Optimal Scheduling of Plug-in-Hybrid Electric Vehicles with Distributed Energy Sources using Meta Heuristic Techniques

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DECLARATION

I, hereby declared that the presented work in the thesis entitled "**OPTIMAL SCHEDULING OF PLUG-IN-HYBRID ELECTRIC VEHICLES WITH DISTRIBUTED ENERGY SOURCES USING META HEURISTIC TECHNIQUES**" in fulfilment of degree of **Doctor of Philosophy (Ph. D.)** is outcome of research work carried out by me under the supervision Dr. Suresh Kumar Sudabattula, working as Associate Professor, in the School of Electronics and Electrical Engineering of Lovely Professional University, Punjab, India. In keeping with general practice of reporting scientific observations, due acknowledgements have been made whenever work described here has been based on findings of other investigator. This work has not been submitted in part or full to any other University or Institute for the award of any degree.

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CERTIFICATE

This is to certify that the work reported in the Ph.D. thesis entitled “**OPTIMAL SCHEDULING OF PLUG IN HYBRID ELECTRIC VEHICLES WITH DISTRIBUTED ENERGY SOURCES USING META HEURISTIC TECHNIQUES**” submitted in fulfillment of the requirement for the reward of degree of **Doctor of Philosophy (Ph.D.)** in the Department of Electrical Engineering, is a research work carried out by G. Naresh Kumar, 41800740 , is bonafide record of his original work carried out under my supervision and that no part of thesis has been submitted for any other degree, diploma or equivalent course.

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ABSTRACT

In the Transportation sector, the Internal combustion engines (ICEs) are one of the most important technological advancements to transport people and commodities more rapidly and efficiently. Incremental innovation, more oil exploration and industrial development have all propelled the use and expansion of vehicles throughout the decades. As India's population and economy rise, so do its transportation emissions. These emissions must be quantified at regular intervals to analyze emission levels and the effect of control strategies to be implemented. These carbon dioxide emission levels from the transport sector, the depletion of oil fuel reserves and the creeping increase in crude oil prices have continued to rise in recent decades.

Transport sector electrification is probably the most viable choice for minimizing transport emissions and so Electric Vehicle (EV) growth is supposed to increase dramatically over the upcoming generations. Current trends suggest that EVs have become a potential innovation for the transportation sector of roads, because of their technological and environmental advantages; so, the EVs are becoming a viable substitute for conventional vehicles. As a result of the significant advances made in the area of energy efficiency, the number of EVs on the road has substantially increased. The growing demand for EVs has led to an increase in the number of charging stations, which in turn has had a substantial impact on the electrical system. There are several charging techniques and grid integration approaches that are currently being developed to reduce the negative impacts of EV charging and maximize the potential benefits of EVs being integrated into the grid. The distribution system is negatively impacted when rapid electric vehicle charging stations (EVCSs) are not planned and implemented appropriately. Identifying the optimal planning for the electrical distribution system, particularly regarding the positioning and size of FCSs, is one of the most critical challenges faced by the distribution system operator.

After the optimal placement of EVCS in the Distribution System (DS), As the EV load is going to be the additional load to the existing system, On the distribution grid, a voltage drops and a violation of the flow of power may occur while vehicles are being charged. If the charging is not regulated, the peak load demand of the distribution system will coincide with the charging of EVs, which will have a loading effect on the distribution grid. So, there is a need to go for an alternative solution to reduce the impact of EV load on the grid, Here the Distributed Generators (DGs) through the renewable energy resources which are eco-friendly are integrated into the DS to support the excess load demand. Due to the growing demand for electrical energy, DG sources have become more significant in distribution networks. The placement and capacity of DGs will influence power distribution system losses and voltages. The improper planning of DGs will have a significant impact on the DS. Therefore, the distribution system operator has a substantial issue in choosing the optimum placement for DGs in the distribution power network as well as the optimal sizing of it.

From the optimal positioning of EVCS in the DS, due to the stochastic nature of the DGs and EV load, the integration of DGs alone to the DS might reduce power losses and raise the voltage level but not up to the extent which might not improve the system stability. So, there is a need to go for an alternate method where the EVs can act as an energy source with its bidirectional mode of charging and discharging operation from the DS. Vehicle to Grid (V2G) is a novel resource for energy storage and provision of high and low regulation. It supplies and permits a solution for the volatility caused by the large proportion of renewable energy in the grid, in addition to alleviating grid congestion and reducing the need for grid capacity expansion.

In the proposed research, the Loss Sensitivity Factor (LSF) approach is considered for the optimal positioning of EVCS, the bus location sequence is determined by the descending order of the values for the LSF component to locate the best position vector. The meta-heuristic algorithms of Particle Swarm Optimization and Harris Hawks Optimization are chosen for the positioning of EVCS, the simulation results were compared with the conventional system. LSF approach is considered to identify the weak buses for the optimal placement of DGs, the simulation is carried out for reducing the losses by the simultaneous deployment of EVs and DGs in the DS. The total load of the DS is analysed for a 24-hour horizon and the optimal scheduling of EVCS and DGs is carried out for a 24-hour load profile by Arithmetic Optimization Algorithm. The research work is tested on a standardized IEEE 33-node distribution system to analyse the performance of the proposed work. The analysis is carried, out for proper planning of EVs to charge and discharge based on the constraints of State of Charge

(SoC), Power and intermittent load demand, and also estimates the off and peak load times over a period of time. Due to the intermittent nature of the EVCS and DGs, by the effective utilization of EVs as one of the sources with smart charging methodology, the losses will be further reduced and enhance the voltage profile in comparison with EVCS and DGs. Simulation results are carried out for various possible cases to assess the effective utilization of Vehicle to Grid (V2G) for stable and reliable operation of the DS. To bring down the price level of charging and to analyse the benefits provided by the V2G method to the end-user, the cost-benefit analysis is also determined for Grid to Vehicle (G2V) and V2G mode of operation for a 24-hour horizon with the EVs connected to the respective EVCS over a period of time.

PREFACE/ACKNOWLEDEMENT

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LIST OF ABBREVATIONS

S.No	Notation	Abbreviation
1.	PCC	Point of Common Coupling
2.	FCS	Fast Charging Stations
3.	e-amrit	Accelerated e-Mobility Revolution for India's Transportation
4.	PSOCFA	Particle Swarm Optimization with Constriction Factor Approach
5.	MINLP	Mixed Integer Non-Linear Programming
6.	MPDIPA	Modified Primal Dual Interior Point Algorithm
7.	CSPP	Charging Station Placement Problem
8.	OCEAN	Optimizing eleCtric vEhicle chArging statioN
9.	HGAPSO	Hybrid Genetic Algorithm and Particle Swarm Optimization
10.	GA	Genetic Algorithm
12.	APSO	Accelerated Particle Swarm Optimization
13.	GAMS	General Algebraic Modelling System
14.	HSLC-PS	Hybrid Soccer League Competition-Pattern Search
15.	SLC	Soccer League Competition
16.	GWO	Grey Wolf Optimization
17.	SMFO	Swarm Moth Flame Optimization
18.	SA	Simulated Annealing
19.	HHO	Harris Hawks Optimization
20.	AVDI	Average Voltage Deviation Index
21.	VSI	Voltage Stability Index
22.	TLBO	Teaching Learning based Optimization
23.	NPL	Network Power Loss
24.	DSS	Distribution System Simulator
25.	NSBSA	Non-Dominated Sorting Backtracking

		Algorithm
26.	ESS	Energy Storage Systems
27.	FSA	Future Search Algorithm
28.	RDN	Radial Distribution Networks
29.	DRR	Distributed Renewable Resources
30.	ABC	Artificial Bee Colony
31.	RDG	Renewable Distributed Generation
32.	HNM-CS	Hybrid Nelder Mead Cuckoo Search
33.	VaR	Value-at-Risk
34.	MILP	Mixed Integer Linear Programme
35.	PSCAD	Power Systems Computer Aided Design
36.	TOU	Time of Use
37.	MOMVO	Multi Objective Multiverse Optimization
38.	GHG	Green House Gas
39.	SSA	Salp Swarm Algorithm

CHAPTER 1

INTRODUCTION

1.1 Introduction

The fundamental cause of global climate change is carbon dioxide (CO_2) emissions. It is widely acknowledged that the world to reduce pollution as early as possible to alleviate the most severe effect of global warming. Global CO_2 emissions from power and heat generation were 13.13 billion metric tonnes ($GtCO_2$) in 2020, which accounted for almost 37% of worldwide CO_2 emissions [1]. The transportation industry, which generated 7.29 $GtCO_2$, was the second-largest carbon dioxide emitter shown in Fig. 1.1. Coal is the most widely utilized fuel for electricity production, the power industry is a crucial source of emissions. When coal is burned, it releases the most CO_2. China, the world's top coal emitter, released to the environment 7.4 $GtCO_2$ in 2020 because of its coal consumption. India, the world's second-largest emitter, released 1.6 $GtCO_2$ because of coal consumption.

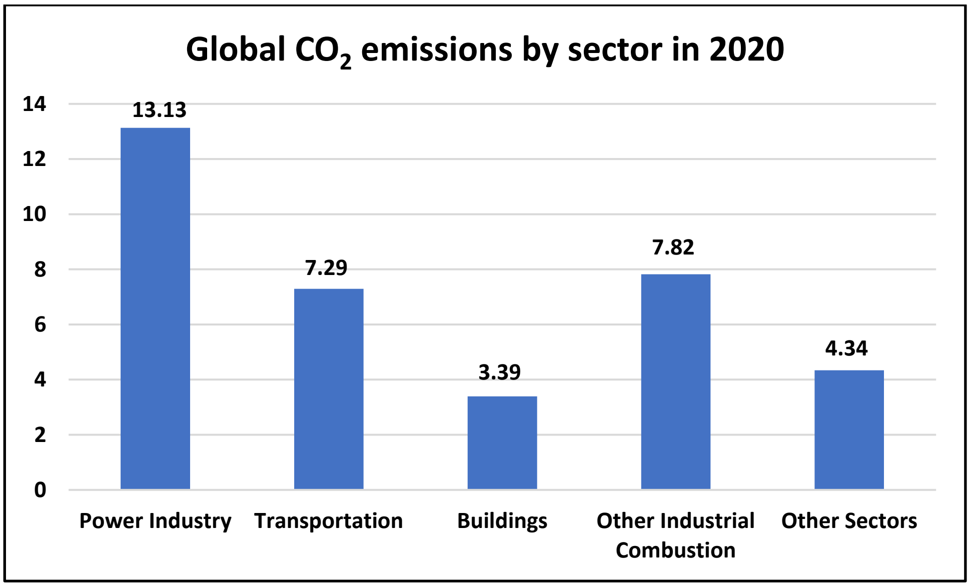


Fig. 1.1. Global CO_2 emissions by sector in 2020 (in billion metric tons of CO_2)

As India's population and economy rise, so do its transportation emissions. These emissions must be quantified at regular intervals to analyze emission levels and the effect of control strategies to be implemented.

Internal combustion engines (ICEs) are one of the most important technological advancements that have made it possible to transport people and commodities more rapidly and efficiently. Incremental innovation, more oil exploration, industrial development has all propelled the use and expansion of vehicles throughout the decades.

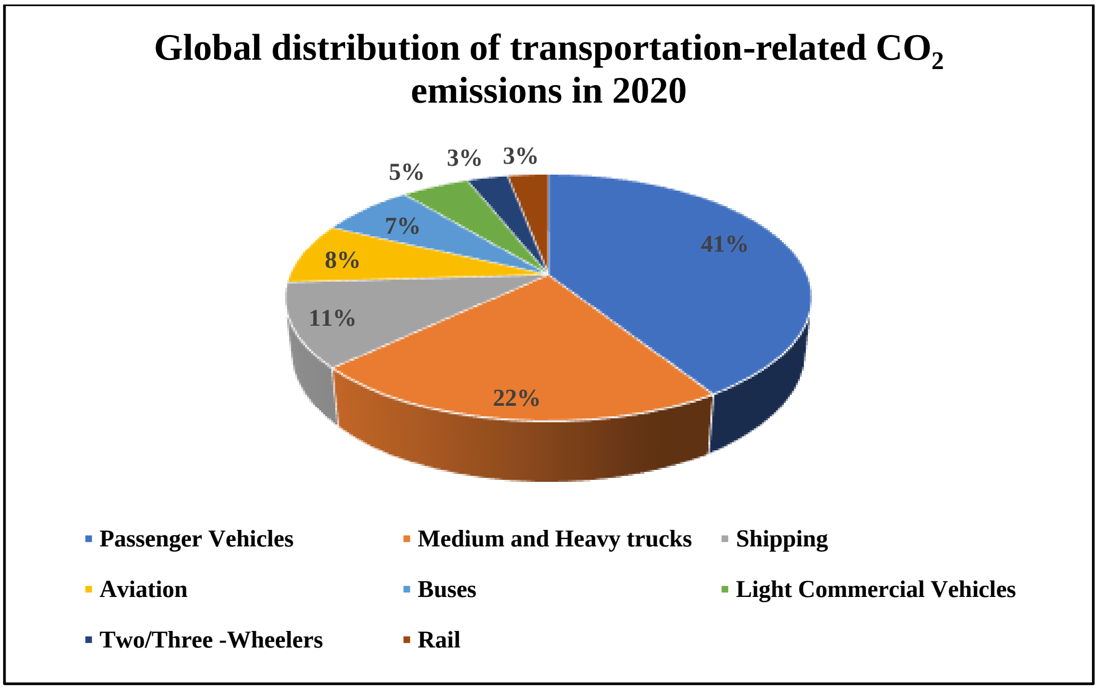


Fig. 1.2. Global distribution of transportation-related CO_2 emissions in 2020

Over 7.3 billion metric tonnes of CO_2 will be emitted by the transportation sector in 2020. Fig. 1.2 shows that in that year, emissions caused by passenger vehicles accounted for 41% of the total emissions caused by transportation globally. CO_2 emissions from passenger automobiles have risen steadily in recent decades, reaching a high of 3.2 billion metric tonnes in 2019. The COVID-19 outbreak caused a reduction in car emissions in 2020. Medium and heavy vehicles, which account for 22 percent of the overall emissions caused by transportation, are the second-largest polluters [2]. Even though their emissions were only half as high as those of passenger vehicles, there were far fewer trucks on the road which is an indication of how destructive global road freight is. Around two billion metric tonnes of CO_2 were emitted into the atmosphere by heavy-duty vehicles in the year 2020.

The road transportation system is found to be the main source in India with 78% of total Carbon dioxide emissions. Existing ICEs directly burn fuel which can create dangerous emissions like CO_2 and carbon monoxide (CO). The massive use of ICE vehicles for the combustion of fossil fuels such as petroleum-based products especially diesel and gasoline contribute dramatically to the release of GHG into the atmosphere which causes vigorous Environmental Pollution.

Governments all over the globe have agreed in the previous decade to seek sustainable economic growth, with transportation reform at the forefront of the agenda. With the advent of vehicles that operate on alternative fuels and energy, transportation is poised to take yet another technological breakthrough. Because the industry, business and society as a whole must gradually transition away from the combustion of fossil fuels to reduce CO_2 and other greenhouse gas emissions, the electrification of mobility and transportation will continue to accelerate. Electrification of the transport network has substantial benefits, which include enhanced fuel portfolio diversification, reduction in the dependence on fossil-based sources, reduced cost of ownership, and economic stability.

The Road network is almost the largest emitter in the transportation sector, accounting for almost half of total GHG emissions [3]. Global attempts to decrease worldwide GHG emissions from transportation are being hindered by rapidly expanding mobility requirements and vehicle ownership. Electric vehicles (EVs) are a low-carbon replacement for traditional fossil-fuel vehicles and switching to electrification for road transport has been emphasized as a key solution to lower direct CO_2 emissions and reduce the oil supply-demand imbalance [4]. Apparently by the International Energy Agency (IEA) analysis, the global network of EVs grew from 5,000 in 2008 to over two million in 2016. Attributes so as rising environmental concerns, reduced battery costs, and more charging facilities are all contributing to this. All of this has prompted experts to project a fast increase in EV adoption over the next couple of years, with growth predictions ranging from 27% to 33% for the current year to 2030 [5].

1.2. Scope of Electric Vehicles in India

India's transportation industry is presently the fifth-largest in the world, with plans to make it the third-largest by 2030. The traditional means of fuel-intensive transit will not be able to meet the needs of such a large domestic market. In India, the government is pursuing new paths to deliver efficient, clean, and cost-effective transportation services, reducing consumption of oil imports while also reducing human and environmental health impacts. With the transition to EVs, India stands to benefit on several fronts, including the abundance of renewable energy sources and the availability of skilled workers in the technical and industrial sectors. Fig. 1.3 shows that by 2030, 70% of commercial vehicles, 30% of private vehicles, 40% of buses, and 80% of two and three-wheelers could be electrified [6]. As a result, India is actively encouraging the use of electric vehicles throughout the country by providing further incentives to consumers and production companies at both the central and provincial levels. It is critical for a nation that still relies largely on coal for producing electricity to adopt stringent measures to meet its goals for the future.

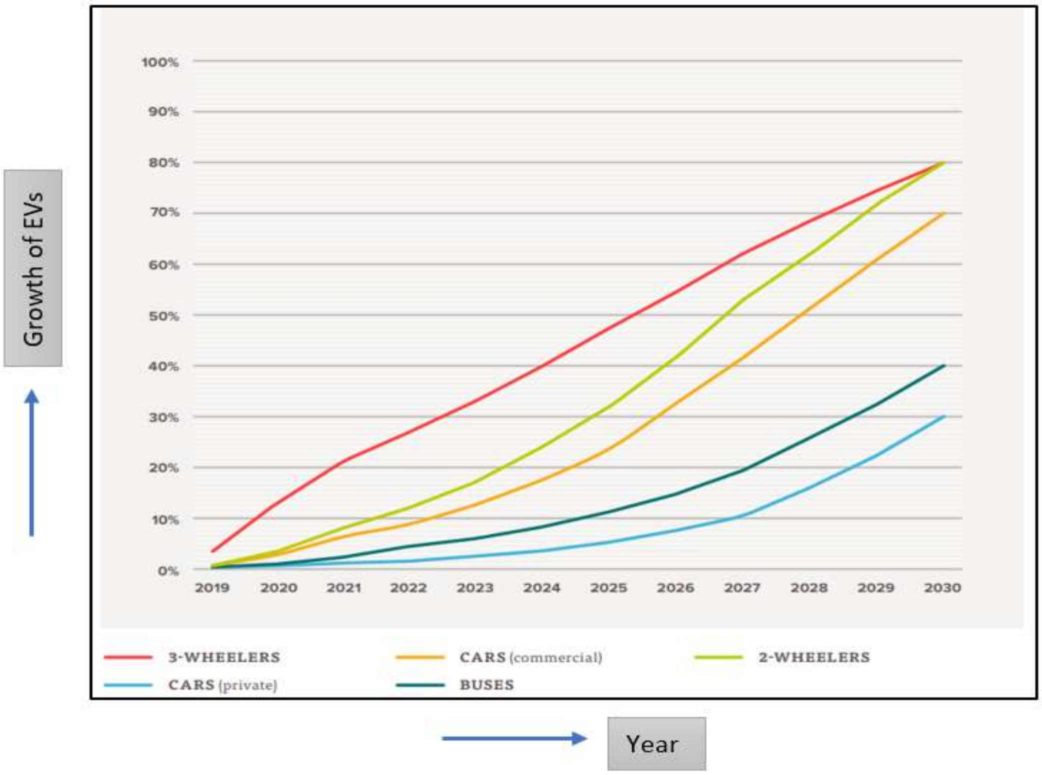
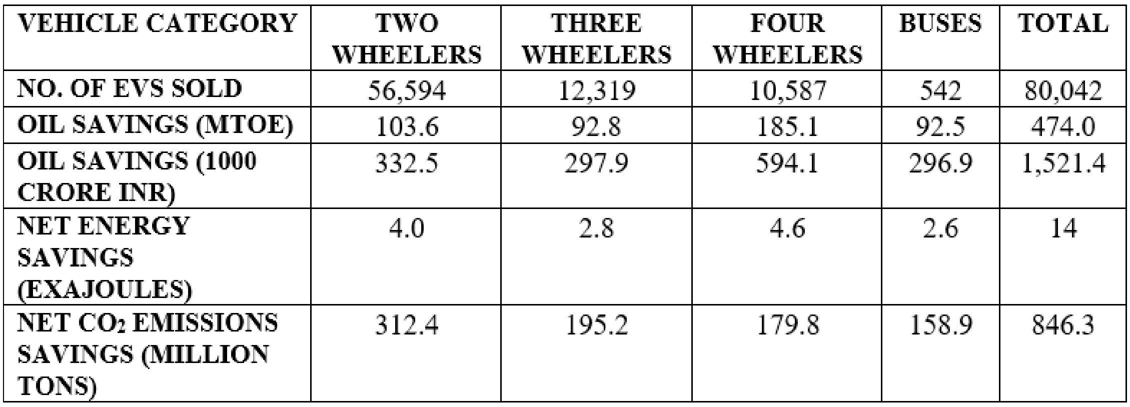


Fig. 1.3. EV Sales Penetration by 2030

The NITI Aayog and Rocky Mountain Institute evaluated the FAME II scheme, which covers the oil, net energy, and net CO_2 emissions reduction over the lifespan of the two, three, and four-wheeled vehicles and buses, as well as the operating expenses associated with higher levels of adoption by the year 2030. The data analyses the oil, net energy and CO_2 reduced emissions of all automobiles through 2030 to determine the contribution of savings related to rising EV adoption levels by 2030. In India, an EV ecosystem is emerging, with regulations and initiatives being developed and implemented to encourage the early growth of e-mobility solutions. FAME II is one such strategy that builds on the insights gained from its predecessor and it is well placed to achieve its objective of accelerating EVs usage and production. If India has achieved the above-mentioned sales penetration of EVs by 2030, the following energy and CO_2 reductions would be noticed [6].

Table. 1.1. Potential energy and CO_2 savings by 2030



VEHICLE CATEGORY	TWO WHEELERS	THREE WHEELERS	FOUR WHEELERS	BUSES	TOTAL
NO. OF EVS SOLD	56,594	12,319	10,587	542	80,042
OIL SAVINGS (MTOE)	103.6	92.8	185.1	92.5	474.0
OIL SAVINGS (1000 CRORE INR)	332.5	297.9	594.1	296.9	1,521.4
NET ENERGY SAVINGS (EXAJOULES)	4.0	2.8	4.6	2.6	14
NET CO_2 EMISSIONS SAVINGS (MILLION TONS)	312.4	195.2	179.8	158.9	846.3

Electric vehicles produced till 2030 will save 474 tonnes of oil equivalent, valuing INR 1521 billion. This would result in a net savings of 14 hexajoules of energy and 846 million tonnes of carbon dioxide throughout the lifetime of the EVs that were deployed. If electric buses are put into service by the year 2030, they would drive over 334 billion kilometers in their lifetime.

Industry initiatives have supported the governments rely on EVs as the major technological pathway for future transportation. To encourage the production of EVs in India, the Indian government decreased taxes on imported components in January 2019. This is expected to prompt investments in crucial components, according to the automobile industry. Manufacturers of battery cells and packs have made large joint development investments in India to contribute to the 'Make in India' initiative. Some of the states in India have improved mobility to provide safe, inclusive, affordable, and ecologically friendly transportation alternatives for their inhabitants. The initiatives in table 1.2 were produced in front of NITI Aayog's MOVE Summit in September 2018. Many more states are working on EV regulations.

Table. 1.2. State-level EV policies in India

S. No	State	Key Policy elements/ Targets
1	Andhra Pradesh	➢ To reach 10 Lakh Electric Vehicles by 2024. ➢ To install 1 lakh rapid and slow EVCS by 2024.
2	Delhi	➢ The goal is to achieve 50% of all public transportation powered by EVs by 2023. ➢ Tends to encourage the reuse and recycling of used electric vehicle batteries.
3	Karnataka	➢ The goal is for all commercial vehicles transporting commodities to be electrified by the year 2030. ➢ Encourages entrepreneurs to create business models that support EV economic solutions.
4	Kerala	➢ By 2022, the state aims to have 1 million electric vehicles. ➢ By the year 2022, the state intends to run a fleet of 2 lakh two-wheelers, 50,000 three-wheelers, 1,000 freight vehicles, 3,000 buses and 100 ferry boats.
5	Maharashtra	➢ Increase the number of electric vehicle registrations in Maharashtra to 5 lakhs. ➢ Invest Rs. 25,000 crores towards the production of electric vehicles and create job opportunities for 1 lakh people.
6	Telangana	➢ Telangana State Transport Corporation plans to deploy 100 percent electric buses for intracity, intercity, and interstate transportation by 2030.

		➢ Installation of 100 fast charging stations in GHMC and other cities over a while.
7	Uttar Pradesh	➢ By the year 2030, the state intends to have 1,000 electric buses in operation. ➢ By 2030, autorickshaws, taxis, school buses/vans, and other vehicles in five cities will be completely electrified.
8	Uttarakhand	➢ To make Uttarakhand a desirable location for EV manufacturing capacity investment. ➢ There would be loans of up to Rs.500 million available to MSME - sized businesses interested in producing EVs.

To promote the establishment of Electric vehicle Charging Infrastructure (EVCIs) and improve EV sales, The Regulations and Standards state that: (a) privately charging at houses or offices is permitted; and (b) a public Electric charging station will provide prioritized access to electric power by the authorized power distributor (DISCOM) (c) To address the concern of EV users who are facing the problem while trying to identify the EVCIs when traveling over large distances, to establish at least one public EV charging point in a grid of 3 km x 3 km and within 25 kilometers on each side of major highways and roads. To support the rise of EVs in India, states should concentrate on creating public awareness about the advantages of EVs over IC engines, in addition to the market subsidies granted to customers and the activities undertaken so that EVs and batteries may be made more affordable. The reduced operating cost, operation and maintenance of EVs, absence of pollutants and the availability of charging infrastructure, should be the emphasis of an awareness campaign.

1.3. Impact of Electric Vehicles adoption in Distribution System

EVs may be used for transportation, but they also have an impact on other areas. As a result, the transition in the automotive world caused by EVs has a substantial impact on the environment, economics, and power in huge parts of electrical systems [7]. Fig. 1.4 shows the effect of EVs on the Electricity grid, climate, and economic growth. The situation becomes very concerning when charging occurs during rush hours, resulting in overloading the system, network equipment damage, the removal of protective relays and ultimately installation cost increases [8]. The grid's voltage stability is affected by the location, penetration level and EV charging time of electric vehicles. An increase in load demand is caused by the unpredictable nature of EV connection points, penetration levels, and the times of connection and disconnection of the charging.

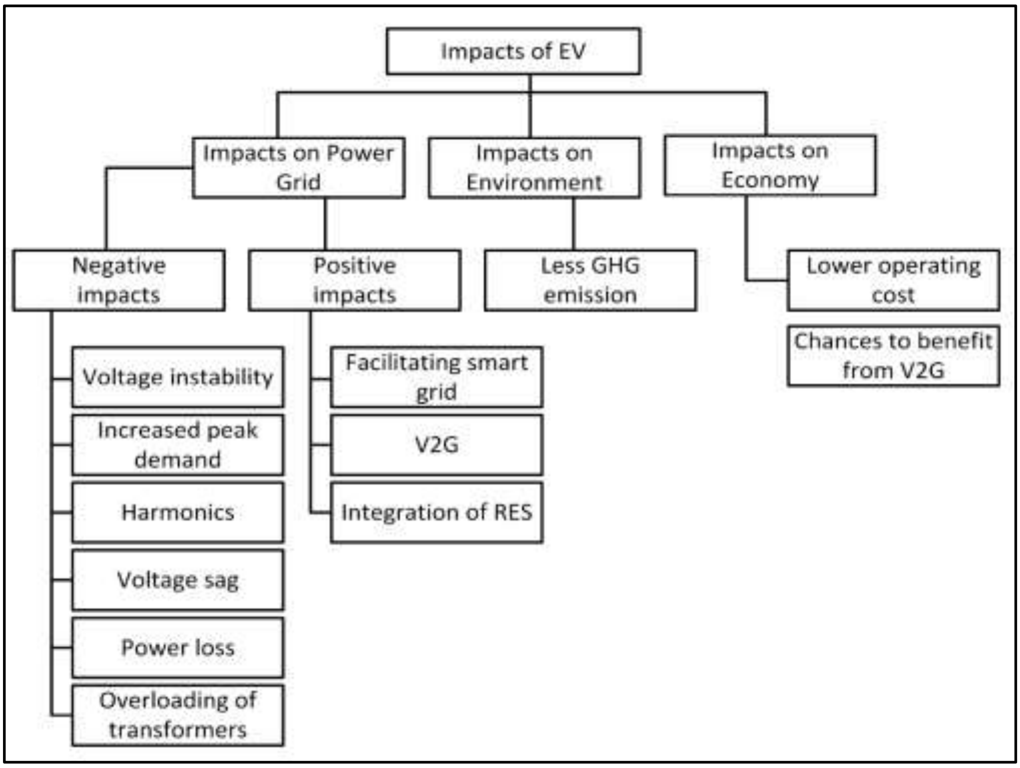


Fig. 1.4. Impact of EVs on Power Grid, Environment and Economy

The widespread usage of EVs, on the other hand, brings about problems with the quality of distribution networks. These problems include inadequate network capacity, three-phase voltage imbalance and off-nominal frequency concerns. Because EVs are portable single-phase loads, they can be connected along with any one of the three phases within distribution systems. This results in the power lines being heavily loaded while the electrical connections in the other two phases are not loaded that much. Unbalanced three-phase loads have the potential to bring about a wide variety of problems with the power quality, such as the failure of the transformer, the malfunctioning of the equipment, and the relays. In addition, electric vehicles have a high degree of spatial and temporal variability, which makes it difficult to manage them as excess loads while simultaneously preserving the stability and security of the grid. The time of electric vehicle home charging and residential demand peaks coincide, which causes additional system peaks at that moment. In addition, the presence of a greater number of EVCSs in the same region might result in the generation of significant harmonics, which results in poor power quality [9]. As a consequence of this, the incorporation of a significant number of EVs into distribution networks is a predominant subject of concern among the research and engineering community. In particular, the community is interested in finding ways to increase the efficiency and productivity of EV charging to reduce the impact of the concerns. Increased utilization of EVs will result in a substantial demand for electricity transmission, which will, in turn, lead to an increase in the amount of power reduction in the distribution system's feeders, hence lowering the system's overall efficiency.

Uncoordinated charging, uncontrolled charging or dumb charging is described as charging without any consideration of drawing power from the grid. This can result in the inclusion of EV usage during rush hours which can sometimes lead to load imbalance, power shortages, volatility and reduced quality and loss of power efficiency. Building for the future, however, the growing need for Plugin Hybrid Electric Vehicles (PHEVs) would have an enormous effect on electricity demand and the production of new power stations. Recent findings have shown that the explosive growth of PHEVs and the increased demand for energy would likely have significant implications for the current network [10].

Therefore, implementation of large PHEV integration in power grids would require:

1) Upgrade of existing network infrastructure to accommodate coordinated charging.
2) Introduction of smart grid technologies to manage PHEV charging through real-time monitoring and control.

Nevertheless, providing the extra charge levied by charging PHEVs from traditional electricity generation sources would move transport sector pollution to the power generation sector. To mitigate the issue, Renewable Energy Sources (RESs) are projected in playing a significant role in enhancing the transport field [11]. The RES penetration rates grew adequately because of policy incentives and technological improvement in this region.

1.4. Impact of Distributed Generators on Distribution System

Utilities are continuing to expand their electrical network connections to keep up with demand and appropriately serve their customers. Developing new substations or upgrading existing ones is the typical solution. Power Generating stations, mostly hydro, thermal, and nuclear is part of the conventional electrical power system. Electricity is transferred from the production end to the consumer end through extensive transmission and distribution lines. The power plants, transmission, and distribution systems are all fully loaded, and there is no way to load them much higher. Overloading the system might result in a voltage drop, which could result in the system being completely shut down. The only way to fulfil the rising electricity demand is to increase production and expand the transmission and distribution infrastructure, which is both costly and damaging to the environment [12].

As a result, an alternate way to resolve this issue is to produce power at the consumer level, which is known as DG. Wind, solar, fuel cells, and micro-turbines are examples of DGs. The DG units could be connected to the load, bypassing the utility grid or in tandem with it. Due to the intermittent nature of renewable sources such as wind, solar, etc. voltage regulation, power quality and reliability should be considered while operating alone, as in a micro grid. When running in parallel with the central grid, attention must be given to ensuring grid synchronization, as well as the voltage stability and losses [13]. DGs may be beneficial to the environment since they lower the amount of electricity that is required to be produced from centralized power plants. This, in turn, reduces the negative effects that centralized production has on the natural atmosphere. With the integration of DG, the power quality may be affected by numerous factors, including the kind of DG, its interfacing with the distribution system, the size of the unit, the total capacity of the DG on the system capacity, the size of production with a load at the distribution level and the response of feeder voltage regulation.

The penetration of DGs is continuing to increase as the annual electric energy demand rises. The owner, utility, and the end-user, all will benefit from integrating DG into an electrical power distribution system. DG improves power quality, increases distribution system stability, and can fill valleys and peak values. However, integrating DG into current systems has presented a number of technological, economic, operational challenges and legal concerns. An existing distribution system's integration of a DG may have a significant effect, with power distribution protection being one of the most serious concerns. Furthermore, DG connectivity increases the system's failure level and allows it to lose its radial power flow.

