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Optimal Planning of Type-1DGs in EV Incorporated Radial Distribution Network

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***Abstract*:** A vital task for effective operation of distribution system is reducing power losses and to save energy. One of the most effective methods to reduce losses is distributed generation (DG). The proper planning of EVCSs is a significant problem for distribution system operators as the installation of Electric Vehicle Charging Stations (EVCSs) for Electrical Vehicles (EVs) increases on a larger scale. Power losses and generation-demand mismatch rise with EV load adoption in the electrical grid. As a result, there will be impact on voltage levels and the voltage stability margin deteriorates. It is critical to integrate EVCSs at appropriate locations to reduce the negative effects of increasing EV load penetration on Radial Distribution Systems (RDS). The integration of EVs into distribution systems undergoes charging and discharging modes of operation for power exchange with the grid, resulting in energy management. Inadequate EVCS planning has a negative influence on the distribution system, causing voltage variation and an increase in power losses. DG units are integrated with EVCSs to reduce this. The DGs help to keep the voltage profile within limits which reduces power flows and losses and thus results in improved power quality and reliability. Therefore, the DGs and EVCS should be properly allocated and sized to avoid issues such as protection, voltage rise, and reverse power flow. This research demonstrates an approach for minimizing losses in an EV-integrated radial distribution system by optimizing the location and sizing of DGs. This study proposes the sizing and location of renewable (wind, solar) DG units (type-1 DG) incorporated in radial distribution network. This methodology decreases power losses while simultaneously improving network voltages. The accuracy of the proposed method is elaborated in four scenarios. The proposed methodology is implemented in IEEE 33 bus and 69 bus systems using the Particle Swarm Optimization technique (PSO). The results show that the suggested optimization technique increases system efficiency and performance by optimizing the planning and operation of both DGs and EVs.

Index Terms: *EV Charging Station, Distributed Generation, Real Power, Particle Swarm Optimization (PSO), Optimal Location.*

1. INTRODUCTION

Environmental pollution and rising energy usage along with advancements in battery technology resulted in a new era in transportation electrification. Electric Vehicles (EVs) are seen to be the most promising solution for the road transportation system. With the use of EVs, we may reduce our reliance on fossil fuels, as well as our emissions of greenhouse gases and air pollutants, both of which have a substantial influence on global warming. According to Business Intelligence and Strategy (BIS) study, the EV market is expected to grow at a CAGR (Compound Annual Growth Rate) of 43.13% between 2019 and 2030 [1]. However, the growing number of EVs, as well as the rapid expansion and growth of EV markets in the transportation sector, presents great potential and difficulties to grid operators, as charging demand rises. Optimal planning and operation are critical components in reducing the operational risk of leveraging existing distribution networks [2] and deploying a large number of EVs. Aside from cutting emissions, several experts are looking at the benefits of using EVs on the grid. The development of Electric Vehicle Charging Stations (EVCSs) brings an extra strain on the power network since the high charging rates of rapid EVCS decrease the operating characteristics of the distribution network. Massive EV deployment will have an impact on aging infrastructure, power losses, assist voltage, and harmonic distortions when charging is introduced into the distribution network. Proper site selection of EVCS is required to reduce the negative effects of EVs. To avoid overburdening the network and optimize operational flexibility, Distribution System Operators (DSOs) should carefully examine EV charging stations. As a result, Distributed Generation (DG) units are incorporated to boost EV penetration and limit the influence of EVCSs on operational components of the distribution system like as current, voltage, and losses.

Distributed generating is the way of the future for satisfying client demand. The use of modular technologies in DG has a significant impact on reducing the pressure on the distribution system. It is in reality, a small-scale power generator that has seen significant advancements during the last 10 to 15 years. To gain the full benefits of DG sources, it is critical to establish their optimal capacity and position in distribution networks [4]. The use of DG is one of the most effective ways for decreasing losses caused by the rapid development of EVs. Integration of EVCS with DG units aids in mitigating EV charging impacts. To avoid voltage increases, increased losses, and reverse power flow issues, as well as to offer protection, DGs and EVCS must be effectively assigned and scaled. The optimal placement of DG and EVCS in the network is critical for maximizing efficiency and reaping the greatest benefits from EVCS installation. Exploiting future EV capabilities is regarded as one of the potential strategies for promoting the inclusion of renewable energies into energy systems. The ultimate goal is to assure the optimal positioning and size of renewable (wind and solar) DGs with EVCS by employing an optimization technique that minimizes total losses while maintaining power system dependability and stability.

