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Original research article

Hybrid Ant Colony Optimization and Bees Algorithm for Planning of Public Fast Charging Stations on a Residential Power Distribution System

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ABSTRACT

Nowadays, the plug-in electric vehicle industry vastly grows into transportation sector worldwide. Hence, the public fast charging stations (FCSs) must be prepared to serve this emerging plug-in electric vehicle charging demand. Moreover, planning for FCSs within the urban area is quite important. A hybrid swarm optimization technique blending beneficial characteristics of Ant Colony Optimization (ACO) with Bees Algorithm (BA), named HACOBA, is developed in this paper to find the optimal locations of FCSs that are placed on the residential power distribution grid such that it maximizes the fast charging serviceability subject to power distribution system limit and public road traffic constraints. In order to verify the effectiveness of the proposed method, it has been investigated on the IEEE-69-bus test system for two sizes of the fast charger of FCSs. From the obtained simulation results, it is found that the proposed algorithm shows its competitiveness with traditional techniques.

Keywords: Covering location principle; Fast charging stations; Heuristic algorithms; Optimal planning; Plug-in electric vehicles; Power distribution system; Residential zone; Urban area

1. Introduction

Plug-in electric vehicle (PEVs) are intended to be the most environmentally friendly mobile machine replacing an internal combustion engine vehicle, especially in the urban area, in the near future

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[1-3]. However, the driving range of PEVs per full charge of a battery is still lower than an internal combustion engine vehicle which is powered by a full tank of the gasoline [4]. Moreover, another substantial lagging factor for PEVs owner is the wastage of time (in hours) for charging PEVs batteries [5]. Therefore, the large deployment of public fast charging stations (FCSs) with dump charging functions that can charge PEVs (in minutes in-stead of hours) should be widely planned and installed to meet PEVs customer satisfaction in the service area as discussed in [6,7]. Unfortunately, it is not practically feasible to install the FCS at the individual residence as they require high electric current for their operation as well as having high investment cost and operating costs [8]. Some important key points that should be considered by the FCS planner while setting the planning scheme for FCSs [9]: (i) the potential impact of the growing PEVs charging demand on the electric power distribution system [10,11]. Hence, smart grid functions for the power distribution system are efficiently implemented to manage the rising PEVs charging demand [12], (ii) estimation of PEVs charging demand through surveys from potential PEVs customers [13,14], (iii) queuing system at FCSs, the main service point in the traffic system network, used for the FCSs planning [14-18], (iv) the total cost associated with FCSs [8], and lastly (v) FCSs planning comprising several other important factors mostly depends both on traffic characteristics and PEVs behavior of FCSs.

This paper proposes a mathematical optimization model which is formulated as the NP- hard combinatorial optimization problem [19]. It is solved using a novel hybrid artificial swarm optimization technique that improves the performance of Ant Colony Optimization (ACO) Algorithm [20,21] by employing the strength of the Bees Algorithm (BA) [22], named HACOBA. The proposed algorithm is applied to find the optimal locations of FCSs such that it maximizes the fast charging serviceability subject to various constraints, i.e. the traffic service distance of FCSs, limit of waiting time in M/M/s queuing system at FCSs, and the residential power distribution system, respectively. In order to ensure the effectiveness of the proposed system and method being employed, the IEEE-69-bus test system as a standard test system has been considered, which is placed in the Tianjin Development Zone, with two size of the fast charger head. In this paper, the obtained simulation results related to the proposed system have also been compared with other traditional swarm intelligence based optimization techniques.

2. Optimization Model and Solution Methods

The proposed optimal FCSs planning model is based on the Covering Location Principle (CLP) [23-25]. This optimal FCSs planning model in the traffic network of the residential zone is planned under concept, system, and method in [25] as follow:

2.1 Mathematical Formulation of the Optimal Planning Model

According to the CLP [23], it can be presumed that most of the demand is initiated from the fixed locations within a traffic network, where traffic network is a path between supply node, i.e. location of the main service point, and demand node, i.e. centroid of the small area, within a service area; it can possess either linear or non-linear pattern while the service area is divided into various small areas which follow a tessellation pattern and represented as a discrete point. To justify the CLP, the PEV demand node is assumed to be at the fixed location in a traffic network such that PEVs owner reside on the PEV demand node can travel to FCSs site for the recharging on a daily basis. The purpose of this objective is to serve the PEVs charging demand maximally within the full and partial coverage distance. As per the description of the full and partial concept defined in [24], demand nodes located within full coverage distance will have coverage factor equal to one, and demand nodes located within full and partial coverage distance will have coverage factor less than one and it will be calculated by performing a penalizing operation as an amount proportional to their distance. For demand nodes located out of the partial distance will be rejected, and their coverage factor will be set to zero. For conclusion, it can be formulated in form of mathematical optimization model using following equations.

