The Optimal Placement of Electric Vehicle Fast Charging Stations in the Electrical Distribution System with Randomly Placed Solar Power Distributed Generations

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Abstract

The growing use of electric vehicles (EVs) in today's transport sector is gradually reducing the use of petroleum-based vehicles. However, as EV penetration grows, the EV's demand influences distribution network parameters such as power loss, voltage profile. Therefore, an improved bald eagle search (IBES) algorithm is suggested for the optimal placement of FCSs into the distribution network with high penetration of randomly distributed solar power generation (SPDG). This study suggests a two-stage approach for placing FCSs. The charging station investor decision index (CSIDI) was

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introduced in the first stage, taking into account the land cost index (LCI) and the electric vehicle population index (EVPI). The CSIDI was developed to decrease land costs while increasing EV population for FCS installation. In the next one, an optimization problem is constructed to minimize total active power loss while taking distribution system operator (DSO) constraints into consideration. The IEEE-34 bus distribution system is used as the proposed network. The simulation is carried out in MATLAB to integrate the EVCSs in three cases in the distribution network with SPDGs randomly placed. Therefore, The IBES found the best optimal positions with a power loss of 198.43 kW. When compared to the PSO technique, the IBES technique has a reduced average power loss of 2.02%.

Keywords: Charging stations, electric vehicle population, land cost, improved bald eagle search algorithm, optimal placement.

List of Abbreviations

CS	Charging Station
LCI	Land Cost Index
EVPI	Electric Vehicle Population Index
CSIDI	Charging Station Investor Decision Index
DSO	Distribution System Operator
EV	Electric Vehicle
FCS	Fast Charging Station
PSO	Particle Swarm Optimization
GWO	Grey Wolf Optimization
BFS	Backward Forward Sweep
SPDG	Solar Power Distributed Generation
BES	Bald Eagle Search
IBES	Improved Bald Eagle Search

1 Introduction

Electric vehicles (EVs) are gaining popularity among government organizations and the automotive industry due to significant reductions in CO_2 emissions and maintenance costs when compared to the most populous internal combustion vehicles [1]. Furthermore, according to a study, the fossil fuel reserves will be depleted in this century, with oil lasting 51 years, natural gas lasting 53 years, and coal lasting 114 years [2]. Moreover, the researchers examined data to determine that the development of EVs could reduce CO_2 emissions by 28% by 2030 [3]. As a result, the global EV population is growing, posing new challenges for DSO. In addition, new business opportunities are developing, such as service providers for EV consumers, load demand management, and ancillary services. As a result, excessive electrical power demand may affect distribution system parameters such as bus voltages, power loss, reliability, harmonic distortion, voltage imbalance and power quality [4]. Furthermore, the rapidly expanding EV population necessitates the development of well-developed charging infrastructure. Charging stations (CSs) are classified as slow, medium, fast and ultra-fast based on their charging time and power rating [5].

FCSs are an appropriate choice for charging EV batteries in 20–30 minutes [6]. As a result, installing FCSs is a beneficial option for EV customers; nevertheless, installing FCSs has a negative influence on the distribution system [7]. Furthermore, the proper placement of FCS can reduce the burden on the distribution system [8]. Furthermore, the number of FCSs and their locations are critical problems for DSOs, charging station investors and EV consumers. As a result, the number of FCSs and the appropriate location of FCSs have become more interesting study topics in the previous decade. Furthermore, most studies have published their findings on FCS placement by including DSO parameters such as bus voltage, power loss, and reliability [9]. On the other hand, the placement of FCSs has taken into account the investment cost as well as the EV user's approach. The authors are motivated by the current literature to place the FCS using the DSO approach, the EV users approach, and the FCS investor approach.

1.1 Literature Review

Most of the researchers have worked for the placement of slow or medium charging stations whereas, some authors have discussed the optimal location for FCS. In addition, very little research has been published on the integration of medium and fast charging together. In [10], optimal siting and sizing of CS optimization problem is formulated for obtaining the optimal results by considering investment cost, connection cost, active power losses cost and demand response, which is solved by PSO algorithm. The authors created a multi-objective mixed integer non-linear problem (MINLP) in [11] including FCS development costs, EV specific energy consumption costs, electrical network power loss costs, DGs costs, and voltage variation costs. In addition, the simultaneous allocation of EV parking lots and the distributed renewable

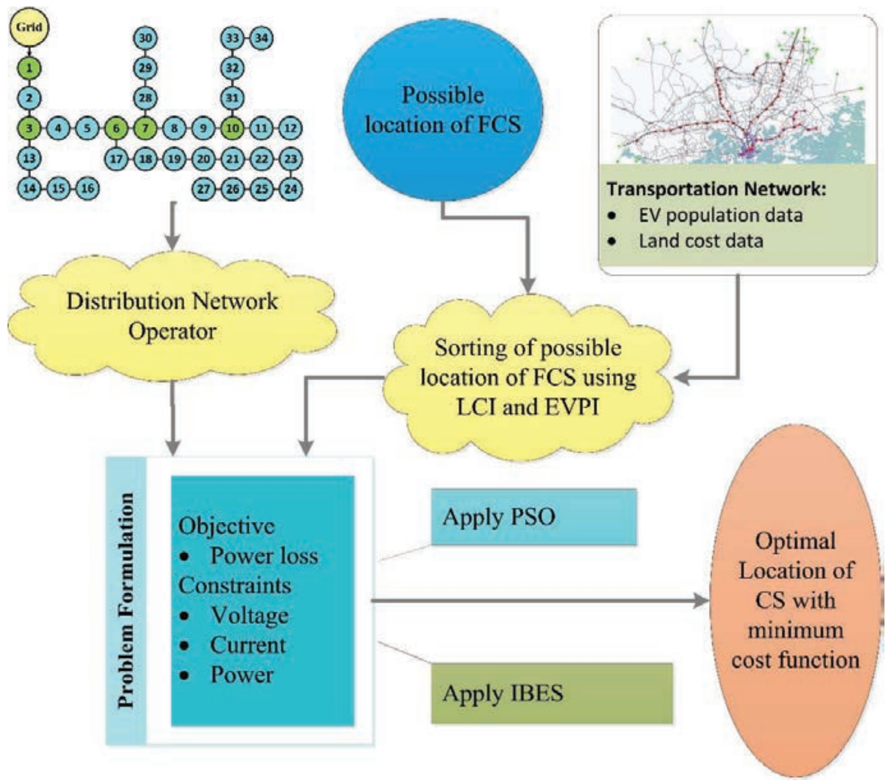


Figure 1 The framework of the proposed problem.

resources have been placed at the optimal location through the ant colony optimization (ACO) algorithm [12]. Eventually, a multi-objective problem has formulated considering the minimization of power loss and maximizing the EV population for the optimal CS location which was gained by the grey wolf optimization (GWO) technique [13].

