CHARGING INFRASTRUCTURE PLANNING FOR ELECTRIC VEHICLES

A thesis

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By

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CERTIFICATE

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ABSTRACT

The ever increasing energy demand accompanied by fossil fuel depletion and environmental degradation has paved the path of transportation electrification. Electric Vehicles (EVs) are environmental friendly alternative to conventional Internal Combustion Engine (ICE) driven vehicles. For large scale deployment of EVs sustainable charging infrastructure needs to be developed. The charging station placement problem is a complex problem involving power distribution network and road network. Charging stations must be placed in the distribution network in such a way that the negative impact of placement of charging stations on the operating parameters of the distribution network is minimized. Also, the location of charging station must be optimized considering the route choice behavior of EV drivers and charging demand of the EVs computed based on the driving range of the EV. Hence, motivated by all the aforementioned factors this thesis aims to delve into charging infrastructure planning for EVs.

The impact of EV charging stations on operating parameters of the distribution network such as voltage stability, reliability and power losses are thoroughly analyzed in this thesis. And, a novel index named Voltage Stability Reliability Power Loss (VRP) index is formulated having the capability of considering voltage stability, reliability and power loss under a single frame.

Initially, a single objective formulation of charging station placement is proposed considering cost as the objective function. The operating parameters of the distribution network are taken into account in this formulation by imposing penalty for violation of safe limits of these operating parameters. A multi-objective formulation of the charging station placement problem is also proposed considering cost, VRP index and accessibility index as objective functions. Further, a two stage robust planning model of charging station placement is proposed. In the two stage planning model, the first stage is concerned with screening the candidate locations for placement of charging stations by Mamdani Fuzzy Inference (MFI). The second stage involves finding the optimal locations for placing charging stations, nature of charging stations, number of charging stations as well as number of servers by solving the optimization problem with cost, VRP index, accessibility index and waiting time as charging stations. The first stage involving screening of the candidate location of charging stations will reduce the size of search space and reduce the complexity of the problem.

The objective functions of the charging station placement problem are highly non-linear in nature. The classical optimization algorithms have their limitations in solving this problem. Hence, the present work utilizes metaheuristics for solving the charging station placement problem. A novel hybrid algorithm considering amalgamation of Chicken Swarm Optimization (CSO) and Teaching Learning Based Optimization (TLBO) is developed and used for solving the charging station placement problem. It is expected that amalgamation of CSO with TLBO will improve the quality of solution and fast convergence towards the optimal solution will be favoured. The efficacy of the proposed hybrid CSO TLBO algorithm is tested on standard benchmark problems as well as charging station placement problem. Further, a Pareto dominance based CSO TLBO algorithm is developed to solve the multi-objective charging station placement problem.

The proposed formulations of charging station placement problem are validated on superimposed IEEE 33 bus distribution and 25 node road network, city of Tianjin, and highway network of Guwahati.

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CONTENTS

NOMENCLATURE

ABBREVIATIONS

EV	Electric Vehicle
CO_2	Carbon Dioxide
PEV	Plugged In Electric Vehicle
PHEV	Plugged In Hybrid Electric Vehicle
BEV	Battery Electric Vehicle
EREV	Extended Range Electric Vehicle
BSS	Battery Swapping Station
IEEE	Institute of Electrical and Electronics Engineers
THD	Total Harmonic Distortion
SOC	State of Charge
FCLM	Flow Capturing Location Model
FCRM	Flow Capturing Refueling Model
MCLM	Maximum Covering Location Model
FRLM	Flow Refueling Location Model
ICE	Internal Combustion Engine
DRP	Demand Response Program
DG	Distributed Generation
V2G	Vehicle to grid
ASIDI	Average Service Interruption Duration Index
FACTS	Flexible alternating current transmission system
GA	Genetic Algorithm
PSO	Particle Swarm Optimization
DE	Differential Evolution
BA	Bat Algorithm
VRP	Voltage Stability, Reliability, Power loss
VSF	Voltage Sensitivity Factor
VSI	Voltage Stability Index
IEEE	Institute of Electrical and Electronic Engineers
R/X	Resistance/Reactance ratio
SAIFI	System Average Interruption Frequency Index
SAIDI	System Average Interruption Duration Index
CAIDI	Customer Average Interruption Duration Index
ENS	Energy Not Served
AENS	Average Energy Not Served

CSO	Chicken Swarm Optimization
TLBO	Teaching Learning Based Optimization
VD	Voltage Deviation
BLSA	Binary Lighting Search Algorithm
SAA	Sampling Average Approximation
GAMS	General Algebraic Modelling Solver
NDS	Non Dominated Solution
ZDT	Zitzler Deb Thiele function
DTLZ	Deb Thiele Laumann Zitzler function
BN	Bayesian Network

LIST OF SYMBOLS

Variables

Symbol	Description	Unit
I	Current flowing through the branch having resistance r and impedance x	Ampere
I_i	Current through branch i	Ampere
I'_i	Current through branch i after the placement of charging station	Ampere
L_j	Load demand of bus j	Watt
N_j	Number of consumers connected at bus j	---------------
P_{j+1}	Active power of the bus $j+1$	Watt
Q_{j+1}	Reactive power of bus $j+1$	VaR
U_j	Annual outage duration of bus j	hr/year
$V_j<\delta_j$	Voltage of bus j	Volt
$V_{j+1}<\delta_{j+1}$	Voltage of bus $j+1$	Volt
λ_j	Failure rate of bus j	Failure/yr
λ_i	Failure rate of i^{th} bus	Failure/yr
λ'_i	Failure rate of i^{th} bus after the placement of charging station	Failure/yr
λ_p	Failure rate of bus p	
λ'_p	Failure rate of bus p after the placement of charging station	
P_j	Power losses through j^{th} branch	Watt
N_{Fb}	Number of fast charging station at bus b	---------------
N_{Sb}	Number of slow charging station at bus b	---------------
SS_i	Reactive power of bus i	VaR
n_i	(0 or 1), n_i =1 if CS is at bus i else n_i =0	---------------

$N_F^{\,i}$	Number of fast charging station at i^{th} bus	---------------
N_S^{i}	Number of slow charging station at i^{th} bus	---------------
$V_i^{\,base}$	Voltage of i^{th} bus for base case	Volt
V_i	Voltage of i^{th} bus after placement of charging station	Volt
$VD_{\,i}$	Voltage Deviation of i^{th} bus	Volt
L_i	Load at i^{th} bus	Watt
U_i	Duration of interruption at i^{th} bus	hr/Watt
N_i	Number of consumer at i^{th} bus	---------------
P_{gi}	Active power generation of i^{th} bus	Watt
P_{di}	Active power demand of i^{th} bus	Watt
Q_{gi}	Reactive power generation of i^{th} bus	Var
Q_{di}	Reactive power demand of i^{th} bus	Var
P_i	Active power at the i^{th} bus	Watt
P_{i+1}	Active power at $(i+1)^{th}$ bus	Watt
P'_i	Active power at i^{th} bus after the placement of charging stations	Watt
P_i	Active power at the i^{th} bus	Watt
Y_{ij}	Magnitude of $(i,j)^{th}$ term of bus admittance matrix	mho
θ_{ij}	Angle of Y_{ij}	radian
δ_i	Voltage angle of i^{th} bus	radian
δ_j	Voltage angle of j^{th} bus	radian
p	Position of charging stations in the network	---------------
N_{fastp}	Number of fast charging stations placed at p	---------------
N_{slowp}	Number of slow charging stations placed at p	---------------
VSI^i_{base}	Base value of VSI of the i^{th} bus	Volt
VSI^i_l	VSI of the i^{th} bus after the placement of the charging stations	Volt
V_i	Voltage of i^{th} bus for base case	Volt
V_{i+1}	Voltage of $(i+1)^{th}$ bus for base case	Volt
V'_i	Voltage of i^{th} bus after the placement of charging station	Volt
V'_{i+1}	Voltage of $(i+1)^{th}$ bus after the placement of charging station	Volt
P_i	Active power at the i^{th} bus	Watt

P_{i+1}	Active power at $(i+1)^{th}$ bus	Watt
P'_i	Active power at i^{th} bus after the placement of charging stations	Watt
P_p	Active power at bus p	Watt
P'_p	Active power at bus p after the placement of charging station	Watt
Q_i	Reactive power at the i^{th} bus	Var
Q_{i+1}	Reactive power at $(i+1)^{th}$ bus	Var
Q'_i	Reactive power at i^{th} bus after the placement of charging stations	Var
Q'_{i+1}	Reactive power at $(i+1)^{th}$ bus after the placement of charging stations	Var
U'_i	Outage duration of i^{th} bus after the placement of the charging station	hr/yr
U_p	Outage duration of bus p	---------------
U'_p	Outage duration of bus p after the placement of charging station	---------------
r_i	Resistance of the branch between bus i and $i+1$	ohm
x_i	Reactance of the branch between bus i and $i+1$	ohm

Parameters

$CAIDI_l$	CAIDI after increase in load	hr/year
C_{direct}	Direct cost	$
$C_{indirect}$	Indirect cost	$
$C_{installationfast}$	Installation cost of fast charging stations	$
$C_{installationslow}$	Installation cost of fast charging stations	$
CP_{fast}	Power consumption of fast charging stations	Watt
CP_{slow}	Power consumption of slow charging stations	Watt
$CAIDI_{base}$	Base value of CAIDI	hr/year
L_{max}	Loading margin of the network	Watt
n_{fastCS}	Maximum number of fast charging stations that can be placed at each bus	--------------
n_{slowCS}	Maximum number of slow charging stations that can be placed at each bus	--------------
P	Set of nodes where charging stations are placed	--------------

P_t	Total power losses of the network	Watt
P_{loss}^{l}	Power losses after increase in load	Watt
$P_{lossbase}$	Power losses for the base case	Watt
r	Real part of Impedance	Ohm
S	Set of strong nodes of the distribution network based on voltage stability	--------------
$SAIFI_l$	SAIFI after increase in load	Interruption/year
$SAIDI_l$	SAIDI after increase in load	hr/year
$SAIFI_{base}$	Base value of SAIFI	Interruption/year
$SAIDI_{base}$	Base value of SAIDI	hr/year
SS_{min}	Lower bound of reactive power	VaR
SS_{max}	Upper bound of reactive power	VaR
T	Set of nodes of the road network with charging demand	--------------
TS	Set of superimposed nodes	--------------
VSI_l	VSI after increase in load	--------------
x	Imaginary part of Impedance	Ohm
w_1	Weight assigned to *A*	--------------
w_2	Weight assigned to *B*	--------------
w_3	Weight assigned to *C*	--------------
w_{21}	Sub weight assigned to SAIFI	--------------
w_{22}	Sub weight assigned to SAIDI	--------------
w_{23}	Sub weight assigned to CAIDI	--------------
Z	Impedance of branch	Ohm
Θ_z	Angle of *Z*	radian
$P_{electricity}$	Per unit cost of electricity	$
P_{VD}	Penalty paid by the utility for per unit voltage deviation	$/Volt
P_{AENS}	Penalty paid by the utility for per unit energy not served	$/kWhr
$T_{cost\ EV}$	Cost of travelling per km for EV	$
N_D	Total number of buses of the distribution network	---------------
N_T	Total number of nodes of the road network	---------------

T_t	Planning period	Year
$C_{installation}$	Installation cost of charging station	\$
$C_{operation}$	Operating cost of charging station	\$
$C_{penalty}$	Penalty paid by utility	\$
$VD_{penalty}$	Penalty for net voltage deviation	\$
$AENS_{penalty}$	Penalty for net energy not served	\$
C_{travel}	Travelling distance cost from point of charging station to point of placement of charging station	\$
N_{CS}	Total number of charging stations in the network	---------------
N_{fastCS}	Total number of fast charging stations in the network	---------------
N_{slowCS}	Total number of slow charging stations in the network	---------------
P_{VD}	Penalty of unit voltage deviation	\$/Volt
P_{AENS}	Penalty for unit AENS	\$/kwh
d_{CS}	Distance between the point of charging demand and point of placement of charging station	km
gen	Generation count	---------------
t	Iteration count	---------------
pop	Population size	---------------
RN	Set of roosters	---------------
HN	Set of hens	---------------
CN	Population of chicks	---------------
MN	Set of mother hens	---------------
PN	Population of swarm	---------------

T_k	Teacher	---------------
m_k	mean value of decision variable	---------------
R_t	Random number between 0 and 2	---------------
$c1, c2, w$	Algorithm- specific parameter of PSO	---------------
CR, F	Algorithm- specific parameter of DE	---------------
$\alpha,\gamma,f_{maxBA},A_0,r_0$	Algorithm- specific parameter of BA	---------------
p	Position of charging stations in the network	---------------
N_{fastp}	Number of fast charging stations placed at p	---------------
N_{slowp}	Number of slow charging stations placed at p	---------------
m	Maximum number of locations in which charging station will be placed	---------------
I_i	Current through branch i	Ampere
I'_i	Current through branch i after the placement of charging station	Ampere
q	Total number of charging demand points	--------------
d_ic_j	Distance between i^{th} charging demand point and j^{th} charging station where i=1,2, ...q and j=1,2, ...m	km
D	Distance Matrix	---------------
DD	Reduced Distance matrix	---------------
n_{fastp}	Maximum number of fast charging stations placed at bus p	---------------
n_{slowp}	Maximum number of slow charging stations placed at bus p	---------------
$Q_i^{\min}$	Lower limit of reactive power of bus i	Var
$Q_i^{\max}$	Upper limit of reactive power of bus i	Var

$P_i^{\min}$	Lower limit of active power of bus i	Watt
$P_i^{\max}$	Upper limit of active power of bus i	Watt
x_l	Lower limit of decision variable	--------------
x_u	Upper limit of decision variable	--------------
μ_i	Fuzzy membership function	--------------
OF_i	i^{th} objective function	--------------
OF_i^{min}	Minimum value of i^{th} objective function	--------------
OF_i^{max}	Maximum value of i^{th} objective function	--------------
$F_n[i]_m$	m^{th} objective function value of i^{th} solution in the front F_n	--------------
$F_n[i]_{dist}$	Crowding distance value of i^{th} objective function	--------------
M	Number of objective function	--------------
pop_{intl}	Initial Population matrix	--------------
A_{pop} B_{pop} C_{pop} D_{pop} E_{pop}	Population sub matrices	--------------
P_{RS}	Probability that the residential single lane road is congested	--------------
P_{RD}	Probability that the residential double lane road is congested	--------------
P_R	Probability that residential area is congested	--------------
P_O	Probability that office area is congested	--------------
W_t	Waiting time in charging stations	hr
A	Accessibility index	/km
W_f	Waiting time in fast charging stations	hr
W_s	Waiting time in fast charging stations	hr
λ_f, λ_s	Arrival rate of EVs in fast and slow charging stations	Car/hr
ρ_f, ρ_s	Utilization rate of fast and slow charging stations	hr
P_0^f , P_0^s	Probability of no EVs in fast & slow charging stations	--------------

F_{max}, f_{max}	Maximum number of fast charging stations and charging points for the two-stage planning model	---------------
S_{max}, s_{max}	Maximum number of slow charging stations and charging points for the two- stage planning model	---------------
F_{min}, f_{min}	Minimum number of fast charging stations and charging points for the two-stage planning model	---------------
S_{min}, s_{min}	Minimum number of slow charging stations and charging points for the two-stage planning model	---------------

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PUBLICATIONS

Peer Reviewed Journals

[P1] **Deb, S.**, Tammi, K., Kalita, K., & Mahanta, P. (2018) Review of recent trends in charging infrastructure planning for electric vehicles. *Wiley Interdisciplinary Reviews: Energy and Environment*, e306. (IF- 3.297)

[P2] **Deb, S.**, Tammi, K., Kalita, K., & Mahanta, P. (2018). Impact of Electric Vehicle Charging Station Load on Distribution Network. *Energies*, *11*(1), 178 (IF-2.676)

[P3] Deb, S., Gao, X. Z., Tammi, K., Kalita, K., & Mahanta, P. (2019). Recent Studies on Chicken Swarm Optimization algorithm: a review (2014–2018). *Artificial Intelligence Review, Springer*, 1-29. (accepted) (IF-5.095)

[P4] **Deb, S.**, Tammi, K., Kalita, K., & Mahanta, P., Charging Station Placement Problem for Electric Vehicles: a Case Study of Guwahati city, India. *IEEE Access* (accepted) (IF-4.098)

[P5] **Deb, S.**, Gao, X. Z., Tammi, K., Kalita, K & Mahanta P, A new teaching learning based Chicken Swarm Optimization Algorithm. *Soft Computing, Springer* (accepted)

[P6] **Deb, S.**, Tammi, K Gao, X. Z., Kalita, K & Mahanta,P, A Robust two-stage planning model for charging station placement problem considering road traffic uncertainty, *IEEE Transactions on Intelligent Transportation System* (Second Revision submitted)

[P7] **Deb, S.**, Gao, X. Z., Tammi, K., Kalita, K & Mahanta P, A Pareto Dominance based Multi-Objective Chicken Swarm Optimization and Teaching Learning Based Optimization Algorithm for Charging Station Placement Problem. *Neural Computing and Applications, Springer* (under review)

[P8] **Deb, S.**, Tammi, K., Kalita, K., & Mahanta, P., Overview and Comparison of Different Planning Models for Charging Station Placement Problem, *IEEE Transactions on Intelligent Transportation System* (under review)

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[P12] **Deb, S.**, Kalita, K., Gao, X. Z., Tammi, K., & Mahanta, P. (2017, November). Optimal placement of charging stations using CSO-TLBO algorithm. In *Research in Computational Intelligence and Communication Networks (ICRCICN), 2017 Third International Conference on* (pp. 84-89). IEEE

[P13] **Deb, S.**, Kalita, K., & Mahanta, P. (2017, December). Review of impact of electric vehicle charging station on the power grid. In *2017 International Conference on Technological Advancements in Power and Energy (TAP Energy)*. IEEE

[P14]] **Deb, S**., Kalita, K., & Mahanta, P. (2017, December).Impact of Electric Vehicle Charging Station Loads on Reliability of Distribution Network. In *2017 International Conference on Technological Advancements in Power and Energy (TAP Energy)*. IEEE

CHAPTER 1

INTRODUCTION

1.1. Motivation

The ever growing energy demand, fossil fuel depletion, environmental pollution, and harsh climatic conditions are some of the major concerns of the researchers of 21st century. Research works confirm that the transportation sector is one of the major agents of CO_2 emission (Wang et al. 2015; Wang et al. 2016; Blesl et al. 2007). Cars contribute to nearly two third of total CO_2 emission in United States (Schipper et al. 2011). Moreover, it is predicted that the oil consumption of the transport sector will rise by 54% until 2035 (Source: Petroleum, British, and BP Energy Outlook 2030. *London, United Kingdom* 2011). As a measure to decrease the greenhouse gas contributions of the transport sector, 21st century has witnessed the replacement of conventional Internal Combustion Engine (ICE) driven vehicles with Electric Vehicles (EVs). Researchers have predicted that transportation electrification will reduce the greenhouse gas emissions by 50% by the year 2050 (Source: MIT-energy-initiative-report-guidance-evolving-electric-power-sector 2016). The reduction in CO_2 emissions attained by the use of EVs has motivated many countries to promote the use of EVs. EVs have potential to reduce CO_2 contribution of the transportation sector if majority of the electric power used in EVs originate from renewable or nuclear power plants. Apart from exhaust reduction, low noise, minimal maintenance, and lower operating cost are some of the additional benefits achieved by the use of EVs (Teixeira et al. 2016; Hoyer et al. 2008; Graham et al. 2012). The drive train of EV is equipped with the provision to use any renewable energy source for transport whereas conventional engines need liquid or gaseous fuels. The replacement of conventional vehicles by EVs will reduce the heat emission by a considerable amount which will indeed be a great initiative to tackle the serious concern of climate change and global warming.

The first half of 21st century is characterized by the expansion of EV market. However, still there are many issues inhibiting the large-scale use of EVs. Limitations in battery technology, inadequate charging infrastructure, lack of public charging stations, improper placement of charging stations, uncoordinated charging in the charging stations are some of the key factors inhibiting the large-scale deployment of EVs (Mukherjee et al. 2015; Sortomme et al. 2010). A well-planned and incentivized exploitation of charging stations would lead to enhanced livability, along with increased adoption of the EVs. Charging infrastructure planning is a challenging problem involving convolution of both transport and distribution networks. The road and grid infrastructure have existed for decades before the boom of EVs. As a consequence of which the planning of charging station becomes challenging if the strong points of the power grid do not merge with significant hubs in traffic network. Establishment of charging stations mean increase in the load demand of the utility grid that account for increased peak demand and decreased reserve margin. Improper placement of charging stations in the distribution network may result in voltage fluctuations, power loss, and power quality related problems (Aghaei et al. 2016; Hu et al. 2016).Charging stations must be placed in the distribution network in such a way that the negative impact of placement of charging stations on the operating parameters of the distribution network is minimized. Also, the location of charging station must be optimized considering the route choice behavior of EV drivers and charging demand of the EVs computed based on the driving range of the EV (Hanabusa et al. 2011). Hence, motivated by all the aforementioned factors this thesis aims to delve into charging infrastructure planning for EVs.

1.2. Different categories of Electric Vehicles

With the motive of electrification of the transportation sector, the automobile industry has started manufacturing different categories of EVs like Plugged In Electric Vehicle (PEV), Plugged In Hybrid Electric Vehicle (PHEV). This section provides a brief discussion of different types of EVs. A Plug in Electric Vehicle (PEV) uses energy from battery as its primary driving source and can be recharged from charging stations when required (Ramalingam et al. 2015).A Battery Electric Vehicle (BEV) is completely electric. The vehicle is driven by the on-board battery instead of gasoline (Ramalingam et al. 2015). An Extended Range Electric Vehicle (EREV) is similar to BEVs with the additional feature of an on-board gasoline fuelled generator to provide additional energy, when the batteries are low (Ramalingam et al. 2015). A Plug-in Hybrid Electric Vehicle (PHEV) has both an electric motor and a typical gasoline or diesel engine to provide driving force to the car. The electric and gasoline drives are controlled by the onboard computer to give the car power to get very efficient overall mileage. These cars have an on-board battery to support the electric motor and will be plugged-into fully recharge the battery. The batteries also use the regenerated energy from the braking and deceleration and recycle it through the battery to power the vehicle (Ramalingam et al. 2015). A PHEV is usually designed for series-hybrid, parallel-hybrid, or combined series parallel hybrid configuration (Khajepour et al. 2014; Ehsani et al. 2009).In series-hybrid configuration only the electric motor provides power to drive the wheels. Sources of electrical energy are either the battery pack (or ultra-capacitors) or a generator powered by a thermal engine (Ramalingam et al. 2015; Khajepour et al. 2014; Ehsani et al. 2009). On the other hand in parallel-hybrid configuration both the electric motor and fossil powered engine provides power in parallel to the same transmission (Ramalingam et al. 2015). Power split or series/parallel hybrid combines the advantages of both parallel and series hybrid concepts. This allows running the vehicle in an optimal way by using the electric motors only, or both the IC Engine and the electric motors together, depending on the driving conditions.

1.3. Charging types and infrastructure for Electric Vehicles

For smooth operation of EVs, there is an urgent need of establishing proper charging infrastructure .A battery charger is a device used to transfer energy to an EV battery by processing and controlling the electric current through it (Ehsani et al. 2009). A rectifier is incorporated in an EV charger to recharge an EV battery by converting AC to DC. The charging types of EVs are broadly classified as-

I Conductive charging- Conductive charging scheme transfers power through direct contact. This scheme uses a conductor to connect the electronic devices to the extent of energy transfer. Conductive charging is simple and highly efficient. It can be an on-board or off-board method. An on-board charger is mainly utilized for slow charging, and the charging activity is conducted inside the EV, whereas an off-board charger is installed at fixed locations to offer rapid charging service (Ehsani et al. 2009).

II Inductive charging-Inductive charging, also known as wireless charging uses an electromagnetic field to transfer electricity to an EV battery. The benefit of inductive charger is that it provides electrical safety under all-weather conditions. The drawbacks of inductive chargers are low efficiency and high power loss (Ehsani et al. 2009).

III Battery swapping- Battery swapping is a scheme by which users can swap their empty battery with a fully charged one from a battery swapping station (BSS). BSSs have several benefits, such as long battery lives, low time consuming, and comparatively minimal cost to manage, given that batteries are collected and managed in centralized locations (Ehsani et al. 2009).

Charging stations are regarded as the point of fuelling EVs. Cords, connectors, and interface with the power grid are the key equipments of charging station. Good charging infrastructure is one of the key factors for deployment of EVs. The Electric Power Research Institute (EPRI) has characterized the charging levels as follows-(Hussain et al. 2016).

1. AC Level 1
2. AC level 2
3. DC Fast charging

Table 1.1 gives a comparative analysis of different charging levels considering input voltage, current as well as charging time and typical applications of different variety of charging station.

Table 1.1- Comparative Analysis of different charging levels (Hussain et al. 2016; Botsford et al. 2009; Falvo et al. 2014; Francfort et al. 2010)

Type	**Input voltage**	**Input current**	**Charger location**	**Charging time**	**Typical use**
AC Level 1	120 V	15 A	On board	(10-13) hr	Home or Office
AC Level 2	240 V	40 A	On board	(1-3) hr	Private or Commercial
DC Level 1	208 V	80 A	Off board	(0.5-1.44) hr	Public

1.4. General Overview of Charging Infrastructure Planning

Charging station placement problem is a typical planning problem concerned with optimal allocation and sizing of charging stations considering economic factors, operating parameters of distribution network and EV driver's convenience. The characteristics of a good charging station placement model are-

- The model must take into account both transport and distribution network parameters
- The model must have the ability to consider economic factors associated with establishment of charging stations
- The model must consider EV drivers convenience
- The model must take into account the security of the distribution network
- The model should be able to produce the output planning results with less computational costs

A systematic overview of the charging station placement problem is as shown in Fig.1.1. As shown in Fig.1.1 the first step of charging station placement problem is selection of the test network where charging stations will be placed. Then, the input parameters required for computing the optimal locations and number of charging stations are set. After that the objective functions and constraints are defined and finally optimization is performed.

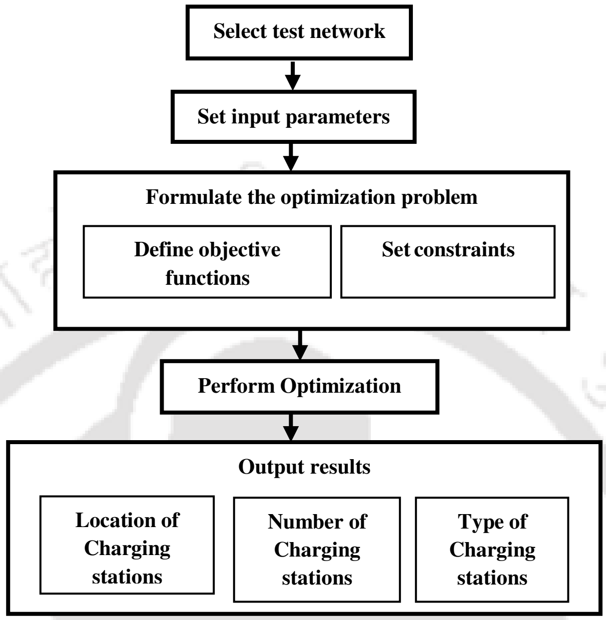

Fig. 1.1- Overview of charging station placement problem

Charging infrastructure planning problem mimics a typical planning problem concerned with placement of charging stations in the road network in such a way that the operating parameters of the power grid are least affected. A generalized mathematical formulation of the problem is given by Eq. (1.1) to Eq. (1.4).

$$Min(Z) = f(p, u_{fast}, u_{slow}) \tag{1.1}$$

where Z is the objective function, p, u_{fast} , u_{slow} are the decision variable vectors. p represents the locations of charging stations. p can be the nodes of distribution/ transport /superimposed transport and distribution network depending upon the modelling approach adopted. u_{fast} and u_{slow} represent the number of fast and slow charging stations placed at p respectively. In charging station placement problem, the decision variable can include the nodes of distribution/ transport /superimposed transport and distribution network, number of charging stations at the nodes, the type of charging stations. The type of charging station means that whether the charging station is a fast charging station or a slow charging station. Z can include cost, EV flow, distance, power loss, voltage deviation, net benefit etc. When the placement problem is modelled considering only transport network, Z can be cost, EV flow, or distance. When the placement problem is modelled considering only distribution network, Z can be cost, power loss, net benefit, or voltage deviation. If the placement problem is modelled considering superimposition of transport and distribution network then all the aforementioned objective functions can be considered together.

Subject to

$$u_{fast}^{min} \leq u_{fast} \leq u_{fast}^{max} \text{ and } u_{slow}^{min} \leq u_{slow} \leq u_{slow}^{max} \tag{1.2}$$

$$g_j(p, u_{fast}, u_{slow}) = 0 \tag{1.3}$$

$$j = 1, 2..........m$$

$$h_k(p, u_{fast}, u_{slow}) \leq 0 \tag{1.4}$$

$$k = 1, 2.............n$$

Constraint given by Eq. (1.2) includes the upper and lower limit of charging stations to be placed. In Eq. (1.2) u_{fast}^{min} and u_{fast}^{max} represent the maximum and minimum number of fast charging stations that can be placed at position p respectively. Similarly, u_{slow}^{min} and u_{slow}^{max} represent the maximum and minimum number of slow charging stations that can be placed at position p respectively. Equality constraint given by Eq. (1.3) can include power balance equation, charging demand balance etc. When the placement problem is modelled considering only transport network, then the equality constraint can include charging demand balance. When the placement problem is modelled considering only distribution network, then power balance equation can be considered as an equality constraint. And, when the problem is modelled considering superimposition of transport and distribution network, then both charging demand balance and power balance equation can be considered as equality constraint. Inequality constraint given by Eq. (1.4) can include voltage limit, current limit, budget limit etc if the problem is modelled considering only distribution network. When the problem is modelled considering only transport network then inequality constraint can be the budget limit. If superimposition of transport and distribution network is considered while modelling the problem then all the aforementioned inequality constraints can be considered together.

1.5. Research Objectives

The thesis aims to delve into different perspectives of charging infrastructure planning problem. Tactical formulation of the charging station placement problem and utilizing efficient algorithms for solution of the complex placement problem are two prime activities performed in this research work. The major objectives of this research work are as follows-

1. To analyze the impact of the load of EV charging stations on distribution networks
2. To formulate planning models for charging station placement
3. To propose efficient evolutionary algorithms for solving charging station placement problem
4. To propose a scheme for integrated planning of EV charging stations for Guwahati city, India

The aforementioned research objectives are further elaborated in the subsequent sub-sections.

1.5.1. Analysis of the impact of EV charging station load on distribution network

The voltage stability, reliability, and power losses are some of the operational parameters that are affected due to the introduction of EV charging station loads in the distribution network. Thus, the first objective of this research work is to quantify the impact of EV charging station loads on the aforementioned parameters of the distribution networks. The analysis will be carried out on IEEE 33 bus radial distribution network. The purpose of performing this analysis is to identify the parameters of the network that are affected due to the placement of the EV charging station loads. This will help in assigning proper weights to all the operating parameters while obtaining the optimal placement of charging stations considering multi-objective approach.

1.5.2. Formulation of planning models for charging station placement

The placement of charging station is a complex problem which involves the interaction of both transport and distribution networks. The charging stations must be positioned in such a way that the operating parameters of the distribution network are least affected and simultaneously the EV drivers convenience must also be taken into consideration. Therefore, the second objective of this research work is optimal placement of charging station considering the superposition of transport and distribution networks. This research work will propose single-objective modelling, multi-objective modelling as well as a two-stage modeling of the charging station placement problem. The single-stage planning models will be validated on a test network formed by superimposing 33 bus radial distribution network and a 25 node road network. And, the two-stage planning model will be validated on a test network formed by superimposing IEEE 33 bus radial distribution network and a 25 node road network as well as real time network of Tianjin, China.

1.5.3. Solution of charging station placement problem by efficient evolutionary algorithms

In recent years, the paradigm of combinatorial optimization has witnessed the discovery of a number of novel meta-heuristic algorithms. Many real-world engineering optimization problems are difficult to solve by classical algorithms because of the non-linear nature of the objective functions involved. The charging station placement problem is one such complex problem involving a number of variables, non-linear objective functions, and constraints. Hence, there is necessity of devising efficient and fast algorithms for the solution of the placement problem. Thus, the third objective of the research work is to develop and propose efficient evolutionary algorithms for solution of the charging station placement problem.

1.5.4. Integrated planning of EV charging stations for Guwahati city

The final objective of this research work is to propose a scheme for sustainable development of EV charging stations for the city of Guwahati, India. A scheme for apposite placement of EV charging stations in the superimposed road and distribution network of Guwahati will be proposed. The cost, reliability, voltage stability as well as EV drivers convenience will be given due consideration while planning EV charging stations for the city of Guwahati.

1.6. Outline of the thesis

The organization of the thesis is as follows. Chapter 1 elaborates the background of charging infrastructure planning problem. Chapter 2 reports the existing research works related to the charging infrastructure planning problem. Chapter 3 reports the impact of EV charging station placement on distribution network. Chapter 4 presents the single-objective formulation of charging station placement problem and propose a new hybrid CSO TLBO algorithm for solving charging station placement problem. Chapter 5 presents the multi-objective formulation of the charging station placement problem and propose Pareto dominance based multi-objective CSO TLBO for charging station placement problem. Chapter 6 presents a novel two-stage planning model for charging station placement problem. Chapter 7 presents an integrated planning scheme for charging station placement in the context of Guwahati city, India. Finally, chapter 8 summarizes the key findings of the research work and presents the future works possible in this paradigm.

Note- Some parts of this chapter are reproduced from the publication-

- **Deb, S., Tammi, K., Kalita, K., & Mahanta, P. (2018) Review of recent trends in charging infrastructure planning for electric vehicles. *Wiley Interdisciplinary Reviews: Energy and Environment*, 7(6), e306.**

CHAPTER 2

LITERATURE REVIEW

2.1. Introduction

This chapter reviews the existing literature on various aspects of charging infrastructure planning like impact of charging station load on distribution network, formulation of charging station placement problem and optimization algorithms applied for solving the placement problem. Summary of the literature review, limitations of the existing literature and scope of present research are also elaborated at the end of this chapter.

2.2. Impact of EV charging station on power grid

Although the electrification of the transportation sector has many favorable impacts like less CO_2 emission, reduced pollution as well as less global warming, the detrimental impacts of the EV chargers on the power distribution network cannot be neglected. The operating parameters affected by placement of charging station are illustrated in Fig.2.1.Increased penetration of EVs in the market results in increased power demand for charging which may have some adverse impacts on the power grid. This sub-section elaborates the adverse impacts of EV charging on different parameters of power grid.

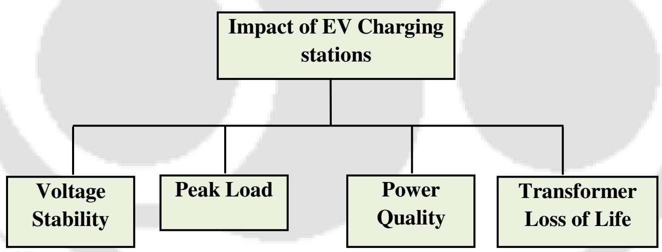

Fig.2.1. Impact of EV charging station on power grid

2.2.1. Impact of EV charging station on voltage stability

The threat to voltage stability is one of the most crucial adverse impacts of EV charging station. Theoretically, voltage stability is the ability of power system to maintain steady voltages at all the buses after withdrawal of disturbances from a given initial operating condition (Kundur et al. 1994; Kessel et al. 1986). A sudden increase in load is one of the key factors responsible for voltage instability. Due to charging of EVs there is sudden increase in load which results in voltage instability. Geske et al. (2010) presented a simulation model of EV penetration in the power system distribution network of Otto-von-Guericke University Magdeburg. The different scenarios of EV penetration were generated based on real time data of arrival and departure of the vehicles. They investigated the voltage stability at each and every node of the distribution network and concluded that the generated scenarios do not cause voltage instability. Juanuwattanakul et al.(2011) identified the weakest bus in the 13 bus network in presence of plugged in hybrid vehicle (PHEV) charging station based on a positive sequence voltage ranking index. Rahman et al. (2013) analyzed the variation of voltage sensitivity index of a 16 bus commercial distribution network in presence of PHEV charging load and they also provided a scheme for optimal placement of EV charging station based on this voltage sensitivity index. Dharmakeerthi et al. (2013) analyzed the effect of EV load on oscillatory stability of the power system. Zhang (2014) analyzed the effect of EV charging loads on transient voltage stability index of IEEE 16 bus system. Later, Dharmakeerthi et al. (2014) analyzed the effect of EV charging load on static voltage stability margin of IEEE 43 bus industrial test system. Ul Haq et al. (2015) analyzed the impact of EV charging load on voltage unbalance of an urban distribution network. They also presented a comparative analysis of the impact of uncoordinated and tariff based charging scheme. De Hoog et al. (2015) analyzed the impact of EV charging station on L index of two practical distribution network of Australia. Dharmakeerthi et al. (2015) analyzed the effect of EV charging load on static voltage stability of IEEE 14 bus system. Zhang (2016) analyzed the effect of EV load on the voltage stability of a simplified 2 bus distribution network in PSCAD software. Ma et al. (2017) analyzed the impact of EV charging station load on nodal voltage deviation of IEEE 30 bus distribution network. The authors concluded that the nodal voltage deviation depends on EV permeability, node type and node position. Kongjeen et al. (2018) analyzed the impact of EV load on voltage deviation of IEEE 33 bus test network by considering different model of EV charger load like constant power load, constant current load, and constant impedance load. The authors concluded that the lowest increased value of voltage deviation caused by EV load is 0.062 pu. Further, the authors also commented that the detrimental impact of EV load on voltage stability can be compensated by coordinated charging to certain extent. Further, Kongjeen et al. (2019) analyzed the impact of EV load on voltage stability by considering different EV load models such as polynomial load, constant current load, and voltage dependent load by modified forward backward sweep algorithm.

2.2.2. Impact of EV charging station on peak load

The increased load demand for EV charging results in rise of the peak load demand of the grid that is accompanied by decrease in reserve margin. Putrus et al. (2009) analyzed the effect of uncontrolled EV charging on daily load profile. They also showed the improvement in load profile by incorporating coordinated charging. McCarthy et al. (2010) examined the effect of PHEV load on the Metropolitan distribution network of Australia. They concluded that with uncoordinated charging and with 100% PEV penetration 41% peak load shifting is required. Fan et al. (2013) concluded that disorderly charging will increase the peak load demand and recommended tariff based charging. Jiang et al. (2016) presented the daily load variation with different penetration of EV. Gnann et al. (2018) made an attempt to analyze the impact of EV chargers on peak load demand by considering various scenarios of EV penetration. The authors commented that increase in evening peak load caused by charging of commercial EVs is less than the increase in load caused by home charging of private EVs. Shinde & Swarup (2018) studied the impact of EV load on the upsurge in load demand and proposed a demand response program for profit maximization. Li et al. (2019) reported that uncoordinated EV charging increases the peak load demand and proposed a charging discharging model to regulate the peak load.

2.2.3. Impact of EV charging station on power quality

Theoretically, power quality is defined as the ability of power system to supply a stable and disturbance free output which is within voltage and frequency tolerances (Bollen 2000). The non-linear characteristic of the EV charging load is a threat to power quality. Harmonics (De 2006; Maslowski 1993), Voltage sag (Lamoree et al. 1994; Yaleinkaya 1998) are some of the common power quality problems. Harmonics are sub-components of current or voltage waveforms whose frequency is integral multiple of the reference frequency (De 2006). Harmonic is measured in terms of total harmonic distortion (THD) which is defined as the level of difference between actual obtained and reference frequency (Shmilovitz 2005). Staats et al. (1998) investigated the effect of EV charging load on harmonic voltages of distribution system based on some statistical analysis. They classified the chargers based on THD produced. They also concluded that even with 45% of EV penetration there is negligible voltage distortion during summer. Gomez et al. (2003) analyzed the effect of non-linear EV charging load on power quality of the distribution system. They also reported how the performance and life cycle of the distribution network equipments like transformer, circuit breakers, and fuses are affected by harmonic distortion produced by EV loads. Basu et al. (2004) reported that EV battery charging load can cause current harmonic distortion of even 50%. They also designed EV battery charger with inherent power quality control feature. Jiang et al. (2014) simulated the harmonics caused by PHEV chargers by probabilistic Monte Carlo approach considering all the uncertainties. They concluded that residential Level 1 chargers have severe impact on power quality. Xu et al. (2014) presented the harmonic analysis of EV charging load on IEEE 34 node test network. They concluded that EV with higher SOC will cause less power quality problems. They suggested that the locations of EV charging stations should be far away from the transformers and the charging stations in industrial area should impose a limit regarding number of EV charged per day to reduce power quality problems. Dubey et al. (2015) presented the impact of EV charging load on distribution network and proposed techniques for mitigating these problems. They concluded that coordinated charging of EV will solve most of the power quality problems. Nitsoo et al. (2015) analyzed the effect of non-linear EV load on residential distribution network. They concluded that an EV penetration level of more than 25% would affect the power quality. Ul Haq et al. (2015) presented the effect of EV charging load on voltage profile and harmonics of an urban low voltage distribution network. Lucas (2015) presented the impact of fast EV chargers on power quality of distribution network and compared how THD can be reduced by adopting a planned coordinated charging strategy. Torquato et al. (2016) presented a comparative analysis of charging stations on power quality in the distribution network of Brazil. Supponen et al. (2016) monitored and analyzed the effect of EV charging on power quality based on real time data. Hernandez et al. (2016) performed harmonic analysis in presence of EV charging load and found a significant increase in third harmonic current in presence of EV charging loads. Woodman et al. (2018) analyzed the impact of Level 2 and Level 3 chargers on harmonics of distribution network.

2.2.4. Impact of EV charging station on transformer loss of life

Large-scale deployment of EVs produces additional stress on the distribution transformers which plays a prominent role in decreasing the life cycle of the transformer. Increase in load causes increase in hot spot temperature of the transformer (Godina et al. 2015a). The charging of EVs cause increase in load which in turn causes increase in hot spot temperature. Grahn et al. (2011) analyzed the impact of coordinated charging; tariff based charging and uncoordinated charging on transformer loss of life and concluded that uncoordinated charging is detrimental to the performance of transformer. Later, many researchers did similar type of analysis and concluded that uncoordinated charging accelerates the ageing of transformers (Gong et al. 2012; Godina et al. 2015b; Godina et al. 2016; Qian et al. 2015).

2.3. Optimal Placement of Charging Stations

The optimal placement of charging station is a multi-dimensional, complex problem that involves the interaction of both distribution and transportation network. Researchers adopted different strategy to deal with this problem. The research works that investigate and deal with this placement problem can be broadly classified as illustrated in Fig.2.2.

