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A particle swarm optimizer-based optimization approach for locating electric vehicles charging stations in smart cities☆

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ABSTRACT

Conventional fossil fuel-powered vehicles are gradually being replaced by electric and hydrogen vehicles in the transportation sector. Even with all the recognized benefits and recent advancements in energy efficiency, decrease of noise, and environmental impact reduction, the market of electric and hydrogen mobility is still not up to par. Allocating charging stations in metropolitan areas for electric vehicles is considered as one of the most significant obstacles preventing electric and hydrogen vehicles from becoming more widely used. In this paper, an efficient approach aimed at finding optimal locations for electric vehicles (EV) charging stations in urban areas is proposed. Particle Swarm Optimization algorithm technique is utilized with the proposed approach. Various parameters were taken into consideration in this work, such as the horizontal distance that EVs travel to reach charging stations (CSs), and positive slope that EVs face to reach charging stations. The optimization problem is formulated as a Mixed-integer problem. The objective function works on minimizing the energy consumption of EVs to reach CSs in the investigated area. Difference constraints are incorporated with the proposed approach in order to increase the accuracy and efficiency of the proposed approach. The proposed approach is applied on real world datasets and is experimentally validated using through comparison with Genetic Algorithm and the greedy approach. The results demonstrate that the proposed approach saves energy about 22% and 43% compared to the genetic algorithm and greedy technique, respectively.

1. Introduction

Carbon dioxide (CO_2) emissions which result from internal combustion engines (ICEs) vehicles are considered as one of the most significant contributors to these issues in the transportation sector worldwide [1]. The transportation sector participates in about 14% of total Greenhouse gas (GHG) emissions, with road transport accounting for about 13% [2].

All the mentioned challenges in transportation sector have made electric and hydrogen vehicles ideal solutions to creating a new environmentally friendly transportation system [3]. Electricity and hydrogen share the advantages of being highly flexible in terms of basic energy sources and the ability to choose from a variety of renewable energy options [4]. Furthermore, the existence of new technologies such as proton exchange membrane fuel-cells (PEMFC) is considered a promising achievement in the field of transportation and will greatly help in the spread of these vehicles instead of internal combustion electric vehicles (ICEVs), due to their advantages such as starting at low temperatures and generating low emissions. This electrochemical equipment can convert hydrogen and oxidants into electricity, heat, and water (H_2O) at varying temperatures [5].

Therefore, there is a global trend towards electric and hydrogen cars due to the economic and environmental problems caused by the transportation of fossil fuels, especially in smart cities [5]. Fig. 1 shows an

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example of electric vehicles (EVs) charging stations (CSs) in smart cities [6]. Fig. 2 shows an illustration example of Hydrogen Fuel Cell Vehicle with Station Ecology, while Fig. 3 illustrates an example of smart hydrogen vehicle CS.

Recently, the number of EVs increased dramatically globally, because of the policies that encourage people to have EVs instead of ICEVs, mainly to save energy and reduce the CO_2 emissions [7]. In Norway, the Netherlands, and China, the market share of EVs is already 28.8%, 6.4%, and 1.4%, respectively. Many other nations have set goals to achieve 100% EV penetration in the near future. However, the public's satisfaction of EVs, the design of the traffic network, and the convenience of EV drivers could all suffer from the improper location of charging stations in cities [8].

Finding the best sites for CSs in cities is a crucial element that impacts the global penetration of EVs and the energy consumption in transportation sector [9]. As a result, effective methodologies must be used to find an energy efficient placement for Electric CSs. Aiming to install an energy effective CSs for sustainable urban transportation's sector. In the last few years, there has been an increased focus on proposing new methodologies and strategies for identifying the optimal locations for EVs charging point in cities. Methods for decision-making have emerged as the most common and efficient tools in recent research. These techniques have employed multiple variables and different level of constraints in order to solve the placement problem.

The technology and city planning problems listed above are primarily portrayed as optimization difficulties. These challenges encompass both linear and nonlinear programming problems according to the sort of obtained equations [10]. Integer Programming (IP) and real-valued programming (RVP) are typically present in the same problem of EVCS, and their respective solutions depend on the acceptable values of the decision variables [11]. Researchers introduced distinct single objective [12,13], and multi-objectives [14,15] according to the number of proposed objective functions. On occasion, a game theory is used to analyze these optimization problems [16,17].

Many algorithms have been incorporated with these objective functions, to solve the stated optimization problems, for example but not limited to Genetic algorithm (GA) [18–20], particle swarm Optimization [21], Branch and Bound algorithm [22], Ant Colony algorithm [23], a gradient free optimization algorithm such as Jaya algorithm and other optimization techniques [24–27], etc. These solvers, however, did not take the constraints' convexification into account. As such, they were unable to ensure a global minimum.

In [28], Human behaviors have been studied rather than focusing on the technological issues in placing CSs in urban areas. So, they used the drivers' charging and driving behaviors to determine the optimal locations of these charging points in the investigated area. Moreover, they

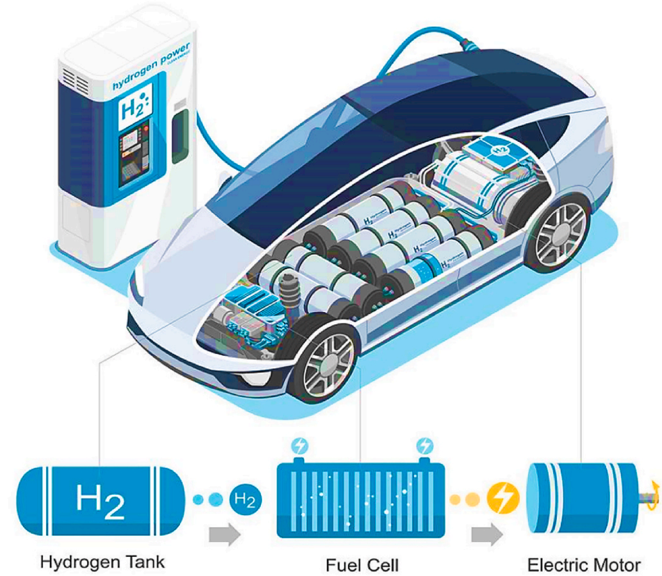

Fig. 2. Fuel cell of Hydrogen vehicle with Station Ecology.

