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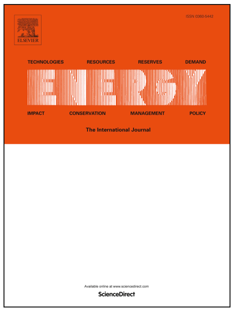

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A Novel Chicken Swarm and Teaching Learning based Algorithm for Electric Vehicle Charging Station Placement Problem

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Abstract-The current concern about the ever-escalating demand for energy, exhaustive nature of fossil fuels, global warming accompanied by climate change has necessitated the development of an alternate pollution-free mode of commute. Electric Vehicles (EV) are an environmentally friendly alternative to reduce the reliance on fossil fuel and pollution. For public acceptance of EVs, functionality and accessibility of charging stations is of paramount importance. Improper planning of EV charging stations, however, is a threat to the power grid stability. EV charging stations must be placed in the transport network in such a way that the safe limit of distribution network parameters is not violated. Thus, charging station placement problem is an intricate problem involving convolution of transport and distribution networks. A novel and simple approach of formulating the charging station placement problem is presented in this work. This approach takes into account integrated cost of charging station placement as well as penalties for violating grid constraints. For obtaining an optimal solution of this placement problem, two efficient evolutionary algorithms, such as Chicken Swarm Optimization (CSO) and Teaching Learning Based Optimization algorithm (TLBO) are amalgamated together thereby extracting the best features of the both algorithms. The efficacy of the proposed algorithm is tested by solving selected standard benchmark problems as well as charging station placement problem. The result of this hybrid algorithm is further compared with other algorithms used for this purpose.

Keywords-Charging station, Distribution network, Transport network, Optimization, Cost, CSO, TLBO, Hybrid algorithm

Nomenclature

Decision variables

b- Bus number where charging station is to be placed

N_{Fb}- Number of fast charging station at bus *b*

N_{Sb}- Number of slow charging station at bus *b*

Sets

T- Set of nodes of the road network with charging demand

TS- Set of superimposed nodes

P- Set of nodes where charging stations are placed

S- Set of strong nodes of the distribution network based on voltage stability

Constant Parameters

$C_{installation\ fast}$- Installation cost of fast charging stations

$C_{installation\ slow}$- Installation cost of fast charging stations

CP_{fast}-Power consumption of fast charging stations

CP_{slow}- Power consumption of slow charging stations

$P_{electricity}$- Per unit cost of electricity

P_{VD}- Penalty paid by the utility for per unit voltage deviation

P_{AENS}- Penalty paid by the utility for per unit energy not served

$T_{cost\ EV}$ - Cost of travelling per km for EV

$\mathrm{n}_{\mathrm{fast\ CS}}$- Maximum number of fast charging stations that can be placed at a particular bus

$n_{slow\ CS}$- Maximum number of fast charging stations that can be placed at a particular bus

S_{min}- Lower bound of reactive power limit of each bus

S_{max}- Upper bound of reactive power limit of each bus

L_{max}- Loading margin of the network

N_D- Total number of bus of the distribution network

N_T- Total number of nodes of the road network

T_t- Planning period

Functions

$C_{installation}$- Installation cost of charging station

$C_{operation}$- Operating cost of charging station

$C_{penalty}$- Penalty paid by utility

$VD_{penalty}$- Penalty for voltage deviation

$AENS_{penalty}$- Penalty for energy not served

C_{travel} - Travelling distance cost from point of charging station to point of placement of charging station

Abbreviations

EV- Electric Vehicle

AENS- Average Energy Not Served

VD- Voltage Deviation

GA-Genetic Algorithm

PSO-Particle Swarm Optimization

BA-Bat Algorithm

DE-Differential Algorithm

CSO-Chicken Swarm Optimization

TLBO- Teaching Learning Based Optimization

Indices

i- Bus no of the distribution network

N_{CS}- Total number of charging stations in the network

$N_{fast\ CS}$- Total number of fast charging stations in the network

$N_{slow\ CS}$- Total number of slow charging stations in the network

n_i-(0 or 1), n_i =1 if CS is at bus *i*else n_i=0

Variables

$N_F{}^i$- Number of fast charging station at ithbus

$N_S{}^i$- Number of slow charging station at ithbus

$V_i{}^{base}$- Voltage of ith bus for base case

V_i - Voltage of ith bus after placement of charging station

VD_i- Voltage Deviation of ithbus

L_i- Load at ithbus

U_i -Duration of interruption at ithbus

N_i- Number of consumer at ithbus

d_{CS}- Distance between the point of charging demand and point of placement of charging station

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 j^{th} 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

CSO parameters

RN- Set of roosters

HN- Set of hens

CN- Population of chicks

MN-Set of mother hens

PN- Population of swarm

TLBO parameters

T_k- Teacher

m_k-Mean value of decision variable

R_t- Random number between 0 and 2

pop- Population size of learners

1. Introduction

Generally speaking, both transportation sector and power generation sector are fossil fuel reliant. For example, the oil consumption of transport sector will rise by 54% until 2035 [1]. Thus, the research community is constantly preoccupied with concerns about the exhaustive nature of fossil fuels as well as greenhouse gas emissions responsible for the global change in climate conditions. As a measure to ameliorate the adverse impact of the emission of the transportation sector on the environment, the 21st century has witnessed a bold initiative of replacement of Internal Combustion Engine (ICE) driven vehicles with EVs. However, range anxiety of the EVs is one of the barriers hindering their broad acceptance. The development of fully furnished charging infrastructure is of prime importance to facilitate large-scale deployment of EVs. The current pace gives time for electric grid designers to adapt with the increasing number of EVs. A sudden replacement of the ICE vehicles with EVs roughly means more than doubling the electric power production in the world [2]. Unfortunately, charging station placement without careful design and charging management strategies may considerably degrade the operating parameters of the distribution network, such as voltage stability, power loss, reliability, etc. [2], [3], [45], [46]. Furthermore, uncontrolled charging is detrimental to EV battery life [49], [50]. For a passenger vehicle with a consumption is 0,2 kWh/km. 10 kW charger can charge 50 km per one hour; 100 kW charger can charge 500 km per one hour, etc. Thus, the charger capacity and charging techniques affect driving range and battery lifetime to certain extent. The placement of EV charging stations in the road network must be coordinated with the distribution network. Indeed, the optimal placement of EV charging stations has attracted the interest of researchers in the community. Diversity in the approaches to problem formulation and optimization algorithms applied for its solution makes the charging station placement problem unique and challenging [5]. Tactical formulation of the placement problem and employment of efficient algorithms are the two most important topics in the optimal placement of charging stations. The complex nature of the charging station placement problem has resulted in the extensive applications of nature-inspired algorithms in tackling this demanding problem.

