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Optimal siting and sizing of rapid charging station for electric vehicles considering Bangi city road network in Malaysia

Md. Mainul ISLAM[1,*], Hussain SHAREEF[2], Azah MOHAMED[1]
[1]Universiti Kebangsaan Malaysia, Bangi, Selangor, Malaysia
[2]United Arab Emirates University, 15551, 1 Al-Ain, UAE

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Abstract: Recently, electric vehicles (EVs) have been seen as a felicitous option towards a less carbon-intensive road transport. The key issue in this system is recharging the EV batteries before they are exhausted. Thus, charging stations (CSs) should be carefully located to make sure EV users can access a CS within their driving range. Considering geographic information and traffic density, this paper proposes an optimization overture for optimal siting and sizing of a rapid CS (RCS). It aims to minimize the daily total cost (which includes the cost of substation energy loss, traveling cost of EVs to the CS, and investment, variable, and operational costs of the stations simultaneously) while maintaining system constraints. The binary gravitational search algorithm, genetic algorithm, and binary particle swarm optimization algorithm were employed to optimize the daily total cost by finding the best location and sizing of the RCS in a given metropolitan area in Malaysia. The results show that the proposed methods can find optimal locations and sizing of a RCS that can benefit EV users, CS developers, and the power grid.

Key words: Electric vehicles, rapid charging station, optimal planning, gravitational search algorithm, genetic algorithm, particle swarm optimization

1. Introduction

Air and sound pollution, diminishing fossil fuels, and climate change continue to motivate the search for new transportation solutions. As such, electric vehicles (EVs) have become a green solution for those problems. The first and foremost advantage of EVs, among others, is that they do not emit pollution like automobiles with internal combustion engines. Another important advantage of an EV is that it is clean, it produces little sound, and the battery can be recycled [1]. EV acceptance depends on the availability of charging stations (CSs), charging time and cost, user facilities, and convenience. Nonetheless, inappropriate placement of EV CSs could have negative effects on the public acceptance of EVs, the layout of the traffic network, and the convenience of EV drivers [2].

Different CS models have different charging behaviors and system impact. AC slow chargers have a small or even negligible impact on the grid, but the scenario is totally different for rapid charging. Rapid charging stations (RCSs) can enforce massive loading with the increase of EV connections to the grid. EVs, with their immense batteries ranging from 5 kWh to 36 kWh, act as a bulk load, which can create mammoth problems as the rapid charging draws out a lot of power from the grid in a short period of time [3]. This may result in overloading and high power losses, in addition to power quality problems like voltage fluctuations, unbalance,

*Correspondence: mhsm.eee@gmail.com

etc. To reduce the power loss, the CS should be placed near the substation. However, the main urban road or vehicle position can be far from the CS, which leads to more transportation energy loss in traveling to the CS. These issues reveal that RCS placing and sizing is a convoluted problem that needs to consider not only the investment cost of the CS, but also the cost of grid power loss and EV user convenience.

In recent years, several studies have been conducted on optimal EV CS placement. These studies can be divided into methods based on economics and engineering concepts. From economic and social points of view, Ge et al. [4] proposed an EV CS placement method for an existing city traffic network. It was based on grid partitioning, which minimizes transportation cost using the genetic algorithm (GA) to access the CS. This method considers traffic density and station capacity as constraints. Moreover, Mehar et al. [5] introduced a model that considered investment and transportation costs to find optimal locations. The model was solved using the GA. However, in the above cases, a cost function (which includes land cost, operating costs, etc.) was not taken into consideration to optimize the system; thus, the outcome was not a globally optimal solution. For the same purpose, Kameda and Mukai developed an optimization routine for locating the CS that depends on taxi data and focuses on the on-demand local bus transportation system. The GA was again proposed for an on-demand bus transportation system to optimize the route [6]. The result was mainly based on computer simulation without justification on a practical network. In a related work, Liu et al. [7] declared an optimal location of a CS based on construction (e.g., land price) and maintenance costs, considering geographic information and traffic flow as constraint conditions. They utilized the standard particle swarm optimization algorithm (PSO) and an improved PSO algorithm by changing the inertia factor on an existing CS and then compared the results. Frade et al. [1] presented a facility location model based on maximization of demand coverage to optimize the demand, which distinguished between night- and daytime EV demands. It also emphasized population (households) and employment (jobs) for optimal locations. These CS locations are only suitable for slow charging. Furthermore, Rastegarfar et al. [3] established a cost model with reference to total investment and operation cost for optimization. This method considered geographic conditions, traffic, and local access to find the optimal locations. A computer program was developed in MATLAB to calculate the costs and optimum combination of CSs. Nonetheless, transportation cost is also important to accurately model the cost function.

On the other hand, concerning power system issues, Liu et al. [2] obtained optimal CS sites based on environmental factors and maximum coverage of service, as well as developed a cost function associated with power system loss cost to get the optimal sizing of the stations. The method was tested on the IEEE 123-node test feeder system using modified primal-dual interior point algorithm. In the meantime, Dharmakeerthi et al. [8] developed an EV model that used a combination of constant power and voltage-dependent load to find the best location in a power grid based on voltage stability margins, grid power loss, and cable flow ratings. Masoum et al. [9] designed a new smart load management control scheme based on peak demand shaving, voltage profile improvement, and power loss minimization for coordinating multiple EV chargers while considering daily residential load patterns. The proposed approach was tested on the IEEE 31 distribution test system. In a similar work, Pazouki et al. [10] introduced an optimal sizing model of CSs in relation to power loss. Traffic and distribution networks were taken into account to find the best location for CSs and the GA was used to solve the problem. Meanwhile, Wang et al. [11] introduced a traffic-constrained multiobjective pattern, taking into account the traffic system in addition to power loss for optimal CS placement. In [8–11], the authors mainly concentrated on the power issues, regardless of cost parameters. However, to make the suggested models more realistic, the cost function is imperative. Phonrattanasak and Nopbhorn [12] found an optimal location of

EV CSs on the distribution grid by minimizing total costs and real power loss while maintaining power system security and traffic flow as constraints. Ant colony optimization was used to find the best location of a CS in the existing distribution grid. The IEEE 69-bus system was utilized to validate the proposed technique. Ge et al. [13] proposed a model of EV CSs for a new city traffic network in relation to construction, operation, maintenance, and power loss costs. The allocations of CSs were optimized using queuing theory to minimize the transportation wastage cost. This planning model is not realistic for existing city road structures.

