A Hybrid Multi-Objective Chicken Swarm Optimization and Teaching Learning Based Algorithm for Charging Station Placement Problem

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ABSTRACT A new hybrid multi-objective evolutionary algorithm is developed and deployed in the present work for the optimal allocation of Electric Vehicle (EV) charging stations. The charging stations must be positioned on the road in such a way that they are easily accessible to the EV drivers and the electric power grid is not overloaded. The optimization framework aims at simultaneously reducing the cost, guaranteeing sufficient grid stability and feasible charging station accessibility. The grid stability is measured by a composite index consisting of Voltage stability, Reliability, and Power loss (VRP index). A Pareto dominance based hybrid Chicken Swarm Optimization and Teaching Learning Based Optimization (CSO TLBO) algorithm is utilized to obtain the Pareto optimal solution. It amalgamates swarm intelligence with teaching-learning process and inherits the strengths of CSO and TLBO. The two level algorithm has been validated on the multi-objective benchmark problems as well as EV charging station placement. The performance of the Pareto dominance based CSO TLBO is compared with that of other *state-of-the-art* algorithms. Furthermore, a fuzzy decision making is used to extract the best solution from the non dominated set of solutions. The combination of CSO and TLBO can yield promising results, which is found to be efficient in dealing with the practical charging station placement problem.

INDEX TERMS Accessibility index, charging station, chicken swarm optimization, teaching learning optimization, cost, electric vehicle.

I. INTRODUCTION

Road transportation sector is one of the major emitters of greenhouse gases [1]. EVs have emerged as an environmentally friendly alternative to traditional Internal Combustion Engine (ICE) driven vehicles, because they have the potential to reduce greenhouse gas emissions. However, the large-scale deployment of EVs may be a major threat to electric power grid, due to increase and variance in power demand by the charging stations of EVs. Actually, the degradation of voltage

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stability and reliability indices, reduced reserve margin, and increased power losses are the consequences of improper positioning of EV charging stations in the electric power distribution network [2]–[4].

In [5], a sketchy overview of the latest drift in charging infrastructure planning problem was given thereby elaborating modelling approaches, objective functions, and constraints of the placement problem. In [6], a comprehensive survey of the optimization and control aspects of EV fleet management was provided. In [7], an overview on the computational scheduling methods for integrating EVs with power grid is given. In [8], charging station placement problem was

TABLE 1. Comparison of the proposed formulation of charging station placement with some of the existing formulations.

Reference	Objective Functions				
	Cost	Voltage Stability	Power loss/ Energy loss	Reliability	EV driver convenience
[8]	✓				
[9]		✓	✓		✓
[10]	✓		✓		✓
[11]	✓				
[12]	✓				
[13]	✓				
[14]	✓	✓	✓		
Proposed Formulation	✓	✓	✓	✓	✓

formulated under a single objective framework with cost as the objective function. The candidate sites for charging stations were identified based on service radius, environmental factors and the optimization problem was attacked by using Modified Primal-Dual-Interior Point Algorithm (MPDIPA). In [9], the placement problem was framed with the considering of the EV flow, voltage deviation, and power loss as objective functions. A Cross-Entropy (CE) method was used for obtaining the Pareto front, and Data Envelopment Analysis (DEA) was applied for the final decision-making. In [10], the problem was modelled with cost, annualized traffic flow, and energy losses as objective functions. A Multi-Objective Evolutionary Algorithm (MOEA) was utilized for obtaining the Pareto optima, and the final planning scheme was decided by fuzzy logic. In [11], cost was considered as the main objective function of the placement problem, and the placement problem was solved by using Binary Firefly Algorithm (BFA). In [12], the authors proposed a placement scheme for public charging stations with cost as the objective function. A Varonoi diagram based technique was employed to decide the service region, and Particle Swarm Optimization (PSO) algorithm was applied to cope with the non-linear optimization problem. In [13], cost and utilization rate of chargers were considered as objective functions in problem modelling. Moreover, a novel Strengthened Pareto Evolutionary Algorithm II (SPEA II) was used for obtaining the best locations for placing the charging stations. In [14], the authors modelled the placement problem under a multi-objective framework with cost, real power loss reduction index, reactive power loss reduction index, and voltage profile improvement index as the objective functions. A hybrid GA PSO algorithm was deployed to handle this problem. In [15], the authors presented an optimal placement scheme for charging stations considering stochastic charging. In [16], [17], the authors provided an optimal planning scheme for EV charging stations based on voltage sensitivity indices. In [18], the authors presented an optimal placement and charging scheme for EV charging stations under contingent conditions in smart distribution grid. In [19], the authors presented a scenario based planning model of charging

station placement with the network reconfiguration being taken into account, and solved this problem using a coevolutionary approach. In [20], the authors proposed a multi-objective framework of charging station placement with the voltage deviation, power losses, and EV flow. The Multi-objective Grey Wolf Optimization (MOGWA) was further developed in their work. In [21], the authors investigated a robust chance constrained model for the similar charging station placement problem.

Literature [8]–[21] reveals that the charging station placement is a complex and demanding problem involving a number of objective functions and constraints. However, the reliability of the power grid network is neglected in most of the formulations of charging station placement. Exclusion of reliability indices while formulating the charging station placement problem is a major research gap. Hence, in this paper, we strategically address the charging station placement problem by giving the due consideration to the reliability indices simultaneously considering other planning objectives like cost, power loss, voltage deviation, and accessibility. Table 1 highlights the differences between the proposed formulation of charging station placement problem and the formulations of charging station placement problem present in the existing literature. From Table 1 it is clear that the proposed formulation of charging station problem is superior to the existing formulations as it has the capacity of addressing economic factors, security of the power grid as well as EV driver's convenience. The current study does not focus on the home charging of EVs, because the authors find public charging infrastructure vital for large penetration of EVs in metropolitan cities. Moreover, from [8]–[21], it is clear that researchers have applied a large variety of meta-heuristics and classical optimization algorithms for coping with the charging station placement problem. The existing methodologies in handling the placement problem are summarized and given in Table 2. Heuristics or meta-heuristics can give near-optimal solutions in lesser time as compared to analytical methods in handling complex non-linear problems like the charging station placement problem [5]. Hence, the need for developing efficient

TABLE 2. Methodologies used for solving charging station placement problem.

| Ref.	Methodology
[8]	MPDIPA
[9]	CE and DEA
[10]	MOEA
[11]	BFA
[12]	PSO
[13]	SPEA II
[14]	GA PSO
[21]	MOGWA
Present work	CSO TLBO

and fast meta-heuristics remains. CSO and TLBO are the two *state-of-the-art* nature-inspired algorithms successfully applied by researchers for complex engineering optimization problems. In [22], the authors have reviewed different variants, applications of CSO as well as efficacy of CSO in solving different real-world problems. For example, CSO is applied for solving economic load dispatch [23], fault diagnosis of pumping wells [24], ascent trajectory optimization [25], train energy saving [26], robot path planning [27] etc. Similarly, TLBO is successfully used to cope with parameter optimization of machining process [28], transmission expansion planning [29], economic load dispatch problem [30], optimization of heat exchangers [31], optimal configuration of microgrid [32], optimization of space trusses [33], groundwater prediction [34], energy demand estimation [35], parameter extraction of photovoltaic models [36], glazing system design [37], PID controller design [38], wind speed forecasting [39], energy performance assessment of buildings [40], etc. CSO is a popular evolutionary algorithm, in which the search space can be effectively explored. The features of CSO are its powerful utilization of population and efficient exploration of search space. However, in some cases, it is observed that CSO gets stuck in the local optima. Actually, TLBO may be combined with CSO to combat with this drawback. Therefore, the synergy of CSO and TLBO can enhance the overall search capability and avoid premature convergence.

The contribution of our work is threefold:

1. A new multi-objective formulation of charging station placement problem is proposed. The formulation strategically addresses the charging station placement problem considering cost, operating parameters of the power grid as well as EV user's convenience.
2. A novel Pareto dominance based CSO TLBO algorithm for the charging station placement problem is proposed.
3. A number of multi-objective benchmark problems and the problem to locate electric vehicle charging stations areattacked by CSO TLBO, and the performance of the proposed algorithm is statistically weighted against the up-to-date algorithms.

