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Multiobjective Planning Strategy for the Placement of Electric-Vehicle Charging Stations Using Hybrid Optimization Algorithm

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ABSTRACT Electric Vehicle (EV) charging station placement problem is a facility location problem. The EV charging station placement problem concerns about the total coverage in traffic network, the system losses and node voltage deviations in electric distribution system. To address the loss reduction and voltage profile improvement, the distribution systems are normally equipped with shunt capacitors for reactive power compensation. In this paper mathematical model comprising three objective functions, maximization of coverage and minimization of loss and node voltage deviations subjected to constraints is proposed for the simultaneous placement of EV charging stations and shunt capacitors. The control variables for optimization are the rating and location of charging stations and shunt capacitors. A hybrid optimization algorithm (PSO-DS) combining particle swarm optimization algorithm and direct search method is proposed for the solution of the mathematical model. The performance of PSO-DS is justified by comparing it with other state-of-the-art algorithms in solving the standard benchmark functions. Simulations are carried out on a 33-bus distribution system and a 25-node traffic network system to determine the different planning strategy for the placement of charging stations.

INDEX TERMS Charging station, electric vehicle (EV), facility location problem, particle swarm optimization (PSO), direct search (DS).

NOMENCLATURE

a_i	Coverage at i.
P	Total Facility Coverage.
L	Length of the shortest path from u to v.
$u\&v$	Vertices in the graph.
p	Shortest Path from u to v, Passes through Vertices in T.
I	Set of demand nodes.
J	Set of facility sites.
T	Vertices set.
φ_1	Self-adjustment weight.
φ_2	Social-adjustment weight.
g_{ij}	Conductance of feeder connecting i^{th} node and j^{th} node.
k	Iteration number, k=1, 2, ... k_{max}.
N_i	Set of facility sites eligible to provide "cover" to demand point i.
N_{bus}	Total number of buses in the distribution system.
$\vec{p}_i$	Personal best solution.
$\vec{p}_g$	Global best solution.
P_{Di}	The total active load on bus i without EV charging station active load.
Q_{Di}	The total reactive load on bus i without EV charging station reactive load.
$rand_1$	Random numbers between 0 and 1.
$rand_2$	Random numbers between 0 and 1.
S	Distance beyond which a demand point is considered "uncovered".
S_{ij}	Apparent power in line connected between i^{th} and j^{th} bus with maximum limit S_{ij}^{max}
V_i	Voltage at bus i.
$V_{i,min}$	Lower limit of bus i.
$V_{i,max}$	Upper limit of bus i.
v_i	Velocity of the particle.

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V_o	Nominal voltage (1.0 p.u.).
w	Inertia Weight.
x_l	Position of the Particle.
s_s	Step size
Δs	Decrement in step size.
UEV	Binary variable to include EV.
VSC	Binary variable to include shunt capacitor.

TABLE 1. Description of unimodal benchmark function.

Functions	Range	Optimal Value
$f_1 = \sum_{i=1}^{n} x_i^2$	[-100, 100]	0
$f_2 = \sum_{i=1}^{n} \|x_i\| + \prod_{i=1}^{n} \|x_i\|$	[-10, 10]	0
$f_3 = \sum_{i=1}^{n} \left(\sum_{j=1}^{i} x_j\right)^2$	[-100, 100]	0
$f_4 = max_i \left\{\|x_i\|,\ 1 \leq i \leq n\right\}$	[-100, 100]	0
$f_5 = \sum_{i=1}^{n-1} \left[100\left(x_{i+1} - {x_i}^2\right) + (x_i - 1)^2\right]$	[-30, 30]	0
$f_6 = \sum_{i=1}^{n} (x_i + 0.5)^2$	[-100, 100]	0
$f_7 = \sum_{i=1}^{n} i x_i^4 + random[0, 1]$	[-128, 128]	0

I. INTRODUCTION

Conventional road transportation system is one of the major emitters of greenhouse gases [1]. EVs have emerged as the best alternative to traditional Internal Combustion Engine (ICE). Still, the increased arrival of electrical vehicles (EV) demands sufficient charging infrastructure placed on the cruising path to avoid driving anxiety. Various mathematical models have been proposed for the placement of charging infrastructure. The model consists of objective parts like minimizing investment cost, loss reduction and voltage profile improvement. Some papers consider only the traffic network, and some include both traffic networks and the electric distribution network for the solution.

In [2], the travelling behaviour of EVs is modelled. The site and ratings of Electric Vehicle Charging Station (EVCS) infrastructure were obtained with loss minimization and voltage profile improvement using the cross-entropy method. The uncertainties of EV load were incorporated in the model, and PSO is used to find the solution [3]. In [4], the driving range is considered for the placement of EVCS. Iterative Mixed-Integer Linear Programming (MILP) method, greedy approach, effective MILP and Chemical Reaction Optimization (CRO) are utilized for the solution. The driving range and destination patterns were analyzed, and charging locations were identified in [5]. In [6], the traffic dynamics of EV vehicle is incorporated into the energy consumption, and the identification of charging infrastructure was made using a novel nanoscopic city-scale traffic simulation-based method. In [7], charging station infrastructure investment cost is optimized in the strategic presence of wind power generation. A non-Dominated Sorting Genetic Algorithm (NSGA-II) was used to solve the optimization problem. An optimization model was proposed to incorporate the stochastic mobility behaviour of EV drivers in [8], the quality of service was also executed. A stochastic flow-capturing location model was proposed to consider the uncertainty of EV charging demands in optimizing the number of charging stations [9]. In [10], the installation cost of charging stations was computed with and without considering the limited battery size. Multiple backtracking and greedy algorithm were utilized to find the optimal solution. In [11], Grasshopper Optimizer Algorithm (GOA) was applied to identify the location of battery swapping stations and distributed generation for energy loss reduction and voltage stability improvement. The charging station placement was done considering Vehicle-to-Grid (V2G) trading in [12], a novel heuristic quantum binary lightning search algorithm was utilized to solve the mathematical model. Demand Response Programmes (DRPs) identifies charging station locations taking the total cost function as the objective function in [13]. The number of charging stations required to cover every two road network nodes was obtained in [14]. Integer linear programming technique was utilized to find the solution. The voltage regulation cost and protection device up-gradation cost were considered while selecting locations for charging stations [15]. [16] proposed a mathematical model comprising line losses, voltage profile and reliability of the distribution system as objective functions. A hybrid optimization algorithm that combines Chicken Swarm Optimization (CSO) algorithm and Teaching Learning Based Optimization (TLBO) was applied to find the locations of charging stations.

In the past, various optimization techniques were used to find the optimal location of EV charging stations. The charging station location problem is a planning activity; the solutions directly influence the total investment cost. Therefore, the selection of a proper optimization algorithm is significant. This work combines PSO and the direct search method to form a new hybrid optimization algorithm called PSO-DS. PSO is a well-estabilized robust algorithm that can effectively explore search space. However, in some cases, the PSO struck at local optima. Like PSO, the direct search method solves optimization problems without requiring any information about the gradient of the cost function. Robert Hooke and T.A.Jeeves first used the phrase "Direct Search" in a paper published in the journal of the association of computing machinery [17]. The advantage of the direct search method is that it is straightforward to implement. The alone application of the direct search method does not yield fruitful results. Here we utilize the PSO to solve the optimization problem and direct search method to support the convergence and accuracy. The PSO-DS algorithm's effectiveness has been demonstrated by its application to the standard benchmark functions and by comparing it with other well-known optimization algorithms.

