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Charging Station Placement for Electric Vehicles: A Case Study of Guwahati City, India

SANCHARI DEB[1], (Student Member, IEEE), KARI TAMMI[2], (Member, IEEE), KARUNA KALITA[3], AND PINAKESWAR MAHANTA[3,4]

[1]Centre for Energy, IIT Guwahati, Guwahati 781013, India
[2]Department of Mechanical Engineering, Aalto University, 02610 Espoo, Finland
[3]Department of Mechanical Engineering, IIT Guwahati, Guwahati 781013, India
[4]Department of Mechanical Engineering, National Institute of Technology, Yupia 791110, India

Corresponding author: Sanchari Deb (sancharideb@yahoo.co.in)

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ABSTRACT The ever-increasing population of India accompanied by the recent concerns regarding fossil fuel depletion and environmental pollution has made it indispensable to develop alternate mode of transportation. Electric vehicle (EV) market in India is expanding. For acceptance of EVs among the masses, development of charging infrastructure is of paramount importance. This paper formulates and solves the charging infrastructure-planning problem for Guwahati, India, that will develop as a smart city soon. The allocation of charging station problem was framed in a multi-objective framework considering the economic factors, power grid characteristics, such as voltage stability, reliability, power loss, as well as EV user's convenience, and random road traffic. The placement problem was solved by using a Pareto dominance-based hybrid algorithm amalgamating chicken swarm optimization (CSO) and the teaching learning-based optimization (TLBO) algorithm. Finally, the Pareto optimal solutions were compared by fuzzy decision-making.

INDEX TERMS City, cost, charging station, electric vehicle, optimization, traffic.

NOMENCLATURE

Constant Parameters

P_R	Congestion probability of residential area
P_O	Congestion probability of office area
C_{fast}	Installation cost of fast charging stations
C_{slow}	Installation cost of slow charging stations
CP_{fast}	Power consumption of fast charging stations
CP_{slow}	Power consumption of slow charging stations
P_{elec}	Per unit cost of electricity
m	Maximum number of locations in which charging station will be placed
q	Total number of charging demand points
w_1	Weight assigned to V
w_2	Weight assigned to R
w_{21}	Weight assigned to SAIFI
w_{22}	Weight assigned to SAIDI
w_{23}	Weight assigned to CAIDI
w_3	Weight assigned to Power loss
VSI_{base}	Base value of Voltage Stability Index
$SAIFI_{base}$	Base value of SAIFI
$SAIDI_{base}$	Base value of SAIDI
$CAIDI_{base}$	Base value of CAIDI
P_{loss}^{base}	Base value of power loss
N_D	Total number of buses of the distribution network
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
$Q_i^{\min}$	Lower limit of reactive power of bus i
$Q_i^{\max}$	Upper limit of reactive power of bus i
$P_i^{\min}$	Lower limit of active power of bus i
$P_i^{\max}$	Upper limit of active power of bus i
λ_f, λ_s	Arrival rate of EVs in fast and slow charging stations
ρ_f, ρ_s	Utilization rate of fast and slow charging stations
P_0^f, P_0^s	Probability of no EVs waiting in fast & slow charging stations

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Variables

$C_{installation}$	Net installation cost associated with placement of charging stations
$C_{operation}$	Net operation cost associated with placement of charging stations
VSI^i_{base}	Base value of VSI of the i^{th} bus
VSI^i_l	VSI of the i^{th} bus after the placement of the charging stations
VSI_l	VSI after after the placement of EV charging stations
P^l_{loss}	Power loss after the placement of EV charging stations
$SAIFI_l$	SAIFI after the placement of charging stations in the distribution network
$SAIDI_l$	SAIDI after the placement of charging stations in the distribution network
$CAIDI_l$	CAIDI after the placement of charging stations in the distribution network
V_i	Voltage of i^{th} bus for base case
V_{i+1}	Voltage of $(i+1)^{th}$ bus for base case
V'_i	Voltage of i^{th} bus after the placement of charging station
V'_{i+1}	Voltage of $(i+1)^{th}$ bus after the placement of charging station
P_i	Active power at the i^{th} bus
P_{i+1}	Active power at $(i+1)^{th}$ bus
P'_i	Active power at i^{th} bus after the placement of charging stations
P'_{i+1}	Active power at $(i+1)^{th}$ bus after the placement of charging stations
Q_i	Reactive power at the i^{th} bus
Q_{i+1}	Reactive power at $(i+1)^{th}$ bus
Q'_i	Reactive power at i^{th} bus after the placement of charging stations
Q'_{i+1}	Reactive power at $(i+1)^{th}$ bus after the placement of charging stations
P_p	Active power at bus p
P'_p	Active power at bus p after the placement of charging station
r_i	Resistance of the branch between bus i and $i+1$
x_i	Reactance of the branch between bus i and $i+1$
Z	Impedance of the branch between bus i and $i+1$
λ_i	Failure rate of i^{th} bus
N_i	Number of consumers connected at i^{th} bus
U_i	Outage duration of i^{th} bus
λ'_i	Failure rate of i^{th} bus after the placement of charging station
NDS	Non Dominated Solution
U'_i	Outage duration of i^{th} bus after the placement of the charging station
λ_p	Failure rate of bus p
λ'_p	Failure rate of bus p after the placement of charging station
U_p	Outage duration of bus p
U'_p	Outage duration of bus p after the placement of charging station
I_i	Current through branch i
I'_i	Current through branch i after the placement of charging station
d_ic_j	Distance between i^{th} charging demand point and j^{th} charging station where $i_{=1,2,\ldots q}$ and $j_{=1,2,\ldots m}$
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

I. INTRODUCTION

EVs have emerged as a transportation mode free from local emissions. India being a signatory of the Paris agreement is planning to be an EV nation by 2030 [1]. However, absence of easily accessible charging stations is one of the encumbrances affecting the EV market in India. Therefore, the government of India has recently started taking many initiatives for development of sustainable and easily accessible charging stations [1]. Inappropriate positioning of charging stations may affect smooth operation of the power grid causing voltage instability, increased power loss, harmonics and lower reliability indices [2], [3]. Additionally, charging stations should be easily accessible to EV drivers preferably causing no extra congestion. The complex and haphazard nature of the power grid and road network of India makes the charging infrastructure-planning problem a tedious and challenging task. Motivated by the recent concerns related to environmental pollution and energy crisis, we make an attempt to formulate and solve the charging station allocation problem in the context of Guwahati city, India. Guwahati is one of the upcoming smart cities [1]. Hence, it is expected that in future, a large number of EVs will ply on the roads of Guwahati resulting in necessity of charging stations.

