Optimal Planning of Electric Vehicle Fast Charging Stations and Distributed Generators in Distribution System

Submitted in partial fulfilment of requirement for the award of the degree of

Doctor of Philosophy

By

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CERTIFICATE

This is to certify that the dissertation work entitled **"Optimal Planning of Electric Vehicle Fast Charging Stations and Distributed Generators in Distribution System**", which is being submitted by **Mr. Battapothula Gurappa** (Roll No: 716117), is a bonafide work submitted to National Institute of Technology, Warangal in partial fulfilment of the requirement for the award of the degree of **Doctor of Philosophy** in Electrical Engineering. To the best of our knowledge, the work incorporated in this thesis has not been submitted elsewhere for the award of any degree.

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DECLARATION

This is to certify that the work presented in the thesis entitled "Optimal Planning of Electric Vehicle Fast Charging Stations and Distributed Generators in Distribution System" is a bonafide work done by me under the supervision of Dr. Chandrasekhar Yammani, Assistant Professor and Dr. Maheswarapu Sydulu, Professor, Department of Electrical Engineering, National Institute of Technology, Warangal, India and was not submitted elsewhere for the award of any degree.

I declare that this written submission represents my ideas in my own words and where others ideas or words have been included, I have adequately cited and referenced the original sources. I also declare that I have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in my submission. I understand that any violation of the above will be a cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

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CONTENTS

ABSTRACT

In recent times it has been observed that Electrical Vehicle (EV) is a promising technology for road transportation. There is a substantial increase in the number of EVs due to improved Energy efficiency and reduction in environmental impact as compared with internal combustion engine vehicles. The improper planning of Fast Charging Stations (FCSs) causes a negative impact on the Distribution System. In this context, the Distribution System operator has to face a significant challenge to identify the optimal location and sizing of FCSs in the Distribution Power Network.

The large-scale construction of FCSs for EVs is helpful in promoting the EV population. Even though the FCSs are optimally planned, it added additional load to the existing Distribution System. To ease these, addition of DGs in Distribution System is one of the suitable solutions. A multi-objective optimization problem has been formulated for the simultaneous placement and sizing of FCSs and DGs in the distribution system. The EV population in various zones and the possible number of FCSs based on the road as well as electrical distribution network topology have been considered as constraints in the proposed approach. This optimization problem is formulated as Mixed Integer Non-linear Problem (MINLP) and it is solved by using Non-dominated Sorting Genetic Algorithm-II (NSGA-II) to optimize the selected objectives like EV user loss, Network power loss, FCS development cost and improving the Voltage profile of the Electrical Distribution System.

From the last decade onwards, the EV population is greatly increased due to advanced developments in Batteries and its Charging technologies. This requires that the present and future increase in EV population has to be considered for optimal planning of FCSs and DGs in coupled Transportation and Electrical Distribution Network. A multi-objective optimization problem is formulated for optimal planning of FCSs and DGs with the objective of minimizing the Voltage deviation, Network power loss, DGs cost and the energy consumption of EV users. This optimization problem is solved for different levels of increase in future EV population for various cases. To solve the complex combinatorial problems a newly proposed Hybrid Shuffled Frog Leaping-Teaching Learning Based Optimization (SFL- TLBO) algorithm is implemented to solve the above multi-objective problem. The performance of the proposed algorithm is compared with prior-art algorithms in the literature.

To analyse the impact of load of Charging Station in Distribution System an accurate EV load model is required. The inaccurate modelling of EV load may overload the Distribution System which increases Network Power Loss (NPL) and maximum Voltage deviation. In literature, the Constant Power (CP) load model is more popularly used to model both the conventional and EV loads in the Distribution System. But the CP load modelling cannot provide accurate information about different types of voltage-dependent conventional loads and EV charging process. To address these aspects, the EV loads are modelled as constant Impedance-constant Current-constant Power (ZIP), Exponential and Constant Current (CC) load models. Then the conventional loads are modelled as Constant Power and Residential-Industrial-Commercial (RIC) loads. With these EV load models, the impact of FCS in the Distribution System has been analysed.

Nowadays, Battery Swapping Station (BSS) charging method is more popular, due to its short charging time just like gas refuelling station. This has increased travel range with the increased high capacity batteries. Further, the EV users need not pay the total initial cost of the battery. In addition to this, the batteries are charged in slow-charging mode to extend their life. The multi-objective BSS model is developed in order to optimize the number of new batteries taken from battery stock, charging damage and electricity charging cost of batteries. The dynamic electricity price is also considered for the EVs batteries in BSS. A BSS model with finite EV battery swapping demand in each hour of the day is solved by using a multi-objective Shuffled Frog Leaping Algorithm (SFLA).

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NOMENCLATURE

ACD	Average Charging Damage
BSS	Battery Swapping Station
BS^{max}	Maximum number of batteries taken from stock
BCC	Battery Charging Cost
BEV	Battery Electric Vehicle
C_{init}	Fixed cost of station development.
C_{lan}	Yearly land rental cost (in $/m^2$)
C_{con}	Charging connector development cost (in $/kW)
CPEV(h)	Charging probability of EVS in hour h of the day.
CFCS(j)	Capacity of j^{th} FCS
C_I	Investment cost of DGs.
$Cost_{INV,g}$	Inverter cost of g^{th} DG unit.
C_{OP}	Operational cost of DGs/MWh.
C_M	maintenance cost of DGs/MWh.
CP	Constant Power
d(z,j)	Distance between zone z and charging station j.
DG	Distributed Generation
DGPC	Distributed Generation Power Cost
DSM	Distribution SystemManager
EP	The Electricity Price ($/MWh)
EVUC	Electrical Vehicle User Cost
EV	Electric Vehicle
EVCS	Electric Vehicle Charging Station
FCS	Fast Charging Station
ICE	Internal Combustion Engine
INF_R	Inflation rate
INT_R	Interest rate
LCV	Light Vommercial Vehicle
Mcost	Maintenance cost of DG/MWh.
MINLP	Mixed Integer Non-Linear Problem
MVD	Maximum Voltage Deviation

NPLC	Network Power Loss Cost
NSGA-II	Non-dominated Sorting Genetic Algorithm-II
NEV(z)	Number of EVs in zone z.
NY	Total number of years in the planning horizon.
N_{DG}	Number of DGs.
Opcost	Operation cost of DG ($/MWh).
PC	Rated Power of Charging connector (in kW).
$P_{DG,g}$	Real power generation of g^{th} DG unit.
PHEV	Plug-in Hybrid Electric Vehicle
PLDV	Passenger Light-Duty Vehicle
RIC	Residential-Industrial-Commercial
SDC(j)	Station Development Cost of j^{th} FCS
S(j)	Number of connectors in j^{th} FCS.
SEC	Specific Energy Consumption of EV (in kW/km).
SOC	State of Charge
SFLA	Shuffled Frog Leap algorithm
SFL-TLBO	Shuffled Frog Leap-Teaching and Learning Based Optimization algorithm
TH(ω)	Total number of hours in each season.
Th	Total number of hours in year.
TNEV	Total Number of Electric Vehicles in study area.
TLBO	Teaching and Learning Based Optimization Algorithm
TOU	Time of Use
ZIP	Constant impedance-Constant current-Constant power

Chapter-1

Introduction

1.1 Introduction

1.1.1 History of the Electric Vehicles

For the development of human society, mobility is an advanced level of a basic need. In the early days of carriages, the horses were the principal source of power. Later, the horse power became a ‘unit of power’. Richard Trevithick built a steam powered carriage in 1801. This is the first horseless transportation. 30 years later of the noise and dirty Steam Engine, the first battery powered Electric Vehicles (EVs) were developed in 1834. After over 50 years, the first petrol powered Internal Combustion Engine (ICE) vehicle was built in 1885. The EVs are not new; it is about 50 years older than internal combustion vehicles. In early 1990s, the EVs were better than internal combustion ICE vehicles. After over 70 years the EV population declined due to the following reasons [1],

- By the 1920s, the United States had a better road system with the interconnection of all cities, which resulted in a need for long range vehicles.
- The reduction in the price of gasoline by the Texas crude oil unit could offer more affordable price to the average consumer.
- In 1912, Charles Kettering invented the electric starter which eliminated the need of hand crank.

The above initiation gave opportunity the mass production of internal combustion EVs by Henry Ford and made these vehicles widely available and affordable in the \$500–\$1000 price range. In 1912, the price of electric roadster sold was \$1750, while a gasoline car sold for \$650 [1].

The development of EVs has its own characteristics in different historical stages. The momentum or a driving force for the inventions, the technical features, applications, charging infrastructure, and business model were not all the same in different historical periods. However, the same spirit, fundamental principles, and philosophy remain today, inspiring us and providing useful references for current EV development.

From 1970s onwards, the EVs are blooming because they were clean, quiet, easy to start and drive, as compared to the steam cars or Internal Combustion Engine (ICE) vehicles that were noisy, smelly, produced a lot of smoke, and needed crankshaft to start an engine, as well as gear shift to drive. The major components of the Propulsion system were

DC motor drive and Lead-Acid batteries and these were used for low-speed, short-distance city driving purpose. Currently, the EVs may become a renewed and popular means of mobility. The internal combustion engine has the following disadvantages as compared to the electric motor [1],

1. The operation and construction of ICE is more complex and heavy in weight. Also, it is more expensive.
2. In ICE 75% of energy is wasted. It requires more maintenance.
3. It cannot run on Renewable Energy Sources like Solar, Wind etc.
4. The ICE produces an unhealthy exhaust. The every litre of gasoline produces the 2.3 kg of CO2.
5. The current transportation system is responsible for about 23% of greenhouse gas emissions worldwide.

The main advantages of the EV are that it mainly runs on a less cost and freely available Renewable Energy Sources (RESs), require less maintenance due to reduction in moving parts. But its major disadvantage is the requirement of large batteries for long range. At present the research is going on to improve the energy density of battery technology. In early 1990s, the size and weight of the battery were very high and the EVs were not that popular. Now days the energy density of battery is exponentially increased with time. Further, there is lot of research is going on Lithium-Air battery technology and its energy density is exactly equal to gasoline as shown in Table I [1].

Table 1.1: Energy density of different energy sources

Energy source	Year	Energy density (Whr/kg)
Lead-acid	1900	10
Lead-acid	2000	35
NiMH	2000	80
Lithium-ion	2015	250
Lithium-ion	2025	400
Gasoline or Lithium-air	1900-till date	12000

The total cost of ownership of ICE and EVs are compared in below table II. In table II the EVs in year 2000 and year 2030 are compared. This comparison clearly indicates that there are significant improvements added to the battery and drive train technologies.

Table 1.2: Total cost of ownership of ICE and EVs [2]

Vehicle part	Gasoline	EVs in 2000	EVs in 2030
Drive train cost ($)	15k	20k	5k
Battery cost ($)	0	100k	10k
Fuel cost/Year ($)	17k-40k	6k-10k	6k-10k
Maintenance cost/Year ($)	18k	12k	6k
Total cost ($)	50k-73k	65k-92k	19k-46k

Current trends suggest that the EV is a promising technology for road transportation. There is a substantial increase in the number of EVs due to improved energy efficiency and reduction in environmental impact as compared with ICE vehicles.

The International Energy Agency (IEA) global electric vehicle outlook 2018 made a survey on EVs sales and its charging infrastructure. Over 1 million electric cars were sold in 2017 – a new record – with more than half of global sales in China. The total number of electric cars on the road surpassed 3 million worldwide, an expansion of over 50% from 2016. The EV sales in different countries during last six years are listed below [1]. The recent figure is about 4.2 million electric cars in 2018.

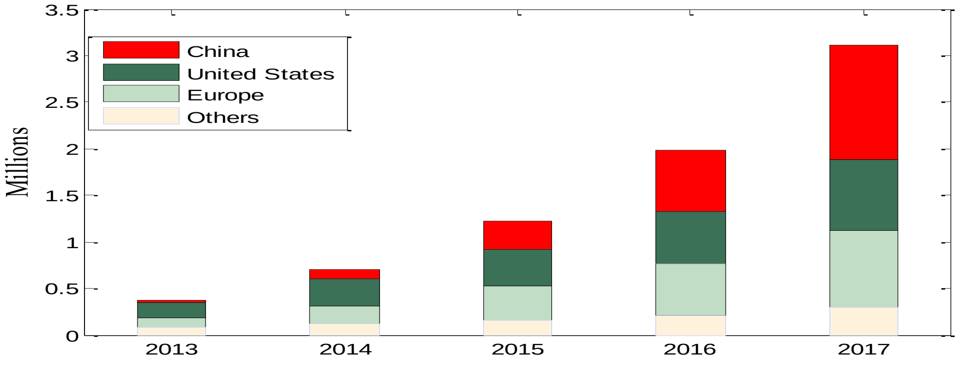


Figure 1.1: Number of global electric cars in circulation

The government of different countries is setting goals towards the EV deployment, providing more subsidy to EV users and manufacturing companies. Further, ten countries are giving great importance to improve the EV population collectively representing over 60% of the global electric car stock, endorsed the EV30@30 Campaign in 2017, pledging to actively pursue the collective objective of 30% EV sales by 2030. Also, a few regions or the national governments are pledged their intention to end the registration and sales of ICE vehicles in coming few years. The Table 1.3 summarises deployment goals and objectives for the 2020-2030 time frame.

Table 1.3: The EV deployment goals during 2020-2030 for various countries [3]

Region or Country	EV 30% @2030	2020-2030 EV Goals
China	Yes	✓ 5 million EVs by 2020, including 4.6 million PLDVs, 0.2 million buses and 0.2 million trucks ✓ Number of EVs sales share: 7-10% by 2020, 15-20% by 2025 and 40-50% by 2030.
Canada	Yes	40% of new passenger vehicle sales by 2040.
European Union	Yes	15% EV sales by 2025 and 30% by 2030
Finland	Yes	250000 EVs by 2030.
India	Yes	30% electric car sales by 2030. 100% BEV sales for urban buses by 2030.
Ireland		• 500000 EVs and 100% EV sales by 2030
Japan	Yes	20-30% electric car sales by 2030.
Netherlands	Yes	100% electric public bus sales by 2025 and 100% electric public bus stock by 2030.
New Zealand		64000 EVs by 2021.
Norway	Yes	100% EV sales in PLDVs, LCVs and urban buses by 2025.
United states		3300000 EVs in eight states combined by 2025.

There are different types of EV charging methods existing in literature like Conductive charging, Inductive charging, Capacitive charging and Smart charging. Among these the Conductive charging is more popularly used to recharge the EVs.

1.2 Conductive Charging

Conductive charging requires a metal-to-metal connection between the charger and the device requiring charging. Basically the conductive charging can be classified into two types. The first one is AC (Alternating Current) charging. It consists of level 1 and level 2 charging.

1.2.1 Level 1 AC charging:

Almost all PHEVs come with a Level 1 charging cord. One end of the cord is a standard connector that can be plugged directly to a wall outlet at home. The other end is a SAE J1772 standard connector that plugs into the vehicle's J1772 charge port [2]. Therefore, there is no need for additional charging equipment. Level 1 charging can be provided, by using an on-board charger, up to 1.9 kW through 120 V single-phase AC. This is mainly used in the countries where the single phase voltage is 120 V. The level 2 will address the case of 230 V AC supply.

In Japan and North America, many of the EVs are using the SAE J1772 charging connector, which contains five pins and a mechanical lock. The level 1 charging cord and SAE J1772 five pin plug are as shown in figure 1.2.

Charging cord

SAE J1772

Figure 1.2: Level 1 charging cord [8]

1.2.2 Level 2 AC charging:

This charging option uses the same SAE J1772 charging cord as in level 1, but it offers better output power up to 19.2 kW by using an on-board charger. Level 2 charging is applicable to premise the supply of AC at 208 or 240 V, and requires dedicated electric circuit to support a higher current up to 80 amp. This option is suitable for charging at home, as well as at public charging facilities, although residential level 2 charging operates at a lower current (about 30 amp) and a lower power of 7.2 kW, as compared to the public ones. Level 2 is preferred over level 1 due to short charging time.

Level 2 charging uses the Mennekes connector; this connector has seven pins and takes advantage of the three-phase alternating charging. The exception to this regional breakdown is Tesla, which uses a proprietary connector for its vehicles sold in North America, although adapters to SAE J1772 are available. In Europe and Asia, Tesla vehicles have the Type 2 plug and it is as shown in Figure 1.3.

Mennekes | Tesla (US)

Figure 1.3: Level 2 charging connector types [8]

1.2.3 Level 2 AC charging (3-phase AC at 480 V):

This is a new charging option which is being developed by Society of Automotive Engineers (SAE) to supply up to 130 kW for very rapid restoration of State of Charge (SOC), using 3-phase AC at 480 V and high current [2]. This 3-phase power distribution is common at Commercial and Industrial locations. To support the high output power, level 2 chargers are much larger in size and heavier in weight as compared to level 1 and level 2 single phase charger. Also, level 2 *3-phase chargers* require dedicated cooling equipment for high power electronics equipment. As a result, level 2 *3-phase chargers* are not installed on-board, but they are located externally (off-board). It is likely that SAE J1772 connector will not be suitable for this option.

Main disadvantage of AC charging system is that it has to be converted in to DC for charging the battery, which results in low efficiency. Now a day's level 3 or DC Fast Charging Station is more popularly used due to its high powered fast charging system for highway charging on long distance journeys.

1.2.4 Level 3 (DC fast charging)

The DC fast charging offers an experience almost similar to Gasoline refueling for longer-distance travel. It requires off board EV charging connector along with the proper communication between EV and charging post. Further, more safety is needed due to its high power ratings. *There are three charging standards for DC fast charging*. The first one is CHAdeMO connector, its means "charge to move". CHAdeMO connector is developed by Tokyo Electric Power Company in 2011. Currently, CHAdeMO is more popularly used in United States in the Nissan Leaf and Mitsubishi EVs. At present the CHAdeMO fast chargers are rated up to 70 kW and the company announced that it would be upgraded to a rating of 150 kW [2].

The next or second standard DC fast charging is Coast Clutch Solenoid (CCS) or SAE Combo. The word combo means the plug consists of both AC and DC charging facility. It is developed by a group of European and US auto manufacturers in 2011. At present the CCS fast chargers offer charging power up to 50 kW. The third DC fast charging standard is developed by Tesla in 2012. It is operated at 480 V and with the maximum power rating of 120kW. Tesla Company announced that it would be upgrade the Tesla connector to a rating of 350 kW [2].

CHAdeMO | CCS (North America) | CCS (Europe)

Figure 1.4 DC fast charging connector types [8]

The advantage of DC fast charging is that it connects directly to the battery input system. Level 3 charging is typically around 480 V and 100 Amps. The maximum output power available is 120 kW and this has the potential to add 200 miles of range in 1 hour, or 100 miles in 30 mins. The actual power is “negotiated” between the charger and the EV battery management system, on a real time basis. Thus, the actual current varies greatly according to the Temperature of the battery and the State of Charge (SoC). The comparison of different charging levels of EVs is listed in Table 1.4.

Table 1.4: The comparison of different charging methods of EVs [3]

Charging method	Charge Time	Power(kW)/ Voltage(V)/ Current(A)	Power Equivalent
Level 1	2 to 5 miles of range per hour of charging	1.2-2.4/120/15	Toaster
Level 2	10 to 20 miles of range per one hour of charging	7.2-7.6/240/40	Clothes dryer
DC Fast Charging	80to 100 miles if range per 20 minutes of charging	100-120/480/125	CHAdeMO

1.2.5 Charging Communication Protocols

The Charging communication protocols are necessary for both the EV users and grid operators. For optimal charging of EV battery the EV user needs to know the state of charge, state of health, battery voltage and required safety information. Further, the EV user has to know Time-of-Use (ToU) Pricing, Distribution network capacity and the Demand response measures. The CHAdeMO uses a communication protocol knows as CAN and the CCS or SAE Combo uses the PLC protocol. In United States and Europe Open Charge Point Protocol is more popularly using, it is developed by Open Charging Alliance.

1.3 Wireless Power Charging (WPC)

The wireless charging is working based on the principle of inductive coupling. It is also known as inductive charging. In this kind of coupling, charging pad is placed on the pavement and the charging pad is placed underneath of the EV. The electric current is passed through the pavement pad, which creates a circular magnetic field that is captured by EV receiving pad to charge the EVs batteries.

The wireless EV charging system has four methods: 1) traditional inductive power transfer charging 2) Capacitive wireless power transfer (WPT) charging 3) Magnetic gear wireless power transfer 4) Resonant inductive power transfer. The comparison of above wireless power transfer technologies for EVs is given Table 1.5.

Table 1.5: Comparison of different WPT methods for EVs charging [6]

WPC methods	Performance			Price	Suitability for EV charging
	Efficiency	EMI	Frequency range (kHz)		
Inductive	Medium/High	Medium	10-50	Medium/High	High
Capacitive	Low/Medium	Medium	100-600	Low	Low/Medium
Permanent magnet	Low/Medium	High	0.05-0.5	High	Low/Medium
Resonant inductive	Medium/High	Low	10-150	Medium/High	High

Further the WPT can be classified in two types: 1) Static charging 2) Dynamic charging

1.3.1 Static Charging

The static WPT charging technology is used when the vehicle is stationary. Static wireless charging can easily replace the EV with minimal driver participation and it solves the safety hazards like trip hazards and electric shock. The following are the merits and demerits of static charging.

Merits:

1. Static charging is more convenient

2. It is suitable for self-driving EVs
3. It is more safety charging method

Demerits:

1. High initial investment required for static charging
2. More induction losses occurred
3. It creates radiation exposure

1.3.2 Dynamic charging

At present the EVs are greatly suffered from two major drawbacks-initial cost and range anxiety. To overcome these drawbacks the EVs are required to charge frequently or install large capacity battery. This creates additional problems such as increase in cost and weight of EVs. The dynamic wireless charging system is a promising technology, which can reduce the problems associated with range anxiety and cost of EVs. The following are the merits and demerits of dynamic charging [7].

Merits:

1. Dynamic charging reduces the stand-in charge time
2. Minimum battery depth of discharge, it increases the life time of battery
3. Smaller EV battery required

Demerits:

1. The abrasion and foreign objects on road surface reduces the efficiency
2. High magnetic flux leakage
3. Real-time coil misalignment estimation is required

1.4 Battery Swapping Station

In recent years, the people are moving towards the Battery Swapping Station (BSS) methodology, due to its own advantages. In BSS technology the EV owners swap their depleted batteries in nearby BSS with the fully charged batteries. This process takes around three minutes just like gasoline refueling stations. In BSS method, the EV driving into a battery switching bay and the automated system will position the EV and current battery is replaced with the fully charged battery [3]. The depleted batteries are charged (with appropriate Level-1, Level-2 and Level-3 charging options) in BSS based on next hour’s demand and electricity price. The BSS charging method has more advantages as compared to the conductive and inductive charging. The following are the advantages of BSS charging method,

1. The BSS provide fully charged battery, without waiting for battery charging.
2. The range anxiety is eased to some extent.
3. The charger is outside of EV, so there is no limitation on size and power levels of charger.
4. The BSS provides high flexibility on the charging power as well as charging time of battery based local load demand.

However, the BSS charging method is not so popular due to the following reasons.

1. A standardized battery and its interface devices required across the all EV users and BSS.
2. The EV users cannot accept the not owning the battery.
3. The frequent connection and disconnection of EV battery causes safety issues.
4. There should be a reliable way to estimate the state of health of battery and a better communication (arrival time, state of charge and travelling distance) required between EV users and BSS.

1.5 Distributed Generations (DGs)

Distributed Generations (DGs) in Distribution System networks are rapidly increased as the load demand on the Distribution System is growing exponentially. DG is small-scale power generation and usually located in distribution network. DG units are mainly energized by Wind, Solar and Fuel cell and have many advantages over centralized power generation. The optimum DG placement and sizing at planning stage of distribution system is necessary to achieve reduction of power system losses and improve the voltage profile. However, installing of DG units at non-optimal place may get an opposite effect to what is desired.

Selecting the best places for installing DG units and their preferable sizes in large distribution systems is a complex combinatorial optimization problem. Further, the optimal planning of FCSs and DGs in distribution system, and optimal scheduling of EV batteries in BSS are the complex combinatorial (the objective function with two more objective parameters) optimization problems. To solve these, multi-objective meta-heuristic techniques with good exploration and exploitation are popularly used.

1.6 Multi-Objective Optimization

Multi-objective can be defined as the problem of finding "a vector of decision variables which satisfies the constraints and optimize a vector function whose elements represent the objective function". These objective functions are from mathematical description of relevant performance criteria and are usually conflicting with each other. Hence, the term 'optimize' means finding a solution which give the values of all objective functions that are acceptable [8].

Though the multi-objective optimization offers a set of solutions which are all optimal, the user needs only one final solution. The user needs some higher level information to choose one solution from the set of optimal solutions. Often, such higher level information is non-technical, qualitative and experience driven. Therefore, in a multi-objective optimization, idealist effort must be made in finding the set of trade-off optimal solutions by considering the all objections simultaneously. After a set of such trade off solutions are found, the user can use high level information to make a choice. Higher level information is usually taken from domain expertise.

The principle of an ideal multi-objective optimization procedure is to: 1) find multiple trade-off optimal solutions with a wide range of values for objectives 2) choose one of the solutions using higher level information. This approach is depicted in Figure 1.5.

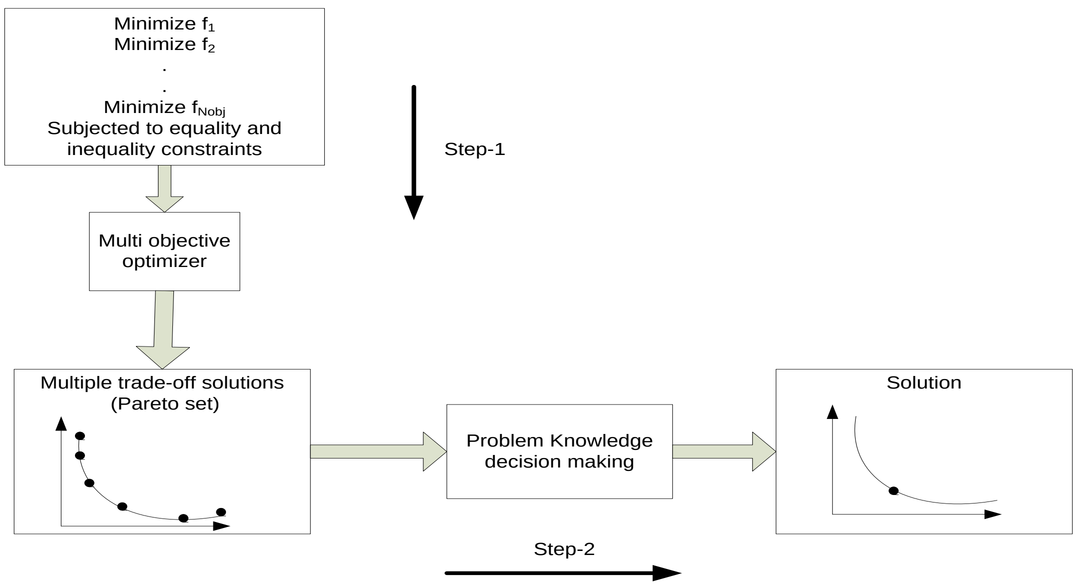


Figure 1.5: Schematic of an ideal multi-objective optimization procedure [10]

The Figure 1.5 shows the principle of an ideal multi-objective optimization procedure. Step-1 is achieved by blocks vertically downwards where optimization is performed for f_1 to f_{Nobj} using Multi-objective optimizer. Step-2 is achieved by horizontal blocks towards the right. The single objective problem doesn't require step-2. But, in case of objective function optimization with multiple global solutions, both steps are necessary.

In multi-objective optimization, a solution could be best, worst and also totally different from other solutions, with respect to the objective function values. Best solution means a solution which is not worst in any of the objectives, but at least better in one of the objective functions. The optimal solution is the solution set that is not dominated by any other solution in the search space. Such an optimal solution is called a Pareto-optimal solution and the entire set of such optimal trade-off solutions is called a Pareto-optimal set.

1.7 Meta-heuristics Techniques

Most conventional or classic algorithms are deterministic. For example, the Simplex method in linear programming is deterministic. Some deterministic optimization algorithms have used the Gradient information and they are called Gradient-based algorithms. The well-known Newton-Raphson algorithm is Gradient-based approach, as it uses the function values and their derivatives, and it works extremely well for smooth uni-modal problems. Even though, if there is some discontinuity in the objective function, it works well. But it gives a single optimal solution. The multi-objective optimization gives multiple optimal solutions as an optimal Pareto front. The solutions present in the optimal front are optimal.

For stochastic algorithms, in general we have two types: heuristic and meta-heuristic, though their difference is small. Generally speaking, heuristic means "to find" or "to discover by trial and error." Quality solutions to a tough optimization problem can be found in a reasonable amount of time, but there is no guarantee that the solutions have reached the optimal solutions. It can be expected that these heuristic algorithms work most but not all the time. This is good when we do not necessarily want the best solutions or rather good solutions are easily reachable. Further development of heuristic algorithms is the so-called meta-heuristic algorithms. Here Meta means "beyond" or "higher level," and these algorithms generally perform better than simple heuristics. In addition, all meta-heuristic algorithms use certain trade-offs of randomization and local search. It is worth pointing out that no agreed definitions of heuristics and Meta-heuristics exist in the literature; some use the terms heuristics and Meta-heuristics interchangeably. However, the recent trend is to name all stochastic algorithms with randomization and local search property as Meta-heuristic. Here we also use this convention. Randomization provides a good way to move away from local search to another search on a global scale. Therefore, almost all Meta-heuristics algorithms tend to be suitable for global optimization.

Two major components of any meta-heuristic algorithm are intensification and diversification, or exploitation and exploration. Diversification means to generate diverse solutions so as to explore the search space on a global scale. Intensification means to focus on the search in a local region by exploiting the information that a current good solution is found in this region. This is in combination with the selection of the best solutions. The selection of the best solution ensures that the solutions will converge to the optimality, whereas the diversification via randomization avoids the solutions being trapped at local optima and, at the same time, increases the diversity of the solutions. The good combination of these two major components will usually ensure that the global optimality is achievable [8].

Meta-heuristics, in their original definition, are solution methods that organize an interaction between local improvement procedures and higher level strategies to create a process capable of escaping from local optima and performing a robust search of a solution space. Over time, these methods have also come to include some procedures that employ strategies for overcoming the trap of local optimality in complex solution spaces.

A number of tools and mechanisms that have emerged from the creation of metaheuristic methods have proved to be remarkably effective. With that Meta-heuristics have moved into the spotlight in recent years as the preferred line of attack for solving many types of complex optimization problems, particularly those of a combinatorial nature.

The problem considered in this dissertation is “Multi-objective optimal planning of FCSs and DGs in distribution system” and it is also a complex combinatorial problem with many constraints. To obtain optimal solution for these types of problems a suitable multi-objective optimization Algorithm is required.

Due to the great improvements in charging methodologies and increase in EV population, the literature survey initially focussed on optimal planning of FCSs in distribution system. Even though the FCSs are optimally planned, it added load to the distribution system. To ease these, the addition of DGs along with FCSs in distribution system is one of the suitable solution. Further, the survey is continued on effect of EV load modelling in distribution system and optimal scheduling of EV batteries in BSS.

1.8 Literature Review

1.8.1 Optimal planning of Charging Stations in Distribution System

Wang .G et al., have considered the power distribution network, traffic network and EV owners driving behavior to formulate a multi-objective charging station planning method in [9]. The objectives in multi-objective optimization problem are to minimize the power loss and voltage deviation in the distribution network and the maximization of the service capability of charging station. To solve this optimization problem an efficient Cross-Entropy method is used and obtains the optimal Pareto solutions. However, the EV demand for services has been assumed to occur at fixed locations of the traffic network.

To investigate the optimal site for EV charging station, the impact of fast charging at several specified sites in an existing distribution system has been calculated in [10]. The short circuit and protection studies were carried out at these sites using the utility-grade software packages.

In [11], the authors firstly, the optimal location of EV charging station have identified by a two-step screening method with the account of environmental factors and the service radius of EVCSs. Secondly, a modified Primal-Dual Interior Point algorithm was proposed to determine the size of charging station by considering the total cost associated with the charging stations. The developed model was applied on IEEE 123 bus test system. The results indicated that the proposed method was significantly faster in minimization of distribution network power loss and improvement in voltage profile. But the EVs charging demand and their uncertainties were not considered.

Sadeghi-Barzani P et al., have proposed a Mixed Integer Non-Linear Programming (MINLP) problem to solve the optimal planning (placement and sizing) of FCS, with the account of the cost of charging station, EV energy loss, electrification and electrical power loss in the distribution system in [12]. The geographic information has been used to calculate the EV energy loss and station electrification cost. The size and location of charging station have been determined by solving the optimization problem using Genetic Algorithm (GA).

Albert et al., the EV charging station placement problem was formulated as Mixed Integer Linear Problem (MILP) based on the convenience of drivers and the charging station coverage in [13]. The authors proved that the optimization problem was nondeterministic polynomial-time hard. To tackle this optimization problem the iterative MILP, Greedy Approach, effective MILP and Chemical Reaction optimization techniques were applied. The above each optimization method has its own characteristics and it was suitable for different situations like solution accuracy, problem size and existence of system prerequisite.

The state of California uses freeway exits and highway intersections as moderate candidate charging station locations and also solves the optimization problem to optimize the number of FCSs in [14]. This study suggests that, the reservation system can benefit both the EV users and FCS operators by reducing the waiting time and minimizing the extra charging connecters needed.

Guo et al., a multi-criteria decision making method has been used for selecting the most sustainable site of EVCSs by considering environmental, economic and social criteria in [15]. Further, to reflect the vagueness and ambiguity due to the judgements of decision makers, fuzzy Technique for Order Preference by Similarity to Ideal Situation (TOPSIS) method was applied for optimal charging station site selection.