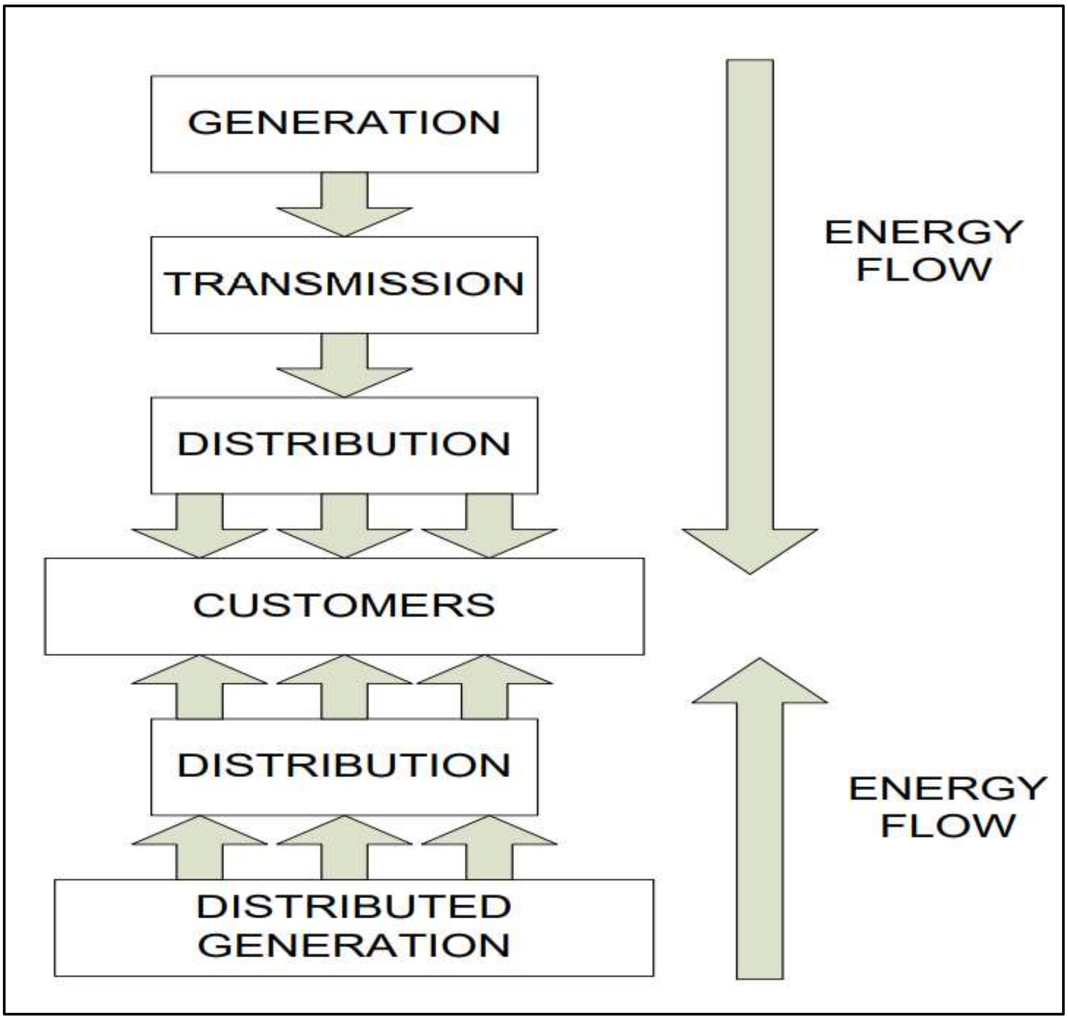


Fig. 1.5. Conventional and Distributed Generation power flow to end-user

Typical DGs in the residential sector are:

- Solar PV systems

- Wind turbines
- Fuel cells run on natural gas
- Gasoline or diesel-fueled emergency backup generators

In the commercial and industrial sectors, the DGs such as:

- Systems that combine heat and electricity
- Solar PV systems
- Wind turbines
- Hydropower
- Cofiring with biomass
- The burning of municipal waste
- Fuel cells that run on natural gas or biomass
- Oil-fueled reciprocating internal combustion engines as a source of backup power

1.4.1. DG's Impact on Voltage Regulation

The inclusion of generating stations in the distribution system, such as DGs, potentially has a major influence on the network process of voltage at home appliances and utility infrastructure. By the variation in the direction and amplitude of active and reactive power flows, the interconnection of DG may cause variations in voltage profile along a feeder. However, based on the features of the distribution system, as well as the positioning of DG, the influence on voltage control might be beneficial or harmful [14]. Without the coordinated effort among the DG and voltage regulator controller is meticulously constructed, DG might create an excess deviation in the voltage or under the acceptable limit in different areas of the feeder, leading to undesirable effects of voltage regulation [15].

Voltage control might be achieved by active voltage regulation if the utility and the DG owner come to a decision. By lowering (or absorbing, if required) their reactive power output, DGs such as synchronous machines and self-commuting inverters could regulate the voltage stability profile. The reactive power output of the DG may be reduced to compensate for any voltage rise caused by an increase in actual power production. In the case that high voltages occur, this range of adjustment may not be satisfactory. Step type voltage Regulators (SVRs) have the potential to provide the appropriate voltage control in these situations. Operating the DG in a move that maintains a constant voltage is the best way to exercise control over the distribution voltage at the PCC. When distributed generation is networked in smaller residential areas that share a distribution transformer, it has the potential to create excessive voltages. If the main voltage of the transformer has already reached its maximum, the DG could minimize the amount of voltage drop that occurs via the transformer and secondary circuits. As a result, additional customers who are served by the transformer may be subjected to excessive voltages [16].

1.4.2. DG's Impact on Losses

DGs might have a significant effect on the losses that occur in a feeder. The placement of the DG units on major priority must be considered to accomplish the goal of improving the system's reliability while also cutting down on losses. Because DG is often installed near load centers, its integration into the distribution network may contribute to a rise in both active and reactive losses [14].

The positioning of DG units to ensure stability is analogous to the arrangement of capacitor banks to minimize losses. The major contrast that can be made between the two circumstances is that DG has the potential to offer combined active and reactive power (P and Q). In contrast to this, the capacitor banks are solely responsible for contributing to reactive power flow (Q). The power factor of the majority of the system's generators is in the region of 0.85 lagging to unity when it is operating at full capacity. However, due to the availability of synchronous generators and inverters contributes to the system's ability to compensate for reactive power (leading current). Conventional distribution system characteristics are altered by DG installation. Most power distribution networks are set up to only allow one direction of power flow. The addition of a DG expands the system's potential energy sources. Power flow is reversed between the DG and substation when the DG power is greater than the downstream load.

1.4.3. DG's Impact on Harmonics

The amount of DG capacity that is connected to the power grid is yet another aspect that might affect the degree to which the power system exhibits harmonic distortion. Several research studies have focused their attention on the effects of power quality due to the high portion of DGs integrated into the system. When grid components interact with DG systems, it might lead to an increase in the amount of harmonic distortion. In addition to this, the positioning of DG is another factor that contributes to the levels of harmonic distortion in the power system [17,18]. The placement of DG at higher voltage levels in a circuit result in reduced harmonic distortion as compared to the installation of DG at lower voltage levels.

This system is extremely sensitive to the propagation of harmonics, despite the benefits of radial dispersion due to its wide spacing between components. The progression of time, followed by advances in technology, will evaluate based on the employment of semiconductor devices and other non-linear loads. A current that is not sinusoidal is produced by the source of the harmonics, which is inherently faulty since each periodic wave does not have the shape of a sinusoidal that contains harmonics. Harmonics at high current levels on the system are caused by non-linear loads, which may also lead to losses that occur during the process of electrical energy distribution and the deterioration of equipment that is already in use [19].

1.5. Electric Vehicle Charging Station Infrastructure

EVs give a rising potential for distribution companies to harness additional sources of flexibility in the demand, while simultaneously generating income from a group of potential clients who will considerably expand throughout the decade. As India's present vehicle fleet switches to electric models, the demand for grid electricity would rise by terawatt-hours, forcing advanced planning to bring down the prices and increase the benefits for both users as well as distribution companies. In addition, the considerable FAME II subsidy is available to a wide variety of vehicle segments, which will encourage the quick adoption of electric vehicles in the vehicle sectors that are being targeted. However, for FAME II to be effective in promoting the electric vehicle sector, direct assistance of charging infrastructure would be required. This new substantial and variable load will boost economic development and the operational efficiency of the distribution company if it is handled appropriately and planned effectively. On the other hand, if additional demand is not handled proactively, distribution companies may face challenges in the form of a huge number of requests for connections and a lack of control over the additional load. As a consequence, there will be a loss to manage demand on the supply side and a stalling of demand growth [20]. It is anticipated that the bulk of the interconnection requests would originate from the fleet owners and operators of commercial vehicles, bus transport companies, and industrial EV charging network providers who serve both the corporate and personal automotive sectors during the early stages of EV expansion. Based upon the count and the kinds of vehicles, these additional loads will be rather substantial and may consume ranging from several hundred to megawatts of electricity. It will be crucial to encourage the adoption of EVs and to provide new and sustained income for the utility provider if interconnection and permission requests are processed in a timely way and simplified manner.

The electric vehicle charging industry has converged on a uniform standard known as the Open Charge Point Interface (OCPI) protocol, which specifies the charging station hierarchy, is as follows: location, Electric Vehicle Supply Equipment (EVSE) port and connectors [21].

1.5.1 Location of a Station

The location of an EV charging station has a significant impact on the infrastructure's requirements [22].

1.5.1.1 Private locations

For EVs, the most common scenario will include overnight charging at their owners' residences. In most circumstances, overnight recharging is sufficient to completely charge the batteries of EVs with a wider range. The most cost-effective method is to restrict the charging power to 3.7 kW. The infrastructure is secured from damage or abuse since it is located in a secure location.

1.5.1.2 Semipublic locations

Charging infrastructure is considered to be semipublic if it is situated in a private location but allows several users to utilize it at the same time. Examples of this may be seen in parking lots, employee parking lots, and parking lots at commercial malls. The most promising strategy for increasing the number of kilometers traveled by electrically powered vehicles is to provide charging infrastructure at places of employment. On the one hand, companies may avoid charging owner-operators for their energy use to save money on the expense of infrastructure, and on the other, they could encourage more people to switch to electric vehicles by offering financial incentives. Because the overall profit is still relatively low, the infrastructure must be set up in the most financially prudent manner possible. It's important to remember that building new infrastructure in these areas is mostly a marketing technique. Charging infrastructure at recreation centers has a considerably greater impact, but since these venues are so widely dispersed, the infrastructure costs associated with their installation would be prohibitive.

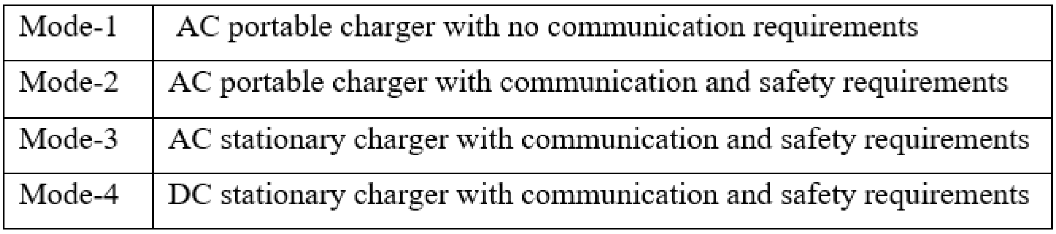
1.5.1.3 Public locations

Charging infrastructure includes FCS on highways, battery swap stations, and charging outlets for on-street parking, that may be found on public land. Because authorization and payment processes need to be deployed, as well as measuring instruments that need to be calibrated, this form of charging infrastructure is the most expensive. In addition to this, there is a need to implement preventative measures against vandalism. Depending on the requirements of the area, a grid connection access point may need to be set up.

1.5.2 EVSE Port

The device that holds EVSE ports is frequently referred to as a charging port, and this unit might have one or more EVSE ports depending on its configuration. Even though it may have more than one connection, an EVSE port can only provide electricity to a single vehicle at a time while charging it. The following table 1.3 shows the communication and safety requirements of EV charger type.

Table. 1.3. Communication, and safety requirements with IEC 61851 Standard



Mode-1	AC portable charger with no communication requirements
Mode-2	AC portable charger with communication and safety requirements
Mode-3	AC stationary charger with communication and safety requirements
Mode-4	DC stationary charger with communication and safety requirements

1.5.3 Connector:

Connectors are being used to charge a car once they have been plugged into the vehicle. There may be more than one kind of connection and connector accessible on a single EVSE port (for example, CHAdeMO and CCS), but only one vehicle may be charged at a time using that port. Plugs are another name for connectors in various contexts. EV charging cables often feature two connectors, one of which connects to the socket in the vehicle, and the other of which plugs into the charge point itself. This is similar to the design of the cables used to charge mobile phones. It's important to note that the kind of connection you'll require depends on your vehicle and the charging speed. You must ensure that the outlet of the charging station matches the outlet of your car if you want to charge your electric vehicle at home, work, or at a public station. The cable that links your car to the charging station must have the correct plugs on both ends.

AC plugs may be divided into two categories:

- Type 1 plugs have a single-phase and are used in both American and Asian electric vehicles. As long as you have enough charging power in your vehicle and the grid, you may charge your vehicle at up to 7.4 kW.
- There are three more wires for electricity to flow via Type 2 plugs, making them three-phase plugs. Consequently, they may charge your vehicle more quickly. You can charge at 22 kW at home, but public charging stations can reach 43 kW, depending on your car's charging power and the grid's capacity to support it.

For DC charging, there are two distinct types of plugs:

- CHAdeMO is a rapid charging technology that was created in Japan. It is capable of extremely high charging capabilities and can charge in both directions. At the moment, Asian automobile manufacturers are at the forefront of the race to create electric vehicles that can be plugged in using a CHAdeMO connector. It is possible to charge up to 100 kW using it.

- The CCS plug is an improved version of the Type 2 plug. It has two extra power connections for rapid charging, making it compatible with the CCS standard. Both AC and DC charging is supported by this device. It is possible to charge at speeds of up to 350 kilowatts.

Table. 1.4. Levels of EV charging

Level of Charging	**Voltage**	**Current**	**Load Charging**	**Time to charge**
Level-1	120V (1-Phase AC)	12 to 16 Amps	1.4 to 1.9kW	Range of 3-5 miles per hour
Level-2	208V-240V (1-Phase AC)	12 to 80 Amps	2.5 to 19.2kW	Range of 10-20 miles per hour
Level-3 (DC Fast Charge)	208V-480V (3-Phase AC)	Up to 125 Amps	Up to 90kW	80 Percent charge in 20-30 minutes

1.5.4 Types of EV Charging Hardware

The pace at which the batteries are charged is used to categorize the different types of charging equipment for EVs. The amount of time it takes to recharge a battery is contingent not only on the battery's charge, but also on the kind of battery being used, the amount of energy it can store, and the sort of charging equipment being deployed. There are three types of chargers employed for EV charging systems shown in Fig. 1.6. In general, a charging system can either be unidirectional or bidirectional, and it can be driven by one-phase or three-phase voltage. This flexibility is included in all charging systems. As a result of the huge power rating of off-board chargers, these types of devices often make use of three-phase voltage for their source of power. There is no other way for power to enter the battery but only from the grid when using unidirectional chargers. Power can only flow from the grid into the battery with unidirectional chargers. A bidirectional charger may also provide electricity from the battery back to the grid. Charging arrangements may vary from as simple as a single-phase unidirectional charger to as complex as a three-phase bidirectional wireless charger. The single-phase unidirectional charger is the most fundamental one.

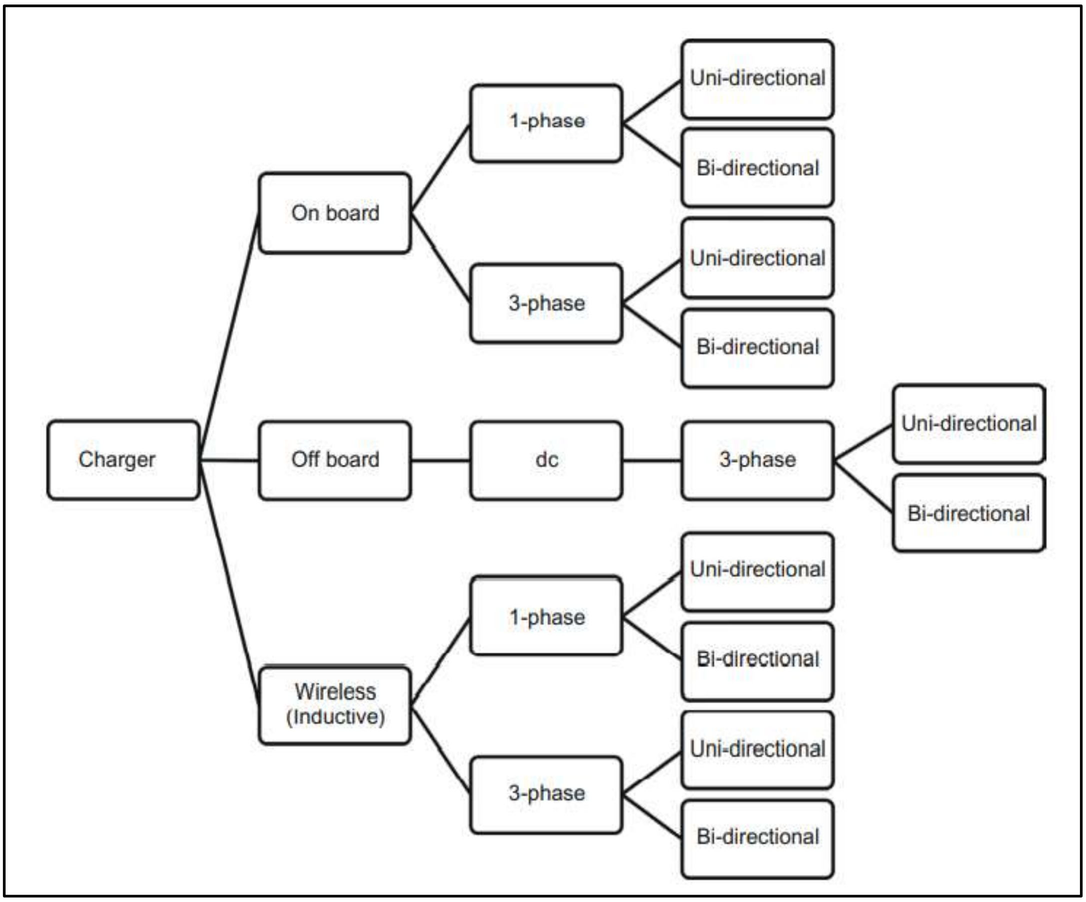


Fig. 1.6. An overview of Charger layouts

1.5.4.1 On-board Charger

The majority of modern automobiles include an on-board charging system that is capable of transforming the alternating current (AC) that is supplied by the electrical system into direct current (DC) that is necessary to keep the vehicle's battery charged. Onboard chargers are the best choice for charging capacities under 11kW. These chargers have the benefit of being able to be customized to a particular battery pack and being able to be recharged using regular power outlets. Due to rigorous automobile regulations, onboard chargers have a disadvantage. They also take up more space and add to the vehicle's weight shown in Fig 1.7. It is possible to eliminate the additional weight by using a drive inverter for recharging [23]. With an onboard charger, a vehicle can charge directly from a conventional household outlet (slow AC) at the driver's residence, business premises, or other public areas.

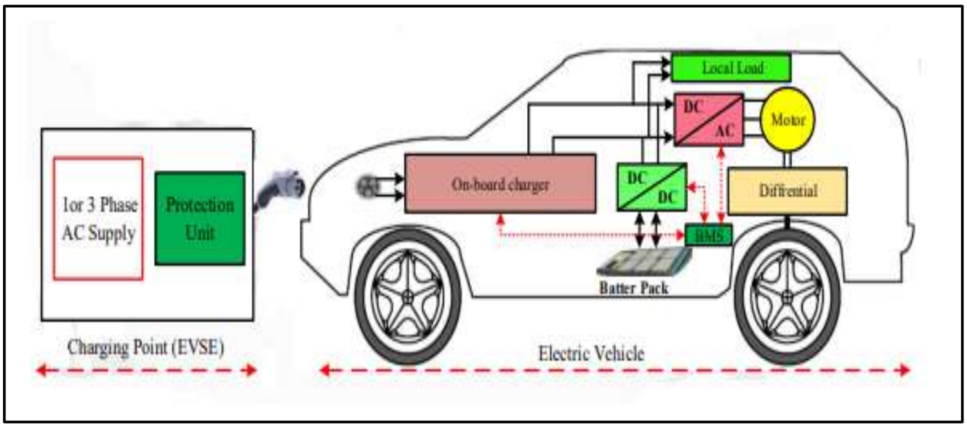


Fig. 1.7. On-board charger

Chargers that circumvent the onboard converter instead and provide direct current to the vehicle's battery are known as DC fast chargers because of their increased speed at which they can recharge. A degree of intelligence that can manage user authentication, vehicle communications, data collecting and monitoring, as well as payment, is often included in charging equipment. In certain circumstances, the bi-directional operation will make it possible for a dispatch system to control and limit the quantity of power that is received in response to pricing signals and stored in the battery. There are a few types of chargers that are often referred to as "dumb" chargers since they do not communicate or control the power from the grid and merely manage the appropriate levels of voltage and current for charging the battery. To involve in demand response or time of use pricing, corporate charging infrastructure operators should be encouraged to build chargers that are smart and have a certain degree of management and dispatching functionalities.

1.5.4.2 Off-board Charger

DC charging stations are a viable choice for charging devices with higher power levels. By using direct current, the battery receives charging power from the charger. Because the chargers' power electronics are placed outside the vehicle (off-board), they are lighter and take up less storage space shown in Fig 1.8. There is a risk of customer dissatisfaction with off-board chargers since the user cannot recharge at regular power outlets.

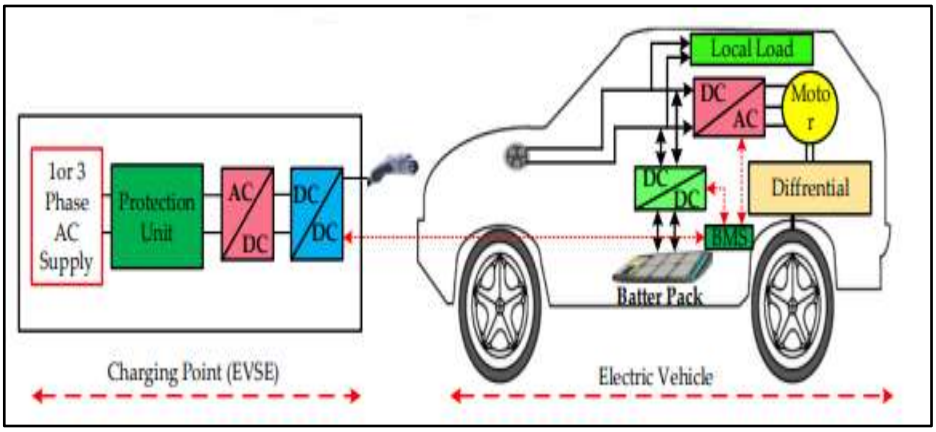


Fig. 1.8. Off-board charger

1.5.4.3 Wireless Charging

A physical connection is used for the conductively connected charging method. Sparking occurs during the plugging and unplugging of the device since the charging process involves a large amount of electricity. Because of these factors, wireless charging is the most convenient method for powering the device. No electrical connection is required when using wireless charging systems. Chargers are powered by high-frequency magnetic fields generated by a stationary portion of the charging system. A power electronics system with a receiver coil is installed in the electric car to charge the battery. As a result of these different components, on-board and off-board chargers are combined in wireless systems shown in Fig 1.9. The operation of an inductive power transfer (IPT) is analogous to that of a transformer with a big air gap, which results in inadequate magnetic coupling and an excessive amount of leakage flux [24]. Slow charging time, power transfer limit and reduction in efficiency with an increase in distance are the technical challenges in the developed wireless charging.

Fig. 1.9. Wireless charger

1.6. EV charging deployment Initiatives in India

Different government agencies have been allocated specific EVSE implementation elements including standards, incentives, deployment and execution as part of the broader electric vehicle adoption campaign. The entities, as well as their functions and responsibilities, are listed in the table below.

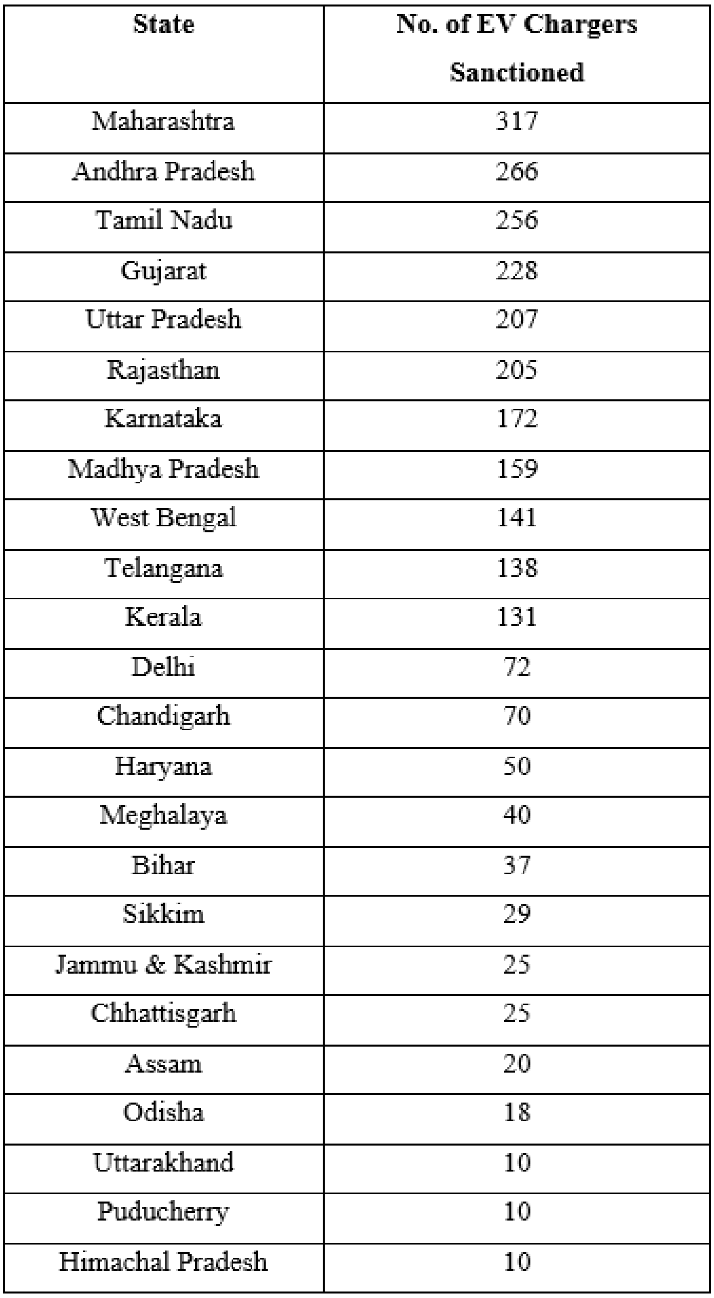
Table. 1.5. Government entities' roles and responsibilities

Organization	Roles and Responsibilities
Department of Heavy Industries (DHI)	➢ Ensuring that FAME II, India's program to speed up the adoption and production of electric and hybrid vehicles, gets off to a good start. ➢ Invited ideas for using incentives under FAME II for the implementation of EV charging infrastructure.
Ministry of Power (MoP)	➢ Issued a set of guidelines and standards for charging infrastructure for electric vehicles. ➢ The process of recharging electric vehicles should be seen as a utility, not a commodity.

Department of Science and Technology (DST) & Bureau of Indian Standards (BIS)	➢ There is a joint effort between BIS and DST to develop indigenous charging standards. ➢ Industry-academia cooperation to produce low-cost, locally manufactured chargers is being supported by DST.
Central Electricity Authority (CEA)	➢ To keep track of all public charging stations around the country, the CEA has been given the responsibility of creating a national database.
Bureau of Energy Efficiency (BEE)	➢ Under MoP's standards, BEE serves as the key nodal agency for the deployment of EV public charging infrastructure.
State discoms	➢ Unless a state government prefers alternative metropolitan localities or public sector entities, state discoms are the state's default nodal agency.
GST Council	➢ Reduction in the tax rate from 18 percent down to 5 percent for electric vehicle chargers and charging stations. (Effective as of the first of August in 2019)

A budget of Rs. 10,000 crores have been allocated by the government to support the expansion of India's electric car market via the FAME 2 program. India has committed up to $1 billion for the construction of electric car charging infrastructure throughout the country. Interconnecting renewable energy sources with charging facilities will also be encouraged under FAME 2.

Table. 1.6. Number of state-authorized EV chargers



State	No. of EV Chargers Sanctioned
Maharashtra	317
Andhra Pradesh	266
Tamil Nadu	256
Gujarat	228
Uttar Pradesh	207
Rajasthan	205
Karnataka	172
Madhya Pradesh	159
West Bengal	141
Telangana	138
Kerala	131
Delhi	72
Chandigarh	70
Haryana	50
Meghalaya	40
Bihar	37
Sikkim	29
Jammu & Kashmir	25
Chhattisgarh	25
Assam	20
Odisha	18
Uttarakhand	10
Puducherry	10
Himachal Pradesh	10

The government may provide financial incentives to encourage the purchase of 7,090 electric buses, 20,000 hybrid vehicles, 35,000 four-wheelers, and 500,000 three-wheelers, all of which would cost $3,545 crore. The GST rate for chargers and charging stations has been reduced from 18 percent to 5 percent. In addition, loans for the purchase of an electric vehicle would be tax-exempt for up to Rs 1.5 million.

Additionally, there will be an "upfront bonus" on the purchase of an EV. Investing in start-ups will also be tax-exempt as a result of this new policy.

An Expression of Interest (EoI) has been released by the Department of Heavy Industries (DHI) in August 2019 inviting proposals for using the incentive in cities to develop EV charging facilities. The incentive has been allocated to 2,636 EV charging stations as of January 2020, among those 1,633 of these rapid chargers may be found in 24 states and territories.

1.7. Organization of the Thesis

The thesis is separated into seven chapters, which are detailed in the following sequence:

Chapter 1 elaborates on the effect of Greenhouse emissions on various fields in the atmosphere, the need for the electrification of the transport sector and the effect of EV adoption and DGs that are part of the distribution system and the overview of the Electric Vehicle Charging Infrastructure and the initiatives carried out by the Government for the encouragement of EVs in India.

Chapter 2 includes a complete literature survey of major works in the fields of optimal positioning and placement of EVCS in the distribution system, optimal siting and placement of DGs and simultaneous placement of EVCS and DGs in the distribution system with scheduling for fluctuation in load demand and EV acting as a load and source via G2V and V2G model based on textbooks, technical reports, and research articles. Also included the research objectives, which were developed through the literature review.

Chapter 3 presents the planning for the optimum location of EVCS in the distribution system. Loss Sensitivity Factor approach and modeling, identification of strong bus in the distribution system for the placement of EVCS using meta-heuristic techniques and the effect of stochastic nature of EV load demand on the distribution system. The proposed method is implemented in the standard test system.

Chapter 4 covers the optimal siting of DGs in the distribution system, the Loss Sensitivity Factor method, modeling, the identification of weak bus in the distribution system for the placement of DGs and the impact of the intermittent nature of DGs in the distribution system. Simulations are carried out in the standard test system.

Chapter 5 presents the impact of the Integrated installation of DGs and EVCS into the distribution system at the same time, estimation of 24-hour EV load demand and the optimal scheduling of DGs over the distribution system for a 24-hour horizon using meta-heuristic techniques.

Chapter 6 illustrates the effect of EV acting as a load and source using G2V and V2G methodology, mode of operation based on off and peak load demand for 24- hour horizon and impact of V2G method due to variation of intermittent EV load demand on the distribution system. Cost analysis for G2V and V2G is carried out for the benefit of the end-user.

Chapter 7 highlights the numerous conclusions obtained in the individual chapters, as well as the substantial contribution of research work and allows for future study in this field.

CHAPTER 2

LITERATURE REVIEW

Over the last decade, the EV sector has seen a phase of tremendous growth. India committed to achieve a net-zero reduction in its carbon emissions by the year 2070 at the recent COP26 conference, which has recently finished. By the year 2030, India intends to have electric vehicle (EV) sales account for thirty percent of the country's private automobile market, seventy percent of its commercial vehicle market, and eighty percent of its two- and three-wheeler market. Only 7,96,000 electric cars registration has been completed in India till December 2021, and only there are about 1,800 public charging stations in existence, according to a recent study by the Accelerated e-Mobility Revolution for India's Transportation (e-amrit) portal. It's going to take a while for the nation to meet the desired ratio. This is because there is a lack of adequate charging infrastructure, poor charging times, and range anxiety. Convenient and fast charging infrastructures might be constructed as a solution to these problems. The charging infrastructure acts as an interface between the transport network and the distribution system. When it comes to the design of EVCS, it is essential to do research on the characteristics of charging loads and to make forecasts of their demands. Installing EVCS will result in an increased demand for distribution systems, which will harm the functioning of such systems. The detrimental impact of charging load may be addressed by integrating the local renewable power into the system, and getting charged using renewable would further decrease the emissions of greenhouse gases. However, because the renewable sources of energy, such as solar, wind, etc. generate power on an intermittent basis, the additional demand may not be able to be sustained at certain times of the day. As a result, it is essential to research the effects of rapid charging for electric vehicles to support distribution operators in their decision-making processes in the case of any system violations.

2.1 Optimal location of EVCS in the Distribution System

Frade et al. study the construction of charging stations by estimating demand at each point in the region. The customer demand is well measured in this approach but the cost to society is not taken into consideration [25]. The distribution network's technological limitations are not taken into consideration which makes this solution unfeasible.

Richardson et al. illustrate, how improved usage of current networks may be achieved by regulating the pace at which electric cars charge. To optimize the total power that can be given to the cars while still functioning within the restrictions of the network, a strategy that is based on linear programming is used. This approach is responsible for determining the ideal charging rate for each EV [26]. A portion of a home distribution network is used to test the technology. The findings indicate that significant penetrations may be supported on current home networks by managing the charging rate of individual cars. This reduces or eliminates the need to upgrade the network infrastructure.

Abhishek et al. have analyzed the effective design (siting and size) of the infrastructure of charging stations in the city of Allahabad in India. In this scenario, the placement of charging stations in the Allahabad distribution system is optimized with the use of a hybrid method that is derived from genetic algorithms and improved versions of standard particle swarm optimization [27]. The particle swarm optimization method re-optimizes the received sub-optimal solution (location and the size of the station), which results in an increase in the functioning of the process and enhances the overall effectiveness of the model.

Dixit et al., The purpose of this research is to provide the ideal positioning of EVs inside a radial distribution network. The enhancement of the voltage profile of the system is the main objective of this study, while simultaneously reducing the overall power losses as much as possible [28]. For optimum positioning of EVs on the IEEE-33 radial distribution test system, the PSOCFA approach was considered.

Payam Sadeghi et al., In this study, an MINLP optimization technique is presented for determining the ideal positioning and size of fast-charging stations. The cost of developing the station, the amount of energy lost by electric vehicles, the amount of energy lost by the electric grid, as well as the placement of electric substations and urban highways are some of the criteria that are considered by this method. The cost of station electrification and the amount of energy that is lost by electric vehicles has been determined with the use of geographical information [29]. Using the genetic algorithm approach, the optimization issue was addressed.

M. Z. Zeb et al., show an effective combination of all three kinds of EV chargers for reducing installation costs, losses, and transformer loading. Stochastic processes are used to simulate electric vehicle load because of the ambiguity of the drivers. To solve the restricted nonlinear stochastic problem, PSO is adopted [30]. For the model simulation, MATLAB and Open DSS (Distribution System Simulator) are used. The actual distribution system of Pakistan's National University of Science and Technology (NUST) has been used to test the proposed model.

The placement of EVCS at an improper location has a significant and detrimental effect on the power quality. of the distribution network, which in turn has inflicted harm on the effectiveness of the system. Chakraborty et al., detailed the process of installing Distributed EVCS in the IEEE 33 bus system. The Distribution Network (DN) has been segmented into multiple sections so that it may reach charging stations situated in different parts of an area, and it has been made certain that each of these areas will have at least one charging station allotted to it [31]. The issue is being referred to as an optimization problem, and Symbiotic Organisms Search Algorithm (SOS) has been used to solve it and come up with the best possible solution for EVCS.

Kunj Tripti et al., a strategy is suggested to determine the optimal location for charging stations in distribution networks, as well as the appropriate size of each station by preserving stability conditions. By examining the active loss, the reactive loss, the amount of power flowing through the transmission line and the voltage variation, this article also explores how charging stations for electric vehicles might effect on the electric distribution network [32]. The approach that was employed in this article estimates the maximum usage of primary energy resources, taking into account all of the operational constraints and the Distribution network's reliability. We explore the effects of one, two and three charging stations with varied capacities on a distribution network to select the optimal placement for charging stations as well as their capacity. Using an IEEE 33-node distribution network to perform tests that validate the efficacy of the proposed system.