Charging station placement problem concerns researchers across the world. Deb et al. [1] reviewed various aspects of charging infrastructure planning like global scenario, modeling approaches, objective functions, and constraints.

The charging station placement problem is formulated considering only transport network in [4]–[6]. Liu *et al.* [4] considered construction cost and running cost as the objective functions along with the charging need as a constraint in their formulation. They applied Adaptive Particle Swarm optimization (APSO) for solving the complex problem.

The aforesaid approach was tested on a road network of Beijing. Bendiabdellah *et al.* [5] formulated the charging station allotment problem for the city of Cologne in Germany. They considered installation cost and cost of commuting the distance between charging demand point and charging stations as objective functions. The allocation problem was solved by a hybrid method amalgamating k means of clustering and Genetic Algorithm (GA). Tu *et al.* [6] formulated the charging infrastructure planning problem for a road network of Shenzhen city in China. They considered maximization of travel time of EVs and minimization of waiting time in the charging stations as the objective functions. The range of EV, capacity of charging stations, time required for charging were considered as constraints in the planning model. The allocation problem was solved by applying GA.

References [7]–[9] have formulated the charging station placement problem by considering only distribution network. Liu *et al.* [7] have presented an approach for placing the charging stations considering cost as the objective function for IEEE 123 bus test network. Modified Primal Dual Interior Point Algorithm (MPDIPA) was utilized for solving the placement problem. Zheng *et al.* [8] presented a unique scheme for charging and battery swapping station placement considering cost as the objective function and power consumption limit, voltage limit, current limit as constraints. A modified version of Differential Evolution (DE) was utilized for solving the placement problem. The authors tested the proposed approach on IEEE 15 and IEEE 43 bus distribution network. Simorgh *et al.* [9] considered the cost and demand response as the objective functions and solved the placement problem by applying PSO. Further, they showed that demand response program can reduce grid losses and the total cost.

On the contrary, references [10]–[12] modeled the placement problem in a multi-disciplinary approach by giving consideration to both transport and distribution network. Wang *et al.* [10] used a multi-objective EV charging station planning model ensuring charging service and simultaneously considering power loss and voltage deviation of the distribution network. The placement problem was solved by using Data Envelopment Analysis (DEA) as well as by a Cross-Entropy based method (CE). The authors validated the proposed approach on superimposed IEEE 33 bus distribution network and 25 node road network. Rajabi-Ghahnavieh and Sadeghi-Barzani [11] modeled the charging station placement problem for northwest Tehran, Iran. They considered zonal traffic circulation in the formulation of charging station placement along with station development cost and grid operator cost. Subsequently, the problem was solved by using GA. Deb *et al.* [12] modeled the charging station allotment problem with cost as the objective function where the characteristics of the distribution network such as voltage deviation, reliability and power losses were also taken into account in the planning model by enforcing penalty for infringing the safe limits of these factors. Further, a novel CSO TLBO algorithm was applied for obtaining the apposite sites of the charging stations. The proposed approach was validated on superimposed IEEE 33 bus distribution network and 25 node road network.

References [4]–[12] highlight the contributions of contemporary researches in the arena of charging station placement. However, the existing studies on charging station planning fail to take into account some of the key factors such as resiliency of distribution network, waiting time in the charging stations, and traffic intensity. Moreover, only few studies formulate the placement problem in the context of an Indian city. Compared with the existing research works related to charging infrastructure planning, the main contributions of the present work are:

1. The present work models the charging station placement problem in the context of Guwahati, India. Guwahati is one of the upcoming smart cities of India. In future, a large number of EVs will ply on the roads of Guwahati. Hence, there will be necessity of sustainable charging infrastructure.
2. High traffic density along with low grid stiffness make it a challenging problem to find charger locations Our work presents the approach, tools, and performance indicators to find optimal charger locations taking into account both the traffic and electric grid.
3. The work proposes a two stage-planning model for the charging station allotment. In the first stage, the candidate locations for placing the charging stations are identified by a novel methodology of Bayesian network. In the second stage, optimization is performed to select the best locations, type of charging stations and number of charging points at the charging stations.

II. CHARGING STATION PLACEMENT PROBLEM

Solving the charging station placement problem requires the positioning of the charging stations in the road network considering economic factors, operating parameters of the power grid, and EV users' ease. The present work utilizes a two-stage modeling of the charging station placement problem as illustrated in the subsequent sub-sections. It is expected that the two-stage planning model will reduce the computational time and effectively locate the charging stations.

A. SCREENING OF THE CANDIDATE LOCATIONS FOR CHARGING STATION PLACEMENT

In the first stage, the potential locations for the placement of charging stations is determined by using a probabilistic approach based on Bayesian network [13]–[17]. It seems to be a common practice to situate the charging stations at the meeting points of distribution and road network [10], [12]. Thus, we can say that the superimposed nodes or the nodes of the road network adjacent to the buses of the distribution network are the candidate sites for the assignment of charging stations. However, some of these nodes can be crammed with high traffic intensity. Also, the chance of some of these nodes being vulnerable points of the grid in terms of voltage stability cannot be disregarded. In the present work, distance of the road network nodes from the nearest bus of the distribution network, traffic intensity and grid stability are considered as key factors for finding the candidate sites for placing the charging stations. The potential of Bayesian network to deal with uncertainty and interaction among different events is used in the present work The Bayesian network utilized in the present work to find the candidate locations for the placement of charging stations is as shown in Fig.1.

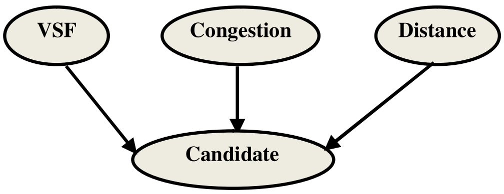

FIGURE 1. Bayesian Network for finding candidate sites for charging station placement.