In [16], a heuristic algorithm has been employed to determine the optimal location and sizing of charging stations by considering the various aspects like initial investment cost and distribution system power quality parameters (real power loss reduction index, reactive power loss reduction index and voltage profile improvement index), in the objective function for the city of Allahabad in India. The improved version of Particle Swarm Optimization (PSO) was compared with the conventional GA and PSO algorithm and it was found that improved version of PSO has offered better results with minimum computational time.

A zonal approach and the geographic information associated urban roads, city zones and electric substations have been considered in [17], for optimal planning of FCSs in distribution system. The EV user behavior and hourly load profiles were considered to evaluate the expected charging demand, EV user cost and electric grid losses in distribution system. The extra power losses due to EV charging were also calculated by using AC load flow. The optimization problem was formulated as MINLP and it was solved by using the Genetic Algorithm to determine the optimal location and capacity of charging stations. For the optimal planning of FCSs the EV user charging preference plays a major role. But in this paper, the uncertainties regarding to initial SOC and charging start time of EVs have not considered.

X. Wang et al., the EV charging stations were placed at selected bus stops, to minimize the total installation cost of charging stations. For optimal planning of FCSs the two different scenarios were considered in [18]. The first one was by considering the battery size of EV and the second one was without considering the battery size of EV. Both the problems were formulated as integer nonlinear programs and solved by using Linear Programming Relaxation algorithm to get an optimal solution. The results demonstrate that, larger size of battery results in minimization of total cost of charging stations at selected bus stop.

C. Luo et al., have applied a nested logit model to analyze the charging preference of the individual EV user and to predict the aggregated charging demand of each charging station in [19]. To determine the optimal location and size of FCSs, the authors have considered both the transportation network graph and the electric power network graph. The EV virtual city 1.0 Simulation Software was developed using the Java to investigate the interactions among the EV users, transportation network, electrical network and charging stations. A series of experiments were conducted on the city of the San Pedro District of Los Angeles, CA, USA, by collecting demographic and geographic data and it was found that, the charging station placement was highly consistent with the traffic flow. The authors have not considered the power quality parameters of distribution system in different stages of problem solving.

The interactions between the road transportation and electrical network have been considered for optimal planning of FCSs in distribution system in [20]. The capacitatedflow refueling location model has been used to capture the EV charging demand on the road transportation network under the constraints of different driving ranges. Then MINLP model was formulated for EV FCS planning with the electrical and transportation network constraints, which can be solved by using the deterministic Branch-and-Bound methods.

In [21], a realistic model has been developed for the FCS placement problem in cities like Singapore by considering the interactions among charging stations, EV users charging activities, traffic congestion and queuing time. Initially, the FCS planning problem was formulated as bi-level optimization problem, later it is converted in single level optimization problem by exploiting the equilibrium point of EV charging game.

Liu H et al., have determined the moderate location of EVCS by using the Integrated Multiple Criteria Decision Making approach based on Grey Decision making trial and Evaluation Laboratory and uncertain linguistic multi-objective optimization in [22]. Grey Decision making trial and Evaluation Laboratory method was used to calculate the criteria weights and the uncertain linguistic multi-objective optimization by ratio analysis plus full multiplicative form has been used to select the optimal location of FCS.

The Bayesian network model has been used to determine the optimal location of charging stations based on a sustainability perspective with the consideration of both qualitative and quantitative factors in [23]. Further, the sensitivity analysis was applied to validate the model and to identify the impactful factors on charging station location problem.

Xiangning Lin et al., the analytic hierarchy process and load density method were used to calculate the cost coefficients of the objective function and to optimize the capacity of the charging station in [24]. Further, the authors have considered the aspect of Vehicle-to-Grid. The optimization problem has been solved with the inclusion of the initial investment, operational and maintenance costs of feeders, substations and charging stations.

In [25], the EVCS location has been determined in two stages. In the first stage, the service range of EVCS was evaluated using trip success ratio with the account of the uncertainty of trip distance and uncertainty in the remaining electric charge of EVs. In the second stage, the service range of charging station has been determined for the optimal location of the charging station. The optimization problem was formulated as the maximum covering location problem in order to identify the optimal location of EVCSs in the distribution network.

1.8.2 Simultaneous planning of FCSs and DGs in Distribution System

In [26], the joint planning of EVCS and distributed Photovoltaic generation in the distribution system has been solved by using an accelerated generalized Benders Decomposition algorithm. A multidisciplinary approach has been proposed with the account of investment cost (the fixed cost of EVCS and PV power plant, variable cost for adding an extra charging spot in EVCS and per unit PV panel in PV power plant) and maintenance cost (the cost of electricity, penalty for unsatisfied PEV charging demand and penalty for undesirable voltage deviation), for identifying the location and size of EVCS and PV plant.

In [27], an optimization model has been presented for the optimal planning of DG units, EVCSs, and Energy Storage systems within the electrical distribution system. The optimal planning of charging stations, renewable DG units and energy storage systems in the distribution system was solved by using a Second-Order Conic Programming problem, to optimize the active power loss and the penetration of DG, EVCS and energy storage systems within the distribution system. In this paper, most of the data was derived from probabilistic distributions which were not realistic.

The optimized design of the EV charging station was explained in [28] with the integration of Renewable Energy Sources (RESs) and energy storage system. The Monte Carlo simulation was used to model the EV charging demand and the Renewable Energy Generation. Further, the GA was employed to maximize the net profit value. In this paper, the authors have not considered the simultaneous planning of both the charging stations and Renewable Energy Generation units. The optimization problem was attempted by using the weighted sum approach.

Mohammad H et al., have determined the simultaneous optimal location and size of RESs and charging stations with the minimization of network power loss, voltage deviation and charging cost of EVs as objectives in [29]. The optimization problem was solved by using the multi-objective Differential Evaluation algorithm to get an optimal location and size of charging stations and RESs. Further, the objective coefficients were calculated to increase the load factor by shifting the EV charging peak demand in to the domain of the hours with high solar radiation and wind speed.

1.8.3 Impact of EV load modelling in Distribution System

Mota .L et al., have obtained the realistic system analysis by using an accurate load model in [30]. The aim of this model was to optimize the operating cost while maintain the system security and reliability. However, the load modeling was a complex problem due to distinctive feature of different type of loads in the distribution system. The Exponential and the ZIP load models have been used to estimate the load parameters and the Weighted Least Squares method in recursive form was applied for dynamic parameter estimation.

In [31], a group of well-defined EVs have been established to analyse their energy consumption and storage in the context of heavily electrified road transportation. The same requirements have been applied on European Union residential load profile to evaluate the impact of increased EV load and the potential for residential and EV load integration.

The comparative studies have been carried out in [32] for various charging methods like uncontrolled domestic charging and off-peak domestic charging, smart charging and uncontrolled public charging. The optimization problem was stochastically formulated in order to account the stochastic nature of individual SOC and the starting charging time of each battery. The expected changes in future electricity tariffs and EV load have been incorporated in the above four scenarios. The degree of accuracy of results obtained by using proposed algorithm has not reported.

Mullan .J et al., the potential impacts of EV charging has been tested on the Western Australian electricity grid by using constant power load model with the account of constraints on the system’s capacity to supply electricity for EV recharging in [33]. The test results demonstrated that, if the EV charging behaviors were managed from outside, then the electrical utility and transmission companies can get the significant short-term and long term benefits. Further, it has been investigated how the EV demand will affect the various components in electrical network.

Li .G et al., have applied the probabilistic power flow load model to analyze the impact of PHEVs charging on electrical distribution system in [34]. Basically it emphasized a single PHEV charging load model and then focused on Queuing theory to describe the behavior of multiple PHEVs in the distribution system. Two more scenarios have been carried out. The first one was modelling the overall EV charging demand at a charging station and the second one was modelling the overall EV charging demand in a local residential community. At the end a comparison has been made for results of the probabilistic power flow load model and Monte Carlo simulation.

In [35], the multistate ZIP EV load model has been developed for Nissan Leaf using the level-1 charging. The results demonstrated that the Nissan Leaf with level-1 charging was similar to Constant Current load model. The multistate ZIP load model was compared with the Constant Current load, which indicated that the predicted losses were lower in ZIP load model as compared with Constant Current load model.

Stephen Schey et al., [36] summarizes the usage of Electric Vehicle Supply Equipment (EVSE) in households with Nissan leafs. To analyse the charging usage of EV, the data aggregation model has been developed by means of two metrics i.e. the charging demand and charging availability. Further, the impact of large scale EVs and the AC and DC EV charging methods were analysed.

To study the impact of Plug in Hybrid Electric Vehicle (PHEV) in distribution system, a comprehensive load model has been developed in [37], by considering the battery capacity, SOC, number of electric vehicles, penetration level for upcoming years and energy consumption in daily trips. The impact of load of PHEVs charging has been tested with IEEE 34-bus radial distribution system. Further, the sensitivity analysis has been carried out to study the effects of PHEV operation modes in distribution network.

A multistage time-variant ZIP EV load model is proposed in [38] for the accurate analysis of EV battery charging. An accurate voltage dependent FCS EV load model has been presented with the account of power consumption, grid voltage and SOC of EVs.

Purvins et. al., have proposed an accurate EV charging system by considering the constraints in the power converter which connects battery to electric grid [39]. To analyse the variation of power losses and voltage deviation in distribution system, the different voltage dependent EV load models have been presented in [40].

1.8.4 Optimal scheduling of EV Batteries in BSS

In [41] and [42] the authors have explained that, over the past decade the EV population was greatly increased to reduce reliance on fossil fuels and lower environmental pollution. However, many car owners were still deterred to buy EVs due to certain major drawbacks of EVs, such as long charging time, range anxiety, expensive EV batteries and short life time with fast charging. An efficient solution to these problems is the deployment of BSS to encounter all the drawbacks. Firstly, The BSS provides a short charging time just like gas refuelling station. Secondly, the range is increased with high capacity batteries and by swapping a battery in nearby BSS. Thirdly, the EV users need not to pay the total initial cost of battery. Fourthly, in BSS technology, the batteries are charged in slow-charging mode to extend their life.

Q. Dai et al., have proposed an universal EV charging load forecasting method for Battery Swapping Station (BSS). To analyze the stochastic nature of BSS, the numbers of buses for battery swapping, charging start time, charging duration and the travelled distance were considered in [43]. The Monte Carlo simulation was used to estimate the uncontrolled energy consumption of BSS. Further, to estimate the uncertainty of EV charging demand the Generic Nonparametric method was employed. But, the parameters like battery degradation cost and the electricity Time of Unit (ToU) price were not considered.

N. Liu et al., [44] have proposed a novel charging strategy to improve the operational performance of PV based BSS, with the account of self-consumption of PV energy, the service availability and operational profit. The specialty of proposed method was that a new decision-making approach was implemented instead of optimization algorithm. The charging methodology has been considered for simultaneous operation of the power distribution and battery-swapping service model.

M. R. Sarker et al., have developed an optimization framework model for operational scheduling of EV batteries in BSS in [45]. It has considered the day-ahead scheduling process. In this optimization problem, the battery demand uncertainty and the electricity price uncertainty were modelled with Inventory Robust Optimization and Multi-band Robust Optimization respectively. Further, the batteries were scheduled in BSS to operate in the mode of Grid to Battery (G2B), Battery to Grid (B2G) and Battery to Battery

(B2B). The results obtained from the proposed model were helpful to stakeholders for the design and operation of BSS, to enhance the environmental sustainability of the power system with the integration of RESs and it allows taking short-run and long-run market decisions that exploit the storage capabilities of BSS. However, the authors have not incorporated the EVs demand uncertainties.

Q. Kang et al., [46] have proposed a novel centralized charging strategy for EVs in BSS by considering the optimal charging location and charging priority based on spot electricity price. A population based optimization algorithms i.e. GA and PSO were used to minimize the charging cost, electric power loss and voltage deviation of electrical distribution system. Further, to get more accurate results a hybrid PSO-GA with dynamic crossover and adaptive mutation strategy was proposed and it has been compared with the GA, PSO and IPSO.

In [47], a two level hierarchical model has been proposed. In which the unit model follows a transition-based battery allocation technique and the station model offers a system-view platform. Based on the above hierarchical model, the grid scheduling strategy with battery reservation and the general grid scheduling were evaluated in terms of average battery life and net profit using South Australia and New South Wales electricity demand profiles. The test results demonstrate that, the grid scheduling strategy with battery reservation results in maximization of both profit and life time of batteries.

Hao .W et al., have formulated a multi-objective optimization problem for BSS in order to optimize the number of batteries taken from stock and charging of damage batteries using different charging methods in [48]. The varied population Genetic Algorithm (GA) and varied population Differential Evaluation (DE) algorithm have been proposed in order to calculate the optimal solution and these algorithms were compared with conventional GA, Particle Swarm Optimization (PSO) and IPSO. The results demonstrate that the varied population GA and varied population DE were giving better results with less computational time.

In [49], the optimization problem was formulated in order to minimize the cost by determining the optimal scheduling of EV batteries in BSS. Here, the cost includes the number of batteries taken from stock to serve for the all incoming EVs swapping demand, charging of damage EV batteries with the use of high power rating chargers and electricity charging cost of EVs during different time periods of the day. An integrated algorithm has been proposed to solve the above optimization problem, which was inspired by the GA, DE and PSO. The proposed method was not suitable, if the depleted battery inventory has few or no batteries.

B. Sun et al., have proposed an optimal charging policy with the aim of minimizing charging cost while ensuring the Quality-of-Service in [50]. The charging scheduling problem has been formulated as a constrained Markov Decision process and the optimal policy was derived by the standard Dynamic Programming and Lagrangian method. Further, to avoid the curse of dimensionality in practical applications the structure of the optimal policy and Dynamic Programming procedure transform into an equivalent threshold optimization problem with a discrete separable convex objective function.

P. You et al., have proposed an optimal charging scheduling problem for BSS that assigns each EV to optimal charging station to swap its depleted battery based on its current location and state of charge in [51]. The optimal charging scheduling problem considers to minimize the weighted sum of travelled distances of EVs and electricity charging cost with the account of EV range and grid operational constraints. To solve the optimization problem the Second-Order Cone Programming Relaxation of optimal power flow and generalized Benders Decomposition algorithms have been used.

In [52], the optimal scheduling of EVs batteries in BSS has been proposed and it was solved by using Non-dominated Sorting Genetic Algorithm-II to optimize the battery charging cost, distribution network power loss cost, voltage profile and network power loading capacity. Further, the Dynamic Pricing model was applied for EV battery charging scheduling.

In [53], the scheduling of charging bays in BSS have been proposed with the aim of minimizing charging cost while satisfying the fully charged batteries demand. Basically, the BSS has two types of operations. The first one is loading the depleted batteries in to charging bays and unloading the fully charged batteries. The second one is controlling the charging rate of individual charging bay. The optimization problem as formulated has Mixed Integer Non-Linear with quadratic battery degradation cost and it was solved by using Benders Decomposition algorithm. The significance of proposed algorithm was that it solves own sub problem in each charging bay and then each sub problem was partitioned into multiple independent and identically structured problems for efficient parallel implementation.

1.9 Motivation

From the above literature review, it is observed that the maximum benefits can be obtained from the optimal planning of FCSs and DGs in the distribution system. But there is a greatest challenge to create adequate charging infrastructure to meet the present and future increased EV population demand. The increased EV charging infrastructure will cause certain problems (increase of power losses, line loading and the voltage deviation) in the distribution system.

- ✓ To overcome the above mentioned problems, the simultaneous planning of FCSs and DGs in the distribution system is required. Further, the optimal planning of FCSs and DGs in distribution system has to be addressed by considering the present and future increase in EV population.

- ✓ Next, for analyzing the impact of the load of charging stations on the performance of distribution system an accurate EV load model is required.

- ✓ Multi-objective optimal scheduling of EV batteries in BSS has to be developed in order to optimize the number of batteries taken from battery stock, charging damage and electricity charging cost of batteries.

1.10 Objectives of Thesis

The objectives of this thesis include:

- To develop a multi-objective optimization model for simultaneous optimal planning of FCSs and DGs in distribution system.
- To propose an optimization algorithm that enhances the exploration and exploitation of the optimization problem in a multi-objective environment. Thus, a novel hybrid Shuffled Frog Leap-Teaching Learning Based Optimization (SFL-TLBO) algorithm is proposed and implemented to solve the optimization problem for optimal planning of FCSs and DGs in the distribution system for the present and future EV load enhancement.

- Further, to analyze the impact of load of FCS in distribution system with various EV load models.
- To develop multi-objective BSS model to optimize the number of batteries taken from battery stock, battery degradation and electricity charging cost of batteries.

1.11 Outline of Research Work

In the majority of previous works, the authors have considered the optimal planning of charging stations only as it strongly affects the distribution system power losses and voltage profile. It also causes the over loading in distribution system. From the literature, it is noticed that the optimal planning of DGs in distribution system results in improved voltage profiles, reduced real and reactive power losses. Hence, there is a need of simultaneous planning of both the FCSs and DGs in distribution system. The improper planning of FCSs and DGs causes a negative impact on the distribution system. In this context the distribution system operator has to face a significant challenge to identify the optimal location and size of FCSs and DGs in the distribution power network.

In this research work, the simultaneous placement of both FCSs and DGs were optimally planned to minimize the investment cost of FCSs and DG units, the specific energy consumption of EV users, voltage deviation and power losses in the coupled electrical distribution system and transportation network.

Meta-heuristic techniques are more popular to solve the combinatorial complex optimization problems. To date, there are numerous meta-heuristic optimization algorithms available in the literature. The more popular meta-heuristic algorithms are Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Shuffled Frog-Leaping Algorithm (SFLA), Teaching-Learning-Based Optimization (TLBO). Considering the exploration and exploitation abilities of TLBO and SFLA, these algorithms are considered for optimal planning of FCSs and DGs in the distribution system. Further, a novel attempt of hybridization of SFLA and TLBO (Shuffled Frog Leaping- Teaching-Learning-Based Optimization (SFL-TLBO)) has been made to enhance search ability and the obtained results found to be superior.

Furthermore, the present and future growth of EV population have been considered for simultaneous planning of FCSs and DGs in the electrical distribution system, which is essential for better operation of the distribution system.

Inaccurate modeling of EV load in the distribution system may result in imprecise calculation for Network Power Loss (NPL) and voltage deviation. The Constant Power (CP) load model is the more popularly used load model to model both the conventional and EV loads in the distribution system. But the CP load modeling cannot provide accurate information about different types of voltage-dependent conventional loads and EV charging process. Hence, as a part of this research work, for optimal planning of FCSs and DGs in the distribution system, the EV loads are modeled as Constant impedance-Constant current-Constant power (ZIP), Exponential and Constant Current load models. The conventional loads are modeled as Residential-Industrial-Commercial (RIC) loads. With these EV load models, the impact of FCS on the distribution system has been analyzed.

Any optimization approach for optimal planning of FCSs and DGs in the distribution network demands a load flow algorithm. The research work is initiated by developing software for "Current Injection based distribution Load Flow (CILF) method which can work for Radial and Meshed distribution networks.

The BSS methodology is more popularly used to recharge EV batteries due to its several advantages. As a part of this research work, the multi-objective BSS model is developed in order to optimize the number of batteries taken from battery stock, charging damage and electricity charging cost of batteries. Further, the dynamic electricity pricing model is considered to avoid new peaks of battery charging demand in BSS.

1.12 Thesis Organization

The thesis is organized into six chapters and presented as below;

The first chapter presents the detailed literature survey, key issues and motivation for the research work carried out in the area of "Optimal planning of Fast Charging Stations (FCSs) and DGs in Distribution System." In this chapter, an in-depth literature review is carried out on simultaneous planning of FCS and DGs in distribution system, impact analysis of FCS in distribution system and the operational scheduling of Electric Vehicles (EVs) in Battery Swapping Station (BSS). The objectives, motivation of the thesis and chapter wise summary are also outlined.

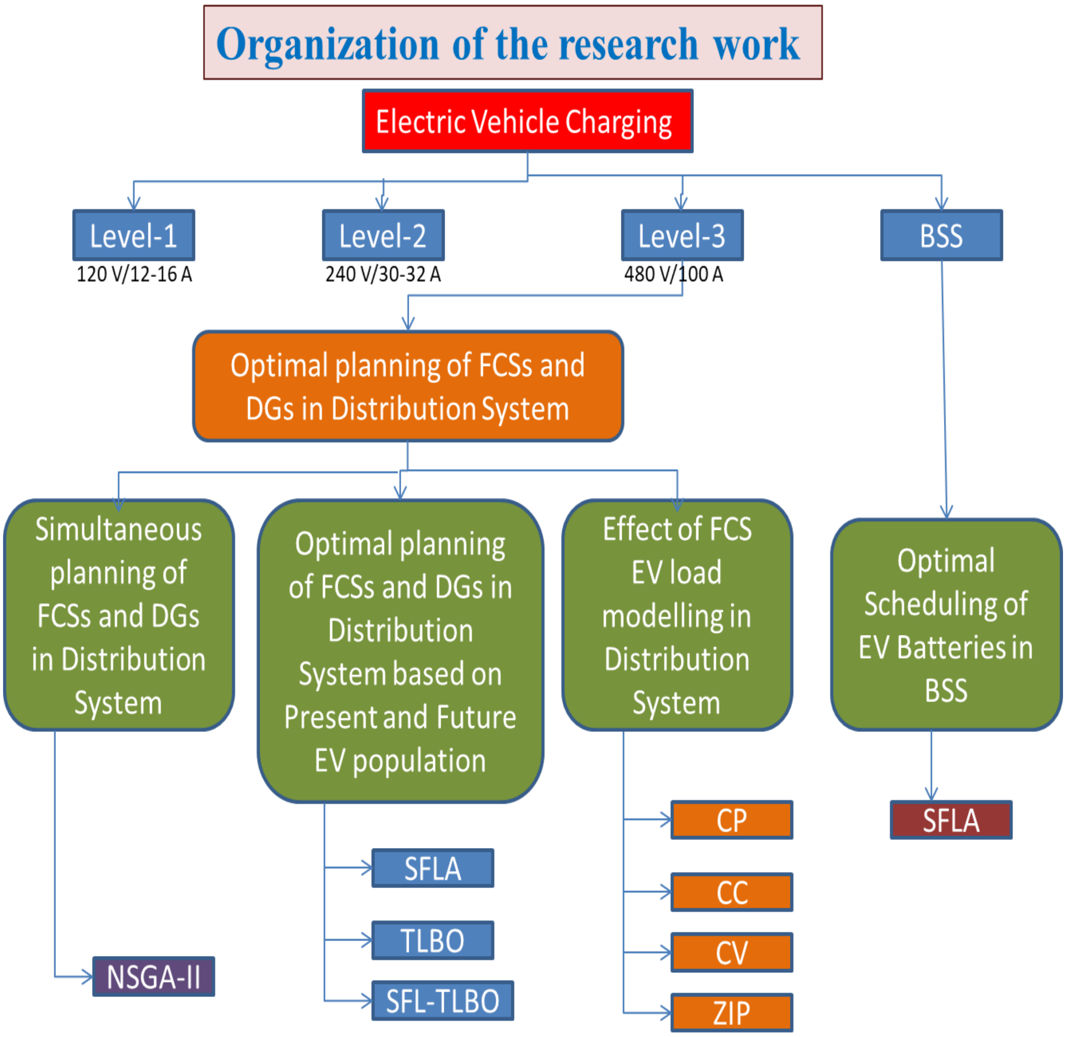
Second chapter reports "a Multi-objective optimization problem is formulated to obtain the simultaneous placement and sizing of FCSs and DGs with the constraints as the number of EVs in all zones and possible number of FCSs based on the Road and Electrical network in the proposed system." The problem is formulated as a Mixed Integer Non-Linear Problem (MINLP) to optimize the EV user loss cost, Network power loss cost, FCS development cost and improve the Voltage profile of the electrical Distribution System. Non-dominated Sorting Genetic Algorithm-II (NSGA-II) is used for solving the MINLP.

Third chapter delineates the "optimal planning of FCSs and DGs with the account of the present and future increase in EV population." A Multi-objective optimization problem is formulated for optimal planning of FCSs and DGs with the objective of minimizing the Voltage deviation, Distribution network power loss, DGs cost and the Energy consumption of EV users. This optimization problem is solved for different levels of increase in EV population for various cases. A novel hybrid Shuffled Frog Leaping-Teaching Learning Based Optimization (SFL-TLBO) algorithm is proposed and implemented to solve the above multi-objective optimization problem. The performance of the proposed algorithm is compared with Shuffled Frog Leaping (SFLA) and Teaching Learning Based Optimization (TLBO) algorithms.

Fourth chapter elaborates the "Impact of EV Load Modeling on FCSs planning in electrical Distribution System." EV loads are modelled as constant impedance-constant current-constant power (ZIP), Exponential, Constant Current and Constant Power load models and the conventional loads are modeled as Constant Power and Residential-Industrial-Commercial (RIC) load models. With these EV load models, the impact of FCS on the performance of distribution system is analyzed. A newly proposed multi-objective hybrid SFL-TLBO algorithm has been used for optimal planning of FCSs in distribution system with the objective of minimizing all three aspects like Network Power Loss (NPL), Maximum Voltage Deviation (MVD) and EV User Cost (EVUC). To consider the uncertainty of initial State of Charge (SOC) of EVs, Monte-Carlo simulation is used. These studies are carried out on 37-bus distribution system. The results establish that the ZIP load model is accurate for modeling the EV loads and the RIC load model is more appropriate for modeling the conventional load.

Fifth chapter covers "the operational scheduling of EV batteries in BSS in order to optimize the number of batteries taken from battery stock, battery degradation and electricity charging cost of batteries." Further, a newly proposed dynamic electricity pricing model is employed to avoid new peaks of battery charging demand in BSS. A BSS model with finite EV battery swapping demand in each hour of the day is solved by using a multi-objective Shuffled Frog Leaping Algorithm (SFLA). The simulation results demonstrate the effectiveness of multi-objective optimization and dynamic pricing model.

Finally, Sixth chapter highlights the various conclusions drawn in different chapters and the significant contribution of research work and provides scope for further research in this area. The complete research work is presented in the form of flow chart as shown in the figure 1.6.



FCSs: Fast Charging Stations; DGs: Distributed Generations; NSGA-II: Non-dominated Sorting Genetic Algorithm-II; SFLA: Shuffled Frog Leaping Algorithm; TLBO: Teaching and Learning Based Optimization Algorithm; SFL-TLBO: Shuffled Frog Leap-Teaching and Learning Based Optimization algorithm; CP: Constant Power; CC: Constant Current; ZIP: Constant Impedance-Constant Current-Constant Power, BSS: Battery Swapping Station

Figure 1.6: Flow chart for work flow

Chapter-2

A Multi-Objective Simultaneous Optimal Planning of Electric Vehicle Fast Charging Stations and DGs in Distribution System

2.1 Introduction

The large-scale construction of FCSs for EVs charging is helpful in promoting the EVs. It creates a significant challenge for the Distribution System operator to determine the optimal planning, especially the siting and sizing of FCSs in the electrical distribution system. Inappropriate planning of Electric Vehicle Charging Stations (EVCSs) cause a negative impact on the distribution system [10].

One of the greatest challenges in developed and developing countries is reducing the greenhouse gas emissions. The fossil fuel vehicles with Internal Combustion Engines (ICE) and electrical power generation from fossil fuels are the major causes of the greenhouse gas emissions [10]. The most promising pathway to energy security and reducing emissions is facilitating the global deployment of 20 million EVs by 2020 and the use of renewable distributed DGs [54]. If this rate is maintained to 2050, Electric vehicles will replace 62% of fleet vehicles. The EVs cause lower emission and require less energy for transit for a mile, as compared to ICEs. Hence they are required as a promising tool to combat the challenges related to energy sustainability and global warming. Therefore, governments, automobile companies, energy agencies, etc., have made significant efforts to enhance the EV population [55], [56].

This chapter present a multi-objective optimization problem to obtain the simultaneous placement and sizing of FCSs and DGs with the constraints such as the number of EVs in all zones and possible number of FCSs based on the road and electrical network in the proposed system.

2.1.1 Fast Charging Station

The schematic diagram of FCS is shown in Figure 2.1 and it shows that, arrangement requires only one AC-DC Grid Tied converter to realize a DC bus and the EVs are charged by DC-DC converters. In this the DC bus facilitates to connect the Renewable Energy Sources (RESs) generating units directly through a simple DC-DC converter. Three phase transformer is used to step down the voltage from the distribution grid voltage level to EVs battery voltage levels. Three phase AC/DC converter transforms the AC power into DC power and it forms a DC bus. EVs get connected to the DC bus for charging through DC/DC converters.

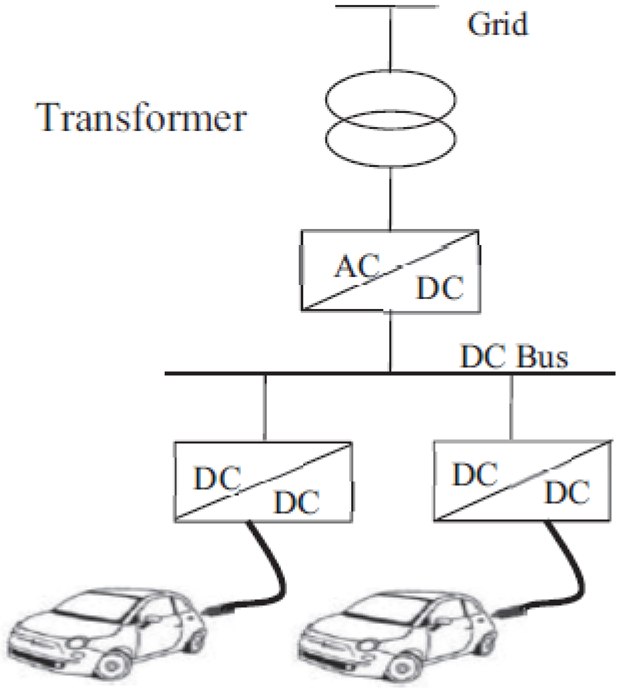


Figure 2.1: The schematic diagram of FCS [61]

The following aspects have to be considered while designing a FCS

- Available area for parking of electric vehicles; this determines the number of vehicles which can be charged.
- The EVs charging demand estimation for FCS in a particular area.
- Network constraints like nominal and permissible voltage profile.
- The power flows at the point of common coupling.
- Allowable rated charging power to be supplied to EV.

2.2 Problem formulation

This section presents the formulation of the objective function to minimize (i). FCS development cost, (ii). Cost of specific energy consumption of EVs, (iii). Electrical Network Power Loss (NPL) cost, (iv). DG power generation cost and (v). maximum voltage deviation (MVD) in the electrical distribution network.

For determining the optimal FCS location and EVs position, the proposed approach uses an area with the number of zones as shown in Figure 2.2. The area divided into zones as Z1, Z2, and Z3 for which the EVs data are available. EV population in each zone is distributed and it is assumed that the EV population in each zone is located at the geographic centre of the zone.

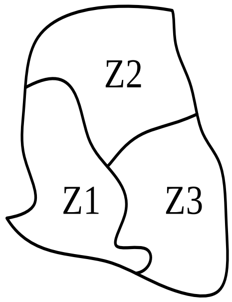


Figure 2.2: Proposed area with zones

Assume that in a *considered day*, the total number of EVs (N_{TEV}) in the *study area* are charged by the FCS. The N_{TEV} in study area calculated as

$$N_{TEV} = \sum_{z=0}^{n_z} N_{EV,z} \tag{2.1}$$

Where $N_{EV,z}$ is the number of dedicated EVs in zone Z, i.e., all dedicated vehicles are regular costumers of that zonary FCS and n_z is the number of zones in the considered study area.

2.2.1 Station Development Cost (SDC)

The considered j[th] station development cost mainly depends on the number of charging connectors in j[th] FCS (S(j)), and its rated capacity (P_C) [17].

$$SDC(j) = C_{init} + 25 \cdot C_{lan} \cdot S(j) \cdot N_Y + C_{con} \cdot (S(j) - 1) \cdot P_C \tag{2.2}$$

where C_{init} is the station fixed cost ($); C_{lan} is the yearly land rental cost ($ per square meter); C_{con} is the charger development cost ($/kW) of j[th] station and NY is the number of years in the study period; S(j) and P_C are the number of connectors in the jth charging station and rated power of charging connector (kW); The number of connectors in the j[th] charging station S(j) is calculated as:

$$S(j) = \sum_{z=1}^{n_z} (max(C_{PEV}) \cdot N_{EV,z} \cdot SE(z,j)) \tag{2.3}$$

Where the variable C_{PEV} is a vector having the probability of EV charging in the hour (h) of the day; $SE(z, j)$ is binary decision variable, equals to 1 if EVs in the zone z is charged by the station j, otherwise, zero. The selection of EVs in the zone z to jth charging station depends on the minimum distance between jth charging station to zone z as compared to the other CSs.

The area required for each connector and the minimum clearance between the connectors are 25m^2 and 3m respectively. The rating of charging connector varies in the range of 50-250 kW based on the connector technology [13]. The capacity of jth FCS is determined as:

$$C_{FCS}(j) = s(j) \cdot P_C \tag{2.4}$$

2.2.2 Electrical Vehicle User Cost (EVUC)

The EV user should drive a certain trajectory to reach to the FCS. EV user cost represents the cost associated with the energy consumed by EV to reach the FCS. For EVs located in zone Z, the EV user cost to reach nearest FCS for being charged at charging station j, $EVUC(z, j)$ is calculated as follows [17]:

$$EVUC(z,j) = d(z,j) \cdot SEC \cdot \sum_{h=1}^{24} C_{PEV}(h) \cdot N_{EV,z} \cdot C_{EP} \tag{2.5}$$

Where $d(z, j)$ is the distance between zone z and charging station j. SEC and C_{EP} are the specific energy consumption of EVs (kWh) and electricity price during hour h. The distance to displacement ratio depends strongly on the optimality of the road network in the study area. For an optimal road network, the distance approaches the displacement. Hence, choosing the displacement rather than distance in this approach to obtained CSs are still optimal for the optimal road network.

2.2.3 Network Power Loss (NPL) Cost

The higher FCS charging demand increases the line and substation loading. It causes an increase in Distribution System losses. The Distribution System loss has a nonlinear relationship with the system loading. The variable Distribution System loss is significant due to EV charging demand, hence the precise calculation of electrical grid loss is required by considering the variation in grid load.