2. RELEVANT BACKGROUND

Many research have been undertaken to determine the best location and size of EVCS. Md. Mainul Islam et al. [5] presented a thorough investigation on several strategies utilized to address EVCS placement and size issues. Mondeep Mazumder and Sanjoy Debbarma [6] conducted a thorough investigation of the practicality of introducing EVs into the existing distribution infrastructure while accounting for slow and quick charging. Sanchari Deb et al [7] investigated the influence of EVCS loads on voltage stability, power losses, dependability, and economic losses.Yuttana Kongjeen and Krischonme Bhumkittipich [8] discussed the impact of EVs incorporated into a power distribution system using voltage-dependent regulation. The static voltage stability was demonstrated in this study utilizing the novel load flow approach. Galiveeti Hemakumar Reddy et al [9] investigated the influence of EV connectivity on system dependability and suggested an energy index EENC for determining EVCS position and avoiding not charging owing to distribution system failures. Kang Miao Tan et al [10] examined the V2G framework, benefits, and restrictions, as well as the primary optimization strategies with multiple constraints. Mingsheng Zhang [11] presented a methodology for charging station location that reduced investment and charging costs. Priyanka Shinde and K.Shanti Swarup [12] investigated the impact of EVCS load linked to the grid and recommended that optimizing EV reactive power may be utilized to enhance the voltage profile in the system. M. Bagheri Tookanlou et al [13] created a scheduling strategy that is largely based on assuring the incentives of both V2G and G2V operators. Using a hierarchical evolutionary algorithm, Xiangwu Yan et al [14] established a multi-objective model for assessing losses and investment costs. Several heuristic optimization strategies have recently been applied to handle EVCS placement difficulties in conjunction with DGs. Hassan Fathabadi [15] investigated the impact of electric vehicles (EVs) and plug-in hybrid electric vehicles (PHEVs) with V2G connectivity and renewable energy sources utilized as DGs on a power distribution network. Leila Bagherzadeh [16] addresses a multi-objective optimization issue in the smart grid with EVs and DGs to assure the best grid operating schedule. To handle renewable resource uncertainties in the model, the distribution techniques Beta and Weibull were utilized. The Cuckoo Bird Optimization Algorithm was employed to tackle the optimization problem. In the test system, Mahnaz Moradijoz [17] implemented simultaneous deployment of DGs and parking lots. The presence of DG units and parking lots results in a large decrease in losses. The simulation results demonstrate that changes in the charge rate and the number of EVs on the parking lot affect the best position of the charging station and the DG. Zhipeng Liu [18] created a mathematical model for appropriate EVCS size, with the goal of minimizing overall cost associated with EVCS planning.

In light of the preceding works, this research proposes an effective strategy for minimizing losses through optimal position and size of different types of DGs, as well as appropriate location of EVCS, which minimizes total network power losses. The Particle Swarm Optimization (PSO) approach is used for optimization. EV is regarded a dynamic load in the framework for power flow calculation, and EV charging with respect to time is not considered under balanced load conditions. The proper positioning of EVCS load in the system optimizes efficiency by retaining the original size of the DG. As a result, this strategy (placement of DG and EV load) is extremely useful for power utilities, which can decrease power losses by selecting the best places for DG and EVCS.

In this research, PSO approach was established for optimal placement and size of DGs and EVCS in radial distribution networks. To calculate the losses and voltage levels, EVs with and without DGs are conducted. The different DG and EV limits are considered, and the maximum permitted capacities for both DG and EV are specified. Different types of DGs with varying power factors are explored, and implementation for various bus systems is completed. EVCS and various types of DGs are placed with the EV acting as

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the load and the DG itself. As a result, the suggested algorithm contributes to the reduction of power losses in the distribution network. In this work, the effect of the EVCS on actual power loss, reactive power loss, and voltage magnitude is thoroughly examined.