The Bayesian network has three parent nodes [13] named 'Congestion', 'Voltage Sensitivity Factor (VSF)' and 'Distance'. As shown in Fig.1 'Candidate' is the child node [13] of 'Congestion', 'Voltage Sensitivity Factor (VSF)' and 'Distance'. The states of 'Congestion' are {Low, High}, states of 'VSF' are {Low, Medium, High}, states of 'Distance are {Low, Medium, High} and the states of the child node 'Candidate' are {Yes, No}. The probability that a particular node is a candidate location is computed by bucket elimination algorithm [14]–[17] as given by Eq. (1).

$$\begin{aligned} P(candidate = yes) &= P(candidate|VSF, congestion, distance) \\ &\quad \times P(VSF) \times P(congestion) \times P(distance) \end{aligned} \tag{1}$$

The distance of the node of the road network from the nearest bus of the distribution network is calculated graphically. The computational procedures for finding VSF, congestion probability are elaborated as follows:

1. VSF- The present work uses VSF for analyzing the stability of the distribution network. VSF is defined as the ratio of variation in voltage and variation in load [18].

$$VSF = \left|\frac{dV}{dP}\right| \quad \forall P < P_{\max} \tag{2}$$

The forward and backward sweep algorithm [19] is used for determining the voltage of the buses of the distribution network. The maximum value of load for which the load flow converges is called realistic loading margin of the system. The computation of realistic loading margin is necessary to ascertain how vulnerable the system is to change of load. The flowchart illustrating the procedure to compute VSF and realistic loading margin is shown in Fig.2.

2. Congestion Probability- A probabilistic approach based on Bayesian network is utilized in the present work for finding the probability of congestion of the nodes of the road network. The Bayesian network model used for finding congestion probability is shown in Fig.3. The probability of a road network being congested depends on the traffic flow that in turn depends on day of the week, time of the day, and area covered by the road. Thus, 'Day', 'Time', and 'Area', are the parent nodes [13] of the Bayesian network. And, 'Traffic Flow' is the child node [13] of the nodes 'Day', 'Time', and 'Area'. Similarly, 'Congestion' is the child node of 'Traffic Flow'. The probability of congestion being high or low is computed by bucket elimination algorithm [13]–[17]. The states of the root nodes 'Day', 'Time', and 'Area' are {Weekday, Weekend},{AM Peak, Work, PM Peak, Leisure, Rest}, {Residential(R), Office (O), Market (M), School (Sc)} respectively. The states of the child node 'Traffic flow' are {Low (L), Medium (M), High (H)}. The states of the node

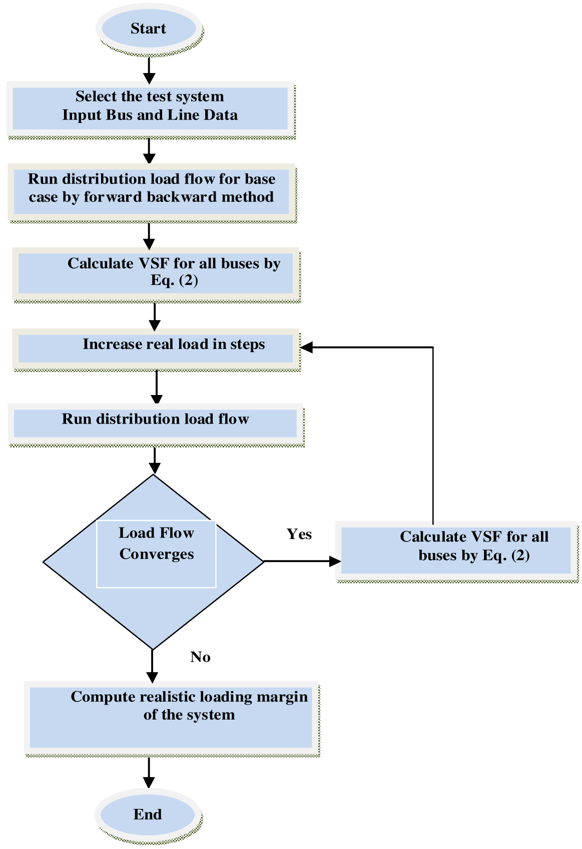

FIGURE 2. Flowchart for computation of VSF [2].

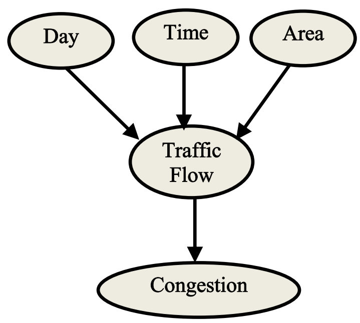

FIGURE 3. Bayesian Network for computation of congestion probability.

'Congestion' are {Low (L), High (H)}.The congestion probabilities of residential and Office areasare:

$$P_R = P(\text{Area} = \text{R})|P(\text{congestion} = \text{H}) \tag{3}$$

$$P_O = P(\text{Area} = \text{O})|P(\text{congestion} = \text{H}) \tag{4}$$

The congestion probabilities of other areas can be found by replacing the numerator of Eq. (3) and Eq. (4) accordingly based on area.

B. OPTIMIZATION

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_c), number of fast/ slow charging stations (F_p, S_P) and the number of fast/ slow charging points or servers(f_p, s_p). Thus, the decision variables of the optimization problem are-

$$\begin{aligned} p &= \{p_1, p_2, \ldots p_m\} \\ F_p &= \{F_1, F_2 \ldots F_m\} \\ S_p &= \{S_1, S_2 \ldots S_m\} \\ f_p &= \{f_1, f_2 \ldots f_m\} \\ s_p &= \{s_1, s_2 \ldots s_m\} \end{aligned}$$

where m is the maximum number of locations for the placement of charging stations.

The placement problem is formulated as a multi-objective optimization problem with cost, VRP index, accessibility index and waiting time in the charging stations as objective functions. An overview of the multi-objective formulation with objective functions and constraints is presented in this section.

The objective functions and constraints of the placement problem are elaborated as follows:

1. Cost-The optimization concerns the curtailment of the installation and operation cost

$$Cost = C_{installation} + C_{operation} \tag{5}$$

$$\begin{aligned} C_{installation} &= \{(\sum_{i=1}^{m} F_i \times f_i) \times C_{fast}\} \\ &\quad + \{(\sum_{i=1}^{m} S_i \times s_i) \times C_{slow}\} \end{aligned} \tag{6}$$

$$\begin{aligned} C_{operation} &= \{(\sum_{i=1}^{m} F_i \times f_i) \times CP_{fast}\} \\ &\quad + \{(\sum_{i=1}^{m} S_i \times s_i) \times CP_{slow}\} \times P_{elec} \end{aligned} \tag{7}$$

From Eq. (6) it can be inferred that the installation cost depends on the cost of installing fast and slow chargers, number of fast and slow charging stations, as well as number of fast and slow charging points. Similarly, from Eq. (7) it can be inferred that the operation cost depends on the power consumption of fast and slow chargers, per unit cost of electricity, number of fast and slow charging stations, as well as number of fast and slow charging points. The installation and operation cost is a function of number of fast and slow charging stations as well as number of fast and slow charging points.

