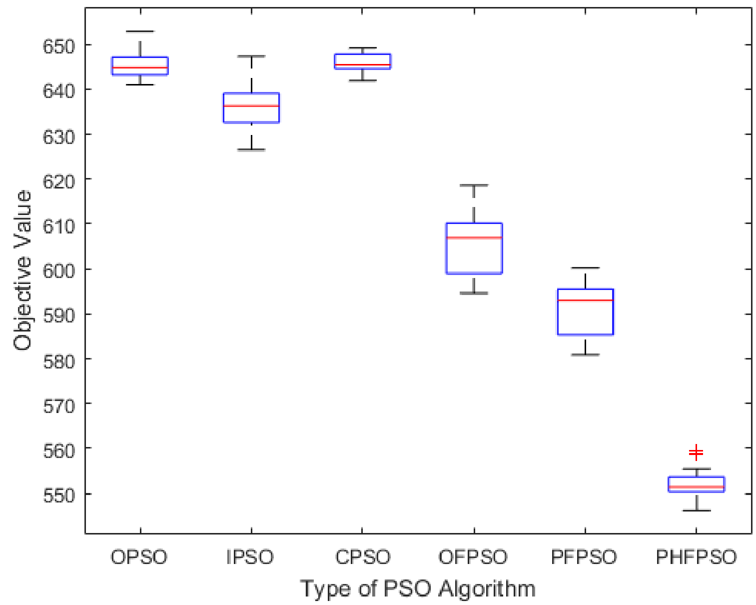

Fig. 5. Box plot of objective values with 100 EVs.

Fig.6 shows the convergence curves of the mean objective values obtained by the six algorithms. It is clear that the performance of the proposed PHFPSO algorithm is significantly better than the other algorithms, which is followed by the PFPSO, OPSO and the three versions of PSO algorithms. In this case, the performance of the proposed fuzzy PSO algorithms is relatively better than the original fuzzy PSO, and both fuzzy algorithms outperform the PSO algorithms without the fuzzy system.

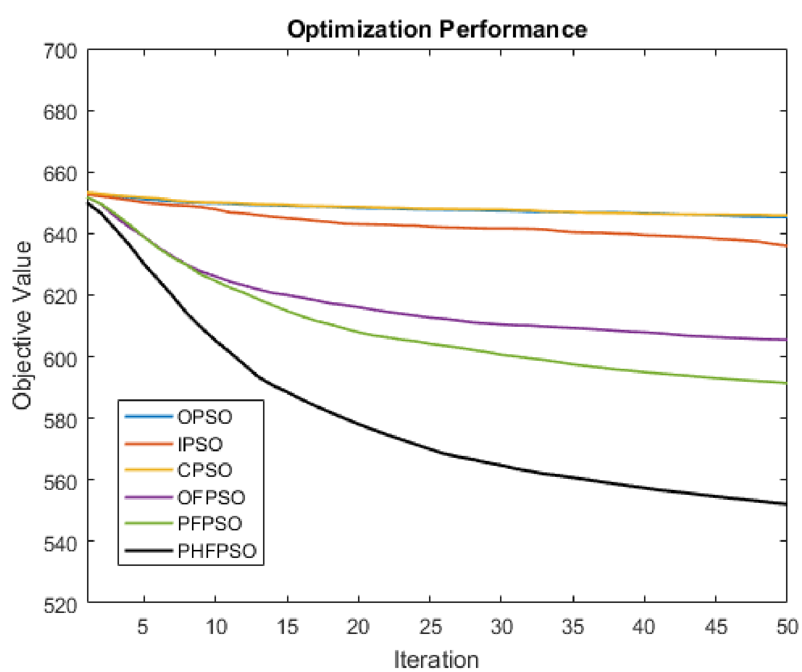

Fig. 6. Optimization performances with 100 EVs.

The electricity costs determined by the random search (RS), first-in-first-serve (FIFS), earliest-deadline-first (EDF) mechanisms are 642.9, 659.6 and 660.7 respectively. Compared with the results in Table 7, the performance of the PSO algorithms are significantly better than the scheduling mechanisms without optimization. With the use of the proposed algorithm (PHFPSO), the electricity costs of RS, FIFS and EDF are reduced by 17.73%, 20.78% and 20.99% respectively.