3. MODELLING OF ELECTRIC VEHICLE LOAD

An EV load model is expressed as:

$$EV_{Power} = S_0 \times k_p \times \left(\frac{V_i}{V_{io}}\right)^{n_{pi}}$$

where S_0 indicates the apparent load power (kVA) at nominal voltage V_{i0}, n_{pi} is the exponential index value for EV load equals to 2.59, k_p is representing the load power factor (pf) given as k_p= 0.995 lagging taking into account the values from available EV chargers in market. EV load in this paper is considered as dynamic load. The total amount of load varies from normal values of 3715 kW to 3926.41 kW respectively for 33 Bus systems when load flow is applied. At this point, it can be said that the integration of EVs to the distribution system increases the overall load of the system and should be adequately planned to enhance technical and economic benefits and consequently to improve the inclusion rate of EV technologies.

The amount of power needed to charge an EV with the efficiency of the charger is as follows:
EVs with Li-ion batteries are considered for modeling the EVCS and assumed that it delivers only required real power to batteries of EV. In this paper, charging level of type 3 fast charging EVCS is considered which has the charging power of 50 kW for each EV and rated voltage/current of 480V/167A.
In terms of actual and reactive power supply capabilities, DG units can be divided into four main categories according to their terminal features [19]:

- DGs of Type 1 are only capable of injecting active power
- DGs of Type 2 are only able to deliver reactive power
- DGs of Type 3 capable of injecting active as well as reactive power
- DGs of Type 4 capable of injecting active power but absorbs reactive power

4. OBJECTIVE FUNCTION

The line losses are estimated as:

$$P_{Loss} = \sum_{i=1}^{nb} I_i^2 R_i$$

Hence, growing demand for load of a single bus would lead to net growth in the distribution network's total power losses. Minimization of the total power losses including both active and reactive power losses and enhanced voltage profile with EVs inclusion are the main objectives of this paper:
Minimization $\{P_{Loss}\}$ (4)

5. DG AND EV CONSTRAINTS

Current limit
$|I_{ij}| \leq I_{maximum}$ (5)
Where I_{ij} is the capacity of line current flow between I and j, I_{max} is the maximum current carrying capacity of the power line.

Voltage limit
$V_{Bus\_min} \leq V_{Bus} \leq V_{Bus\_max}$

0.95 pu $\leq V_{Bus} \leq$ 1.05 pu

where V_{Bus} is the bus voltage, V_{Bus_min} is the minimum allowable bus voltage, and V_{Bus_max} is the maximum allowablebus voltage.

EV battery SOC limit

EV battery SOC (State of Charge) should be kept within the specified range to reduce battery degradation. In addition, the EV battery cannot completely be discharged because those energy quantities are allocated for use with the EV drive.

$$EV_{SOC\_min} \leq EV_{SOC} \leq EV_{SOC\_max}$$

where EV_{SOC} is the state of charge for EV, EV_{SOC_min} is the minimum acceptable EV SOC and EV_{SOC_max} is themaximum acceptable EV SOC.

Power distribution limit

The electric energy supplied form the grid and DGs including the EVs connected to the grid should meet the demand for load and system losses with EVCS.

$$P_{Grid} + \sum_{i=1}^{N} P_{DGi} = \sum_{i=1}^{N} (P_{iLoad} + P_{iEVCS}) + P_{Losses}$$

where P_{Grid} is the power generated from grid generator, P_{EVCS} is the power related to EVCS and P_{iLoad} is the loaddemand.

DG sizing limit
$50 \leq DG_{Sizing} \leq 3500$

Type-1DG is considered with limits in kW. Type I: DG capable of injecting real power only, like photovoltaic based DG, wind based DG, fuel cells etc. are the good examples of type-I DG.

6. PROPOSED SCHEME:

According to [1], [6] and [7], particle swarm optimization (PSO) provides simple computation methodology in finding the nearest optimal solution. But, researchers are not discussing the impact of addition of EVCS on to the distribution network in terms of voltage profile, real power losses and reactive power losses. In this paper a methodology is proposed to select the optimal bus for incorporating EVCS in an existing radial distribution system and to examine the impact of EVCS. To validate the proposal the performance of the RDS is studied under the following scenarios using PSO.