The distribution NPL cost during one year for all seasons is calculated as follows:

$$C_{NPL} = \sum_{\omega=1}^{n_{\omega}} \sum_{h=1}^{24} L_{TP}(h,\omega) \cdot N_{TH}(\omega) \cdot C_{EP} \tag{2.6}$$

Where n_{ω} is the number of seasons; L_{TP} is the total electrical power loss including FCS load; and N_{TH} is the total number of hours in each season of the year.

The total power loss (L_{AP}) for hour h, during the season ω due to FCS charging demand, is calculated as follows [23]:

$$L_{TP}(h,\omega) = L_{GP}(h,\omega) + L_{AP}(h,\omega) \tag{2.7}$$

Where L_{TP} is the total power loss including FCS load; and L_{GP} is the gross power loss with conventional load (without FCS load).

2.2.4 DG Power Cost

The DG power cost consists of investment cost (C_I), operation cost (C_{OP}) and maintenance cost (C_M) of DGs. Investment cost contains unit construction, installation and essential equipment cost. Operation cost includes the cost of replacing components during their technical lifetime and maintenance cost contains costs of renewing, repairing, and restoring unit equipment in case of necessity [58]-[59] and [57].

$$C_I = \sum_{g=1}^{N_{DG}} (P_{DG,g} \cdot C_{INV,g}) \tag{2.8}$$

$$C_{OP} = \sum_{y=1}^{N_Y} \sum_{g=1}^{N_{DG}} \left(P_{DG,g} \cdot T_h \cdot C_{OP}' \cdot \left(\frac{1+R_{INF}}{1+R_{INT}}\right)^{N_Y} \right) \tag{2.9}$$

$$C_M = \sum_{y=1}^{N_Y} \sum_{g=1}^{N_{DG}} \left(P_{DG,g} \cdot T_h \cdot C_M' \cdot \left(\frac{1+R_{INF}}{1+R_{INT}}\right)^{N_Y} \right) \tag{2.10}$$

$$C_{DG} = C_I + C_{OP} + C_M \tag{2.11}$$

where $P_{DG,g}$ and $C_{INV,g}$ are the rated real power (kW) and inverter cost of g^{th} DG unit; C_{OP}' and C_M' are the operating cost (MWh) and maintenance cost (MWh) of each DG unit; R_{INF} and R_{INT} are the inflation rate and interest rate of each DG unit; T_h is total number of hours in a year; NY and NDG are number of years and the number of DGs considered for the study. The above-mentioned parameters required to calculate DG power cost are taken from [58].

2.2.5 Maximum Voltage Deviation (MVD)

Inappropriate placement of FCSs and DGs causes voltage instability in the distribution network. Both of over and under voltages affect the power quality of supply. The bus voltage deviation (p.u.) in four seasons for 24 hours is considered. The MVD of electrical Distribution System is calculated as follows,

$$max\ v_{dev} = max\{1 - min(v(i))\} \qquad \forall\ i = 1,2, \dots n \tag{2.12}$$

Where, min(v(i)) the minimum per unit voltage at bus i, n is the number of buses in a considered electrical distribution system.

2.2.6 Objective function

$$min\left\{\sum_{j=1}^{N_{FCS}} SDC(j) + \sum_{k=1}^{N_{TEV}} EVUC(k) + C_{NPL} + C_{DG} + max\ v_{dev}\right\} \tag{2.13}$$

Where N_{FCS} is the optimal number of FCS obtained from the optimization algorithm. The objective function is to minimize the total cost related to FCSs, DGs, NPL and minimize the bus voltage deviation of the electrical Distribution System by meeting the following constraints.

2.3 System Constraints

The multi-objective optimization function (2.13) is bounded to the power balance, voltage, thermal and DG power generation constraints as explained in [27]-[29].

At least one charging station should be selected to recharge the EVs in the study area with the following condition:

$$\sum_{j=1}^{N_{PC}} X(j) > 0 \qquad \forall c = 1,2, \dots, N_{PC} \tag{2.14}$$

Where N_{PC} is number of possible Charging Stations (CSs) and $X(j)$ is the binary decision variable, which is equal to 1 if jth charging station is selected, otherwise, zero.

At least one charging connector should be considered for each selected charging station, with the following condition given by (2.15):

$$S(j) \geq 0 \qquad \forall j = 1,2, \dots, N_{PC} \tag{2.15}$$

Where $\mathrm{S(j)}$ is the number of charging connectors in j^{th} FCS.

EVs in each zone should select one optimal FCS based on the displacement between $\mathrm{j^{th}}$ charging station and zone Z.

$$\sum_{z=1}^{n_z} \mathrm{SE(z,j)X(j)} = 1 \qquad \forall\ 1,2,\dots,n_z \tag{2.16}$$

Where $\mathrm{SE(z,j)}$ is 1 if the EVs in zone z are selected j^{th} charging station, otherwise zero.

2.4 Modelling of DG units in Load Flow Studies

In Distribution System the DG units, such as Photovoltaic systems, Fuel cells, Micro- turbines and the Wind turbine units are injected into the system via power electronic interfaces [62]. In such cases, the modelling of a DG unit in load flows depends on the control method employed in the converter control circuit. The DG units which have control over ‘P’ and ‘V’ independently may be model as PV type. Other DG units such as Induction generator based units which have control over ‘P’ and ‘Q’ independently may be modelled as PQ type. Using these models for DG units, Current Injection based Load Flow method is employed for Distribution System studies.

2.4.1 Current Injection Based Load Flow (CILF)

Any optimization approach for optimal placement and sizing of DG units in distribution network demands a good load flow algorithm. The traditional load flow methods such as Gauss-Seidel, Newton-Raphson and Fast Decoupled techniques are inefficient to solve Distribution networks due to the radial structure and wide range of resistance with low X/R ratios. Several methodologies have been proposed to solve the power flow problem in Distribution Systems such as Vector based Distribution load flow, Primitive Impedance Distribution load flow and Forward & Backward Sweep Distribution load flow. But, all these methods have limitations such as, not applicable for meshed Distribution Systems and implementation become complex when control devices are present in the system. The CILF (Appendix-III) [34] can be used for both radial and mesh systems and easy to accommodate the implementation of control devices.

The present research work is initiated by developing software for “Current Injection based Distribution Load Flow” (CILF) method which can work for radial and meshed distribution networks with and without the role of DG units. The working of this load flow technique is tested on IEEE 38 and 118-bus radial systems.

2.5 NSGA-II for Simultaneous Optimal Planning of FCSs and DGs

Non-dominated Sorting Genetic Algorithm-II (NSGA-II) is one of the most popularly used multi-objective optimization algorithm in different applications, due to its high performance for finding a set of Pareto solutions. The performance of NSGA-II is majorly depends on its evolution operators, mainly on the aspects of non-dominated sorting and crowing distance operator. Initially, a random parent population $\mathrm{P_t}$ of size N is generated, then it is sorted based on non-domination. Assign a rank to each solution based on its fitness value. The Binary Tournament selection, Recombination, and Mutation operators are used to generate offspring population $\mathrm{Q_t}$ of size N. Get the combined population $\mathrm{R_t}$ ($\mathrm{P_t} \cup \mathrm{Q_t}$) of size 2N. Then, the population $\mathrm{R_t}$ is sorted according to its non-domination. The solutions in the first front $\mathcal{F}_1$ are of good solutions as compared to the other front solutions in the combined population. If the size of the first front ($\mathcal{F}_1$) is less than N, then choose all populations of front $\mathcal{F}_1$ for the new population $\mathrm{P_{t+1}}$. Then the remaining members of the new population are chosen from subsequent fronts in order of their ranking. To choose exact N members for new population $\mathrm{P_{t+1}}$ from the subsequent fronts we use crowded distance operator [62]. The crowding distance operator guides the selection process at various stages of the algorithm, to determine the density of solutions that are surrounding a particular solution [63].

Table 2.1: Best NSGA-II parameters for optimal planning of FCSs and DGs

NSGA-II parameters	Values
Population size (N)	100
Number of iterations (N_{ite})	400
Crossover probability (P_c)	0.8
Mutation probability (P_m)	0.03

The best parameter values for the NSGA-II which are selected through multiple test simulation runs for the optimal planning of FCSs and DGs in a coupled electrical distribution and transportation network are given in Table 2.1.

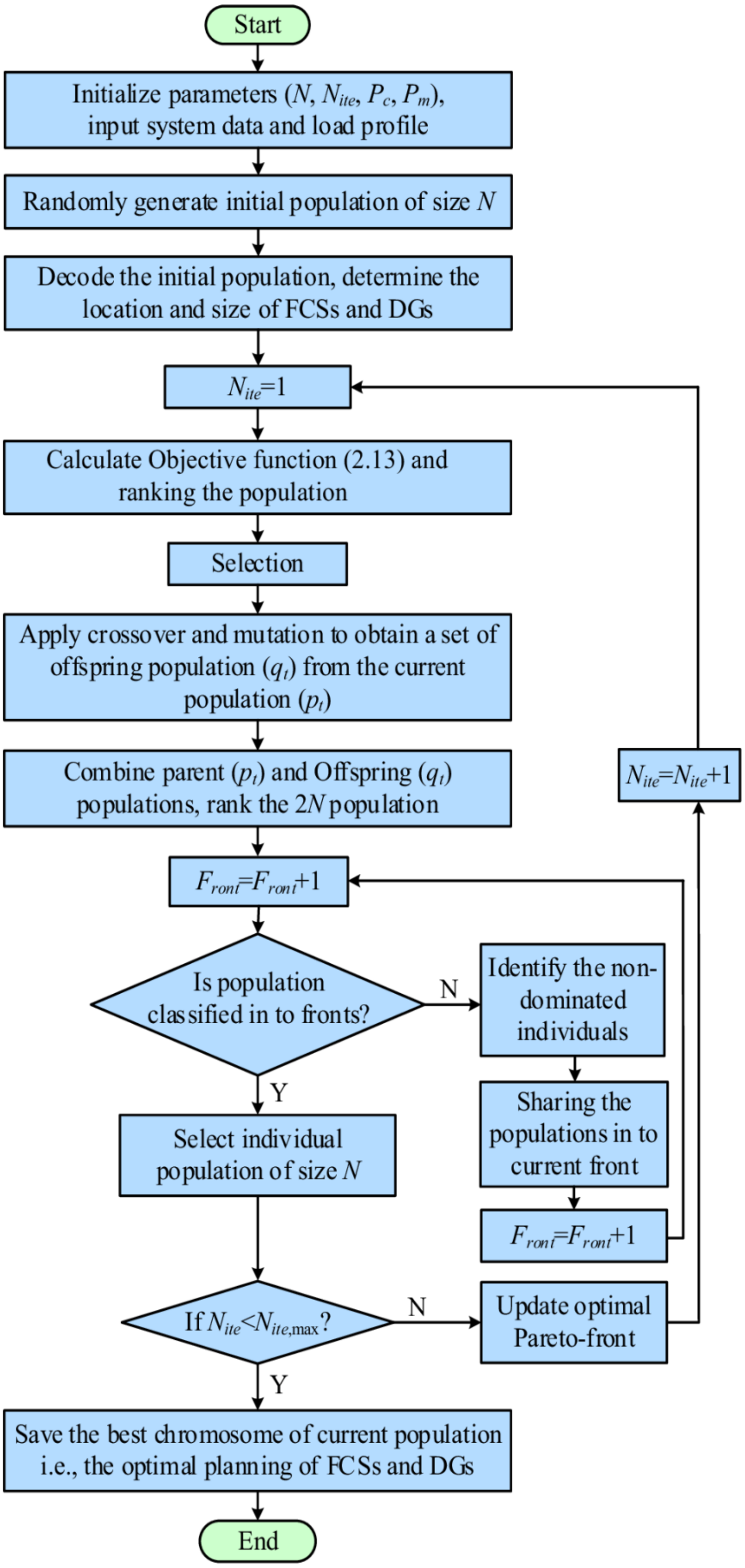


Figure 2.3: NSGA-II flow chart for optimal planning of FCSs and DGs [64]

In NSGA-II algorithm, the non-dominated sorting technique and crowding distance operator is used to rank the individual populations and to get good spread in the optimal Pareto front respectively. The selection operator is to “select the best and discard the rest” from a population keeping the population size constant. The crossover operator is used to create new solutions from the existing solutions available in the mating pool after applying selection operator. Mutation is the occasional introduction of new features in to the solution strings of the population pool to maintain diversity in the population and avoid premature convergence. The flowchart for optimal planning of FCSs and DGs in a coupled electrical Distribution System and transportation network with the NSGA-II algorithm is shown in Figure 2.3.

2.6 Simulation Results and Observations

To analyse the effectiveness of the proposed optimal planning of FCSs and DGs in a coupled electrical distribution and transportation network, three scenarios with multiple case studies are considered.

2.6.1 Proposed System Data

To test the proposed methodology, a study area of 720 km^2 surface has been considered. The study area consists of 180 zones, and each zone has an equal area of 4 km^2 (2 km×2 km).

Table 2.2: EVs population in each zone of test system

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
1	0	3	5	3	4	6	4	0	0	3	7	5	6	4	0
2	3	5	4	6	4	6	7	8	7	9	8	7	5	6	4
3	7	11	16	9	9	13	12	10	11	14	17	6	9	5	3
4	6	1	7	15	16	17	17	9	15	7	14	17	9	15	1
5	4	6	9	10	8	16	16	14	0	14	16	11	7	9	7
6	0	13	14	10	16	14	19	15	17	14	12	8	15	9	4
7	7	11	0	16	16	17	13	18	17	15	9	19	12	8	0
8	4	9	15	14	12	11	4	16	19	9	12	17	17	12	6
9	8	13	14	19	17	15	17	0	13	12	11	13	9	15	8
10	3	12	9	16	13	14	9	14	16	15	17	16	15	13	3
11	0	6	7	8	7	5	6	4	8	5	4	6	4	0	0
12	0	5	3	4	6	4	0	7	3	0	5	6	4	3	4

Table 2.2 presents the assumed EV population in each zone of the study area. The total population in the study area is 1632 and among the total EVs population only some probability of EVs is charging in each hour during a day. The 118 bus electrical Distribution System is assumed to be available on the study area for electrical power supply.

The percentage of electrical power load variation during the day for different seasons is taken from [25]. The base values of 118 Distribution System are 10 MVA, 11 KV and the total real and reactive power load on the system is 22.71 MW and 17.041MVAr. Figure 2.4 shows the single line diagram of 118 bus distribution network associated with the case study.

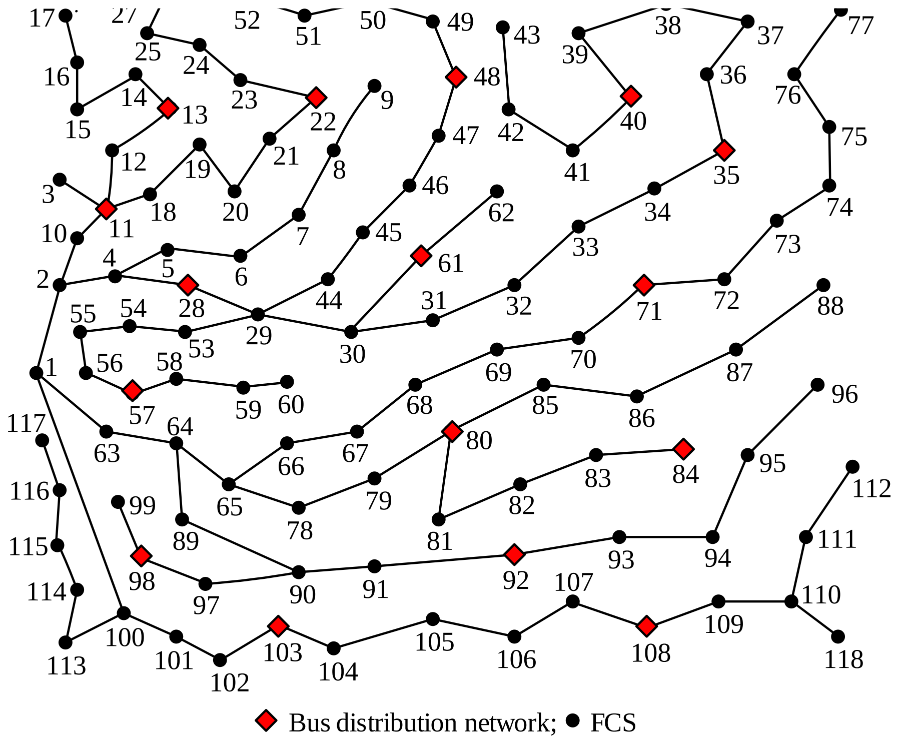


Figure 2.4: 118-bus radial distribution test system

The possible placement of 16 FCSs (based connectivity of road and electrical Distribution network system connectivity) has been assumed to be placed along the main roads of the study area, with constraints of approximately equal distance among the FCSs. Rhombus symbol in Figure 2.4 shows the locations of possible FCSs. The Distribution System and charging station parameters used in the proposed system are listed in Table 2.3.

Table 2.3: EV and FCS parameters [13]

Parameter	Value	Parameter	Value
N_{TEV}	1632	SEC	0.142 kWh/km
N_Y	5	C_{EP}	87.7 $/MWh
N_{PC}	16	C_{lan}	240 $/M^2.Yr
		C_{init}	70000 $
		C_{con}	208.33 $/kW
		P_C	96 kW

N_{TEV}- Total Number of Electric Vehicles N_Y-Number of Years N_{PC}-Number of Possible Charging stations SEC- Specific Energy Consumption C_{EP}-Electricity Price Cost	C_{lan}-Yearly land rental cost (in $/m^2) C_{init}-Fixed cost of station development. C_{con}-Charging connector development cost (in $/kW) P_C-Rated power of each connecter

The charging probability of EVs (CPEV) in each hour during the day is shown in Figure 2.5. It is assumed that EVs are charged at their respective FCSs from 5:00 to 21:00 hours a day.

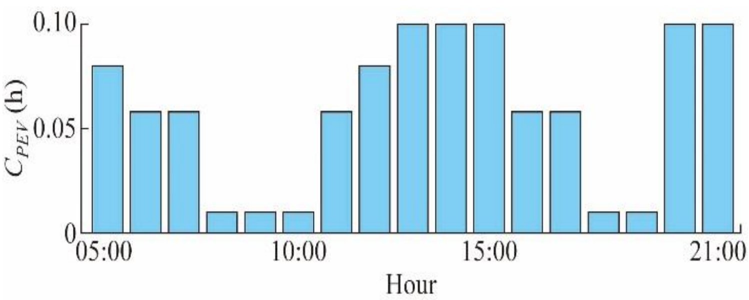


Figure 2.5: Variation of Charging probability (C_{PEV})

To verify the effectiveness and feasibility of the proposed optimal planning of FCSs and DGs in the radial distribution network, three different scenarios are proposed as case studies.

2.6.2 Scenario 1:Optimal placement of FCSs in coupled Electrical Distribution and Transportation Network

The optimal number and locations of FCSs have been determined by considering the minimization of EV user's cost, NPL cost and the MVD in the distribution network. The optimal placement of FCSs is determined considering load variation during four different seasons (Appendix-IV). The optimization algorithm presented in Figure 2.2 is employed to evaluate the fitness function given in (2.13) against the different number of

FCSs in the network. This algorithm determines the optimal capacity and locations of FCSs in the study area. Since, the DGs are not considered in this scenario, the DG_c in (2.13) is zero. The objective function for the different number of FCSs is compared in Figure 2.6. From this comparison, the optimal number of FCSs is determined to be 6.

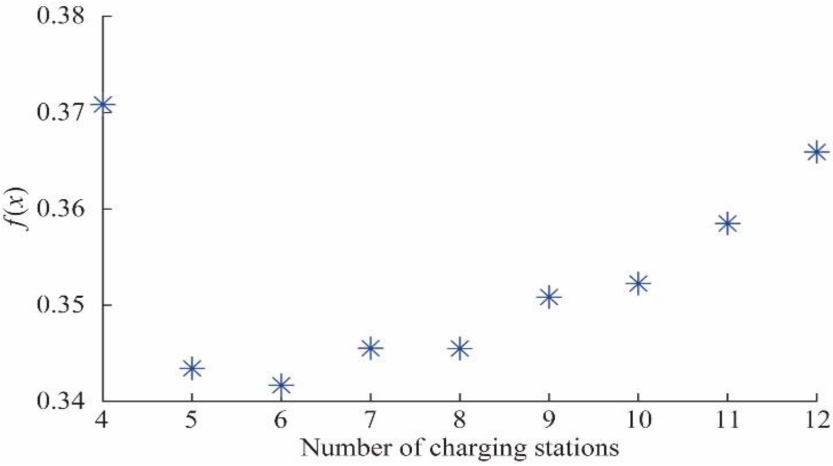


Figure 2.6: Optimal number of FCSs in the coupled electrical distribution and transportation network

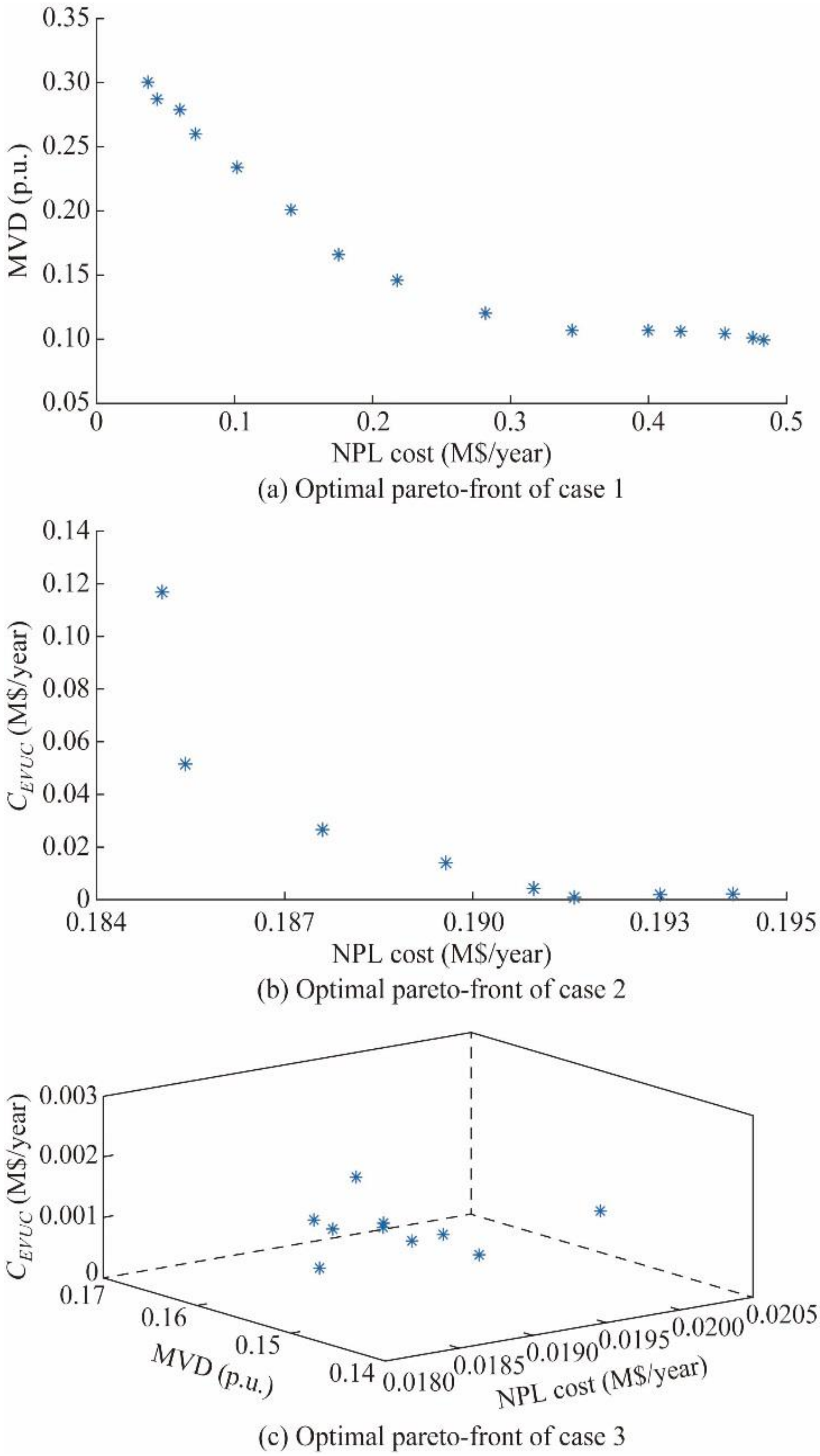
In scenario 1, based on the objective functions to minimize viz. NPL cost, EVUC and MVD, the following three cases are considered. The variation of Station Development Cost (SDC) does not impact significantly on the overall objective function, since the total number of connectors in all CSs is approximately constant. Hence, SDC is not considered as an objective to minimize.

Case 1: Minimization of NPL cost and MVD

Case 2: Minimization of NPL cost and EVUC

Case 3: Minimization of NPL cost, MVD and EVUC

The optimal Pareto-front for the minimization of NPL cost, EVUC and MVD (Max. VD) simultaneously for all case studies of scenario 1 is shown in Figure 2.7.



(a) Optimal pareto-front of case 1

(b) Optimal pareto-front of case 2

(c) Optimal pareto-front of case 3

Figure 2.7: Optimal Pareto-front plots for scenario 1

Table 2.4: Optimal planning of FCSs for scenario 1

	S No. FCS number	1	2	3	4	5	6
Case 1	FCS location	92	40	98	61	28	108
	Number of EVs to FCS	243	187	187	469	300	246
Case 2	FCS location	28	42	92	71	35	57
	Number of EVs to FCS	307	83	330	358	307	247
Case 3	FCS location	61	108	103	57	80	98
	Number of EVs to FCS	661	274	89	281	262	65

From the optimal Pareto front the best compromised solution is obtained using a min-max optimization technique as discussed in [31]. For the obtained compromised or moderate solution, the optimal FCS location and number of EVs connected to FCS for various cases in scenario-1 are presented in Table 2.4. The optimal objective parameters for scenario 1 are listed in Table 2.5.

Table 2.5: Optimal objective parameters for scenario 1

Case	SDC (M$)	EVUC (M$/year)	NPL cost (M$/year)	MVD (p.u.)
1	2.053	0.02178	0.2178	0.1459
2	2.052	0.01896	0.1876	0.156
3	2.041	0.01399	0.18857	0.156

(M$=Millions of Dollars)

The SDC has been evaluated based on the total number of connectors in each FCS. The SDC, EVUC, NPL cost and MVD are obtained as 2.053 (M$), 0.02178 (M$/year), 0.2178 (M$/year) and 0.1459 (p.u.) respectively in case 1 of scenario 1. In case 2, it has approximately same SDC. The EVUC, NPL cost and MVD are 0.01896 (M$/year), 0.1876 (M$/year) and 0.156 (p.u.) respectively. When three objective parameters are considered (Case 3) the SDC, EVUC, NPL cost and MVD are comparatively minimum as compared to case 1 and case 2 of scenario 1. From the Table 2.5 the optimal values of the SDC, EVUC, NPL cost and MVD in scenario 1 are 2.041 (M$), 0.01399 (M$/year), 0.18857 (M$/year) and 0.156 (p.u.) respectively.

Even after optimal placement of FCSs, the voltage profile of the 118 bus Distribution System violates the system voltage constraints. To improve the voltage profile, in next scenario i.e. scenario 2, the optimal planning of DGs is considered in the coupled electrical distribution and transportation network.

2.6.3 Scenario 2:Optimal placement of DGs in proposed study system with previous optimal FCS load

Optimal placement of DGs has been considered to improve the voltage profile in proposed distribution system. Objective function (2.13) includes the DG cost, SDC, EVUC, NPL cost and MVD in Distribution System with the optimal FCSs load obtained in case 3 of scenario 1. The optimal placement of DGs is determined considering load variation during four different seasons (. The optimization algorithm presented in Figure 2.8 is employed to evaluate the objection function presented in (2.13) against different number of DGs in the network. This algorithm determines the optimal size and placement of DGs in the network.

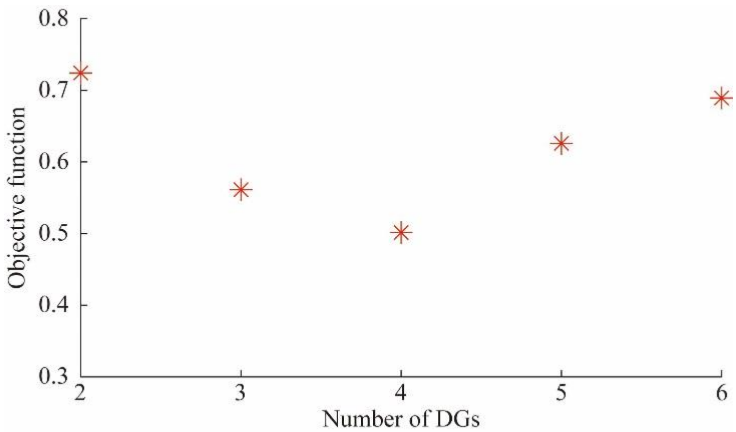
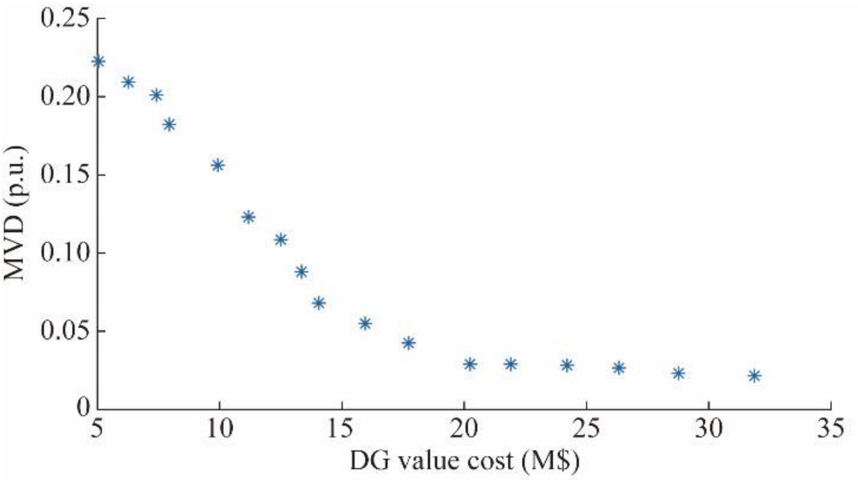
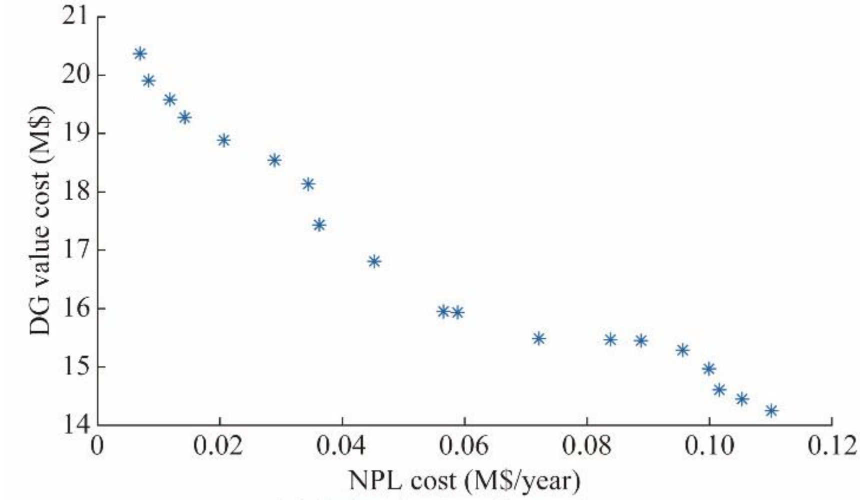


Figure 2.8: Optimal number of DGs in the coupled electrical distribution and transportation network

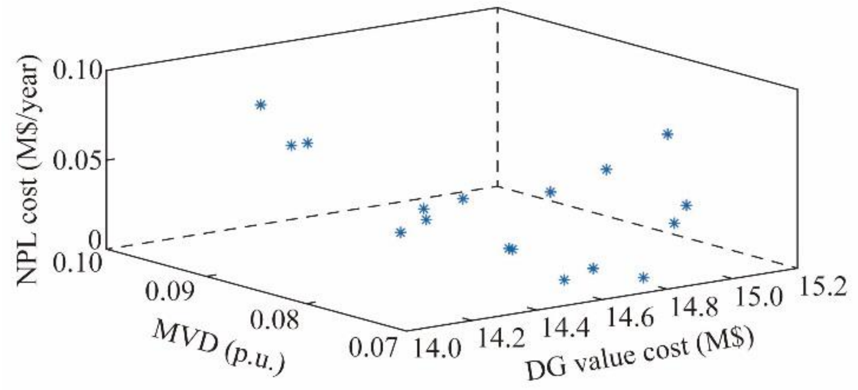
The objective function for different number of DGs is compared in Figure 2.8. From this comparison the optimal numbers of DGs is determined to be 4. In scenario 2, three cases are conducted to determine the optimal location and size of DGs with the account of the optimal FCSs load obtained in case 3 of scenario 1. The SDC and EVUC in scenario 2 are same as the case 3 of scenario1 and its value is constant.



(a) Optimal pareto-front of case 4



(b) Optimal pareto-front of case 5



(c) Optimal pareto-front of case 6

Figure 2.9: Optimal Pareto-front plots for scenario 2

Case 4: Minimization of DG value cost and MVD

Case 5: Minimization of NPL cost and DG value cost

Case 6: Minimization of DG value cost, MVD and NPL cost

The Pareto-front for different case studies in scenario 2 is shown in Figure 2.9.

From the above optimal Pareto fronts the best moderate location and size of DG units are determined using min-max method. The optimal location and size of DG units for different case studies in scenario 2 are presented in Table 2.6.

