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Intelligent algorithm-based efficient planning of electric vehicle charging station: A case study of metropolitan city of India

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Abstract. Electric Vehicles (EVs) have gained rising popularity and become the mainstream mode of transportation in urban and rural areas in India and will be globally pervasive in the next few years. Certain issues should be taken into account in the adoption of EVs such as proper charging infrastructure, charging time and more significantly, sizing and siting of the Charging Stations (CSs), particularly in urban areas where the cost of land and location are of high significance. Therefore, it is important that the CS location be easily accessible and cost-effective for EV users. In this regard, this study presents an intelligent algorithm-based efficient planning of Electric Vehicle Charging Stations (EVCS), considering the geographical information and road network. The cost function was considered as the sum of the investment, charging station electrification, electric vehicle energy loss, and travel time costs. An intelligent algorithm-based approach was then employed to solve the planning problem of EVCS. Further, the impact on the reliability of the grid was evaluated by determining the charging cost loss at each considered location. The result revealed that the applied method provided better-optimized solutions that were beneficial to EV users, CS operators, and utility grid.

1. Introduction

In recent years, Electric Vehicles (EVs) have gained ever-increasing popularity owing to their lower fossil fuel consumption and higher demand in the power sector [1,2]. Cost-effectiveness and eco-friendly nature of the EVs are their major superiority, justifying the deployment of EV on a large scale [3,4]. They can be categorized into two types of battery and hybrid EVs [5,6]. Electric Vehicle Charging Stations (EVCS) are installed to supply the needed electricity for charging EVs. The capacity of the EV battery generally ranges from 20 to 60 kWh. The number of charging levels is also available for EV charging based on which three standard charging levels to be predominantly used have been developed. Charging level 1 is based on a single-phase AC system in which a 20 kWh battery is charged in seven hours, while charging level 2 is based on a three-phase AC system in which a 20-kWh battery is fully charged in an hour. In addition, charging level 3, also known as the fast charging level, is based on a

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DC system in which the battery gets fully charged in 20 to 30 minutes [7] and for this reason, building fast-charging stations for vast adoption of EVs has become a necessity [8]. Charging Station (CS) is directly connected to the power grid. Some equipment such as transformers and rectifiers are installed to generate DC voltage in the station. Charging connectors are placed in the station that use DC voltage to charge the batteries in 20–30 minutes. Therefore, CS serves the electric supply to the EVs for charging purposes. The easy availability of fast CS is the key to the commercial deployment of EVs [9]. Different issues concerning the development of fast CS have been discussed in the literature, among the most prominent of which are the charging time [7], battery life, accessibility of public CS [10], and integration to the energy supply grid. In addition, energy consumption and availability of the renewable energy sources for fast CS have also been discussed [11]. Moreover, building EVCSs based on the renewable energy generated from wind farms has been specifically discussed [12]. Further, recent public sector funding in the commercial deployment of the fast CS in the US and Japan have been studied [13]. According to the literature, a supply of at least 100 kW is necessary for charging 36 kWh battery-based EVs in 20 minutes. Therefore, in a practical scenario that simultaneously considers charging 10 EVs, the CS will require at least 1000 kW from the electric supply grid, which incurs significant losses [14].

1.1. Related works

Numerous researches have been conducted on the optimal planning of EVCS and its integration into the electric power network. In this regard, some authors have established a spatiotemporal model to analyze the impact of different EV charging strategies on the electric grid [15]. According to their studies, in order to reduce the losses, the CS should be placed closer to electric substations. However, the substations are generally located far away from urban areas, and this long distance will in turn increase the energy consumption in the EV while traveling to the CS. Hence, both travel cost and grid losses are critical while determining the location of the CS. Moreover, the CS capacity is dictated by the area; in other words, expanding the land area for CS would increase the number of EVs that can be simultaneously served as well as the cost associated with development charges and land cost. In this regard, placement and sizing of the CS is a non-trivial problem that necessitates a comprehensive study that addresses the aforementioned issues [16]. A few of the research works have addressed the placement and sizing problems for the CS [17–24]. In [17], a partitioning-based technique for optimizing the location of the CS was proposed by minimizing the traffic loss. An optimal location for the CS was derived for the city of Lisbon in [18]. The location of the CS was optimized for a minimum station development cost in [19]. The CS location for the driving pattern of the EVs was optimized in [20]. Graph theory-based study on optimal placement and sizing of EVCS was carried out in [21]. Further, a two-step-based technique was proposed in [22] to optimize the location and size of the CS, while Particle Swarm Optimization (PSO) was used for finding the optimal location [23]. A Jaya algorithm was used in [24] for the optimal placement of EVCS by optimizing the operating cost, installation cost, and power grid loss. A hybrid approach to Chicken Swarm Optimization (CSO) and Teaching-Learning-Based Optimization (TLBO) was utilized in [25] to allocate the EVCS, considering various economic and grid operating issues. Several cost functions including the operating, investment, and maintenance costs were considered to optimize the PSO, considering the network operating constraints [26]. The EVCS allocation in the IEEE-123 bus distribution network was conducted in [27] using Grey Wolf Optimization (GWO) without violating system constraints. The optimal placement of EVCS in the IEEE-33 bus radial distribution system was achieved, considering the uncertainties related to the quantity of the EVs to be charged [28]. In another study, GWO/WOA was employed to solve the placement problem. The EVCS planning in a distribution network superimposed with road network was done. Uncertainties related to EVs were taken into account based on 2 m Point Estimate Method (2 m PEM). Differential Evolution (DE) and Harris Hawks Optimization (HHO) algorithm were used for optimizing the objectives [29]. Optimal placement of the EV parking lot was implemented in Beijing district to minimize the total cost and power loss [30]. In [31], a two-stage approach to the allocation of EV parking lot and Renewable Energy Sources (RESs) in a distribution network was proposed. An appropriate bus for the EV parking and RESs was selected, considering the economic objectives in order to reduce the system loss using Genetic Algorithm (GA) and PSO algorithm. The results proved the effectiveness of the simultaneous allocations of RESs and EV parking lots over the independent allocation of distributed energy resources and EV parking lots. In [32], some improvements in the voltage profile, power loss, and loading capabilities of the IEEE-69 bus radial distribution system with PV/Battery Energy Storage System (BESS)-powered EV charging stations were suggested. An energy management strategy was then introduced to direct the power flow among the EVCS, solar panel, BESS, and utility grid based on the times of using the electricity price. Multi-Course Teaching-Learning-Based multi-objective Optimization (MCTLBO) was then employed to optimize the size of PV/BESS system and locations of CSs in each zone and minimize the annual CS operating costs as well as the system active power loss. Allocation of EVCS in the presence of capacitors in a distribution network was done to minimize the active power losses and maximize the net profit without violating the operational constraints [33]. Optimal CS planning was done within the traffic-constrained framework [34]. Although the CS development is highly dependent on the public sector policies, not much has been studied regarding the impact of public policy on the development of charging infrastructure. The grid loss and CS construction cost for optimal sizing and placement of EVCS were discussed in [35]. GA was then used to solve the optimization problem. In [36], PSO was used with some applied modifications in the inertia factor for optimal planning of CS. Both construction and maintenance costs were considered as an objective function. Proper placement of EVCS was carried out, considering the cost of installation in the traffic network [37]. The cost functions were modeled for optimal sitting of EVCS, taking into consideration the traffic and geographical constraints [38]. The main emphasis of this article was put on minimizing the transportation cost. In [39], the power losses were reduced by optimal sizing of Distributed Generation (DG) and optimal sitting of EVCS. Initially, DG of the optimal size was located to reduce the power losses. In the second step, CS was optimally installed to ensure a further reduction in power losses. The results were tested in the IEEE 33-bus radial distribution network. It was also shown that this approach to the sequential placement of DG and CS introduced additional new load to the system. Table 1 provides an insight into the optimization algorithms used for handling multi-objective cost-based functions.