Scenario-1: Placement of EVCS on an existing radial distribution system. (Single step optimization process)

Scenario-2: Placement of EVCS before reconfiguration for an existing radial distribution system. (Two step optimization process)

Scenario-3: Placement of DG after reconfiguration and EVCS location for an existing radial distribution system. (Two step optimization process)

Scenario-4: Placement of DG along with reconfiguration and EVCS location for an existing radial distribution system. (Simultaneous two step optimization process)

7. PARTICLE SWARM OPTIMIZATION (PSO) METHODOLOGY

The complete structure of the work to solve the optimal multiple DGs and EVCS placement along with the sizing of four different types of DGs operating at different power factors using PSO is shown in Figure1.

Kennedy and Eberhart developed the early PSO technique as a stochastic optimization strategy based on swarming behavior. It offers solutions for complicated numerical maximization or minimization of constrained nonlinear problems. Due to a number of benefits compared to certain other heuristic optimization algorithms, PSO was preferred to mitigate the optimization problem in this article. The adaptive and exhaustive nature to the essence of the objective function with requirement of low memory size and computation time made this method more advantageous. A decreased reliance on the set of initial points also ensures that the convergence algorithm will be versatile and vigorous. Particles travel in a certain velocity through the multi-dimensional problem field in this method. Each particle in the swarm is in a position to interact. This helps them to change their moving speed in accordance with their own and other particle movement patterns.

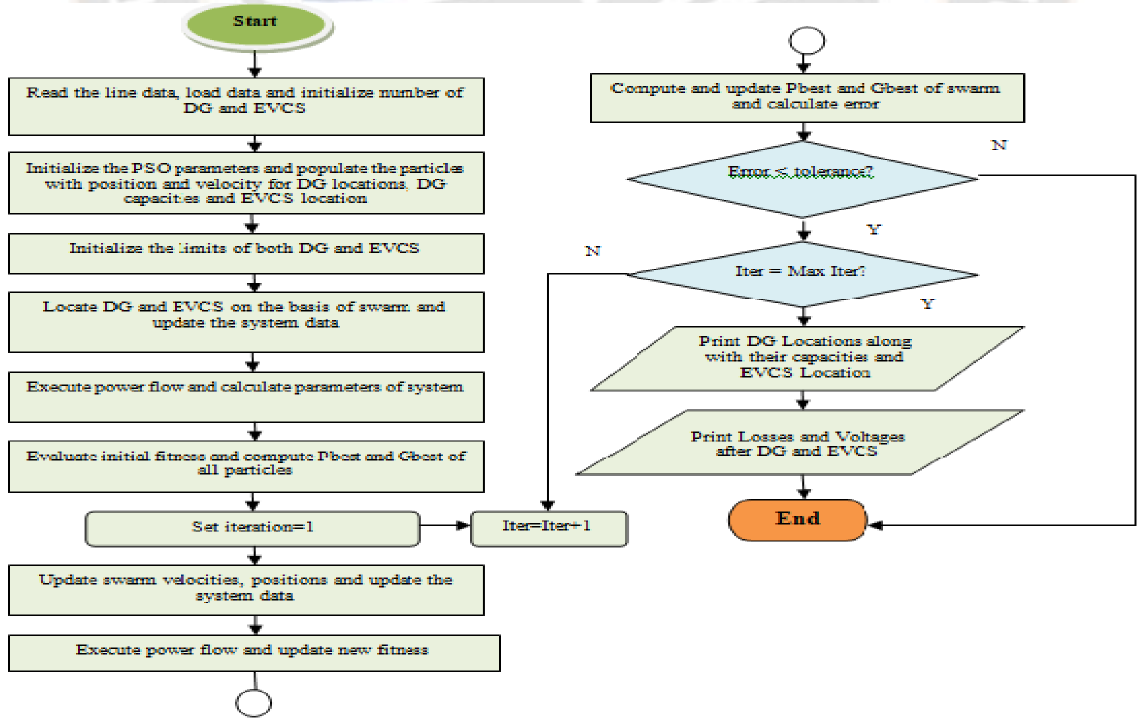

Figure 1. Flowchart for simultaneous placement of DG and EVCS using PSO methodology