In [14], The authors employed a hybrid Chicken Swarm Optimization and Teaching Learning Based Optimization method to reduce the investment cost for establishing the charging station, as well as a voltage deviation, reliability, and power loss (VRP) index to improve distribution system characteristics. Furthermore, in [15], the same authors have published a literature review on optimal location and sizing of CSs, the impact on distribution systems, and techniques for solving the corresponding problem.

Furthermore, the authors in [16], proposed a capacitated-flow refueling location model (CFRLM) and formulated an optimization problem that included investment cost, penalty for unsatisfied charging demands, and power distribution network cost, which is solved by branch and bound (B&B) technique. Moreover, the stability and power loss minimization is the objective function of the optimization problem which is solved by the adaptive particle swarm optimization (APSO) algorithm [17]. Similarly, in [6], the power loss and voltage deviation have been selected as objective functions for CS placement with the integration of PV generation while formulated problem solved by PSO method. Furthermore, a mixed-integer programming model has been established to express the problem of optimizing total plug-in EV populations in the network, and the GA has been utilized to solve the suggested problem [18]. In [19], the authors have suggested the multi-objective approach for the placement of CSs and DGs with V2G strategy, whereas an improved harmony PSO algorithm has obtained the optimal results of the proposed problem. Moreover, the authors in [20], have suggested the fuzzy grasshopper optimization algorithm for optimal placement of CSs, DGs, and shunt capacitors. Furthermore, in [9] authors have obtained the optimal location of CS by minimizing the development cost of CS, power loss, and maximizing the voltage quality, and formulated problem is solved by a balanced mayfly algorithm.

1.2 Objectives and Contribution of the Proposed Work

The objective of this research is to determine the optimal locations for FCSs while reducing investment costs and increasing profit from installation, as well as to optimize distribution system parameters. Therefore, for the modeling of the optimization problem, land cost, EV population, and power loss of distribution system are considered as the objective for the placement of charging stations. All the existing structures aim to achieve the optimal location of the CS considering various objective functions. However, to the best of the authors' knowledge, no such method has considered the land cost and EV population in the optimization problem. In this paper, a novel approach for the location of FCSs is proposed considering the land cost, EV population, and power loss cost. This synchronic approach significantly enhances the productivity of smart distribution networks in terms of reaching the best degree of loss reduction by incorporating both the charging station investor's decision factor and distribution network constraints.

The optimal location of FCSs is identified in two stages. CSIDI is optimized in the first phase for sorting the possible locations for FCSs that increase EV population while minimizing land cost. Furthermore, power loss is reduced for the next phase to get the optimal locations. The majority of the presented study has determined the optimal location of CS by taking installation costs, quality enhancement parameters of distribution systems, and their combination into account. For the placement of FCSs in this study, installation cost, quality enhancement component of the distribution system, and profit were all taken into account.

The main contribution of this paper is expressed as:

- A two-stage novel optimization problem is developed to maximize the EV population while reducing investment costs and power loss costs for the FCSs deployment.
- In the first step, the charging station investor decision index (CSIDI) is developed to reduce the optimization algorithm's search space. Furthermore, the LCI and EVPI are established to optimize the value of land cost and EV population for the investor to receive more return with less capital for FCS installation.
- In the second phase, a single objective optimization problem with power loss cost as the objective function is created to identify the optimal positions from the first stage identified locations. Furthermore, the Improved Bald Eagle Search algorithm has been proposed for the optimal solutions of the specified optimization problem to optimize the FCSs position to increase their performance in terms of power loss, and the obtained results were compared with the PSO algorithm.
- The integration of EV charging stations with randomly placed solar power distribution generation (SPDG) for distribution network is presented realistically and thoroughly, taking into account electrical and geographic limits.

1.3 Organization of the Paper

The remainder of this work is structured as follows: Section 2 presents the problem formulation for optimal FCS placement. Section 3 illustrates the optimization technique for achieving the optimal solution. Section 4 further explains the results of the presented problem. Section 5 brings the paper to a conclusion.

2 Problem Formulation

Figure 1 is suggested the problem framework for optimal FCS location, therefore the EV charging station investor decision index (CSIDI) is framed by including the land cost for FCS installation and EVs population at each bus. Furthermore, the objective function under the distribution system operator approach is suggested with some distribution constraints. Afterward, the price of land in the cities is very high and sometimes changes within a city with very high differences. Therefore, the FCS investors first ruminate the land cost for the placement of FCS. On the other side, the FCS location should be accessible by the EV users, therefore the FCS investors investigate the EV population at all possible FCS locations to maximize the profit. Eventually, the optimization problem is created to minimize the power loss of the distribution system with network constraints for the optimal FCS location. In addition, first, calculate the number of FCS in the proposed area with the IEEE-34 bus system to obtain the optimal location.

2.1 Formulation of Charging Station Investor Decision Index

The number of FCSs in the intended region was calculated by looking at the overall EV population in the area, battery capacity, load factor, and charging time, which is expressed in (1) [21]. As a result, the number of FCS (N_{FCS}) is illustrated.

$$N_{FCS} = \left[\frac{p * N_{EV} * ch\_time}{st * q * C_{FCS} * lf} \right] \tag{1}$$

Where p is the mean power of EVs, N_{EV} is the number of EVs to be charged per day, *ch_time* is the charging time, *st* is the charger service time, C_{FCS} is the capacity of fast charger, q is charging efficiency, *lf* is the load factor of the charger.