Table 2.6: Optimal place and sizes of DGs

DG no.	Case 4		Case 5		Case 6	
	DG location	DG size (MW)	DG location	DG size (MW)	DG location	DG size (MW)
1	32	0.1032	40	0.1262	37	0.2
2	36	0. 1	42	0.101	42	0.1996
3	70	0.1265	72	0.1164	74	0.1982
4	118	0.1071	111	0.0749	111	0.1896

(M$=Millions of Dollars)

From the Pareto front provided in Figure 2.9, best compromised objective parameters for the case 4, case 5 and case 6 are reported in Table 2.7.

Table 2.7: Optimal cost values with DGs placement

Case	SDC cost (M$)	EVUC (M$/year)	NPL cost (M$/year)	DG cost (M$)	MVD (p.u.)
4	2.041	0.01399	0.07212	14.06	0.0681
5	2.041	0.01399	0.05625	15.95	0.899
6	2.041	0.01399	0.05651	14.82	0.072

There are two observations that can be made by analysing the results provided in Table 2.7. The first one is that as both NPL cost and MVD decreases, the DG cost increases. The NPL cost and MVD directly depend on DGs location and their size. The second one is that SDC and EVUC are constant. In scenario 2, the optimal planning of DGs is determined with the account of optimal FCS load (case 3 of scenario 1) in the electrical distribution system. Therefore, the SDC and EVUC are constant in all three cases of scenario 2.

In case 4, DG cost and MVD are considered for optimal planning of DGs in the electrical distribution system. For which the NPL cost, DG cost and MVD are 0.07212 (M$/year), 14.06 (M$), 0.0681 (p.u.) respectively. Similarly, the NPL cost, DG cost, and

MVD are 0.05625 (M$/year), 15.95 (M$), 0.899 (p.u.) respectively for case 5. Furthermore, in case 6, three objective parameters are considered for optimal planning of DGs in the distribution system. Because of the participation of three objective parameters in optimization processes, case 6 provided a best economical solution as compared to case 4 and case 5 in scenario 2. The optimal values of the NPL cost, DG cost, and MVD are 0.05651 (M$/year) 14.82 (M$), 0.072 (p.u.) respectively. It can be observed that case 6 of scenario 2 gives best economical solution as compared to the case 4 and case 5. Furthermore, to minimize the NPL cost, DG cost and MVD, the simultaneous placement of FCSs and DGs in coupled electrical distribution and transportation network is considered in scenario 3.

2.6.4 Scenario 3:Simultaneous placement of FCSs and DGs in coupled Electrical Distribution and Transportation Network

In this scenario, the FCSs and DGs are simultaneously placed in the distribution network, with the objective of decreasing the EVUC, NPL cost, DG cost and MVD. In scenario 3, the following four different cases are considered for the simultaneous optimal placement of FCSs and DGs in coupled electrical distribution and transportation network.

Case 7: Minimization of NPL cost and EVUC

Case 8: Minimization of DG value cost and MVD

Case 9: Minimization of NPL cost and DG value cost

Case 10: Minimization of DG value cost, MVD and NPL cost

The algorithm presented in Figure 2.3 is employed to evaluate the fitness function given in (2.13) against the different number of FCSs and DGs in the distribution network. This algorithm determines the optimal size and placement of FCSs and DGs in the distribution network, for the same number of FCSs and DGs as in scenario 1 and scenario 2 respectively. The Pareto-front for minimization of NPL cost, DG cost, EVUC and MVD for various case studies of scenario 3 are shown in Figure 2.10.

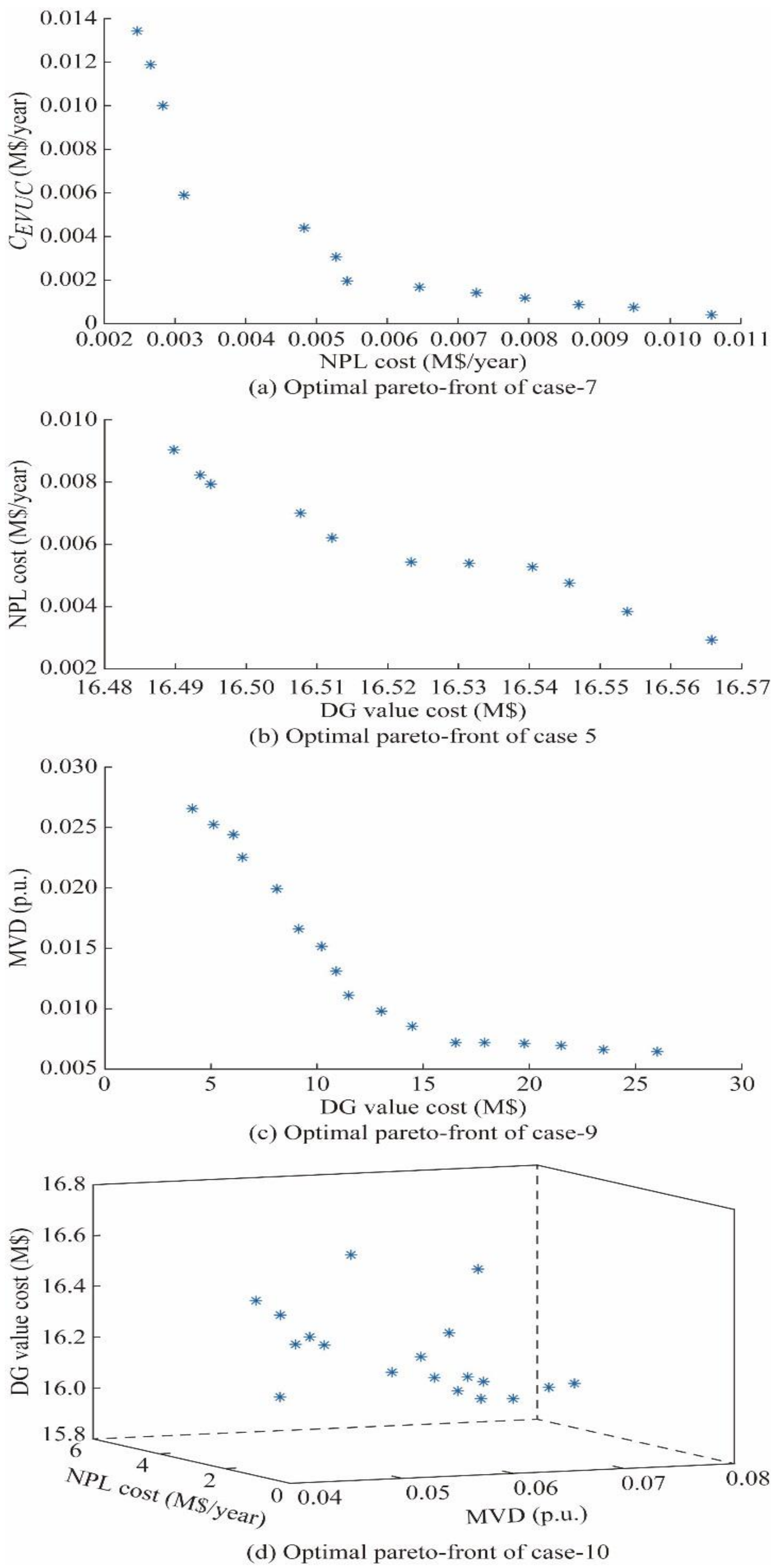


Figure 2.10: Optimal Pareto-front plots for scenario 3

The optimal capacity and location of FCSs and DGs are listed in Table 2.8 and Table 2.9.

Table 2.8: Optimal planning of FCSs in scenario 3

FCS No.	Case 7		Case 8		Case 9		Case 10	
	FCS location	No. of EVs to FCS	FCS location	No. of EVs to FCS	FCS location	No. of EVs to FCS	FCS location	No. of EVs to FCS
1	28	245	61	428	13	94	83	576
2	71	570	48	200	103	165	28	251
3	22	245	40	76	71	591	80	156
4	98	136	71	376	28	236	103	254
5	80	354	92	276	80	356	48	249
6	103	82	103	276	22	189	92	146

Table 2.9: Optimal planning of DGs in scenario 3

DG No.	Case 7		Case 8		Case 9		Case 10	
	DG location	DG size (MW)	DG location	DG size (MW)	DG location	DG size (MW)	DG location	DG size (MW)
1	95	0.0711	83	0.0867	97	0.0698	36	0.2
2	59	0.0611	43	0.0764	30	0.1074	74	0.1749
3	93	0.0751	28	0.0885	103	0.0626	83	0.1498
4	32	0.1811	114	0.1516	46	0.0935	11	0.1947

From the obtained Pareto fronts, the moderate solution is determined using the min-max technique.

Table 2.10: Optimal cost values in scenario 3

Case	SDC cost (M$)	EVUC (M$/year)	NPL cost (M$/year)	DG cost (M$)	MVD (p.u.)
7	2.038	0.01958	0.05432	17.95	0.0998
8	2.041	0.02359	0.06312	16.52	0.072
9	2.04	0.01969	0.05389	16.53	0.0899
10	2.0101	0.005963	0.054323	15.951	0.0613

Table 10 presents the optimal objective parameters of different cases of scenario 3. In case 7, optimized values of NPL cost and EVUC are 0.05432 (M$/year) and 0.01958 (M$/year) respectively, for which the DG cost and MVD are 17.95 (M$) and 0.0998 (p.u.). In case 8, the optimized values of the DG cost and MVD are 16.52 (M$) and 0.072 (p.u.), for which EVUC and NPL cost is maximum, i.e., 0.02359 (M$/year) and 0.06312 (M$/year). Similarly, the optimized values of the DG cost and NPL cost are 16.53 M$ and 0.05389 (M$/year) in case 9, for which the optimal EVUC and MVD are 0.01969 (M$/year) and 0.0899 (p.u.) respectively. Furthermore, three objectives, i.e., MVD, NPL cost and DG cost optimized values are 0.0613 (p.u.), 0.054323 (M$/year) and 15.951 (M$) respectively. In scenario 3 the NPL cost and EVUC are considerably reduced for approximately same investment. The NPL cost and EVUC are variable ones, with the reduction of this losses result in benefit to both the EV users and charging station owners.

The optimal objective parameters namely NPL cost, MVD, EVUC and DG cost for the best cases (case 3 in scenario 1; case 6 in scenario 2; and case 10 in scenario 3) in the above three different scenarios are presented in Table 2.11. From Table 2.11, it is clear that case 10 gives best compromised solution as compared to the other cases of scenario 3.

Table 2.11: Optimal cost comparison results in three scenarios

Case	SDC (M$)	EVUC (M$/year)	NPL cost ($/year)	DG cost (M$)	MVD (p.u.)
10	2.0101	0.0059636	543.23	15.951	0.0613
6	2.041	0.013996	565.17	16.5233	0.0721
3	2.041	0.013996	188.57	-	0.156

In scenario 3, the EVUC and NPL cost and MVD are significantly reduced as compared to the scenario 2 and scenario 1. The simultaneous planning of FCSs and DGs in the coupled electrical distribution and transportation network of case 10 has a 60.7% and 14.97% reduction of MVD as compared to the case 3 and case 6. Also, the NPL cost reduced by 71.2% and 3.8% in case 10 as compared to the case 3 and case 6. Furthermore, there is a 57.3% reduction of EVUC in case 10 as compared to other cases. Therefore, the proposed method is capable of providing the best economical solution for the simultaneous optimal placement of FCS and DGs in coupled electrical distribution and transportation network.

In order to investigate the impact of parameters mentioned in Table 2.3, the following four additional cases are considered.

In case I, the objective parameters have been calculated by considering 75% of EV population and 50% of EV population is considered in case II. The optimal parameters are listed Table II. The optimal Pareto fronts to optimize the MVD, NPL cost and DG value cost in case I and Case II is shown in Figure 2.11 and Figure 2.12 respectively.

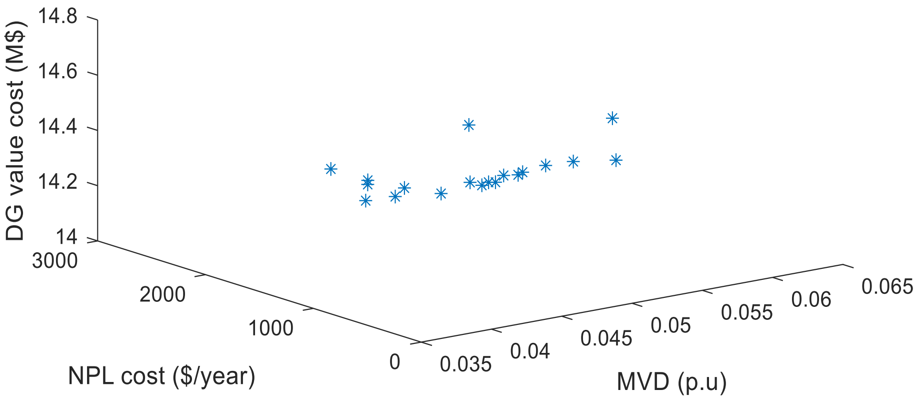


Figure 2.11 Optimal Pareto fronts of case I

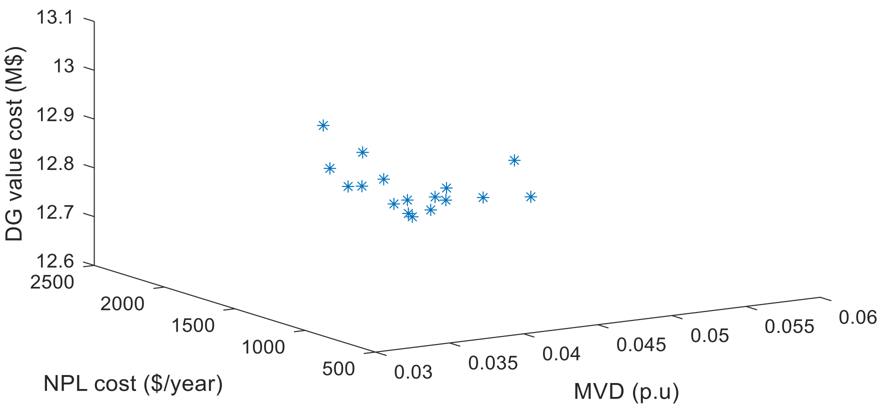


Figure 2.12 Optimal Pareto fronts of case II

In case III and Case IV, the objective parameters have been calculated by considering 13 possible FCSs and 10 possible FCSs (in original study it is 16 possible FCSs (NPC). The optimal parameters are listed Table II. The optimal Pareto fronts to optimize the MVD, NPL cost and DG value cost in case III and Case IV are shown in Figure 13 and Figure 14 respectively.

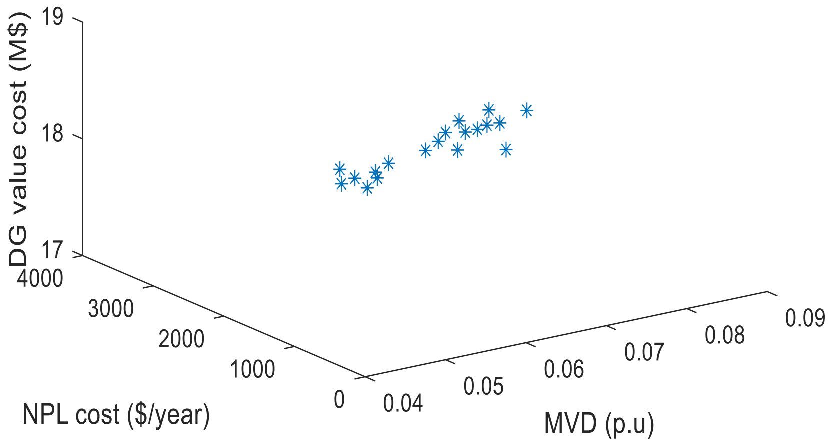


Figure 2.13 Optimal Pareto fronts of case III

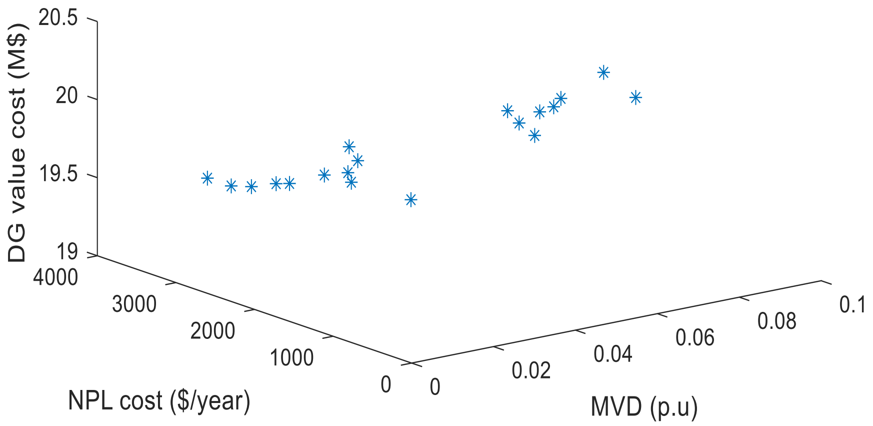


Figure 2.14 Optimal Pareto fronts of case IV

Table 2.12 Optimal parameters for case I, case II, case III and case IV

Case	NPL cost ($/year)	DG cost (M$)	MVD (p.u.)
Case I	473.28	14.5992	0.0519
Case II	371.25	12.6416	0.0316
Case III	934.1	18.5569	0.0621
Case IV	1818.59	19.63	0.0803
Case 10	543.23	15.951	0.0613

(Case I, case II, case III and case IV are conducted to investigate the impact of parameters mentioned in Table I and it compared with case 10).

From the above analysis, it is concluded that the NPL cost, DG cost and MVD are decreases as the total number of EVs are reduced to 75% in case I and 50% in case II. And the NPL cost, DG cost and MVD are increases as the numbers of possible FCSs are decreased to 13 FCSs in case III and 10 FCSs in case IV. So, for analysis purpose, Table I parameters are considered for various case studies in the Thesis.

In summary, this chapter has covered the simultaneous placement of DGs and FCSs in radial distribution system. Simulation results emphasize the importance of optimal concurrent placement of both FCSs and DGs in the distribution system. In the proposed approach, ‘optimal planning of FCSs’ and ‘optimal planning of DGs with the account of optimal FCSs load’ are compared to ‘simultaneous planning of FCSs and DGs’ in coupled electrical distribution and transportation network. The simultaneous placement of FCSs and DGs results in more reduction in EVUC and NPL cost for the same SDC and DG power cost investment. The EVUC and NPL cost are variable with respect to time. Hence, reduction in this cost will prove beneficial for both EV and charging station owners. It is clear that the optimal simultaneous placement of both FCSs and DGs in Distribution System provides significant benefits to all involved.

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The next stage of investigation is focused of Optimal Planning of FCSs and DGs in Distribution System with Future EV Load Enhancement and the same is reported in chapter 3.

Chapter-3

Multi-Objective Optimal Planning of FCSs and DGs in Distribution System with Future EV Load Enhancement

3.1 Introduction

Current trends suggest that EV is a promising technology for road transportation. There is a substantial increase in the number of EVs due to improved energy efficiency and reduction in environmental impact as compared with internal combustion engine vehicles. The improper planning of FCSs and DGs causes a negative impact on the Distribution System [65]. So the Distribution System operator has a significant challenge to identify the optimal location and sizing of FCSs in distribution power network. This part work presents optimal planning of FCSs and DGs with the account of the present and future increase in EV population.

From the last decade onwards, the EVs have great attention from the government agencies and automobile industries due to a significant reduction in overall operating cost and emission as compared to the internal combustion engine vehicles. According to the Electric Power Research Institute survey, 35% of total vehicles in the USA will be EVs by 2020 [66]. The increasing population of EVs creates new challenges to the power Distribution System operator to develop adequate charging facilities to the EV users in distribution system. The rapid increase of EV population requires efficient fast charging stations (FCS). Charging at home is an alternative way for the EV users, but it requires too much time (which can take 6 to 8 hours). Therefore, the charging station with high voltage is necessary for EV user's convenience, because it can charge the EVs at least 12 times faster than charging at home [66]. The higher adoption of EVs may cause a potential impact on the distribution grid.

A multi-objective optimization problem is formulated for optimal planning of FCSs and DGs with the objective of minimizing the voltage deviation, distribution network power loss, DGs cost and the energy consumption of EV users in the coupled transport and electrical distribution network by considering the present and different levels of future increase of EV population demand.

3.2 Problem formulation

This section reports the formulation of the objective function to minimize FCS development cost (SDC), cost of specific energy consumption of EVs (SEC of EVs cost), electrical Network Power Loss (NPL) cost, DG power generation cost and Maximum Voltage Deviation (MVD) in the electrical distribution network.

3.2.1 Objective function

The objective parameters in this optimization function are same as the parameters which are considered in objective function (2.13) in section 2.2. With this optimization problem the optimal planning of FCSs and DGs are determined for the present and different levels of future increase of EV population demand in the coupled road and electrical distribution system.

- ✓ FCS development cost (SDC)
- ✓ EV user cost (EVUC)
- ✓ Electrical network power loss cost (NPLC)
- ✓ DG power generation cost (DGPC)
- ✓ Maximum Voltage Deviation (MVD)

Considering all the five objectives, the objective function is formulated as

$$\min\left\{\sum_{j=1}^{NFCS} SDC(j) + \sum_{k=1}^{TNEV} EVUC(k) + NPLC + DGPC + MVD\right\} \quad (3.1)$$

Where NFCS is the optimal number of FCS obtained from the optimization algorithm. The objective function is to minimize the total cost related to FCS, DGs and Network power losses; and minimize the bus voltage deviation of the electrical Distribution System by meeting the following constraints.

3.3 Constraints

3.3.1 Charging Station Constraints

At least one charging station should be installed in the proposed area to meet the EV loads and it is described as below:

$$\sum_{j=1}^{NFCS} FCS(j) > 0 \quad \forall \quad j = 1,2, \dots \dots \dots, NPC \quad (3.2)$$

Where NPC is the number of possible FCSs based on the optimality of road transport network and electrical distribution network. At least one charging connector should be considered for each selected FCS i.e.

$$S(j) \geq 0 \quad \forall \ j = 1,2,3, \dots \dots \dots, NPC \quad (3.3)$$

EVs in each zone should select one optimal FCS based on the distance between j^{th} charging station and zone z.

$$\sum_{z=1}^{nzone} \mathrm{Select}(z, j) X(j) = 1 \quad \forall\ 1,2,3 \ldots \ldots z \tag{3.4}$$

Where $\mathrm{Select}(z, j)$ is 1 if the EVs in zone z are selected j^{th} charging station, otherwise zero. X(j) is the binary decision variable, which is equal to 1 if j^{th} FCS is selected, otherwise, zero.

3.3.2 DG Constraints

Each Distributed Generation source has its own real and reactive power generation limits. In this work, the DG is modelled as a negative P-Q model. The DGs should meet the following constraints,

$$P_{DG,g}^{min} \leq P_{DG,g} \leq P_{DG,g}^{max} \tag{3.5}$$

$$Q_{DG,g}^{min} \leq Q_g \leq Q_{DG,g}^{max} \tag{3.6}$$

Where $P_{DG,g}^{min}$, $Q_{DG,g}^{min}$ and $P_{DG,g}^{max}$, $Q_{DG,g}^{max}$ are the minimum and maximum of real and reactive power generation of g^{th} DG unit. The per unit voltage of each bus in each time step does not decrease below the predefined minimum voltage, which is assumed 0.9 p.u. for all the cases considered.

3.4 Hybrid SFL-TLBO Algorithm and System Data

In all classical methods like weighted objectives method, the multiple objectives functions are formulated as a single objective function by choosing suitable weights for each objective. In determining the optimal value of the proposed single objective function, it has majorly two problems. The first one is the optimization of that single objective function may guarantee a single optimal solution, but in all practical applications, the decision makers need an alternative solution in decision making. The second one is the selection of suitable weights for each objective parameter in single objective function. Moreover, if the objective function is more noisy and the variables are discontinuous in search space, the classical methods cannot work effectively [74]. To overcome the above problems, multi-objective Pareto front optimization algorithms are necessary for solving multi-objective problems. Furthermore, the hybrid algorithms are highly efficient in finding optimal solution. A new hybrid Shuffled Frog Leaping-Teaching Learning Based Optimization (SFL-TLBO) algorithm is developed by combining the best features of Shuffled Frog Leaping (SFL) and Teaching Learning Based Optimization (TLBO) algorithms for solving the optimal planning of FCSs and DGs in the coupled road and electrical distribution system. This optimization problem has been solved by considering the present and different levels of future increase of EV population demand.

3.4.1 Shuffled Frog Leap Algorithm (SFLA)

The SFLA is a population-based optimization algorithm, and the population consists of a set of frogs that is divided into subsets referred to as memeplexes. Each frog in the population represents a solution in search space and its hold ideas, which can be influenced by the ideas of other frogs and evolve through a process of memetic evaluation. After a certain number of memetic evaluation steps, ideas are passed among the memeplexes in the shuffling process. The exploration and the shuffling processes continue until it reaches the specified convergence criteria as explained in [74].

3.4.2 Teaching Learning Based Optimization (TLBO)

TLBO is a teaching- learning process based inspired algorithm, in which teaching – learning is an important process where every individuals tries to improve their knowledge by interacting with others (i.e either a teacher or student or both), which simulates the traditional teaching-learning phenomenon of a class room. TLBO proposed by R.V. Rao et al. in 2011. In TLBO algorithm, the best learner is regarded as a teacher and rest individuals within the population are seen as students. To determine better optimal solution the TLBO algorithm consists of two phases: teacher phase and learner phase. During the teacher phase, a teacher wants to increase his or her students' knowledge level up to his or her knowledge level. Thus the individual knowledge level of students is various with the following expression: [75], [76]

$$\mathrm{X_{new,i}} = \mathrm{X_{old,i}} + \mathrm{rand}(\mathrm{X_{teacher}} - \mathrm{X_{mean}}) \tag{3.7}$$

Where $\mathrm{X_{teacher}}$ and $\mathrm{X_{mean}}$are the best learner in the population and the current mean value of the individuals respectively. rand is the a uniform random number in between 0 and 1.

In the learner phase, the knowledge of learner increases through the interaction between classmates. A learner $(\mathrm{X_i})$ randomly interacts with his/her classmate $(\mathrm{X_j})$ within the population and the selected classmate trains a learner. If the learner knowledge is better than the former one, then it is replaced with the newly generated population. The individual knowledge level of the learner is updated with the following expression:

$$X_{new,i} = X_i + rand(X_j - X_i) \quad (3.8)$$

Where X_j and X_i are two individual learners in the current population.

TLBO is a population based algorithm and its operation is explained below with step by step procedure.

Step 1: Define the optimization problem as minimization or maximization of f(X). Where f(X) is the objective function and X is a vector of design variables.

Teacher phase :

Step 2: Initialize the population (a group of learners) as P_1, P_2, P_3 - - - - - P_n. And take the design variables of optimization problem (number of subjects) as x_1, x_2, x_3 - - - - - -x_m.

Step 3: Determine the objective function value for each population, Identify the optimal objective function value $f(x)_{best}$ who act as a teacher and its respective population is x_{mbest}.

Step 4: Calculate the mean and difference mean of each design variable respectively. Mean is the average of each design variable with respect to population size and the difference mean is calculated by

$$\text{Difference\_mean}_m = rand*(x_{mbest} - mean_m) \quad (3.9)$$

Where Difference_mean_m , x_{mbest} and $mean_m$ are the difference mean, best of population and the average of m^{th} design variable respectively.

Step 5: Based on this difference mean, the existing population is updated according to the following equation

$$xnew_{n,m} = xold_{n,m} + \text{Difference\_mean}_m \quad (3.10)$$

Evaluate the objective function value with $xnew_{n,m}$ population.

Learner phase:

Step 6: In learner phase, their knowledge is increased by randomly interacting with other learners which are present in current iteration. This algorithm uses the tournament selection operator for random selection of learners.

Step 7: If the knowledge of updated learner is less than current learner accept the current learner. Otherwise accept the updated learner. And continue this process for all learners which are presented in the current population.

Step 8: Repeat the procedure from step 3 to step 7 until the termination criterion is met.

The flowchart for Hybrid SFL-TLBO algorithm is shown in figure 3.1.

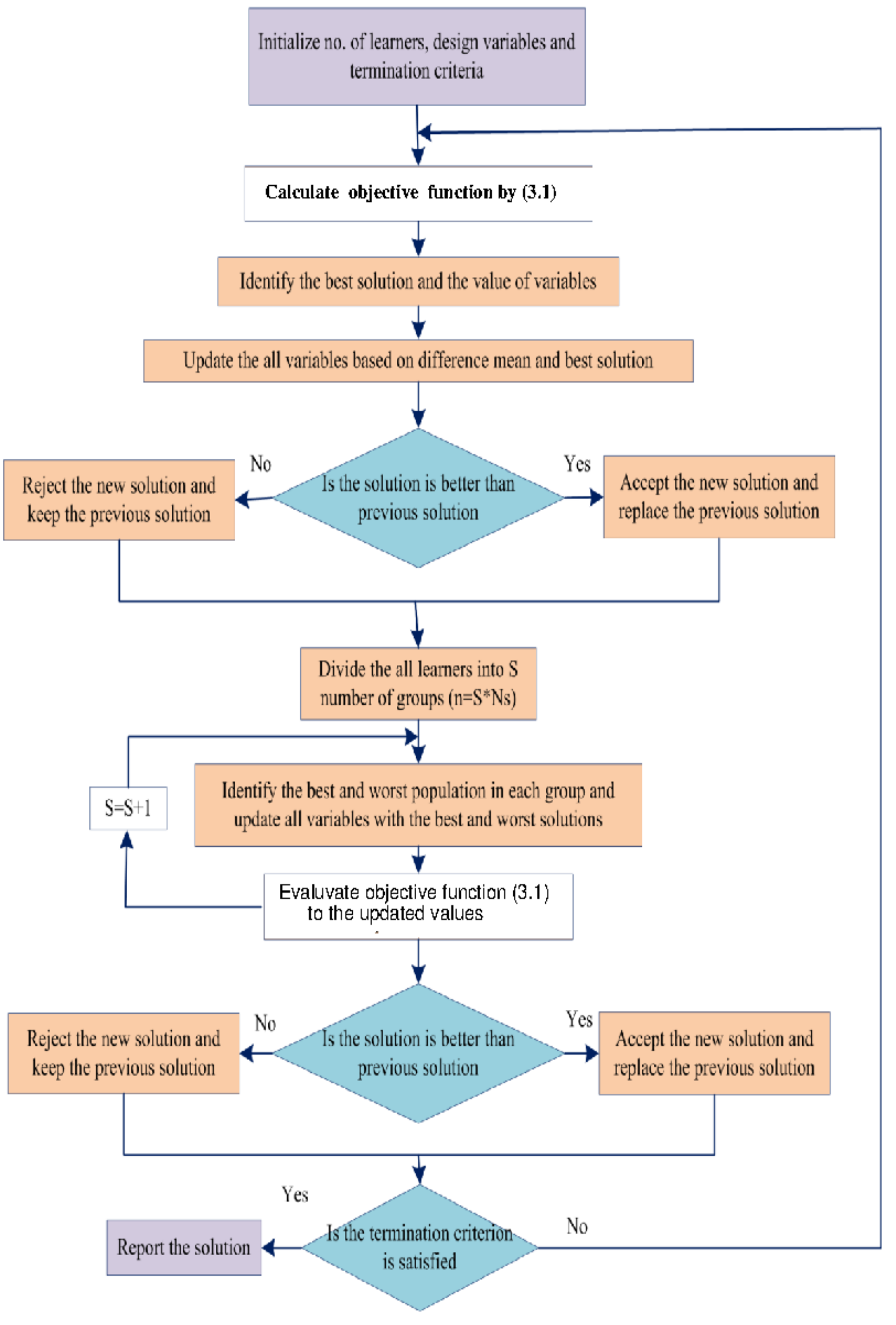

Figure 3.1: Flow chart for Hybrid SFL-TLBO algorithm

3.4.3 Hybrid SFL-TLBO Algorithm

The hybrid SFL-TLBO algorithm is a real-coded population-based meta-heuristic optimization technique that is newly formed by combining the strengths of SFLA [38] and TLBO [39]. In the SFLA, each memeplex evolves independently to local search at different regions of the search space. Then, the memeplexes are shuffled and re-divided into new memeplexes to enhance the exploration capability through exchanging the information with each other. On evaluating the fitness and formation of a memeplex, the frogs with the best and the worst fitness are identified as Xb and Xw, respectively. The position of the frog with the worst fitness is adjusted as follows

$$\mathrm{D_i} = \mathrm{rand}(\mathrm{X_b} - \mathrm{X_w}) \tag{3.12}$$

$$\mathrm{D_{max}} \geq \mathrm{D_i} \geq -\mathrm{D_{max}} \tag{3.13}$$

$$\text{new}\, \mathrm{X_w} = \text{current position of}\, \mathrm{X_w} + \mathrm{D_i} \tag{3.14}$$

The equation (3.14) clearly says that, when the difference in position between Xw and Xb become small, the change in position of frog Xw (new) is small that may lead to reaching the local optimum, i.e., premature convergence.

TLBO algorithm has excellent exploration capability but lack in exploiting the solution space locally [40]. To enhance the exploitation capability of the TLBO algorithm, it is combined with SFLA which is having good local search ability [38]. Hybrid SFL-TLBO optimization algorithm has been developed to determine the simultaneous optimal planning of FCS and DGs for the present and different levels of future EV load enhancement.

3.5 Operational procedure of Hybrid SFL-TLBO Algorithm

The SFL-TLBO is a population-based algorithm and its operation is explained below with step by step procedure.

Step 1) Define the optimization problem as minimization or maximization of f(X). Where f(X) is the objectives function and X is a vector of decision variables.

Teacher phase:

Step 2) Initialize the parameters, population (a group of learners) as X1, X2, X3 - - - Xn and the design variables of optimization problem (number of subjects) as xa, xb, - - xm.