2. VRP index-The second objective function is the minimization of VRP index [1]. VRP index is a composite index formulated by Deb *et al.* [1] that takes into account distribution network operating parameters such as voltage stability, reliability, and power loss together under a single frame. One more salient feature of the VRP index is that it takes into account both frequency and duration based reliability indices. The suitable value, such as minimum or maximum of the VRP index cannot be generalized and is dependent on the test network. A low value of VRP index is desirable. Ideally, the minimum value of VRP index is 1 when there is no increase in the load. VRP index is mathematically expressed as in Eq. (8)

$$VRP = f(p, F_p, S_p, f_p, s_p) = w_1 V + w_2 R + w_3 P \tag{8}$$

where

$$V = \frac{VSI_l}{VSI_{base}} \quad P = \frac{P^l_{loss}}{P^{base}_{loss}}$$

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

$$\begin{aligned} VSI_{base} &= \sum_{i=1}^{N_D} 2V_i^2 V_{i+1}^2 - 2V_{i+1}^2 (P_{i+1} r_i + Q_{i+1} x_i) \\ &\quad - |z|^2 (P_{i+1}^2 + Q_{i+1}^2) \end{aligned} \tag{9}$$

$$\begin{aligned} P'_p &= P_p + \{(F_p \times f_p) \times CP_{fast}\} \\ &\quad + \{(S_p \times s_p) \times CP_{slow}\} \end{aligned} \tag{10}$$

$$\begin{aligned} VSI_l &= \sum_{i=1}^{N_D} 2V_i'^2 V_{i+1}'^2 - 2V_{i+1}'^2 (P'_{i+1} r_i + Q'_{i+1} x_i) \\ &\quad - |z|^2 (P_{i+1}'^2 + Q_{i+1}'^2) \end{aligned} \tag{11}$$

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

$$\text{and} \quad CAIDI_{base} = \frac{\sum_{i=1}^{N_D} U_i N_i}{\sum_{i=1}^{N_D} \lambda_i N_i} \tag{12}$$

$$SAIFI_l = \frac{\sum_{i=1}^{N_D} \lambda'_i N_i}{\sum_{i=1}^{N_D} N_i} \quad SAIDI_l = \frac{\sum_{i=1}^{N_D} U'_i N_i}{\sum_{i=1}^{N_D} N_i}$$

$$\text{and} \quad CAIDI_l = \frac{\sum_{i=1}^{N_D} U'_i N_i}{\sum_{i=1}^{N_D} \lambda'_i N_i} \tag{13}$$

$$\lambda'_p = \frac{\lambda_p}{P_p} \times P'_p \qquad U'_p = \frac{U_p}{P_p} \times P'_p \tag{14}$$

$$P_{loss}^{base} = \sum_{i=1}^{N_D} I_i^2 r_i \qquad P_{loss}^{l} = \sum_{i=1}^{N_D} I_i^{'2} r_i \tag{15}$$

From Eq. (8) it is seen that VRP index is a function of the position where charging stations are placed, type of charging stations, number of charging stations and charging points. Eq. (9) and Eq. (11) mathematically describes the voltage stability index before and after the placement of charging stations. Eq. (10) is used for computing the increase in load due to EV charging stations. Eq. (12) and Eq. (13) is used to compute the reliability indices such as SAIFI, SAIDI, and CAIDI before and after the placement of charging stations. From Eq. (12) and Eq. (13) it is seen that SAIFI is a frequency based reliability index and it depends on the frequency of interruption. On the other hand, SAIDI is a duration based reliability index and it depends on the duration of interruption. The frequency and duration of interruption after the placement of charging stations is calculated by unitary method as shown in Eq. (14). Eq. (15) explains the computation of power loss before and after the placement of charging stations.

3. Accessibility index-The Accessibility of the charging stations is chosen as the third objective function. For computation of accessibility (A) the distance matrix (D) and reduced distance matrix (DD) first need to be computed. The distance matrix, D gives the distance between the charging point demand and charging stations. And, reduced distance matrix, DD identifies the nearest charging stations for each of the charging point demand and gives the distance between the charging point demand and its nearest charging station. D, DD, d and Aaret computed as follows:

$$D = \begin{bmatrix} d_1c_1 & d_1c_2 & \dots & d_1c_m \\ d_2c_1 & d_2c_2 & \dots & d_2c_m \\ . & . & . & . \\ . & . & . & . \\ d_qc_1 & d_qc_2 & \dots & d_qc_m \end{bmatrix}$$

$$DD = \begin{bmatrix} \min(d_1c_1, d_1c_2, \dots d_1c_m) \\ \min(d_2c_1, d_2c_2, \dots d_2c_m) \\ . \\ . \\ . \\ \min(d_qc_1, d_qc_2, \dots d_qc_m) \end{bmatrix} \qquad d = \sum_{i=1}^{q} DD_i$$

$$A = \frac{1}{|d|} \tag{16}$$

4. Waiting time

The waiting time (W_t) in the charging stations cause inconvenience to the EV drivers. Hence, the optimization aims to minimize the waiting time. In the present work, the waiting time in the charging stations is modeled by M/M/c queuing theory [20]–[22]. The waiting times in the fast and slow charging stations are:

$$W_f = \frac{\sum_{i=1}^{m} \frac{\rho_f^{f_i+1}}{(f_i-1)!\times(f_i-\rho_f)^2} \times P_0^f}{\lambda_f} \tag{17}$$

$$Ws = \frac{\sum_{i=1}^{m} \frac{\rho_s^{s_i+1}}{(s_i-1)!\times(s_i-\rho_s)^2} \times P_0^s}{\lambda_s} \tag{18}$$

From Eq. (17) and Eq. (18) it can be inferred that the waiting time in the charging stations depends on the number of charging points or servers in the charging stations.

