Optimal Placement of Charging Station and Distributed Generator along with Scheduling in Distribution System using Arithmetic Optimization Algorithm

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Received: 28.04.2022 Accepted:10.05.2022

Abstract- Transport sector electrification is probably the most viable choice for minimizing transport emissions and so Plug-in Electric Vehicle (PEV) growth is expected to increase dramatically for the decades to come. The massive use of electric vehicles corresponds to a rise in the number of charging stations, which has a significant effect on the electrical grid. The integration of Distributed Generators (DGs) with the EV charging station and the optimal scheduling of DGs in the system for an intermittent load demand is a major problem. In this paper an optimal placement of EV Charging Station (EVCS) and DGs in IEEE 33 bus system was proposed by using Loss Sensitivity Factor (LSF) approach and optimal Scheduling of DGs for a 24-hour load profile is carried out by Arithmetic Optimization Algorithm (AOA). The proposed hybrid model attempts to schedule both the EVs and DGs for the reduction of the losses in the power and achieve an improved voltage profile. Due to the stochastic nature of EV load demand and DGs in the distribution system, several analyses were conducted to analyse the persistence of the proposed methodology. Finally, the optimal scheduling of DG in 24-hour load setting for an IEEE 33 bus system is presented.

Keywords Electric Vehicle Charging Station (EVCS), Distributed Generator (DG), Arithmetic Optimization Algorithm (AOA), Optimal Scheduling.

1. Introduction

Due to the depletion of the fossil fuels and the environmental consequences connected by its usage, the number of electric vehicles (EVs) are expected to grow dramatically over the upcoming years. The global electrification of transportation has been encouraged due to the economic and environmental difficulties associated with fossil fuel transportation. As a result, initiatives to reduce polluting emissions in cities have increased and are being coordinated. As per current trends, electric vehicles (EVs) are a promising technology for road transportation, because of its technological and environmental advantages; so, the EVs are becoming a viable substitute for conventional vehicles. In contrast to internal combustion engines, Electric vehicles are becoming more popular due to its enhanced energy efficiency and reduced environmental effect [1]. The increasing penetration of electric vehicles has resulted in a rise in the number of charging stations, which has a significant influence on the electrical grid. Various charging techniques and grid integration approaches are being developed to reduce the negative impacts of EV charging simultaneously enhancing the potential advantages of EV grid integration. The present available energy is not able to meet the demand, in the future an electric vehicle consumes more energy than a typical household appliance, Industries etc. Voltage drops and power flow violations on the Distribution System (DS) may exist as a result of vehicle charging. In the case of unregulated charging, DS peak load demand will coincide with EV charging, causing a load effect on the distribution network. Due to growing demand for electrical energy, Distributed Generation (DG) sources have become more significant in distribution networks (DNs). The placement and size of DGs will have an influence on power distribution system losses, voltages. The improper planning of DGs harm the distribution system, determining the best position and size of DGs in the DNs will experience a severe problem by the Distribution system operators. By overcoming the difficulties created by their fluctuating nature, a proper mix of solar, wind and Battery Energy Storage System (BESS) based DGs with the coordinated charging strategies may enhance the effectiveness and sustainability of the system. Due to the unpredictable nature of the EV load demand on various charging patterns, the optimal scheduling of DGs plays a vital role for effective operation of the DS. The formulation of a multi-objective optimization problem having, optimal placement of DG and its optimal scheduling are necessary with the integrated distribution network for stable and reliable operation of the DS.