II. PROBLEM FORMULATION

The charging station placement is a multifaceted problem involving multiple decision variables, objective functions,
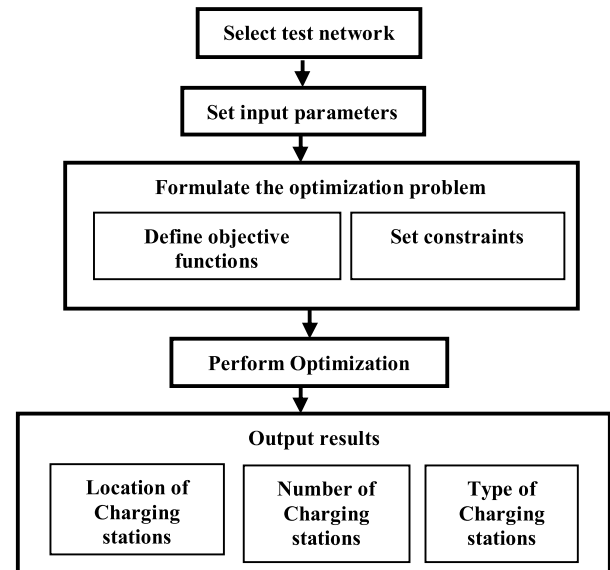
FIGURE 1. Schematic overview of charging station placement problem.

and constraints. A schematic overview of the charging station placement problem is shown in Fig.1. In the present work, the charging station placement is formulated as a multi-variable, multi-objective, and non-linear optimization problem. One of the salient features of the charging station placement problem presented here is multi-objective formulation of the problem with cost, VRP index, and accessibility index as the objective functions. Thus, we consider economic objectives, driver's convenience as well as safety limits of the distribution network parameters in modelling the charging station placement problem. However, we do not convert reliability indices and power loss to their equivalent cost, since conversion of reliability indices and power loss to their equivalent cost is an approximate method.

A. DECISION VARIABLES

The allocation and sizing of the charging stations are the activities performed in this placement problem. The charging service speed provided can be slow or fast. Thus, the position, charging speed, and number of chargers are considered as decision variables. The decision variables are p, N_{fastp}, and N_{slowp}

$$p = \{p_1, p_2 \ldots p_m\} \text{ and } p \in TS$$
$$N_{fastp} = \{N_{fastp_1}, N_{fastp_2}, \ldots N_{fastp_m}\} \text{ and}$$
$$N_{slowp} = \{N_{slowp_1}, N_{slowp_2}, \ldots N_{slowp_m}\}$$

B. OBJECTIVE FUNCTIONS

Large investments associated with the establishment of charging stations give motivation for careful optimization of the charging infrastructure with respect to the traffic and electric grid [41]. The three prime factors: cost, VRP index, and accessibility index must be considered in the formulation of the charging station placement problem. Therefore, the

objective function is expressed as

$$F = \min(\cos t) + \min(VRP \; index)$$
$$+ \max(Accessibility \; index) \quad (1)$$

The explanation of these three objective functions is presented below.

1) COST

The optimization is concerned with the minimization of the overall cost. The installation cost is the monetary investment associated with the construction of charging stations. The land cost, building cost, labour cost, and charger cost are all included in the installation cost. The operation cost is the cost of the electric power for imparting the service of charging to the EVs.

The total cost function includes:

$$Cost = C_{installation} + C_{operation} \quad (2)$$

$$C_{installation} = f(N_{fastp}, N_{slowp})$$
$$= \sum N_{fastp} \times C_{fast}$$
$$+ \sum N_{slowp} \times C_{slow} \quad (3)$$

$$C_{operation} = f(N_{fastp}, N_{slowp})$$
$$= (\sum N_{fastp} \times CP_{fast}$$
$$+ \sum N_{slowp} \times CP_{slow})$$
$$\times P_{electricit\,y} \quad (4)$$

As given in Eqs.(3) and (4),the installation and operating costs are only dependent on the number of fast and slow charging stations, and are independent of the location of charging stations, because of the assumption that the land, building, labour, charger, and electricity cost are the same for all the nodes of the entire network.

2) VRP INDEX

The VRP index is recently formulated by Deb *et al.* [2] with the voltage stability, reliability, and power loss considered together. Moreover, both the frequency based and duration based reliability indices are taken into account. Charging stations increase the load demand of the power grid, and possibly result in the deterioration of voltage profile, reliability, and increase in power loss. Hence, in our work, the impact of EV charging stations on the power grid is considered by regarding the minimization of the VRP index as one of the objective functions. The VRP index and terms associated are

$$VRP = f(p, N_{fastp}, N_{slowp}) = w_1 V + w_2 R + w_3 P \quad (5)$$

where $V = \frac{VSI_{base}}{VSI_l}$,

$$R = w_{21} \frac{SAIFI_l}{SAIFI_{base}} + w_{22} \frac{SAIDI_l}{SAIDI_{base}} + w_{23} \frac{CAIDI_l}{CAIDI_{base}}$$

and

$$P = \frac{P_{loss}^l}{P_{loss}^{base}}$$

$$VSI_{base} = \sum_{i=1}^{N_D} VSI_{base}^i \; and$$

$$VSI_{base}^i = 2V_i^2 V_{i+1}^2 - 2V_{i+1}^2 (P_{i+1} r_i + Q_{i+1} x_i)$$
$$- |z|^2 (P_{i+1}^2 + Q_{i+1}^2) \quad (6)$$

$$P_p' = P_p + (\sum N_{fastp} \times CP_{fast})$$
$$+ (\sum N_{slowp} \times CP_{slow}) \quad (7)$$

$$VSI_l = \sum_{i=1}^{N_D} VSI_l^i \; and$$

$$VSI_l^i = 2V_i'^2 V_{i+1}'^2 - 2V_{i+1}'^2 (P_{i+1}' r_i + Q_{i+1}' x_i)$$
$$- |z|^2 (P_{i+1}'^2 + Q_{i+1}'^2) \quad (8)$$

$$SAIFI_{base} = \frac{\sum_{i=1}^{N_D} \lambda_i N_i}{\sum_{i=1}^{N_D} N_i} \quad SAIDI_{base} = \frac{\sum_{i=1}^{N_D} U_i N_i}{\sum_{i=1}^{N_D} N_i}$$

$$CAIDI_{base} = \frac{\sum_{i=1}^{N_D} U_i N_i}{\sum_{i=1}^{N_D} \lambda_i N_i} \quad (9)$$

$$SAIFI_l = \frac{\sum_{i=1}^{N_D} \lambda_i' N_i}{\sum_{i=1}^{N_D} N_i} \quad SAIDI_l = \frac{\sum_{i=1}^{N_D} U_i' N_i}{\sum_{i=1}^{N_D} N_i}$$

$$CAIDI_l = \frac{\sum_{i=1}^{N_D} U_i' N_i}{\sum_{i=1}^{N_D} \lambda_i' N_i} \quad (10)$$

$$\lambda_p' = \frac{\lambda_p}{P_p} \times P_p' \quad U_p' = \frac{U_p}{P_p} \times P_p' \quad (11)$$

$$P_{loss}^{base} = \sum_{i=1}^{N_D} I_i^2 r_i \quad P_{loss}^l = \sum_{i=1}^{N_D} I_i'^2 r_i \quad (12)$$

3) ACCESSIBILITY INDEX

The charging stations must be easily accessible to the EV drivers to reduce the driving range anxiety. The placement of charging stations needs to be optimized with the routes followed by the EVs and charging point demand. If the locations of the charging stations are too far away from the charging demand points, additional charge will be wasted to travel that distance, and in the worst condition, the battery may run short of charge. Thus, in our work, the accessibility index is considered as the third objective function:

$$Accessibility \; index = f(p) = \frac{1}{|d|} \quad (13)$$

where d is the distance between the charging demand points and charging stations.