5. Constraints

The different constraints of the charging station placement problem are as follows:

$$0 < F_p \leq F_{\max} \text{ and } 0 < f_p \leq f_{\max} \tag{19}$$

$$0 < S_p \leq S_{\max} \text{ and } 0 < s_p \leq s_{\max} \tag{20}$$

$$Q_i^{\min} \leq Q_i \leq Q_i^{\max} \tag{21}$$

$$P_i^{\min} \leq P_i \leq P_i^{\max} \tag{22}$$

$$P_{gi} - P_{di} - V_i \sum_{j=1}^{N_D} V_j Y_{ij} \cos(\delta_i - \delta_j - \theta_{ij}) = 0 \tag{23}$$

$$Q_{gi} - Q_{di} - V_i \sum_{j=1}^{N_D} V_j Y_{ij} \cos(\delta_i - \delta_j - \theta_{ij}) = 0 \tag{24}$$

Eq. (19) and Eq. (20) takes into account the maximum and minimum number of fast as well as slow charging stations and charging points that can be placed. Eq. (21) and Eq. (22) takes into account the upper and lower limits of active and reactive power respectively. Eq. (23) and Eq. (24) considers the power balance equation.

III. OPTIMIZATION ALGORITHMS

A multi-objective hybrid CSO-TLBO algorithm presented in [23] was harnessed to solve the optimisation problem. CSO is a swarm intelligence inspired algorithm that mimics the behaviour of chicken swarm. TLBO is a Nature Inspired Optimization (NIO) algorithm that mimics the teaching and learning process. The implementation of CSO and TLBO for solving the optimization problem is explained by Algorithm 1 and Algorithm 2 respectively. The grading mechanism of CSO is amalgamated with TLBO to improve the utilization rate of population and convergence speed of the algorithm. It is expected that amalgamation of CSO with TLBO reduces the chances for premature convergence of CSO in computationally expensive problems. Being hybrid algorithm, TLBO is activated for all the generation and CSO is invoked periodically depending on the value of an algorithm-specific control parameter named *INV*. The flowchart for implementing multi-objective CSO TLBO is shown in Fig. 4. The computation of rank and crowding distance can be found in [23].

Algorithm 1 Pseudo Code of Multi-Objective CSO [23]

Initialize the population of chicken 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 chicken, $t = 0$, 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 $(0, \sigma^2)$ *is a Gaussian distribution function with mean 0 and standard deviation* σ^2
End if
If $i ==$ *hen*
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 which is* i^{th} *hen's group mate. And* $r2 \in [1, N]$ *is an index of the rooster or hen which is randomly chosen such that r1 is not equal to r2, f denotes 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 in between 0 and 2*
End if
Compute the rank of all the individual of the population
If rank(t)< rank(t − 1)
Update the solution
If rank(t) = rank(t − 1)
Compute crowding distance of all the individual 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 2 Pseudo Code of Multi-Objective TLBO [23]

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 mean of the decision variable vector*
Compute the rank of all the individual of the population;
If rank(t) < rank(t − 1)
Update the solution;
If rank(t) = rank(t − 1)
Compute crowding distance of all the individual 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 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* $Z_{new} = Z_{old} + rand \times (Z_i - Z_j)$; *% rand is a random number*
Else
Replace i^{th} *learner by* $Z_{new} = Z_{old} + rand \times (Z_j - Z_i)$;
End if else
End for
Compute the rank of all the individual of the population
If rank(t) < rank (t − 1)
Update the solution
If rank(t) = rank (t − 1)
Compute crowding distance of all the individual 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
$k = k + 1$
End while

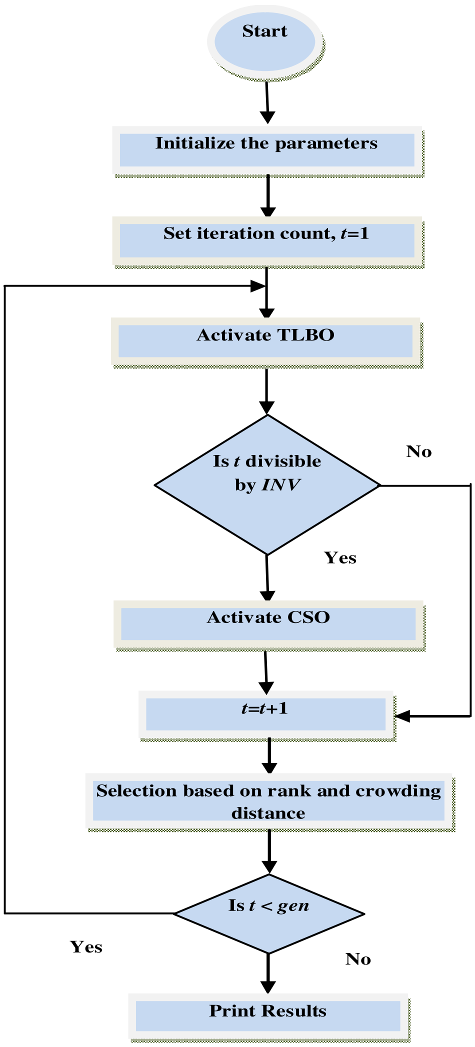

FIGURE 4. Flowchart of CSO TLBO.

IV. SOLUTION PROCEDURE

The procedure for solution of the charging station placement problem is as follows- *Step 1:* Initialization

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

Step 1.2: Generate feasible initial population randomly.

The initial feasible population is of the form

$$pop_{intl} = [A_{pop} B_{pop} C_{pop}\, D_{pop}\, E_{pop}]$$

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

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

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

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

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

A randomly generated initial solution is feasible if it satisfy all the constraints of charging station placement problem explained in section II (B)

Step 1.3: Evaluate the four objective functions cost, VRP index, accessibility and waiting time for the initial population. The rank and crowding distance were computed as in [23].The first Pareto front with rank one is designated as T_k

Step 2: Run TLBO

Step 2.1: Run TLBO and update the solution based on rank and crowding distance [23]

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

Step 2.3: Else, check feasibility of the solution. If the solution is infeasible repeat step 2.1 and 2.2 until feasible solution is obtained.

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

Step 3.1: If t is divisible by INV run CSO

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

Step 3.3: Repeat step 2.2.

Step 3.4: Else, check feasibility of the solution. If the solution is infeasible repeat step 3.2 and 3.3 until feasible solution is obtained.

Step 3.5: Update the iteration count

Step 4: Check whether maximum generation count is reached. If maximum generation count is reached print the Pareto front. Else, repeat step 2 to step 4.

Step 5: Selection of the best compromise solution from the set of non-dominated solution is made by using the fuzzy decision making [24]–[26].