Maximize: $$FCSA = \sum_{l=1}^{n_L} npev_l \times z_l \quad (2.1)$$

$$cv_{n,l} = \begin{cases} 1 & d_{n,l} \le d_{\text{fullc}} \\ \dfrac{d_{\text{partc}} - d_{n,l}}{d_{\text{partc}} - d_{\text{fullc}}} & d_{n,l} \le d_{\text{partc}} \\ 0 & d_{n,l} > d_{\text{partc}} \end{cases} \quad (2.2)$$

$$n = (1, 2, \ldots n_{\text{FC}}),\ l = (1, 2, \ldots n_{\text{L}})$$

$$z_l = \max\left\{cv_{1,l}, cv_{2,l}, .., cv_{n_{\text{FC}},l}\right\}, l = (1, 2, \ldots n_{\text{L}}) \quad (2.3)$$

where,

n_{L}	The number of PEVs demand node in the residential zone (node)
$npev_l$	The number of PEVs in l^{th} demand node (cars)
z_l	Maximum value of coverage factor at l^{th} demand node
$d_{\text{fullc}}, d_{\text{partc}}$	Full/ partial coverage distance (km)
$d_{n,l}$	The on- road traffic distance between n^{th} FCS and l^{th} demand node (km)
n_{FC}	The number of FCSs in the residential zone (station)
$cv_{n,l}$	Coverage factor of FCS at bus n on l^{th} demand node

Subject to:

1) Traffic service distance constraints

$$0 < z_l \le 1,\ l = (1, 2, \ldots n_{\text{L}}) \quad (2.4)$$

$$D_{FCS}^{\min} < D_{FCS} < D_{FCS}^{\max};\ D_{FCS} = k * l_{FCS} \quad (2.5)$$

where,

l_{FCS}	Line length of the feeders between two adjacent FCSs
k	Buckling coefficient
D_{FCS}	Actual on-road traffic distance of two adjacent FCSs
$D_{FCS}^{\max}, D_{FCS}^{\min}$	Maximum, Minimum distance limit of two adjacent FCSs

2) Queuing constraints

$$W_n^{\text{RH}} < W^{\max}, n = (1, 2, \ldots n_{\text{FC}}) \quad (2.6)$$

where,

W^{Max}	Maximum allowed waiting time
W_n^{RH}	Average waiting time in line of n^{th} FCS (minute)
W_n^{RH}	can be calculated from [25].

3) Power flow balance constraints

$$S_n^{\text{FCS}} = \frac{P_{\text{CH}} \times h}{eff_{\text{FCS}} \cos\phi},\ P_n^{\text{FCS}} = \frac{P_{\text{CH}} \times h}{eff_{\text{FCS}}} \quad (2.7)$$

$$\begin{cases} P_{\text{Loss}j} = \left|I_j\right|^2 R_j, \forall j \in [1, N_S] \\ P_{\text{SUB}} = \sum_{j=1}^{N_S} P_{\text{Loss}j} + \sum_{i=1}^{N_B} P_{\text{D}i} + \sum_{n=1}^{n_{FC}} P_n^{\text{FCS}} \end{cases} \quad (2.8)$$

$$\begin{cases} -P_{\text{D}i} - P_n^{\text{FCS}} = V_i \sum_{j=1}^{N_B} V_j (G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij}) \\ -Q_{\text{D}i} - Q_n^{\text{FCS}} = V_i \sum_{j=1}^{N_B} V_j (G_{ij} \sin\theta_{ij} - B_{ij} \cos\theta_{ij}) \end{cases} \forall i \in [1, N_B] \quad (2.9)$$

$$Vd = \sum_{i=1}^{N_B} \left|1.0 - V_i\right| \quad (2.10)$$

where,

P_{CH}	The rated output power of DC fast charger (kW)
h	The number of fast chargers at the FCS

eff_{FCS}	Efficiency of fast charger
$\cos\phi$	Power factor of fast charger
S_n^{FCS}	Apparent power input or maximum charging demand of n^{th} FCS (kVA)
P_n^{FCS}	Input active power of n^{th} FCS (kW)
Q_n^{FCS}	Input reactive power of n^{th} FCS (kvar)
N_{S}	Number of branches in the power distribution system
N_{B}	The number of buses in the power distribution system (bus)
$P_{\mathrm{Loss}j}$	Active power loss at j^{th} line with FCS (kW)
I_j	Current of j^{th} line (Amp)
R_j	Resistance of j^{th} line (Ohm)
P_{SUB}	Active power from substation (kW)
$P_{\mathrm{D}i}, Q_{\mathrm{D}i}$	Active/Reactive power demand at i^{th} bus
G_{ij}, B_{ij}	Conductance/Susceptance between bus i^{th}, j^{th}
θ_{ij}	Voltage angle difference between bus i^{th}, j^{th}
V_i	Voltage magnitude at i^{th} bus
Vd	Total voltage deviation of all buses