For a road network having q charging demand locations and m charging stations, the computation of the accessibility index is a tedious task. The distance matrix D and reduced distance matrix DD need to be first calculated. Distance matrix represents the distance between the charging demand locations and charging stations. The reduced distance matrix, DD, identifies the nearest charging stations for each of the charging demand locations, and gives the distance between the charging demand locations and its nearest charging station. D, DD, and d are:

$$D = \begin{bmatrix} d_1c_1 & d_1c_2 & \ldots & d_1c_m \\ d_2c_1 & d_2c_2 & \ldots & d_2c_m \\ . & . & . & . \\ . & . & . & . \\ d_qc_1 & d_qc_2 & \ldots & d_qc_m \end{bmatrix} \quad (14)$$

$$DD = \begin{bmatrix} \min(d_1c_1, d_1c_2, \ldots d_1c_m) \\ \min(d_2c_1, d_2c_2, \ldots d_2c_m) \\ . \\ . \\ . \\ \min(d_qc_1, d_qc_2, \ldots d_qc_m) \end{bmatrix} \quad (15)$$

$$d = \sum_{i=1}^{q} DD_i \quad (16)$$

C. CONSTRAINTS

The optimization is carried out with a number of equality and inequality constraints given by Eqs. (17)-(21).

$$0 < N_{fastp} \leq n_{fastp} \quad (17)$$

$$0 < N_{slowp} \leq n_{slowp} \quad (18)$$

$$Q_i^{min} \leq Q_i \leq Q_i^{max} \quad (19)$$

$$P_i^{min} \leq P_i \leq P_i^{max} \quad (20)$$

$$P_{gi} - P_{di} - V_i \sum_{j=1}^{N_D} V_j Y_{ij} \cos(\delta_i - \delta_j - \theta_{ij}) = 0$$

$$Q_{gi} - Q_{di} - V_i \sum_{j=1}^{N_D} V_j Y_{ij} \sin(\delta_i - \delta_j - \theta_{ij}) = 021) \quad (21)$$

The constraints depicted by Eqs. (17) and (18) consider the maximum and minimum number of fast and slow charging stations placed at the candidate locations. Eqs. (19) and (20) are related to the safety limit of the active and reactive power, respectively. The amount of the generated power at all the buses must satisfy the load demand and losses. Thus, the power balance equations given in Eqs. (21) and (21) are considered as the equality constraints in this charging station placement problem.

III. OVERVIEW OF MULTI-OBJECTIVE OPTIMIZATION

The result of multi-objective optimization is usually a set of solutions providing the best trade-off amongst the objectives that are conflicting in nature. The multi-objective optimization problem yields

$$Minimize/Maximize(f_1(x), f_2(x) \ldots \ldots f_k(x)) \quad (22)$$

$$\text{subject to} \quad \left. \begin{array}{l} g_j(x) \geq 0 \\ h_k(x) = 0 \\ x_l \leq x \leq x_u \end{array} \right\} \quad (23)$$

As we know that finding the best compromise solution in presence of conflicting objectives is a complex task. The best compromise solution is found by evaluating the ranks assigned to the solutions based on the non-dominance or Pareto optimality concept and the crowding distance value. In multi-objective optimization problems, a set of optimal solutions called non-dominated solution or Pareto optimal solution exist [42], [43]. The boundary defined by the Pareto optimal solutions is called Pareto front [42], [43].

A solution x_1 is said to dominate solution x_2, if the following two conditions are satisfied [44]

- The solution x_1 is no worse than x_2 in all objectives,
- The solution x_1 is strictly better than x_2 in at least one objective.

There are numerous techniques for finding the Pareto optimal solution, e.g., Kung's algorithm [44] and Ding's algorithm [44]. In this paper, the method proposed by Mishra and Harit [44] is utilized to identify the Pareto optimal solution due to its simplicity, which can be elaborated by Algorithm 1. The Pareto optimal solution obtained by the aforementioned algorithm is assigned rank one, put in the first front, and removed from the set P. The algorithm for finding the Pareto optimal solution is similar. The second Pareto front is assigned rank two. The same procedure is repeated until set P becomes an empty set [42], [43]. For obtaining a well-spread Pareto front, the concept of crowding distance is introduced [42], [43]. The crowding distance of a solution is an estimation of the density of solutions neighboring that solution. Algorithm 2 follows the solution procedure according to [42].

IV. OPTIMIZATION ALGORITHMS

Heuristics or meta-heuristics can give near-optimal solutions in less time as compared to analytical methods for dealing with complex non-linear problems. Hence, Pareto dominance based multi-CSO TLBO is employed in this paper to handle the charging station placement problem. TLBO is free from any algorithm-specific control parameters, and has a fairly good convergence property. It is expected that when the grading mechanism of CSO is combined with TLBO, the rate of utilization of the population can improve, and a faster convergence towards the optimal solution is favoured. An overview of these algorithms is given in this section.

A. MULTI-OBJECTIVE CSO

CSO mimics the behaviour of the chicken swarm and the food searching procedure of the swarm [22], [45]. The group is divided into the dominant rooster, hens, and chicks on the

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Algorithm 1 Pseudo Code for Finding Pareto Optimal Solution Put Forwarded by Deb [42]

Sort P in descending order based on $f_1(x)$ and store in set O

Initialize $S_1 = O_1$

for i=2:size(O)

Compare O(i) with S_1

if S_1 dominates O(i)

Delete O(i) from O

Algorithm 1 continued

end if

if O(i) dominates S_1

Delete the solution from S_1

end if

if O(i) is non dominated to S_1

Update $S_1 = S_1 \cup O(i)$

end if

if S_1 = null set

Add immediate solution at immediate solution to S_1

end if

end for

Print Pareto optimal solution, S_1

Algorithm 2 Pseudo Code of Crowding Distance Computation

$k = |F_n|$

While i<k do

Set $F_n[i]_{dist} = 0$

end

While m<M do

$F_n[1]_{dist} = F_n[k]_{dist} = \infty$

i=2

i=i+1

end

end

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basis of the rank of the chickens. Roosters have the highest rank, hens the intermediate, and chicks the lowest. The random assignment of the mother-child relationship in the swarm is also a salient feature of the algorithm. After every G steps, the hierarchal order and mother-child relationship is updated. The algorithm efficiently uses the biological behaviors of hens to follow their group mate rooster and chicks to follow their mother in the search of food. This algorithm also assumes that the chickens may try to steal the food found by others resulting in a competition for food in the group.

In the initialization phase, the general and algorithm-specific parameters of CSO are defined. In multi-objective CSO, the division of the population into rooster, hen, and chick is based on the rank instead of fitness value as in the single-objective CSO [45]. The rank of all the individuals of the population is obtained by the idea mentioned in Section 3, and a hierarchal order is established according to the rank of the individuals in the population. The mother hen selection is

made randomly. The algorithm assumes that the number of chicks is smaller than that of hens, and hens are the largest in the group [22]. There aresome differences in the food searching process of roosters, hens, and chicks. The update or food searching process of roosters is:

$$x_{i,j}^{t+1} = x_{i,j}^t \times (1 + \text{randn}(0, \sigma^2)) \qquad (24)$$

$$\text{If } f_i \leq f_k \, \sigma^2 = 1 \qquad (25)$$

$$\text{Else, } \sigma^2 = \exp(\frac{(f_k - f_i)}{|f_i| + \varepsilon}) \qquad (26)$$

where randn $(0,\sigma^2)$ represents a Gaussian distribution with the mean and standard deviation equal to 0 and σ^2, respectively. The variable f is the normalized fitness value of the corresponding x, k is the randomly selected rooster's index. ϵ is a small constant used to avoid division by zero. f is calculated by the weighted sum method [46].

Hens follow the path of their group roosters in food searching. Additionally, chickens may steal food found by other chickens. Their update strategy is:

$$x_{i,j}^{t+1} = x_{i,j}^t + S1 \times \text{rand} \times (x_{r1,j}^t - x_{i,j}^t)$$
$$+ S2 \times \text{rand} \times (x_{r2,j}^t - x_{i,j}^t) \qquad (27)$$

$$S1 = \exp(\frac{f_i - f_{r1}}{\text{abs}(f_i) + \varepsilon}) \qquad (28)$$

$$S2 = \exp(f_{r2} - f_i) \qquad (29)$$

where rand is a randomly generated number between in [0,1]. $r1 \in [1, N]$ is an index of the rooster, the ith hen's group mate. $r2 \in [1, N]$ is an index of the rooster or hen, a random number such that r1 $\neq$ r2.

The inherent tendency of chicks to follow their mother is expressed as:

$$x_{i,j}^{t+1} = x_{i,j}^t + FL \times (x_{m,j}^t - x_{i,j}^t) \qquad (30)$$

where $x_{m,j}^t$ represents the position of the ith chick's mother. FL is a parameter signifying that the chick would follow its mother. FL is generally chosen between 0 and 2.

The pseudo code of multi-objective CSO is given in Algorithm 3.

B. MULTI-OBJECTIVE TLBO

TLBO is a population-based evolutionary algorithm inspired from the interactive process of teaching and learning [47], [48]. In TLBO, learners constitute the population. The teacher is an erudite scholar, and he transfers his knowledge to the learners. The performance of the learners is dependent of the knowledge and teaching ability of the teacher. The algorithm is divided into two parts: Teacher phase, where the students learn from the teacher and Learner phase, where the students learn from each other by mutual interaction [47], [48].