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The particle swarm's spontaneous motion keeps the solution from being stuck at local minimum. Each particle maintains control of its own location in the problem space throughout the PSO iteration. For each iteration, the present position of each particle is evaluated if it can be found to be greater than all the values that have previously been found, and then these coordinates are stored as $P_{Best,i}$. A variable named $G_{Best,i}$ store the best value of the function. With prior experience, current velocity and the best perceptions of the neighbors, every particle decides about evolution based on its own experience as well as that of its neighbors. The particles position and velocity are updated with each iteration. If taken k number of iterations with i number of particles, for each particle the position(X) and velocity (V) can be reckoned by [20]:

$$X_i^{k+1} = X_i^k + V_i^{k+1}$$

$$V_i^{k+1} = \omega^k \times V_i^{k+1} + C_1 \times rand_1 \times (P_{Best,i}^k - X_i^k) + C_2 \times rand_2 \times (G_{Best,i}^k - X$$

$$\omega^k = \omega_{max} - \left(\frac{\omega_{max} - \omega_{min}}{k_{max}}\right) \times k$$

where ω is the inertia weight factor, C_1andC_2 are acceleration coefficients, rand1 and rand2 are the random variableswith a uniform distribution between 0 and 1, $P_{Best,i}$ is the local best of particle i and $G_{Best,i}$ is the global best of the group.

The following are the steps involved in applying the PSO algorithm to solve the problem of optimal EVCS and DG allocation:

Step 1: Initialize the bus data, number of DGs and EVCSs subjected to equality and inequality constraints
Step 2: Initialize the parameters corresponding to upper and lower limits of DG sizes in kW, EVCSs, PSO parameters and maximum number of iterations
Step 3: Initialize population of particles having positions X and velocities V Step 4: Set iteration =1
Step 5: Using forward-backward load flow, evaluate the initial population and objective function values (3) and find the index of the best particle
Step 6: Select Pbest and Gbest
Step 7: Update positions and velocities of particles using (12) and (13)
Step 8: Evaluate fitness and find the index of the best particle for both DGs and EVCS Step 9: Update Pbest and Gbest of total population and calculate error
Step 10: If iteration is equal to maximum iterations, then increment iteration by 1 and go to step 6 instead go to step 11
Step 11: Print Gbest as the optimal solution and stop.

The parameters used for PSO are given in Table 1.

Table 1 Parameters of PSO considered for this study.

S.No	Parameter	Value
1	Generations	100
2	Particles	50
3	Maximum inertia	0.9
4	Minimum inertia	0.2
5	Initial velocity	2
6	Final velocity	2

8. RESULTS AND DISCUSSIONS

This research proposes the sizing and location of renewable (wind, solar) DG units (type-1 DG) incorporated in IEEE 33 and 69 bus radial distribution networks. The performance of the proposed research is studied under the following scenarios using the Particle Swarm Optimization technique (PSO).

For IEEE 33 bus radial distribution network (with EV along with reconfiguration):

Size of EV is 3.71 MW. The voltage profile in four scenarios is shown in Figure 2. The real power losses in four scenarios are shown in Figure 3.

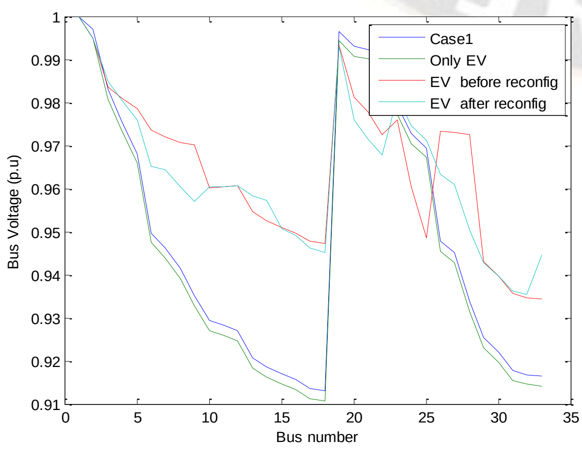

Figure 2. Voltage profile during four scenarios

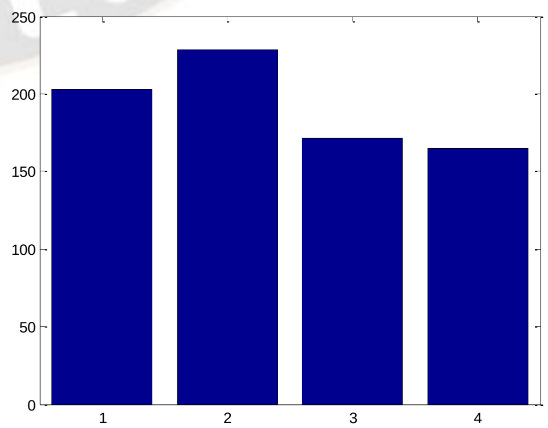

Figure 3. Real power losses during four scenarios

Table 2. Comparison of real power losses of IEEE 33 bus radial distribution network (with EV along with reconfiguration):