Z. Liu et al., identifies the best locations for EV charging stations using a two-step screening approach that considers environmental parameters and the service radius of EV charging stations. This is followed by a method that uses an MPDIPA to solve the mathematical model for determining the best location of EVCS while keeping the overall cost of the stations as low as possible. It has shown that the developed model and technology may reduce network loss and improve the voltage profile of EVCS, according to simulation results from the IEEE 123-node test feeder.

Y. Xiong et al., consider that the cost of charging for an EV user is dependent on the other EV customer’s considerations which include the expense of driving to the charging station and the time spent waiting in line. This is done so that we can capture the strategic and competitive charging behaviours of EV users. In the first step, we give the CSPP, the form of a bilevel optimization problem. After that, to simplify the issue, we use the EV charging game equilibrium to reduce the bilevel optimization to a single-level one [34]. After that, we analyse the properties of CSPP and propose an algorithm called OCEAN to determine the most effective way for the distribution charging stations. Also proposed a heuristic method called OCEAN that uses continuous variables to solve large-scale problems that occur in the real world.

Primatama et al., The Hybrid model of HGAPSO was employed to address the placement of charging station issue that was tested in this work. The HGAPSO is successful in maintaining a healthy equilibrium between exploitation and exploration. In addition, the risk of being caught in a premature convergence or a local optimal phase is reduced to a minimum by using HGAPSO [35]. The simulation results show that the HGAPSO is superior to other metaheuristics, such as the GA and the PSO, in terms of its ability to solve the issue for placement of EVCS.

Islam, M.M et al., present a method for determining the ideal placement and size of FCSs that takes into account build-up costs, transportation losses and power losses in the grid. In the strategy that has been proposed, Battery charge, road traffic density and grid power losses are all taken into account while using the Google Maps API for vehicle location. One of the most recent additions to the search algorithm canon, the binary lightning search algorithm, is also being used as an optimization tool for the planning of FCS [36]. The capabilities of the strategy that was proposed were evaluated in a metropolitan setting. According to the findings, the proposed method can determine the best position for an FCS as well as its optimal size, which may benefit

EV users and the utility grid. In addition, when compared to the conventional approaches, the results of the recommended method were shown to be more accurate.

Hou Hui et al., present a new approach of planning the EVCS. A system for predicting the distribution of urban fast-charging demand for electric vehicles was developed. Further, an entirely new mathematical model is being developed to take into account the joint benefit of EV owners and grid operators, to reduce the overall cost to society of charging stations. The Voronoi diagram and improved PSO are then used to find a solution. The findings of the simulation demonstrate that the suggested methodology can find the best locations and capacities for each charging station in an urban region. PSO and improved PSO are compared to determine which is more successful in obtaining the global optimum solution.

2.2 Optimal placement of DGs in the Distribution System

Kansal et al., propose the use of PSO to determine the best position and size for the installation of DG in radial distribution systems for real power compensation, intending to lower actual power losses and enhance voltage profile. In the first segment, the ideal DG size at each bus is computed using the precise loss formula [38]. In the second segment, the optimal DG placement is identified using the loss sensitivity factor. The analytical expression uses the loss formula. The appropriate size and position of DG are computed for each bus using the precise loss model and the loss sensitivity factor.

There is still a difficulty with maximizing the advantages of DG by determining the best size and placement for it in distribution systems. As a means of minimizing the overall amount of power lost by the system due to the addition of excess load, Mahesh et al., make use of a novel technique known as APSO. The method fulfills the requirements for the restrictions of power balance, bus voltage, and system capacity. On a conventional IEEE 33 bus radial distribution system, the approach is examined and evaluated for use with two distinct forms of DG [39]. It has been determined that the suggested strategy is quite successful in reducing power loss while maintaining a high rate of convergence.

Vijay Babu et al., a unique application of the GAMS software is presented to estimate the load flow solution both in radial and mesh distribution networks. Through the interface of GAMS and MATLAB, placement and size of DGs in radial and mesh DS can be accomplished effectively [40]. This helps for a more efficient distribution system and to achieve a better voltage profile.

Suresh et al., proposed a new method inspired by nature the Dragonfly algorithm, which is employed in this work to identify the ideal DG unit size. Based on dragonflies' unique natural behavior, it was developed [41]. This algorithm focuses mostly on the dragonflies' search for food and their avoiding of adversaries. The suggested approach is tested on IEEE 15, 33, and 69 test systems. The proposed methods are evaluated in terms of their performance and compared to those of previous evolutionary algorithms. Comparatively, the Dragonfly algorithm is the most effective.

To achieve a reduction in power loss and the cost of DG, Sattianadan et al., illustrates the GA to identify the most effective placement of DG and its size. The goals of reducing power loss and reducing costs conflict. Furthermore, in such a situation, only one compromise option that meets both objectives can be found by the decision-maker [42]. These two goals are solved using the NSGA-II multi-objective optimization method to yield a set of Pareto optimum solutions.

Remha et al., focused on the DG's location as well as its overall size in radial distribution networks. To accomplish this goal, three different kinds of technology were used (active and reactive power injection and a combination of both). As a measure of performance, total active power losses are being used here, with a novel optimization approach of the Bat Algorithm being applied [43]. On the standard 33, 69 bus test feeders, an investigation was conducted. The suggested methodology's efficacy and robustness are shown via simulations.

Dogan et al., presents a multi-objective weighted sum function for minimizing power loss, raising voltage level, and integrating DGs, EVCSs, and ESSs. HSLC-PS method is suggested to fine-tune optimization performance [44]. Simulations address time-varying and stochastic PV, WT, and EVCS load demand. The developed method's performance on the test systems with 33-bus and 85-bus, under varied situations, is compared to SLC and GWO to prove its efficacy.

Karunaratne et al., provide multileader particle swarm optimization (MLPSO) for determining ideal DG placements and sizes to minimize active power loss. A complete performance study is done on the standard IEEE 33 bus system and a genuine radial bus system in Malaysia [45]. Comparing results with different optimization approaches showed MLPSO's efficacy in DG location and size.

To provide a more stable, reliable, and efficient power system, grid planners must take capacity, type, and location into account while determining the best DG authentication method to use. An SMFO technique Zhukui et al., is employed to address the problem by taking into account a variety of factors such as power losses, voltage drop and emissions. Based on the IEEE-33 bus, the suggested algorithm's efficacy has been determined.

Satish Kumar et al., determine the appropriate placements and sizes of DGs improve voltage profile and reduce loss. LSF method is utilized to identify candidate sites for the number of DG placements and SA estimates the optimum DG size at the ideal locations [47]. The analysis is tested by radial distribution systems for 33 and 69 buses and the suggested approach is compared to other methods, which provides a better solution.

Using several load models and numerous objectives, Rama Prabha et al., provide a multi-objective method for locating and sizing multiple DG units in the distribution network. The placement of DGs is determined by the LSF approach. The use of a meta-heuristic population model based on weed behavior is known as invasive weed optimization (IWO). To determine the best size for the DGs, this approach might be used. Radial Distribution Systems (RDS) based on IEEE-33 bus and 69 bus, the suggested approach was evaluated for various load models [48]. Comparing this strategy to other nature-inspired optimization methods has been done.

The Differential Evolution Algorithm (DEA) is proposed by Nayak et al., as a means to increase the voltage distribution of the DG in the RDS and lower the overall real power loss. DE algorithm is used to identify the ideal size and position of multi-DGs [49]. An IEEE 69-bus test system is used to evaluate the suggested technique, which is then compared to other methods in the literature. For both qualities of solution and computing efficiency, the suggested technique surpassed the other methods.

To minimize power losses and fluctuations in voltage, Kaya et al., provide a model of multi-objective optimization for distributed generating systems. Based on the particle swarm algorithm and whale optimization technique, 40 bus real radial networks were used to test the proposed model [50]. The performance of the particle swarm and whale optimization techniques under various load levels are compared.

El-Zonkol et al., provides a distribution network with varying load models and multi-objective index-based techniques for identifying the appropriate size and location for multi-distributed generating units. A short circuit level parameter represents the protective device needs in the proposed multi-objective function that must be improved [51]. The suggested function also takes into account a broad variety of technical factors, such as the system's active and reactive power losses, the voltage level, line loads, and grid MVA. The PSO optimization approach is presented and the impact of DG units on the most vulnerable buses is determined using a continuous power flow analysis. The IEEE 30-bus mesh network and the 38-bus radial system are used for testing and the findings demonstrate the efficacy of the suggested method.

Balu et al., proposed a novel metaheuristic optimization technique to locate and size DGs in radial power networks. This issue is intertwined by reducing the active power loss, the total voltage fluctuation and the voltage stability index of the system while taking into account the various models of load. A new metaheuristic optimization method known as student psychology-based optimization (SPBO) is proposed as a possible solution to the aforementioned Multi-objective DG allocation problem based on weighing parameters [52]. To get optimal results with the elements being weighted, a multi-criteria method is used. The SPBO algorithm's simulation results are compared to the HHO method's simulation results, as well as other algorithms are also considered.

An optimization model for fast charging station design is suggested by Phonrattanasak et al., to minimize the losses while also taking distribution line constraints and traffic conditions into account, which calculates the number of fast-charging stations in a residential neighborhood [53]. An ant colony optimization is used and for verification of the suggested method, an IEEE 69 bus system in a residential neighborhood was considered. Fast charging stations may be located in residential power distribution systems with minimal total cost or loss while meeting a wide range of technical and geographic restrictions.

2.3 Simultaneous placement of EV and DG in the Distribution System

Venkata Ponnam et al., focus on an optimization having multi-objective approach to achieve the best location and size of EVCS and DG simultaneously. Optimization of actual power losses, AVDI and VSI of the electrical distribution system is formulated as the objective problem [54]. The conventional test systems for the IEEE 33-bus and IEEE 69-bus were used for simulation, here TLBO and HHO algorithms were used to test the efficacy. Simulated system performance was shown to be significantly enhanced by the suggested method. HHO is the more effective of the two options when it comes to achieving the intended outcomes.

Optimizing both EV charging stations and solar power production via two-layer optimization has been explored by Arnab Pal et.al, and the issue was solved using Harris Hawks Optimization and Differential Evolution, the final solutions were confirmed using eight additional well-established optimization methods [55]. To account for the EV and PV uncertainties, the 2m point estimate approach was used. In order to cross-check the performance, Monte-Carlo simulation is also used. The cost of land and the accessibility of charging stations have been taken into consideration when deciding where to site the stations.

Battapothula et al., addressed a multi-objective optimization problem for location and size of FCS and DGs in the proposed system at the same time, with limitations for instance, the total number of FCSs that may be used depending on the road and electrical network, and the total number of EVs in all zones [56]. To minimize EV user loss, NPL, FCS investment costs, and to improve the electrical network's voltage profile, the solution is formulated as MINLP. The MINLP is solved using the NSGA-II. The suggested method performance is measured using the 118-bus electrical distribution system.

The impact of PEV connection on system reliability is examined by Hema Kumar et al., to assess the effect at various PEV penetration levels. To minimize the effect of PEV charging on the grid, the DG units are connected with charging stations. Charging stations are combined with solar PV units in increasing the desire to use PEVs [57]. Expected Energy Not Charged (EENC) is recommended to assess the stability of the PEVs in the system in addition to the systems reliability. The impacts of combining PEV charging with DGs are also investigated.

Matheswaran et al., addressed using an upgraded Ant-lion optimization method as a multi-objective problem. In MATLAB R2020a, the suggested approach is developed and tested on IEEE – 33, 69, and 94 radial bus systems [58]. The proposed method's effectiveness is assessed by comparing it to existing approaches such as the GA, HHO, and PSO.

Injeti, S.K et al., illustrates the integration of DGs into radial distribution systems including PEV loads and associated charging strategies under hourly load patterns by considering daily power loss and voltage improvement as system desirable outcomes [59]. Using backward-forward sweep-based load flow to simulate the PEV load in the two charging scenarios, this work develops a multi-objective function that can address daily active power loss and voltage fluctuation under 24-hour load patterns spanning residential, industrial, and commercial loads.

Kongjeen et al., propose an optimal DG size and placement in the power system by applying PEVs load demand probability. The findings were solved using MATLAB m-file scripts and Open DSS by adjusting the percentage penetration level of PEVs. An optimization strategy based on GA is being used to explore the optimal method of DG installation [60]. Because of its optimal placement, the DG was able to contribute to an improvement in the overall line loss as well as a reduction in the total amount of electricity used by the grid. The grid improved the stability of the electrical system and decreased the effect caused by the widespread use of PEVs.

The behavior of EV owners and a two-point estimate approach was used to predict the power of charging stations, the uncertainty of load, and the uncertainty of the price of energy in power networks respectively. Masoumian et al., propose the NSBSA algorithm was used to optimize the contribution coefficient of charging stations as well as wind production units as a distribution system [61]. The effectiveness of this method was confirmed using the IEEE 9-bus test system, and the simulation was carried out using MATLAB.

Erdinç et al., present a complete optimization model for the size and location of various DG units based on renewable resources, EV charging stations and ESSs in the distribution system [62]. This model is built on a second-order conic programming paradigm that explicitly considers time-varying DG production and consumption, in contrast to prior studies, which depended on a defined set of values.

FSA proposed by Janamala V et al., is for the first time to address the simultaneous optimal allocation of DG and EV fleets, taking into account both technological and environmental elements, in the operation of the RDN. Real power losses and voltage stability indexes are used to create a multi-objective techno-environmental function [63]. The suggested objective function is minimized while taking into account the limits imposed by RDN's active and reactive power compensation, in addition to its other operating constraints. Case studies on a rural residential feeder with 36 buses and an agricultural feeder with 106 buses are utilized to illustrate the effectiveness of the proposed strategy. These case studies are used to simultaneously allocate EV fleets and DGs. It is also compared with other current algorithms in terms of global optimum and convergence characteristics.

M.Hadi et al., proposed a two-stage strategy model for allocating EV parking and DRRs in the power grid. It includes both parking lot investor economics and network operator technical restrictions. Firstly, the parking lot investor provides economic candidate buses to the distribution network operator. The distribution network decides to limit system loss [64]. The suggested system reduces the distribution network loss. For the optimization issue, two strategies of GA and PSO are used to minimize the distribution system losses. An IEEE standard distribution test system evaluates the proposed strategy for the allocation of DRRs and EV parking areas.

GOA and fuzzy multi-objective method a two-stage model is presented by S R Gampa et al., to identify the optimal size and location of DGs, SCs and EVCS in distribution networks. As a first step, the Fuzzy GOA technique is used to determine the best possible DG and SC configuration to optimize the substation's power factor, reduce actual power loss and enhance the distribution system's voltage profile [65]. For determining the best sites for EVCS and the most appropriate number of charging stations, the fuzzy GOA technique is utilized in the second stage, which takes into account the distribution system's integration with DGs and SCs. The benefits of the proposed model over the usual objective-based simultaneous optimization approach are proven via simulation results on 51 bus and 69 bus distribution systems.

Boonraksa et al., focus on a charging station for EVs that utilizes power sources from distribution networks and hybrid renewable energy systems. Energy from photovoltaic (PV) and wind turbines were used to charge the EVs [66]. To address the challenge, the modified IEEE 33 bus system was used and the ABC algorithm was applied to solve the problem. Results suggest that charging EVs using a hybrid renewable energy system improves electrical networks' reliability during peak demand periods.

Raja et al., present a hybrid bi-level programming technique to improve system dependability by optimally integrating EVCS and the RDG simultaneously. Based on the results of contingency analysis, a non-linear objective function is made to reduce the energy not supplied (ENS) to consumers [67]. Two significant contributions are made to this method. Firstly, the simultaneous selection of the RDG and charging station's ideal placement has been acknowledged. Following the consideration of the simultaneous integration of the EVCS and RDG, a method that is based on the HNM-CS algorithm is put into operation to minimize the ENS. This method, in turn, reduces the power loss while simultaneously increasing the voltage magnitude of the system. Several RDGs, including solar and fuel cell systems, are taken into consideration in connection to the distribution networks of the standard IEEE 33-bus and the real-time Tamil Nadu (TN) 84 bus.

Xie et al., provide a thorough two-stage technique for locating and sizing stand-alone EVCS on highways. First, the siting of personal vehicles and the charging services are determined from Monte Carlo simulations given with traffic demand and battery data; an integer programming model is presented to establish the optimal placements of charging stations from prospective candidates, and the geographical and temporal distribution of charging demand is calculated. Stage two involves creating an optimization model based on data that takes into account the distributional robustness of renewable power and energy storage units at each charging station [68]. Two risk-theoretic reformulations of the robust model are proposed. A MILP based on Value-at-Risk (VaR) is more accurate than a conservative approach based on Conditional VaR. The proposed approach' efficacy has been validated numerically on a real test system.

Ahmadi et al., examined the impact of distributed generating resources and a demand-response system on the location of charging/discharging stations and the optimal use of electric cars in a distribution system. The simulations include the price-based demand-response program to regulate customer loads and soften the load profile. An imperialist-competitive hybrid meta-heuristic algorithm was used to locate the best operating point. The simulations were carried out using an IEEE 69-bus network [69]. Concerning the optimum placement of EVCS and its utilization, this research examined the impact of renewable energy supplies and a price-based demand-response mechanism.

Shengnan et al., explore the use of distributed energy storage (DES) to mitigate the dynamic effects that plug-in electric vehicles (PEVs) and photovoltaic DG units have on power DNs is discussed. This is investigated by using PSCAD models of PV-DGs, PEVs, and DESs to carry out the research. The outcomes of dynamic simulations, which include voltage profiles at crucial places on a test distribution feeder and the operations of a load tap changer (LTC), are given and analyzed in the proposed model [70]. The results of the simulation demonstrate the potential of DES for enhancing the dynamic performance of distribution feeders in the presence of an increasing number of PV-DGs and PEVs.

Turan et al., presented an analysis of the optimal size and integrated studies for the EV parking lot and solar power plants deployment on the campus distribution network, intending to stabilize the voltage regulation and take optimal sizing criteria into account. These studies were performed to enhance the voltage regulation of the solar power plant when it is operating throughout the day and the random charging profile of EVs [71]. Within the framework of the smart grid, the proposed network will be supplied with an adaptive protection system. This will ensure the continuity of service and the reliability of the distribution network.

Qi Sun et al., a multi-objective distribution network reconstruction model with DG and EV is developed to address the issue of distribution networks. To limit the probability of infeasible solutions, two guidelines for opening the loop are presented. The traditional Gravitational Search algorithm (GSA) improvements are provided in the form of several measures. Initially, the PSO is used to optimize the update formulas for speed and position [72]. In this approach, the GSA's global search capacity is improved, giving it the best performance when it comes to escaping local traps. Finally, dynamic reconstruction takes into account the variations of load, DG and EV. The paper case examples illustrate the validity of the optimization method and refactoring technique.

An optimal charging station location must take into account factors such as power losses, voltage and economics in a distributed system as well as the best possible size for DG at the location. The system performance indicators such as power loss, charging cost, voltage variation and reliability indices, determine the minimum value of the multi-objective function. Dhiraj Kumar Singh et al., used PSO to find the best possible arrangement of DGs and EV charging stations [73]. Using the MATPOWER tool, the city of Durgapur's modified IEEE 33 bus DS is analyzed to determine the optimal distribution of EVFCS and DGs. It is observed that there is an improvement in the reliability of EV charging stations using DGs.

To reduce congestion in distribution lines, Subhashish et al., suggest a charging coordination technique for PEVs. Firstly, the Active Power Flow Sensitivity Factors (PFSFs) are developed to forecast branch flows or congestion caused by PEV charging that is not regulated. Second, to alleviate congestion in the radial distribution system, a coordination method for PEV charging-discharging is developed utilizing various heuristic-based algorithms [74]. The suggested approach also illustrates that overall active power loss may be reduced while keeping grid limits. On an IEEE 10 bus radial distribution system connected with residential systems, the current work is simulated and assessed. Some of the case studies are examined to highlight the importance of the proposed work.

2.4 EV acting as Load (G2V) and Source (V2G) in the Distribution System

RES and PEV penetration are expected to be at a greater extent in the Smart Distribution System, which is the primary focus of Ramakrishna Reddy et al., the stability of the distribution network is explored about the effects of intermittent RES and uncoordinated PEVs. Solar and wind power production variations might be minimized by using PEVs as storage units with bidirectional power flow [75]. A case study based on real-time data from the Danish distribution network is employed to portray how PEVs may be used to provide grid ancillary support.

The optimal position and size of numerous DGs and EVCS operating in G2V and V2G modes are used as a strategy to reduce losses. Chippada et al., propose the sizing and positioning of several kinds of DG units, both renewable and non-renewable, as well as an EV charging station. Overall, this strategy decreases power losses while simultaneously increasing network voltages. For the IEEE 15, 33, 69, and 85 bus systems, the PSO algorithm is used to test the performance of the system [76]. The findings suggest that by improving the planning and operation of both DGs and EVs, the proposed optimization approach increases the system's efficiency and performance.

The V2G function of EVs is incorporated by LuoLizi et al., with the optimization model for the deployment of EVCS and distributed generating resources. Linearized Distflow equations and an exact second-order conic relaxation are used to make the optimization model optimally convex [77]. It is thus possible to solve the proposed model using commercial solvers off the shelf in polynomial time while still obtaining effective allocation methods with low annualized societal costs. Finally, a real-world metropolitan region in China with a 31-bus distribution system is chosen as a test system for the suggested technique, and numerical data are studied to validate its efficacy.

Zheng et al., proposed two charging and discharging load modes for EVs which were developed in consideration of V2G. There were two modes of charging and discharging, one based on travel patterns and the other on TOU pricing; the Monte Carlo approach proved the case. It was hypothesized that the solar charging station's capacity might be maximized under two separate charging and discharging modes using V2G. The developed mathematical models have the objective function of charging system's energy efficiency maximization, reduction of investment and minimizing operating cost. The range of choice factors, the restrictions of the power balancing need, and the approach for exchanging energy were provided [78]. Verification of the instances was carried out using either the NSGA-II or the NSGA-SA algorithms. In terms of reducing strain on the power grid, the disorderly charging and discharging method are inferior to the ordered charging and discharging mode that employs V2G, decreasing system investment and increasing energy efficiency in both algorithms by comparing simulation results for the two distinct modes.

A rigorous and efficient technique is used to examine the effects of EVs and V2G on the reliability, cost and emissions of the electricity grid. The contribution of this approach is that it can be used in a wide range of power grids with varying patterns and characteristics in terms of the proportion of RESs electricity production by explicitly addressing the stochastic factors affecting the daily demand/supply curves. Bijan et al., presents two new indices for measuring power grid performance based on the availability of RESs under different: stochastic and constant power supply system's [79]. To cover all the possibilities, a Monte Carlo simulation is used to analyze the influence of the investigated situations on reliability, emission, and cost of power grid reliability, as well as the impact of alternative charging types, locations, and schedules. The findings of the quantitative study revealed that the integration of EVs and V2G systems in stochastic power supply enhances the performance of the power grid in terms of reducing overall costs and emission rates.

Sami et al., illustrate the interaction of Smart Buildings (SB) with energy storage devices, Power EVs, to shift grid load, trim peaks and reduce yearly energy consumption. The key issues that are addressed and studied include, interface with the V2G, charging and discharging speeds, battery backup and reliability [80]. Models of simulations using V2G and G2V are presented to examine the effects of different grid-interface network settings. Grid stabilization and control, as well as V2G and G2V grid-interconnected systems, were examined in this case study.

Chen et al., provide an authentication strategy for V2G networks that is both safe and efficient while also protecting user privacy. With this system, the charging/discharging station can anonymously identify and dynamically manage PEVs [81]. Additionally, the monitoring data acquired by the charging/discharging station may be forwarded to a local aggregator in the batch process. There is no need to refresh the membership certificate and key pair before a PEV logs out since the verification time is independent of the number of PEVs engaged.

Chtioui et al., explore the simulation environment modeling of a micro-grid that is connected to a fleet of EVs and has a restricted vehicle-to-grid application. The discharging mode is only used if peak demand occurs alongside an extremely slow response time. In this presentation, the fundamental components of this micro grid are modeled and analyzed [82]. This article analyses the charging and discharging situations and goes further into the management strategies that were used in this simulation to control the power.

Since EVs produce both active and reactive power, J. Singh et al., examine the effects of both on schedule. By exploiting V2G operations of EVs, both solutions aim to reduce system losses [83]. Optimized charging and discharging of the EVs is achieved by using an Active Power dispatch (APD) based method. The reactive Power dispatch (RPD) technique, on the other hand, reduces losses by optimizing charging and reactive power injection from the EVs. Distribution system reconfiguration (DSR) is studied in system operation and planning using two alternative scheduling methodologies before its positive impact is assessed. A 33-bus distribution system is used to simulate the efficacy and viability of the suggested strategy and the results are encouraging.

Raveendran et al., seek to contribute to the implementation of the EVCS deployed at various sites by providing V2G support and vehicle charging to help the grid during various needs. Vehicle charging, harmonic removal and reactive power compensation have all been examined and the results shown with waveforms in a particular instance of EVCS installed in the Kochi Metro Rail System [84]. An actual hardware arrangement was also utilized to confirm the simulation's outcomes were accurate.

When examining an optimal driving pattern, Kasturi et al., proposed a charging/discharging technique to improve the utility of EVs for a controlled schedule. EVs connected to a radial distribution system's bus may charge or discharge at their place of employment or residence [85]. An algorithm known as MOMVO is used to determine the optimal number of EVs and the bus to which they must be connected. This is done not only to limit the effect of EV charging and discharging on the grid but also to decrease the operational expenditures incurred by EV owners as well as utility providers. EV owners and utility companies will both benefit. The findings show that the recommended technique is both technically and economically feasible.

Mousavi et al., propose a unique strategy for simultaneous placement of DG and V2G parking lots, based on the value-based pricing mechanism. Value-based pricing is used as a means of encouraging investors to participate in a network by finding the best location and capacity for electric car parking lots and distributed production resources, as well as lowering the network losses and improving the voltage profile. As a result of this strategy, DG energy prices are determined using value-based pricing, which takes into account the DG's value in terms of active loss reduction [86]. Since value-based pricing for DG and V2Gs must be taken into account during their optimum placement, the Planet Search Algorithm is the major contribution of this study. The two methods of bird assembly and genetics are being compared to address the optimization challenge. IEEE 33 bus distribution systems have been used to test the method, it has been shown via simulation studies that the suggested approach is successful in attracting investors because of the network strengths and incentive schemes it offers. The effect that EVs and renewable energy sources have on the grid is investigated by Vasiliki et al., a MATLAB/Simulink model is used to do an in-depth analysis of the integration of EVs and renewable energy sources with a conventional IEEE 13-bus test feeder [87]. This analysis is carried out under a variety of different scenarios that are vital to the stability of the grid.

An innovative study of the V2G system in the JAMALI grid is accomplished by Huda et al., in terms of changes in feed-in tariff schemes, such as regular, natural, and demand response tariffs. The findings reveal that using electric vehicles may lower peak-hour supply by up to 2.8 percent (for coal) and 8.8 percent (for natural gas). EVs owned by entrepreneurs as operating vehicles with a normal tariff have the greatest potential for ancillary services, with charging costs reduced by up to 60.15% [88]. V2G increases yearly income by 3.65% for power companies due to the fuel substitution.

Amamra et al., offer an optimal bidirectional V2G operation using a fleet of EVs coupled with a distributed power infrastructure through charging stations. The system may schedule EV charging/discharging a day ahead to save charging costs by using frequency and voltage control services. An optimization technique for V2G scheduling takes into account initial battery SoC, EV plug-in time, regulatory pricing, targeted EV departure time, battery degradation cost and vehicle charging needs [89]. The suggested system is illustrated by utilizing a 33-node IEEE distribution system with five EVCS. Two case studies were done to validate this sophisticated energy supervision technique. Comprehensive modeling findings suggest V2G can offer frequency and voltage assistance while decreasing EV charging costs, particularly during on-peak times when active and reactive power demand is high.

Ali Ahmed et.al., introduces a unique paradigm for the independent and simultaneous allocation of various DG units in DS, one that takes into account both fluctuating load demand and probabilistic DG production. The performance of the innovative framework for optimum allocation of DG units is confirmed via implementation on the 69-bus system, and the efficacy of the suggested SSA-PSO hybrid technique is verified by validation on seventeen benchmark functions [90]. Compared to existing meta-heuristics methods, the findings show that the suggested hybrid strategy performs better.

A. Pal et al., presents a solution that is both practical and environmentally friendly for the problem of deciding the location of EVFCS and the capacity of those stations, as well as the optimal multistage expansion of the distribution network, in order to deal with the predicted increase in load [91]. The whole work is organized into three levels and a sub-layer. The 2m point estimation approach is used to estimate uncertainties in EV driving patterns, energy needs, traffic congestion, load, and renewable production. Different metaheuristic techniques and integer linear programming are used to carry out the solution and validate it.

2.5 Research Gaps and Objectives

The following research gaps have been identified based on the current state-of-the-art literature:

- According to current trends, EVs might be a viable option for roadway mobility. Improved energy efficiency and less environmental effect have led to significant growth in the number of EVs on the road.
- An increase in the number of EVCS has a substantial impact on the electrical system. A variety of charging techniques and grid integration approaches are being developed to reduce the negative impacts of EV charging and enhance the benefits of EV grid integration.
- Due to the growing demand for electrical energy, DGs have become more significant in distribution networks. The placement and capacity of DGs will influence power distribution system losses, voltages.
- Inappropriate planning of EVCS and DGs adversely affects the distribution system. The determination of the optimal position and size of EVCS and DGs

within the electrical distribution system is a significant challenge for the operator of the distribution system.

- In certain cases, where demand is naturally intermittent, DGs alone will not be able to provide sufficient energy. Power engineers have supplemented the system with a backup unit, which is BESS, provided by EV with the bi-directional mode of operation as V2G to alleviate the intermittency.
- Due to the unpredictable nature of the EV load demand, the SoC on various charging patterns, the identification of an off load and peak load during a period is challenging.

Based on the motivation presented above, the primary goal of this research proposal is to minimize the losses and enhance the voltage level for simultaneous placement of EVCS and DG in a standard test system. This includes a list of the objectives that this research aims to achieve in this regard:

- ✓ To analyze the impact on siting and placement of EVCS in the distribution system using PSO and HHO algorithms.
- ✓ Optimal positioning and sizing of DGs in the DS.
- ✓ To develop the multi-objective problem on the simultaneous placement of EVs and DGs in the DS. Further to optimize the Scheduling of EVs and DGs for a 24-hour horizon using the Arithmetic Optimization Algorithm.
- ✓ To measure the impact of EVCS as a load (G2V) and source (V2G) with its bidirectional mode due to the intermittent nature of EV load demand and DGs in the distribution system.
- ✓ To analyze the cost-benefit factor of EVCS and end-user based on the operational constraints for a 24- hour horizon.

2.6 Proposed Methodology

The electrification of the automobile would have a massive effect on the electricity grid as energy usage rises. Intelligent coordination for automotive charging and discharging is essential for such situations to be under control. The majority of the former studies have focused on optimal planning of the charging station because it has a significant impact on distribution system power losses and voltage profile. It also leads to an overburdening of the distribution infrastructure. According to the research, the proper planning of DGs in distribution systems leads to a better voltage profile and reduces the real power losses. As a result, in the distribution system, simultaneous placement of EVCS and DGs must be planned at the same time. The improper planning of EVCS and DGs has a detrimental effect on the distribution system as a whole. Because of this, the distribution system operator has a significant challenge upfront of them in finding the best position for EVCS and DGs in the distribution power network.

In the proposed work, the Loss Sensitivity factor approach is considered for identifying the strong bus in the standard test system for optimal siting of EVCS. The Meta-heuristic algorithms of PSO and HHO are used to achieve the most suitable location for the EVCS, the additional load demand of EVCS with the existing base load demand is estimated and the corresponding increase in the losses for the system were determined. The weak bus is identified using the LSF method for the appropriate positioning of DGs in the common test system. The sizing of the DGs is determined within their boundary limits. The reduction in the losses and progression in the voltage is observed with the placement of DGs in the system.

Multi-objective optimization for the simultaneous placement of EVCS and DGs is carried out for the reduction of the true power losses and enhancement of the voltage level. The performance of the test system is analyzed from the simulation studies. A 24-hour load demand is estimated for the EVCS based on the load setting and the Dynamic programming method is implemented for the selection of the DG operation over the respective time of operation. The optimal scheduling of intermittent load demand and DGs is carried out by the Arithmetic Optimization Algorithm (AOA) for a 24-hour load profile.

Due to the volatile nature of the renewable DGs, there is a need to go for an alternative backup provided by the Battery Management System (BMS) with the bi-directional mode of operation of EVs. The Vehicle to Grid (V2G) technology has a major role in this area as it allows electricity to be fed power back to the grid through EVs to help in supplying the power in periods of extreme demand, which act as an additional distributed energy source. The size of an EV acting as a DG is limited to the boundary limits. Based on the operational constraints of SoC, Load demand and Power the mode of operation like charging, discharging and neutral of EVs is estimated. With the simultaneous placement of DGs and EVs acting as a load (G2V) and source (V2G) based on the operational constraints, with the smart charging system the losses are further reduced and enhanced the Voltage profile compared to the case of EVs and DGs for the stable and reliable operation of the system. Finally, the cost-benefit analysis is carried out for the operation of G2V and V2G mode on a 24-hour load profile.

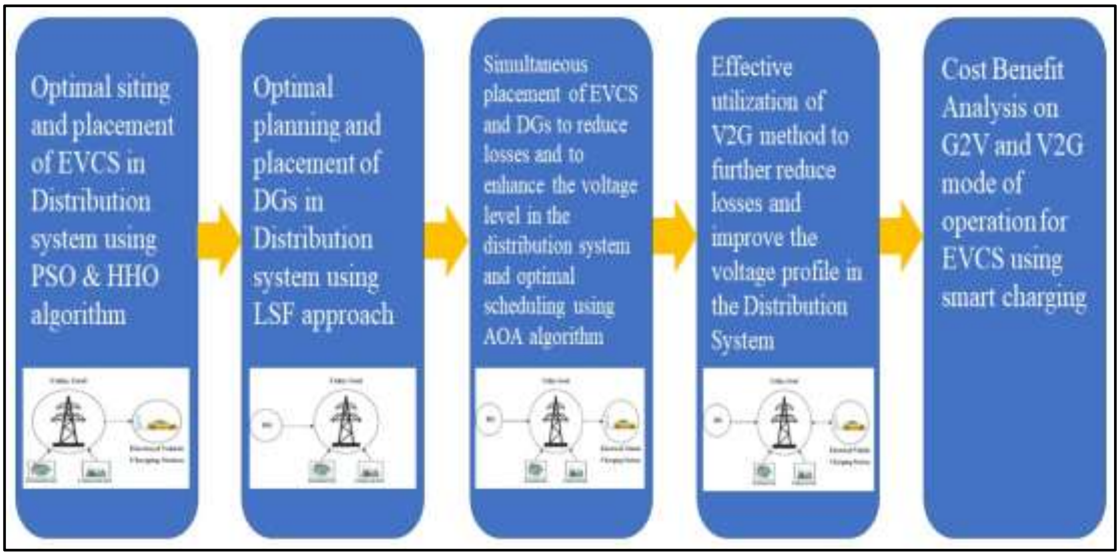


Fig. 2.1. Proposed Methodology flowchart

CHAPTER 3

OPTIMAL PLACEMENT OF EVCS IN THE DISTRIBUTION SYSTEM

3.1. Introduction

People are becoming more aware of the environmental and economic benefits of EVs, and this trend is expected to continue as more people get educated about the technology. The installation of EVCS in the distribution system to accommodate the rising demand for electric vehicles' charging has certain drawbacks in implementing fast-charging stations, as the distribution system has a lower voltage profile and experiences power loss. To overcome these negative consequences, the EVCS should be strategically placed and integrated into the existing distribution system. The charging station's power needs should be met by the distribution system. Plug-in Hybrid Electric Vehicles (PHEVs) have several benefits, but their widespread use and uncontrolled charging will contribute to a rise in peak demand. To enhance the distribution system voltage profile in the presence of EVCS, optimal planning of EVCS is necessary. So, the proper siting of EVCS placement in the distribution system has a considerable impact.