2.2 Formulation of Charging Station Investor Decision Index

2.2.1 Land cost index

The land prices in cities are quite high, and they vary greatly within the city. As a result, FCS investors first analyze the land costs of each possible FCS location. Furthermore, for the probable position of FCS, each bus of the proposed IEEE-34 distribution system should be evaluated. In addition, the land cost index is proposed to include the land cost in problem design. As a result, the load cost data on the buses, branch line data, and EV population on each bus are stated in Table 1 for the IEEE-34 bus system, and a single line diagram of the IEEE-34 bus system is represented in Figure 2. Furthermore, the normalized LCI is represented in (2) for each bus, which is calculated by dividing the land cost of each bus by the maximum land cost of the buses.

Table 1 IEEE34 Bus Load data, line data, and EV population

Bus No.	Load (kW)	Load (kVAR)	EVs Population	From Bus	To Bus	Resistance (ohm)	Reactance (ohm)
1	0	0	0	1	2	0.117	0.048
2	230	142.5	10	2	3	0.1072	0.044
3	0	0	100	3	4	0.1644	0.0456
4	230	142.5	20	4	5	0.1495	0.0415
5	230	142.5	30	5	6	0.1495	0.0415
6	0	0	30	6	7	0.3144	0.054
7	0	0	40	7	8	0.2096	0.036
8	230	142.5	40	8	9	0.3144	0.054
9	230	142.5	50	9	10	0.2096	0.036
10	0	0	50	10	11	0.131	0.0225
11	230	142.5	50	11	12	0.1048	0.018
12	137	84	50	3	13	0.1572	0.027
13	72	45	60	13	14	0.2096	0.036
14	72	45	80	14	15	0.1048	0.018
15	72	45	100	15	16	0.0524	0.009
16	13.5	7.5	120	6	17	0.1794	0.0498
17	230	142.5	150	17	18	0.1644	0.0456
18	230	142.5	170	18	19	0.2079	0.0473
19	230	142.5	200	19	20	0.189	0.043
20	230	142.5	30	20	21	0.189	0.043
21	230	142.5	20	21	22	0.262	0.045
22	230	142.5	20	22	23	0.262	0.045
23	230	142.5	10	23	24	0.3144	0.054
24	230	142.5	10	24	25	0.2096	0.036
25	230	142.5	10	25	26	0.131	0.0225
26	230	142.5	10	26	27	0.1048	0.018
27	137	85	30	7	28	0.1572	0.027
28	75	48	30	28	29	0.1572	0.027
29	75	48	20	29	30	0.1572	0.027
30	75	48	20	10	31	0.1572	0.027
31	57	34.5	20	31	32	0.2096	0.036
32	57	34.5	20	32	33	0.1572	0.027
33	57	34.5	10	33	34	0.1048	0.018
34	57	34.5	10	1	2	0.117	0.048

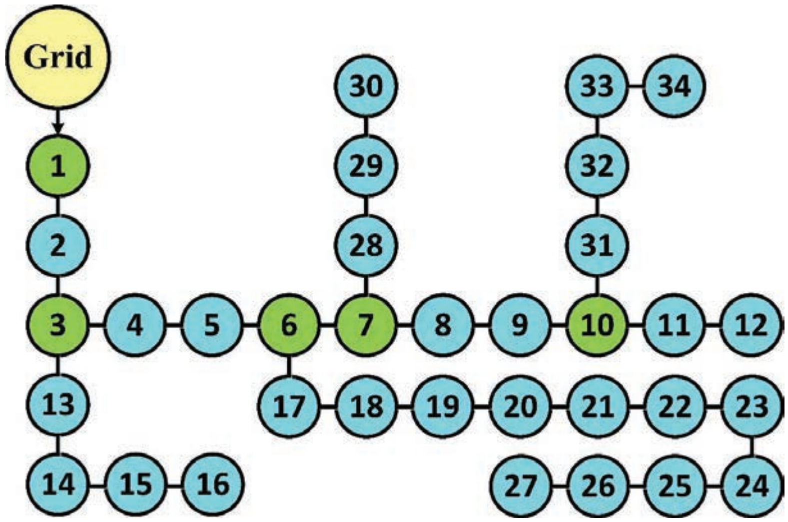


Figure 2 Presentation of an IEEE-34 bus system.

Therefore, the LCI lay between 0 and 1 according to the land cost on buses.

$$LCI_i^{Nb} = \frac{LC_i^{Nb}}{max\{LC_i^{Nb}\}} \tag{2}$$

where, LC_i is the land cost at ith bus, Nb is the total buses in the distribution system.

2.2.2 Electric vehicle population index

Furthermore, the number of EVs charged at the FCS will decide the investor profit. In other words, the profit is determined by the number of EVs on the bus. Furthermore, for each bus, an electric vehicle population index (EVPI) is produced, which is used to rank the buses with the highest EV population. Furthermore, the normalized EVPI at each bus is calculated, which is stated in (3) as the EVs at each bus divided by the maximum EVs of the buses.

$$EVPI_i^{Nb} = \frac{EVP_i^{Nb}}{max\{EVP_i^{Nb}\}} \tag{3}$$

where, EVP_i is the EV population at ith bus.

Finally, the charging station investor decision index (CSIDI) is represented in (4), which is the combination of the normalized LCI and EVPI for each bus.

$$CSODI_i^{Nb} = \alpha \times LCI_i^{Nb} - \beta \times EVFI_i^{Nb} \tag{4}$$

where α and β are the positive coefficients that are used to change the priorities in decision making between land cost and EV population. In addition, α and β both have 0.5 values for equal weightage for the land cost and EV population.

According to the proposed CSIDI, the investor chooses to install the FCS in the bus, which meets the following conditions. (1) cheaper land cost attracts investors for FCS installation, and (2) large EV population at buses is also chosen by investors for maximum profit.

2.3 Objective Function

As stated in the CSIDI formulation, the possible location for FCS has been narrowed down due to land cost and EV population sorting. In the second step, the optimization problem is phrased further by employing power loss as an objective function with certain inequality constraints. As a result, the objective function for minimizing distribution network power loss is depicted in (5).

$$f = min\left(\sum_{j=1}^{br} P_{loss,j}\right) \tag{5}$$

where, $P_{loss,j}$ is the power loss for jth branch in the distribution system, *br* is the total number of branches in the distribution system.

