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A Scheduling and Control System for Electric Vehicle Charging at Parking Lot

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Abstract— **This paper proposes a new electric vehicle (EV) charging scheduling and control system for a parking lot (PL), which would minimize the PL's electricity cost of recharging all the EVs. This system is to determine an optimal charging schedule for each incoming EV by allocating the electric quantities to the parking time slots of each EV considering the varied electricity price during the day. The schedule would satisfy the EV's charging rate limit and the PL's transformer limit. This paper proposes a heuristics & proportion-based assignment (HPBA) method to generate the initial population, and adapts the particle swarm optimization (PSO) algorithm to solve the optimization problem. The performance of the proposed system is compared with random search (RS), first-in-first-serve (FIFS) and earliest-deadline-first (EDF) mechanisms, and the results show that the new scheduling system would achieve the goal on minimizing the electricity cost and satisfying the charging demands and constraints.**

I. Introduction

The rapid growth of electric vehicle (EV) population in the past decade [1] has attract attention from the electric power sectors and transportation departments because of the limited public EV parking lots (PLs) and the high electric requirement of charging infrastructure. The main limitations of EV parking lot scheduling include long charging time, uncertain parking periods, varied charging demands and limit of transformer limit. Currently, most of the parking lots deal with the EVs' charging requests using the first-come-first-serve (FIFS) or earliest-deadline-first (EDF) charging strategies.

In this paper, an EV charging scheduling and control system is proposed due to the following reasons. First, a lot of people work in urban areas and live in apartments in Asian cities, and many of them cannot install private charging facilities at home. Hence, they have to choose an alternative way to recharge their vehicles during parking in a public PL with specialized EV charging facilities, and the charging process may take several hours. In this case, it is essential for a PL to have a scheduling and control system to manage the EV charging during parking. Secondly, due to the electrical power system and safety precaution of EVs, the transformer limit and the EVs' charging rate limit are also important considerations of PL. Thirdly, the current FIFS or EDF scheduling mechanisms are only rudimentary methods. With these methods, some of the late arrival requests cannot be fulfilled because the PL cannot allocate the proper resources for the EVs in advance. Lastly, the PL would buy a large quantity of electricity from the power company to recharge to the EVs. Because many power companies provide a time-of-use electricity price model by varying the electricity price at different time, the PL can make more revenue by recharging EVs at a low-price period on the condition that the parking times of the EVs cover the high and low price period.

Some researches [2] – [4] have been working to optimize the charging strategy for the parking lot. Kuran et.al [2] proposed a PL management system for a centralized EVs recharging system. The object was to maximize the parking lots revenue or maximizing the total number of EVs fulfilling their requirements. An AIMNS system was used to determine the schedule for the regular EVs, and used the FIFS and EDF mechanisms were used to deal with the irregular EVs. Their results showed the system increased the performance of the FIFS and EDF mechanisms. However, this paper only solved the optimization model using a commercial software and the detailed algorithm is not given. Zhang and Li [3] developed an optimal scheduling of PL using game-theoretic approach considering the dynamic electricity price and a transformer capacity limit. Three cases with 3, 30 and 100 players are used to evaluate the method. However, the vehicle profiles they used overlapped for 30 time intervals and the charging demands were very low, so that the candidate solutions are easy to be found. Also, the electricity prices in the 30 and 100 cases are not specified, then the results cannot be compared. Yao et.al. [4] developed a real time charging schedule for vehicle-to-grid (V2G) of a parking station using fuzzy logic. The aim was to satisfy the EV charging demand and minimize the charging cost. However, the batteries dis-charging damage was not considered when selling electricity to grid, so that V2G process is not considered in our paper.

Some works [5] - [6] focus on the optimization of the PLs' location and distribution. Mirzaei et. al. [5] proposed a probabilistic method to optimize the capacity and location of PLs considering the technical and economic aspects. The aim of their work was to maximize the distribution network's benefit by deciding on the capacity and location of each PL in the network. V. Katic et.al. [6] proposed a procedure for determining the place of PLs and the number of chargers in each PL. They concerned the power quality and concluded that the parking lot with 2 to 6 chargers are most suitable at the city center. However, we will not build the EV parking lots network currently, but will develop an optimization scheduling and control system for a PL in this paper.