To determine an optimal solution of the 100 EVs, the average computational times of OPSO, IPSO, CPSO, OFPSO, PFPSO and PHFPSO are 6.2s, 6.4s, 6.5s, 8.6s, 8.5s and 23.6s respectively. Here, the computational time of the PHFPSO algorithm is longer than other algorithms because the heuristic process is employed to search for better solutions. In actual operation, the computational procedure runs only at the beginning of each timeslot to determine the charging schedule for the immediate 30-minutes. Compared with the improvement on the objective value, the computational time of 23.6 seconds should be acceptable.

6.3. Dynamic Simulation with 40 EVs

Forty EVs with 10 timeslots were considered here, and the electricity price in Table 4 was used. The transformer limit and the charging rate limit were set to 110 kW and 9.6 kW respectively. Five simulation scenarios were used on EVs with and without appointments at different proportions. In each scenario, the results were obtained by the proposed PHFPSO algorithm, and then compared with the FIFS and EDF scheduling mechanisms. The dynamic system can determine a charging schedule at the beginning of each timeslot with the use of all the EVs with appointments and the arrived EVs, and then the PL can charge the arrived vehicles with the use of the schedule for the immediate timeslot. At the beginning of each timeslot, the computational process has to be executed. In order to acquire safe statistical analysis results, the program was repeated five times and the mean of the results presented.

Table 8 shows the results of the five scenarios, with different proportions of EVs, with and without appointments. In scenario 1, all EVs arrive at the PL with appointments. With the use of proposed PHFPSO algorithm, the total cost of buying electricity is 113.5, which is 28.02% and 28.46% less than using the FIFS and EDF mechanisms respectively. In other scenarios, our algorithm also outperforms the FIFS and EDF significantly on electricity cost. Comparing the five scenarios, the results show that the more EVs that have appointments, the better the objective value. This shows the advantage to the PL if the EVs make appointments. The average computational time of the dynamic case is also given in Table 8. The decision is obtained at the beginning of each timeslot, and the computational time is acceptable.

Table 8
Results of the Dynamic Case with 40 EVs

Scenario	*1*	*2*	*3*	*4*	*5*
Number of EVs With/without appointments	40/0	30/10	20/20	10/30	0/40
Cost with PHFPSO	**113.5**	**115.5**	**118.1**	**119.2**	**123.7**
Cost with FIFS	145.3	145.3	145.3	145.3	145.3
Cost with EDF	145.8	145.8	145.8	145.8	145.8
Average Time	7.5s	6.9s	6.4s	6.4s	5.9s

- The simulations have been carried out for five times, and the mean costs are presented in this table.

An example schedule for the third scenario (20 EVs with appointment and 20 EVs without appointment) is given in Fig.7. FIFS, EDF and PHFPSO are used to determine charging schedules for the 40 EVs, with the electricity costs of 145.3, 145.8 and 118.1 respectively. In Fig.7, the real-time power load in each timeslot is shown in the bar graph, along with the electricity price. It is clear that the proposed method occupies most of the transformer limit in timeslots 5 and 6 when the electricity price is the lowest. Also, the power load in timeslot 3 and 8 is very low because of the high electricity price. The results show that the proposed method can make full use of low price resources while avoiding the high-price timeslots.

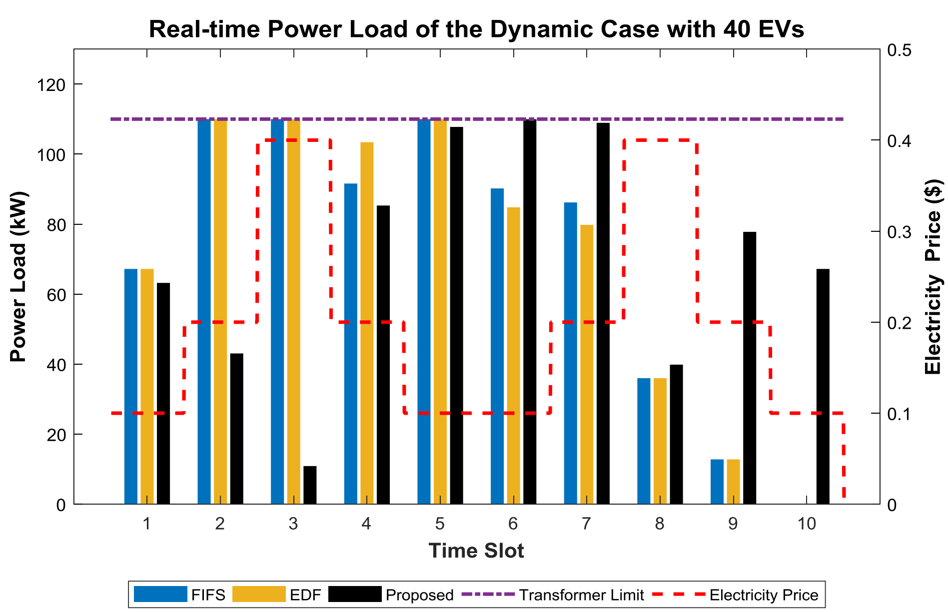

Fig. 7. Power load of the dynamic case with 40 EVs
(based on Scenario 3, transformer limit of 110 kW)