To the best of the author's knowledge, numerous studies have been conducted so far, primarily aiming at sitting and sizing of EVCS in distribution and transportation networks. However, a few of them have addressed the aforementioned problem by taking into account the realistic data of EVs. In addition, the impact on the grid reliability in terms of Charging Cost Loss (CCL) was rarely examined in past research

Table 1. Analysis of various intelligent algorithms used for handling the cost-based objective functions [40].

Ref.	Cost functions	Algorithm	Category	Attributes
[36]	Minimizing investment cost	ACO	Swarm intelligent	Exploitation capability is weak
[37]	Minimizing connection cost	PSO	Swarm intelligent	Processing time is longer for multi-modal problems.
[37]	Minimizing EV energy loss cost	PSO	Swarm intelligent	Depending on its own parameters such as inertia weight, social parameters, and cognitive term.
[35]	Minimizing EV energy loss cost	GA	Evolutionary	Issue in tuning the parameter due to complex mutation, speed of convergence, and crossover operator.
[38]	Minimizing installation cost	TLBO	Population-based optimization	Memory required for computation purpose is low.
[38]	Minimizing travel time cost	TLBO	Population-based optimization	Initially, it failed to solve the problems continuous in nature

projects. Reliability evaluation is an important factor to be incorporated in the optimal planning of EVCS. In addition, intelligent meta-heuristic technique for a particular case study has not been applied in the former works. This research primarily focuses on the optimal planning of EVCS in different well-known areas of South Delhi considering the land cost, coordinates (latitude and longitude), elevation, and population density of CS location. Moreover, reliability analysis is carried out to investigate the impact on the grid. It also employed Grey Wolf Optimization (GWO) to plan CS in the proposed site. GWO is simple to implement owing to its simple structure, few storage and computational requirements, good convergence due to the continuous search space reduction, fewer decision variables, and ability to avoid local minima and search for the global minima over a large search range.

1.2. Motivations

Availability of charging facilities in public places is the key prerequisite for adoption and rollout of EVs. The charging infrastructure must be smart that can be managed by the government agencies and/or private organizations. The feasibility studies should be carried out prior to the installation of CS. The services were offered with the main objective of enhancing the end user customer experience and further promoting the charging the ease and convenience of charging EVs. These could include smart end user applications to show the location and real-time status of the chargers, simple methods for payment, expert customer support, and service and maintenance of the stations.

The main problem arises when several EVs are plugged into the grid simultaneously that may cause grid interruptions. Therefore, a proper and robust battery management system was required to simultaneously manage the CS for charging a considerable number of EVs. In order to adopt the swapping approach, a greater number of batteries are required that consequently increase the cost of the system. Undoubtedly, it is not desirable; hence, the necessity of the development of charging strategies comes to the fore.

Given the increase in the EV adoption, it is expected that the CS infrastructure will keep pace with the predicted growth scenarios. However, planning the charging infrastructure is a difficult task because it demands simultaneous consideration of a number of consumer and local constraints. Some of the factors that will affect the EV adoption are EV purchasing expenses, regulations by the government that encourage applications of the EVs, availability of the electrical energy, role of renewable energy resources, and concerns about the access and availability of fast-charging stations. Due to all of these factors, uncertainty about the rate of EV adoption might increase, thus posing questions about whether the expected charging infrastructure supports the demand.

1.3. Contributions

Inspired by the current research on the planning of EVCS, this research work contributes to the overall planning of EVCS around the world by putting its main focus on the different most populated areas of New Delhi. To this end, various intelligent algorithms have been employed to deal with this planning problem. Few of these algorithms search for the optimum solution only in the neighborhood space and do not pay much attention to the global area. Such techniques are susceptible to getting trapped in a local optimum solution only. On the contrary, some other techniques are good enough to achieve the global solution, but they cannot explore the local solution. Due to these shortcomings, more efficient algorithms are required for premature concurrence and must have a good exploration capability. In this respect, GWO was utilized owing to its ability to make a good balance between the local and global search spaces.

The main contributions of the proposed work are summarized in the following:

- This research work emphasizes the planning of EVCS in the most populated areas of South Delhi, India. Allocation of the EVCS is done based on minimizing the overall cost, which includes the investment, CS electrification, EV energy loss, and travel time costs;
- Reliability evaluation is one of the major concerns in the location planning of EVCS. Hence, Charging Cost Loss (CCL) as an important measure for determining the impact on reliability of grid was investigated. CCL refers to the cost of EV which remains uncharged because of improper functioning of the grid or grid failure. It was evaluated for each CS site for reliability evaluation;
- The proposed algorithm relies on the hunting behavior of the grey wolves, balancing the exploration and exploitation capability. The performance and stability of the proposed algorithm were examined by implementing it on various objective functions considered for the optimal planning of EVCS in the most populous areas of South Delhi, India. The supremacy of the proposed technique was verified by comparing the obtained results with other existing methods discussed in the literature. The GWO results confirmed the effectiveness of the proposed technique in determining the global solution in terms of the quality of solution and computational burden.

This paper is organized in six sections. Section 2 focuses on the modeling of optimization problem. Section

3 discusses the constraints and adopted methodology. Section 4 shows the applied intelligent algorithm, i.e., GWO and its flow chart. Section 5 presents the obtained results and simulation analysis. Section 6 concludes the study.

2. Components and models of electric vehicle charging station

Figure 1 shows the interaction among the CSs, EVs and electric substation in which CS is connected to the electric substation and EV takes power from CS.

Figure 2 depicts the single-line diagram of the interconnection of the charging station (m) and substation (x) based on feeder (F_m). High- and low-voltage bus bars of the electric substation are denoted by D6x and D4x, respectively. Two transformers are assumed to be connected in parallel in the electric substation. In addition, D4i indicates the incoming bus bar of the CS.

2.1. Investment Cost (IC)

The investment cost can be divided into three parts. The first part is the cost incurred by establishing the equipment and facilities for CS. The second part is the rental cost of land, and the third part is the cost needed for developing the connectors. Investment cost can be mathematically formulated as follows [37]:

$$IC = \sum\nolimits_{i=1}^{N_{CS}} (C_{initial} + B.C_{land}.NC_i + C_{con}.CP.(NC_i - 1)), \tag{1}$$

where N_{CS} is the number of CSs, $C_{initial}$ the initial fixed cost of CS, B the area requirement per connector in m^2, C_{land} the rental cost of land for different sites in areas of South Delhi, NC_i the number of charging connectors in the ith CS, C_{con} the development cost of connector, and CP the rated power of the connector.

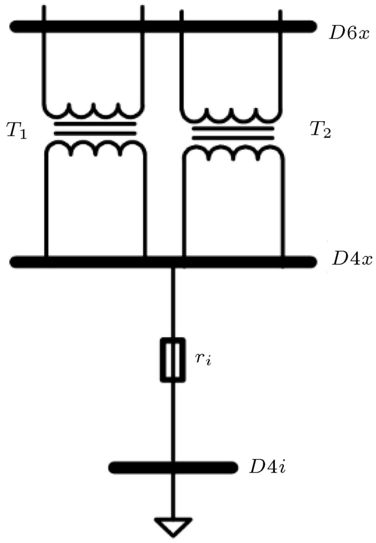

Figure 2. Single-line diagram for station connection to the electric grid [35].

In the current study, it is assumed that the land is rented for five years; therefore, the operational and maintenance cost was ignored. In addition, area requirement per connector is considered to be 25 m^2 [41].

The cost of equipment depends on the CS capacity. The rental cost of land depends on the quality of land and varies in different city locations. In the proposed methodology, CS is installed at locations with different land costs. Given that the development cost of the charging connectors will decrease in the future with technological advancement, a considerable portion of the investment cost depends on it. Figure 3 shows the typical layout of the EVCS per connector. As shown in this figure, the minimum width and length of the connector should be 2.74 m and 5.28 m, respectively. In addition, the minimum clearance of 0.92 m is needed between the two connectors in the case of using more than one connector.