From the above existing research work on the optimal planning of RCSs, it is clear that it is difficult to systematically address all important parameters. Most of them mainly focus on economic parameters and ignore others, such as real city transportation networks. This paper therefore proposed an optimization overture to minimize the daily total cost with reference to build up (BU), transportation energy loss (TEL), and substation energy loss (SEL) due to EV charging costs using the binary gravitational search algorithm (BGSA).

The rest of this paper is organized as follows: Problem formulation for optimal RCS placement is described in Section 2. The overview and procedures of the BGSA are presented in Section 3. A test system description is given in Section 4. Simulation and test results are presented in Section 5. Finally, conclusions are drawn in Section 6.

2. Problem formulation for optimal RCS placement

The 3 common elements required in the binary optimization are the decision vector, objective function, and optimization constraints. Each element is formulated and explained to obtain the optimal solution of the RCS siting and sizing problem. The following subsections describe the details of the 3 common elements required for the RCS siting and sizing problem.

2.1. Decision vector

The decision vector represents the position of each possible CS in the road network system to be considered during the optimization process; in this case, it is called the CS placement (CSP) vector. The CSP is a binary string containing n bits. A bit 0 (zero) in the CSP indicates that no CS needs to be installed at that specified site, whereas a bit 1 (one) indicates that a CS should be built at that particular site in the road network. Thus, the CSP vector can be mathematically expressed as:

$$CSP(i) = \begin{cases} 1, & \text{if } CS \text{ is required} \\ 0, & \text{otherwise} \end{cases} \qquad i = 1, 2, 3, \ldots, n \tag{1}$$

2.2. Multiobjective functions

To solve the optimal RCS placement and sizing problem, various costs must be considered. Thus, a multiobjective optimization function consisting of 3 subobjective functions is formulated as below.

2.2.1. TEL cost

EV drivers need to move a certain distance to reach the CS for recharging their EVs. If the CS is located far away, the EVs need to utilize a lot of energy to reach the CS, which can be regarded as the TEL. As a first step in transportation energy loss calculation, the trajectory length from the jth EV (EV_j) to the ith CS (CS_i) is obtained as:

$$\mathbf{l}_{ij} = diag(\mathbf{CSP}) \times \left\| loc_{EV}^{j} - loc_{CS}^{i} \right\| i = \ 1,2,3,\ldots,N_{CS} \tag{2}$$

where N_{CS} is the number of considered possible sites for CSs, while loc_{EV}^{j} and loc_{CS}^{i} are the locations of EV_j and CS_i, respectively.

Then the minimum length ($L_{j\,\min}$) to the CS from location EV_j can be obtained as:

$$L_{j\,\min} = \min(\mathbf{l}_{ij}) \tag{3}$$

Finally, the cost of transportation energy loss TEL for EV_j to access the nearest CS can be expressed as:

$$TEL_j = P_E \times S_{EC} \times L_{j\,\min} \tag{4}$$

where P_E is the electricity price in \$/kWh and S_{EC} is the specific electricity consumption in kWh/km. The normalized total TEL cost (TEL_{norm}) is expressed as follows:

$$TEL_{norm} = \frac{\sum_{j=1}^{N_{EV}} TEL_{j\,\min}}{TEL^{max}} j = \ 1,2,3,\ldots,N_{EV} \tag{5}$$

where N_{EV} is the number of EVs and TEL^{max} is the maximum TEL cost when a single CS is selected as an optimum CS site.

2.2.2. BU cost

Station BU cost consists of the land cost and the cost of the number of chargers and the distribution transformer. It should also incorporate underground distribution cable cost and operational costs. As shown in Figure 1, in general, a station requires a 4.9 × 2.75 m area for every vehicle to access the charger, where it would overhang the curb by up to 0.08 m. The CS includes a new concrete pad set behind the curb. Parking vehicles should avoid the EV supply equipment and users should safely maneuver in front of the vehicles. The electrical conduit to the CS can be placed beneath the landscaping. A letting-off space equal to 0.9–1.5 m is required between the chargers if more than 1 charger is needed. In this paper, including landscaping and the sidewalk, a single charger area is considered as 30 m^2 and the entire cost of the station is assumed to be recovered in 10 years. However, the total area and cost of equipment required for the specific station depend on the number of chargers to be installed. This can be estimated by knowing the approximate number of EVs utilizing the specific CS ($N_{EV}^{CS_i}$), as shown in the expression below.