In multi-objective TLBO, the learner having the best ranking a randomly generated population is generally assigned the role of teacher. Each learner learns from the teacher

as follows:

$$Z_{diff} = rand \times (T_k - R_t m_k) \tag{31}$$
$$Z_{new} = Z_{old} + Z_{diff} \tag{32}$$

The learner learns by mutual interaction among themselves. For each learner Z_i, any learner Z_j is arbitrarily chosen from the learner matrix. The objective function values are arbitrarily compared for the two selected learners. If the value of the objective function of Z_i is lower than the objective function of Z_j, the ith learner is modified:

$$Z_{new} = Z_{old} + rand \times (Z_i - Z_j) \tag{33}$$

Otherwise, the learner is modified as follows:

$$Z_{new} = Z_{old} + rand \times (Z_j - Z_i) \tag{34}$$

Algorithm 3 Pseudo Code of Multi-Objective CSO
___
Initialize the population of chicken having size PN and define other algorithm specific parameters like G, size of RN, HN,CN, and MN;
Evaluate the rank of all chickens, t=0, establish the hierarchal order in the swarm based on rank as well as mother child relationship;
While (t<gen)
t=t+1;
If(t% G==0)
Establish the hierarchal order in the swarm as well as mother child relationship;
Else
For i=1:PN
If i==rooster
Update its solution by Eq.(24);
End if
If i==hen
End if
If i==chick
Update its solution by Eq.(30);
End if
Selection based on rank and crowding distance;
End for
End if else

The pseudo code of multi-objective TLBO is given in Algorithm 4.

C. MULTI-OBJECTIVE CSO TLBO

A multi-objective version of the hybrid CSO-TLBO presented by Deb *et al.* [49] is developed in this paper. The mechanism of grading prevalent in CSO, when combined with TLBO, can improve the utilization rate of the population and lead to a faster convergence towards the optimal solution. The hybridization of CSO and TLBO is expected to reduce the probability of premature convergence of CSO for computationally expensive problems. In the hybridization scheme, TLBO is performed for all the generation, and CSO is invoked

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Algorithm 4 Pseudo Code of Multi-Objective TLBO
___
Set k=1;
Initialize the population size(PN) and generate the initial population of students randomly;
Compute the rank for all the individuals of the population;
while(k<gen)
Teacher Phase
Assign the teacher based on the rank;
for i=1:PN
Modify each learner by Eq.(31), Eq.(32);
Update the new solutions based on rank and crowding distance;
End of teacher phase
Learner Phase
Choose two learners Z_i and Z_j, i≠j;
if(fitness of Z_i better than Z_j)
Replace i^{th} learner by Eq.(33);
Else
Replace i^{th} learner by Eq.(34);
End if else
End for
Update based on rank and crowding distance
k=k+1
End while

---

periodically depending on the value of *INV*. It must be noted that *INV* is a user defined algorithm-specific parameter of CSO TLBO that must be tuned properly. The frequency of introduction of CSO directly depends on *INV*. The flowchart and pseudo code of multi-objective CSO TLBO are provided in Algorithm 5.

Algorithm 5 Pseudo Code of Pareto Dominance Based Multi-Objective CSO TLBO
___
Initialize the population size, gen and the other algorithm specific parameters of CSO TLBO
Set t=1
While (t<gen)
Activate TLBO
If (t mod INV)>0
Activate CSO
End if
t=t+1
Selection based on rank and crowding distance
End while

V. FUZZY DECISION MAKING

Selecting the best compromise solution from the set of Pareto optimal solution is always tricky and difficult. The final decision making is performed by the fuzzy evaluation system [50]–[52]. In the fuzzy evaluation framework, each objective function is represented by a scaled membership function in the range of 1-10 given by Eq. (35). The range

of objective function associated with all the membership functions or scores can be found by the back calculation in Eq. (35).

$$\mu_i = \begin{cases} 10 & OF_i \leq OF_i^{\min} \\ 10 \times \dfrac{OF_i^{\max} - OF_i}{OF_i^{\max} - OF_i^{\min}} & OF_i^{\min} \leq OF_i \leq OF_i^{\max} \\ 1 & OF_i^{\max} \leq OF_i \end{cases}$$

(35)

In a word, the net score for all the Pareto optimal solutions are evaluated, and the Pareto optimal solution having the highest score is preferred.

VI. SOLUTION METHODOLOGY OF CHARGING STATION PLACEMENT PROBLEM

In this paper, multi-objective CSO TLBO is employed to handle the charging station placement problem elaborated in Section 2. The systematic step-by-step procedure is as follows [50]:

Step 1: Initialization

Step 1.1: Initialize algorithm settings. Set the road network, distribution network data, upper and lower limits of different constraints, and set the different control parameters of CSO TLBO, such as *gen*, *PN*, *RN*, *CN*, *HN*, *G*, and *INV*.

Step 1.2: Generate feasible initial population randomly.

The initial feasible population is of the form $pop_{intl} = [A_{pop} B_{pop} C_{pop}]$ where

$$A_{pop} = \begin{bmatrix} p_{11} & p_{12} & p_{13} & \cdots & p_{1m} \\ p_{21} & p_{22} & p_{23} & \cdots & p_{2m} \\ p_{31} & p_{32} & p_{33} & \cdots & p_{3m} \\ . & . & . & \cdots & . \\ p_{N1} & p_{N2} & p_{N3} & \cdots & p_{Nm} \end{bmatrix}$$

$$B_{pop} = \begin{bmatrix} N_{fastp_{11}} & N_{fastp_{12}} & N_{fastp_{13}} & \cdots & N_{fastp_{1m}} \\ N_{fastp_{21}} & N_{fastp_{22}} & N_{fastp_{23}} & \cdots & N_{fastp_{2m}} \\ N_{fastp_{31}} & N_{fastp_{32}} & N_{fastp_{33}} & \cdots & N_{fastp_{3m}} \\ . & . & . & \cdots & . \\ N_{fastp_{PN1}} & N_{fastp_{PN2}} & N_{fastp_{PN3}} & \cdots & N_{fastp_{PNm}} \end{bmatrix}$$

$$C_{pop} = \begin{bmatrix} N_{slowp_{11}} & N_{slowp_{12}} & N_{slowp_{13}} & \cdots & N_{slowp_{1m}} \\ N_{slowp_{21}} & N_{slowp_{22}} & N_{slowp_{23}} & \cdots & N_{slowp_{2m}} \\ N_{slowp_{31}} & N_{slowp_{32}} & N_{slowp_{33}} & \cdots & N_{slowp_{3m}} \\ . & . & . & \cdots & . \\ N_{slowp_{PN1}} & N_{slowp_{PN2}} & N_{slowp_{PN3}} & \cdots & N_{slowp_{PNm}} \end{bmatrix}$$

A randomly generated initial solution is feasible, if it satisfies all the constraints explained in Section 2.3.

Step 1.3: Evaluate the three objective functions cost, VRP index and accessibility index for the initial population. Compute the rank and crowding distance by the methodology elaborated in Section 3. The first Pareto front with rank one is designated as T_k.

Step 2: Run TLBO.

Step 2.1: Run TLBO, and update the solution based on rank and crowding distance.

TABLE 3. Algorithm-specific parameters of CSO TLBO.

Parameter	Value
RN	$0.3 \times PN$
HN	$0.4 \times PN$
CN	PN-RN-HN
INV	3
G	3

Step 2.2: If the elements B_{pop} exceed n_{fastp}, element is made equal to n_{fastp}. If the elements of C_{pop} exceed n_{slowp}, element is made equal to n_{slowp}.

Step 2.3: Check feasibility of the solution. If the solution is infeasible, repeat Steps 2.1 and 2.2 until a feasible solution is obtained.

Step 3: Check whether the iteration count t is divisible by *INV*. If yes, go to Step 3.1. Otherwise, go to Step 3.5.

Step 3.1: If t is divisible by *INV*, run CSO.

Step 3.2: Run CSO, and update the solution based on ranking and crowding distance.

Step 3.3: If the elements B_{pop} exceed n_{fastp}, element is made equal to n_{fastp}. If the elements of C_{pop} exceed n_{slowp}, element is made equal to n_{slowp}.

Step 3.4: Check feasibility of the solution. If the solution is infeasible, repeat Steps 3.2 and 3.3until a feasible solution is obtained.

Step 3.5: Update the iteration count.

Step 4: Check whether the maximum generation count is reached. If the maximum generation count is reached, obtain the Pareto front. Otherwise, repeat Step 2 to Step 4.

Step 5: Selection of the best compromise solution from the set of non dominated solution is made by using the fuzzy decision making explained in Section 5.