3.2. Optimal planning of EVCS

The abrupt integration of EVCS over the existing grid system results in major problems with the power quality, including electrical harmonics, a low power factor, unstable voltage, and voltage imbalance. Distribution equipment such as cables, conductors and transformers are reduced in capacity due to these issues as well as experience a huge distribution loss, which lowers the system's overall efficiency. When EVs are being charged, the distribution branches of the system carry a substantial amount of current, which has a major effect on both the generation and transmission systems. The influence on the distribution system is contingent on a wide variety of parameters, such as the methodologies for charging, the population density of cars at their individual charging stations and so on.

3.2.1. Methodology

The optimal location of the EVCS in the grid-connected system has a significant impact on the functioning of the electric grid, which is a major concern. A standard 33 bus test system was evaluated in the present approach for optimum EVCS placement, taking into consideration the optimal loads of the buses. The bus system's layout in all 33 radials is given by the number of lines: 32, Slack bus number: 1, Base Voltage: 12.66 kV, MVA: 100 MVA, The total Real Power: 3.715MW and Reactive Power: 2.295Mvar.

3.2.1.1 Newton Raphson Load flow

Power flow, also referred to as load flow is an important concept in the operation and design of power systems. Modeling the flow of electrical energy in a power system is constructed with the use of the relevant data on the network, load, and generation. The voltages at the various buses, the line flows across the network and the system losses are all elements of outputs from the power flow model. By solving the corresponding nodal power balance equations, these outputs can be determined. Iterative approaches, such as the Newton-Raphson method, the Gauss-Seidel method, and the fast-decoupled method, are often used to solve the nonlinear equations in this problem.

A power flow analysis's objective is to establish the voltages (magnitude and angle) for a certain load, generator, and network state. If the voltages of all buses are known, it is possible to compute the line flows and losses. The first step in resolving problems with power flow is identifying the system's known and unknown components. [92]. It has quadratic properties of convergence. The conventional works were carried out for standard IEEE 33 BUS system data and power flow run by the Newton Raphson method, the convergence is very quick and the number of iterations will be unaffected by the device's length. High-precision methods will almost often be used in two to three iterations for both small and large implementations. The power flow equation that was used in the process of resolving a network issue uses Voltage and Power equations.

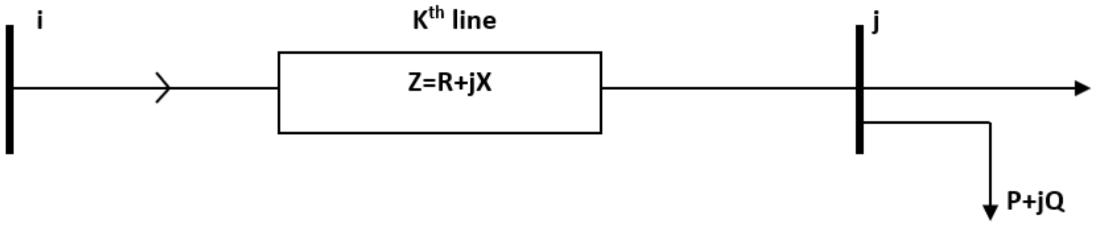


Fig. 3.1. Representation of a distribution system with two nodes and one branch

In a power system, the power equations in bus k are applied to the voltage and current as follows.

The apparent power is given by Eq. 3.1.

$$\overrightarrow{S_\imath} = \overrightarrow{V_\imath}\,\overrightarrow{I_\imath} \qquad (3.1)$$

Where

V_i is the voltage at bus i

I_i is the current at bus i

The input current is given by Eq. 3.2.

$$\overrightarrow{I_\imath} = \frac{\vec{P_i} + \overrightarrow{Q_\imath}}{\overrightarrow{V_\imath}} \qquad (3.2)$$

The Newton-Raphson approach is used to solve the power flow equation, which will be shown in the following equations Eq. 3.3. and Eq. 3.4.

$$P_{G_i} - P_{D_i} = V_i \sum_{i=1}^{N_B-1} V_j (G_{ij} \cos\delta_{ij} + B_{ij} \cos\delta_{ij}) \qquad (3.3)$$

$$Q_{G_i} - Q_{D_i} = V_i \sum_{i=1}^{N_{PQ}} V_j (G_{ij} \sin\delta_{ij} + B_{ij} \sin\delta_{ij}) \qquad (3.4)$$

The real and reactive power fed to the system ‘i’ is P_{G_i} and Q_{G_i} The active power and reactive power demand is given by P_{D_i} and Q_{D_i} respectively. The angle for the ith and jth bus Voltage is given by δ_{ij} , The number of buses and loads are given by

N_B and N_{PQ} , The conductance and susceptance at the feeder 'ij' are given by G_{ij} and B_{ij} .

3.2.1.2 Loss Sensitivity Factor

The sensitivity factor approach is based on the notion that the original nonlinear equation may be linearized around the initial operating point. This reduces the dependency on the total number of possible solution spaces.

Active Power loss in the kth line is given by $(I_k{}^2 * R_k)$ shown in Eq. 3.5.

$$P_L[j] = \frac{(P^2[k] + Q^2[k]) * R_k}{(V[j])^2} \tag{3.5}$$

Similarly, the Reactive Power loss is given by Eq. 3.6.

$$Q_L[j] = \frac{(P^2[k] + Q^2[k]) * X_k}{(V[j])^2} \tag{3.6}$$

Where "P and Q are the Effective values of active and reactive power at bus j".

Loss sensitivity parameters are used to identify the best possible locations for the placement of EVCS in the DS. The reduction of the search area is facilitated by the estimation of these sensitive nodes.

The Loss sensitivity factor is given in Eq. 3.7.

$$\frac{\partial P_L}{\partial Q} = \frac{(2 * Q[j] * R_k)}{(V[j])^2} \tag{3.7}$$

To determine the loss sensitivity factors, load flow is used. Then, for each line, the resulting values are sorted in decreasing order of importance.

The following Eq. 3.8. is used to get the normalized magnitudes of voltage on all buses:

$$V_N[i] = \frac{V[i]}{0.95} \tag{3.8}$$

The buses with the normalized voltage greater than or equal to 1.01 are identified as the strong bus, suitable for the location of the charging station. Loss Sensitivity parameters determine the order in which buses should be examined for the location of charging stations, and normalized voltage values determine whether a certain bus is appropriate for positioning or not.

3.3. Metaheuristic algorithms

The field of metaheuristic optimization focuses on the use of various metaheuristic algorithms to find solutions to optimization problems. A metaheuristic algorithm is a search process meant to discover a satisfactory solution to a complicated and difficult-to-solve optimization issue. In this real world with limited resources, it is critical to identify a near-optimal solution based on incomplete or partial data. One of the most important breakthroughs of the past two decades in operations research is the advent of metaheuristics for handling such optimization issues.

Metaheuristics are important in many fields. Multi-objective functions with non-linear constraints are common in optimization. Most complicated engineering issues are non-linear and multi-objective. AI and machine learning challenges depend significantly on enormous datasets, making optimization challenging. Metaheuristics help to address real issues that can’t be solved by standard optimization approaches [93]. Effective search or optimization algorithms are necessary to obtain the optimal solution. In general, meta-heuristic algorithms use two optimization processes: exploration and exploitation. A global search in the search space is known as exploration, whereas a local search is known as exploitation. exploration and exploitation are certainly incompatible. Figuring out a way to stabilize them is probably the most difficult challenge. Numerous optimization algorithms can be categorized in several ways based on their intent and requirements. PSO and HHO are some of the available search algorithms used in the proposed approach for the optimal placement of EVCS.

3.3.1. Particle Swarm Optimization

Stochastic population-based optimization, inspired by the intelligent collective behavior of certain creatures such as bird flocks or schools of fish, gives rise to PSO, which is a method of evolutionary computation that relies on the swarm's intelligence.

In other words, when a bird is soaring and randomly hunting for food, all of the birds in the flock may share their discoveries and assist the whole flock in getting the finest hunt. Each bird in a flock is helping us discover the best solution in a high-dimensional solution space, and we can envision that the best solution found by all of the birds will be the greatest solution in all of that space [94]. This is a heuristic approach since we cannot verify that the genuine global optimum solution can be discovered, and it is typically not. However, we've discovered that the PSO approach is typically quite near to the global optimum. The PSO process begins by arbitrarily initializing a series of possible solutions, after which it repeats the quest for the best solution. The best particles are followed in the PSO algorithm to find the optimum location, here the velocity of the particle is operated by the Loss Sensitivity factor (LSF). In comparison to Evolutionary Algorithms (EAs), PSO has a broad intellectual context and is easier to implement. Fig 3.2. shows the operation flowchart of PSO.

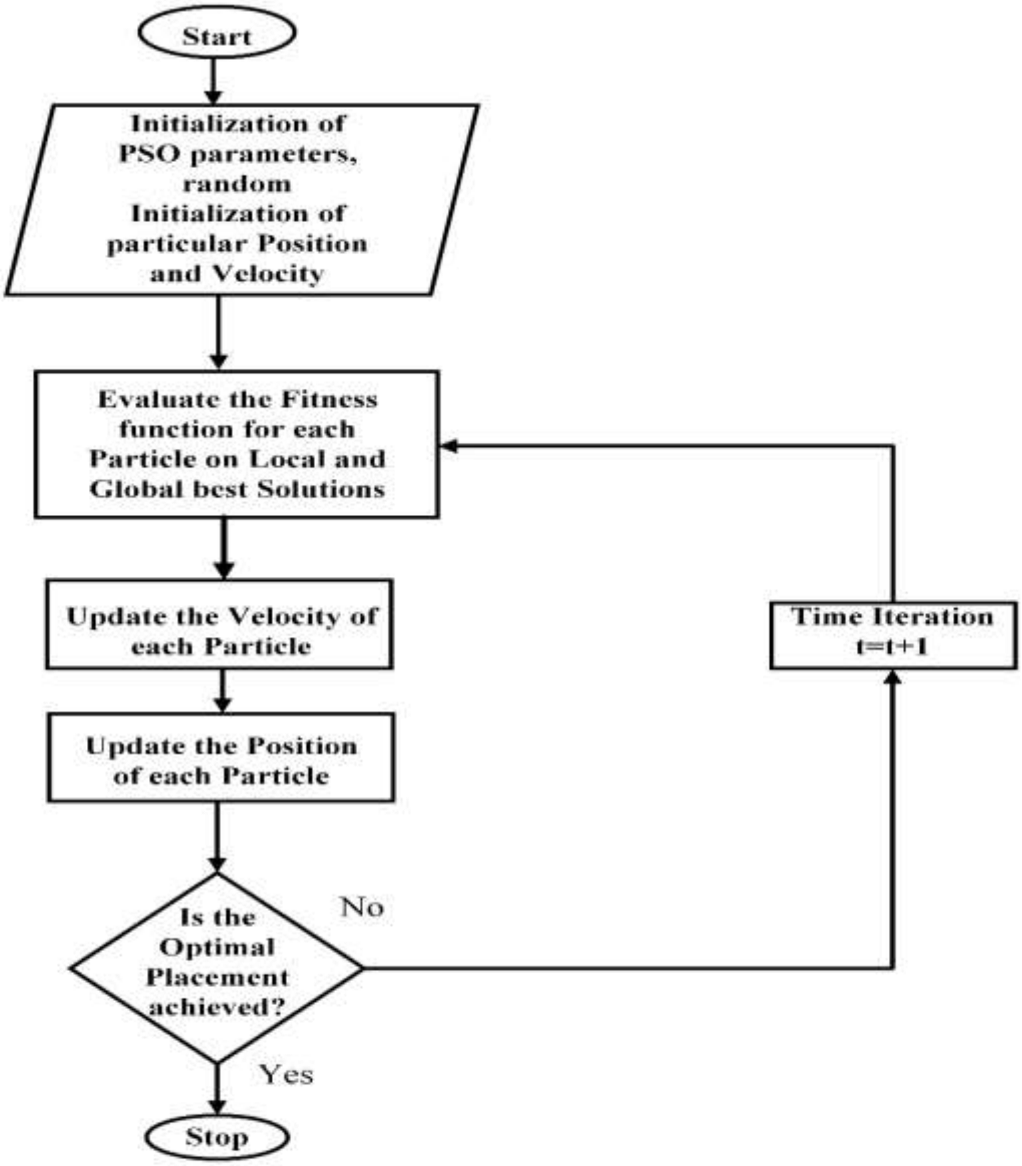


Fig. 3.2. PSO Algorithm Flowchart

3.3.2. Harris Hawks Optimization

Harris' hawks in nature use a cooperative movement and chase style of ambush pounce, which is the primary source of inspiration for Harris Hawks Optimization (HHO). Several hawks work together to ambush prey by pouncing it from distinct viewpoints. Due to the complex nature of situations and the prey's fleeing habits, Harris hawks disclose some different chasing trends. The Harris hawk is one of nature’s most sophisticated and esteemed threat birds, with unique mutual chasing skills trying to trace, surround rinsing and catch the potential food animal (rabbit) in a mob. The initial population is thought to be a group of hawks that use a random pounce to chase the desired rabbit (solution of the optimization problem) from various directions. The leader hawk attempts to catch the prey at first; if it fails due to the prey's dynamic disposition and fleeing behavior, the swapping strategies are used, in which the other party members (hawks in the group) strike the escaping prey before it is caught [95]. The primary aspect of this cooperative strategy is that the birds will track down the pointed rabbit by puzzling and exhausting the fleeing prey, here the birds select to catch the nearest rabbit based on LSF. The Harris Hawks are the applicant solutions in HHO, while the expected prey is the best/global solution. Fig 3.3. shows the operation flowchart of HHO.

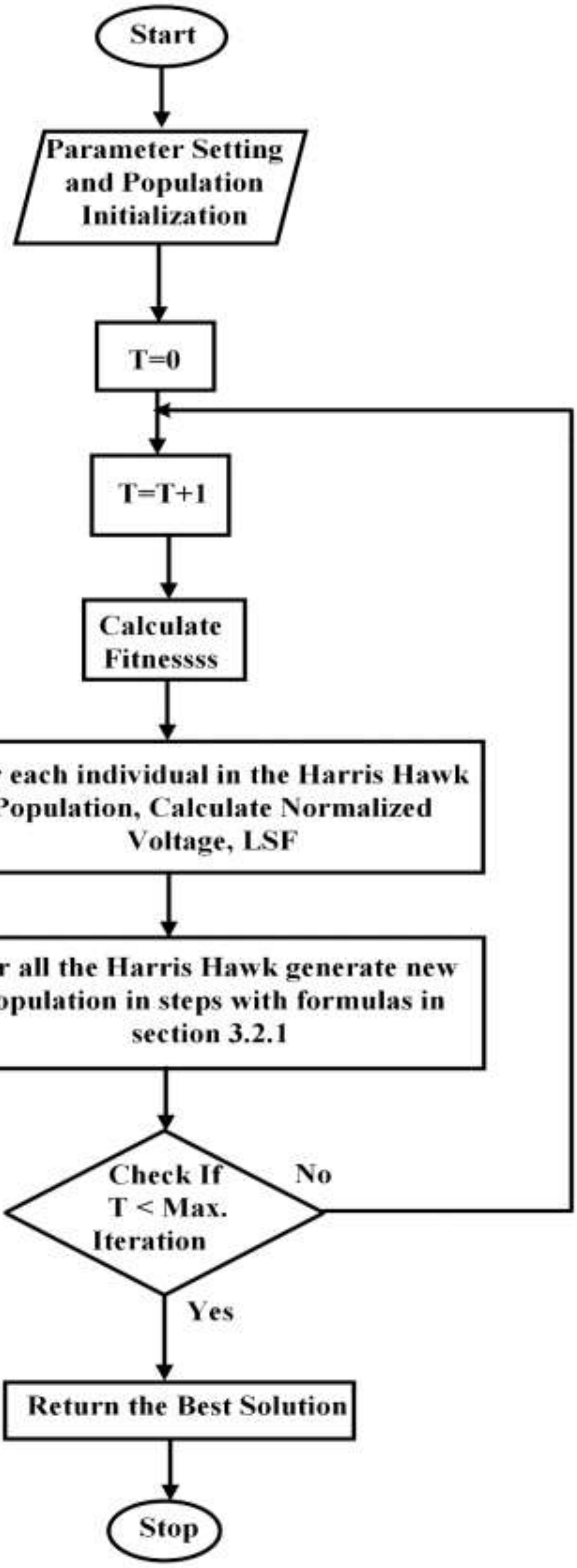


Fig. 3.3. HHO Algorithm Flowchart

3.4. Results and Discussion

In the proposed approach, the PSO and HHO algorithms are used to find the best position for an EVCS in the standard IEEE 33 bus distribution system. Base loads with an increase in the various types 1,2 and 3 loads are used to evaluate the suggested algorithm's efficacy. The Active and Reactive Power ratings of the Loads injected into the system are given in the following Table 3.1.

Table. 3.1. Power rating of the Loads

Nature of Load	Active Power	Reactive Power
Base Load	201.58kW	134.45kVAR
Load a	223.34kW	149.06kVAR
Load b	258.10kW	172.33kVAR
Load c	275.97kW	184.64kVAR

With the presence of the base load the variation in the system voltage, nominal voltage and LSF for the 33-bus system using Eq. 3.7 and 3.8 are shown in the following table 3.2. The buses with a nominal voltage greater than or equal to 1.01(nominal voltage severity factor) are identified as the strong bus and chosen as the proper location for the operation of EVCS.

Table. 3.2. Loss Sensitivity Factor approach for conventional system

Bus No.	Sysvolt1	Voltnom1	LSF	LSFd	EV
2	0.997	1.0495	0.0001	0.0011	0
3	0.983	1.0347	0.0004	0.0011	0
4	0.9755	1.0269	0.0003	0.001	0
5	0.9682	1.0191	0.0003	0.0008	0
6	0.9498	0.9998	0.0006	0.0008	1
7	0.9464	0.9962	0.0001	0.0008	1
8	0.9415	0.9911	0.0005	0.0007	1
9	0.9353	0.9845	0.0008	0.0007	1

10	0.9295	0.9784	0.0008	0.0007	1
11	0.9286	0.9775	0.0001	0.0006	1
12	0.9271	0.9759	0.0003	0.0006	1
13	0.921	0.9695	0.0011	0.0006	1
14	0.9188	0.9672	0.0004	0.0006	1
15	0.9174	0.9657	0.0004	0.0005	1
16	0.916	0.9642	0.0006	0.0005	1
17	0.914	0.9621	0.001	0.0004	1
18	0.9134	0.9615	0.0006	0.0004	1
19	0.9965	1.049	0.0001	0.0004	0
20	0.9929	1.0452	0.0011	0.0004	0
21	0.9922	1.0445	0.0003	0.0003	0
22	0.9916	1.0438	0.0005	0.0003	0
23	0.9794	1.031	0.0003	0.0003	0
24	0.9727	1.0239	0.0007	0.0003	0
25	0.9694	1.0204	0.0007	0.0003	0
26	0.9479	0.9978	0.0002	0.0003	1
27	0.9454	0.9951	0.0002	0.0002	1
28	0.934	0.9831	0.0008	0.0002	1
29	0.9258	0.9745	0.0006	0.0002	1
30	0.9223	0.9708	0.0004	0.0001	1
31	0.9181	0.9664	0.0007	0.0001	1
32	0.9172	0.9654	0.0002	0.0001	1
33	0.9169	0.9651	0.0003	0.0001	1

The comparison between the system voltage and nominal voltage for the various loads considered in the 33-bus test system is shown in Fig 3.4(a),3.4(b),3.4(c) and 3.4(d).

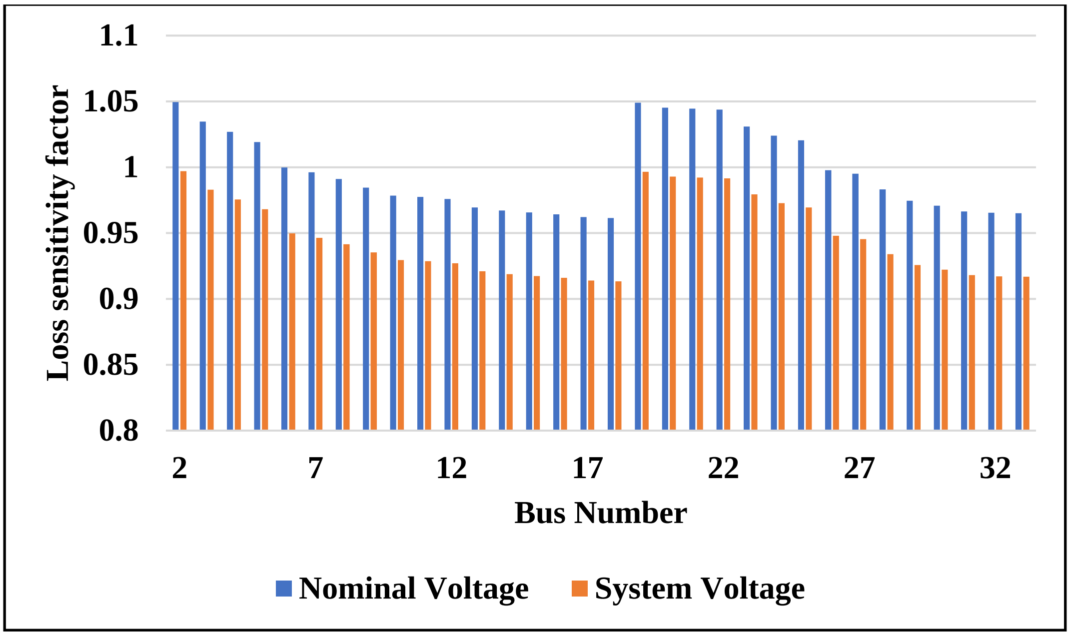


Fig. 3.4(a). Loss Sensitivity factor variation for Base Load

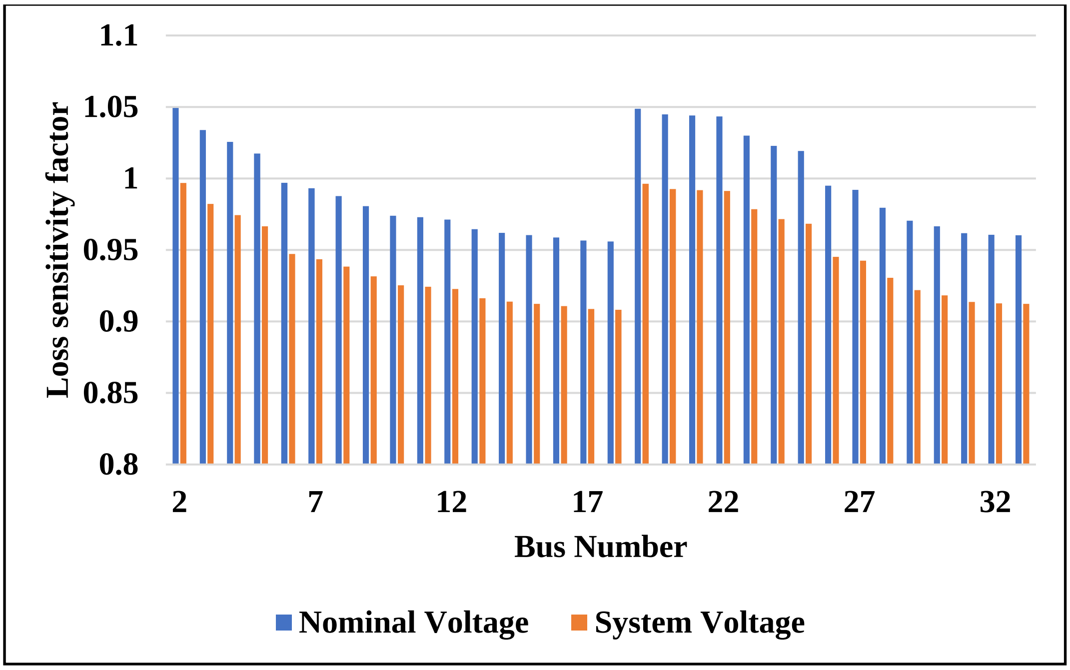


Fig. 3.4(b). Loss Sensitivity factor variation for type 1 Load

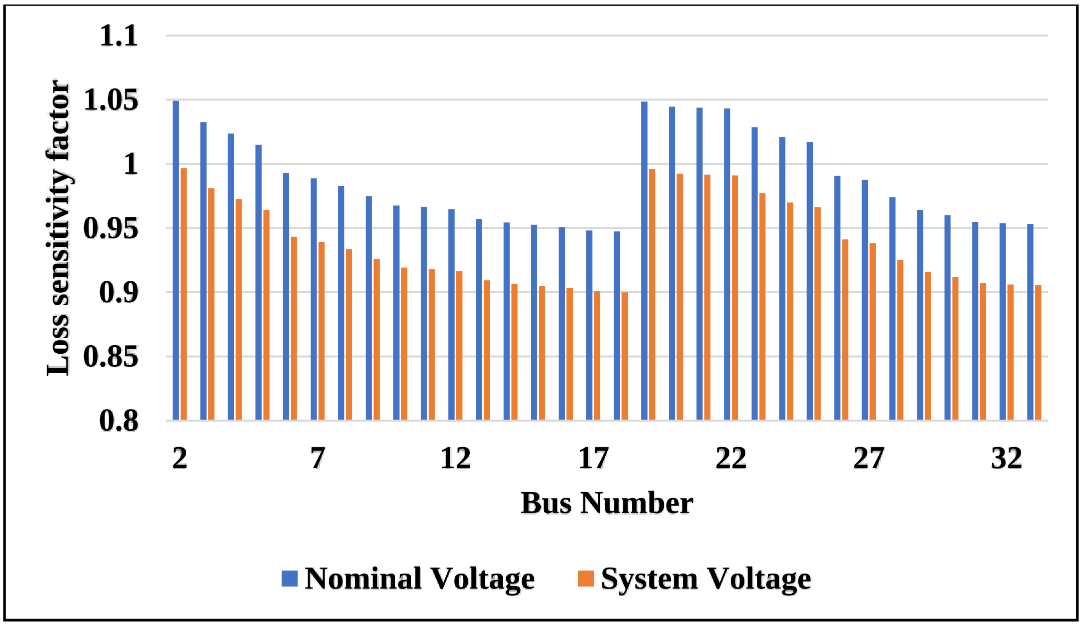


Fig. 3.4(c). Loss Sensitivity factor variation for type 2 Load

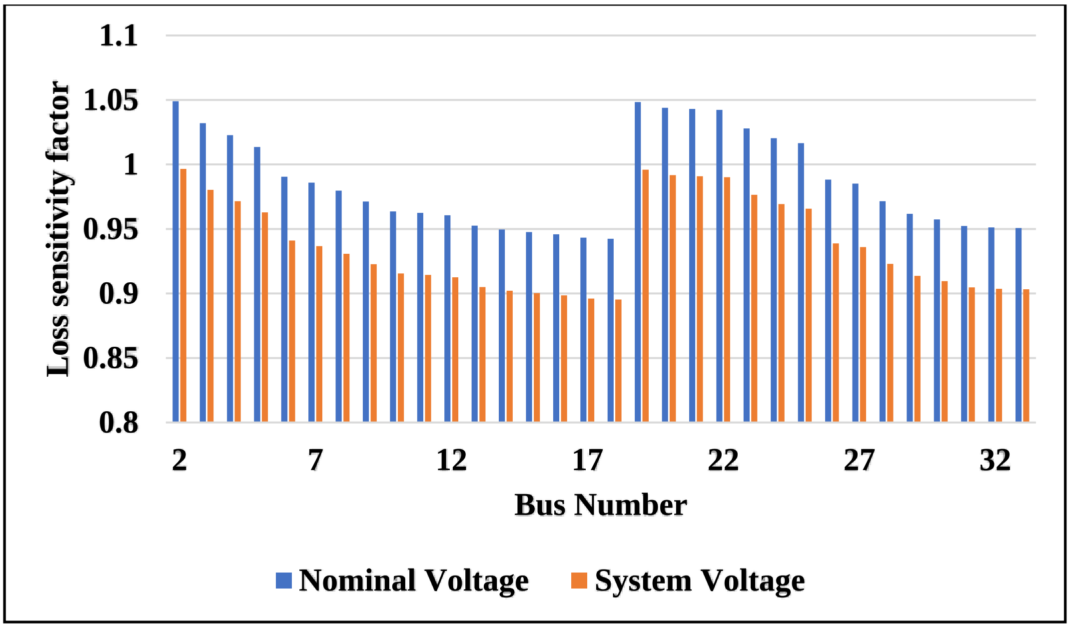


Fig. 3.4(d). Loss Sensitivity factor variation for type 3 Load

The variation in the system voltage and nominal voltage for the conventional system and using PSO are shown in Fig. 3.5(a) and 3.5(b), which shows the increase in the nominal voltage of PSO compared to the conventional system.

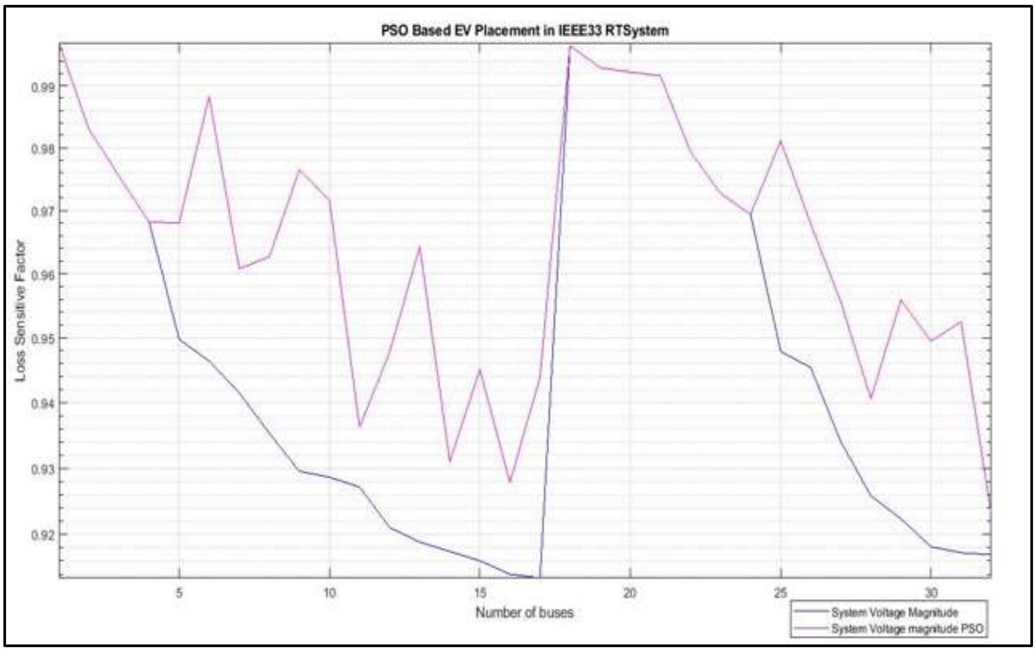


Fig. 3.5(a). System Voltage using conventional and PSO

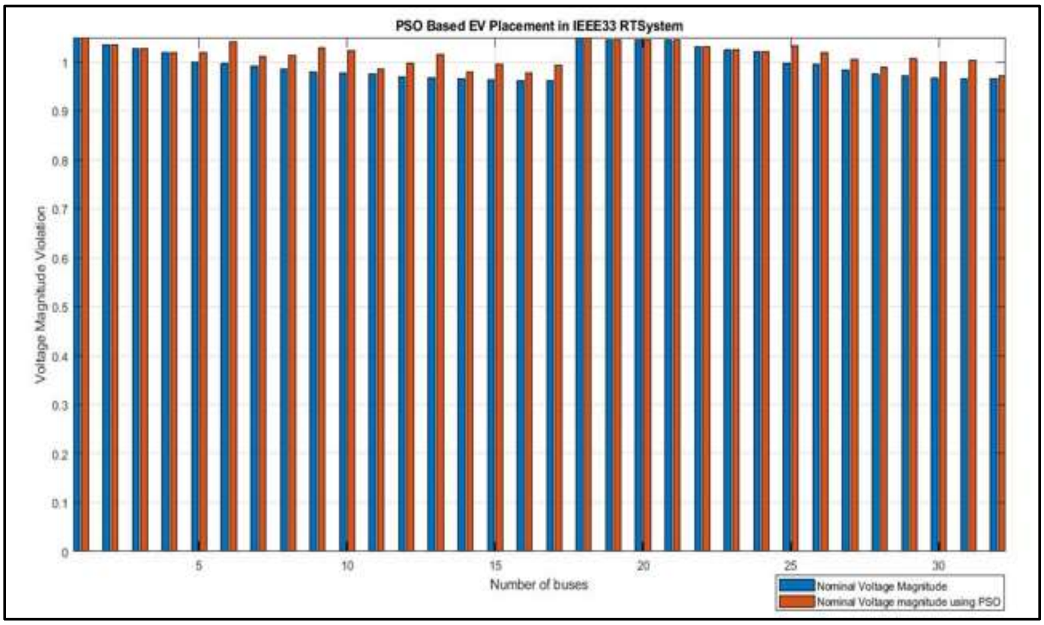


Fig. 3.5(b). Nominal Voltage using conventional and PSO

The variation in the system voltage and nominal voltage for the conventional system and using HHO shown in Fig. 3.6(a) and 3.6(b) shows the enhancement of the nominal voltage of HHO compared to the conventional system.

Fig 3.7.