In this paper, a novel optimization algorithm based on the amalgamation of CSO and TLBO is proposed for dealing with the above charging station placement problem. CSO is a *state-of-the-art* evolutionary algorithm that mimics the food searching process of chicken, and TLBO mimics the teaching learning procedure. It is expected that the hybridization of these two distinguishing algorithms can exploit the strengths of each algorithm, thus yielding better optimization results. The present work is a significant extension of the conference paper by Deb et al. [4] with the following new scientific contributions:

1. A single-objective framework of charger placement is developed and validated on test network.
2. Two different hybridization schemes of the CSO TLBO algorithm are proposed and compared with each other.
3. The new algorithms are evaluated on the basis of the selected benchmark functions.
4. The statistical performance comparison is conducted between the CSO TLBO algorithm and other cutting-edge methods like GA, PSO, TLBO, and CSO to demonstrate its efficiency and effectiveness.
5. The impact of the placement of EV charging station loads on different operating parameters of the distribution network is analyzed.

2. Literature Review

In the recent years, considerable research endeavour has been devoted to the optimal placement of EV charging stations. The existing research work in the paradigm of EV charging station is discussed in this section.

2.1. Related Work

The charging station placement is a complicated problem involving objective functions and constraints as well as both transport and distribution networks. Deb et al. [5] discussed different modelling approaches, objective functions, and constraints deployed in the charging station placement problem. The placement problem is modelled either by considering the road network or the distribution network. In some recent research contributions, the placement problem has been modelled by superimposing road and distribution networks. Another feature of the charging station placement problem is involvement of many objective functions and constraints. Both classical and evolutionary optimization algorithms have been used for the solution of this problem.

In [6]-[10], the charging station placement problem has been solved by only considering transport network. Ge et al. [6] presented a placement scheme of EV charging station in a test road network with 48 intersection points. The authors considered the cost of user's loss on the way to charging station as the objective function. The charging demand of the nodes and the maximum and minimum number of charging stations at the nodes were regarded as constraints in the aforementioned literature. The authors divided the test network into a number of partitions and employed GA to compute the optimal number of charging stations for each partition. Liu et al. [7] formulated the charging station placement problem considering construction cost and running cost as the objective functions along with the highest charging requirement as a constraint. They applied Adaptive Particle Swarm Optimization (APSO) to cope with this complex problem and made a comparison of the results of APSO with PSO. The adjustment of inertia factor automatically in APSO makes it superior to that of PSO. The efficacy of APSO was validated on a road network of Beijing. Bendiabdellah et al. [8] formulated a novel hybrid method combining k means of clustering and GA for the charging station placement problem. This algorithm was capable of finding the location and number of charging stations, thereby minimizing installation, and travel time cost of EV drivers on their way to the point of charging station from the point of charging demand. The efficacy of the hybrid algorithm was validated on a road network of Cologne, Germany. Dong et al. [9] formulated the charging station placement problem for the road network of Seattle with the minimization of missed trip as the objective function and budget as the constraint. The authors applied GA in their solutions. Tu et al. [10] modelled the charging station placement problem for a road network of Shenzhen, China considering maximization of travel time of EVs and minimization of waiting time in the charging stations as the objective function. The EV range, capacity of charging stations, and charging time were regarded to be the constraints in the planning model, and GA was used to obtain the optimal solutions.

Literature [11]-[16] considered only distribution network while modelling the charging station placement problem. Liu et al. [11] formulated the charging station placement problem in a single objective framework with cost as the objective function. Firstly, the candidate sites of charging stations were identified based on service radius as well as environmental factors, and optimization was next performed. Modified Primal Dual Interior Point Algorithm (MPDIPA) was utilized in this work, and the proposed approach was validated on IEEE 123 bus test system. Yan et al. [12] considered investment cost as the objective function, power loss limit, and maximum capacity of charging stations as constraints in their planning model. The authors employed HGA based novel algorithm involving encoding, genetic operators, and tabu table so as to obtain the optimal solutions. The effectiveness of design was validated on IEEE 33 bus distribution network. Phonrattanasak et al. [13] used ACO in the similar charging station placement problem. The model developed by them is capable of maximising charging serviceability subject to traffic constraints as well as distribution network constraints. Zheng et al. [14] presented a unique scheme for charging and battery swapping station placement in IEEE 15 and IEEE 43 bus distribution network considering cost as the objective function and power consumption limit, voltage limit, current limit as constraints. A modified form of Differential Evolution (DE) was utilized by them. Pazouki et al. [15] considered financial, technical, and environmental aspects while formulating the charging station placement problem and employed GA as the solution. In the aforementioned planning approach, cost, power loss, reliability, voltage penalty, emission were considered as objective functions and bus voltage limit, line current limit, capacity of charging station, power balance of the network as constraints. Zhang et al. [16] proposed an integrated planning framework for EV charging infrastructure development. The summation of installation cost, operating cost, maintenance cost, time cost, and electricity cost was considered as the objective function in their work. They utilized Voronoi diagram to find the service region of charging station and optimally allocated the candidate places of charging station by PSO. Consideration of the impact of ambient temperature, possession rate of private and public charging spot on EV charging station placement is another noteworthy contribution of this work.

Similarly, literature [17]-[20] modelled the placement problem considering superimposition of transport and distribution network. Wang et al. [17] proposed a multi-objective EV charging station planning method, which ensured charging service and took into account power loss and voltage deviation of the distribution network. They handled this multi-objective problem by using Data Envelopment Analysis (DEA) and a Cross-Entropy based method (CE), and compared the performances obtained with PSO. Their results clearly demonstrated the superiority of CE over PSO in terms of quality of solution as well as computational time. The proposed approach was validated on superimposed IEEE 33 bus distribution network and 25 node road network. Yao et al. [18] modelled the placement problem with cost, annualized traffic flow and energy losses as objective functions. A Multi-Objective Evolutionary Algorithm (MOEA) was utilized for obtaining the pareto front and the final planning scheme was decided by fuzzy logic. Awasthi et al. [19] presented a novel placement scheme of charging station placement for the city of Allahabad in India by utilizing hybrid GA PSO. The authors considered cost, active power loss reduction index, and reactive power loss reduction index, voltage profile improvement index as objective functions and bus voltage limit, line current limit, capacity of charging stations as the constraints. The results presented in their work reveal the superiority of hybrid GA PSO over GA and PSO in terms of quality of the solution. Islam et al. [20] formulated the charging station placement problem with cost as the objective function and power limits, charging station capacity, line current limit as constraints. The authors utilized BLSA to attack this optimization problem. The proposed approach was validated on a test network formed by superimposing IEEE 34 bus distribution network and the road network of Bangi, Malaysia. Literature [6]-[20] discussed the contributions of different researchers in the paradigm of charging station placement thereby revealing the multifarious nature of problem formulation and optimization algorithms employed.