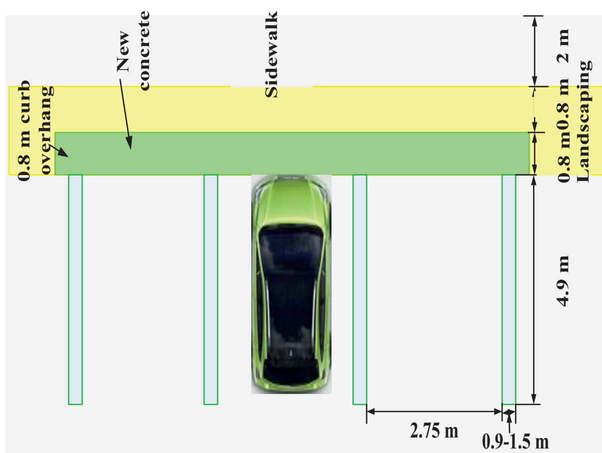

Figure 1. Charging station layout.

$$N_{EV}^{CS_i} = \sum_{j=1}^{N_{EV}} \mathbf{CSP}(1 + sign(L_{j\,\min} - l_{ij})j = 1,2,3,\ldots,N_{EV} \tag{6}$$

Therefore, the number of chargers (N_{cha}) required for CS_i is obtained as:

$$N_{cha}^{i} = \frac{N_{EV}^{CS_i} \times N_{cha}^{max}}{N_{EV}} \tag{7}$$

The capacity (S_{cap}) of the CS_i can be calculated as:

$$S_{cap}^{i} = P_{cha} \times N_{cha}^{i} \tag{8}$$

where N_{cha}^{max} is the maximum permissible number of chargers for any CS and P_{cha} is the charger rated power in kW.

Considering the above information, the BU cost for CS_i is calculated as [14]:

$$BU_i = (C_{fixed} + 30 \times C_{lan} \times N_{cha}^{i} + S_{cap}^{i} \times C_{cha} + C_{ugc} + C_{x-former} + C_{oper}) \tag{9}$$

$$C_{ugc} = C_{con}^{i} \times D_i \tag{10}$$

$$C_{x-former} = C_{tc}^{i} \times VA_i \tag{11}$$

$$C_{oper} = C_{mms}^{i} \times CS_i \tag{12}$$

where station fixed cost, C_{fixed}, represents the cost associated with facilities needed to establish the CS_i; C_{lan} is the land cost based on local price and land shape in \$/m^2; C_{cha} is the charger BU cost in \$/kW; and C_{ugc} denotes distribution cable cost, in which C_{con}^{i} is the conductor cost of the underground cable in \$/km. C_{con}^{i} cost depends on the conductor diameter, which relies on power drawn through it; D_i is the distance in kilometers between the CS_i to the nearest substation; $C_{x-former}$ is the step-down transformer cost in which C_{tc}^{i} is the transformer cost in \$/kVA; and VA_i is the transformer rating based on the load demand of CS_i. C_{oper} represents operational cost, in which C_{mms}^{i} stands for the cost of material, maintenance, and staff salaries of CS_i. Therefore, the normalized total BU cost (BU_{norm}) can be derived from Eq. (9) as:

$$BU_{norm} = \frac{\sum_{i=1}^{N_{CS}} BU_i \times \mathbf{CSP}}{BU^{max}} i = 1,2,3,\ldots,N_{CS} \tag{13}$$

where BU^{max} is the maximum cost when all CSs are selected.

2.2.3. SEL cost

When a new CS is connected to the substation, the power follows pattern changes due to the nonlinear behavior of EV charging. CSs are regarded as loads for the substation when EVs are charged and it leads to additional power loss.

The EV load (L_{EV}) for CS_i is calculated as:

$$L^i_{EV} = N^i_{cha} \times N^{CS_i}_{EV} \times P_r \tag{14}$$

where P_r is the power requirement for each EV battery.

Additional power loss APL_{EV} due to the CS is then obtained as:

$$APL_{EV} = TPL_{EV} - TPL_{original} \tag{15}$$

where TPL_{EV} is the total power loss when CSs are connected to the substation with original load and $TPL_{original}$ is the total loss without CS load connected.

Finally, the substation energy loss *SEL* cost for substation bus (m) with EV load is calculated as:

$$SEL_m = APL_{EV} \times t_{ef}(m) \times P_E \tag{16}$$

where t_{ef} (m) is the effective operating hours of CSs connected to bus (m). t_{ef} is vital for precisely calculating the power loss for the substation. Hence, t_{ef} charged via bus (m) is formulated as:

$$t_{ef}(m) = tev(m) * T/tc(m)[h] \tag{17}$$

where *tev(m)* indicates the total number of EVs charged via bus(m), *tc(m)* indicates the total number of chargers connected to bus (m), and T is the average charging time of an EV.

Finally, the normalized total *SEL* cost (SEL_{norm}) is expressed as follows:

$$SEL_{norm} = \frac{\sum_{m=1}^{N_{bus}} SEL_m}{SEL^{max}} m = \ 1,2,3,\ldots,N_{bus} \tag{18}$$

where N_{bus} is the number of buses and SEL^{max} is the maximum *SEL* cost.

All subobjective functions in Eqs. (5), (13), and (18) have been converted to per-unit by normalizing each component to maintain the values between 0 and 1.

All the subobjective functions above can be combined into a single objective function by adding them up. Hence, the final multiobjective function to solve the optimization problem in this study is expressed as:

$$F = W_1.TEL_{norm} + W_2.BU_{norm} + W_3.SEL_{norm} \tag{19}$$

where W_1, W_2, and W_3 are the relative fixed-weight factors assigned to the individual subobjective function. In this study, the same unit-weight factors are considered for all subobjectives to ensure equal priority [15].

2.3. System constraints

The optimization algorithm must be implemented while satisfying all constraints used to determine the optimal number of RCSs for the defined road network system. The CS is imperative for EVs. For this reason, at least 1 CS should be selected from the predefined possible locations where the CS should be placed, as shown in Eq. (20)

$$\sum_{i=1}^{N_{CS}} CS_i \times \mathbf{CSP} > 0 i = \ 1,2,3,\ldots,N_{CS} \tag{20}$$

Moreover, at least 1 charger should be considered for each selected CS, expressed as:

$$N_{cha}^{i} \geq CS_i \times \mathbf{CSP} i = \ 1,2,3,\ldots,N_{CS} \tag{21}$$

The permitted capacity of CS_i should not exceed the maximum allowable capacity for each station, as shown in Eq. (22):

$$S_{cap}^{i} \leq S_{cap}^{imax} i = \ 1,2,3,\ldots,N_{CS} \tag{22}$$

where S_{cap}^{imax} is the maximum capacity of CS_i.