Step 3) Determine the objective function value for each population, identify the optimal objective function value f(Xbest) who act as a teacher and its respective variables set is Xgbest =[xabest, xbbest, - - xmbest]

Step 4) Calculate the mean ($\mathrm{mean_m}$) and difference mean ($\mathrm{diff\,mean_m}$) of each design variable respectively. Mean is the average of each design variable with respect to population size and the difference mean is calculated by

$$\mathrm{diff\,mean_m} = \mathrm{rand} * (\mathrm{X_{gbest}} - \mathrm{mean_m}) \tag{3.15}$$

Where the Xgbest, $\mathrm{mean_m}$ are the best population and difference mean of all variables for n number of population.

Step 5) Based on this difference mean, the existing population is updated according to the following equation

$$\mathrm{Xnew_{n,m}} = \mathrm{Xold_{n,m}} + \mathrm{Diff\,mean_m} \tag{3.16}$$

Evaluate the Teacher phase objective function $f(x)_T$ value with $\mathrm{Xnew_{n,m}}$ population.

Learner phase:

Step 6) Divide the population (Xn) into G number of student groups (memeplex) and each group having S number of students i.e, Xn=g*S.

student group$_1$		student group$_2$			student group$_G$	
population	f(x)	population	f(x)	……………..	population	f(x)
P_1	$f_1(x)$	P_2	$f_2(x)$	……………..	P_G	$f_G(x)$
P_{G+1}	$f_{G+1}(x)$	P_{G+2}	$f_{G+2}(x)$	……………..	P_{2G}	$f_{2G}(x)$
P_{2G+1}	$f_{2G+1}(x)$	P_{2G+2}	$f_{2G+2}(x)$	……………..	P_{3G}	$f_{3G}(x)$
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
$P_{G(S-1)+1}$	$f_{G(S-1)+1}(x)$	$P_{G(S-1)+2}$	$f_{G(S-1)+2}(x)$		P_{SG}	$f_{SG}(x)$

Identify the group best student in each student group (Xgroup_best) and its respective population. Based on this Xgroup_best, update the existing population in that group with the help of the following expression.

$$\mathrm{Xnew_{s,g} = Xold_{s,g} + rand\left(X_{group\_best_{s,g}} - Xold_{s,g}\right)} \tag{3.17}$$

Combine all student groups and evaluate the learner phase objective function $f(x)_L$ value with $\mathrm{Xnew_n}$ population. If $f(x)_L$ is not optimal than $f(x)_T$ then update the population with the overall population best ($\mathrm{X_{best\_pop}}$) following expression

$$\mathrm{Xnew_{s,g} = Xold_{s,g} + rand\left(X_{best\_pop_{s,g}} - Xold_{s,g}\right)} \tag{3.18}$$

Similarly calculate $f(x)_L$ value with $\mathrm{Xnew_{s,g}}$ population. If $f(x)_L$ is optimal than $f(x)_T$, then consider that population for next iteration. Otherwise generate a new population randomly within limits.

Step 7) Combine all students groups and sort them based on non-dominated sorting technique [41], [42]. Identify the best population Xbest and its fitness value f(Xbest) i.e Fbest.

Step 8) Save the Xbest and Fbest as the global best Xgbest and global fitness Fgbest in each iteration.

Step 9) Repeat the procedure from step 4 to step 8 until the termination criterion is met.

Algorithm 1.Pseudo code of proposed hybrid SFL-TLBO

Initialize parameters
Number of populations (n), student groups (g),
Define $f(X)$ X= $(x_a, x_b, x_c \dots\dots\dots x_d)$ *d*=no. of decision variables.
Initialize the group of learners randomly X_i *i*= 1,2,3……..n.
Evaluate objective function value for group of learners $f(X)$
Identify the best solution as teacher X_{gbest}
For iter=1to maximum iterations
  for i=1 to n // Teacher phase//
    Calculate the mean of each variable $mean_m$
    Calculate difference mean of each variable ($diff\ mean_m$)
    $diff\ mean_m = rand * (X_{gbest} - mean_m)$
    Update each solution based on best solution
    $Xnew_{n,m} = Xold_{n,m} + Diff\ mean_m$
    Evaluate the objective value for new mapped solution $f(Xnew_{n,m})$
      If $f(Xnew_{n,m}) \le f(X_i)$ i.e., ($Xnew_{n,m}$ is better than X_i)
        $X_T = Xnew_{n,m}$

$F_T = f(X_T)$
else
$X_T = X_i$
$F_T = f(X_T)$
end if
end for n loop // End of teacher phase //
Sort the population based on non-dominated sorting technique
Divide the learners into g Number of groups
for i=1to g // Learner phase//
for i=1to s
Identify the best solution in each group $X_{group-best}$
$Xnew_{s,g} = Xold_{s,g} + rand\left(X_{group\_best_{s,g}} - Xold_{s,g}\right)$
Calculate objective function value $f\left(Xnew_{s,g}\right)$
If $f\left(Xnew_{s,g}\right)$ is better than $f(X_T)$
$X_i = Xnew_{s,g}$
else
$Xnew_{s,g} = Xold_{s,g} + rand\left(X_{best\_pop_{s,g}} - Xold_{s,g}\right)$
$X_i = Xnew_{s,g}$ $(X_{gbest} = X_i)$
Otherwise generate a random population
end if
end for ---------s loop
end for-------g loop //End of learner phase//
end for ---------iter loop (Termination criterion)
X_{gbest} ------------------- $---best\ population$
$F_{gbest} ----bestfitness$
Save the optimal population and its fitness value.

The current injection load flow method is used to analyse the Distribution System power flows, voltage profiles and current flows in each branch of the distribution network. The objective function is solved by considering the distribution network constraints, DG constraints and FCS constraints.

3.6 Proposed Test System Data

For the proposed work we considered an urban city having surface area of 720 km^2. This consist of 180 zones, each zone has an equal area of 4 km2 (2km×2km).

Table 3.1 presents the EV population in each zone of the study area. The total EV population in the study area is 1632 and among the total EVs population only some probability of EVs is charging in each hour during a day. The 118 bus electrical Distribution System is assumed to be available on the study area for electrical power supply. The charging probability of EVs (CPEV (h)) in each hour during the day is shown in Figure 3.2. It is assumed that EVs are charged at their respective FCSs from 5:00 to 21:00 hours a day.

Table 3.1: EVs population in each zone of test system

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
1	0	3	5	3	4	6	4	0	0	3	7	5	6	4	0
2	3	5	4	6	4	6	7	8	7	9	8	7	5	6	4
3	7	11	16	9	9	13	12	10	11	14	17	6	9	5	3
4	6	1	7	15	16	17	17	9	15	7	14	17	9	15	1
5	4	6	9	10	8	16	16	14	0	14	16	11	7	9	7
6	0	13	14	10	16	14	19	15	17	14	12	8	15	9	4
7	7	11	0	16	16	17	13	18	17	15	9	19	12	8	0
8	4	9	15	14	12	11	4	16	19	9	12	17	17	12	6
9	8	13	14	19	17	15	17	0	13	12	11	13	9	15	8
10	3	12	9	16	13	14	9	14	16	15	17	16	15	13	3
11	0	6	7	8	7	5	6	4	8	5	4	6	4	0	0
12	0	5	3	4	6	4	0	7	3	0	5	6	4	3	4

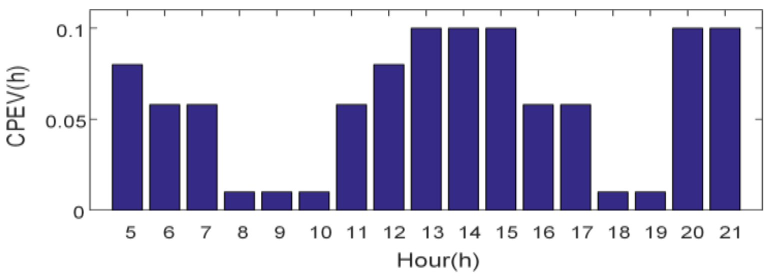

Figure 3.2: Variation of CPEV (h)

Figure 3.3 shows the single line diagram of the 118 bus radial Distribution System associated with the study area, which is considered as the electric test system. The percentages of load variation in each hour during the day for four seasons are taken from [34]. The Base values of 118 Distribution System are 10 MVA, 11 KV and the total load on the system is 22.71 MW and 17.041MVAr.

In the proposed Distribution System the possible 16 candidate FCSs have been assumed to be placed along the main roads of the study area, with constraints of approximately equal distance among the FCSs. The locations of possible charging stations are shown by rhombus symbol in the electrical distribution network as shown in Figure 3.3. The Distribution System and charging station parameters used in the proposed system are listed in Table 3.2.

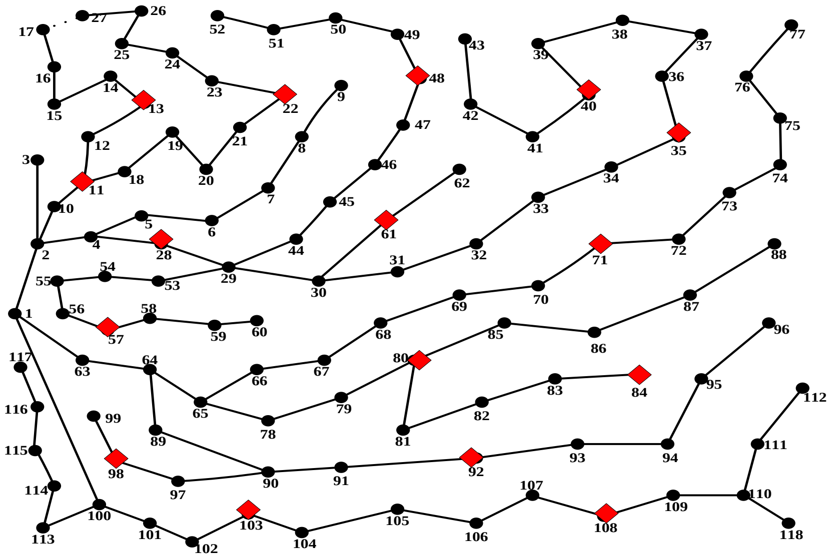

Figure 3.3: 118-bus Distribution System in the study area

Table 3.2: EV and FCS parameters [79]

Parameter	Value	Parameter	Value	Unit
T_{NEV}	1632	SEC	0.142	kWh/kM
N_Y	5	EP	87.7	\$/MWh
N_{PC}	16	C_{lan}	240	\$/M^2.Yr
		C_{init}	70000	\$
		C_{con}	208.33	\$/kW
		PC	96	kW

TNEV- Total Number of Electric Vehicles N_Y-Number of Years N_{PC}-Number of Possible Charging stations SEC- Specific Energy Consumption C_{EP}-Electricity Price Cost	C_{lan}-Yearly land rental cost (in \$/m^2) C_{init}-Fixed cost of station development. C_{con}-Charging connector development cost (in \$/kW) P_C-Rated power of each connecter

3.7 Results and Analysis

To demonstrate the effectiveness of proposed hybrid SFL-TLBO algorithm, IEEE 118 bus test system has been considered in this chapter. The newly proposed SFL-TLBO algorithm is employed to evaluate the fitness value given in objective function (3.1) against the different number of FCSs and DGs in the network for the simultaneous planning of FCSs and DGs in the coupled electrical distribution and transportation network.

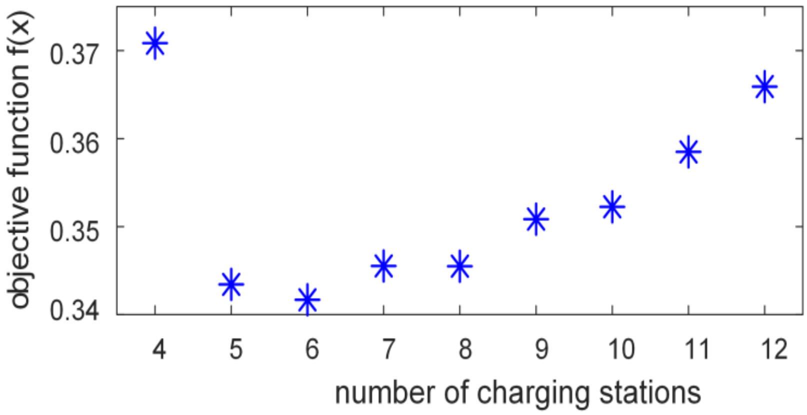

Figure 3.4: Optimal number of FCSs in the coupled electrical distribution and transportation network.

This algorithm determines the optimal capacity and locations of FCSs and DGs for the present and future penetration of EVs in the study area. The objective function for the different number of FCSs is compared in Figure 3.4. From this comparison, the optimal number of FCSs is determined to be 6. The optimal planning of FCSs is determined by considering load variation during four different seasons.

The objective function for different number of DGs is compared in Figure 3.5. From this comparison the optimal number of DGs is determined to be 4.

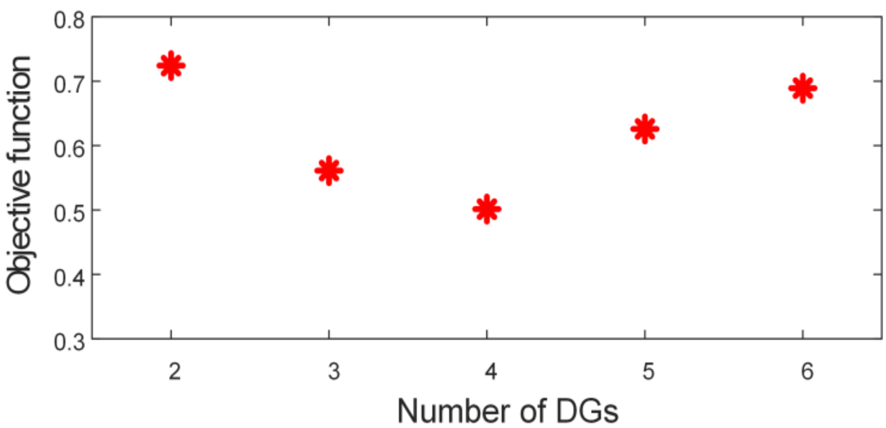

Figure 3.5: Optimal number of DGs in the coupled electrical distribution and transportation network.

The optimal planning of FCSs and DGs has been determined with the objective of reducing the DGPC, NPLC, SEC of EVs and MVD by using TLBO, SFLA and a newly proposed hybrid SFL-TLBO algorithm and the performance of proposed algorithm is compared with the SFLA and TLBO algorithm for the present and different levels of future penetration of EVs.

The following three scenarios are considered for optimal planning of FCSs and DGs in the coupled electrical distribution and transportation network.

Scenario-1: Optimal size of FCSs and DGs for their fixed location.

Scenario-2: Optimal size of all FCSs and DGs for half of fixed location of FCSs and DGs.

Scenario-3: Optimal location and size of FCSs and DGs.

Four different cases are evaluated in each scenario to study the effect of increased EV population demand on optimal planning of FCSs and DGs in the coupled electrical distribution and transportation network.

Case-1: Optimal planning of FCSs and DGs for the present EV population demand.

Case-2: Optimal planning of FCSs and DGs with 10% penetration of EVs.

Case-3: Optimal planning of FCSs and DGs with 20% penetration of EVs.

Case-4: Optimal planning of FCSs and DGs with 30% penetration of EVs.

The proposed algorithm can be applicable for any percentage penetration of EVs, but to test the algorithm performance these four cases have been considered.

3.7.1 Scenario 1: Optimal size of FCSs and DGs for their fixed location

The parameter DGPC, NPLC, SEC of EVs and MVD of distribution network has been calculated for Case 1, Case 2, Case 3 and Case 4 for the current location of FCSs and DGs. The newly proposed hybrid SFL-TLBO algorithm has been used for the optimal planning of FCSs and DGs in the multi-objective environment. The obtained results are compared with pre-existing SFLA and TLBO algorithms and the results are listed in Table 3.3. The variation of DGPC, MVD and NPLC in the form of Pareto fronts for the present EV population and future penetration of EVs at different levels are shown in Figure 3.6 for various case studies.

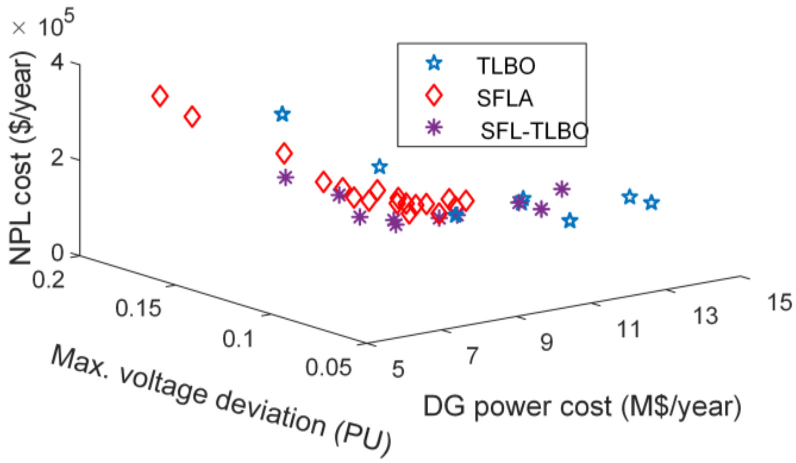

Figure 3.6.1 Optimal Pareto fronts for case 1

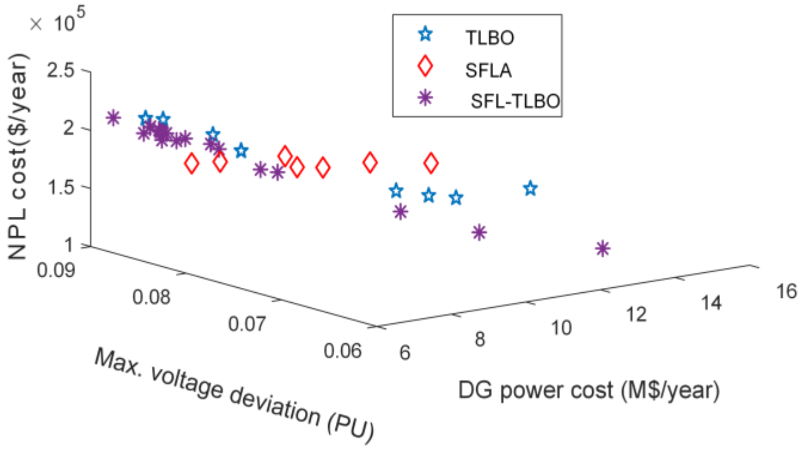

Figure 3.6.2 Optimal Pareto fronts for case 2

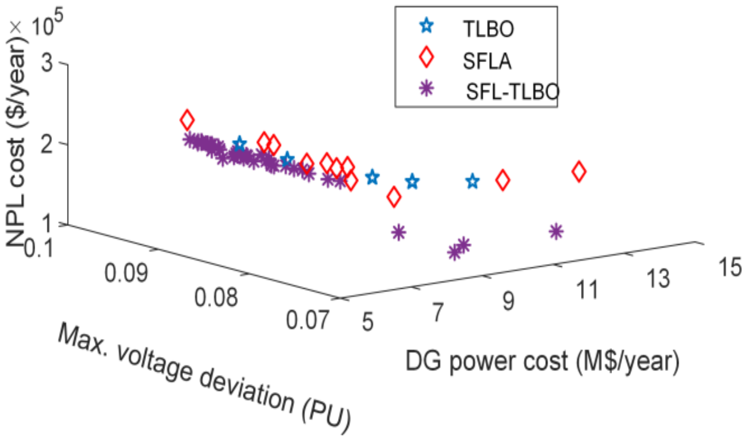

Figure 3.6.3 Optimal Pareto fronts for case 3

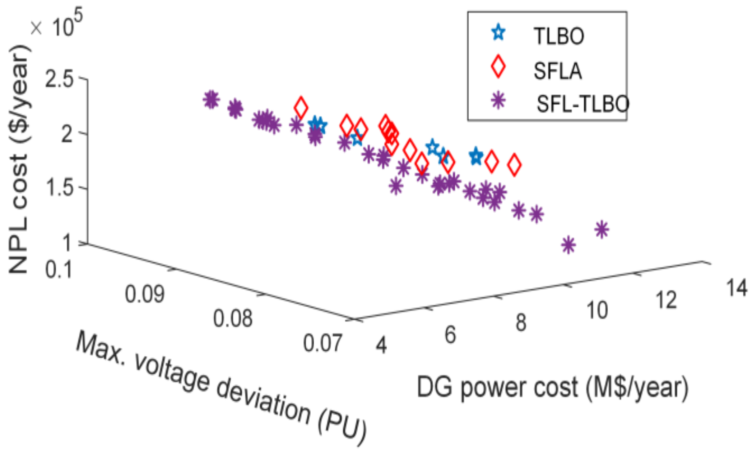

Figure 3.6.4 Optimal Pareto fronts for case 4

Figure 3.6: Optimal Pareto-front for Scenario 1

In Table 3.3, size of FCS resembles the number of charging connectors in that respective charging station and each connector is having 96 kW of rated power. The optimal moderate solutions, obtained from Pareto front solutions using min-max method, contain number of connectors and DG sizes for various case studies are shown in Table 3.3. The number of connectors in each charging station varies with the location of FCS (bus number) and with the increase of EV population demand.

Table 3.4 presents the variation of NPLC, SEC of EVs and MVD for the present and future penetration of EVs at different levels. There are four observations made by analysing the results provided in Table 3.4. The first one is the variation of the SEC of EVs in various levels of EV population demand using different algorithms. The SEC of EV users directly depends on the location of charging station and EVs load demand. The second one is related to the NPLC and DGPC which are conflicting to each other i.e., as the DGPC increases, the NPLC decrease. The better planning of FCSs and DGs results in the reduction of both NPLC and DGPC. The third one is related to the DGPC which is having a major share of total cost. The DGPC includes the investment cost, operation and maintenance cost for the period of one year. The fourth one is related to the performance of the proposed SFL-TLBO algorithm and it is found to be better due to its efficient search ability. The hybridization of SFLA and TLBO brings a high degree of balance between intensification and diversification during the efficient searching process.

Table 3.3: Optimal planning of FCSs and DGs in scenario 1

Algorithm	Parameters								
TLBO	FCSs		Location	22	48	57	92	98	108
	DGs			74		85	108	110	
	FCS	Case-1	No. of connectors	9	13	9	11	3	8
		Case-2		10	14	10	12	4	9
		Case-3		11	16	11	14	4	10
		Case-4		12	17	12	15	4	11
	DG	Case-1	Size (MW)	1.596		0.687	0.904	1.015	
		Case-2		1.781		1.909	1.835	1.143	
		Case-3		0.576		0.512	0.707	0.899	
		Case-4		0.635		1.855	0.874	1.089	
SFLA	FCSs		Location	98	92	61	57	13	35
	DGs			43		50	64	75	
	FCS	Case-1	No. of connectors	3	16	16	7	6	7
		Case-2		4	17	17	8	7	7
		Case-3		4	19	19	9	7	8
		Case-4		4	20	21	9	8	9
	DG	Case-1	Size (MW)	0.833		0.654	1.031	0.733	
		Case-2		1.048		1.304	1.223	1.57	
		Case-3		0.875		1.012	0.725	1.338	
		Case-4		1.369		0.992	0.852	0.809	
Hybrid SFL-TLBO	FCSs		Location	92	40	98	61	28	108
	DGs			40		71	84	112	
	FCS	Case-1	No. of connectors	8	7	6	16	10	7
		Case-2		9	7	7	17	11	8
		Case-3		10	8	7	19	12	9
		Case-4		11	9	8	20	13	9
	DG	Case-1	Size (MW)	1.0453		0.653	0.8216	0.6712	
		Case-2		1.325		1.364	1.752	0.793	
		Case-3		1.686		1.557	0.568	0.747	
		Case-4		0.889		1.415	1.732	1.004	

Comparing the TLBO, SFLA and hybrid SFL-TLBO in all levels of EV population, the proposed hybrid algorithm is offering better results as shown in Table 3.4. In Case 1, the DGPC, NPLC, SEC of EVs and MVD obtained with hybrid SFL-TLBO algorithm are 7.2759 (M$), 1.8078✕105 ($/year), 4.7436✕105 ($/year) and 0.0792 (PU) respectively which are minimum as against 8.8948 (M$) 1.7704✕105 ($/year) 4.9705✕105 ($/year) and 0.0797 (PU) in TLBO algorithm and 7.4147 (M$) 2.2128✕105 ($/year) 4.78332✕105 ($/year) and 0.0812 (PU) in SFLA. Furthermore, the proposed hybrid SFL-TLBO algorithm is yielding the optimal values of DGPC, NPLC, SEC of EVs and MVD even for the Case 2, Case 3 and Case 4. The NPLC and SEC of EVs are the two major objective functions of the optimization problem due to their variable nature with respect to time. The reduction in SEC of EVs and NPLC is beneficial for both EV users and EV charging station owners. The station development cost (SDC) is constant in all the proposed optimization techniques for each penetration level of EVs demand, as the number of connectors for that respective penetration level is constant. Furthermore, the variation of SEC of EVs is nearly constant in each penetration level of EVs. In view of this, these two parameters are not plotted.

Table 3.4: Optimal results for the scenario 1

Case No.	Algorithm	DGPC ($/year)	NPLC ($/year)	SEC of EVs ($/year)	MVD (P.U)
1	TLBO	8.8948×10^6	1.7704×10^5	4.9705×10^5	0.0797
	SFLA	7.4147×10^6	2.2128×10^5	4.78332×10^5	0.0812
	Hybrid SFL-TLBO	7.2759×10^6	1.8078×10^5	4.7436×10^5	0.0792
2	TLBO	11.6473×10^6	1.4089×10^5	5.4452×10^5	0.08
	SFLA	7.0899×10^6	1.937×10^5	5.3263×10^5	0.0797
	Hybrid SFL-TLBO	8.5056×10^6	1.446×10^5	5.3783×10^5	0.0684
3	TLBO	6.144×10^6	2.3701×10^5	5.9721×10^5	0.0856
	SFLA	8.9964×10^6	1.6895×10^5	5.899×10^5	0.0797
	Hybrid SFL-TLBO	9.213×10^6	1.04403×10^5	5.9206×10^5	0.0752
4	TLBO	10.0177×10^6	2.0462×10^5	6.4076×10^5	0.0874
	SFLA	9.175×10^6	1.9399×10^5	6.3735×10^5	0.0797
	Hybrid SFL-TLBO	11.4917×10^6	1.1642×10^5	6.3735×10^5	0.0752

3.7.2 Scenario 2: Optimal size of all FCSs and DGs for half of fixed locations of FCSs and DGs

In this case, half of the number of FCSs and DGs locations is changed and the remaining FCSs and DGs locations are kept same as the present location (Previous scenario locations) but the capacities are considered to change due to increase in EV population i.e. to meet the increased EV load. To avoid the duplication with in the scenario-2 and scenario-3, present EV population demand case (case-1) is not discussed. The Pareto fronts of variation of DGPC, MVD and NPLC to the different penetration levels of EVs demand are shown in Figure 3.7 for various case studies.

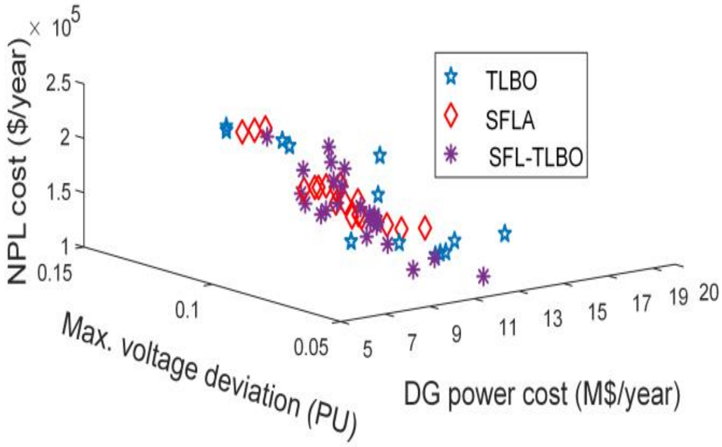

Figure 3.7.1: Optimal Pareto fronts for case 2

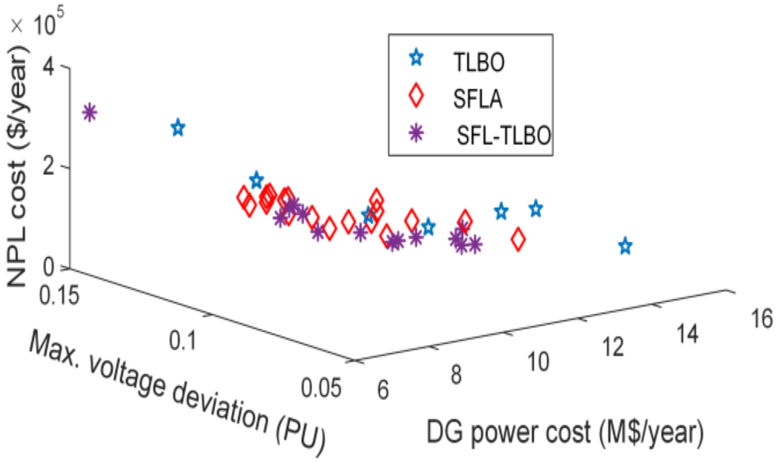

Figure 3.7.2: Optimal Pareto fronts for case 3

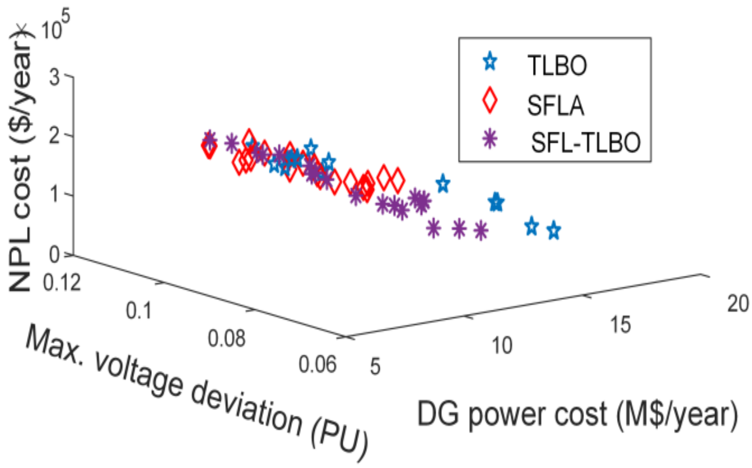

Figure 3.7.3 Optimal Pareto fronts for case 4

Figure 3.7: Optimal Pareto-fronts for Scenario 2

Table 3.5: Optimal planning of FCSs and DGs in scenario 2

Algorithm	Parameters								
TLBO	FCS	Location	Case-2	22	57	92	80	61	71
			Case-3	22	57	92	40	11	28
			Case-4	22	57	92	80	48	13
		No. of connectors	Case-2	8	12	8	7	8	17
			Case-3	12	9	24	10	3	8
			Case-4	6	14	15	16	15	6
	DG	Location	Case-2	110	74	35	76		
			Case-3	110	74	65	23		
			Case-4	110	74	52	4		
		Size (MW)	Case-2	0.794	0.969	0.944	1.388		
			Case-3	1.016	0.913	1.217	1.038		
			Case-4	1.473	1.155	1.155	0.997		
SFLA	FCS	Location	Case-2	35	57	92	61	28	98
			Case-3	35	57	92	80	61	22
			Case-4	35	57	92	84	98	40
		No. of connectors	Case-2	7	5	17	17	9	4
			Case-3	8	13	14	9	13	9
			Case-4	10	16	8	20	4	10
	DG	Location	Case-2	43	75	111	86		
			Case-3	43	75	108	109		
			Case-4	43	75	88	9		
		Size (MW)	Case-2	0.859	1.533	0.896	0.922		

			Case-3	0.675	0.931	0.855	1.145		
			Case-4	1.141	1.123	1.128	1.154		
Hybrid SFL-TLBO	FCS	Location	Case-2	28	40	92	71	35	57
			Case-3	28	40	92	71	61	108
			Case-4	28	40	92	48	71	80
		No. of connectors	Case-2	13	3	12	16	6	9
			Case-3	17	4	9	15	11	9
			Case-4	20	3	10	10	16	12
	DG	Location	Case-2	71	84	43	62		
			Case-3	71	84	104	97		
			Case-4	71	84	46	67		
		Size (MW)	Case-2	1.105	0.761	0.925	0.895		
			Case-3	1.723	1.258	1.625	0.557		
			Case-4	0.977	1.012	1.295	0.893		

For the all levels of EV population investigated in scenario 2, the FCSs and DGs location and sizes are obtained from Pareto front solutions (Figure 3.6) using min-max method and their values are listed in Table 3.5. It can be visualized that with the change in location of half of the number of FCSs causes the change in number of connectors in the present location of charging stations. Therefore in scenario 2, the location of half of the number of DGs is same as scenario 1 but their sizes are not same as scenario 1.

Table 3.6 presents the consolidated results of DGPC, NPLC, SEC of EVs and MVD in the radial distribution network with the new location of FCSs and DGs for the selected penetration levels of EV population. With the new location of half of FCSs and DGs, the DGPC is approximately equal to scenario 1, but the NPLC and SEC of EVs are drastically reduced in scenario 2 against case 2. Similarly, for the case 3 and case 4, the NPLC and SEC of EVs cost are reduced.

Table 3.6: Optimal objective parameters in scenario 2

Case number	Algorithm	DGPC (M$/year)	NPLC ($/year)	SEC of EVs ($/year)	MVD (p.u)
2	TLBO	9.0857	1.3787×10^5	4.9632×10^5	0.0814
	SFLA	9.372	1.4238×10^5	5.2497×10^5	0.0697
	Hybrid SFL-TLBO	8.4052	1.4231×10^5	5.2182×10^5	0.0792
3	TLBO	9.0361	1.8299×10^5	5.9123×10^5	0.0849
	SFLA	8.159	1.8937×10^5	5.7409×10^5	0.0759
	Hybrid SFL-TLBO	10.0606	1.2857×10^5	5.3621×10^5	0.0677
4	TLBO	7.3093	2.1127×10^5	6.0966×10^5	0.0878
	SFLA	9.3648	1.2587×10^5	6.5774×10^5	0.0686
	Hybrid SFL-TLBO	9.5254	1.7491×10^5	5.9534×10^5	0.0979

With the increase in EV population, we can observe that the rise in NPLC and SEC of EVs is predominantly high in scenario 1 as compared with scenario 2. Furthermore, the optimal values are realized with the proposed new hybrid multi-objective optimization are minimum as compared to the SFLA and TLBO algorithm. The primary reason for the better performance of above scenario is due to the optimal size and location of the new half of the number of FCSs and DGs in the coupled electrical distribution and transportation network, which results in a significant reduction in network power loss and SEC of EVs.