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The contributions of this work are presented as follows. The PL scheduling and control system for EV charging has been developed. First, the EV charging problem is formulated with the use of proportions to represent the allocated charging electric quantities. Secondly, considering the transformer limit and the charging rate limit, a heuristics & proportion-based assignment (HBPA) method is proposed to improve the pass rate for generating the initial population of solutions. Thirdly, a particle swarm optimization (PSO) algorithm is implemented to solve the optimization problem. The proposed HPBA PSO algorithm is compared with the random search, FIFS and EDF, and the simulation results show our algorithm is significantly better than the other scheduling mechanisms.

The remaining of this paper is organized as follows: the problem formulation is described in Section II. In Section III, the HPBA method and the PSO algorithm are presented. The simulation case studies are presented in Section IV, and conclusion and future work complete this paper in Section V.

II. Problem Formulation

In this paper, the aim is to determine an optimized charging schedule for the EVs with the minimum electricity cost. Two types of EVs are used for computation: arrived EVs and EVs with appointments. Here, arrived EVs would give the expected departure times and charging demands, and the EVs with appointments would give the expected arrival times, departure times and charging demands. The EVs are encouraged to make advanced appointments to reserve a parking space for charging before arrival. At the beginning of each time slot, an optimized charging schedule is determined for the immediate time slot and the subsequent time slots with the minimum electricity cost. The notation of variables used in this model is shown in Table I.

TABLE I. Notation

Variables	Descriptions
E	Set of EVs with index i
T	Set of time slots with index t
X	Set of solution
τ	Time slot
$numE$	Number of EVs
$numT$	Number of time slots
$numV$	Number of variables in a solution
arr_i	Arrival time of EV i
dep_i	Departure time of EV i
dem_i	Charging demand capacity EV i
A_i^t	Availability of EV i at time t
EP_t	Electricity price at time t
x_i^t	Proportion of EV i's demand to time slot t
C_i^t	Allocated capacity of EV i to time t
TC_t	Total capacity of parking lot in the time slot t
$limC$	Limit of charging rate in a time slot
$limT_t$	Limit of transformer capacity in time slot t

A. EV profile

The unit of time slot is defined as 30 minutes, and the arrival time arr_i, departure time dep_i and charging demand of electricity dem_i is known by the system. We assume the EV arrives right before arr_i and departure right after dep_i, which means that the EV charging process is between arr_i and dep_i. We also assume each EV will be fully recharged with the demand capacity when it departs the PL. A_i^t denotes the availability of EV i at time slot t in (1)

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

B. Solution

The solution of this model is to determine the electric quantities allocated to available time slots of each incoming EVs. Hence, the number of variables $numV$ is derived by

$$numV = \sum_{t \in T} \sum_{i \in E} A_i^t \cdot \tag{2}$$

The solution is denoted as

$$\mathrm{X} = \{x_1^{arr_1}, ,..., x_1^{dep_1}, x_2^{arr_2}, ..., x_2^{dep_2}, ..., x_i^t, ..., x_{numE}^{arr_{numE}}, ..., x_{numE}^{dep_{numE}}\}$$

, which is a set of allocated electricity proportions corresponding to the available time slots. In vector **X**, the number of variables is $numV$, and x_i^t denotes the proportion of EV i's demand assigned to the time slot t.

C. Objective function

The objective of this model is to minimize the cost on buying electricity by a PL from a power company considering the varied electricity price at different time slots.

$$\text{minimize} \quad \sum_{i=1}^{numE} \sum_{t=arr_i}^{dep_i} x_i^t \cdot dem_i \cdot EP_t \tag{3}$$

s.t.:

$$\sum_{t=arr_i}^{dep_i} x_i^t = 1 \quad \forall i \in E \tag{4}$$

$$C_i^t = x_i^t \cdot dem_i \quad \forall t \in [arr_i, dep_i], \forall i \in E \tag{5}$$

$$TC_t = \sum_{i \in E} C_i^t \quad \forall t \in T \tag{6}$$

$$C_i^t \le limC \quad \forall i \in E, \forall t \in T \tag{7}$$

$$TC_c \le limT_t \quad \forall t \in T \tag{8}$$

Here, the minimum cost on electricity can be achieved by allocating more charging demands to the time slots when the electricity price is low.