4) Constraints of apparent power and voltage limit on lines and buses

$$V_i^{\min} \le V_i \le V_i^{\max},\ \forall i \in [1, N_B] \quad (2.11)$$

$$S_j \le S_j^{\mathrm{limit}},\ \forall j \in [1, N_S] \quad (2.12)$$

where,

$V_i^{\max}, V_i^{\min}$	Maximum, Minimum voltage limit at i^{th} bus
$S_j, S_j^{\mathrm{limit}}$	Apparent Power and Upper limit in j^{th} line

Eq. (2.1), Eq. (2.2) show the method of finding the value of the charging serviceability and coverage factor. Eq. (2.3) states that the maximum value of coverage factor of n^{th} FCS will be selected to recharge PEVs in the l^{th} demand node. Eq. (2.4) shows the traffic service distance constraints, it also states that the FCS must be placed within the partial coverage distance. Eq. (2.5) shows constraints of the actual distance between two adjacent FCSs [5]. Eq. (2.6) shows the waiting time in the queuing system as the constraint. Eq. (2.7) – Eq. (2.9) show the power flow balance constraint with the FCSs. Eq. (2.10) shows the total voltage deviation of all buses. Eq. (2.11) , Eq. (2.12) represent the apparent power and its upper limit, and voltage limit on lines and buses, respectively. The EV's arrival pattern to FCSs for recharging of EVs batteries with M/M/s queuing system is shown in Fig.1. In this paper, the queuing in the rush hour period will be considered in the residential area due to the possible occurrence of serious business activity or urgent charging demand during this period in this area [25].

2.2 Mathematical Formulation of the Solution Method

In this paper, a new metaheuristic optimization algorithm is developed to solve the aforementioned problems. Metaheuristic algorithms are based on the global diversification and the local intensification of optimization [19]. Diversification means to generate the diverse solutions in the global search space region. Intensification means to focus on the local search space region for the generation of the current good solutions. To ensure the achievability of the global optimal solution and to know about the speed of convergence related to the proposed algorithm, an optimal balance and feasible combination of diversification and intensification are needed. Here, we proposed a hybrid artificial swarm optimization algorithm blending seminal characteristics of ACO with BA, namely, HACOBA, to improve the computation effectiveness and performance in finding the optimal locations of FCSs on the proposed model. The details and procedure of the proposed technique are provided as follows.

2.2.1 Ant Colony Optimization

ACO, a well- known metaheuristic optimization algorithm, is inspired by the natural foraging behavior of real ant colony. A number of artificial ants are evaluated in all iterations due to the iterative nature of ACO. A stochastic mechanism, which is based on the pheromone quantity, is principally adopted by the ants for selecting the routes to be visited in each single step of the solution construction. From the perspective of the solution quality constructed by the ants, the pheromone trail value will be updated to encourage the ants in walking towards the routes having a higher concentration of pheromone than the previous iteration. ACO uses this mechanism to build an algorithm.

2.2.2 Bees Algorithm

BA, also a well- known optimization technique, is inspired by the natural foraging behavior of honeybees. Bees have no knowledge about food source in the search space field and bee initializes its search as a scout bee. When the scout bee locates the food source, it will return back to the hive and be raised as an employed forager bee. After this, many recruited employed foragers will follow the employed foragers who memorizes the location of the food source to exploit the nectar spread around the neighborhood area of the food source. After finishing the task of employed foraging, bee loads a small amount of nectar from the food source and then returns back to the hive During this step, some food source having a low energy concentration will be abandoned by the employed foragers. After then, these bees become new scout bees to search new food sources. The last process is called as the reinitializing process, i. e. searching of the food source will start again.