In case 2 of scenario 2, the optimal values of the DGPC, NPLC and SEC of EVs are 8.4052 (M$/year), 1.4231✕105 ($/year) and 5.2182✕105 ($/year) respectively and these are obtained by using an SFL-TLBO algorithm. These objectives values of scenario 2 are minimum as compared to scenario 1. In scenario 1 of case 2, the DGPC, NPLC and SEC of EVs are 8.5056 (M$/year), 1.446✕105 ($/year) and 5.3783✕105 ($/year) respectively using an SFL-TLBO algorithm. Similarly, in case 3 and case 4, the total DGPC, NPLC and SEC of EVs are optimal as compared to that of case 3 and case 4 of scenario 1.

3.7.3 Scenario 3: Optimal location and size of FCSs and DGs

In this case, to meet the increased number of EV population, new optimal location and sizes of both FCSs and DGs are determined. For each level of increases in EV population the objective parameters DGPC, NPLC, SEC of EVs and MVD of distribution network have been determined separately.

The Pareto fronts of variation of DGPC, MVD and NPLC to the case 2, case 3 and case 4 for scenario 3 are shown in Figure 3.8.

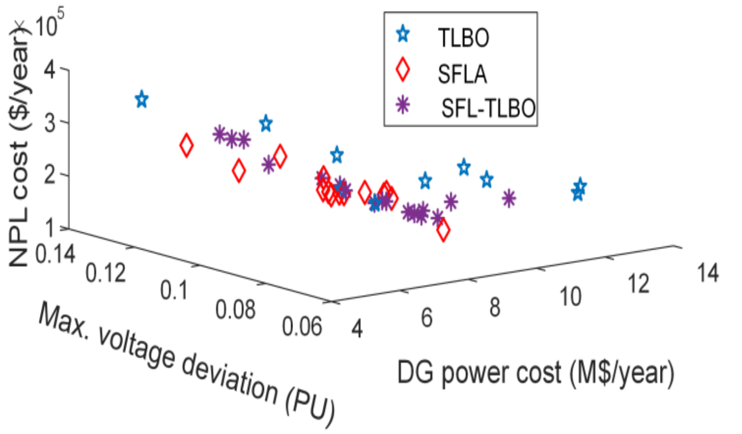

Figure 3.8.1: Optimal Pareto fronts for case 2

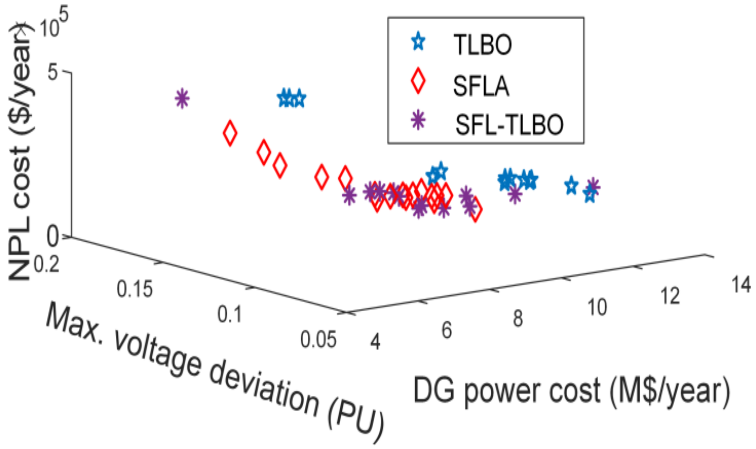

Figure 3.8.2: Optimal Pareto fronts for case 3

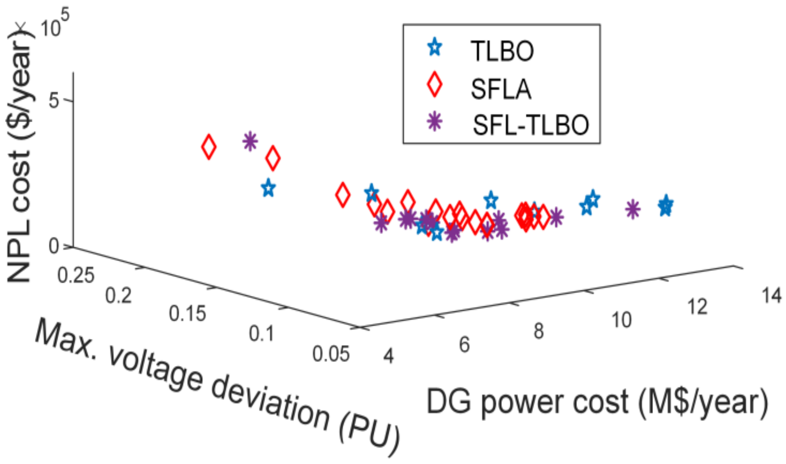

Figure 3.8.3: Optimal Pareto fronts for case 4

Figure 3.8: Optimal Pareto-fronts for Scenario 3

Table 3.7: Optimal new location and sizes of FCSs and DGs in scenario 3

Algorithm	Parameters								
TLBO	FCS	Location	Case-2	28	71	22	98	80	103
			Case-3	61	48	40	71	92	103
			Case-4	13	103	71	28	80	22
		No. of connectors	Case-2	9	21	9	5	13	3
			Case-3	17	8	3	15	11	11
			Case-4	4	7	25	10	15	8
	DG	Location	Case-2	95	59	93	32		
			Case-3	83	43	28	114		
			Case-4	97	30	103	46		
		Size (MW)	Case-2	0.711	1.111	0.751	1.811		
			Case-3	0.867	0.764	0.885	1.516		
			Case-4	1.448	1.074	1.376	0.935		
SFLA	FCS	Location	Case-2	98	28	57	40	48	61
			Case-3	57	92	35	28	80	40
			Case-4	48	40	57	71	22	98
		No. of connectors	Case-2	6	9	5	6	7	27
			Case-3	9	11	10	15	14	6
			Case-4	6	3	12	30	12	8
		Location	Case-2	35	42	77	81		

	DG		Case-3	66	80	73	84		
			Case-4	96	109	63	33		
		Size (MW)	Case-2	0.842	0.966	0.706	1.053		
			Case-3	0.773	1.247	1.185	0.718		
			Case-4	0.621	0.875	1.604	0.654		
Hybrid SFL-TLBO	FCS	Location	Case-2	71	92	80	103	57	22
			Case-3	71	98	84	48	108	13
			Case-4	57	35	103	22	92	28
		No. of connectors	Case-2	19	8	8	5	10	11
			Case-3	16	14	14	4	4	14
			Case-4	17	4	8	5	23	13
	DG	Location	Case-2	23	41	31	11		
			Case-3	29	21	86	77		
			Case-4	39	74	12	95		
		Size (MW)	Case-2	1.276	0.716	1.393	0.846		
			Case-3	1.178	0.951	0.652	0.856		
			Case-4	1.666	0.722	1.542	0.722		

For various EV loads, location and sizes of FCSs and DGs are obtained from Pareto front solutions (Figure 3.8) using min-max method for scenario-3 and they are listed in Table 3.7. The new location and size of both FCSs and DGs in the coupled electrical distribution and transportation network have resulted in the reduction of NPLC, SEC of EVs and MVD as compared to that of scenario 1 and scenario 2.

In case 2 of scenario 3, the total DGPC, NPLC and SEC of EVs are calculated by using proposed new hybrid SFL-TLBO algorithm and their values are 8.0737 (M$/year), 1.4614×105 ($/year) and 5.0623×105 ($/year) respectively. These values are comparatively less as compared to 8.4052 (M$/year), 1.4231×105 ($/year) and 5.2182×105 ($/year)) respectively for the case 2 of scenario 2; and 8.5056 (M$/year), 1.446×105 ($/year) and 5.3783×105 ($/year) for the case 2 of scenario 1 obtained using an SFL-TLBO algorithm. Consequently, for the case 3 and case 4 of the scenario 3 better results are observed compared to the scenario 1 and scenario 2. Furthermore, the consolidated results in Table 3.8 clearly explain the effectiveness of proposed a multi-objective hybrid SFL-TLBO algorithm. It may be noted that due to huge investment cost, the DGPC is very high as compared to the NPLC in all cases. To calculate DGPC we have considered the operation and maintenance cost for one year in addition to investment cost. These results underline the fact that the future penetration of EVs are playing a significant role in the optimal planning of FCSs and DGs in a coupled electrical distribution and transportation system.

Table 3.8: Optimal objective parameters in scenario 3

Case No.	Algorithm	DGPC (M$/year)	NPLC ($/year)	SEC of EVs ($/year)	MVD (p.u)
2	TLBO	9.6818	2.3028×10^5	4.9892×10^5	0.0992
	SFLA	8.1305	1.9179×10^5	5.1897×10^5	0.0709
	Hybrid SFL-TLBO	8.0737	1.4614×10^5	5.0623×10^5	0.0797
3	TLBO	9.2305	2.3028×10^5	5.4519×10^5	0.1052
	SFLA	8.8053	2.1889×10^5	5.8295×10^5	0.09
	Hybrid SFL-TLBO	8.3501	1.625×10^5	5.3599×10^5	0.0718
4	TLBO	10.3383	2.2733×10^5	5.8815×10^5	0.0929
	SFLA	9.1479	2.1523×10^5	6.2701×10^5	0.0797
	Hybrid SFL-TLBO	8.0463	1.6128×10^5	5.8935×10^5	0.0884

This chapter mainly focused on multi-objective hybrid SFL-TLBO algorithm, for better planning of the FCSs and DGs in the coupled electrical distribution and transportation network considering the objectives of voltage deviation, NPLC, DGPC and the energy consumption of EV users. Further, the optimal planning of FCSs and DGs has been determined for the present and future increase in EV population. The results obtained using the hybrid SFL-TLBO algorithm is compared with the SFLA and TLBO algorithm. Results have shown that the DGPC and SEC of EVs constitute the major share of the total cost. Optimization of FCSs location has a drastic impact on SEC of EVs, so did the increase in EV population.

The results suggest that proper erection of new FCSs in Distribution System is required to address the future penetration of EVs. Otherwise, the NPLC and SEC of EVs are financially more expensive. The proposed hybrid SFL-TLBO is tested on IEEE 118 bus benchmark test system. It is verified that proposed hybrid algorithm is reliable and robust in covering different levels of EV population demand in three scenarios. Therefore, the proposed optimal planning FCSs and DGs technique can be used for the planning study of charging stations in the coupled electrical distribution and transportation network.

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The next stage of investigation is focused on an accurate EV load model. This is required to optimize the operating cost while maintaining the system security and reliability. However, the load modeling is a complex problem due to distinctive feature of different type of loads in the distribution system. To analyze the impact of load of EV in distribution system, the EV battery load is modeled by considering the start time and the initial State of Charge (SOC) of individual battery and the same is reported in chapter 4.

Chapter-4

Impact of EV Load Modelling on Fast Charging Station Planning in Electrical Distribution System

4.1 Introduction

In recent years, the significant developments in energy battery technologies such as high energy density (longer EV range), longer life and DC FCS have led to fast growth in EV population. If the FCSs are not optimally planned, the increased penetration of load of FCS has a disruptive impact on distribution system. The FCSs load characteristics are different from the conventional load demand. The impact of addition of FCS on the Distribution System depends on FCS location, charging level, driving pattern, number and types of EVs, battery capacity and initial State of Charge (SoC). Hence, it is necessary to know whether the current Distribution System is capable of handling a massive EV penetration or not [31].

The realistic system analysis has been obtained by using an accurate load model. This is required to optimize the operating cost while maintain the system security and reliability. However, the load modelling is a complex problem due to distinctive feature of different type of loads in the Distribution System [32]. To analyze the impact of EV load in distribution system, the EV battery load is modeled by considering the start time and the initial SOC of individual battery. The charging load and its charging methodologies play significant role in distribution system. The inaccurate modelling of EV load may overload the Distribution System components, increase in network power loss (NPL) and maximum voltage deviation. The Constant Power (CP) load model is more popularly using to model both the conventional and EV loads in distribution system. But the CP load modelling cannot provide accurate information of different types of voltage dependent conventional loads and EV charging process.

In this work, the EV loads are modelled as Constant (i). Impedance-Constant Current-Constant Power (ZIP), (ii). Exponential, (iii). Constant Current and (iv). Constant Power load models and the conventional loads are modelled as (a). Residential-Industrial-Commercial (RIC) and (b). Constant Power load models. With these EV load models, the impact of load of FCS in distribution system has been analysed.

4.2 EV Load model and Problem formulation

4.2.1 EV load model

In the aforementioned literature [30]-[36], EV charging was modelled as Constant Power load model and the same is updated in Distribution System load flow for each time interval to analyse electrical power losses, voltage deviation and a daily load profile. The variation in voltage at load buses have a greater impact on the power consumption of the loads. In EV charging, at low SOC of the battery it draws the high power. Power flow from converter to battery depends on converter to battery current (I) and battery voltage (V). The battery terminal voltage depends on its SOC [67]-[73].

In this chapter, the voltage dependent load modelling has been used to analyse the impact load of FCS in distribution system.

4.2.2 ZIP load model

The ZIP or Polynomial model is combination of Constant Current, Constant Power and Constant Impedance. The ZIP load model is an expansion of Exponential load model, which has been widely used to analyse the voltage dependence of loads.

$$P_{EV}^{1} = P_0 \left[Z_p \left(\frac{V}{V_0} \right)^2 + I_p \left(\frac{V}{V_0} \right) + P_P \right] \tag{4.1}$$

Where $\mathbf{P_0}$ is the active power at the nominal voltage $\mathbf{V_0}$ (1.0 p.u); **V** is the actual voltage; $\mathbf{Z_p}$, $\mathbf{I_p}$ and $\mathbf{P_P}$ are the constants associated with the impedance, current and power of active load at particular bus. The$\mathbf{Z_p}$, $\mathbf{I_p}$ and $\mathbf{P_P}$ values are -0.1773, 0.9949 and 0.1824 [80] respectively.

4.2.3 Exponential load model

The second type of EV load model is represented with the help of constant power term($= \mathbf{b}$), exponent constant ($= \mathbf{a}$) and exponent indices ($= \boldsymbol{\beta}$) as follows:

$$P_{EV}^{2} = P_0 \left[a \left(\frac{V}{V_0} \right)^{\beta} + b \right] \tag{4.2}$$

Where **a**, **β** and **b** are the constants of Exponential load model and their values are considered as 0.0122, -1.9392 and 0.9878 [81] respectively.

4.2.4 Constant Current load model

The Constant Current load model is obtained by using an exponential load model and is given below:

$$P_{EV}^{3} = P_0 \left(\frac{V}{V_0} \right)^{\alpha} \tag{4.3}$$

where α is an exponential index and its value is taken as 1.

4.3 Objective function formulation

In the distribution network, the network power losses, voltage profile and the power flows through the line are greatly depend on EV load modelling and its load profiles. The variation of Distribution System parameters like distribution network power losses, bus voltages and power flows, from their rated values is measured by the system performance indices.

It is assumed that, in a selected day, the total number of EVs (TNEV) in the study area is charged by the FCS. The TNEV in study area is calculated as

$$\boldsymbol{TNEV} = \sum_{\boldsymbol{z=0}}^{\boldsymbol{nzone}} \boldsymbol{NEV(z)} \tag{4.4}$$

Where NEV(z) is the number of dedicated EVs in zone z, i.e., all dedicated vehicles are regular costumers of that zone FCS and nzone is the number of zones in the selected study area.

4.3.1 EVUC (Electric Vehicle User Cost) index

The EV user should drive a certain trajectory to reach to the FCS. EVUC represents the cost associated with the energy consumed by EVs to reach the FCS. For EVs located in zone z, the EV user cost to reach nearest FCS for being charged at j^{th} charging station $\mathrm{EVUC(z, j)}$ is calculated as follows [36].

$$EVUC = \sum_{z=1}^{nzone} \sum_{j=1}^{ncs} d(z,j) SEC \sum_{h=1}^{24} CPEV(h) NEV(z) EP \tag{4.5}$$

where $\mathrm{d(z, j)}$ is the distance between zone z and j^{th} charging station SEC and EP are the specific energy consumption of EVs (kWh) and electricity price during hour h respectvely. the variable CPEV(h) is a vector having the probability of EV charging in the hour (h) of the day. The distance to displacement ratio strongly depends on the optimality of the road network in the selected study area. For an optimal road network, the distance approaches the displacement. Hence, choosing the displacement rather than distance in this approach to obtain charging stations are still optimal for the optimal road network.

The EVUC index reflects the minimization of EVUC from the maximum EVUC and it is calculated as follows

$$EVUCI = \frac{EVUC_{max} - EVUC}{nzone * ncs} \tag{4.6}$$

where the $EVUC_{max}$ is the maximum possible EVUC as compared to all possible FCSs locations and ncs is number of FCSs.

4.3.2 Power loss index (PLI)

The higher FCS charging demand increases the line and substation loading. It causes an increase in Distribution System power losses. The Distribution System loss has a nonlinear relationship with the system loading. The variable Distribution System loss is significant due to EV charging demand, hence the precise calculation of electrical grid loss is required, with the account of the variation in grid load [39].

The distribution network power losses (NPL) during a day is calculated as follows,

$$NPL^{TL} = \sum_{h=1}^{24} \sum_{t=1}^{n_p} PL(h,t) \tag{4.7}$$

$$GPL(h,t) = PL(h,t) + APL(h,t) \tag{4.8}$$

$$NPL^{TLEV} = \sum_{h=1}^{24} \sum_{t=1}^{n_p} GPL(h,t) \tag{4.9}$$

where $PL(h,t)$ is the power losses with conventional load at time t during hour h. The GPL and APL are the total electrical power loss including FCS load and added power losses due to FCS load at time t during hour h. The PLI is related the difference in power losses with and without load of FCSs. The PLI is calculated as follows

$$PLI = \frac{NPL^{TLEV} - NPL^{TL}}{N_l N_p} \tag{4.10}$$

where N_p and N_l are the number of time periods in the load profile and number of lines in the test system. NPL^{TLEV}And NPL^{TL} are the distribution network power losses with and without FCS load respectively.

4.3.3 Voltage profile index (VPI)

Inappropriate planning of FCSs causes voltage instability in the distribution network. Both of over and under voltages affect the power quality of supply. The VPI for load modelling is related to the voltage deviation between each bus V_i and the root bus voltage (v_0) considering the time varying voltage magnitude for EV load demand at each time interval. The lower value of VPI means better the network performance.

$$VPI = \frac{\sum_{t=1}^{N_p} \sum_{i=1}^{N_b} |V_0^t - V_i^t|}{N_b N_p} \tag{4.11}$$

where N_b is the number of buses in the distribution system. V_0 and V_i are the voltage magnitude at the slack and bus i respectively.

4.3.4 Apparent power performance index (APPI)

The APPI reflects the violation of branch active power flows in the distribution system. It measures the severity of the branch or line over loads considering EV load demand at each time interval [23]. The APPI is calculated as follows

$$APPI = \frac{\sum_{t=1}^{N_p}\sum_{l=1}^{N_l}\frac{S_l^t}{S_l^{max}}}{N_p N_l} \tag{4.12}$$

where N_l is the number of lines in the distribution network. S_l and S_l^{max} are the actual power flow and the maximum power flow limit in line l respectively.

4.3.5 Objective function

$$optimization\ of\ \{EVUCI,\ PLI,\ VPI,\ APPI\} \tag{4.13}$$

The objective function is the minimization of EVUCI, PLI, VPI and APPI of the electrical Distribution System by meeting the following constraints,

$$\sum_{j=1}^{NFCS} FCS(j) > 0 \quad \forall \quad j = 1,2, \dots \dots \dots, NPC \tag{4.14}$$

$$S(j) \geq 0 \quad \forall \ j = 1,2,3, \dots \dots \dots, NPC \tag{4.15}$$

$$\sum_{z=1}^{nzone} Select(z, j)X(j) = 1 \qquad \forall\ 1,2,3 \dots \dots z \tag{4.16}$$

$$0 \leq bat_{i,t}^{chg} \leq \left(1 - y_{i,t}\right) * PC \qquad \forall\ t \in T, \forall\ i \in TNEV \tag{4.17}$$

$$SOC_{min} \leq SOC_{i,t} \leq SOC_{max} \quad \forall\ t \in T, \forall\ i \in TNEV \tag{4.18}$$

Equation (4.14) represents, at least one charging station should be installed in the selected area to meet the EV loads [24]. The NPC is the number of possible FCSs based on road transport network and electrical distribution network. Equation (4.15) and (4.16) represent, at least one charging connector should be considered for each selected FCS. The EVs in each zone should select one optimal FCS based on the distance between j^{th} charging station and zone z. These $\mathrm{Select}(z, j)$ is 1 if the EVs in zone z are selected j^{th} charging station, otherwise it is zero. $X(j)$ is the binary decision variable, which is equal to 1 if j^{th} FCS is selected, otherwise it is zero.

Table 4.1 Comparison of SFLA and TLBO with hybrid SFL-TLBO algorithm

	SFLA	TLBO	Hybrid SFL-TLBO algorithm	Adapted from	Reason for combination
Initial population	Randomly real code generated within the limits	Randomly real code generated within the limits	Randomly real code generated within the limits	-	SFLA, TLBO and Hybrid SFL-TLBO algorithm
Memeplex creation	Divide the population in to number of memeplexes	Not Applicable	Divide the TLBO population in to students groups	SFLA	To enhance the exploration capability. Through exchanging the information with each other.
Convergence criteria	Combine all memeplexes in to single population and check for convergence	Maximum number of iterations	Combine all memeplexes in to single population and check for convergence with maximum number of iterations	SFLA, TLBO	To get better convergence criteria
formation of next iteration population	The next iteration population is formed by moving weak frogs to towards frogs	The next iteration population is formed by updating student knowledge towards teacher.	Initially the students are updated towards best student within the group and later towards the teacher.	SFLA, TLBO	To enhance the exploration and exploration capabilities.

Each battery has a maximum charging power as given in (4.17). and $bat_{i,t}^{chg}$ is the charging power of i^{th} EV battery at time t. The $y_{i,t}$ is the swapping status of i^{th} EV at time t.

$SOC_{i,t}$ is the SOC of i[th] EV battery at time t and it should be with in minimum SOC (SOC_{min}) and maximum SOC of battery (SOC_{max}).

4.4 Multi-objective hybrid Optimization Algorithm

To analyze the impact of EV load modelling on optimal planning of FCSs and DGs in distribution system the proposed SFL-TLBO hybrid optimization algorithm has been used. The concept of SFL-TLBO algorithm and its step by step procedure was explained in section 3.5 and 3.6 respectively. The comparison between the proposed SFL-TLBO, SFLA and TLBO algorithms are reported in Table 4.1.

Algorithm 1.Pseudo code of proposed hybrid SFL-TLBO

```
Initialize NPS, CPEV, distribution system parameters, EV load model parameters and termination criteria
Number of populations (n), student groups (s),
Define f(X)      X= (x_a, x_b, x_c ... ... ... x_d)  d=no. of decision variables.
Initialize the group of learners randomly X_i     i= 1,2,3........n.
Evaluate objective function value for group of learners f(X)
Identify the best solution as teacher X_gbest
For iter=1to maximum iterations
    for i=1 to n                // Teacher phase//
        Calculate the mean of each variable mean_m
        Calculate difference mean of each variable (diff mean_m)
        diff mean_m = rand * (X_gbest - mean_m)
        Update each solution based on best solution
        Xnew_{n,m} = Xold_{n,m} + Diff mean_m
        Evaluate the objective value for new mapped solution f(Xnew_{n,m})
            If f(Xnew_{n,m}) ≤ f(X_i)  i.e., (Xnew_{n,m} is better than X_i)
                X_T = Xnew_{n,m}
                F_T = f(X_T)
            else
                X_T = X_i
                F_T = f(X_T)
            end if
    end for   n loop            // End of teacher phase //
```

Sort the population based on non-dominated sorting technique

Divide the learners into g Number of groups

for i=1to g // Learner phase//

for i=1to s

Identify the best solution in each group $X_{group-best}$

$$Xnew_{s,g} = Xold_{s,g} + rand\left(X_{group\_best_{s,g}} - Xold_{s,g}\right)$$

Calculate objective function value $f\left(Xnew_{s,g}\right)$

If $f\left(Xnew_{s,g}\right)$ is better than $f(X_T)$

$X_i = Xnew_{s,g}$

else

$Xnew_{s,g} = Xold_{s,g} + rand\left(X_{best\_pop_{s,g}} - Xold_{s,g}\right)$

$X_i = Xnew_{s,g}$ ($X_{gbest} = X_i$)

Otherwise generate a random population

end if

end for ---------s loop

end for-------g loop //End of learner phase//

end for ---------iter loop (Termination criterion)

X_{gbest} ------- optimal location and size of FCSs

F_{gbest} -------- optimal $EVUCI,\ PLI,\ VPI,\ APPI$ values

Save the optimal population and its fitness value.

4.5 Test system Data and Performance comparison of proposed Algorithm

4.5.1 Test System Data

The IEEE 38 bus test system has been used as case study to analyze the impact of FCS EV load modelling in distribution system. For this test system, base voltage and base MVA are 12.66 kV and 1 MVA respectively. The total real and reactive power loads on the test system are 5084.26 kW and 2547.32 kVAr [79].

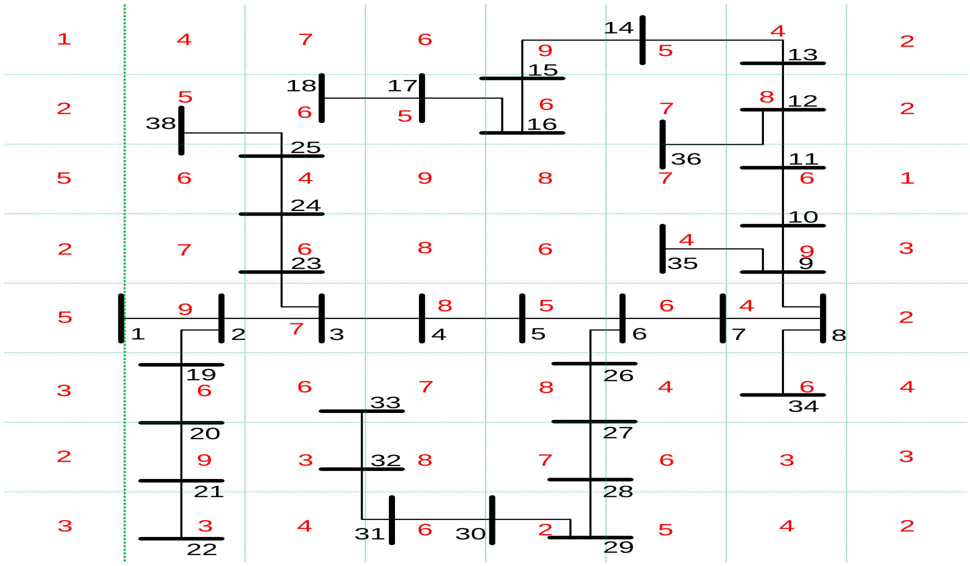

Figure 4.1: 38-bus Distribution System with zones

Figure 4.1 shows the single line diagram of 38 bus system associated with uniformly divided EV zones. To analyze the impact of EV load modeling a study area of 256 km^2 surface area has been considered. It consist of 64 uniformly divided EV zones, with the area of each zone is 4km^2. The EV population in zone is mentioned in middle of each zone. The total EV population in study area is considered as 330. The variation of conventional load in each hour during a day is considered for investigation purpose and it is shown in Figure 4.2.

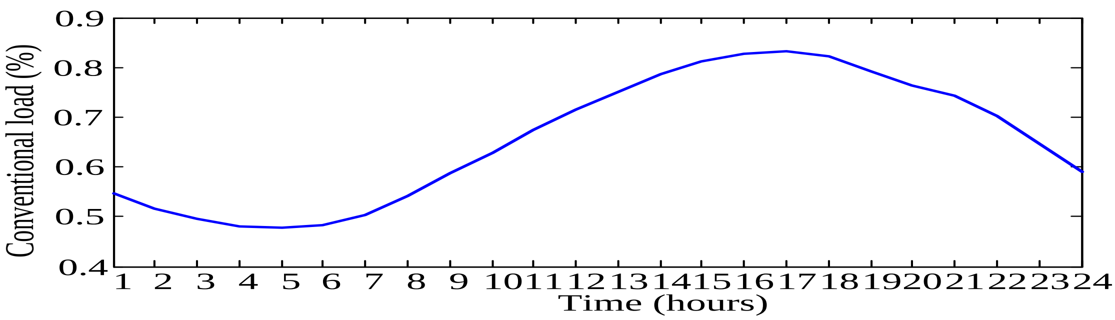

Figure 4.2: Hourly conventional load profile during a day

To consider the uncertainty of arrival EVs, a charging probability distribution function (CPEV(h)) is considered. The charging probability distribution function is shown in Figure 4.3. It has been divided in to 17 probability levels [72].

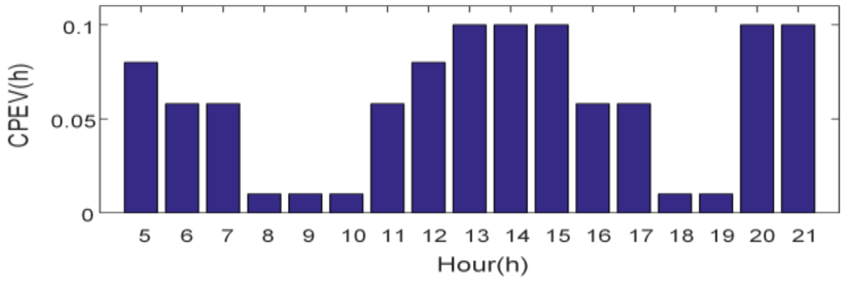

Figure 4.3: Variation of CPEV (h)

Furthermore, to consider the uncertainty of the initial SOC of the EVs in load flow the Monte-Carlo simulation has been used. This uncertainty is modelled as normal distribution function with mean 20 and standard deviation is 5 as shown in Figure 4.4.

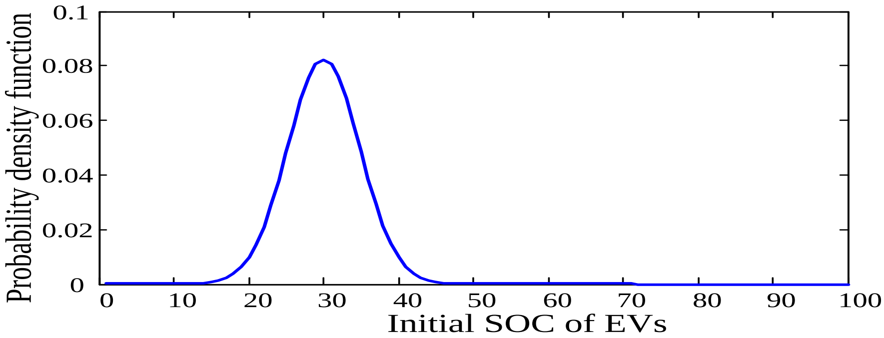

Figure 4.4: EVs initial SOC PDF

A normal distribution is a random variable x with mean (μ) and variance σ^2 is a statistical distribution with probability distribution function. The normal distribution function is calculated as follows

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-(x-\mu)^2/(2\sigma^2)} \tag{4.26}$$

The distribution network and EV parameters are listed in Table 1.

Table 4.2: EV and FCS parameters [79]

Parameter	Value	Parameter	Value	Unit
TNEV	330	SEC	0.142	kWh/kM
NPC	9	EP	87.7	$/MWh
		PC	30	kW
		BC^{max}	24	kWh

4.6 Performance comparison of Hybrid SFL-TLBO with SFLA and TLBO

The performance comparison of multi-objective optimization is more complex as compared with single objective optimization, because the optimization goal itself consists of multiple objectives. The performance of proposed Hybrid SFL-TLBO algorithm is compared with SFLA and TLBO by using two metrics. To calculate these metrics the algorithms are executed for 20 runs with random initial seeds [71].

4.6.1 Convergence metric (C-metric)

The C-metric is evaluating the progress towards the optimal pareto-front. The set convergence metric C (A, B) calculates the proportion of solutions in B which are weakly dominated by solutions of A.

$$C(A,B) = \frac{|\{b\epsilon B; \exists\ a\epsilon A: a \preccurlyeq b\}|}{|B|} \tag{4.27}$$

4.6.2 Spacing metric (S-metric)

The S-metric is evaluating the spread of solutions in pareto-front. It is defined as the distance variance of each solution to nearest neighbor and it is calculated as follows;

$$S = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(\bar{d} - d_i)^2} \tag{4.28}$$

Where d_i is the distance of the i^{th} individual to its closest neighbor, and $\bar{d}$ is the mean of among individuals. The $\bar{d}$ and d_i are calculated as follows;

$$\bar{d} = \frac{\sum_{i=1}^{n} d_i}{n} \tag{4.29}$$

$$d_i = \min\left\{\sum_{m=1}^{N_{obj}} \frac{|f_m(x_i) - f_m(x_j)|}{f_{m,max} - f_{m,min}}\right\} \tag{4.30}$$

The boxplots of C-metric and S-metric are shown in Figure 4.5 and Figure 4.6. It shows that the proposed Hybrid SFL-TLBO has the better performance as compared to the SFLA and TLBO. Therefore, the proposed algorithm has been used for different cases of scenario 1 and scenario 2.

