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A Robust Two-Stage Planning Model for the Charging Station Placement Problem Considering Road Traffic Uncertainty

Sanchari Deb, *Student Member*, *IEEE*, Kari Tammi, *Member, IEEE*, Xiao-Zhi Gao, Karuna Kalita, Pinakeswar Mahanta, Sam Cross

***Abstract*—The current critical global concerns regarding fossil fuel exhaustion and environmental pollution have been driving advancements in transportation electrification and related battery technologies. In turn, the resultant growing popularity of electric vehicles (EVs) calls for the development of a well-designed charging infrastructure. However, an inappropriate placement of charging stations might hamper smooth operation of the power grid and be inconvenient to EV drivers. Thus, the present work proposes a novel two-stage planning model for charging station placement. The candidate locations for the placement of charging stations are first determined by fuzzy inference considering distance, road traffic, and grid stability. The randomness in road traffic is modelled by applying a Bayesian network (BN). Then, the charging station placement problem is represented in a multi-objective framework with cost, voltage stability reliability power loss (VRP) index, accessibility index, and waiting time as objective functions. A hybrid algorithm combining chicken swarm optimization and the teaching-learning-based optimization (CSO TLBO) algorithm is used to obtain the Pareto front. Further, fuzzy decision making is used to compare the Pareto optimal solutions. The proposed planning model is validated on a superimposed IEEE 33-bus and 25-node test network and on a practical network in Tianjin, China. Simulation results validate the efficacy of the proposed model.**

***Index Terms*—Bayesian network, Charging station, Congestion, CSO TLBO, Electric vehicle, Optimization**

I. Introduction

In recent years, EVs have gained popularity principally as a cleaner alternative to fossil fuel-based transportation. Electrification of transport has the potential to reduce CO2 emissions over the vehicle lifecycle if the electric power production has low CO2 intensity [1]. Naturally, for a wider acceptance of EVs; the development of charging stations is required. The charging station placement problem is a complex and demanding problem concerned with questions such as:

- Where charging stations should be placed?
- What type of charging stations should be placed (slow/fast)?
- How many charging stations should be placed?

In other words, the charging station placement problem is an optimization problem where the decision variables are the locations, number, and type of charging stations; the objective functions include cost and operating parameters of the power grid such as power loss, voltage stability, reliability, and EV driver convenience; and the constraints include the upper and lower limits of charging stations and the power balance equation.

Improper placement of charging stations is a threat to the power system and may cause voltage instability and power loss [2], [3]. Moreover, the placement of charging stations at highly congested nodes in the road network will delay the time taken by EV drivers to reach the charging stations, thereby causing inconvenience. Thus, the optimal placement of charging stations is a complicated problem, as it involves interactions between distribution and road networks. Recently, many researchers have delved into the aforementioned placement issue. Deb *et al.* [4] comprehensively presented modelling approaches, objective functions, and constraints of the charging station placement problem. Liu *et al.*[5] identified candidate sites for EV charging station placement, taking into account environmental factors and EV service radius thereby solving the problem by using the modified primal-dual interior point algorithm (MPDIPA) with cost as objective function . In [6], the charging station placement problem was rendered in a multi-objective framework with EV flow, power loss, and voltage deviation as the objective functions and solved by data envelope analysis (DEA) combined with cross entropy (CE). In [7], the placement problem was formulated for fast charging stations in a multi-objective framework with cost, EV flow, and energy losses as the objective functions and solved by multi-objective evolutionary algorithm (MOEA). The placement problem was formulated for public parking lots and roadside fast-charging stations with cost as the objective function [8]. Further, in the same paper, a Voronoi

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diagram and particle swarm optimization (PSO) were employed to solve the placement problem. In [9], zonal traffic circulation was considered in the formulation of charging station placement along with station development cost and grid operator cost and solved by Genetic Algorithm (GA). In [10], cost and a demand response program were considered as the objective functions, and the problem was solved by applying PSO. Deb *et al.*[11]modelled the charging station placement problem with cost as the objective function while also accounting for the operating parameters of the distribution network, such as voltage deviation, reliability, and power loss, by imposing a penalty for violating the safe limits of these parameters . Furthermore, the authors also employed a novel CSO TLBO algorithm to obtain the optimal locations of charging stations. In [12], the authors presented a two-stage closed model for charging station placement considering the heterogeneous driving range and charging demand of EVs and solved the problem in CPLEX solver. The change in charging demand with time was captured by a modified capacitated flow refuelling location model. Reference[13] presented a two-stage planning model for optimal placement of charging stations considering stochastic arrival, dwell time of EVs, uncertainties in the state of charge of the batteries of EVs, charging choices, charging demand, and rate of adoption of EVs. This planning model was concerned with maximizing the convenience for EV drivers, thereby increasing the accessibility of charging stations [13]. In addition, the problem was solved by the sampling average approximation (SAA) technique and novel heuristics inspired by a score-measuring mechanism [14]. In [15], the authors presented a coordinated planning strategy for EV charging stations considering the establishment cost of charging stations, charging spots and lanes, travel cost from charging demand points to charging stations, and distribution network expansion cost and the problem was solved in a GAMS solver. In Zhang *et al.*[16], formulated the charging station placement problem as a mixed integer linear program considering charging station building cost, distribution network upgrade cost, cost of energy, and penalty for unsatisfied charging demand as objective functions. They also proposed a capacitated flow refuelling location model to address uncertainties related to driving range and finally, the problem was solved in a CPLEX solver. Rahmani-Andebili *et al.*[17] solved parking lot allocation for EVs considering cost, power loss, and expected energy not served as objective functions. The optimization problem was solved by using a quantum-inspired simulated annealing (QSA) algorithm.

Previous studies [5]–[17] reported the contributions of different researchers in the paradigm of charging station placement. A comparative analysis of the contributions of the present work with those of the existing literature is shown in Table I. Table I reveal that existing research neglects the reliability of distribution networks when modelling the charging station placement problem. Nevertheless, Deb et al.[3] reported the serious impact suffered by the placement of charging stations at the buses of a distribution network with a high failure rate on the reliability and security of the power system. Thus, neglecting the reliability of the power network while modelling the charging station placement problem is a highly significant research gap. Moreover, the existing studies on charging station planning do not take into account some of the key factors, such as the waiting time in the charging stations and congestion probabilities of the road network. Further, the planning models reported in [5], [8]–[10] and [17] show that the objective functions and constraints related to distribution networks are modelled comprehensively. However, these models neglected EV driver convenience. On the other hand, in the planning model reported in [13], EV driver convenience and the accessibility of charging stations are modelled effectively, but the security of the power grid is neglected. Thus, to address the aforementioned research gaps, a robust two-stage model for charging station placement is proposed in the present work that takes into account cost, voltage stability, reliability, power loss, EV driver convenience and waiting time in charging stations and simultaneously addresses road traffic uncertainty.

TABLE I
COMPARISON OF THE CONTRIBUTIONS OF THE PRESENT WORK WITH THOSE OF THE EXISTING LITERATURE

Ref	**Stages**	**Objective functions**	**Traffic uncertainty**	**Solution methodology**
[5]	Two	Cost	Not considered	MPDIPA
[6]	One	EV flow, power loss and voltage deviation	Not considered	DEA and CE
[7]	One	Cost, EV flow and energy losses	Not considered	MOEA
[8]	One	Cost	Not considered	Voronoi diagram and PSO
[9]	One	Cost	Considered	GA
[10]	One	Cost and demand response program	Not considered	PSO
[11]	One	Cost	Not considered	CSO TLBO
[12]	Two	Cost	Considered	CPLEX solver
[13]	Two	EV user convenience	Considered	SAA and novel heuristics based on score-measuring mechanism
[15]	One	Cost	Not considered	GAMS solver
[16]	One	Cost	Considered	CPLEX solver
[17]	One	Cost, power loss and energy not served	Not considered	QSA
Proposed approach	Two	Cost, VRP index, accessibility index, and waiting time	Considered	Pareto dominance-based CSO TLBO

Compared with the existing research works related to charging infrastructure planning, the main contributions of the present work are summarized as follows.