V. RESULTS

A. TEST SYSTEMS AND INPUT PARAMETERS

The present work solved the charging infrastructure planning problem for the city of Guwahati, India. Fig.5 shows

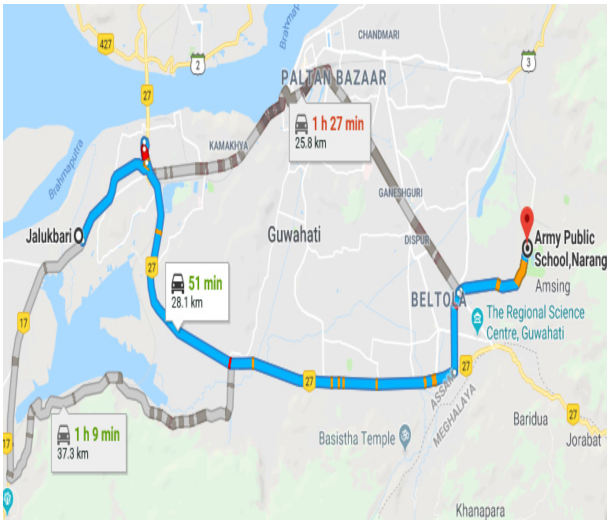

FIGURE 5. Highway network of Guwahati.

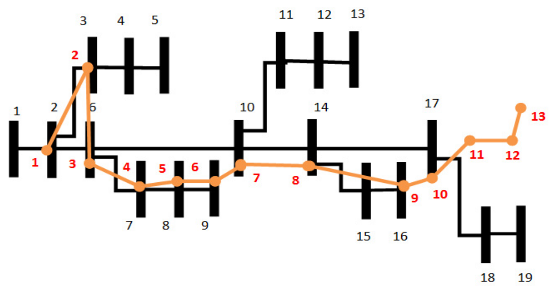

FIGURE 6. Superimposed road and distribution network of Guwahati.

TABLE 1. Types of nodes of the road network.

Node	Type	Node	Type
1	School	8	Office
2	School	9	Residential
3	Residential	10	Market
4	Residential	11	Market
5	Residential	12	Market
6	Office	13	Market
7	Office		

TABLE 2. Input parameters.

Parameter	Value	Parameter	Value
C_{fast}	3000 \$	m	3
C_{slow}	2500 \$	F_{max}	2
CP_{fast}	50 kW	f_{max}	6
CP_{slow}	19.2 kW	S_{max}	3
P_{elec}	65 \$/MWhr	s_{max}	10
λ_f	5.6/hr	λ_s	1.4/hr

TABLE 3. Algorithm specific parameters of CSO TLBO.

Parameter	Value
Gen	50
PN	10
RN	0.3×*PN*
HN	0.4×*PN*
CN	*PN-RN-HN*
INV	3
G	3

the highway network of Guwahati connecting Jalukbari with Narangi. Fig.6 shows the superimposed road and distribution network for the Guwahati city. The bus and line data of the distribution network are available in Ref [27]–[30] and the outage data of the distribution network were taken from the log book of the substations. The road network data were recorded from Google maps. The recorded traffic data from Google API was used for computing congestion probability of the road network nodes. The distance between the different nodes of the road network that was required for computing the Accessibility index (third objective function of the optimization problem) was also recorded from the Google maps. 24 hour traffic data was recorded for both weekdays and weekends. The characteristics of the nodes of the road network are reported in Table 1. Table 2 presents the different input parameters required for optimization. Table 3 presents the algorithm- specific control parameters of CSO TLBO.

B. CANDIDATE LOCATIONS

At the first stage, the candidate locations for placement of the charging stations were screened by the methodology reported in section II (A). The VSF of the buses of the distribution network are reported in Table 4. The VSF of bus 19 was highest indicating that it was the weakest point of the power distribution network. The congestion probabilities of different types of the nodes of the road network computed by Bayesian network are reported in Table 5. The nodes sprawling market areas are heavily congested with congestion probability of 0.643. Table 6 reports the probability of being a candidate location for placement of charging stations for all the buses of the distribution network. The buses for which the probability of being candidate location was high were selected as the candidate locations for charging station placement as reported in Table 7. Assuming EV driving range of 150 km [31] and EVs completing 10 round trips from Jalukbari to Narangi, the charging demand nodes were computed as reported in Table 7. It should be noted that this work does not consider stochastic driving cycles reported in [32].

C. OPTIMAL ALLOCATION OF CHARGING STATIONS

At the second stage, the optimal locations for the charging stations placement were selected from the set of candidate locations by solving the optimization problem reported in section II (B). The optimization problem was solved by using CSO TLBO algorithm. In this case, the optimization yielded

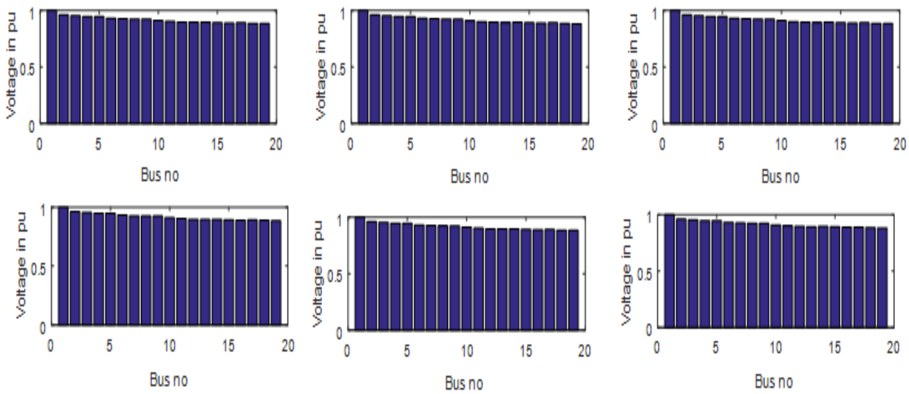

FIGURE 7. Impact of charging station placement on voltage profile of distribution network.

TABLE 4. VSF of the buses of distribution network.

Bus no	VSF for critical loading	Bus no	VSF for critical loading
2	0.1439	11	0.3966
3	0.1678	12	0.4217
4	0.1862	13	0.4346
5	0.1898	14	0.4247
6	0.2623	15	0.4499
7	0.2827	16	0.4704
8	0.2893	17	0.4573
9	0.2936	18	0.4826
10	0.3601	19	0.5030

TABLE 5. Congestion probability of road network.

Node type	Congestion Probability
Market	0.643
Residential	0.259
School	0.283
Office	0.372

TABLE 6. Probability of being candidate location.