2. Literature review

In this study [2] the use of electric vehicles and batteries for capturing the fluctuations of energy prices and load demands is proposed and the framework is focused on developing a long-term and efficient method for managing the resource requirements. A novel approach for various uncertainties related to electricity markets, such as wind turbine deployment and solar system demand is presented. Hybrid energy sources making use of various resources such as solar, wind, and storage are more efficient than traditional approaches. A test case is also carried out. to study the optimal capacity of these systems. The model that has been proposed using a mixed-integer linear programming problem (MILP) to determine the capacity of solar, wind, and battery electric storage systems (BESSs). The outputs of the problem are then analysed and optimized. The rapid growth of the EV penetration is expected to create various challenges for utilities as they try to accommodate the increasing number of vehicles [3]. This paper explores the various strategies that utilities can use to charge EV's during peak times. The factors that determine the impact of charging on a DS are analysed. The paper then explores the different charging modes and their potential impact on the DS at a given level. A simulation of a residential DS is also conducted. The paper aims to develop a novel method to numerically estimate the amount of time it takes for electric vehicles to charge and to analyse the effects of charging on a DS under different scenarios [4]. The proposed method would allow utilities to identify and manage the load impacts of charging on their networks in a robust and realistic manner. The increasing acceptance of electric vehicles in the transport industry has raised concerns regarding their effect on the electricity market. The placement of EV charging stations and DGs at the optimal places to reduce the loading impact of electric vehicles on the radial DS. The paper tackles the issues of the average voltage deviation index and actual power losses [5]. The paper's main contribution is to identify the optimal locations of EVCSs and to consider the various factors that affect their operation, such as system bus voltage regulation and DS losses. The increase in the number of plug-in electric cars (PEVs) is expected to have a substantial influence on the DSs performance. This paper explores to minimize the effects of charging behaviour and power loss on the system by integrating DGs into radial DSs. A multi-objective function is formulated to analyse the performance of the system. The results are analysed using particle swarm optimization and butterfly optimization techniques [6]. This paper aims to address for a 24-hour load pattern, where there is a daily active power loss as well as a recurrent voltage variance. It also presents a backward-forward load flow model. The random charging of EVs can cause various issues when compared to the grid's regular operation. This issue might be solved through the DGs for its proper placement and sizing. This article aims to improve the planning and selection of charging stations for EVs by proposing an enhancement model [7]. The presence of charging stations increases the system's losses due to the lack of charging infrastructure. The objectives of the paper include reducing the losses associated with the integration of DGs, so as to increase the number of charging stations to enhance Green Transportation. This paper tackled the issue of optimizing the size and positioning of FCS and DGs in a proposed approach with the proportion of EVs as a limitation in each zone [8]. The proposed problem is a mixed integer non-linear algorithm known as the MINLP. It is formulated to address the loss of an EV consumer, the loss of network power and the expense of development of a DS. This paper [9] presents a study on the power grid, the capacity of charging stations and the volatility of electricity prices using a couple of simple models, one of which is a two-point estimate method. It then compares the coefficient of contribution for various DG units and EVs to maximize their benefit. The NSBSA algorithm was used to optimize the participation rate of charge stations and wind generation units in the DS. The purpose of this study is to improve the credibility of the findings by integrating the Hybrid Vehicle Charging Station (VCS) and the Renewable DGs (RDG) simultaneously. The objective of this paper [10] is to reduce the Energy Not-Sufficient (ENS) to the end users. It has been established that the optimal place for both charging station and RDG is identified. A hybrid algorithm-based method known as HNelder-Mead Cuckoo Search is proposed to minimize the ENS by taking the advantages of both RDG and VCS. The availability of charging stations depends on the location of the charging station. The voltage deviation and energy loss of the network are also affected by the location of charging stations. This paper [11] presents the solution to the problem of determining the optimal location of charging stations by using Harris Hawks optimization methods and differential evolution. It has been successfully implemented using Monte-Carlo simulation. The simultaneous allocation of solar DG and EVCS is a complex problem that can be solved using soft-computing techniques. This paper aims to integrate solar power, wind power, and rechargeable batteries transforming it into a DC microgrid-based on EVCS. The objective is to provide enough, energy which is used to charge the automobiles during overcast. Connection to the power grid can also be used to export power when the system's generation exceeds its demand [12]. Second–life lithium–ion batteries are proposed to be included in the system as an energy storage device and backup energy source in the case of a grid outage. This paper [13] presents a well-balanced mix of three different types of EV chargers for minimizing the electricity consumption and improving the efficiency of the charging process. The study also considers the effects of solar power on the EVs load. The proposed method is based on the particle swarm optimization (PSO) technique to find a solution to the stochastic constrained issue. This paper [14] aims to boost fast-charging station profitability by reducing the excess energy consumption associated with them. It also includes a renewable energy storage system. The profitability of electric car charging stations is computed using a Monte Carlo approach and a genetic algorithm. The latter achieves its goal by taking into account the DGs and the demand. After that, a genetic algorithm (GA) is used to optimize configuration and management of an electric vehicle fast-charging station. It finds for the best option on increasing profits as measured by net present value (NPV). This study [17] presents a charging/discharging methodology for microgrids with electric vehicles. Micro Grid uses multi-objective optimization to reduce operational costs and grid vulnerability while improving the usage of solar (PV) power and EVs as energy storage systems (ESSs). The base load and PV power generation are evaluated and combined for energy monitoring in our strategy to maximize the utility of EV discharged power. The charging amount of energy required for EVs at home and in public places was modelled using Monte Carlo Simulation (MCS) on real data in this article [18]. The findings revealed that instead of charging at home, lower peak demand in public locations can meet the charging need. For a current-fed resonate compensated network with power sharing and voltage doubler [19], this study compares the efficiency of a modified wireless power transfer (WPT) system with a current-fed dual-active half-bridge converter configuration to a complete bridge converter. The numerous approaches for wireless charging an EV battery are thoroughly reviewed in this study [20]. Static EV charging and dynamic EV charging are two different strategies for delivering electricity in wireless mode to charge the EV battery. This study also covers the design and comparable circuit analysis of a static wireless EV battery charging system. By interconnecting the utility grid with the battery charging system, the proposed method [21,22] allows for uninterruptible charging of a solar (PV) fed plug-in electric vehicle (EV) battery charging system, regardless of solar irradiation conditions. The system includes a bidirectional cycloconverter (BDCC) to use the power system as a source or sink during various operation modes, which are dependent on solar power supply. To validate the efficacy, the proposed system was simulated using PSIM simulation software and an experimental prototype was developed and analysed for various modes of operation. The stability of a smart grid is investigated in this work [24] employing co-simulations in the baseline scenario with no defects and the scenarios with errors in the inclusion or exclusion of DGs. The power control using the SOC-based coordinated charging approach was presented in this work [25] on the existing power grid, allowing flexible charging of EVs utilizing actual data-driven charging profiles. The current research focuses [26] on integrating renewable energy sources into the smart grid to enable optimal energy management. This paper identifies the advantages and drawbacks of integrating clean energy supplies, as well as the various control systems that enable this. The data utilised in this study [27] is based on real EV charging sessions in the Perth and Kinross region during a one-day period. The begin and end timings of charging for electric vehicles are included in this dataset. A total of 5000 transportation dataset for Monte Carlo Simulation (MCS) were generated using this data at 15-minute intervals.