VII. PERFORMANCE OF PARETO DOMINANCE BASED CSO TLBO ON MULTI-OBJECTIVE BENCHMARK PROBLEMS

The proposed Pareto dominance based CSO TLBO algorithm was first tested on some basic multi-objective benchmark functions. The algorithm-specific parameters of CSO TLBO were tuned as in Table 3. Moreover, the performance of the proposed algorithm in attacking the benchmark problems was compared with NSGA II and other hybrid algorithms like multi-objective DE PSO, multi-objective cultural PSO, and its variants. The aforesaid algorithms were statistically compared by on the basis of the hypervolume, which is a metric proposed by Zitzler [53] used to analyze the distribution of Pareto optimal solutions. Hypervolume physically signifies the volume occupied by the non dominated solution set. It is concluded in [54] that maximizing hypervolume is equivalent to producing a well distributed Pareto front.

A. COMPARISON OF PARETO DOMINANCE BASED CSO TLBO WITH DE PSO AND NSGA II

The performance of Pareto dominance based CSO TLBO algorithm was compared with that of DE PSO and NSGA II

TABLE 4. Comparison of CSO TLBO with DE PSO and NSGA II based on normalized hypervolume.

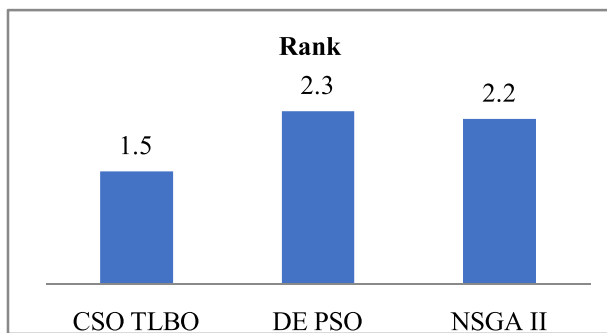| Benchmark function	Algorithm		
	CSO TLBO	DE PSO	NSGAII
ZDT4	0.6728 ± 0.00305	0 ± 0	0.6636 ± 0.0042
ZDT6	0.4035 ± 0.00235	0.4033 ± 0.0027	0.4025 ± 0.00243
DTLZ1	0.7937 ± 0.00312	0.7749 ± 0.00358	0.7852 ± 0.00322
DTLZ3	0 ± 0	0 ± 0	0.4084 ± 0.0012
DTZL6	0.0962 ± 0.0012	0.0959 ± 0.00167	0.0957 ± 0.0015

FIGURE 2. Comparison of Friedman ranks of CSO TLBO with DE PSO and NSGA II for ZDT and DTLZ benchmark functions.

on two objective ZDT [55] and three objective DTLZ [56] benchmark problems. The three algorithms were statistically compared by computing hypervolume for a total of 50 independent trials. The results of DE PSO and NSGA II were directly taken from [57]. For a fair comparison, the population size (*PN*) and generation (*gen*) of CSO TLBO were kept the same as in [57]. Each benchmark problem was examined by CSO TLBO with the values of *PN* and *gen* as 200 and 750, respectively. The test problems were compared based on the normalized hypevolume (Table 4). It was observed that CSO TLBO performed better than DE PSO and NSGA II on ZDT4, DTLZ1, and DTLZ6. The performance of CSO TLBO was equivalent to that of DE PSO on DTLZ3. For a further analysis, Friedman rank test was performed (see results in Fig.2). The CSO TLBO achieved the best rank in comparison to the other optimization algorithms.

B. COMPARISON OF PARETO DOMINANCE BASED CSO TLBO WITH CULTURAL PSO AND ITS VARIANTS

The performance of Pareto dominance based CSO TLBO algorithm was compared with that of cultural PSO and its variants on two objective ZDT [57] and three objective DTLZ [56] benchmark problems. The algorithms were statistically compared by computing the hypervolume for 30 independent trials. The results of PSO and its variants were

TABLE 5. Comparison of CSO TLBO with PSO and its variants based on hypervolume.

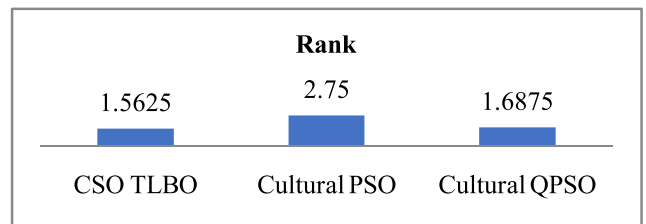| Benchmark function	Algorithm		
	CSO TLBO	Cultural PSO	Cultural QPSO
ZDT1	0.894 ± 0.0034	0.842 ± 0.3665	0.866 ± 0.00365
ZDT2	0.484 ± 0.0023	0.420 ± 0.00246	0.472 ± 0.00245
ZDT3	0.967 ± 0.00132	0.761 ± 0.00165	0.939 ± 0.00154
ZDT4	0.6256 ± 0.0016	0 ± 0	0.867 ± 0.00101
ZDT6	0.5123 ± 0.004	0.465 ± 0.0051	0.503 ± 0.0012
DTLZ1	0.6532 ± 0.0032	0 ± 0	0 ± 0
DTLZ3	0 ± 0	0 ± 0	0.715 ± 0.00405
DTZL6	0 ± 0	0.236 ± 0.00345	0.421 ± 0.00212

FIGURE 3. Comparison of Friedman ranks of CSO TLBO with cultural PSO and its variants for ZDT and DTLZ benchmark functions.
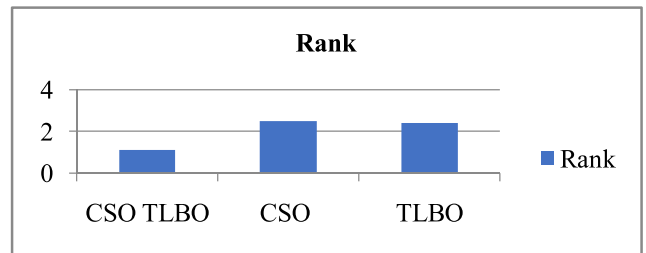

FIGURE 4. Comparison of Friedman ranks of CSO TLBO with CSO and TLBO for ZDT and DTLZ benchmark functions.

directly taken from [58]. For a fair comparison, the population size (*PN*) and generation (*gen*) of CSO TLBO were kept the same as in [58]. Each benchmark problem was attacked by CSO TLBO with the value of *PN* and number of function evaluation as 100 and 30,000, respectively. The optimization results were compared on the normalized hypervolume (Table 5). CSO TLBO performed better than cultural PSO and cultural QPSO on ZDT1, ZDT2, ZDT3, ZDT6, and DTLZ1. The ranks of the different algorithms obtained by Friedman test aregiven in Fig.3, in which the CSO TLBO obtained the best rank.
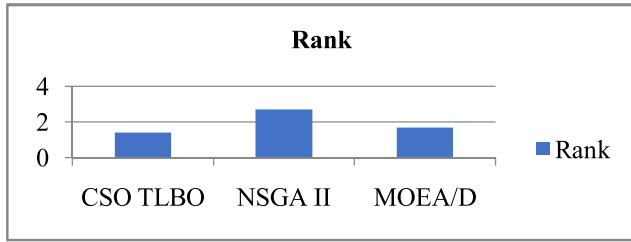
FIGURE 5. Comparison of Friedman ranks of CSO TLBO with NSGA II and MOEA/D for CEC 2009 benchmark functions.

FIGURE 6. Test network [38].

C. COMPARISON OF PARETO DOMINANCE BASED CSO TLBO WITH CSO AND TLBO

The performance of Pareto dominance based CSO TLBO was compared with that of CSO as well as TLBO on two objective ZDT [55] and three objective DTLZ [56] benchmark problems. The algorithms were statistically compared by computing the hypervolume for 30 independent trials. Each benchmark problem was examined by CSO TLBO with the values of *PN* and *gen* as 200 and 750, respectively. The test problems were compared based on the normalized hypevolume (Table 6). From Table 5, it is observed that the proposed algorithm performed better than the standalone CSO and TLBO algorithm on all the benchmark functions. The ranks of the different algorithms obtained by Friedman test are given in Fig.5, in which the CSO TLBO yielded the best rank among all the methods involved.