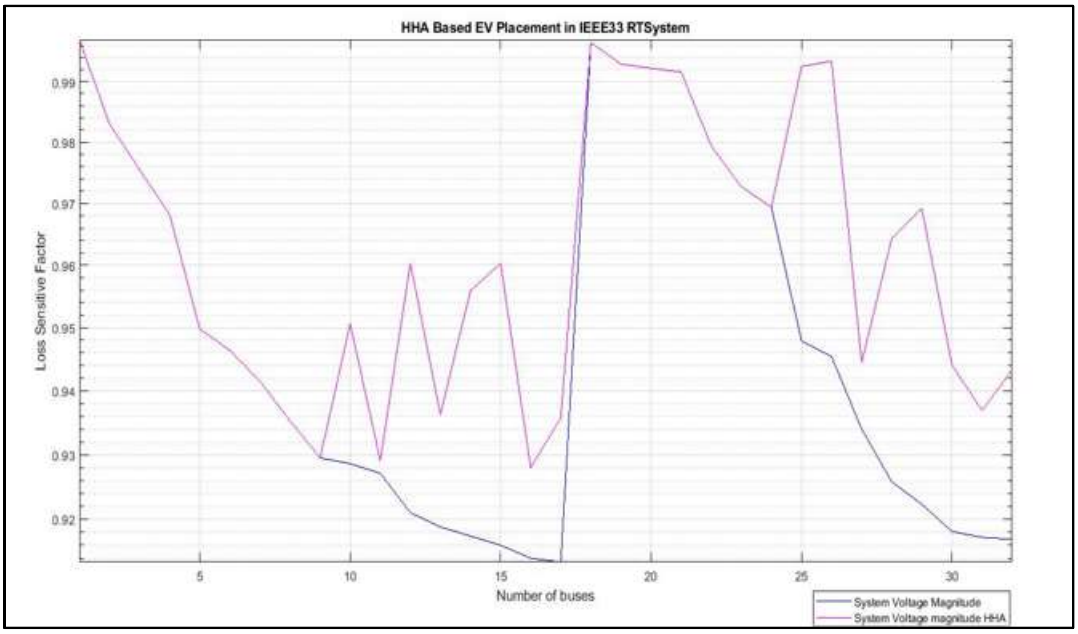


Fig. 3.6(a). System Voltage using conventional and HHO

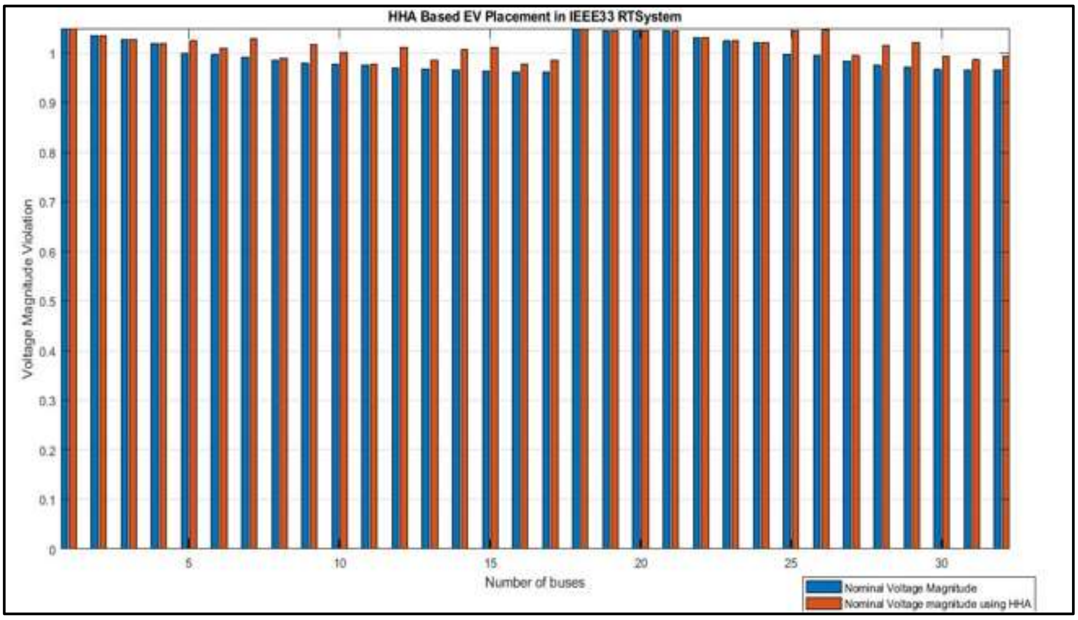
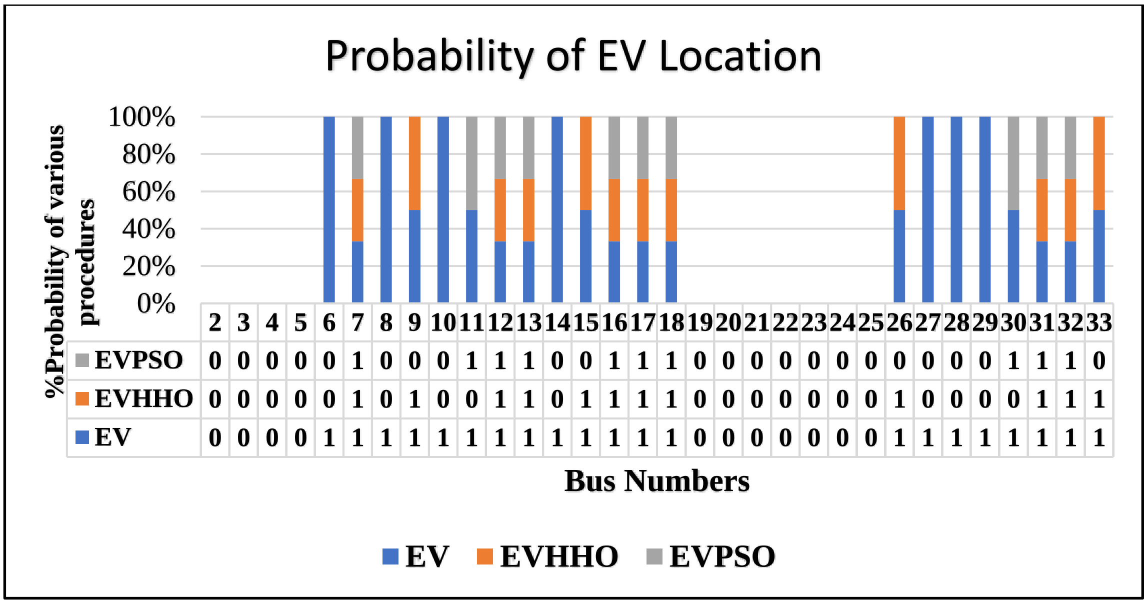


Fig. 3.6(b). Nominal Voltage using conventional and HHO

Based on the LSF and nominal voltage factor, the probability of EVCS location in the IEEE 33 bus system using a conventional system, PSO and HHO have been shown in Fig 3.7.



	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33
▨ EVPSO	0	0	0	0	0	1	0	0	0	1	1	1	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0
▨ EVHHO	0	0	0	0	0	1	0	1	0	0	1	1	0	1	1	1	1	0	0	0	0	0	0	0	1	0	0	0	0	1	1	1
▨ EV	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1

Fig. 3.7. Probability of EV location Placement

In an IEEE 33 bus system for the positioning of EVCS, the LSF approach is considered. The identification of the strong bus and weak bus can be assessed based on the LSF component and the priority of the bus order is taken from the descending order of the LSF in the system.

In Fig. 3.7, where 1 represents a weak bus and 0 indicates the strong bus help to locate the placement of the EV.

To assess the severity of the IEEE 33 bus system, the three possible cases of the weak bus (17), moderate bus (30) and strong bus (10,14) are considered. The four buses 10,14,17 and 30 are identified for the positioning of an EVCS. Due to the effect of an additional EV demand on the existing base load in the system, there is a substantial increase in the losses in the DS and the voltage profile is reduced. The based load for a standard IEEE 33 bus system is 3715kW and the real power loss is 202kW. Due to the placement of EVCS in the DS, with the addition of EV load to the four buses (10,14,17 and 30) shown in table 3.3 for the existing base load, the overall load was increased to 4735kW and the losses were increased to 374kW with the increment of 85.1% of the losses compared with the real power losses as represented in table 3.4. The comparison of losses for base and EV load of an IEEE 33 bus system is shown in Fig.3.8.

Table. 3.3. EV Load placement at respective buses

Bus Number	Base Load(kW)	EV Load(kW)	Total Load(kW)	Losses (kW)
10	60	300	360	15.11402
14	120	150	270	2.875179
17	60	250	310	1.731052
30	200	320	520	6.057493

Table. 3.4. Power Loss and Voltage profile in 33-bus system with EV load

Bus No.	P_L (kW)	Q_L (kVAR)	Power Loss (kW)	Voltage (Volts)
2	100	60	18.590432	0.996332
3	90	40	82.266326	0.978493
4	120	80	36.592819	0.968244
5	60	30	35.354684	0.957967
6	60	20	73.24624	0.933514
7	200	100	4.970004	0.929359
8	200	100	14.829096	0.920877
9	60	20	16.29375	0.909605
10	360	20	15.114015	0.898752
11	45	30	1.56157	0.897305
12	60	35	2.681446	0.894694
13	60	35	9.106732	0.88456
14	270	80	2.875179	0.880956
15	60	10	1.346935	0.878579
16	60	20	1.333514	0.875955
17	310	20	1.731052	0.871984

18	90	40	0.0583461	0.871368
19	90	40	0.161181	0.995804
20	90	40	0.833348	0.992228
21	90	40	0.1009	0.991524
22	90	40	0.0436958	0.990888
23	90	50	3.21103	0.974895
24	420	200	5.191502	0.968203
25	420	200	1.299457	0.964868
26	60	25	3.794238	0.931086
27	60	20	4.906116	0.927826
28	60	20	16.899462	0.913767
29	120	70	11.815879	0.903565
30	520	600	6.057493	0.898769
31	150	70	1.677731	0.894531
32	210	100	0.22445	0.8936
33	60	40	0.0138639	0.893312
	4735	2295	**374.182483**	

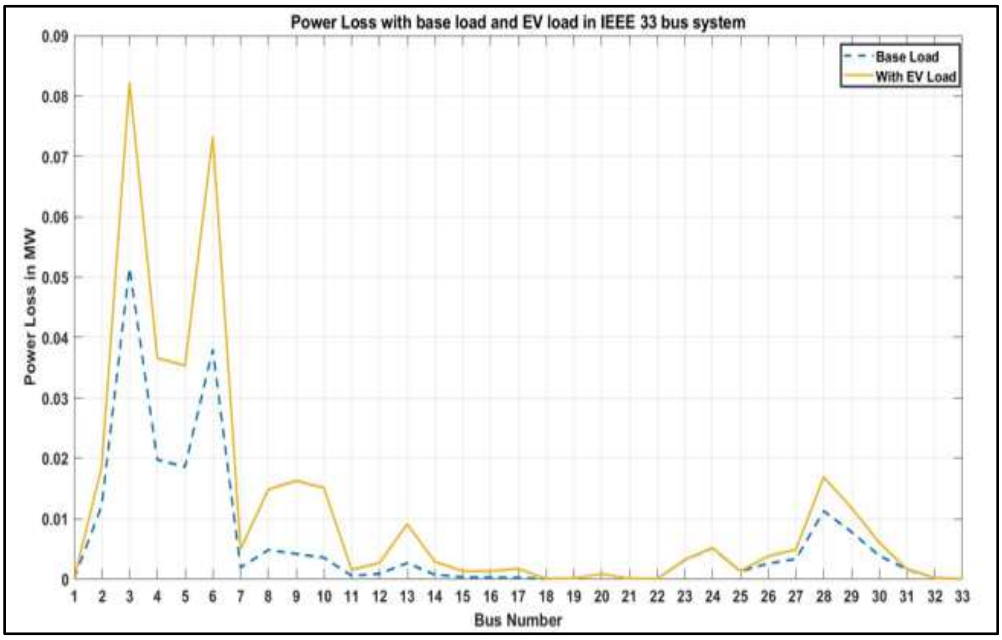


Fig. 3.8. Power Loss comparison of base and EV load in IEEE 33 bus system

After identification of the buses for the positioning of EVCS and its sizing, the following Fig 3.9 shows the optimal placement of EVCS in the IEEE 33 bus system.

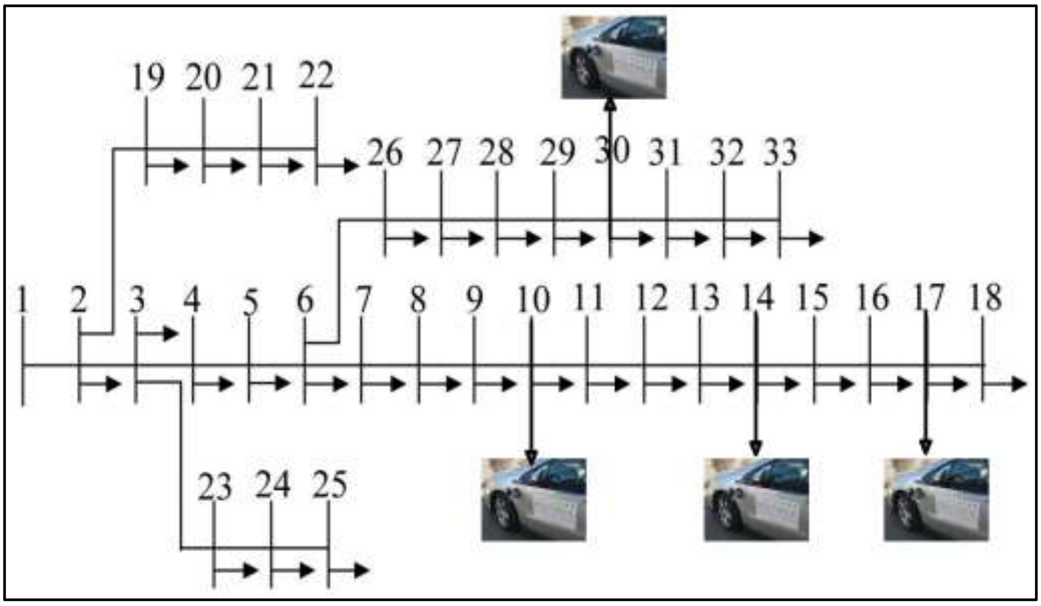


Fig. 3.9. Optimal placement of EVs in IEEE 33 bus system

3.5. Chapter Summary

For the implementation of EVCS, an IEEE 33 bus system was taken into consideration. The Newton-Raphson Load flow has been carried out to quantify the power flow. PSO and HHO algorithms are chosen for the optimal siting of EVCS, the simulation results were compared with the conventional system, showing the variation of LSF for various buses concerning Nominal and System Voltages. The bus location sequence will be determined by the descending order of the values for the LSF component to locate the best position vector. Finally, a reliability test comparison was made for conventional, PSO and HHO for IEEE 33 bus system and concluded that buses 10, 14, 17 and 30 total of four buses were identified as the locations for the optimal placement of EVCS in this chapter, which can balance the corresponding buses based on their load demand (during off and peak loads).

CHAPTER 4

IMPACT OF EV AND DG IN THE DISTRIBUTION SYSTEM

4.1. Introduction

Numerous measures are being enacted to reduce emissions of undesirable gases and the global heating that they cause. Alternative approaches to lowering emissions may be found in distributed generation systems that utilize various sources of renewable energy. In addition to its positive effects on the natural world, DGs also help in reducing the costs incurred during on-peak hours of operation, minimizes losses and boost the amount of service offered to clients. DGs are less substantial in size, and as a result, their construction takes less time and requires less investment. Therefore, DGs are becoming an appealing choice for locations that have a higher population density as well as for rural areas that have higher transmission and distribution costs. The growing pace of global energy consumption is leading to a fast increase in the amount of penetration of DG units within the DS. Using DG in a contemporary power system allows customers to have their needs met with a level of quality and consistency that is acceptable, and as a result, the advances made by DG are more efficient and reliable.

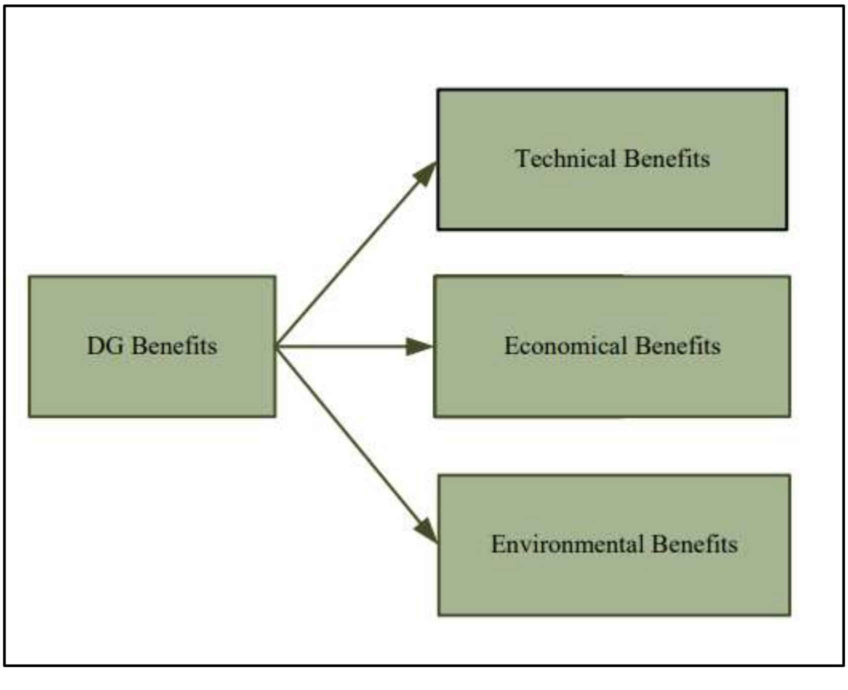


Fig. 4.1. Multiple benefits of DG installation

The following table 4.1gives an overview of the advantages of DG penetration in terms of technology, economics, and the environment:

Table. 4.1. Technical, Economic and Environment benefits of DG

Technical Benefits			**Economic Benefits**	**Environmental Benefits**
Reliability Improvement	Voltage Profile	Line loss/ Energy reduction		
Improved power system reliability	Improving the quality of the voltage	Reduced line losses	Reduced Operational and maintenance costs	Reduction in land use effects
Reduced capacity release	Reduced voltage flicker	Better control of reactive power	No fuel cost with renewable DG	Reduction in health costs with renewable DG
Improved generation diversity	Better regulation and support for voltage	-	Reduction in losses associated with costs	Renewable DG is beneficial to the environment.
Peak power reduction	-	-	Reduction in auxiliaries' costs	Renewable DG for GHG emission reductions

The global economy is expanding in tandem with the rise in load demand, which calls for the provision of electricity that is of high quality and uninterrupted. Small-scale power generating owners have been allowed to join the competitive energy market as a result of the destruction of the monopoly structure and the developments in technology. These small electric utilities create energy, which they could sell to the local utilities to benefit from the cost savings associated with this system. It is projected that distributed generation will have a major impact on the generating system in the future. On-site generating, also known as distributed generation, makes use of low-capacity power production sources that are situated near the consumer who is being supplied. DGs may range in size from less than one kilowatt up to several megawatts. The functioning of the distributed system is profoundly impacted by the proper selection of DG location, as well as the allocation and size of DG resources. A decrease in the reliability levels, as well as an increase in the amount of power losses, may be attributed to the improper placement of DG.

4.2. Objective Function

Due to the presence of substations, there are no geological constraints on the placement of DGs in distribution networks. A lack of electricity is the most significant constraint. In this case, there is no need for any regulations on the positioning of the DG since it all relies on the customers' requirements. Some electrical elements, such as the placement of the DG, must be taken into consideration if it is owned by a DG beneficiary.

Increased EV penetration produces huge power loss in the DS. The main aim is to minimize the losses of true power shown in Eq.4.1 as well as enhance the voltage profile, by the integration of DG with the grid by considering the EV as an additional load to the existing system.

The true power losses are given by

$$MinP_L = \sum_{i=1}^{N} I_i^2 R_i \tag{4.1}$$

Voltage constraints are in the range given below

$$0.95 \le V_i \le 1.05 \tag{4.2}$$

The Power balance equation in Grid to Vehicle (G2V) mode is given by

$$P_{Grid} + \sum_{i=1}^{N} P_{DG_i} = \sum_{i=1}^{N} (P_{iBaseLoad} + P_{iEVCS}) + P_{Losses} \tag{4.3}$$

Where P_{Grid} is the Grid Power Supply, P_{DG_i} is the Distributed Power Generation, $P_{iBaseLoad}$ is the Base Power load, P_{iEVCS} is the load power at EVCS, P_{Losses} is the real Power Loss.

EVs Power charging limits

$$P_{ch,n,\Delta t} \le P\max_{ch,n} \tag{4.4}$$

State of Charge (SoC) limits of EV

$$SoC_{\min} \le SoC_n \le SoC_{\max} \tag{4.5}$$

Boundary limits of DG

$$100 \le P_{DG} \le 1000 \tag{4.6}$$

Here limits are in kW

4.3. Methodology

The addition of EVCS as an actual system load increases the system's total losses. Being one of the most key metrics in loss minimization, proper planning on incorporating the placement and size of DGs is beneficial to make the grid system more efficient. The deployment of DGs will connect the grid system's current and future technological issues, in addition to eliminating losses and meeting demand growth. For an IEEE 33-bus system, the positioning of the electric vehicle charging stations must be determined, the optimal placement and operation of DGs are tested and assessed. The weak bus placement approach using the Loss Sensitivity Factor is deployed for the best siting location of DG.

LSF is used in the process of identifying the location in which the dispersed generations will be placed. To narrow down the search space, the LSF approach is used while positioning the DGs. To find the sensitive buses where the DGs are going to be installed, the sensitivity factor of active power loss is related to the kind of DG that can inject active power by itself, which allows the sensitive buses to be located.

The LSF approach is based on the linearization concept as its directing methodology. In LSF, the initial non-linear loss equation is linearized, which makes selecting buses for DG installation a simplified process. This is one of the benefits of using LSF. The LSF, which is determined by Eq. 3.7, is used to locate the positioning of the DG.

The buses with the nominal voltage calculated by Eq.4.7 using the critical factor, having less than 1.01(nominal voltage severity factor) are identified as the weak bus and chosen as potential sites for the installation of DG, the bus voltages and losses are considered while creating a priority list using Loss sensitivity factor. DG is assigned to one of the system's weakest buses prior.

$$V_{nom[i]} = \frac{V_i}{C} \tag{4.7}$$

Table. 4.2. Optimal location of DG

Critical factor (C)	**Bus Numbers**	**Optimal location of DG**
0.95	5,6,7,8,9,10,11,12,13,14,15,16,17,18,26,27,28,29,30,31,32,33	5
0.93	6,7,8,9,10,11,12,13,14,15,16,17,18,26,27,28,29,30,31,32,33	-
0.91	7,8,9,10,11,12,13,14,15,16,17,18,26,27,28,29,30,31,32,33	-
0.9	8,9,10,11,12,13,14,15,16,17,18,28,29,30,31,32,33	8,28
0.89	9,10,11,12,13,14,15,16,17,18,19,29,30,31,32,33	-
0.88	10,11,12,13,14,15,16,17,18,19,30,31,32,33	11,32
0.87	13,14,15,16,17,18	15
0.86	14,15,16,17,18	-
0.85	17,18	18

Based on the LSF and nominal voltage severity factor approach, seven buses (5,8, 11,15,18,28 and 32) are chosen for the suitable positioning of DGs in the IEEE 33 bus system to enhance the voltage levels and reduce the system losses. The sizing of the DG's is within the constraints of Eq.4.6 with the sizing of seven DG's obtained from [96]. The operating range and size of the DGs are given in table 4.3.

Table. 4.3. Operating range and sizing of DG

Bus Number	**Type of DG**	**Operating Range (P_{min} & P_{max}) in kW**	**Power Generation (kW)**
5	DG1	200 & 600	400
8	DG2	200 & 500	350
11	DG3	200 & 500	300
15	DG4	100 & 400	250
18	DG5	100 & 1000	200
28	DG6	200 & 600	500
32	DG7	100 & 800	400

4.4. Results and Discussion

The increased adoption of electric vehicles has a detrimental impact on the EVCS infrastructure. When a substantial majority of EVs are plugged into the grid simultaneously, there are more Network Power Losses and significant voltage changes at buses that are in remote from the sources. To enhance the voltage levels of the bus and reduce the losses, the integration of DGs with the EVCS in the distribution network is necessary. The placement of EVCS was located at 4 buses (10,14,17&30) and the optimal location of DGs is identified at 7 buses (5,8,11,15,18,28&32) for IEEE 33 bus system shown in Fig. 4.2. With the simultaneous deployment of EVs and DGs for an IEEE 33 bus system, the true power losses and voltage levels are to be examined for the system.

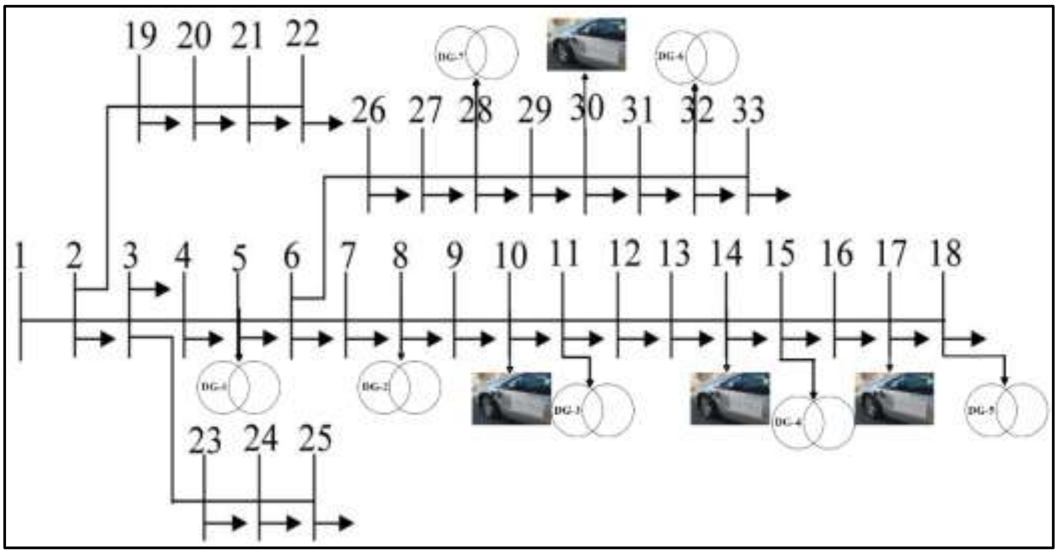


Fig. 4.2. Optimal placement of EVs and DGs for an IEEE 33 bus system

4.4.1. Optimal Placement of DG in the Distribution system

The based load for a standard IEEE 33 bus system is 3715kW and the real power loss is 202kW. From the comparison of conventional, PSO and HHO for the IEEE 33 bus system, four locations are identified for the optimal placement of EVCS in the system. Due to the addition of EV load to the existing based load on the 33-bus system, the overall load was increased to 4735kW and the losses were increased to 374kW which enhanced to 85.1% compared to the base case. Based on the LSF and nominal voltage severity factor approach, seven buses are chosen for the optimal placement of DGs in the IEEE 33 bus system. With the integration of DGs alone into the system, the losses were reduced to 141kW which was reduced to 43.2% compared to the base load shown in Fig. 4.3.

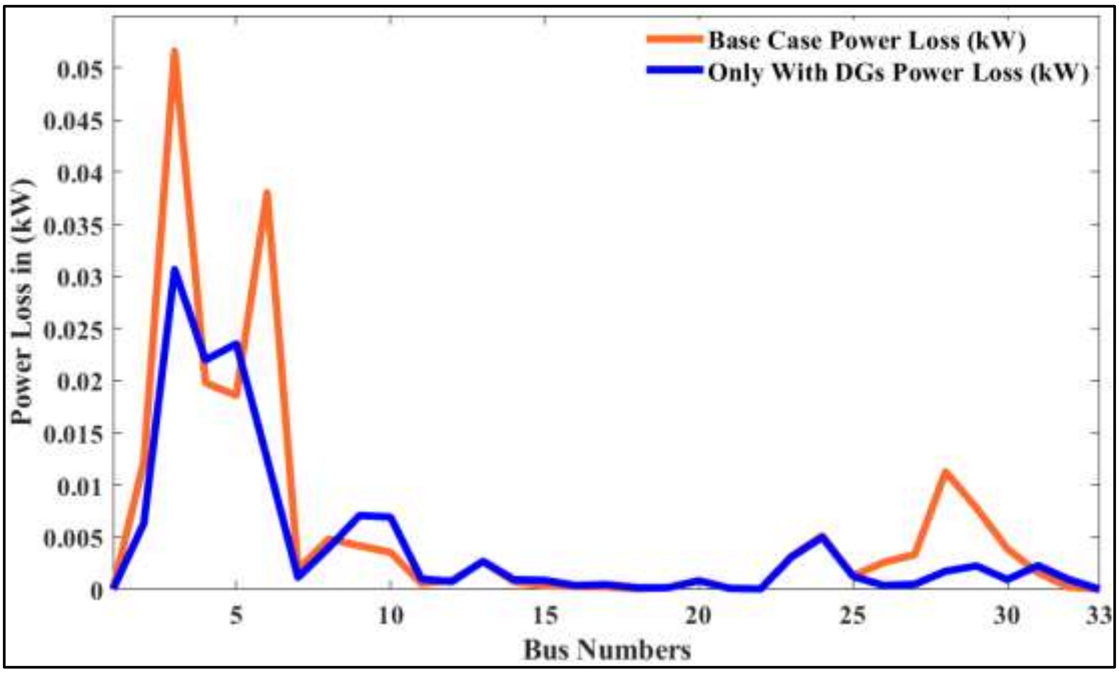


Fig. 4.3. Power Loss of integrated DGs in the distribution system

4.4.2. Simultaneous integration of EV & DG in the Distribution system

With the coordinated deployment of EVs and DGs in the IEEE 33 bus system, even though there is an overall increase in the load i.e with base load and EV load of 4735kW, by the optimal placement of DGs in the respective buses and the integration of DGs in the DS the losses were reduced to 163kW with a decrement of 56.4%.

Table. 4.4. Comparison of real power losses

Cases	**Power Loss**
With Base Load only	202kW
With Base Load and EV Load connected to System	374kW
With only DG Integrated System	141kW
With EV & DG Integrated System	163kW

The following Fig. 4.4 shows the variation of real power losses of EV and DG for the possible cases showing that the combination of EVs and DGs integrated into DS the losses were reduced.

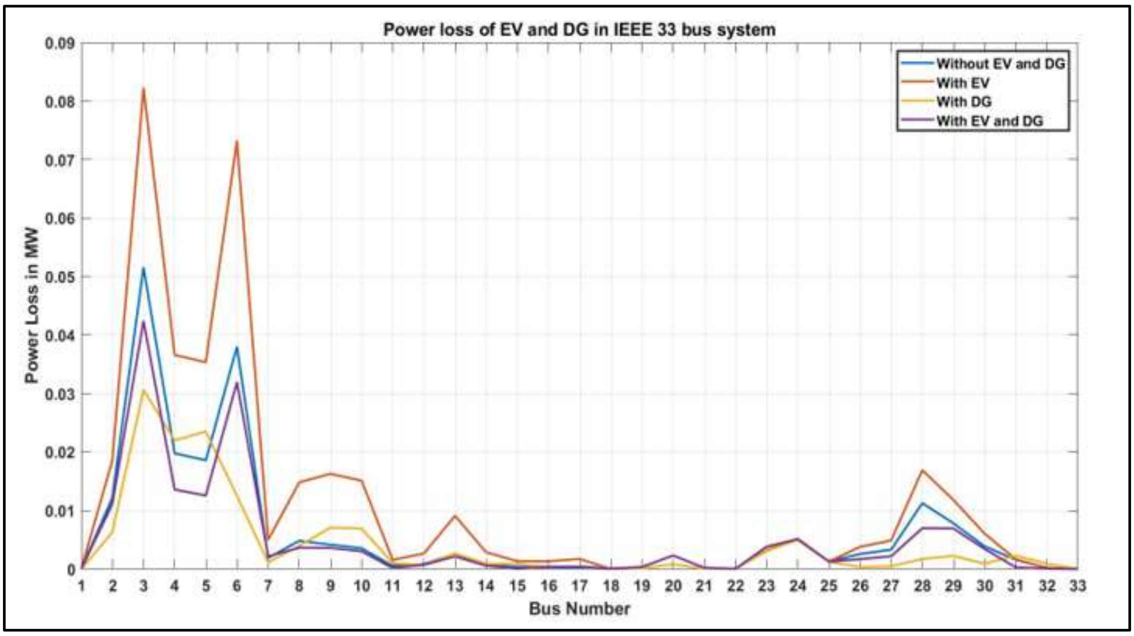


Fig. 4.4. Power Loss in IEEE 33 Bus system with possible cases.

With the simultaneous integration of EVs and DGs in the distribution system, the voltage profile is improved for various possible cases shown in table 4.5. Also, the graphs are compared on the possible cases in the 33-bus system shown in Fig. 4.5.

Table. 4.5. Comparison of Voltage profiles for possible cases

Bus Number	**Voltage profile Without EV & DG in Volts**	**Voltage profile With EV in Volts**	**Voltage profile With DG in Volts**	**Voltage profile With EV & DG in Volts**
1	1	1	1	1
2	0.997	0.996	0.999	0.997
3	0.983	0.978	0.997	0.985
4	0.976	0.968	0.998	0.979
5	0.968	0.958	1	0.974

6	0.950	0.934	0.999	0.957
7	0.946	0.929	1.001	0.953
8	0.941	0.921	1	0.949
9	0.935	0.910	1	0.943
10	0.929	0.899	1	0.937
11	0.929	0.897	1	0.937
12	0.927	0.895	0.999	0.936
13	0.921	0.885	0.998	0.93
14	0.919	0.881	0.999	0.928
15	0.917	0.879	1	0.927
16	0.916	0.876	0.999	0.926
17	0.914	0.872	0.999	0.923
18	0.913	0.871	1	0.924
19	0.997	0.996	0.999	0.996
20	0.993	0.992	0.995	0.99
21	0.992	0.992	0.994	0.989
22	0.992	0.991	0.994	0.989
23	0.979	0.975	0.993	0.981
24	0.973	0.968	0.987	0.974
25	0.969	0.965	0.984	0.971
26	0.948	0.931	0.999	0.956
27	0.945	0.928	0.999	0.954
28	0.934	0.914	1	0.946
29	0.926	0.904	0.996	0.939
30	0.922	0.899	0.995	0.935
31	0.918	0.895	0.998	0.934
32	0.917	0.894	1	0.934
33	0.917	0.893	1	0.933

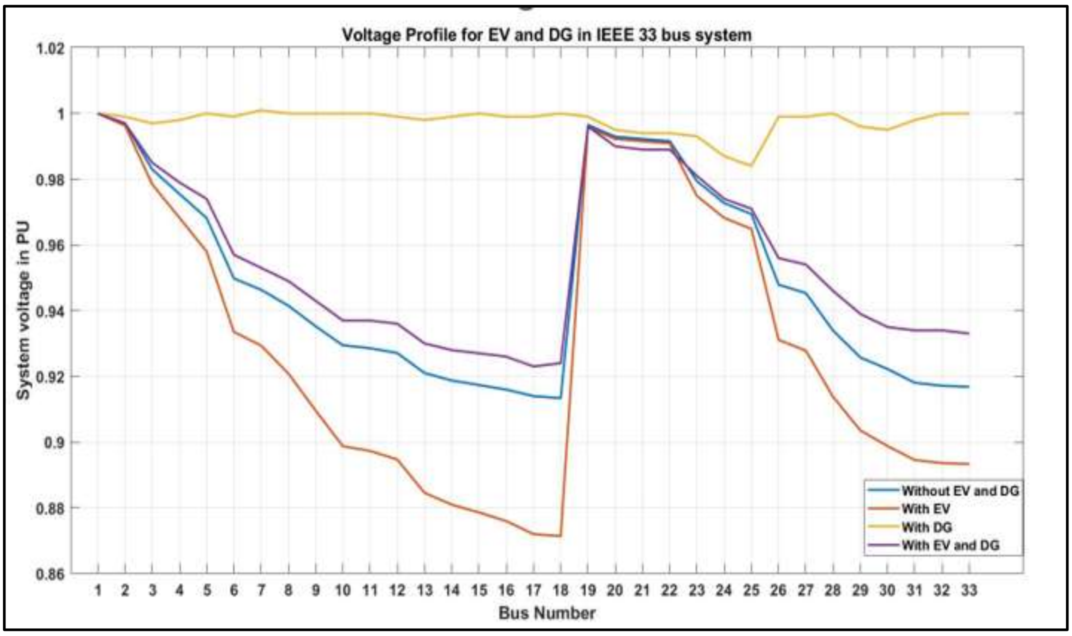


Fig. 4.5. Voltage profile in IEEE 33 Bus system with possible cases

4.5. Chapter Summary

The increase in the penetration of electric vehicles has a significant effect on the power grid. When a massive proportion of EVCSs are coupled to the electrical grid, system voltage swings and power losses at distant buses from sources will rise. In this chapter, simultaneous integration of EVCS and DG for a standard IEEE 33 bus system was considered. Using the LSF approach the simulation results showed that by considering the EV load to the existing base load in the system, the losses were raised to 374kW and reduction in the voltage profile. With the integration of DG into the EV connected grid system the losses were reduced to 163kW, with an improvement of the voltage profile in the distribution system

CHAPTER 5

OPTIMAL SCHEDULING OF EVAND DG IN THE DISTRIBUTION SYSTEM

5.1. Introduction

As a key component of an intelligent network that is capable of controlling itself, electrical distribution networks are emerging in the form of smart grids. The integration of energy is a key aspect of the transition from traditional distribution networks to smart distribution networks. To reduce excess, the supply of energy, the strategies for lowering carbon emissions to mitigate the effects of climate change, voltage regulation, and power flow management are all aspects that contribute to the integration of the power system. DGs in distribution networks, particularly their effectiveness in dealing with time-varying loads, is an essential aspect of the system. To optimize voltage profile, minimize power losses and accomplish actions such as peak shaving, DGs are used. Due to the stochastic nature of the DGs and the demand side response, coordinated scheduling plays a key role in the Distribution system [97].