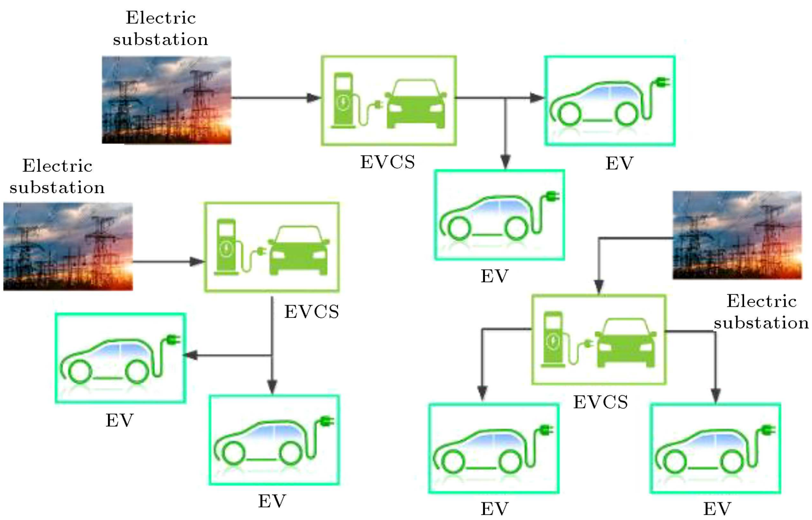

Figure 1. Interaction among the CSs, EVs, and electric substation.

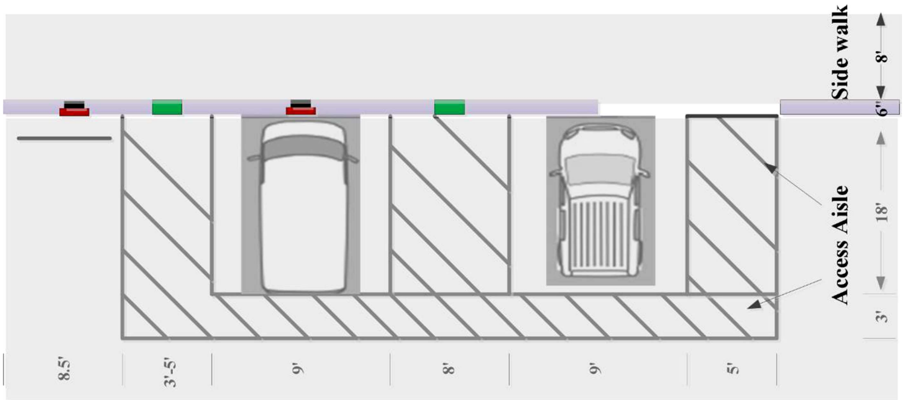

Figure 3. General CS station layout per connector [42].

It should be noted that the CS capacity is a function of the number of charging connector (NC_i) and the rated power of connector (CP).

Based on the following equation, the capacity of the ith CS can be measured as [42]:

$$CS_c\left(i\right) = CP \times NC_i. \tag{2}$$

2.2. CS electrification cost (CSEC)

The overall connection cost strongly depends on the separation between the CS and the nearest electric substation as well as the connection technology. The CS and electric substation are assumed to be directly connected by dedicated overhead lines. Table 2 lists some conductors that are easily available and frequently used for overhead lines. In addition, it presents the rated current for different types of conductors used for overhead lines in the cross-section area.

The transmission cost of the overhead line depends on the cross-section area of the line and can be measured through the following equation [35]:

$$CT_i = 8000 + 65.7\ w, \tag{3}$$

where w denotes the cross-section area of the transmission line in mm^2. The overall connection cost of the ith CS can be determined as [37]:

$$CSEC = \sum_{i=1}^{N_{CS}} \left(CT_i * D_i\right). \tag{4}$$

D_i represents the distance of the ith CS from the nearest electric substation in Km, CT_i the transmission cost of the ith CS in per km, and the matrix that calculates the distance of the ith CS from the nth electric substation in Km. The matrix $d_{i,n}$ can be accurately determined using the geographic information.

Table 2. Conductor used for dedicated overhead line [45].

Name	Cross section area in mm^2	Rated current in ampere
FOX	42.77	192
MINK	73.6	288
DOG	118.5	380
PARTRIDGE	156.9	460

2.3. EV energy Loss Cost (EVLC)

For charging the batteries of EV, the definite path must be followed by EV to reach the nearest charging station. For the jth EV, the charging loss can be determined as follows [42]:

$$P_{EVL} = \sum_{j=1}^{N_{EV}} \left(SEC * S_j\right), \tag{5}$$

where SEC is the specific electricity consumption of the EV in kWh/Km, S_j the distance between the EV and CS in Km, and P_{EVL} the EV energy loss.

Thus, the EV energy loss cost can be calculated as follows:

$$EVLC = P_{EVL} * PE * TD. \tag{6}$$

Here, PE denotes the electricity price and TD the total number of days in five years.

In this study, S_j is assumed to be the distance travelled between the EV and CS that can be measured considering the urban roads. The values of S_j are calculated using the geographic information.

2.4. Travel Time Cost (TTC)

Travel time cost is the cost required for reaching the nearest CS from the point of charging demand. It depends on the distance between the EV position and the nearest CS as well as the cost of travelling per Km of EV. According to [38], it can be mathematically written as:

$$TTC = S_j * C_{EV/Km}, \tag{7}$$

where TTC is the travel time cost, S_j the distance between the EV position and CS location, and CEV/Km the cost of traveling of EV per Km.

3. Optimization problem

This section describes the optimization model based on the minimization of the aforementioned objective functions, associated constraints, and methodology in order to assign the EVs to the nearest CS.

3.1. Aim of the optimization

The aim of the optimization problem is to minimize the total cost related to the charging demand of EV.

$$\min F = \sum_{i=1}^{N_{CS}} (IC_i + CSEC_i) + \sum_{j=1}^{N_{EV}} EVLC_j + \sum_{j=1}^{N_{EV}} TTC_j, \tag{8}$$

where N_{CS} indicates the number of CSs and N_{EV} the number of EVs charged in a day.

3.2. Constraints

The optimization problem for CS optimal sizing and placement is subjected to some existing constraints associated with CS and EVs, as shown in the following:

(a) Each CS must have at least one charging connector.

$$NC_i \geq 1 \qquad i = 1, 2, 3 \cdots N_{CS}, \tag{9}$$

(b) The connector must be able to charge all EVs.

$$\sum_{i=1}^{N_{CS}} (NC_i \times DE) \geq N_{EV}, \tag{10}$$

where DE denotes the maximum number of EVs that can be charged by a connector in one day.

(c) The trajectory length of each EV to the CS can be determined as follows:

$$S_j = \min\left(S_{i,j}\right), \tag{11}$$

where $s_{i,j}$ is the trajectory length of the jth EV to the ith CS.

(d) The maximum number of EVs that can be charged in one CS is limited by:

$$NC_i \times DE \geq N_{EV_i}. \tag{12}$$

(e) The number of EVs charged by each CS is determined based on the following equation:

$$N_{EV_i} = \sum_{j=1}^{N_{EV}} \left(1 + \operatorname{sgn}\left(S_j - S_{i,j}\right)\right)/2. \tag{13}$$

3.3. Assumptions

Various assumptions were made in this work that are listed in the following:

- The positions of EVCS and EV are considered to be distributed normally;
- The number of EVs in a given area decides the number of EVCS in that area;
- EV owner charges their EVs in a fixed CS.