Constraints:

Voltage constraint: The magnitude of the voltage at each node must be kept within acceptable limits, which is expressed in (6).

$$V^{min} < V_i < V^{max} \quad \text{where } i = 1, 2 \ldots Nb \tag{6}$$

where V^{min} and V^{max} are the minimum and maximum voltage limits of buses, V_i is the voltage of ith bus.

Current constraint in branches: The capacity of the distribution line must not be exceeded (7).

$$I_j < I^{max} \quad \text{where } j = 1, 2 \ldots br \tag{7}$$

where and I^{max} is the maximum current limits of buses, I_j is the current flow in jth line.

Table 2 Placement of SPDGs with capacity

Types of DGs	Location at Bus	Capacity (kW)
SPDG1	6	250
SPDG2	11	250
SPDG3	22	500

Reactive power constraints: to maintain the reactive power of each bus within limitations, a reactive power restriction has been created (8).

$$Q^{min} < Q_i < Q^{max} \quad \text{where } i = 1, 2 \ldots Nb \tag{8}$$

where Q^{min} and Q^{max} are the minimum and maximum reactive power limits of buses, Q_i is the reactive power at ith bus.

2.4 Solar Power Distributed Generation

By 2040, global energy demand will increase by one-third, owing mostly to increased transportation use in China, India, and other Asian countries [22]. Solar power distributed generation (SPDG) is a fast-growing source of renewable energy for the grid. As a result, there have already been a huge number of articles on solar efficiency and solar converters. Furthermore, the integration of FCSs into the grid has resulted in a mismatch between power consumption and electricity output. As a result, the SPDG position was generated at random on the distribution network buses, as shown in Table 2. Furthermore, including SPDG into the distribution network world minimizes grid stress induced by EV load. The SPDG locations are eventually determined at random because the authors only recommended the FCS placement in this article.

3 Solution Technique

To get the optimum solution or the unconstrained maxima and minima of continuous and differentiable functions, classical optimization techniques can be applied. Furthermore, because they need objective functions that are not continuous and/or differentiable, classical approaches have limited practical use. As a result, advanced optimization techniques are employed to achieve the best solution to the defined optimization problem. The results of unimodal function from F1–F7 are represented in Table 3 for proposed techniques. Further, the results of the multimodal benchmark from F8–F13

Table 3 Parameters

Parameters Name	Value	Unit
Number of EVs (N_{EV})	1620	–
Charging time (Ch_time)	0.33	hours
Capacity of FCS (C_{FCS})	480	kW
Service time of FCS (st)	18	hours
Average power for each EV (p)	96	kW
Load factor of FCS (lf)	0.95	–
Charging efficiency (q)	0.9	–

Table 4 Results of unimodal benchmark functions

Functions		PSO	BES	IBES
F1	Best	1.00×10^{-23}	0	0
	Worst	9.21×10^{-21}	0	0
	Mean	1.92×10^{-21}	0	0
F2	Best	4.32×10^{-13}	0	0
	Worst	1.03×10^{-10}	1.37×10^{-270}	4.47×10^{-303}
	Mean	1.96×10^{-11}	6.85×10^{-272}	2.73×10^{-304}
F3	Best	5.08×10^{-50}	0	0
	Worst	7.79×10^{-45}	0	0
	Mean	4.20×10^{-46}	0	0
F4	Best	3.69×10^{-11}	0	0
	Worst	5.29×10^{-10}	1.51×10^{-260}	1.60×10^{-294}
	Mean	2.49×10^{-10}	7.56×10^{-262}	8.32×10^{-296}
F5	Best	26.20355	23.42343	23.49114
	Worst	28.72399	25.76698	25.32653
	Mean	27.28987	24.26849	24.66361
F6	Best	0.03963	6.7×10^{-7}	1.43×10^{-5}
	Worst	0.228144	7.96×10^{-5}	0.249381
	Mean	0.102408	1.79×10^{-5}	0.03938
F7	Best	0.000839	1.58×10^{-5}	2.25×10^{-6}
	Worst	0.009435	0.000348	0.00031
	Mean	0.002914	0.000142	8.49×10^{-5}

are given in Table 4. Moreover, the results of composite benchmark functions from F14–F23 are obtained in Table 5 for the suggested algorithm. For the benchmark function, the IBES algorithm got the best results, therefore the authors in this paper proposed an IBES algorithm for the optimal location of the charging station.

Table 5 Results of multimodal benchmark functions

Functions		PSO	BES	IBES
F8	Best	-1830.71	-1777.18	-1731.16
	Worst	-1642.02	-1043.35	-1354.55
	Mean	-1720.61	-1503.62	-1543.11
F9	Best	0	0	0
	Worst	0	0	0
	Mean	0	0	0
F10	Best	8.88×10^{-16}	8.88×10^{-16}	8.88×10^{-16}
	Worst	3.7×10^{-8}	20	20
	Mean	4.09×10^{-9}	18	11
F11	Best	0	0	0
	Worst	2.04×10^{-9}	0	0
	Mean	1.02×10^{-10}	0	0
F12	Best	0.000366	2.91×10^{-9}	6.53×10^{-6}
	Worst	0.00209	3.41×10^{-7}	9.95×10^{-5}
	Mean	0.001236	1.04×10^{-7}	4.13×10^{-5}
F13	Best	0.104263	2.24745	1.95995
	Worst	0.475712	2.966102	2.968414
	Mean	0.2188	2.904654	2.916155

3.1 Particle Swarm Optimization Technique

The PSO is a well-known algorithm that was inspired by the social behavior of birds flocking or fish schooling and was enhanced by Kennedy and Eberhard in [23]. Furthermore, when compared to mathematics and other evolutionary algorithms, the PSO method stands out for its easy implementation, parameter controllability, and ability to explore global and local minimum points.