Adding EV charging stations to the distribution system will increase the loss and significantly reduce bus voltages. Distribution systems have shunt capacitors installed for loss reduction and voltage profile improvement. During the planning of the EV charging stations location, we have to coordinate the shunt capacitor location with the EV charging station location. This paper uses the PSO-DS algorithm to

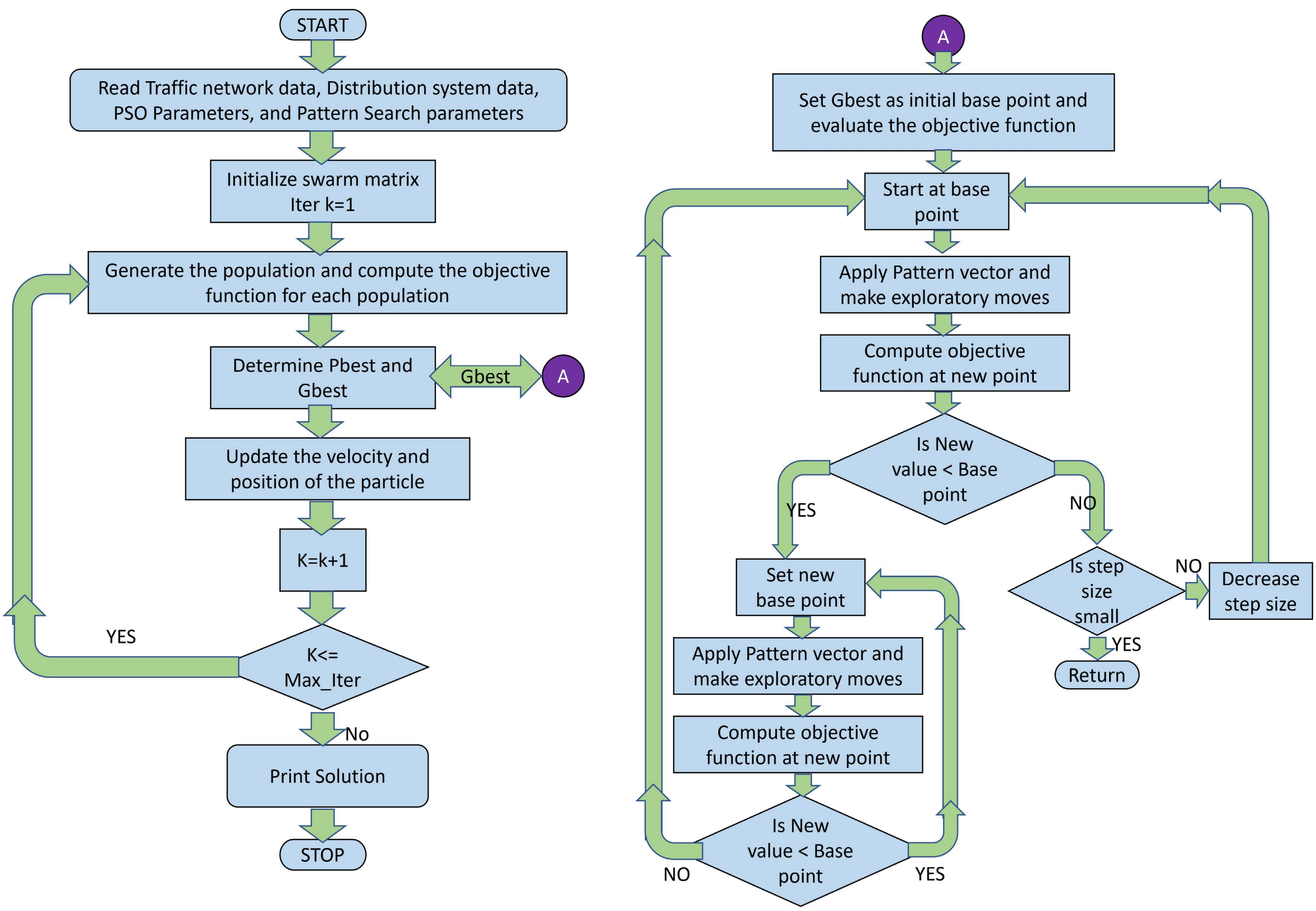

FIGURE 1. Flow of the solving methodology.

TABLE 2. Description of multi-modal benchmark function.

Functions	Range	Optimal Value
$f_8 = \sum_{i=1}^{n} -x_i \sin\left(\sqrt{\lvert x_i \rvert}\right)$	[-500, 500]	-418.9829
$f_9 = \sum_{i=1}^{n} \left[x_i^2 - 10\cos(2\pi x_i) + 10\right]$	[-5.12, 5.12]	0
$f_{10} = -20exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right) - exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)\right) + 20 + e$	[-32, 32]	0
$f_{11} = \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n}\cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	[-600, 600]	0
$f_{12} = \frac{\pi}{n}\left\{10\sin(\pi y_1) + \sum_{i=1}^{n-1}(y_i - 1)^2\left[1 + 10\sin(\pi y_{1+1})\right] + (y_n - 1)^2\right\} + \sum_{i=1}^{n} u(x_i, 10, 100, 4)$	[-50, 50]	0
$= k(x_i - a)^m,\ x_i > a$		
$= 0 - a,\ -a < x_i < a$		
$= k(-x_i - a)^m,\ x_i < -a$		
$f_{13} = 0.1\left\{sin(3\pi x_i)^2 + \sum_{i=1}^{n}(x_i - 1)^2\left[1 + sin(3\pi x_i + 1)^2\right] + (x_n - 1)^2\left[1 + sin(2\pi x_n)^2\right]\right\} + \sum_{i=1}^{n} u(x_i, 5, 100, 4)$	[-50, 50]	0

obtain the various constructive plans for a 33-bus distribution system and a 25 node traffic network system. The constructive graph shows the relationship between the number of charging stations selected to install and coverage, power loss and voltage profile. The remainder of this paper is organized as follows. The mathematical model with three objective functions and the constraints is presented in Section II. A brief explanation of the PSO-DS algorithm and the detailed flowchart is discussed in Section III. The performance of the PSO-DS algorithm on different benchmark functions and its application to obtain the construction plans for a test system is given in Section IV. Finally, conclusions are drawn in Section V.

II. DEVELOPMENT OF PLANNING MODEL

The planning model consists of three objective functions. The first one is the maximization of coverage; it ensures EV drivers at any point in the traffic network get access to charging infrastructure within maximal service distance. The second and third objectives are related to the electric

TABLE 3. Description of multi-modal benchmark function with fixed dimensions.

Functions	Range	Optimal value
$f_{14} = \left(\frac{1}{500} + \sum_{i=1}^{25} \frac{1}{i + \sum_{j=1}^{2} (x_i - aij)^6} \right)^{-1}$	[-65, 65]	1
$f_{15} = \sum_{i=1}^{11} \left[a_i - \frac{x_1 (b_i^2 + b_i x_2)}{b_i^2 + b_i x_3 + x_4} \right]^2$	[-5, 5]	0.0003
$f_{16} = 4x_1^2 - 2.1x_1^4 + \frac{1}{3}x_1^6 + x_1 x_2 - 4x_2^2 + 4x_2^4$	[-5, 5]	-1.0316
$f_{17} = \left(x_2 - \frac{5.1}{4\pi^2} x_1^2 + \frac{5}{\pi} x_1 - 6 \right)^2 + 10 \left(1 - \frac{1}{8\pi}\right) \cos (x_i) + 10$	[-5, 5]	0.398
$f_{18} = \left[1 + (x_1 + x_2 + 1)^2 \left(19 - 14x_1 + 3x_1^2 - 14x_2 + 6x_1 x_2 + 3x_2^2\right) \right] \left[30 + (2x_1 - 3x_2)^2 \ \left(18 - 32x_1 + 12x_1^2 + 48x_2 - 36x_1 x_2 + 27x_2^2\right) \right]$	[-2, 2]	3
$f_{19} = - \sum_{i=1}^{4} c_i \ exp \left(- \sum_{j=1}^{3} a_{ij} (x_j - p_{ij})^2 \right)$	[0, 1]	-3.86
$f_{20} = - \sum_{i=1}^{4} c_i \ exp \left(- \sum_{j=1}^{6} a_{ij} (x_j - p_{ij})^2 \right)$	[0, 1]	-3.32
$f_{21} = - \sum_{i=1}^{5} \left[(x - a_i)(x - a_i)^T + c_i \right]^{-1}$	[0, 10]	-10.1532
$f_{22} = - \sum_{i=1}^{7} \left[(x - a_i)(x - a_i)^T + c_i \right]^{-1}$	[0, 10]	-10.4028
$f_{23} = - \sum_{i=1}^{10} \left[(x - a_i)(x - a_i)^T + c_i \right]^{-1}$	[0, 10]	-10.5363

TABLE 4. Results obtained for unimodal function.