2.3.1. Optimal placement of charging stations considering only transportation network

A considerable number of studies consider only the transportation network while determining candidate location of re-fueling or charging stations of EVs. The optimal location of charging station in the transportation network depends on the spatial units which are to be served and is further sub-divided into three sub-sections. These units can be nodes, arcs, and paths. In addition, based on the spatial units to be served this approach can be sub-divided into following categories-

I Node based Approach

II Path based Approach

III Tour based Approach

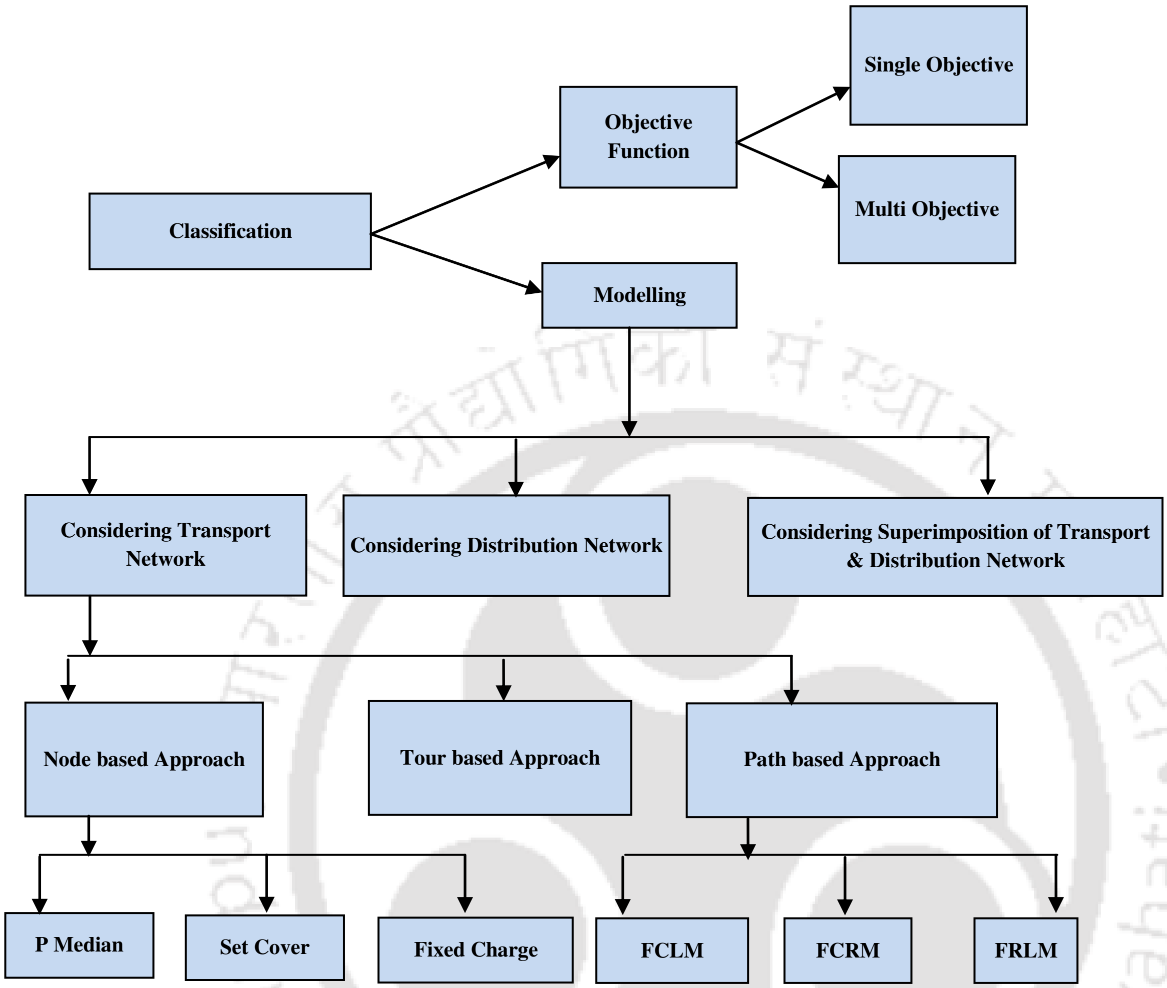

Fig. 2.2-Schematic Overview of classification of research works on charging infrastructure planning problem

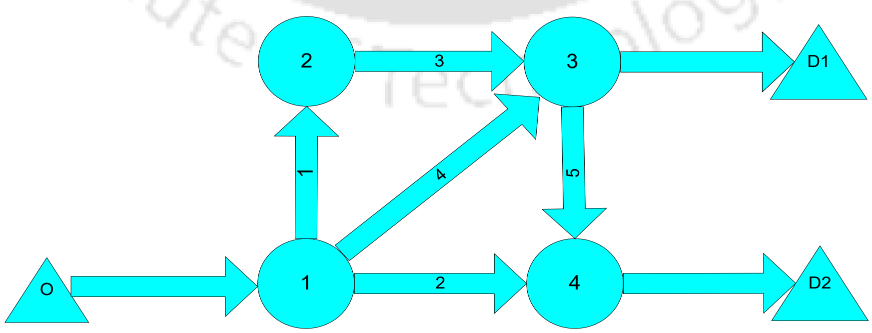

Fig. 2.3- An ideal transportation network

Fig.2.3 represents an ideal transportation network. The circles represent nodes and the arrow heads represent paths. O represents the origin or start point of the journey, D1 and D2 represents destination. The journey from origin to destination by any one route or path is tour.

Though the main objective of all the aforementioned approach is same but the modelling is different in all the approaches.

I. Node based approach

Nodes are considered as the most commonly covered spatial units in the transportation network. In the transportation network, nodes are defined as the point of intersection of the geographic zones (Weiping & Wu 1989).The p median model developed by Hakimi in 1964 is one of the most appealing nodal based methods adopted by researchers for optimal allocation of refueling stations in the transport network. P median model is a graph theoretic approach of location allocation problem that locates p facilities and allocates demand nodes *i* to facilities *j* to minimize the total distance travelled by consumers to facilities. Hakimi (1964) used this novel approach for optimal location of police stations in highways. P median based approach is adopted by many researchers for modeling of the charging station placement problem (Nicholas et al. 2004; Nicholas et al. 2006; Miyagaya 2013; Hong & Kuby 2016).

Other node based approaches include the set cover developed by Toregas in 1971. The Location Set Covering Problem involves finding the lowest number of facilities and their locations in such a way that each and every demand is covered by at least one facility. The set cover based approach is used by many researchers for determining optimal location of recharging or refueling stations in transportation network (Wang & Wang 2010; Gopalakrishnan 2016). Wang & Wang (2010) proposed a hybrid model based on the set covering approach with multi-objective function of cost minimization as well as maximum population coverage. Gopalkrishnan et al. (2016) selected an optimal subset from a given set of candidate location of charging stations.

Another node based approach which attracts the interest of the researchers is the fixed charge model developed by Belinski in 1965.The fixed charge based modeling involves nonlinear modeling of the network and gives upper and lower bound of optimal value of the objective function. The fixed charge based approach is utilized for finding optimal location of charging station in the transportation network by a number of modern researchers (Baouche et al. 2014a; Baouche et al. 2014b). One of the advantages of node based method is the minimal data requirement. It requires only road network data and the population data. Random type of commuting is ignored in the node based approaches. In most of the node based approaches, assumption is made that the users make only single trip from home or work place to the utility. As a result of which this approach suffers from the inherent shortcoming of incapability of representation of real world situations.

II. Path based approach

Path based approaches are typically flow capturing models which aims at maximizing the passing flows by allocating one or more units along the path. Flow Capturing location model (FCLM) introduced by Hodgson in 1990 and Flow Capturing Refueling model (FCRM) introduced by Kuby and Lim in 2005 are path based approaches adopted by modern researchers for optimal placement of charging station problem. FCLM has originated from Maximal covering location model (MCLM) (Church et al. 1975). However, it takes cannibalization into account which makes it superior to MCLM. FCLM takes into account variety of trips of the user from workplace or home to other destinations like shopping malls. FCLM is based on capturing the traffic flow and requires record of detailed origin destination flow data unlike the nodal based approaches. Flow capturing approach is utilized to find optimal location of charging stations in the transportation network in (Wu et al. 2016; Zambrano et al. 2013; Lin et al. 2015). Wu et al. (2016) used a stochastic flow capturing based approach which takes into account the uncertainty in EV flows. Cruz et al. (2013) applied an advanced flow capturing model for optimal location of charging station in the city of Barcelona with the aim of maximizing profitability and public service Lin et al. (2015) utilized flow capturing based model to intercept the largest charging demand. Flow Refueling Location Model (FRLM) introduced by Kuby and Lim in 2005 mimics FCLM with the additional assumption that a single facility may not be able to capture the entire flow. FRLM just like its predecessor FCLM is based on the demand arising due to flow and not nodes. The FRLM is a path-based demand model which determines *p* stations to maximize the number of trips on their shortest paths. Upchurch et al. (2010) discussed the superiority of FRLM over p median based nodal approach for optimal location of alternative fuel vehicle charging station problem. Tran et al. (2015) reviewed the literature related to optimal placement of recharging stations considering flow based approaches. Later in 2012, Kim and Kuby introduced a novel approach named FRLM taking into account the deviation from the shortest path on the way to refuel or recharge. FRLM based approach is utilized for determination of optimal location of charging station in the transportation network in (Ahn et al. 2015; Zhao et al. 2016; Chang et al. 2014; You & Yi 2014).

III. Tour based approach

The tour based approach is a realistic approach of representation of the charging station placement problem as it has the capability to represent real time situations like round trip, random trip. Tour based approach requires a significant amount of travel data, travel route and driving behaviour of the EV users. But it gives a realistic flavour and a much strategic representation of the problem. Andrews et al. (2013) proposed a scheme for finding optimal location of charging stations based on tour data of the vehicles. Gonzaleb et al. (2014) modelled the daily spatial and temporal behaviour of EVs by considering the daily tour data of the vehicles.

Table 2.1-Summary of research works related to optimal placement of charging stations considering only transportation network

Author	**Diligence**	**Approach**
Wang & Wang (2010)	Locating passenger vehicle refueling stations	Set Covering based nodal approach
Ge et al.(2011)	The Planning of Electric Vehicle Charging Station Based on Grid Partition Method	Nodal based approach
Jia et al. (2012)	Optimal Siting and Sizing of Electric Vehicle Charging Stations	Tour based Approach
Kim & Kuby (2012)	The Deviation Flow Refueling Location Model for Optimizing a Network of Refueling Stations	FRLM with deviation
Andrews et al. (2013)	Modeling and Optimization for Electric Vehicle Charging Infrastructure	Tour based approach
Miyagaya (2013)	Distribution of Deviation Distance to Alternative Fuel Stations	P median based nodal approach

Author	Diligence	Approach
Wang & Chuah (2013)	Locating multiple types of recharging stations for battery-powered electric vehicle transport	Set covering and MCLP based approach
Cai et al. (2014)	Siting public electric vehicle charging stations in Beijing using big-data informed travel patterns of the taxi fleet	Tour based Approach
Gonzaleb et al.(2014)	Determining electric vehicle charging point locations considering drivers' daily activities	Tour based approach
Gavranovic et al. (2014)	Optimizing the electric charge station network of EŞARJ	P median based approach
Gimenez et al. (2016)	Optimal location of battery electric vehicle charging stations in urban areas: A new approach	MCLM based approach
Baouche et al.(2014a)	Electric Vehicle Charging Stations Allocation Model	Fixed charge model
Baouche et al. (2014b)	Efficient Allocation of Electric Vehicles Charging Stations: Optimization Model and Application to a Dense Urban Network	Fixed charge model
You & Yi. (2014)	A hybrid heuristic approach to the problem of the location of vehicle charging stations	FRLM based approach
Lu et al. (2015)	A location-sizing model for electric vehicle charging station deployment based on queuing theory	FRLM based approach
He et al.(2015)	Deploying public charging stations for electric vehicles on urban road networks	Tour based approach
Lin et al. (2015)	The Flow Capturing Location Model and Algorithm of Electric Vehicle Charging Stations	FCLM based approach

Author	Diligence	Approach
Ahn et al.(2015)	An Analytical Planning Model to Estimate the Optimal Density of Charging Stations for Electric Vehicles	FRLM based approach
Wang et al. (2016)	Electric Vehicle Charging Station Placement for Urban Public Bus Systems	Tour based approach
Nahrstedt et al. (2016)	Placement of Energy Sources for Electric Transportation in Smart Cities	FRLM based approach
Zhu et al. (2016)	Charging station location problem of plug-in electric vehicles	Modified FRLM
Arslan et al. (2016)	A Benders decomposition approach for the charging station location problem with plug-in hybrid electric vehicles	FRLM based approach
Asamer et al. (2016)	Optimizing charging station locations for urban taxi providers	MCLP based approach
He et al.(2016)	Incorporating institutional and spatial factors in the selection of the optimal locations of public electric vehicle charging facilities: A case study of Beijing, China	P median and MCLP based approach
Davidov et al. (2016)	Planning of electric vehicle infrastructure based on charging reliability and quality of service	Set covering based approach
Tu et al. (2016)	Optimizing the locations of electric taxi charging stations: A spatial–temporal demand coverage approach	spatial–temporal demand coverage approach
Gopalakrishnan et al. (2016)	Demand Prediction and Placement Optimization for Electric Vehicle Charging Stations	Tour based approach

Author	Diligence	Approach
Kuby et al.(2016)	A threshold covering flow based location model to build a critical mass of alternative fuel stations	FRLM based approach
Wu et al.(2016)	A Stochastic Flow-Capturing Model to Optimize the Location of Fast-Charging Stations with Uncertain Electric Vehicle Flows	FCLM based approach
Zhao et al. (2016)	Optimal Siting of Charging Stations for Electric Vehicles Based on Fuzzy Delphi and Hybrid Multi-Criteria Decision Making Approaches from an Extended Sustainability Perspective	FRLM based approach

Table 2.1 represents a summary of the works in which the optimal placement of charging station problem in the transportation network is considered.

2.3.2. Optimal placement of charging stations considering only distribution network

Appropriate placement of charging station is necessary to reduce the adverse effects on the power grid. Improper placement of charging station is indeed a big threat to power system security and reliability. Voltage stability, reliability, power losses are some of the key issues which need to be addressed while selecting optimal location of charging station in the distribution network. Leemput et al. (2015) gave an analysis of the effect of EV charging station on power grid based on statistical data. Nyns et al. (2010) reported the impact of placement of charging station in the distribution network in a very lucid manner. Schneider et al. (2008) gave an overview of the impact of PHEV on Pacific Northwest distribution systems. The authors assume the reasons for PHEV focus are the following - ICE serves as a backup when the battery is empty, power grid is less affected by use of PHEV, and it is a good option for developing countries. All the aforementioned research works unanimously conclude that the improper placement of EV charging stations in the distribution network is detrimental to the power grid.

Hu et al. (2012) gave a scheme for distribution network expansion planning and optimal siting and sizing of EV charging station. They carried out the simulations on 18 node test system. The problem was modelled as a multi stage planning problem with three stages of 1 year, 1 year, and

2 years respectively. At the end of planning period they proposed construction of 8 new lines and replacement of 3 existing lines of the distribution network. Liu et al. (2013) provided optimal location of charging stations in IEEE 123 node test feeder. They also provided a scheme for network loss minimization as well as voltage profile improvement. Yan et al. (2014) provided optimal location of charging station in IEEE 33 bus system considering investment cost minimization as objective function and energy loss as constraint condition. Zheng et al. (2014) presented a framework for battery charging/ swapping station in the distribution network considering life cycle cost (LCC). In order to meet the demand of increased power requirement during charging they also proposed a scheme of reinforcement of the distribution network. They verified the proposed method on modified IEEE 15 bus system as well as 43 bus radial distribution network. Prasomthong et al. (2014) provided optimal placement of vehicle to grid charging station in 9 bus radial network. They also considered the net benefit earned from vehicle to grid (V2G) scheme in their problem formulation. V2G is a scheme in which EVs can earn revenue by returning electricity to the grid. Mohsenzadeh et al. (2015) provided candidate place of EV charging station in IEEE 33 bus test network considering net installation cost, penalty cost power loss as objective function and voltage limit and traffic as constraint. Khalkhali et al. (2015) presented a novel methodology for optimal placement of PHEV charging station in the distribution network considering economic benefits as well as voltage profile improvement. Mohsenzadeh et al. (2015) presented a novel methodology for optimal planning of parking lots in distribution network considering power loss and voltage profile. Pazouki et al. (2015) presented a scheme for efficient planning of plugged in electric vehicle (PEV) charging stations and Distributed generation (DG) considering financial, technical and environmental effects. They carried out the simulation study on IEEE 33 bus radial distribution network. Pazouki et al. (2015) presented a unique scheme for optimal allocation of charging stations and capacitors in the distribution network for improving voltage profile and reduction of power loss. Martins et al. (2015) presented a new time series based approach for optimal allocation of EV charging station in the urban network. They also considered the hourly variation of load in their analysis which was neglected in most of the studies. Shojaabadi et al. (2016) presented a novel approach for PHEV charging stations considering demand response program as well as uncertainty. The optimal planning was performed considering the rate of customers' participation in demand response programs (DRPs) and the presence of some uncertainties associated with the

load values and electricity market price. Sachan et al. (2016) presented a methodology for optimal placement of centralized EV charging station in IEEE 34 distribution network considering a 24 hour period variable load demand. Shojaabadi et al. (2016) presented a new strategic approach for simultaneous planning of PHEV charging stations and wind power generation station in distribution network considering uncertainties in load demand and wind speed. Pan et al. (2016) provided a planning scheme for centralized charging station in IEEE 123 bus test network. Simorgh et al. (2017) considered cost and demand response program as objective functions while formulating the charging station placement problem and solved the problem by applying PSO. Further, it was concluded that application of demand response program has the potential of reducing grid losses. Aljanad et al. (2018) presented a placement scheme for V2G enabled charging stations considering line loading, voltage deviation, and power loss as objective functions and subsequently the placement problem was solved by a novel quantum inspired BLSA. Syed et al. (2018) solved the charging station placement problem considering THD as the objective function by applying modified LSA.

2.3.3. Optimal placement of charging stations considering both transport and distribution network

Optimal placement of charging station is a non-convex non combinatorial problem which involves interaction of both transport and distribution network. Candidate places for charging station must be based on both transport and distribution network. However the number of literature which considers both transport and distribution network for planning of charging station is yet rare.

Pazouki et al. (2013) reported optimal placement of charging station in IEEE 33 bus test network considering traffic constraint. Wang et al. (2013) presented a novel methodology for traffic-constrained multi-objective planning of EV charging stations considering superposition of IEEE 33 bus radial network and 25 node road network. Yao et al. (2014) provided a multi-objective planning methodology for optimal planning of charging station in coupled 23 node distribution and 25 node transport network as well as 54 node distribution and 25 node transport network. Islam et al. (2015) presented optimal allocation of charging station in a superimposed network comprising of 14 bus test network and the road network of Bangi, Malaysia. Leeprechanon et al. (2016) provided optimal location of EV charging station in a superimposed network of IEEE 69 bus test system and residential network of Tianjin. Zhang et al. (2016)

formulated the placement problem for public parking lots and roadside fast charging stations with cost as the objective function. Further, in the same paper Voronoi diagram and Particle Swarm Optimization (PSO) was employed to solve the placement problem. Xiang et al. (2016) solved this complicated placement problem in a coupled network of IEEE 33 bus radial network and 18 node road network. Zhang et al. (2017) presented a two-stage closed model for charging station placement considering the heterogeneous driving range and charging demands of the EVs. The change in charging demands with time was captured by a modified capacitated flow refueling location model. In addition, Zhang et al. (2017) modelled the charging station placement problem as a stochastic mixed-integer second order cone programming model considering charging station building cost, distribution network upgrade cost, cost of energy, and penalty for unsatisfied charging demands as objective functions. Finally, the optimization problem was solved in a CPLEX solver. Faridimehr et al. (2018) presented a two-stage planning model for optimal placement of charging stations considering stochastic arrival, dwell time of EVs, uncertainties in state of charge of the batteries of the EVs, charging choices, charging demands, and rate of adoption of EVs. This planning model was concerned with maximizing the convenience for the EV drivers, thereby increasing the accessibility of the charging stations. In addition, the problem was solved by Sampling Average Approximation (SAA) technique and a novel heuristics inspired by a score-measuring mechanism (Tsiligirides 1984). Wang et al. (2018) 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, as well as distribution network expansion cost. The problem was formulated as a mixed integer linear program and solved in a GAMS solver. Zhang et al. (2018) 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 demands as objective functions. They also proposed a capacitated-flow refueling location model to address the uncertainties related to driving range. Finally, the problem was solved in a CPLEX solver. Rahmani-Andebili et al. (2018) solved the 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. Cui et al. (2019) considered charging station cost, distribution network expansion cost, voltage regulation cost, protection device upgradation cost while formulating the charging station placement problem and solved the problem by convexification method.

2.4. Objective function and optimization target

Different researchers have considered different approaches of defining the objective functions as reported in Table 2.2. Cost, reliability, power loss, voltage stability index, waiting time are the key factors which must be taken into account while defining the objective function for optimal placement of charging station problem. A brief elaboration of some of the commonly used objective functions as well as different constraints considered in case of the charging infrastructure planning problem is elaborated in the subsequent sub-sections. Further, a mapping between different modelling approaches and objective function, constraints is presented in Table 2.3. From Table 2.3, the superiority of modelling approach considering superimposition of transport and distribution network is clearly established.

2.4.1. Objective Functions

A general overview of different objective functions taken into account while formulating the charging infrastructure planning problem is presented in this sub-section.

I. Cost

Cost is considered as an objective function in many research works as illustrated in Table 2.2. The cost function can be sub-divided as shown in Fig. 2.4. The installation cost is the one time investment associated with setting up the charging stations which are further sub-divided into Land cost, Construction cost, Charger cost and Labour Cost as shown in Fig. 2.6 (Ge et al. 2011; Jia et al. 2012). Operating cost is the annual cost of electricity required for providing charging service. Access cost is defined as the additional cost incurred by the EV drivers while travelling from the point of charging demand to the point of charging station (Ahn et al. 2015). Penalty cost implies the revenue paid by the utility for violation of the safe limits of some distribution network parameters like power loss. Waiting time cost is the cost incurred because of waiting in the charging station due to unavailability of vacant charging spots.

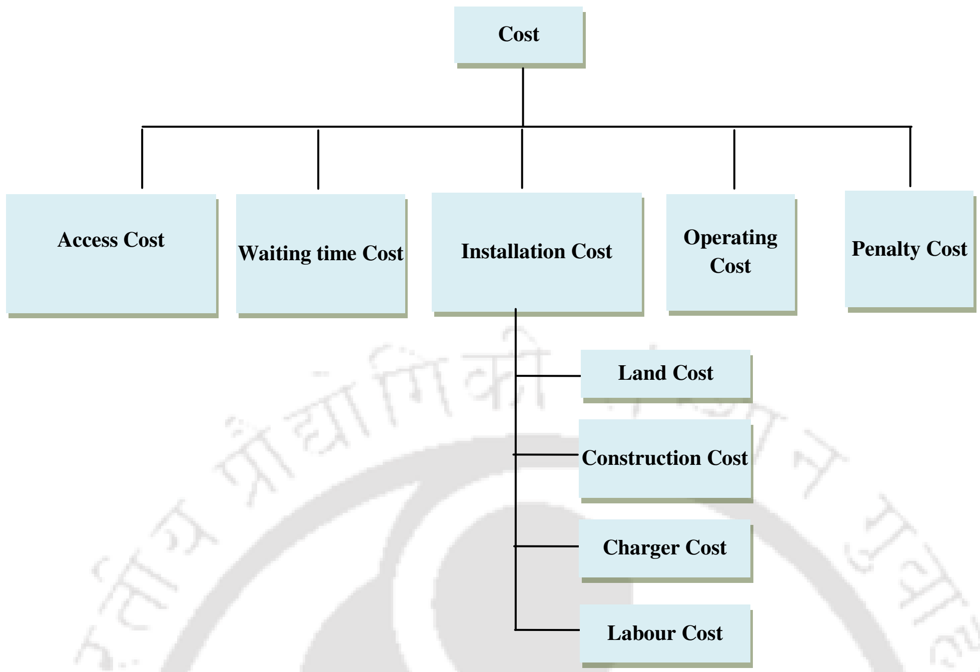

Fig. 2.4- Sub-divisions of Cost function

II.Net Benefit

Charging stations have the capability of acting as the coupling point between EVs and the power grid. And the EVs can supply additional power to the grid via charging stations by the V2G scheme. Net benefit is considered as an objective function for the planning of V2G enabled charging stations (Khalkhali et al. 2015, Shojaabadi et al. 2016).The further sub-divisions of this objective function are as in Fig. 2.5.

Benefit of Discharging is the monetary profit earned by the charging stations by buying power from the EV owners instead of the grid at a cheaper price during peak load hours. By discharging, EVs are supporting the grid by acting as temporary energy storages (V2G scheme).

It is beneficial to charge EVs during the night due to low load demand and lower price of electricity during the night. However, with the increasing number of EVs in the market accompanied by increasing charging demand daytime charging is becoming essential. The charging stations are earning revenue by proving daytime charging facility at a comparatively higher price (Khalkhali et al. 2015, Shojaabadi et al. 2016).

Benefit of providing power from upstream grid is the revenue earned by charging stations by proving power to the grid during peak load hours (Khalkhali et al. 2015, Shojaabadi et al. 2016).

Benefit of reliability and voltage profile improvement refers to revenue earned by the charging stations because of improvement in reliability indices and voltage profile by the implementation of the V2G scheme (Khalkhali et al. 2015, Shojaabadi et al. 2016).

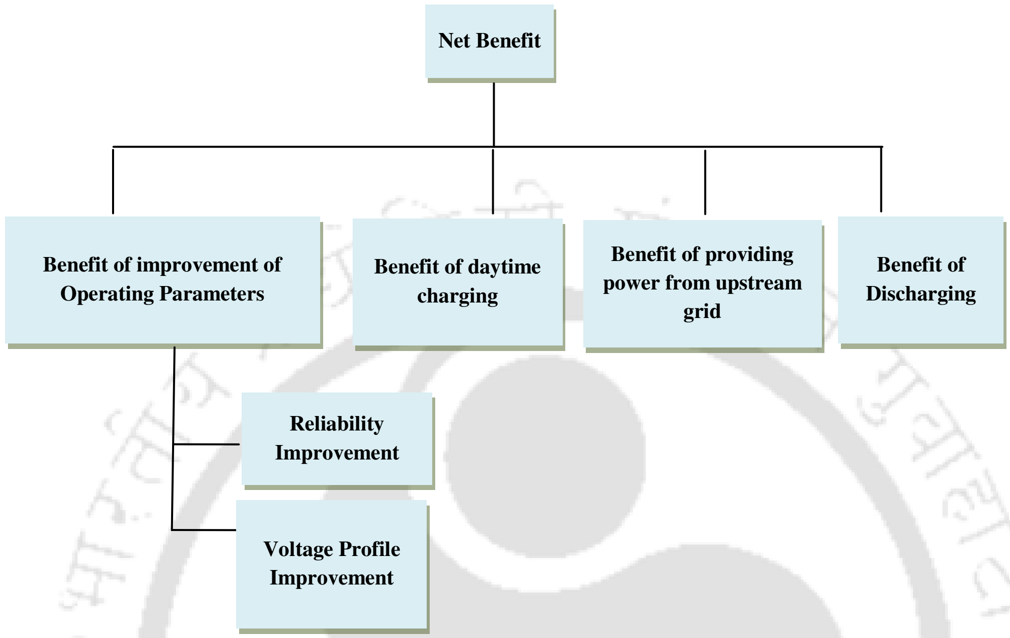

Fig.2.5- Subdivisions of Net Benefit function

III.EV flow

The charging stations must be placed in such a way that they can provide charging service to maximum number of EVs. Thus, the maximization of EV flow must be considered while planning charging stations (Yao et al. 2015). The objective function is as in Eq. (2.1)

$$Max\ f = \sum_{v \in V} f_v y_v \tag{2.1}$$

where V is the set of non- zero flow paths, f_v is the rate of traffic flow. And,

$$y_v = \begin{cases} 1 & \text{if atleast one facility is located on path v} \\ 0 & \text{otherwise} \end{cases}$$

In many research works, EV flow is referred to as charging coverage or population coverage.

IV. Others

Apart from the aforementioned objective functions mentioned in the previous sub-sections power loss, distance, covered trip, power supply moment balance index are also considered as objective functions while dealing with the charging infrastructure planning problems.

Placement of charging station increases the load of the existing network. An increase in load will further cause increase in power loss. Thus, charging stations must be placed in the distribution network in such a way that the increase in power loss is minimized (Martins et al. 2015).

The location of charging station must be optimized keeping in mind the route choice of EV drivers and point of charging demand. Thus, the distance of EV charging station from the point of charging demand must be minimized formulating the charging station placement problem (Andrews et al. 2013; Baouche.et al. 2014).

A commercial EV must be able to complete maximum number of trips to earn profit. Thus EV charging stations must be placed in such a way that the time wasted for EV charging is minimized, thereby maximizing the number of covered trips of the EV driver (Asamer et al. 2016).

The power supply moment balance is an index expressing the deviation as well as the dispersion degree of power supply (Pan and Zhang 2016). A better value of this index implies less power supply fluctuation, reduced power loss, and enhanced stability of the system. Thus, minimization of power supply moment balance index must be taken into account while formulating charging infrastructure planning problem.

2.4.2. Constraints

The charging infrastructure planning problem is carried out subject to a number of equality as well as inequality constraint as elaborated in Fig. 2.6.

Equality constraints like power flow equation as in Eq. (2.2), Eq. (2.3), and charging demand balance equation as in Eq. (2.4) must be satisfied.

$$P_{gi}-P_{di}-V_i\sum_{j=1}^{N_D}V_jY_{ij}\cos(\delta_i-\delta_{j\_}\theta_{ij})=0 \tag{2.2}$$

$$Q_{gi}-Q_{di}-V_i\sum_{j=1}^{N_D}V_jY_{ij}\cos(\delta_i-\delta_j-\theta_{ij})=0 \tag{2.3}$$

where P_{gi} is active power generation of i^{th} bus, P_{di} is active power demand of i^{th} bus, Q_{gi} is reactive power generation of i^{th} bus, Q_{di} is reactive power demand of i^{th} bus, V_j is voltage of j^{th} bus, Y_{ij} is magnitude of $(i,j)^{th}$ term of bus admittance matrix, θ_{ij} is angle of Y_{ij} , δ_i is voltage angle of i^{th} bus, δ_j is voltage angle of j^{th} bus

$$P_{CS}^{i} - P^{i} = 0 \tag{2.4}$$

where $P_{CS}{}^{i}$ is the charging demand of i^{th} charging station, P^{i} is the capacity of i^{th} charging station

The limits such as the voltage of each bus, current flow, or thermal limit of each bus must be satisfied after the placement of charging stations in the distribution network. The minimum and maximum number of charging stations to be placed must also be assigned. Also, the charging stations must not be placed too close to each other. The distances between the charging stations are taken into account by the distance constraint.

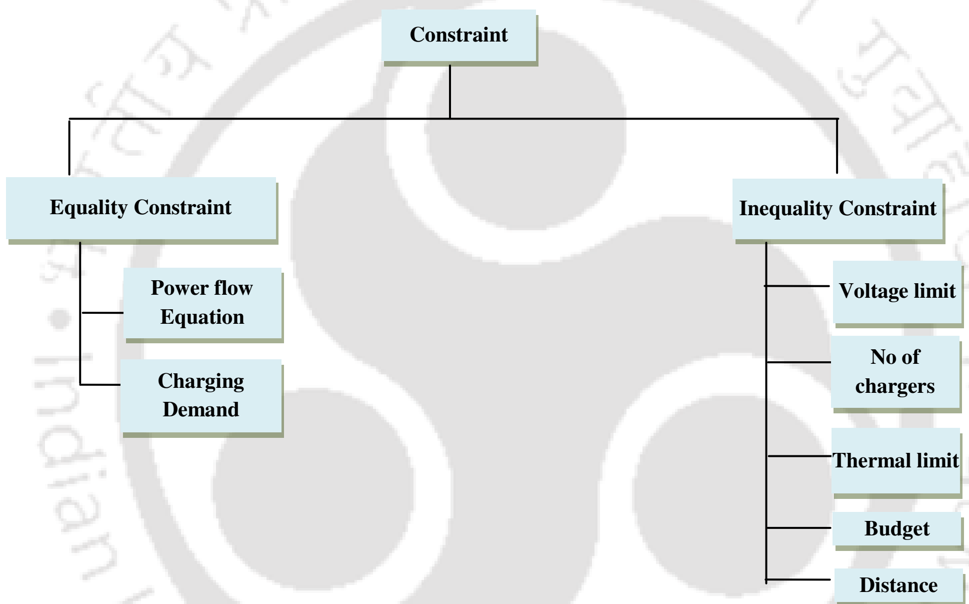

Fig.2.6- Different constraints of charging infrastructure planning problem

Table 2.2- Summary of Classification of research works based on objective function

Author	Approach	Type	Objective function
Hong et al. (2016)	Considering only transportation network	Multi-objective	Volume coverage and classic FRLM objective
Wang et al.(2010)	Considering only transportation network	Multi-objective	Cost and population
Gopalakrishnan et al. (2016)	Considering only transportation network	Single-objective	Cost
Baouche et al. (2014)	Considering only transportation network	Multi-objective	Fixed charge and travel time cost
Baouche et al.(2014)	Considering only transportation network	Multi-objective	Fixed charge and travel time cost
Wu et al. (2016)	Considering only transportation network	Multi-objective	EV volume that can be captured and caught
Lin et al. (2015)	Considering only transportation network	Single-objective	EV flow
Kim et al. (2012)	Considering only transportation network	Single-objective	EV flow
Ahn et al. (2015)	Considering only transportation network	Single-objective	Cost
Zhao et al.(2016)	Considering only transportation network	Multi-objective	Cost and Environmental factors
You et al.(2014)	Considering only transportation network	Single-objective	Population Coverage
Andrews et al.(2013)	Considering only transportation network	Single-objective	Total Distance to charging station

Author	Diligence	Approach	Objective Function
Ge et al. (2011)	Considering only transportation network	Single-objective	Cost
JIA et al. (2012)	Considering only transportation network	Single-objective	Cost
JIA et al. (2012)	Considering only transportation network	Single-objective	Cost
Wang et al.(2013)	Considering only transportation network	Single-objective	EV flow
Gavranovic et al. (2014)	Considering only transportation network	Single-objective	Cost
Diego et al. (2014)	Considering only transportation network	Single-objective	Charging Coverage
Lu et al. (2015)	Considering only transportation network	Single-objective	EV flow
He et al.(2015)	Considering only transportation network	Single-objective	Tour time (travelling time and recharging time)
Hosseini et al.(2015)	Considering only transportation network	Single-objective	Cost
Wang et al. (2016)	Considering only transportation network	Single-objective	Cost
Nahrstedt et al. (2016)	Considering only transportation network	Single-objective	EV flow
Zhu et al. (2016)	Considering only transportation network	Single-objective	Cost
Arslan et al. (2016)	Considering only transportation network	Single-objective	Distance travel

Author	Diligence	Approach	Objective Function
Asamer et al.(2016)	Considering only transportation network	Single-objective	Sum of covered trip count
He et al. (2016)	Considering only transportation network	Single-objective	Total level of demand
Davidov et al.(2016)	Considering only transportation network	Single-objective	Cost
Hu et al. (2013)	Considering only distribution network	Single-objective	Cost
Liu et al. (2013)	Considering only distribution network	Single-objective	Cost
Yan et al.(2014)	Considering only distribution network	Single-objective	Cost
Zheng et al.(2014)	Considering only distribution network	Single-objective	Cost
Mohsenzadeh et al. (2015)	Considering only distribution network	Single - objective	Net cost comprising of installation, operation cost and penalty for unreliability and power loss
Khalkhali et al.(2015)	Considering only distribution network	Single - objective	Net Benefit
Mohsenzadeh et al.(2015)	Considering only distribution network	Single - objective	Cost
Pazouki et al. (2015)	Considering only distribution network	Multi - objective	Cost, Power loss, Emission

Author	Diligence	Approach	Objective Function
Pazouki et al. (2015)	Considering only distribution network	Multi - objective	Cost, Voltage Profile, Power loss
Marcelo et al. (2015)	Considering only distribution network	Multi-objective	Active power loss, accumulated loss during the day
Shojabaadi et al. (2016)	Considering only distribution network	Single - objective	Net benefit
Pan et al.(2016)	Considering only distribution network	Multi-objective	Cost and Power supply moment index
Simorgh et al. (2017)	Considering only distribution network	Multi - objective	Cost and Demand Response program
Aljanad et al. (2018)	Considering only distribution network	Multi-objective	Line loading, voltage deviation and power loss
Syed et al. (2018)	Considering only distribution network	Single - objective	THD
Islam et al. (2015)	Considering both transportation and distribution network	Multi-objective	Transportation Energy loss cost, Build up cost and Substation energy loss cost

Author	Diligence	Approach	Objective Function
Leeprechanon et al. (2016)	Considering both transportation and distribution network	Single - objective	Charging service
ZHANG et al.(2016)	Considering both transportation and distribution network	Single - objective	Investment cost
Xiang et al.(2016)	Considering both transportation and distribution network	Single - objective	Cost
Zhang et al. (2017)	Considering both transportation and distribution network	Multi-objective	Charging station building cost, distribution network upgrade cost, cost of energy, and penalty for unsatisfied charging demands
Faridimehr et al. (2018)	Considering both transportation and distribution network	Single-objective	Accessibility of the charging stations
Wang et al. (2018)	Considering both transportation and distribution network	Multi-objective	Establishment cost of charging stations, charging spots and lanes, travel cost from charging demand points to charging stations, as well as distribution network expansion cost

Author	Diligence	Approach	Objective Function
Zhang et al. (2018)	Considering both transportation and distribution network	Multi-objective	Charging station building cost, distribution network upgrade cost, cost of energy, and penalty for unsatisfied charging demands
Rahmani-Andebili et al. (2018)	Considering both transportation and distribution network	Multi-objective	Cost, power loss, and expected energy not served

Table 2.3-Mapping between objective function, decision variables, constraints, and different approaches of dealing with charging station placement problem

Feature		Considering only transport network	Considering only distribution network	Superposition of both transport and distribution network
Objective function that can be modelled	Installation cost	✓	✓	✓
	Maintenance cost	✓	✓	✓
	Operating cost	✓	✓	✓
	Waiting time cost	✓		✓
	Power loss penalty		✓	✓
	Net benefit of V2G		✓	✓
	Reliability		✓	✓
	Voltage stability		✓	✓
	EV flow	✓		✓
	Distance	✓		✓
	Transformer loss of life		✓	✓
Decision Variable	Bus number of distribution network		✓	✓
	Node of road network	✓		✓
	Charging station density	✓		✓
	Number of chargers	✓	✓	✓
Constraints	Budget	✓	✓	✓
	Power flow		✓	✓
	Thermal limit		✓	✓
	Voltage limit		✓	✓
	Number of charging point	✓	✓	✓
	Charging demand	✓		✓

2.5. Optimization Algorithms

The objective function in case of optimal placement of charging station problem is multi-variable and complex. Researchers have utilized both classical and evolutionary optimization algorithms for the solution of this problem. A brief review of the optimization techniques utilized for the solution of optimal placement of charging station problem is presented in this section.

I. Classical Optimization Algorithm

The traditional or classical optimization methods inspired by the differential calculus can be utilized for obtaining the optimum value of continuous as well as differentiable function (Rao et al. 2007). Integer programming, Linear programming, Primal-Dual Method, Game Theoretic Approach are some of the classical optimization techniques having application in evaluating the solution of the charging station placement problem. An integer programming is an optimization technique where all or some of the variables are restricted to be integers (Lenstra et al. 1983). A mixed integer programming is an optimization technique where only some of the variables are restricted to be integers (Bixby 2012). Linear integer programming is used for solution of the charging station placement problem in many literature (Bouche et al. 2014; Bouche et al. 2014; Cruz et al. 2013; Chung et al. 2015; Wang et al. 2017; Davidov et al. 2016; Worley et al. 2012). Mixed integer linear programming is utilized for the solution of the charging station placement problem in a number of literature (Wang et al. 2010; You et al. 2014; Andrews et al. 2013; Gonzalez et al. 2014; Jia et al. 2012; Hosseini et al. 2015; Asamer et al. 2016).

II. Evolutionary Algorithm

Evolutionary algorithms are nature inspired algorithms based on the principle of "Survival of the fittest" (Back et al. 1996). The central idea of most of the evolutionary algorithm is similar. It initiates the search with a randomly generated set of population. As the search progresses only the best candidates survive in the subsequent generations. Some of the advantages of these evolutionary algorithms are-

1. Computational and conceptual simplicity
2. Broad range of applications starting from simple problem to complicated engineering problems
3. Hybridization with classical algorithms
4. Faster convergence criterion

Because of all these aforementioned advantages, evolutionary algorithms have extensive application in the charging station placement problem. A brief review of the applications of the evolutionary algorithms in charging station placement problem is presented in Table 2.4. Table 2.5 represents a comparative analysis of different evolutionary algorithms in terms of computational burden, computational time, and convergence criteria.

Table 2.4- Evolutionary Algorithms applied to optimal placement of charging station problem

Evolutionary Algorithm	Origin	Literature where the algorithm is applied
Genetic Algorithm	Natural process of evolution of new offspring from a set of randomly generated population by the process of selection, crossover and mutation	Ge et al. (2011), He et al. (2015), Zhu et al. (2016), Tu et al. (2016), Yan et al. (2014), Mohsenzadeh et al. (2015), Pazouki et al. (2015), Pazouki et al. (2015), Martins et al. (2015), Shojabadi et al. (2016), Shojabadi et al. (2016), Pan et al. (2016), Pazouki et al. (2013)
Differential Evolution	Evolution of new offspring by adding weighted difference between population vector and target vector	Khalkhali et al. (2015), Yao et al. (2014)
Firefly Algorithm	Movement of firefly towards light	Islam et al. (2015)
Ant Colony Optimization	Trail laying and following behaviour of real ants	Leeprechanon et al. (2016)

Table 2.5-General comparative analysis of different optimization algorithms applied to charging station placement problem

Optimization algorithm	**Computational Complexity**	**Computational time**	**Convergence Criteria**
Genetic Algorithm	Less than other evolutionary algorithms	More than other evolutionary algorithms	More than other evolutionary algorithms
Particle Swarm Optimization	More than GA	Less than GA	Premature Convergence (the algorithm ending up with local solution)
Differential Evolution	More than GA	Less than GA	Less than GA
Firefly Algorithm	Less than PSO	Less than PSO	Less than PSO
Ant Colony Optimization	Less than PSO	Uncertain	Uncertain

2.6. Summary of Literature Review

A comprehensive review of the literature related to different aspects of charging infrastructure planning of electric vehicles is presented in this chapter. All the literature in the paradigm of impact of EV charging station on power grid unanimously conclude that introduction of EV charging station load degrade the operating parameters of the power grid. Fig.2.7 presents a comparative analysis of literature related to impact of EV charging station on power grid.

Moreover, the diversity of modelling approach, objective functions is a salient feature of the charging station placement problem. Fig. 2.8 presents yearly distribution of literature on different approaches of optimal placement of charging station problem.