2.1. Necessity of new meta-heuristics

During recent years, the paradigm of combinatorial optimization has witnessed the discovery of a number of novel meta-heuristic algorithms. Many practical engineering optimization problems are difficult to solve by classical algorithms because of their non-linear nature. The charging station placement problem is one of such complex problems involving numerous variables, objective functions, and constraints. Hence, there is necessity of devising efficient and fast algorithms for the placement problem. CSO and TLBO are two latest evolutionary algorithms successfully applied by researchers in solving complex engineering optimization problems. For example, CSO was applied to handle feature selection [21], community detection [22], Wireless Sensor Network (WSN) localization [23], speed reducer design [24], trajectory optimization [25], etc. Similarly, TLBO was successfully applied for parameter optimization of machining process [26], transmission expansion planning [27], economic load dispatch problem [28], optimization of heat exchangers [29], optimal configuration of microgrid [30], etc. Therefore, motivated by the success of CSO as well as TLBO in coping with such a wide range of optimization problems, these two algorithms are amalgamated together to form the hybrid CSO TLBO algorithm. The amalgamation of CSO TLBO can improve the quality of solution and speed up convergence towards to the optimal solution.

3. Problem formulation

The charging station placement problem is a typical planning problem involving the interaction between transport and distribution networks. Placement and sizing of charging stations are the two prime activities performed in the placement problem. From the perspective of EV drivers, the locations of the charging stations must be easily accessible and close to the point of charging demand. In addition, the placement of these charging stations should not degrade the operating parameters of the distribution network like voltage profile and reliability. Therefore, the placement of charging stations in the road network must be coordinated with the distribution network. The literature reported in Section 2 shows that researchers have formulated the placement problem in a lot of ways with different objective functions and constraints. The problem of charging station placement is formulated in this work as a non-linear constrained optimization problem. The salient features and the difference of the present formulation from the formulation of charging station present in the existing literature are as follows.

1. The charging station placement problem is modelled in our work under a single objective framework with cost as the objective function. The operating parameters of the distribution network are taken into account by imposing penalty for violation of the safe limit of the operating parameters. In other words, we model the complex placement problem in a simple single objective framework and also consider all the operating parameters of the power grid, whose violation may be detrimental to the safe operation of the network.
2. The reliability of the power distribution network is neglected in most of the recent works related to charging station placement. Unfortunately, exclusion of reliability indices while formulating the charging station placement problem is a major research gap. In the present work, reliability of the distribution network is taken into consideration by imposing penalty for the violation of AENS.
3. The EV driver's convenience is also considered by minimizing the cost of travelling from the point of charging demand to the charging stations.

The decision variables, objective function, and constraints of this placement problem are elaborated in the next subsections.

3.1. Decision variables

The charging station placement problem is a multi-variable problem. The locations and number of charging stations are the outputs. In this analysis, the optimal location and number of both fast and slow charging stations are designated as decision variables. Symbolically, the decision variables are as follows.

- b
- N_{Fb}
- N_{Sb}

$b \in P$

The charging stations are placed at the superimposed road and distribution network nodes. Moreover, it is assumed that the charging stations will only be placed at the strong nodes of the distribution network, which are not vulnerable to voltage instability. Thus, P is a subset of both S and TS.

3.2. Objective function

The objective function is on the basis of minimization of overall cost associated with the establishment of charging stations. Furthermore, the cost can be subdivided into the direct and indirect cost. Mathematically, the objective function yields:

$$Min\ (C_{direct} + C_{indirect}) \tag{1}$$

The direct cost includes the cost directly associated with establishment of charging station like the installation cost and operating cost elaborated as:

$$C_{direct} = C_{installation} + C_{operation} \tag{2}$$

$$C_{installation} = (N_{fastCS} \times C_{installationfast} + N_{slowCS} \times C_{installationslow}) \tag{3}$$

$$C_{operation} = (N_{fastCS} \times CP_{fast} + N_{slowCS} \times CP_{slow}) \times P_{electricity} \times T_t \tag{4}$$

$$N_{fastCS} = \sum_{i=1}^{N_D} n_i \times N_F^i \tag{5}$$

$$N_{slowCS} = \sum_{i=1}^{N_D} n_i \times N_S^i \tag{6}$$

$$n_i = 1 \ \forall \ i \in P \tag{7}$$

From (3) and (4), it is clear that the installation and operation cost are dependent on the number of fast and slow charging stations to be installed. The installation and operating cost are independent of the location of charging stations because of the assumption that the land, floor, building, labour, charger, and electricity cost are same for all the nodes of the entire network.

The indirect cost is the summation of the penalty paid and travel time cost. One of the salient features of this problem formulation is distribution network parameters are included by imposing penalties for voltage deviation and

AENS. The travel time cost is the additional cost of travelling from the node of charging demand to the node of placement of charging station. The various terms associated with the indirect cost are as follows:

$$C_{indirect} = C_{penalty} + C_{travel} \tag{8}$$

$$C_{penalty} = VD_{penalty} + AENS_{penalty} \tag{9}$$

$$VD_{penalty} = P_{VD} * \sum_{i=2}^{N_D} VD_i \tag{10}$$

$$VD_i = V_i^{base} - V_i \tag{11}$$

As illustrated in (8), the voltage deviation is the change in voltage of the buses after the introduction of charging station loads. If after the increase of load the voltage of the buses of the distribution network drops to less than 0.9 per unit, the utility has to pay the penalty for voltage deviation. In our work, the voltage of all the buses of the network is computed by forward backward sweep algorithm [31].

$$AENS_{penalty} = P_{AENS} * AENS \tag{12}$$

$$AENS = \frac{\sum L_i U_i}{\sum N_i} \tag{13}$$

$$C_{travel} = d_{CS} \times T_{\cos tEV} \tag{14}$$

As illustrated in (13), AENS is a load oriented reliability index of distribution network giving an idea how much energy is not served during a particular time period. (14) shows that the travel time cost is dependent on the distance between the charging point demand and the charging stations. Thus, inference can be drawn that the travel time cost is a function of the locations, where charging stations are placed.

3.3. Constraints

The objective function formulated in the previous subsection is minimized in agreement with some inequality and equality constraints as follows:

$$0 < N_{Fb} \leq n_{fastCS} \tag{15}$$

$$0 < N_{Sb} \leq n_{slowCS} \tag{16}$$

$$S_{\min} \leq S_i \leq S_{\max} \tag{17}$$

$$L \leq L_{\max} \tag{18}$$

The constraints given by (15) and (16) use the maximum and minimum number of fast and slow charging stations placed at the candidate locations. (17) considers the upper and lower limit of reactive power. (18) takes into account the maximum safe limit of load that can be added to the network.