D. Constraints

Constraint (4) shows the sum of the allocated proportions to any EV equals to 1, which means the charging demands by EVs are fully satisfied during its parking period. Equation (5) defines the electricity amount allocated to EV i in the time slot t, and (6) determines the required capacity of the parking lot at time slot t by summarizing the individual allocated capacities by each EV. Considering the EV's charging rate limit, constraint (7) states that the allocated capacity to any EV at any time slot should be within the defined charging rated $limC$. Constraint (8) indicates that the total capacity in the time slot t should not exceed the maximum transformer capacity limit $limT_t$.

III. METHODOLOGY

In this paper, we have proposed an algorithm to solve the optimization problem, which is based on the particle swarm optimization algorithm and heuristics. The complexities for determining the optimal schedule are as follows. Firstly, the number of variables in a decision vector is *NumV* and the variables are all real numbers. Secondly, due to the transformer limit and charging rate limit in the time slots, the decision model needs to check the constraints (7) and (8) after obtaining the candidate schedules. Lastly, considering various electricity prices during the whole time period, it is essential to apply optimization operation to minimize the PL's cost. The flow chart of the proposed algorithm is shown in Fig. 1.

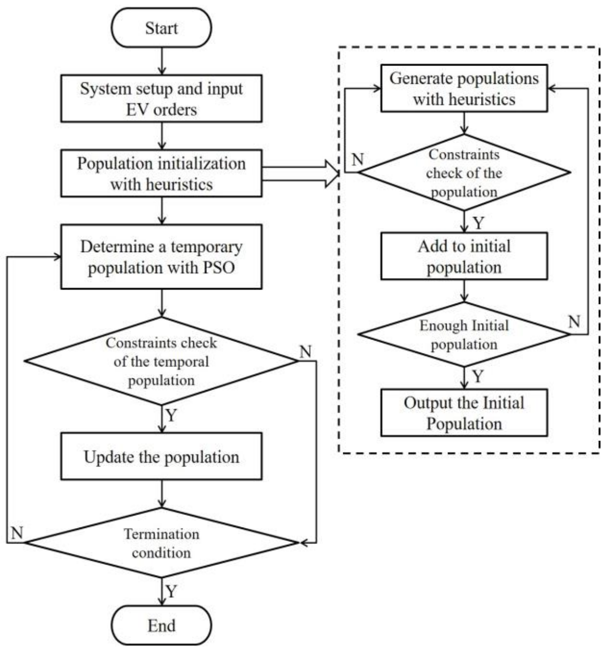

Figure 1. Flow chart of the proposed algorithm.

A. Parameters setup

The number of iterations is denoted by *numI*. The number of population in each iteration is denoted by *numP*, which is also number of initial population generated by the heuristics. The dimension of the solution is *numV*, which is derived by the set of EVs. We also denote *numRep* as the number of repeats for the algorithm to evaluate the performance.

B. Heuristics & Proportion-Based Assignment

As shown in Section II, the initial population contains the proportions of electric quantities of each EV. The use of proportion would make sure that the EVs' demands are satisfied. In the progress of the evolutionary algorithm, the initial population is usually generated randomly. In this paper, a heuristics & proportion-based assignment (HPBA) method is proposed to improve the efficiency of generating the initial population by heuristics. The basic steps of HPBA method are as follows. First, the charging demand of each EV is assigned to its available time slots by an average quantity. Let M_i^t be the mean/average electricity amount of EV i assigned to time slot t, which is derived by

$$M_i^t = \frac{dem_i}{dep_i - arr_i + 1}. \tag{9}$$

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

$$TC_t = \sum_{i=1}^{numE} M_i^t. \tag{10}$$

As the arrival time, charging demand and stay time are different for each EV, the electricity demand for each time slots could vary a lot. The following would calculate the proportion value P_i^t used for allocating EV's charging demand at time slot t by

$$P_i^t = 1 - \left(TC_t \Big/ \sum_{t=arr_i}^{dep_i} TC_t \right). \tag{11}$$

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

The pseudo-code for the proposed HPBA method is shown in Algorithm 1. In line 4 – 9, the aim is to allocate the electric quantities on average to all the available time slots of each EV. The total electric quantities of the time slots are calculated in line 10 – 12. A set of initial population with *numP* solutions is generated in the loop (line 13 – 31), and a candidate is determined in line 15 – 30. From the perspective of EV i, the proportion x_i^t is calculated in line 17 – 24. After determining a candidate solution **P'**, it will be checked by the constraint check function. The solution would be saved to the population only if it passes the check. The population initialization process will finish when the number of candidates reaches *numP*.