Benchmark Functions	Metrics	Firefly	SimAnn	GA	PSO	PSO-DS
	Median	3.56965E-05	2204.1	0.168345	2.1842E-09	3.40E-10
	Mean	3.78812E-05	2733.2	0.456729024	4.15318E-09	9.53E-10
f_1	STD	2.40726E-05	2078.2501	0.685214455	5.16212E-09	1.39E-09
	Worst	0.00011726	7998.7	3.2266	2.2006E-08	5.11E-09
	Best	2.1816E-06	288.97	0.00017773	9.8544E-11	5.65E-14
	Median	-10020	10.454	9.04295	-1444500	1.61E-08
	Mean	-13003.66667	10.60749	13.86423167	-2360949.667	2.83E-08
f_2	STD	16432.88471	4.6687151	15.02381255	5274912.975	3.33E-08
	Worst	-9980	21.218	67.131	-777990	1.45E-07
	Best	-100010	2.6325	0.51301	-30150000	5.25E-09
	Median	0.000124505	2767.25	12.099	5.3389E-08	3.40E-09
	Mean	0.000176485	3126.2969	19.46824867	3.7887E-07	8.15E-09
f_3	STD	0.000171412	2249.9187	20.39192192	1.05625E-06	1.35E-08
	Worst	0.000955	8494.4	74.966	5.5954E-06	6.39E-08
	Best	0.000023976	34.648	0.94666	2.7627E-09	5.97E-11
	Median	4	37.537	5	4	4.61E-08
	Mean	4.033333333	36.943267	5	4.033333333	6.18E-08
f_4	STD	0.182574186	13.864151	0	0.182574186	5.29E-08
	Worst	5	75.701	5	5	1.91E-07
	Best	4	11.142	5	4	5.57E-09
	Median	0.00148525	250520	30.4025	0.18776	2.08E+02
	Mean	0.002600238	1403662.6	193.235534	8.399190567	8.97E+03
f_5	STD	0.005134757	3097317	294.2791158	40.90551605	41130.47
	Worst	0.0291	12347000	1081.9	224.77	2.26E+05
	Best	0.00032446	5298.6	0.42752	0.003598	2.03E-01
	Median	2.94545E-05	3438.45	0.391465	1.6999E-09	4.57E-10
	Mean	3.1845E-05	3397.9677	0.56466621	3.5676E-09	1.80E-09
f_6	STD	2.3048E-05	2121.9475	0.657934632	5.24313E-09	4.18E-09
	Worst	0.00012772	11150	2.8536	2.4427E-08	2.26E-08
	Best	5.9406E-06	529.45	0.0074153	1.9597E-10	3.19E-11
	Median	4	15683500	0.418435	4	2.89E-03
	Mean	4.033333333	26118171	1.8578825	4.033333333	5.20E-03
f_7	STD	0.182574186	32004284	4.387639821	0.182574186	0.006426
	Worst	5	140370000	19.414	5	2.94E-02
	Best	4	18268	0.044475	4	1.21E-04

TABLE 5. Results obtained for multi-modal function.

Benchmark Functions	Metrics	Firefly	SimAnn	GA	PSO	PSO-DS
	Median	-1557.5	-838.5	-288.735	-430.82	-2.18E+33
	Mean	-1587.253333	-888.642	-306.2136667	-431.6226667	-3.11E+34
f_8	STD	109.1128828	245.3469	91.46782044	4.396386395	1.14E+35
	Worst	-1439.1	-556.35	-195.16	-430.82	-1.01E+31
	Best	-1976.5	-1411.9	-573.23	-454.9	-6.23E+35
	Median	0.99497	34.4765	18.969	2.66735E-07	1.99E+00
	Mean	0.663316683	33.167633	23.11760333	0.729636084	5.63E+00
f_9	STD	0.707565048	9.5114437	14.18374256	1.075205944	7.825746
	Worst	1.9899	60.257	54.732	3.9798	2.49E+01
	Best	3.1846E-06	13.146	2.0355	1.2028E-08	2.14E-09
	Median	0.0036184	17.9445	9.6973	3.95965E-05	2.00E+01
	Mean	0.0033333	17.955967	9.6973	0.172031981	2.01E+01
f_{10}	STD	0.000958716	1.5371541	3.61345E-15	0.654531104	0.056094
	Worst	0.0053585	19.967	9.6973	2.5799	2.02E+01
	Best	0.0011593	14.211	9.6973	5.8727E-06	2.00E+01
	Median	0.0124675	32.306	1.0172	2.62595E-09	5.79E-02
	Mean	0.012128475	34.889497	1.010760667	0.015450726	7.36E-02
f_{11}	STD	0.008514015	20.088971	0.034282314	0.038636727	0.05749
	Worst	0.027431	86.082	1.0172	0.15783	2.46E-01
	Best	0.00001895	5.689	0.82932	3.4305E-10	7.54E-08
	Median	0.051930022	452320000	9.4248	0.000762545	7.16E+00
	Mean	0.295876225	462421333	9.382386667	0.014732056	7.54E+00
f_{12}	STD	0.539089678	222375228	0.232307394	0.036271099	3.328861
	Worst	2.4369	895170000	9.4248	0.10776	1.35E+01
	Best	0.00004128	118060000	8.1524	0.00012163	1.90E+00
	Median	0.000907765	710225000	1.3498E-32	0.0023249	1.39E+01
	Mean	0.00090451	795025667	1.3498E-32	0.005891588	1.66E+01
f_{13}	STD	0.000177004	436606981	8.3511E-48	0.005731239	8.859562
	Worst	0.0012595	1.722E+09	1.3498E-32	0.016468	4.45E+01
	Best	0.00058978	188830000	1.3498E-32	0.00056873	5.42E+00

distribution system. Shunt capacitors are usually installed in the primary distribution system to reduce power losses and improve the voltage profile of the buses. As the EV infrastructure acts as an additional load to the existing distribution system, the optimal location and rating of shunt capacitors should be computed along with the placement of EV charging infrastructure. Therefore, the second and third objectives of the model are the minimization of power losses and node voltage deviations after the incorporation of EV charging infrastructure and shunt capacitors. The planning objectives and their constraints will be described in detail below.

A. MAXIMIZATION OF COVERAGE

The EV charging stations placement problem is a facility location problem. In the classical facility location problem, the demand for service is assumed to occur at fixed locations within a traffic network. The total weighted distance or time for travel to the facilities and the distance or time that the user most distant from a facility would have to travel to reach that facility is taken as the control parameter for placement [18].

The mathematical model to select the facility location that will maximize the coverage is given below

$$Maximize\ F_1 = \sum_{i \in I} a_i y_i \tag{1}$$

subject to the constraints,

$$\sum_{j \in N_i} x_j \geq y_i, \quad \forall\ i \in I \tag{2}$$

$$\sum_{j \in J} x_j = P \tag{3}$$

$$x_j = \begin{cases} 1, & \textit{if a facility is allocated to site } j \\ 0, & \textit{otherwise} \end{cases} \tag{4}$$

$$y_j = \begin{cases} 1, & \textit{if one or more facilities are established} \\ & \quad \textit{at sites in the set } N_i \\ 0, & \textit{otherwise} \end{cases} \tag{5}$$

$$L(v) = p, \quad \forall\ v \in T \tag{6}$$

TABLE 6. Results obtained for multi-modal function with fixed dimensions.