In the meantime, to maintain the power system voltage stability, the allowable voltage limits for each bus are considered as:

$$0.95 \leq V_m \leq 1.05 m = \ 1,2,3,\ldots,N_{bus} \tag{23}$$

Furthermore, the allowable power limits for each transmission line are considered as:

$$P_l \leq P_{l-max} l = 1,2,3,\ldots N_{line} \tag{24}$$

where P_l is the apparent power. Line l must not exceed its maximum thermal limits, P_{l-max}, under steady-state operation.

3. BGSA as optimization tool

Recently, heuristics optimization techniques have been firmly accepted to solve multidimensional problems in various fields [16]. The gravitational search algorithm (GSA) is a novel heuristic optimization algorithm proposed by Rashedi et al. that mimics the concept of Newton's gravitational force. The original version of the GSA was designed for multidimensional continuous space but it was recently modified as the BGSA to solve binary optimization problems [17].

In this algorithm, the BGSA operator calculates the agent's acceleration (a_{ij}) based on Newton's law in each iteration.

The best and worst values are updated using the following expressions:

$$best(t) = \min_{i \in \{1,\ldots N\}} fit_i \ (t) \tag{25}$$

$$worst(t) = \max_{i \in \{1,\ldots N\}} fit_i \ (t) \tag{26}$$

Each agent's mass (M_i) is then calculated as follows:

$$M_i(t) = \frac{m_i(t)}{\sum\limits_{i=1}^{N} m_i(t)} \tag{27}$$

where:

$$m_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)} \tag{28}$$

The force acting on mass i from mass k is defined as follows:

$$F_{ij}^{k}(t) = G_0 \left(1 - \frac{t}{T}\right) \frac{M_i(t) \times M_k(t)}{R_{ik}(t) + \varepsilon} \left(x_{kj}(t) - x_{ij}(t)\right) \tag{29}$$

$$F_{ij}(t) = \sum_{k \in Kbest, k \neq i} r \times F_{ij}^{k}(t) \tag{30}$$

Next, the agent acceleration (a_{ij}) is updated as follows:

$$a_{ij}(t) = \frac{F_{ij}(t)}{M_i(t)} \tag{31}$$

Based on current velocity and acceleration, the next agent's velocity ($v_{ij}(t+1)$) could be calculated as in Eq. (32). However, the agent's position ($x_{ij}(t+1)$) is updated following the probability function of updated velocity with a condition as shown in Eq. (33). To achieve a good convergence rate, the velocity is limited to the interval [–6, 6] [17].

$$v_{ij}(t+1) = r \times v_{ij}(t) + a_{ij}(t) \tag{32}$$

$$x_{ij}(t+1) = \begin{cases} \overline{x_{ij}(t)}, & \text{if } r < |\tanh(v_{ij}(t+1))| \\ x_{ij}(t), & \text{otherwise} \end{cases} \tag{33}$$

where G_o is the initial gravity constant, N is the number of agents, *fit* indicates the fitness value, T is the total number of iterations, F is the gravitational force action, M is the agent gravitational mass, R_{ik} is the hamming distance between the ith agent and kth agent, ε is a small positive coefficient of 2^{-52}, r is a uniform random variable in the interval [0, 1], and *Kbest* is the selection number of the best agent applying force to the system that decreases monotonously in percentage from *Kbestmax* to *Kbestmin* along with iterations.

3.1. Implementation of the BGSA

To determine the optimal location and size of the RCS in Malaysian road network systems, the BGSA was applied to minimize the objective function given in Eq. (19), subject to the constraints in Eqs. (20)–(24), in each generation. Figure 2 presents the flowchart of the implementation procedure for the proposed BGSA in the CS siting and sizing problem.

4. Test system description

Two network systems (namely, road networks where an EV CS is likely to be placed, and the power system network that provides power to the CS) are illustrated here in detail.

4.1. Road network

The proposed approach was applied to an area of 256 km^2 in the city of Bangi, Malaysia, as shown in Figure 3. The figure demonstrates the population density, number of EVs, and land price, and it is assumed that 1000 EVs will be charged each day. Locations of charging EVs in the whole area are generated based on population density of different areas in the Cartesian geographic system, as shown in Figure 4. Considering the urban area, 20 possible CSs are assumed, with about 2.5 km between them. Twenty substations are presumed to be selected based on the availability of substations near each possible CS. In Figure 4, green rectangles, yellow circles, and yellow rectangles represent the CSs, EVs, and substation buses of the power system considered in this study, respectively. Furthermore, Table 1 lists the parameters used in calculating the objective function in Eq. (19).