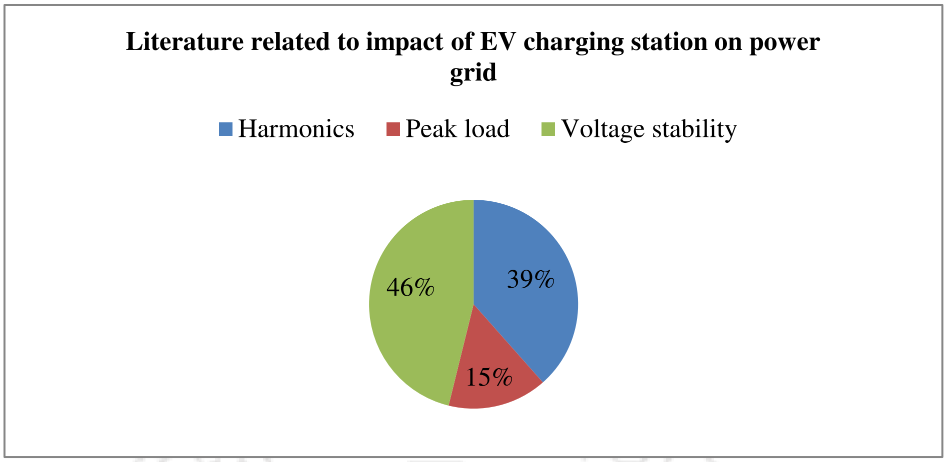

Fig. 2.7- Comparative analysis of literature related to impact of EV charging station on power grid

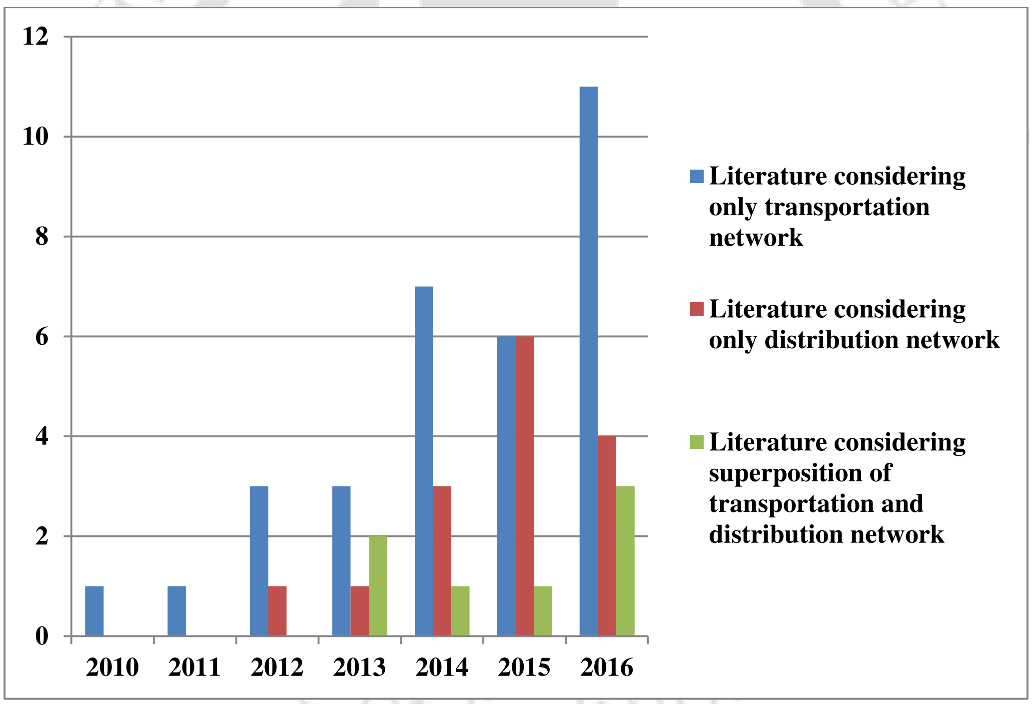

Fig.2.8–Yearly distribution of literature on different approaches of optimal placement of charging station problem till 2016

The available research works in this area have several limitations. After reviewing the existing literature of this paradigm, the limitations of the existing research works are summarized as follows-

1. The impact of EV charging load on customer and energy oriented reliability indices of the distribution network is not analyzed in the available research works.

2. The economic losses incurred in terms of penalty paid by the utility after EV charging station placement is neglected in the available research works.
3. In most of the research works the impact of EV charging load is analyzed on one or two operating parameters separately. There is relatively less work which analyzes the impact of EV charging load on voltage stability, power loss, reliability, harmonics, and economic loss together in a quantitative way.
4. The reliability index considered in most of the available research works for optimal placement of EV is Average System Interruption Duration Index (ASIDI) that takes into account only the duration of interruption. The frequency of interruption duration is not taken into account in ASIDI. The optimal placement of EVs with a composite reliability index as objective function taking into account both frequency and duration of interruption is not present in any of the research works.
5. Moreover, the problem formulation for optimal placement of charging stations present in all the available research works has several limitations like negligence of penalty imposed for unreliability, power losses, road traffic uncertainty and waiting time in the charging stations.
6. The optimization algorithms applied for solving the charging station placement problem are mostly limited to GA and PSO. The latest efficient optimization algorithms are not utilized for solution of the placement problem.
7. The solution of this optimization problem by applying hybrid algorithms is not yet explored in the existing research works.

2.7. Scope for research

An attempt has been made in the present research work to address some of the limitations of the existing literature reported in section 2.6. In order to address the limitations of the existing research work the following activities are performed-

1. Analysis of the impact of EV charging station load on operating parameters of distribution network like voltage stability, reliability, power loss together in a quantitative way
2. Formulation of the charging station placement problem strategically in both single and multi-objective framework
3. Solution of charging station placement problem by efficient hybrid algorithms

4. Formulation and solution of charging station placement problem in the context of Guwahati city

The next chapters will address different aspects of charging infrastructure planning problem such as impact of EV charging stations on power distribution network, formulation of charging station placement problem in a comprehensive manner.

Note- This chapter is reproduced from the following publications-

- **Deb, S., Tammi, K., Kalita, K., & Mahanta, P. (2018) Review of recent trends in charging infrastructure planning for electric vehicles. *Wiley Interdisciplinary Reviews: Energy and Environment*, 7(6), e306.**
- **Deb, S., Kalita, K., & Mahanta, P. (2017, December). Review of impact of electric vehicle charging station on the power grid. In *2017 International Conference on Technological Advancements in Power and Energy (TAP Energy)*. IEEE.**

CHAPTER 3

IMPACT OF ELECTRIC VEHICLE CHARGING STATION LOAD ON DISTRIBUTION NETWORK

3.1. Introduction

The perpetually escalating demand for energy and the finite nature of the fossil fuel supply, accompanied by global warming and climate change are the main concerns of environmentalists and researchers of the 21st century. The CO_2 emission from the transportation sector is one of the main causes of global warming and climate change (Wang et al. 2015; Wang et al. 2016; Blesl et al. 2007). Researchers have stressed the positive impact of replacing Internal Combustion Engine (ICE) driven vehicles with Electric Vehicles (EVs) to minimize the greenhouse gas contributions of the transport sector. The paradigm shift from conventional vehicles to EVs has many environmental and economic advantages. The increasing number of EVs is however accompanied by a rise in charging demand. Hence, the development of the charging infrastructure has become necessary to meet the requirements of substantial operation of the EVs. The establishment of charging stations imposes an additional burden on the power grid, as the high charging loads of fast EV charging stations will degrade the operating parameters of the distribution network. The degradation of voltage profile, increase in peak load, harmonic distortions are some of the consequences of the uncoordinated charging of EVs.

In this chapter, the impact of the EV charging station load on voltage stability, reliability, power losses of the 33 bus network representing a standard distribution network is analyzed for different cases of placement of charging station load. Further, a strategy for optimal placement of charging stations in the distribution network is proposed based on a newly formulated Voltage Stability, Reliability, and Power Loss (VRP) index. The organization of the chapter is as follows. Section 3.2 elaborates the methodology for computation of voltage stability, reliability, power losses, and economic loss. Section 3.3 elaborates the formulation of VRP index. Section 3.4 reports the results related to the impact of placement of EV charging station load on the distribution network. Section 3.5 presents a brief discussion of the results reported in section 3.4. Finally, section 3.6 concludes the chapter.

3.2. Methodology

The voltage stability, reliability, and power losses are the three important operational parameters of the distribution network. A brief overview of the methodology to compute voltage stability, reliability, power losses, and economic loss of the distribution network is elaborated in this section. Further, the overall computational methodology adopted for analyzing the impact of EV charging station load on distribution network is also presented in this section.

3.2.1 Voltage Stability

The voltage stability problem has concerned power system engineers for many years. Voltage stability is the power system's capability to maintain steady acceptable voltages at all the system buses under normal operating conditions and when an external disturbance is applied (Kundur 1994; Kessel et al. 1986). During voltage instability phenomena, the bus voltage of the network declines progressively and uncontrollably. The system may become unstable because of sudden disturbances, fault conditions, single, or multiple contingencies, line overloading or increased load. A voltage stability criterion used in many stability studies is that voltage of all the system buses must be within acceptable limits. Voltage stability is indeed a local phenomenon but in some cases, it may lead to severe voltage collapse (Kundur 1994). In this work, Voltage Sensitivity Factor (VSF), Voltage Stability Index (VSI) are used for voltage stability analysis.

I. Voltage Sensitivity Factor

Voltage stability studies generally obey a static approach as the factors affecting it are slow in nature. The voltage stability is analysed based on the determination of VSF from the Power Voltage (PV) curve (Kundur 1994; Rahman et al. 2013). The PV curve is a graphical representation of active power and voltage (Kundur 1994). It signifies the trend of voltage change with increasing active power as shown in Fig.3.1.

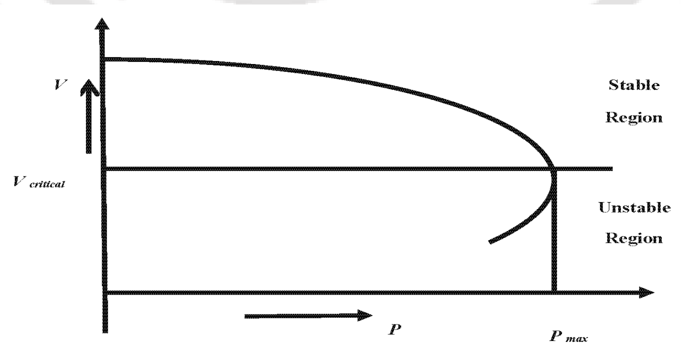

Fig. 3.1- Active Power Voltage Curve (PV curve).

The first step for drawing the PV curve is the determination of the voltage of all the buses of the distribution network. For determination of voltage of a radial distribution network, the typical methods of load flow analysis like the Newton Raphson method have their limitations because of high R/X ratio. The R/X ratio is quite predominant in distribution system compared to transmission system due to low inductance of the line The Jacobian matrix may become singular because of high R/X ratio. Hence, the voltage of the buses is determined by the forward and backward sweep algorithm (Rupa et al. 2014). From the PV curve shown in Fig.3.1, it is clear that as the active power increases, the voltage decreases up to a point where the active power is highest (P_{max}, $V_{critical}$). That point corresponds to the critical operating condition known as the limit of stable operation. VSF is the ratio of change in voltage and change in loading. Mathematically, it is expressed by Eq. (3.1)

$$VSF = \left|\frac{dV}{dP}\right| \quad \forall P \langle P_{\max} \tag{3.1}$$

A high VSF value indicates that even for a small change in loading, there is a considerable voltage drop, thereby signifying weakness of the bus (Rahman et al. 2013). In voltage stability analysis of distribution networks, the voltage of all the buses must be within an acceptable limit. The VSFs of all the buses are determined for increasing loading factor. The loading for which the voltages of all the buses are within acceptable range is called the realistic loading margin of the system (Rahman et al. 2013). The flowchart illustrating the methodology of computation of VSF is shown in Fig.3.2.

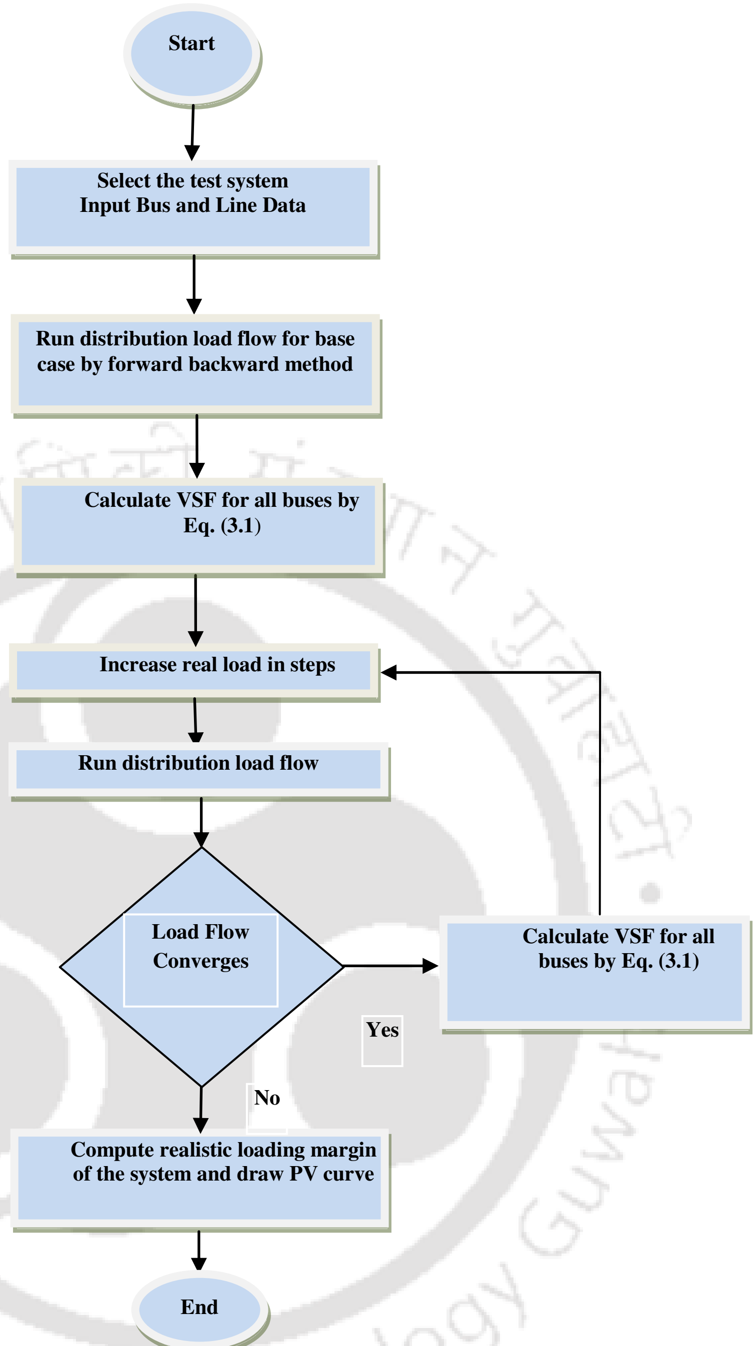

Fig.3.2-Flowchart for computation of VSF

II. Bus Voltage Stability Index

The voltage stability index developed by Eminoglu et al. (2007) is utilized in this work. The mathematical formulation of the index is illustrated by taking an example of a simple 2 bus system as shown in Fig.3.3. The mathematical formulation of this index is elaborated by Eq. (3.2) to Eq. (3.8).

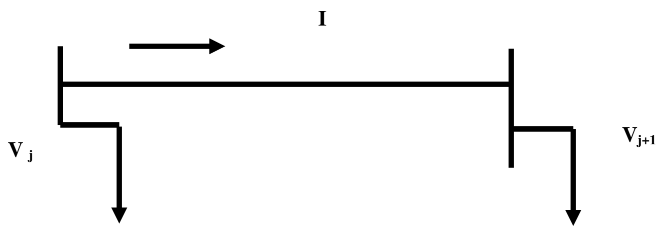

Fig. 3.3-Single line diagram of a simple two bus system

Fig.3.3 illustrates the single line diagram of a two bus system where j and $j + 1$ are the two buses of the system. $V_j < \delta_j$ and $V_{j+1} < \delta_{j+1}$ are the voltage at bus j and bus $j + 1$ respectively. I is the current flowing through the branch having resistance r and impedance x:

$$I = \frac{V_j - V_{j+1}}{r + \mathbf{i}x} \tag{3.2}$$

$$P_{j+1} - \mathbf{i}Q_{j+1} = V_{j+1}^{*} I \tag{3.3}$$

Substituting value of I in Eq. (3.3), equating real parts and on further simplification Eq. (3.4) is obtained:

$$V_{j+1}^4 + 2V_{j+1}^2 (P_{j+1} r + Q_{j+1} x) - V_j^2 V_{j+1}^2 + (P_{j+1}^2 + Q_{j+1}^2)|Z|^2 = 0 \tag{3.4}$$

From Eq. (3.4) the transferrable active and reactive power can be written as in Eq. (3.5) and Eq. (3.6), respectively:

$$P_{j+1} = \frac{M \pm \sqrt{N}}{|Z|} \tag{3.5}$$

where: $M = -\cos\theta_z V_{j+1}^2$.

and: $N = \cos^2\theta_z V_{j+1}^4 - V_{j+1}^4 - |Z|^2 Q_{j+1}^2 - 2V_{j+1}^2 Q_{j+1} x + V_j^2 V_{j+1}^2$

$$Q_{j+1} = \frac{P \pm \sqrt{Q}}{|Z|} \tag{3.6}$$

where: $P = -\sin\theta_z V_{j+1}^2$.

and: $Q = sin^2\theta_z V_{j+1}^4 - V_{j+1}^4 - |Z|^2 P_{j+1}^2 - 2V_{j+1}^2 P_{j+1} r + V_j^2 V_{j+1}^2$

Thus, the conditions of existence of transferrable active and reactive power are as in Eq. (3.7):

$$N \geq 0 \text{ and } Q \geq 0 \tag{3.7}$$

Substituting the actual values of N, Q and adding them leads to the inequality defining the stability criterion of the system:

$$2V_j^2 V_{j+1}^2 - 2V_{j+1}^2 (P_{j+1} r + Q_{j+1} x) - |Z|^2 (P_{j+1}^2 + Q_{j+1}^2) \geq 0 \tag{3.8}$$

The value of Eq. (3.8) is known as VSI. This is a criterion for determination of voltage stability. VSI will decrease with increase of active power. Increasing the active power beyond a certain limit will cause the system to become unstable. The flowchart illustrating the methodology of computation of VSI is shown in Fig.3.4.

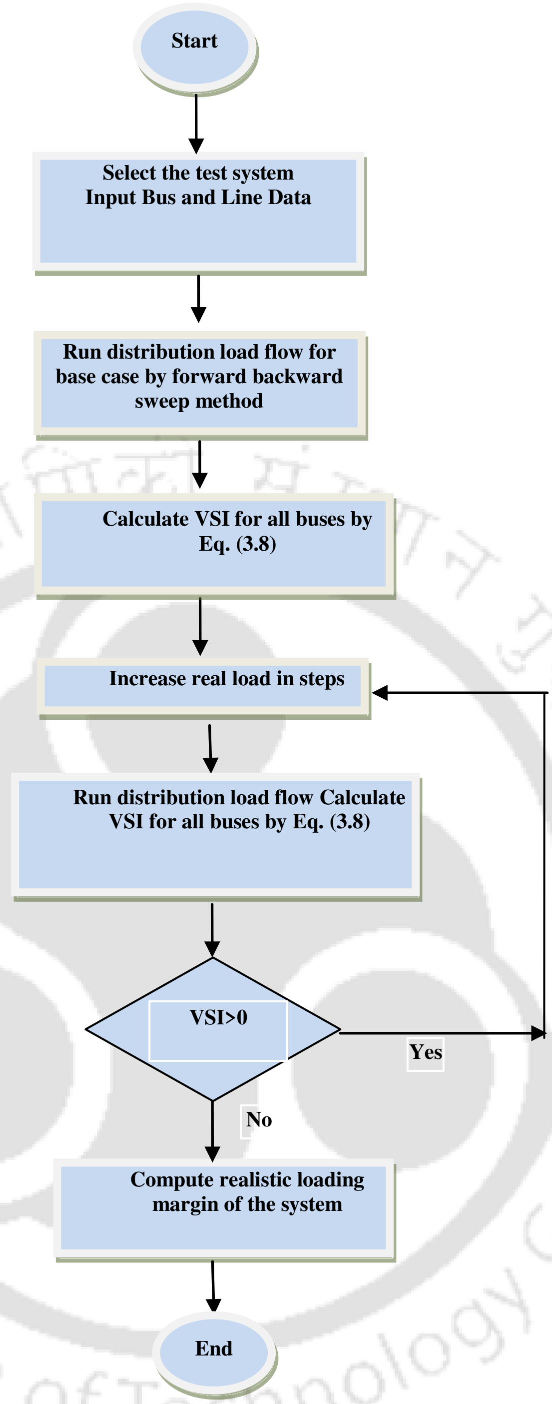

Fig.3.4- Flowchart for computation of VSI

3.2.2. Reliability

The reliability analysis of the power system has emerged as an exigent arena of research. Reliability is the probability that a system will operate satisfactorily for a given period of time under a given set of operating conditions (Chowdhury et al. 2015). In power system reliability analysis, the emphasis is laid on the reliability of generation, transmission, as well as distribution. The reliability of the distribution network is closely related to the satisfaction level of the customers. For evaluation of the reliability indices of the distribution network, statistical data of failure rate, repair rate, average outage duration, and number of consumers of the buses or load points of the distribution network are required (Chowdhury et al. 2015; Billington 1994). The detailed categorization of the distribution network reliability indices is as shown in Fig.3.5. As mentioned in Fig.3.5 the reliability indices of distribution network are broadly categorized into customer oriented and energy oriented reliability indices. SAIFI, SAIDI, and CAIDI are the three major classifications of customer oriented reliability indices. The energy-oriented reliability indices can be again sub divided into ENS and AENS.

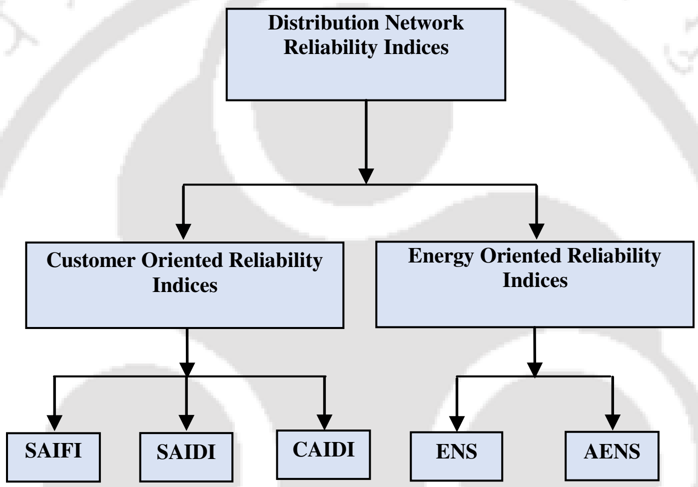

Fig.3.5-Distribution Network Reliability Indices

A comprehensive overview and the formulae of different customer and energy-oriented reliability indices are presented in Table 3.1. SAIFI and SAIDI are related to frequency and duration of interruption respectively. CAIDI gives a measure of customer dissatisfaction because of interruption. AENS can be regarded as the average load curtailment index because of interruption of service. The typical causes of the interruption are as follows:

- Outages resulting in interruption
- Equipment failure disrupting the operation of the power system
- Sudden increase in load demand resulting in load shedding
- Scheduled maintenance requiring an interruption
- Extreme weather damaging the infrastructure

For further elaboration the flowchart for computation of the reliability indices is presented in Fig.3.6.

Table 3.1-Overview of different customer and energy oriented reliability indices

Index	Definition	Formula	Physical Significance
SAIFI	Number of times a system customer experiences interruption during a particular time period	$\frac{\sum \lambda_j N_j}{\sum N_j}$	SAIFI illustrates the condition of the system in terms of interruption
SAIDI	Average interruption duration per customer served	$\frac{\sum U_j N_j}{\sum N_j}$	SAIDI illustrates the condition of the system in terms of duration of interruption
CAIDI	Average interruption duration time for those customers interrupted during a year	$\frac{\sum U_j N_j}{\sum \lambda_j N_j}$	CAIDI gives the average outage duration that any given customer would experience.
ENS	ENS gives the total energy not supplied by the system.	$\sum L_j U_j$	ENS is an indicator of energy deficiency of the system
AENS	AENS is regarded as the average system load curtailment index	$\frac{\sum L_j U_j}{\sum N_j}$	AENS is the index giving an idea of how much energy is not served during a particular time period.

3.2.3. Power Losses

Power losses of a distribution network refer to typical I^2R losses of the line. For the two bus system represented in Fig.3.3 the mathematical expression for computing the line losses is as given in Eq. (3.9):

$$P_j = I^2 r \tag{3.9}$$

And, the total power losses of the system are given as in Eq. (3.10):

$$P_t = \sum_{j=1}^{N_D} P_j \tag{3.10}$$

From Eq. (3.9) and Eq. (3.10) it is clear that increase in load demand of even a single bus will contribute to net increase in power losses of the distribution network.

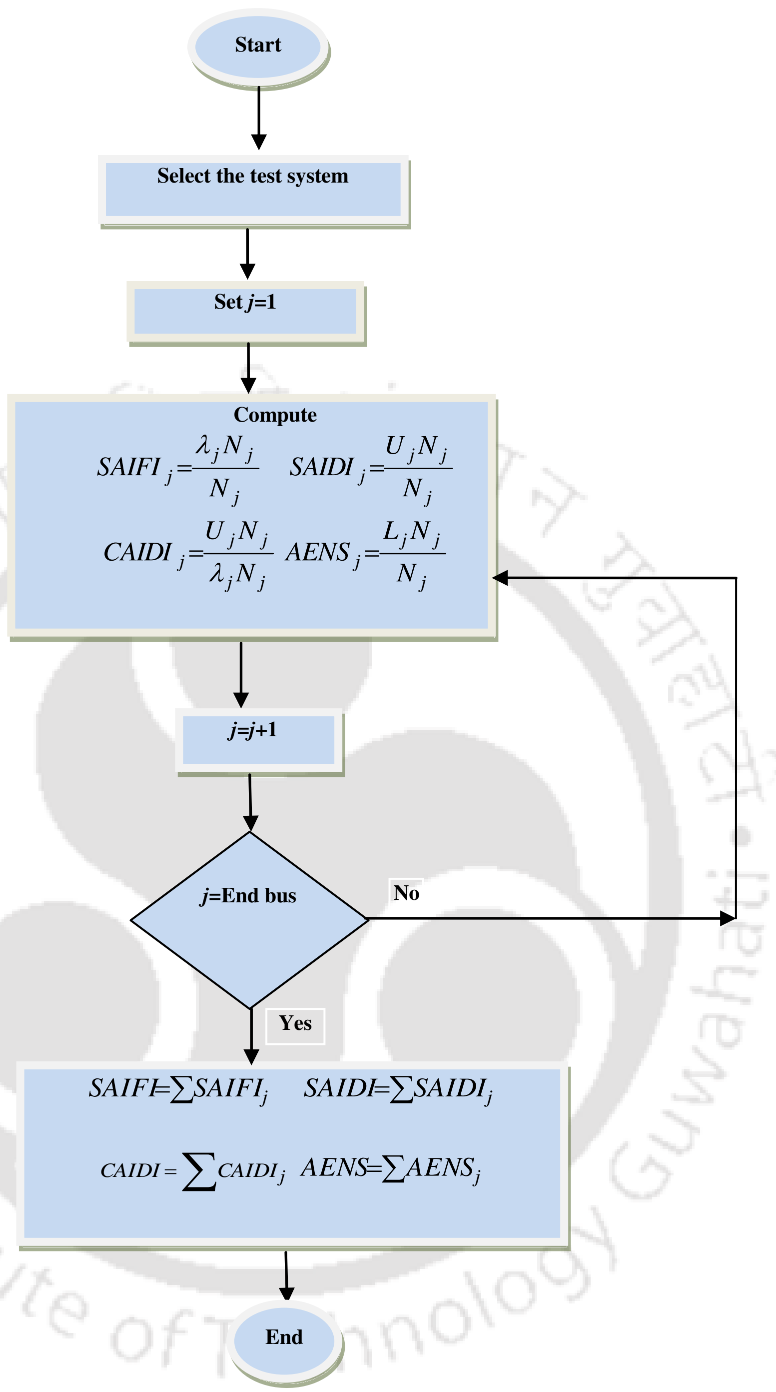

Fig.3.6- Flowchart for computation of reliability indices

3.2.4. Economic Losses

Voltage deviation beyond a certain limit as well as AENS are critical for the system and impose penalty on the utility thereby causing economic loss. For the IEEE 33 bus system the voltage beyond which penalty is imposed is 0.9 per unit. The penalty imposed is given as in Eq. (3.11):

$$Penalty = VD^2 \times 1{,}000{,}000 \quad if \ V < 0.9 \tag{3.11}$$

All the reliability indices explained in Section 3.2.2 can be utilized to decide a criterion for penalty imposed on utility. In this work penalty imposed for unreliability is expressed in terms of AENS. Numerically it is 0.18 $/kWh energy not served.

3.2.5. Computational Methodology for Analyzing the Impact of EV Charging Station Load on Distribution Network

It is anticipated that the coming years will witness a rapid and significant EV charging load integration to the power distribution network. In this context, the impact of EV charging station load on economic loss and different operating parameters of the distribution network must be analysed for different scenarios of placement of EV charging stations.

The methodology adopted for analysing the impact of EV charging station load on the distribution network is illustrated in Fig.3.7.

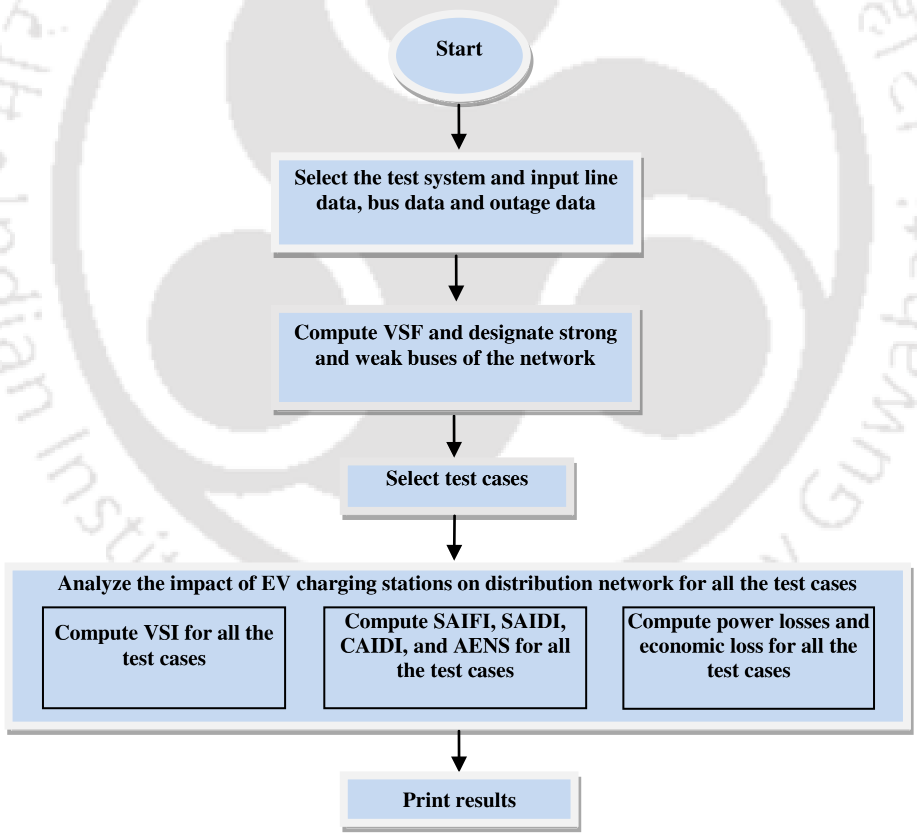

Fig.3.7- Flowchart of computational methodology for analyzing impact of EV charging station load on Distribution Network

3.3. VRP Index

In power system studies, there is a dearth of indices giving information about the three main operating parameters like voltage stability, reliability, and power losses together. Hence, a new index named Voltage Stability, Reliability and Power loss (VRP) index is formulated in this work. This index gives information about three prime operating parameters of the distribution network after the network is subjected to any sort of disturbance. This index can be applied for:

- Optimal placement of charging stations.
- Distribution network planning in presence of distributed generation.
- Microgrid planning.
- Reconfiguration of distribution networks.

The mathematical formulation of the VRP index is exemplified in this subsection by Eq. (3.12) to Eq. (3.16):

$$VRP=w_1A+w_2B+w_3C \tag{3.12}$$

$$A=\frac{1}{a} \tag{3.13}$$

$$a=\frac{VSI_l}{VSI_{base}} \tag{3.14}$$

$$B=w_{21}\frac{SAIFI_l}{SAIFI_{base}}+w_{22}\frac{SAIDI_l}{SAIDI_{base}}+w_{23}\frac{CAIDI_l}{CAIDI_{base}} \tag{3.15}$$

$$C=\frac{P_{loss}^{l}}{P_{lossbase}} \tag{3.16}$$

3.3.1.Charging Station Placement Based on VRP Index

As an example for the usage of the VRP index, we present briefly a novel methodology for the placement of the charging stations in the distribution network based on this index. The main objective of charging station placement problem is optimal allocation of EV charging stations in the distribution network in such a way that the operating parameters of the distribution network are least affected. Thus, VRP index is selected as the objective function for charging station placement problem because of its capability of taking into account voltage stability, reliability and power losses under a single umbrella.

The decision variables, objective functions, and constraints for the optimal placement of charging stations in the distribution network based on VRP index are presented in this sub-section.

The decision variables are:

- Buses of the distribution network in which charging stations will be placed, b
- Number of fast charging stations placed at the buses, N_{Fb}
- Number of slow charging stations placed at the buses, N_{Sb}

The optimization is aimed at minimization of VRP index. Mathematically:

$$\min(VRP) \quad \text{where } VRP = f(b, N_{Fb}, N_{Sb}) \tag{3.17}$$

Subject to the following constraints:

$$\left.\begin{array}{c} 0 \le N_{Fb} \le n_{fastCS} \\ 0 \le N_{Sb} \le n_{slowCS} \\ S_{min} \le S_i \le S_{max} \\ L \le L_{max} \end{array}\right\} \tag{3.18}$$

In addition to the aforementioned constraints, the power flow balance equation must be taken as an equality constraint. A flowchart illustrating the optimal placement of charging stations based on the VRP index is shown in Fig. 3.8, where as shown, the EV charger load is first modelled and the test cases are simulated. Then, the impact of the EV charging station load on voltage stability, reliability, and power loss is evaluated for all the test cases A comparative analysis of the impact of the EV charging station load on the aforementioned parameters is made so that appropriate weights can be assigned to all the terms of the VRP index. The weights assignment of the individual terms of the VRP index is based on the change in the operating parameters after the introduction of the EV charging station load. The most severely affected parameter is assigned the highest weight. After formulation of the VRP index the charging station placement problem is formulated. Lastly, optimization is performed and charging stations are allocated optimally in the distribution network.

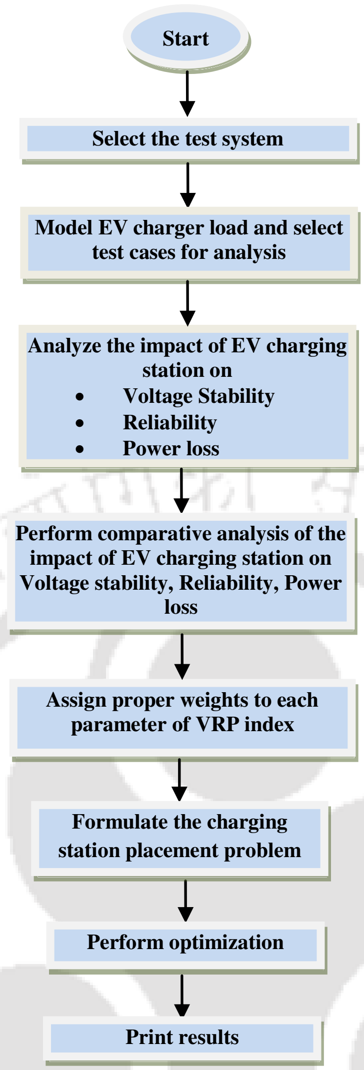

Fig.3.8- Flowchart for charging station placement based on VRP index

3.4. Results

Massive penetration of EVs increases the load demand thereby degrading the operating parameters of the distribution network. The impact of the EV charging station load on voltage stability, power loss, reliability, and economic losses of the distribution network are analysed for different scenarios and a charging station placement scheme based on the VRP index is presented in this work. The results of the aforementioned analyses are presented in this section.

3.4.1. Description of the Test System and Different Scenarios Considered for Analysis

The entire analysis is performed on 33 bus test system as shown in Fig. 3.9. It is a radial distribution network with 33 bus and 32 branches. The line data, branch data of this test network can be found in Table A1, Table A2, of Appendix respectively. The outage data can be found in the Reference Bhadra et al. 2015.

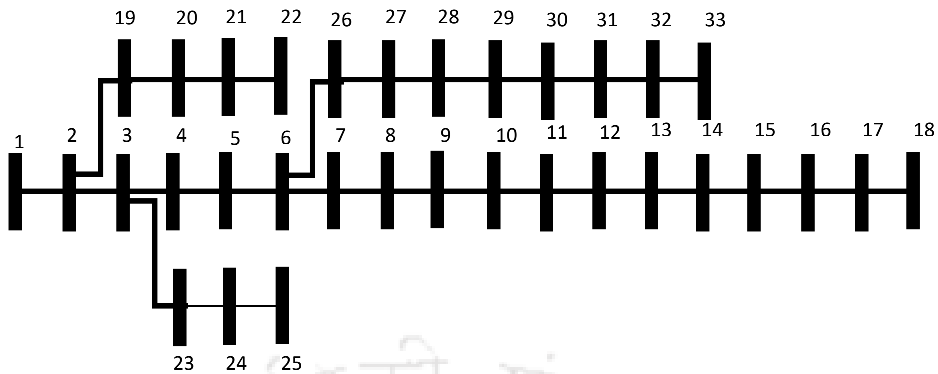

Fig.3.9- 33 bus Test Network

Based on the methodology of computing VSF of the buses described by Eq. (3.1) of Section 3.2.1 the strong and weak buses of the system are determined. Fig.3.10 illustrates the PV curve of the 33 bus system for different loading factors. From the figure, it is clear that as the loading of the system increases the deviation of the bus voltage from base values becomes more and more prominent. Table 3.2 reports the VSF of all the buses for different loading factor. The VSF of bus 14 for loading factor 2, 3, and 4 are 0.1163, 0.2707, and 0.5533, respectively. The values of VSF of bus 14 were highest in comparison to the other buses. Thus, bus 14 is regarded as the weakest bus of the system. Similarly, the VSF of bus 2 is least for all the loading factors making it the strongest bus of the system. The VSF values also signify that bus 19 and bus 15 are the second strongest and second weakest bus respectively.

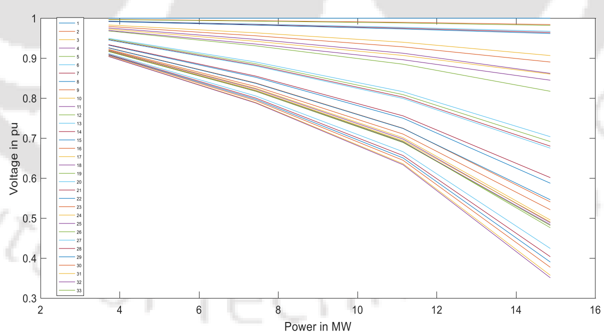

Fig.3.10- PV curve with load increased in steps in all the buses

Table 3.2- VSF at different loading factor

Bus No.	VSF at Loading Factor 2	VSF at Loading Factor 3	VSF at Loading Factor 4
2	0.0034	0.0074	0.0129
3	0.0196	0.0431	0.0764
4	0.0284	0.0631	0.1134
5	0.0372	0.0831	0.1509
6	0.0593	0.1335	0.2461
7	0.0636	0.1436	0.2662
8	0.0803	0.1826	0.3452
9	0.0882	0.2015	0.3857
10	0.0956	0.2192	0.4250
11	0.0967	0.2218	0.4311
12	0.0986	0.2265	0.4420
13	0.1064	0.2458	0.4877
14	0.1163	0.2707	0.5533
15	0.1156	0.2687	0.5477
16	0.1129	0.2621	0.5297
17	0.1112	0.2576	0.5179
18	0.1093	0.2530	0.5060
19	0.0039	0.0085	0.0146
20	0.0076	0.0158	0.0257
21	0.0083	0.0173	0.0279
22	0.0089	0.0186	0.0299
23	0.0234	0.0510	0.0890
24	0.0305	0.0659	0.1126
25	0.0341	0.0733	0.1245
26	0.0617	0.1389	0.2563
27	0.0647	0.1460	0.2701
28	0.0786	0.1780	0.3324
29	0.0886	0.2015	0.3796

Bus No.	VSF at Loading Factor 2	VSF at Loading Factor 3	VSF at Loading Factor 4
30	0.0930	0.2118	0.4011
31	0.0981	0.2241	0.4273
32	0.0993	0.2268	0.4332
33	0.0996	0.2277	0.4351

Fig.3.11 gives the comparative analysis of voltage of all the buses for the base case and critical loading. From the figure, the deviation of voltage of all the buses is quite prominent.

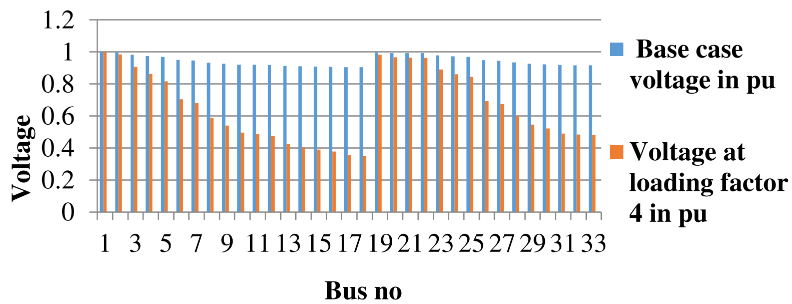

Fig.3.11- Comparison between voltage of base case and critical loading case for all buses in per unit

The EV charger load is modelled as in Rahman et al. (2013) and based on the data that a fast EV charger consumes 50 kW power and slow charger consumes 19.2 kW power (Dubey et al. 2015) the entire analysis is performed for all the cases illustrated in Table 3.3.

Table 3.3-Different cases considered for analyzing the impact of placement of charging station

Case	Description	Increase in Load (kW)
2	Fast Charging station is placed at bus 2	1500
3	Fast charging station is placed at bus 2	3000
4	Fast Charging station is placed at bus 2	7500
5	Fast Charging station is placed at bus 2 and bus 19	3000 (1500 each)
6	Fast Charging station is placed at bus 14	1500
7	Fast Charging station is placed at bus 14 and bus 15	3000 (1500 each)

Case 1 is considered as the base case without charging stations in the entire analysis. In case 2 a fast charging station is placed at bus 2 representing the strongest bus of the system with 30 serving points. Assuming that each charger consumes 50 kW the charging station possessed the capability of charging 30 EVs simultaneously. In case 3 two charging stations are placed at bus 2 and in case 4 five fast charging stations are placed at bus 2. In case 5, a fast charging station is placed at bus 2 and 19 representing the strongest and second strongest bus respectively. In case 6, a single fast charging station is placed at bus 14 representing the weakest bus of the system. In case 7, a fast charging station is placed at bus 14 and 15 representing the weakest and second weakest bus respectively.

3.4.2. Impact of EV Charging Station Load on Distribution Network

The impact of EV charging station load on voltage stability, reliability, power losses, and economic losses of the distribution network is analyzed for all the cases as mentioned in Table 3.3 and the results of this analyses are reported in this sub-section.

I. Impact of EV Charging Station Load on Voltage Stability

The impact of EV charging load on voltage stability of 33 bus test network is reported in this sub- section. The value of VSI is calculated for all the buses by utilizing the methodology elaborated in Section 3.2.2.

Table 3.4 reports the VSI for the base case and different cases of the placement of the EV charging station. It is observed that for case 7 where charging station is placed at the weakest bus the VSI of bus 14 is as low as 0.2073. Thus, placement of charging station at the weakest bus caused severe degradation of the voltage stability.