Bus no	Probability	Bus no	Probability
2	0.717	11	0.015
3	0.667	12	0.01
4	0.011	13	0.001
5	0.001	14	0.627
6	0.741	15	0.371
7	0.726	16	0.445
8	0.628	17	0.228
9	0.625	18	0.001
10	0.628	19	0.0001

six non-dominated solution or planning schemes as shown in Table 8. Table 9 reports the values of the four objective functions for the six plans. From Table 9, it is clear that all the six plans were unique and it was tricky to select the best plan.

TABLE 7. Candidate locations and charging demand nodes.

Candidate Location (wrt to distribution network)	2	3	6	7	8	9	10	14
Charging demand nodes (wrt to road network)	1	2	3	6	7	8	9	----

TABLE 8. Optimal allocation of charging stations.

NDS	p	F_p	S_p	f_p	s_p	NDS	p	F_p	S_p	f_p	s_p
1	2	1	1	3	6	4	2	2	2	5	10
	3	1	2	3	6		7	1	2	5	10
	8	1	1	3	6		8	2	2	5	10
2	2	2	2	5	10	5	2	1	2	4	7
	9	2	2	5	10		6	1	2	5	9
	10	2	2	5	10		7	1	2	3	16
3	2	2	2	4	8	6	2	1	2	5	10
	8	1	2	4	8		3	1	1	5	7
	9	2	2	4	8		10	1	2	3	10

TABLE 9. Objective function values for the planning schemes.

Planning Scheme	Cost ($\$\times10^6$)	VRP	A	W_t (hr)
1	3.0206	11.3011	0.0279	1.3603
2	8.8900	11.7391	0.1053	0.0807
3	7.1120	11.7018	0.0279	0.4165
4	7.9977	11.8097	0.0459	0.0730
5	5.0883	10.9291	0.0221	0.4103
6	5.9284	11.3119	0.0806	0.3448

D. EFFECT OF CHARGING STATION PLACEMENT ON DISTRIBUTION NETWORK

The charging stations affect the operating parameters of the distribution network such as voltage deviation, reliability, and power loss. However, the voltage profiles of all the buses (Fig. 7) were within acceptable limit for all the six plans reported in Table 8. Fig. 8, Fig. 9 and Fig. 10 show the impact of charging station placement on the three reliability indices named SAIFI, SAIDI, and CAIDI respectively.

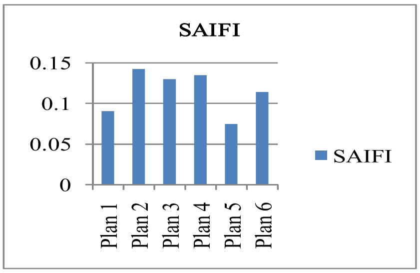

FIGURE 8. Impact of charging station placement on SAIFI.

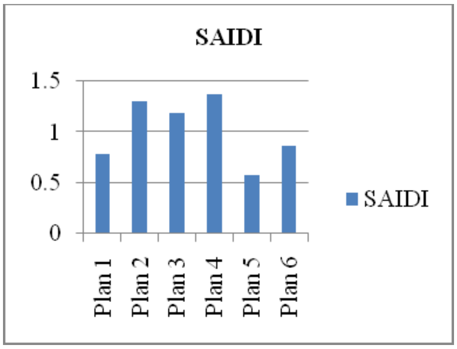

FIGURE 9. Impact of charging station placement on SAIDI.

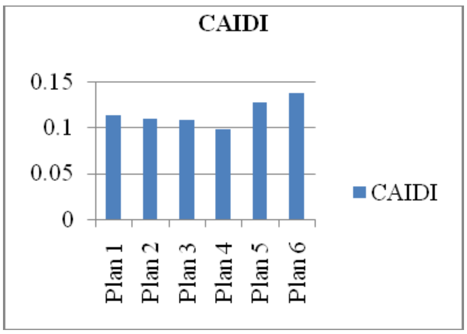

FIGURE 10. Impact of charging station placement on CAIDI.

The reliability indices degraded due to increased charging load. However, the degraded values were less than the critical values of these reliability indices reported in [33], [34]. The power losses of the distribution network after positioning the charging stations was also within acceptable limit as shown in Fig. 11. Thus, the two-stage planning model of charging station placement was capable of allocating charging stations with least harm to the distribution network of Guwahati.

E. DECIDING BETWEEN PARETO OPTIMAL SOLUTIONS

The final step was the selection among the plans. Selection of the best plan among the six plans was a tricky task due to involvement of opposing objectives. In real world, some criteria cannot be measured by crisp values due to indistinctness arising from human qualitative judgment [26]. Hence, a fuzzy evaluation system was used for the final decision making [26]. Cost, VRP index, accessibility index, and waiting time were chosen as the four aspects of decision making in the charging station placement problem. In the fuzzy decision

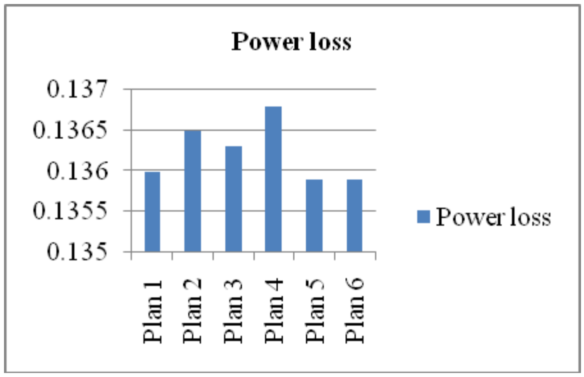

FIGURE 11. Impact of charging station placement on power loss.

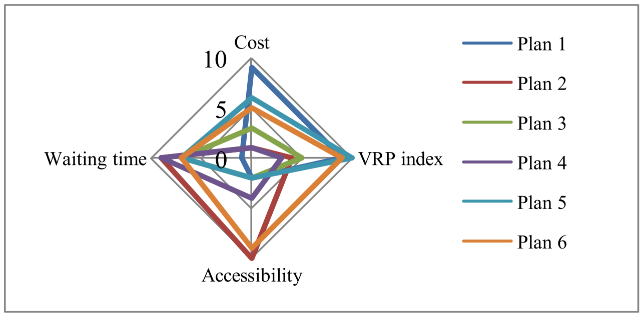

FIGURE 12. Radar charts of all the planning schemes.