In addition to the aforementioned constraints, the power flow balance equation given by (19) and (20) must be considered as an equality constraint.

$$P_{gi}-P_{di}-V_i\sum_{j=1}^{N_D}V_jY_{ij}\cos(\delta_i-\delta_j-\theta_{ij})=0 \quad (19)$$

$$Q_{gi}-Q_{di}-V_i\sum_{j=1}^{N_D}V_jY_{ij}\cos(\delta_i-\delta_j-\theta_{ij})=0 \quad (20)$$

4. Optimization Algorithms

CSO TLBO algorithm was employed in the present work to deal with the charging station placement problem defined in the previous section. An overview of CSO, TLBO and newly developed CSO TLBO algorithm is given in this section.

4.1. CSO

CSO is a bio-inspired algorithm proposed by Meng et al. [32] in 2014, which is inspired by the behavior of chicken swarm, where the intelligence of chicken swarm is effectively utilized to obtain the optimal solution. It imitates the hierarchal order in a chicken swarm and the food searching process of the swarm. The population of chicken in the group is subdivided into dominant rooster, hens, and chicks depending on the fitness values of the chickens. The chickens with the highest fitness value are assigned as roosters, chickens with the least fitness value are assigned as chicks, and the chickens with intermediate fitness value are assigned as hens. Establishment of mother-child relationship in a random manner is another salient feature of this algorithm. After every *G* time steps, the hierarchal order, and mother-child relationship are updated. Moreover, the algorithm utilizes the natal behavior of hens to follow their group mate rooster and chicks to follow their mother. Chickens try to steal the food found by others, which gives rise to a competition for food in the group. The algorithm is divided into two steps-Initialization and Update.

In Initialization, the population size and other related parameters of CSO are first defined. The fitness values of the population of chicken are evaluated and a hierarchal order is established based on this fitness value as illustrated in Fig.1. It is assumed that the number of hens is the highest in the group [32]. All the hens are not mother hens, and the mother hens are selected randomly from the set of hens. Despite the fact that each hen can have more than one chick, it is assumed that the number of chicks is less than the number of hens [32], [33].

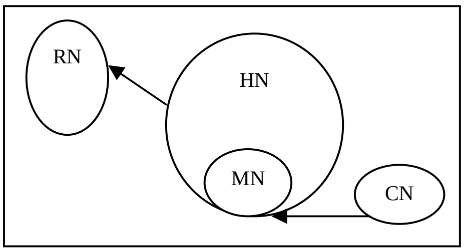

Fig. 1. Hierarchal relationship in the chicken swarm

Utilizing the concepts of set theory, (21) and (22) are deduced:

$$MN \subset HN \quad (21)$$

$$PN = RN \cup HN \cup CN \tag{22}$$

The food searching capacity of different members of the group actually varies. In the update step, the fitness values of the initial population are updated according to the food searching capacities of the different members of the group. The update formula of roosters, hens, and chickens are also different, as explained in (23) to (29). The food searchingcapacity of roosters depend on their fitness values updated according to formulae:

$$x_{i,j}^{t+1} = x_{i,j}^{t} \times (1 + Randn(0, \sigma^2)) \tag{23}$$

If $f_i \leq f_k$

$$\sigma^2 = 1 \tag{24}$$

else

$$\sigma^2 = \exp\left(\frac{(f_k - f_i)}{|f_i| + \varepsilon}\right) \tag{25}$$

where $randn(0,\sigma^2)$presents a Gaussian distribution with 0 mean and σ^2 standard deviation. The variable f is the fitness value of the corresponding x, and k is randomly selected rooster's index.ϵ is a small positive constant to prevent division by zero.

Hens follow their group mate roosters while searching food. Interestingly, chickens also have a tendency to steal the food found by other chickens. Their update algorithm is given as follows:

$$x_{i,j}^{t+1} = x_{i,j}^{t} + S1 \times rand \times (x_{r1,j}^{t} - x_{i,j}^{t}) + S2 \times rand \times (x_{r2,j}^{t} - x_{i,j}^{t}) \tag{26}$$

$$S1 = \exp\left(\frac{f_i - f_{r1}}{abs(f_i) + \varepsilon}\right) \tag{27}$$

$$S2 = \exp(f_{r2} - f_i) \tag{28}$$

where *randn* is a randomly generated number between 0 and 1. $r1 \in [1, N]$ is an index of rooster, which is i^{th} hen's group mate. $r2 \in [1, N]$ is an index of rooster or hen randomly chosen such that $r1$ is not equal to $r2$.

The natural tendency of chicks to follow their mother is represented as follows.

$$x_{i,j}^{t+1} = x_{i,j}^{t} + FL \times (x_{m,j}^{t} - x_{i,j}^{t}) \tag{29}$$

where $x_{m,j}^{t}$ represents the position of i^{th}chick's mother. *FL* is the parameter making the chicks follow its mother. *FL* is generally chosen between 0 and 2.

The pseudo code of CSO is as shown in Algorithm 1.

Algorithm 1-Pseudo code of CSO [32] [43] [44]
Initialize the population of chicken having size N and define other algorithm specific parameters like G, size of RN, HN,CN, and MN;
Evaluate the fitness value of N chicken, t=0 , establish the hierarchal order in the swarm 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 (23);
End if
If i==hen
Update its solution by (24);
End if
If i==chick
Update its solution by (24);
End if
Evaluate the new solutions;
Update the new solutions if they are better than the previous one;
End for
End if else
End while

4.2. TLBO

TLBO is an evolutionary algorithm introduced by Rao et al. [34]-[36], whichis a population-based optimization algorithm mimicking the interactive process of teaching and learning. A class of learners constitutes the population. The teacher's knowledge is being transferred to the learners. The students can learn from their teacher as well as their fellow students. The performance of the learners depends on the knowledge and capability of the teacher. The algorithm is divided into two phases: 1. Teacher phase and subsequent 2. Learner phase [34]-[36].

1. Teacher phase- In this phase, the students learn from the teacher, who is an erudite scholar with profound knowledge and skill. The learner having the best fitness in a randomly generated population of teachers is generally assigned the role of teacher. Each learner learns from the teacher, and is modified as:

$$Z_{diff} = rand \times (T_k - R_t m_k) \tag{30}$$

$$Z_{new} = Z_{old} + Z_{diff} \tag{31}$$

The objective function value for each learner set modified by transfer of knowledge by the teacher is recalculated. If the new value of the objective function for any learner is better than the previous one, it is replaced by the new value. Otherwise, the old learner is kept as it is.