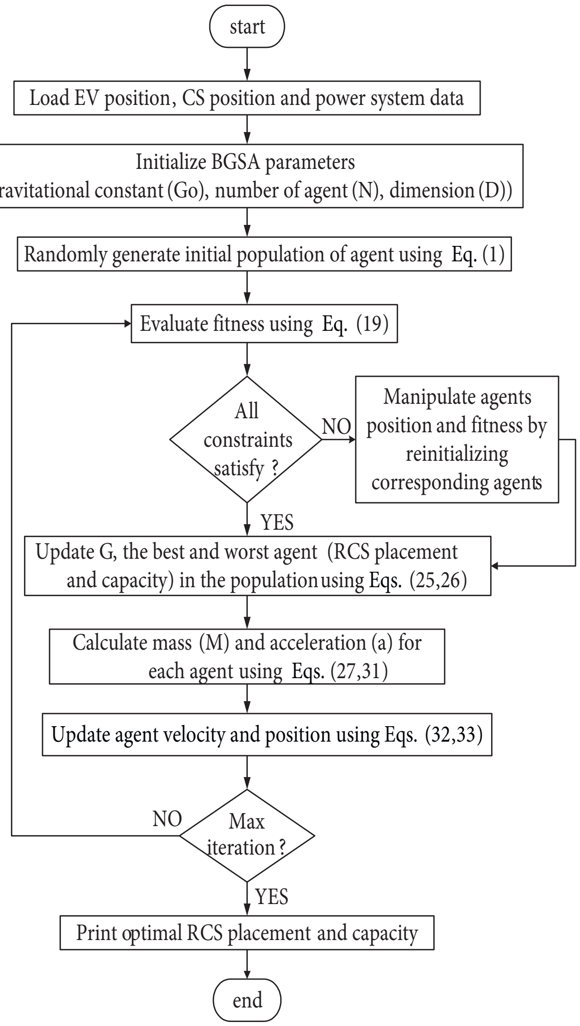

Figure 2. BGSA implementation procedure to solve the RCS placement and sizing problem.

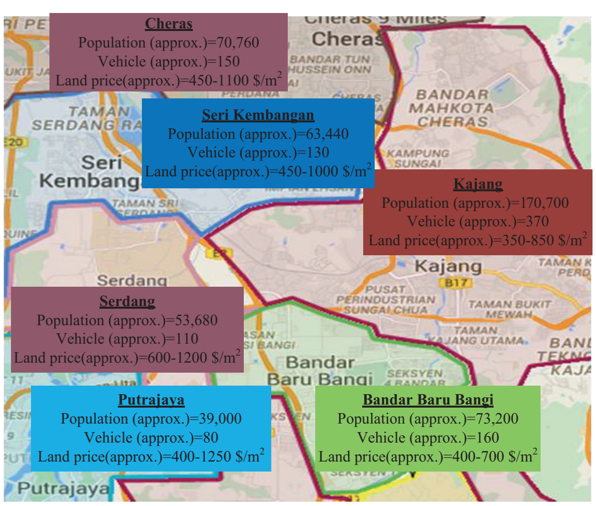

Figure 3. Geographical view of Bangi city, Malaysia.

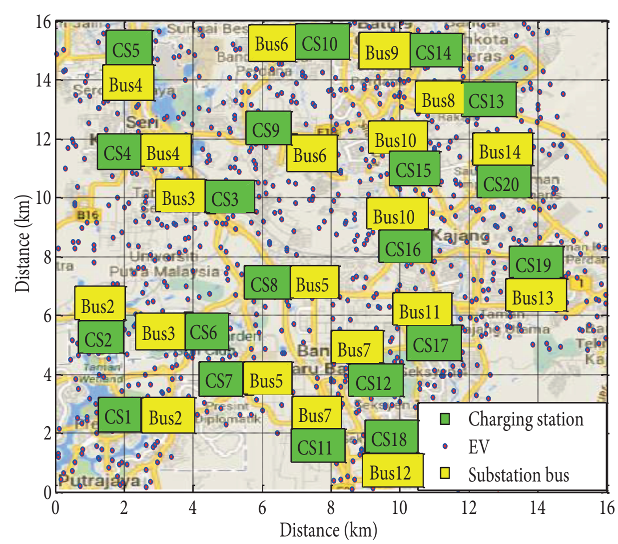

Figure 4. Road network of Bangi, Malaysia and EV distribution.

Table 1. Study parameters.

Parameter name	Parameter	Value	Unit
Number of EVs	N_{EV}	1000 (Figures 3 and 4)	
Station fixed cost	C_{fixed}	12	\$/day
Station land cost	C_{lan}	0.1–0.24 (Figure 3)	\$/m^2 per day per charger
Charger build up cost	C_{cha}	0.06	\$/kW per day per charger
Charger rated power	P_{cha}	96 [4]	kW per charger
Conductor cost (underground)	C_{con}	2.5–4	\$/km per day
Transformer cost	C_{tc}	4	\$/kVA per day
Power factor (assumed)		0.95	
Maintenance, material cost, and staff salaries	C_{mms}	100	\$/day
Power requirement for each EV battery	P_r	50 [13,18]	kW
Electricity price	P_E	0.11	\$/kWh
Specific energy consumption	S_{EC}	4 [13]	kWh/km
Average charging time of an EV	T	0.4 [12,14]	h
Maximum permissible number of charger	N_{cha}^{max}	20	

4.2. Power system network

Due to the nonlinear nature of the loads, numerical methods should be employed to calculate the power loss correctly. IEEE distribution test systems were utilized in [2,9,12] to calculate power loss. In this paper, Newton–Raphson power flow was applied to calculate power loss in the IEEE 14-bus test system, where EVs were assumed to be connected during rapid charging. The system consists of 2 generators, 3 EV CSs, 11 consumers, and 20 branches. Figure 5 represents the single-line diagram of IEEE-14 bus system.

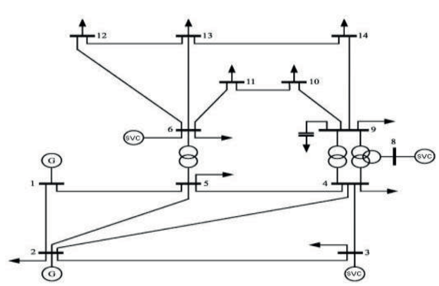

Figure 5. Single-line diagram for the IEEE 14-bus system.

5. Test results and discussion

In this section, numerical results of 5 tactics are illustrated and discussed. Furthermore, the performance comparison of the suggested BGSA with respect to the GA [4–6,10] and PSO [7] is presented.