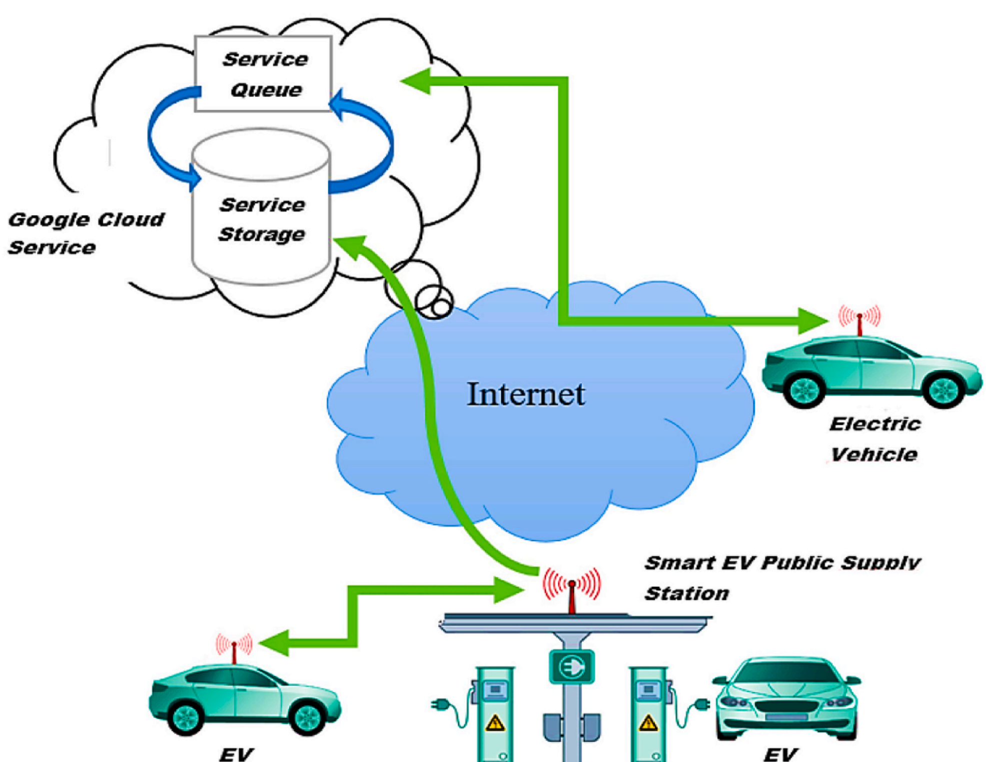

Fig. 1. EV charging stations in smart cities.

Fig. 3. Hydrogen vehicle refueling station.

also considered the mobility of the drivers in different areas, where they work, live and visit. In this paper, the problem has been formulated as an optimization problem, considering different types of parameters and constraints. Although the authors have discussed the placement of EVCSs as an optimization problem in Ref. [29]. However, the authors have mainly focused on a hybrid model considering various preferences of the owners of CSs, EVs' users, and the operators of distribution electricity networks. The problem also has been formulated by uncertain Mixed Integer programming problem (MIPP). The proposed approach was compared to the crisp models in order to demonstrate the obtained results.

Travels pattern of EVs' users and practices of charging has been considered in Ref. [30], charging slots in nearby zones, traffic congestion, charging demand for every zone have also been taken into account in this study. Authors used the NSGA-II in order to determine charging demand that each CS should cover. A multi-objective function was utilized to make a tradeoff between the maximization of the system benefits and maximization of minimum level of coverage.

In [31], the problem of CSs sites was discussed in terms of motivation others to have EVs, which in turn leads to spread EVs in urban areas. A new model called (nested Logit) has been incorporated to investigate the charging behavior and preference of EVs' driver, also estimate the overall charging demand for each CS. A Mixed Integer Nonlinear (MINLP) optimization model was presented in Ref. [32]. The loss in EV energy, power grid, build-up cost, road networks, urban roads were taken into consideration in this approach. In Ref. [33], a zonal-based technique was presented in order to find the optimal location of CSs, and calculate the capacity of each CS. Other costs related to the development of CSs, electric grid operators were taken into account in this introduced approach. The problem was formulated as a MINLP problem to reduce the total cost of EVCSs, and GA was utilized to solve this problem.

In [34], a novel fuzzy decision model was employed to determine the best site for EVCS. The main objective of this paper is to minimize the losses of grids and CSs. Achieving mobility sustainability is another parameter that was considered in Ref. [35]. A comprehensive technique to find the optimal size and locations of CSs has been introduced in Refs. [36,37], considering the loss in electric grids, and EVCSs' development cost. A new modified version of BLSA was performed as another optimization approach for the planning of CSs.

As far as we know, the previous approaches in the literature have not taken into consideration the difference in elevation between the locations of EVs and CSs which has an impact factor as a geographical parameter on the decision of placing EVCSs in cities. The presented approach in this paper is unique in this, as we consider the impact of the difference in positive slope between the sites of EVs and CSs.

The main contributions of this study are listed as follows.

- An energy-efficient approach for selecting the best sites for EVCSs in cities, considering the horizontal energy consumption of EVs to arrive CSs. The hallmark of this approach is a realistic and accurate model to calculate the energy consumption of EVs considering the difference in elevation between the positions of EVs and CSs.
- The EVCSs location problem was formulated as a Mixed linear Programming (MLP) problem. A PSO technique was utilized in order to resolve the presented problem based on real dataset data of the environment. The positions of EVs and charging points, and the elevations of both have been taken from Google maps.
- The Haversine equation has been incorporated with the proposed approach as a separate model. The results obtained from this model are comparable and accurate compared with the results obtained by Euclidean distance equation.