2. Learner phase-The learners learn by mutual interactions among themselves. For each learner Z_i , any learner $Z_j$is chosen arbitrarily in the learner matrix. The objective function values are compared arbitrarily between two learners. If the value of the objective function of $Z_i$is lower than the objective function of Z_j,the i^{th}learner yields to:

$$Z_{new} = Z_{old} + rand \times (Z_i - Z_j) \tag{32}$$

Otherwise, it becomes:

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

The pseudo code of TLBO is given in Algorithm 2.

Algorithm 2- Pseudo code of TLBO [34]
Set k=1;
Initialize the population size and generate the initial population of students randomly;
Compute the objective function for all the individuals of the population;
while(k<gen)
{Teacher Phase}
Assign the teacher based on the fitness value;
for i=1:pop
Modify each learner by (30), (31);
Evaluate the new solutions;
Update the new solutions if they are better than the previous one;
{End of teacher phase}
{Learner Phase}
Choose two learners Z_i *and* Z_j*,*$i \neq j$*;*
if(fitness of Z_i *better than* Z_j*)*
Replace i^{th} *learner by (32);*
Else
Replace i^{th} *learner by (33);*
End if else
End for
k=k+1
End while

4.3. CSO TLBO

A novel hybrid algorithm CSO TLBO is proposed in this section. We aimed at a solution that combines the advantages of CSO and TLBO. In order to improve TLBO performance, the grading mechanism of CSO was introduced in TLBO. Two different hybridization schemes of CSO TLBO were developed, as described in Algorithm 3 and Algorithm 4, respectively. In Scheme 1, TLBO was performed in all the generations, and CSO was periodically invoked in some generations. It was expected that if CSO was invoked periodically, the utilization rate of the population can accelerate. In Scheme 2, either CSO or TLBO was performed in each generation. Due to the involvement of too many algorithm specific parameters in CSO, there was a possibility of premature convergence, if the parameters were not properly tuned. The solutions obtained by CSO were refined by TLBO.

Algorithm 3- Pseudo code of CSOTLBO (Scheme 1)
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
End while

Algorithm 4- Pseudo code of CSOTLBO (Scheme 2)
Initialize the population size, gen and the other algorithm specific parameters of CSO TLBO

Set t=1
While (t<gen)
Activate CSO
Activate TLBO
t=t+1
End while

5. Methodology for solution of charging station placement problem by CSO TLBO

CSO TLBO was employed to cope with the charging station placement problem elaborated in Section 3. The systematic procedure for solution of the charging station placement problem by CSO TLBO is as follows.

Step 1: Initialization

Step 1.1: Input the road network, distribution network data, upper and lower limits of different constraints, and set the different algorithm specific parameters of CSO TLBO like *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 $A_{pop} = \begin{bmatrix} p_{11} & p_{12} & p_{13} & \cdots & p_{1m} \\ p_{21} & p_{22} & p_{23} & \cdots & p_{2m} \\ p_{31} & p_{32} & p_{33} & \cdots & p_{3m} \\ . & . & . & \cdots & . \\ p_{PN1} & p_{PN2} & p_{PN3} & \cdots & p_{PNm} \end{bmatrix}$ $B_{pop} = \begin{bmatrix} N_{fastp_{11}} & N_{fastp_{12}} & N_{fastp_{13}} & \cdots & N_{fastp_{1m}} \\ N_{fastp_{21}} & N_{fastp_{22}} & N_{fastp_{23}} & \cdots & N_{fastp_{2m}} \\ N_{fastp_{31}} & N_{fastp_{32}} & N_{fastp_{33}} & \cdots & N_{fastp_{3m}} \\ . & . & . & \cdots & . \\ N_{fastp_{PN1}} & N_{fastp_{PN2}} & N_{fastp_{PN3}} & \cdots & N_{fastp_{PNm}} \end{bmatrix}$

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

The randomly generated initial solution is feasible, if it satisfies all the constraints of charging station placement problem explained in Section 3.3.

Step 1.3: Evaluate the fitness function for the initial population. Arrange the population in the ascending order according to the fitness function.

Step 1.4: For Scheme 1 of combining CSO TLBO, the individual with best fitness value is assigned as the teacher. Steps 2a and 3a are followed. For Scheme 2 of combining CSO TLBO RN, HN, and CN are assigned based on the fitness value, and Steps 2b and 3b are followed.

Step 2a: Run TLBO.

Step 2a.1: Run TLBO, and update the solution based on fitness value.

Step 2a.2: If the elements B_{pop} exceed n_{fastp}, that element is made equal to n_{fastp}. If the elements of C_{pop} exceed n_{slowp}, that element is made equal to n_{slowp}.

Step 2a.3: Otherwise, check feasibility of the solution. If the solution is infeasible, repeat Step 2a.1 and 2a.2 until a feasible solution is obtained.

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

Step 3a.1: If *t* is divisible by *INV,* run CSO.

Step 3a.2: Run CSO, and update the solution based on fitness values.

Step 3a.3: If the elements B_{pop} exceed n_{fastp}, that element is made equal to n_{fastp}. If the elements of C_{pop} exceed n_{slowp}, that element is made equal to n_{slowp}.

Step 3a.4: Otherwise, check feasibility of the solution. If the solution is infeasible, repeat Step 3.2 and 3.3 until a feasible solution is obtained.

Step 3a.5: Update the iteration count.

Step 2b: Run CSO

Step 2b.1: Run CSO, and update the solution based on rank and crowding distance.

Step 2b.2: If the elements B_{pop} exceed n_{fastp}, that element is made equal to n_{fastp}. If the elements of C_{pop} exceed n_{slowp}, that element is made equal to n_{slowp}.

Step 2b.3: Otherwise, check feasibility of the solution. If the solution is infeasible, repeat Step 2b.1 and 2b.2 until feasible solution is obtained.

Step 3b: Run TLBO

Step 3b.1: Run TLBO and update the solution based on ranking and crowding distance.

Step 3b.2: If the elements B_{pop} exceed n_{fastp}, that element is made equal to n_{fastp}. If the elements of C_{pop} exceed n_{slowp}, that element is made equal to n_{slowp}.

Step 3a.3: Otherwise, check feasibility of the solution. If the solution is infeasible repeat Step 3b.1 and 3b.2 until feasible solution is obtained.

Step 3a.4: Update the iteration count.

Step 4: Check whether the maximum generation count is reached. If true, yield the solution. Otherwise, repeat Step 2 to Step 4.

6. Numerical Analysis

The performances of CSO TLBO in solving some benchmark problems and charging station placement problem are demonstrated as follows.