In Section IV.A, the proposed heuristic and proportion-based assignment method for generating initial population are compared with random search method. The results have shown that the computational time of the HPBA method is 42% shorter that the random method, and the pass rate of HPBA is 70% higher than the random method.

C. Particle Swarm Optimization Algorithm

In this model, we have adapted the particle swarm optimization (PSO) algorithm [7] – [9] to solve the proposed problem. The pseudo-code is given in Algorithm 2. At the beginning of the PSO algorithm, the solution with minimum objective value is assigned as the personal best particle P^{best} and global best particle G^{best} from the initial population in line 3 – 12. In line 13 and 14, the initial population is assigned to particle set **X**, and the initial velocity **V** is randomly assigned within the range of [-v_{min}, v_{min}]. The PSO loop for determining the optimal solution is shown in line 15 – 33.

Within each iteration, the particles in the population are updated in line 17 – 30. In line 17, the velocity is derived by the previous velocity **V**, the difference between the particle **X** and personal best solution P^{best}, and the difference between the particle **X** and global best solution G^{best}. Then, the particle **X'**

Algorithm 1 Population Initialization with Heuristics

1: **Input**: EVs list **E**, number of EVs *numE*; number of variables *numV*, number of population *numP*;
2: **Output**: A set of populations/solutions **P** ;
3: Calculate the maximum time slots in ***E*** as T_{max} ;
4: **for** $i = 1$ to *numE* **do**
5: $ave_i = dem_i / (dep_i - arr_i + 1)$;
6: **for** $t = arr_i$ to dep_i **do**
7: $al_{it} = ave_i$;
8: **end for**
9: **end for**
10: **for** $t = 1$ to T_{max} **do**
11: $TC_t = \sum_{i=1}^{numE} C_i^t$;
12: **end for**
13: **while** $numP' \geq numP$ **do**
14: **P'** = *null* ;
15: **for** $i = 1$ to *numE* **do**
16: $T = arr_i$ to dep_i;
17: **for** $t = arr_i$ to dep_i **do**
18: $P_i^t = 1 - \left(TC_t / \sum_{t=arr_i}^{dep_i} TC_t \right)$
19: **end for**
20: calculate the minimum value in P_i^T as P^{min} ;
21: **for** $t = arr_i$ to dep_i **do**
22: $x_i^t = P_i^t + P^{min} - 2 \times P^{min} \times rand(1);$
23: **end for**
24: scale x_i^T to range [0,1];
25: insert x_i^T to **P'**;
26: **end for**
27: **if** check(**P'**) $\neq$ -1 **then**
28: insert **P'** to **P**;
29: **end if**
30: calculate the size of **P'** as *numP'* ;
31: **end while**
32: **return P**

Algorithm 2. Particle Swarm Optimization Algorithm

1: **Input**: EVs list **E**, initial population **P**;
2: **Output**: An optimized solution for allocating electric quantity to EVs;
3: P^{best} = **P**;
4: $i\_G^{best} = 0;$
5: $f\_G^{best} = obj\ (\boldsymbol{P}(1,:))$;
6: **for** $iP = 1$ to *numP* **do**
7: $f\_P^{best}(iP) = obj\ (\boldsymbol{P}(iP,:))$;
8: **if** $f\_P^{best}(iP) < f\_G^{best}$ **then**
9: $f\_G^{best} = f\_P^{best}(iP)$;
10: $\mathbf{G}^{best} = \boldsymbol{P}(iP,:)$;
11: **end if**
12: **end for**
13: **X = P**;
14: **V** = $v_{min} - 2 \times v_{min} \times$ rand(1, *numP*);
15: **for** *it* = 1 to *numIt* **do**
16: **for** *iP* = 1 to *numP* **do**
17: $\mathbf{V}(iP,:) = k \times \mathbf{V}(iP,:) + c_1 \times rand(1,numV) \times [\mathbf{P}^{best}(iP,:) - \mathbf{X}(iP,:)] + c_2 \times rand(1,numV) \times [\mathbf{G}^{best} - \mathbf{X}(iP,:)]$;
18: $X' = \mathbf{X}(iP,:) + \mathbf{V}(iP,:)$;
19: **if** check(X') $\neq$ -1 **then**
20: $\mathbf{X}(iP,:) = X'$;
21: **end if**
22: $obj = obj\ (\boldsymbol{X}(iP,:))$;
23: **if** $obj < f\_P^{best}(iP)$ **then**
24: $P^{best}(iP,:) = \boldsymbol{X}(iP,:)$;
25: $f\_P^{best}(iP) = obj$;
26: **end if**
27: **if** $f\_P^{best}(iP) < f\_G^{best}$ **then**
28: $\mathbf{G}^{best} = P^{best}(iP,:)$;
29: $f\_G^{best} = f\_P^{best}(iP)$;
30: **end if**
31: **end for**
32: $perf(it) = f\_G^{best}$;
33: **end for**
34: **return** $\mathbf{G}^{best}$