First, this work proposes a two-stage planning model for the charging station placement problem. In the first stage, the candidate locations for the placement of charging stations are identified by applying fuzzy logic considering the distance between a node in the road network and the nearest bus in the distribution network, traffic intensity, and grid stability. In the second stage, optimization is performed to select the optimal locations, type, and number of charging points considering cost, VRP index, accessibility index, and waiting time as objective functions. The first stage involving screening of the candidate locations of charging stations will reduce the size of the search space and reduce the complexity of the problem. To the best of the authors' knowledge, the screening of candidate locations for the placement of charging stations by applying fuzzy logic is performed for the first time in the paradigm of the charging station placement problem. The key features of the proposed robust two-stage planning model are as follows:

(1) Reduction in the search space by screening the candidate locations for the placement of charging stations by applying fuzzy logic

(2) Consideration of voltage stability, reliability, power losses, accessibility index, and waiting time in charging stations as objective functions

Second, the congested nodes in the road network with high traffic intensity are computed by a probabilistic approach based on a Bayesian network (BN). The capacity of the BN to deal with uncertainties is effectively utilized in the present work to find the congestion probabilities of the road network. Last, the planning model is validated on a standard IEEE 33-bus distribution network and 25-node road network as well as a real time-network in Tianjin.

II. Two-Stage Planning Model

A two-stage planning model is used to solve the charging station placement problem. In the first stage, the candidate locations for the placement of charging stations are identified by applying fuzzy logic considering the distance between a node in the road network and the nearest bus in the distribution network, traffic intensity, and grid stability. In the second stage, optimization is performed to select the optimal locations, type, and number of charging stations as well as charging points considering cost, VRP index, accessibility index, and waiting time as objective functions. The first stage involving screening of the candidate locations of charging stations will reduce the size of the search space and reduce the complexity of the problem.

A. Stage I: Determination of Candidate Locations for Charging Station Placement

In Stage I, the candidate locations for the placement of charging stations are determined by using Mamdani fuzzy inference (MFI) [18]. It is common practice to place the charging stations at the superimposed nodes of the distribution and road networks [6], [7], [11]. Thus, we can say that the superimposed nodes, or the nodes of the road network close to the buses of the distribution network, are the candidate locations for the placement of charging stations. However, some of these nodes might be congested with high traffic flow. Moreover, we cannot ignore the possibility that some of these nodes are weak points in the grid in terms of voltage stability. Hence, in the present work, the distance between a node in the road network and the nearest bus in the distribution network, traffic intensity, and the voltage sensitivity factor (VSF) are considered for finding the candidate locations for placing charging stations. The vagueness related to the aforementioned factors considered for finding the candidate locations for the placement of charging stations has motivated the authors to apply MFI. Fig. 1 shows MFI utilized in the present work to find the candidate locations for the placement of charging stations.

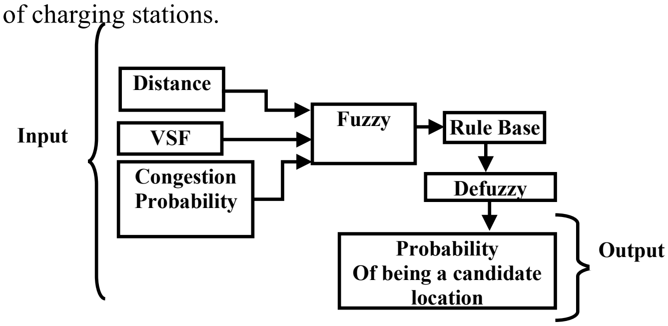

Fig. 1. Mamdani fuzzy inference used to find the candidate locations for the placement of charging stations.

The first input of MFI is the distance between a node in the road network and the nearest bus in the distribution network, which can be graphically calculated. The second input is the voltage sensitivity factor (VSF). The computational methodology of the second input of Mamdani Fuzzy inference, the VSF, can be found in [3]. The third input is the congestion probability of the road network nodes. The computational methodology of the congestion probability is illustrated in Section II (B). The linguistic variables associated with the three inputs are high (H), medium (M), and low (L). The linguistic variables associated with the output are high (H) and low (L). Triangular membership functions are used for both the input and output of MFI. The rule base of MFI is shown in Table II. Defuzzification is performed using the centre of gravity method [18]. The locations of the test network with high values of the defuzzified output are the candidate locations for the placement of charging stations. The details of the VSF and congestion probability are elaborated below. In addition, the distance is graphically calculated between the transport network node and its nearest distribution network bus.

TABLE II
RULE BASE OF MAMDANI FUZZY INFERENCE

Input			Output
VSF	**Distance**	**Congestion probability**	**Probability of being a candidate location**
L	L	L	H
L	L	M	H
L	L	H	L
L	M	L	H
L	M	M	L
L	M	H	L
L	H	L	L
L	H	M	L
L	H	H	L
M	L	L	L
M	L	M	L
M	L	H	L
M	M	L	L
M	M	M	L
M	M	H	L
M	H	L	L
M	H	M	L
M	H	H	L
H	L	L	L
H	L	M	L
H	L	H	L
H	M	L	L
H	M	M	L
H	M	H	L
H	H	L	L
H	H	M	L
H	H	H	L

- VSF- The VSF quantifies the change in the bus voltage upon increasing the active power or loading. Mathematically, it is defined as:

$$VSF=\left|\frac{dV}{dP}\right| \tag{1}$$

where dV indicates the change in bus voltage and dP indicates the change in active power.

The present study models the placement problem in the context of a radial distribution network. Due to the high resistance-to-reactance (R/X) ratio in the case of a radial distribution network, there is a possibility that the Jacobian matrix may become singular. Thus, the conventional Newton-Raphson method cannot be used for computing the voltages of the buses in the case of a radial distribution network. Hence, the voltage of the buses is determined by the forward and backward sweep algorithm [19]. The pseudo-code illustrating the computation of the VSF is shown in Algorithm 1.

Algorithm1- Pseudo-code for computation of the VSF [19]

Input the bus data and line data;
Run distribution load flow for base case by forward backward method;
For i=1: total number of bus;
$VSF_{base}(i)=\frac{dV(i)}{dP(i)}$;
End for
k=1;
While k< Realistic loading margin
Increase load in steps;
Run distribution load flow by forward backward sweep algorithm;
If load flow converges
k=k+1;
else

Algorithm 1 continues

Compute VSF for critical loading;
End if else
End while

- Congestion probability of road network- The present work proposes a probabilistic approach based on a BN for finding the nodes of the road network with high traffic intensity. The capability of the BN in handling uncertainty and interaction among different events is effectively utilized in the present work [20]. The BN model used for the computation of congestion probability is shown in Fig.2. Table III presents a summary of the node types and states of different nodes of the proposed BN. The probability that a road network is congested depends on the traffic flow, which, in turn, depends on the day of the week, time of day, area covered by the road, and lanes of the road. Thus, 'Day', 'Time', 'Area', and 'Lane' are the root nodes [20] of the BN. In addition, 'Traffic Flow' is the child node [20] of the nodes 'Day', 'Time', 'Area', and 'Lane'. Similarly, 'Congestion' is the child node of 'Traffic Flow'. The probability of congestion being high or low can be computed with a bucket elimination algorithm [20]–[23]. The congestion probabilities of residential single- and double-lane roads are:

$$P_{RS}=P(\text{Area=R,Lane=S})|P(\text{congestion=H}) \tag{1}$$

$$P_{RD}=P(\text{Area=R,Lane=D})|P(\text{congestion=H}) \tag{2}$$

where P_{RS} and P_{RD} are the probabilities that residential single-lane and double-lane roads are congested.

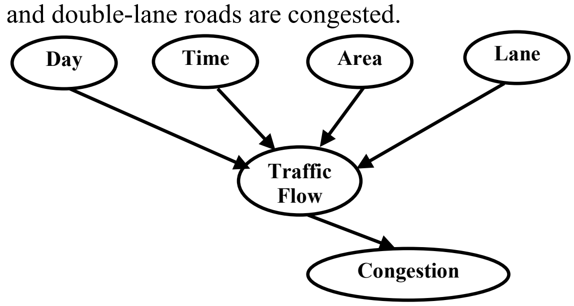

Fig. 2. BN model for congestion of a road network.