The rest of the paper is structured as follows. Section II is devoted to system modeling, problem formulation, and optimization problems. Numerical results and discussion will be presented in Section III. Section IV concludes the paper.

NOMENCLATURE

EV	Electric Vehicle
CS	Charging Station
ICEV	Internal Combustion Engine Vehicle
PSO	Particle Swarm Optimizer
GA	Genetic Algorithm
PEMF	Proton Exchange Membrane Fuel-cells
GHG	Greenhouse Gas
IP	Integer Programming
R–VP	Real-valued Programming
MINP	Mixed Integer Nonlinear Programming
MIPP	Mixed Integer Programming Problem
Symbols	
CO_2	Carbon Dioxide
H_2	Hydrogen
H_2O	Water
$N = \{1, \ldots, a, \ldots, N\}$	The set of EVs, an EV a has its own attributes.
$M = \{1, \ldots, b, \ldots, M\}$	The set of CSs, a CS b has its own characteristics.
$Q_z = \{1, \ldots, k, \ldots, Z\}$	The set of zones in the study area. Each zone has its attributes.
K	The total number of charging stations in the investigated area.
N	The total number of electric vehicles in the investigated area.
μ	represents the total # of zones.
dis_{ab}	Distance between positions of EV a and the intended CS b.
ηe_{ab}	Total energy that EV consumes per *km* to arrive intended CS (in *kWh/km*).
εab	Total energy that EV consumes per *km* to overcome the positive slope in its way to the intended CS in *kWh/km*).
$x(ab)$	Binary variable used as indicator of selecting a CS or not, it is 1 if the CS is chosen by an EV, while 0 if another one is selected.
Ms_{EV}	The mass of an EV in (*kg*).
Hg_{ab}	The difference in positive slope between the positions of EV and targeted CS
L_b	The number of connectors that are required at selected CS b.
Cr	The connector rated power, i.e., connector capacity.
CHr	The maximum number of EVs that can be charged by a connector.

2. Problem formulation

In this study, we deal with the problem of finding the best sites for EVCSs as an integer problem (binary integer problem). Our suggested method looks for the best positions of EVCSs in the investigated area, based on the least amount of energy that EVs spend to arrive targeted CS.

2.1. Entities

In our model, we have N number of EVs in the investigated area. An electric vehicle a has three features: ev_a^n, ev_a^v, ev_a^p, where EV_a^n, ev_a^v, EV_a^p are the EV's ID, the elevation and the coordinates, respectively.

Regarding the CSs, in our proposed approach, there are K number of CSs in all zones. Candidate CS b has three attributes: cs_b^n, cs_b^v, cs_b^p, where cs_b^n represents the ID of CS, cs_b^v is its height and cs_b^p is its positions on the Google map. Fig. 4 shows all the entities of the EV charging model.

2.2. Energy consumption model

To determine the precise amount of required energy for all EVs to reach CS, i.e., ξ_{ab}, of EV a to arrive CS b, both energy consumption that is needed from the mobility of EV to the intended CS, as well as the total amount of energy consumption that EV a requires to deal with the positive slope to arrive CS b. ξ_{ab} can be calculated as shown below:

$$\xi ab = (\eta ab + \varepsilon ab) \times dis_{ab.} \tag{1}$$

Where ηe_{ab} is energy that EV a consumes to arrive CS b, and the ε_{ab} is the amount of energy that EV a requires to deal with the difference in positive slope for the positions of EV a and CS b. dis_{ab} denotes the horizontal movement of EV a to the position where a CS b is located.

dis_{ab} is calculated by haversine (hav) formula. The haversine is used to find the shortest path between two locations on a sphere, using their latitudes and longitudes as shown in Fig. 5.

$$h_{aver}(\theta) = sin^2\left(\frac{\theta}{2}\right) \tag{2}$$

The haversine is calculated as follows:

$$h_{av}\left(\frac{dis_{ab}}{R}\right) = h_{av}(\delta_b - \delta_a) + cos(\delta_a)\cos(\delta_b)h_{av}(l_b - l_a) \tag{3}$$

Where R represents the radius of the earth, δ_a, l_a are the EV's latitude and longitude, and δ_b, l_b are the CS's latitude and longitude, respectively.

The haversine finds only half of the angle θ's versine. The distance dis_{ab} can be calculated using the inverse of (sin) function as shown below:

$$dis_{ab} = 2R\ sin^{-1} \times \left(\sqrt{h_{av}(\delta_b - \delta_a) + cos(\delta_b)h_{av}(l_b - l_a)}\right)$$

$$= 2R\ sin^{-1} \times \left(\sqrt{sin^2\left(\frac{\delta_b - \delta_a}{2}\right) + cos(\delta_a)cos(\delta_b)sin^2\left(\frac{l_b - l_a}{2}\right)}\right) \tag{4}$$

η_{ab} is the amount of energy that EV requires to consume by its horizontal mobility of EV a to reach CS b. In our proposed approach we assume it as in Refs. [33,38].

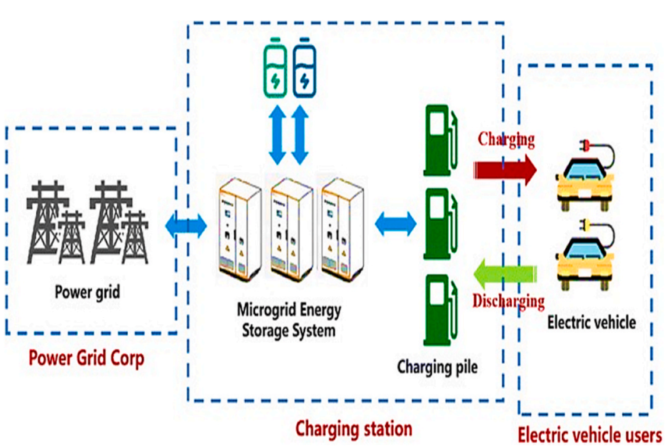

Fig. 4. EV charging model entities.