is determined by adding up the previous particle and the current velocity in line 18. If the constraint check is passed, the particle **X'** is assigned to particle **X**. When the updated particle **X** is determined, the objective value *obj* of **X** will be compared with the f_P^{best} and f_G^{best} in line 22 – 30. After the *numIt*-th iteration, the global best particle G^{best} is returned as the optimal solution, and the objective value is f_G^{best}.

D. Random Search, First-In-First-Serve and Earliest-Deadline- First

In this paper, we have used three basic scheduling mechanisms, random search (RS), first-in-first-serve (FIFS) and earliest-deadline-first (EDF), to compare with the proposed PSO algorithm. The RS mechanism is to assign the proportions to the available time slots of each EV randomly. With the use of the RS method, all of the EVs' demands can be satisfied. The RS is to generate a large number of candidate solutions, then the solution with the minimum objective value is chosen as the final decision. The FIFS mechanism is to sort the EVs according to their arrival times, and then assign the sorted EVs to their available time slots. The assignment strictly follows the transformer limit and charging rate limit. If the constraints are not met, the mechanism will assign the remaining demand to the next time slot. The EDF mechanism is to sort the EVs according to their departure times, and then the assignment procedure is the same as FIFS mechanism. It is important to mention that the FIFS and EDF mechanisms may not satisfy all of the EVs' charging demands.

IV. Simulation Studies

Simulation studies have been used to evaluate the performance of the proposed algorithm. Firstly, we present the result of the proposed heuristics & proportion-based assignment (HPBA) method and then compare with a random search method to generate some initial populations of candidate solutions. Secondly, we use the HPBA-PSO algorithm to determine the optimal charging schedule with different sets of EV profiles, and the performances are compared with random search (RS), first-in-first-serve (FIFS), earliest-deadline-first (EDF) scheduling mechanisms.

In this paper, we consider the Nissan Leaf model 2017 [10] as the type of electric vehicle, which equipped a 30 kWh lithium-ion battery with 107 mile traveling distance. We assume the parking lot uses SAE J1772 [11] as its standard EV connector, whose charging power can reach 19.20 kW with the use of AC Level 2 mode. The limited charging rate *limC* in a time slot is 9.60 kW. The time slot unit is defined as 30 minutes, and the earliest arrival time is set to the time slot 1. Then, we have simulated a parking profile for 20 EVs in Table II. For example, the EV_1 arrives at the parking lot at the first time slot and departure 1.5 hours later at the third time slot, and the charging demand of EV_1 is 18 kWh. We define a dynamic electricity price pattern EP_t in Table III. Here, the varied electricity price would affect the PL's cost spend on buying electricity from energy company.

TABLE II. 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	1	10	28
5	2	3	15	15	1	5	16
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	3	7	14
10	6	9	20	20	4	8	16

TABLE III. ELECTRICITY PRICE AT TIME SLOT

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

A. Population Initialization

As shown in Section III, Algorithm 1 introduces the HPBA method to generate initial population. In this part, the proposed method is compared with the random method by generating the same number of initial candidates. We have analyzed the performance of the population initialization methods, and found that the transformer limit *limT* has a grave effect on generating the candidate solutions.

Here, we have compared the performance of HPBA and random search methods with different set of EVs and different *limT*. The results are listed in Table IV. The number of population is 100, and the initialization process will terminate when the number of solutions pass the constraint check reaches 100. In this table, three sets of parking pattern are used with five, ten and twenty arrival EVs. In each case, different transformer limits are set as a constraint, and then the computational time and pass rate using HPBA and random search are recorded. The pass rate is denoted as the ratio of the solutions that pass the constraint check.