VIII. PERFORMANCE OF PARETO DOMINANCE BASED CSO TLBO ON CEC 2009 BENCHMARK FUNCTIONS

The proposed Pareto dominance based CSO TLBO algorithm was further tested on CEC 2009 benchmark functions. The algorithm-specific parameters of CSO TLBO were tuned as in Table 3. Moreover, the performance of the proposed algorithm in attacking the benchmark problems was compared with that of NSGA II and MOEA/D. The aforesaid algorithms were statistically compared on the basis of the hypervolume. The performances of NSGA II and MOEA/D on CEC 2009 benchmark functions were taken from [49]. The general control parameters of CSO TLBO were set the same as [61]. Table 7 reports the performance comparison of the proposed algorithm with NSGA II and MOEA/D on CEC 2009 benchmark functions. It is observed that our method performed better than NSGA II and MOEA/D on all the benchmark functions except F8 and F9. In addition, the Friedman ranks of the three algorithms are shown in Fig. 5. It is observed that the Pareto dominance based CSO TLBO yielded the best rank.

IX. PERFORMANCE OF PARETO DOMINANCE BASED CSO TLBO ON CHARGING STATION PLACEMENT PROBLEM

A. TEST SYSTEM AND INPUT PARAMETERS

The EV charging station placement problem was validated on the test network formed by superimposition of IEEE 33 bus distribution network and 25 node road network as shown
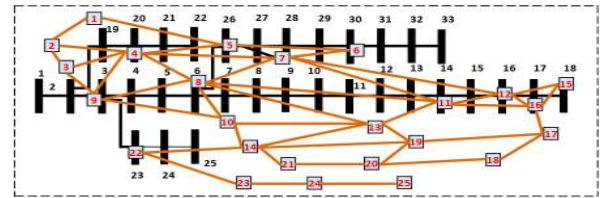
TABLE 6. Comparison of CSO TLBO with CSO and TLBO based on hypervolume.

Benchmark function	Algorithm		
	CSO TLBO	CSO	TLBO
ZDT4	0.6728± 0.00305	0.4356± 0.00408	0.5678± 0.0056
ZDT6	0.4035± 0.00235	0.3133± 0.0032	0.2092± 0.0034
DTLZ1	0.7937± 0.00312	0.5749± 0.00387	0.7852± 0.0041
DTLZ3	0±0	0±0	0.1123± 0.0012
DTZL6	0.0962± 0.0012	0.0345± 0.0024	0.0534± 0.0035

TABLE 7. Comparison of CSO TLBO with CSO and TLBO based on hypervolume.

Benchmark function	Algorithm		
	CSO TLBO	NSGA II	MOEA/D
F1	3.3355± 0.0016	3.2934± 0.0014	3.3276± 0.0018
F2	3.1567± 0.0027	2.1773± 0.0025	3.0233± 0.0026
F3	2.9937± 0.00121	2.9247± 0.00132	2.9318± 0.0014
F4	4.0003± 0.0345	3.3103± 0.037	3.8813± 0.033
F6	13.654± 0.0045	8.8261± 0.00465	13.597± 0.0044
F7	5.8976± 0.0018	3.5387± 0.0024	4.6764± 0.0026
F8	2.3312± 0.003	3.8939± 0.0043	4.2083± 0.0048
F9	3.0543± 0.0015	3.6627± 0.0023	3.9585± 0.0033

in Fig.6. The line, branch, and outage data of IEEE 33 bus test network were taken from [2]. The road network data was from [9]. The EVs were assumed to follow the two following routes:Route 1- (1-2-3-4-5-6-7-8-9-10-13-11-12-15-16-17-18-20-21-14-22-23-24-25) and Route 2-(1-2-3-4-5-6-7-8-9-10-13-11-12-15-16-17-19-20-21-14-22-23-24-25)

Table 8 presents the superimposed nodes with respect to distribution as well as road network and the points of charging demand. The points of charging demand were computed
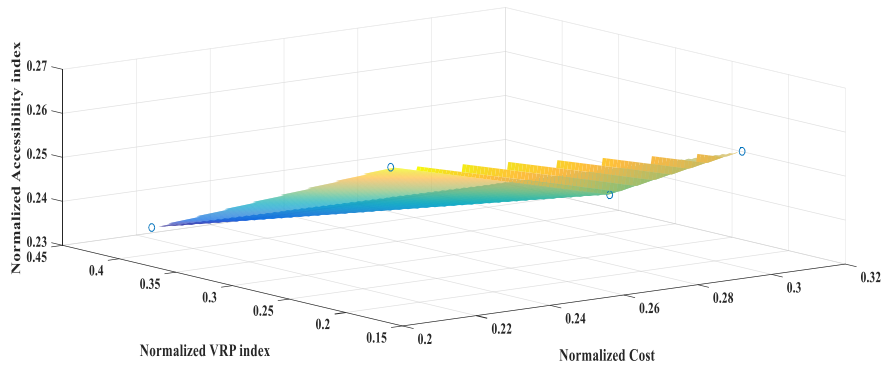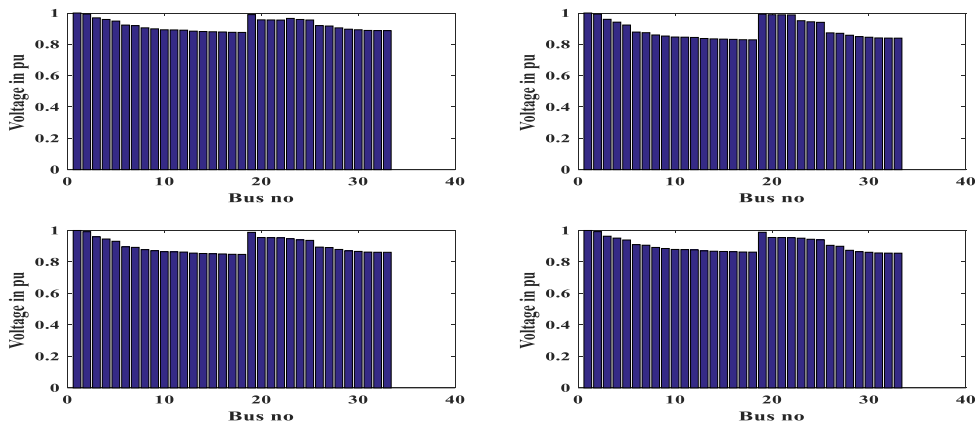
FIGURE 7. Pareto front obtained by CSO TLBO.

FIGURE 8. Voltage Profile for the Pareto optimal solutions obtained by CSO TLBO.

TABLE 8. Superimposed and charging demand nodes.

Bus Of Distribution Network	3	28	14	16	17	23	6	30	26	20
Node of Road Network	9	7	11	12	16	22	8	6	5	4
Charging demand nodes	4	7	9	13	15	18	22	25	---	---

based on the consideration that the driving range of EV was 150 km [52], [53], and it followed either Route 1 or Route 2. The values of the input parameters were selected as in Table 9. In the simulations, it was assumed that each fast charging station had 10 servers or charger units, and each slow charging station had 20 servers or charger units.. The algorithm-specific parameters of CSO TLBO were tuned as in Table 3.

B. OPTIMAL ALLOCATION OF CHARGING STATIONS

The optimization problem explained in Section 2 was explored using CSO TLBO. Table 10 shows the best Pareto optimal solutions obtained by CSO TLBO. The algorithm

yielded four Pareto optimal solutions or planning schemes. In Scheme 1, the positions of charging stations were selected as bus number 3, 23, and 26. The number of fast charging stations placed at bus 3, 23, and 26 were 1, 2, and 1, respectively. 3, 3, and 2 number of slow charging stations were placed at bus number 3, 23, and 26, respectively. In planning Scheme 2, the positions of charging stations were selected at bus number 23, 6, and 26. The number of fast charging stations placed at bus number 23, 6, and 26 were all 1. 3, 3, and 2 number of slow charging stations were placed at bus 23, 6, and 26, respectively. In planning Scheme 3, the positions of charging stations were 20, 6, and 23. The number of fast charging stations placed at bus number 20, 6, and 23 were all 2. The number of slow charging stations placed at bus number 20, 6, and 26 were all 3. In planning Scheme 4, the positions of charging stations were bus number 20, 23, and 28. The number of fast charging stations placed at bus number 20, 23, and 28 were all 2. The number of slow charging stations placed at bus number 20, 23, and 28 were 3, 3, and 1, respectively.