3.4. Methodology

3.4.1. Determination of S and D matrices

Two matrices are modeled that indicate the distance between the CS and electric substation, and the CS and EV locations. Here, D matrix shows the distance of each CS from every substation, and S matrix indicates the distance of each EV from every CS.

Matrix D describes the distance between the ith CS and nth electric substation. Therefore, the order of matrix D would be $(i \times n)$.

$$D = \left[d_{i,n}\right]_{N_{CS} \times N_{ES}},$$

where:

$$d_{i,n} = \sqrt{\left(x_{CS_i} - x_{ES_n}\right)^2 + \left(y_{CS_i} - y_{ES_n}\right)^2}. \tag{14}$$

Here, i indicates the number of CSs, and n the number of electric substations: $i = 1, 2, 3 \cdots\cdots N_{CS}$ and $n = 1, 2, 3 \cdots\cdots N_{ES}$.

Matrix S represents the distance between the jth EV and ith CS. Thus, the order of matrix L is $(j \times i)$.

$$S = \left[S_{i,j}\right]_{N_{EV} \times N_{CS}},$$

where:

$$S_{i,j} = \sqrt{\left(x_{CS_i} - x_{EV_j}\right)^2 + \left(y_{CS_i} - y_{EV_j}\right)^2}$$

$$j = 1, 2, 3 \cdots\cdots N_{EV}. \tag{15}$$

The values of x and y are computed based on the geographical information in the area under study.

3.4.2. Implementation of the proposed approach

The main objective of the EVCS optimal sitting and sizing is to determine the location of CS installation in order to minimize the investment and electrification costs for CS and minimize the energy loss and travel time costs for the EVs. The flow chart of the proposed approach is shown in Figure 4 based on the following steps:

Step 1. Define the input data such as the fixed cost, connector development cost, and other parameters;

Step 2. Position EVCSs along the main urban roads in South Delhi and generate locations of EVs randomly based on the normal distribution functions;

Step 3. Select each charging station and assign EV to each CS based on the minimum distance criterion;

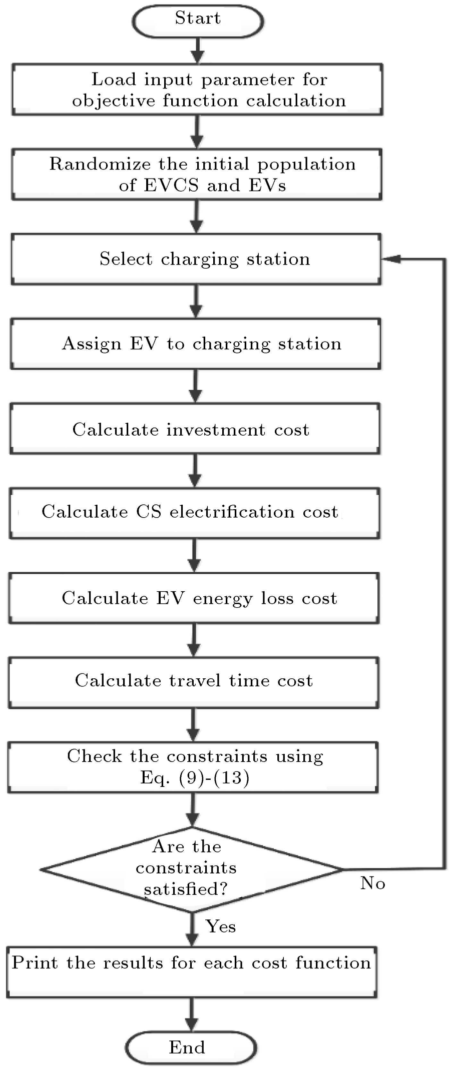

Figure 4. Flowchart of the proposed approach.

Step 4. Calculate various objective functions, i.e., investment, CS electrification, EV energy loss, and travel time costs;

Step 5. Check the subjected constraints using Eqs. (9)–(13). If satisfied, print the results for each cost function; otherwise, go to Step 2.

4. Proposed algorithm for optimization problem

4.1. Brief overview of GWO

Syedali Mirjalili and Lewis [43] (2014) proposed a novel meta-heuristic-based intelligent algorithm called GWO. Grey wolves prefer to live in a pack of 5–12 members. They follow a dominant social hierarchy level in which alphas (α) and betas (β) occupy the first and second levels of hierarchy, respectively. Delta (δ) wolves follow alphas and betas. The omega (ω) wolves are the lowest level wolves that act as a scapegoat for the pack. Figure 5 shows the grey wolf hierarchy.

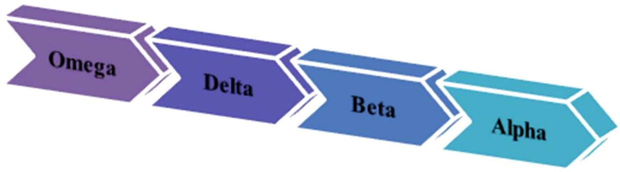

Figure 5. Social hierarchy in the grey wolves.

4.2. Mathematical Modeling of GWO

The major steps involved in the mathematical modeling of GWO include the social hierarchy of GWO, prey encircling, and prey hunting.

4.2.1. Social hierarchy of GWO

In this algorithm, alpha (α) and beta (β) are considered the best and the second best solutions, respectively. In addition, delta (δ) is considered the third best solution, followed by omega (ω).

4.2.2. Grey wolves encircling prey

The hunting process starts with the encircling of prey. The steps of encircling are listed in [43] as:

$$\overrightarrow{M} = \left| \overrightarrow{C}.\overrightarrow{Z_p(t)} - \overrightarrow{Z(t)} \right|, \tag{16}$$

$$\overrightarrow{Z}(t+1) = \overrightarrow{Z_p}(t) - \overrightarrow{N}.\overrightarrow{M}, \tag{17}$$

where t indicates the current iteration number; $\vec{N}$ and $\vec{C}$ represent the coefficient vectors; $\vec{Z}$ and $\overrightarrow{Z_P}$ denote the position vector of the prey and grey wolf, respectively, determined by the following equations:

$$\overrightarrow{N} = 2n.\overrightarrow{r_1} - \overrightarrow{a}, \tag{18}$$

$$\overrightarrow{C} = 2.\overrightarrow{r_2}, \tag{19}$$

where r_1 and r_2 are random numbers with values between 0 and 1 and a decreases linearly from 2 to 0 over the course of iterations.

4.2.3. Hunting prey

In order to simulate the hunting process of the grey wolves in a mathematical form, it is assumed that α, β, and δ can provide more detailed information about the position of the prey. In addition, α, β, and δ are the best three solutions offered so far and saved while other search agents update their positions at each iteration with respect to their best position. The following mathematical equations [37] were developed in this context:

$$\overrightarrow{M_\alpha} = \left| \overrightarrow{C}.\overrightarrow{Z_\alpha} - \overrightarrow{Z}(t) \right|, \qquad \overrightarrow{M_\beta} = \left| \overrightarrow{C}.\overrightarrow{Z_\beta} - \overrightarrow{Z}(t) \right|,$$

$$\overrightarrow{M_\delta} = \left| \overrightarrow{C}.\overrightarrow{Z_\delta} - \overrightarrow{Z}(t) \right|, \tag{20}$$