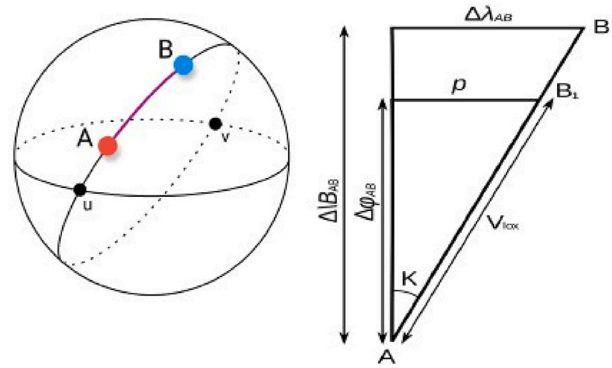

Fig. 5. An illustration of haversine formula.

ε_{ab} is calculated based on the formula of a hill climbing force as shown in Fig. 6, which in turn finds the force that EV a spends to overcome the difference in elevation between its position and the position of CS b, as shown below:

$$Fs = MS_{EV} \times g \times sin\ \beta\ [N\ or\ kgm/s^2]. \tag{5}$$

Where Fs denotes the force of hill climbing, MS_{EV} is the EV's mass (kg), g is the force of earth gravitational, which is almost (9.8 m/s^2), and β is the road slope's angle that results from the difference in elevation between the positions of EV and CS:

$$\beta = sin^{-1}\ (Hg_{ab}/dis_{ab}) \tag{6}$$

Where Hg_{ab} is the difference in elevation between EV a and CS b. Fig. 6 shows the force of slope resistance that EV requires to overcome to arrive candidate CS. The value of ε_{ab} can be calculated as shown below:

$$\mathrm{E}_{ab} = Fc \times 2.78 \times 10^{-4}\ [kWh/km]. \tag{7}$$

2.3. Optimization problem

In our experiment, we assume that the set of CSs is K = {1, …, b, …, K}, the set of EV population is represented by N = {1, …, a, …, N}. The set of zones is denoted by Q_z = {1, …, k, …, Z}. The EVs' elevation and position characteristics are the same of the center of the zones where their owners live. Each zone k in the study are has 4 features; $\mu_k^n, \mu_k^i, \mu_k^v$, and μ_k^{cp}, where μ_k^{id} is the ID of the zone, μ_k^i denotes the population of EVs μ_k, μ_k^v is the height of μ_k^{cp} and μ_k^{cp} is the zone's center coordinates of μ_k.

Following is the optimization problem (the mathematical model), including both the main objective function of our proposed approach and all the proposed system constraints.

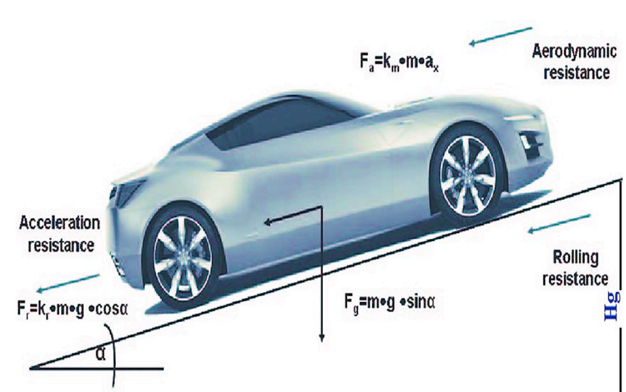

Fig. 6. Hill climbing force slope.

- Objective Function

$$\min_{y,X} \sum_{b\in y, y\subset k} \sum_{a\in N} \varepsilon_{ab} \times x_{ab} \tag{8}$$

- Subject to:

$$\sum_{b\in k} x_{ab} = 1, \forall a \in N \tag{9}$$

$$\sum_{a=1}^{N} x_{ab} \leq \vartheta_b, \forall b \in y \tag{10}$$

$$x_{ab} \in \{0,1\}, \forall a \in N, \forall b \in y \tag{11}$$

As shown in (8), the proposed objective function aims to minimize the total energy consumption of the movement of EV to reach a CS, considering the horizontal movement of EV, and also difference in height between the positions of EV and CS. Eq (9), illustrates that each EV can only select one charging station. In Eq. (10), $\vartheta_{(b)}$ represents the total number of EVs that can be allocated to a particular CS. As shown in Eq. (11), $x_{(ab)}$ is the binary decision variable that is used to show whether EV a is assigned to a CS b or not, the value of $x_{(ab)}$ is one if EV a chooses CS a, otherwise the value of $x_{(ab)}$ is set to zero.

2.4. PSO-based solution

One of the most well-known naturalistic swarm-based optimization methods is particle swarm optimization (PSO). This nature-inspired method has experienced a huge rise in popularity as a result of its adaptability and simplicity. Every branch of research is now paying close attention to particle swarm optimization (PSO). This algorithm models how flocks of birds interact with one another to reach their food destination. A flock of birds approaches their food source using their collective social and personal experience. They constantly reposition themselves to achieve the finest configuration possible based on their best position as well as the optimum position for the entire swarm. The velocity of particle k in the swarm in the $(j+1)^{th}$ generation, is modified, based on Eq. (12):

$$V_k(j+1) = V_k(j) + c1 \times r1\ (p^k_{best,j} - X_k(j)) + \tag{12}$$

$$c2 \times r2\ (g_{best,j}) - X_K(j))$$

The position of each particle k, at every generation $(j+1)^{th}$, varies according to Eq. (13):

$$V_k(j+1) = V_k(j) + V_k(j+1) \tag{13}$$

Fig. 7 shows the flowchart of PSO algorithm and Fig. 8 shows the Pseudocode of PSO Algorithm.