5.2. Objective Function

Increased EV penetration produces huge power loss in the DS. The main objective is to reduce actual power losses and enhance voltage distribution, by the integration of DG with the grid by considering the EV as an additional load to the existing system. Initially, the LSF technique is used to establish the optimal placement of EVCS and DGs, Here the analysis of research is carried for the Type 1 DGs of injecting only the real power into the System. Also, a 24-hour load setting of an EV is determined and the losses are obtained from Eq.5.1. Finally, optimal scheduling of intermittent load for a 24-hour profile is done using Arithmetic Optimization Algorithm (AOA). The challenge of optimization considering the constraints of equality and inequality includes the position of EVCS and DGs as the decision variables. The amount of power that is lost across the distribution system as well as the voltage fluctuations should be reduced as much as possible. The objective function may be formulated mathematically as follows:

The true power loss for a 24-hour load profile is given by

$$MinP_L = \sum_{j=1}^{24} I_j^{\,2} R_j \tag{5.1}$$

The Power balance equation in Grid to Vehicle (G2V) mode for the 24-hour load profile is given by

$$P_{Grid} + \sum_{i=1}^{24} P_{DG_i} = \sum_{i=1}^{24} [(P_{iBaseLoad} + P_{iEVCS}) + P_{Losses}] \tag{5.2}$$

5.3. Methodology

With the optimal positioning of EVCS and DGs in the IEEE 33 bus system, by the LSF method, bus numbers 10,14,17 and 30 are identified for their placement of EVs and bus numbers 5,8,11,15,18,28 and 32 inject the power into the system. Here the analysis is carried out for the intermittent load demand in a 24-hour load profile for the DS shown in table 5.1. [98]. Finally, the optimal scheduling of DGs is carried out by using AOA for the variations in the load demand over a 24-hour period.

Table. 5.1. Load setting for 24-hour load profile

Data setting	
Time in hrs	load setting
1	0.66
2	0.62
3	0.6
4	0.58
5	0.58
6	0.6
7	0.75
8	0.87
9	0.94
10	0.95

11	0.94
12	0.93
13	0.92
14	0.95
15	0.93
16	0.92
17	0.96
18	0.99
19	1
20	0.95
21	0.9
22	0.85
23	0.73
24	0.63

5.3.1. Arithmetic Optimization Algorithm

An AOA is a new meta-heuristic technique based on the distribution behaviour of the major arithmetic operators in mathematics is proposed and was used for an optimal power scheduling of an IEEE 33 bus distribution system. To execute optimization operations across a wide range of search areas, AOA is theoretically developed and implemented. The optimization technique in AOA commences with a group of randomly generated candidate solutions, and the best candidate solution in each iteration is chosen as the best-obtained solution or approximately the best solution. To illustrate the importance of exploration and exploitation shown in Figure 5.1, the parameter Math Optimizer Accelerated (MOA) coefficients raised linearly from 0.2 to 0.9. When r1 > MOA, candidate solutions attempt to diverge from the near-optimal solution, and when r1< MOA, they attempt to converge [99].

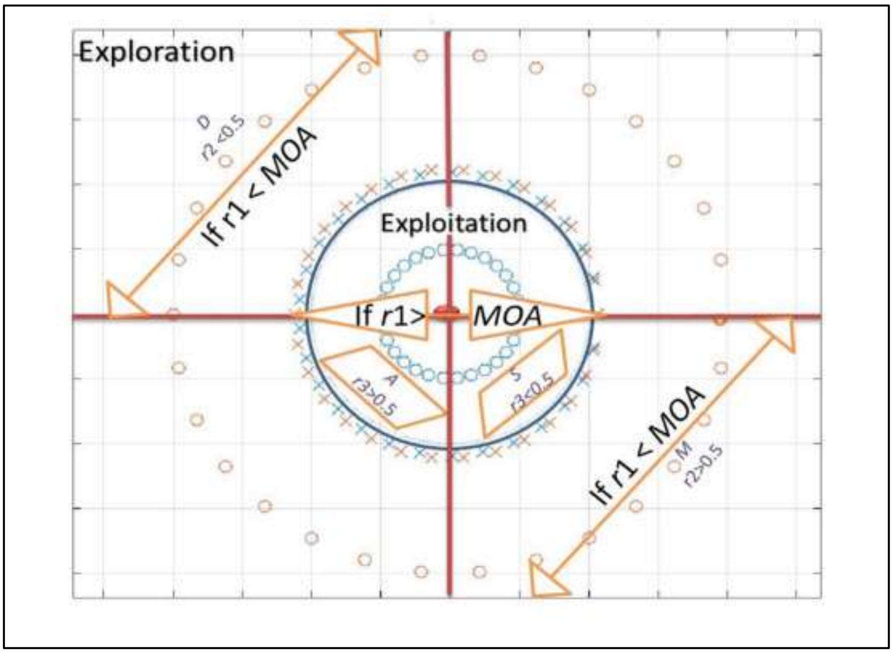


Fig. 5.1. The Search stages of AOA

On the test functions, the AOA exceeded other algorithms in terms of global search experience and convergence speed. This indicates that the AOA has a better rate of convergence and a much more effective search capability than the operating flowchart shown in Figure 5.2.

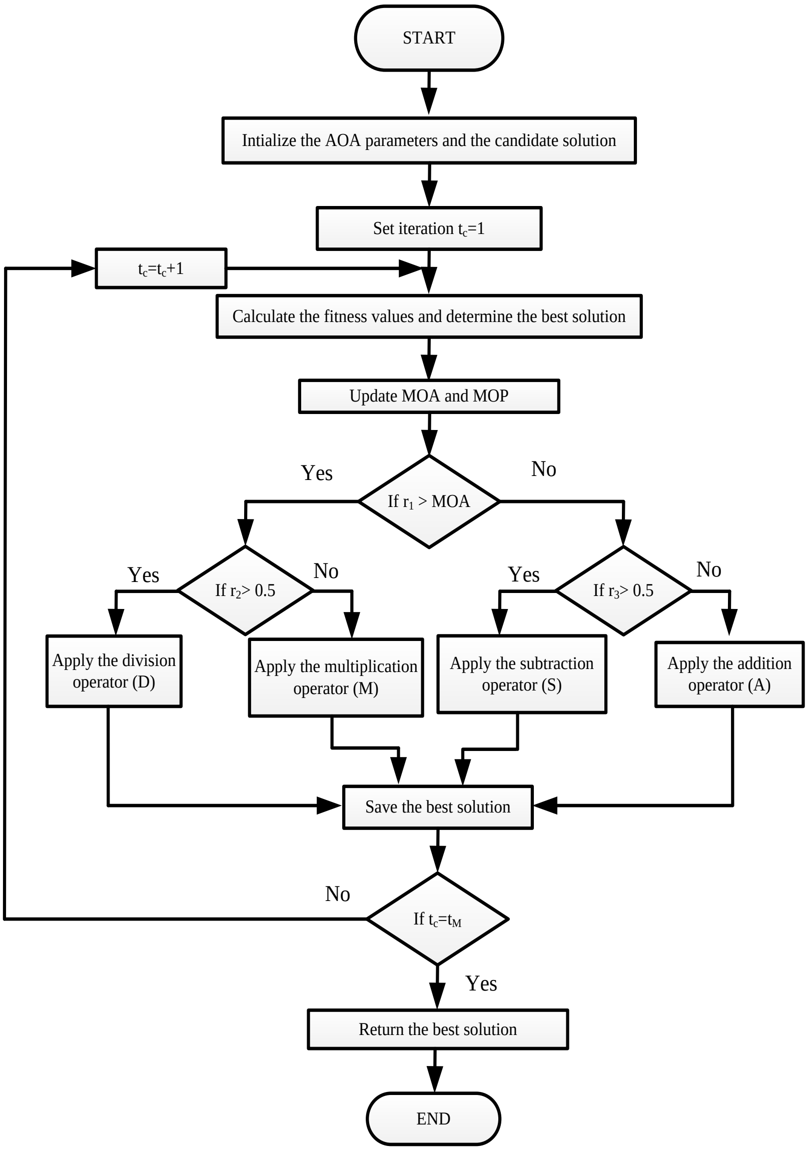


Fig. 5.2. The Operating flowchart of AOA

5.4. Results and Discussion

The analysis is carried out for the following three cases for a 24-hour load setting for the distribution system.

5.4.1. Without EV and DG

The intermittent load demand for a 24-hour horizon without the placement of EVCS and DG in the distribution system is given by 73334.1kW having a real power loss of 4.00722MW.

5.4.2. With only EV

The variation of the load demand for a 24-hour horizon with the placement of EVCS load in the DS, the load is increased to 93468.9kW, the corresponding real power loss also increased to 7.38276MW with an increase of 84.2 percent.

5.4.3. With EV and DG

With the integration of DGs and EVCS simultaneously in the distribution system, the load is given by 93468.9kW, by the injection of real power in the system from the corresponding buses as DG the real power loss was decreased to 3.21762 MW.

Table. 5.2. Load and Loss profile for a 24-hour horizon in the Distribution System

	With Out EV &DG		**With EV**		**With EV & DG**	
Time in hr	Load (kW)	Loss (MW)	Load (kW)	Loss (MW)	Load (kW)	Loss (MW)
1	2451.9	0.13398	3125.1	0.2468	3125.1	0.1076
2	2303.3	0.12586	2935.7	0.2319	2935.7	0.1011
3	2229	0.1218	2841	0.2244	2841	0.0978
4	2154.7	0.11774	2746.3	0.2169	2746.3	0.0945
5	2154.7	0.11774	2746.3	0.2169	2746.3	0.0945
6	2229	0.1218	2841	0.2244	2841	0.0978
7	2786.25	0.15225	3551.25	0.2805	3551.25	0.1223
8	3232.05	0.17661	4119.45	0.3254	4119.45	0.1418
9	3492.1	0.19082	4450.9	0.3516	4450.9	0.1532
10	3529.25	0.19285	4498.25	0.3553	4498.25	0.1549
11	3492.1	0.19082	4450.9	0.3516	4450.9	0.1532
12	3454.95	0.18879	4403.55	0.3478	4403.55	0.1516

13	3417.8	0.18676	4356.2	0.3441	4356.2	0.15
14	3529.25	0.19285	4498.25	0.3553	4498.25	0.1549
15	3454.95	0.18879	4403.55	0.3478	4403.55	0.1516
16	3380.65	0.18473	4308.85	0.3403	4308.85	0.1483
17	3566.4	0.19488	4545.6	0.359	4545.6	0.1565
18	3677.85	0.20097	4687.65	0.3703	4687.65	0.1614
19	3715	0.203	4735	0.374	4735	0.163
20	3529.25	0.19285	4498.25	0.3553	4498.25	0.1549
21	3343.5	0.1827	4261.5	0.3366	4261.5	0.1467
22	3157.75	0.17255	4024.75	0.3179	4024.75	0.1386
23	2711.95	0.14819	3456.55	0.273	3456.55	0.119
24	2340.45	0.12789	2983.05	0.2356	2983.05	0.1027
Total	73334.1	4.00722	93468.9	7.3828	93468.9	3.2176

The following Figure 5.3 and 5.4 shows the variations in the load demand and the real power losses for the 24-hour load profile of the DS.

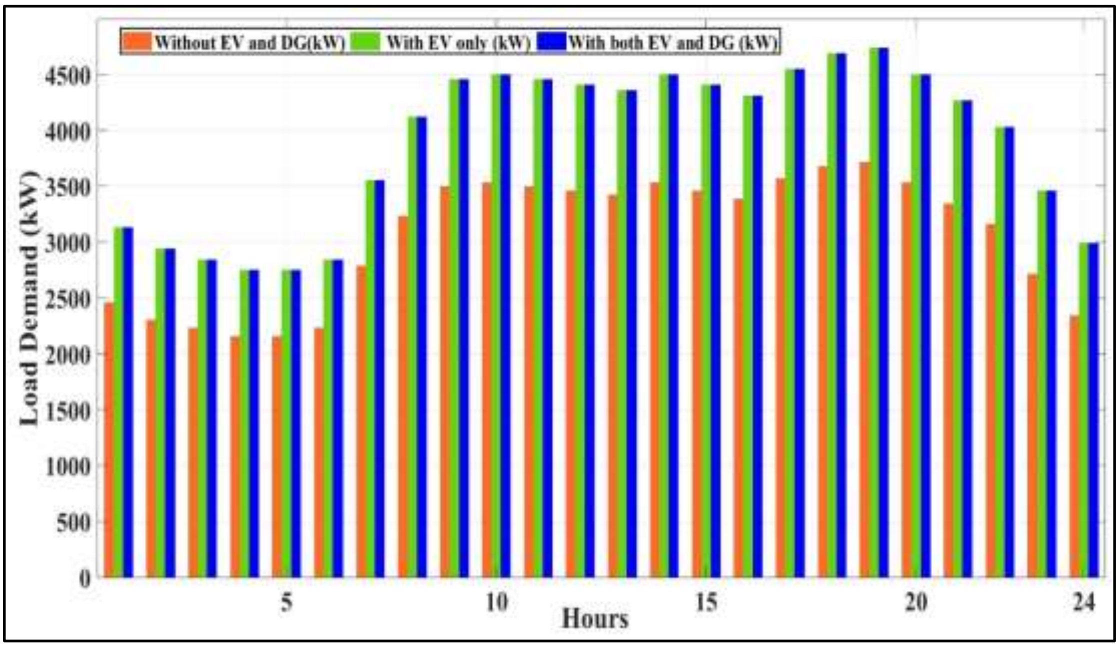


Fig. 5.3. Load profile for 24-hour load horizon with possible cases.

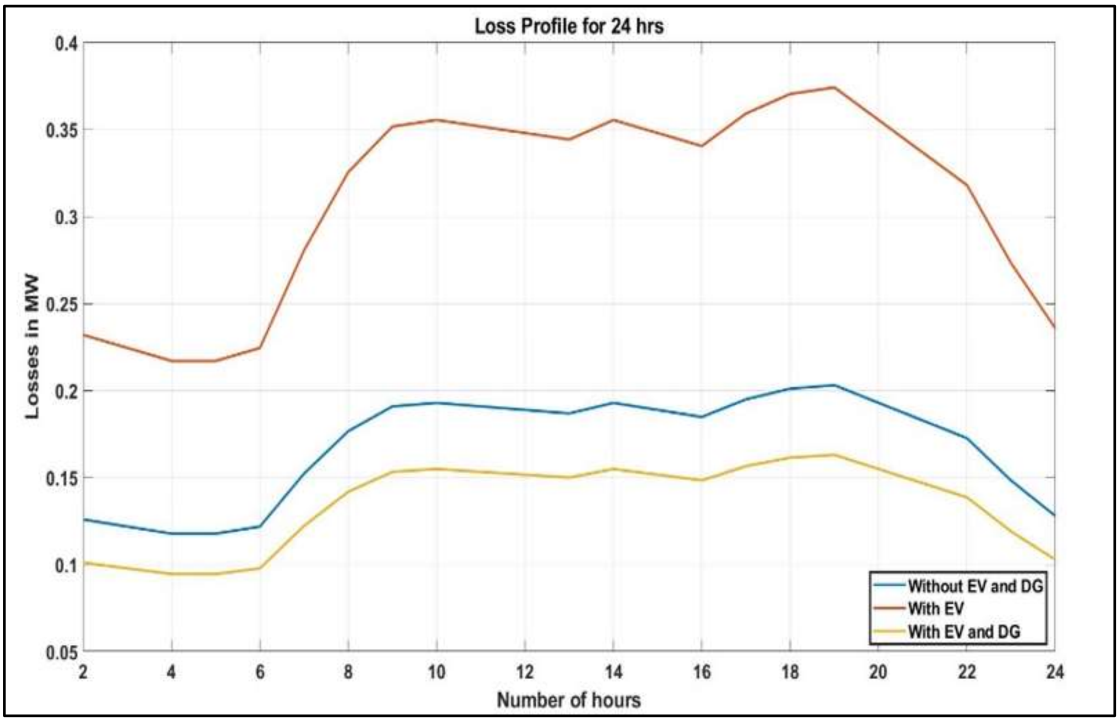


Fig. 5.4. Loss profile for 24-hour load horizon with possible cases.

After the placement of DG in the IEEE 33bus system, the optimal commitment of DG with respective to consider load demand on 24 hrs horizon was carried out by Dynamic Programming procedure, with the operating of DG over a period of time as shown in table 5.3.

Table. 5.3. Operating of DGs over a 24-hour horizon in the Distribution System

Time in hr	**Slack Bus**	**DG-1**	**DG-2**	**DG-3**	**DG-4**	**DG-5**	**DG-6**	**DG-7**
1	1	1	1	1	1	0	1	0
2	1	1	1	0	1	0	1	1
3	1	1	0	1	1	1	1	0
4	1	1	0	1	1	0	1	1
5	1	1	0	1	1	0	1	1
6	1	1	0	1	1	1	1	0
7	1	1	1	1	1	1	1	0
8	1	0	0	1	1	0	1	1
9	1	0	1	0	1	1	1	0
10	1	0	1	1	1	0	1	0
11	1	0	1	0	1	1	1	0
12	1	0	1	0	1	1	1	0
13	1	0	1	0	1	0	1	1
14	1	0	1	1	1	0	1	0
15	1	0	1	0	1	1	1	0
16	1	0	1	0	1	0	1	1
17	1	0	0	1	1	1	1	1
18	1	1	0	1	1	0	1	0
19	1	0	1	0	1	1	1	1
20	1	0	1	1	1	0	1	0
21	1	0	0	1	1	1	1	0

22	1	0	0	0	1	1	1	1
23	1	1	1	1	1	0	1	1
24	1	1	1	0	1	0	1	1

An AOA technique was used for optimal power scheduling of an IEEE 33 bus distribution system. The following Figure 5.5 shows the Fitness function of EV load for the 4735-kW load setting using the AOA algorithm.

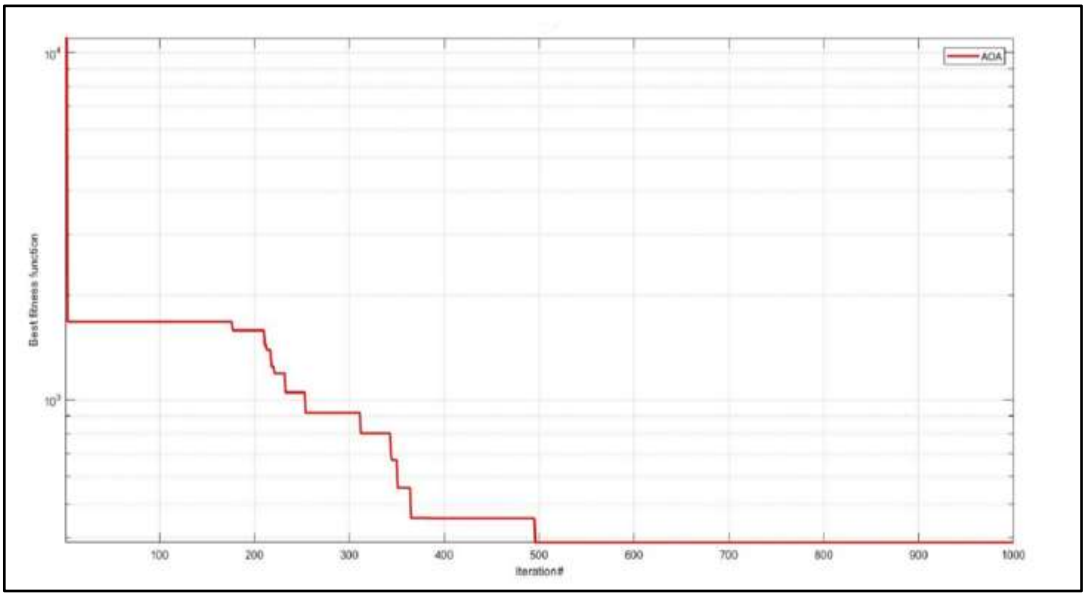


Fig. 5.5. The Fitness function of EV load for 4735 kW load setting using the AOA

5.4.4. Optimal Scheduling of DG for 24- hour load profile with EV load

With the simultaneous integration of EVs and DGs in the DS, the optimal scheduling of DG is carried for a 24-hour load profile by considering the intermittent EV load. The day is divided into 24-time slots of one hour each to solve the optimization issue. The optimal scheduling of DGs integrated with the grid-connected system on 24-hour load demand in a day, for every one hour is given in table 5.4 and its variation for time is shown in Figure 5.6. The maximum load was observed in the 19th hour, for a 24-hour load profile shows that the integrated grid-connected system would reduce the effect on the DS by sharing the additional load of EV with the respective DGs over a period of time for stable and reliable operation of the system.

Table. 5.4. Optimal scheduling and sizing of DG for 24- hour load profile using AOA.

Time in hr	**Slack bus**	**DG1 (5)**	**DG2 (8)**	**DG3 (11)**	**DG4 (15)**	**DG5 (18)**	**DG6 (28)**	**DG7 (32)**	**Total Load(kW)**
1	525	600	500	500	400	0	600	0	3125
2	736	600	500	0	400	0	600	100	2936
3	578	600	0	500	400	301	462	0	2841
4	946	600	0	500	400	0	200	100	2746
5	946	600	0	500	400	0	200	100	2746
6	271	600	0	472	343	555	600	0	2841
7	920	600	458	458	400	114	600	0	3551
8	2088	0	0	500	400	0	600	532	4119
9	2500	0	258	0	400	693	600	0	4451
10	2500	0	498	500	400	0	600	0	4498
11	2500	0	258	0	400	693	600	0	4451
12	1904	0	500	0	400	1000	600	0	4404
13	2500	0	500	0	400	0	600	356	4356
14	2500	0	498	500	400	0	600	0	4498
15	1904	0	500	0	400	1000	600	0	4404
16	2500	0	500	0	400	0	600	309	4309
17	2500	0	0	492	400	454	600	100	4546
18	2588	600	0	500	400	0	600	0	4688
19	2800	0	500	0	400	100	600	335	**4735**
20	2500	0	498	500	400	0	600	0	4498
21	1762	0	0	500	400	1000	600	0	4262
22	2800	0	0	0	400	100	600	124	4025
23	949	600	410	207	336	0	600	353	3457
24	80	600	500	0	400	0	600	800	2983

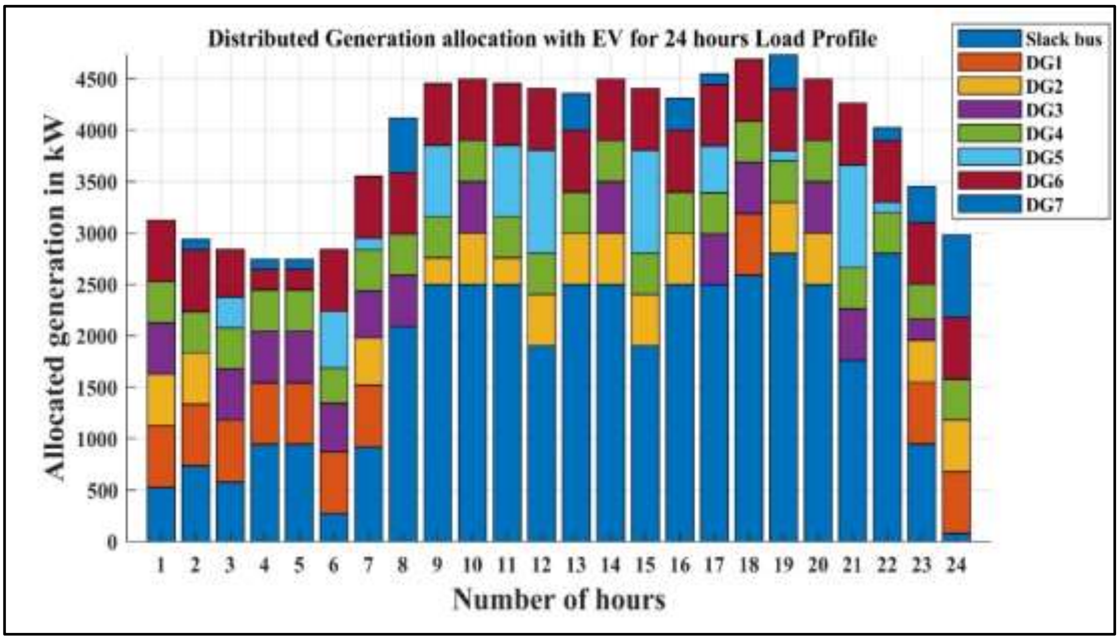


Fig. 5.6. Optimal Scheduling of DGs for 24-hour load profile using AOA

5.5. Chapter Summary

In this chapter, the simultaneous integration of EVCS and DG in a DS with an intermittent 24-hour load demand of EVs was considered. The simulation results have shown that by considering the EV load to the existing base load in the system, the losses were raised to 7.382 MW. With the integration of DG into the EV-connected grid system, the losses were reduced to 3.217 MW. The operating of the DG over a period of time is given by the Dynamic Programming procedure. Finally, the optimal scheduling and sizing of DGs for an intermittent EV load demand on a 24-hour horizon were carried out by AOA, thus reducing the effect on the DS for the reliable operation of the system.

CHAPTER 6

IMPACT OF VEHICLE TO GRID IN THE DISTRIBUTION SYSTEM

6.1. Introduction

The growth in popularity of EVs indicates that the charging of such vehicles will have a major impact on the distribution network. The rapid deployment of EVs and fast chargers will eventually lead to an increase in the amount of energy that is required to meet demand, which in turn will cause congestion on the power grid, regardless of the EV charging strategy that is ultimately chosen and put into action. Finding a means to move this charging to off-peak times has been identified as a critical issue for the large-scale incorporation of EVs into the existing electricity networks. It is possible to alleviate many of these concerns by using DG, where the electricity production is positioned close to the demand and often located on the same site. The intermittent nature of the DGs is one of the concerns for system stability. ESS, have been proposed as a possible solution to this issue because of their capacity to control the amount of power that is sent into the grid via DGs, so ensuring grid stability. Electric vehicle batteries have the potential to serve as portable distributed energy storage systems. In G2V mode, the batteries can store energy in a way that corresponds to that of a load, and in V2G mode, they can provide energy to the grid in a way that corresponds to that of a power generating unit. The V2G approach is being implemented to enhance the functioning of the electric grid in a manner that is both technically and economically feasible. Energy may be exchanged between EVs and the utility grid using bidirectional G2V and V2G techniques. This exchange of energy helps to support several technological and economic advantages; it is beneficial to the electric grid as well as the consumer (EV owner).

V2G is a novel resource for power storage and provision of high and low regulation. It provides and enables a solution to the volatility caused by the large proportion of DG in the grid, as well as a solution to grid congestion and the circumvention of the need to improve grid infrastructure. Integration of V2G technology with Generating units is an effective way to address potential issues connected to high EV adoption and the intermittent power supply.V2G establishes the development of a new circular economy, increases energy security, promotes a cleaner environment and reduces noise pollution caused by car engines. EVs and V2G will rebuild the city's lifestyle and infrastructure, resulting in a massive rise in global development. The most significant goals of the V2G system's development are to reduce peak demand and improve grid stability [100]. Interpreting the V2G's impact on the system load profile is a good technique to assess the V2G's efficiency.

6.2. Objective Function

The main objective is to provide a smart EV charging schedule, that takes into account the effective usage of V2G model, for the DG integrated grid-connected system with an EV charging station. A TOU -based tariff plan of charging/discharging schedule is the main focus, which tries to discover the number of EVs that is optimal to secure both financial and technological benefits for the utility grid and the customer

(1) Maximize utility grid benefits by reducing losses using smart charging and

(2) improve consumer benefits by reducing the charging cost.

The operational constraints of EV are taken into account to optimize the DNs voltage profile and decrease network power loss, customer’s priorities are taken for the technical and economic validation of the V2G's ability to deliver grid services. The objective function may be formulated mathematically as follows:

Firstly, to minimize the total real power losses with V2G acting as a source with its bidirectional model shown in Eq.6.1.

$$MinP_L = \sum_{i=1}^{N} I_i^{\,2} R_i \tag{6.1}$$

The power balance equation for the EV acting as a load is given by

$$P_G + \sum_{i=1}^{N} P_{DG} = P_D + P_{EVL} + P_L \tag{6.2}$$

The power balance equation for the EV acting as a source (DG) is given by

$$P_G + \sum_{i=1}^{N} P_{DG} + P_{EVDG} = P_D + P_L \tag{6.3}$$

Where P_G is the real power supply from the grid, P_{DG} is the Distributed Generator, P_D is the existing base load, P_{EVL} is the EV as a load, P_{EVDG} is the EV as a source, P_L is the real Power Loss.

EVs Power charging, discharging limits

$$P_{ch,n,\Delta t} \leq Pmax_{ch,n} \tag{6.4}$$

$$P_{disch,n,\Delta t} \leq Pmax_{disch,n} \tag{6.5}$$

Each electric vehicle battery's state of charge (SoC) must be kept within certain ranges shown in Eq. 6.6

$$SoC_{min} \leq SoC_n \leq SoC_{max} \tag{6.6}$$

Boundary limits of DG and EV acting as a DG

$$100 \leq P_{DG} \leq 1000 \tag{6.7}$$

Here the limits are in kW

6.3. V2G Framework in the Distribution system

Due to the intermittent nature of DGs integrated into the grid-connected system, in the recent research analysis V2G technology is playing a vital role in being one of the sources to act as an additional DG to the existing grid-connected system. With the bi-directional converter, the EVCS can operate in dual mode i.e., as a load and source at the times based on the off and peak loads shown in Figure 6.1. By the effective utilization of EVs as one of the sources based on the intermittent load demand with smart charging, the losses will be further reduced and enhance the voltage profile. The DGs and EV batteries are perceived as negative loads and are thus mitigated for the objective of minimizing the losses. The best location and size of the DGs are determined by its positioning with the minimum losses over the respective sizes.

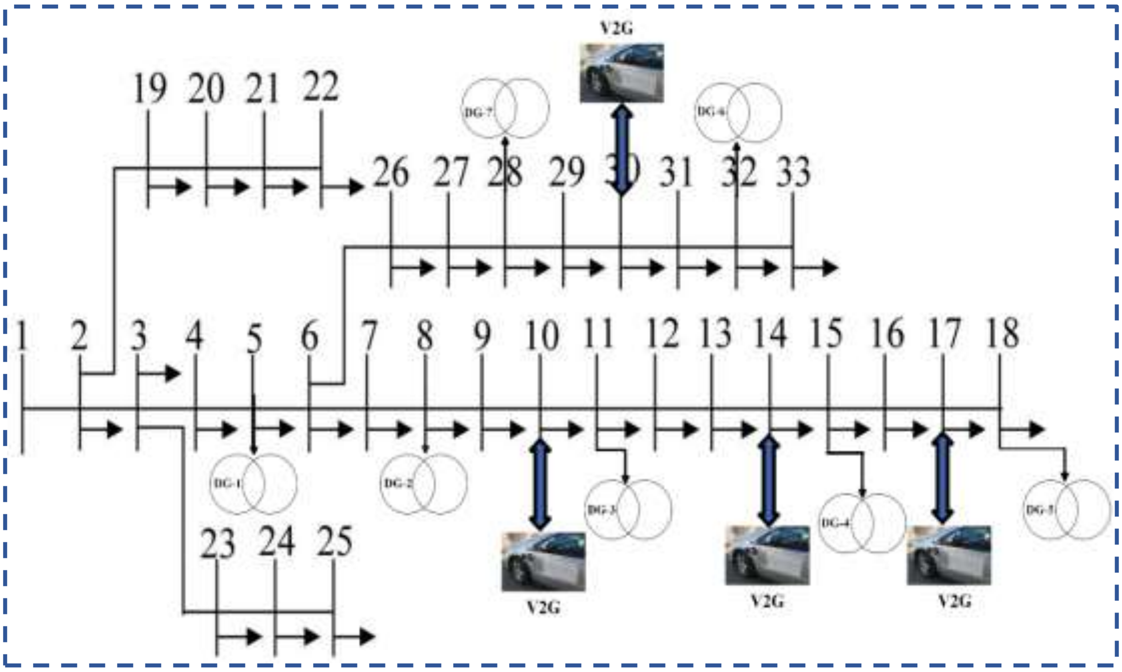


Fig. 6.1. Simultaneous Placement of EVCS and DGs in IEEE 33 bus system operating in G2V and V2G mode

The real power constraints of the DGs placement for the respective buses along with EVs as the source are in the range given in the following table 6.1.