Cases	Real power losses (kw)	Minimum voltage (p.u)	Optimal location of EVCS of size 3.71 MW (Bus Number)
Case-1 (without EV)	200.7	0.9150	-
Case-2 (with EV)	237.3	0.9105	2
Case-3 (EV before Reconfiguration)	170.9	0.9500	2
Case-4 (EV after Reconfiguration)	160.3	0.9490	2

For IEEE 33 bus radial distribution network (with DG's in EV Incorporated RDS):

Size of EV is 3.71 MW and Size of Type1 DG's (DG1 and DG2) is 352 kW at each case. The voltage profile in four scenarios is shown in Figure 4. The real power losses in four scenarios are shown in Figure 5.

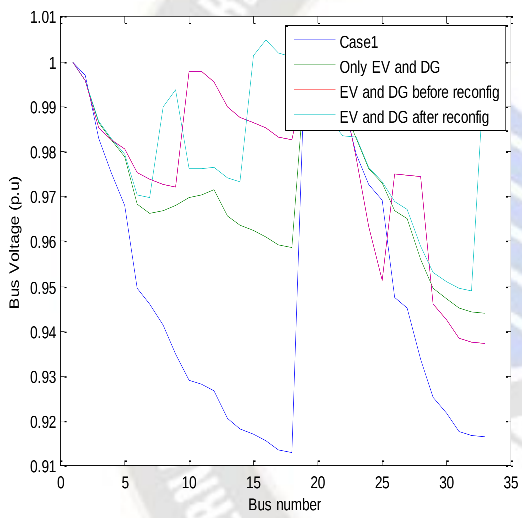

Figure 4. Voltage profile during four scenarios

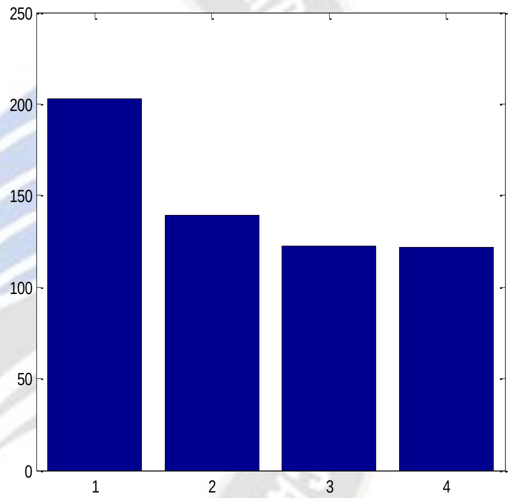

Figure 5. Real power losses during four scenarios

Table 3. Comparison of real power losses of IEEE 33 bus radial distribution network (with DG's in EV Incorporated RDS:

Cases	Real power losses (kw)	Minimum voltage (p.u)	Optimal location of EVCS of size 3.71 MW (Bus Number)	Optimal location of DG1 and DG2 (Bus Numbers)
Case-1 (Only EV)	200.7	0.9150	2	-
Case-2 (with EV and DG's without reconfiguration)	139.5	0.9650	2	12 and 31
Case-3 (EV and DG's before reconfiguration)	122.6	0.9850	2	16 and 31
Case-4 (EV and DG's after reconfiguration)	122.0	0.9750	2	11 and 23

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For IEEE 69 bus radial distribution network (with DG's in EV Incorporated RDS):

Size of EV is 3.80 MW and Type1 DG's (Size of DG1is 459 kW and Size of DG2 is 429 kW).

Case-1 (Only EV without reconfiguration):
The voltage profile in this scenario is shown in Figure 6.