Benchmark Functions	Metrics	Firefly	SimAnn	GA	PSO	PSO-DS
	Median	0.998	19.8545	12.671	11.719	9.98E-01
	Mean	1.19628	77.360107	9.770956667	11.559	3.18E+00
f_{14}	STD	0.658313471	130.48895	5.071077752	0.667028408	4.17469
	Worst	3.9683	484.96	14.563	12.671	1.83E+01
	Best	0.998	1.0483	0.998	10.763	9.98E-01
	Median	0.00049764	0.0305335	0.0074558	0.00137795	1.80E-03
	Mean	0.000577923	0.4050941	0.01379907	0.002253795	1.78E-03
f_{15}	STD	0.000294263	1.5674103	0.016398658	0.003275362	0.000108
	Worst	0.0012232	8.3819	0.068132	0.019278	1.94E-03
	Best	0.00030749	0.0021644	0.0014482	0.00081724	1.28E-03
	Median	-1.0316	-0.25031	-1.03145	-1.0316	-1.03E+00
	Mean	-1.0316	2.3161591	-0.991666	-1.0316	-8.68E-01
f_{16}	STD	6.77522E-16	10.877358	0.141197931	6.77522E-16	0.332037
	Worst	-1.0316	56.981	-0.33074	-1.0316	-2.15E-01
	Best	-1.0316	-1.0316	-1.0316	-1.0316	-1.03E+00
	Median	0.39789	1.4069	0.40331	0.39789	3.98E-01
	Mean	0.39789	3.079807	0.425087333	0.39789	3.98E-01
f_{17}	STD	1.6938E-16	3.4964321	0.055115391	1.6938E-16	1.69E-16
	Worst	0.39789	14.458	0.61116	0.39789	3.98E-01
	Best	0.39789	0.39791	0.39789	0.39789	3.98E-01
	Median	3	30.9915	3.00105	3	3.00E+00
	Mean	3	32.925927	20.1359	4.8	1.02E+01
f_{18}	STD	0	27.73444	32.93482561	6.850119556	21.19271
	Worst	3	118.6	84.903	30	8.40E+01
	Best	3	3.2427	3	3	3.00E+00
	Median	-3.8628	-3.2311	-0.30048	-3.8628	0.00E+00
	Mean	-3.8628	-3.2170267	-0.430674333	-3.811266667	0.00E+00
f_{19}	STD	3.16177E-15	0.4265364	0.624078299	0.196116386	0
	Worst	-3.8628	-1.8844	-0.30048	-3.0898	0.00E+00
	Best	-3.8628	-3.8496	-3.6983	-3.8628	0.00E+00
	Median	-3.322	-0.968175	-0.000034085	-3.2031	0.00E+00
	Mean	-3.270476667	-1.138787	-0.000034085	-3.230843333	0.00E+00
f_{20}	STD	0.059926424	0.6020592	0	0.051148767	0
	Worst	-3.2031	-0.33495	-0.000034085	-3.2031	0.00E+00
	Best	-3.322	-2.4546	-0.000034085	-3.322	0.00E+00
	Median	-10.153	-0.555235	-5.0552	-5.0552	-5.10E+00
	Mean	-8.9781	-0.6387653	-5.0552	-5.617926667	-6.13E+00
f_{21}	STD	2.446252865	0.4915368	1.80672E-15	2.739854846	3.06004
	Worst	-2.6305	-0.27206	-5.0552	-2.6305	-2.63E+00
	Best	-10.153	-2.9786	-5.0552	-10.153	-1.02E+01
	Median	-10.403	-0.53014	-5.0877	-5.0877	-5.13E+00
	Mean	-10.18037667	-0.7041413	-5.0877	-6.106423333	-5.84E+00
f_{22}	STD	1.219358215	0.4813122	9.03362E-16	3.235076851	3.169992
	Worst	-3.7243	-0.22108	-5.0877	-1.8376	-1.84E+00
	Best	-10.403	-2.0341	-5.0877	-10.403	-1.04E+01
	Median	-10.536	-0.711975	-5.1285	-4.48195	-4.48E+00
	Mean	-9.11465	-0.9178063	-5.1285	-5.50499	-5.96E+00
f_{23}	STD	2.903503988	0.4643159	1.80672E-15	3.500747951	3.657293
	Worst	-2.4273	-0.3543	-5.1285	-1.6766	-1.68E+00
	Best	-10.536	-2.3638	-5.1285	-10.536	-1.05E+01

A node is "covered" when the closest facility to that node is at a distance less than or equal to S.The shortest distance between a node and the nearest facility location is computed using [19].

Algorithm 1: Algorithm

Step1: Obtain the gbest computed by PSO and assign $x_0 = gbest$
Step2: Evaluate objective function at x_0.
Step3: Start at base point $x = x_0$.
Step4: Apply pattern vectors to x to make exploratory move.
$s_s \times [1, 0, \ldots 0] + x = x^1$
$s_s \times [0, 1, \ldots 0] + x = x^2$
.
.
.
$s_s \times [0, 0, \ldots 1] + x = x^N$
$s_s \times [-1, 0, \ldots 0] + x = x^{N+1}$
$s_s \times [0, -1, \ldots 0] + x = x^{N+2}$
.
.
.
$s_s \times [0, 0, \ldots -1] + x = x^{2N}$
where, $x^1, x^2, \ldots, x^{2N}$ are the new possible points around x
N the total number of independent variables to be optimized.
Step5: Compute the objective function at all points in the order $x^1, x^2, \ldots x^{2N}$ and identify x_k that gives smallest objective function value in the set.
Step6: If $objectivefunction\left(x^k\right) < objectivefunction(x)$, then set $x = x_k$ go to step 2. Otherwise, go to step 5.
Step7: If $\left|objectivefunction\,(x) - objectivefunction(x^k\,)\right| \leq \varepsilon$, go to step 6, otherwise set $s_s = s_s - \Delta s_s andsetx = x_k$ go to step 2.
Step8: Send the solution vector to PSO for velocity updating.

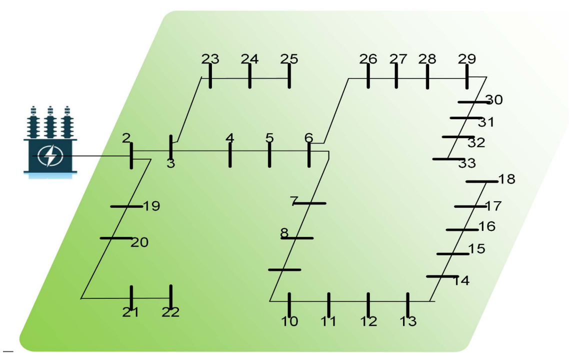

FIGURE 2. IEEE 33 bus test system.

B. MINIMIZATION OF TOTAL POWER LOSS AND VOLTAGE DEVIATION

The installation of EV charging infrastructure to the distribution system changes the power flow pattern in the feeders as well the voltage profile of the system will have changed. The total EV load will increase the power loss

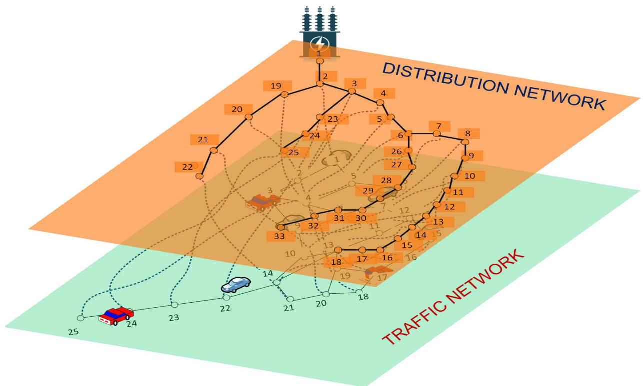

FIGURE 3. Overlapping of traffic nodes in the distribution system.

TABLE 7. Parameter setting of PSO-DS.