2.2.3 Applying the proposed HACOBA to the FCS Planning

The computational procedure of the HACOBA algorithm to solve FCS planning problem can be elaborated as follows:

***Step 0**: Initialization*

- Read system data and set initial parameters.
- Start iteration; $t = 0$
- Set $X = [x_1, x_2, x_3, ..., x_{n_{FC}}]$ as a control vector of an ant.
- Initial trail intensity on route is set at $\tau_{ni}(0) = 1$ and initial probability distribution on route is set at $\rho_{ni}(0) = 1$.
- Calculating the heuristic function, the heuristic function is defined as visibilities of the objective function of the station at the bus which can be expressed as in Eq. (2.13).

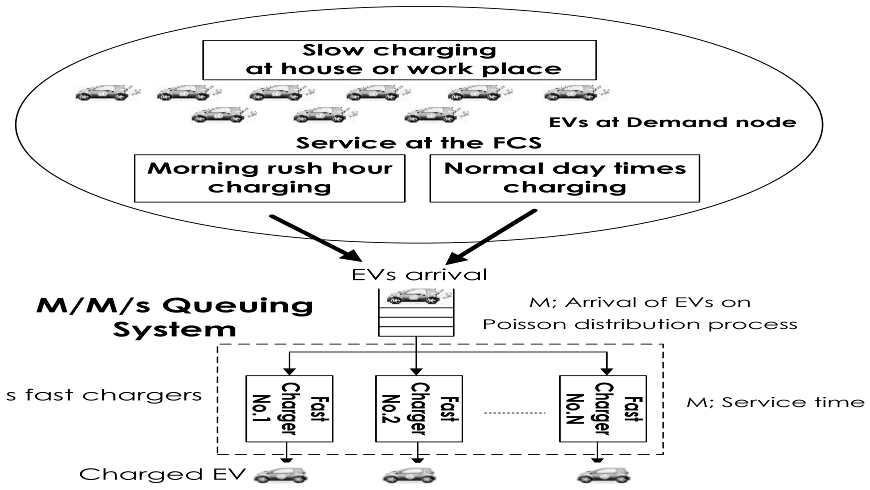

Fig. 1. EVs arrival pattern to FCSs with M/M/s queuing system during each period.

$$\eta_{ni} = \frac{1}{Obj_{ni}} \tag{2.13}$$

where,

Obj_{ni} Objective function of n^{th} station at i^{th} bus

τ_{ni} Trail intensity of n^{th} station at i^{th} bus

ρ_{ni} Pheromone evaporation coefficient of n^{th} station at i^{th} bus

Step 1: *Constructing ant solutions*

- Update iteration; $t = t + 1$
- Constructing ant population: $x_{nk}, (n = 1,2,3,......, n_{FCU})$, $(k = 1,2,3,....,m)$.

The state transition rule guiding the ant movement, an ant of k of n^{th} station choses i^{th} bus by applying the pseudo-random proportion rule using following equation.

$$i = \begin{cases} \arg\max_{i \in N_B} (\tau_{ni}(t))^{\alpha} (\eta_{ni}(t))^{\beta} & \text{if } q \le q0 \\ \hat{i} & \text{otherwise} \end{cases} \tag{2.14}$$

The parameter $q0$ can be set from 0 to 1 and q is a random number in a range of [0,1] . For $(n = 1,2,...., n_{\mathrm{FCU}})$ and $(\hat{i} = 1,2,....., N_{\mathrm{B}})$, $\hat{i}$ is a bus to be selected according to the probability distribution function that can be expressed as follows:

$$\rho_{n\hat{i}}(t) = \frac{(\tau_{n\hat{i}}(t))^{\alpha} (\eta_{n\hat{i}}(t))^{\beta}}{\sum_{i=1}^{N_B} (\tau_{ni}(t))^{\alpha} (\eta_{ni}(t))^{\beta}} \tag{2.15}$$

where,

α Relative influence of the pheromone trail information

β Relative influence of heuristic information

The selection process on the bus $\hat{i}$ on n^{th} station of ant k is based on spinning the roulette wheel by using the probability calculated in Eq. (2.15).

Step 2: *Evaluating objective function to find the best solution*

The objective function of all new ants is evaluated under all constraints; if it is feasible, then it is a candidate solution. The new best solution is searched from all candidate solutions using sorting method. Then, the new best solution is compared with the old best solution of the previous iteration. If the new best solution is better than the old best solution, then it will be the best solution of the problem *(*x^{best}*).*

Step 3: *Recruiting bees around the best solution*

The bees are recruited to search around the best solution as $xn_{nw}, (n = 1,2,3,....., n_{\mathrm{FCU}})$, $(w = 1,2,...., nba)$. The number of bees around the best solution are nba. These bees are recruited to generate the neighborhood solution around the best solution within patch sizes expressed as follows:

$$xn_{nw} = x^{\text{best}} + rand(0,1) \times ngh \times (x_n^{\max} - x_n^{\min}) \tag{2.16}$$

This process facilities to search carefully the new solution in determined area controlled by patch size (*ngh*). Moreover, this process can also help ant to release from the trap of local optima and premature convergence problem.