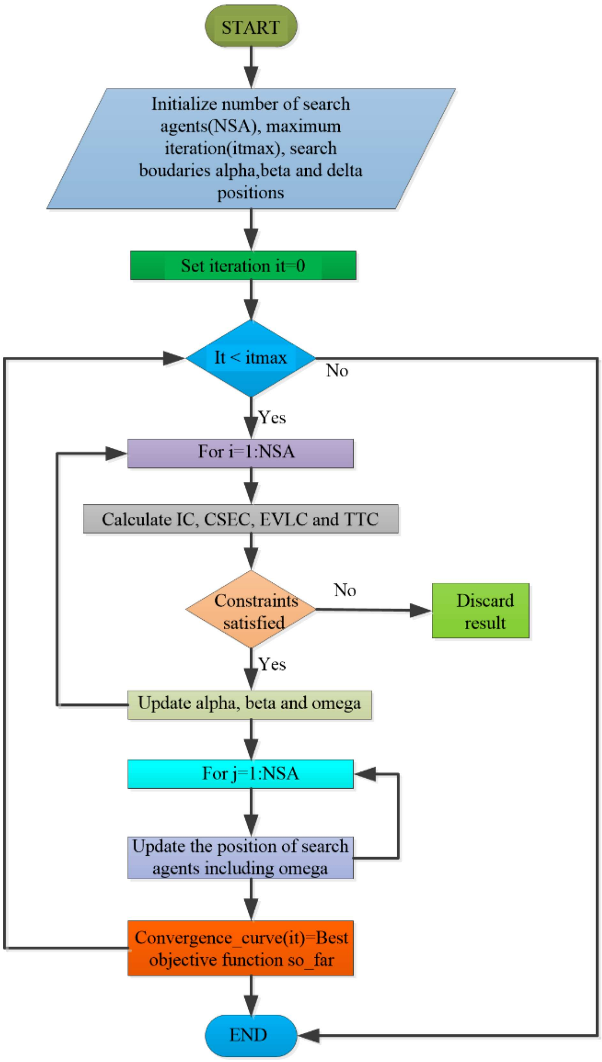

Figure 6. Flowchart of GWO algorithm for the proposed approach.

$$\overrightarrow{Z_1} = \overrightarrow{Z_\alpha} - \overrightarrow{N}.\overrightarrow{M_\alpha}, \qquad \overrightarrow{Z_2} = \overrightarrow{Z_\beta} - \overrightarrow{N}.\overrightarrow{M_\beta},$$

$$\overrightarrow{Z_3} = \overrightarrow{Z_\delta} - \overrightarrow{N}.\overrightarrow{M_\delta}, \tag{21}$$

$$\overrightarrow{Z}(t+1) = \frac{\overrightarrow{Z_1} + \overrightarrow{Z_2} + \overrightarrow{Z_3}}{3}. \tag{22}$$

The GWO exploration ability represents the search process of grey wolves, while the exploitation ability indicates the attacking process of grey wolves.

4.3. GWO algorithm for the optimal sitting and sizing of EVCS

A series of steps were adopted for implementing GWO to minimize the multi-objective cost-based functions. The procedure is explained based on the flowchart given in Figure 6. The initially chosen number of iterations, problem dimension, and Number of Search Agents (NSA) were also taken into account.

Step 1: Initialization. The driving source of the algorithm including NSA, max iteration, dimension and boundaries of the problem is first initialized. In this study, NSA is assumed to be 30 while the maximum number of iterations is 100;

Step 2: Grey wolf positions generation. Population of all search agents is randomly generated using GWO and the first three positions are initialized as alpha, beta, and delta. Then, the objective function values for each search agent are calculated;

Step 3: Quality solution. The constraints are checked next to determine the quality solution. If the constraints are satisfied, the objective function is calculated and if the constraints are violated, the results are discarded;

Step 4: Selecting the best positions of search agent. The positions of alpha, beta, and delta wolves are updated, excluding the omega wolf. Eqs. (20)–(22) are utilized to select the best solution;

Step 5: Determining the new positions of search agents. The new positions of all search agents are determined, and the whole process is repeated;

Step 6: Termination criteria. The termination criteria are set as the maximum number of iterations in the proposed work. In case the number of iterations exceeds the assigned number of iterations, the simulation will be stopped, and the optimized value of objective functions will be displayed.

5. Result and discussion

This section provides an explanation of the planning region, reliability analysis, simulation results, and main findings.

5.1. Description of system under study

The approach was applied to an area of 218.5 km^2 in South Delhi, New Delhi, India. The coordinates, elevation, and population density of different CS locations are provided in Table 3.

There are 15000 vehicles assumed to be EVs in the study zone out of which only three percentages of the total EVs are considered for daily charging. Around 500 EVs were assumed to be charged every day, and their positions were generated randomly based on the Cartesian geographic system, as shown in Figure 7. In this study, 11 substations are located near 20 CSs that can provide the required electric supply for the nearby CS. In Figure 7, green circle, red star, and blue diamond represent the EVs, CSs, and electric substations, respectively.

A total of 20 CSs were placed in different well-known areas of South Delhi and located on Google Map, as shown in Figure 8. In addition, the input

Table 3. Charging station information [45].

Charging station location	Coordinates		Elevation (m)	Population density (people per Km^2)
	Latitude	Longitude		
Saket	28.5221	77.2012	240	20110
Shivalik	28.5340	77.2053	227	19557
Greater Kailash	28.5555	77.2337	224	26450
Lajpat Nagar	28.5649	77.2403	211	34599
New friends Colony	28.5675	77.2691	208	8956
Kalkaji	28.5400	77.2592	239	24803
Hauz Khas	28.5479	77.2031	223	7974
Safdarjung	28.5647	77.1949	221	29682
Vasant Vihar	28.5603	77.1617	240	17475
Green Park	28.5584	77.2029	218	35903
Panchsheel	28.5415	77.2161	224	11576
Defence Colony	28.5734	77.2326	212	16837
Nehru Place	28.5503	77.2502	231	24036
Chanakyapuri	28.5972	77.1904	220	7498
Chirag Delhi	28.5376	77.2283	225	22552
Vasant Kunj	28.5293	77.1484	264	10536
Chhatarpur	28.4959	77.1848	261	13101
RK puram	28.5660	77.1767	229	14620
Golf Links	28.5973	77.2323	209	5919
Malviya Nagar	28.5342	77.2094	226	29945

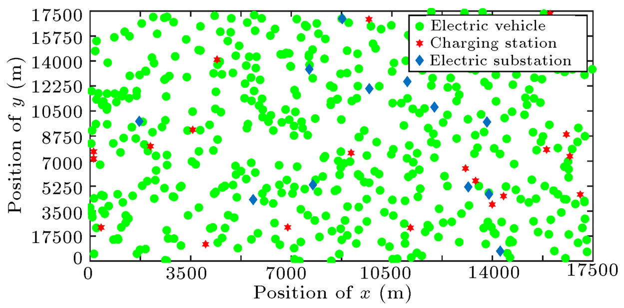

Figure 7. Positions of EVs, charging stations and electric substations.

parameters required for solving the objective functions are listed in Table 4.

5.2. Impact on reliability of utility grid

Reliability impact of the electric grid is an important factor that must be taken into account in the optimal planning of EVCS [47]. Deterioration of the electric substation components such as substation transformer and line causes disruption in providing electric supply to the CSs. Of note, EV charging loss may cause some problems for the CS operators and EV owners economically. The number of models and reliability indices should address the reliability issue of the utility grid for the EVCS optimal planning.

Table 4. Input parameter required for objective function calculation [37,38].