Figure 7 elaborates the Pareto front obtained by CSO TLBO. Table 11 represents the values of the three objective functions for the four planning schemes mentioned in Table 10. In Plan 1, the optimized values of cost,
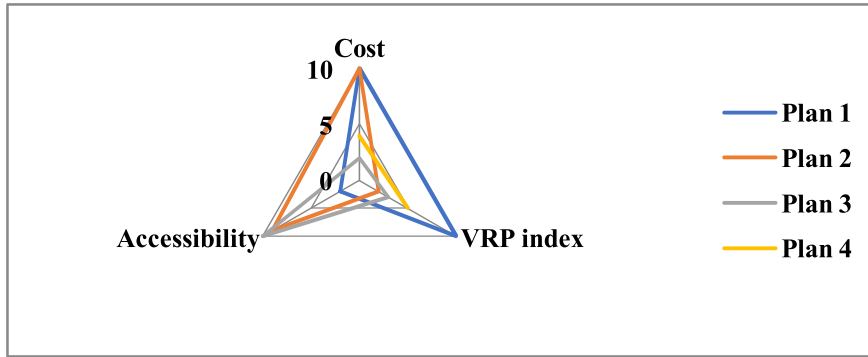
FIGURE 9. Radar charts of the four plans.

TABLE 9. Input parameters.

Parameter	m	C_{fast}	C_{slow}	CP_{fast}	CP_{slow}	$P_{electriciy}$	n_{fastp}	n_{slowp}
Value	3	3000 \$	2500 \$	50 kW	19.2 kW	65 \$/MWhr	2	3

VRP index, and accessibility index were 1.5389×10^7\$, 12.5010, and 0.0006, respectively. In Plan 2, the optimized values of cost, VRP index, and accessibility index were 1.4783×10^7\$, 14.0792, and 0.0013, respectively. The values of cost and accessibility index of plan 2 were better than that of Plan 1. However, the value of VRP index of Plan 1 was better than that of Plan 2. In Plan 3, the optimized values of cost, VRP index, and accessibility index were 2.1316×10^7\$, 13.7128, and 0.0014, respectively. The value of cost for Plan 3 was worse than that of Plan 1 and Plan 2. However, the value of accessibility index of Plan 3 was better than that of Plan 1and Plan 2. In Plan 4, the optimized values of cost, VRP index, and accessibility index were 2.1316×10^7\$, 13.7128, and 0.0014, respectively. The cost associated with Plan 4 was better than Plan 3 but much worse than Plan 1 and Plan 2. The value of VRP index for Plan 4 was better than Plan 2 and Plan 3 but worse than Plan 1. The value of accessibility index for Plan 4 was equal to Plan 2 and better than Plan 1 but worse than Plan 3. Figure8 illustrates the voltage profile of the buses for all the four plans in Table 10. The voltage profile of the buses after placement of charging stations (charging stations were placed at the locations obtained by pareto optimal solutions listed in Table 10 by using CSO TLBO) degraded as shown in Fig. 8. From Fig.8, it is clear that the voltage profile of Plan 1 is better than the other three plans.

C. FINAL DECISION MAKING

The four simulated plans obtained by CSO TLBO are shown in Table 10. The characteristics of those four plans are discussed in the previous sub-section. However, it is difficult to select the best plan among these four plans because of conflicting objective functions. In practice, some criteria cannot be measured by crisp values, due to the ambiguity arising from human qualitative judgement [61]. For the

TABLE 10. Best Pareto optimal solution obtained by CSO TLBO.

Solution	p (wrt to distribution network)	N_{fastp}	N_{slowp}
1	3	1	3
	20	2	3
	26	1	2
2	23	1	3
	6	1	3
	26	1	2
3	20	2	3
	6	2	3
	23	2	3
4	20	2	3
	23	2	3
	28	2	1

quantification of such cases, fuzzy reasoning can be used. In the present work, a fuzzy evaluation system was applied for the final decision making [55]. The cost, VRP index, and accessibility indices were chosen as the three aspects for final decision making. In the fuzzy decision making, low cost, low VRP index and high accessibility were preferred features and hence received a higher evaluation. Table 12 gives the scale of the three objective functions based on the aforementioned fuzzy criteria. The scores of each plan obtained by the fuzzy evaluation system are provided in Table 13. The radar charts of all the four plans are shown in Fig. 9. Table 14 reports the area occupied by the radar charts of the four plans shown in Fig. 9. The area occupied by the radar chart is computed by Heron's formula. The four plans had their respective
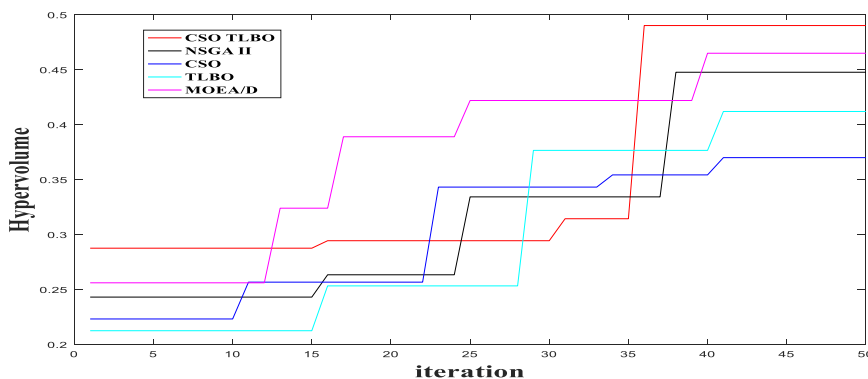
FIGURE 10. Convergence graph of CSO TLBO and NSGA II.

TABLE 11. -Objective function values for different planning schemes (obtained by CSO TLBO).

Planning scheme no	Cost ($\times 10^7$)	VRP index	Accessibility index(/km)
1	1.5389	12.5010	0.0006
2	1.4783	14.0792	0.0013
3	2.1316	13.7128	0.0014
4	1.8959	13.3707	0.0013

TABLE 12. -Scale of the fuzzy evaluation.

Scale	Cost($\times 10^7$)	VRP index	Accessibility index($m^{-1} \times 100$)
1	More than 2.1316	More than 14.0792	Less than 0.06
2	2-2.1316	13.7636-14.0792	7.6×10^{-1}-0.06
3	1.93561-2	13.6057-13.7636	7.6×10^{-1}-8.4×10^{-1}
4	1.8703-1.93561	13.4479-13.6057	8.4×10^{-1}-9.2×10^{-1}
5	1.8050-1.8703	13.2901-13.4479	9.2×10^{-1}-0.01
6	1.7396-1.8050	13.1323-13.2901	0.01-0.108
7	1.6743-1.7396	12.9745-13.1323	0.108-0.116
8	1.6090-1.6743	12.8166-12.9745	0.116-0.124
9	1.5436-1.6090	12.6588-12.8166	0.124-0.13
10	Less than 1.5436	Less than 12.6588	More than 0.13

TABLE 13. Scores of each plan.

Plan	Cost	VRP index	Accessibility index
1	10	10	2
2	10	2	9
3	2	3	10
4	4	5	9

TABLE 14. Scores of each plan.

Plan	Area
1	12.5041
2	11.5853
3	6.9825
4	8.3715

advantages and disadvantages. The area occupied by Plan 1 is the biggest as compared to the other three plans indicating that Plan 1 is the most advantageous plan.

D. COMPARISON OF THE PERFORMANCE OF CSO TLBO WITH OTHER STATE OF ART ALGORITHMS

For examining the proposed Pareto dominance based CSO TLBO algorithm, its performance was further compared with that of NSGA II algorithm. In order to compare the quality of

the solutions of multi-objective CSO TLBO and NSGA II, a statistical analysis was made for 50 independent trials. These two algorithms were statistically compared by computing hypervolume, diversity index, and number of Pareto solutions of the results obtained by the aforesaid algorithms for 50 independent trials. Table 15 gives the results of statistical comparison of CSO TLBO with NSGA II algorithm, which clearly shows that the hypervolume of CSO TLBO was more than that of NSGA II. Thus, the spread and closeness

TABLE 15. Statistical comparison of CSO TLBO with NSGA II algorithm.

Algorithm	Hypervolume		Diversity index		Number of Pareto solutions	
	Best	Worst	Best	Worst	Best	Worst
CSO TLBO	0.4902	0.4016	0.06182	0.06029	4	3
NSGA II	0.4477	0.3917	0.0063	0.0057	4	3
CSO	0.37	0.298	0.0034	0.0029	4	3
TLBO	0.412	0.3167	0.0056	0.0039	4	3
MOEA/D	0.465	0.321	0.0062	0.0031	4	3

TABLE 16. Average run time comparison of CSO TLBO with NSGA II algorithm.

Algorithm	Average Run time (sec)
CSO TLBO	1800
NSGA II	1680
MOEA/D	1600

of the Pareto front obtained by CSO TLBO were better than that of NSGA II. The diversity index is regarded as a measure of diversity existing between the non- dominated solutions obtained by the algorithms [54]. A large value of the diversity index indicates the algorithm yields Pareto optimal solutions that are diverse in nature. The best and the worst diversity index of CSO TLBO were more than that of NSGA II (Table 15). Thus, we can conclude that the solutions obtained by CSO TLBO are more diverse in nature. Furthermore, the convergence graph of CSO TLBO, CSO, TLBO, and NSGA II is shown in Fig. 10.