Table 3.4- Impact of EV charging station load on VSI

Bus No.	VSI for Base Case	VSI for Case 2	VSI for Case 3	VSI for Case 4	VSI for Case 5	VSI for Case 6	VSI for Case 7
2	0.9998	0.9981	0.9981	0.9908	0.9981	0.9998	0.9997
3	0.9868	0.9834	0.9834	0.9696	0.9799	0.9815	0.9743
4	0.9327	0.9294	0.9294	0.9161	0.9261	0.9054	0.8709
5	0.9051	0.9018	0.9018	0.8887	0.8985	0.8622	0.8090
6	0.8766	0.8734	0.8734	0.8604	0.8701	0.8171	0.7438
7	0.8126	0.8095	0.8095	0.7971	0.8064	0.7248	0.6209
8	0.7961	0.7930	0.7930	0.7807	0.7899	0.6984	0.5788
9	0.7558	0.7528	0.7528	0.7408	0.7498	0.6052	0.4403

Bus No.	VSI for Base Case	VSI for Case 2	VSI for Case 3	VSI for Case 4	VSI for Case 5	VSI for Case 6	VSI for Case 7
10	0.7355	0.7326	0.7326	0.7208	0.7296	0.5555	0.3687
11	0.7180	0.7151	0.7151	0.7034	0.7121	0.5114	0.3092
12	0.7151	0.7122	0.7122	0.7005	0.7093	0.5034	0.2984
13	0.7092	0.7063	0.7063	0.6947	0.7034	0.4871	0.2745
14	0.6905	0.6877	0.6877	0.6762	0.6848	0.4290	0.2073
15	0.6845	0.6816	0.6816	0.6702	0.6788	0.4180	0.1860
16	0.6800	0.6772	0.6772	0.6658	0.6744	0.4146	0.1792
17	0.6753	0.6725	0.6725	0.6612	0.6697	0.4109	0.1768
18	0.6695	0.6667	0.6667	0.6554	0.6639	0.4064	0.1739
19	0.9879	0.9846	0.9846	0.9708	0.9780	0.9834	0.9777
20	0.9837	0.9804	0.9804	0.9667	0.9709	0.9792	0.9735
21	0.9713	0.9680	0.9680	0.9544	0.9586	0.9669	0.9611
22	0.9680	0.9647	0.9647	0.9511	0.9553	0.9636	0.9579
23	0.9329	0.9296	0.9296	0.9163	0.9262	0.9059	0.8720
24	0.9138	0.9105	0.9105	0.8973	0.9072	0.8871	0.8535
25	0.8892	0.8859	0.8859	0.8729	0.8827	0.8628	0.8297
26	0.8136	0.8105	0.8105	0.7980	0.8073	0.7258	0.6220
27	0.8069	0.8038	0.8038	0.7914	0.8007	0.7195	0.6162
28	0.7972	0.7941	0.7941	0.7818	0.7910	0.7103	0.6077
29	0.7589	0.7559	0.7559	0.7439	0.7529	0.6743	0.5744
30	0.7316	0.7286	0.7286	0.7168	0.7257	0.6485	0.5506
31	0.7208	0.7179	0.7179	0.7062	0.7150	0.6384	0.5413
32	0.7091	0.7062	0.7062	0.6946	0.7033	0.6274	0.5312
33	0.7069	0.7040	0.7040	0.6924	0.7011	0.6253	0.5293

Table 3.5 lists the voltage of all the buses for the base case as well as after placing charging stations for all the cases mentioned in Table 3.3. The voltage of bus 14 for case 2 is 0.9082 pu. Thus, the magnitude of the voltage of bus 14 for case 2 is less than the base case voltage, but still within the acceptable range. However, for case 4 when five charging stations are placed at bus 2

the voltages of bus 17 and bus 18 drops to 0.8984 pu and 0.8978 pu respectively. These values are not within the tolerance limit. In case 5 where a single charging station of 1500 kW is placed at bus 2 and bus 19 respectively it is observed that voltage drops of all the buses are less than that of case 3 where a single charging station of 3000 kW is placed at bus 2. Thus, distributing the charging stations between a number of buses is advantageous than concentrating the charging stations at a single bus. In case 6 where the charging station is placed at bus 14 representing a weak bus the voltage drops to 0.7351 which cannot be tolerated. Similarly, for case 7 where two charging stations are placed at the two weak buses the voltage drop is prominent.

Table 3.5-Impact of EV charging station load on voltage profile

Bus No.	Voltage for Base Case	Voltage for Case 2	Voltage for Case 3	Voltage for Case 4	Voltage for Case 5	Voltage for Case 6	Voltage for Case 7
2	0.9970	0.9959	0.9947	0.9913	0.9948	0.9954	0.9931
3	0.9829	0.9818	0.9806	0.9771	0.9807	0.9724	0.9580
4	0.9754	0.9743	0.9731	0.9696	0.9732	0.9584	0.9350
5	0.9680	0.9669	0.9657	0.9621	0.9658	0.9442	0.9114
6	0.9496	0.9484	0.9472	0.9436	0.9473	0.9084	0.8528
7	0.9461	0.9449	0.9437	0.9401	0.9438	0.8969	0.8322
8	0.9325	0.9313	0.9300	0.9264	0.9301	0.8501	0.7407
9	0.9262	0.9249	0.9237	0.9200	0.9238	0.8239	0.6867
10	0.9203	0.9191	0.9178	0.9141	0.9179	0.7979	0.6319
11	0.9195	0.9182	0.9170	0.9132	0.9171	0.7938	0.6228
12	0.9179	0.9167	0.9155	0.9117	0.9155	0.7863	0.6057
13	0.9118	0.9105	0.9093	0.9055	0.9094	0.7508	0.5264
14	0.9095	0.9082	0.9070	0.9032	0.9071	0.7351	0.4910
15	0.9081	0.9068	0.9056	0.9018	0.9056	0.7333	0.4752
16	0.9067	0.9054	0.9042	0.9004	0.9042	0.7316	0.4726
17	0.9047	0.9034	0.9022	0.8984	0.9022	0.7291	0.4688
18	0.9041	0.9028	0.9016	0.8978	0.9016	0.7284	0.4677
19	0.9965	0.9954	0.9942	0.9908	0.9921	0.9948	0.9926

Bus No.	Voltage for Base Case	Voltage for Case 2	Voltage for Case 3	Voltage for Case 4	Voltage for Case 5	Voltage for Case 6	Voltage for Case 7
20	0.9929	0.9918	0.9906	0.9872	0.9885	0.9912	0.9890
21	0.9922	0.9911	0.9899	0.9865	0.9878	0.9905	0.9883
22	0.9916	0.9904	0.9893	0.9858	0.9871	0.9899	0.9876
23	0.9793	0.9782	0.9770	0.9735	0.9771	0.9688	0.9543
24	0.9727	0.9715	0.9703	0.9668	0.9704	0.9620	0.9475
25	0.9693	0.9682	0.9670	0.9635	0.9671	0.9587	0.9441
26	0.9477	0.9465	0.9453	0.9417	0.9454	0.9064	0.8506
27	0.9451	0.9439	0.9427	0.9391	0.9428	0.9037	0.8478
28	0.9337	0.9325	0.9313	0.9276	0.9314	0.8917	0.8350
29	0.9255	0.9243	0.9231	0.9193	0.9231	0.8831	0.8258
30	0.9220	0.9207	0.9195	0.9158	0.9196	0.8794	0.8218
31	0.9178	0.9166	0.9153	0.9116	0.9154	0.8750	0.8172
32	0.9169	0.9156	0.9144	0.9107	0.9145	0.8741	0.8161
33	0.9166	0.9154	0.9141	0.9104	0.9142	0.8738	0.8158

II. Impact of EV Charging Station Load on Reliability

The impact of EV charging station load on the reliability of the distribution network is analysed for all the cases mentioned in Table 3.3. The results of this analysis are reported in this sub-section. The failure rate, repair rate and outage duration of the system for increased load demand are computed based on unitary method (Bhadra et al. 2015).Table 3.6 reports the impact of the placement of the EV charging stations on different reliability indices. The value of SAIFI for case 2 was 0.1195 interruption/customer yr. This value is more than the base case SAIFI but less than the critical or dead zone value of SAIFI. Similar trend is observed for SAIDI, CAIDI, as well as AENS. It is observed that for case 6 and case 7 the reliability indices degraded to a value that cannot be tolerated. Thus, for an increased load demand due to EV charging load the interruption, duration of interruption per customer increased. These are the chief causes of customer dissatisfaction.

Table 3.6- Impact of EV charging station load on different reliability indices

Case	SAIFI (Interruption/Year)	SAIDI (h/Year)	CAIDI (h/Interruption)	AENS (kWh/Year)
Base case	0.0982	0.5048	5.1385	1.9369
2	0.1195	0.6321	5.2915	10.2612
3	0.1407	0.7594	5.3984	33.27
4	0.2043	1.1413	5.5858	314.5049
5	0.1361	0.7155	5.2558	16.3547
6	0.1235	0.7578	6.1341	15.1578
7	0.1366	0.8448	6.1850	23.9717

For further analysis, Table 3.7 reports the equivalent events like increase in the number of customers responsible for degrading the reliability indices. Table 3.7 reports that the establishment of charging infrastructure of 30, 60, and 150 EVs is equivalent to increasing the number of customer of the distribution network by 106, 154, and 254 respectively in terms of the degradation of SAIFI.

Table 3.7- Equivalent events producing the SAIFI similar to addition of charging station

Case	Number of EVs That Can Be Charged	SAIFI	Increase in Load Producing Same SAIFI (kW)	Increase in Number of Consumers Producing Same SAIFI
2	30	0.1195	407.69	106
3	60	0.1407	590.095	154
4	150	0.2043	976.45	254

III. Impact of EV Charging Station Load on Power Loss

The impact of the EV charging station load on the power loss of the distribution network are analyzed for all the cases as mentioned in Table 3.3 and the results of this analysis are reported in this subsection. The power loss of the distribution network is computed by Eq. (3.10).

Table 3.8 reports the magnitude of power loss of the network for different cases of placement of charging station. The power loss of the distribution network after the placement of charging stations is high as compared to without the charging stations. The power loss of case 5 is less than that of case3 signifying the advantage of distributing the charging station load between two buses. For case 6 and 7 where charging stations are placed at weak buses, the power losses are 0.0090 and 0.0247 respectively. Thus, these values are quite high in comparison to the base case.

Table 3.8-Impact of EV charging station load on power loss

Case	Power Loss (pu)
Base case	0.0021
2	0.0022
3	0.0024
4	0.003
5	0.0023
6	0.0090
7	0.0247

IV. Impact of EV Charging Station Load on Economic Loss

A detailed analysis of the economic losses incurred because of degradation of voltage profile and reliability indices are reported in this sub-section. Table 3.9 reports the economic losses incurred by the utility due degradation of voltage profile and reliability after placement of charging stations. For case 2, case 3 and case 4 where charging stations are placed at the strongest bus of the network the penalty for voltage deviation is almost negligible. However, for case 4 the penalty for AENS is 56.610 \$. On the other hand, when charging station is placed at bus 14 the penalty for voltage deviation is as high as 70,289 \$. Despite the fact that improper placement of charging station results in economic losses the EVs must be welcomed as the net benefit earned by implementing V2G scheme cannot be neglected.

Table 3.9-Impact of EV charging station load on economic loss

Case	Penalty for Voltage Deviation ($)	Penalty for Energy Not Supplied ($)
2	0	1.84
3	0	5.9886
4	0.4892	56.610
5	0	2.9438
6	70289	2.728
7	1397700	4.3149

V. Comparative Analysis of EV Charging Station Load on Voltage Stability, Power Loss, and Reliability

A comparative analysis of the impact of EV charging station load on different operational parameters of the system like voltage stability, power loss, and reliability is performed and the results are in this sub-section.

Table 3.10 gives a comparative analysis of the effect of EV charging station load on different indices of the distribution network. From this table it is clear that the reliability indices are more affected than power loss and voltage stability for case 2, case 3 and case 4 where charging station is placed at strong buses. However, for case 7 where charging stations are placed at bus 14 and 15 power loss is most severely affected. As illustrated in Fig.3.12 for case 4 the power loss is affected less than reliability indices. On the other hand, as illustrated in Fig.3.13 the % change in power loss for case 7 is 85%.

Table 3.10- Comparative Analysis of different parameters after placement of charging stations

Case	Change in				
	VSI	Power Loss	SAIFI	SAIDI	CAIDI
2	0.00173	0476	0.2169	0.2521	0.0297
3	0.00362	0.1428	0.4327	0.5043	0.0505
4	0.00912	0.42857	1.08044	1.26	0.08762
5	0.00347	0.0952	0.3859	0.417	0.0228
6	0.1950	2.1904	0.417	0.5011	0.1937
7	0.3299	8.9523	0.0228	0.67022	0.2036

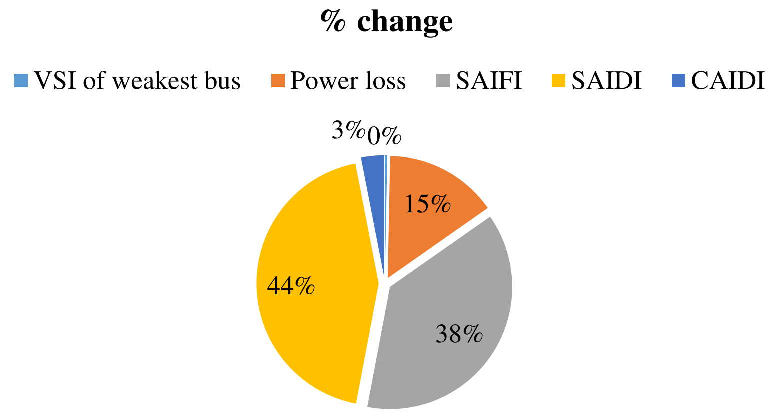

Figure 3.12- Comparative analysis of placement of charging station on VSI, power loss and reliability indices for Case 4

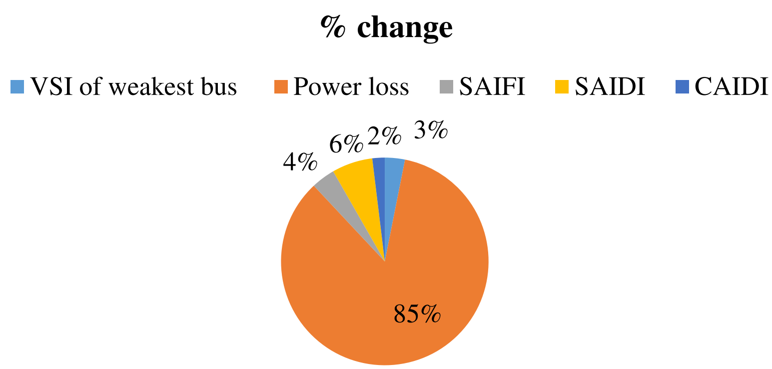

Figure 3.13- Comparative analysis of placement of charging station on VSI, power loss and reliability indices for Case 7

3.4.3. Optimal Placement of Charging Stations Based on VRP Index

As a motivating example for the usage of VRP index, we present briefly a novel methodology for the placement of the charging stations in the distribution network based on the VRP index. GA is used for solving the optimization problem. The results of the optimal placement of the charging stations are reported in this subsection. Table 3.11 reports the values of the different input parameters required for performing optimization. Table 3.12 reports the optimal locations of the charging stations in the 33 bus distribution network computed based on VRP index. The optimal locations are bus number 19, 20, and 2. The number of fast charging stations placed at bus number 19, 20, and 2 are 2, 1, and 2 respectively. The number of slow charging stations placed at bus number 19, 20, and 2 are 3, 2, and 1 respectively.

Table 3.11- Input Parameters for charging station placement problem with VRP index as objective functions

Parameter	Value
w_1	0.1
w_2	0.7
w_3	0.2
w_{21}	0.2
w_{22}	0.4
w_{23}	0.1
n_{fastCS}	2
n_{slowCS}	3

Table 3.12- Optimal Placement of Charging Stations based on VRP index

Bus No.	Number of Fast Charging Stations	Number of Slow Charging Stations
19	2	3
20	1	2
2	2	1

3.5. Discussions

EVs reduce the local emissions and have a positive impact on the environment. However, the detrimental impact of the EV charging station loads on the electricity distribution network cannot be neglected. The focus of this work is to present a detailed analysis of the impact of the EV charging station load on the different technical as well as economic parameters of IEEE 33 bus test system. The impact of the EV charging stations on voltage stability, reliability, power loss, and economic loss are analysed profoundly in this work and the key findings of the work are summarized as follows:

1) The 33 bus test system is robust enough to withstand the placement of four charging stations at bus 2 representing the strongest bus of the system. It is observed that when five charging

stations are placed at bus 2 the SAIDI increased by 44%. Thus, for increasing the number of charging stations beyond four up gradation of the network is required.

2) The placement of the fast charging station at the weak bus of the network is detrimental to the security of the system. On placement of even a single charging station at the weakest bus the voltage of the weakest bus drops to 0.7351 pu. The reliability indices also deteriorate significantly on placement of fast charging stations at the weak buses. Moreover, it is observed that on placement of a single charging station at bus 14 and 15 representing the weak buses of the network the power losses increase by 85%. However, slow charging stations of 19.2 kW can be placed even at the weak buses.
3) Distributing the charging stations between a number of buses was advantageous than concentrating the charging stations at a single bus in terms of voltage deviation, reliability as well as power loss. Also, in some cases, if the strong nodes of the distribution network and nodes of the road network with high traffic concentration merge then the routes leading to that node will be too congested. Therefore, another advantage of distributing the charging station is making the charging facility accessible to a larger number of EVs plying in different routes. This in turn will reduce the traffic congestion of the specific routes leading to the bus in which charging stations are concentrated.
4) A considerable economic loss was incurred by the utility for placement of charging stations at the weak buses. It is observed that on placement of even a single fast charging station at the weakest bus 1,397,700.5 $ of economic loss is incurred. However, despite the fact that improper placement of charging station results in economic losses the EVs must be welcomed as the net benefit earned by implementing V2G scheme cannot be neglected. In V2G scheme the charging stations can earn revenue by selling the electricity back to the grid when the charging demand is low.
5) The reliability indices are more affected than power loss and voltage stability for case 2, case 3 and case 4 where the charging station is placed at strong buses. However, for case 7 where charging stations are placed at bus 14 and 15 power loss is most severely affected.

All the aforementioned findings must be taken into account while dealing with the problem of optimal placement of charging stations. From the results obtained it is obvious that voltage stability, power loss as well as reliability indices degrade with the addition of EV charging station loads. Thus, for optimal placement of charging stations in the distribution network all the three parameters must be considered. A novel index named VRP index taking into account the voltage stability, reliability and power loss was also formulated. The novelty of VRP index lies in the fact that has the capability of considering voltage stability, power loss, and reliability together under a common frame. Further, a strategy for the placement of the charging stations in the distribution network based on VRP index was presented in this work. The results of the optimal placement of the charging stations based on VRP index established the efficacy of the index.

3.6. Conclusions

EVs are a favorable alternative to reduce the emissions of the transport sector. The growing popularity of EVs has led to the establishment of charging stations; however, the detrimental impact of the resulting EV charging station loads on the distribution network cannot be neglected. This work meticulously analyzed the impact of EV charging station loads on the voltage stability, reliability indices, power losses, and economic loss of the 33 bus test system. The results obtained showed that the impact of placing fast charging stations at the weak buses affected the smooth operation of the power distribution network. A considerable amount of economic loss is also incurred if fast charging stations are placed at the weak buses of the network. However, the system is strong enough to withstand the placement of charging stations at the strong buses. Further, the placement of the charging stations in the distribution network based on a new VRP index is proposed in this work. GA is used to solve the charger location problem with VRP index as the objective function. The results obtained indicate the efficacy of the VRP index in finding the most suitable locations for charging stations in the 33 bus test network. Thus, this work will serve as a guide to the power system engineers and help in planning of distribution networks in presence of EV charging loads.

Note- This chapter is reproduced from the publication-

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CHAPTER 4

SINGLE-OBJECTIVE FORMULATION OF CHARGING STATION PLACEMENT PROBLEM

4.1. Introduction

Globally, both transportation and power generation sectors are fossil fuel reliant. The oil consumption of transport sector will rise by 54% until 2035 (Source: Petroleum, British, and BP Energy Outlook. "2030." *London, United Kingdom* 2011). Thus, the research community is constantly preoccupied with concerns about the exhaustive nature of fossil fuels as well as greenhouse gas emissions responsible for the global change in climate conditions. The 21st century has witnessed a bold initiative of replacement of Internal Combustion Engine (ICE) driven vehicles with EVs. The researchers and environmentalists believe the deployment of the EVs will ameliorate the adverse impact of the emission of the transportation sector on the environment. In addition to cost, driving range anxiety of the EVs is one of the barriers inhibiting acceptance of the EVs among the masses. Thus, the development of a fully furnished charging infrastructure is of prime importance to facilitate large-scale deployment of the EVs. The current pace gives time for electric grid designers to adapt with the increasing number of EVs. A sudden replacement of ICE vehicles with EVs would roughly mean more than doubling the electric power production in the world. An improper placement of charging stations will degrade the operating parameters of the distribution network like the voltage stability, power loss, reliability etc (Dubey et al. 2015). Thus, the placement of the EV charging stations in the road network must be coordinated with the distribution network.

In the context of the aforementioned background, optimal placement of the EV charging stations has attracted researcher's interest globally. Diversity in the approach of the problem formulation, as well as optimization algorithms, applied for its solution in different literature presented in Chapter 2, makes the charging station placement problem unique and challenging. Chapter 2 discusses the contributions of different researchers in the paradigm of the charging station placement revealing the multifarious nature of the problem formulation and optimization algorithms applied. However, the existing literature on the optimal placement of the EV charging station have several limitations. They are incapable of addressing the problem strategically taking into account both the distribution and transportation network parameters. Moreover, the optimization algorithms applied for solution of this problem are mostly limited to GA and PSO.

The capability of efficient and latest evolutionary algorithms in solving the complex problem is not explored by the researchers. With the aforesaid background, this work makes an attempt to model the charging station placement problem in a simple single objective framework. The impact of distribution network parameters like Voltage Deviation (VD), Average Energy Not Served (AENS) on optimal placement of charging station is taken into account by imposing penalties for the degradation of these parameters. The impact of transport network parameters is taken into account by the inclusion of travel time cost in the problem formulation. Two latest evolutionary algorithms such as Chicken Swarm Optimization (CSO) and Teaching Learning Based Optimization (TLBO) algorithm are employed for the solution of this problem. Further, a new hybrid algorithm combining CSO and TLBO is proposed for the solution of charging station placement problem.

The rest of the chapter is organized as follows. Section 4.2 presents the single objective formulation of charging station placement problem. Section 4.3 elaborates the optimization algorithms. Section 4.4 presents methodology of solving charging station placement problem. Section 4.5 presents the results of optimal placement of charging stations. Section 4.6 discusses the results presented in Section 4.5. Finally, Section 4.7 concludes the chapter.

4.2. Problem Formulation

The charging station placement problem mimics a typical planning problem involving the interaction of both the transport and distribution networks. The placement and sizing of the charging stations are the two prime activities performed in the problem. From the perspective of the EV drivers, the locations of the charging stations must be easily accessible and close to the point of charging demand. A large distance between the point of charging demand and charging station would result in a high value of travel time or reachability cost. Travel time cost or reachability cost is the additional cost incurred by the EV drivers for travelling the distance between the charging demand points and charging stations. The placement of the charging stations must not degrade the operating parameters of the distribution network such as the voltage deviation and AENS. Voltage deviation is the change in the bus voltage due to the increase of load. AENS is a reliability index which quantifies how much energy is not served during a particular time period (Chowdhury et al. 2011). Thus, the placement of the charging stations in the road network must be coordinated with the distribution network. The problem of the charging station placement is formulated in this work as a non-linear constrained optimization problem. The salient features and the difference of the present formulation from the formulations of charging station present in the existing literature are as follows-

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

The decision variables, objective function, as well as constraints of this placement problem, are defined in the next subsections.

4.2.1. Decision variables

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

- p
- N_{fastp}
- N_{slowp}

$p \in P$

P is subset of both S and TS.

4.2.2. Objective function

The objective function is concerned with minimization of overall cost associated with the establishment of charging stations. The cost can be divided into the direct and indirect cost. The direct cost includes the installation cost and operating cost. The indirect cost includes the penalties for voltage deviation, AENS and travelling time or reachability cost. Mathematically, the objective function is as in Eq. (4.1)

$$Min\ (C_{direct} + C_{indirect}) \tag{4.1}$$

I. Direct cost

The direct cost includes the cost directly associated with establishment of charging station like the installation cost and operating cost as elaborated by Eq. (4.2) - Eq. (4.7).The installation cost is a onetime investment whereas the operation cost is calculated for a specified timeframe.

$$C_{direct} = C_{installation} + C_{operation} \tag{4.2}$$

$$C_{installation} = (N_{fastCS} \times C_{installationfast} + N_{slowCS} \times C_{installationslow}) \tag{4.3}$$

$$C_{operation} = (N_{fastCS} \times CP_{fast} + N_{slowCS} \times CP_{slow}) \times P_{electricity} \times T_t \tag{4.4}$$

$$N_{fastCS} = \sum_{i=1}^{N_D} n_i \times N_F^i \tag{4.5}$$

$$N_{slowCS} = \sum_{i=1}^{N_D} n_i \times N_S^i \tag{4.6}$$

$$n_i = 1 \ \ \forall \ \ i \in P \tag{4.7}$$

II. Indirect Cost

The indirect cost is the summation of the penalty paid and travel time cost. One of the salient features of this problem formulation is distribution network parameters are taken into account by imposing penalties for voltage deviation and AENS. The travel time cost is the additional cost of travelling from the node of charging demand to the node of placement of charging station. Eq. (4.8) - Eq. (4.14) elaborate various terms associated with the indirect cost.

$$C_{indirect} = C_{penalty} + C_{travel} \tag{4.8}$$

$$C_{penalty} = VD_{penalty} + AENS_{penalty} \tag{4.9}$$

$$VD_{penalty} = P_{VD} \times \sum_{i=2}^{N_D} VD_i \tag{4.10}$$

$$VD_i = V_i^{base} - V_i \tag{4.11}$$

If after the increase of load the voltage of the buses of the distribution network drops to less than 0.9 per unit then the utility has to pay the penalty for voltage deviation.

$$AENS_{penalty} = P_{AENS} \times AENS \tag{4.12}$$

$$AENS = \frac{\sum L_i\, U_i}{\sum N_i} \tag{4.13}$$

$$C_{travel} = d_{CS} \times T_{\cos tEV} \tag{4.14}$$

4.2.3. Constraints

The objective function formulated in the previous sub-section is minimized in agreement with a number of inequality and equality constraints as explained by Eq. (4.15) – Eq.(4.18) and Eq.(4.19)- Eq.(4.20) respectively.

$$0 < N_{fastp} \leq n_{fastp} \tag{4.15}$$

$$0 < N_{slowp} \leq n_{slowp} \tag{4.16}$$

$$SS_{\min} \leq SS_i \leq SS_{\max} \tag{4.17}$$

$$L \leq L_{\max} \tag{4.18}$$

In addition to the aforementioned constraints, the power flow balance equations must be considered as equality constraints.

$$P_{gi} - P_{di} - V_i \sum_{j=1}^{N_D} V_j Y_{ij} \cos(\delta_i - \delta_j - \theta_{ij}) = 0 \tag{4.19}$$

$$Q_{gi} - Q_{di} - V_i \sum_{j=1}^{N_D} V_j Y_{ij} \cos(\delta_i - \delta_j - \theta_{ij}) = 0 \tag{4.20}$$

The constraints given by Eq. (4.15) and Eq. (4.16) take into account the maximum and minimum number of fast as well as slow charging stations placed at the candidate locations. Eq. (4.17) takes into account the upper and lower limit of reactive power. Eq. (4.18) takes into account the maximum safe limit of load that can be added to the network. In addition to the aforementioned constraints, the power flow balance equation given by Eq. (4.19) and Eq. (4.20) must be considered as an equality constraint.

4.3. Optimization Algorithms

An overview of the optimization algorithms used for solving the charging station placement problem is presented in this section.

4.3.1. Necessity of new meta-heuristics

In recent years, the paradigm of combinatorial optimization has witnessed the discovery of a number of novel meta-heuristic algorithms. Many real-world engineering optimization problems are difficult to solve by classical algorithms because of the non-linear nature of the objective functions involved. The charging station placement problem is one such complex problem involving a number of variables, objective functions, and constraints. Hence, there is necessity of devising efficient and fast algorithms for the solution of the placement problem. CSO and TLBO are the two latest evolutionary algorithms which have been successfully applied by researchers for solving complex engineering optimization problems. For example, CSO is applied to solve feature selection (Hafez et al. 2015), community detection (Ahmed et al. 2016), Wireless Sensor Network (WSN) localization (Shayokh and Shin 2017), speed reducer design (Chen et al. 2015), trajectory optimization (Li et al. 2017) etc. Similarly, TLBO is successfully applied to solve parameter optimization of machining process (Rao et al. 2011), transmission expansion planning (Zakeri et al. 2017), economic load dispatch problem (Krishnanand et al. 2011), optimization of heat exchangers (Rao et al. 2013), optimal configuration of microgrid (Deb et al. 2016) etc. Hence, motivated by the success of CSO as well as TLBO in solving such a wide range of optimization problems these two algorithms are amalgamated together to form hybrid CSO TLBO. It is expected that amalgamation of CSO TLBO will improve the quality of solution and fast convergence towards the optimal solution will be favoured.

4.3.2. CSO

CSO is one of the latest bio-inspired algorithms proposed by Meng et al. (2014). The CSO algorithm is inspired by the behavior of chicken swarm where the intelligence of chicken swarm is utilized effectively to obtain the optimal solution. It imitates the hierarchal order in a chicken swarm and the food searching process of the swarm. The population of chicken in the group consists of the dominant rooster, hens, and chicks depending upon the fitness values of the chickens. The chickens with the highest fitness value are assigned as roosters, chickens with least fitness value are assigned as chicks, and the chickens with intermediate fitness value are assigned as hens. The algorithm randomly assigns the mother-child relationship in the swarm. The hierarchal order and mother-child relationship are updated after every G time steps. The natal behavior of hens to follow their group mate rooster and chicks to follow their mother in the quest for food is mimicked by the algorithm. It is also assumed that the chickens would try to steal the food found by others thereby giving rise to a competition for food in the group. The algorithm can be broadly divided into two steps-Initialization and Update.

In Initialization, the population size and other related parameters of CSO are defined. The fitness values of the population of chicken are evaluated and a hierarchal order is established based on this fitness value as illustrated in Fig.4.1. It is assumed that the number of hens is highest in the group (Meng et al. 2014). The mother hens are selected randomly from the set of hens. Despite the fact that each hen can have more than one chick, it is assumed that the number of chicks is less than the number of hens (Meng et al. 2014).

Utilizing the concepts of set theory Eq. (4.21) and Eq. (4.22) are deduced.

$$MN \subset HN \tag{4.21}$$

$$PN = RN \cup HN \cup CN \tag{4.22}$$

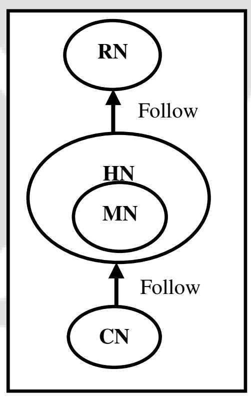

Fig.4.1- Hierarchal relationship in the chicken swarm

Update is explained by Eq. (4.23) – Eq. (4.29). The food searching capacities of rooster depend on their fitness value and their position after update is as in Eq. (4.23) – Eq. (4.25).

$$x_{i,j}^{t+1} = x_{i,j}^{t} \times (1 + \mathrm{randn}(0, \sigma^2)) \tag{4.23}$$

If $f_i \leq f_k$

$$\sigma^2 = 1 \tag{4.24}$$

Else,

$$\sigma^2 = \exp(\frac{(f_k - f_i)}{|f_i| + \varepsilon}) \tag{4.25}$$

where randn$(0,\sigma^2)$ is a Gaussian distribution function with mean 0 and standard deviation σ^2.f is the fitness value of corresponding x, k is randomly selected rooster's index.ϵ is a small constant value which is used to avoid zero division error.

Hens follow their group mate roosters in their quest for food. Moreover, there is also a tendency among the chickens to steal the food found by other chickens. The mathematical representation of their update formula is as follows-

$$x_{i,j}^{t+1} = x_{i,j}^{t} + S1 \times \text{rand} \times (x_{r1,j}^{t} - x_{i,j}^{t}) + S2 \times \text{rand} \times (x_{r2,j}^{t} - x_{i,j}^{t}) \tag{4.26}$$

$$S1 = \exp(\frac{f_i - f_{r1}}{\text{abs}(f_i) + \varepsilon}) \tag{4.27}$$

$$S2 = \exp(f_{r2} - f_i) \tag{4.28}$$

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

The natural tendency of chicks to follow their mother is mathematically formulated as follows-

$$x_{i,j}^{t+1} = x_{i,j}^{t} + FL \times (x_{m,j}^{t} - x_{i,j}^{t}) \tag{4.29}$$

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

The flowchart and pseudo code of CSO are as shown in Fig. 4.2 and Algorithm 4.1 respectively.

Algorithm 4.1-Pseudo code of CSO

Initialize the population of chicken having size N and define other algorithm specific parameters like G, size of RN, HN,CN, and MN;
Evaluate the fitness value of N chicken, t=0 , establish the hierarchal order in the swarm as well as mother child relationship;
While (t<gen)
t=t+1;
If(t%G==0)
Establish the hierarchal order in the swarm as well as mother child relationship;
Else
For i=1:PN
If i==rooster
Update its solution by Eq.(4.23);
End if
If i==hen
Update its solution by Eq.(4.24);
End if
If i==chick
Update its solution by Eq.(4.26);
End if
Evaluate the new solutions;
Update the new solutions if they are better than the previous one;
End for
End if else
End while

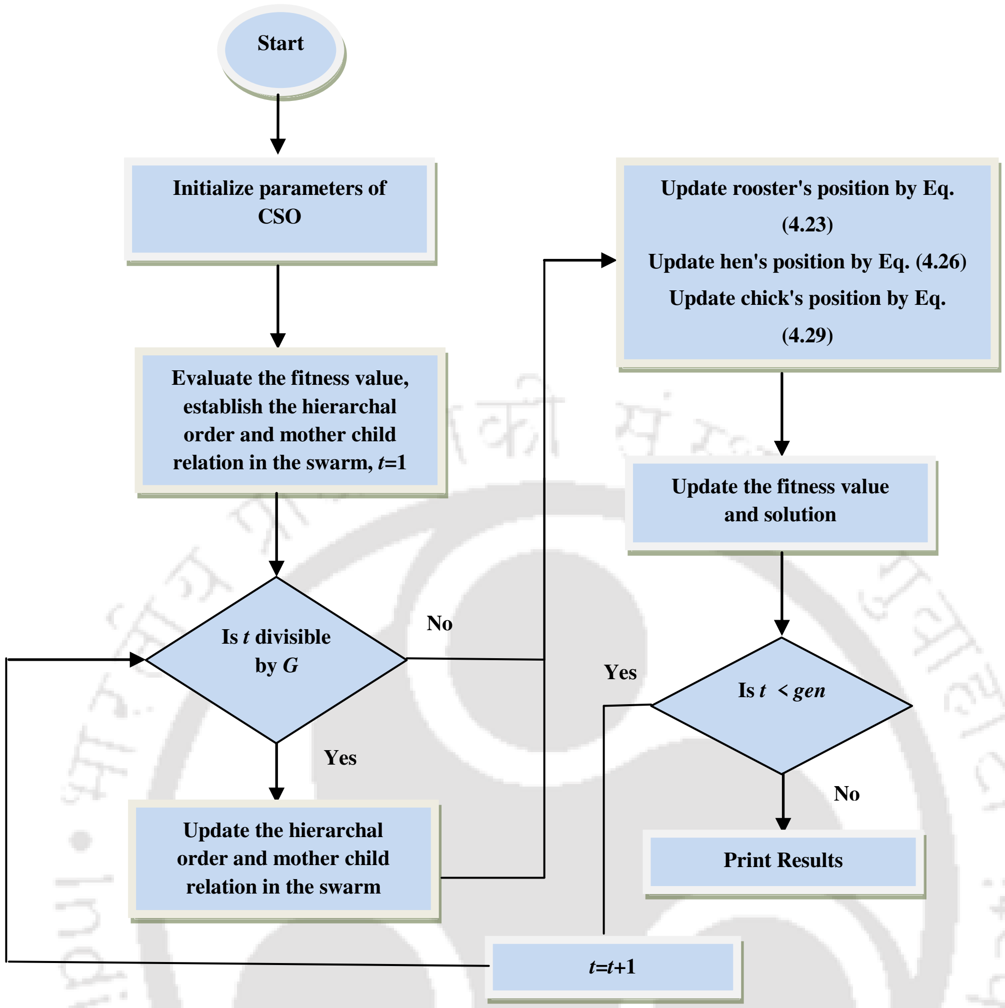

Fig.4.2. - Flowchart of CSO

4.3.3. TLBO

TLBO is a latest evolutionary algorithm introduced by Rao et al. (2011). TLBO is a population-based evolutionary algorithm mimicking the interactive process of the teaching and learning. A class of learners constitutes the population here. The teacher transfers his/her knowledge to the learners. The performance of the learners depends on the knowledge and capability of the teacher. The students can learn from the teacher as well as learn from each other by mutual interaction. Thus the algorithm is divided into two parts- Teacher phase and

Learner phase (Rao et al. 2011).

In this phase, the students learn from the teacher who is an erudite scholar with profound knowledge and skill. The learner having the best fitness in a randomly generated population of teachers is generally assigned the role of teacher. Each learner learns from the teacher and is modified by Eq. (4.30) and Eq. (4.31).

$$Z_{diff} = \text{rand} \times (T_k - R_t m_k) \tag{4.30}$$

$$Z_{new} = Z_{old} + Z_{diff} \tag{4.31}$$

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

In this phase of learning the learner learns by mutual interaction among themselves. For each learner Z_i any learner Z_j is chosen arbitrarily from the learner matrix. The objective function values are compared arbitrarily for the two aforementioned learners. If the value of the objective function of Z_i is lower than the objective function of Z_j then the i^{th} learner is modified by Eq. (4.32).

$$Z_{new} = Z_{old} + \text{rand} \times (Z_i - Z_j) \tag{4.32}$$

Else, the learner is modified by Eq. (4.33)

$$Z_{new} = Z_{old} + \text{rand} \times (Z_j - Z_i) \tag{4.33}$$

The flowchart and pseudo code of TLBO are as shown in Fig. 4.3 and Algorithm 4.2 respectively.

Algorithm 4.2- Pseudo code of TLBO

Set k=1;
Initialize the population size and generate the initial population of students randomly;
Compute the objective function for all the individuals of the population;
while(k<gen)
{Teacher Phase}
Assign the teacher based on the fitness value;
for i=1:pop
Modify each learner by Eq.(4.30), Eq.(4.31);
Evaluate the new solutions;
Update the new solutions if they are better than the previous one;
{End of teacher phase}
{Learner Phase}
Choose two learners Z_i *and* Z_j, $i \neq j$;
if(fitness of Z_i *better than* Z_j*)*
Replace i^{th} *learner by Eq.(4.32);*
Else
Replace i^{th} *learner by Eq.(4.33);*
End if else
End for
k=k+1
End while

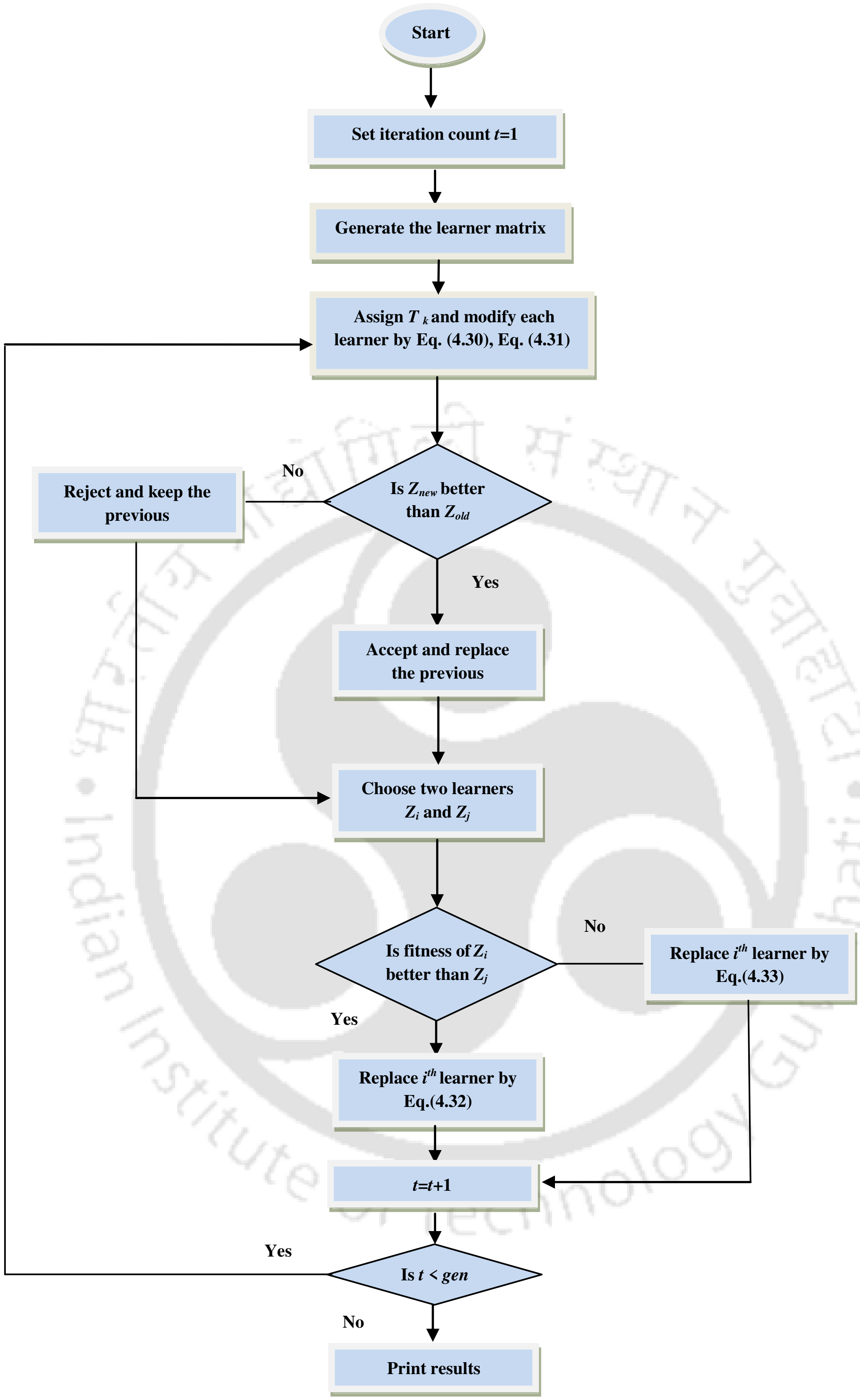

Fig. 4.3- Flowchart of TLBO

4.3.4 CSO TLBO

A novel hybrid algorithm CSO TLBO is proposed in the present work which inherits the advantages of both CSO and TLBO. In order to improve the performance of TLBO, the grading mechanism of CSO is introduced in it. Two different hybridization schemes of CSO TLBO are proposed in the work as mentioned in Algorithm 4.3 and Algorithm 4.4 respectively. In scheme 1, TLBO is performed in all the generations and CSO is periodically invoked in some generations. It is expected that if CSO is invoked periodically the utilization rate of the population will enhance. On the other hand in scheme 2 both CSO and TLBO is performed in each generation. Due to the involvement of too many algorithm-specific control parameters in CSO there is possibility of premature convergence if the parameters are not tuned properly. Hence, the solutions obtained by CSO are fine-tuned by TLBO to avoid premature convergence.

Algorithm 4.3- Pseudo code of CSO TLBO (Scheme 1)

```
Initialize the population size, gen and the other algorithm specific parameters of CSO TLBO
Set t=1
While (t<gen)
Activate TLBO
If (t mod INV)>0
Activate CSO
End if
t=t+1
End while
```

Algorithm 4.4- Pseudo code of CSO TLBO (Scheme 2)

```
Initialize the population size, gen and the other algorithm specific parameters of CSO TLBO
Set t=1
While (t<gen)
Activate CSO
Activate TLBO
t=t+1
End while
```

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

In the present work, CSO TLBO is employed to solve the charging station placement problem elaborated in section 4.2. The systematic procedure for solution of the charging station placement problem by CSO TLBO is as follows-

Step 1: Initialization

Step 1.1-Input the road network and distribution network data, upper and lower limits of different constraints and set the different algorithm specific parameters of CSO TLBO like *gen*, *PN*, *RN*, *CN*, *HN*, *G* and *INV*.

Step 1.2: Generate feasible initial population randomly.

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

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

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

The randomly generated initial solution is feasible if it satisfy all the constraints of charging station placement problem explained in section 4.2.3.

Step 1.3: Evaluate the fitness function for the initial population. Arrange the population in ascending order based on the fitness function.

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

Step 2a: Run TLBO

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

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

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

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

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

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

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

Step 3a.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 3a.5: Update the iteration count

Step 2b: Run CSO

Step 2b.1: Run CSO and update the solution based on fitness value.

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

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

Step 3b: Run TLBO

Step 3b.1: Run TLBO and update the solution based on fitness value

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

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

Step 3b.4: Update the iteration count

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

4.5. Numerical Analysis

The performance of CSO TLBO in solving a number of benchmark functions as well as charging station placement problem is reported in this section.