Furthermore, the PSO algorithm is investigated for selecting the best position for FCSs. The PSO is a population-based evolutionary algorithm in which each solution confirms its position and velocity. Furthermore, each particle adapts its new position by modifying its velocity based on its own experience. Equations (9) and (10) calculate the particles' new velocity and location, respectively.

$$V^{new} = w{*}V^{old} + c_1 * rand(p^{local} - p^{old}) + c_2 * rand(p^{global} - p^{old}) \quad (9)$$

$$x^{new} = x^{old} + V^{new} \quad (10)$$

Table 6 Composite benchmark functions results

Functions		PSO	BES	IBES
F14	Best	0.998004	0.998004	0.998004
	Worst	3.96825	12.67051	0.998004
	Mean	1.196218	1.978449	0.998004
F15	Best	0.000307	0.000307	0.000307
	Worst	0.020363	0.020363	0.001223
	Mean	0.001647	0.001356	0.000358
F16	Best	−1.03163	−1.03163	−1.03163
	Worst	−1.03163	−1.03163	−1.03163
	Mean	−1.03163	−1.03163	−1.03163
F17	Best	0.397887	0.397887	0.397887
	Worst	0.397887	0.397887	0.397887
	Mean	0.397887	0.397887	0.397887
F18	Best	3	3	3
	Worst	3	3	3
	Mean	3	3	3
F19	Best	0.03963	−0.30048	−0.30048
	Worst	0.228144	−0.30048	−0.30048
	Mean	0.102408	−0.30048	−0.30048
F20	Best	−3.322	−3.322	−3.322
	Worst	−3.2031	−3.2031	−3.2031
	Mean	−3.28633	−3.29822	−3.28633
F21	Best	−10.1532	−10.1532	−10.1532
	Worst	−5.0552	−5.0552	−5.05483
	Mean	−7.60386	−7.60275	−8.1162
F22	Best	−10.4029	−10.4029	−10.4029
	Worst	−3.7243	−4.68994	−5.08767
	Mean	−7.34321	−7.94017	−8.01313
F23	Best	−10.5364	−10.5364	−10.5364
	Worst	−2.42734	−3.83543	−5.12848
	Mean	−7.11694	−9.38996	−9.99511

where, $\mathrm{p}^{\mathrm{local}}$ and $\mathrm{p}^{\mathrm{global}}$ are the best local and best global position of the particle, c_1 and c_2 can have 1 or 2 integer values, rand$(\cdot)$ generate the random number between 0 and 1.

The PSO algorithm is good at exploitation but not so good at exploration. Furthermore, exploitation implies that the algorithm does a very good local search. Exploration ability, on the other hand, boosts its ability to discover suitable starting positions, maybe around the global minimum. As a result,

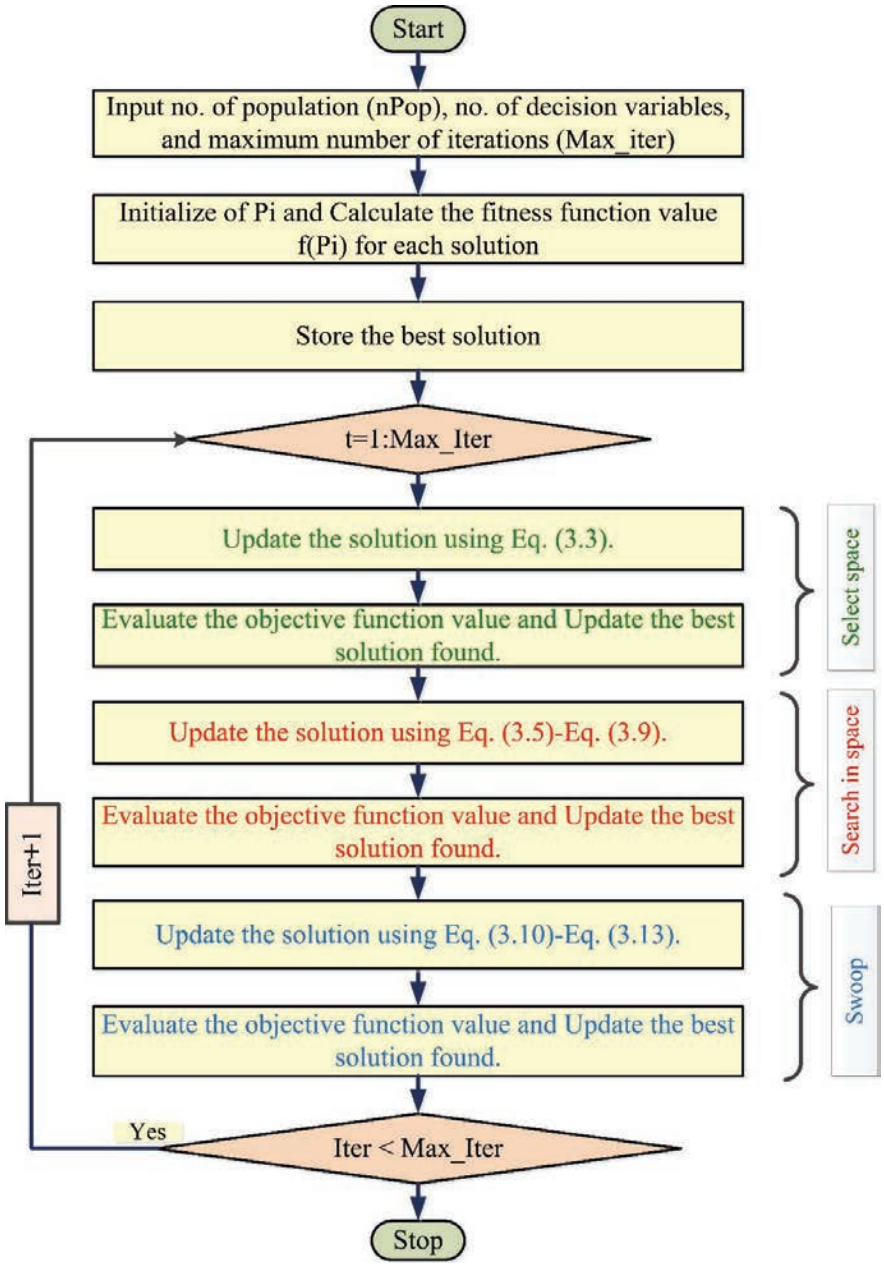


Figure 3 Flowchart of IBES.

a well-designed algorithm strikes a balance between exploitation and exploration. PSO suffers from converging to a local minimum due to exploration capabilities when the starting location of the PSO algorithm is distant from the global minimum.