3. Numerical results

3.1. System settings

Our proposed model was applied on some post codes of Newcastle upon Tyne city, UK. The investigated area is (10 × 5) km. In our experiments, we assume that the horizontal energy consumption of EV is about 1 kWh to travel for 7 km [33,38]. Table 1 illustrates the zone ID for the seven zones that are included in the study area. Furthermore, the height and coordinates of the geographical center of each zone, and the population of EVs is presented in Table 1 as well.

In our proposed model, during the process of implementation, 12 candidate CSs are distributed on the main streets in the seven post zones. Fixed distance between these candidate CSs is assumed as well. Fig. 9 shows the proposed locations of the candidate CSs over the investigated area. It is assumed that the total number of vehicles is about 100 thousand, we assume that the percentage of EVs is 5% of the total vehicles' population. Moreover, we assume that 20% of EVs will travel to CSs for charging during the 3 charging peak hours. We assume that a charger at any CS can charge 2 EV/h, and the EV's state of charge (SoC) is zero when it arrives at a CS.

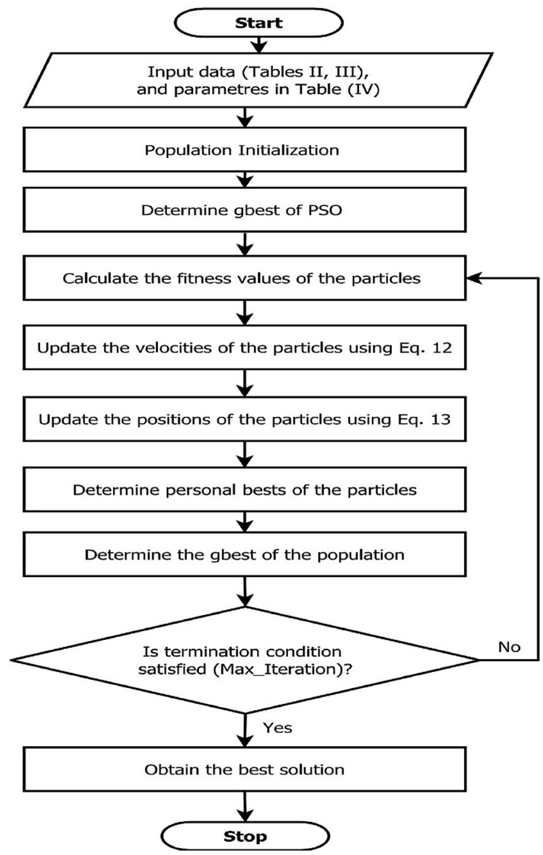

Fig. 7. Flowchart of proposed approach using PSO.

Algorithm 1 The Pseudocode of PSO Algorithm

Input: $Fitness - function,\ lb,\ ub, Population\ Size\ (p_{ss}),$ $ii\ (\#\ of\ Iter),\ !,\ user\ selects\ \ c1\ , and\ c2.$

Output : $Optimal\ \xi_{(ab)}$

begin:
Initialize random Pop and Velocity s.t boundaries
Evaluate objective function (Eq. 8).
Assign p_best as P and f_best as f;
Find the answer that has the best fitness, then designate it as gbest and fitness as fgbest.
for $i = 1$ to ii **do**
  for $u = 1$ to p_{ss} **do**
    Determine the velocity of k^{th} particle;
    Determine the new position of k^{th} particle;
    Evaluate objective function (Eq. 8) s.t system constraints (Eqs. 9-11)
    Update the population (Step 1)
    Update p^k_{best} and $f_{p_{best}}$ if $f_k < f^k_{p_{best}}$ then $\begin{cases} p^k_{best} = X_K \\ f_{p_{best}} = f_K \end{cases}$
    Update g_{best} and $f_{g_{best}}$ if $f^k_{p_{best}} < f_{g_{best}}$ then $\begin{cases} g_{best} = p^k_{best} \\ f_{g_{best}} = f^k_{p_{best}} \end{cases}$
  end for
end for
Return $Optimal\ \xi_{(ab)}$

Fig. 8. Pseudocode of PSO algorithm.

Table 1
Zones information.

Zone ID	Elevation	EVs Pop	Position	
			Latitude	Longitude
NE_1	0.0419	238	54.972794	−1.613160
NE_2	0.0531	101	54.991047	−1.606179
NE_3	0.0679	141	55.004470	−1.619863
NE_4	0.103	188	54.975670	−1.641451
NE_5	0.076	91	55.013533	−1.723296
NE_6	0.053	162	54.976902	−1.578134
NE_7	0.0668	79	54.998768	−1.588817

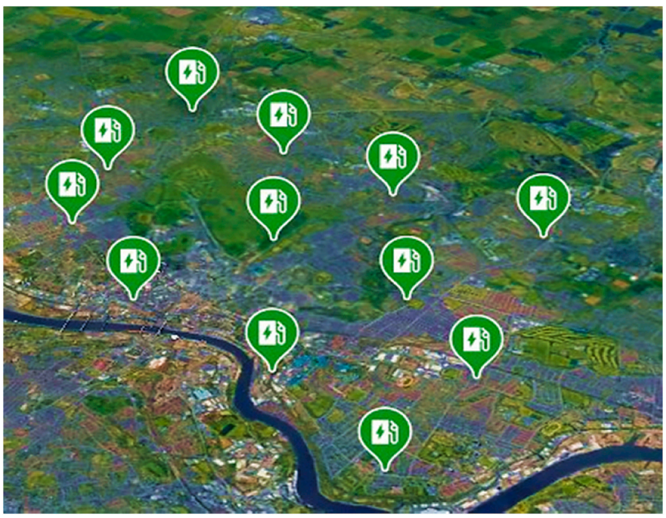

Fig. 9. The study area map.