TABLE III
SUMMARY OF THE NODES OF THE PROPOSED BN

Node name	Type	States
Day	Parent	{Weekday, Weekend}
Time	Parent	{AM Peak, Work, PM Peak, Leisure, Rest}
Area	Parent	{Residential(R), Office (O), Market (M), School (Sc)}
Lane	Parent	{Single (S), Double (D)}
Traffic Flow	Child	{Low (L), Medium (M), High (H)}
Congestion	Child	{Low (L), High (H)}

The congestion probabilities of other roads can also be found by replacing the numerators of Eq. (1) and Eq. (2) accordingly based on the area and lanes.

B. Stage II: Optimal Locations of Charging Stations

The second stage of the proposed planning model involves finding the best or optimal locations for the placement of charging stations (p) from the set of candidate locations ($p_{candidate}$), the number of fast/slow charging stations, and the number of fast/slow charging points or servers. The logical relationship between charging stations and chargers or charging points cannot be explained mathematically. Chargers represent the charging points or servers present in the charging stations to perform the charging service.

The objective functions are cost, voltage stability reliability power loss (VRP) index, accessibility index, and waiting time in the charging stations. The constraints include the voltage limit, active and reactive power limits, power balance equations, maximum and minimum numbers of fast and slow charging stations placed at each location and maximum and minimum numbers of fast and slow charging points in the respective charging stations. The objective functions and constraints of the placement problem are elaborated in this section.

List of Notation used in the planning model

Decision variables	
p	Optimal locations for the placement of charging stations
F_P, S_P	Number of fast/slow charging stations at location p
f_p, s_P	Number of fast/slow servers at location p
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_{elec}	Per-unit cost of electricity
VSI_{base}	Base value of voltage stability index
$SAIFI_{base}$	Base value of system average interruption frequency index (SAIFI)
$SAIDI_{base}$	Base value of system average interruption duration index (SAIDI)
$CAIDI_{base}$	Base value of customer average interruption index (CAIDI)
P_{loss}^{base}	Base value of power loss
F_{max}, f_{max}	Maximum number of fast charging stations and charging points
S_{max}, s_{max}	Maximum number of slow charging stations and charging points
F_{min}, f_{min}	Minimum number of fast charging stations and charging points
S_{min}, s_{min}	Minimum number of slow charging stations and charging points
Functions	
$C_{installation}$	Installation cost
$C_{operation}$	Operation cost
V	Voltage stability index
R	Composite reliability index
P	Power loss
A	Accessibility index
W_t	Waiting time in charging stations
Variables	
m	Maximum number of locations in which charging stations will be placed
q	Total number of charging demand points
w_1	Weight assigned to voltage stability index
w_2	Weight assigned to composite reliability index
w_3	Weight assigned to power loss
w_{21}	Weight assigned to SAIFI
w_{22}	Weight assigned to SAIDI
w_{23}	Weight assigned to CAIDI
VSI_l	Voltage stability after placement of charging stations
$SAIFI_l$	SAIFI after placement of charging stations
$SAIDI_l$	SAIDI after placement of charging stations
$CAIDI_l$	CAIDI after placement of charging stations
P_{loss}^{l}	Power loss after placement of charging stations
d_ic_j	Distance between i^{th} charging demand point and j^{th}charging station
W_f	Waiting time in fast charging stations
W_s	Waiting time in slow charging stations
λ_f, λ_s	Arrival rates of EVs in fast and slow charging stations
ρ_f, ρ_s	Utilization rates of fast and slow charging stations
P_0^f , P_0^s	Probabilities of no EVs in fast and slow charging stations
P_{gi}	Active power generation of i^{th} bus
P_{di}	Active power demand of i^{th} bus
Q_{gi}	Reactive power generation of i^{th} bus
Q_{di}	Reactive power demand of i^{th} 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 i^{th} bus
δ_j	Voltage angle of j^{th} bus
d_ic_j	Distance between i^{th}charging station and j^{th}charging demand point where i=1,2...q and j=1,2...m
Matrices	
D	Distance matrix
DD	Reduced distance matrix

The present work is concerned with minimization of cost, VRP index, and waiting time in the charging stations simultaneously with maximization of the accessibility index.

Thus, the objective function can be mathematically expressed as:

$$F=\min(cost)+\min(VRP\ index)+\max(Accessibility\ index)+\min(waiting\ time) \tag{3}$$

$$Cost=C_{installation}+C_{operation} \tag{4}$$

$$C_{installation}=\{(\sum_{i=1}^{m}F_i\times f_i)\times C_{fast}\}+\{(\sum_{i=1}^{m}S_i\times s_i)\times C_{slow}\} \tag{5}$$

$$C_{operation}=\{(\sum_{i=1}^{m}F_i\times f_i)\times CP_{fast}\}+\{(\sum_{i=1}^{m}S_i\times s_i)\times CP_{slow}\}\times P_{elec} \tag{6}$$

$$VRP=f(p,F_p,S_p,f_p,s_p)=w_1V+w_2R+w_3P \tag{7}$$

where $V=\dfrac{VSI_{base}}{VSI_l}$

$$R = w_{21}\frac{SAIFI_l}{SAIFI_{base}} + w_{22}\frac{SAIDI_l}{SAIDI_{base}} + w_{23}\frac{CAIDI_l}{CAIDI_{base}} \quad P=\frac{P_{loss}^{l}}{P_{loss}^{base}}$$

$$Accessibility\ index=f(p)=\frac{1}{|d|} \tag{8}$$

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

$$d=\sum_{i=1}^{q} DD_i \tag{9}$$

$$Waiting\ time(W_t) = W_f + W_s \tag{10}$$

$$W_f=\frac{\sum_{i=1}^{m}\frac{\rho_f^{f_i+1}}{(f_i-1)!\times(f_i-\rho_f)^2}\times P_0^f}{\lambda_f} \tag{11}$$

$$W_s=\frac{\sum_{i=1}^{m}\frac{\rho_s^{s_i+1}}{(s_i-1)!\times(s_i-\rho_s)^2}\times P_0^s}{\lambda_s} \tag{12}$$

Subject to

$$F_{\min} < F_p \le F_{\max} \quad \text{and} \quad f_{\min} < f_p \le f_{\max} \tag{13}$$

$$S_{\min} < S_p \le S_{\max} \quad \text{and} \quad s_{\min} < s_p \le s_{\max} \tag{14}$$

$$P_{gi}-P_{di}-V_i\sum_{j=1}^{N_D}V_jY_{ij}\cos(\delta_i-\delta_j-\theta_{ij})=0 \tag{15}$$

$$Q_{gi}-Q_{di}-V_i\sum_{j=1}^{N_D}V_jY_{ij}\sin(\delta_i-\delta_j-\theta_{ij})=0 \tag{16}$$

As illustrated in Eq. (5) and Eq. (6), the installation and operating costs are only dependent on the number of fast and slow charging stations and the number of fast and slow servers. It is assumed that the land, floor, building, labour, charger, and electricity costs are the same for all nodes in the entire network. As illustrated by Eq. (7), the VRP index is a function of the locations and numbers of charging stations and servers. The detailed mathematical formulations of the VRP index can be found in Deb et al.[3]. As illustrated by Eq. (9), the distance matrix, *D,* gives the distance between the charging point demand and charging stations. In addition, the reduced distance matrix, *DD,* gives the distance between the charging point demand and its nearest charging station. The waiting time (W_t) in charging stations causes inconvenience to EV drivers. Hence, the optimization aims to minimize the waiting time. In the present work, the waiting time in charging stations is modelled by the M/M/c queuing theory [24]–[26]. An M/M/c queue is a stochastic process with state space in the set {0, 1, 2, 3 ...}, where the value corresponds to the number of EVs in the system, including any currently in service. Arrivals occur at rate λ according to a Poisson process and move the process from state i to state i+1. Service times have an exponential distribution with utilization factor μ. The detailed mathematical formulations of the waiting time can be found in Ref [24]–[26].