6.1. Solution of some standard benchmark functions

Selected benchmark functions listed in Table 1 were attacked using the proposed CSO TLBO. The performance of CSO TLBO on the standard benchmark functions was compared with a few state-of-the-art algorithms, such as DE, PSO, BA, CSO, and TLBO. The statistical analysis of the results was performed based on a total of 50 independent runs. The number of iterations was 1000 for the benchmark functions. The algorithm-specific parameters used are given in Table 2.

Table 1- Benchmark Functions [32]

ID	Benchmark Function	Dimension	Bound	Optimum
F1	Sphere	20	[-100,100]	0
F2	Ackley	20	[-32,32]	0
F3	Griewank	20	[-600,600]	0
F4	Rastrigin	20	[-5,10]	0
F5	Axis parallel hyper-ellipsoid	20	[-5.12,5.12]	0
F6	Step	20	[-100, 100]	0
F7	Brown	20	[-1, 4]	0
F8	Exponential	20	[-1, 1]	-1

Table 2- Algorithm specific parameters [32]

Algorithm	Parameters
PSO	c1=c2=1.49445,w=0.729
DE	CR=0.9, F=0.6
BA	$\alpha=\gamma=0.9, f_{max}=2, A_0 \epsilon [0,2], r_0 \epsilon [0,1]$
CSO	RN=0.2*PN, HN=0.6*PN, CN=PN-RN-HN, MN=0.1*PN, G=10
CSO TLBO	RN=0.2*PN, HN=0.6*PN, CN=PN-RN-HN, MN=0.1*PN, G=10, INV=3

Table 3- Statistical comparison of CSO TLBO with other state of art algorithms

Benchmark function	Algorithm	Best	Worst	Mean
F1	PSO	0	0	0
	DE	0	0	0
	BA	1.867408	2.94197	4.18701
	CSO	0	0	0
	TLBO	0	0	0
	CSO TLBO (Scheme 1)	0	0	0
	CSO TLBO (Scheme 2)	0	0	0
F2	PSO	0	0	0
	DE	0	0	0
	BA	1.48288	2.59402	3.07403
	CSO	0	0	0
	TLBO	0	0	0
	CSO TLBO (Scheme 1)	0	0	0

	CSO TLBO (Scheme 2)	0	0	0
F3	PSO	0	0	0
	DE	0	0	0
	BA	0.004	2.82906	15.42094
	CSO	0	0	0
	TLBO	0	0	0
	CSO TLBO (Scheme 1)	0	0	0
	CSO TLBO (Scheme 2)	0	0	0
F4	PSO	10.94454	21.26284	41.78822
	DE	8.41884	22.70527	43.9751
	BA	88.44729	121.99296	167.60654
	CSO	0	0	0
	TLBO	0	0	0
	CSO TLBO (Scheme 1)	0	0	0
	CSO TLBO (Scheme 2)	0	0	0
F5	PSO	0	1.29	8
	DE	0	0	0
	BA	24.34652	39.73613	63.15
	CSO	0	0	0
	TLBO	0	0	0
	CSO TLBO (Scheme 1)	0	0	0
	CSO TLBO (Scheme 2)	0	0	0
F6	PSO	0	0	0
	DE	0	0	0
	BA	1	3.41	6
	CSO	0	0	0
	TLBO	0	0	0
	CSO TLBO (Scheme 1)	0	0	0
	CSO TLBO (Scheme 2)	0	0	0
F7	PSO	10.94454	21.26284	41.78822
	DE	0	0	0
	BA	0	0	0
	CSO	0	0	0
	TLBO	0	2.1	5
	CSO TLBO (Scheme 1)	0	0	0

	CSO TLBO (Scheme 2)	0	0	0
F8	PSO	-1	-1	-1
	DE	-1	-1	-1
	BA	-0.41494	-0.20415	-0.12952
	CSO	-1	-1	-1
	TLBO	-1	-1	-1
	CSO TLBO (Scheme 1)	-1	-1	-1
	CSO TLBO (Scheme 2)	-1	-1	-1

Table 3 reports the results related to statistical comparison of CSO TLBO with other state-of-the-art algorithms. The performance of PSO, DE and BA in optimizing the benchmark functions in Table 1 was studied in [32]. It was observed that for benchmark function F1, F2, F3,F5, F6,F8, the performance of CSO TLBO was equivalent to PSO, DE, TLBO, CSO. For benchmark function F1, F2, F3,F5, F6,F8, the performance of CSO TLBO was much better than BA. For benchmark function F4, the performance of CSO TLBO was better than PSO, DE, BA and equivalent to CSO and TLBO. For benchmark function F7, the performance of CSO TLBO was better than PSO, TLBO and equivalent to DE, BA, and CSO. As a conclusion, the performance of the proposed CSO TLBO algorithm was found equal to or better than the selected methods. It was discovered that the performance of the two schemes of combining CSO and TLBO was equivalent on the benchmark functions in Table 1. However, the number of function evaluation was more for Scheme 2 as compared to Scheme 1,because in Scheme 2, both CSO and TLBO were performed in all the generations.

6.2. Solution of charging station placement problem

IEEE 33 bus radial distribution network was coupled with 25 node transport network as shown in Fig.2 to validate the efficacy of the aforementioned algorithms. The bus data and line data of IEEE 33 bus distribution network were taken from [37],[38] and the road network data from [6]. The input parameters related to objective function and optimization algorithm were given in Table 4 and Table 5, respectively. It was assumed that the superimposed nodes were the candidate locations for placement of charging stations. The EVs were assumed to follow the two 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)
- 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)

TS={3,28, 14,16,17,23,6,30,26,20} with respect to the distribution network. TS={9,7,11,12,16,22,8,6,5,4} with respect to transport network.

The driving range of EV was 150 km [39],[40], and the EVs followed two routes named Route 1 or Route 2. The point of charging demand were computed and given by T={4,7,9,13,15,18,22,25}.Table 4 presents the input parameters of the charging station placement problem. Table 5 presents the algorithm specific parameters of different popular algorithms for the charging station placement problem. The optimal values of the decision variables for minimization of the overall cost and the best value of the fitness function were given in Table 6. The optimization was carried out by employing the two schemes of CSO TLBO as mentioned in Section 4.3 and some conventional algorithms like CSO, TLBO, PSO, DE, and GA. The value of the best fitness function obtained by the two hybridization schemes of CSO TLBO was 1.4841, which was the least as compared to other solutions. The supremacy of CSO TLBO in solving charging station placement problem was clearly revealed from the results (Table 6). Figure 3 represents the convergence curve of different algorithms for the best fitness value. It reveals that the rate of convergence of both the hybridization schemes of CSO TLBO was better than the others. Another important observation from Fig. 3 was that the rate of convergence of Scheme 2 of combining CSO TLBO was better than Scheme 1. The main reason behind this was due to improved exploration of search space in Scheme 2 as compared to Scheme 1. Figure4 illustrates the location of charging stations in the road network obtained by CSO TLBO. Node 9 and 22 of the road network were the location of charging station and point of charging demand of EV. Intersection of the point of placement of charging station and charging demand would make it convenient for the EV drivers to charge the batteries on their way without having to travel any further distance. EVs having charging demand at node 4 ,7 and 13 could access the charging station located at node 8. But for node 15, 18 and 25 that were the points of charging demand of EV, there was no charging station in their neighborhood. These nodes were actually far away from the substation, and the strong buses of the distribution network were far away from them. The charging demand arising at these nodes can be satisfied by the charging stations supported by local renewable resources or battery swapping stations.