5.1. Study tactics

Table 2 represents 5 tactics with possible combinations of subobjective functions for analyzing the CS placement and sizing problem. Each tactic is symbolized with ($\surd$) and ($\times$) signs, respectively. The sign ($\surd$) indicates that a particular subobjective function is considered in the problem, while the symbol ($\times$) indicates that the subobjective function is not considered in the problem. The algorithm-dependent parameter settings for each algorithm in the comparison are listed in Table 3. Table 4 and Figures 6–10 show the best optimization results obtained by the BGSA, GA, and BPSO. Note that in Table 4, the dusky unit corresponds to the components that have not been considered in the objective function, but were calculated only for demonstration purposes.

Table 2. Study tactics.

Tactics	TEL	BU	SEL
1	√	√	√
2	√	√	×
3	×	√	√
4	×	√	×
5	√	×	√

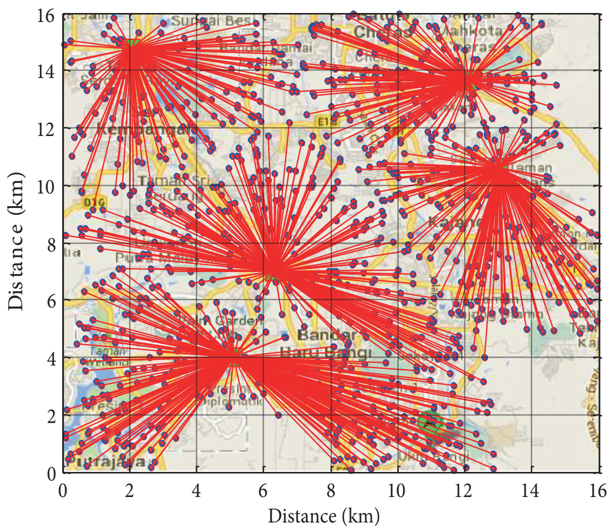

Figure 6. Optimal CS for tactic 1.

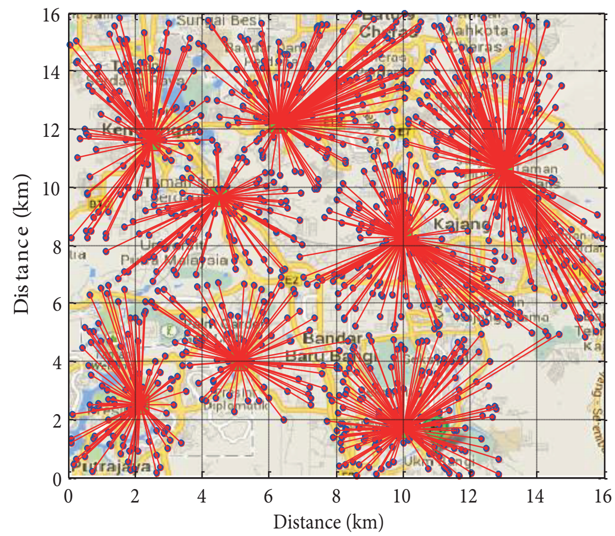

Figure 7. Optimal CS for tactic 2.

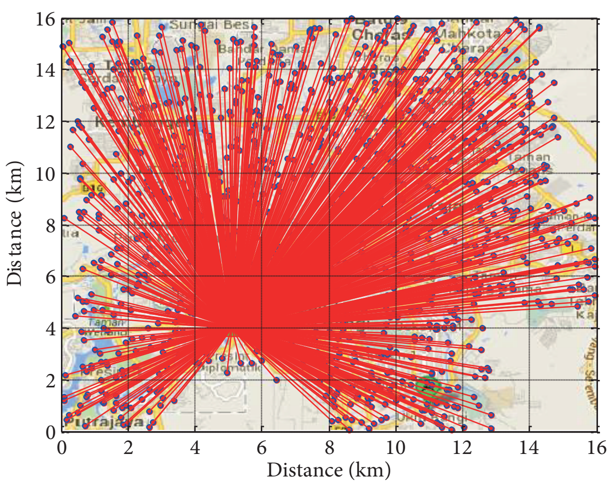

Figure 8. Optimal CS for tactic 3.

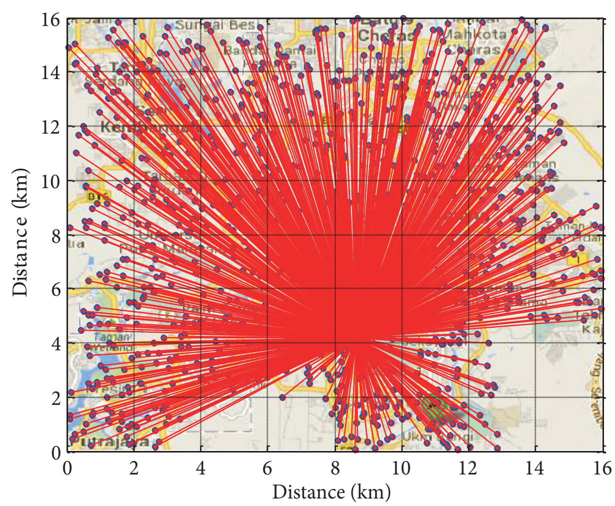

Figure 9. Optimal CS for tactic 4.

According to Table 4, the results for the various tactics can be summarized as follows.

1. Tactic 1 consisted of the desired objective function, which minimizes all BU, TEL, and SEL costs. Results of tactic 1 show that the BU cost provides 43% of the total cost, while TEL and SEL costs are more than 39% and 17% of total cost, respectively. Compared with the total cost of all of the other tactics, the total

cost of tactic 1 is the lowest. In this case, the BGSA, GA, and BPSO techniques identified 5 CSs to be installed at locations 5, 7, 8, 13, and 20, based on the lowest fitness value to cover the whole area, as shown in Figure 6. This tactic can be practiced by decision makers to consider and minimize all the costs induced by different situations.