The constraints depicted by Eq. (13) and Eq.(14) consider the maximum and minimum numbers of fast and slow charging stations placed at the candidate locations and the maximum and minimum numbers of fast and slow servers placed at the candidate locations. The amount of power generated at all buses must satisfy the load demand and losses. Hence, the power balance equations given by Eq. (15) and Eq. (16) are considered equality constraints in the charging station placement problem.

III. Optimization Algorithms

The solution methodology applied for solving the charging station placement problem reported in Section II leans on nature-inspired optimization algorithms. The present work uses a novel Pareto dominance-based CSO TLBO algorithm proposed by Deb *et al.*[27] as a tool to solve the optimization problem. CSO is a nature-inspired optimization algorithm proposed by Meng *et al*. [28] mimicking the food searching process of chickens in a swarm. Salient features of CSO are good utilization of the population and a good balance between exploration and exploitation. Similarly, TLBO is also a nature-inspired algorithm proposed by Rao *et al*. [29] mimicking the teaching and learning process. For the sake of completeness, the pseudo-codes of multi-objective CSO, TLBO, and Pareto dominance-based CSO TLBO are given by Algorithms 2-4, respectively.

Algorithm 2-Pseudo-code of multi-objective CSO [27]

Initialize the population of chickens having size PN and define other algorithm specific parameters such as G, size of rooster, hen, chicken and mother hen;
Evaluate the rank of PN chickens, t=0, establish the hierarchal order in the swarm based on rank and form 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:
$x_{i,j}^{t+1}=x_{i,j}^{t}\times(1+\mathrm{randn}(0,\sigma^2))$;
%where randn(0,σ^2) is a Gaussian distribution function with mean 0 and standard deviation σ^2
End if
If i==hen

Algorithm 2 continues

Update its solution by:

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

%where $S1=\exp(\frac{f_i-f_{r1}}{\mathrm{abs}(f_i)+\varepsilon})$ $S2=\exp(f_{r2}-f_i)$

rand *is a randomly generated number between 0 and 1.* $r1\in[1,N]$ *is an index of the rooster thatisthei*th *hen's group mate. In addition,* $r2\in[1,N]$ *is an index of the rooster or hen thatis randomly chosen such that r1 is not equal to r2, f denotes the fitness function,* ε is a small number

End if
If i==chick
Update its solution by $x_{i,j}^{t+1}=x_{i,j}^{t}+FL\times(x_{m,j}^{t}-x_{i,j}^{t})$ *;*

%where $x_{m,j}^{t}$ *represents the position of the i*th *chick's mother. FL is a parameter signifying that the chick would follow its mother. FL is generally chosen between 0 and 2*
End if
Compute the rank of all the individuals of the population
If rank(t)<rank(t-1)
Update the solution
If rank(t)=rank(t-1)
Compute crowding distance of all the individuals of the population
If crowding distance(t)>crowding distance(t-1)
Update the solution
Else
Retain the existing solution
End if else
Else
Retain the existing solution
End if else
End for
End if else
End while

Algorithm 3- Pseudo-code of multi-objective TLBO [27]

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 (T_k*)based on the rank;*
for i=1:PN
Update each learner by: $Z_{new}=Z_{old}+\mathrm{rand}\times(T_k-R_t m_k)$
% where rand is a random number, R_t*is random number between 0 and 2,*m_k*is the mean of the decision variable vector*
End if else
{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 ith*learner by* $Z_{new}=Z_{old}+rand\times(Z_i-Z_j)$ *; % rand is a random number*
Else
Replace ith*learner by* $Z_{new}=Z_{old}+rand\times(Z_j-Z_i)$ *;*
End if else
End for
Compute the rank of all the individuals of the population
If rank(t)<rank(t-1)
Update the solution
If rank(t)=rank(t-1)
Compute crowding distance of all the individuals of the population
If crowding distance(t)>crowding distance(t-1)
Update the solution
Else
Retain the existing solution

Algorithm 3 continues

End if else
Else
Retain the existing solution
End if else
k=k+1
End while

Algorithm 4- Pseudo-code of Pareto dominance-based multi-objective CSO TLBO [27]

Initialize the population size, gen and other algorithm-specific parameters of CSO TLBO
Set t=1
While (t<gen)
Activate TLBO
If (t mod INV)>0 % INV is the frequency of introducing CSO
Activate CSO
End if
t=t+1
Selection based on rank and crowding distance
End while

IV. SOLUTION OF CHARGING STATION PLACEMENT PROBLEM BY CSO TLBO

Pareto dominance-based multi-objective CSO TLBO is employed in the present work to solve the charging station placement problem. The systematic procedure for the solution of the charging station placement problem by CSO TLBO is as follows:

Step 1: Initialization

Step 1.1: Input data. Input the road network and distribution network data and upper and lower limits of different constraints, and set the different algorithm-specific parameters of CSO TLBO.

Step 1.2: Generate a feasible initial population randomly.

The initial feasible population is of the form:

$$pop_{\mathrm{int}l}=[A_{pop}\,B_{pop}\,C_{pop}\,D_{pop}\,E_{pop}]$$

where

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

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

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

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

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

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

Step 1.3: Evaluate the four objective functions, cost, VRP index, accessibility, and waiting time, for the initial population. Compute the rank and crowding distance by the methodology elaborated in Ref [30], [31]. 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 the rank and crowding distance.

Step 2.2: If the elements of B_{pop} exceed F_{max} and the elements of C_{pop} exceed S_{max}, then those elements are made equal to F_{max} and S_{max}, respectively. Similarly, if the elements of D_{pop} exceed f_{max} and the elements of E_{pop} exceed s_{max}, then those elements are made equal to f_{max} and s_{max}, respectively.

Step 2.3: Otherwise, check the feasibility of the solution. If the solution is infeasible, repeat Step 2.1 and Step 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: Run CSO.

Step 3.2: Update the solution based on the ranking and crowding distance.

Step 3.3: Repeat Step 2.2.

Step 3.4: Otherwise, check the feasibility of the solution. If the solution is not feasible, repeat Step 3.1 and Step 3.2 until 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, print the Pareto front. Otherwise, repeat Steps 2 to 4.

Step 5: The best compromise solution is selected from the set of non-dominated solutions by using fuzzy decision making [32]–[34].

V. Results

A. Test System and Input Parameters

The proposed two-stage planning model is validated on a superimposed IEEE 33-bus distribution network and 25-node road network as well as a practical network in Tianjin, China. The superimposed IEEE 33-bus distribution network and 25-node road network are shown in Fig. 3.The second test system is a real-time network in Tianjin, China, as shown in Fig. 4.The power distribution network in Tianjin resembles the standard IEEE 69-bus system [35]. The bus and line data of the IEEE 33-bus system and 69-bus system can be found in [3], [35].The types of nodes and charging demand points in the road network are reported in Table IV for Test system 1 and Test system 2. Table V reports the input parameters of the charging station placement problem. Table VI reports the values of the upper and lower limits of the constraints of the charging station placement problem. It is assumed that EVs follow the routes(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 (1-2-3-4-5-6-7-8-9-10-13-11-12-15-16-17-19-20-21-14-22-23-24-25) for Test system 1 and (1-2-3-4-5-10-9-8-6-11-12-13-14-15-16-21-20-19-18-17) and (1-2-3-4-5-10-9-8-6-11-12-13-14-15-16-21-20-19-18-26-22-27-23-28-24-25) for Test system 2. The driving range of EVs is considered to be 150 km. The power consumption of fast and slow chargers can be found in [3].

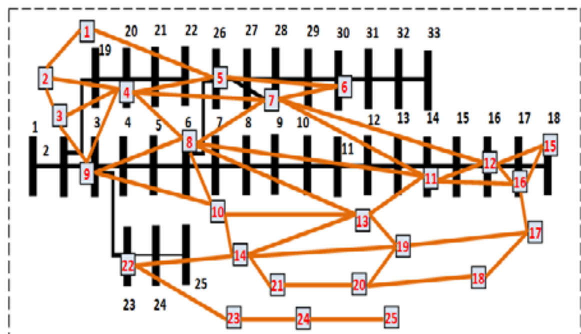

Fig. 3. Superimposed IEEE 33-bus distribution and 25-node road networks [11].