4.5.1. Solution of some standard benchmark functions

Some of the standard benchmark functions listed in Table 4.1 are solved using the proposed CSO TLBO for better evaluation of the algorithm. The performance of CSO TLBO on the standard benchmark functions is compared with other state-of-art algorithms like DE, PSO, BA, CSO, and TLBO. The statistical analysis of the results is performed based on 50 independent runs. The number of iteration is 1000 for all the benchmark functions and population size is

10.The different algorithm-specific control parameters of the aforesaid algorithms are listed in Table 4.2.

Table 4.1- Single-objective benchmark functions (Meng et al. 2014)

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

Table 4.2-Algorithm specific parameters (Meng et al. 2014)

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

Table 4.3- Statistical comparison of CSO TLBO with other state of art algorithms

Benchmark function	Algorithm	Best	Worst	Mean
F1	PSO	0	0	0
	DE	0	0	0
	BA	1.867408	2.94197	4.18701
	CSO	0	0	0
	TLBO	0	0	0
	CSO TLBO (Scheme 1)	0	0	0
	CSO TLBO (Scheme 2)	0	0	0
F2	PSO	0	0	0
	DE	0	0	0
	BA	1.48288	2.59402	3.07403
	CSO	0	0	0
	TLBO	0	0	0
	CSO TLBO (Scheme 1)	0	0	0
	CSO TLBO (Scheme 2)	0	0	0
F3	PSO	0	0	0
	DE	0	0	0
	BA	0.004	2.82906	15.42094
	CSO	0	0	0
	TLBO	0	0	0
	CSO TLBO (Scheme 1)	0	0	0
	CSO TLBO (Scheme 2)	0	0	0
F4	PSO	10.94454	21.26284	41.78822
	DE	8.41884	22.70527	43.9751
	BA	88.44729	121.99296	167.60654
	CSO	0	0	0
	TLBO	0	0	0
	CSO TLBO (Scheme 1)	0	0	0
	CSO TLBO (Scheme 2)	0	0	0

F5	PSO	0	1.29	8
	DE	0	0	0
	BA	24.34652	39.73613	63.15
	CSO	0	0	0
	TLBO	0	0	0
	CSO TLBO (Scheme 1)	0	0	0
	CSO TLBO (Scheme 2)	0	0	0
F6	PSO	0	0	0
	DE	0	0	0
	BA	1	3.41	6
	CSO	0	0	0
	TLBO	0	0	0
	CSO TLBO (Scheme 1)	0	0	0
	CSO TLBO (Scheme 2)	0	0	0
F7	PSO	10.94454	21.26284	41.78822
	DE	0	0	0
	BA	0	0	0
	CSO	0	0	0
	TLBO	0	2.1	5
	CSO TLBO (Scheme 1)	0	0	0
	CSO TLBO (Scheme 2)	0	0	0
F8	PSO	-1	-1	-1
	DE	-1	-1	-1
	BA	-0.41494	-0.20415	-0.12952
	CSO	-1	-1	-1
	TLBO	-1	-1	-1
	CSO TLBO (Scheme 1)	-1	-1	-1
	CSO TLBO (Scheme 2)	-1	-1	-1

Table 4.3 reports the results related to the statistical comparison of CSO TLBO with other state-of-art algorithms. The performance of PSO, DE and BA in solving the benchmark functions

mentioned in Table 4.1 is studied from the literature Meng et al. 2014. It is observed that for benchmark function F1, F2, F3,F5, F6,F8 the performance of CSO TLBO is equivalent to PSO, DE, TLBO, CSO and much better than BA. For benchmark function F4, the performance of CSO TLBO is better than PSO, DE, BA and equivalent to CSO and TLBO. For benchmark function F7, the performance of CSO TLBO is better than PSO, TLBO and equivalent to DE, BA, and CSO. Thus, we can say that the performance of the proposed CSO TLBO algorithm is competitive as compared to the aforementioned state of art algorithms. The performance of the two schemes of combining CSO and TLBO is same on the benchmark functions reported in Table 4.1. However, the number of function evaluation is more for scheme 2 as compared to scheme 1 as in scheme 2 both CSO and TLBO are performed in all the generations.

4.5.2 Solution of charging station placement problem

33 bus radial distribution network is coupled with 25 node transport network as shown in Fig.4.4 to validate the efficacy of the proposed algorithms. The line data, branch data of this test network can be found in Table A1, Table A2, of Appendix respectively. The outage data can be found in the Reference Bhadra et al. 2015.The road network data is taken from the literature Wang et al. (2013).

It is assumed that the superimposed nodes are the candidate locations for placement of charging stations. It is considered that the EVs follow the two following routes-

- Route 1- (1-2-3-4-5-6-7-8-9-10-13-11-12-15-16-17-18-20-21-14-22-23-24-25)
- Route 2-(1-2-3-4-5-6-7-8-9-10-13-11-12-15-16-17-19-20-21-14-22-23-24-25)

TS= {3,214,16,17,23,6,30,26,20} with respect to the distribution network. And TS={9,7,11,12,16,22,8,6,5,4} with respect to transport network.

Based on the consideration that the driving range of EV is 150 km and it follows either route 1 or route 2 the point of charging demand are given by T={4,7,9,13,15,18,22,25}.Table 4.4 presents the input parameters of the charging station placement problem. Table 4.5 presents the algorithm-specific parameters of different state of art algorithms for the charging station placement problem. The optimal value of the decision variables for minimization of the overall cost and the best value of the fitness function is as reported in Table 4.6. The optimization is carried out by employing the two schemes of CSO TLBO as mentioned in section 4.3 as well as other state of art algorithms like CSO, TLBO, PSO, DE, and GA. The value of the best fitness function obtained by the two hybridization schemes of CSO TLBO is 1.4841 that is least as compared to other algorithms. Thus, the supremacy of CSO TLBO in solving charging station placement problem is clearly revealed from the results presented in Table 4.5. Fig. 4.5 represents the convergence curve of different algorithms for the best fitness value. Fig.4.5 reveals that the rate of convergence of both the hybridization schemes of CSO TLBO is better than the other state of art algorithms. Another important observation from Fig. 4.5 is that the rate of convergence of scheme 2 of combining CSO TLBO is better than scheme 1. The main reason behind this is better exploration of search space in scheme 2 as compared to scheme 1.

Fig. 4.6 illustrates the location of charging stations in the road network obtained by CSO TLBO. Node 9 and 22 of the road network are the location of charging station as well as point of charging demand of EV. Intersection of the point of placement of charging station and charging demand will make it convenient for the EV drivers to charge their battery on their way without having to travel any further distance. EVs having charging demand at node 4 ,7 and 13 can access the charging station located at node 8. But for node 15, 18 and 25 which are the points of charging demand of EV there is no charging station in their neighborhood. These nodes are actually far away from the substation and the strong buses of the distribution network are far away from them. In order to meet the charging demand arising at these nodes charging stations supported by local renewable resources or battery swapping stations can be installed at these locations.

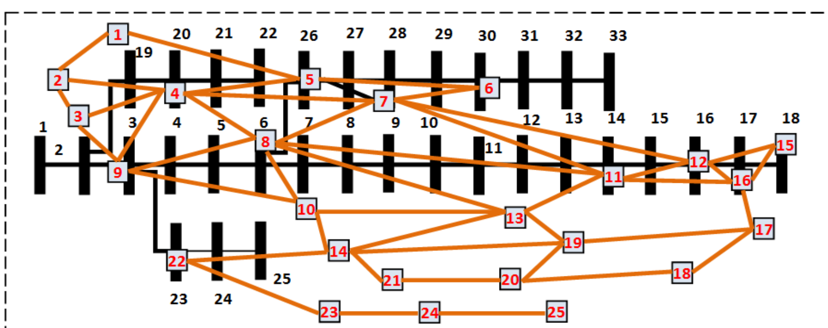

Fig.4.4- Test network for validation of single-objective charging station placement problem

Table 4.4- Input parameters of the charging station placement problem (Dubey et al. 2015; Shojaabadi et al. 2016)

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

Table 4.5-Algorithm-specific parameters of different state of art algorithms for charging station placement problem

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

Table 4.6- Optimal allocation of charging stations

Optimization technique	**Fitness value (best)**	***p* (wrt to distribution network)**	N_{Fp}	N_{Sp}
CSO TLBO(scheme 1)	1.4841	6	1	2
		3	1	3
		23	1	3
CSO TLBO(scheme 2)	1.4841	6	1	2
		3	1	3
		23	1	3
CSO	1.4870	6	1	3
		23	1	3
		3	1	2
TLBO	1.4878	3	1	3
		23	1	3
		28	1	2
PSO	1.4898	23	1	2
		6	1	3
		3	1	3
DE	1.4898	23	1	2
		6	1	3
		3	1	3
GA	1.5075	23	1	2
		3	1	3
		28	1	3

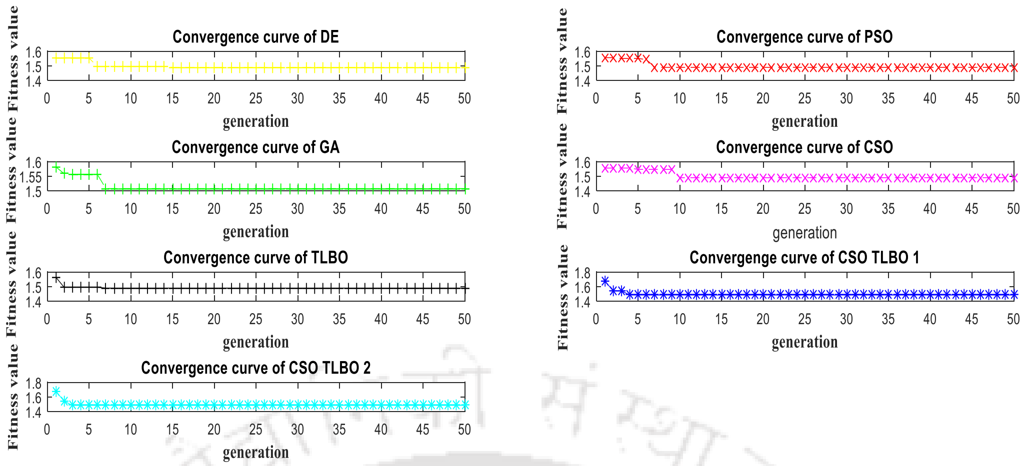

Fig.4.5- Convergence curve of different algorithms for the best fitness value

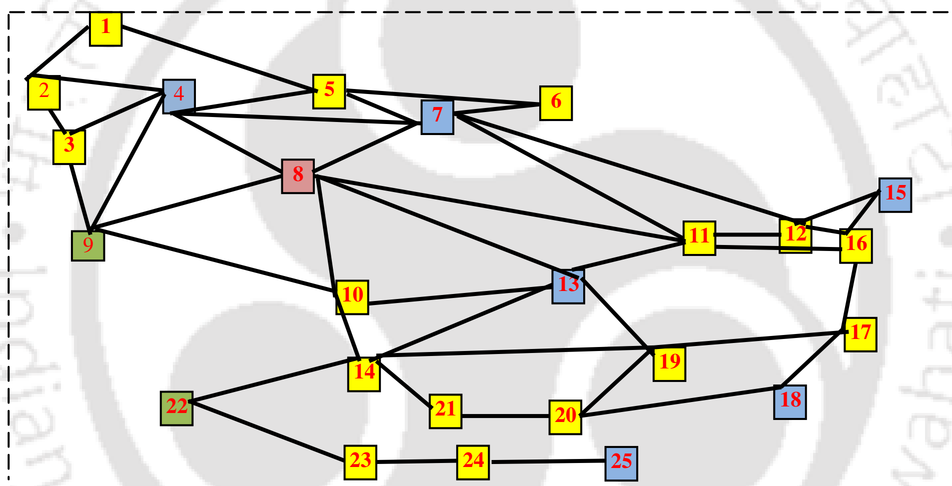

Fig.4.6- Optimal placement of charging station in the road network obtained by CSO TLBO

4.5.3. Impact of charging station on distribution network

For extended analysis, the impact of optimal placement of charging stations on different operating parameters of the distribution network is analyzed. Table 4.7 outlines the value of voltage deviation, reliability indices and power loss before and after the placement of charging stations. The value of voltage deviation and power loss after the placement of charging stations increased to 0.0058 pu and 0.0053 pu respectively. It is evident that the increased values of voltage deviation and power loss after the placement of charging stations is within the acceptable limit. As reported in Table 4.7 the reliability indices degrade with the placement of charging stations. However, the degraded values of reliability indices are far below the dead zone value of these indices reported in the literature Chowdhury et al. 2011. Thus, we can conclude that this approach is capable of allocating charging stations with the least harm to the distribution network and is partially capable of making the charging stations accessible to EV drivers without driving range anxiety.

Table 4.7- Value of different operating parameters of distribution network before and after placement of charging stations (by CSO TLBO)

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

4.5.4 Statistical comparison of different optimization algorithms

A statistical comparison of the quality of solution as well as, time complexity is performed for all the algorithms, the results of which are reported in this section. The proposed algorithms are tested in MATLAB 2016a software installed on a computer with the processor of 64 bit Intel i7 CPU. One of the salient features of the evolutionary algorithm is the random generation of the population. As a consequence of this, different solutions are obtained for every independent trial. So in order to compare the quality of solutions and time complexity of different algorithms a statistical analysis is done for 50 independent trials. Table 4.8 reports the statistical comparison of CSO TLBO algorithm with other state of art algorithms. The best fitness, worst fitness, mean fitness of both the hybridization scheme of CSO TLBO is better than the other algorithms. Table 4.8 also reports that the average execution time of CSO TLBO is more than other algorithms. The average execution time of CSO TLBO is more due to the involvement of two algorithms in it. Another observation is that the average execution time of scheme 2 of combining CSO TLBO is more than scheme 1. Fig.4.7 reports the results of Friedman rank test. The CSO TLBO is having better rank compared to the other algorithms. Also, the rank of scheme 2 of combining CSO TLBO is better than scheme 1. Thus, we can say that despite having more average execution time the second scheme of combining CSO TLBO is more competitive than the first scheme for the charging station placement problem. Table 4.9 reports the results of paired t test. From these results, inference can be drawn that there is difference in the mean value of objective functions of all pairs. In addition, the positive t-value indicates that the mean value of the objective function of CSO TLBO is far better (less) than the other algorithms.

Table 4.8- Statistical comparison of CSO TLBO with other algorithms in solving charging station placement problem

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

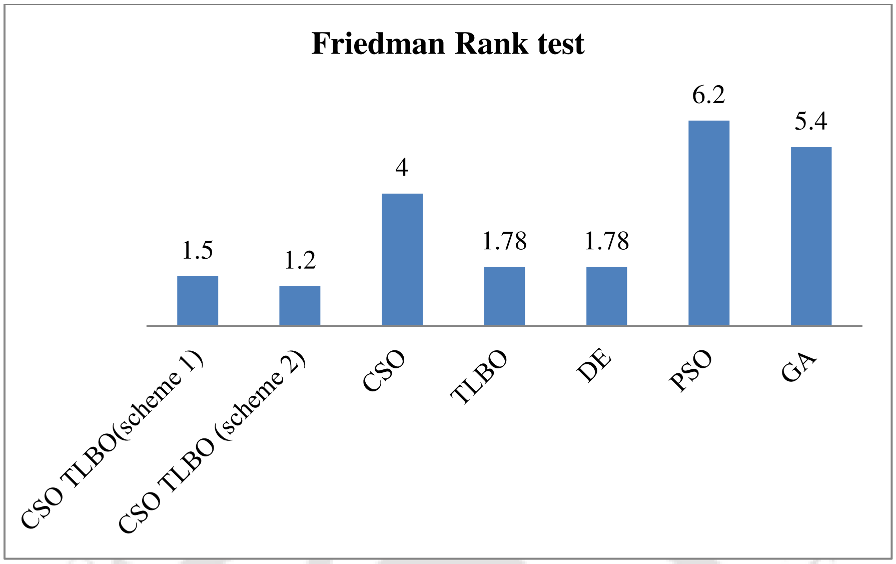

Fig. 4.7- Friedman rank test for charging station placement problem

Table 4.9- T test results

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

4.6. Discussions

A novel CSO TLBO algorithm is proposed in the present work for solving the charging station placement problem. Despite the fact that existing meta-heuristics have good success rate in solving many real-world optimization problems, it is always recommended to develop new algorithms with superior performances for a particular type of problem. Moreover, No-Free-

Lunch (NFL) states that it is impossible to for a single algorithm to perform well on all the problems (Ho and Pepyne 2002). For the aforementioned reasons, we have proposed a new algorithm for solving the charging station placement problem. Some of the key findings of the work are listed below-

1. The two schemes of combining CSO and TLBO is equally competitive or even better as compared to other state of art algorithms like GA, PSO, DE, CSO, TLBO, and BA in solving the benchmark functions mentioned in Table 4.1.
2. CSO TLBO outperforms GA, DE, PSO, CSO, and TLBO in solving the charging station placement problem. However, the average execution time of the proposed algorithm is more than the other state- of- art algorithms.
3. The convergence rate of the second scheme of combining CSO TLBO is slightly better the first scheme. However, the average execution time and the number of function evaluations of the second scheme of combining CSO TLBO is more than the first scheme.
4. The proposed approach optimally allocates the charging stations with least harm to the distribution network and simultaneously considers EV drivers convenience.

4.7. Conclusions

With the ever-increasing popularity of EVs, the establishment of charging infrastructure has become urgent to meet the charging demand. This work would be helpful in developing the charging infrastructure of EVs with minimum cost and without affecting the operating parameters of the distribution network. The contribution of this work not only lies in proposing a simple single objective framework for charging station placement problem but also combining swarm intelligence with TLBO. The superiority of the proposed hybrid algorithm in solving charging station placement problem is clearly revealed in this work. Thus, we can conclude that the charging station placement scheme is efficient enough to be implemented in real-world environment.

Note- Some parts of this chapter are reproduced from the following publications-

- **Deb, S., Kalita, K., Gao, X. Z., Tammi, K., & Mahanta, P. (2017, November). Optimal placement of charging stations using CSO-TLBO algorithm. In *Research in Computational Intelligence and Communication Networks (ICRCICN), 2017 Third International Conference on* (pp. 84-89). IEEE.**

- **Deb, S., Gao, X. Z., Tammi, K., Kalita, K., & Mahanta, P. (2019). Recent Studies on Chicken Swarm Optimization algorithm: a review (2014–2018).** ***Artificial Intelligence Review*****, 1-29.**

CHAPTER 5

MULTI-OBJECTIVE FORMULATION OF CHARGING STATION PLACEMENT PROBLEM

5.1. Introduction

The scarcity of fossil fuels and the environmental pollution created by burning them have led researchers to delve into alternate sources of energy. Globally, transport sector is one of the major emitters of greenhouse gases (Source: Petroleum, British, and BP Energy Outlook. "2030." *London, United Kingdom* 2011). As a measure to reduce the greenhouse gas emissions of transport sector, EVs have emerged as an environmental friendly alternative of traditional Internal Combustion Engine (ICE) driven vehicles. However, the large scale deployment of charging stations is a threat to the security of the power system. The degradation of voltage stability and reliability indices, reduced reserve margin, and increased power loss are some of the consequences of improper placement of charging stations in the distribution network (Dubey et al. 2015). Thus, the charging stations must be placed in the road network in such a way that the operating parameters of the distribution network are least affected.

Chapter 2 reveals that in recent years a lot of research endeavour have been devoted to the optimal placement of EV charging stations. Strategic formulation of the placement problem and applying efficient algorithms for its solution are the two main activities concerning the researchers working with optimal placement of charging stations. Literature reported in Chapter 2 reveals that the charging station placement is a complex problem involving a number of objective functions and constraints. However, the reliability of the power distribution network is neglected in most of the recent works related to charging station placement. Exclusion of reliability indices while formulating the charging station placement problem is a major research gap. Hence, in the present research work an attempt has been made to strategically address the charging station placement problem by giving due consideration to the reliability indices and simultaneously considering other planning objectives like cost, power loss, voltage deviation, accessibility and others. Thus, this chapter reports a multi-objective formulation of charging station placement problem taking into account the operating parameters of distribution network, cost as well as EV driver's convenience. From literature reported in Chapter 2 it is clear that researchers have applied a variety of evolutionary as well as classical optimization algorithms for solution of the charging station placement problem. However, still there is necessity of devising efficient and fast algorithms for solution of the placement problem. CSO and TLBO are the two latest evolutionary algorithms which have been successfully applied by researchers for solving complex engineering optimization problems. For example, CSO is applied to solve feature selection (Hafez et al. 2015), community detection (Ahmed et al. 2016), speed reducer design (Chen et al. 2015), trajectory optimization (Li et al. 2017) etc. Similarly, TLBO is successfully applied to solve parameter optimization of machining process (Rao et al. 2011), transmission expansion planning (Zakeri et al. 2017), economic load dispatch problem (Krishnanand et al. 2013), optimization of heat exchangers (Rao et al. 2011), optimal configuration of microgrid (Deb et al. 2016) etc. Hence, motivated by the success of CSO as well as TLBO in solving such a wide range of optimization problems these two algorithms are applied for solving the complex problem of charging station placement involving conflicting objective functions. Further, a novel multi-objective hybrid algorithm named CSO TLBO extracting the best features of the individual algorithms is proposed for solving the aforesaid placement problem.

The rest of the chapter is organized as follows. Section 5.2 presents the mathematical formulation of the multi-objective charging station placement problem. Section 5.3 presents an overview of multi-objective optimization. Section 5.4 elaborates the optimization algorithms. Section 5.5 elaborates the fuzzy decision making. Section 5.6 presents the solution methodology of charging station placement problem. Section 5.7 reports the performance of proposed Pareto dominance based CSO TLBO on multi-objective benchmark functions. Section 5.8 presents the optimal results of multi-objective charging station placement. Finally, Section 5.9 concludes the work.

5.2. Problem Formulation

The charging station placement is a multifaceted problem involving a number of decision variables, objective functions, and constraints. In the present work the charging station placement is formulated as a multi-variable, multi-objective, and non linear optimization problem. One of the salient features of the formulation of charging station placement problem of the present work is multi-objective formulation of the problem with cost, VRP index, and accessibility index as the objective functions. Thus, the present work consider economic objectives, driver's convenience as well as safe limits of the operating parameters of the distribution network while modelling the charging station placement problem. An overview of the decision variables, objective functions, and constraints of the charging station placement problem is presented in this section.

5.2.1. Decision Variables

The charging station placement problem is concerned with the placement as well as sizing of the charging stations. The charging service provided can be slow or fast in nature. Thus, the position, number, and nature of chargers are considered as decision variables in the present work. Symbolically, the decision variables are as follows-

- p
- N_{fastp}
- N_{slowp}

where $p = \{p_1, p_2 \ldots\ldots\ldots \ldots\ldots\ldots .p_m\}$ and $p \in TS$

$N_{fastp} = \{N_{fastp_1}, N_{fastp_2}, \ldots\ldots\ldots N_{fastp_m}\}$ and $N_{slowp} = \{N_{slowp_1}, N_{slowp_2}, \ldots\ldots\ldots N_{slowp_m}\}$

5.2.2. Objective Functions

The cost associated with establishment of charging stations, accessibility of the charging stations to the EV drivers and the impact of charging stations on the distribution network are the three prime factors which must be taken into account while formulating the charging station placement problem. Hence, in the present work the optimization is concerned with minimization of cost and VRP index simultaneously with maximization of accessibility index.

Thus, the objective function can be mathematically expressed as:

$$F = \min(Cost) + \min(VRPindex) + \max(Accessibility\ index) \tag{5.1}$$

The explanation of the three objective functions is presented below.

I. Cost

The optimization is concerned with minimization of overall cost which can be subdivided into installation and operation cost. Installation cost is the one time investment associated with the establishment of charging stations. The land cost, floor cost, building cost, labour cost, charger cost are included in the installation cost. The operation cost includes the cost of electricity required for providing the charging service to the EVs.

Mathematically, formulation of the cost function is given by Eq. (5.2) to Eq. (5.5)

$$Cost = C_{installation} + C_{operation} \tag{5.2}$$

$$C_{installation}, C_{operation} = f(N_{fastp}, N_{slowp}) \tag{5.3}$$

$$C_{installation} = \sum N_{fastp} \times C_{installationfast} + \sum N_{slowp} \times C_{installationslow} \tag{5.4}$$

$$C_{operation} = (\sum N_{fastp} \times CP_{fast} + \sum N_{slowp} \times CP_{slow}) \times P_{electricity} \tag{5.5}$$

II. VRP index

VRP index is a novel index having the capability of taking into account voltage stability, reliability, and power loss under a single frame. In the present work the impact of EV charging stations is taken into account by considering VRP index as one of the objective functions. The mathematical formulation of the VRP index and the different terms associated with it are elaborated by Eq. (5.6) to Eq. (5.14).

$$VRP = w_1 V + w_2 R + w_3 P \tag{5.6}$$

where $V = \frac{VSI_l}{VSI_{base}}$, $R = w_{21}\frac{SAIFI_l}{SAIFI_{base}} + w_{22}\frac{SAIDI_l}{SAIDI_{base}} + w_{23}\frac{CAIDI_l}{CAIDI_{base}}$ and $P = \frac{P^l_{loss}}{P^{base}_{loss}}$

$$V = R = P = f(p, N_{fastp}, N_{slowp}) \tag{5.7}$$

$$VSI_{base} = \sum_{i=1}^{N_D} VSI^i_{base} \qquad VSI^i_{base} = 2V_i^2 V_{i+1}^2 - 2V_{i+1}^2 (P_{i+1} r_i + Q_{i+1} x_i) - |z|^2 (P_{i+1}^2 + Q_{i+1}^2) \tag{5.8}$$

$$P'_p = P_p + (\sum N_{fastp} \times CP_{fast}) + (\sum N_{slowp} \times CP_{slow}) \tag{5.9}$$

$$VSI_l = \sum_{i=1}^{N_D} VSI^i_l \qquad VSI^i_l = 2V'^2_i V'^2_{i+1} - 2V'^2_{i+1} (P'_{i+1} r_i + Q'_{i+1} x_i) - |z|^2 (P'^2_{i+1} + Q'^2_{i+1}) \tag{5.10}$$

$$SAIFI_{base} = \frac{\sum_{i=1}^{N_D} \lambda_i N_i}{\sum_{i=1}^{N_D} N_i} \qquad SAIDI_{base} = \frac{\sum_{i=1}^{N_D} U_i N_i}{\sum_{i=1}^{N_D} N_i} \qquad CAIDI_{base} = \frac{\sum_{i=1}^{N_D} U_i N_i}{\sum_{i=1}^{N_D} \lambda_i N_i} \tag{5.11}$$

$$SAIFI_l = \frac{\sum_{i=1}^{N_D} \lambda'_i N_i}{\sum_{i=1}^{N_D} N_i} \qquad SAIDI_l = \frac{\sum_{i=1}^{N_D} U'_i N_i}{\sum_{i=1}^{N_D} N_i} \qquad CAIDI_l = \frac{\sum_{i=1}^{N_D} U'_i N_i}{\sum_{i=1}^{N_D} \lambda'_i N_i} \tag{5.12}$$

$$\lambda'_p = \frac{\lambda_p}{P_p} \times P'_p \qquad U'_p = \frac{U_p}{P_p} \times P'_p \tag{5.13}$$

$$P^{base}_{loss} = \sum_{i=1}^{N_D} I_i^2 r_i \qquad P^l_{loss} = \sum_{i=1}^{N_D} I_i^2 r_i \tag{5.14}$$

The voltages of the buses of the distribution network are computed by forward backward sweep algorithm (Rupa et al. 2014).

III. Accessibility index

Limited driving range is one of the inherent shortcomings of the EVs. The EVs need to recharge their batteries after travelling a certain distance. The charging stations must be easily accessible to the EV drivers to reduce the driving range anxiety. The placement of charging stations must be optimized keeping in mind the routes followed by the EVs and the charging point demand. Hence, in the present work Accessibility index is considered as the third objective function. The mathematical formulation of the Accessibility index is :

$$\text{Accessibility index} = f(p) = \frac{1}{|d|} \tag{5.15}$$

For a road network having q charging demand points and m charging stations the computation of accessibility index is a tedious task. The distance matrix D and the reduced distance matrix DD first needs to be calculated for that. The mathematical expressions for computing D, DD and d are as follows:

$$D = \begin{bmatrix} d_1c_1 & d_1c_2 & \dots & d_1c_m \\ d_2c_1 & d_2c_2 & \dots & d_2c_m \\ . & . & . & . \\ . & . & . & . \\ d_qc_1 & d_qc_2 & \dots & d_qc_m \end{bmatrix} \qquad DD = \begin{bmatrix} \min(d_1c_1, d_1c_2, \dots d_1c_m) \\ \min(d_2c_1, d_2c_2, \dots d_2c_m) \\ . \\ . \\ . \\ \min(d_qc_1, d_qc_2, \dots d_qc_m) \end{bmatrix} \tag{5.16}$$

$$d = \sum_{i=1}^{q} DD_i \tag{5.17}$$

As illustrated in Eq. (5.16) 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.

For further illustration of the Accessibility index, a simple road network with origin destination pair OD is considered as shown in Fig.5.1. CD_1, CD_2 and CD_3 are the points of charging demand. CS_1 and CS_2 are the locations of charging station.

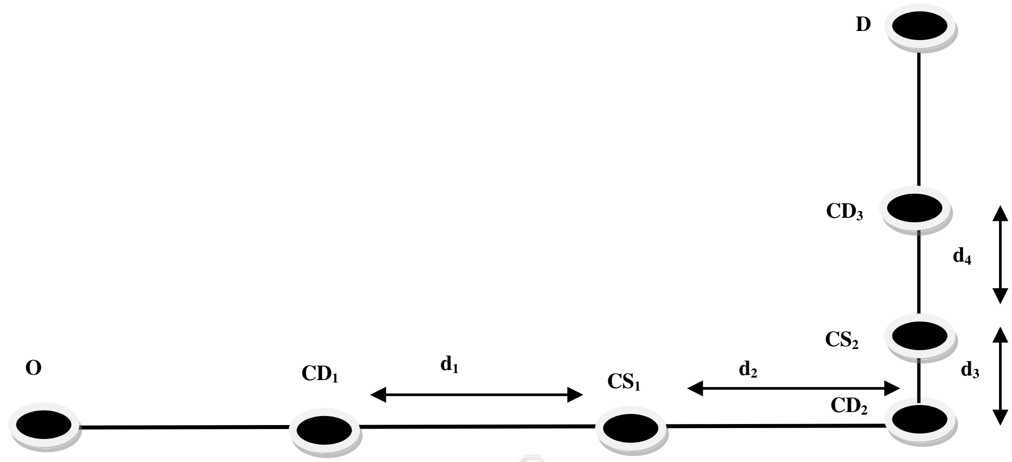

Fig.5.1- Diagram illustrating computation of Accessibility Index

For the road network illustrated in Fig.1, the value of *D*, *DD* and *d* are as follows:

$$D = \begin{bmatrix} d_1 & d_1 + d_2 + d_3 \\ d_2 & d_3 \\ d_4 + d_3 + d_2 & d_4 \end{bmatrix} \qquad DD = \begin{bmatrix} d_1 \\ d_3 \\ d_4 \end{bmatrix} \qquad d = d_1 + d_2 + d_3$$

Thus, we can say that lesser distance between the charging stations and the point of charging demand increase the Accessibility index and is more preferable.

5.2.3. Constraints

The optimization is carried out in agreement with a number of equality as well as inequality constraints. The different constraints of the charging station placement problem are given by Eq. (5.18) – Eq. (5.23)

$$0 < N_{fastp} \leq n_{fastp} \tag{5.18}$$

$$0 < N_{slowp} \leq n_{slowp} \tag{5.19}$$

$$Q_i^{\min} \leq Q_i \leq Q_i^{\max} \tag{5.20}$$

$$P_i^{\min} \leq P_i \leq P_i^{\max} \tag{5.21}$$

$$P_{gi} - P_{di} - V_i \sum_{j=1}^{N_D} V_j Y_{ij} \cos(\delta_i - \delta_j - \theta_{ij}) = 0 \tag{5.22}$$

$$P_{gi} - P_{di} - V_i \sum_{j=1}^{N_D} V_j Y_{ij} \cos(\delta_i - \delta_j - \theta_{ij}) = 0 \tag{5.23}$$

The constraints depicted by Eq. (5.18) and Eq.(5.19) consider the maximum and minimum number of fast as well as slow charging stations placed at the candidate locations. Eq. (5.20) and Eq. (5.21) consider the safe limit of active and reactive power respectively. The amount of generated power at all the buses must satisfy the load demand and losses. Hence, the power balance equations given by Eq. (5.22) and Eq. (5.23) are considered as equality constraint in the charging station placement problem.

5.3. Overview of Multi-objective Optimization

Multi-objective optimization involves more than one objective function which may be conflicting in nature. The result of multi-objective optimization is a set of solutions that provide the best trade-off between the conflicting objectives. Mathematically, multi-objective optimization is defined by the Eq. (5.24) and Eq. (5.25).

$$Minimize/Maximize(f_1(x), f_2(x) \dots\dots\dots \dots f_k(x)) \tag{5.24}$$

Subject to:

$$\left.\begin{array}{l} g_j(x) \geq 0 \\ h_k(x) = 0 \\ x_l \leq x \leq x_u \end{array}\right\} \tag{5.25}$$

In multi-objective optimization problem, the goal is to find the best compromise solution instead of a single solution. However, finding the best compromise solution in presence of conflicting objectives is a complex task. In multi-objective optimization, the task of finding the best compromise solution is done by comparing the rank assigned to the solutions based on the non-dominance or Pareto optimality concept and the crowding distance value.

In multi-objective optimization problem, there are a set of optimal solutions called non dominated solution or Pareto optimal solution (Deb et al. 2014; Pei et al. 2017). The boundary defined by the Pareto optimal solutions is called the Pareto front (Deb et al. 2014; Pei et al. 2017).

A solution x_1 is said to dominate solution x_2 if the following two conditions are satisfied-(Mishra and Harit 2010)

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

There are many algorithms for finding the Pareto optimal solution like Kung's algorithm (Mishra and Harit 2010), Ding's algorithm (Mishra and Harit 2010) and others. In this work, the algorithm put forwarded by Mishra and Harit (2010) is utilized for finding the Pareto optimal solution because of its simplicity.

Algorithm 5.1-Algorithm for finding Pareto optimal solution put forwarded by Mishra and Harit

Sort the solutions in descending order based on $f_1(x)$ and store in set O
Initialize $S_1 = O_1$
for i=2:size(O)
Compare O(i) with S_1
if S_1 dominates O(i)
Delete O(i) from O
end if
if O(i) dominates S_1
Delete the solution from S_1
end if
if O(i) is non dominated to S_1
Update $S_1 = S_1 U\ O(i)$
end if
if S_1 =null set
Add immediate solution at immediate solution to S_1
end if
end for
Print Pareto optimal solution, S_1

The Pareto optimal solution obtained by the aforementioned algorithm is assigned rank one, put in the first front and removed from the set *P*. The algorithm for finding the Pareto optimal solution is repeated and the second Pareto front is obtained. The second Pareto front is assigned rank two. The same procedure is repeated until set *P* becomes an empty set (Deb et al. 2014; Pei et al. 2017).

In order to obtain well-spread Pareto front the concept of crowding distance is introduced (Deb et al. 2014; Pei et al. 2017). The crowding distance of a solution is actually an estimation of the density of solutions surrounding that solution. Geometrically, the crowding distance value of a particular solution is the mean distance of its two neighboring solutions. The computation of crowding distance requires sorting the population according to each objective function value in ascending order. For each objective function, the boundary solutions (solutions with smallest and largest function values) are assigned an infinitely large distance value. All other solutions are assigned a distance value equal to the absolute normalized difference in the objective function values of two adjacent solutions. The same calculation is continued with the other objective functions. The overall crowding distance value is calculated as the sum of individual distance values corresponding to each objective. Before calculating the crowding distance each objective function is normalized. The pseudo code for computation of crowding distance is elaborated by Algorithm 5.2.

Algorithm 5.2- Pseudo code of crowding distance computation

$k=|F_n|$
While i<k do
Set $F_n[i]_{dist}=0$
end
While m<M do
$F_n[1]_{dist}=F_n[k]_{dist}=\infty$
i=2
While i≤k-1do
$F_n[i]_{dist}=F_n[i]_{dist}+{(F_n[i+1]_m-F_n[i-1])}\big/{f_m^{\max}-f_m^{\min}}$
i=i+1
end
end

5.4. Optimization Algorithms

Pareto dominance based multi- CSO TLBO is employed for solving the charging station placement problem. CSO has a good utilization rate of population where a good balance between exploration and exploitation is maintained. TLBO does not have any algorithm-specific control parameters and have good convergence criteria. It is expected that the grading mechanism of CSO, when amalgamated with TLBO the utilization rate of the population will improve and a faster convergence towards the optimal solution will be favoured. An overview of the aforementioned algorithms used in the work is presented in this section.

5.4.1. Multi-objective CSO

CSO is one of the latest and efficient evolutionary algorithms proposed by Meng et al. (2014). The algorithm mimics the behaviour of chicken swarm and the food searching process of the swarm. The population of chicken in the group is divided into dominant rooster, hens, and chicks based on the rank of the chickens. The chickens with the maximum rank are assigned as roosters, chickens with minimum rank are assigned as chicks, and the chickens with intermediate rank are assigned as hens. The mother-child relationship in the swarm is also randomly assigned in the algorithm. The hierarchal order and mother-child relationship are updated after every G time steps. The biological behavior of hens to follow their group mate rooster and chicks to follow their mother in the search of food is utilized efficiently in the algorithm. The algorithm also assumes that the chickens would try to steal the food found by others thereby giving rise to a competition for food in the group. The algorithm is divided into two steps- Initialization and Update.

In Initialization, the population size and other related parameters of CSO are defined. In multi-objective CSO the division of the population into rooster, hen, and chick is done based on rank instead of fitness value as in single-objective CSO (Meng et al. 2014). The rank of all the individuals of the population is computed by the algorithm mentioned in Section 5.3 and a hierarchal order is established based on the rank of the individuals in the population. It is assumed that the number of hens is highest in the group (Meng et al. 2014). The mother hen selection is done randomly from the set of hens. Despite the fact that each hen can have more than one chick, the algorithm assumes that the number of chicks is less than the number of hens (Meng et al. 2014).

Update is explained by Eq. (5.26) to Eq. (5.32). The food searching process of roosters, hens and chicks are different. The update or food searching process of rooster is explained by Eq. (5.26) to Eq. (5.28).

$$x_{i,j}^{t+1} = x_{i,j}^{t} \times (1 + \mathrm{randn}(0, \sigma^2)) \tag{5.26}$$

If $f_i \le f_k$

$$\sigma^2 = 1 \tag{5.27}$$

Else,

$$\sigma^2 = \exp\left(\frac{(f_k - f_i)}{|f_i| + \varepsilon}\right) \tag{5.28}$$

where randn$(0,\sigma^2)$ is a Gaussian distribution function with mean 0 and standard deviation σ^2. f is the normalized fitness value of corresponding x, k is randomly selected rooster's index.ϵ is a small constant value which is used to avoid zero division error. f is calculated by the weighted sum method (Marler et al. 2010).

Hens follow their group mate roosters in their quest for food. Moreover, there is also a tendency among the chickens to steal the food found by other chickens. The mathematical representation of their update formula is as follows-

$$x_{i,j}^{t+1} = x_{i,j}^{t} + S1 \times \mathrm{rand} \times (x_{r1,j}^{t} - x_{i,j}^{t}) + S2 \times \mathrm{rand} \times (x_{r2,j}^{t} - x_{i,j}^{t}) \tag{5.29}$$

$$S1 = \exp\left(\frac{f_i - f_{r1}}{\mathrm{abs}(f_i) + \varepsilon}\right) \tag{5.30}$$

$$S2 = \exp(f_{r2} - f_i) \tag{5.31}$$

where 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*.

The natural tendency of chicks to follow their mother is mathematically formulated as follows-

$$x_{i,j}^{t+1} = x_{i,j}^{t} + FL \times (x_{m,j}^{t} - x_{i,j}^{t}) \tag{5.32}$$

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

The flowchart and pseudo code of multi-objective CSO are as shown in Fig. 5.2 and Algorithm 5.3 respectively.

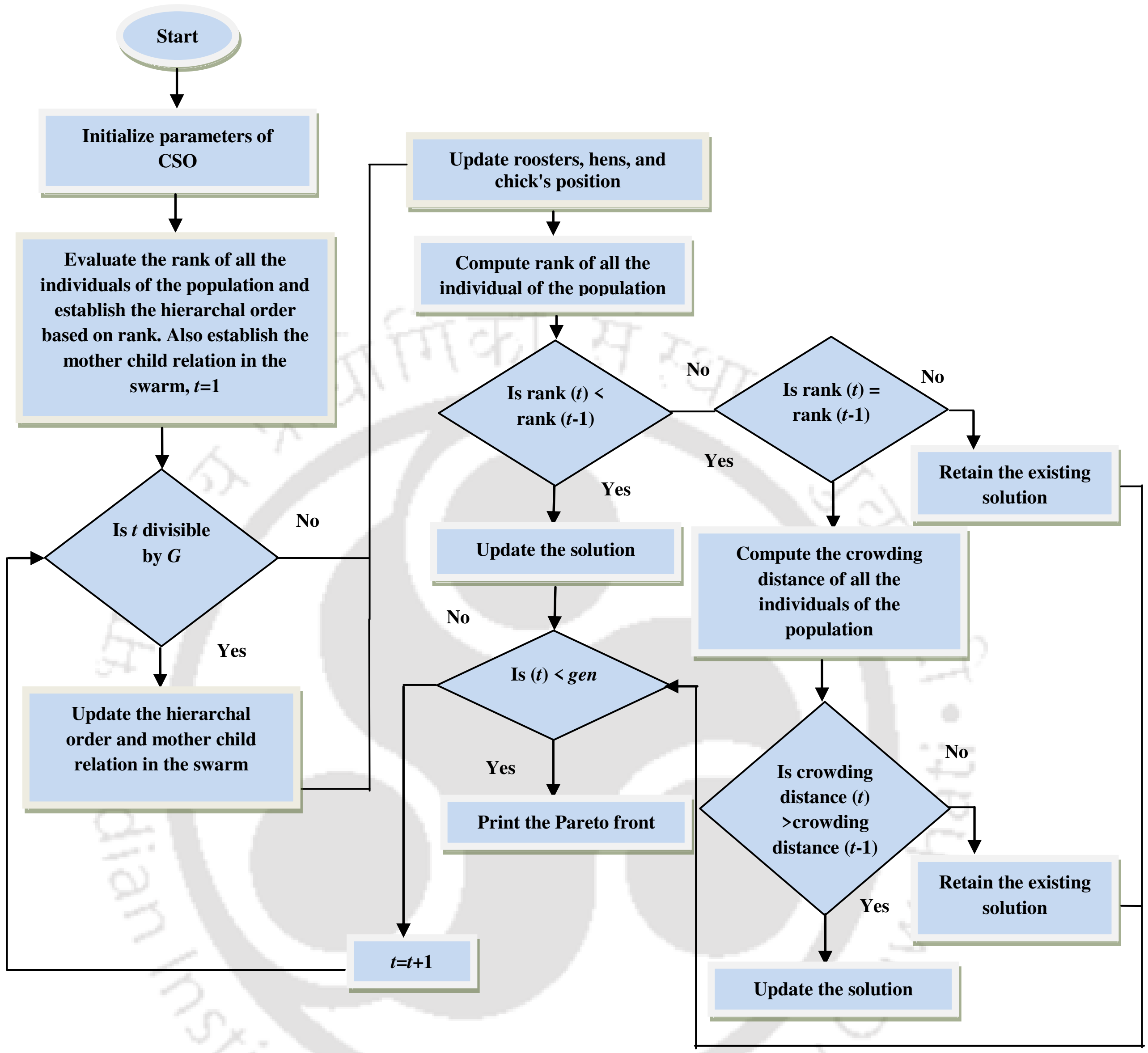

Fig.5.2- Flowchart of Multi-objective CSO

Algorithm 5.3-Pseudo code of Multi-objective CSO

Initialize the population of chicken having size PN and define other algorithm specific parameters like G, size of RN, HN,CN, and MN;
Evaluate the rank of all chickens, t=0 , establish the hierarchal order in the swarm based on rank as well as mother child relationship;
While (t<gen)
t=t+1;
If(t%G==0)
Establish the hierarchal order in the swarm as well as mother child relationship;
Else
For i=1:PN
If i==rooster
Update its solution by Eq.(5.26);
End if
If i==hen
Update its solution by Eq.(5.29);
End if
If i==chick
Update its solution by Eq.(5.32);
End if
Selection based on rank and crowding distance;
End for
End if else
End while

5.4.2. Multi-objective TLBO

TLBO is an efficient evolutionary algorithm introduced by Rao et al. (2011).TLBO is a population based evolutionary algorithm which mimics the interactive process of teaching and learning. In TLBO a class of learners constitutes the population and the teacher is an erudite scholar who transfers his knowledge to the learners. The performance of the learners depends on the knowledge and teaching capability of the teacher. The students can learn from the teacher as well as learn from each other by interaction. Thus, the algorithm is divided into two parts - Teacher phase and Learner phase (Rao et al. 2011).