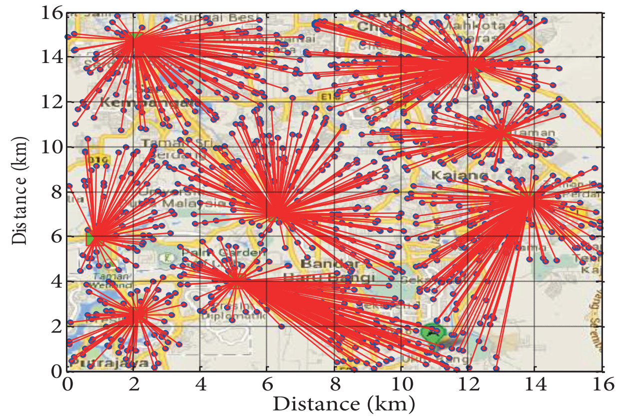

Figure 10. Optimal CS for tactic 5.

2. Tactic 2 assumed that power system energy loss is not important in CS planning. Observing normalized results from tactics 1 and 2, it can be shown that by disregarding the SEL cost, total cost increased by 26%. Thus, CSs increased from 5 to 8, as shown in Figure 7.

3. Tactic 3 shows the impact of ignoring TEL cost. In the absence of TEL, the problem tends towards minimizing BU and SEL costs. In fact, only 1 large CS at location 7, as shown in Figure 8, was identified as an optimum location with a 1920 kW capacity.

4. Tactic 4's objective was to only minimize BU. As shown in Table 4 and Figure 9, only 1 large CS at location 12, with a capacity of 1920 kW, was selected as an optimum location. Tactics 3 and 4 are not realistic because EV users need to travel a long distance to reach the station for charging, resulting in higher overall TEL costs.

5. Tactic 5 overlooked the BU and therefore TEL cost decreased by 18%. On the other hand, SEL cost increased by 23% compared to tactic 1. The number and placement of CSs increased from 5 to 8, as shown in Figure 10. This tactic could be realistic if the public sector/government participates in CS development and it is more convenient for EV users.

5.2. Comparative study on the selection of optimization techniques for CS planning

As mentioned previously, the BGSA optimization technique was compared with the GA and BPSO to evaluate the effectiveness of these techniques in solving the same problem. To validate the results, all techniques were executed 50 times for each tactic. All the optimization parameters were standardized, as shown in Table 3, to ensure a fair comparison. As noted in Table 4, all 3 methods could find the same optimum solution in at least 1 run out of 50 executions. However, this does not mean that the optimization algorithms are efficient for CS siting and sizing. Therefore, in order to distinguish whether the BGSA, GA, or BPSO is more suitable for the current problem, the best and worst solutions and consistency rate in finding the global minimum must be considered. The consistency rate can be calculated from the ratio of the number of runs that contain the same results to the total number of runs (50 executions in this case). Considering these, Table 5 and Figure 11 represent the performance of the BGSA, GA, and BPSO with respect to fitness value, optimized number

Table 3. Parameter settings used in BGSA, GA, and BPSO.

Parameter	BGSA	GA	BPSO
Population size	80	80	80
Max. iteration	50	50	50
G_o	1	-	
Kbestmin	2%	-	
Kbestmax	100%	-	
Selection rate	-	0.50	
Mutation rate	-	0.07	
C1 and C2	-	-	1
$\text{Weight}_{\text{min}}$	-	-	0.5
$\text{weight}_{\text{max}}$	-	-	0.9

Table 4. Optimization results for each tactic using BGSA, GA, and BPSO.

	RCS location	Capacity of RCS	TEL ($)	BU ($)	SEL ($)	Total cost ($)
Tactic 1	5, 7, 8, 13, 20	288, 576, 480, 384, 384	0.5193	0.5697	0.2266	1.3156
Tactic 2	1, 3, 4, 7, 9, 16, 18, 20	192, 192, 192, 192, 288, 288, 288, 384	0.3598	0.5997	0.6951	1.6546
Tactic 3	7	1920	1.1383	0.4705	0.0237	1.6325
Tactic 4	12	1920	1.0542	0.4698	1.5799	3.1039
Tactic 5	1, 2, 5, 7, 8, 13, 19, 20	192, 192, 288, 384, 384, 384, 384, 192	0.4260	0.6856	0.2793	1.3909

Table 5. Performance of the BGSA, GA, and BPSO in obtaining optimal CS placement and sizing solutions.

		Tactic 1		Tactic 2		Tactic 3		Tactic 4		Tactic 5	
		Best	Worst	Best	Worst	Best	Worst	Best	Worst	Best	Worst
BGSA	FT	1.3156	×	0.9595	0.9622	0.4942	×	0.4698	×	0.7052	×
	CS	5	×	8	8	1	×	1	×	8	×
	Con.	100	×	90	10	100	×	100	×	100	×
	Iter.	9	14	16	22	8	15	6	12	11	16
	ET	113.45	120.10	154.80	163.32	86.53	93.81	83.83	92.72	140.04	151.37
GA	FT	1.3156	1.3541	0.9595	0.9602	0.4942	×	0.4698	×	0.7052	×
	CS	5	5	8	7	1	×	1	×	8	×
	Cons.	92	8	74	6	100	×	100	×	100	×
	Iter.	10	12	15	39	9	20	8	16	8	23
	ET	124.95	135.26	165.62	179.06	100.61	108.93	90.36	99.83	151.19	160.12
BPSO	FT	1.3156	1.4207	0.9595	0.9807	0.4942	0.7406	0.4698	0.4709	0.7052	0.7632
	CS	5	2	8	7	1	2	1	1	8	9
	Cons.	42	6	24	14	10	12	80	4	52	18
	Iter.	22	38	17	40	19	37	21	37	15	42
	ET	168.11	181.78	182.39	196.84	154.11	160.04	143.65	148.54	182.59	197.47

FT = fitness value, CS = optimized charging station, Cons. = consistency percentage of fitness value, Iter. = lowest number of iterations in which optimization results started to converge with lowest best fitness value, ET = elapsed time.