Parameter	Value	Unit
N_{EV}	500	–
N_{CS}	20	–
N_S	11	–
SEC	7	Km/kWh
PE	90.48	$
$C_{initial}$	72204.52	$
C_{con}	214.89	$/kW
CP	96	kW
DE	30	–
TD	1825	Days
w	156.9	Mm^2
T	0.5	hr
$C_{EV/Km}$	0.34	$/Km

Availability (ξ) of a basic element can be described in terms of the rate of failure as well as the rate of repair of the basic component of substation, i.e., transformer and lines [46]. In the following, the availability (ξ) can be given as:

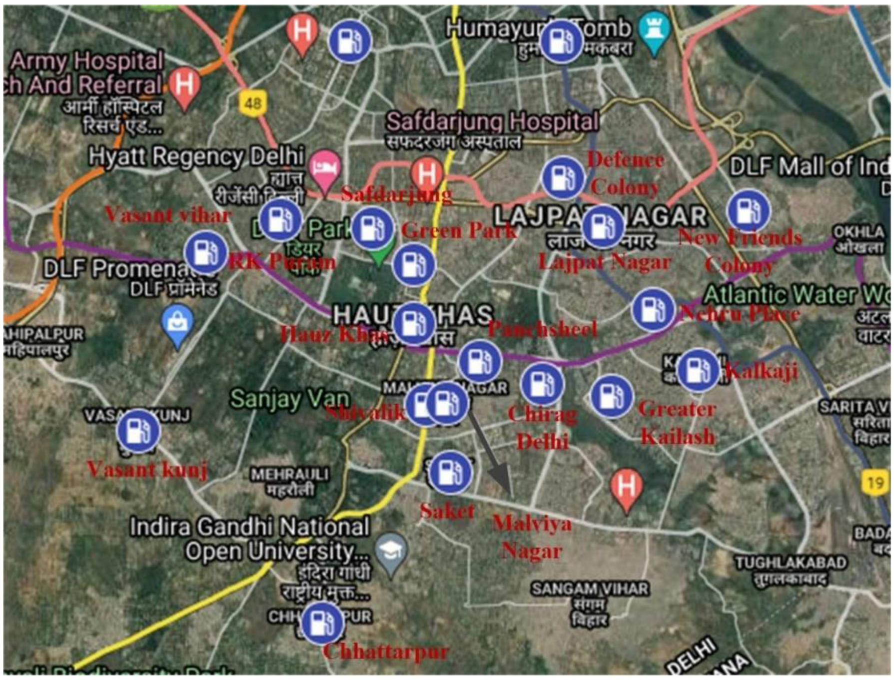

Figure 8. Location of CS in South Delhi areas in Google map [44].

Table 5. Data required for determining the reliability [46].

		Value	Unit
Line	Failure rate	0.1	Failure/Km/year
	Repair time	4	Hour
Transformer	Failure rate	0.1	Failure/year
	Repair time	100	Hour
ICC		0.90	\$/kWh

$$\xi = \frac{\psi}{\psi + \chi}, \tag{23}$$

where χ represents the failure rate (failure per year), Ψ the repair rate (repair per year), and $r = 8760\Psi$ the repair time in hour. Table 5 presents the failure and repair rates for the substation transformer and lines.

One of the important indices that measures the reliability impact of utility grid is Charging Cost Loss (CCL). It refers to the cost of EVs that remain uncharged due to the collapse in the utility grid.

CCL may be defined in terms of the operating hours of each CS, CS capacity, unavailability of the electric supply for the ith CS, and uninterrupted charging cost. CCL can be calculated as:

$$CCL\,(i) = 1825 * \rho\,(i) * C\,(i) * \eta_i * ICC, \tag{24}$$

where 1825 represent the number of days in five years, $\rho(i)$ the average operating hours of each CS, ηi the unavailability of electric supply at the ith CS, and ICC the uninterrupted charging cost in \$/kWh.

Average operating hours, i.e., $\rho(i)$, of each CS can be determined as follows:

$$\rho\,(i) = \frac{N_{EV_i}}{NC_i} * T, \qquad \text{in hours}, \tag{25}$$

where N_{EV_i} represents the total number of eVs charged at the ith CS, NC_i the number of charging connectors required at the ith CS, and T the average charging time of an EV in hour.

ICC refers to the cost paid by CS operator and EV owner due to disruption in EV charging because of collapse in grid.

Unavailability of electric supply for the ith CS can be calculated as follows:

$$\eta_i = 1 - \xi_i, \tag{26}$$

$$\xi_i = \xi_{f_i} * \xi_{D4x}, \tag{27}$$

where ξ_{fi} denotes the station feeder availability of feeder fi, and ξ_{D4x} the availability of electric supply on bus $D4x$. Availability of electric supply on bus $D4x$ can be calculated as follows:

$$\xi_{4x} = \xi_{6x}\left(1 - (1 - \xi_T)^2\right), \tag{28}$$

where ξ_T is the availability of power transformer in substation, and ξ_{D6x} the availability of electric supply on bus D_{6x}.

Calculation of ξ_{D6x} depends on the nature of substation, i.e., whether or not it is PQ bus.

$$\xi_{6x} = \left(1 - (1 - \xi_T)^2\right). \tag{29}$$

5.3. Simulation results and main achievements

The optimized value of the objective function strongly depends on the CS capacity, number of EVs charged at each CS, and number of charging connectors utilized to recharge the EVs. For charging, EV will follow the path of minimum distance to reach the CS. Number of EVs charged at each CS can be approximately determined by Eq. (13). Figure 9 shows the number of EVs assigned at each CS.

Thus, the number of charging connectors installed at each CS can be obtained as follows:

$$NC_i = \frac{N_{EV_i} \times NC\,(\max)}{N_{EV}}, \tag{30}$$

where N_{EV_i} shows the number of EVs charged at $CS(i)$, and $NC(\max)$ the maximum limit of the charging connectors. Therefore, the number of charging connectors used at each CS for feeding the assigned number of EVs is displayed in Table 6. In this regard, different cost functions considered in this paper can be evaluated.

Investment cost mainly depends on the land cost and number of charging connectors. The areas under study in Delhi are divided into categories A to H based on the land cost. In the study zone, different areas belong to different categories. Table 7 shows the land cost of different considered areas.

The investment cost for different CS sites was evaluated using the proposed GWO. The overall investment cost incurred by utilizing GWO was 8657600 \$. The effectiveness of the proposed GWO was confirmed by comparing the results with those from other intelligent techniques such as PSO (9143400 \$). According to findings, the investment cost calculated using GWO was 5.3% less than that of PSO. This comparison shows the preeminence of GWO over PSO. Figure 10 shows the comparative analysis of the investment cost based on different intelligent algorithms. Of note, the investment costs are high in areas with high land costs, thus needing larger numbers of charging connectors. CSs that demand a greater number of connectors have higher setup costs, hence a substantial increase in the

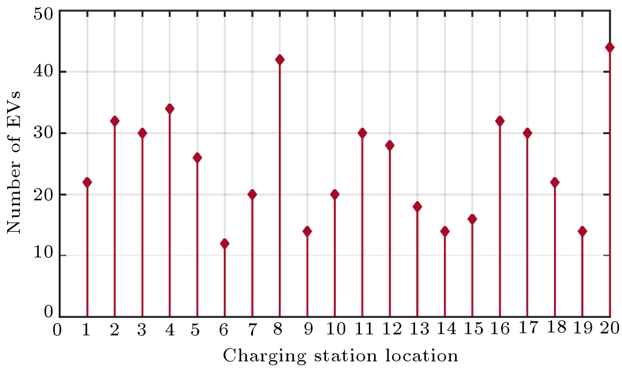

Figure 9. Number of EVs charged at each CS.

Table 6. Optimized number of charging connectors required at different CS installed in South Delhi areas.

Charging station location	Number of used charging connectors
Saket	3
Shivalik	4
Greater Kailash	3
Lajpat Nagar	4
New Friends Colony	3
Kalkaji	2
Hauz Khas	2
Safdarjung	5
Vasant Vihar	2
Green Park	2
Panchsheel	3
Defence Colony	3
Nehru Place	2
Chanakyapuri	2
Chirag Delhi	2
Vasant Kunj	4
Chhatarpur	3
RK puram	3
Golf Links	2
Malviya Nagar	5

Table 7. Land cost of areas in South Delhi [48].