Parameter	Value
Maximum Iterations	200
Swarm Size	50
Self-adjustment weight	1.49
Social adjustment weight	1.79
Inertia range	[0.1,1.1]
Initial Point s_S	0.5
Step Size Δs_S	0.05

in the distribution system. However, we can bring this loss to a minimum value by optimizing the location of EV charging infrastructure. The EV station is modelled as a constant load. The shunt capacitors are installed in the primary distribution system to compensate for the absorption of reactive power. The system's total loss depends on the location and ratings of EV charging infrastructure and shunt capacitors. Keeping the other load in the distribution system constant, we take the location and rating of EV charging infrastructure and shunt capacitor as the design variables. The second function (F2) for minimization is the total active power loss of the distribution system is mathematically expressed in equation (7). The reactive power compensation by the shunt capacitor will also minimize the voltage deviations. Equal importance should be given to voltage profiles like total power loss. Function F3 is created to take care of the voltage profile of the system, which is expressed in equation (8) with the constraints listed in the equations from (9) to (16)

$$F_2 = \sum_{i=1}^{Nbus} \sum_{j=1}^{Nbus} g_{ij}(V_i^2 + V_j^2 - 2V_iV_jcos\theta_{ij}) \tag{7}$$

$$F_3 = \sum_{I=1}^{Nbus} \frac{|V_i - V_0|}{V_0} \tag{8}$$

subject to the constraints,

$$-P_{Di} - UEV_iP_{EV,i} = \sum_{j=1}^{N_{bus}} \left|Y_{ij}\right| \left|V_j\right| |V_i|\, cos\left(\theta_{ij} + \delta_j - \delta i\right) \tag{9}$$

TABLE 8. Comparison results for the proposed function for 1 - 4 EVCS (without capacitor).

No of EVCS	Parameter		Firefly	SimAnn	GA	PSO	PSO-DS
1	Power Loss (kW)	Best	226.3	226.3	226.3	226.3	226.3
		Worst	226.3	226.3	226.3	226.3	226.3
		Average	226.3	226.3	226.3	226.3	226.3
	Total Voltage Deviation (%)	Best	5.340909	5.340909	5.340909	5.340909	5.340909
		Worst	5.340909	5.340909	5.340909	5.340909	5.340909
		Average	5.340909	5.340909	5.340909	5.340909	5.340909
	Coverage (%)	Best	37.6	37.6	37.6	37.6	37.6
		Worst	37.6	37.6	37.6	37.6	37.6
		Average	37.6	37.6	37.6	37.6	37.6
	Objective Value	Best	2.2287	2.2287	2.2287	2.2287	2.2287
		Worst	2.2287	2.2287	2.2287	2.2287	2.2287
		Average	2.2287	2.2287	2.2287	2.2287	2.2287
2	Power Loss (kW)	Best	273.8	228	228	228	214
		Worst	213.8	213.8	213.8	213.8	289
		Average	243.8	220.9	220.9	220.9	251.5
	Total Voltage Deviation (%)	Best	6.098788	5.409091	5.409091	5.409091	5.27303
		Worst	5.323636	5.27303	5.27303	5.27303	6.30697
		Average	5.711212	5.341061	5.341061	5.341061	5.79
	Coverage (%)	Best	48.9	54.2	54.2	54.2	48.3
		Worst	48.3	48.3	48.3	48.3	40.3
		Average	48.6	51.25	51.25	51.25	44.3
	Objective Value	Best	1.9732	1.9732	1.9732	1.9732	1.9843
		Worst	1.9843	1.9843	1.9843	1.9843	1.9732
		Average	1.97875	1.97875	1.97875	1.97875	1.97875
3	Power Loss (kW)	Best	220.5	220.2	217.6	230	215
		Worst	270.5	226.5	225.8	217.7	270.5
		Average	245.5	223.35	221.7	223.85	242.75
	Total Voltage Deviation (%)	Best	5.34303	5.340303	5.316061	5.416061	5.292424
		Worst	6.052424	5.397273	5.391212	5.325758	6.052424
		Average	5.697727	5.368788	5.353636	5.370909	5.672424
	Coverage (%)	Best	64.9	64.9	64.9	61.8	64.9
		Worst	48.9	64.9	64.9	59.1	48.9
		Average	56.9	64.9	64.9	60.45	56.9
	Objective Value	Best	1.8099	1.8099	1.8098	1.8097	1.8102
		Worst	1.8109	1.811	1.8111	1.8115	1.8099
		Average	1.8104	1.81045	1.81045	1.8106	1.81005
4	Power Loss (kW)	Best	224.2	224	220.6	226.7	216
		Worst	237.9	267.7	235.5	364.3	364.3
		Average	231.05	245.85	228.05	295.5	290.15
	Total Voltage Deviation (%)	Best	5.381212	5.369394	5.346061	5.407576	5.304848
		Worst	5.615455	5.980909	5.521818	7.136061	7.136061
		Average	5.498333	5.675152	5.433939	6.271818	6.220455
	Coverage (%)	Best	75.7	75.7	75.7	75.7	75.7
		Worst	76.2	73.1	76.2	47.4	47.4
		Average	75.95	74.4	75.95	61.55	61.55
	Objective Value	Best	1.7388	1.7387	1.7386	1.7381	1.7401
		Worst	1.7535	1.7675	1.7707	1.8012	1.8012
		Average	1.74615	1.7531	1.75465	1.76965	1.77065

$$-Q_{Di} - UEV_i Q_{EV,i} + VSC_i Q_{SC,i} = -\sum_{j=1}^{N_{bus}} |Y_{ij}| |V_j| |V_i| \sin(\theta_{ij} + \delta_j - \delta i) \tag{10}$$

$$V_i^{min} \leq V_i \leq V_i^{max} \quad i \neq 1 \tag{11}$$

$$S_{ij} \leq S_{ij}^{max} \tag{12}$$

$$Q_{SC}^{min} \leq Q_{SC,i} \leq Q_{SC}^{max} \tag{13}$$

$$UEV_i = \begin{cases} 1, & \text{if the EVCS is located at bus } i \\ 0, & \text{otherwise} \end{cases} \tag{14}$$

TABLE 9. Comparison results for the proposed function for 5 - 8 EVCS (without capacitor).

No of EVCS	Parameter		Firefly	SimAnn	GA	PSO	PSO-DS
5	Power Loss (kW)	Best	220.4	226.6	234.2	243.9	218
		Worst	237.8	236.1	245.6	260.4	237.8
		Average	229.1	231.35	239.9	252.15	227.9
	Total Voltage Deviation (%)	Best	5.351515	5.462121	5.555758	5.706364	5.332424
		Worst	5.59	5.599394	5.733333	5.959697	5.59
		Average	5.470758	5.530758	5.644545	5.83303	5.461212
	Coverage (%)	Best	78.4	78.4	78.4	87	78.4
		Worst	60.9	65.5	82.1	76.7	60.9
		Average	69.65	71.95	80.25	81.85	69.65
	Objective Value	Best	1.6978	1.6974	1.6932	1.693	1.7068
		Worst	1.7272	1.729	1.7394	1.7427	1.7272
		Average	1.7125	1.7132	1.7163	1.71785	1.717
6	Power Loss (kW)	Best	228.3	242.1	263.5	232.4	225
		Worst	279.3	272	229.7	249.2	254
		Average	253.8	257.05	246.6	240.8	239.5
	Total Voltage Deviation (%)	Best	5.469394	5.641818	5.956061	5.542727	5.383939
		Worst	6.140909	6.075455	5.427879	5.751818	5.824545
		Average	5.805152	5.858636	5.69197	5.647273	5.604242
	Coverage (%)	Best	89.7	89.2	89.7	95.6	83.8
		Worst	82.8	57.4	76.2	77.9	66
		Average	86.25	73.3	82.95	86.75	74.9
	Objective Value	Best	1.6672	1.6653	1.6622	1.6586	1.708
		Worst	1.7101	1.7148	1.7447	1.7476	1.7003
		Average	1.68865	1.69005	1.70345	1.7031	1.70415
7	Power Loss (kW)	Best	273.8	239.6	273.8	241.6	230
		Worst	248.2	265.5	308.1	234.9	269.4
		Average	261	252.55	290.95	238.25	249.7
	Total Voltage Deviation (%)	Best	6.09	5.604848	6.079697	5.672424	5.490303
		Worst	5.729394	5.978182	0.65303	5.575152	5.778485
		Average	5.909697	5.791515	3.366364	5.623788	5.634394
	Coverage (%)	Best	97.8	89.7	87	97.8	87.2
		Worst	87.5	82.8	80.7	82.1	67.7
		Average	92.65	86.25	83.85	89.95	77.45
	Objective Value	Best	1.6701	1.6694	1.6569	1.6527	1.6968
		Worst	1.7119	1.7196	1.7216	1.7369	1.6754
		Average	1.691	1.6945	1.68925	1.6948	1.6861
8	Power Loss (kW)	Best	258.6	246.3	251.7	246.3	240.1
		Worst	348.7	314.6	239	317.3	269.4
		Average	303.65	280.45	245.35	276.8	254.75
	Total Voltage Deviation (%)	Best	5.922727	5.781515	5.753636	5.755152	5.630303
		Worst	6.958485	6.605455	5.631818	6.634242	6.059697
		Average	6.440606	6.193485	5.692727	6.090152	5.845
	Coverage (%)	Best	88	95.6	98.3	98.3	99.5
		Worst	82.9	79	93.6	84.3	71.9
		Average	85.45	87.3	95.95	91.3	85.7
	Objective Value	Best	1.6632	1.6589	1.6554	1.6529	1.22818
		Worst	1.7281	1.7335	1.7445	1.7501	1.7119
		Average	1.69565	1.6962	1.69995	1.7015	1.47004