3. Problem Formulation

Increased EV penetration produces huge power loss in the DS. The main purpose is to minimize the true power losses shown in equation (1) and improve the voltage profile, by the integration of DG with the grid by considering the EV as an additional load to the existing system. First optimal location of EVCS and DGs are determined using LSF method and the sizing of DGs are maintained within the boundary constraints. Also, a 24-hour load setting of an EV is determined and the losses are obtained from equation (2). Finally optimal scheduling of intermittent load for a 24-hour profile is done using AOA.

$$\text{Min } P_L = \sum_{i=1}^{N} I_i^2 R_i \tag{1}$$

Where P_L is the Power loss, I is the current, R is the Resistance, N is the number of buses.

$$\text{Min } P_L = \sum_{j=1}^{24} I_j^2 R_j \tag{2}$$

Voltage limits

$$0.95 \le V_i \le 1.05 \tag{3}$$

Power equation

$$P_G + \sum_{i=1}^{N} P_{DG} = P_D + P_{EV} + P_L \tag{4}$$

Where P_G is the Grid Power Supply, P_{DG} is the Distributed Power Generation, P_D is the Base Power load, P_{EV} is the EV Load Power, P_L is the real Power Loss.

EVs Power charging, discharging limits

$$P_{ch,n,\Delta t} \le Pmax_{ch,n} \tag{5}$$

$$P_{disch,n,\Delta t} \le Pmax_{disch,n} \tag{6}$$

EV SoC limits

$$SoC_{min} \le SoC_n \le SoC_{max} \tag{7}$$

Boundary limits of DG

$$100 \le P_{DG} \le 1000 \tag{8}$$

Here limits are in kW

4. Loss Sensitivity Factor (LSF) Method

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 is tested and assessed. The weak bus placement approach using Loss Sensitivity Factor is deployed for the best siting location of DG.

True power loss in the k^{th} line can be found from the following expression

$$PL(j) = \frac{[P^2(j) + Q^2(j)] * R_k}{V(j)^2} \quad (9)$$

Where R_k is the resistance of the k^{th} line; V(j) is the voltage across the j^{th} bus; P(j) is the net real power supplied and Q(j) is the net reactive power supplied.

$$\frac{\partial PL}{\partial Q} = \frac{[2*Q(j)]*R_k}{V(j)^2} \quad (10)$$

After determining the true power losses, The Loss sensitivit factor was calculated from load flow for all the buses usin equation (10).