In the teacher phase, the students learn from the teacher having profound knowledge and skill. In multi-objective TLBO, the learner having the best rank in a randomly generated population is generally assigned the role of teacher. Each learner learns from the teacher and is modified by Eq. (5.33) and Eq. (5.34).

$$Z_{diff} = rand \times (T_k - R_t m_k) \quad (5.33)$$

$$Z_{new} = Z_{old} + Z_{diff} \quad (5.34)$$

In the learner phase, the learner learns by mutual interaction among themselves. For each learner Z_i any learner Z_j is chosen arbitrarily from the learner matrix. The objective function values are compared arbitrarily for the two aforementioned learners. If the value of objective function of Z_i is lower than the objective function of Z_j then the If Z_i is better than Z_j i^{th} learner is modified by Eq. (5.35).

$$Z_{new}=Z_{old}+\text{rand}\times(Z_i-Z_j) \tag{5.35}$$

Else, it is modified by Eq. (5.36)

$$Z_{new}=Z_{old}+\text{rand}\times(Z_j-Z_i) \tag{5.36}$$

The flowchart and pseudo code of multi-objective TLBO are as shown in Fig. 5.3 and Algorithm 5.4 respectively.

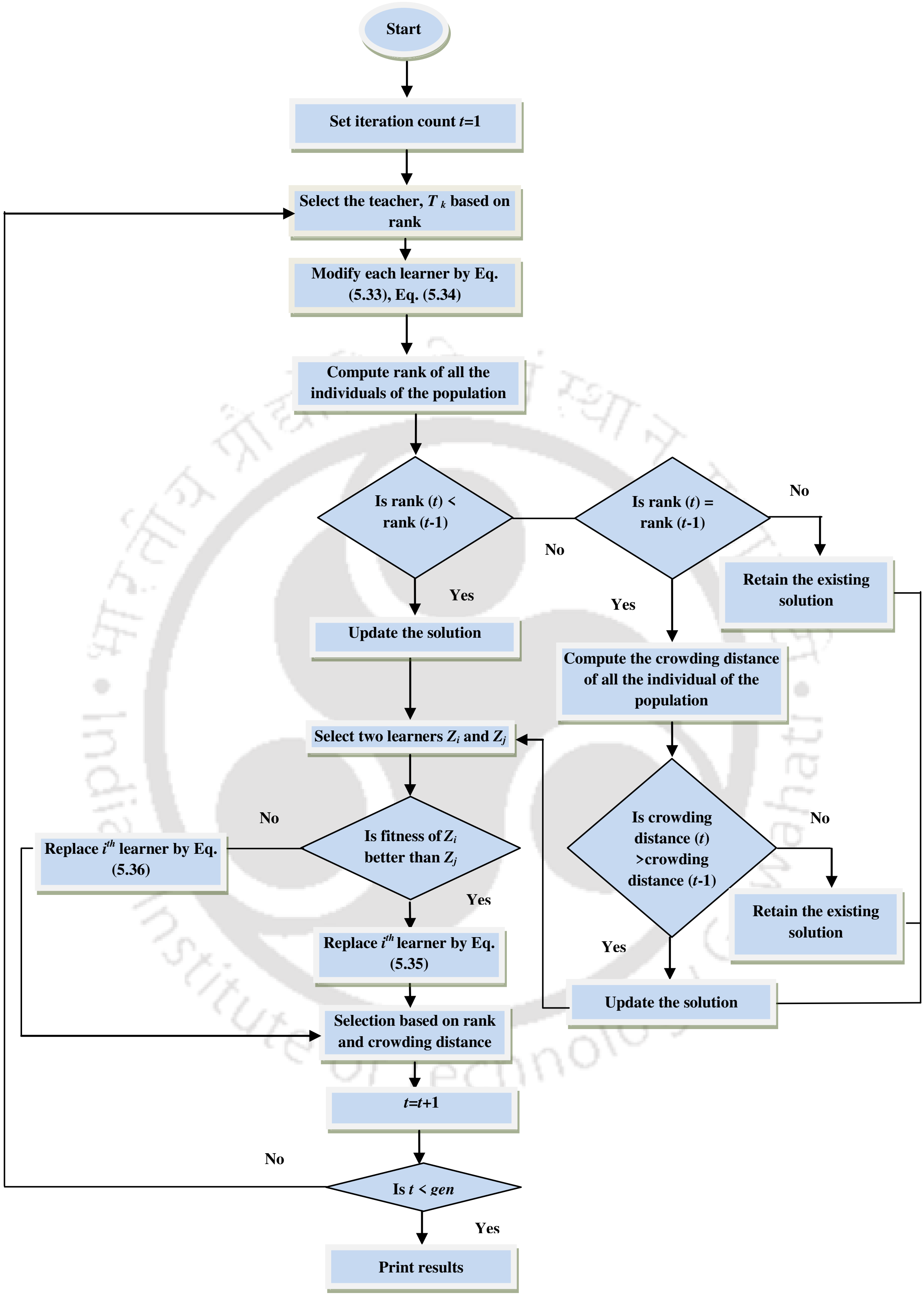

Fig.5.3- Flowchart of Multi-objective TLBO

Algorithm 5.4- Pseudo code of Multi-objective TLBO

Set k=1;
Initialize the population size(PN) and generate the initial population of students randomly;
Compute the rank for all the individuals of the population;
while(k<gen)
{Teacher Phase}
Assign the teacher based on the rank;
for i=1:PN
Modify each learner by Eq.(5.33), Eq.(5.34);
Update the new solutions based on rank and crowding distance;
{End of teacher phase}
{Learner Phase}
Choose two learners Z_i and Z_j, $i \neq j$;
if(fitness of Z_i better than Z_j)
Replace i^{th} learner by Eq.(5.35);
Else
Replace i^{th} learner by Eq.(5.36);
End if else
End for
Update based on rank and crowding distance
k=k+1
End while

5.4.3. Multi-objective CSO TLBO

A multi-objective version of the hybrid CSO-TLBO is developed in the present work. The grading mechanism of CSO when amalgamated with TLBO will improve the utilization rate of the population and a faster convergence towards the optimal solution will be favoured. In the hybridization scheme TLBO is activated for all the generation and CSO is invoked periodically depending on the value of *INV*. The flowchart and pseudo code of multi-objective CSO TLBO is as shown in Fig. 5.4 and Algorithm 5.5 respectively.

Algorithm 5.5- Pseudo code of Pareto dominance based multi-objective CSO TLBO

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

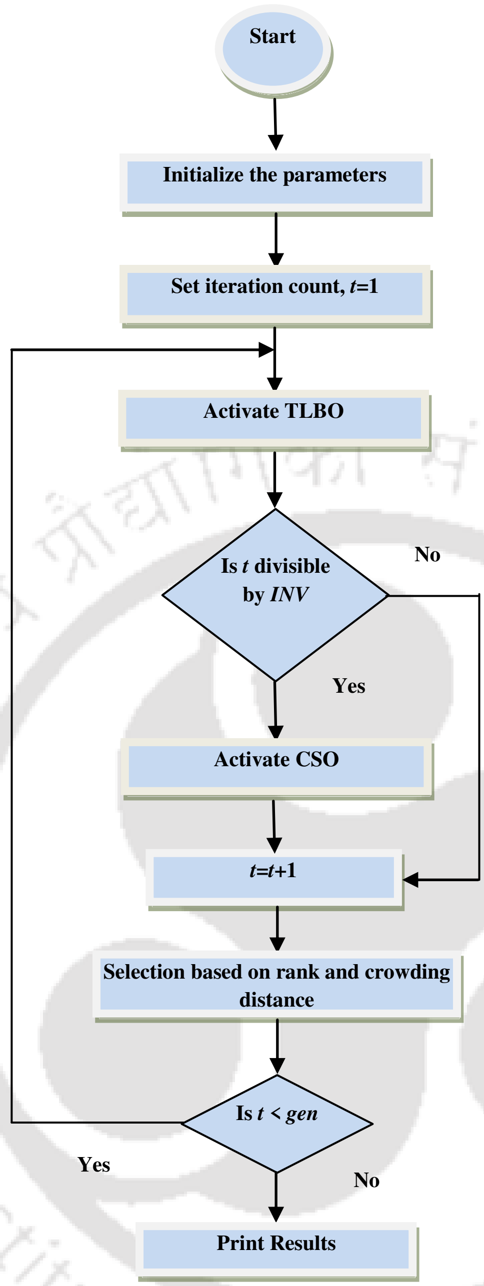

Fig. 5.4- Flowchart of Multi-objective CSO-TLBO

5. 5. Fuzzy Decision Making

The multi-objective optimization yields a number of Pareto optimal solution instead of a single solution. Selection of the best compromise solution from the set of Pareto optimal solution is rather difficult. In the present work, the final decision making is performed by the fuzzy evaluation system (Li et al. 2017). In the fuzzy evaluation system, each objective function is represented by a scaled membership function in the range of 1-10 given by Eq. (5.37). The range of objective function associated with all the membership function or score can be found by back calculation from Eq. (5.37).

$$\mu_i=\begin{cases}10 & OF_i \le OF_i^{min} \\ 10\times\dfrac{OF_i^{max}-OF_i}{OF_i^{max}-OF_i^{min}} & OF_i^{min}\le OF_i \le OF_i^{max} \\ 1 & OF_i^{max}\le OF_i\end{cases} \tag{5.37}$$

The net score for all the Pareto optimal solutions is evaluated and the Pareto optimal solution having the highest score is preferred.

5.6. Solution of charging station placement problem by multi-objective CSO TLBO

In the present work multi-objective CSO TLBO is employed to solve the charging station placement problem elaborated in section 5.2. The systematic step by step procedure for 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, upper and lower limits of different constraints and set the different algorithm specific parameters of CSO TLBO like *gen*, *PN*, *RN*, *CN*, *HN*, *G* and *INV*.

Step 1.2: Generate feasible initial population randomly.

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

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

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

The randomly generated initial solution is feasible if it satisfy all the constraints of charging station placement problem explained in section 5.2.3.

Step 1.3: Evaluate the three objective functions cost, VRP index and Accessibility index for the initial population. Compute the rank and crowding distance by the methodology elaborated in section 5.3. The first pareto front with rank one is designated as T_k.

Step 2: Run TLBO

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

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

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*.

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

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

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

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: If *t* is not divisible by *INV* 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 explained in section 5.5.

The flowchart of the solution methodology adopted for solving the charging station placement problem is as shown in Fig.5.5.

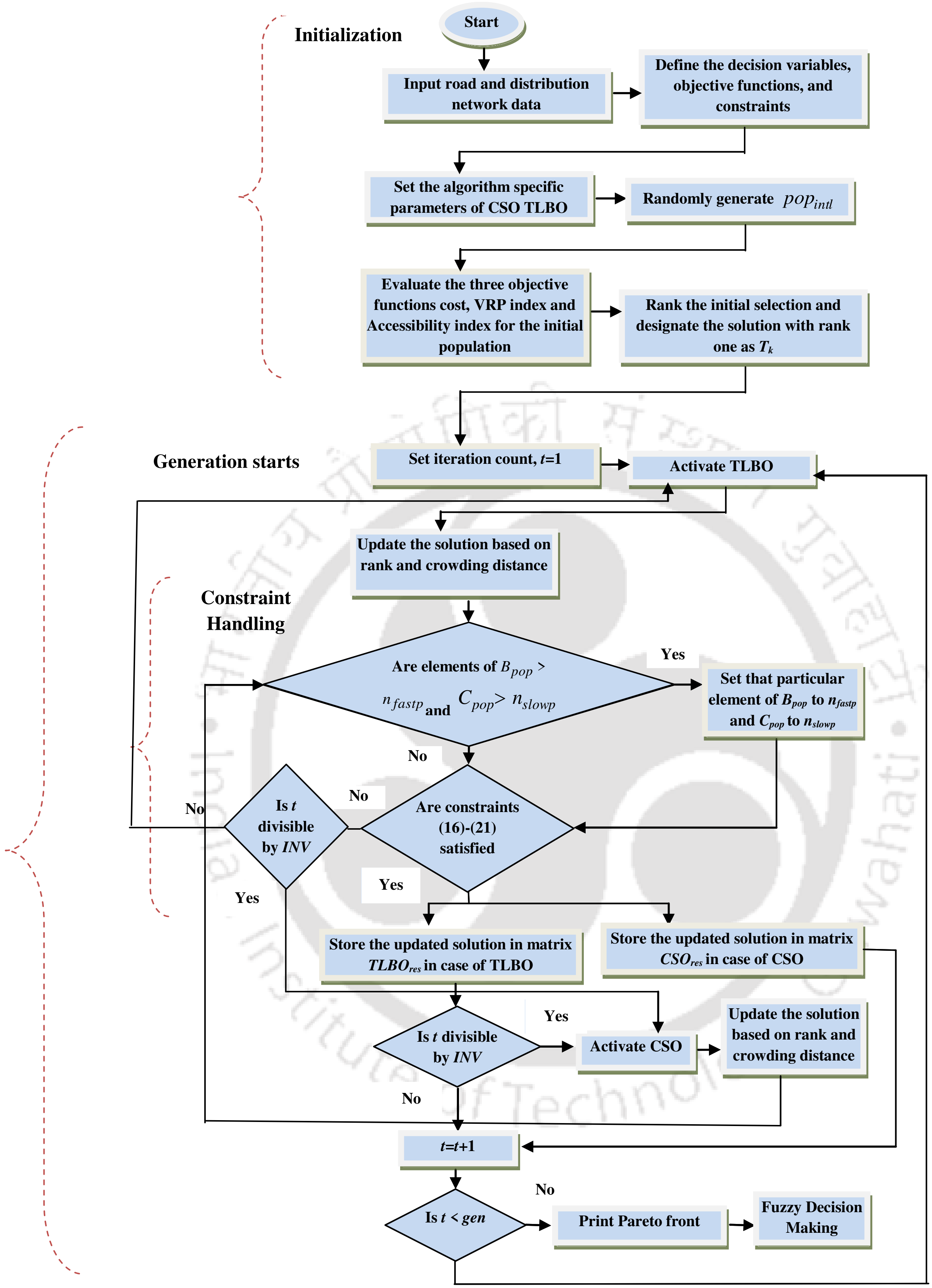

Fig. 5.5- Flowchart of solution methodology of charging station placement problem by CSO TLBO

5.7. Performance of Pareto dominance based CSO TLBO on multi-objective benchmark problems

The proposed Pareto dominance based CSO TLBO algorithm is first tested on some basic multi-objective benchmark functions. The algorithm-specific parameters of CSO TLBO are tuned as in Table 5.1. The algorithm-specific parameters are the parameters that are specific to the algorithm. All the Nature Inspired Optimization (NIO) algorithms require common control parameters like population size *(PN)*, number of generations *(gen)*. Besides the common control parameters, different algorithms require their own algorithm-specific control parameters for execution.

. Table 5.1-Algorithm-specific parameters of multi-objective CSO TLBO

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

Further, the performance of the proposed algorithm in solving the benchmark problems is compared with NSGA II and other hybrid algorithms like multi-objective DE PSO, multi-objective cultural PSO, and its variants. The aforesaid algorithms were statistically compared by computing the hypervolume. Hypervolume is a metric proposed by Zitzler (Zitzler 1999) that is used to analyze the distribution of Pareto optimal solutions. Hypervolume physically signifies the volume occupied by the non dominated solution set. Maximizing hypervolume is equivalent to producing well distributed Pareto front (Emmerich et al. 2005).

5.7.1. Comparison of Pareto dominance based CSO TLBO with DE PSO and NSGA II

The performance of Pareto dominance based CSO TLBO algorithm is compared with DE PSO and NSGAII on two objective ZDT (Zitzler et al. 2000) and three objective DTLZ (Deb et al. 2005) benchmark problems. The three algorithms are statistically compared by computing hypervolume for 50 independent trials. The results of DE PSO and NSGA II are directly taken from the reference (Wickramasinghe & Li 2008). For fair comparison, the population size (*PN*) and generation (*gen*) of CSO TLBO are kept same as in the reference (Wickramasinghe & Li

2008). Each benchmark problem is solved by CSO TLBO considering the value of *PN* and *gen* as 200 and 750 respectively. Table 5.2 reports the average value of hypervolume for the test problems. It is observed that CSO TLBO performs better than DE PSO and NSGA II on ZDT4, DTLZ1, and DTLZ6. The performance of CSO TLBO is equivalent to DE PSO on DTLZ3. For further analysis, Friedman rank test is performed. The ranks of the different algorithms obtained by Friedman test, is as shown in Fig.5.6. It is observed that CSO TLBO obtained the best rank in comparison to the other algorithms.

Table 5.2- Comparison of CSO TLBO with DE PSO and NSGA II based on normalized hypervolume

Benchmark function	**Algorithm**		
	CSO TLBO	**DE PSO**	**NSGAII**
ZDT4	0.6728	0	0.6636
ZDT6	0.4035	0.4033	0.4025
DTLZ1	0.7937	0.7749	0.7852
DTLZ3	0	0	0.4084
DTZL6	0.0962	0.0959	0.0957

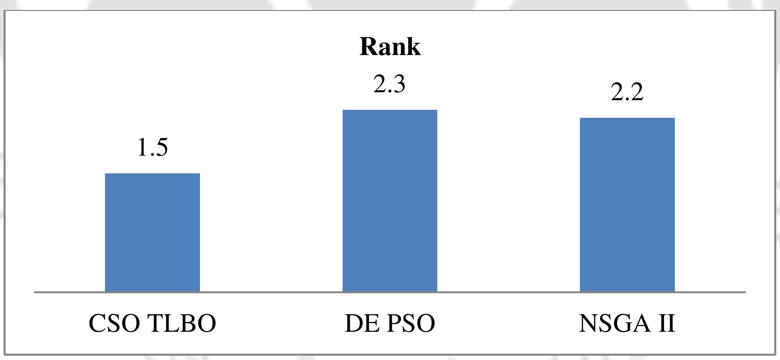

Fig.5.6-Comparison of Friedman ranks of CSO TLBO with DE PSO and NSGA II for ZDT and DTLZ benchmark functions

5.7.2. Comparison of Pareto dominance based CSO TLBO with cultural PSO and its variants

The performance of Pareto dominance based CSO TLBO algorithm is compared with cultural PSO and its variants on two objective ZDT (Zitzler et al. 2000) and three objective DTLZ (Deb et al. 2005) benchmark problems. The algorithms are statistically compared by computing hypervolume for 30 independent trials. The results of PSO and its variants were directly taken from the reference (Jia & Zhu 2017). For fair comparison, the population size (*PN*) and generation (*gen*) of CSO TLBO are kept same as in the reference (Jia & Zhu 2017). Each benchmark problem is solved by CSO TLBO considering the value of *PN* and number of function evaluation as 100 and 30,000 respectively. Table 5.3 reports the average value of hypervolume for the test problems. It is observed that CSO TLBO performs better than cultural PSO and cultural QPSO on ZDT1, ZDT2, ZDT3, ZDT6, and DTLZ1. For further analysis Friedman rank test is performed. The ranks of the different algorithms obtained by Friedman test is as shown in Fig.5.7. It is observed that CSO TLBO obtained the best rank in comparison to the other algorithms.

Table 5.3- Comparison of CSO TLBO with PSO and its variants based on hypervolume

Benchmark function	**Algorithm**		
	CSO TLBO	**Cultural PSO**	**Cultural QPSO**
ZDT1	0.894	0.842	0.866
ZDT2	0.484	0.420	0.472
ZDT3	0.967	0.761	0.939
ZDT4	0.6256	0	0.867
ZDT6	0.5123	0.465	0.503
DTLZ1	0.6532	0	0
DTLZ3	0	0	0.715
DTZL6	0	0.236	0.421

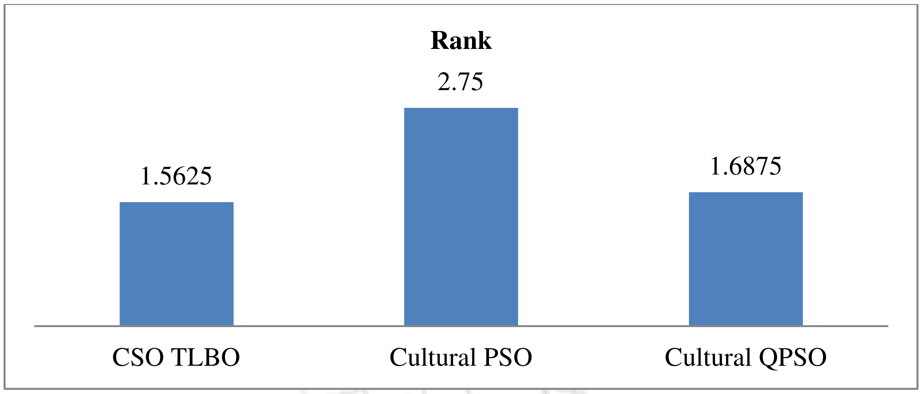

Fig.5.7-Comparison of Friedman ranks of CSO TLBO with cultural PSO and its variants for ZDT and DTLZ benchmark functions

5.8. Performance of Pareto dominance based CSO TLBO on charging station placement problem

The optimization is aimed at minimization of cost as well as VRP index along with maximization of the accessibility index as elaborated in section 5.2. The results and discussion of the optimization performed are reported in this section.

5.8.1. Test System and input parameters

In the present work the charging station placement problem is validated on the test network formed by superimposition of 33 bus distribution network and 25 node road network. The test network selected for validation of the charging station placement problem is as shown in Fig. 5.8. The line data, branch data of this test network can be found in Table A1, Table A2, of Appendix respectively. The outage data can be found in the Reference Bhadra et al. 2015.The road network data is taken from literature Wang et al. (2013). The EVs are assumed to follow the two following routes-

- Route 1- (1-2-3-4-5-6-7-8-9-10-13-11-12-15-16-17-18-20-21-14-22-23-24-25)
- Route 2-(1-2-3-4-5-6-7-8-9-10-13-11-12-15-16-17-19-20-21-14-22-23-24-25)

Table 5.4 presents the superimposed nodes with respect to distribution as well as road network and the points of charging demand. The points of charging demand are computed based on the consideration that the driving range of EV was 150 km and it followed either route 1 or route 2. Table 5.5 represents the values of input parameters. In the entire analysis, it is assumed that each fast charging stations has 10 servers and each slow charging station has 20 servers. The algorithm-specific parameters of CSO TLBO are same as Table 5.1.

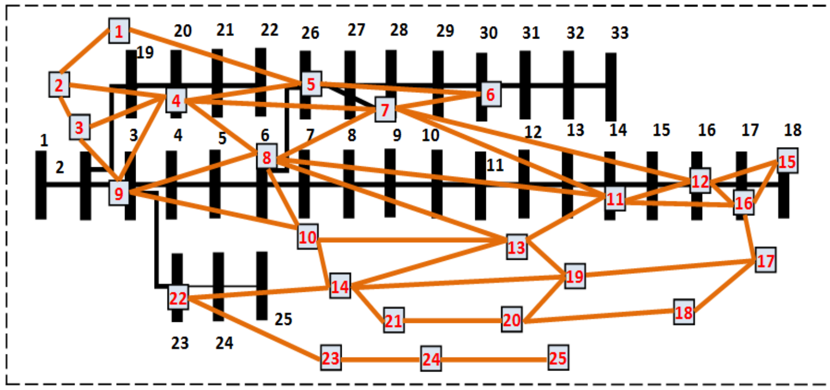

Fig. 5.8- Test Network for validation of multi-objective charging station placement problem

Table 5.4- Superimposed nodes and charging point demand nodes

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

Table 5.5- Input Parameters of multi-objective charging station placement problem

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

5.8.2. Optimal allocation of charging stations

The optimization problem reported in section 5.2 is solved by using CSO TLBO. In multi-objective optimization a number of Pareto optimal solutions are obtained instead of a single optimal solution due to involvement of conflicting objectives. Table 5.6 reports the Pareto optimal solutions obtained by CSO TLBO. The algorithm yielded four Pareto optimal solutions or planning schemes. In scheme 1, the positions of charging stations are selected as bus number 3, 23, and 26. The number of fast charging stations placed at bus 3, 23, and 26 are 1, 2, and 1 respectively. The number of slow charging stations placed at bus 3, 23, and 26 are 3, 3, and 2 respectively. In planning scheme 2, the positions of charging stations are selected at bus number 23, 6, and 26. The number of fast charging stations placed at bus number 23, 6, and 26 are all 1. The number of slow charging stations placed at bus 23, 6, and 26 are 3, 3, and 2 respectively. In planning scheme 3, the positions of charging stations are 20, 6, and 23. The number of fast charging stations placed at bus number 20, 6, and 23 are all 2. The number of slow charging stations placed at bus number 20, 6, and 26 are all 3. In planning scheme 4, the positions of charging stations are bus number 20, 23, and 28. The number of fast charging stations placed at bus number 20, 23, and 28 are all 2. The number of slow charging stations placed at bus number 20, 23, and 28 are 3, 3, and 1 respectively. Fig.5.9, Fig.5.10, Fig.5.11 and Fig.5.12 shows the placement of charging stations in the test network for the four planning schemes. Fig. 5.13 elaborates the Pareto front obtained by CSO TLBO. Table 5.7 represents the values of the three objective functions for the four planning schemes mentioned in Table 5.6. In plan 1, the optimized values of cost, VRP index, and accessibility index are 1.5389×10^7\$, 12.5010, and 0.0006 respectively. In plan 2, the optimized values of cost, VRP index, and accessibility index are 1.4783×10^7\$, 14.0792, and 0.0013 respectively. The values of cost and accessibility index of plan 2 are better than that of plan 1. However, the value of VRP index of plan 1 is better than that of plan 2.In plan 3, the optimized values of cost, VRP index, and accessibility index are 2.1316×10^7\$, 13.7128, and 0.0014 respectively. The value of cost for plan 3 is worse than that of plan 1 and plan 2. However, the values of accessibility index of plan 3 are better than that of plan 1 and plan 2. In plan 4, the optimized values of cost, VRP index, and accessibility index are 2.1316×10^7\$, 13.7128, and 0.0014 respectively. The cost associated with plan 4 is better than plan 3 but much worse than plan 1 and plan 2. The value of VRP index for plan 4 is better than plan 2 and plan 3 but worse than plan 1. The value of accessibility index for plan 4 is equal to plan 2 and better than plan 1 but worse than plan 3. Fig.5.14 illustrates the voltage profile for all the four plans reported in Table 5.6. From Fig. 5.14 it is clear that the voltage profile of plan 1 is better than the other three plans.

Table 5.6- Best Pareto Optimal solution obtained by CSO TLBO

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

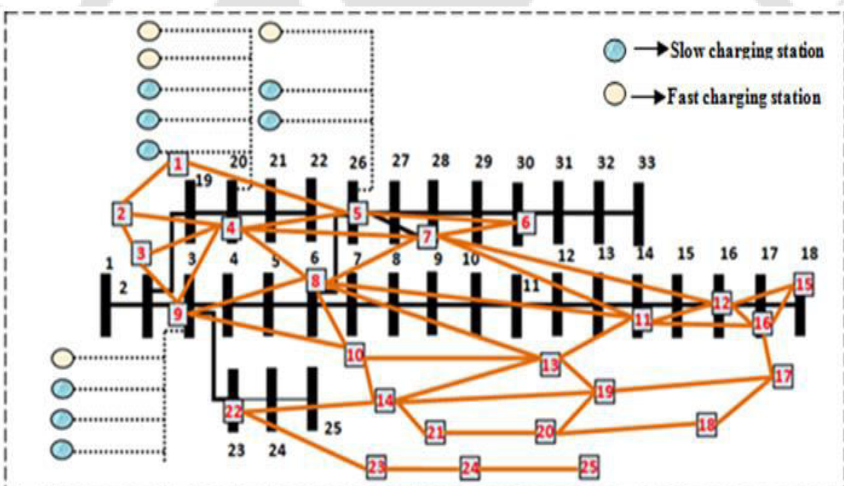

Fig.5.9- Optimal placement of charging stations in Planning Scheme 1

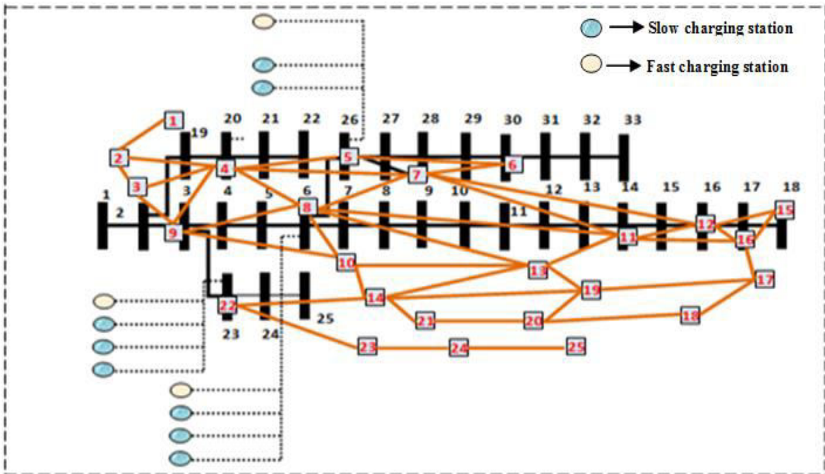

Fig.5.10- Optimal placement of charging stations in Planning Scheme 2

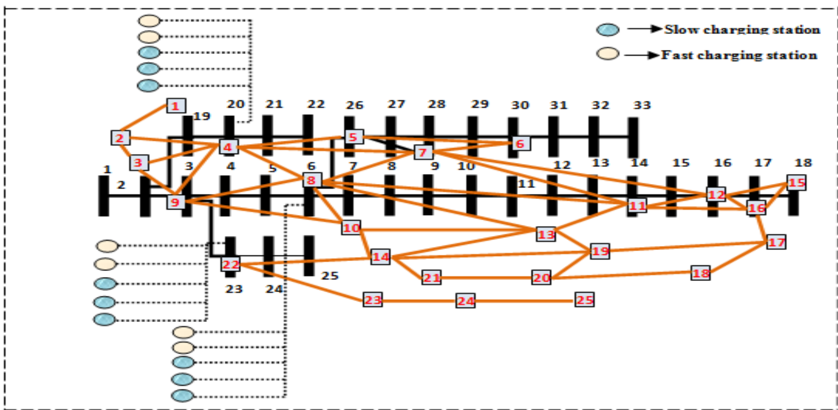

Fig.5.11- Optimal Placement of charging stations in Planning Scheme 3

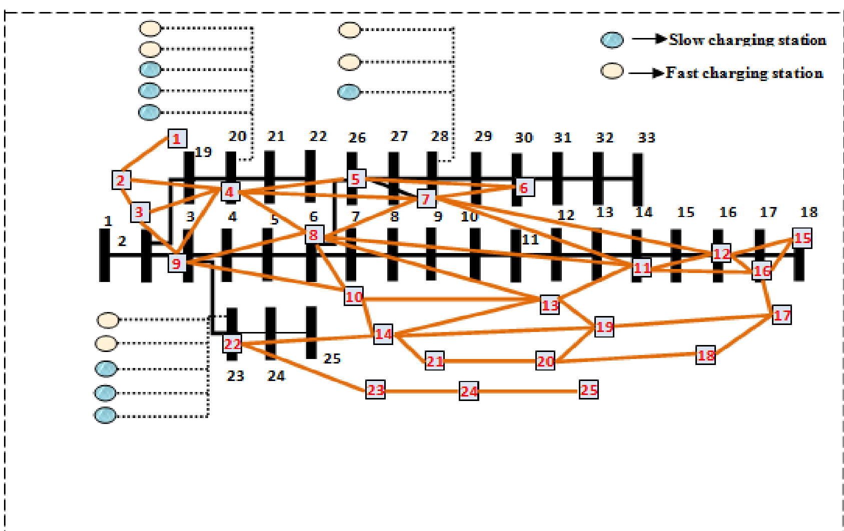

Fig.5.12- Optimal placement of charging stations in Planning Scheme 4

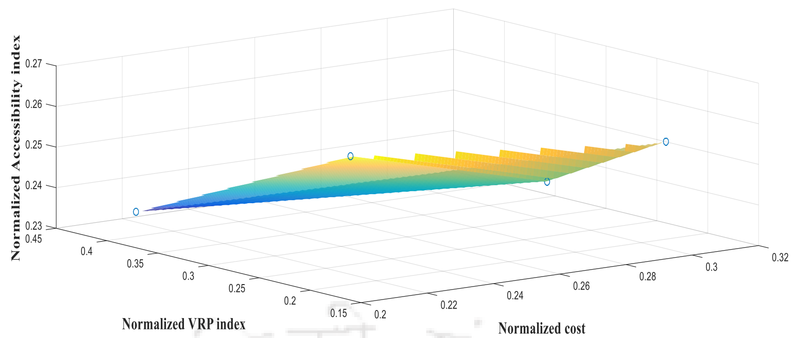

Fig.5.13- Pareto front obtained by CSO TLBO

Table 5.7- Objective Function Values for different planning schemes (obtained by CSO TLBO)

Planning scheme no	Cost ($\$\times10^7$)	VRP index	Accessibility index
1	1.5389	12.5010	0.0006
2	1.4783	14.0792	0.0013
3	2.1316	13.7128	0.0014
4	1.8959	13.3707	0.0013

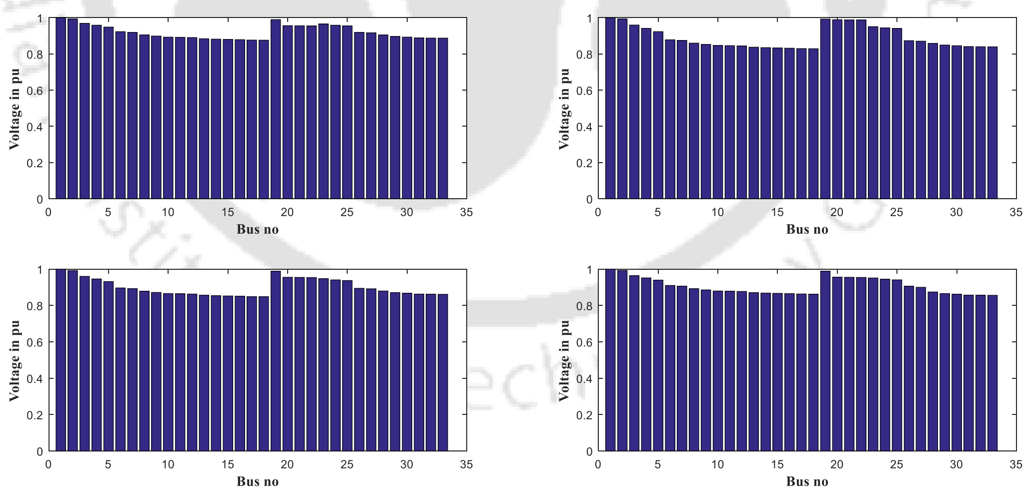

Fig.5.14- Voltage Profile for the Pareto optimal solution obtained by CSO TLBO

5.8.3. Final Decision Making

The four simulated plans obtained by CSO TLBO are shown in Table 5.6. The characteristics of the four plans are also discussed comprehensively in the previous sub-section. It is difficult to select the best plan among the four plans because of involvement of conflicting objective functions. In real-world, some criterion cannot be measured by crisp values due to ambiguity arising from human qualitative judgement. For quantification of such cases fuzzy can be used. In the present work, a fuzzy evaluation system is used for the final decision making. Cost, VRP index, and accessibility index are chosen as the three aspects of decision making in the charging station placement problem. In the fuzzy decision making, low cost and VRP index received a higher evaluation. And high accessibility received a higher evaluation. Table 5.8 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 5.9. The radar charts of all the four plans are shown in Fig 5.15 to Fig 5.18. The four figures indicate that all the four plans have their respective advantages and disadvantages. The area of Fig. 5.15 is biggest as compared to the other three figures indicating that plan 1 is the most advantageous plans. The area of Fig. 5.17 is least indicating that plan 3 is the worst or most disadvantageous plan. Plan 2 and plan 4 can be considered as moderate plans.

Table 5.8- Scale of fuzzy evaluation for multi-objective charging station placement problem

Scale	**Cost ($\$\times10^7$)**	**VRP index**	**Accessibility index**
1	More than 2.1316	More than 14.0792	Less than 0.0006
2	2-2.1316	13.7636-14.0792	$7.6*10^{-4}$-0.0006
3	1.93561-2	13.6057-13.7636	$7.6*10^{-4}$-$8.4*10^{-4}$
4	1.8703-1.93561	13.4479-13.6057	$8.4*10^{-4}$-$9.2*10^{-4}$
5	1.8050-1.8703	13.2901-13.4479	$9.2*10^{-4}$ -0.0001
6	1.7396-1.8050	13.1323-13.2901	0.0001-0.00108
7	1.6743-1.7396	12.9745-13.1323	0.00108-0.00116
8	1.6090-1.6743	12.8166-12.9745	0.00116-0.00124
9	1.5436-1.6090	12.6588-12.8166	0.00124-0.0013
10	Less than 1.5436	Less than 12.6588	More than 0.0013

Table 5.9- Scores of each plan for multi-objective charging station placement problem

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

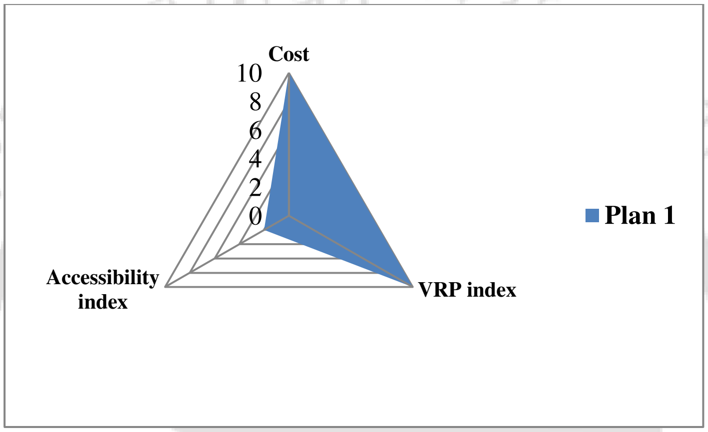

Fig.5.15- Radar chart for plan 1

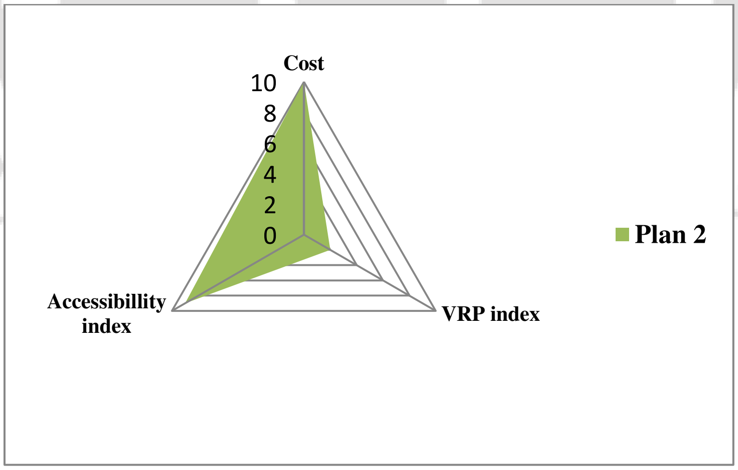

Fig.5.16- Radar chart for plan 2

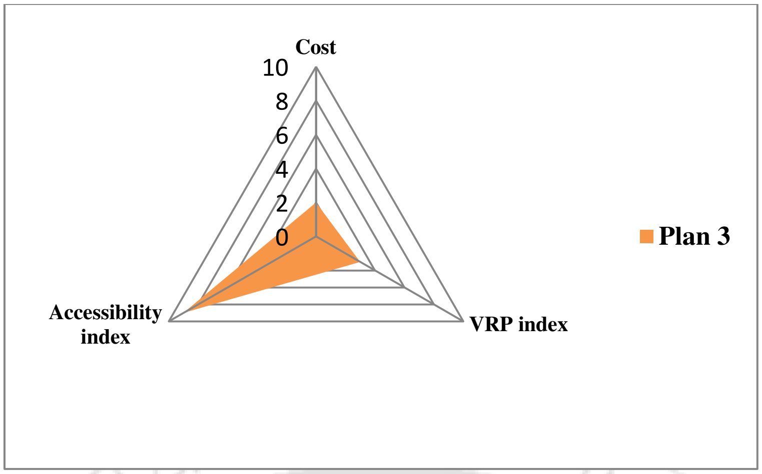

Fig.5.17- Radar chart for plan 3

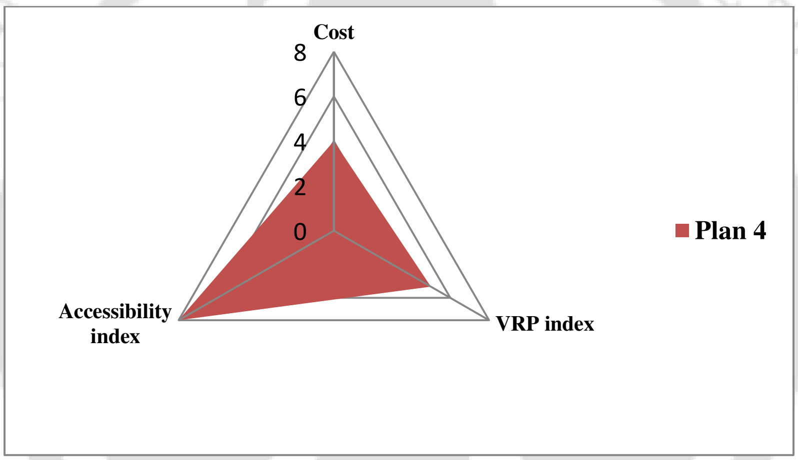

Fig.5.18- Radar chart for plan 4

5.8.4. Comparison of the performance of CSO TLBO with NSGA II

For establishing the efficacy of the proposed Pareto dominance based CSO TLBO algorithm, its performance is compared with NSGA II algorithm. One of the salient features of the evolutionary algorithm is random generation of the population. As a consequence of this, different solutions are obtained for every independent trials. So in order to compare the quality of solutions of multi-objective CSO TLBO and NSGA II a statistical analysis is done for 20 independent trials.The two algorithms are statistically compared by computing hypervolume, diversity index and number of Pareto solutions of the results obtained by the aforesaid algorithms for 20 independent trials. Hypervolume is a metric proposed by Zitzler (1999) used to analyse the distribution of Pareto optimal solutions. Hypervolume physically signifies the volume occupied by the non dominated solution set. It is concluded by (Emmerich et al. 2005) that maximizing hypervolume is equivalent to producing well distributed Pareto front. Table 5.8 reports the results of statistical comparison of CSO TLBO with NSGA II algorithm. Table 5.10 shows that the hypervolume of CSO TLBO is more than that of NSGA II. This indicates that the spread and closeness of the Pareto front obtained by CSO TLBO are better than that of NSGA II. The graphical representation of the hypervolume for the best solution obtained by CSO TLBO and NSGA II are shown in Fig. 5.19 and Fig.5.20 respectively. The diversity index is regarded as a measure of diversity existing between the non dominated solutions obtained by the algorithms. A large value of the diversity index indicates the algorithm yields Pareto optimal solutions that are diverse in nature. Table 5.8 reports that the best as well as the worst diversity index of CSO TLBO are more than NSGA II. Thus, we can say that the solutions obtained by CSO TLBO are more diverse in nature. The number of Pareto solutions is another metric used to compare the performance of multi-objective evolutionary algorithms. The algorithm that yields more number of Pareto solutions is more preferable as it gives the decision maker more number of alternatives. Table 5.10 reports that the number of Pareto solutions obtained by CSO TLBO and NSGA II are same. Thus, we can say that both the algorithms give the decision maker equal number of alternative planning schemes.