Table. 6.1. Power Generation limits of DG & EVs as DG

Bus Number	**Operating Range (P_{min} & P_{max}) in kW**	**Power Generation (kW)**
5	200 & 600	400
8	200 & 500	350
11	200 & 500	300
15	100 & 400	250
18	100 & 1000	200
28	200 & 600	500
32	100 & 800	400
EV1 10	240 &528	480
EV2 14	150&330	300

EV3 17	220&484	440
EV4 30	250&550	500

6.4. Smart Charging Schedule using TOU

To analyze the smart charging framework from the installation of EVs and DGs in the distribution network simultaneously, the load demand is estimated per unit for a 24-hour horizon of a day. To examine the off and peak load demand for the efficient operation of the smart charging technique, the State of Charge (SoC), Demand and power are determined at each EVCS. Based on the load demand and the SoC level of the EV battery the charging, discharging and neutral operation takes place in EVCS shown in the following table 6.2.

Table. 6.2. SoC, Demand and Power constraints for EVCS at 17th bus

Time in hr	**Demand (P.U)**	**SoC (P.U)**	**C/D**	**Power (P.U)**
1	0.6	0.9	1	0.484
2	0.6	0.9	1	0.484
3	0.6	0.9	1	0.484
4	0.7	0.9	1	0.484
5	0.75	0.9	1	0.484
6	0.8	0.8	3	0.44
7	0.85	0.7	3	0.44
8	0.9	0.6	3	0.44
9	0.93	0.6	1	0.44
10	0.93	0.6	1	0.44
11	0.93	0.6	1	0.44
12	0.95	0.65	1	0.44
13	0.97	0.7	1	0.44
14	0.94	0.8	2	0.484

15	0.9	0.85	2	0.484
16	0.8	0.9	2	0.484
17	0.7	0.9	2	0.484
18	0.7	0.9	1	0.484
19	0.6	0.9	1	0.44
20	0.6	0.9	1	0.44
21	0.5	0.9	1	0.44
22	0.5	0.8	3	0.44
23	0.6	0.7	3	0.44
24	0.7	0.75	3	0.44

Based on the TOU, the following are the possible modes of operation for the EV battery under intermittent load demand based on the SoC level, Demand and Power flow.

6.4.1. Neutral Mode

When the Demand is greater than the Generation and the SoC of the battery is less than the SoC minimum or the Generation is greater than the Demand SoC of the battery is greater than the SoC maximum. Under this circumstance it is not good to adhere to charging or discharging represented in equations 6.8 and 6.9, So the EV will be operating in the neutral mode represented with 1 throughout the analysis in this chapter. The mathematical equations are given below

$$P_D > P_G \text{ and } SoC < SoC_{min} \tag{6.8}$$

$$P_G > P_D \text{ and } SoC > SoC_{max} \tag{6.9}$$

6.4.2. Charging Mode

If the Generation is greater than the Demand and the SoC of the battery is below the SoC maximum, then the Charging operation takes place represented with 2 throughout the analysis in this chapter. The mathematical equation is given by

$$P_G > P_D \text{ and } SoC < SoC_{max} \tag{6.10}$$

6.4.3. Dis-Charging Mode

If the Demand is greater than the Generation and the SoC of the battery is greater than the SoC minimum, then the Dis charging operation takes place represented with 3 throughout the analysis in this chapter. The mathematical equation is given by

$$P_D > P_G \text{ and } SoC > SoC_{min} \tag{6.11}$$

6.5. Smart Charging methodology of EVCS for 24-hour load profile

With the addition of EV load to the existing based load on the system, it is suggested not to go for dumb charging based on the SoC of the EV, which might increase the charging cost for the consumer and become more strain on the power grid system. So, by the efficient utilization of the V2G and G2V model based on the SoC, demand and available power from the smart charging methodology will reduce the charging cost or additional incentives can be provided to the end-user and also will reduce the stress on the Distribution system. Firstly, to analyze the off and peak loads over a period of time then choose for charging, discharging and neutral mode of operation for an EV by smart charging system.

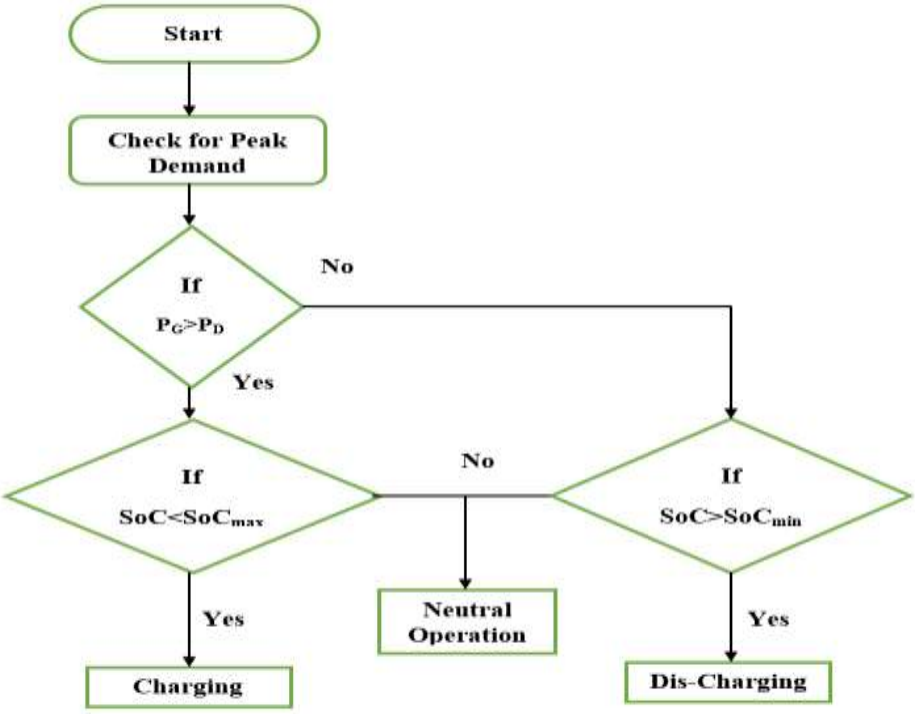


Fig. 6.2. Smart charging based on load demand, SoC and Power

The Figure 6.2. shows the operating flowchart of smart charging based on the SoC level, Demand and Power flow constraints.

Here the Figure 6.3 shows the variation of SoC, Demand and Power curve with respect to time for the EVCS operating at17th bus. Here initially the Demand is constant and the generation is high, So the SoC of the battery operates in neutral mode. At the 6th hour, the demand is increasing and the generation is low, So the SoC of the battery starts operating in discharging mode. From the 9th hour, the demand is still increasing, but the available SoC of the battery is minimum, so the EV operates in a neutral mode. At the 11th hour for a considerable change in demand, the SoC of the battery starts charging. At the 16th hour, the SoC of the battery reaches its maximum position and the load demand is minimum, so it operates in a neutral position. Finally, from the 21st hour, the demand starts increasing and available power is minimum, Therefore the SoC of the battery starts discharging.

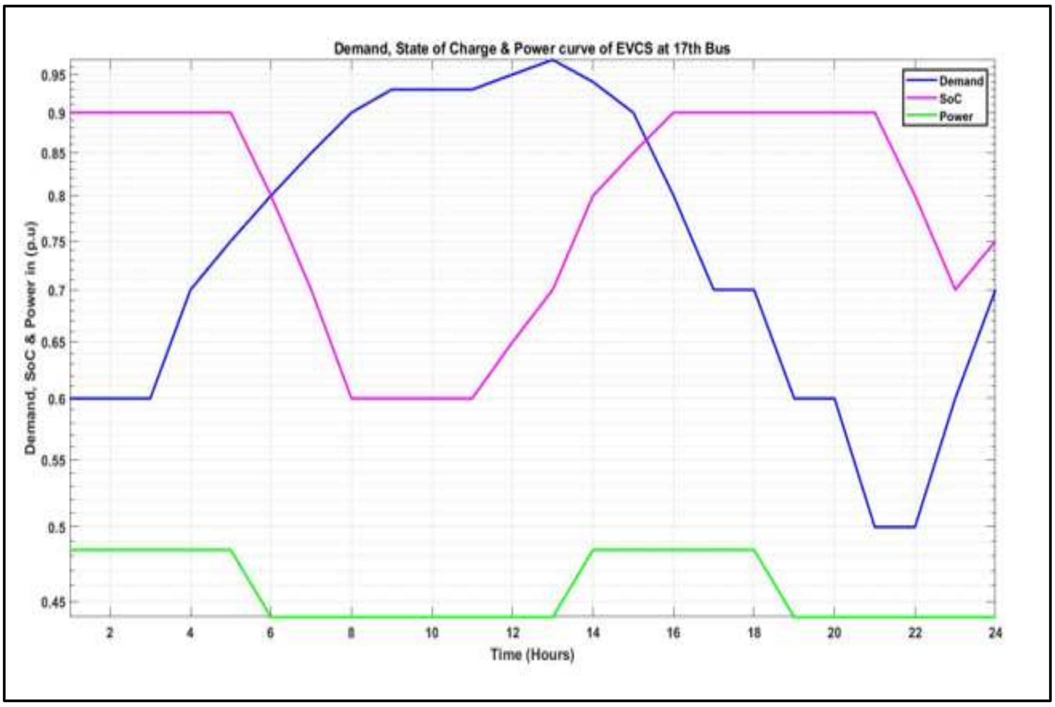


Fig. 6.3. SoC, Demand and Power curve of the EVCS at the 17th bus

The same procedure is employed for the remaining EVCS based on the constraints. The following Figures 6.4,6.5 and 6.6 shows the variation in Demand, SoC and Power in the EVCS for a 24-hour horizon at the remaining buses of 10,14 and 30.

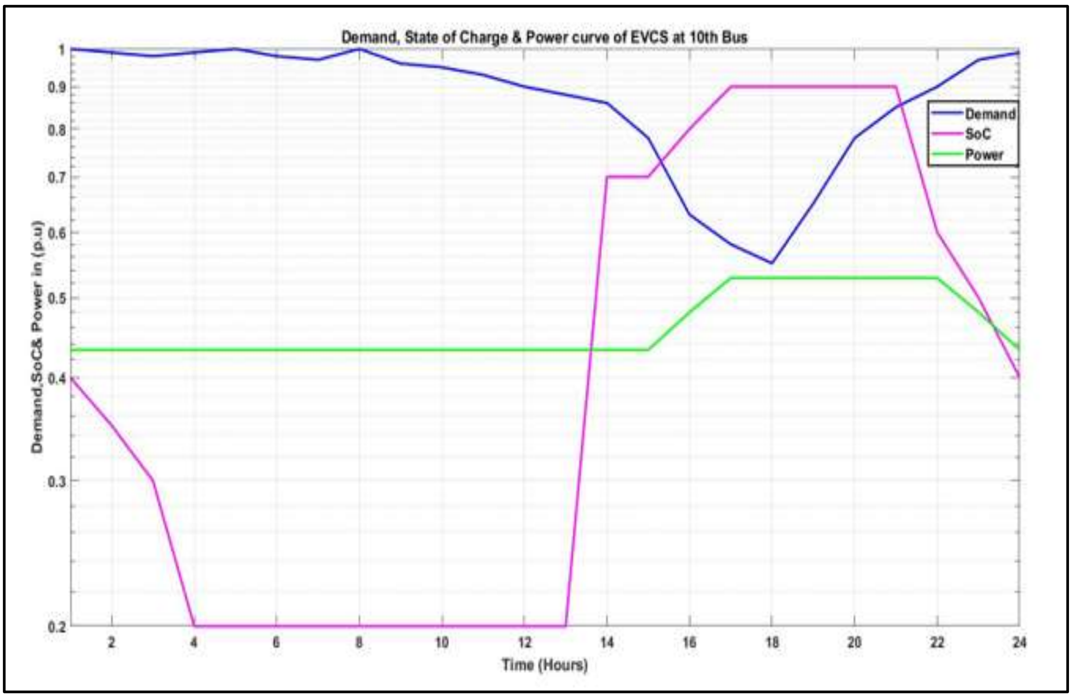


Fig. 6.4. SoC, Demand and Power curve of the EVCS at the 10th bus

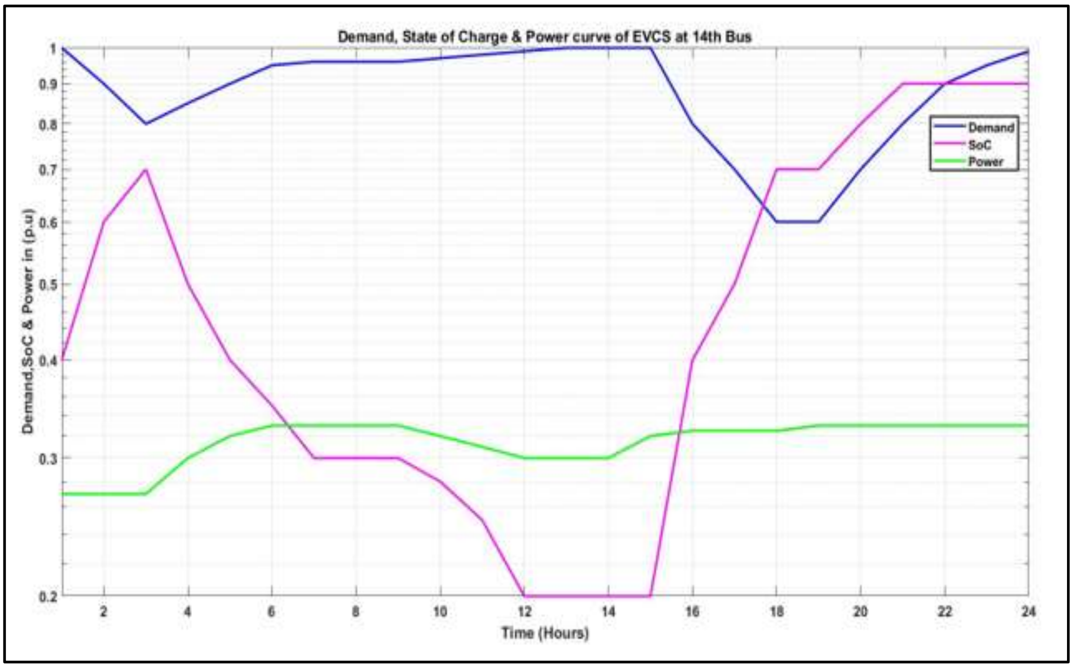


Fig. 6.5. SoC, Demand and Power curve of the EVCS at the 14th bus

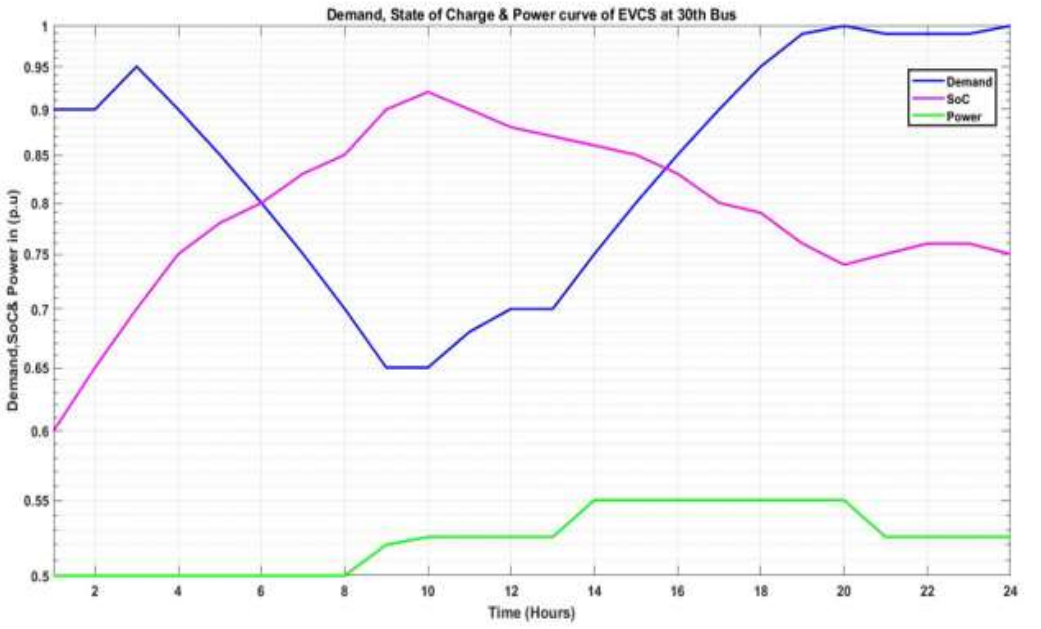


Fig. 6.6. SoC, Demand and Power curve of the EVCS at the 30th bus

6.6. Results and Discussion

The extreme peak load on the electric system mandates ineffective peak power facilities raises grid operational costs and brings system stability at risk. Peak shaving, or minimizing the amplitude of daily peaks, may save grid operators time and money while also lowering consumer prices. The economic benefit of the end-user of an EV is considered based on the demand, SoC and power over a period of time. For each hour, it is expected that there exist EVs in a certain region with known origin and destination, as well as initial SoC. The optimal hourly Electricity price supplied by the Energy Supplier (ES) to the EVCS for a 24-hour horizon is given in the following Figure 6.7.

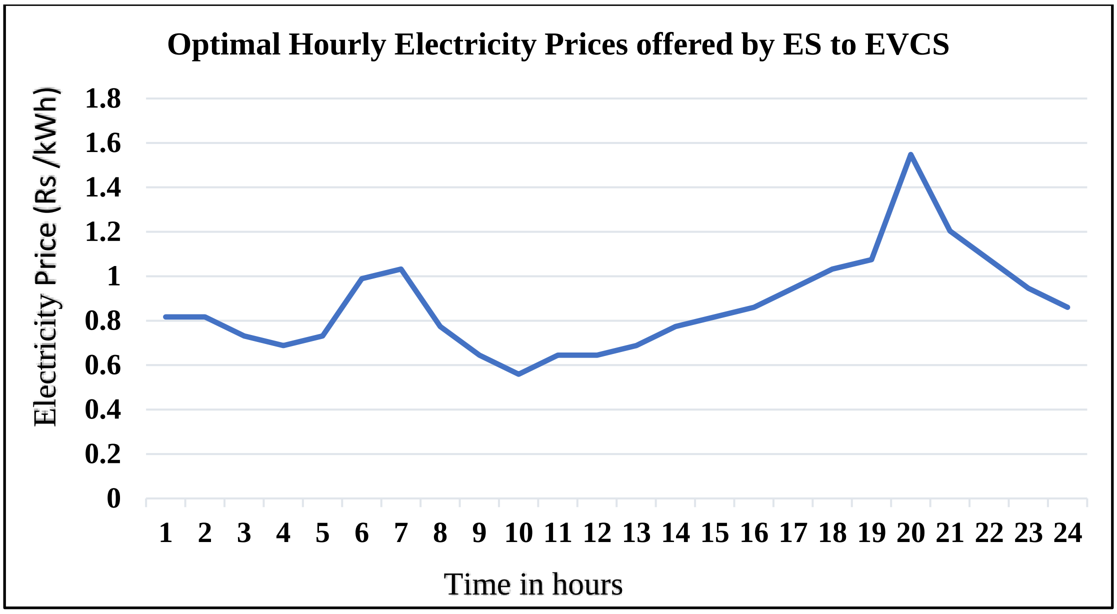


Fig. 6.7. Optimal hourly Electricity price supplied by the ES to the EVCS

The SoC at each hour based on the charging and discharging mode is represented by Eq.6.12 and Eq.6.13. The battery power is given by Eq.6.14. The battery is charged at its rated capacity, with the initial difference that exists between supply and demand as shown in Eq.6.15. The efficiency during charging and discharging is assumed to be 90 percent.

$$SoC(t)= SoC(t-1) +P_{batt}(t)*\Delta t*\eta c \quad \text{charging mode} \qquad (6.12)$$

$$SoC(t)= SoC(t-1)-P_{batt}(t)*\Delta t*\eta d \quad \text{discharging mode} \qquad (6.13)$$

$$P_{batt}(t)=SoC(t)*E \qquad (6.14)$$

$$\text{Initial Power}= \text{Generation-Load} \qquad (6.15)$$

Here

SoC(t) is SoC in present hour

SoC(t-1) is SoC in previous hour

ηc, ηd efficiency under charging and discharging mode

E is the energy of the battery in kWh

Δt is the respective time interval

The Limits for SoC are between 0.2 and 0.9 pu.

The mean of the Electricity price supplied by the ES to each EVCS is varied due to the intermittent load demand, at the 30th bus is 0.87 Rs/kWh.

Benefit factor=(Power/SoC) *Demand

Total electricity price at each hour in cents/kWh is given by

Ep= (Mean price of ES to EVCS) + (Benefit factor* Mean price of ES to EVCS)

Net profit earned in cents/kWh = Ep- Mean price of ES to EVCS.

Table 6.3 gives the data regarding the net benefit provided by the EVCS and end-user with its charging and discharging mode in a 24-hour horizon based on the smart charging methodology.

Table. 6.3. Net Profit earned by EVCS at 30th bus in the 24-hour horizon by G2V and V2G mode by smart charging.

Time in hrs.	Mode	Total electricity price in (Rs/kWh)	Net Profit per EV (Rs/ kWh)	Percentage increase per EV	No. of EVs connected to EVCS	Net Profit (Rs/ kWh)	Net Profit (Rs/kWh) in G2V Mode	Net Profit (Rs/kWh) inV2G Mode
1	3	1.51	0.647	42.86	6	3.884	3.884	0
2	3	1.461	0.598	40.91	5	2.988	2.988	0
3	3	1.449	0.586	40.43	7	4.1	4.1	0
4	3	1.381	0.518	37.5	5	2.589	2.589	0
5	3	1.333	0.47	35.27	4	1.881	1.881	0
6	3	1.295	0.432	33.33	6	2.589	2.589	0
7	3	1.253	0.39	31.12	5	1.95	1.95	0
8	3	1.218	0.355	29.17	4	1.422	1.422	0
14	2	1.277	0.414	32.42	4	1.656	0	1.656
15	2	1.31	0.447	34.11	3	1.34	0	1.34
16	2	1.349	0.486	36.03	5	2.431	0	2.431
17	2	1.397	0.534	38.22	7	3.738	0	3.738
18	2	1.434	0.571	39.81	4	2.283	0	2.283
19	2	1.481	0.618	41.74	6	3.71	0	3.71

The simulation is carried out for a cost-benefit analysis of each EVCS based on smart charging. Figure 6.8 shows the variation of cost analysis for EVCS at the 30th bus on each hour, with the EVs connected to the respective charging station by G2V and V2G methodology. The percentage increase in profit by G2V methodology is maximum at 1st hour with 42.8 percent and V2G mode is maximum at the 19th hour with 41.7 percent. The same process is employed for the remaining EVCS at the 10th,14th and 17th buses based on their charging and discharging mode of operation shown in Figures 6.9,6.10 and 6.11.

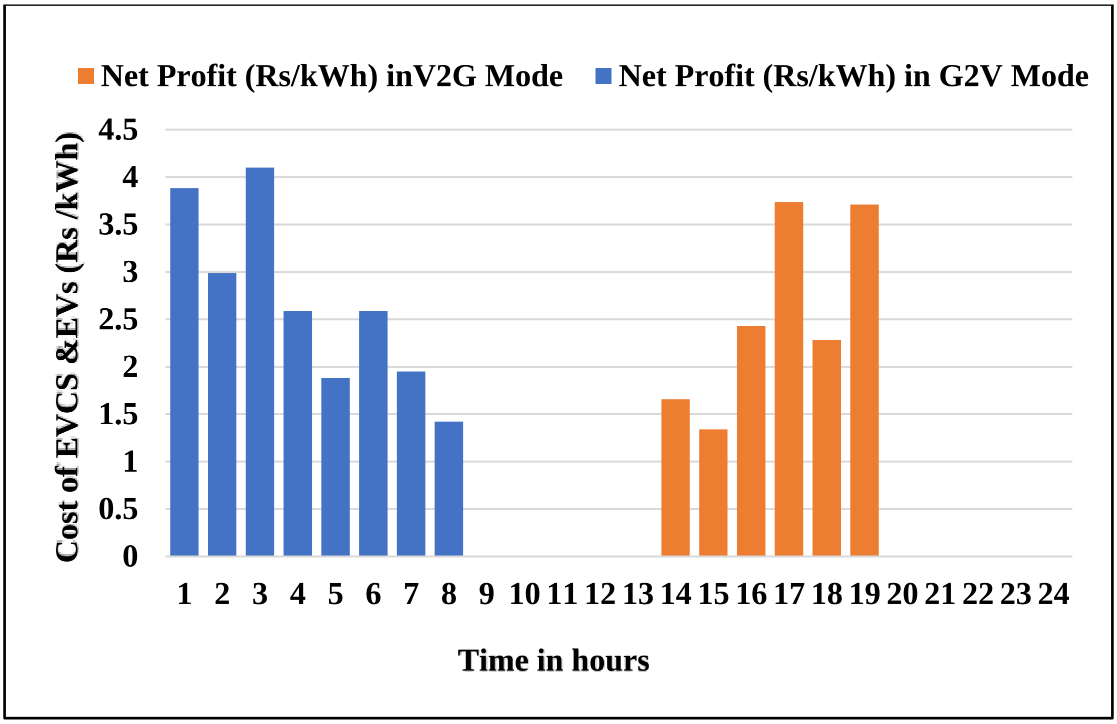


Fig. 6.8. Cost-benefit analysis of EVCS at 30th bus by G2V and V2G mode

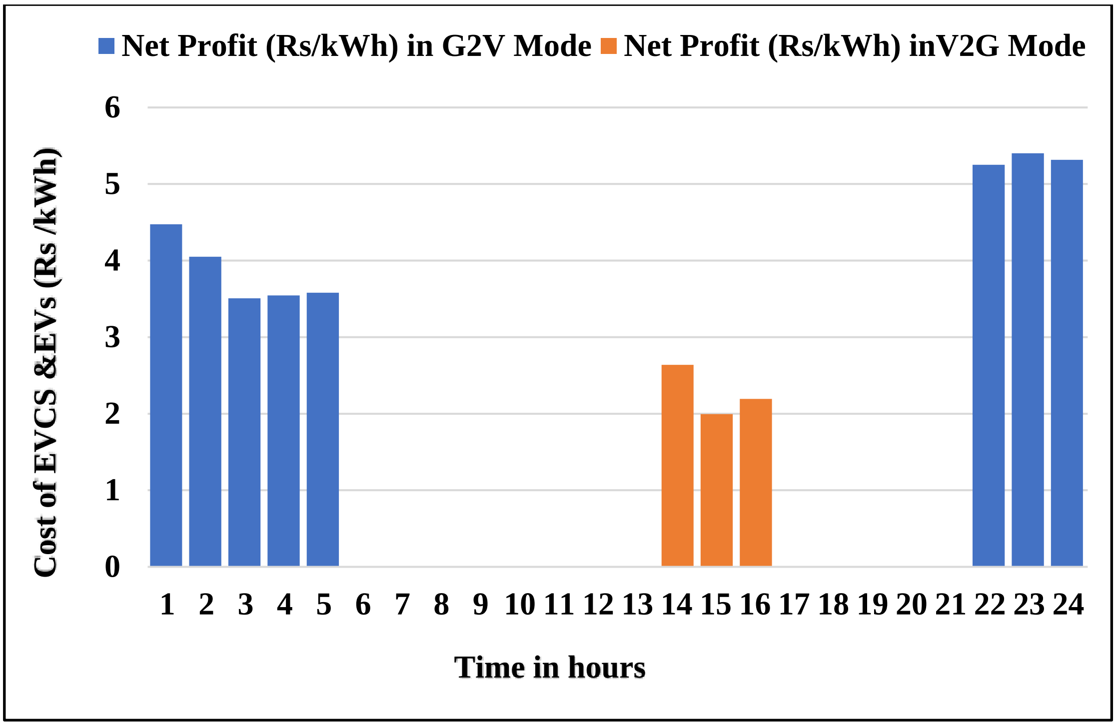


Fig. 6.9. Cost-benefit analysis of EVCS at 10th bus by G2V and V2G mode

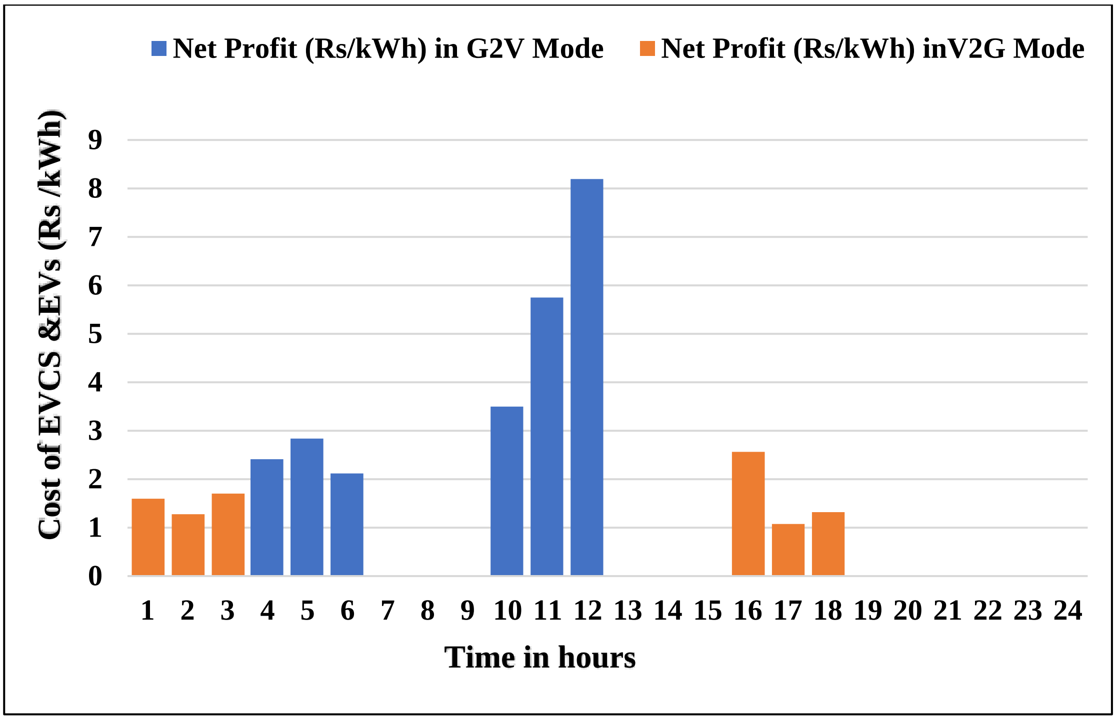


Fig. 6.10. Cost-benefit analysis of EVCS at 14th bus by G2V and V2G mode

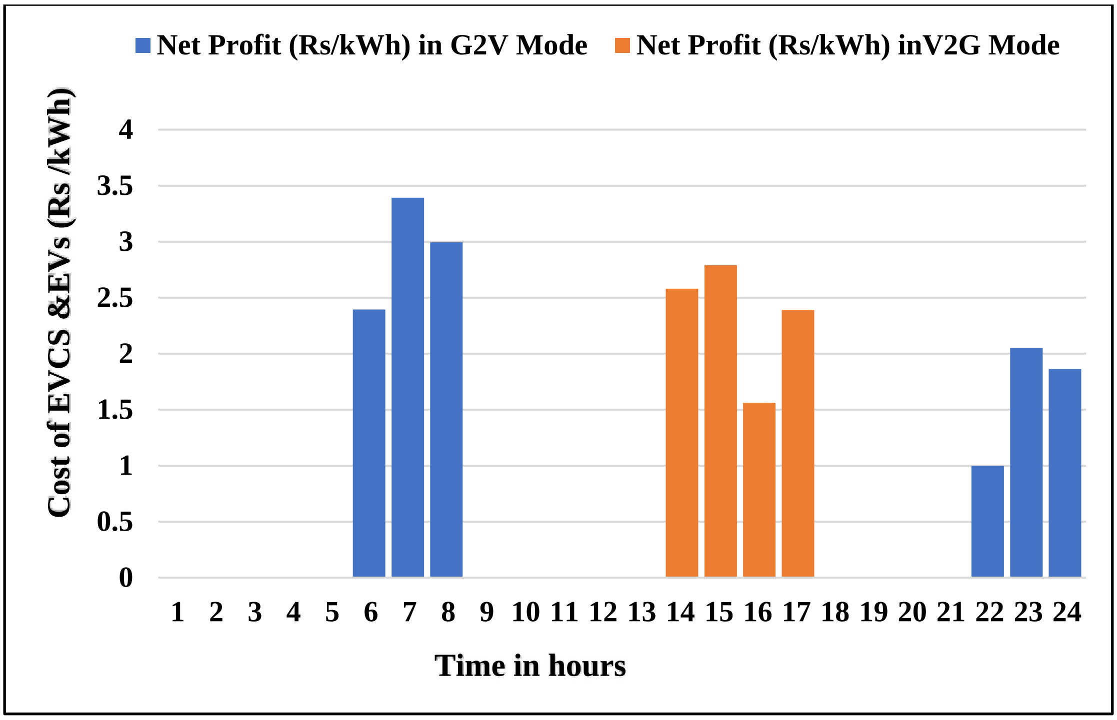


Fig. 6.11. Cost-benefit analysis of EVCS at 17th bus by G2V and V2G mode

The net profit earned by the respective EVs at the 30th bus undergoing V2G methodology during 14,15,16,17,18 &19th hours is shown in Figure 6.12. It is observed that the maximum profit earned at the 17th hour is 3.738 Rs/kWh. The same process is employed for the remaining EVCS at the 10th,14th and 17th buses based on its charging and discharging mode of operation shown in Figures 6.13,6.14 and 6.15.