TABLE IV. POPULATION INITIALIZATION PERFORMANCE

EV Set[a]	*limT* (kWh)	HPBA		Random	
		Time (s)	Pass Rate	Time (s)	Pass Rate
I	35	**0.0852**	**14.29%**	0.1032	10.00%
I	30	**0.1114**	**11.11%**	0.1508	5.88%
I	25	**0.4910**	**1.82%**	1.2925	0.53%
I	23	**2.8842**	**0.28%**	11.6742	0.05%
II	40	**0.3599**	**4.35%**	0.4986	2.50%
II	35	**0.4816**	**3.57%**	0.5469	2.05%
II	30	**0.6678**	**2.50%**	1.2946	0.96%
II	25	**18.6495**	**0.084%**	39.7943	0.030%
III	60	**1.0654**	**2.86%**	1.1987	1.92%
III	55	**1.6310**	**1.85%**	1.7852	1.27%
III	50	**6.4398**	**0.45%**	8.3731	0.26%
III	48	**26.0275**	**0.11%**	34.2564	0.064%

a. Set I: EV 1 – 5 in Table II; Set II: EV 1 – 10 in Table II; Set III: EV 1 – 20 in Table II.

We use the first 5 EVs in Table II as an example. It is clear that the computational time of HPBA is always shorter than the random search case, and the pass rate with HPBA is always higher than using random. If the transformer limit is 35kWh, the HPBA is 17% faster than random. If the transformer limit is 23kWh, the HPBA is 75% faster than random. Hence, the proposed HPBA method performs notably better than random search when the constraint check is tighter. We also use the first 10 and 20 EVs in Table II as the parking pattern. When the transformer limit is high, the performances between HPBA and random methods are comparable. However, when the transformer limit drops, the HPBA performs better than the random considering the computational time and pass rate. The results in this part have shown the proposed HPBA method performs better than random method to generate initial populations. The advantage using heuristics is significant when the constraint gets tighter.

B. Simple Case with 5 EVs

The first five EVs in Table II are used as the parking pattern in this part. The number of time slots *numT* in this case is 5. The transformer limit in this case is set to 25 kWh. The electricity costs using the proposed PSO, RS, FIFS and EDF mechanisms are 15.72, 18.06, 25.06 and 20.74 respectively. It is clear that the PSO can get the minimum objective value than the other mechanisms. The PSO, RS and EDF can satisfy all of the charging demands, but FIFS mechanism cannot satisfy the EV 5's demand (9.6 out of 15 kWh).

Table V shows the schedule result determined by the PSO algorithm. The total electric quantities of the time slots are 19.20, 25.00, 6.80, 20.80, 19.20. In this case, the time slot 2 is fully occupied, and the time slot 3 is the minimum quantity occupied because its electricity price is the most expensive among the five time slots. The results in this simple case show that the proposed PSO algorithm can achieve the goal on minimizing the electricity cost, and the performance of PSO is better than the RS, FIFS and EDF methods.

TABLE V. PERFORMANCE WITH 5 EVS

	T 1	T2	T3	T4	T5
EV1	9.60	8.40	0	0	0
EV2	0	0	0	5.40	9.60
EV3	9.60	0	0	5.80	9.60
EV4	0	8.40	0	9.60	0
EV5	0	8.20	6.80	0	0

C. Case with 20 EVs

In this section, we use all of the 20 EVs in Table II as the parking pattern and the electricity price listed in Table III. The number of time slots is the same as the previous case, but the congestion in this case is seriously increased. Based on the evaluation in Table IV, we set 60 as the transformer limit in this case, and the charge rate limit is set to 9.6. The number of solutions in the initial population is set to 200, and number of iterations is set to 500. In order to avoid the fluctuation of the PSO's performance, we repeat the program for four times and the best result is chosen as the optimal solution. Also, the RS method is repeated four times for choosing the best solution.

The results show that the objective value determined by PSO, RS, FIFS and EDF are 61.69, 70.10, 73.52 and 73.69 respectively. In this case, both the FIFS and EDF mechanism can satisfy all the EVs' demands because the transformer limit is higher than the previous cases. Table VI shows the optimal solution determine by the proposed PSO algorithm with the total electricity cost of 61.69. The column and row refer the time slots and EVs respectively.