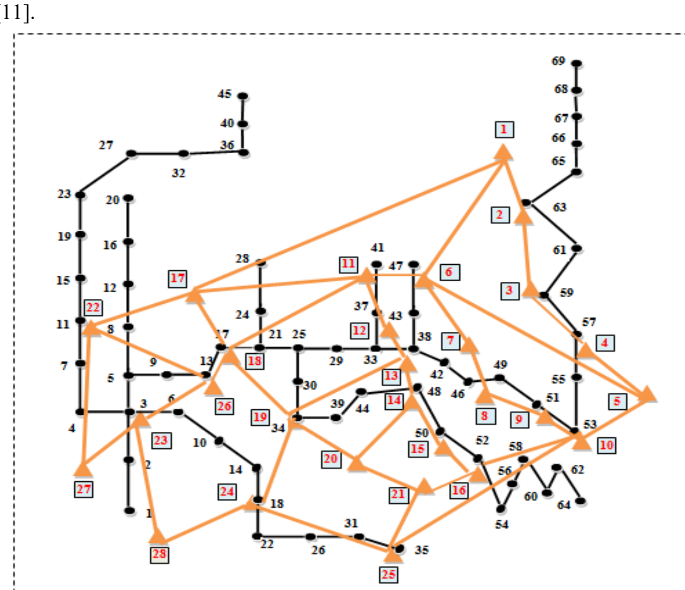

Fig. 4. Superimposed distribution and road networksinTianjin [35].

TABLE IV

TYPES OF NODES IN THE ROAD NETWORK

Test system 1		Test system 2	
Type	**Node no.**	**Type**	**Node no.**
Residential	1, 2, 3, 4, 18,20,21, 22, 23, 24, 25	Residential	1,2, 12, 13, 14, 15, 16, 22, 23
School	10, 11, 13, 14, 19	School	3, 6, 7, 8, 17, 19, 24
Market	12, 15, 16, 17	Market	5, 11, 20, 21, 26, 27
Office	5, 6, 7, 8, 9	Office	4, 9, 10, 18, 25,28
Single lane	3, 5, 6, 7, 8, 9, 10, 14, 22, 23, 24, 25	Charging demand	1, 7, 12, 15, 20, 25
Double lane	1, 2, 4, 7, 11, 12, 13, 15, 16, 17, 18, 19, 20, 21, 22	In the case of Tianjin, no information regarding single- and double-lane roads was available.	
Charging demand	4, 7, 9, 13, 15, 18, 22, 25		

TABLE V

INPUT PARAMETERS [3]

Parameter	Value	Parameter	Value
C_{fast}	3000 \$	w_2	0.7
C_{slow}	2500 \$	w_{21}	0.2
CP_{fast}	50 kW	w_{22}	0.4
CP_{slow}	19.2 kW	w_{23}	0.1
$P_{electricity}$	65 \$/MWhr	w_3	0.2
w_1	0.1	λ_f	5.6/hr
λ_s	1.4/hr		

TABLE VI

UPPER AND LOWER LIMITS OF CONSTRAINTS

Test system 1				Test system 2			
S_{max}	3	s_{max}	20	S_{max}	3	s_{max}	20
F_{max}	2	f_{max}	10	F_{max}	2	f_{max}	10
S_{min}	1	s_{min}	5	S_{min}	1	s_{min}	6
F_{min}	1	f_{min}	3	F_{min}	1	f_{min}	4

B. Screening of Candidate Locations for Charging Station Placement

The candidate locations for the placement of charging stations are found by applying MFI, as elaborated in Section II. The first input of MFI named the VSF is computed by the pseudo-code elaborated by Algorithm 1 in Section II (A). The VSFs of the IEEE 33-bus and IEEE 69-bus distribution networks are shown in Fig. 5 and Fig.8, respectively. Fig. 5 reveals that bus 14 of the IEEE 33-bus distribution network has the highest VSF, indicating that it is most vulnerable to voltage instability. Fig. 8 indicates that bus 65 of the IEEE 69-bus distribution network has the highest VSF, indicating that it is the weakest bus in the system. Fig.6 and Fig.9 provide graphical representations of the distance between a road network node and its nearest bus in the distribution network for Test system 1 and Test system 2, respectively. Table VII reports the congestion probabilities of the nodes in the road network computed by a BN for Test system 1 and Test system 2. The set of candidate locations of charging stations is computed by fuzzy logic illustrated in Section II with the VSF, distance, and congestion probability as input parameters. The values of defuzzified outputs representing the probability of being a candidate location for EV charging station placement for Test system 1 and Test system 2 are shown in Figs.7 and 10, respectively. The buses with high values of the defuzzified output are the candidate locations for EV charging station placement. Thus, for Test system 1, the candidate locations are $P_{candidate}$= {2, 4, 5, 7, 21, 22, 24, 25, and 27}, and, for Test system 2, the candidate locations are $P_{candidate}$= {5, 9, 13, 28, 30, 31, 34, 35, 39, 41, 42, 46, 47, 49, and 51}. For Test system 1, the search space is reduced by 72.73%, and for Test system 2, the search space is reduced by 78.26%.

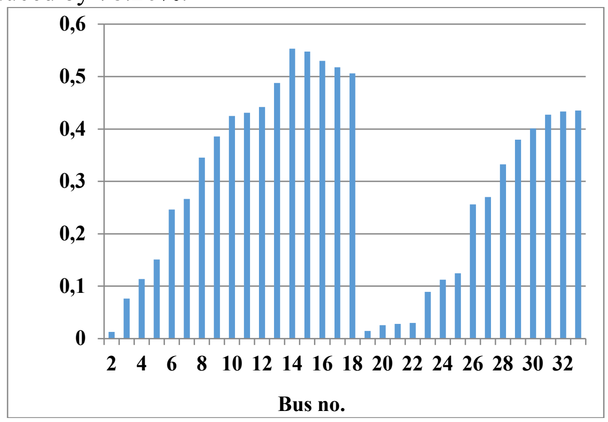

Fig. 5. VSF of IEEE 33-bus distribution network.

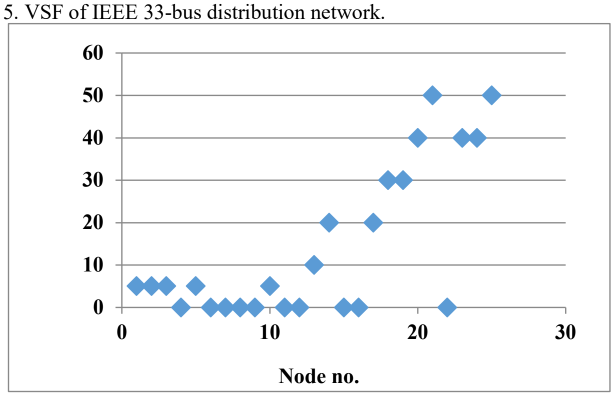

Fig. 6. Distances between the road network and the nearest bus in the distribution network for Test system 1.

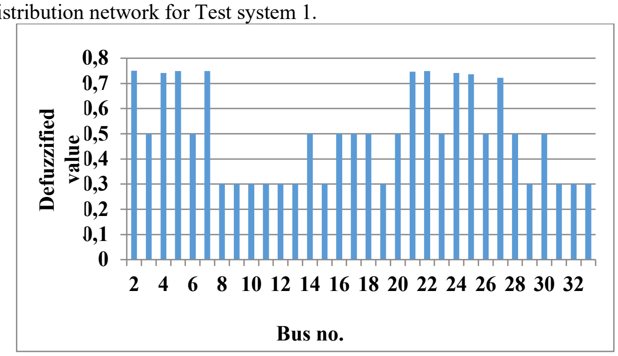

Fig. 7. Defuzzified values representing the probability of being a candidate location of charging station placement for Test system 1.

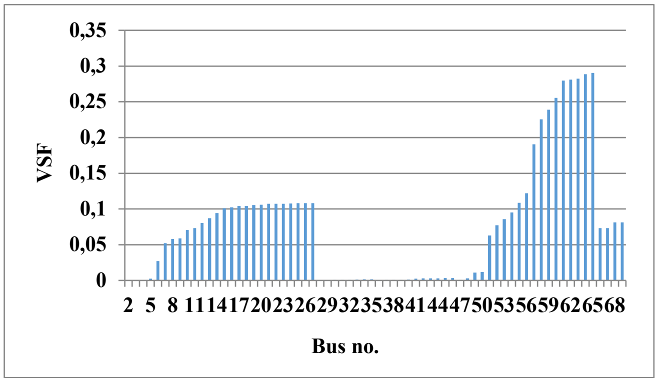

Fig. 8. VSF of IEEE 69-bus distribution network.