of CSs, consistency of results, minimum number of iterations in which optimization results started to converge with lowest best fitness value, and elapsed time. From Table 5 and Figure 11a, it can be seen that the best fitness values and interrelated optimal CSs of these 3 techniques were the same for all individual tactics, but worst-case fitness values were different among the BGSA, GA, and BPSO. Referring to Figure 11b, the BGSA and GA techniques found the same solutions consistently for the last 3 tactics; however, for the first 2 important tactics, the BGSA was more consistent than the GA. BPSO could determine an optimum solution but it was not consistent like the other 2 methods. Figure 11c illustrates the convergence statistics of the algorithms in obtaining the best optimal solution for the CS placement problem. In this comparison, the BGSA required fewer iterations than the GA to find the optimal solution for tactics 1, 3, and 4. Nonetheless, BPSO always required more iterations to find the best solution. As seen in Table 5 and Figure 11d, the BGSA provided much faster solutions than the GA and BPSO for all tactics in almost every run. Therefore, from this comparison it can be concluded that the BGSA is more suitable for the optimal CS siting and sizing problem.

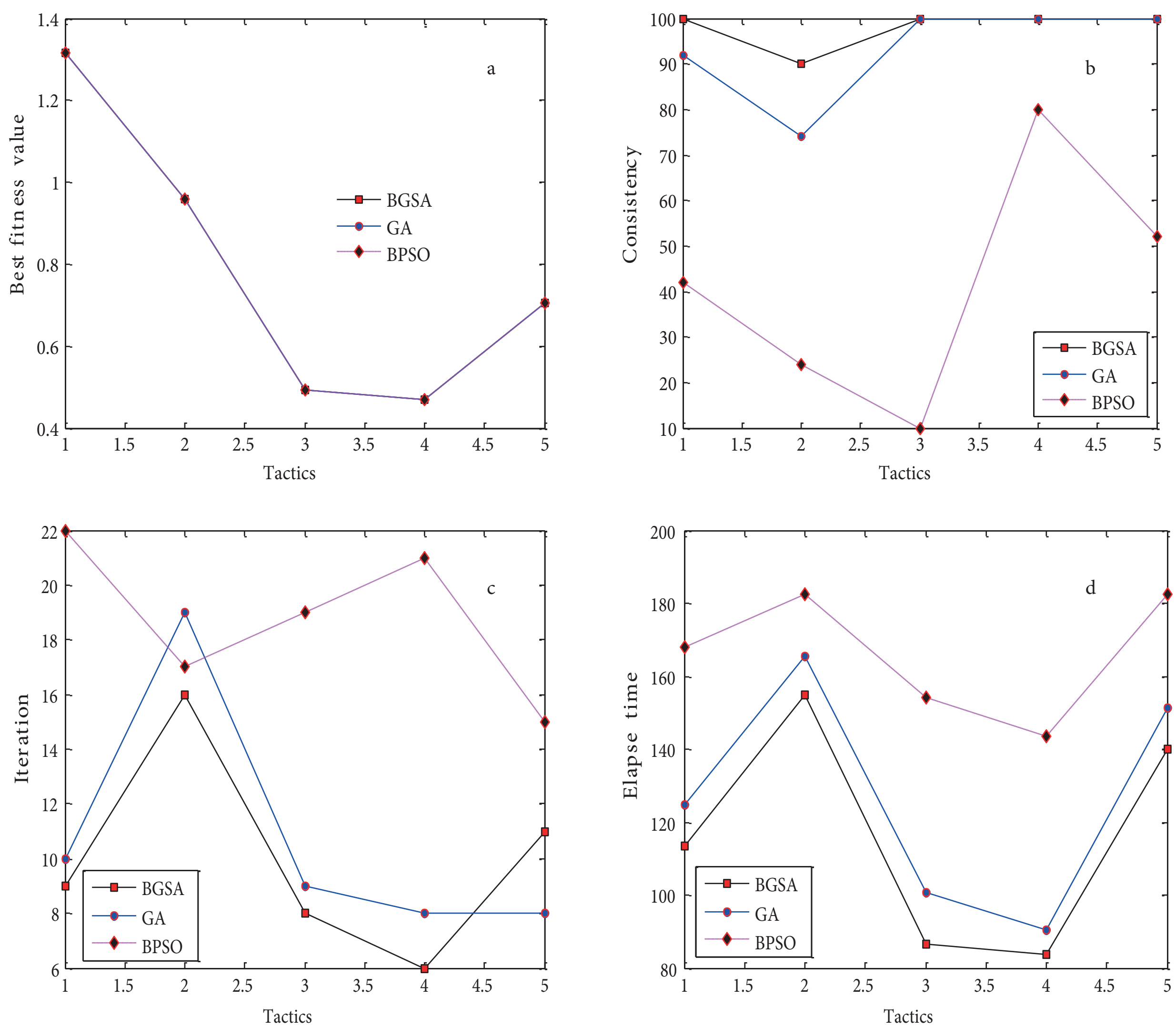

Figure 11. Graphical comparison of the BGSA, GA, and BPSO in terms of best values of a) fitness, b) consistency, c) iterations, and d) elapsed time.

6. Conclusion

This paper has presented a method to solve multiobjective optimization problems for optimal CS siting and sizing in the city of Bangi, Malaysia. The optimization problem formulation is mainly based on BU, TEL, and SEL costs and it is solved by utilizing the proposed BGSA to minimize the total cost. These results were compared with the results from the GA and BPSO. From the numerical results, it can be concluded that TEL, BU, and SEL costs are important to consider during EV CS planning. The results also revealed that TEL and BU cannot be ignored in optimal CS siting and sizing. Finally, the case study showed that the presented methods and models can be beneficial for CS developers to site and size the CSs with minimum cost without jeopardizing EV users' convenience and stressing the power system.

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