$$VSC_i = \begin{cases} 1, & \textit{if the shunt capacitor is installed at bus } i \\ 0, & \textit{otherwise} \end{cases} \tag{15}$$

$$Y_{ij} = G_{ij} + jB_{ij} = \left|Y_{ij}\right| \angle\theta_{ij} \tag{16}$$

Equation (16) is the element of bus admittance matrix, the real part stands for conductance and imaginary part stands for susceptance.

The proposed mathematical model consists of three-objective functions. The pareto solutions of the multi-objective

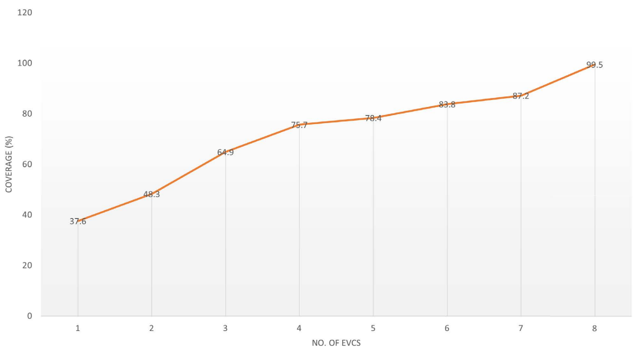

FIGURE 4. **No of EVCS vs coverage.**

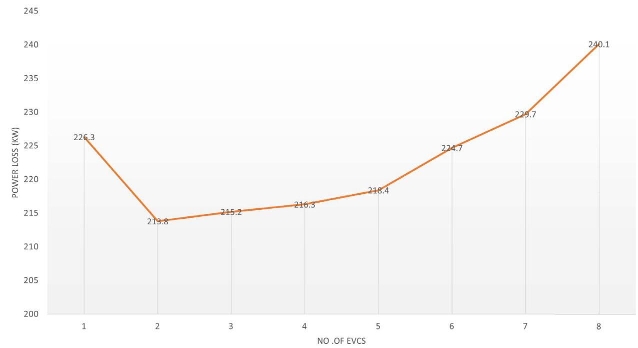

FIGURE 5. **No of EVCS vs power loss.**

optimization problem can be obtained by using different weighting coefficients and then converting the problem into a single objective problem.

$$Minimize\ F = \alpha_1 \left(\frac{1}{F_1}\right) + \alpha_2 F_2 + \alpha_3 F_3 \tag{17}$$

The three objective functions namely coverage, loss and voltage deviations are of different order of magnitudes, we need to normalize these objectives. In this paper, advanced normalization method [20] is utilized.

III. IMPLEMENTATION OF PSO-DS ALGORITHM

PSO is an evolutionary computation algorithm developed by [21], which was inspired by the social behaviour of bird flocking and fish schooling. It creates a ''population'' of particles that fly through the problem hyperspace with given velocities. At each iteration, the velocities of the individual particles are updated according to the historical best position for the particle itself and the neighbourhood best position. Both the particle best and the neighbourhood best are derived according to a user defined fitness function. For a given problem, each individual possible solution can be modelled as a particle that moves through the problem hyperspace. The position of each particle is determined by the vector $x_i \in R^n$ and its movement by the velocity of the particle $v_i \in R^n$ as given below

$$\vec{x_i(t)} = x_i(t \vec{-} 1) + \vec{v_i(t)} \tag{18}$$

The particles can gain information by their own experience or from the knowledge of other individuals in its neighbourhood. It is reasonable to apply random weights to each part to give relative importance between these two that can vary one decision to other. The velocity will be determined by

$$\begin{aligned} \vec{v_i(t)} = v_i(t \vec{-} 1) + \varphi_1.rand_1 \left(\vec{p_i} - x_i\,(t \vec{-} 1)\right) \\ + \varphi_2.rand_2.\left(\vec{p_g} - x_i\,(t \vec{-} 1)\right) \end{aligned} \tag{19}$$

The equation (19) consists of three components, the first component is related to the tendency of the particle to continue in the same direction it has been traveling, the

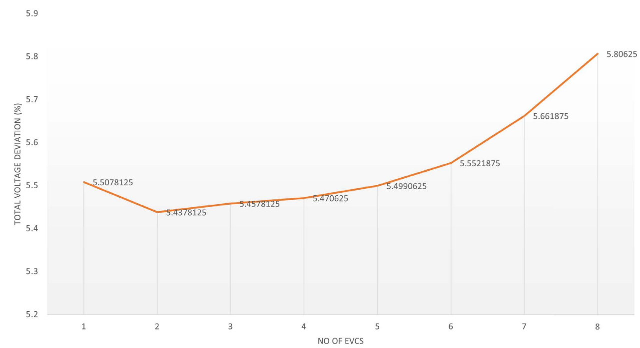

FIGURE 6. **No of EVCS vs total voltage deviation.**

second component makes the particle to move towards the best position ever found by the given particle p_l (Pbest) and the third component attracts the particles towards the best position found by any particle: p_g (Gbest). The third component is termed as '' social knowledge'' or ''group knowledge''. In this paper, we want to integrate the direct search method into particle swarm optimization (PSO) to search for better Gbest. It applies the expansion or contraction around the gbest particle computed by PSO. The value of the objective function either decreases or remains the same from Gbest particle. This integration avoids the major drawback of the direct search method which lies in the selection of the starting point. It also improves the convergence and accuracy of canonical PSO.

The computational procedure for the optimization of the proposed multi-objective function using PSO-DS is given in the algorithm (1).

In this paper, the location of EVCS and shunt capacitors are integers but the computation procedure of PSO-DS are with real numbers. To incorporate integers, during initialization as well as the updating, the concerned variable is rounded to the nearby integer. Backward/Forward sweep load flow algorithm is used to compute the total active power loss and voltage profile of the test system at each iteration of PSO-DS [22]. The flowchart of PSO-DS algorithm for the placement of EV charging infrastructure and shunt capacitors is shown in figure (1).

TABLE 10. Pareto solution of the objective function.