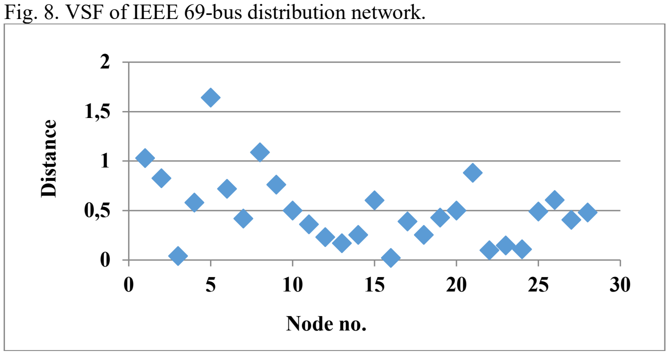

Fig. 9. Distances between the road network and the nearest bus in the distribution network for Test system 2.

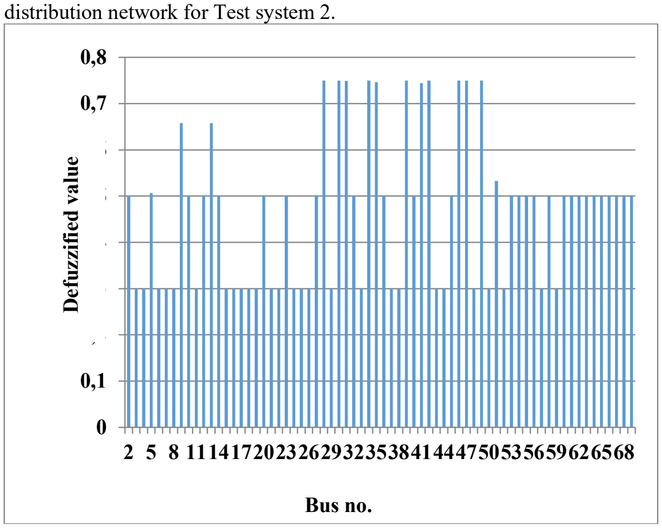

Fig. 10.Defuzzified values representing the probability of being a candidate location of charging station placement for Test system 2.

TABLE VII
CONGESTION PROBABILITIES OF THE NODES IN THE ROAD NETWORK

Test system 1					
Area	**Lane**	**Congestion Probability**	**Area**	**Lane**	**Congestion Probability**
Residential	Single	0.619	Market	Single	0.524
Residential	Double	0.44	Market	Double	0.39
School	Single	0.283	Office	Single	0.387
School	Double	0.185	Office	Double	0.179
Test system 2					
Area		**Congestion Probability**	**Area**		**Congestion Probability**
Residential		0.72	Market		0.54
School		0.153	Office		0.198

C. Optimal Allocation of Charging Stations

The second stage of the proposed two-stage planning model involves selecting the best locations for EV charging station placement from the set $P_{candidate}$. The optimization problem reported in Section III is solved by the Pareto dominance-based CSO TLBO algorithm explained earlier in Section IV. The optimization is run for a population size of 10 and generation size of 20. The values of algorithm-specific control parameters of CSO TLBO are the same as those in Deb et al. [11].In multi-objective optimization, a number of optimal solutions are obtained instead of a single optimal solution due to the involvement of conflicting objectives. For both Test system 1 and Test system 2, the optimization yielded six non-dominated solutions (NDSs) or planning schemes, as shown in Table VIII. Table IX reports the values of the four objective functions for the six planning schemes. It is observed that for Test system 1, Plan 3 is the most economical, whereas Plan 6 is the most expensive. However, in Plan 3, the values of the accessibility index and waiting time in charging stations are not satisfactory and may cause inconvenience to EV drivers. The optimized values of the VRP index are satisfactory for all six plans. For Test system 2, Plan 6 is the most economical, while Plan 3 is the most expensive. Plan 3 seems to be the most suitable plan if EV driver convenience is taken into account.

TABLE VIII
OPTIMAL ALLOCATION OF CHARGING STATIONS

Test System 1											
NDS	**p**	**F_p**	**S_p**	**f_p**	**s_p**	**NDS**	**p**	**F_p**	**S_p**	**f_p**	**s_p**
1	4	1	1	9	6	4	21	1	1	3	9
	24	1	1	4	6		5	1	2	5	9
	2	1	1	4	13		2	1	1	6	7
2	2	1	1	8	13	5	2	1	1	10	7
	7	1	1	4	10		7	1	1	10	7
	25	1	1	6	10		24	1	1	6	16
3	5	1	1	4	8	6	7	1	1	6	9
	2	1	1	3	9		4	1	3	5	14
	7	1	1	4	9		22	1	1	6	11
Test System 2											
1	13	1	1	6	11	4	39	1	1	6	10
	35	1	1	10	8		34	1	1	6	11
	34	1	1	7	8		28	1	1	6	11
2	34	1	1	5	7	5	39	1	2	5	9
	28	1	1	5	8		28	1	1	6	8
	13	1	1	5	8		35	2	1	4	11
3	34	1	1	8	8	6	28	1	1	3	9
	39	1	1	7	16		34	1	2	6	7
	28	1	1	6	14		13	1	1	3	6

TABLE IX
OBJECTIVE FUNCTION VALUES FOR THE PLANNING SCHEMES

Test system 1				
Planning Scheme	**Cost ($\$\times10^6$)**	**VRP**	**A(/km)**	**W_t(hr)**
1	4.5073	11.5071	0.0006	0.5311
2	5.1572	11.7378	0.0010	0.0388
3	3.4954	11.5666	0.0009	0.2390
4	4.5023	11.3693	0.0011	0.2812
5	5.1589	11.6957	0.0009	0.3084
6	6.6878	11.9560	0.0019	0.0295
Test system 2				
1	5.6960	21.5313	0.1347	0.0828
2	4.0325	21.3883	0.1171	0.2030
3	5.9873	20.9884	0.1253	0.0437
4	5.0983	20.9716	0.1253	0.0155
5	5.5714	21.0038	0.1241	0.1332
6	3.8506	21.3488	0.1171	0.6446

D. Impact of Charging Stations on Distribution Network

The impact of EV charging station placement on the distribution network is examined for further analysis. The voltage profiles of all the buses in the IEEE 33-bus distribution network and IEEE 69-bus distribution network for the six planning schemes are shown in Figs.11 and 12, respectively. The voltage profiles of all the buses are within an acceptable range. The impact of EV charging stations on different reliability indices such as SAIFI and SAIDI is shown in Figs.13-16 for Test system 1 and Test system 2, respectively. The reliability indices of the network, such as SAIFI and SAIDI, have degraded due to the increased EV load. Nevertheless, the degraded values are far less than the dead zone values of the reliability indices reported in Chowdhury and Koval[36].

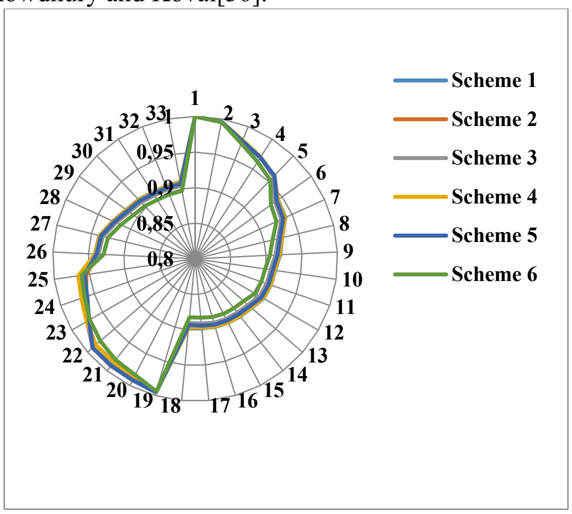

Fig. 11. Voltage profile of the IEEE 33-bus distribution network after charging station placement.