Step 4: *Evaluating objective function of the new solutions*

The objective function of the new solutions is evaluated as well as compared with the recent best solution; if new solution is found better than the recent best solution then it will become the best-updated solution of the problem.

Step 5: *Global updating rule*

The global updating rule is carried out in the best tour from all ants. The update pheromone is implemented as follows:

$$\tau_{ni}(t+1) = (1-\rho)\tau_{ni}(t) + \Delta\tau_{ni}^{\text{best}}(t) \tag{2.17}$$

$$\Delta\tau_{ni}^{\text{best}}(t)=\begin{cases}\dfrac{1}{\left(Obj^{\text{best}}/Obj^{\max}\right)} & \text{if } (n,i) \text{ belongs to the best solution at iteration } t\\ 0 & \text{otherwise}\end{cases} \tag{2.18}$$

where,

$Obj^{\max}$ Maximize the objective function

Obj^{best} Objective function of the best solution

Step 6: *Reinitializing the trail intensity*

To mitigate the over-accumulation of pheromones on some routes of ant, it may encounter stagnation behavior in the step of searching. The reinitializing process for the pheromone trail intensity means the initialization of BA again which is as follows:

If $t = t_r$ then reset tail intensity as $\tau_{ni}(t)=1$

where,

t_r Reinitialize iteration value

Step 7: *Stopping criteria*

If $cpu_{time} > cpu_{limit}$ then end;
else go to ***Step 1***
where,

cpu_{time} Total CPU time (in seconds) taken by the program in its execution

cpu_{limit} CPU time limit in runtime computation

The flowchart of the proposed HACOBA to solve the FCSs planning problem is shown in Fig. 2.

3. Case Studies and Discussion

This section presents the numerical examples with two cases of fast chargers which are 50 kW (i.e. *CHAdeMO DC Quick Charge-**Case I***) and 120 kW (i.e. *Tesla's Supercharger-**Case II***) with 24 kWh battery capacity of PEV (i.e. *Nissan Leaf*).

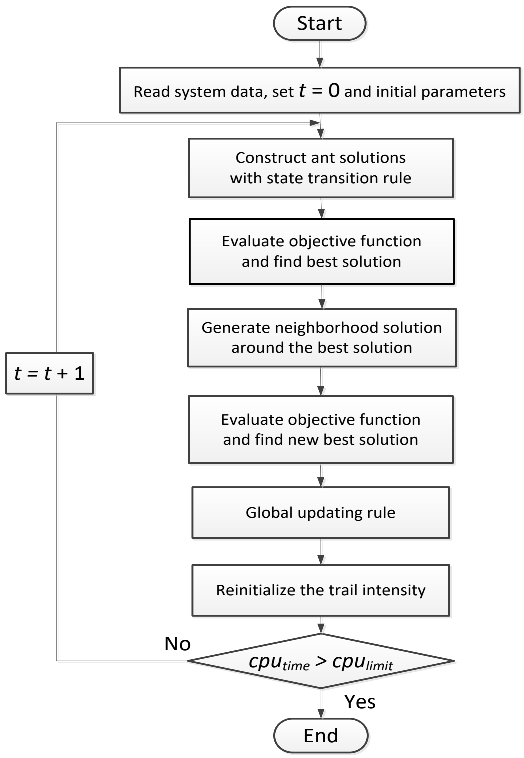

Fig. 2. Flowchart of the HACOBA Algorithm**.**

3.1 Test System Description

A residential area of a Tianjin Development Zone of about 10.5 square kilometers [26] is used as the test area [25]. In this area, IEEE-69-bus test system is placed to supply the electrical power to FCS. The system data of IEEE-69-bus test system can be found in [27], and the location of buses is the candidate site of FCSs. For this residential area, it is planned that there will be at least 3,140 PEVs by the year 2020 [26]. The number of PEVs at each demand node and their locations in the service area can be found in [26]. The on-road traffic distance between the PEV demand node and each bus can be found in Appendix presented in [25]. The site location of each bus in IEEE-69-bus test system and PEVs demand node can also be found in [25]. The IEEE-69-bus test system has 68 line sections with a daily peak load of 3.802 MW and 2.693 MVar. The rated apparent power flow in each section of the feeder is 10 MVA with base voltage of

12.8 kV. This system has the value of total real and the total reactive power losses as 195.95 kW and 89.93 kVar, respectively. The maximum and minimum limits of the voltage bus are 1.05 pu. And 0.95 pu., respectively. For the calculation of system operating conditions of the IEEE-69-bus test system, the backward- forward sweep distribution power flow has been employed in this paper. This method incorporates the potential benefits of the radial system nature [29]. From Table 1, it can be seen that the cost of the land use will be higher if it is in the vicinity of the center of the service area [25].