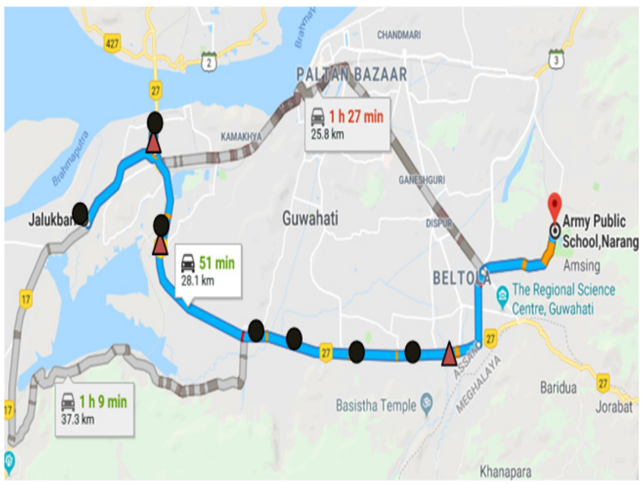

FIGURE 13. The charging station locations obtained according to plan 6.

making, low cost, VRP index, and waiting time received a higher evaluation. And, high accessibility received a higher evaluation. Table 10 lists the scale of the three objective functions based on the aforementioned criteria. The scores of each plan obtained by fuzzy evaluation system are reported in Table 11. Fig. 12 shows the radar charts for all the six planning schemes. The area occupied by plan 6 is highest indicating that it is the most beneficial plan. The area occupied by plan 2 and plan 3 is least indicating that they are the least convenient plan. Fig.13 shows the optimal locations of charging stations obtained by the best planning scheme (plan 6) and the charging demand points. In Fig. 13, the red

TABLE 10. Scale of fuzzy evaluation.

Scale	Cost ($\$\times10^6$)	VRP index	A(/km)	W_t (hr)
1	More than 7.1792	More than 11.92	Less than 0.0221	More than 1.1023
2	7.1792-7.7161	11.8320-11.92	0.0221-0.0304	0.9733-1.1023
3	6.5422-7.1792	11.7730-11.8320	0.0304-0.0387	0.8443-0.9733
4	5.9553-6.5422	11.7140-11.7730	0.0387-0.0471	0.7153-0.8443
5	5.3684-5.9553	11.6650-11.7140	0.0471-0.0554	0.5863-0.7153
6	4.7814-5.3684	11.5960-11.6650	0.0554-0.0637	0.4573-0.5863
7	4.1945-4.7814	11.5370-11.5960	0.0637-0.0720	0.3283-0.4573
8	3.6075-4.1945	11.4780-11.5370	0.0720-0.0803	0.1993-0.3283
9	3.0206-3.6075	10.9690-11.4780	0.0803-0.0887	0.0703-0.1993
10	Less than 3.0206	Less than 10.9680	More than 0.0887	Less than 0.0703

TABLE 11. Score of the planning schemes.

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

triangles denote the charging stations and the black circles denote the charging demand points.

VI. CONCLUSION

Sustainable development of charging infrastructure is must to promote EVs. This work solved the charging station placement problem in the context of Guwahati city, an upcoming smart city. The charging station placement problem was modeled in a multi-objective framework considering cost, operating parameters of distribution network such as voltage stability, reliability, power loss, factors affecting EV driver's convenience like accessibility to the charging stations, waiting time in the charging stations. A novel CSO TLBO algorithm was harnessed to solve the optimization problem. Fuzzy decision making was utilized to choose between various Pareto-optimal solutions. The results showed that the proposed approach is capable of allocating the charging stations with least harm to the operating parameters of the power distribution network and simultaneously considering EV drivers' convenience. Moreover, the authors will try to reach the concerned authorities and implement the planning model on the entire Guwahati city as well as other Indian cities in future. Our future work will also address some of the critical issues related to charging infrastructure planning like pricing strategies in the charging stations, planning of Vehicle to Grid (V2G) enabled charging stations and planning of charging stations powered by renewable resources.

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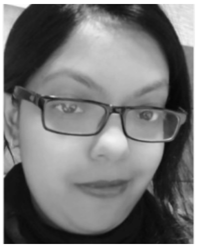

SANCHARI DEB (S'16) received the Master of Engineering degree in power system. She is currently pursuing the Ph.D. degree with the Centre for Energy, IIT Guwahati, India. Her research interests include power systems, energy, electric vehicles, charging infrastructure, optimization, and evolutionary algorithms. She is a member of the IEEE PES.

KARI TAMMI (M'15) was born in 1974. He received the M.Sc., Lic.Sc., and D.Sc. degrees from the Helsinki University of Technology, in 1999, 2003, and 2007, respectively. He received the Teacher's Pedagogical Qualification from the Häme University of Applied Sciences, in 2017. He was a Researcher with CERN, the European Organization for Nuclear Research, from 1997 to 2000, and a Postdoctoral Researcher with North Carolina State University, USA, from 2007 to 2008. From 2000 to 2015, he was a Research Professor, a Research Manager, the Team Leader, and other positions at the VTT Technical Research Centre of Finland. He has been an Associate Professor with Aalto University, since 2015. He currently serves in the Finnish Administrative Supreme Court as a Chief Engineering Counselor. He has authored over 60 peer-reviewed publications cited in over 1500 other publications. He is a member of the Finnish Academy of Technology. He serves as the Deputy Chair for IFTOMM Finland.

KARUNA KALITA received the B.E. degree from Dibrugarh University, Dibrugarh, India, in 1995, the M.Tech. degree from the IIT Guwahati, Guwahati, India, in 2002, and the Ph.D. degree from the University of Nottingham, Nottingham, U.K., in 2006. He was with the Converteam (currently GE Power Conversion), Rugby, U.K., from 2006 to 2008. He was with the University of Nottingham as a Lecturer, from 2008 to 2010. He is currently an Associate Professor with the Department of Mechanical Engineering, IIT Guwahati. He has published 16 journal papers, 23 conference papers, and two patents in magnetic bearings. He has guided one doctoral researcher and 14 master's students. His current research interests include rotor dynamics, modeling of electromechanical systems, self-bearing machine, and gas foil bearings.

PINAKESWAR MAHANTA received the Ph.D. degree from IIT Guwahati, in 2001, where he is currently a Professor with the Department of Mechanical Engineering. He has been a Faculty Member with IIT Guwahati, since 2001. He is now on deputation to National Institute of Technology, Arunachal Pradesh. His research interests include thermal radiation with participating media, fluidization, energy conservation, and renewable energy.