3.2. Results analysis discussion

The experiments have been applied on the investigated area, as discussed before in Section 3.1. The results have been obtained from over 40 independent experiments on real-data from the study area. The error bars show the standard deviation got from the implementation of these experiments. The system was implemented in the MATLAB numeric computing platform R2023b on PROBOOK (HP), CORE i5 8th Generation, 8 GB RAM, and 8-CPUs 1.6 GHz.

The distribution of EVs in the post codes that have been included in this study is shown in Fig. 10. The center of zones (NE1-NE7) is represented as black dots. The populations of EVs are denoted by blue dots. While the black lines show the borders between adjacent zones.

All information required for the CSs is shown in Table 2. The base

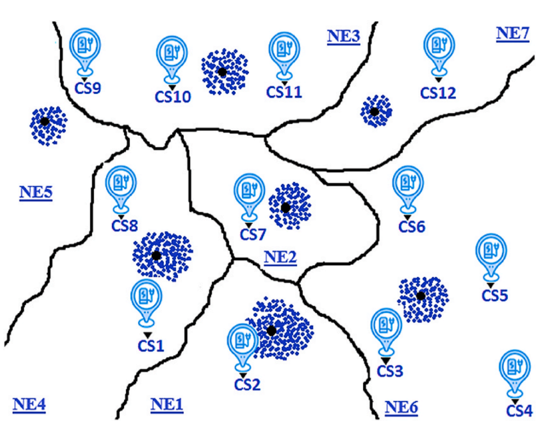

Fig. 10. Distribution of EVs and CSs in the study area.

Table 2
Description of CSs.

CS_{ID}	Elev.	Coordinates	
		Latitude	Longitude
CS_1	0.111	55.97451	−1.643612
CS_2	0.042	55.969061	−1.620001
CS_3	0.02009	55.970018	−1.581501
CS_4	0.0329	55.965391	−1.549907
CS_5	0.0310	55.990001	−1.55700
CS_6	0.0510	55.991743	−1.601001
CS_7	0.061	55.00121	−1.617012
CS_8	0.112	55.000012	−1.657451
CS_9	0.110	54.005233	−1.670604
CS_10	0.0871	54.005007	−1.640329
CS_11	0.0598	54.005601	−1.611205
CS_12	0.0701	54.008974	−1.579150

scenario was implemented based on the information on both Tables 1 and 2 Table 3 shows the basic system settings.

Table 4 shows the selected CSs, and the total number of EVs that have been assigned to each CVS. CS_2, CS_3, CS_7, CS_9, and CS_11 have been selected, due to its proximity to the location of EVs in the investigated area, and also the small difference in positive slope between the EVs and CSs positions. It is easy to see that the total number of EVs that have been assigned to CS_2 is the highest compared to the other CSs as shown in Table 4. The reason behind this is the small difference in elevation and distance between the position of EVs, especially in NE1 and the position of CS_2 in NE1 as shown in Tables 1 and 2 The EVs in zone NE1 do not need to travel a long distance to reach CS_2 and the amount of energy that EVs need to overcome the positive elevation difference is very low. However, it is easy to see that the total number of EVs that have selected CS_9 is the least compared to the other CSs, this is also because of the difference in positive slope between the EVs and CSs sites in zones NE3 and NE5, and the distance that EVs in both zones require to reach CS_9.

Fig. 11 shows the total amount of energy that EVs consume to arrive at selected CSs. Although the total number of EVs selected CS_9 is very low compared to the other CSs as shown in Table 4, the total energy consumption is somewhat high. The reason for this is the difference in positive slope between the locations of EVs and CS_9 and the long distance between them as well.

3.3. Validation of the proposed approach

In this part of work, a comparison between the proposed techniques and other techniques will be discussed. First: we will compare our approach with the Genetic Algorithm (GA) technique, and then will be compared with the greedy technique.

3.3.1. A comparison between the proposed approach and GA technique

In this section, we validate our proposed approach by comparing it with the GA technique. As we did in the previous section, we ran the experiments more than 40 times with the same parameters, constraints, and environment. Table 5 shows the selected CSs by using GA technique and the number of EVs that were assigned to each CS. The only metric

Table 3
System main parameters.

Parameter	Value	Unit
K	12	CSs
ηe_{ab}	00.143	kWh/km [33,38]
Ms_{EV}	1800	kg
N	1000	EVs
gr	9.80665	m/s^2
μ	7	–
CHr	2	$/h$
C_r	95	kW

Table 4
Selected CSs with assigned EVs using proposed technique.

CSs	*CS_2*	*CS_3*	*CS_7*	*CS_9*	*CS_11*
EVs	326	234	198	64	178

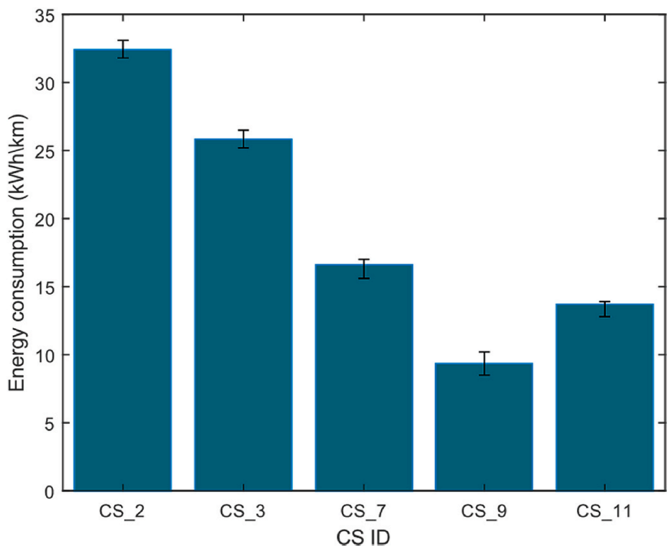

Fig. 11. Total energy-consumption of EVs at each CS using proposed technique.