3.2 Parameter settings for PEV and FCS

Table 2 shows the initial parameters of BA, GA, ACO and HACOBA algorithm, respectively, required to setup in finding the optimal solutions related to the objective taken into account. The following test data is set to perform the numerical calculation. In this paper, these data are taken from diverse sources, mostly from [8], [11], [25] and [30-32].

1) For PEV, $SOC^{F} = 80\%$, $SOC^{Th} = 20\%$, $kWh_{\text{PEV}} = 24$, $V_{\text{PEV}} = 30$, $eff_{\text{CH}} = 90\%$. From [25], $t_{\text{PEV}} = 19.2$.

2) For FCSs Service, $n_{\text{FC}} = 6$, $p = 0.03$, $h = 5$, $d_{\text{fullc}} = 2$, $d_{\text{partc}} = 0.5$, $D_{FCS}^{\max} = 0.5$, $\cos\phi = 0.95$, $RH = 2$, $W^{\max} = 5$.

3.3 Computational Setting

The results were computed by using an Intel® Core™ 2 Duo Processor (2.2 GHz, 2GB RAM) while Matlab® programming language was used in writing a program code. The search space of all cases is the number of buses$^{(\text{number of stations})}$ ($69^6 \approx 1.07918163081 \times 10^{11}$). In each case, 100 trial runs were carried out for all algorithms. It is fair to use the total CPU time to be the "stopping criteria" in each run times. Then, all algorithms taken into account can use this criterion. For the considered cases, $cpu_{limit} = 30$ seconds.

3.4 Solution Quality in maximizing the fast charging serviceability as an objective

Case I: The power output of the fast charger is 50 kW.

The solution of fast charging service ability can be calculated as 82.37%. The positions of FCSs with maximizing fast charging service ability on power distribution system are shown in Fig. 3. The optimal locations of FCSs obtained by the proposed HACOBA are shown in Table 3. The solution quality of fast charging service ability by all algorithms is shown in Table 4.

Case II: The power output of the fast charger is 120 kW.

The solution of fast charging service ability can be calculated as 81.08%. The positions of FCSs with maximizing fast charging service ability on power distribution system are shown in Fig. 3. The optimal locations of FCSs obtained by the proposed HACOBA are shown in Table 3. The solution quality of fast charging service ability by all algorithms is shown in Table 4.

3.5 Parameter Settings for HACOBA and other algorithms

The setting of HACOBA parameters would yield a better solution as well as having less computation time. It has the number of parameters, but the question arises how to adjust these in an optimal manner. From the previous literature, it has been found that the most important parameter is the population. The desired population of the proposed HACOBA is determined by varying them and setting the other parameters as a constant. The boxplot of FCSA solution from the varying population of HACOBA is exemplified in Fig. 4. The population of HACOBA varied from 60 to 240. It can be seen that population of 80 yields a higher fast charging serviceability.

Using this technique, the optimal parameters of HACOBA algorithm and other algorithm will be found. These parameters can be found in Table 2.

3.6 Computational Efficiency

The convergence characteristics of average fast charging serviceability solution obtained by all algorithms in ***Case I*** and ***Case II*** are shown in Fig. 5. It can be seen from the convergence graph that HACOBA can meet the lowest value of average solution on the time span of 30 seconds.

4. Conclusion

This paper proposes the planning model of FCSs based on the covering location principle on the distribution system in the residential zone. The prime objective of the proposed planning model is to maximize the fast charging serviceability subject to various constraints, i.e. the traffic service distance, the limit of waiting during the rush hour period, and the power distribution system, respectively, for two sizes of the fast charger for FCSs. A novel hybrid artificial swarm optimization technique incorporating the beneficial characteristics of ant colony optimization (ACO) and Bees Algorithm (BA), namely HACOBA, is developed to find the optimal locations of the FCSs. The proposed planning model was tested on IEEE-69-bus test system in the residential area of Tianjin Development Zone. Numerical results show that the solution quality of the proposed algorithm has better performance and cost effective than other metaheuristics optimization techniques.