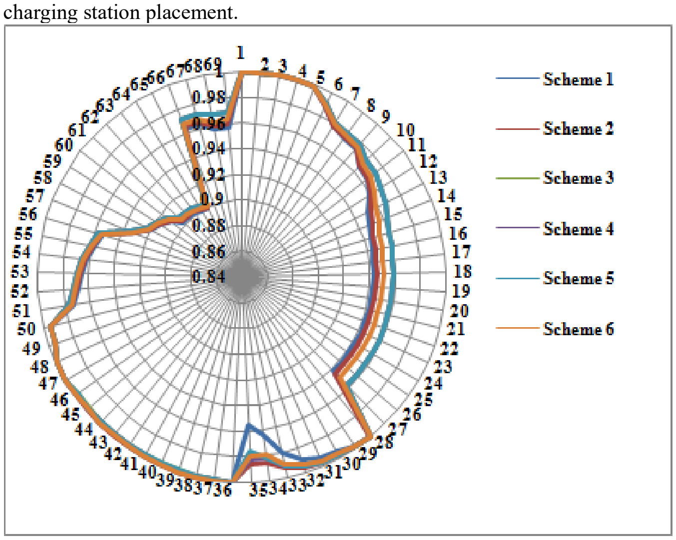

Fig. 12. Voltage profile of the IEEE 69-bus distribution network after charging station placement.

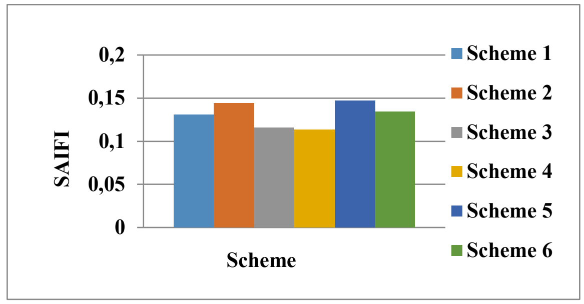

Fig. 13. Impact of EV charging stations on the SAIFI of the IEEE 33-bus distribution network.

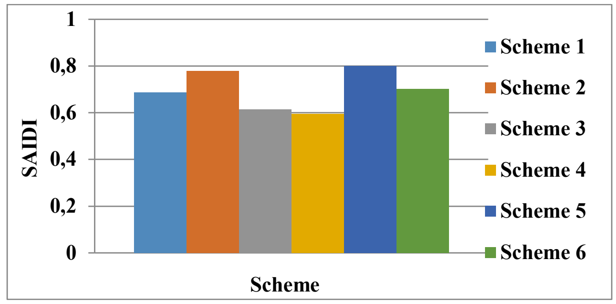

Fig. 14. Impact of EV charging stations on the SAIDI of the IEEE 33-bus distribution network.

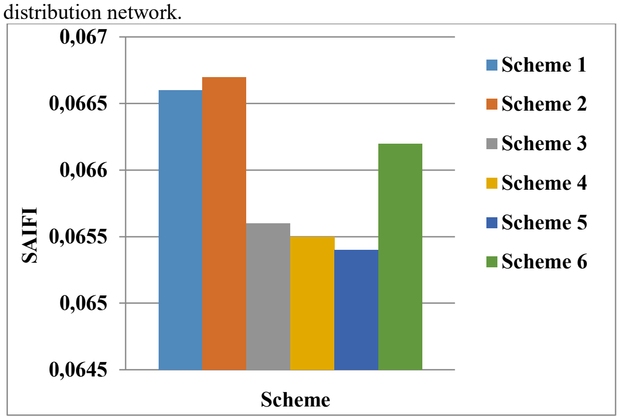

Fig. 15. Impact of EV charging stations on the SAIFI of the IEEE 69-bus distribution network.

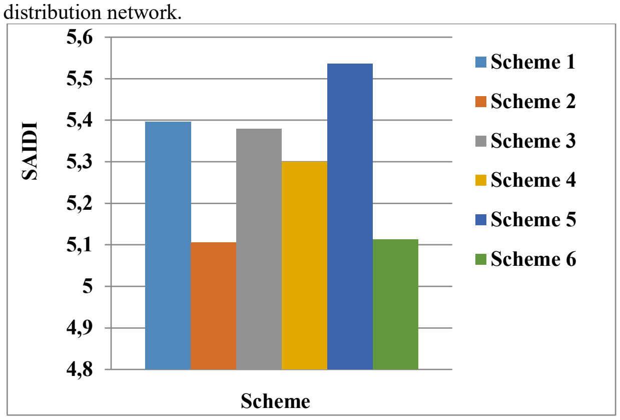

Fig. 16. Impact of EV charging stations on the SAIDI of the IEEE 69-bus distribution network.

E. Final Decision Making

It is difficult to select the best plan out of the six plans presented due to the interaction of conflicting objective functions. In the real world, some criteria cannot be measured by precise values due to the ambiguity arising from human qualitative judgement [34]. Fuzzy evaluation can be used for the quantification of such cases. In the present work, a fuzzy evaluation system is used for the final decision making [34]. The cost, VRP index, accessibility index, and waiting time are chosen as the four aspects of decision making in the charging station placement problem. In fuzzy decision making, low cost, VRP index, and waiting time received higher evaluations. High accessibility also received a higher evaluation. Table X lists the scale of the four objective functions based on the aforementioned criteria for Test system 1 and Test system 2. The scores of each plan obtained by the fuzzy evaluation system are reported in Table XI for Test system 1 and Test system 2. Fig.17 shows radar charts of the six planning schemes for Test system 1. The area occupied by Plan 4 is larger than that of the other five figures, indicating that Plan 4 is the most advantageous plan for Test system 1. Fig.18 shows radar charts of the six planning schemes for Test system 2. It is observed from Fig. 18 that the area occupied by Plan 4 is highest, thus indicating that it is the most preferable plan for Test system 2.

TABLE X
SCALE OF THE FUZZY EVALUATION SYSTEM

Test system 1					Test system 2				
Scale	Cost ($\$\times10^6$)	VRP index	A (10^{-3}/km)	W_t (hr)	Scale	Cost ($\$\times10^6$)	VRP index	A(/km)	W_t (hr)
1	More than 6.68	More than 11.95	Less than 6	More than 0.53	1	More than 5.9873	More than 21.5313	Less than 0.1206	More than 0.6446
2	6.042-6.68	11.832-11.95	6-9	0.4299-0.53	2	5.56-5.9873	21.4194-21.5313	0.1206-0.1224	0.5188-0.6446
3	5.723-6.042	11.773-11.832	9-10-	0.3799-0.4299	3	5.3463-5.56	21.3634-21.4194	0.1224-0.1241	0.4559-0.5188
4	5.404-5.723	11.714-11.773	10-11	0.3298-0.3799	4	5.1326-5.3463	21.3074-21.3634	0.1241-0.1259	0.3930-0.4559
5	5.085-5.404	11.665-11.714	11-12	0.2798-0.3298	5	4.9190-5.1326	21.2515-21.3074	0.1259-0.1277	0.3330-0.3930
6	4.766-5.085	11.596-11.665	12-14	0.2297-0.2798	6	4.7053-4.9190	21.1955-21.2515	0.1277-0.1294	0.2671-0.3330
7	4.447-4.766	11.537-11.596	14-15	0.1797-0.2297	7	4.4916-4.7053	21.1395-21.1955	0.1294-0.1312	0.2042-0.2671
8	4.128-4.447	11.478-11.537	15-16	0.1296-0.1797	8	4.2779-4.4916	21.0835-21.1395	0.1312-0.1329	0.1413-0.2042
9	3.809-4.128	10.969-11.478	16-18	0.0795-0.1296	9	4.0643-4.2779	21.0276-21.0835	0.1329-0.13467	0.0784-0.1413
10	Less than 3.809	Less than 10.9680	More than 18	Less than 0.0795	10	Less than 4.2779	Less than 21.0835	More than 0.13467	Less than 0.1413

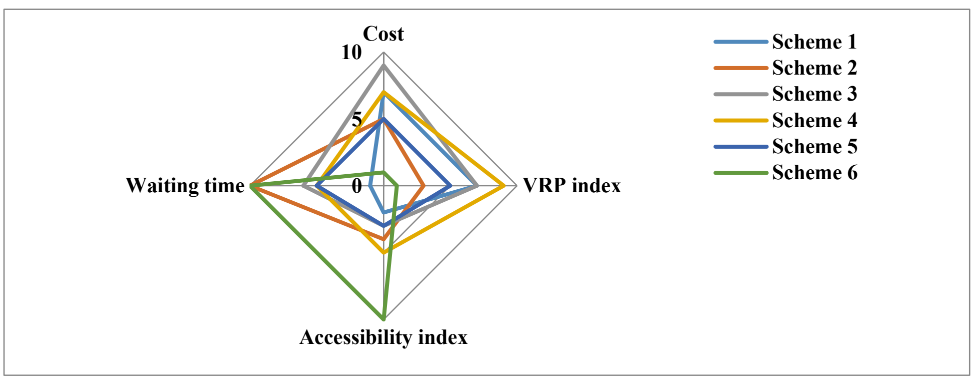

Fig. 17. Radar charts of the planning schemes for Test system 1.