For the base case of the system, the Newton Raphson powe flow model is employed to evaluate the losses and voltag magnitude of each bus.

4.1. Optimal Location of EVCS

For optimal EVCS placement, an IEEE 33 bus systen was examined, as well as the bus system's layout in all 3 radials is given by Number of lines: 32, Slack bus number: 1 Base Voltage: 12.66 kV, MVA: 100 MVA, The total Rea Power: 3.715MW and Reactive Power: 2.295Mvar.

In an IEEE 33 bus system for the positioning of EVCS, Loss sensitivity factor approach is considered. The buses with the nominal voltage greater than or equal to 1.01(nominal voltage severity factor) are identified as the strong bus and chosen as proper location for the operation of EVCS. The priority order of the buses is generated using the Loss Sensitivity Factor approach. To assess the severity of the IEEE 33 bus system in the real time, the three possible cases of 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 EV Charging Station. Due to the effect of an additional EV demand to the existing base load in the system, there is a substantial increase of 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 0.202MW. Due to the placement of EVCS in the DS with an addition of EV load to the four buses (10,14,17 and 30) shown in Table 1 for the existing base load the overall load was increased to 4735kW and the losses was increased to 0.374MW with the increment of 85.1% of the losses compared with the real power losses for the base load of an IEEE 33 bus system shown in Fig.1.

Table 1. EV Load placement of IEEE 33 bus system.

Bus Number	Base Load(kW)	EV Load(kW)	Total Load (kW)	Losses (MW)
10	60	300	360	0.015114015
14	120	150	270	0.002875179
17	60	250	310	0.001731052
30	200	320	520	0.006057493

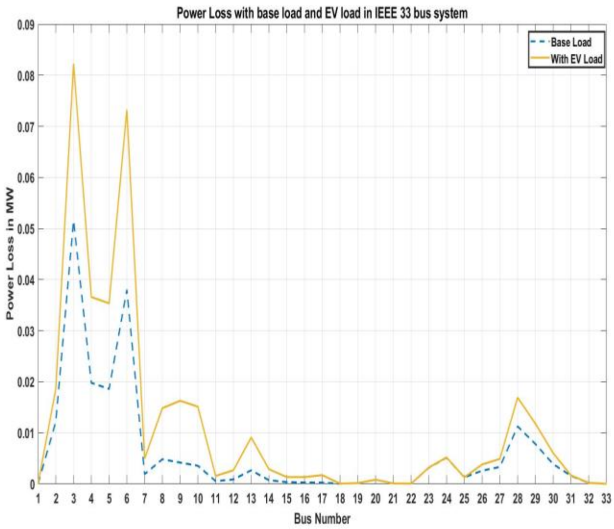

Fig.1. Power Loss of IEEE 33 bus system with EV Load.

4.2. Optimal Placement of Distributed Generator

The buses with the nominal voltage 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 in prior.

$$V_{nom[i]} = \frac{|V(i)|}{C} \quad (11)$$

Where V(i) is the base voltage at the i^{th} bus.

Table 2. Optimal locations 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 optimal positioning of DGs in IEEE 33 bus system to enhance the voltage levels while reducing system losses. The sizing of the DG's is within the constraints of equation 5 and the sizing of seven DG's are obtained from [15].

Table 3. Operating range and sizing of DG.

Bus Number	Type of DG	Operating Range (P_{min} & P_{max})	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

The real power loss for a standard IEEE 33 bus system is 0.202MW, With the integration of DGs to the DS, the losses were reduced to 0.141MW with decrease of 43.2% shown in Fig.2.

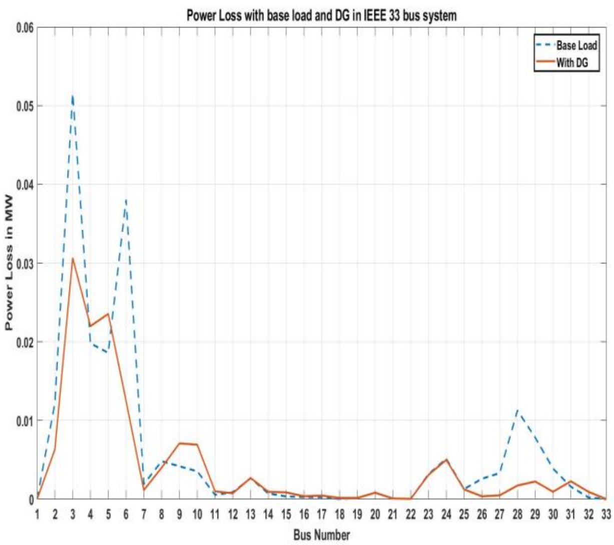

Fig.2. Power Loss of integrated DGs in distribution system.