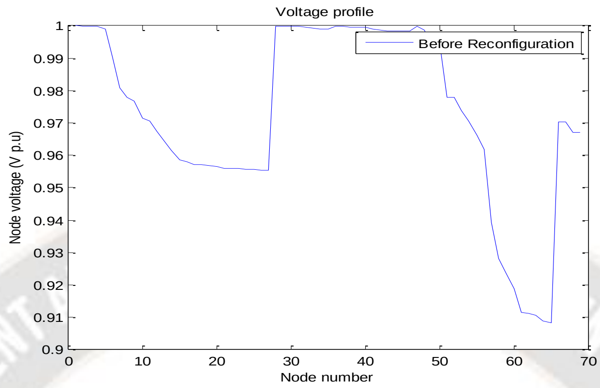

Figure 6. Voltage profile in case-1

Case-2 (with EV then reconfiguration and DG's):

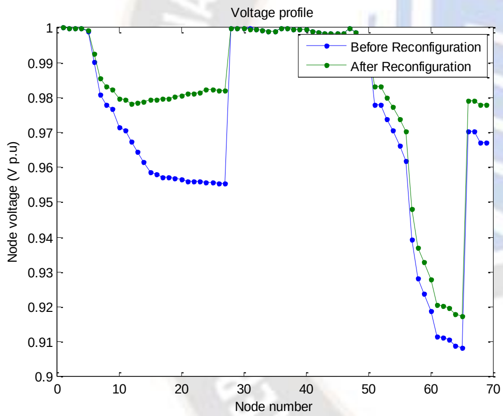

Figure 7. Voltage profile in case-2

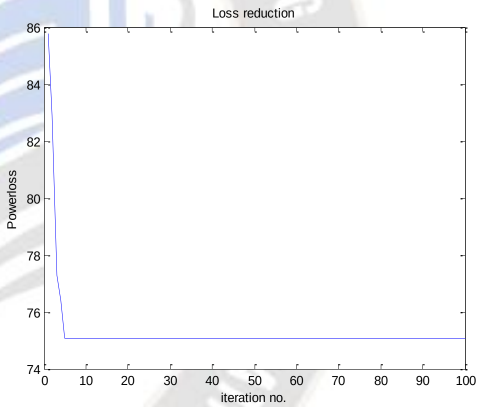

Figure 8. Loss reduction during case-2

The voltage profile in this scenario is shown in Figure 7 and the loss reduction during case-2 is shown in Figure 8.

Case-3 (EV and DG's after reconfiguration):
The voltage profile in this scenario is shown in Figure 9 and the loss reduction during case-3 is shown in Figure 10

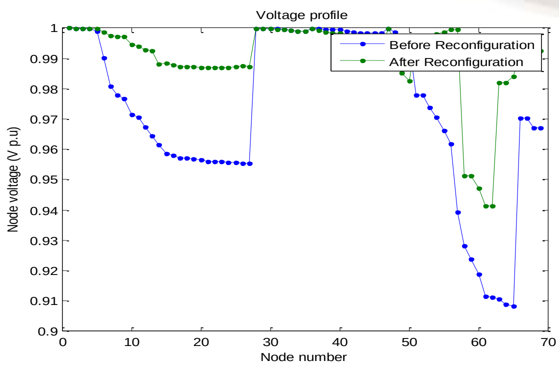

Figure 9. Voltage profile in case-3

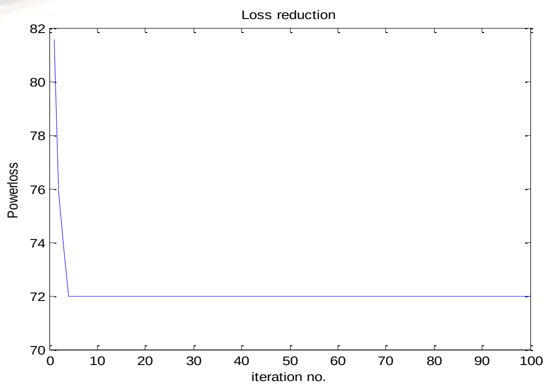

Figure 10. Loss reduction during case-3

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.Case-4 (Simultaneous EV and DG's along with reconfiguration):

The voltage profile in this scenario is shown in Figure 11 and the loss reduction during case-4 is shown in Figure 12.