Charging station location	Land cost (\$/m^2)
Saket	2178.77
Shivalik	3349.87
Greater Kailash	3349.87
Lajpat Nagar	2178.77
New Friends Colony	10539.82
Kalkaji	2178.77
Hauz Khas	3349.87
Safdarjung	3349.87
Vasant Vihar	10539.82
Green Park	3349.87
Panchsheel	3349.87
Defence Colony	3349.87
Nehru Place	10539.82
Chanakyapuri	10539.82
Chirag Delhi	3349.87
Vasant Kunj	2178.77
Chhatarpur	3349.87
RK puram	3349.87
Golf Links	10539.82
Malviya Nagar	2178.77

Table 8. Investment cost and CS electrification cost of each CS installed in South Delhi areas.

Charging station location	Investment cost ($)		CS electrification cost ($)	
	GWO	PSO	GWO	PSO
Saket	284200	298200	227.36	241.5
Shivalik	481600	509600	220.864	232.218
Greater Kailash	373800	387800	266	278.572
Lajpat Nagar	361200	389200	221.424	232.246
New Friends Colony	928200	1083600	181.44	208.026
Kalkaji	207200	221200	204.064	213.696
Hauz Khas	267400	281400	164.752	176.092
Safdarjung	589400	617400	526.288	545.398
Vasant Vihar	637000	651000	462.896	485.8
Green Park	267400	281400	46.704	50.05
Panchsheel	373800	376600	242.032	278.558
Defence Colony	373800	387800	134.4	136.556
Nehru Place	637000	651000	134.064	135.492
Chanakyapuri	637000	665000	618.24	654.92
Chirag Delhi	267400	273000	54.656	57.988
Vasant Kunj	361200	375200	696.416	720.398
Chhatarpur	267400	281400	118.832	120.568
RK puram	267400	281400	375.872	391.384
Golf Links	637000	651000	241.136	262.43
Malviya Nagar	438200	480200	281.792	300.412
Total	**8657600**	**9143400**	**5419.232**	**5722.304**

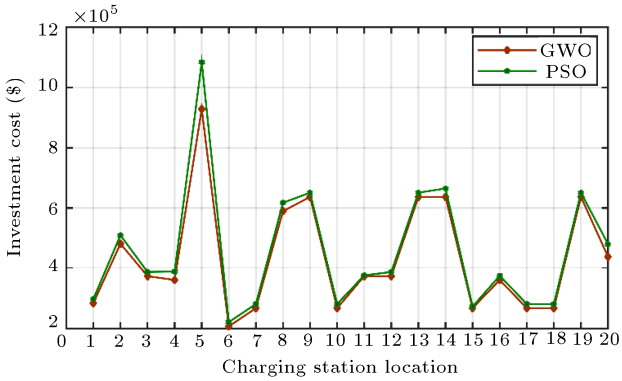

Figure 10. Investment cost for different CS in South Delhi areas.

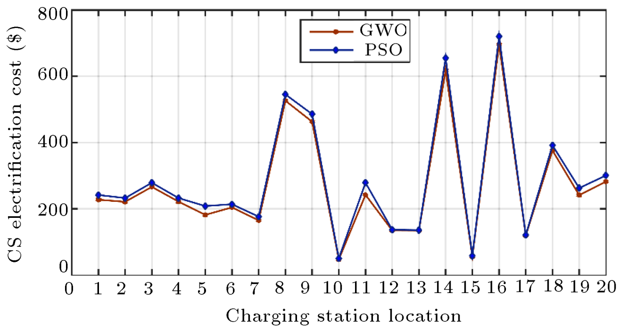

Figure 11. CS electrification cost for different CS in South Delhi area.

investment costs mainly because the connector setup costs account for a significant portion of the total cost. This is the reason why some areas such as New Friends Colony, Vasant Vihar, Chanakyapuri, and Golf Links have high investment costs due to their high land cost and ample quantity of connectors required to serve the EVs in these regions. On the contrary, Saket, Hauz Khas and Kalkaji, etc. have lower investment costs due to lower land costs and a limited number of charging connectors.

Table 8 makes a comparison of the investment costs for each CS site considering both GWO and PSO. Further improvement in the investment cost can be made when the government and public sector unit cooperate in developing the charging stations and using available public lands for their installation.

It should be noted that CS electrification cost is highly affected by the separation between the CS and electric substation. The distance of each CS from every substation was evaluated using the Cartesian geographic information. Accordingly, electrification cost of each CS site was determined using the proposed GWO. Table 8 shows the CS electrification cost using GWO and PSO. The performance of the GWO technique was evaluated by comparing the obtained results with those from PSO. Application of the GWO would result in noticeable improvement in the CS electrification cost by 5.2% less than that of PSO. Figure 11 makes a comparison of the CS electrification cost obtained from GWO and PSO. The greater the distance between the CS and the electric substation, the higher the cost of CS electrification, and vice versa. Table 8 shows that CSs in Safdarjung, Chanakyapuri, and Vasant Kunj areas have high CS electrification costs due to their remote location from the electric substation; however, due to their close proximity to the substation, the Chirag Delhi and Green Park charging station sites have low costs. As a result, in order to ensure lower CS electrification costs, the CS operator must choose the location wisely. Even when the electric utility is obligated to electrify the stations at no cost to the station owners, the cost of CS electrification can be reduced.

Further, EV energy loss or energy consumption cost depends on the distance between the EV position and CS. Here, CS in the neighborhood of the electric substation may be at a far distance from the EV position. Hence, it results in increase in energy loss cost. The distance between each EV (i.e., 500 EVs in this work) and CS is calculated based on the geographic information. EVs are assigned to the nearest charging station based on the minimum distance criterion. In this respect, energy loss cost of 500 EVs was calculated by optimizing the distance to the nearby charge stations. The proposed GWO leads to a considerable reduction in energy loss cost, i.e., 15.5% less than that in the PSO. The obtained results using GWO prove its superiority over other algorithms. The varying behaviors of EV energy loss cost obtained using algorithms considered in this work are shown in Figure 12. It is reported that the smaller the distance between the EV location and the CS site, the lower the EV energy consumption, and vice versa. If the needs of EV owners are neglected, the cost of EV energy loss may be reduced.

Travel time cost depends on the distance between the charging station and the location, where the need for charging EV arises, as well as the cost of EV travelling per Km. The smaller the distance between the EV and CS, the lower the travel time cost paid by the EV owner. Hence, the travel time costs of all 500 EVs to reach the nearby charging station were calculated using the proposed GWO and compared with PSO to prove its dominance. It is observed that GWO results in a significant reduction in travel time cost as compared to the results attained via PSO. GWO provides an optimized value of travel time cost, i.e., 280.43 $ which is 9.1% less than that of PSO (308.72 $). This proves the supremacy of the proposed GWO algorithms over PSO. The travel time cost of each EV (i.e., 500 EVs) is determined using GWO and its comparison with PSO is portrayed in Figure 13. The cost of travel time can be reduced further by placing more charging stations along EV routes, as this decreases the distance that EVs would travel for charging.

The impact of placing charging station on reliability of grid is investigated in terms of CCL. The availability of electric components in electric substation is calculated using Eqs. (26)-(29). CS capacity, effective operating hours, and electric supply availability at each CS site are presented in Table 9.

CCL differs for each CS as it depends on CS capacity, effective operating hours, and electric supply availability. The optimized values of CCL for each CS site are obtained via GWO and its comparison with PSO is shown in Figure 14.

Eqs. (26)–(29) introduce the impact on grid reliability in optimal planning of EVCS. Basic parameters required for the evaluation of reliability are listed in

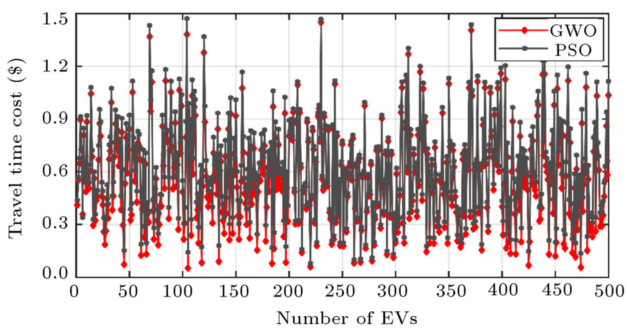

Figure 13. Travel time cost for 500 EVs.