After the placement of EVs and DGs in distribution system, the optimal commitment of DGs with the intermittent load demand on 24hrs horizon was carried out by Dynamic Programming procedure. The optimal scheduling and sizing of DG for 24-hour load profile is done by Arithmetic Optimization Algorithm.

4.3. Arithmetic Optimization Algorithm

An Arithmetic Optimization Algorithm (AOA), a new meta-heuristic technique based on the distribution behavior 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 the best-obtained solution or approximately the best solution. To illustrate the importance of exploration and exploitation shown in Fig.3, the parameter Math Optimizer Accelerated (MOA) coefficient s raised in a linear manner 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 [23]. 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 with the operating flowchart shown in Fig.4.

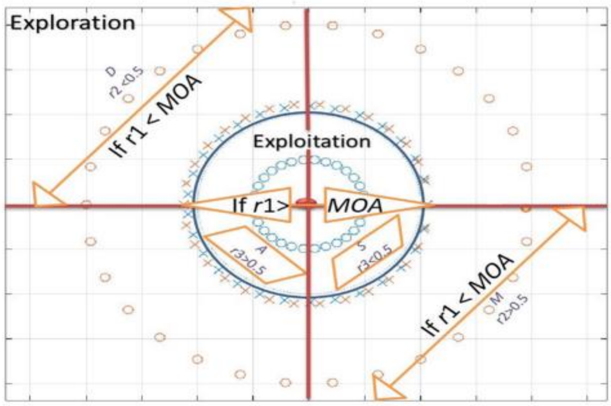

Fig.3. The Search stages of AOA.

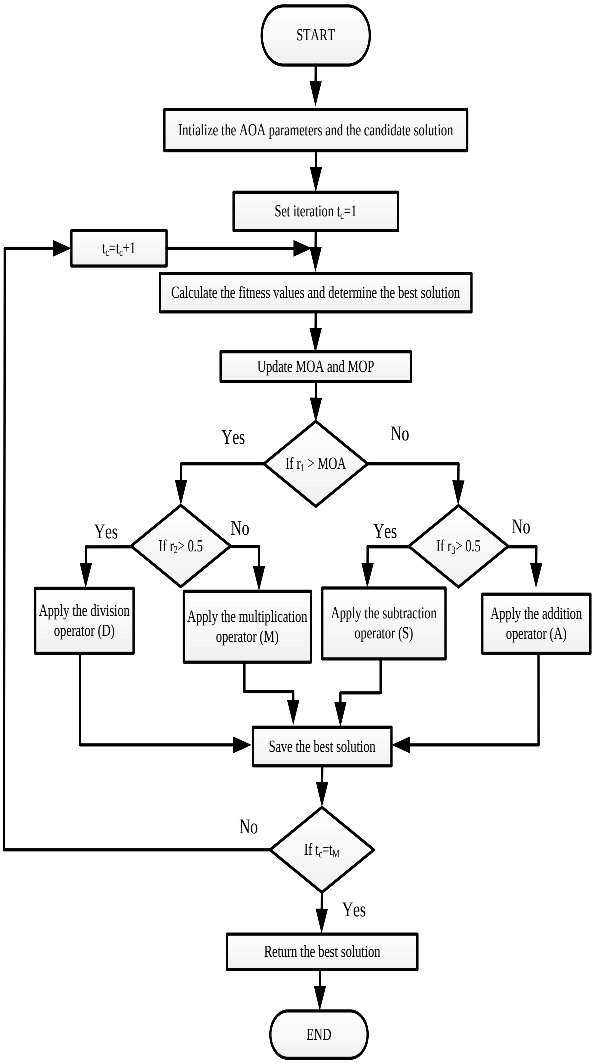

Fig.4. Operating flowchart of AOA

The following Fig.5 shows the best fitness function for optimal power allocation of Distributed Generation with EV, which was carried out for the maximum active load of 4735 kW using AOA algorithm.