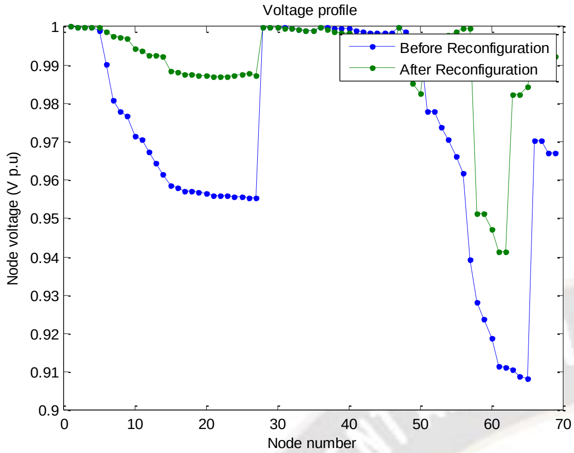

Figure 11. Voltage profile in case-4

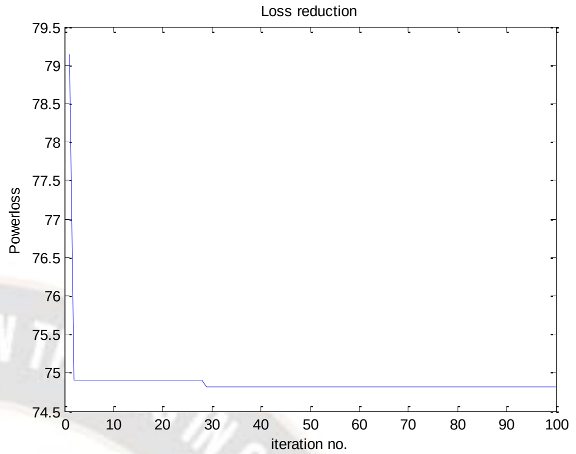

Figure 12. Loss reduction during case-4

Table 4. Comparison of real power losses of IEEE 69 bus radial distribution network (with DG's in EV Incorporated RDS:

Cases	Total Real power losses (kw)	Losses before EV (kW)	Losses After EV (kW)	Optimal location of EVCS of size 3.80 MW (Bus Number)	Optimal location of DG1 and DG2 (Bus Numbers)
Case-1 (Only EV without Reconfiguration)	225.4	-	-	2	-
Case-2 (with EV then reconfiguration and DG's)	180.5	225.4	180.1	2	2 and 24
Case-3 (EV and DG's after reconfiguration)	89.29	225.4	746.0	2	26 and 56
Case-4 (Simultaneous EV and DG's along with reconfiguration)	89.29	225.4	746.0	2	26 and 56

9. CONCLUSION

The research work presented a method of optimally locating the EVCS along with DGs to reduce losses and emissions. The EV charging station load effect on the distribution network power loss is presented and the results tested on IEEE 33 and 69 bus systems are reported in this article. Placement of various renewable DG types and EVCS are done simultaneously in the IEEE 33 and 69 bus systems. The Simulation results illustrate the importance of optimal concurrent placement of both EVCSs and DGs in the distribution system. Thus, optimal integration of DGs into distribution feeder increases the EVs penetration while reducing real and reactive power losses and eventually improving voltage profiles in the distribution system. The present simultaneous method provides the best locations along with their capacities which reduces the computational time, memory and gives more effective results. The proposed algorithm in this paper helps to reduce the power losses problem in the distribution network. Another advantage of using this algorithm is that the computation time needs a smaller number of load flow analysis in the process. Algorithm works fine even with and without DGs present in the distribution network. The main findings of the simulation are summarized as follows:

- Relative to those without the charging stations, the power losses after the placement of the charging stations were high.
- Minimum power losses can be obtained in the system with EVCS placed far from the substation with the presence of DG units.
- The optimum placement and sizing of the Type-1 DGs led to significant reduction in power losses and tovoltage enhancement.

The current state of EVs stations installation is gaining traction all over the world. By utilizing the method in this paper will improve the overall system where power losses can be reduced. There are several intriguing research directions to pursue in the future. One is to examine the impact of EV charging on the power grid by location and time of day using charging demand modelling and second is multiple coordinated charging station development in unbalanced systems.

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