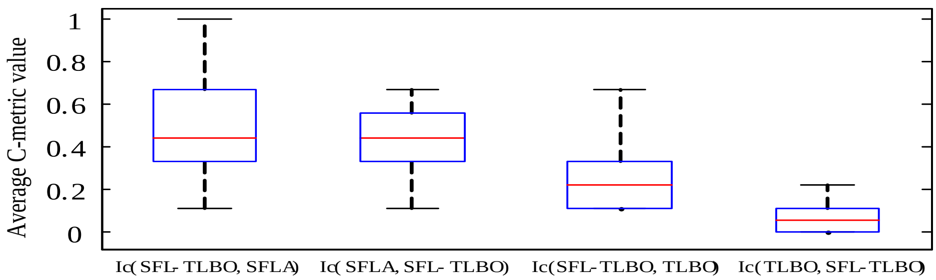

Figure 4.5: Average C-metric value for case 1 of scenario 1

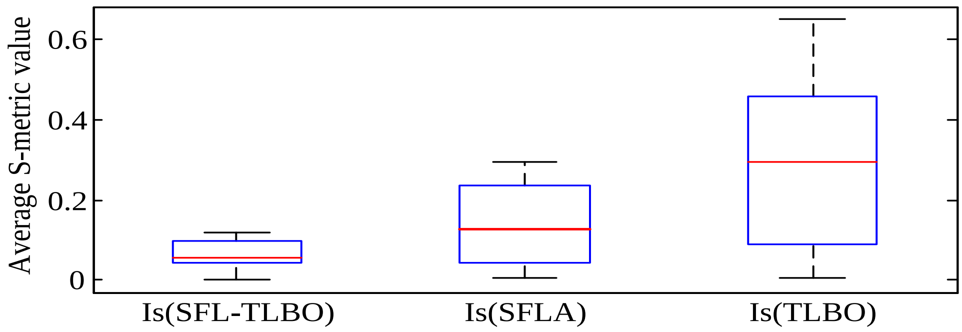

Figure 4.6: Average S-metric value for case 1 of scenario 1

4.7 Results and Analysis

To analyze the impact of FCS EV charging on Distribution System, the network power loss, maximum voltage deviation and EVUC are considered as objectives. Two possible scenarios are considered with different load models. In each scenario the objective is to reveal the impact levels of EV load models on distribution system. For this, the daily conventional loads and the EV loads are not separated. The load variation in each hour during the day has been considered to solve the objective function (4.13). The Current Injection Method (CIM) has been used to analyze load flow in distribution system. In voltage dependent load modelling case, the active and reactive loads are continuously updated after computing the new voltages in order to reflect the changes in bus voltage in each iteration of CIM load flow method.

In each scenario four different cases are considered. In case 1, case 2, case 3 and case 4, the EV load is modelled as Constant Power, ZIP, Exponential and Constant Current load models respectively.

4.7.1 Scenario 1: Different load modelling of EV and treating conventional load as RIC load model

In this scenario the FCSs are optimally planned in order to minimizing the EVUC, MVD and NPL in the distribution network. The SFL-TLBO algorithm has been used to solve the objective function (4.13). This algorithm determines the optimal locations of FCSs in the distribution system. In scenario 1, the conventional load is treated as Constant Power load and it is added with different EV load models. In case 1 of scenario 1 both the conventional and EV loads are modelled as Constant Power load modelling.

The optimal Pareto fronts to optimize the EVUC, MVD and NPL in case1 of scenario 1 is shown in Figure 4.7.

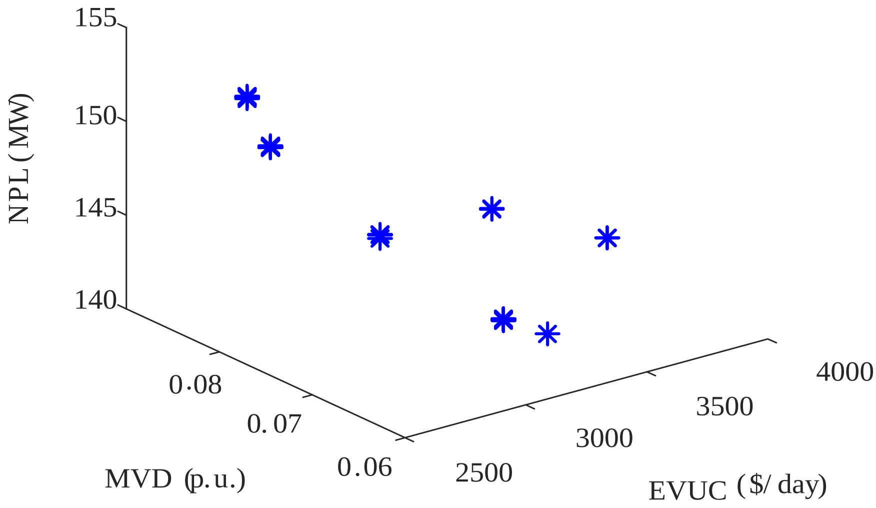

Figure 4.7: Optimal Pareto fronts of case 1 of scenario 1

From the optimal Pareto fronts as shown in Figure 4.7 the compromised solution has been determined using min-max optimization technique for case 1 of scenario 1. Similarly, for case 2, case 3 and case 4 the optimal parameters are calculated and listed in Table 4.3.

Table 4.3: Optimal objective parameters in scenario I

	EVUC ($/day)	MVD (p.u.)	NPL (MW/day)
Case 1	3048.8	0.0776	138.3095
Case 2		0.0772	138.1601
Case 3		0.0775	138.283
Case 4		0.0774	138.4477

In case 1 of scenario 1 the optimal values EVUC, MVD and NPL are 3048.8 ($/day), 0.0776 (p.u.) and 138.3095 (MW/day) respectively. In scenario 1 the EVUC is constant in all the four cases, as the optimal location of three FCSs are same in case 2, case 3 and case 4. Furthermore, the number of connectors in FCS is also been calculated and their values are 15, 7 and 11 respectively. Similarly for case 2 of scenario 1 the MVD and NPL are 0.0772 (p.u.) and 138.1601 (MW/day). These values are minimum as compared to the case 1, case 3 and case 4.

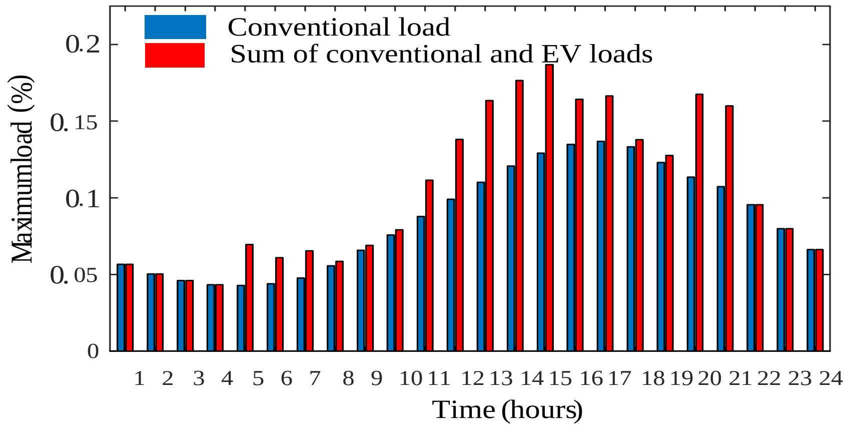

Figure 4.8: Maximum percentage of load in each hour of the day of case 1 of scenario 1

The conventional and EV loads vary with the daily load demand and EVs charging probability respectively. The EV load demand in each FCS directly depends on its location. The variation of sum of maximum conventional and EV load during the day is compared with the conventional load demand as shown in Figure 4.8.

Further, the maximum line flows has been calculated to analyze the impact of EV load modelling. In case 1 of scenario 1 the maximum MVA flows in each line is compared with the line MVA limits and it is plotted as shown in Figure 4.9. In Constant Power load modeling of scenario 1 the line MVA flow is more than line MVA limit.

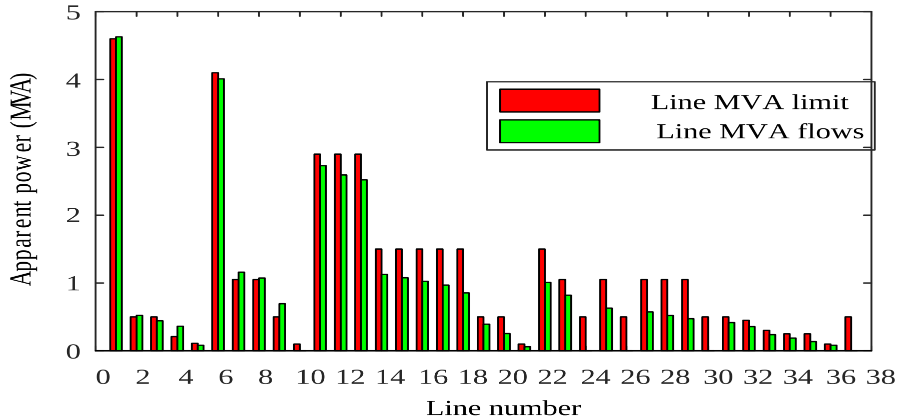

Figure 4.9: Line MVA limit comparison with maximum line flows of case 1 of scenario 1

Furthermore, to quantify the impact of EV load modelling in Distribution System the EVUCI, PLI, VPI and APPI are calculated and listed in Table 4.4.

Table 4.4: Impact of indices with different load models in scenario 1

	FCS bus locations	EVUCI	PLI	VPI	APPI
Case 1	10, 16, 21	0.00457	0.389	0.0357	0.2324
Case 2			0.3916	0.0341	0.2324
Case 3			0.3922	0.0345	0.2325
Case 4			0.3923	0.0353	0.2326

In case 2 of scenario 1, the PLI, VPI and APPI are 0.3916, 0.0341 and 0.2324 respectively. The indices in case 2 of scenario 1are less as compared to the case 1, case 3 and case 4. The case 1 is inaccurate load model, as the conventional load at buses and EV loads are modelled as Constant Power load model. As shown in Table 4.4 the case 2 indices are optimal as compared to the remaining cases in scenario 1. In case 2 the EV load is modeled as ZIP load model and the conventional load is modelled as constant power load.

4.7.2 Scenario 2: Different load modelling of EV and treating conventional load as CP load model

In scenario 2 the conventional load at each bus is modelled with the residential, industrial and commercial (RIC) load models. The conventional load types and their magnitudes are listed in [30] and the EV load is modelled as Constant Power, ZIP, Exponential and Constant Current load models as case 1, case 2, case 3 and case 4 respectively. In each case the optimal site and size of FCSs have been determined by solving the objective function (4.13) using the hybrid SFL-TLBO algorithm. To analyze the impact FCSs EV charging on Distribution System NPL, MVD and EVUC has been determined. Further, the PLI, VPI and APPI indices are also calculated. The optimal Pareto fronts for case 2 of scenario 2 are shown in Figure 4.10. The location and size of three FCSs are same for case 1, case 2, case 3 and case 4. Hence, the optimal pareto-fronts are plotted only for case 2 of scenario 2.

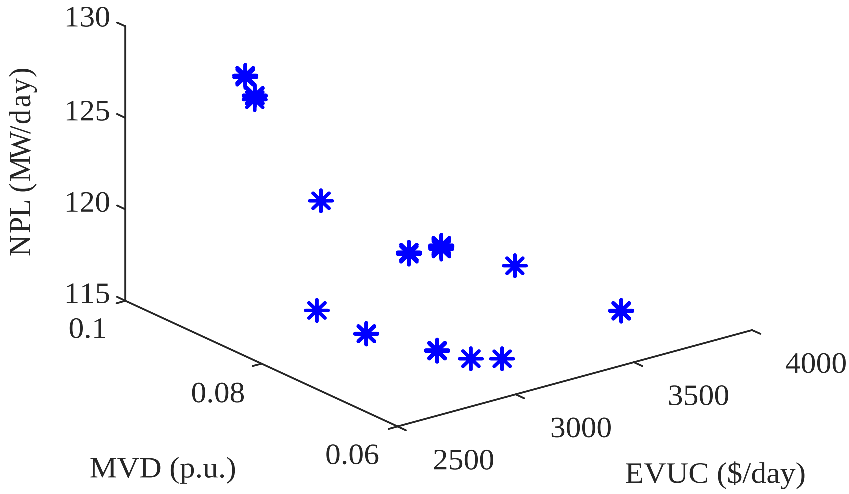

Figure 4.10: Optimal Pareto fronts of case 2 of scenario 2

From Figure 4.10 the best suitable solution has been determined by using the min-max method. Similarly, for case 1, case 3 and case 4 the optimal values are evaluated and listed in Table 4.5.

Table 4.5 Optimal objective parameters in scenario 2

	EVUC ($/day)	MVD (p.u.)	NPL (MW/day)
Case 1	2866.8	0.0667	129.2259
Case 2		0.0662	129.1451
Case 3		0.0667	129.3741
Case 4		0.0664	129.5626

In case 1 of scenario 2, the optimal values EVUC, MVD and NPL are 2866.8 ($/day), 0.0667 (p.u.) and 129.2259 (MW/day) respectively. In scenario 2 also the EVUC is constant for all four cases as the optimal location and size of three FCSs are same in each case. The number of connectors in FCS is also been calculated as 10, 13 and 10 respectively. Similarly for case 2 of scenario 2 the MVD and NPL are 0.0662 (p.u.) and 129.1451 (MW/day). The objective parameters in case 2 of scenario 2 are minimum as compared to the case 1, case 3 and case 4. The main observation from Table 4.5 is that the EVUC, MVD and NPL costs are drastically reduced in scenario 2 as compared to the all cases in scenario 1. Furthermore, case 2 of scenario 2 is yielding more accurate information about the conventional and EV loads in the distribution system.

The variation of sum of maximum conventional and EV loads during the day is compared with the conventional load demand as shown in Figure 4.11.

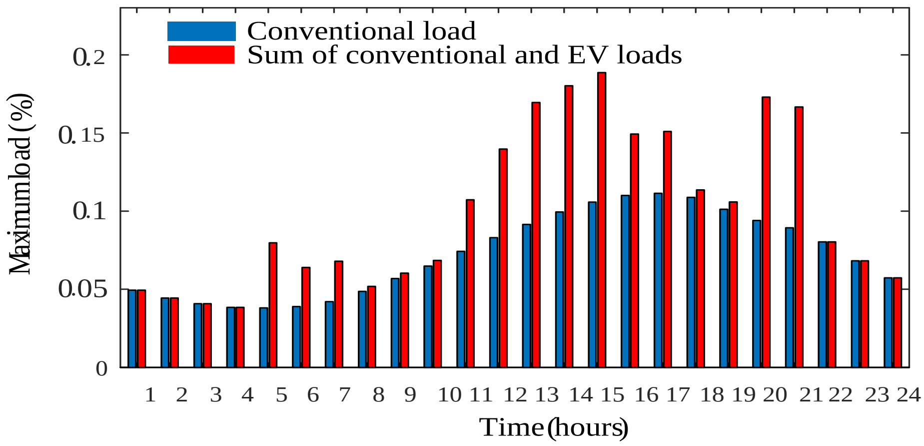

Figure 4.11 Maximum percentage of load in each hour of the day of case 2 of scenario 2

Due to the change in charging probability and initial SOC of EVs the line flows have a chance to exceed the maximum MVA limit. In scenario 2, the line maximum MVA flows are drastically reduced as compared to the all cases of scenario 1. The line MVA flows are compared with the maximum line MVA limit of case 2 of scenario 2 as shown in Figure 4.12.

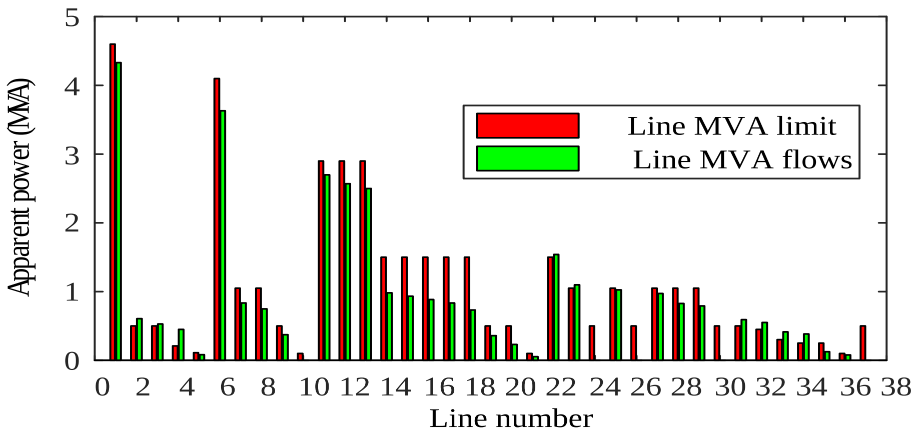

Figure 4.12: Line MVA limit comparison with maximum line flows of case 2 of scenario 2

The PLI, VPI and APPI indices for different cases of scenario 2 are calculated and listed in Table 4.6. These indices are more optimal in scenario 2 as compared to scenario 1. Further, in case 2 of scenario 2 the PLI, VPI and APPI found to be better as compared with other cases of both the scenario 1 and scenario 2.

Table 4.6 Impact of indices with different load models in scenario 2

	FCS bus locations	EVUCI	PLI	VPI	APPI
Case 1	6, 21, 25	0.00552	0.3763	0.0331	0.1682
Case 2			0.3753	0.0321	0.1696
Case 3			0.3781	0.0324	0.1681
Case 4			0.3185	0.0328	0.1703

In summary of this chapter, the conventional loads are modeled as Constant Power and RIC loads and the EV load is modeled as the ZIP, Exponential, Constant Current and Constant Power load models. These have been considered to analyze the impact of EV load on distribution system. A newly proposed multi-objective hybrid SFL-TLBO algorithm has been used for optimal planning of FCSs in Distribution System with the objective of minimizing NPL, MVD and EVUC. The EVUC, MVD and NPL cost are drastically reduced in scenario 2 as compared to the all cases in scenario 1. Further, case 2 of scenario 2 is offering more accurate information about the affect of conventional and EV loads on the distribution system.

Furthermore, in case 2 of scenario 2, the Distribution System indices (PLI, VPI and APPI) are more optimal as compared to the results of scenario 1and other cases of scenario 2. It is observed that there existed a significant difference in Distribution System indices and the objective parameters with different load models for both the conventional and EV loads. The results substantiate that the RIC and ZIP load models are accounting the accurate behaviour of conventional and EV loads respectively.

This part of work is communicated in IET Electrical Systems in Transportation with the title as “Impact of EV Load Modelling on Fast Charging Station Planning in Electrical Distribution System.”

The next stage of investigation is focused on Optimal Scheduling of Electric Vehicle Batteries in Battery Swapping Station and the same is reported in chapter 5.

Chapter-5

Multi-Objective Optimal Scheduling of Electric Vehicle Batteries in Battery Swapping Station

5.1 Introduction

Due to maturity of the Batteries and their charging technology, public incentives and growing criticism on dense air pollution, the EVs gaining more popularity as compared to traditional fuel vehicles.

Over the past decade, the EV population is greatly increased due to reduce reliance on fossil fuels and environmental pollution. However, many car owners are still deterred to buy EVs due to certain major drawbacks of EVs, such as long charging time, range anxiety, expensive EV batteries and short life time with fast charging [41]. An efficient solution to these problems is the deployment of Battery Swapping Stations (BSS) to encounter all the drawbacks. First, the BSS provides a short charging time just like gas refuelling station. Secondly, the range is increased with high capacity batteries by swapping a battery in nearby BSS. Thirdly, the EV users need not to pay the total initial cost of battery. Fourthly, in BSS technology, the batteries are charged in slow-charging mode to extend their life [42]. In [65], the performance of BSS is compared with the FCS and it has been claimed that BSS is more feasible than fast charging stations for EVs charging.

As a part of this research work the multi-objective Battery Swapping Station (BSS) model is developed in order to optimize (i). the number of batteries taken from battery stock, (ii) Charging damage and (iii). electricity charging cost of batteries. Further, the dynamic electricity pricing model is considered to avoid new peaks of battery charging demand in BSS. A BSS model with finite EV battery swapping demand in each hour of the day is solved by using the proposed Multi-objective Shuffled Frog Leaping Algorithm (SFLA).

5.2 Problem formulation

5.2.1 Decision Solution

The decision variable vector of the objective problem consists of different charging methods. The solution decision variable vector is given as

$$S = \{ans(1), ans(2), \ldots ans(j) \ldots \ldots ans(N_{EV})\} \tag{5.1}$$

where, $\mathrm{ans(j)} = \mathrm{m}$ means that charging method m is assigned to recharge $\mathrm{j^{th}}$ EV. $\mathrm{N_{EV}}$ is the number of EVs required battery swapping in each time period.

5.2.2 Mathematical model

In this model, the aim is to minimize the number of batteries taken from stock, battery degradation cost and battery electricity charging cost. In this context, the following equations are more relevant for the investigation.

$$FCB(t) = CB(t-1) - IBS(t) \qquad \Leftrightarrow \ (FCB(t-1) > IBS(t) \tag{5.2}$$

Otherwise

$$BS(t) = BS(t-1) + IBS(t) - FCB(t) \tag{5.3}$$

When battery becomes fully charged at time t, the $\mathrm{FCB}(t)$ is updated as follows

$$FCB(t) = FCB(t-1) + 1 \tag{5.4}$$

$$Obj_1 = BS^{max} = \max(BS) \tag{5.5}$$

$$Obj_2 = ACD = \frac{1}{N_{EV}} \sum_{i=1}^{N_{EV}} CD_i(m) \tag{5.6}$$

Here, the $\mathrm{FCB}(t)$ is the number of incoming batteries recharged and available for swapping, $\mathrm{IBS}(t)$number of incoming batteries for swapping at time ‘t’, $\mathrm{BS}(t)$ is the number of batteries taken from stock and $\mathrm{BS}^{\max}$ is maximum number of batteries taken from stock to serve all incoming EVSs. Equation (5.2) calculates the number of incoming batteries available for swapping ($\mathrm{FCB}(t)$). if $(\mathrm{FCB}(t-1) > 0)$, the $\mathrm{FCB}(t)$ is reduced by one. Otherwise the batteries taken from stock are increased by one and it is calculated by (5.3). If the incoming battery is fully charged then $\mathrm{FCB}(t)$ is increased by one and it is updated as (5.4).

The charging damage of all incoming batteries are calculated as (5.6). In (5.6), ACD is the average charging damage of battery and $\mathrm{CD_i}(m)$ is the charging damage of i^{th} EV battery due to charging method ‘m’. The optimal scheduling of EVs and calculation of objectives have been carried out shown in Figure 5.1.

5.2.3 Dynamic Price Change

The dynamic price change is considered with the addition of Time of Use price (TOU). In TOU price, the low price attracts to charge more number of batteries in BSS and it creates a new peak. To avoid the above drawback the dynamic price change is considered as one of the objectives and it is calculated as bellow:

$if\ (BUC(t) > IBS(t))$ the Battery Charging Cost (BCC) is calculated as bellow:

$$Obj_3 = BCC = \left(\frac{ICB(t) - BUC^{APC}(t)}{\max(ICB)}\right) EP^{pst} + EP(t) \tag{5.7}$$

Here, $\mathrm{BUC(t)}$ and $\mathrm{IBS(t)}$ are the number of batteries charging and number of incoming batteries for swapping at time 't'. $\mathrm{BUC^{APC}(t)}$ batteries under charging right after price change at time 't'. $\mathrm{EP^{pst}}$ and $\mathrm{EP(t)}$ are the predefined electricity step price and electricity price at time 't' respectively.

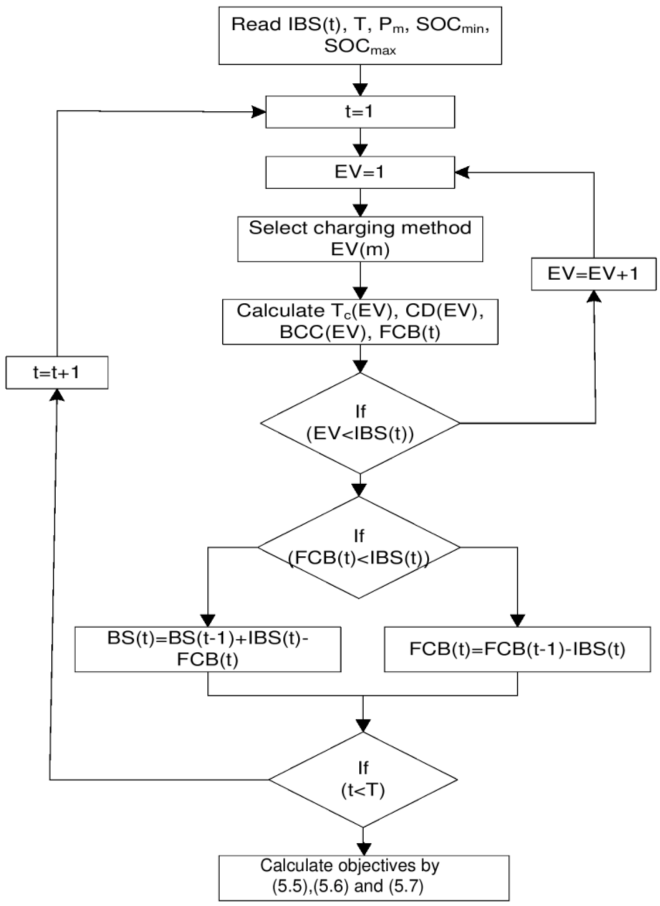

Figure 5.1: Flow chart for optimal scheduling of EVs in BSS

5.2.4 Objective function

$$minimization\ of\ \left(BS^{max}, ACD, BCC \right) \tag{5.8}$$

The following Constraints are considered for optimal scheduling of EVs batteries in BSS.

$$SOC_{min} \leq SOC_j \leq SOC_{max} \tag{5.9}$$

$$SOH_{min} \leq SOH_j \leq SOH_{max} \tag{5.10}$$

$$FCB(t) \geq 0 \tag{5.11}$$

$$CB(t) = BS_{init} + \sum_{t=1}^{T} CB(t+1) \tag{5.12}$$

In (5.9), $\mathrm{SOC_j}$ is the State of Charge (SoC) of $\mathrm{j^{th}}$ EV battery and it should be with in minimum SOC (SOC_{min}) and maximum SOC of battery. With the increases in number cycles of charging and discharging, the State of Health (SOH) of battery is affected. The life cycle of battery is improved by avoiding over charging and discharging. For better operation of BSS the SOH is should follow the constraint (5.10). In (5.12), $\mathrm{CB(t)}$ is the number of charged batteries at time 't'. The BSS needs to have initial number batteries ($\mathrm{BS_{init}}$) in stock to serve for incoming EVs. T is the total time intervals considered for optimal scheduling of EV batteries in BSS.

5.3 Test System Data

In this study, a typical Lithium-ion battery with rated capacity of 85 kWh has been considered (Tesla model S) for optimal scheduling of batteries in BSS. Four types of EV battery charging methods such as super-charging, fast-charging, normal-charging and slow-charging are considered with the power ratings of 120 kW, 80 kW, 60 kW and 40 kW respectively. The battery cost is 21000 ($). The life cycle of battery with above charging rates are 800, 1100, 1150 and 1200 respectively [80]. The "Time of Use (TOU) Price" is listed in Table 5.1.

Table 5.1: Electricity TOU price [80]

Time of the day	TOU period	Price/kWh (USD)
7:00 to 11:00	On-peak	$0.13
11:00 to 17:00	Mid-peak	$0.10
17:00 to 19:00	On-peak	$0.13
19:00 to 7:00	Off-peak	$0.06

The EV battery swapping demand during each hour of a day is given in Figure 5.2.

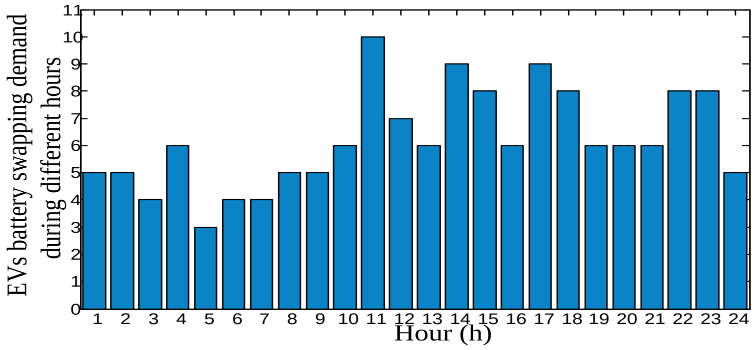

Figure 5.2: EVs battery swapping demand

5.4 Methodology

The aim of this model is to determine the optimal scheduling of incoming EVs in order to minimize the number of batteries taken from battery stock, charging damage and electricity charging cost of batteries. In literature, the optimal scheduling of EVs batteries in BSS is solved by using weighted sum approach method. In all classical methods like weighted objectives method, the multiple objectives functions are formulated as a single objective function by choosing suitable weights for each objective. The approach to determine the optimal value of the single objective has majorly two problems. The first one is the optimization of that single objective function may guarantee a single optimal solution, but in all practical applications, the decision makers need an alternative solution in decision making. The second one is the sensitivity towards weights or demand levels of each objective in a single objection function. Moreover, if the objective function is having more noise and the variables are discontinuous in search space, the classical methods cannot work effectively. To overcome the above problems, multi-objective Pareto front optimizations algorithms are necessary for solving multi-objective problems.

5.4.1 Shuffled Frog Leap Algorithm (SFLA)

The SFLA is a population-based optimization algorithm [74], and the population consists of a set of frogs that is divided into subsets referred to as memeplexes. Each frog in the population represents a solution in search space and its hold ideas, which can be influenced by the ideas of other frogs and evolve through a process of memetic evaluation. After a certain number of memetic evaluation steps, ideas are passed among the memeplexes in the shuffling process. The exploration and the shuffling processes continue until it reaches the specified convergence criteria as explained in [74].

In SFLA, the exploitation and exploration are trying to improve the attempt to determine the optimal solution.

In each iteration, to improve exploitation of the given optimization problem the new population is calculated follows

$$Xnew_{s,g} = Xold_{s,g} + rand\left(X_{group\_best_g} - Xold_{s,g}\right) \tag{5.13}$$

Where $Xold_{s,g}$ is the sorted population divided in to g number of memeplexes and each memeplex has S number of frogs.

$X_{group\_best_g}$ is the optimal solution in g^{th} memeplex.

If the $Xnew_{s,g} < Xold_{s,g}$ the global search has to be done in order to calculate the optimal solution as follows

$$Xnew_{s,g} = Xold_{s,g} + rand\left(X_{best\_pop} - Xold_{s,g}\right) \tag{5.14}$$

Where X_{best_pop} is the global optimal solution in each iteration.

Algorithm 1.Pseudo code of proposed hybrid SFL-TLBO

Initialize parameters

Number of incoming EVs in each hour (n)

Define $f(X)$ X= $(x_a, x_b, x_c \dots \dots \dots x_d)$ *d*=no. of decision variables.

For h=1:number of hours

Initialize the population randomly X_i *i*= 1,2,3……..n.

For iter=1to maximum iterations

for i=1 to n

Evaluate objective function value $f(X_i)$

end for n loop

Sort the population based on non-dominated sorting technique

Divide the frogss into g Number of memeplexes

for i=1to g

for i=1to s

Identify the best solution in each group $X_{group-best}$

$Xnew_{s,g} = Xold_{s,g} + rand\left(X_{group\_best_{s,g}} - Xold_{s,g}\right)$

Calculate objective function value $f\left(Xnew_{s,g}\right)$

If $f\left(Xnew_{s,g}\right)$ is better than $f(X_T)$

$X_i = Xnew_{s,g}$

else

$Xnew_{s,g} = Xold_{s,g} + rand\left(X_{best\_pop_{s,g}} - Xold_{s,g}\right)$

$X_i = Xnew_{s,g}$ $(X_{gbest} = X_i)$

Otherwise generate a random population

end if

end for ---------s loop

end for-------g loop

end for ---------iter loop (Termination criterion)

X_{gbest} ------------------- $---best\ population$

F_{gbest} $----bestfitness$

end for hour loop

Save the optimal population and its fitness value.

5.5 Results and Analysis

The implementation of BSSs is still limited to few countries and in some other countries at demonstration level only. A multi-objective BSS model has been developed in order to optimize the number of batteries taken from battery stock, charging damage and electricity charging cost of batteries. The optimal scheduling has been carried out by considering the dynamic pricing model, to avoid the peak demand during low electricity cost hours. The dynamic pricing provides more realistic scheduling of EV batteries in BSS. The objective function (5.8) has been solved by using a multi-objective SFLA and hybrid SFL-TLBO algorithms. The optimal Pareto fronts for both algorithms are as shown in Figure 5.3.

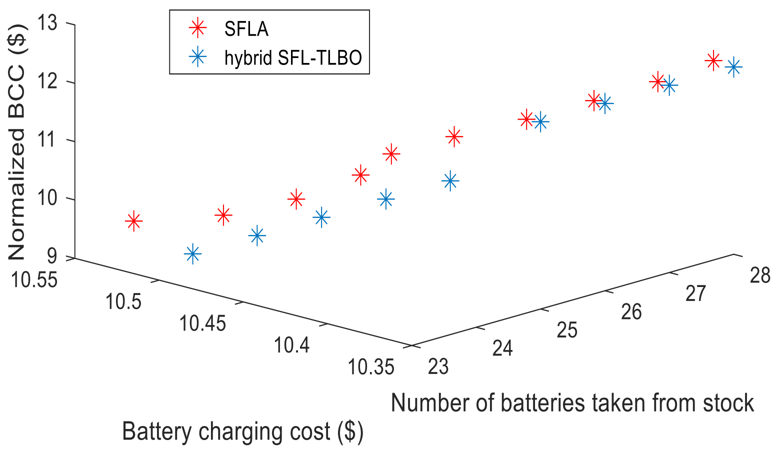

Figure 5.3: Optimal pareto-fronts for a multi-objective BSS model

The min-max method has been used to determine the compromised solution from the optimal Pareto fronts as shown Figure 5.3. The optimal values of the number of batteries taken from battery stock, charging damage and the normalized electricity charging cost of batteries by using the hybrid SFL-TLBO are 23, 10.48 ($/kWh), 9.86 ($) respectively. Similarly, The optimal values of the number of batteries taken from battery stock, charging damage and the normalized electricity charging cost of batteries by using the SFLA are 25, 10.495 ($/kWh), 9.9 ($) respectively. The proposed hybrid SFL-TLBO gives better results as compared to the SFLA. This model has been run for several times and the optimal results are presented. The presented algorithm gave accurate results, due to its good exploration and exploitation capability.