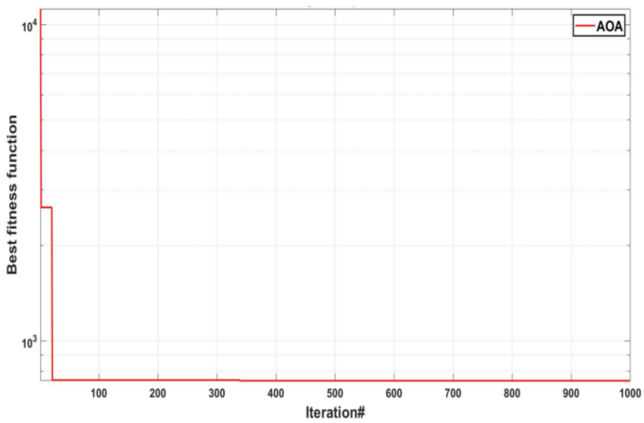

Fig.5. Fitness function of EV load for 4735 kW load setting using AOA algorithm.

5. Results and Discussion

The increased adoption of electric vehicles has a detrimental influence on the electrical infrastructure. When a substantial percentage of EVs are connected to the grid at the same time, there are more Network Power Losses and large voltage deviations at far-flung buses from the sources. To enhance the voltage levels of the bus and reduce the losses, the integration of DGs with the EVCS in distribution network is necessary. The placement of EVCS was located at 4 buses (10,14,17&30) and the optimal location of DGs are identified at 7 buses (5,8,11,15,18,28&32) for IEEE 33 bus system. 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.

5.1. Optimal Positioning of EV& DG

The based load for a standard IEEE 33 bus system is 3715kW and the real power loss is 0.202MW. Due to the placement of EV load on the 33-bus system, the overall load was increased to 4735kW and the losses was increased to 0.374MW which is increased to 85.1% compared to base case. With the integration of DGs to the system, the losses were reduced to 0.141MW which was reduced to 43.2% compared to base case.

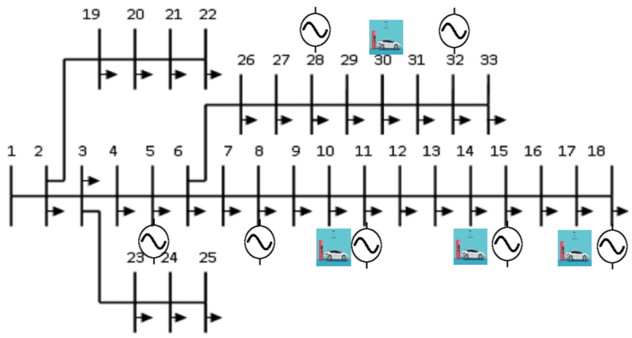

Fig.6. Optimal placement of EVs and DGs for an IEEE 33 bus system.

With the coordinated deployment of EVs and DGs in IEEE 33 bus system shown in Fig.6, even though there is an overall increase in the load of 4735kW, due to the integration of DGs in the DS the losses were reduced to 0.163MW with a decrement of 56.4%. The following Fig. 7 shows the variation of real power losses of EV and DG for the possible cases showing that the combination of EVs and DGs for a DS the losses were reduced.

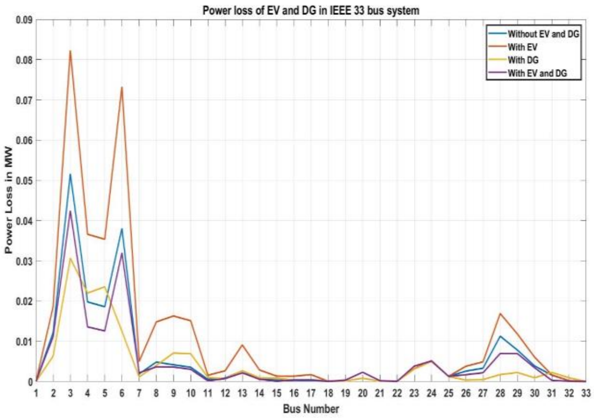

Fig.7. Power Losses in IEEE 33 Bus system with possible cases.

With the simultaneous integration of EVs and DGs in the distribution system, the voltage profile is improved compared to the case of base load with EV in the system shown in Fig.8.