3.2 An Improved Bald Eagle Search Technique

Based on the bald eagle search algorithm [24], the improved bald eagle search (IBES) algorithm is inspired by bald eagle search behavior during the hunting phase [25] and the flowchart of IBES algorithm is given in Figure 3. The hunting technique is divided into three stages: selecting the space, searching the space, and finally swooping in on the prey.

Selecting the space: Based on the previous search information, the bald selects the space at random.

$$\boldsymbol{p_{new,i} = p_{best} + \alpha \times r(p_{mean} - p_i)} \tag{11}$$

Instead of having a fixed value in the original BES method, the parameter alpha for managing position changes can be derived using the following equation.

$$\boldsymbol{\alpha = \frac{1.5 \times (Max_{Iter} - t + 1)}{Max_{Iter}}} \tag{12}$$

This parameter influences the bald position of eagles and improves exploration and exploitation in the IBES approach. r is a number between 0 and 1. The new and current search spaces are denoted by p_{new} and p_{best}, respectively. p_{mean} shows that these eagles have consumed all the information from the previous.

Search stage: To speed up their search for prey in this area, the eagles move in a spiral form. At this point, the eagle's location is updated using Equation.

$$\boldsymbol{p_{i,new} = p_i + y(i) \times (p_i - p_{i+1})p_{best} + x(i) \times r(p_i - p_{mean})} \tag{13}$$

$$\boldsymbol{x(i) = \frac{xr(i)}{max|xr|}, \quad y(i) = \frac{yr(i)}{max|yr|}} \tag{14}$$

$$\boldsymbol{xr(i) = r(i) \times \sin(\theta(i)), \quad yr(i) = r(i) \times \cos(\theta(i))} \tag{15}$$

$$\boldsymbol{\theta(i) = \alpha \times \pi \times \text{rand}} \tag{16}$$

$$\boldsymbol{r(i) = \theta(i) \times R \times \text{rand}} \tag{17}$$

where α is a parameter with a range of 5 to 10, and R is a parameter with a range of 0.5 to 2.

Swooping stage: At this stage, the eagles begin to swing from the optimal search position towards their prey, as expressed in Equation.

$$\begin{aligned} \boldsymbol{p_{i,new}} &= \textbf{rand} \times \boldsymbol{p_{best}} + \boldsymbol{x_1}(\boldsymbol{i}) \times (\boldsymbol{p_i} - \boldsymbol{s_1} \times \boldsymbol{p_{mean}}) \\ &\quad + \boldsymbol{y_1}(\boldsymbol{i}) \times (\boldsymbol{p_i} - \boldsymbol{s_2} \times \boldsymbol{p_{best}}) \end{aligned} \tag{18}$$

$$\boldsymbol{x_1}(\boldsymbol{i}) = \frac{\boldsymbol{xr}(\boldsymbol{i})}{\boldsymbol{max}|\boldsymbol{xr}|}, \quad \boldsymbol{y_1}(\boldsymbol{i}) = \frac{\boldsymbol{yr}(\boldsymbol{i})}{\boldsymbol{max}|\boldsymbol{yr}|} \tag{19}$$

$$\boldsymbol{xr}(\boldsymbol{i}) = \boldsymbol{r}(\boldsymbol{i}) \times \textbf{sinh}(\boldsymbol{\theta}(\boldsymbol{i})), \quad \boldsymbol{yr}(\boldsymbol{i}) = \boldsymbol{r}(\boldsymbol{i}) \times \textbf{cosh}(\boldsymbol{\theta}(\boldsymbol{i})) \tag{20}$$

$$\boldsymbol{\theta}(\boldsymbol{i}) = \boldsymbol{\alpha} \times \boldsymbol{\pi} \times \textbf{rand}, \quad \boldsymbol{r}(\boldsymbol{i}) = \boldsymbol{\theta}(\boldsymbol{i}) \tag{21}$$

where, $\boldsymbol{s_1}$ and $\boldsymbol{s_2}$ have value from 1 to 2.

4 Results

To carry out this work, MATLAB 2018a programming language has been used, which is installed in a computer window 8.1, intel i7 processor, 2.4GHz clock speed with 4GB Ram.

4.1 Results of CSIDI

The number of charging stations has been determined based on the data provided for the proposed region, as shown in Table 3. Furthermore, as mentioned in Section 2, the CSIDI value is determined for each bus in the distribution system. As a result, the LCI for land cost is depicted in Table 4 for three cases, and certain locations do not have land for FCS installation, which is represented by infinite. Furthermore, the value of CSIDI increases from top to bottom, as shown in Table 4 by the bus number. As a result of the low land cost and large EV population, the top buses have the highest priority for placing the FCS. Case-1 (C-1) utilizes the top eight buses to find a feasible position in the optimization problem, whereas Case-2 (C-2) likewise uses the top eight buses to find the optimal location of FCS. Furthermore, case-3 (C-3) looked for the best location of FCS among the top eight buses, as shown in Table 4. In a conclusion, the study for the optimal location of FCSs on the distribution system in the first stage has decreased the searching space for the optimization problem. In addition, the power loss is chosen as an objective