The number of Pareto solutions is another metric used to compare the performances of multi-objective evolutionary algorithms. The algorithm that yields more number of Pareto solutions is more preferable, as it gives the decision maker more alternatives [52]. The number of Pareto solutions obtained by CSO TLBO and NSGA II were the same (Table 15). Therefore, the both algorithms give the decision maker the equal number of alternative planning schemes. The time complexity analysis of the proposed algorithm was also performed. The time complexity or computational time of the proposed algorithm was also compared. Table 16 reports the average run time of CSO TLBO and NSGA II in handling the charging station placement problem. The average run time of CSO TLBO was more than NSGA II. In CSO TLBO, both CSO and TLBO were executed in some generations. As a consequence, the average run time of CSO TLBO was more than that of NSGA II.

X. CONCLUSION

The construction of charging station is indeed very important to promote EVs. The placement of charging stations must consider cost, distribution network characteristics, and accessibility of the charging stations simultaneously. In our paper, the charging station placement problem was represented in a multi-objective framework with cost, VRP index,

and accessibility index as the objective functions. The scientific contribution of this work lies in not only proposing a multi-objective framework to solve the charging station placement problem but also developing a Pareto dominance based multi-objective CSO TLBO for the charging station placement problem and fuzzy selection of Pareto optimal solutions. Thus, we have explored an integrated planning scheme for charging stations by using multi-objective optimization, fuzzy decision making, and radar charting. The hybrid algorithm is found to be superior in handling the charging station placement problem as well as standard benchmark problems. Our future work aims at the performance comparison of this new algorithm in dealing with other optimal placement problems.

NOMENCLATURE

Abbreviations

EV	Electric Vehicles
ICE	Internal Combustion Engine
MPDIPA	Modified Primal-Dual-Interior Point Algorithm
CE	Cross Entropy
DEA	Data Envelopment Analysis
MOEA	Multi-Objective Evolutionary Algorithm
SAIFI	System Average Interruption Frequency index
SAIDI	System Average Interruption Duration Index
CAIDI	Customer Average Interruption Duration Index
VSI	Voltage Stability Index
CSO	Chicken Swarm Optimization
TLBO	Teaching Learning Based Optimization
BFA	Binary Firefly Algorithm
GA	Genetic Algorithm
PSO	Particle Swarm Optimization
SPEA	Strengthened Pareto Evolutionary Algorithm
NSGA	Non Dominated Sorting Genetic Algorithm
DE	Differential Evolution
ZDT	Zitzler Deb Thiele function
DTLZ	Deb Thiele Laumann Zitzler function

Decision   Variables

p	Position of charging stations in the network
N_{fastp}	Number of fast charging stations placed at p
N_{slowp}	Number of slow charging stations placed at p

Sets and Matrices

TS	Set of superimposed nodes
P	Set of solutions in case of multi-objective optimization
O_1	First solution of set O
D	Distance Matrix
DD	Reduced Distance matrix
pop_{intl}	Initial Population matrix
A_{pop}	Population sub-matrix containing initial population of the candidate locations of charging stations
B_{pop}	Population sub-matrix containing initial population of the number of fast charging stations placed at the candidate locations
C_{pop}	Population sub-matrix containing initial population of the number of slow charging stations placed at the candidate locations

Constant Parameters

C_{fast}	Installation cost of fast charging station
C_{slow}	Installation cost of slow charging station
CP_{fast}	Capacity of fast charging station
CP_{slow}	Capacity of slow charging station
$P_{electricity}$	Cost of electricity
m	Maximum number of locations in which charging station will be placed
q	Total number of charging demand points
w_1	Weight assigned to V
w_2	Weight assigned to R
w_{21}	Weight assigned to SAIFI
w_{22}	Weight assigned to SAIDI
w_{23}	Weight assigned to CAIDI
w_3	Weight assigned to Power loss
VSI_{base}	Base value of Voltage Stability Index
$SAIFI_{base}$	Base value of SAIFI
$SAIDI_{base}$	Base value of SAIDI
$CAIDI_{base}$	Base value of CAIDI
P_{loss}^{base}	Base value of power loss
N_D	Total number of buses of the distribution network
n_{fastp}	Maximum number of fast charging stations placed at bus p
n_{slowp}	Maximum number of slow charging stations placed at bus p
Q_i^{min}	Lower limit of reactive power of bus i
Q_i^{max}	Upper limit of reactive power of bus i
P_i^{min}	Lower limit of active power of bus i
P_i^{max}	Upper limit of active power of bus i

Variables

VSI_{base}^i	Base value of VSI of the ith bus
VSI_l^i	VSI of the ith bus after the placement of the charging stations
VSI_l	VSI after after the placement of EV charging stations
P_{loss}^{l-}	Power loss after the placement of EV charging stations
$SAIFI_l$-	SAIFI after the placement of charging stations in the distribution network
$SAIDI_l$	SAIDI after the placement of charging stations in the distribution network
$CAIDI_l$	CAIDI after the placement of charging stations in the distribution network
V_i-	Voltage of ith bus for base case
V_{i+1}-	Voltage of $(i+1)^{th}$ bus for base case
V_i'	Voltage of ith bus after the placement of charging station
V_{i+1}'	Voltage of $(i+1)^{th}$ bus after the placement of charging station
P_i	Active power at the ith bus
P_{i+1}	Active power at $(i+1)^{th}$ bus
P_i'	Active power at i^{th} bus after the placement of charging stations
P_{i+1}'	Active power at $(i+1)^{th}$ bus after the placement of charging stations
Q_i	Reactive power at the ith bus
Q_{i+1}	Reactive power at $(i+1)^{th}$ bus
Q_i'	Reactive power at i^{th} bus after the placement of charging stations
Q_{i+1}'	Reactive power at $(i+1)^{th}$ bus after the placement of charging stations
P_p	Active power at bus p
P_p'	Active power at bus p after the placement of charging station
r_i	Resistance of the branch between bus i and $i+1$
x_i	Reactance of the branch between bus i and $i+1$
Z	Impedance of the branch between bus i and $i+1$
λ_i	Failure rate of ith bus
N_i	Number of consumers connected at i^{th} bus
U_i	Outage duration of ith bus
λ_i'	Failure rate of ith bus after the placement of charging station
U_i'	Outage duration of ith bus after the placement of the charging station
λ_p	Failure rate of bus p
λ_p'	Failure rate of bus p after the placement of charging station
U_p	Outage duration of bus p
U_p'	Outage duration of bus p after the placement of charging station
I_i	Current through branch i

I_i'	Current through branch i after the placement of charging station
dic_j	Distance between i^{th} charging demand point and j^{th} charging station where i=1,2,…q and j=1,2,…m
P_{gi}	Active power generation of ith bus
P_{di}	Active power demand of ith bus
Q_{gi}-	Reactive power generation of ith bus
Q_{di}-	Reactive power demand of ith bus
V_j	Voltage of jth bus
Y_{ij}	Magnitude of $(i,j)^{th}$ term of bus admittance matrix
θ_{ij}	Angle of Y_{ij}
δ_i	Voltage angle of ith bus
δ_j	Voltage angle of jth bus
x_l	Lower limit of decision variable
x_u	Upper limit of decision variable
μ_i	Fuzzy membership function
OF_i	i^{th} objective function
OF_i^{min}	Minimum value of ith objective function
OF_i^{max}	Maximum value of ith objective function
$F_n[i]_m$	m^{th} objective function value of ith solution in the front F_n
f_m^{max} and f_m^{min}	Maximum and minimum value of mth objective function in the same front
M	Number of objective function

CSO and TLBO parameters

PN	Total population
RN	Set of roosters
HN	Set of hens
CN	Population of chicks
MN	Set of mother hens
T_k	Teacher
m_k	mean value of decision variable
R_t	Random number between 0 and 2
gen	Maximum generation
INV	positive constant to introduce the frequency of CSO
t	Current iteration count

Functions

$C_{installation}$	Installation cost
$C_{operation}$	Operation cost
VRP	Voltage Stability, Reliability, and Power loss

COMPLIANCE WITH ETHICAL STANDARDS
CONFLICT OF INTEREST
We have no conflict of interest with this research article.

HUMAN AND ANIMAL RIGHTS
We use no animal in this research.

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