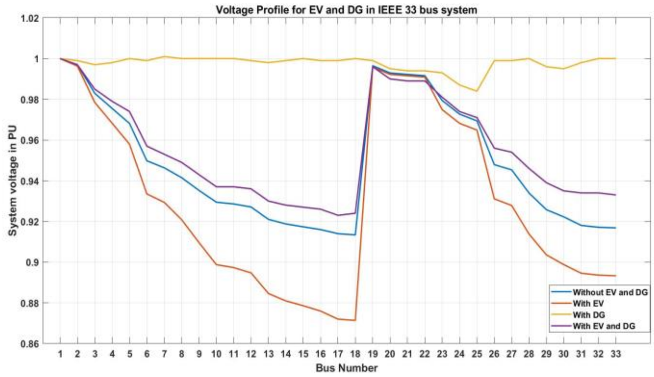

Fig.8. Voltage levels in IEEE 33 Bus system with possible cases.

5.2. *Optimal Scheduling of DG for 24- hour Load Profile*

With the simultaneous integration of EVs and DGs in the distribution system, the optimal scheduling of DG is carried for 24-hour load profile. The day is divided into 24 time slots of one hour each to solve the optimization issue. The forecast data is collected from the load profile setting [16] on hourly basis. The following table.4 gives the data regarding load and loss profile of 24 hour on possible cases. The following Fig.9 shows the variation of 24-hour load profile for the possible cases of without EV load and DG, with EV load and with EV load and DG, where the load is increased due to the addition of EV load to the existing base load.

Table 4. Load and Loss profile of 24- hour load setting for possible cases

	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	0.168379	3125.1	0.295589	3125.1	0.137761
2	2303.3	0.158174	2935.7	0.277674	2935.7	0.129411
3	2229	0.153072	2841	0.268717	2841	0.125237
4	2154.7	0.147969	2746.3	0.25976	2746.3	0.121062
5	2154.7	0.147969	2746.3	0.25976	2746.3	0.121062
6	2229	0.153072	2841	0.268717	2841	0.125237
7	2786.25	0.19134	3551.25	0.335896	3551.25	0.156546
8	3232.05	0.221954	4119.45	0.38964	4119.45	0.181593
9	3492.1	0.239812	4450.9	0.42099	4450.9	0.196204
10	3529.25	0.242364	4498.25	0.425469	4498.25	0.198292
11	3492.1	0.239812	4450.9	0.42099	4450.9	0.196204

12	3454.95	0.237261	4403.55	0.416511	4403.55	0.194117
13	3417.8	0.23471	4356.2	0.412033	4356.2	0.19203
14	3529.25	0.242364	4498.25	0.425469	4498.25	0.198292
15	3454.95	0.237261	4403.55	0.416511	4403.55	0.194117
16	3380.65	0.232159	4308.85	0.407554	4308.85	0.189943
17	3566.4	0.244915	4545.6	0.429947	4545.6	0.200379
18	3677.85	0.252568	4687.65	0.443383	4687.65	0.206641
19	3715	0.25512	4735	0.447862	4735	0.208728
20	3529.25	0.242364	4498.25	0.425469	4498.25	0.198292
21	3343.5	0.229608	4261.5	0.403076	4261.5	0.187855
22	3157.75	0.216852	4024.75	0.380682	4024.75	0.177419
23	2711.95	0.186237	3456.55	0.326939	3456.55	0.152372
24	2340.45	0.160725	2983.05	0.282153	2983.05	0.131499

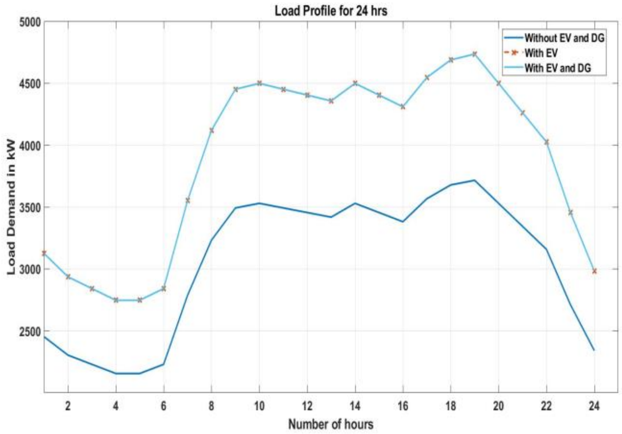

Fig.9. Load profile for 24-hour load setting with possible cases.