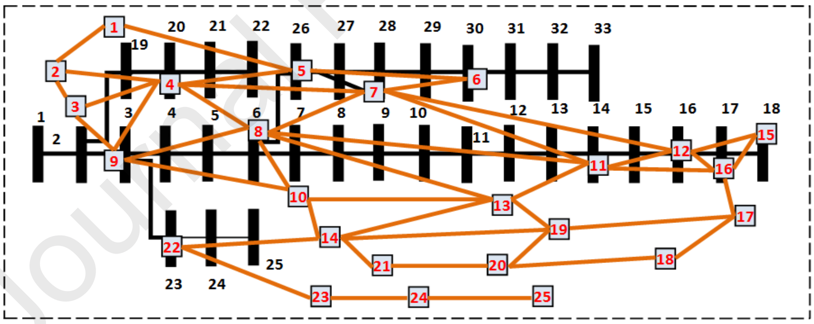

Fig. 2 Test network [4]

Table 4- Input parameters of the charging station placement problem [4]

Parameter	**Value**
$C_{installationfast}$	3000 $
$C_{installationslow}$	2500 $
CP_{fast}	50 kW
CP_{slow}	19.2 kW
$P_{electricity}$	65 $/MWhr
P_{VD}	$(VD)^2$ *1000000)$
P_{AENS}	0.18$/MWhr

Table 5 Algorithm specific parameters of different state of art algorithms for charging station placement problem

Algorithm	Parameters
PSO	c1=c2=2, w=0.1
DE	CR=0.6, F=1.5
CSO	RN=0.2*PN, HN=0.5*PN, CN=PN-RN-HN, MN=0.3*PN, G=5
CSO TLBO	RN=0.3*PN, HN=0.4*PN, CN=PN-RN-HN, MN=0.3*PN, G=3, INV=5

Table 6 Optimal allocation of charging stations

Optimization technique	**Fitness value (best)**	***b***	N_{Fb}	N_{Sb}
CSO TLBO(scheme 1)	1.4841	6	1	2
		3	1	3
		23	1	3
CSO TLBO(scheme 2)	1.4841	6	1	2
		3	1	3
		23	1	3
CSO	1.4870	6	1	3
		23	1	3
		3	1	2
TLBO	1.4878	3	1	3
		23	1	3
		28	1	2
PSO	1.4898	23	1	2
		6	1	3
		3	1	3
DE	1.4898	23	1	2
		6	1	3
		3	1	3
GA	1.5075	23	1	2
		3	1	3
		28	1	3

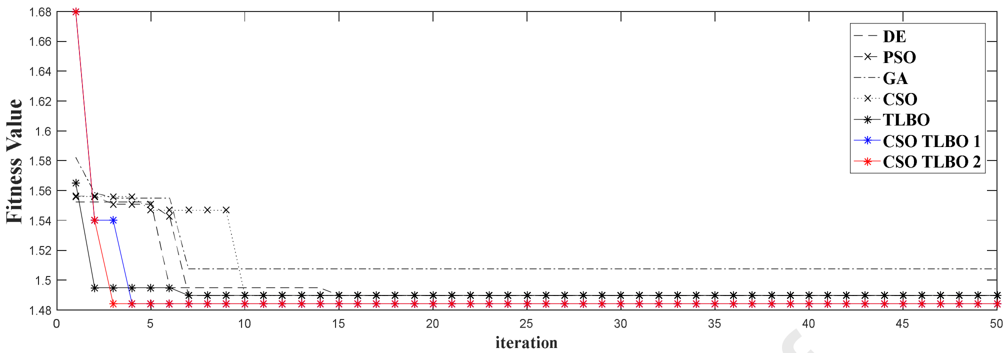

Fig. 3 Convergence curve of different algorithms for the best fitness value

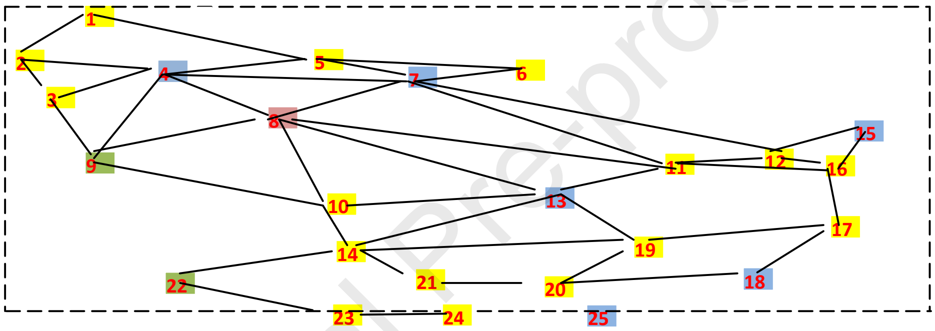

Fig. 4 Optimal placement of charging station in the road network obtained by CSO TLBO

6.3. Impact of charging station on distribution network

For an extended analysis, the impact of optimal placement of charging stations on different operating parameters of the distribution network was analyzed. Table 7 outlines the values of voltage deviation, reliability indices, and power loss before and after the placement of charging stations. The values of voltage deviation and power loss after the placement of charging stations were increased to 0.0058pu and 0.0053pu, respectively. It was evident that the voltage deviation and power loss after the placement of charging stations were within the acceptable limit. As given in Table 7, the reliability indices degraded with placement of charging stations. However, even the degraded values of reliability indices were far below the dead zone values reported in [41]. Thus, we concluded that the charging stations were allocated without compromising the distribution network stability and with making the charging stations accessible to EV drivers.