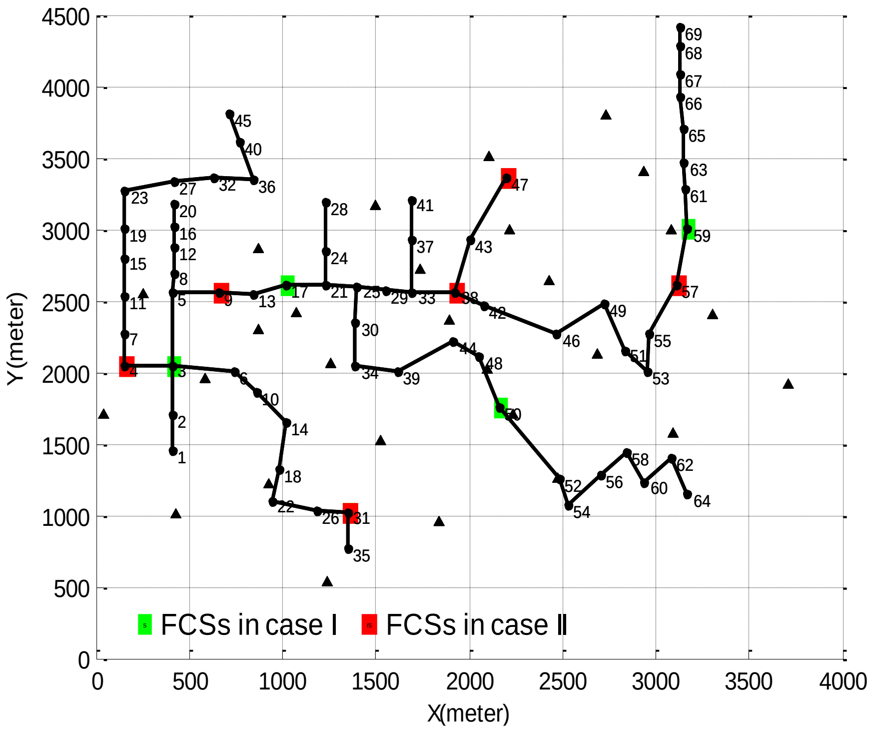

Fig. 3. The positions of FCSs on the power distribution system.

Table 1. Land price per square meter at bus number.

Cost ($)*	Bus Number	Cost ($)	Bus Number
160	47 59 61 63 66 67 68 69	250	1 2 3 6 10 14 18 22 26 31 35
180	4 5 7 8 9 11 12 13 15 16 19 20 23 27 32 36 40 45	275	17 21 24 25 28 29 30 33 34 37 38 39 41 42 43 44 48**
200	46 49 50 51 52 53 54 55 56 57 58 60 62 64		

*Land price per square meter in Tianjin is referred from [28].
**These node bus are closer to the center of the service area.

Table 2. Parameters of BA, GA, ACO and HACOBA Algorithm.

Method	**BA**						**GA**			**ACO**				**HACOBA**						
Parameter	pop	nep	nsp	o	e	ngh	pop	pc	G_{gap}	pop	α	β	d_0	pop	α	β	d_0	nba	ngh	t_r
Case I	100	40	2	3	1	0.03	80	0.7	0.99	100	1.3	1.0	0.1	80	2	1.0	0.1	30	0.03	35
Case II	100	40	2	3	1	0.03	80	0.7	0.99	100	1.3	1.0	0.1	80	2	1.0	0.1	30	0.03	30

Table 3. Optimal Locations of FCSs and Solution Quality of FCSA Obtained by HACOBA Algorithm.

Case	**Optimal Locations of FCSs on Power Distribution System**			**Solution Quality of FCSA**				
	Bus Position (Bus No.)	Sum of Voltage Deviation	Average Waiting time of all FCSs (in minute)	Min.	Avg.	**Max.**	Std. Dev.	Mean
I	3 17 31 47 50 59	2.09	1.27	78.40	81.64	**82.37**	1.00	46
II	4 9 31 38 47 57	2.42	0.01	77.70	80.01	**81.08**	1.02	40