Table 5
Selected CSs with assigned EVs using GA technique.

CSs	*CS_1*	*CS_2*	*CS_3*	*CS_7*	*CS_10*
EVs	188	197	203	122	290

that has been considered to select CS is distance between the position of EVs and charging slots. As shown in Table 5, the distribution of EVs to available CSs is completely different. On the contrary, both metrics, the difference in elevation and the proximity of EVs to the location of charging points were taken into consideration in our proposed approach.

Fig. 12 shows the total amount of energy consumption of EVs to reach CSs using the GA technique. As mentioned previously, the 40 experiments were run over the same parameters and system constraints that have been included in the experiments of the proposed approach. It is easy to see that the total energy consumption of assignment EVs to CSs is more compared to the proposed approach as shown in Fig. 10. Moreover, it is also noticeable that the obtained standard deviation by running of these experiments is larger than the obtained using the proposed approach as well. The reason behind this refers to the good amount of fluctuation or variation among the fitness values that have been obtained using the GA technique.

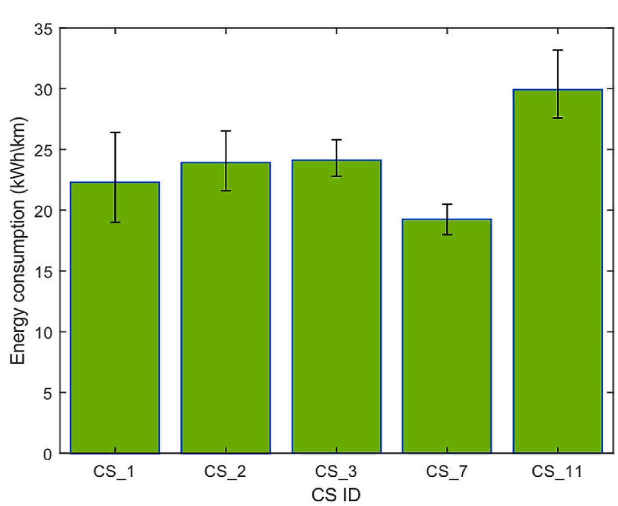

Fig. 12. Total energy-consumption of EVs at each CS using GA technique.

Fig. 13 shows a comparison between the proposed approach and the GA according to the total amount of energy consumption that EVs need to arrive CSs. It is easy to see that the total amount of energy consumption that EVs need to reach CSs using GA increased about 22% compared to the proposed approach.

3.3.2. A comparison between the proposed approach and greedy technique

To demonstrate the impact of the elevation on the decision of selecting CSs and on the proposed technique, a greedy technique will be considered in this part of work. As known, the greedy technique takes into consideration the distance only to decide the best destination, which means that the greedy algorithm will ignore the influence of the elevation on the decision of selecting the charging point. So, the EVs will choose the optimal CSs based on the shortest distance between the locations of EVs and charging facilities as shown in Fig. 14. Eq. (14) shows the Euclidean distance that has been used to calculate the distances between EVs and CSs:

$$d(p,q)^2 = (q_1 - p_1)^2 + (q_2 - p_2)^2 \tag{14}$$

Table 6 shows how the EVs were distributed to the charging points in the investigated area. It is obvious that the distribution of EVs on the CSs is completely different compared to the previous techniques. The reason behind this is that the greedy technique ignored the impact of the difference in elevation between the locations of EVs and CSs. The horizontal distance that the EVs need to spend to reach CSs is the only parameter that has been taken into account in selecting CSs. Referring to Table 6 we see that the majority of EVs selected the CSs in the same zone. The reason behind this is that each EV targeted the closest CS regardless of the difference in heights.

Fig. 15 illustrates the total amount of energy that EVs need to spend to overcome the positive slope between the locations of EVs and CSs. It is obvious that the total amount of energy consumption that the EVs need to reach CS is more compared to the other discussed techniques, i.e., the proposed and greedy techniques. It is also easy to notice that the standard deviation is very low compared to the proposed and greedy technique, and this is because of the assumption in this approach that the

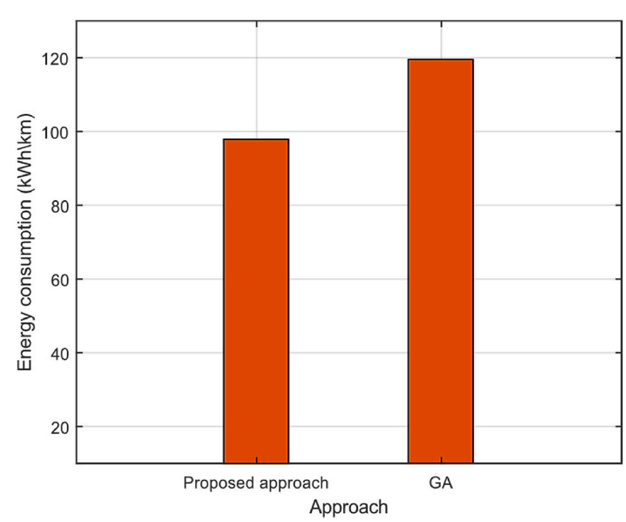

Fig. 13. Comparison between the proposed approach and GA due to energy consumption.