TABLE VI. SECHDULE RESULT FOR 20 EVS

T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
9.25	8.20	0.55	-	-	-	-	-	-	-
-	-	0	6.26	8.74	-	-	-	-	-
9.60	5.35	0	6.15	3.90	-	-	-	-	-
-	2.67	5.78	9.55	-	-	-	-	-	-
-	6.63	8.37	-	-	-	-	-	-	-
-	-	-	-	-	9.60	1.38	0	1.47	9.55
-	-	-	-	-	-	6.00	8.00	-	-
-	-	-	-	-	-	-	0	6.97	9.03
-	-	-	-	-	-	4.02	5.98	-	-
-	-	-	-	-	7.90	1.40	1.35	9.35	-
-	-	0.55	0.06	5.53	9.60	9.60	0.66	-	-
-	7.90	0	2.01	2.75	4.34	-	-	-	-
-	-	-	-	6.07	7.86	1.00	0.07	-	-
3.48	2.17	0	3.86	5.27	4.23	3.29	0	1.19	4.51
1.70	4.17	0	3.83	6.30	-	-	-	-	-
-	-	-	-	1.99	6.40	0.94	2.67	-	-
-	-	-	5.51	4.32	0.60	5.57	-	-	-
-	-	-	-	8.85	4.45	2.74	0	2.96	-
-	-	5.80	1.78	2.84	1.33	2.25	-	-	-
-	-	-	9.37	3.43	3.20	0	0	-	-

The sum of each row is the total electric quantity of the EV's charging demand, and the sum of each column is the total electric quantity in the corresponding time slot. In this case, the total electric quantity in the ten time slots are 24.03, 37.09, 21.05, 48.38, 59.99, 59.51, 38.19, 18.73, 21.94 and 23.09. The most expensive electricity price is at time slot 3 and 8, which is the reason why the total quantity in time slot 3 and 8 are lower than the others. Also, the electric quantity assigned to time slots 5 and 6 are higher because the electricity price at that time is low. In this case, the results have shown that the proposed algorithm is viable for determining an optimal charging schedule for the parking lot, and the performance is better than the RS, FIFS and EDF mechanisms.

D. *Case with 100 EVs*

We also simulate a dataset with 100 EVs to evaluate the proposed system. The arrival and departure times are randomly assigned within ten time slots (5 hours), and the charging demand of each EV is set to an integer value between 4 and 8 kWh randomly. In this case, the number of variables in this dataset is 480. The transformer limit is set to 400, and the charging rate limit is set to 9.6. The size of initial population is set to 53, and the number of iterations is set to 50. In order to avoid the fluctuation of the performances, we repeat the algorithms for 20 times, then the statistic results are illustrated for comparison.

The minimum electricity cost determine by the proposed algorithm is 301.2, while the costs of RS, FIFS and EDF are 369.88, 376.76 and 376.76 respectively. It is clear that the proposed system can significantly reduce the cost spend on buying the electricity from power company. The average computational time for determine a solution using the proposed algorithm is 4.04 seconds. Because the computational procedure is run at the beginning of each time slot, the time in seconds can be considered as an acceptable time for the PL.

V. CONCLUSION

In this paper, we propose a new EV charging scheduling and control system for a parking lot by determining an optimal schedule for each EV. Due to the variation of electricity price, the aim is to minimize the PL's electricity cost by allocating optimal electric quantities to the parking time slots with different electricity price. In order to increase the efficiency for finding the initial population, we have developed a HPBA method to generate the candidates, and a PSO algorithm is used to solve the scheduling problem. In the population initialization case, the HPBA method performs better than a random method on generating initial populations even though the constraints are difficult to meet. The results in the case studies have shown that the proposed HPBA PSO algorithm can achieve the goal on minimizing the electricity cost and satisfying the charging demands and constraints, and the performance is significantly better than other mechanisms.

In the future, we aim to extend this work by adapting the system to a dynamic PL scheduling system. Also, we will define a minimum charging demand of each EV, and then the scheduling system should also determine the total electric quantities for each EV. Lastly, we will implement and compare other algorithms to solve the optimization problem, and improve the performance of the algorithms.

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