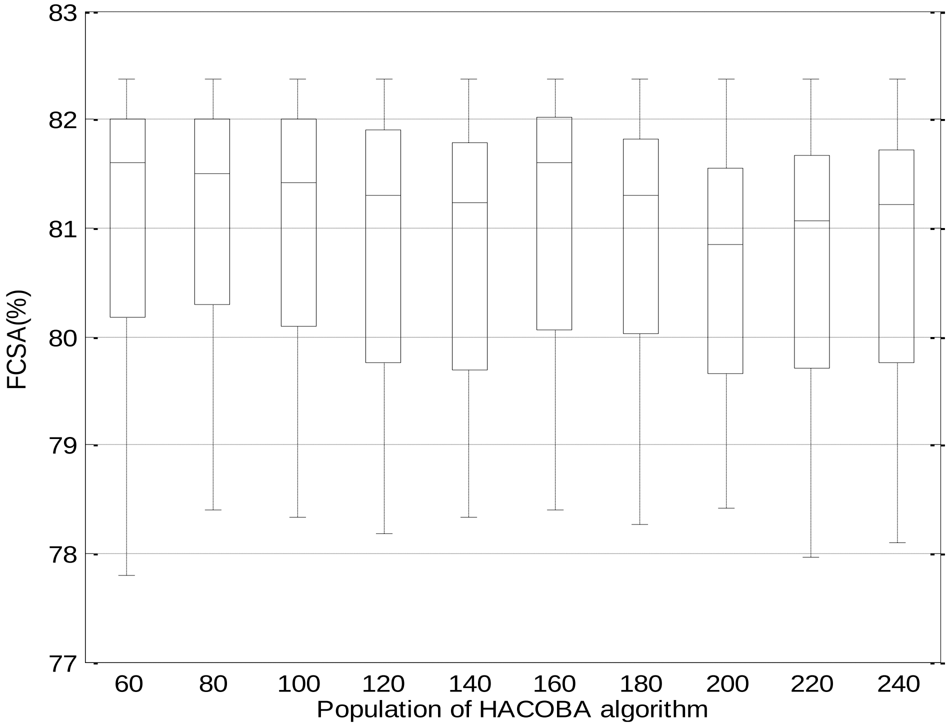

Fig. 4. The boxplot of fast charging serviceability from varying population.

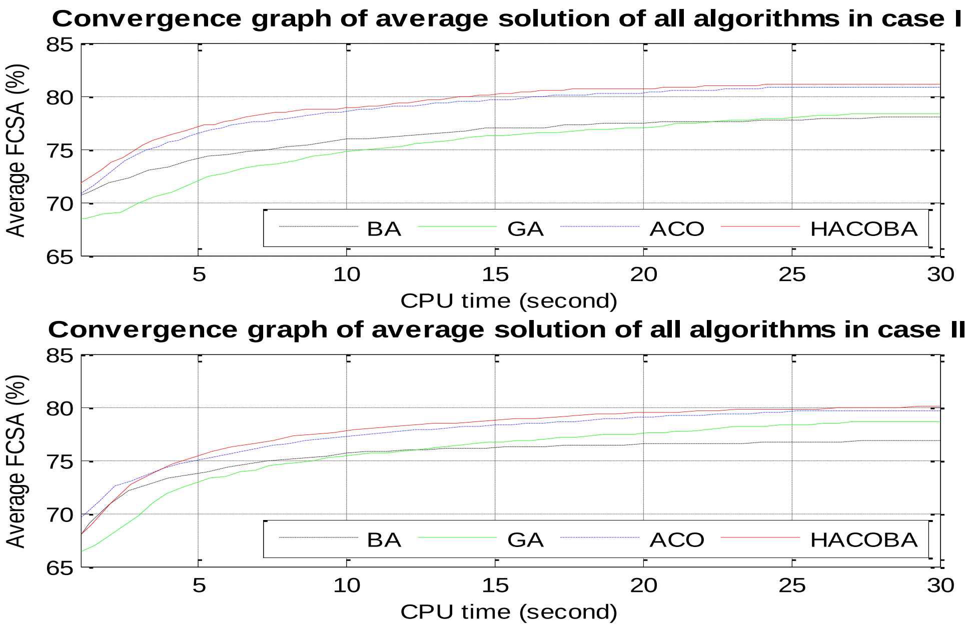

Fig. 5. Convergence graph of the average fast charging serviceability solution on time span of 30 seconds.

Table 4. Comparison of Solution Quality of Fast Charging Serviceability for all algorithms.

Method	Min.	Avg.	Max.	Std. Dev.	Mean Iteration
			Case I		
BA	73.10	79.78	81.24	1.7	42
GA	73.06	77.86	82.02	1.8	45
ACO	77.76	81.59	**82.37**	1.2	69
HACOBA	78.40	81.64	**82.37**	1.0	46
			Case II		
BA	74.51	76.83	79.32	1.03	42
GA	74.84	78.66	**81.08**	1.37	57
ACO	76.90	79.68	**81.08**	1.05	50
HACOBA	77.70	80.01	**81.08**	1.02	40

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