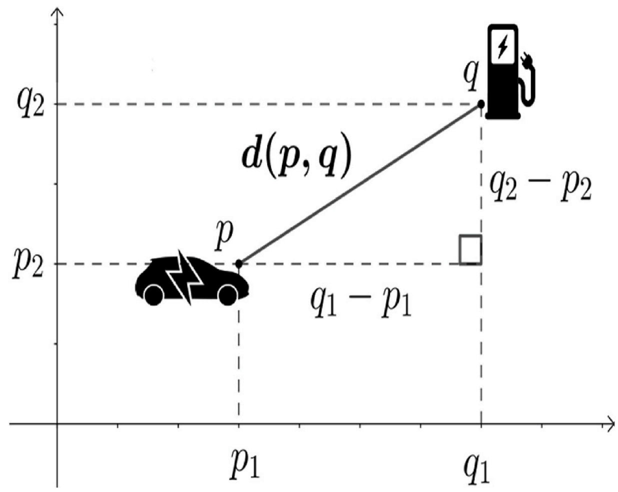

Fig. 14. Total energy-consumption of EVs at each CS using greedy technique.

Table 6
Selected CSs with assigned EVs using greedy technique.

CSs	CS_2	CS_3	CS_7	CS_8	CS_11
EVs	238	162	101	188	311

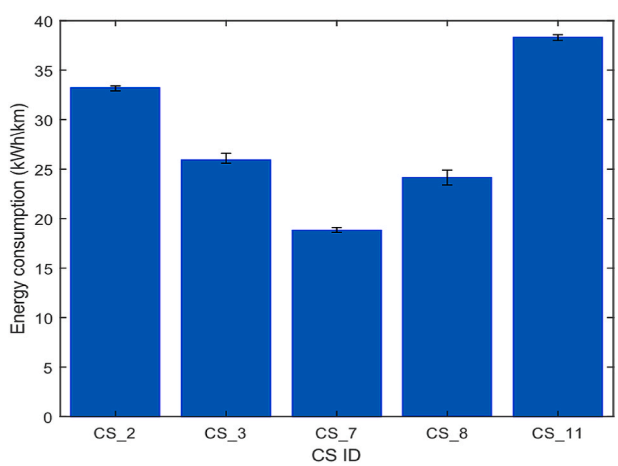

Fig. 15. Total energy-consumption of EVs at each CS using greedy technique.

positive slope is ignored, and the distance is the only metric that has been considered here. CS_8 was selected by EVs in zone NE4 instead of CS_1 which was selected using GA due to the proximity of this CS to the location of EVs in this zone.

Fig. 16 shows a comparison between the proposed approach and the greedy approach in terms of the total amount of energy consumption that EVs need to reach CSs. It is obvious that the total amount of energy consumption that EVs need to reach CSs using greedy technique increased about 43% compared to the proposed approach (base scenario).

Fig. 17 shows a comparison between the three techniques that have been discussed in this paper. It is easy to see that the proposed techniques save a lot of energy compared to the other approaches that have been discussed in this work. Same parameters and system constraints have been taken into account in the proposed approach and the GA technique, the robustness and strength of the proposed approach over GA comes from the efficiency of the PSO algorithm compared to the GA in such kind of problems. However, the greedy approach has the least efficiency because it ignores the variance in elevation between the locations of the EVs and CSs.

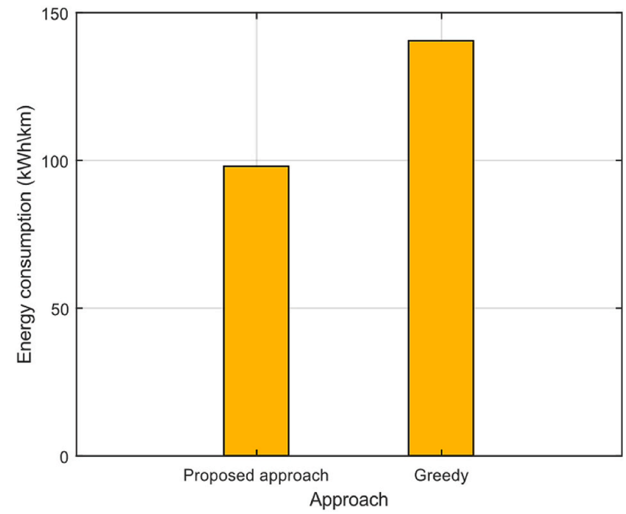

Fig. 16. Comparison between the proposed approach and greedy approach due to energy consumption.

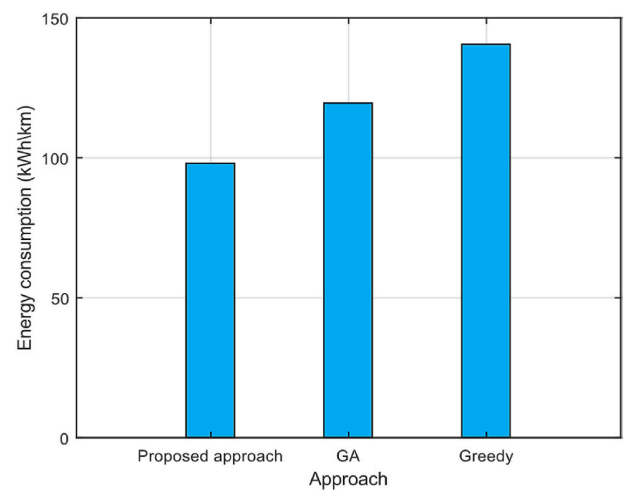

Fig. 17. Comparison between the proposed approach, GA, and greedy technique due to energy consumption.

4. Conclusion

An efficient energy Optimization approach for selecting the optimal locations of electric vehicle charging stations in the metropolitan areas was presented and discussed in this work. In the proposed approach, the horizontal distance that the EVs travel to reach CSs locations was considered. Moreover, the difference in positive elevations has been taken into account in the proposed model. The Haversine formula was used in order to find the actual distance between the positions of EVs and CSs. The results obtained from the experimental attempts showed the robustness and efficiency of the proposed approach in locating CSs in the best locations in the urban areas. In order to validate the proposed approach, a comparison with the genetic algorithm and the greedy technique has been carried out. As shown in the results section, the comparisons showed that the energy consumption increased about 22% and 43% using the GA and greedy techniques compared to the proposed approach, respectively.

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