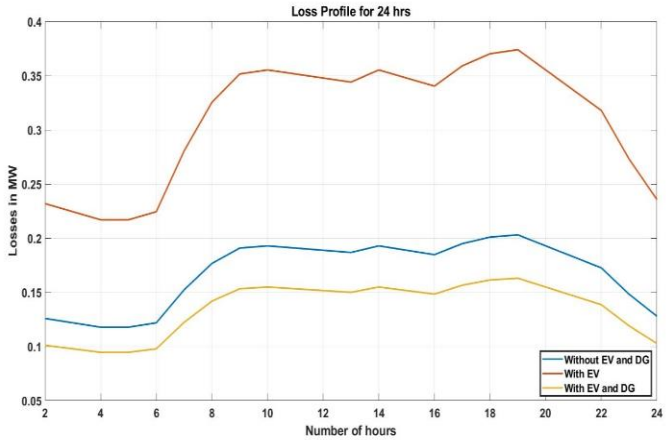

Fig.10. Loss profile for 24-hour load setting with possible cases.

Table 5: 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

The Fig.10 shows the variation of 24-hour loss profile for the possible cases, where the losses are increased due to the presence of EV load to the existing base load. With the integration of EVs and DGs to the grid connected system shows that the losses are reduced on 24-hour horizon. 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 and its variation with respect to time is shown in Fig.11. 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, due to the intermittent variations in the load demand.

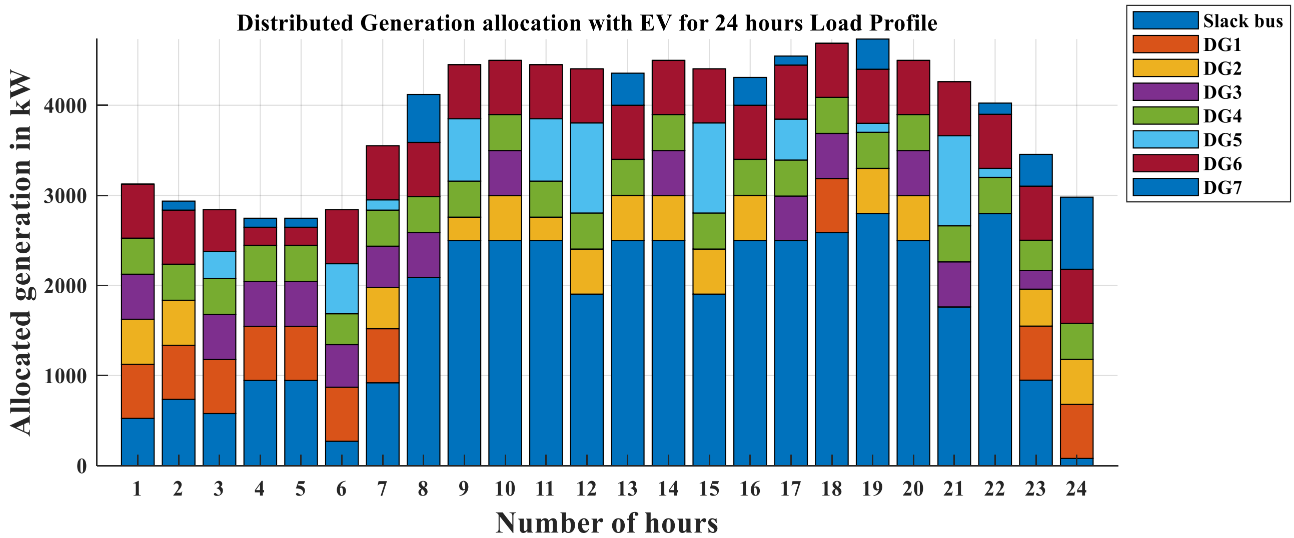

Fig.11. Optimal scheduling of DGs for 24-hour load profile using AOA

6. Conclusion and Future Scope

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 study a simultaneous integration of EVCS and DG for a standard IEEE 33 bus system was considered. Using LSF approach the simulation results shown that by considering the EV load to the existing base load in the system, the losses were raised to 0.374MW and reduction in the voltage profile. With the integration of DG to the EV connected grid system the losses were reduced to 0.164MW, with an improvement of the voltage profile and also for a 24-hour load profile the load and loss estimation was carried out, the simulation results are showing that the losses were reduced due to the integration of DG to the EV connected grid system. Finally, the optimal scheduling of the total load on a 24-hour load setting was done by AOA, showing that by the integration of DG to the grid connected system including with the effect of EV load, reducing the burden on the system, making the stable and reliable operation of the DS. The future scope is extended by considering the same EV to act as a load and DG with consideration of charging and discharging behaviour based on the off and peak load times in the system. To extend the work on Vehicle to Grid technology as one of the DG to the existing DGs to further reduce the losses in the system.

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