Table 5.10- Statistical comparison of CSO TLBO with NSGA II algorithm in solving multi-objective charging station placement problem

Algorithm	**Hypervolume**		**Diversity index**		**Number of Pareto solutions**	
	Best	**Worst**	**Best**	**Worst**	**Best**	**Worst**
CSO TLBO	0.4902	0.4016	0.06182	0.06029	4	3
NSGA II	0.4477	0.3917	0.0063	0.0057	4	3

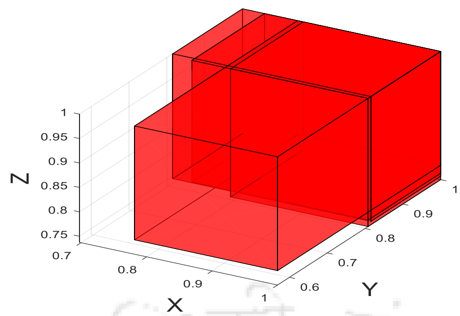

Fig.5.19- Hypervolume of the best solution obtained by CSO TLBO

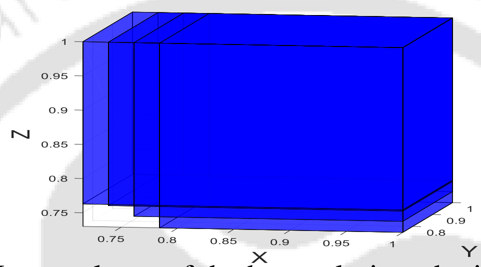

Fig.5.20- Hypervolume of the best solution obtained by NSGA II

5.9. Conclusions

The construction of charging station is important to promote EVs. The placement of charging stations must consider cost, operating parameters of the distribution network and accessibility of the charging stations simultaneously. In the present work, the charging station placement problem was represented in a multi-objective framework with cost, VRP index, and accessibility index as the objective functions. The scientific contribution of this work not only lies in proposing a multi- objective framework to solve the charging station placement problem but also proposing a Pareto dominance based multi-objective CSO TLBO for the charging station placement problem. Thus, the present work proposed an integrated planning scheme for charging stations by using multi-objective optimization, fuzzy decision making and radar charting. The superiority of the proposed hybrid algorithm in solving charging station placement problem was clearly revealed. The simulation results indicate that the algorithm proposed is efficient enough to be implemented in real-world environment.

Note- This chapter is reproduced from the publication-

- **Deb, S., Gao, X. Z., Tammi, K., Kalita, K & Mahanta, A Pareto Dominance based Multi-Objective Chicken Swarm Optimization and Teaching Learning Based**

Optimization Algorithm for Charging Station Placement Problem. ***Neural Computing and Applications, Springer*** **(under review)**

CHAPTER 6

A ROBUST TWO-STAGE PLANNING MODEL FOR CHARGING STATION PLACEMENT PROBLEM CONSIDERING ROAD TRAFFIC UNCERTAINTY

6.1. Introduction

The current consternation regarding fossil fuel exhaustion and environmental pollution accompanied by the advancement in battery technology has initiated transportation electrification. The growing popularity of Electric Vehicles (EVs) calls for the development of sustainable charging infrastructure. Inappropriate placement of charging stations hampers the smooth operation of power grid and cause inconvenience to EV drivers. The present work proposes a novel two-stage planning model for charging station placement. The candidate locations for placement of charging stations are first determined by a fuzzy inference considering distance, road traffic and grid stability. The randomness in road traffic is modelled by applying Bayesian network. Then, the charging station placement problem is represented in multi-objective framework with cost, Voltage Stability Reliability Power loss (VRP) index, distance, and waiting time as objective functions. A hybrid algorithm combining Chicken Swarm Optimization and Teaching Learning Based Optimization Algorithm (CSO TLBO) elaborated in chapter 5 is used to obtain the Pareto front.

The rest of the chapter is organized as follows. Section 6.2 elaborates the two-stage planning model of charging station placement problem. Section 6.3 elaborates the solution methodology of charging station placement problem by CSO TLBO. Section 6.4 presents the results the optimal locations of charging stations obtained by two-stage planning model elaborated in section 6.2.

6.2. 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) (Lee 1999). It is a common practice to place the charging stations at the superimposed nodes of distribution and road network (Wang et al. 2013; Yao et al. 2014).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 can be congested with high traffic flow. Also, the possibility of some of these nodes being weak points of the grid in terms of voltage stability cannot be ignored. Hence, in the present work distance of the node of the road network from the nearest bus of the distribution network, traffic intensity and grid stability are considered for finding the candidate locations where charging stations can be placed. 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. The MFI utilized in the present work to find the candidate locations for the placement of charging stations is as shown in Fig.6.1.

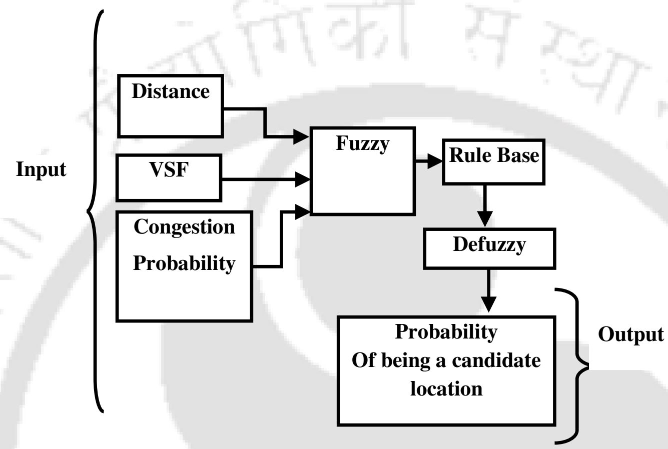

Fig. 6.1- Mamdani Fuzzy Inference used to find the candidate locations for placement of charging stations

The first input of the MFI is the distance of the node of the road network from the nearest bus of the distribution network which can be graphically calculated. The computational methodology of the second input of the Mamdani Fuzzy inference i.e VSF can be found in section 3.2 of chapter 3. The third input is the congestion probability of the road network nodes. The computational methodology of the congestion probability is illustrated in Section 6.2.2. 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 the MFI. The rule base of the MFI is as shown in Table 6.1. Defuzzification is performed using the centre of gravity method (Lee 1999).The locations of the test network with high value of the defuzzified output are the candidate locations for the placement of charging stations.

The distance is graphically calculated between the transport network node and its nearest distribution network bus. The computational procedures of VSF and congestion probability of the road network are illustrated in the subsequent sub-sections.

Table 6.1-Rule Base of the 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

6.2.1. VSF

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

$$VSF=\left|\frac{dV}{dP}\right| \tag{6.1}$$

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 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 case of radial distribution networks. Hence, the voltage of the buses is determined by the forward and backward sweep algorithm (Rupa et al. 2014). The pseudo code illustrating the computation of VSF is as shown in Algorithm 6.1.

Algorithm 6.1- Pseudo code for computation of VSF (Rupa et al. 2014)

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
Compute VSF for critical loading;
End if else
End while

6.2.2. Congestion Probability of Road Network

The present work proposes a probabilistic approach based on BN for finding the nodes of the road network with high traffic intensity. The capability of BN in handling uncertainty and interaction among different events is effectively utilized in the present work (Deb et al. 2016; Santana and Williams 2012). The BN model used for the computation of congestion probability is shown in Fig.6.2. Table 6.2 presents a summary of the node types and states of different nodes of the proposed BN. The probability of a road network being congested depends on the traffic flow, which, in turn, depends on the day of the week, time of the day, area covered by the road, and lane of the road. Thus, 'Day', 'Time', 'Area', and 'Lane' are the root nodes (Deb et al. 2016; Santana and Williams 2012; Ghosh et al. 2017; Deb et al. 2016) of the BN. And, 'Traffic Flow' is the child node (Deb et al. 2016; Santana and Williams 2012; Ghosh et al. 2017; Deb et al. 2016) 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 the bucket elimination algorithm (Deb et al. 2016; Santana and Williams 2012; Ghosh et al. 2017).

The congestion probabilities of residential single and double lane roads are:

$$P_{RS} = P(\text{Area=R,Lane=S}) | P(\text{congestion=H}) \tag{6.2}$$

$$P_{RD} = P(\text{Area=R,Lane=D}) | P(\text{congestion=H}) \tag{6.3}$$

The congestion probabilities of other roads can also be found by replacing the numerator of Eq. (6.2) and Eq. (6.3) accordingly based on area and lane.

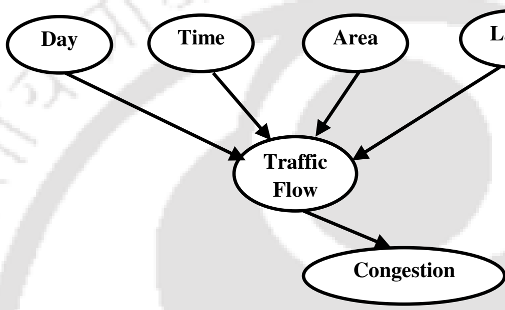

Fig. 6.2- Bayesian Network model for Congestion of Road Network

Table 6.2-Summary of nodes of the Bayesian Network

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)}

6.3. 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_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-

- $p = \{p_1, p_2, ...p_m\}$
- $Fp = \{F_1, F_2..F_m\}$
- $S_p = \{S_1, S_2..S_m\}$
- $f_p = \{f_1, f_2..f_m\}$
- $s_p = \{s_1, s_2..s_m\}$

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

The objective functions are cost, Voltage Stability Reliability Power Loss (VRP) index, distance between charging demand point and charging stations and waiting time in the charging stations. The constraints include the voltage limit, power balance equations, maximum and minimum number of fast as well as slow charging stations placed at each location and maximum and minimum number of fast as well as slow charging points in the respective charging stations.

I. Cost

The optimization is concerned with minimization of overall cost associated with charging stations given by:

$$Cost = C_{installation} + C_{operation} \tag{6.4}$$

$$C_{installation} = \{(\sum_{i=1}^{m} F_i \times f_i) \times C_{installationfast}\} + \{(\sum_{i=1}^{m} S_i \times s_i) \times C_{installationslow}\} \tag{6.5}$$

$$C_{operation} = \{(\sum_{i=1}^{m} F_i \times f_i) \times CP_{fast}\} + \{(\sum_{i=1}^{m} S_i \times s_i) \times CP_{slow}\} \times P_{electricity} \tag{6.6}$$

II. VRP index

The second objective function is the minimization of a VRP index that has the capability of taking into account voltage stability, reliability, and power loss under a single umbrella. The formulation of VRP index is as follows:

$$VRP = f(p, F_p, S_p, f_p, s_p) = w_1 V + w_2 R + w_3 P \tag{6.7}$$

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

$$VSI_{base} = \sum_{i=1}^{N_D} 2V_i^2 V_{i+1}^2 - 2V_{i+1}^2 (P_{i+1} r_i + Q_{i+1} x_i) - |z|^2 (P_{i+1}^2 + Q_{i+1}^2) \tag{6.8}$$

$$P'_p = P_p + \{(F_p \times f_p) \times CP_{fast}\} + \{(S_p \times s_p) \times CP_{slow}\} \tag{6.9}$$

$$VSI_l = \sum_{i=1}^{N_D} 2V'^2_i V'^2_{i+1} - 2V'^2_{i+1}(P'_{i+1}r_i + Q'_{i+1}x_i) - |z|^2 (P'^2_{i+1} + Q'^2_{i+1}) \tag{6.10}$$

$$SAIFI_{base} = \frac{\sum_{i=1}^{N_D} \lambda_i N_i}{\sum_{i=1}^{N_D} N_i} \quad SAIDI_{base} = \frac{\sum_{i=1}^{N_D} U_i N_i}{\sum_{i=1}^{N_D} N_i} \quad \text{and} \quad CAIDI_{base} = \frac{\sum_{i=1}^{N_D} U_i N_i}{\sum_{i=1}^{N_D} \lambda_i N_i} \tag{6.11}$$

$$SAIFI_l = \frac{\sum_{i=1}^{N_D} \lambda'_i N_i}{\sum_{i=1}^{N_D} N_i} \quad SAIDI_l = \frac{\sum_{i=1}^{N_D} U'_i N_i}{\sum_{i=1}^{N_D} N_i} \quad \text{and} \quad CAIDI_l = \frac{\sum_{i=1}^{N_D} U'_i N_i}{\sum_{i=1}^{N_D} \lambda'_i N_i} \tag{6.12}$$

$$\lambda'_p = \frac{\lambda_p}{P_p} \times P'_p \qquad U'_p = \frac{U_p}{P_p} \times P'_p \tag{6.13}$$

$$P_{loss}^{base} = \sum_{i=1}^{N_D} I_i^2 r_i \qquad P_{loss}^{l} = \sum_{i=1}^{N_D} I'^2_i r_i \tag{6.14}$$

III. Accessibility index

The Accessibility or distance of the charging stations from the charging demand points 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. The mathematical formulation of the D, DD, d and A are as follows:

$$D = \begin{bmatrix} d_1c_1 & d_1c_2 & \ldots & d_1c_m \\ d_2c_1 & d_2c_2 & \ldots & d_2c_m \\ . & . & . & . \\ . & . & . & . \\ d_qc_1 & d_qc_2 & \ldots & d_qc_m \end{bmatrix} \text{ and } DD = \begin{bmatrix} \min(d_1c_1, d_1c_2, \ldots d_1c_m) \\ \min(d_2c_1, d_2c_2, \ldots d_2c_m) \\ . \\ . \\ . \\ \min(d_qc_1, d_qc_2, \ldots d_qc_m) \end{bmatrix} \quad d = \sum_{i=1}^{q} DD_i \tag{6.15}$$

IV. 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 modelled by M/M/c queuing theory (Xiang et al. 2016; Hafez and Bhattacharya 2016; Mohammadi et al. 2011).The mathematical formulation of the waiting time is as follows:

$$W_f = \frac{\sum_{i=1}^{m} \frac{\rho_f^{f_i+1}}{(f_i-1)! \times (f_i - \rho_f)^2} \times P_0^f}{\lambda_f} \tag{6.16}$$

$$Ws = \frac{\sum_{i=1}^{m} \frac{\rho_s^{s_i+1}}{(s_i-1)! \times (s_i - \rho_s)^2} \times P_0^s}{\lambda_s} \tag{6.17}$$

$$Waiting\,time(W_t) = W_f + W_s \tag{6.18}$$

V. Constraints

The optimization is carried out in agreement with a number of equality as well as inequality constraints. The different constraints of the charging station placement problem are as follows:

$$F_{\min} < F_p \le F_{\max} \quad \text{and} \quad f_{\min} < f_p \le f_{\max} \tag{6.19}$$

$$S_{\min} < S_p \le S_{\max} \quad \text{and} \quad s_{\min} < s_p \le s_{\max} \tag{6.20}$$

$$P_{gi} - P_{di} - V_i \sum_{j=1}^{N_D} V_j Y_{ij} \cos(\delta_i - \delta_j - \theta_{ij}) = 0 \tag{6.21}$$

$$Q_{gi} - Q_{di} - V_i \sum_{j=1}^{N_D} V_j Y_{ij} \cos(\delta_i - \delta_j - \theta_{ij}) = 0 \tag{6.22}$$

6.4. Solution of charging station placement problem by CSO TLBO

The Pareto dominance based multi-objective CSO TLBO illustrated in chapter 5 is employed in the present work to solve the charging station placement problem. The systematic procedure for 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 data, 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 $pop_{intl} = [A_{pop} B_{pop} C_{pop} D_{pop} E_{pop}]$

where

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

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

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

The randomly generated initial solution is feasible if it satisfy all the constraints of charging station placement problem explained in section 2.

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 chapter 5. 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

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 the 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 elaborated in chapter 5.

6.5. Results

6.5.1. Test system and input parameters

The proposed two-stage planning model is validated on a superimposed 33 bus distribution network and 25 node road network as well as the practical network of Tianjin, China. The superimposed 33 bus distribution network and 25 node road network is as shown in Fig. 6.3.The second test system is the real time network of Tianjin, China as shown in Fig. 6.4.The power distribution network of Tianjin resembles the standard 69 bus system (Leeprechanon et al. 2016). The bus data, line data of 33 bus system and 69 bus system can be found in the Appendix (See Table A1, Table A2, Table A3, Table A4).The outage data of 33 and 69 bus test system can be found in the Reference Bhadra et al. 2015 and Attari et al. 2016. The types of nodes and charging demand points of the road network are reported in Table 6.3 for Test system 1 and Test system 2. Table 6.4 reports the input parameters of the charging station placement problem. Table 6.5 reports the value of upper and lower limits of the constraints of the charging station placement problem. It is assumed that the 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 the Reference (Dubey et al. 2015).

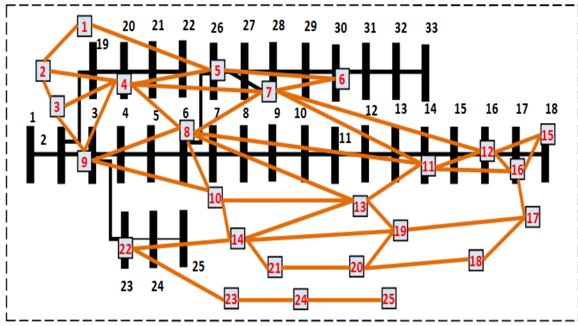

Fig. 6.3- Superimposed 33 bus distribution and 25 node road network

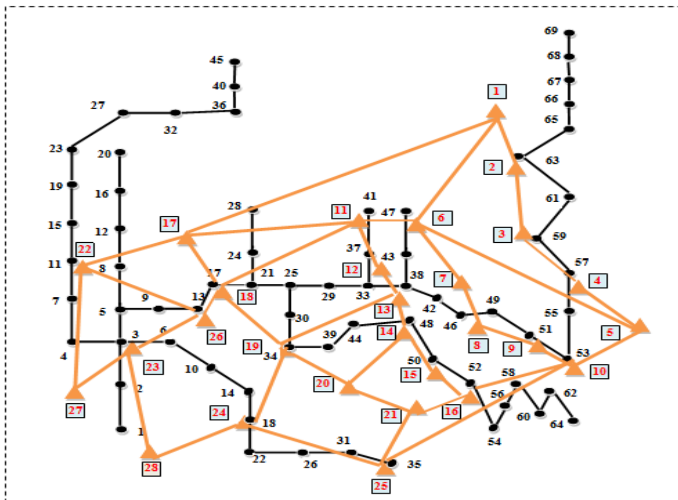

Fig. 6.4.-Superimposed distribution and road network of Tianjin

Table 6.3- Types of nodes of 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 case of Tianjin, no information regarding single and double lane roads is available.	
Charging demand	4, 7, 9, 13, 15, 18, 22, 25		

Table 6.4- Input parameters for robust two stage formulation of charging station placement problem

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 6.5- Upper and lower limits of constraints for robust two stage formulation of charging station placement problem

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

6.5.2. Screening of candidate locations for charging station placement

The candidate locations for the placement of charging stations are found by applying MFI elaborated in Section 6.2. The first input of the MFI named VSF is computed by the pseudo code elaborated by Algorithm 6.1. The VSF of 33 bus and 69 bus distribution network are as shown in Fig. 6.5 and Fig.6.8 respectively. Fig. 6.5 reveals that bus 14 of 33 bus distribution network has the highest VSF, indicating that it is most vulnerable to voltage instability. Fig. 6.8 indicates that bus 65 of 69 bus distribution network has the highest VSF indicating that it is the weakest bus of the system. Fig.6.6 and Fig.6.9 provide a graphical representation of the distance between the road network node and its nearest bus of the distribution network for Test system 1and Test system 2, respectively. Table 6.6 reports the congestion probabilities of the nodes of the road network computed by 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 6.2 with 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 Fig.6.7 and Fig.6.10, respectively. The buses with high values of the defuzzified output are the candidate locations for the EV charging station placement. Thus, for Test system 1, the candidate locations, $P_{candidate}$= {2, 4, 5, 7, 21, 22, 24, 25, and 27} and, for Test system 2 the candidate locations, $P_{candidate}$= {5, 9, 13, 28, 30, 31, 34, 35, 39, 41, 42, 46, 47, 49, and 51}. It is observed that 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%.

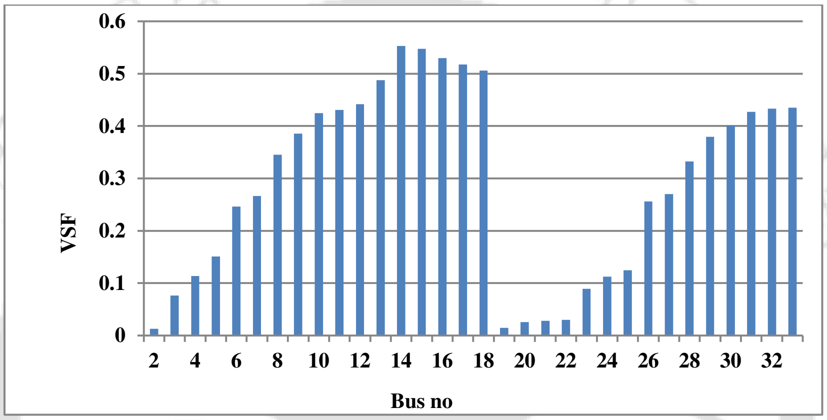

Fig. 6.5- VSF of 33 bus distribution network

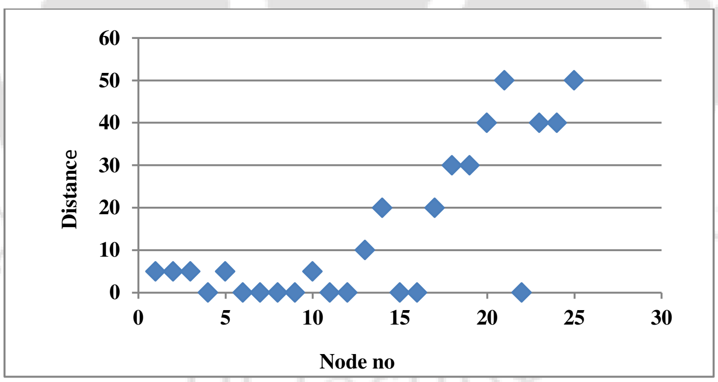

Fig. 6.6- Distance between road network and its nearest bus of the distribution network for Test system 1

Table 6.6- Congestion probabilities of the nodes of 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

Fig. 6.7.-Defuzzified value representing probability of being candidate location of charging station placement for Test system 1

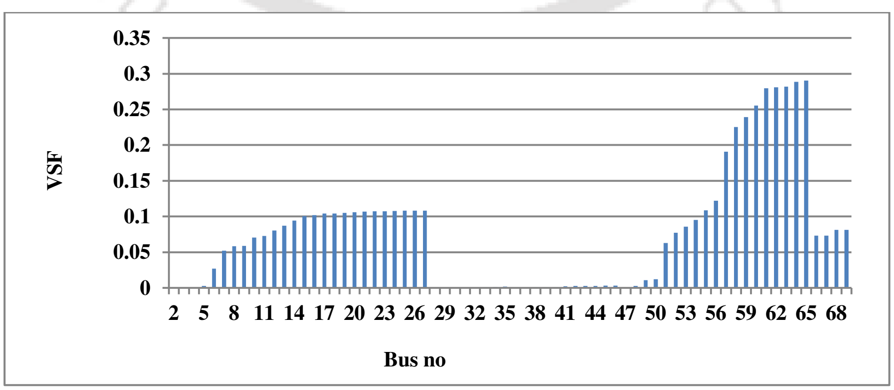

Fig. 6.8- VSF of 69 bus distribution network

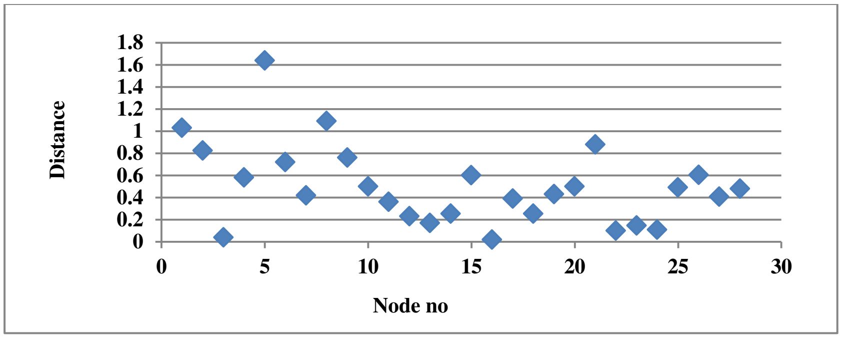

Fig. 6.9- Distance between road network and its nearest bus of the distribution network for Test system 2

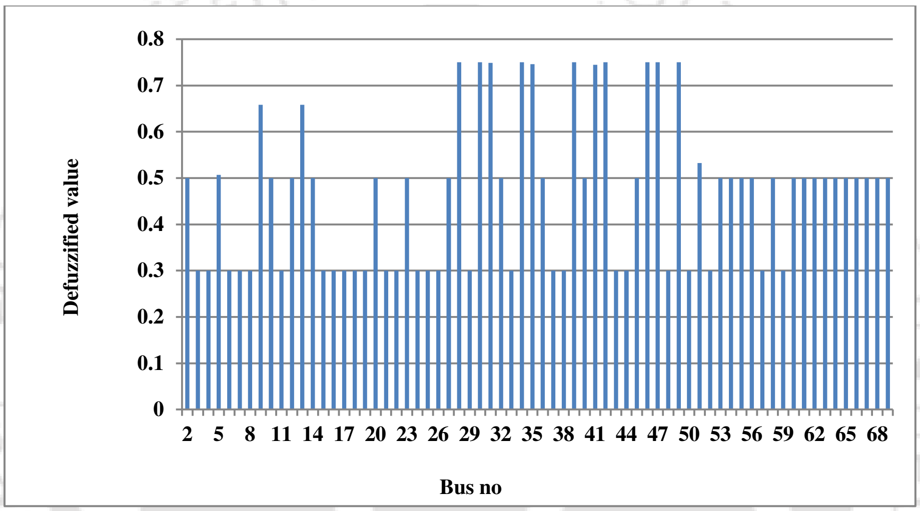

Fig. 6.10.-Defuzzified value representing probability of being candidate location of charging station placement for Test system 2

6.5.3. 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 6.3 is solved by the Pareto dominance based CSO TLBO algorithm earlier explained in chapter 5. 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 in Table 5.1 of chapter 5.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 (NDS) or planning schemes as shown in Table 6.7. Table 6.8 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 accessibility index and waiting time in the charging stations are not that satisfactory and may cause inconvenience to the EV drivers. The optimized values of VRP index are satisfactory for all the 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's convenience is taken into account.

6.7- Optimal allocation of charging stations for Test system 1 and Test system 2

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 6.8- Objective function values for the planning schemes for Test system 1 and Test system 2

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

6.5.4. Impact of EV charging station on Distribution Network

The impact of EV charging stations placement on the distribution network is examined for further analysis. The voltage profile of all the buses of 33 bus distribution network and 69 bus distribution network for the six planning schemes are shown in Fig.6.11 and Fig. 6.12, respectively. It is observed that the voltage profiles of all the buses are within acceptable range. The impact of EV charging stations on different reliability indices such as SAIFI and SAIDI are shown in Fig.6.13, Fig.6.14 and Fig.6.15, Fig.6.16 for Test system 1 and Test system 2, respectively. It is noted that 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 the Reference (Chowdhury and Koval 2011).

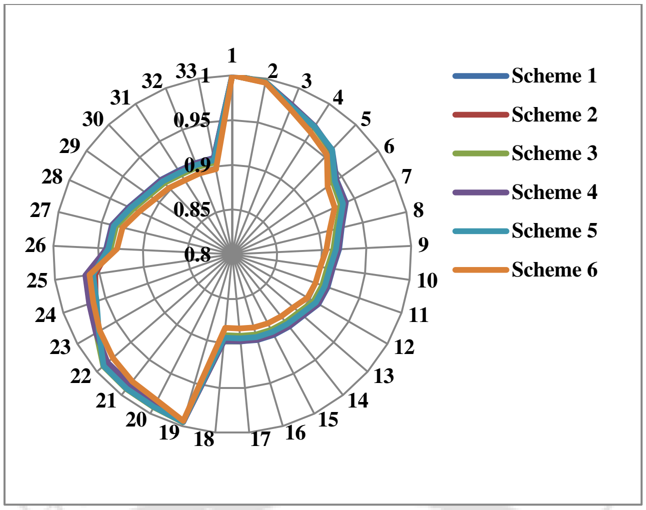

Fig. 6.11-Voltage Profile of 33 bus distribution network after charging station placement

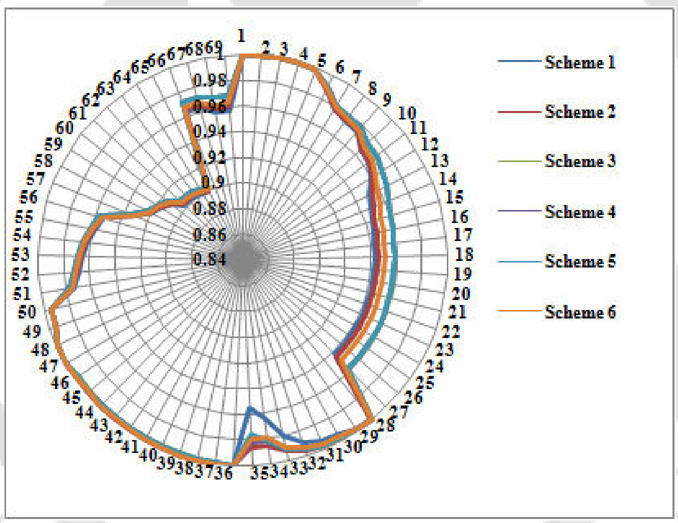

Fig. 6.12-Voltage Profile of 69 bus distribution network after charging station placement

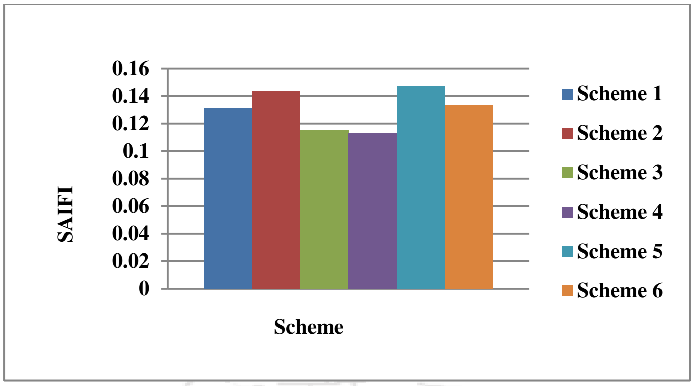

Fig. 6.13- Impact of EV charging stations on SAIFI of 33 bus distribution network

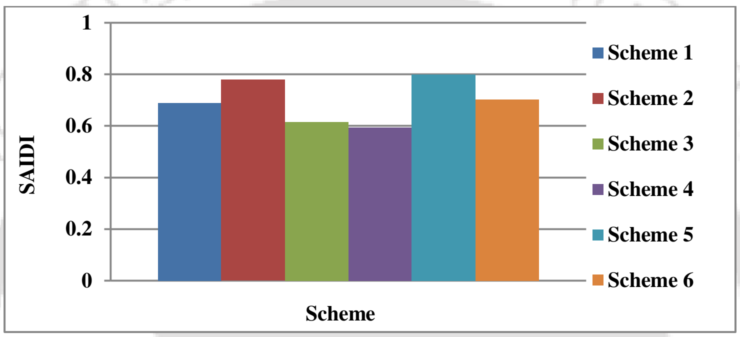

Fig. 6.14- Impact of EV charging stations on SAIDI of 33 bus distribution network

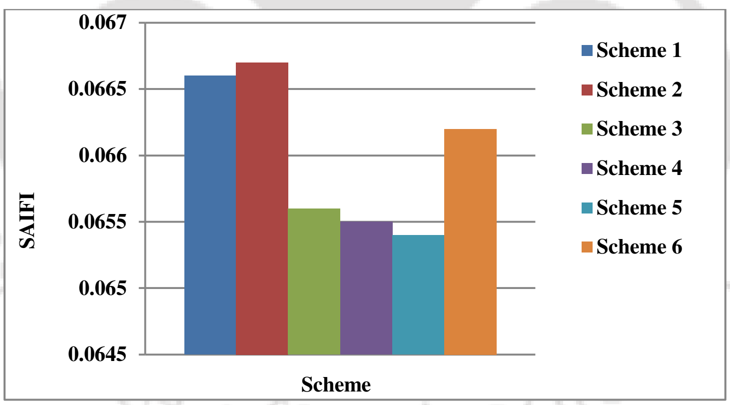

Fig. 6.15- Impact of EV charging stations on SAIFI of 69 bus distribution network

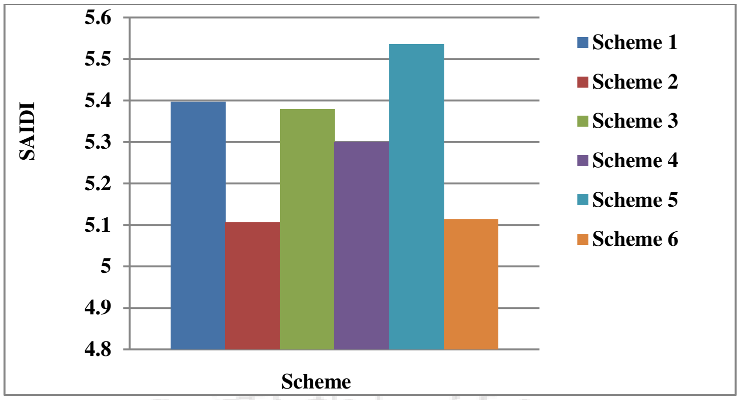

Fig. 6.16- Impact of EV charging stations on SAIDI of 69 bus distribution network

6.5.5. 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 judgment (Li e al. 2017). 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 (Li et al. 2017). Cost, VRP index, accessibility index, and waiting time are chosen as the four aspects of decision-making in the charging station placement problem. In the fuzzy decision-making, low cost, VRP index, and waiting time received a higher evaluation. High accessibility also received a higher evaluation. Table 6.9 lists the scale of the four objective functions based on the aforementioned criteria for Test system 1 as well as Test system 2. The scores of each plan obtained by the fuzzy evaluation system are reported in Table 6.10 for Test system 1 and Test system 2. Fig.6.17 shows the radar charts of the six planning schemes for Test system 1. The area occupied by Plan 4 is largest as compared to the other five figures, indicating that Plan 4 is the most advantageous plan for Test system 1. Fig.6.18 shows the radar charts of the six planning schemes for Test system 2.It is observed from Fig. 6.18, that the area occupied by Plan 4 is highest, thus indicating that it is the most preferable plan for Test system 2.

Table 6.9- Scale of Fuzzy Evaluation System for robust two stage formulation of charging station placement problem

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

Table 6.10- Scores of the six Plans for robust two stage formulation of charging station placement problem

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

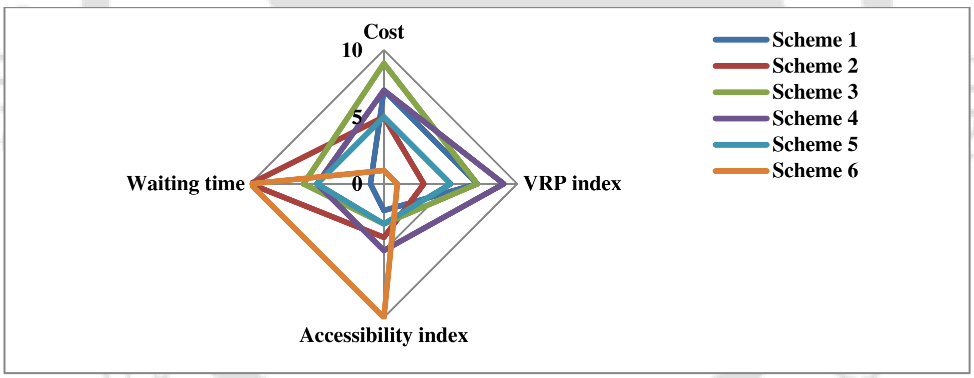

Fig. 6.17-Radar charts of the planning schemes for Test system 1

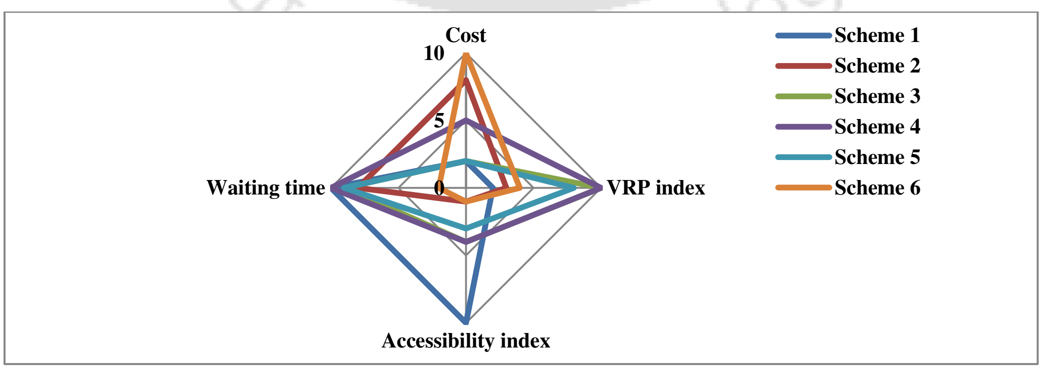

Fig. 6.18-Radar charts of the planning schemes for Test system 2

6.5.6. Statistical Comparison of CSO TLBO with other state-of- art algorithms in solving the proposed problem

The performance of the Pareto dominance based CSO TLBO in solving the charging station placement problem is compared with Non-Dominated Sorted Genetic Algorithm (NSGA II). Evolutionary algorithms are characterized by a random generation of population. Hence, different solutions are obtained for every independent trial. The two algorithms are statistically compared by computing the hypervolume for 20 independent trials. Hypervolume is a metric proposed by Zitzler (1999) used for analysing the distribution of Pareto optimal solutions. Hypervolume physically signifies the volume occupied by the NDS set. Reference (Emmerich et al. 2005) concludes that maximizing 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 6.11. In Table 6.11, it is observed that the performance of CSO TLBO is better than NSGA II for both Test system 1 and Test system 2. However, the average run time of CSO TLBO is more than NSGA II.

Table 6.11- Comparison of CSO TLBO with NSGA II in solving robust two-stage formulation of charging station placement problem

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

6.5.7. Complexity of the proposed two-stage planning model

The time complexity of the proposed two-stage planning model is compared with 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 6.3. The initial screening of search space is neglected in the single-stage planning model considered for the purpose of comparison. The average run time of the proposed model and the single-stage planning model are reported in Table 6.12. From Table 6.12, 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 6.12- Complexity Analysis of the proposed 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

6.6. Discussions

This work proposes a novel two-stage-planning model for optimal allocation of charging stations. The first stage involving screening of the candidate locations for the placement of charging stations reduces the size of search space of the optimization problem thereby reducing the complexity of the problem to some extent. Furthermore, all the key factors, such as distance, traffic intensity, and voltage stability are carefully taken into account while 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 of the road network. This probabilistic approach is capable of efficiently computing the congested nodes of 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 the charging stations as objective functions.

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

6.7. 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 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 are computed as well as the type, and number of charging stations. The simulation results indicate that the planning model is sufficiently efficient to be implemented in a real-world environment.

Note- This chapter is reproduced from the following publications-

- **Deb, S., Tammi, K, Gao, X. Z., Kalita, K & Mahanta,P, A Robust two-stage planning model for charging station placement problem considering road traffic uncertainty,** ***IEEE Transactions on Intelligent Transportation System*** **(under review)**
- **Deb, S., Kalita, K., & Mahanta, P. (2019). Distribution Network planning considering the impact of Electric Vehicle charging station load. In** ***Smart Power Distribution Systems*** **(pp. 529-553). Academic Press, Elsevier.**

CHAPTER 7

CHARGING STATION PLACEMENT FOR ELECTRIC VEHICLES: A CASE STUDY OF GUWAHATI CITY, INDIA

7.1. Introduction

EVs have emerged as a pollution free mode of transportation in the recent years. India being one of the signatories of the Paris agreement has plans to make a paradigm shift to EVs by 2030. However, lack of charging infrastructure is one of the hindrances affecting the EV market in India. Therefore, India has recently started taking several initiatives for development of charging stations. Improper placement of charging stations may affect smooth operation of the power grid causing voltage instability, increased power loss, harmonics, and deterioration of reliability indices (Dubey et al. 2015). Charging stations must be positioned in the road network keeping in mind the EV drivers convenience as well as the safe limits of the operating parameters of the power grid. The complex and haphazard nature of the power grid and road network of India makes the charging infrastructure-planning problem in India a tedious and challenging task. Hence, motivated by the recent concerns related to environmental pollution and energy crisis the present work makes an attempt to formulate and solve the charging station placement problem in the context of Guwahati city, India. Guwahati is one of the upcoming smart cities. Hence, it is expected that in future, a large number of EVs will ply on the roads of Guwahati and there will be necessity of charging stations.

The rest of the chapter is organized as follows. Section 7.2 formulates the charging station placement problem in the context of Guwahati city. Section 7.3 illustrates the solution methodology of charging station placement problem. Section 7.4 presents the results of charging station placement for Guwahati city. Section 7.5 concludes the work.

7.2. Charging Station Placement Problem in the context of Guwahati city

Charging station placement problem involves placement of the charging stations in the road network considering economic factors, operating parameters of the power grid and EV users' convenience. The present work utilizes a two-stage modelling of the charging station placement problem as illustrated in sub-sections 7.2.1 and 7.2.2. The two-stage planning model reduces the computational time and effectively locates the charger locations as mentioned in chapter 6.

7.2.1. Stage I: Screening of the candidate locations for placement of charging station

In stage I the candidate locations for the placement of charging stations is determined by using a probabilistic approach based on Bayesian network (Jensen 1996; Deb et al. 2016; Santana and Williams 2012). It is a common practice to situate the charging stations at the meeting point of distribution and road network. 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. Hence, in the present work distance of the node of the road network from the nearest bus of the distribution network, traffic intensity and grid stability are considered as key factors for finding the candidate sites for placement of the charging stations. The vagueness related to the aforementioned factors considered for finding the candidate sites for the placement of charging stations has motivated the authors to apply Bayesian network. 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.7.1.

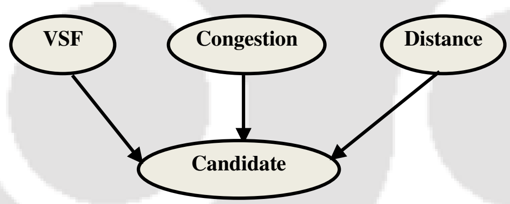

Fig.7.1. Bayesian network for finding candidate sites for placement of charging stations

The Bayesian network has three parent nodes (Jensen 1996; Deb et al. 2016a; Deb et al. 2016b; Santana and Williams 2012) named 'Congestion', 'Voltage Sensitivity Factor (VSF)' and 'Distance'. As shown in Fig.7.1 'Candidate' is the child node (Jensen 1996; Deb et al. 2016; Santana and Williams 2012) 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 (Jensen 1996; Deb et al. 2016; Santana and Williams 2012; Ghosh et al. 2017) as given by Eq. (7.1).

$$P(candidate = yes) = P(candidate \mid VSF, congestion, distance) \times P(VSF) \times P(congestion) \times P(distance) \quad (7.1)$$

The distance of the node of the road network from the nearest bus of the distribution network that can be calculated graphically.