For better operation of BSS the number of batteries taken from stock should be minimum otherwise the cost of BSS is greatly increased. Similarly the charging method is a major factor that decides the degradation cost of EV batteries. In addition to above the optimal scheduling of EV batteries, it gives some more additional benefit to BSS operator. The variation of number of batteries taken from stock, number of batteries available in BSS and the variation of battery charging cost in each hour during the day is shown in Figure 5.4.

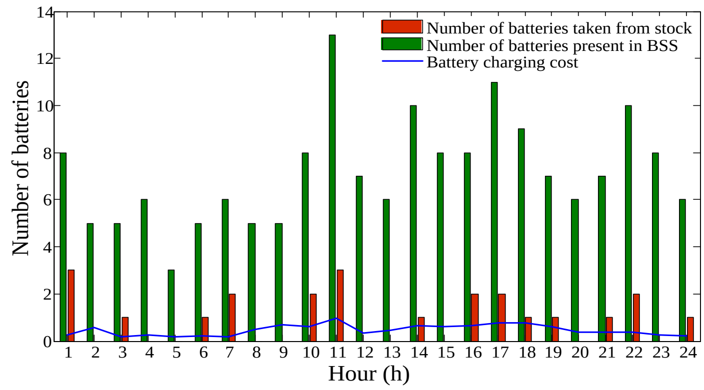

Figure 5.4: Variation of BSS parameters in each hour during the day with optimal scheduling of EV batteries

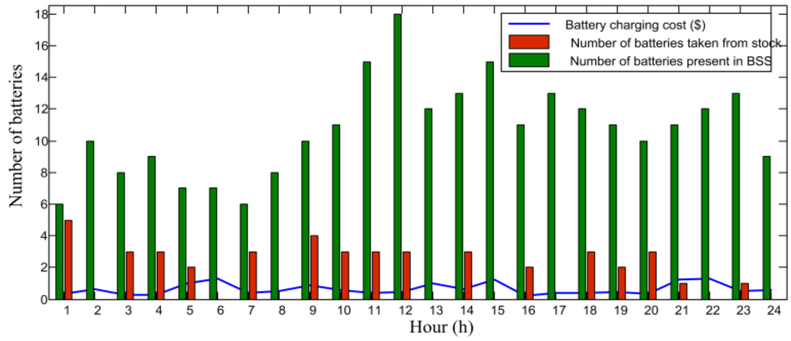

Figure 5.5: Variation of BSS parameters in each hour during the day with random charging of EV batteries

Further, the comparison of optimal scheduling and random charging of EV batteries in BSS has been carried out and the results are as shown in Figure 5.5.

Table 5.2 presents the comparison of number of number of batteries taken from stock, battery charging cost of EVs for both the optimal scheduling and random charging scenarios. In optimal scheduling scenario the total number of batteries taken from stock is 23 and the total BCC during the day is 9.86 ($). In random charging scenario the number of batteries taken from stock is 44 and the total BCC during the day is 15.3757 ($). The above comparison clears indicates that the optimal scheduling is beneficial for both BSS operator and EV user due to significant reduction in number of number of batteries taken from stock to serve all EV swapping demand and the total battery charging cost.

In summary, this chapter has covered the more effective method of EV charging in fast convenient way. In BSS the EV batteries optimally scheduled with suitable charging methods, there by the life time of batteries increases. Further, the charging cost also reduced as compared to the conventional random charging methods.

Table 5.2: Comparison of optimal scheduling and random charging of EVs in BSS

Hour	Optimal scheduling		Random charging	
	BS	BCC ($)	BS	BCC ($)
1	3	0.275	5	0.312
2	0	0.059	0	0.643
3	1	0.176	3	0.29
4	0	0.269	3	0.26
5	0	0.159	2	0.989
6	1	0.214	0	1.323
7	2	0.169	3	0.37
8	0	0.389	0	0.512
9	0	0.655	4	0.896
10	2	0.604	3	0.58
11	3	0.481	3	0.376
12	0	0.333	3	0.477
13	0	0.452	0	0.989
14	1	0.65	3	0.632
15	0	0.595	0	1.231
16	2	0.662	2	0.225
17	2	0.754	0	0.394
18	1	0.773	3	0.4
19	1	0.602	2	0.4667
20	0	0.36	3	0.36
21	1	0.39	1	1.23
22	2	0.361	0	1.32
23	0	0.24	1	0.54
24	1	0.234	0	0.56

A multi-objective BSS optimal scheduling model with dynamic pricing approach, it greatly reduced the electricity battery charging cost and peak demand during low electricity price hours. The number batteries taken from stock are also reduced. Further, the comparison of optimal scheduling and random charging of EV batteries in BSS has been carried out and the results demonstrate that the number batteries taken from stock, battery damage cost and charging cost are minimum in optimal scheduling scenario, it is more beneficial to both the EV users and BSS operator. Therefore, the proposed optimal scheduling of EV batteries can be used for the planning study of BSS.

This part of work is published in IEEE PES Innovative Smart Grid Technologies Europe Conference with the title as "Multi-Objective Optimal Scheduling of Electric Vehicle batteries in Battery Swapping Station" 2019 IEEE Power & Energy Society (PES) Innovative Smart Grid Technologies Europe (ISGT-Europe, 2019) conference held at University POLITEHNICA of Bucharest, Romania from September 29 to October 2, 2019.

Chapter-6

Conclusions and Scope for Future Work

6.1 Conclusions

The following conclusions are drawn based on the investigations carried out at various stages of this research work.

A Multi-objective optimization model for simultaneous optimal planning of EV Fast Charging Stations (FCSs) and Distributed generations (DGs) in the distribution system is developed. The simultaneous planning of FCSs and DGs results in more reduction in Electric Vehicle User cost (EVUC) and Network Power Loss (NPL) cost for the same station Develop Cost (SDC) and DG power cost investment. The EVUC and NPL cost are variable with respect to time. Hence, reduction in this cost will prove beneficial for both EV and charging station owners. It is clear from the results that the optimal simultaneous placement of both FCSs and DGs in Distribution System provides significant benefit to both the EV users and charging station owners.

The multi-objective optimization model is developed for optimal planning of FCSs and DGs in distribution system by considering the present and different levels of increment in future EV population growth using newly proposed SFL-TLBO algorithm. The results obtained using the hybrid SFL-TLBO algorithm is compared with the SFLA and TLBO algorithm. Results have shown that the DGPC and SEC of EVs constitute the major share of the total cost. The optimal FCSs location has a drastic impact on SEC of EVs. The results suggest that for new erection of FCSs in distribution system, it is necessary to consider the present and future penetration of EVs. Otherwise, the NPLC and SEC of EVs would be more expensive. The proposed hybrid SFL-TLBO is tested on IEEE 118 bus distribution system. It is established that the proposed hybrid algorithm is reliable and robust concerning different levels of increase of EV population demand in three scenarios. Therefore, the proposed optimal planning FCSs and DGs technique can be used for the planning study of charging stations in the coupled electrical distribution and transportation network.

To analyze the impact of EV load modeling on FCSs planning in distribution system, the conventional loads are modeled as (a). Constant Power and (b). RIC loads, and the EV load is modeled as the (i). ZIP, (ii). Exponential, (iii). Constant Current and Constant Power load models. A multi-objective hybrid SFL-TLBO algorithm has been used for optimal planning of FCSs in distribution system with the objective of minimizing the Electric Vehicle User cost (EVUC), Maximum Voltage Deviation (MVD) and Network Power Loss (NPL) cost. It is observed that there was significant difference in distribution system indices and the objective parameters with consideration of different load models for both the conventional and EV loads. The results substantiate that the RIC and ZIP load models provide accurate behavior of conventional and EV loads respectively.

An optimal Scheduling of EVs batteries in BSS is analyzed to serve for all incoming EVs swapping demand in order to minimize the charging cost, battery degradation cost and the number of batteries taken from stock. Further, the comparison of optimal scheduling and random charging of EV batteries in BSS has been carried out and the results demonstrate that the numbers of batteries taken from stock, battery degradation cost and charging cost are minimum in optimal scheduling against the random charging. It is more beneficial to both the EV users and BSS operator.

6.2 Scope for Research work

Further, this research work in the area of optimal planning of FCSs and DGs in the distribution system can be extended in the following directions

1. Scheduling of EV batteries in BSS with the integration of RESs.
2. The optimal planning FCSs in distribution system can be attempted by considering the Communication between Vehicle to BSS and Vehicle to Grid.
3. Investigation of grid operation in the presence of BSS incorporating the battery degradation aspect.

List of Publications

Journals Published:

[1] **Gurappa Battapothula**, Chandrasekhar Yammani, Sydulu Maheswarapu, “A Multi-objective simultaneous optimal planning of electrical vehicle fast charging stations and DGs in distribution system” Journal of Modern Power System and Clean Energy. Volume 7, Issue 4, pp. 923–934, 2019. DOI: 10.1007/s40565-018-0493-2. ISSN: 2196-5625 (Indexed in SCI)

[2] **Gurappa Battapothula**, Chandrasekhar Yammani, Sydulu Maheswarapu, “Multi-Objective Optimal Planning of FCSs and DGs in Distribution System with Future EV Load Enhancement.” IET Electrical Systems in Transportation, Volume 9, Issue 3, September 2019, pp. 128 – 139. DOI: 10.1049/iet-est.2018.5066. ISSN:2042-9738. (Indexed in SCI)

Journals Communicated:

[1] **Gurappa battapothula,** Chandrasekhar Yammani, Sydulu Maheswarapu, “Impact of EV Load Modeling on Fast Charging Station Planning in Electrical Distribution System.” IET Electrical Systems in Transportation.

Conferences Published:

[1] **Gurappa Battapothula**, Chandrasekhar Yammani & Sydulu Maheswarapu, "Multi-Objective Optimal Scheduling of Electric Vehicle batteries in Battery Swapping Station" 2019 IEEE Power & Energy Society (PES) Innovative Smart Grid Technologies Europe (ISGT-Europe, 2019) conference held at University POLITEHNICA of Bucharest, Romania from September 29 to October 2, 2019.

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Appendix-I

IEEE 118 bus Distribution System

Number of buses: 118

Number of lines: 117

Base voltage: 12.66 kV

Total active power load= 22.71MW

Total reactive power load=17.041 MVAr

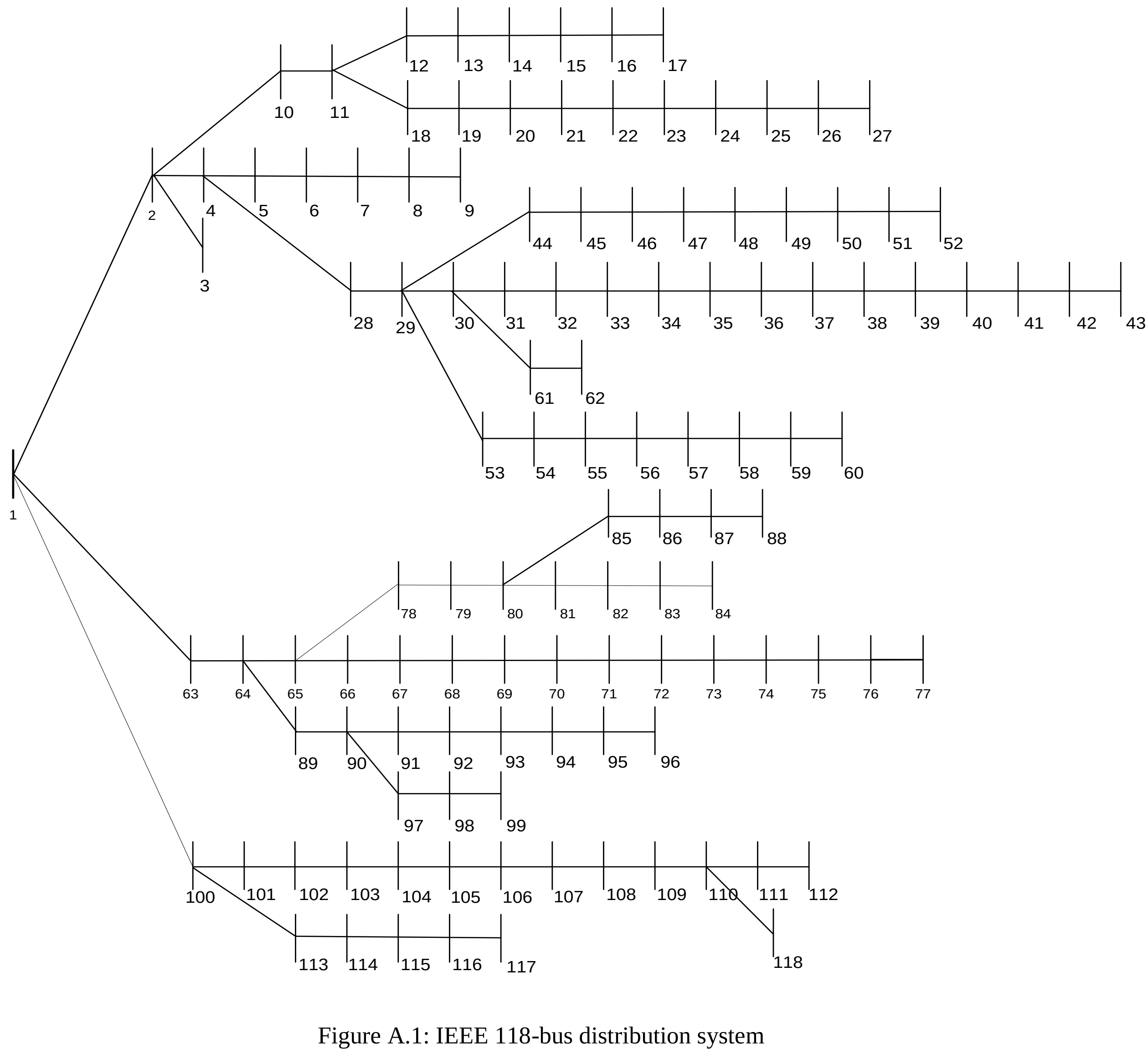

Figure A.1: IEEE 118-bus distribution system

Line Number	From Bus	To Bus	R (Ohms)	X (Ohms)	Pload (kW)	Qload (kW)
1	1	2	0.036	0.01296	133.84	101.14
2	2	3	0.033	0.01188	16.214	11.292
3	2	4	0.045	0.0162	34.315	21.845
4	4	5	0.015	0.054	73.016	63.602
5	5	6	0.015	0.054	144.2	68.604
6	6	7	0.015	0.0125	104.47	61.725
7	7	8	0.018	0.014	28.547	11.503
8	8	9	0.021	0.063	87.56	51.073
9	2	10	0.166	0.1344	198.2	106.77
10	10	11	0.112	0.0789	146.8	75.995
11	11	12	0.187	0.313	26.04	18.687
12	12	13	0.142	0.1512	52.1	23.22
13	13	14	0.18	0.118	141.9	117.5
14	14	15	0.15	0.045	21.87	28.79
15	15	16	0.16	0.18	33.37	26.45
16	16	17	0.157	0.171	32.43	25.23
17	11	18	0.218	0.285	20.234	11.906
18	18	19	0.118	0.185	156.94	78.523
19	19	20	0.16	0.196	546.29	351.4
20	20	21	0.12	0.189	180.31	164.2
21	21	22	0.12	0.0789	93.167	54.594
22	22	23	1.41	0.723	85.18	39.65
23	23	24	0.293	0.1348	168.1	95.178

24	24	25	0.133	0.104	125.11	150.22
25	25	26	0.178	0.134	16.03	24.62
26	26	27	0.178	0.134	26.03	24.62
27	4	28	0.015	0.0296	594.56	522.62
28	28	29	0.012	0.0276	120.62	59.117
29	29	30	0.12	0.2766	102.38	99.554
30	30	31	0.21	0.243	513.4	318.5
31	31	32	0.12	0.054	475.25	456.14
32	32	33	0.178	0.234	151.43	136.79
33	33	34	0.178	0.234	205.38	83.302
34	34	35	0.154	0.162	131.6	93.082
35	35	36	0.21	0.1383	66.195	42.361
36	36	37	0.12	0.0789	73.904	51.653
37	37	38	0.15	0.0987	114.77	57.965
38	38	39	0.15	0.0987	918.37	1205.1
39	39	40	0.24	0.1581	210.3	146.66
40	40	41	0.12	0.0789	66.68	56.608
41	41	42	0.405	0.1458	42.207	40.184
42	42	43	0.405	0.1458	433.74	283.41
43	29	44	0.33	0.194	112.54	55.134
44	44	45	0.31	0.194	53.963	38.998
45	45	46	0.13	0.194	393.05	342.6
46	46	47	0.28	0.15	326.74	278.56
47	47	48	1.18	0.85	536.26	240.24

48	48	49	0.42	0.2436	76.247	66.562
49	49	50	0.27	0.0972	53.52	39.76
50	50	51	0.339	0.1221	40.328	31.964
51	51	52	0.27	0.1779	39.653	20.758
52	29	53	0.391	0.141	62.1	26.86
53	53	54	0.406	0.1461	92.46	88.38
54	54	55	0.406	0.1461	85.188	55.436
55	55	56	0.706	0.5461	345.3	332.4
56	56	57	0.338	0.1218	22.5	16.83
57	57	58	0.338	0.1218	80.551	49.156
58	58	59	0.207	0.0747	95.86	90.758
59	59	60	0.247	0.8922	62.92	47.7
60	30	61	0.187	0.261	448.4	369.79
61	61	62	0.133	0.099	440.52	321.64
62	1	63	0.028	0.0418	478.8	463.74
63	63	64	0.117	0.2016	120.94	52.006
64	64	65	0.255	0.0918	139.11	100.34
65	65	66	0.21	0.0759	391.78	193.5
66	66	67	0.383	0.138	27.741	26.713
67	67	68	0.504	0.3303	52.814	25.257
68	68	69	0.406	0.1461	66.89	38.713
69	69	70	0.962	0.761	467.5	395.14
70	70	71	0.165	0.06	594.85	239.74
71	71	72	0.303	0.1092	132.5	84.363

72	72	73	0.303	0.1092	52.699	22.482
73	73	74	0.206	0.144	869.79	614.775
74	74	75	0.233	0.084	31.349	29.817
75	75	76	0.591	0.1773	192.39	122.43
76	76	77	0.126	0.0453	65.75	45.37
77	65	78	0.669	0.2412	62.93	42.96
78	78	79	0.266	0.1227	30.67	34.93
79	79	80	0.266	0.1227	62.53	66.79
80	80	81	0.266	0.1227	114.57	81.748
81	81	82	0.266	0.1227	81.292	66.526
82	82	83	0.233	0.115	31.733	15.96
83	83	84	0.496	0.138	33.32	60.48
84	80	85	0.196	0.18	531.28	224.85
85	85	86	0.196	0.18	507.03	367.42
86	86	87	0.1866	0.122	26.39	11.7
87	87	88	0.0746	0.318	45.99	30.392
88	64	89	0.559	0.3687	238.15	223.22
89	89	90	0.186	0.1227	294.55	162.47
90	90	91	0.186	0.1227	485.57	437.92
91	91	92	0.26	0.139	243.53	183.03
92	92	93	0.154	0.148	243.53	183.03
93	93	94	0.23	0.128	134.25	119.29
94	94	95	0.252	0.106	22.71	27.96
95	95	96	0.18	0.148	49.513	26.515

96	90	97	0.16	0.182	383.78	257.16
97	97	98	0.2	0.23	49.64	20.6
98	98	99	0.16	0.393	22.473	11.806
99	1	100	0.0625	0.0265	100.66	47.572
100	100	101	0.1501	0.234	456.48	350.3
101	101	102	0.1347	0.0888	522.56	449.29
102	102	103	0.2307	0.1203	408.43	168.46
103	103	104	0.447	0.1608	141.48	134.25
104	104	105	0.1632	0.0588	104.43	66.024
105	105	106	0.33	0.099	96.793	83.647
106	106	107	0.156	0.0561	493.92	419.34
107	107	108	0.3819	0.1374	225.38	135.88
108	108	109	0.1626	0.0585	509.21	387.21
109	109	110	0.3819	0.1374	188.5	173.46
110	110	111	0.2088	0.0753	305.08	215.37
111	111	112	0.2301	0.0828	54.38	40.97
112	100	113	0.6102	0.2196	211.14	192.9
113	113	114	0.1866	0.127	67.009	53.336
114	114	115	0.3732	0.246	162.07	90.321
115	115	116	0.405	0.367	48.785	29.156
116	116	117	0.489	0.438	33.9	18.98
117	110	118	0.2445	0.0879	918.03	898.55

Appendix-II

IEEE 38-bus Distribution System

Number of buses: 38

Number of lines: 37

Base voltage: 12.66 kV

Total active power load= 5084.26 kW

Total reactive power load=2547.32 kVAr

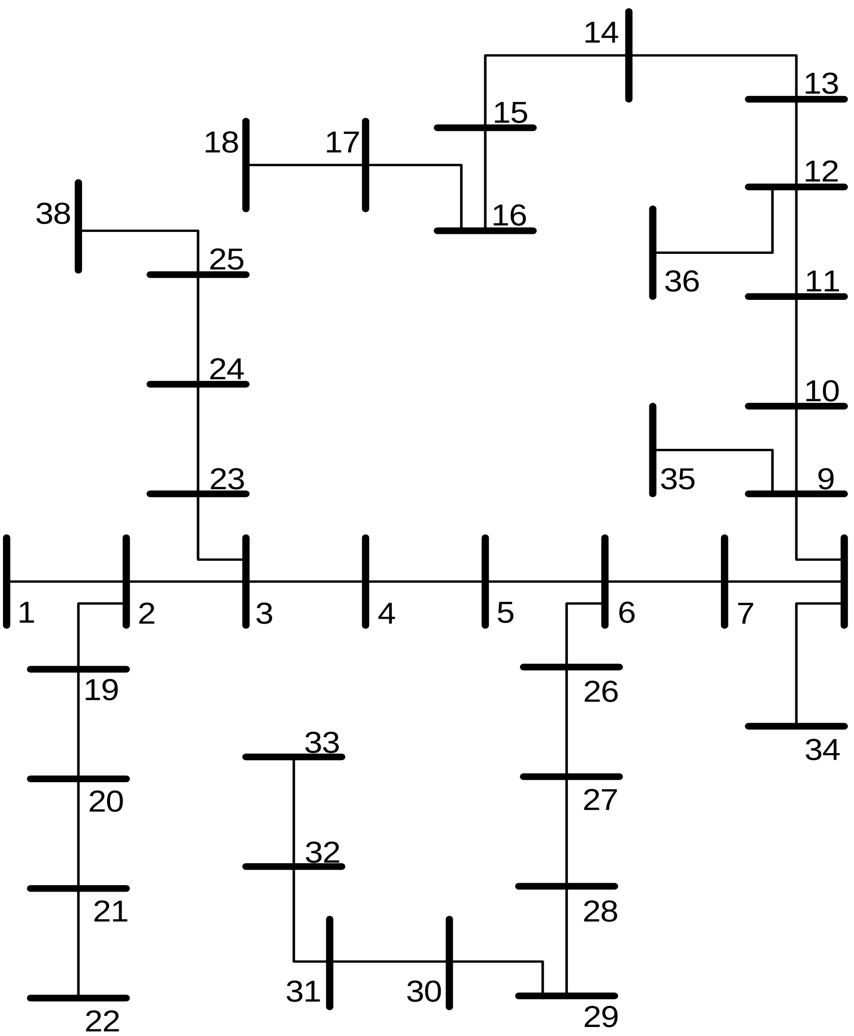

Figure A.2: IEEE 38-bus distribution system

		Line impedance (p.u)		Line limit (p.u)		Loads on to-node (p.u)		
From Bus	To Bus	R (p.u)	X (p.u)	L	S_L	P	Q	L_T
1	2	0.000574	0.000293	1	4.6	0.1	0.06	R
2	3	0.00307	0.001564	6	4.1	0.09	0.04	I
3	4	0.002279	0.001161	11	2.9	0.12	0.08	C
4	5	0.002373	0.001209	12	2.9	0.06	0.03	R
5	6	0.0051	0.004402	13	2.9	0.06	0.02	I
6	7	0.001166	0.003853	22	1.5	0.2	0.1	C
7	8	0.00443	0.001464	23	1.05	0.2	0.1	C
8	9	0.006413	0.004608	25	1.05	0.06	0.02	I
9	10	0.006501	0.004608	27	1.05	0.06	0.02	C
10	11	0.001224	0.000405	28	1.05	0.045	0.03	C
11	12	0.002331	0.000771	29	1.05	0.06	0.035	R
12	13	0.009141	0.007192	31	0.5	0.06	0.035	C
13	14	0.003372	0.004439	32	0.45	0.12	0.08	R
14	15	0.00368	0.003275	33	0.3	0.06	0.01	C
15	16	0.004647	0.003394	34	0.25	0.06	0.02	I
16	17	0.008026	0.010716	35	0.25	0.06	0.02	C
17	18	0.004558	0.003574	36	0.1	0.09	0.04	I
2	19	0.001021	0.000974	2	0.5	0.09	0.04	R
19	20	0.009366	0.00844	3	0.5	0.09	0.04	C
20	21	0.00255	0.002979	4	0.21	0.09	0.04	I
21	22	0.004414	0.005836	5	0.11	0.09	0.04	R
3	23	0.002809	0.00192	7	1.05	0.09	0.05	C

23	24	0.005592	0.004415	8	1.05	0.42	0.2	C
24	25	0.005579	0.004366	9	0.5	0.42	0.2	C
6	26	0.001264	0.000644	14	1.5	0.06	0.025	C
26	27	0.00177	0.000901	15	1.5	0.06	0.025	I
27	28	0.006594	0.005814	16	1.5	0.06	0.02	C
28	29	0.005007	0.004362	17	1.5	0.12	0.07	C
29	30	0.00316	0.00161	18	1.5	0.2	0.6	C
30	31	0.006067	0.005996	19	0.5	0.15	0.07	R
31	32	0.001933	0.002253	20	0.5	0.21	0.1	R
32	33	0.002123	0.003301	21	0.1	0.06	0.04	C
8	34	0.012453	0.012453	24	0.5	0	0	
9	35	0.012453	0.012453	26	0.5	0	0	
12	36	0.012453	0.012453	30	0.5	0	0	
18	37	0.003113	0.003113	37	0.5	0	0	
25	38	0.003113	0.003113	10	0.1	0	0	

L-Line number; S_L-Line MVA limit in p.u; P-Active power load; Q-Reactive power load, L_T-Load Type; R-Residential load; I-Industrial load; C-commercial load.

Appendix-III

Current Injection Distribution System Load Flow Method

Algorithm:

1. Read the system data (input data).
2. Print the input data and cross check it.
3. Form the Y bus by using sparsity technique.
4. Calculate Pinj and Qinj for i=1to n. where n is number of buses.
5. Set iter=0
6. Set ΔIreal max=0 and ΔIimag max=0.
7. Calculate Isp(i)=(Pinj(i)-Qinj(i))/E(i). for i=1to n.
8. Calculate $I_{cal} = Y_{pp} * E_p + \sum_{q=1,q\neq p}^{n} E_q$
9. Calculate ΔI(i)=Isp(i)-Ical(i)
10. Calculate ΔI(i)real and ΔI(i)imag and check for convergence.
11. If ΔI(i)real and ΔI(i)imag are less than epsilon, go to step 16.
12. Form jacobian matrix

    Set A(nslack, nslack)=10^{20} to Δenslack=0.

    Set A(n+nslack, n+nslack)=10^{20} to Δfnslack=0.
13. Solve $\left[\frac{I_{imag}}{I_{real}}\right] = [jacobian\ matrix] * \left[\frac{\Delta e}{\Delta f}\right]$
14. Update complex voltages (voltage magnitude and phase angles)
15. If iter $<$ itermax. Go to step 6.
16. Save the results.

Appendix-IV

AVERAGE DAILY LOAD PROFILE AS A FRACTION OF YEARLY PEAK

Hour	Winter load	Spring load	Summer Load	Autumn Load
1	0.4008	0.398	0.547	0.4108
2	0.3943	0.3821	0.5173	0.3945
3	0.3928	0.372	0.4952	0.3843
4	0.3966	0.3669	0.4806	0.3795
5	0.4112	0.3715	0.4783	0.3857
6	0.4466	0.39	0.484	0.41
7	0.4964	0.4179	0.5037	0.4408
8	0.5195	0.4408	0.5426	0.4595
9	0.5083	0.4568	0.5881	0.4765
10	0.4886	0.4701	0.6292	0.4916
11	0.474	0.4865	0.6751	0.5106
12	0.459	0.5	0.7151	0.5267
13	0.4466	0.5134	0.7519	0.5418
14	0.4366	0.5271	0.7854	0.5561
15	0.4285	0.5386	0.811	0.5656
16	0.4249	0.5468	0.8275	0.5732
17	0.4297	0.5526	0.8331	0.5765
18	0.4604	0.5508	0.8229	0.5799
19	0.5001	0.5432	0.7926	0.5851
20	0.5019	0.5459	0.7628	0.5729
21	0.4949	0.5374	0.7426	0.5491
22	0.483	0.5126	0.7027	0.5213
23	0.4521	0.47	0.6455	0.478
24	0.4168	0.4255	0.59	0.4354

Appendix-V

BOX PLOT

The box and whisker plots are more popularly used to represent the minimum, first quartile, median, third quartile, and maximum of a set of data instead of showing the mean and standard deviation. The statisticians refer to this set of statistics as a five-number summary. The each five-number summary is representing as a box with whiskers. And the box is bounded on the top by the third quartile and on the bottom by the first quartile. The median divides the box into two parts. The layout of chart determines the width of the box. The whiskers are error bars in which first one extends upward from the third quartile to the maximum and the second one extends downward from the first quartile to the minimum.

Notice that the median is not necessarily in the middle of the box and the whiskers are not necessarily the same length.

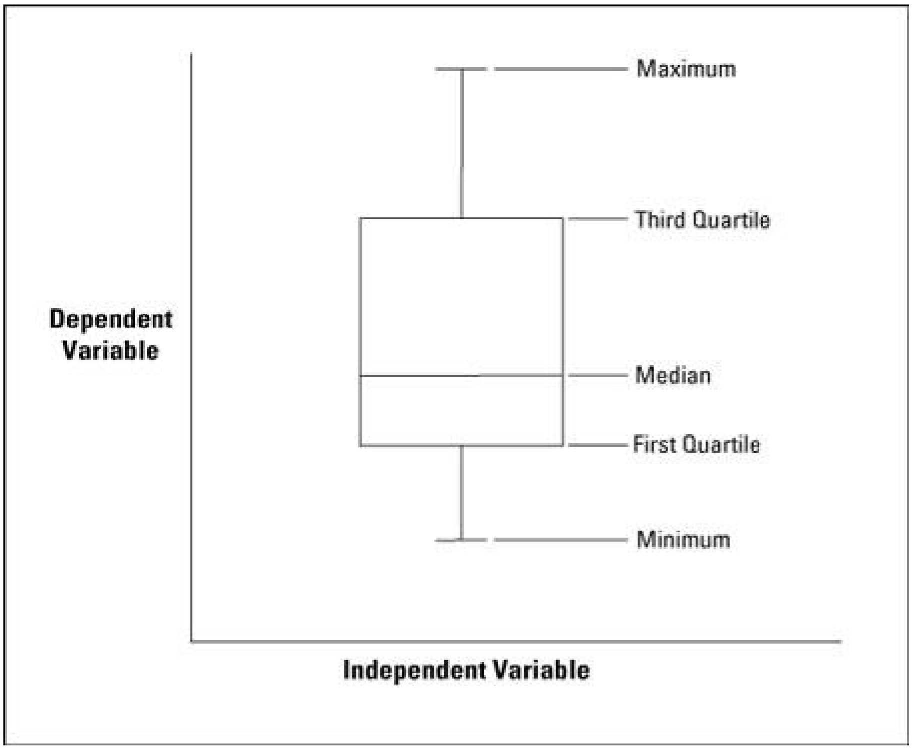

Figure A.3 Vertical box plot

Median

The median (middle quartile) is the mid-point of the data and it is shown by the line that divides the box into two parts. In which the half of the scores are greater than or equal to this value and half are less.

Inter-quartile range

The middle box represents the middle 50% of scores for the set of data. The range of data from first to third quartile is referred to as the inter-quartile range and the middle 50% of scores fall within the inter-quartile range.

Third quartile

Seventy-five percent of the scores fall below the third quartile.

First quartile

Twenty-five percent of scores fall below the first quartile.

Whiskers

The upper and lower whiskers represent scores outside the middle 50%. Whiskers often (but not always) stretch over a wider range of scores than the middle quartile groups.

Example: Box and whisker plots

The below given is recorded data of the number of sales made in each month in a Computer shop. In the past 12 months, the following numbers of computers are sold:

51, 17, 25, 39, 7, 49, 62, 41, 20, 6, 43, 13.

To plot the Box-plot:

First, put the data in ascending order. Then find the median. 6, 7, 13, 17, 20, 25, 39, 41, 43, 49, 51, 62.

Median = (12th + 1st) ÷ 2 = 6.5th value = (sixth + seventh observations) ÷ 2 = (25 + 39) ÷ 2 = 32

There are six numbers below the median, namely: 6, 7, 13, 17, 20, 25. Q1 = the median of these six items = (6 + 1) ÷ 2= 3.5th value = (third + fourth observations) ÷ 2 = (13 + 17) ÷ 2 = 15.

Here are six numbers above the median, namely: 39, 41, 43, 49, 51, 62. Q3 = the median of these six items = (6 + 1) ÷ 2= 3.5th value = (third + fourth observations) ÷ 2 = 46