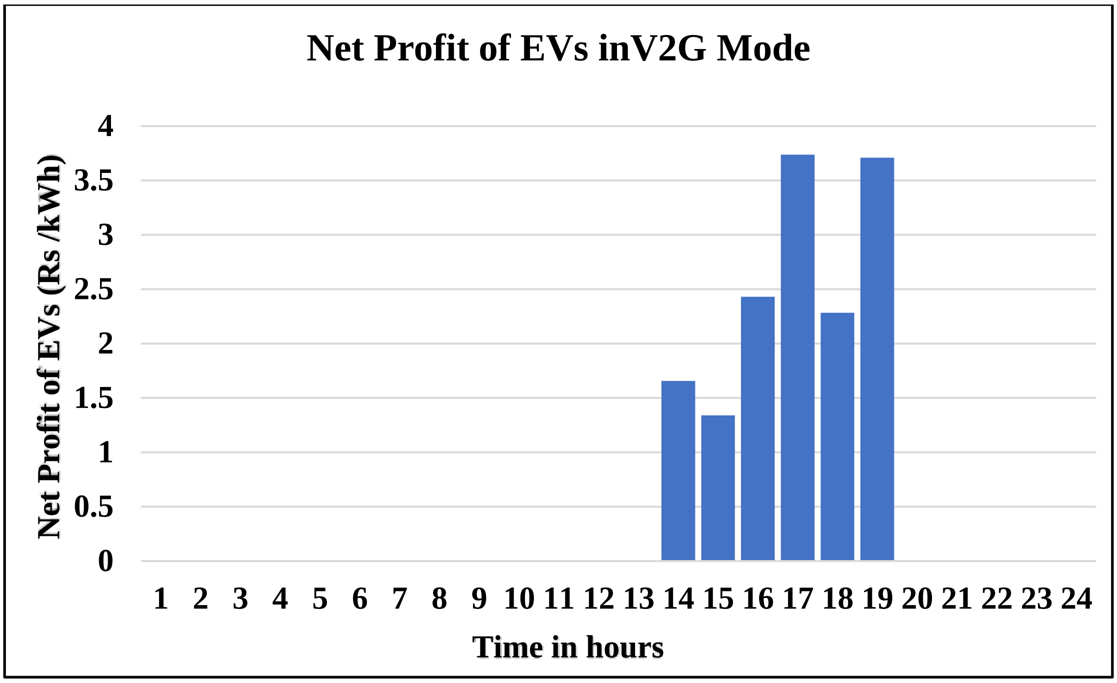


Fig. 6.12. Cost-benefit analysis of EVCS at 30th bus by V2G mode

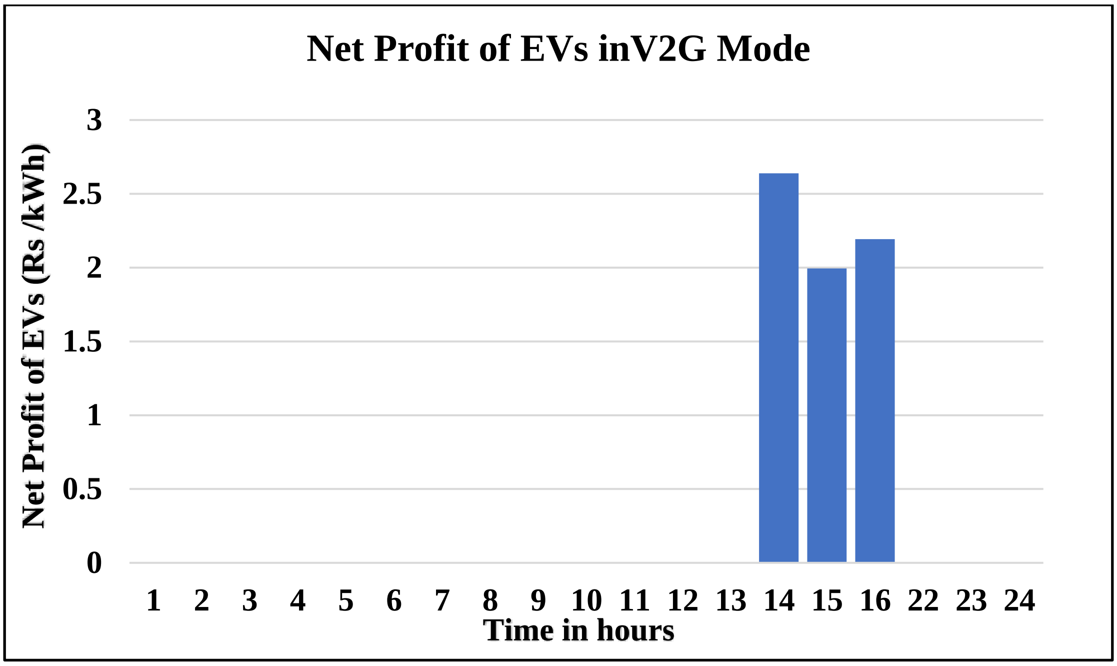


Fig. 6.13. Cost-benefit analysis of EVCS at 10th bus by V2G mode

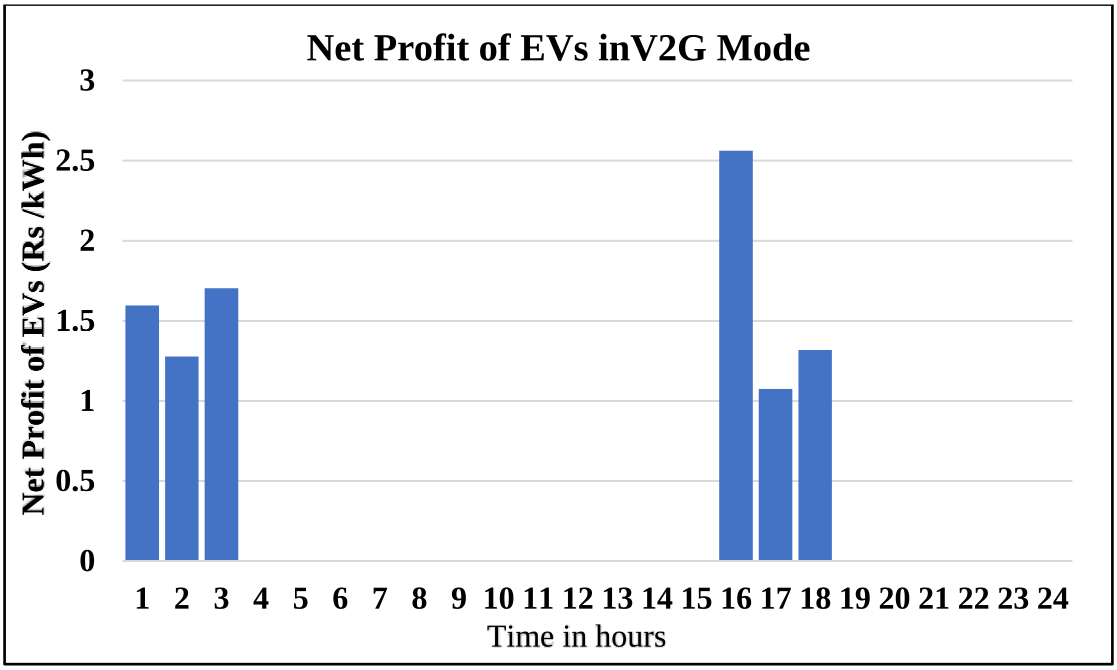


Fig. 6.14. Cost-benefit analysis of EVCS at 14th bus by V2G mode

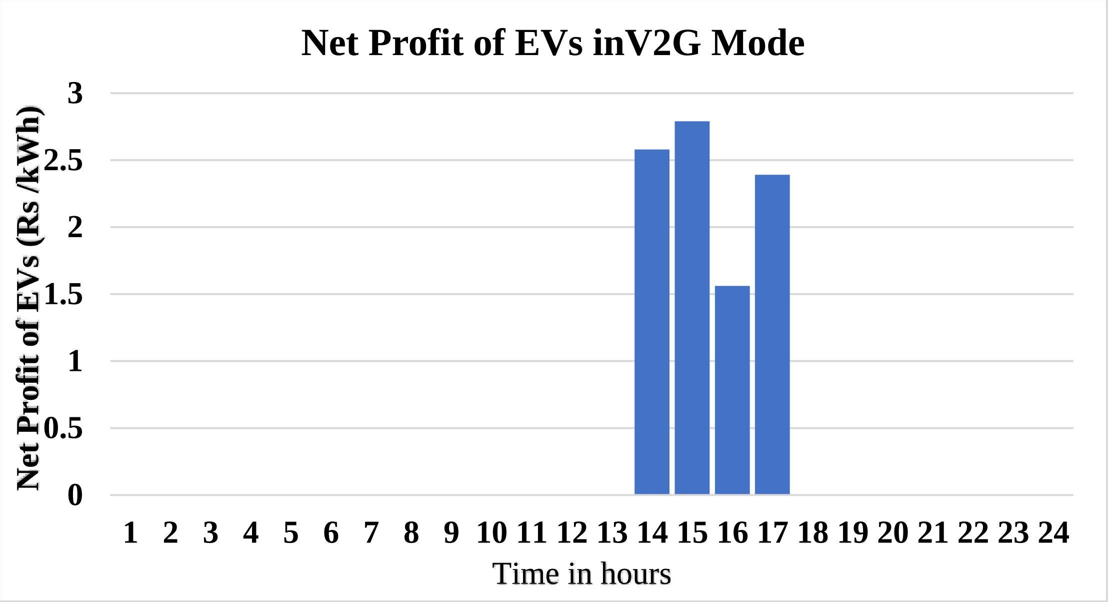


Fig. 6.15. Cost-benefit analysis of EVCS at 17th bus by V2G mode

The following table 6.4 shows the maximum percentage increase in the profit earned by the EVCS and end-user by smart charging at a particular hour of a day from the charging and discharging modes by G2V and V2G methodology.

Table. 6.4. Net Percentage increase per EV in G2V and V2G mode

EVCS at bus number	Time in hrs.	Mode (C/D)	Percentage increase per EV
10	5	3	68.354
	14	2	34.672
14	12	3	59.759
	1	2	40.299
17	8	3	39.759
	14	2	36.253
30	1	3	42.857
	19	2	41.74

6.6.1. Impact of losses and Voltage in the distribution system by V2G mode

With the simultaneous placement of 4 EVCS and 7 DGs in the IEEE 33 bus system, it is observed that the losses were reduced to 163kW. From the smart charging analysis, by the efficient utilization of the V2G methodology, the losses will be further reduced in the distribution system. Here the possibilities of some individual EVs in the respective EVCS will undergo the V2G technology with its bi-directional mode of operation and act as an additional DG and support for the intermittent nature of existing DGs integrated into the system. Also considering the combination of 2,3 and 4 EVCS respectively acting as a DG by V2G method using smart charging based on the load demand and power availability, the simulation is carried out and observed that the losses were reduced further compared with the optimal placement of EVs and DGs represented in table 6.5.

Table. 6.5. Loss comparison in the Distribution system in the proposed model

No. of Possible cases	**Real Power Losses (kW)**
With 4 EVCS	203
With 4 EVCS and 7 DGs	163
With 3 EVCS and (7+ EVCS 1) DGs	63.8
With 3 EVCS and (7+ EVCS 2) DGs	80.1
With 3 EVCS and (7+ EVCS 3) DGs	63.1
With 3 EVCS and (7+ EVCS 4) DGs	79.3
With 2 EVCS and (7+ EVCS 1&2) DGs	**40.1**
With 1 EVCS and (7+ EVCS 1,2&3) DGs	57.6
With (7+ EVCS 1,2,3&4) DGs	62

The real power loss variations of EVCS operating in V2G mode are shown in Figure 6.16 and Figure 6.17 for the possible cases respectively.

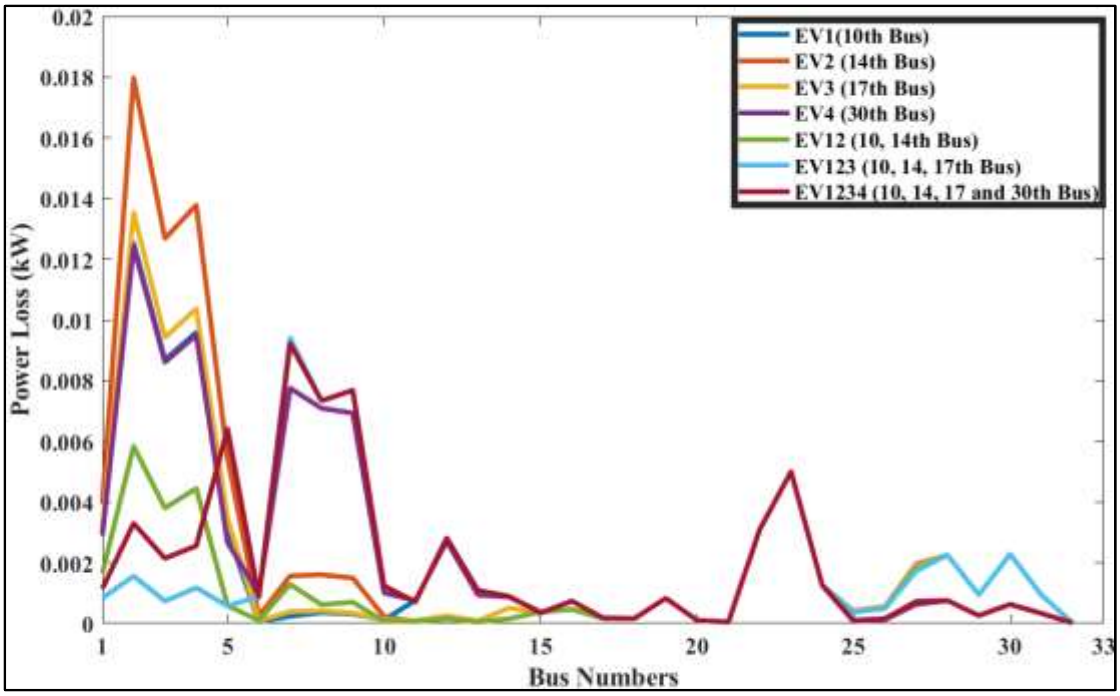


Fig. 6.16. Power Loss of EVs and DGs with various cases operating in V2G mode.

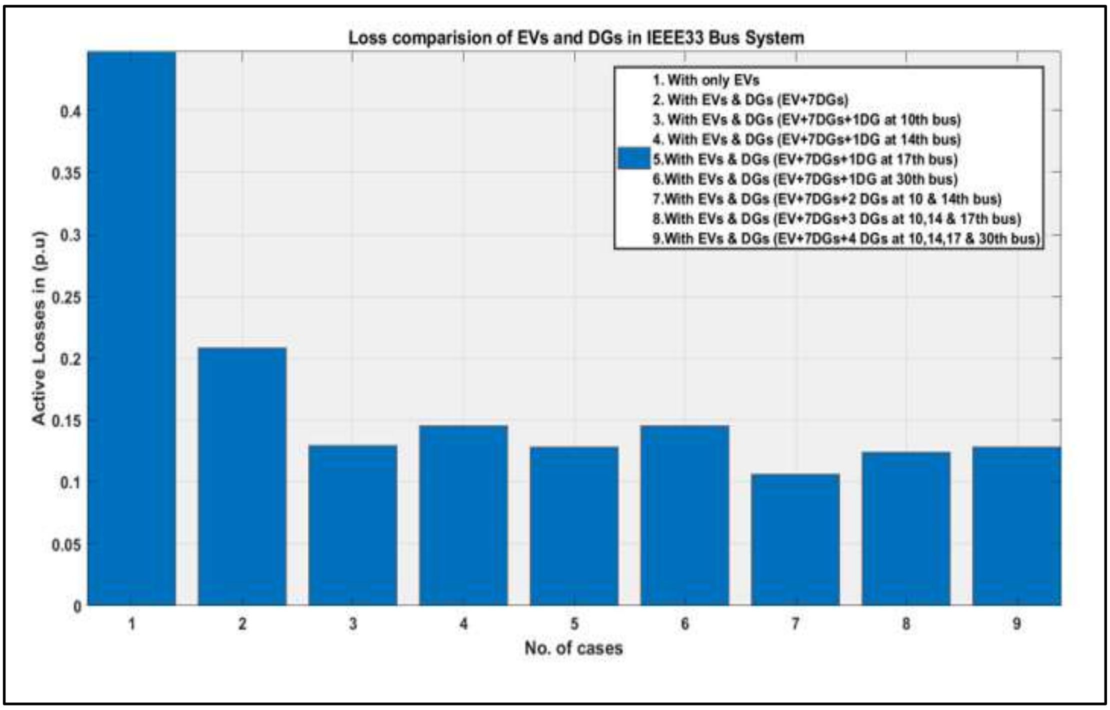


Fig. 6.17. Power Loss of EVs and DGs with various cases operating by V2G mode in PU.

The simulation is carried out for the simultaneous installation of 4 EVCS and 7 DGs in the IEEE 33 bus system, also considering each among 4 EVCS and the combination of 2,3 and 4 EVCS acting as a DG by V2G method using smart charging, it has been noticed that the voltage profile is further enhanced, when compared with the optimal placement of EVs and DGs shown in Figure 6.18.

Table. 6.6. Loss comparison in the Distribution system with the existing work

Reference	**Year**	**Type of Bus**	**Methodology**	**No. of EVCS**	**No. of DG's**	**Active Power Loss (kW)**
Mohd Bilal et. al., [101]	2021	IEEE 33 Bus	HGWOPSO	2	1	103.6
				2	2	85.5
Devisree Chippada et. al., [76]	2022	IEEE 33 Bus	PSO	1	3	72.78

Venkata K. Babu Ponnam et. al., [54]	2020	IEEE 33 Bus	HHO	3	3	94.4
Proposed model	--	IEEE 33 Bus	AOA	4	7 with V2G	40.1

From the table 6.6, the proposed model is compared with the existing literature survey for the simultaneous placement of EVCS and DGs integrated with the IEEE 33 bus system. It was observed that with the simultaneous integration of EVCS and DGs along with V2G method, the losses were further reduced to 40.1kW for the stable and reliable operation of the DS.

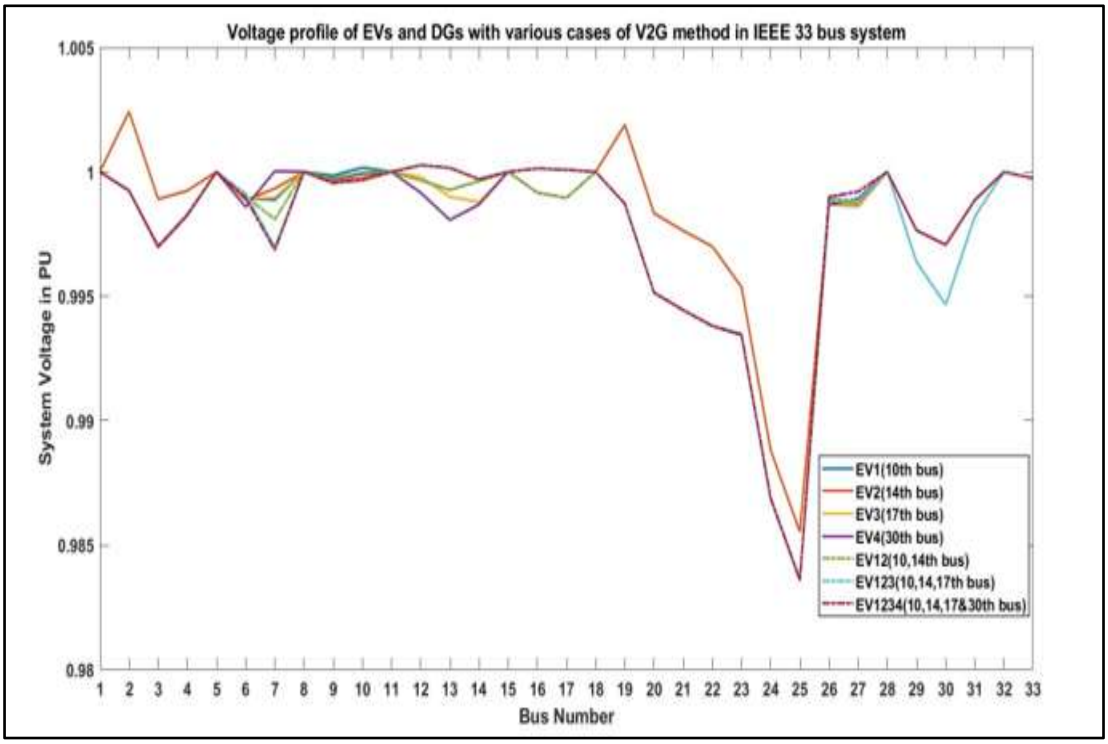


Fig. 6.18. Voltage Profile of EVs and DGs with various cases operating in V2G mode

6.7. Chapter Summary

By the simultaneous placement of EVCS and DGs in the IEEE 33 bus system, in this chapter, the simulation results show that by the effective utilization of the V2G method with smart charging analysis, the overall losses with (7+EVCS1&2) DGs were reduced to 40.1kW i.e., reduced to 75.4% and improved the voltage profile, compared to the losses with EV and DG of 163kW. Due to the stochastic nature of the load demand for EVCS, the simulation results show that the smart utilization of charging, discharging and neutral operation with time, based on the SoC of the battery and Demand will make the distribution system stable and enhance the reliable operation of the grid. In addition, the cost-benefit analysis based on the 24-hour horizon was also carried out for G2V and V2G methodology in this chapter, the simulation results show that by charging the EV during the off-peak times and discharging the EV battery based on the SoC level and available power at the peak demand will lower the price level of charging as well as provide benefits to the end-user.

CHAPTER 7

CONCLUSION & FUTURE SCOPE

7.1. Conclusion

The rapid penetration of the EVs in the market will lead to a greater number of EVCS connected to the distribution network for charging purposes resulting in network performance degradation due to high power losses, system voltage violations and network asset congestion. As a result, it's critical to effectively regulate the supply due to the increase in the charging demand by the network. In the proposed research an IEEE 33 bus system was used to test the efficacy of the system. The inappropriate forecasting of EVCS has a detrimental effect on the distribution system, so firstly the optimal positioning of EVCS is carried out in the distribution system. LSF approach was considered for the optimal siting of EVCS. PSO and HHO algorithms are chosen for the placement of EVCS, the simulation results were compared with the conventional system. Finally, a reliability test comparison was made on conventional, PSO and HHO for IEEE 33 bus system and concluded that the four buses were identified for the optimal placement of EVCS, which can balance the corresponding buses based on their load demand (during off and peak loads).

Due to the growing demand for electrical energy with the addition of EV load to the existing base load on the system, DG sources have become more significant in distribution networks. The improper planning of DGs will influence on power distribution system losses and voltages. Hence for the proper positioning of DGs in the distribution system, the LSF approach is considered to identify the weak buses and the analysis is tested in IEEE 33 bus system for the optimal placement of DGs, where seven buses are identified for the installation of DGs in the DS.

With the simultaneous placement of EVCS and DGs in the IEEE 33 bus system, the simulation results have shown that by considering the EV load to the existing base load in the system, the losses were raised to 374kW and there was a reduction in the voltage profile. With the integration of DG into the EV-connected grid system, the losses were reduced to 163kW, by the enhancement of the voltage profile. Also, for a

24-hour load profile, the loss estimation was carried out and the simulation results are showing that the losses were reduced due to the integration of DG into the EV-connected grid system. Finally, the operation of the respective DG over a period of time is done by the simulation through a dynamic programming procedure and the optimal scheduling of the total load (based load and EV load) on a 24-hour load setting was done by AOA, showing that by the integration of DG to the grid-connected system, reducing the stress on the system, thus making the stable and reliable operation of the DS.

Various charging techniques, in addition to the method of grid integration, are now being developed to minimize the potentially adverse implications of EV charging. Due to the stochastic nature of the DGs and EV load, the integration of DGs alone into the DS may reduce power losses while simultaneously raising the voltage level but not up to the extent which might have an impact on the system stability. So, there is a need to go for an alternate method where the EVs can act as an energy source with its bidirectional mode of charging and discharging operation from the DS. The proper planning of EVs to charge and dis-charge based on the intermittent load demand is important and the effective utilization of V2G plays a vital role in the stable operation of the DS. Due to the unpredictable nature of the EV load demand, SoC over a period of time, the identification of an offload and peak load during a 24-hour horizon was carried out and analyzed the mode of operation (Charging, Discharging and neutral operation) of EV from the smart charging system. However, for the simultaneous placement of EVCS and DGs for an integrated grid-connected system, the simulation results based on the operational constraints of SoC, load demand and power for the proposed V2G smart charging framework reduces the network power losses, further compared to the combination of EVCS and DGs acting alone and enhanced the voltage profile on various possible cases, which were tested for an IEEE 33 bus radial system. In addition, the cost-benefit analysis based on the 24-hour horizon was also carried out for G2V and V2G methodology, the simulation results show that by charging the EV during the off-peak times and discharging the EV battery based on the SoC level at the peak demand to reduce the charging cost as well as provide benefits to the end-user.

7.2. Future Scope

Furthermore, the research work that has been accomplished so far in the field of Optimal Scheduling of PHEVs with DES using Meta-Heuristic Techniques may be extended in the following directions:

- An investigation by the operation of the grid in the presence of energy stored in the battery takes into account the degradation of the batteries.
- Scheduling of energy stored in the batteries for EVs in the V2G model with the integration of DGs in the distribution system.
- Estimating the load demand by considering the driving behaviour of the consumer and various levels of EV charging.
- Reduction in the cost for EVCS and DGs integrated grid-connected system.
- Further, the same analysis of research can be extended to various test systems.

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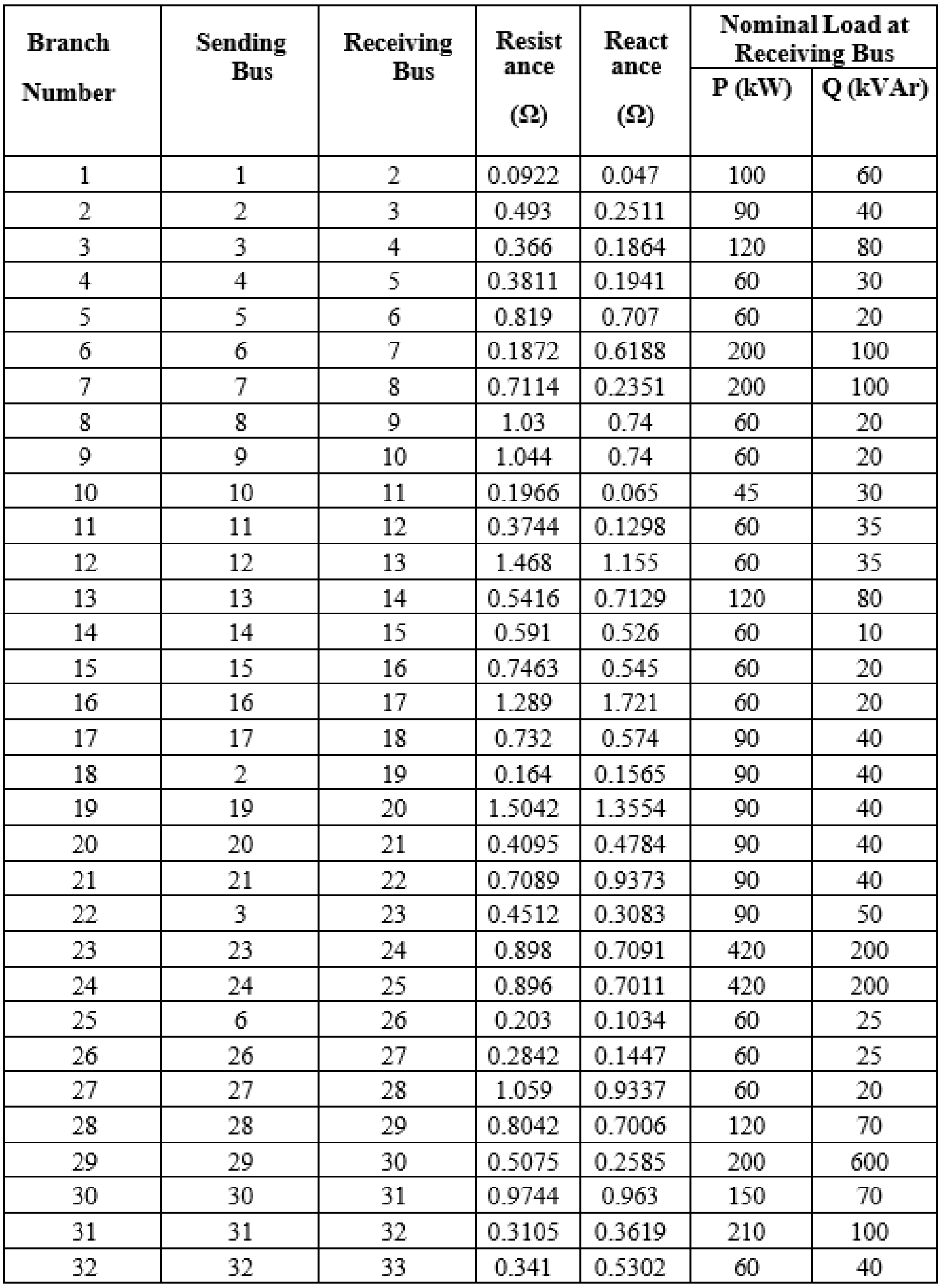
APPENDICES

A.1. The System data for a standard IEEE 33 bus system is given in the following table

Table. A.1. Radial distribution network system data



Branch Number	Sending Bus	Receiving Bus	Resistance (Ω)	Reactance (Ω)	Nominal Load at Receiving Bus	
					P (kW)	Q (kVAr)
1	1	2	0.0922	0.047	100	60
2	2	3	0.493	0.2511	90	40
3	3	4	0.366	0.1864	120	80
4	4	5	0.3811	0.1941	60	30
5	5	6	0.819	0.707	60	20
6	6	7	0.1872	0.6188	200	100
7	7	8	0.7114	0.2351	200	100
8	8	9	1.03	0.74	60	20
9	9	10	1.044	0.74	60	20
10	10	11	0.1966	0.065	45	30
11	11	12	0.3744	0.1298	60	35
12	12	13	1.468	1.155	60	35
13	13	14	0.5416	0.7129	120	80
14	14	15	0.591	0.526	60	10
15	15	16	0.7463	0.545	60	20
16	16	17	1.289	1.721	60	20
17	17	18	0.732	0.574	90	40
18	2	19	0.164	0.1565	90	40
19	19	20	1.5042	1.3554	90	40
20	20	21	0.4095	0.4784	90	40
21	21	22	0.7089	0.9373	90	40
22	3	23	0.4512	0.3083	90	50
23	23	24	0.898	0.7091	420	200
24	24	25	0.896	0.7011	420	200
25	6	26	0.203	0.1034	60	25
26	26	27	0.2842	0.1447	60	25
27	27	28	1.059	0.9337	60	20
28	28	29	0.8042	0.7006	120	70
29	29	30	0.5075	0.2585	200	600
30	30	31	0.9744	0.963	150	70
31	31	32	0.3105	0.3619	210	100
32	32	33	0.341	0.5302	60	40

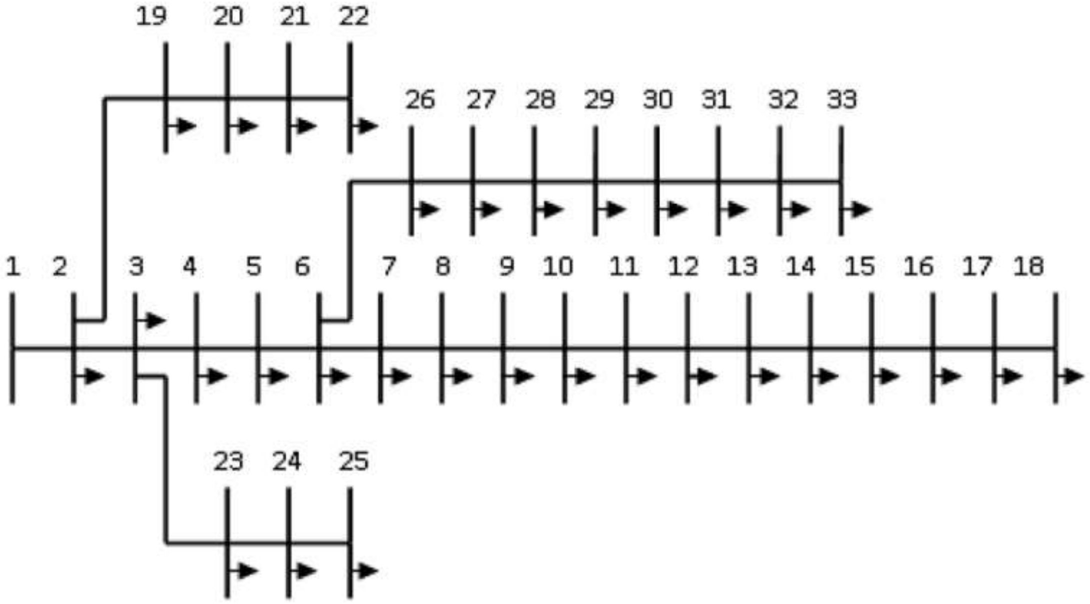


Fig. A.1. Standard IEEE 33 bus radial distribution system

LIST OF PUBLICATIONS

The publications listed below are the contributions made to this study. It consists of book chapters, presentations at conferences and peer-reviewed journals (Published/Under Review).

1. Naresh Kumar Golla, Suresh Kumar Sudabattula, Velamuri Suresh "Optimal Placement of Charging Station and Distributed Generator along with Scheduling in Distribution System using Arithmetic Optimization" **INTERNATIONAL JOURNAL of RENEWABLE ENERGY RESEARCH,** Vol.12, No.2, June 2022, https://doi.org/10.20508/ijrer.v12i2.12964.g8480. **(SCOPUS, ESCI) – Published.**
2. Golla, N.K., Sudabattula, S.K., Suresh, V. (2022). "Optimal placement of electric vehicle charging station in distribution system using meta-heuristic techniques". Mathematical Modelling of Engineering Problems, Vol. 9, No. 1, pp. 60-66. https://doi.org/10.18280/mmep.090108. **(SCOPUS) – Published.**
3. Dharavat N, Golla NK, Sudabattula SK, Velamuri S, Kantipudi MVVP, Kotb H and AboRas KM (2023), Impact of plug-in electric vehicles on grid integration with distributed energy resources: A review. **Front. Energy Res**. 10:1099890. doi: 10.3389/fenrg.2022.1099890 - **(SCI) Published**
4. "Impact of Vehicle-to-Grid on the Distribution Grid with Energy Techno-Economic Benefits from Smart Charging" submitted to **Hindawi (SCI)-Under Review.**
5. "An IoT Based Approach for EV Charging Station Locator" Presented at RDCAPE 2021, Amity University, UP. (Conference, IEEE) – **Presented.**
6. "Impact of Plug-in electric vehicles on grid integration with distributed energy resources: A comprehensive review on methodology of power interaction and scheduling" Presented at ICRSETM-2020, Vaagdevi College of Engineering, TS. (Conference, Materials today proceedings) – **Presented.**

7. “Energy Management Strategy for Plug-in Electric Vehicle with DFIG System” Presented at ICICS 2020, Lovely Professional University, Punjab. (Conference, Taylor and Francis) – **Presented.**
8. “Cost Benefit Analysis on Electrical Vehicle Charging Station using the Vehicle to Grid Technology from Python language” submitted at Flex EV 2022, Manipal University, Jaipur. (Conference, LNEE Springer Book series)- **Presented.**
9. “Impact of Electric Vehicle Charging Station in Distribution System using V2G Technology”, submitted at CIS 2022, CHRIST (Deemed to be University), Bengaluru. (Conference, LNEE Springer Book series)- **Presented.**
10. “Energy Management Strategy for Plug-in Electric Vehicle with DFIG System”, Submitted to Taylor and Francis Book Chapter, Intelligent Circuits and Systems. (Book Chapter) – **Published**.
11. N. K. Golla, S. K. Sudabattula and V. Suresh, "An IoT based approach for EV charging Station Locator," 2021 4th International Conference on Recent Developments in Control, Automation & Power Engineering (RDCAPE), 2021, pp. 422-425, doi: 10.1109/RDCAPE52977.2021.9633642. **IEEE (SCOPUS) Published.**

LIST OF WORK SHOPS

1. Attended for three days online workshop on title “**Electric Vehicle Technology; Challenges, Analysis and Development**” organized by Department of Electrical and Electronics Engineering, Presidency University, Bengaluru held from 26th - 28th February 2021.
2. Attended for one-week online workshop on title “**Renewable and Clean Energy**” organized by Department of Electrical Engineering, “National Institute of Technical Teachers Training and Research” NITTTR, Chandigarh held from 18th – 22nd April 2022.
3. Attended for Five days online workshop on title **"Electric Vehicle Technology: Challenges and Opportunities"** organized by Department of Electrical and Electronics Engineering, Sasi Institute of Technology & Engineering, Tadepalligudem, Andhra Pradesh, India from 19 to 23 December 2022.