6.4. Dynamic Simulation with 150 EVs

Here, we used four scenarios to evaluate the dynamic PL system with 150 EVs. In scenarios 1, 2, 3 and 4, 150, 100, 50 and 0 EVs arrived with appointments respectively. The dynamic system was executed at the beginning of each timeslot, and the schedule for the immediate timeslot and the subsequent timeslots was determined to minimize the electricity cost. The charging rate limit was set to 9.6 kW and the number of iterations was set to 50. The transformer limit was varied from 540 kW to 460 kW.

Table 9 shows the performances of the 150 EVs with the use of the proposed PHFPSO algorithm, FIFS and EDF mechanisms. As the FIFS and EDF are both real time scheduling mechanisms, their scheduled results are the same for all the scenarios. When comparing the performances of the PHFPSO, FIFS and EDF methods, the PHFPSO always outperforms the others in all transformer limit cases.

Table 9
Performances Comparison with 150 EVs

Transformer Limit	Criterions	PHFPSO with Scenarios [a]				FIFS	EDF
		1	2	3	4		
540 kW	Elec. Cost	527	527	531	546	624	631
	Fail EVs	0	0	0	0	5	0
	Fail Dem.	0	0	0	0	11.8	0
520 kW	Elec. Cost	529	546	543	543	623	627
	Fail EVs	0	0	0	9	6	0
	Fail Dem.	0	0	0	39.4	12.2	0
500 kW	Elec. Cost	545	555	544	537	620	627
	Fail EVs	0	0	13	18	8	0
	Fail Dem.	0	0	61.9	103	23.4	0
480 kW	Elec. Cost	563	553	552	533	627	628
	Fail EVs	0	10	16	26	10	2
	Fail Dem.	0	48.7	73.0	155	28.6	10.8
460 kW	Elec. Cost	576	556	543	537	634	632
	Fail EVs	0	19	27	28	10	3
	Fail Dem.	0	98.2	148	181	28.6	12.4

[a] Scenario 1: 150 EVs with appointments, no EV without appointment;
Scenario 2: 100 EVs with appointments, 50 EVs without appointments;
Scenario 3: 50 EVs with appointments, 100 EVs without appointments;
Scenario 4: 150 EVs without appointments, no EV with appointment.

In the first case (transformer limit 540 kW), the results show that the charging demands can be fulfilled in all scenarios, and the electricity costs in all scenarios are comparable. In addition, the scenario with more appointments is usually better. In scenario 4, even though all the EVs arrive without appointments, the electricity cost is also significantly less than the FIFS and EDF results.

When the transformer limit is reduced to 520 kW, the charging demands in 9 EVs cannot be satisfied in scenario 4. It is because the PHFPSO determines a schedule to minimize the electricity cost, and that some low-price timeslots would be occupied in the earlier scheduling without any predicted information. Hence, when some later EVs arrive without appointments, the parking timeslots may not be able to satisfy their charging needs because of the transformer limit. When the transformer limit drops from 500 kW to 460 kW, some of the demand in scenarios 3 and 2 cannot be fulfilled due to the same reason. In scenario 1 where all the EVs arrive with appointments, the demands can be satisfied even though the transformer limit is low. In this case, the appointment process can help the PL to reduce the minimum requirement of the transformer limit to satisfy all the drivers' demands.

A detailed example (based on Scenario 2, transformer limit of 500 kW) is given in Fig.8 for comparing the FIFS, EDF and the proposed PHFPSO algorithm. The electricity costs of the FIFS, EDF and PHFPSO are 620, 627 and 555 respectively, which means the electricity cost by the new algorithm is reduced by 10.5% and 11.5% compared with the FIFS and EDF mechanism. In Fig.8, the new schedule occupied the transformer limits in timeslot 5, 6 and 7 when the electricity price is low. On the contrary, the proposed schedule can avoid using timeslots with high electricity price, while the timeslot 3 is fully used by the FIFS and EDF mechanisms. At the beginning of each timeslot, the dynamic system is executed for determining a solution for that timeslot, as well as plan for subsequent timeslots. The computational times of the ten timeslots are 38.5s, 34.97s, 33.02s, 31.20s, 25.86s, 20.22s, 15.20s, 9.97s, 6.45s and 4.17s respectively. In real-world situation, the computational time for the immediate 30-minutes is acceptable to determine the schedule.