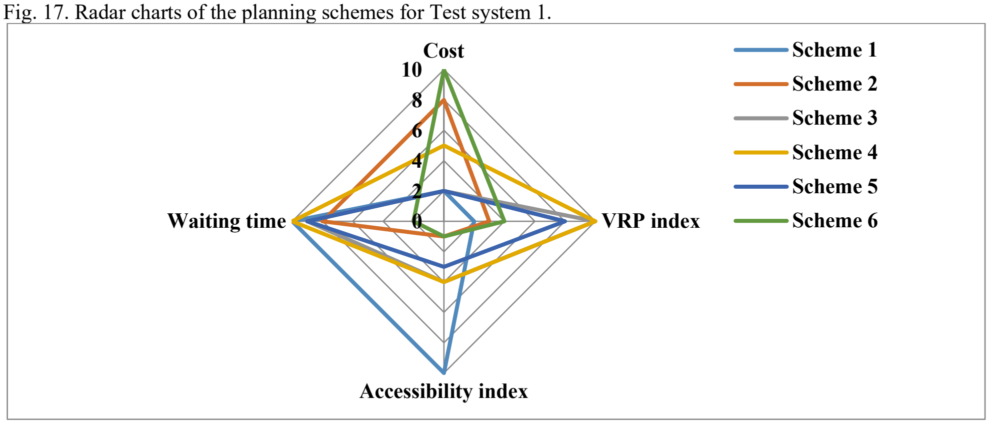

Fig. 18. Radar charts of the planning schemes for Test system 2.

TABLE XI
SCORES OF THE SIX SCHEMES

Test system 1					Test system 2				
Plan	Cost	VRP index	A	W_t	Plan	Cost	VRP index	A	W_t
1	7	7	2	1	1	2	2	10	10
2	5	3	4	10	2	8	3	1	8
3	9	7	3	6	3	2	10	4	9
4	7	9	5	5	4	5	10	4	10
5	5	5	3	5	5	2	8	3	9
6	1	1	10	10	6	10	4	1	2

F. Statistical Comparison of CSO TLBO with Other State-of-the-Art Algorithms for Solving the Proposed Problem

The performance of Pareto dominance-based CSO TLBO in solving the charging station placement problem is compared with that of the non-dominated sorted genetic algorithm (NSGA II). Evolutionary algorithms are characterized by the random generation of a population. Hence, different solutions are obtained for every independent trial. The two algorithms are statistically compared by computing the hypervolume for 20 independent trials. The hypervolume is a metric proposed by Zitzler[37] used for analysing the distribution of Pareto optimal solutions. The hypervolume physically signifies the volume occupied by the NDS set. Reference [38] concludes that maximizing the hypervolume produces a well-distributed Pareto front. The average hypervolume and the average run time comparison of CSO TLBO with NSGA II for Test system 1 and Test system 2 are reported in Table XII. Table XII shows that the performance of CSO TLBO is better than that of NSGA II for both Test system 1 and Test system 2. However, the average run time of CSO TLBO is more than that of NSGA II.

TABLE XII
COMPARISON OF CSO TLBO WITH NSGA II

Test system 1			Test system 2		
Algorithm	Hypervolume	Run time (sec)	Algorithm	Hypervolume	Run time (sec)
CSO TLBO	0.4857	1400	CSO TLBO	0.4098	2000
NSGA II	0.4675	1200	NSGA II	0.3867	1800

G. Complexity of the Proposed Two-Stage Planning Model

The time complexity of the proposed two-stage planning model is compared with that of a single-stage planning model. In the single-stage planning model considered for comparison, only optimization is performed with the objective functions and the constraints reported in Section III. The initial screening of the search space is neglected in the single-stage planning model considered for the purpose of comparison. The average run times of the proposed model and the single-stage planning model are reported in Table XIII. From Table XIII, it is clear that the average run time of the single-stage planning model is more than twice the average run time of the proposed planning model.

TABLE XIII
COMPLEXITY ANALYSIS OF THE PROPOSED PLANNING MODEL

Test system	Run time of single stage planning model (sec)	Run time of proposed two stage planning model (sec)
1	3000	1400
2	4200	2000

VI. DISCUSSION AND FUTURE WORK

This work proposes a novel two-stage planning model for the optimal allocation of charging stations. The first stage involving screening of the candidate locations for the placement of charging stations reduces the size of the search space of the optimization problem, thereby reducing the complexity of the problem to some extent. Furthermore, all of the key factors, such as distance, traffic intensity, and voltage stability, are carefully taken into account when finding the set of candidate locations for the placement of charging stations ($P_{candidate}$). In addition, the present work proposes a probabilistic approach based on Bayesian networks for computing the congested nodes in the road network. This probabilistic approach is capable of efficiently computing the congested nodes in the road network without involving the complexities of traffic modelling. In the second stage, the charging station placement problem is represented in a multi-objective framework with cost, VRP index, accessibility, and waiting time in charging stations as objective functions.

The proposed model is validated on a coupled IEEE 33-bus distribution network and 25-node road network as well as a real-time network in the city of Tianjin in China. A comparison of this planning model with the planning models presented in existing literature [11], [27] shows that the optimized values of cost, VRP index, and accessibility of the proposed model are far better for Test system 1. Furthermore, it is also observed that the proposed model is capable of allocating charging stations in the distribution network with the least harm to the voltage profile and reliability. The planning results indicate that the charging stations are easily accessible to EV drivers and that the waiting times at the charging stations are also within acceptable limits.

It should be noted that a comparison of the proposed planning model with some existing planning models is beyond the scope of this work. The planning models are validated on different test networks with different sets of input parameters. For a fair comparison of the proposed model with existing models, it is necessary to validate all the models on a common test network with the same set of input parameters.

A novel Pareto dominance-based CSO TLBO algorithm is used to solve the optimization problem. The experimental results confirm that CSO TLBO outperforms NSGA II in solving the charging station placement problem.

Although the proposed model is efficient enough, there is still room for improving the model. The proposed planning model does not consider the number of missed trips for EV charging, the net benefit earned by participating in vehicle-to-grid (V2G) schemes, and the uncertainty in the behaviour of EV drivers. The capacity of a BN in dealing with uncertainties can be utilized for modelling stochastic driving behaviour. There is also scope for proposing more efficient algorithms to solve the issue of charging station placement. Our future work will focus on some of the aforementioned research gaps.

VII. Conclusions

The development of a well-designed charging infrastructure is critical for promoting EVs. The present work proposes an effective planning model for EV charging stations considering the fundamental design parameters of a well-functioning charging network, which may be summarized as cost, respecting the operating parameters of the distribution network, and the convenience of the charging network for EV drivers (e.g., accessibility of and waiting times at charging stations). In addition, the present work proposes a two-stage planning model for EV charging stations. First, the candidate locations for the placement of charging stations should be identified by applying fuzzy logic. In the second stage, the optimal locations, type, and number of charging stations are computed. Simulation results indicate that the planning model is sufficiently efficient to be implemented in a real-world environment.

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