Table 7 Value of different operating parameters of distribution network before and after placement of charging stations (by CSO TLBO)

Parameter		Before charging station placement	After charging station placement
Voltage Deviation (pu)		0	0.0058
Reliability	SAIFI (interruption/year)	0.0982	0.1383
	SAIDI(hour/year)	0.5048	0.7566
	CAIDI(hour/interruption)	5.1385	5.8704
	AENS(kWhr/yr)	1.9369	2.5233
Power loss(pu)		0.0021	0.0053

6.4. Statistical comparison of different optimization algorithms

Statistical comparison of the quality of solutionsand time complexity analysis were performed for all the algorithms.The algorithms developed were tested in MATLAB 2016a software installed on a computer with the processor of Intel i7 CPU.One of the salient features of the evolutionary algorithm is the random generation of the population. As a consequence, different solutions are obtained from independent trials [47], [48]. In order to compare the quality of solutions and time complexity of different algorithms, a statistical analysis was done on the basis of a total of 50 independent trials. Table 8 provides the statistical comparison of CSO TLBO algorithm with other relevant algorithms. The best fitness, worst fitness, and mean fitness of both the hybridization scheme of CSO TLBO were found better than those of the other algorithms. The average execution time of CSO TLBO was longer than that of the others, which was due to involvement of both CSO and TLBO. The average execution time of Scheme 2 of combining CSO TLBO was longer than Scheme 1. Figure 5 illustrates the results of Friedman rank test. The CSO TLBO hada better rank thanthree other algorithms. Moreover, the rank of Scheme 2 of combining CSO TLBO was higher than that of Scheme 1. Therefore, depite having longer average execution time, the second scheme combining CSO TLBO was more competive than the first scheme. Table 9 reports the resultsof paired t test. From these results, we could find out that there were differences in the mean value of objective functions of the all pairs. In addition, the positive t-value indicated that the mean value of the objective function of CSO TLBO was far better (less) than the other algorithms.

Table 8 Statistical comparison of CSO TLBO with other algorithms in solving charging station placement problem

Algorithm	Best fitness	Worst fitness	Mean fitness	Average execution time (sec)
CSO TLBO (scheme 1)	1.4841	1.5613	1.5268	31.5
CSO TLBO (scheme 2)	1.4841	1.5637	1.5241	42.6
CSO	1.4870	1.5688	1.5430	7.87
TLBO	1.4878	1.5637	1.5413	25.56
PSO	1.4898	1.5636	1.5413	18.63
DE	1.4898	1.6199	1.5497	9.28
GA	1.5075	1.6199	1.5584	10.12

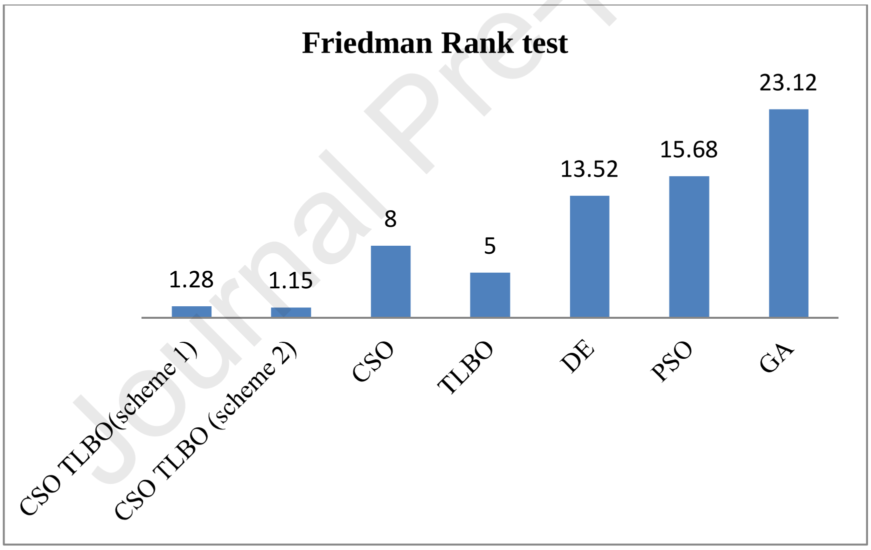

Fig. 5 Friedman rank test for charging station placement problem

Table 9 T test results

Algorithm		T value
CSO TLBO (Scheme 1)	CSO	3.1610
	TLBO	3.7500
	DE	1.9918
	PSO	2.10
	GA	2.05
CSO TLBO (Scheme 2)	CSO	5.1610
	TLBO	3.6324
	DE	1.9924
	PSO	3.4534
	GA	3.7800

7. Discussions

A novel CSO TLBO algorithm was developed in order to solve the EV charging station placement problem. Although the existing meta-heuristics techniques have been successful in dealing with many real-world optimization problems, it is always recommended to develop new algorithms with superior performances for particular types of problems. Moreover, No-Free-Lunch (NFL) states that a single algorithm fails to perform well on all the problems [42]. For these reasons, we have proposed a new algorithm for coping with the charging station placement problem. Some of the key findings of our work are:

1. The two schemes of combining CSO and TLBO are equally competitive or even better than the state-of-the-art algorithms, such as GA, PSO, DE, CSO, TLBO, and BA in optimizing the benchmark functions in Table 1.
2. CSO TLBO outperforms GA, DE, PSO, CSO, and TLBO in solving the problem at hand. However, the average execution time of the proposed algorithm is longer than the other state-of-the-art methods.
3. The convergence rate of the second scheme of combining CSO TLBO is slightly better than the first scheme. However, the average execution time and number of function evaluations of the second scheme of combining CSO TLBO is longer than the first one.
4. The proposed approach can optimally allocate the charging stations with the least impact on the electric power distribution network while simultaneously considering EV drivers' conveniences.

8. Conclusions

With the ever-increasing popularity of EVs, the establishment of charging infrastructure has become urgent to meet the charging demands and consequently abate greenhouse gas emissions. This paper targets at developing the charging infrastructure with the minimum cost and without affecting the operating parameters of the distribution network. The contribution of our work not only lies in proposing a simple single objective framework for charging station placement problem but also combining swarm intelligence techniques with TLBO. The superiority of the proposed hybrid algorithm in attacking charging station placement problem was clearly shown. The optimal charging station placement scheme obtained was found efficient enough to be implemented in real-world environment. Our future work will focus on dealing with the optimal placement of EV charging and swapping stations, planning of V2G enabled charging stations as well as real-time implementation of the planning scheme.

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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Highlights

- Novel formulation of charging station placement problem considering economic factor, grid parameters and drivers' convenience
- Two schemes for hybridization of CSO and TLBO
- Impact of charger placement on power grid

Scheme 1

Algorithm 3- Pseudo code of CSOTLBO (Scheme 1)
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
End while

Scheme 2

Algorithm 4- Pseudo code of CSOTLBO (Scheme 2)
Initialize the population size, gen and the other algorithm specific parameters of CSO TLBO
Set t=1
While (t<gen)
Activate CSO
Activate TLBO
t=t+1
End while

Declaration of interests

☐The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.