No. of EVCS	EVCS Location	EVCS Capacity (kVA)	Capacitor Location	Capacitor value (kVAr)
1	21	800	13, 3, 22, 30	364.4, 873.2, 365.8, 1000
2	21, 1	400, 400	3, 30, 7, 14	712.0, 901.3, 400.5, 276.6
3	22, 1, 21	111.1, 398.4, 290.5	30, 14, 24, 26	889.4, 298.2, 515.0, 424.2
4	22, 21, 1, 2	119.9, 288.0, 360.5, 31.6	14, 30, 24, 7	276.3, 904.8, 512.2, 455.5
5	1, 21, 11, 2, 22	338.2, 38.4, 8.3, 55.2, 359.9	24, 30, 7, 14	548.6, 905.2, 464.5, 278.2
6	1, 2, 4, 18, 21, 23	168.7, 139.5, 41.1, 25.5, 269.2, 156.1	24, 30, 14, 7	553.0, 905.3, 277.0, 460.3
7	18, 2, 23, 6, 1, 8, 20	22.3, 18.8, 82.3, 32.7, 208.1, 88.0, 347.8	14, 30, 24, 7	285.4, 904.4, 519.1, 485.9
8	9, 22, 20, 5, 3, 1, 11, 21	32.7, 25.6, 148.8, 91.7, 141.8, 82.2, 54, 223.3	28, 8, 18, 29	572.1, 690.9, 391.5, 662.5

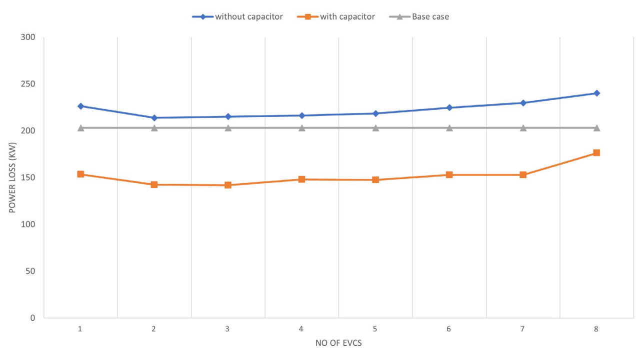

FIGURE 7. Power loss in the system after the installation of EVCS and capacitors.

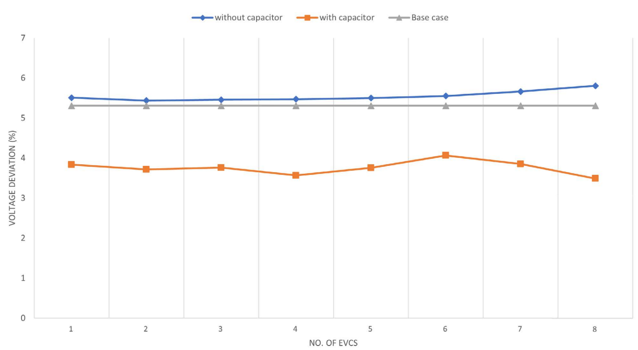

FIGURE 8. Voltage deviation in the system after the installation of EVCS and capacitors.

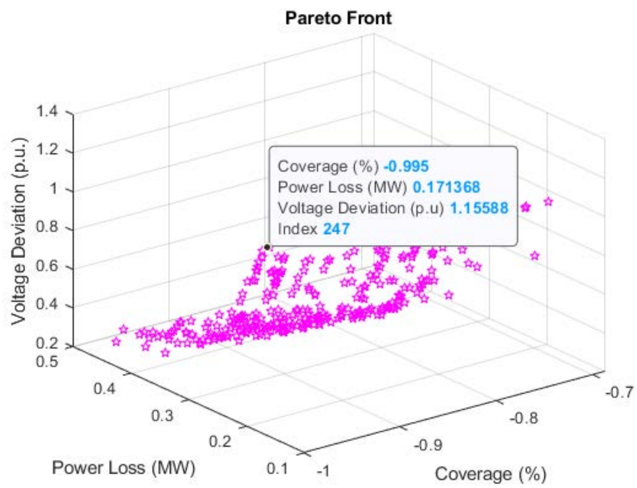

FIGURE 9. Pareto front of the fitness function.

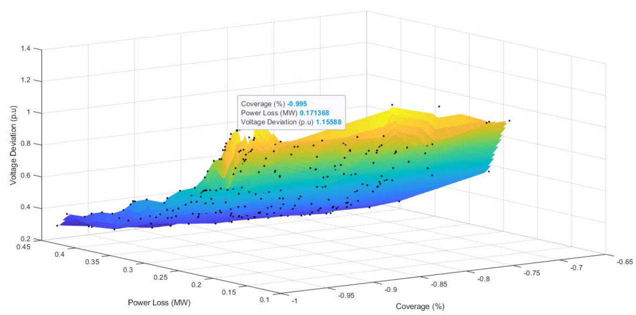

FIGURE 10. Interpolated surface plot of pareto front.

IV. RESULTS AND DISCUSSION

A. PERFORMANCE OF THE ALGORITHMS ON BENCHMARK FUNCTIONS

The performance of the PSO-DS algorithm is compared with other algorithms by applying it to the normal benchmark functions [23]. table(1), table(2) and table(3) shows the various benchmark functions for testing. The order of all test functions is taken as 10. The metrics for validation are best, worst, median, mean and standard deviation. The parameter setting of the PSO-DS optimization algorithm is given in the Table (7) The total number of independent runs for all algorithms is 30. Simulations are performed in MATLAB 2021b using a system configuration of Intel(R) Core(TM) i3-3217U CPU @ 1.80GHz 1.80 GHz, 6.00 GB RAM. The results from table(4), table(5) and table(6) show the PSO-DS algorithm's efficiency over other well-established optimization procedures.

B. SYSTEM DESCRIPTION

After successfully applying the PSO-DS algorithm on benchmark functions, IEEE 33 bus distribution and a 25-node traffic network are taken to obtain constructive plans for charging stations. The one-line diagram of the IEEE 33 bus distribution system is shown in Figure (2). In the test system, the traffic nodes 1-25 geographically overlap with the distribution system nodes 2-26. Node 1 of the distribution system is connected to the grid supply point. The details of the

TABLE 11. Comparison of the simulation results.

Parameter		Without Capacitor	With Capacitor
Power Loss (kW)	Best	240.1	176.2
	Worst	348.7	324.7
	Average	289	247.2
Total Voltage Deviation (%)	Best	1.858	1.1163
	Worst	2.2963	1.7595
	Average	2.0183	1.3909
Coverage (%)	Best	99.5	99.5
	Worst	71.9	71.9
	Average	89.45	89.45
Objective value	Best	1.76114	1.22818
	Worst	2.40233	2.14359
	Average	2.01756	1.6684

TABLE 12. Results for the proposed multi-objective functions.

No. of EVCS	Power Loss (kW) Base Case: 203 kW			Voltage Deviation (%) Base Case: 5.3094 %			Coverage (%)
	Without Capacitor	With Capacitor	Reduction (%)	Without Capacitor	With Capacitor	Reduction (%)	
1	226.3	153.5	32.169686	5.5078125	3.8365625	30.3432624	37.6
2	213.8	142.4	33.395697	5.4378125	3.714375	31.6935808	48.3
3	215.2	141.9	34.061338	5.4578125	3.7609375	31.0907529	64.9
4	216.3	147.9	31.622746	5.470625	3.566875	34.7994973	75.7
5	218.4	147.5	32.46337	5.4990625	3.75375	31.7383645	78.4
6	224.7	152.8	31.99822	5.5521875	4.066875	26.7518433	83.8
7	229.7	152.9	33.434915	5.661875	3.8525	31.9571697	87.2
8	240.1	176.2	26.613911	5.80625	3.4884375	39.919268	99.5

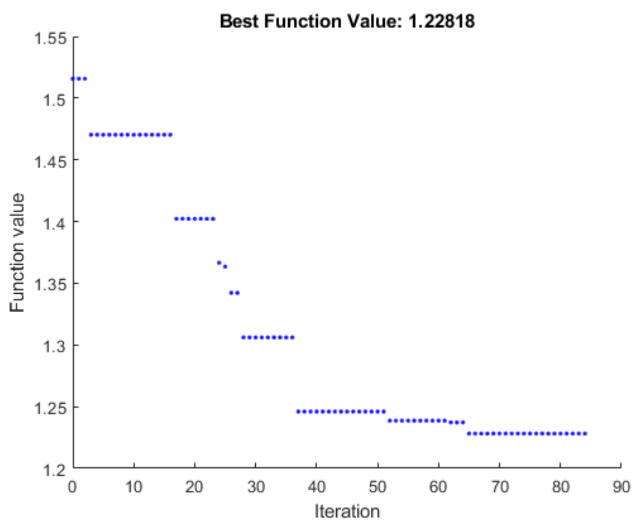

FIGURE 11. Convergence of the fitness function.