Table 7 LCI of 34 bus system and bus order based on CSIDI for IEEE34 Bus system

	C-1				C-2				C-3		
Bus No.	LCI	Bus Order	CSIDI	Bus No.	LCI	Bus Order	CSIDI	Bus No.	LCI	Bus Order	CSIDI
1	Inf	19	−0.933	1	Inf	17	−0.700	1	Inf	18	−0.516
2	0.833	17	−0.700	2	0.050	18	−0.516	2	0.500	15	−0.450
3	Inf	18	−0.516	3	Inf	19	−0.333	3	0.666	19	−0.333
4	0.050	13	−0.233	4	0.500	9	−0.183	4	Inf	17	−0.250
5	0.666	10	−0.200	5	0.033	5	−0.116	5	Inf	28	−0.116
6	0.166	28	−0.116	6	0.333	31	−0.050	6	0.333	21	−0.050
7	0.833	30	−0.083	7	0.833	2	0	7	0.833	32	−0.050
8	0.666	4	−0.050	8	0.666	6	0.183	8	0.666	25	0.016
9	0.333	32	−0.050	9	0.066	28	0.183	9	0.666	3	0.166
10	0.050	6	0.016	10	0.500	29	0.233	10	0.500	6	0.183
11	Inf	24	0.033	11	Inf	30	0.233	11	Inf	29	0.233
12	0.666	9	0.083	12	0.666	10	0.250	12	0.666	30	0.233
13	0.066	29	0.233	13	0.666	34	0.283	13	0.666	10	0.250
14	1	31	0.233	14	1	15	0.333	14	1	34	0.283
15	0.833	34	0.283	15	0.833	20	0.350	15	0.050	20	0.350
16	Inf	15	0.333	16	Inf	13	0.366	16	Inf	13	0.366
17	0.050	20	0.350	17	0.050	4	0.400	17	0.500	31	0.400
18	0.333	12	0.416	18	0.333	32	0.400	18	0.333	9	0.416
19	0.066	8	0.466	19	0.666	12	0.416	19	0.666	12	0.416
20	0.500	5	0.516	20	0.500	8	0.466	20	0.500	2	0.450
21	0.666	21	0.566	21	0.666	21	0.566	21	0.050	8	0.466
22	Inf	14	0.600	22	Inf	14	0.600	22	Inf	14	0.600
23	0.833	26	0.616	23	0.833	26	0.616	23	0.833	26	0.616
24	0.083	33	0.616	24	0.833	33	0.616	24	0.833	33	0.616
25	1	7	0.633	25	1	7	0.633	25	0.066	7	0.633
26	0.666	27	0.683	26	0.666	27	0.683	26	0.666	27	0.683
27	0.833	2	0.783	27	0.833	23	0.783	27	0.833	23	0.783
28	0.033	23	0.783	28	0.333	24	0.783	28	0.033	24	0.783
29	0.333	25	0.950	29	0.333	25	0.950	29	0.333	1	Inf
30	0.016	1	Inf	30	0.333	1	Inf	30	0.333	4	Inf
31	0.333	3	Inf	31	0.050	3	Inf	31	0.500	5	Inf
32	0.050	11	Inf	32	0.500	11	Inf	32	0.050	11	Inf
33	0.666	16	Inf	33	0.666	16	Inf	33	0.666	16	Inf
34	0.333	22	Inf	34	0.333	22	Inf	34	0.333	22	Inf

function for optimal position. Furthermore, the land cost and EV population have been considered in the selection for the best placement of FCS on the distribution system.

As previously noted, the number of possible FCS locations has been decreased from 33 to 8. Following that, the three best locations on the distribution system from the obtained possible locations were selected by minimizing power loss with some distribution limits. As a result, the IEEE 34 bus distribution system proved the efficacy of the suggested FCS planning. The IEEE 34 distribution system proposed includes active power demands of

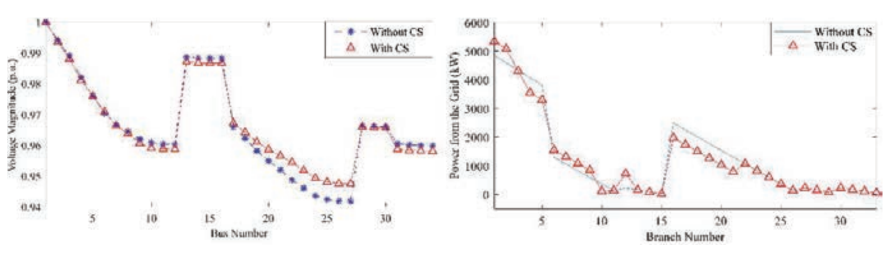
4636.5 kW and reactive power loads of 2873.5 kVAR. The backward forward flow algorithm is used in this study to calculate power flow. Furthermore, total active power loss (221.72 kW), lowest voltage (0.94171 at 27), and highest voltage (0.99414 at 2) are acquired values for the proposed distribution network without any FCS and SPDG installation.

4.2 Results of Optimal Location of FCS Using IBES Technique

According to the previously acquired data, there were eight (19,17,18,13,10, 28,30,4) buses available for FCS installation. Furthermore, the findings for the optimal location of FCS have been achieved by reducing the power loss in C-1 utilizing the previously suggested PSO techniques. Figures 4(a) and 4(b) show the voltage at each bus and the power flow in each line. Furthermore, by reducing power loss, the optimal position of FCS from the possible buses was identified. As a result, Table 5 represents total power loss, minimum voltage, and optimal location on distribution network buses. The acquired bus voltage and power flow data for C-2 are shown in Figures 5(a) and 5(b). Eventually, the obtained results from the PSO algorithm for optimal location of FCSs by minimizing power loss are illustrated in Table 5 for C-3, while the optimal location of FCSs at buses 15, 17, and 18 have total active power losses (221.90 kW), minimum voltage (0.94378 at 27), and maximum voltage (0.99365 at 2). Furthermore, Figures 6(a) and 6(b) show the voltage and power flow findings for buses and lines, respectively.

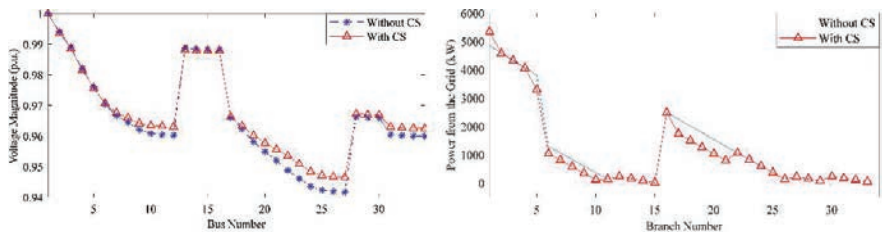
4.3 Results of Optimal Location for FCS Using IBES Technique

Furthermore, the IBES algorithm has recommended a suitable location for the FCS problem. The findings for the optimal location of FCS on the 4,13,17



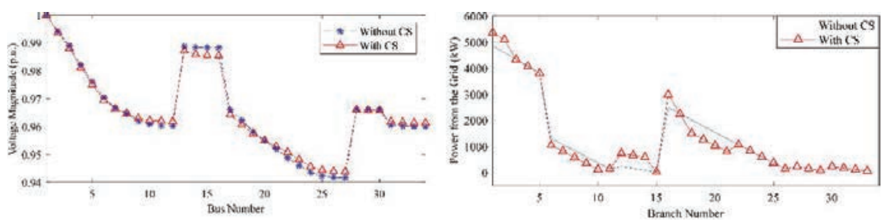
(a) (b)

Figure 4 The bus voltage and power flow using PSO in C-1.