The present work uses VSF for analysing the stability of the distribution network. VSF is defined as the ratio of variation in voltage and variation in load (Rahman et al. 2013).Mathematically, it is expressed as:

$$VSF = \left| \frac{dV}{dP} \right| \; \forall P < P_{max} \quad (7.2)$$

The conventional methods of load flow analysis like the Newton Raphson method have their limitations in determination of voltage of radial distribution network because of a high R/X ratio. Hence, the forward and backward sweep algorithm (Rupa et al. 2014) 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 methodology of computation of VSF and realistic loading margin is shown in Fig.7.2.

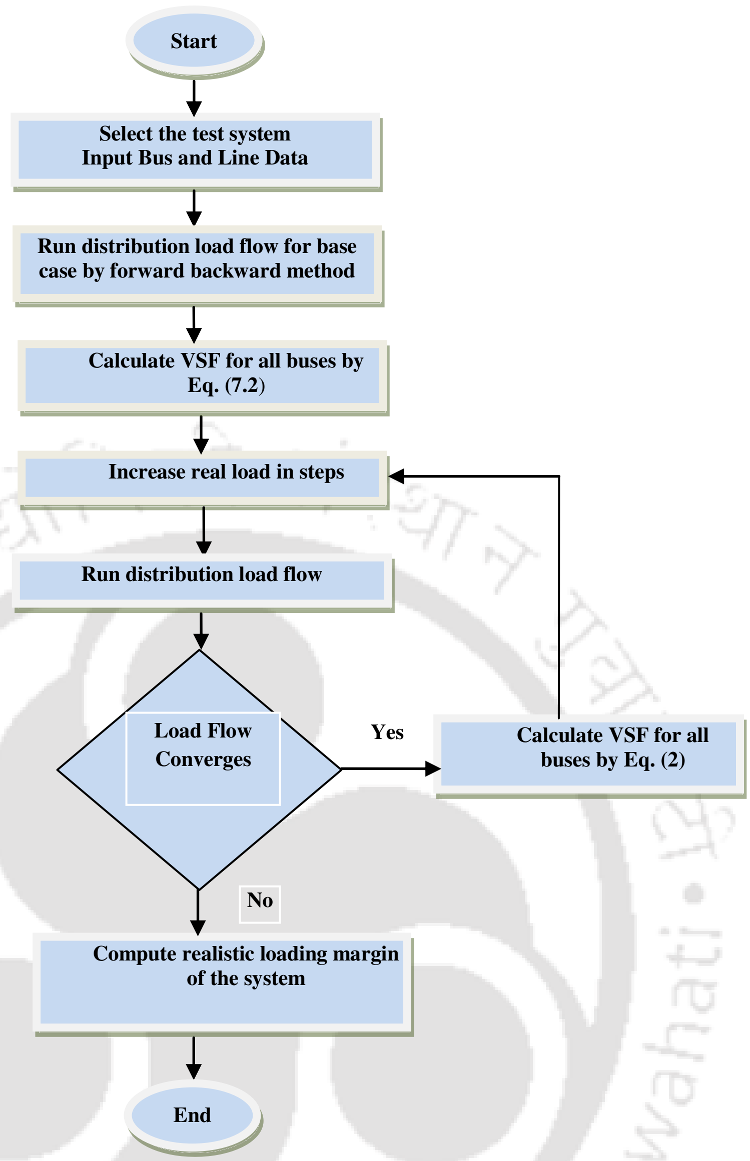

Fig.7.2- Flowchart for computation of the first input of Bayesian Network i.e VSF

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 the finding congestion probability is shown in Fig.7.3.

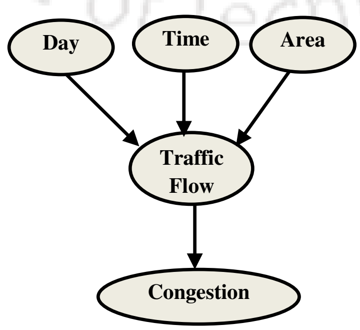

Fig.7.3- Bayesian Network model for Congestion of Road Network of Guwahati

The probability of a road network being congested depends on the traffic flow which in turn depends on day of the week, time of the day, area covered by the road and lane of the road. Thus, 'Day', 'Time', 'Area' and 'Lane' are the parent nodes (Jensen 1996; Deb et al. 2016; Santana and Williams 2012) of the Bayesian network. And 'Traffic Flow' is the child node (Jensen 1996; Deb et al. 2016; Santana and Williams 2012) 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 by bucket elimination algorithm (Jensen 1996; Deb et al. 2016; Santana and Williams 2012). The states of the root nodes 'Day', 'Time', 'Area' and 'Lane' are {Weekday, Weekend},{ AM Peak , Work , PM Peak, Leisure, Rest}, {Residential(R), Office (O), Market (M), School (Sc)} and {Single (S), Double (D)} respectively. The states of the child node 'Traffic flow' are {Low (L), Medium (M), High (H)}. The states of the node 'Congestion' are {Low (L), High (H)}.The congestion probabilities of residential single and double traffic lane roads are:

$$P_R = P(\text{Area=R}) | P(\text{congestion=H}) \tag{7.3}$$

$$P_O = P(\text{Area=O}) | P(\text{congestion=H}) \tag{7.4}$$

The congestion probabilities of other roads can also be found by replacing the numerator of Eq. (7.3) and Eq.(7.4) accordingly based on area.

7.2.2. Stage II: 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- $p=\{p_1,p_2,\ldots p_m\}$, $Fp=\{F_1,F_2..F_m\}$, $S_p=\{S_1,S_2..S_m\}$, $f_p=\{f_1,f_2..f_m\}$ and $s_p=\{s_1,s_2..s_m\}$ where m is the maximum number of locations for the placement of charging stations. The objective functions are cost, Voltage Stability Reliability Power Loss (VRP) index, distance between charging demand point and charging stations and waiting time in the charging stations. The constraints include the voltage limit, power balance equations, maximum and minimum number of fast as well as slow charging stations placed at each location and maximum and minimum number of fast as well as slow charging points in the respective charging stations. The objective functions and constraints of the placement problem are elaborated below.

I. Cost

The optimization is concerned with curtailment of the installation and operation cost associated with the establishment of charging stations. Mathematically, formulation of the cost function is as follows:

$$Cost = C_{installation} + C_{operation} \tag{7.4}$$

$$C_{installation} = \{(\sum_{i=1}^{m} F_i \times f_i) \times C_{installationfast}\} + \{(\sum_{i=1}^{m} S_i \times s_i) \times C_{installationslow}\} \tag{7.5}$$

$$C_{operation} = \{(\sum_{i=1}^{m} F_i \times f_i) \times CP_{fast}\} + \{(\sum_{i=1}^{m} S_i \times s_i) \times CP_{slow}\} \times P_{electricity} \tag{7.6}$$

II. VRP index

The second objective function is the minimization of a VRP index having the capability of taking into account voltage stability, reliability and power loss under a single umbrella. The formulation of VRP index is as follows:

$$VRP = f(p, F_p, S_p, f_p, s_p) = w_1 V + w_2 R + w_3 P \tag{7.7}$$

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

$$VSI_{base} = \sum_{i=1}^{N_D} 2V_i^2 V_{i+1}^2 - 2V_{i+1}^2 (P_{i+1} r_i + Q_{i+1} x_i) - |z|^2 (P_{i+1}^2 + Q_{i+1}^2) \tag{7.8}$$

$$P'_p = P_p + \{(F_p \times f_p) \times CP_{fast}\} + \{(S_p \times s_p) \times CP_{slow}\} \tag{7.9}$$

$$VSI_l = \sum_{i=1}^{N_D} 2V'^2_i V'^2_{i+1} - 2V'^2_{i+1} (P'_{i+1} r_i + Q'_{i+1} x_i) - |z|^2 (P'^2_{i+1} + Q'^2_{i+1}) \tag{7.10}$$

$$SAIFI_{base} = \frac{\sum_{i=1}^{N_D} \lambda_i N_i}{\sum_{i=1}^{N_D} N_i} \quad SAIDI_{base} = \frac{\sum_{i=1}^{N_D} U_i N_i}{\sum_{i=1}^{N_D} N_i} \quad \text{and} \quad CAIDI_{base} = \frac{\sum_{i=1}^{N_D} U_i N_i}{\sum_{i=1}^{N_D} \lambda_i N_i} \tag{7.11}$$

$$SAIFI_l = \frac{\sum_{i=1}^{N_D} \lambda'_i N_i}{\sum_{i=1}^{N_D} N_i} \quad SAIDI_l = \frac{\sum_{i=1}^{N_D} U'_i N_i}{\sum_{i=1}^{N_D} N_i} \quad \text{and} \quad CAIDI_l = \frac{\sum_{i=1}^{N_D} U'_i N_i}{\sum_{i=1}^{N_D} \lambda'_i N_i} \tag{7.12}$$

$$\lambda'_p = \frac{\lambda_p}{P_p} \times P'_p \qquad U'_p = \frac{U_p}{P_p} \times P'_p \tag{7.13}$$

$$P_{loss}^{base} = \sum_{i=1}^{N_D} I_i^2 r_i \qquad P_{loss}^{l} = \sum_{i=1}^{N_D} I'^2_i r_i \tag{7.14}$$

III. Accessibility index

The Accessibility or distance of the charging stations from the charging demand points 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. The mathematical formulation of the *D*, *DD*, *d* and *A* are as follows:

$$D=\begin{bmatrix} d_1c_1 & d_1c_2 & \ldots & d_1c_m \\ d_2c_1 & d_2c_2 & \ldots & d_2c_m \\ . & . & . & . \\ . & . & . & . \\ d_qc_1 & d_qc_2 & \ldots & d_qc_m \end{bmatrix} \text{ and } DD=\begin{bmatrix} \min(d_1c_1, d_1c_2, \ldots d_1c_m) \\ \min(d_2c_1, d_2c_2, \ldots d_2c_m) \\ . \\ . \\ . \\ \min(d_qc_1, d_qc_2, \ldots d_qc_m) \end{bmatrix} \quad d=\sum_{i=1}^{q} DD_i \tag{7.15}$$

IV. 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 modelled by M/M/c queuing theory (Xiang et al. 2016; Hafez and Bhattacharya 2016; Mohammadi et al. 2011).The mathematical formulation of the waiting time is as follows:

$$W_f=\frac{\sum_{i=1}^{m}\frac{\rho_f^{f_i+1}}{(f_i-1)!\times(f_i-\rho_f)^2}\times P_0^f}{\lambda_f} \tag{7.16}$$

$$Ws=\frac{\sum_{i=1}^{m}\frac{\rho_s^{s_i+1}}{(s_i-1)!\times(s_i-\rho_s)^2}\times P_0^s}{\lambda_s} \tag{7.17}$$

$$Waiting\,time(W_t)=W_f+W_s \tag{7.18}$$

V. Constraints

The optimization is carried out in agreement with a number of equality as well as inequality constraints. The different constraints of the charging station placement problem are as follows:

$$F_{\min}<F_p\le F_{\max} \quad \text{and} \quad f_{\min}<f_p\le f_{\max} \tag{7.19}$$

$$S_{\min} < S_p \le S_{\max} \quad \text{and} \quad s_{\min} < s_p \le s_{\max} \tag{7.20}$$

$$P_{gi} - P_{di} - V_i \sum_{j=1}^{N_D} V_j Y_{ij} \cos(\delta_i - \delta_j - \theta_{ij}) = 0 \tag{7.21}$$

$$Q_{gi} - Q_{di} - V_i \sum_{j=1}^{N_D} V_j Y_{ij} \cos(\delta_i - \delta_j - \theta_{ij}) = 0 \tag{7.22}$$

7.3. Solution Methodology of Charging Station Placement Problem

The solution methodology of charging station placement problem for Guwahati city is same as elaborated in section 6.3 of chapter 6.

7.4. Results

7.4.1. Test System and Input parameters

The present work solves charging infrastructure planning problem for the city of Guwahati, Assam. Fig.7.4 shows the highway network of Guwahati connecting Jalukbari with Narangi. Fig. 7.5 shows the superimposed road and distribution network for the Guwahati city. The bus and line data of the distribution network are taken from the reference (Singh et al. 2013; Singh et al. 2012) and the outage data of the distribution network are taken from the log book of the substations. The bus data of the distribution network can be found in Table A5 of Appendix. The road network data are recorded from Google maps. The characteristics of the nodes of the road network are reported in Table 7.1. Table 7.2 presents the different input parameters required for performing optimization. Table 7.3 presents the algorithm- specific control parameters of CSO TLBO.

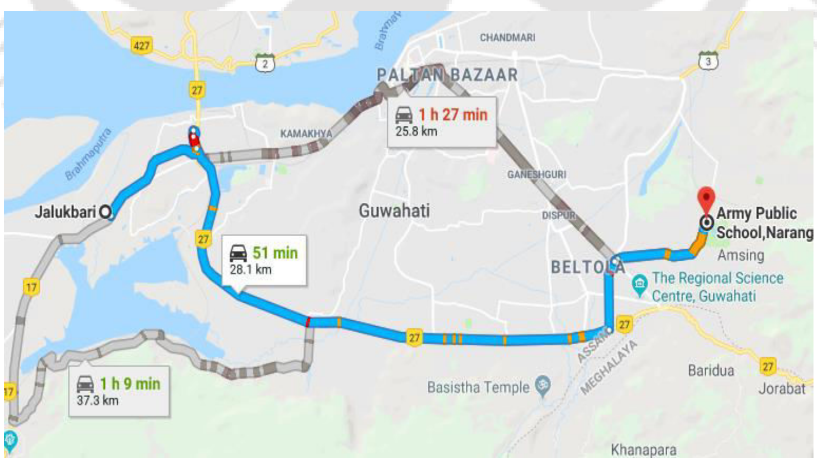

Fig. 7.4- Highway Road Network of Guwahati (Source: Google Map)

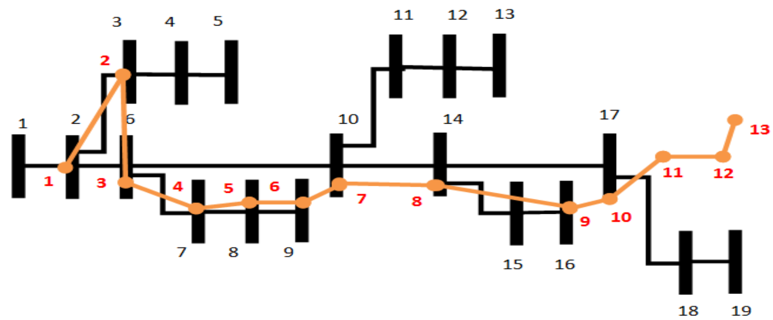

Fig. 7.5- Superimposed road and distribution network of Guwahati

Table 7.1- Type of nodes of the road network for Guwahati

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 7.2- Input Parameters for the network of Guwahati

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 7.3- Algorithm-specific parameters of CSO TLBO for solving charging station placement problem of Guwahati

Parameter	Value
gen	50
PN	10
RN	$0.3\times PN$
HN	$0.4\times PN$
CN	*PN-RN-HN*
INV	3
G	3

7.4.2. Candidate Locations

The candidate locations where charging stations can be placed are evaluated by a probabilistic approach based on Bayesian network as reported in section 7.2.1. The VSF of the buses of the distribution network are reported in Table 7.4. The VSF of bus 19 is highest indicating that it is the weakest point of the distribution network. The congestion probabilities of different types of the nodes of the road network computed by Bayesian network are reported in Table 7.5. It is observed that the nodes sprawling market areas are heavily congested with congestion probability of 0.643. Table 7.6 reports the probability of being a candidate location of placement of charging stations for all the buses of the distribution network. The buses for which the probability of being candidate location is high are selected as the candidate locations for charging station placement as reported in Table 7.7.

Based on the consideration that the driving range of EV is 150 km and the EVs complete 10 round trips starting from Jalukbari to Narangi the charging demand nodes are computed as reported in Table 7.7.

Table 7.4- VSF of the buses of the distribution network of Guwahati

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 7.5- Congestion Probability of the nodes of road network of Guwahati

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

Table 7.6- Probability of being candidate location for the Guwahati network

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

Table 7.7- Candidate Locations and Charging demand nodes for Guwahati

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	----

7.4.3. Optimal allocation of charging stations

The optimal locations for the positioning of charging stations are selected from the set of candidate locations by solving the optimization problem reported in section 7.2.2. The optimization problem is solved by using CSO TLBO algorithm elaborated in section 7.3. Due to the presence of conflicting objectives in multi-objective optimization, a number of optimal solutions are obtained instead of a single optimal solution. In this case, the optimization yielded six non-dominated solution or planning schemes as shown in table 7.8. Table 7.9 reports the value of all the four objective functions. From table 7.9 it is clear that all the six plans are unique and it is difficult to select the best plan.

Table 7.8- Optimal Locations of the charging stations for Guwahati

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 7.9- Objective function values for the planning schemes for Guwahati

Planning Scheme	**Cost ($\$\times10^6$)**	**VRP**	**A(/km)**	**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

7.4.4. Impact of charging station placement on distribution network

The effect of charging stations on different operating parameters of the distribution network like voltage deviation, reliability, and power loss is analyzed. Fig. 7.6 shows the voltage profile of all the buses of the distribution network for all the six planning schemes. It is observed that the voltage profiles of all the buses are within acceptable limit for all the six planning schemes reported in table 7.8. Fig. 7.7, Fig. 7.8 and Fig. 7.9 shows the impact of charging station placement on the three reliability indices named SAIFI, SAIDI, and CAIDI respectively. It is observed that the reliability indices have degraded due to increased charging demand load. The degraded values are more than the base values of these indices without placement of charging stations. However, the degraded values are less than the critical or dead zone values of these reliability indices reported in the reference (Chowdhury and Koval 2011).The power loss of the distribution network after positioning the charging stations is also within acceptable limit as shown in Fig. 7.10. Thus, the two-stage planning model of charging station placement is competent of allocating charging stations with least harm to the distribution network of Guwahati.

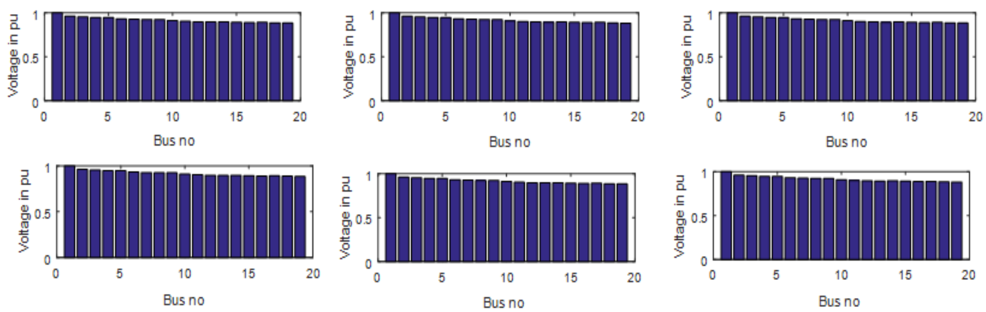

Fig. 7.6- Voltage Profile after the placement of charging stations

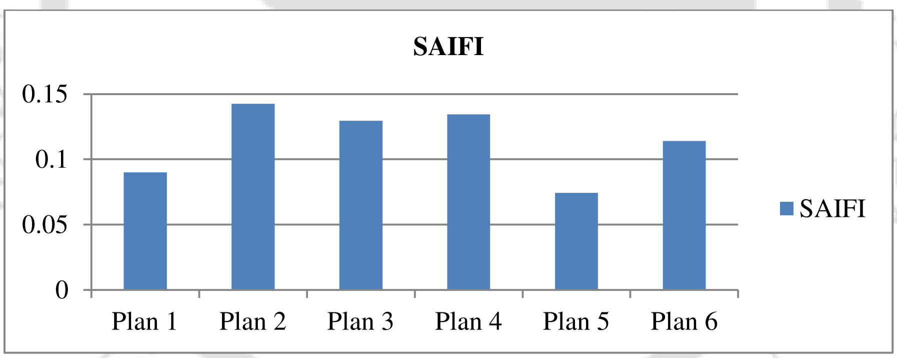

Fig. 7.7- Impact of charging station placement on SAIFI

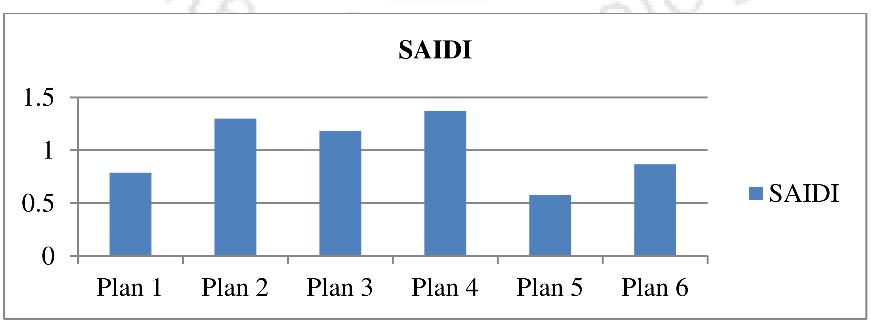

Fig. 7.8- Impact of charging station placement on SAIDI

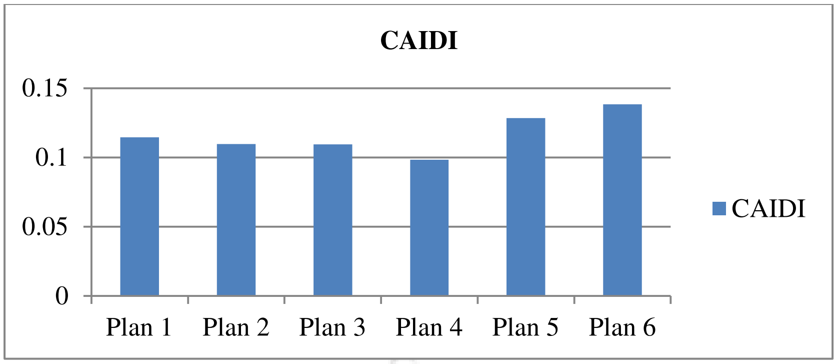

Fig. 7.9- Impact of charging station placement on CAIDI

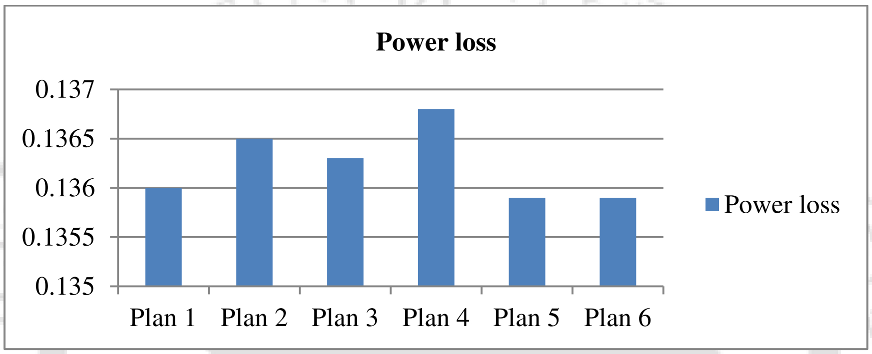

Fig. 7.10- Impact of charging station placement on Power loss

7.4.5. Final Decision Making

Selection of the best plan among the six plans is tricky due to involvement of opposing objectives. In real world, some criterion cannot be measured by crisp values due to indistinctness arising from human qualitative judgement . Hence, a fuzzy evaluation system is used for the final decision making (Li et al. 2017). Cost, VRP index, accessibility index, and waiting time are chosen as the four aspects of decision making in the charging station placement problem. In the fuzzy decision making, low cost and VRP index, waiting time received a higher evaluation. And high accessibility received a higher evaluation. Table 7.10 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 7.11. Fig. 7.11 shows the radar charts for all the six planning schemes. The optimization process yields Pareto-optimal solutions. The radar charts show that pareto optimal solutions include cost-minimizing solutions as well as those minimizing waiting time, maximizing availability or maximizing the grid stability. The radar charts can be utilized to heuristically evaluate those solutions. Traffic authorities and decision makers can then decide the best suiting policy depending upon their requirements.It is observed that plan 1 is good in terms of cost and VRP index. Plan 2 is good in terms of accessibility and waiting time.

Similarly, plan 4 minimizes the waiting time. 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.7.12 shows the optimal locations of charging stations obtained by the best planning scheme and the charging demand points. In Fig. 7.12, the red triangles denote the charging stations and the black circles denote the charging demand points.

Table 7.10- Scale of Fuzzy Evaluation for Guwahati

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 7.11- Scores of the planning schemes for Guwahati

Plan	Cost	VRP index	A(/km)	W_t	Plan	Cost	VRP index	A(/km)	W_t(hr)
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

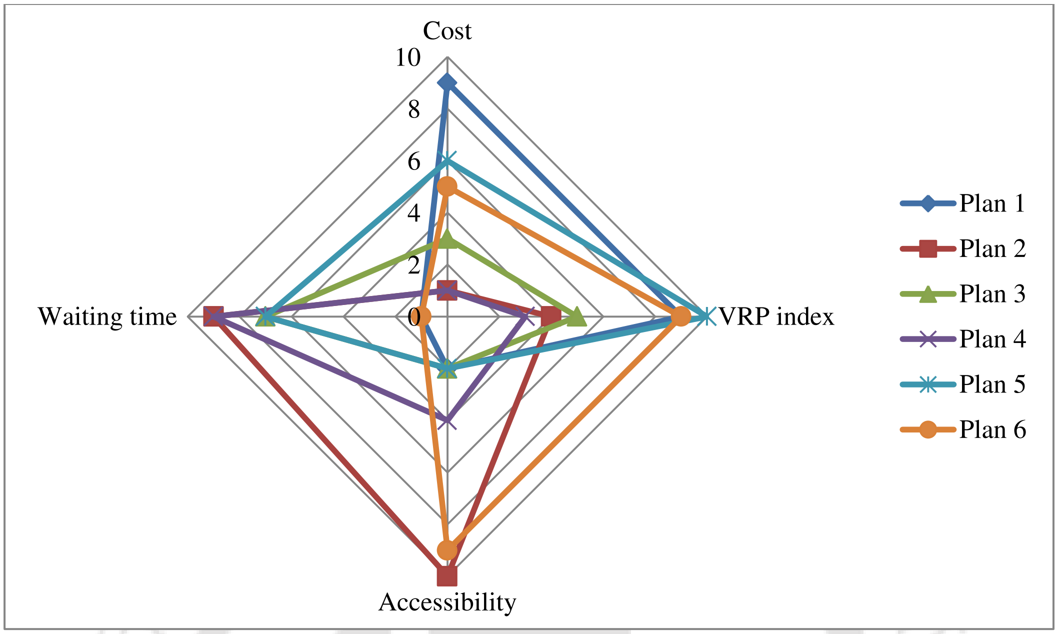

Fig. 7.11- Radar charts of all the plans

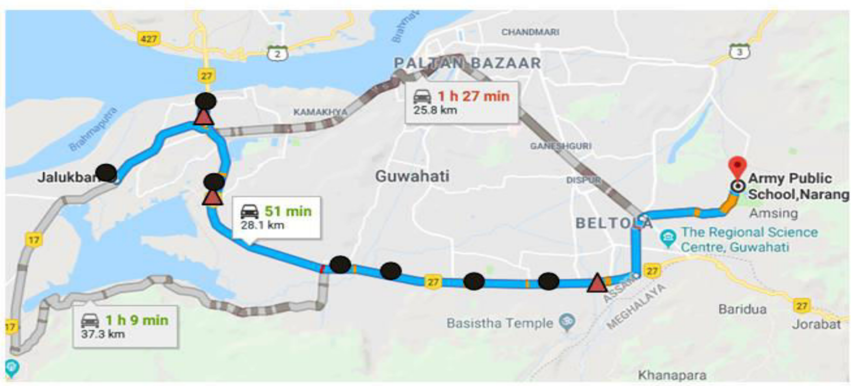

Fig. 7.12- Location of charging stations obtained by plan 6 and charging demand points (Source: Google Map)

7.5. Conclusions

Sustainable development of charging infrastructure is must to promote EVs. This work solves the charging station placement problem in the context of Guwahati city that is considered as an upcoming smart city. The charging station placement problem is modelled in a multi-objective framework considering cost, operating parameters of distribution network like voltage stability, reliability, power loss, factors affecting EV drivers convenience like accessibility of the charging stations, waiting time in the charging stations. A novel CSO TLBO algorithm solves the optimization problem. Allocating the charging stations manually by educated guessing may result in chaotic condition of the grid, more investment of the stakeholders and inconvenience to the EV drivers. Simulation results show that the proposed approach is capable of allocating the charging stations with least harm to the operating parameters of the distribution network and simultaneously considering EV drivers convenience.

Note- This chapter is reproduced from the publication-

- **Deb, S., Tammi, K., Kalita, K., & Mahanta, P. (2019). Charging Station Placement for Electric Vehicles: a Case Study of Guwahati city, India.** ***IEEE Access*****.**

CHAPTER 8

CONCLUSIONS AND FUTURE SCOPE

8.1. Summary of the Research work

With the increasing penetration of EVs in the market, charging infrastructure development has become essential. The present research work deals with different planning issues of sustainable charging infrastructure for EVs. This research work is aimed at planning sustainable charging infrastructure for EVs and applying efficient and novel techniques for solution of the charging station placement problem. Firstly, the impact of EV charging station loads on the distribution network is analyzed. Latter, different planning models for the placement of charging stations are proposed.

Chapter 1 presents the motivation and background of the research work. Chapter 2 presents a comprehensive review of the existing literature related to charging infrastructure planning. The major research gaps of this arena of research are identified. After identifying the major research gaps, the key objectives of the research work are decided.

Chapter 3 deals with the first objective of the research work. In this chapter the impact of EV charging station load on voltage stability, reliability, power losses, and economic loss of 33 bus test system is determined for different cases of charging station placement. From the results presented in chapter 3 it is obvious that voltage stability, power loss as well as reliability indices degraded with the addition of EV charging station loads. Thus, for optimal placement of charging stations in the distribution network all the three parameters must be considered. Further, a novel index named VRP index is proposed which has the capability of considering voltage stability, reliability, and power losses under a common frame. In addition, the charging station placement problem is solved by considering VRP index as objective function.

Chapter 4 proposes a planning model of charging station placement with cost as the objective function. A novel CSO TLBO algorithm is also developed and utilized for solution of the charging station placement problem. The results are validated on a test network formed by superimposition of 33 bus test network and 25 node road network.

In chapter 5, the charging station placement problem is formulated in a multi-objective framework with cost, VRP index, and Accessibility index as objective functions. A novel pareto dominance based multi-objective CSO TLBO is developed and utilized for solution of the placement problem. The results are validated on a test network formed by superimposition of 33 bus test network and 25 node road network.

Chapter 6 proposes a robust two stage planning model of charging station placement problem having the capability of taking into account the random traffic behavior. In the first stage, the candidate locations for the placement of charging stations are identified by applying fuzzy logic considering distance of the node of the road network from the nearest bus of the distribution network, traffic intensity and grid stability. In the second stage, optimization is performed to select the best locations, type and number of charging points. The first stage involving screening of the candidate location of charging stations will reduce the size of search space and reduce complexity of the problem. This planning model also considers waiting time in the charging stations as one of the objective functions along with cost, VRP index and accessibility index.

Chapter 7 models and solves the charging station placement problem in the context of Guwahati city. The charging station placement problem is modelled in a multi-objective framework considering cost, operating parameters of distribution network like voltage stability, reliability, power loss, factors affecting EV drivers convenience like accessibility of the charging stations, waiting time in the charging stations. A novel CSO TLBO algorithm solves the optimization problem. Allocating the charging stations manually by guessing may result in chaotic condition of the grid, more investment of the stakeholders and inconvenience to the EV drivers. Simulation results show that the proposed approach is capable of allocating the charging stations with least harm to the operating parameters of the distribution network and simultaneously considering EV drivers convenience for the highway network of Guwahati city.

8.2. Comparison of different planning models of charging station placement problem

The research work proposes four planning models of charging station placement problem. The four planning models are-

1. Planning Model 1 elaborated in chapter 3
2. Planning Model 2 elaborated in chapter 4
3. Planning Model 3 elaborated in chapter 5
4. Planning Model 4 elaborated in chapter 6

A comparative analysis of the aforementioned planning models is presented in Table 8.1.

Table 8.1- Comparative Analysis of the four planning models

Feature		Planning Model 1	Planning Model 2	Planning Model 3	Planning Model 4
Objective function	Cost		✓	✓	✓
	VRP index	✓		✓	✓
	Accessibility index			✓	✓
	Waiting time				✓
Decision Variable	Location of charging stations	✓	✓	✓	✓
	Number of fast charging stations	✓	✓	✓	✓
	Number of slow charging stations	✓	✓	✓	✓
	Number of fast chargers				✓
	Number of slow				✓
Constraints	Power flow equation	✓	✓	✓	✓
	Thermal limit	✓	✓	✓	✓
	Voltage limit	✓	✓	✓	✓
	Maximum and minimum number of fast charging stations	✓	✓	✓	✓
	Maximum and minimum number of slow charging stations		✓	✓	✓
	Maximum and minimum number of fast chargers				✓
	Maximum and minimum number of slow chargers				✓
Random traffic	Considered				✓
	Not Considered	✓	✓	✓	

8.3. Contributions of the research work

The main contributions of the research work are as follows-

- Profound analysis of the impact of the EV charging station loads on the voltage stability of the distribution network
- Detailed analysis of the impact of the EV charging station loads on the customer and energy oriented reliability indices
- Comprehensive analysis of the economic losses incurred in terms of the penalty paid by the utility due to introduction of the EV charging station load
- Comparative analysis of the EV charging load on different parameters of the distribution network such as the voltage stability, reliability and power losses
- Placement of the charging stations in the distribution network based on VRP index
- Formulation of a simple and new methodology of charging station placement problem with single objective cost function
- Development of a new hybrid CSO TLBO algorithm
- Solution of benchmark functions as well as charging station placement problem by CSO TLBO and comparison of the results obtained by CSO TLBO with other benchmark algorithms
- Formulation of a new multi-objective framework for charging station placement problem with cost, VRP index and Accessibility index as objective functions
- Development of Pareto dominance based multi-objective CSO TLBO
- Formulation of a robust two-stage planning model of charging station placement problem taking into account random road traffic
- Formulation and solution of the charging station placement problem in the context of Guwahati city

8.4. Suggestions for Future Research

The present research work proposes a number of planning models of the charging station placement problem and efficient algorithms for solution of the problem. The contributions of the research work are highlighted in the previous section. However, there is scope of performing future research in this arena. Some suggestions for future research are-

- More strategic formulation of the charging station placement problem taking into account the activity based behavior of the EV drivers can be investigated

- The planning of V2G enabled charging stations with net benefit earned by participating in V2G scheme can be investigated
- EVs are free from local exhaust emissions. However, the power required for charging the EVs produced using non-renewable sources is not emission free. The increasing number of EVs in the market is accompanied by escalated electricity demand to charge them. The grid may not be sufficient to meet the demand, particularly at the moment of a peak demand. Additionally, the peak power should not be satisfied using non-renewable sources of energy. Thus, to reduce CO_2 emissions and satisfy the increasing charging power demand renewable sources of energy must be utilized. In this context, the feasibility analysis of hybrid charging stations is a new promising area of research for the coming years
- The problem of voltage deviation, Average Energy Not Served, harmonics can be solved to certain extent by adopting a smart pricing strategy in the charging stations. If most of the charging activities take place during the off peak hours then the excessive load demand because of the EV load can be controlled. Hence, a dynamic pricing strategy is more beneficial as compared to uniform pricing strategy. However, delaying the charging process may cause inconvenience to the EV drivers. Thus, devising efficient pricing strategies in the charging stations is also a new promising area of research for the coming years
- There is scope of developing more efficient algorithms for solving the charging station placement problem. The proposed CSO TLBO algorithm performs competitively on the charging station placement problem. However, No Free Lunch (NFL) theorem provides motivation for developing more efficient algorithms as a single algorithm cannot always perform satisfactorily on all problems. There is scope of developing an adaptive CSO TLBO algorithm. Moreover, CSO can also be hybridized with other nature inspired algorithms like Jaya algorithm, Sine Cosine Algorithm. It is expected that the hybrid algorithms will demonstrate competitive performance in solving the charging station placement problem.

APPENDIX

Table A1-Bus data of 33 bus distribution network (Bhadra et al. 2015; Aslanzadeh et al. 2014)

Bus no	Real power (pu)	Reactive power (pu)
1	0	0
2	0.0010	0.0006
3	0.0009	0.0004
4	0.0012	0.0008
5	0.0006	0.0003
6	0.0006	0.0002
7	0.0020	0.0010
8	0.0020	0.0010
9	0.0006	0.0002
10	0.0006	0.0002
11	0.0004	0.0003
12	0.0006	0.0004
13	0.0006	0.0004
14	0.0012	0.0008
15	0.0006	0.0001
16	0.0006	0.0002
17	0.0006	0.0002
18	0.0009	0.0004
19	0.0009	0.0004
20	0.0009	0.0004
21	0.0009	0.0004
22	0.0009	0.0004
23	0.0009	0.0005
24	0.0042	0.0020
25	0.0042	0.0020
26	0.0006	0.0003
27	0.0006	0.0003
28	0.0006	0.0002
29	0.0012	0.0007
30	0.0020	0.0060
31	0.0015	0.0007
32	0.0021	0.0010
33	0.0006	0.0004

Table A2-Line data of 33 bus distribution network (Bhadra et al. 2015; Aslanzadeh et al. 2014)

Line no	Starting bus	End bus	R (pu)	X (pu)
1	1	2	0.0575	0.0298
2	2	3	0.3076	0.1567
3	3	4	0.2284	0.1163
4	4	5	0.2378	0.1211
5	5	6	0.5110	0.4411
6	6	7	0.1168	0.3861
7	7	8	1.0678	0.7706
8	8	9	0.6426	0.4617
9	9	10	0.6489	0.4617
10	10	11	0.1227	0.0406
11	11	12	0.2336	0.0772
12	12	13	0.9159	0.7206
13	13	14	0.3379	0.4448
14	14	15	0.3687	0.3282
15	15	16	0.4656	0.3400
16	16	17	0.8042	1.0738
17	17	18	0.4567	0.3581
18	2	19	0.1023	0.0976
19	19	20	0.9385	0.8457
20	20	21	0.2555	0.2985
21	21	22	0.4423	0.5848
22	3	23	0.2815	0.1924
23	23	24	0.5603	0.4424
24	24	25	0.5590	0.4374
25	6	26	0.1267	0.0645
26	26	27	0.1773	0.0903
27	27	28	0.6607	0.5826
28	28	29	0.5018	0.4371
29	29	30	0.3166	0.1613
30	30	31	0.6080	0.6008
31	31	32	0.1937	0.2258
32	32	33	0.2128	0.3308

Table A3-Bus data of 69 bus distribution network (Attari et al. 2016)

Bus no	Real power (pu)	Reactive power (pu)
1	0	0
2	0	0
3	0	0
4	0	0
5	0	0
6	0.0000	0.0000
7	0.0004	0.0003
8	0.0008	0.0005
9	0.0003	0.0002
10	0.0003	0.0002
11	0.0014	0.0010
12	0.0014	0.0010
13	0.0001	0.0001
14	0.0001	0.0001
15	0	0
16	0.0005	0.0003
17	0.0006	0.0004
18	0.0006	0.0004
19	0	0
20	0.0000	0.0000
21	0.0011	0.0008
22	0.0001	0.0000
23	0	0
24	0.0003	0.0002
25	0	0
26	0.0001	0.0001
27	0.0001	0.0001
28	0.0003	0.0002
29	0.0003	0.0002
30	0	0
31	0	0
32	0	0
33	0.0001	0.0001
34	0.0001	0.0001

Bus no	Real power (pu)	Reactive power (pu)
35	0.0001	0.0000
36	0.0003	0.0002
37	0.0003	0.0002
38	0	0
39	0.0002	0.0002
40	0.0002	0.0002
41	0.0000	0.0000
42	0	0
43	0.0001	0.0000
44	0	0
45	0.0004	0.0003
46	0.0004	0.0003
47	0	0
48	0.0008	0.0006
49	0.0038	0.0027
50	0.0038	0.0027
51	0.0004	0.0003
52	0.0000	0.0000
53	0.0000	0.0000
54	0.0003	0.0002
55	0.0002	0.0002
56	0	0
57	0	0
58	0	0
59	0.0010	0.0007
60	0	0
61	0.0124	0.0089
62	0.0003	0.0002
63	0	0
64	0.0023	0.0016
65	0.0006	0.0004
66	0.0002	0.0001
67	0.0002	0.0001
68	0.0003	0.0002
69	0.0003	0.0002

Table A4-Line data of 69 bus distribution network (Attari et al. 2016)

Line no	Starting bus	End bus	R (pu)	X (pu)
1	1	2	0.0003	0.0007
2	2	3	0.0003	0.0007
3	3	4	0.0009	0.0022
4	4	5	0.0157	0.0183
5	5	6	0.2284	0.1163
6	6	7	0.2378	0.1211
7	7	8	0.0575	0.0293
8	8	9	0.0308	0.0157
9	9	10	0.5110	0.1689
10	10	11	0.1168	0.0386
11	11	12	0.4439	0.1467
12	12	13	0.6426	0.2121
13	13	14	0.6514	0.2153
14	14	15	0.6601	0.2181
15	15	16	0.1227	0.0406
16	16	17	0.2336	0.0772
17	17	18	0.0029	0.0010
18	18	19	0.2044	0.0676
19	19	20	0.1314	0.0431
20	20	21	0.2131	0.0704
21	21	22	0.0087	0.0029
22	22	23	0.0993	0.0328
23	23	24	0.2161	0.0714
24	24	25	0.4672	0.1544
25	25	26	0.1927	0.0637
26	26	27	0.1081	0.0357
27	3	28	0.0027	0.0067
28	28	29	0.0399	0.0976
29	29	30	0.2482	0.0820
30	30	31	0.0438	0.0145
31	31	32	0.2190	0.0724
32	32	33	0.5235	0.1757
33	33	34	1.0657	0.3523
34	34	35	0.9197	0.3040

Line no	Starting bus	End bus	R (pu)	X (pu)
35	3	36	0.0027	0.0067
36	36	37	0.0399	0.0976
37	37	38	0.0657	0.0767
38	38	39	0.0190	0.0221
39	39	40	0.0011	0.0013
40	40	41	0.4544	0.5309
41	41	42	0.1934	0.2260
42	42	43	0.0256	0.0298
43	43	44	0.0057	0.0072
44	44	45	0.0679	0.0857
45	45	46	0.0006	0.0007
46	4	47	0.0021	0.0052
47	47	48	0.0531	0.1300
48	48	49	0.1808	0.4424
49	49	50	0.0513	0.1255
50	8	51	0.0579	0.0295
51	51	52	0.2071	0.0695
52	52	53	0.1086	0.0553
53	53	54	0.1267	0.0645
54	54	55	0.1773	0.0903
55	55	56	0.1755	0.0894
56	56	57	0.9920	0.3330
57	57	58	0.4890	0.1641
58	58	59	0.1898	0.0628
59	59	60	0.2409	0.0731
60	60	61	0.3166	0.1613
61	61	62	0.0608	0.0309
62	62	63	0.0905	0.0460
63	63	64	0.4433	0.2258
64	64	65	0.6495	0.3308
65	11	66	0.1255	0.0381
66	66	67	0.0029	0.0009
67	12	68	0.4613	0.1525
68	68	69	0.0029	0.0010

Table A5-Bus data of distribution network of Guwahati

Bus no	Real power (pu)	Reactive power (pu)
1	0	0
2	0.5000	0.2200
3	0.4700	0.2300
4	1.1300	0.6400
5	0.2700	0.1500
6	0.4200	0.2900
7	0.9400	0.4300
8	0.1300	0.0900
9	0.2500	0.1700
10	0.2300	0.1300
11	0.6300	0.3300
12	0.6700	0.2300
13	0.5300	0.3700
14	0.4500	0.3900
15	0.2300	0.1300
16	0.8400	0.4600
17	0.3700	0.1800
18	0.2300	0.1300
19	0.7300	0.4500

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