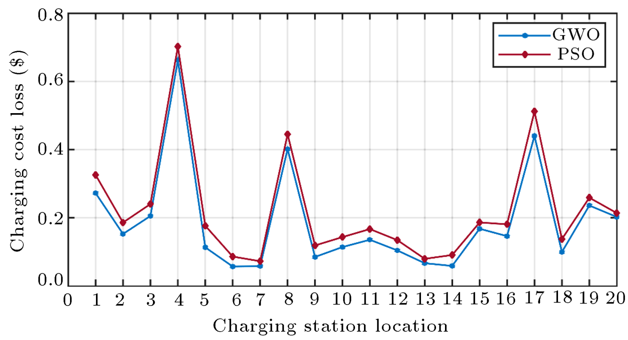

Figure 14. Charging cost loss for CS installed in South Delhi areas.

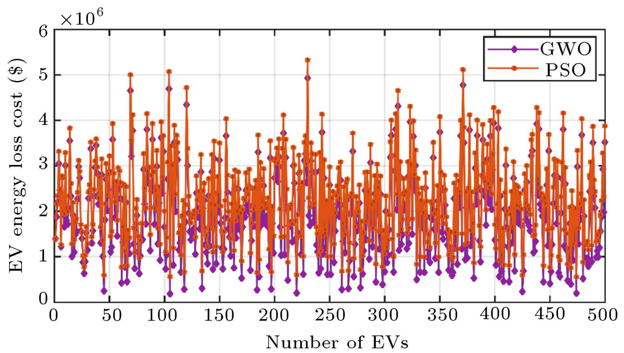

Figure 12. EV energy loss cost for 500 EVs.

Table 9. Average working hours, unavailability of electricity and capacity of each CS.

Charging station capacity (kW)	Effective operating hours of each CS, $\rho(i)$ in hr	Unavailability of electric supply (ξ_i) ($\times 10^{-3}$)
288	3.66	0.2750
384	4	0.1060
288	5	0.1523
384	4.25	0.4343
288	4.33	0.0967
192	3	0.1050
192	5	0.0640
480	4.2	0.2131
192	3.5	0.1347
192	5	0.1267
288	5	0.1004
288	4.66	0.0828
192	4.5	0.0820
192	3.5	0.0929
192	4	0.2333
384	4	0.1015
288	5	0.3271
288	3.66	0.1006
192	3.5	0.3752
480	4.4	0.1024

Table 5. Comparison of the value of CCL for each CS site obtained using GWO and PSO considering the impact on the grid reliability network is shown in Table 10. Moreover, the values of CCL are highly dependent on the availability of electric supply at a particular CS, as shown in Table 10. The CCL value is high for those CSs where the unavailability percentage of electric supply is high, and vice versa.

As seen in Table 5, the ICC is considered to be 10 times the electricity price, indicating the loss due to the power outage.

The objective functions represented by Eqs. (1)–(7) and a set of technical constraints, i.e., Eqs. (9)–(13), were solved using grey wolf optimization.

The optimized values of all the objective functions considered for the optimal planning of EVCS and their impact on the grid reliability are summarized in Table 11. It can be seen in Table 11 that CCL is smaller than the other cost functions, although CCL is of significant value when EV loss is ignored in the optimization problem.

Table 10. Charging Cost Loss (CCL) of each charging station.

Charging station location	Charging cost loss ($)	
	GWO	PSO
Saket	0.272104	0.3255
Shivalik	0.152124	0.18564
Greater Kailash	0.204904	0.23996
Lajpat Nagar	0.662242	0.7021
New Friends Colony	0.112672	0.17612
Kalkaji	0.056504	0.08568
Hauz Khas	0.057484	0.0721
Safdarjung	0.401408	0.44492
Vasant Vihar	0.084574	0.1183
Green Park	0.113638	0.14294
Panchsheel	0.135086	0.16646
Defence Colony	0.103824	0.13412
Nehru Place	0.066192	0.0791
Chanakyapuri	0.058324	0.0903
Chirag Delhi	0.167412	0.18592
Vasant Kunj	0.14567	0.18046
Chhatarpur	0.440104	0.51184
RK puram	0.099078	0.13692
Golf Links	0.235578	0.25858
Malviya Nagar	0.202062	0.2135
Total	**3.770984**	**4.45046**

Table 11. Optimized values of objective functions.

Objective functions	Cost ($)	
	GWO	PSO
Investment cost	8657600	9143400
CS electrification cost	5419.232	5722.304
EV energy loss cost	9.51×10^8	11.26×10^8
Travel time cost	280.4305	308.7251
Charging cost loss	3.770984	4.45046

6. Conclusion

In this paper, a new approach to solving the multi-objective optimization problems for optimal sitting and sizing of EVCS in different areas in South Delhi, New Delhi, India was proposed. Grey wolf optimization was utilized to solve the multi-objective cost functions and the obtained results were compared with particle swarm optimization for validation purposes. The cost function included investment cost, CS electrification cost, EV energy loss cost, and travel time cost. Investment and CS electrification costs of all CSs were calculated, and it was found that the investment cost strongly depended on the land cost and number of connectors used in each CS. CS electrification cost depended on the distance between the CS and electric substation. On the other hand, EV energy loss cost and travel time cost were evaluated for all EVs. It was revealed that travel time cost and EV energy loss cost depended on the distance between the CS and EV location. Based on the results obtained from GWO and PSO, it was revealed that GWO was more effective than PSO in the considered case study. Furthermore, reliability index, i.e., CCL, was an important index, promoting the idea about the reliability of a system. CCL was a function of CS capacity, effective working hours of CS, and unavailability of electric supply at each CS. CCL was determined for each CS, and the results revealed that CCL would be high for each CS with low availability of electric supply, and vice versa.

Nomenclature

IC	Investment Cost
CSEC	Charging Station Electrification Cost
EVLC	Electric Vehicle Energy Loss Cost
TTC	Travel Time Cost
CCL	Charging Cost Loss
SEC	Specific Electricity Consumption of EV
EP	Electricity Price
TD	Total Number of days in 5 years
ICC	Uninterrupted Charging Cost
$C_{initial}$	Initial fixed cost of charging station
C_{land}	Rental cost of land
B	Area requirement per connector
N_{CS}	Number of charging station
N_{EV}	Number of electric vehicles
i	Charging station index
j	Electric vehicle index
NC_i	Number of charging connectors at the ith CS
CP	Rated power of connectors
$CS_C(i)$	Capacity of the ith CS
w	Area of cross section of transmission line
CT_i	Transmission cost of the ith CS
S_j	Trajectory length to the charging station
$s_{i,j}$	Trajectory length of the jth EV to ith CS
D	Distance between the ith CS and the nearest electric substation
P_{EVL}	EV energy loss
DE	Maximum number of EVs that can be charged by a connector
$C_{EV/Km}$	Cost of EV traveling per Km
ES	Electric Substation
N_{ES}	Number of electric substations
x_{CS}	Abscissae of charging station
y_{CS}	Ordinate of charging station
x_{EV}	Abscissae of electric vehicle
y_{EV}	Ordinate of electric vehicle
x_{ES}	Abscissae of electric substation
y_{ES}	Ordinate of electric substation
ξ	Availability of electric supply
χ	Failure rate
Ψ	Repair rate
r	Repair time
$\rho(i)$	Average operating hours of the ith CS
$\eta_(i)$	Unavailability of electric supply at the ith CS
T	Average charging time of an EV
ξ_{fi}	Station feeder availability of feeder fi
ξ_{D4x}	Availability of electric supply on bus $D4x$.
ξ_T	Availability of power transformer in substation
ξ_{D6x}	Availability of electric supply on bus $D6x$

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