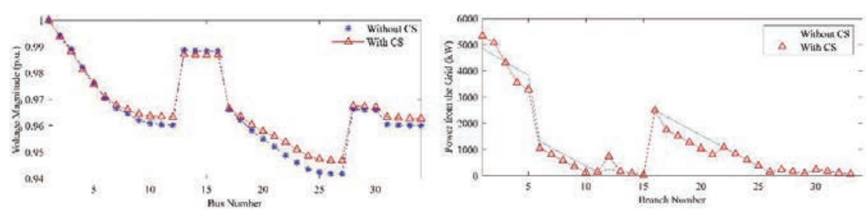
(a) (b)

Figure 5 The bus voltage and power flow using PSO in C-2.



(a) (b)

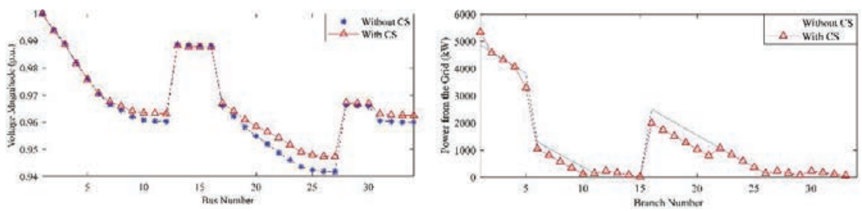
Figure 6 The bus voltage and power flow using PSO in C-3.



(a) (b)

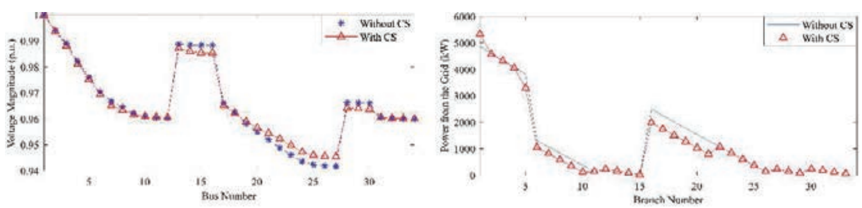
Figure 7 The bus voltage and power flow using IBES in C-1.

bus for reducing power loss while maintaining voltage and power limitations were obtained in C-1. As a result, the minimum voltage at each bus and power flow in each line are shown in Figures 7(a) and 7(b). As already described. The authors obtained some improvements in the IBES technique results, including a 2.68% reduction in power loss. Furthermore, with a power loss of 198.43 kW, the optimal position of FCSs was found to be at 2, 5, 6 in C-2. Figures 8(a) and 8(b) suggest the voltage at each bus and the power flow in each line for optimal FCS position. Furthermore, the IBES approach reduced



(a) (b)

Figure 8 The bus voltage and power flow using IBES in C-2.



(a) (b)

Figure 9 The bus voltage and power flow using IBES in C-3.

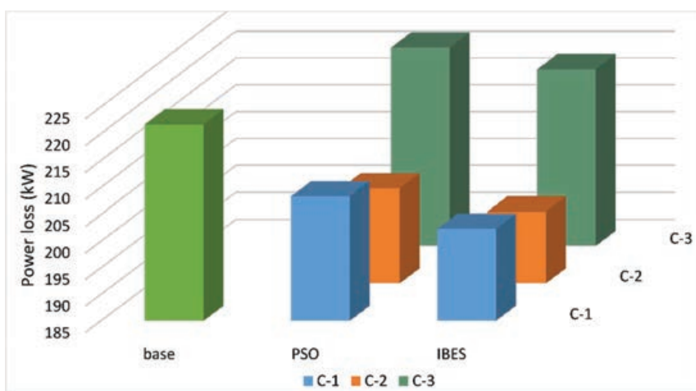


Figure 10 Power loss in different cases.

power loss by 1.89% when compared to PSO. Eventually, the optimal FCS position findings were achieved with a power loss of 217.85 kW. whereas the obtained voltage at each bus and power flow in each line are shown in Figures 9(a) and 9(b) for C-3. As a result, the IBES algorithm achieves a power loss decrease of 1.52%. Power loss for different cases is represented in Figure 10.

Table 8 Results comparison in three scenarios for the IEEE34 bus system

		PSO			IBES		
—	Base Case	C-1	C-2	C-3	C-1	C-2	C-3
Power loss (kW)	221.72	208.32	202.75	221.90	202.34	198.43	217.85
Min. Voltage (p.u.)	0.94171 at bus 27	0.94854 at bus 27	0.94651 at bus 27	0.94378 at bus 27	0.94678 at bus 27	0.94752 at bus 27	0.94542 at bus 27
Max. Voltage (p.u.)	0.99414 at bus 2	0.99372 at bus 2	0.99367 at bus 2	0.99365 at bus 2	0.99369 at bus 2	0.99372 at bus 2	0.99373 at bus 2
FCSs location	–	4,10,17	2,5,17	15,17,18	4,13,17	2,5,6	15,7,28

5 Conclusion and Recommendation

The purpose of this research was to integrate FCS into a distribution network with randomly distributed solar power generation (SPDG) utilizing an IBES optimization technique. The optimization problem was simulated using MATLAB 2018a. The objective was to optimally locate the FCSs so that they would not impact network quality. The objective functions were developed to decrease active power losses, investment costs and maximize the EV population. The SPDGs were randomly sized and sited using Microsoft Excel and then uploaded to MATLAB. When the results of the PSO and BES algorithms are examined, the significance of IBES is verified for the benchmark functions. In all three cases, the simulation results demonstrated the effectiveness of the IBES for obtaining the best locations for the installation of the FCSs across the distribution network. The performance of the IBES was validated by measuring its findings to those obtained while employing PSO for the placement of FCSs in the distribution network with randomly sized and located SPDGs. The simulation results show that the suggested IBES is an effective optimization approach for the placement of FCSs in current distribution networks with random SPDGs.

The future scope of this research will address the daylight variation of solar power generation, EV user driving patterns, distribution network uncertainties, and EV charging time for the best allocation of FCSs in the distribution network.

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