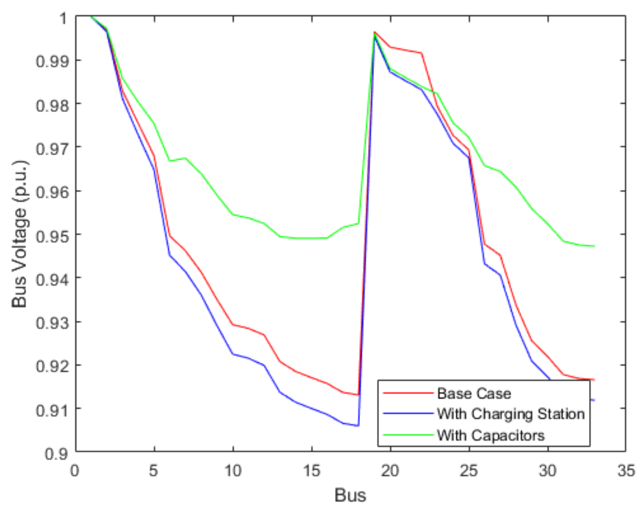

FIGURE 12. Bus voltage variation with 8 EVCS.

IEEE 33 bus distribution system and 25 node traffic network are in the appendix. The superimposed nodes of the traffic network in the electrical distribution system are shown in Figure (3). The traffic network node data was taken from [2].

The maximum EV battery capacity is considered 30 kWh, and the energy consumption rate is 0.25 kWh/km. When the EV is starting from the source node, the SOC of the EV battery is considered as 50%. It is assumed that the total charging demand of EVs in the distribution system is 800 kVA. It means the total installed capacity of EV charging stations in the distribution system should equal 800 kVA. The PSO-DS algorithm is utilized to obtain various constructive

TABLE 13. Traffic network node data.

From Node	To Node	Distance (km)	Weight	From Node	To Node	Distance (km)	Weight
1	2	40	0.54	11	13	30	0.05
1	5	50	0.54	11	16	70	0.05
2	3	30	0.8	11	12	20	0.05
2	4	40	0.8	12	15	40	0.54
3	4	40	0.27	12	16	40	0.54
3	9	40	0.27	13	14	70	0.05
4	9	70	0.27	13	19	40	0.05
4	8	50	0.27	14	19	70	0.54
4	7	50	0.27	14	21	20	0.54
4	5	30	0.27	14	22	40	0.54
5	6	50	0.27	15	16	40	0.27
5	7	50	0.27	16	17	40	0.27
6	7	30	0.07	17	18	30	0.27
7	8	30	0.05	17	19	30	0.27
7	11	80	0.05	18	20	30	1.07
7	12	90	0.05	19	20	30	0.8
8	9	60	0.54	20	21	20	0.27
8	10	60	0.54	21	14	20	0.27
8	11	70	0.54	21	20	20	0.27
8	13	70	0.54	22	23	20	0.54
9	10	60	0.27	23	24	30	0.05
10	13	60	0.54	24	25	30	1.34
10	14	30	0.54	25	24	80	0.05

plans. Graphs like the number of EVCS versus coverage, the number of EVCS versus total power loss, and the number of EVCS versus total voltage deviations are found. The results also include the effect of shunt capacitors on the total power loss and total voltage deviations.

C. DISCUSSION

The proposed multi-objective model is solved by using different algorithms, and the results are displayed in the table (8) and (9). The results show that the PSO-DS algorithm provides the best results among the other algorithms for the multi-objective function. IEEE 33 bus distribution system has a total active power loss of 203 kW and a total voltage deviation of 5.31 % for the base loadings. By adding the single EVCS, all the algorithms converged to the single solution and the power loss increased by 11.48% from its base loss, the voltage deviation increased by 3.74%, the coverage is 37.6% only. The EVCS number is gradually incremented, and the coverage, total loss and total voltage deviation are obtained for all cases. However, the increase of the number of EVCS would increase the power loss and total voltage deviation, which can be understood from the figure (5) and (6). When placing the 8 EVCS, the coverage is maximized (i.e.) the customer from any location in the traffic network can access the charging station with minimized power loss and total voltage deviation. Another case includes the simultaneous placement of EVCS and shunt capacitors. It is clear from the tables that the installation of shunt capacitors at the optimal locations significantly reduces the total loss and enhances the voltage profile.

Table (10) shows the optimal EVCS locations, EVCS ratings, shunt capacitor location, and shunt capacitor rating. The simulation is run for 30 times and the best results have been taken. The table (11) presents the comparative results obtained from the toatl run. The values of the objective functions with respect to the number of EVCS are presented in Table (12). It is clear from Table (12) that the coverage progresses to the maximum value as the EVCS number increases and without the installation of shunt capacitor, the power loss as well the total voltage deviations for the given loading conditions increases.

TABLE 14. IEEE 33 bus test system data.

Bus Data			Line Data			
Bus	Pd	Qd	From Bus	To Bus	R (ohms)	X (ohms)
1	0	0	1	2	0.0922	0.047
2	100	60	2	3	0.493	0.2511
3	90	40	3	4	0.366	0.1864
4	120	80	4	5	0.3811	0.1941
5	60	30	5	6	0.819	0.707
6	60	20	6	7	0.1872	0.6188
7	200	100	7	8	0.7114	0.2351
8	200	100	8	9	1.03	0.74
9	60	20	9	10	1.044	0.74
10	60	20	10	11	0.1966	0.065
11	45	30	11	12	0.3744	0.1238
12	60	35	12	13	1.468	1.155
13	60	35	13	14	0.5416	0.7129
14	120	80	14	15	0.591	0.526
15	60	10	15	16	0.7463	0.545
16	60	20	16	17	1.289	1.721
17	60	20	17	18	0.732	0.574
18	90	40	2	19	0.164	0.1565
19	90	40	19	20	1.5042	1.3554
20	90	40	20	21	0.4095	0.4784
21	90	40	21	22	0.7089	0.9373
22	90	40	3	23	0.4512	0.3083
23	90	50	23	24	0.898	0.7091
24	420	200	24	25	0.896	0.7011
25	420	200	6	26	0.203	0.1034
26	60	25	26	27	0.2842	0.1447
27	60	25	27	28	1.059	0.9337
28	60	20	28	29	0.8042	0.7006
29	120	70	29	30	0.5075	0.2585
30	200	600	30	31	0.9744	0.963
31	150	70	31	32	0.3105	0.3619
32	210	100	32	33	0.341	0.5302
33	60	40				

The installation of 8 EVCS with the total rating of 800 kVA increases the total system loss and total voltage deviation to 240.1 kW and 5.5%. After the successful placement of the capacitor, the losses in the system reduced by 26.61% and the voltage deviation is reduced by 39.92%. Figure (4) shows the variation of coverage with the number of EVCS and this graph will give a quick reference to the decision maker regarding the coverage with respect to number of EVCS. Figure (5) and (6) gives the change of loss and total voltage deviation with respect to the number of EVCS. The effect of shunt capacitor on active power loss as well as total voltage deviation are presented in the Figure (7) and (8). The convergence of the proposed model solved by PSO-DS is displayed in the Figure (11). The pareto front of the proposed multi-objective function is displayed in the Figure (9). The interpolated surface plot of the pareto front is shown in the Figure (10) which projects the solution points in the surface. A sample solution point is marked in the pareto figures which clearly represents the possible solution in the surface.

V. CONCLUSION

The deployment of EVs impose challenges on the secure operation of the electric distribution systems. The EV charging infrastructure location problem should offer charging conveniences while minimizing the negative impacts to the power systems. A new multi-objective EV charging station planning model has been developed in this paper taking the total coverage, loss minimization and voltage profile improvement as objective functions. PSO-DS algorithm has been employed to solve the proposed mathematical model because of its efficiency and simplicity. The case studies shows that the proposed model have successfully yields attractive construction plans of EV charging stations, while maintaining the operation economy and the security of the power system.

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