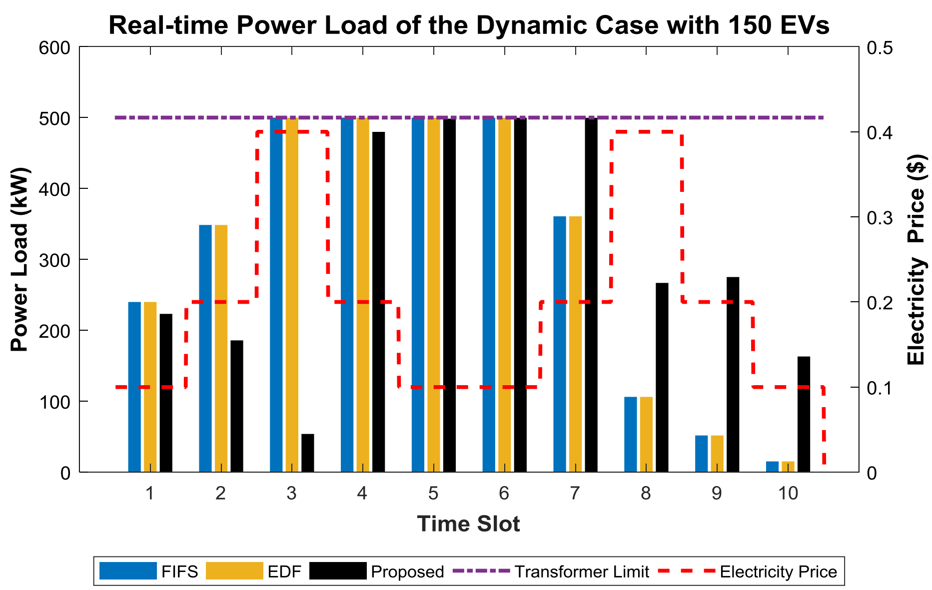

Fig. 8. Power load of the dynamic case with 150 EVs (based on Scenario 2, transformer limit of 500 kW).

In conclusion, the proposed model is feasible for dynamic scheduling no matter the EVs arrive with or without appointments, and the optimized schedule is significantly better than the FIFS and EDF mechanisms. When the transformer limit is low, the appointment process helps the system to know the expected information in the future, and then the PL can determine an optimized schedule with the minimum electricity cost. On the other hand, the appointment process can help the PL to reduce the requirement of the transformer limit, which is also a crucial consideration in the PL's operation. Lastly, we show some case studies which simulate realistic situations such as EVs with appointments but not showing up, or arrived EVs departing earlier than expected. The results show the new operation model and algorithms are also applicable to handle these sudden cases.

7. Conclusion

In this paper, we propose a new dynamic resource allocation system for recharging EVs in a PL with the aim of minimizing the PL's electricity expenditure. In order to solve the optimization problem, we designed a proposed heuristic fuzzy particle swarm optimization (PHFPSO) algorithm based on particle swarm optimization (PSO), fuzzy systems and heuristic technologies. Four case studies are presented to demonstrate the performance of the proposed dynamic system and the PHFPSO algorithm. The results show that the proposed algorithm can achieve an optimal solution and outperform the typical PSO algorithms, and the performance is significantly better than the FIFS and EDF. The results also show the proposed system is not only viable in determining dynamic solutions at the beginning of each timeslot but is flexible in dealing with EVs that arrive without appointments.

In future work, we will develop a business model to generate revenue by charging parking fees and selling electricity to the drivers. We will use multiple PLs in the system, and provide the driver a suggested PL with the use of the appointment process. We will employ the EV's minimum and maximum charging demands in the EV profile, so that the PL can determine a flexible quantity to EV. We will also employ real data in evaluating the proposed system, which include the EVs' practical arrival and departure patterns and their remaining capacities. In this paper, we study the PSO algorithm as the baseline algorithm, and deploy the fuzzy system and heuristics to PSO algorithm. We mainly focus on improving the PSO algorithm in this work, and will study other optimization algorithms with the use of fuzzy system or heuristics in the future.

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