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Optimal Placement of Electric Vehicle Charging Stations in the Active Distribution Network

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ABSTRACT Electrification of the transportation sector can play a vital role in reshaping smart cities. With an increasing number of electric vehicles (EVs) on the road, deployment of well-planned and efficient charging infrastructure is highly desirable. Unlike level 1 and level 2 charging stations, level 3 chargers are super-fast in charging EVs. However, their installation at every possible site is not techno-economically justifiable because level 3 chargers may cause violation of critical system parameters due to their high power consumption. In this paper, we demonstrate an optimized combination of all three types of EV chargers for efficiently managing the EV load while minimizing installation cost, losses, and distribution transformer loading. Effects of photovoltaic (PV) generation are also incorporated in the analysis. Due to the uncertain nature of vehicle users, EV load is modeled as a stochastic process. Particle swarm optimization (PSO) is used to solve the constrained nonlinear stochastic problem. MATLAB and OpenDSS are used to simulate the model. The proposed idea is validated on the real distribution system of the National University of Sciences and Technology (NUST) Pakistan. Results show that an optimized combination of chargers placed at judicious locations can greatly reduce cost from \$3.55 million to \$1.99 million, daily losses from 787kWh to 286kWh and distribution transformer congestion from 58% to 22% when compared to scenario of optimized placement of level 3 chargers for 20% penetration level in commercial feeders. In residential feeder, these statistics are improved from \$2.52 to \$0.81 million, from 2167kWh to 398kWh and from 106% to 14%, respectively. It is also realized that the integration of PV improves voltage profile and reduces the negative impact of EV load. Our optimization model can work for commercial areas such as offices, university campuses, and industries as well as residential colonies.

INDEX TERMS Charging stations placement, distribution system, electric vehicles (EVs), optimization.

NOMENCLATURE

SETS

N	Set of buses in the system
T	Set of time periods
M	Set of line sections
O	Set of types of chargers
E	Set of electric vehicles

INDICES

i	Index of bus number
t	Index of time period
j	Index of line section
l	Index of level of charging station
e	Index of electric vehicle

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PARAMETERS

$P_{j,loss}$	Power loss of jth line section
C	Charging power of a charger
SOC_{init}	Initial state of charge of a battery
c	Cost of a charger
$c_{p,l}$	Per unit electrical energy cost
$S_{j,max}$	Maximum transfer capacity of line section j
η_{ch}	Charging efficiency of EV
d_{max}	Maximum range when EV is fully charged

VARIABLES

n	Number of charging station
$V_{i,t}$	Voltage magnitude of bus i at time interval t
$S_{j,t}$	Power flow through line section j at time interval t
$dist_{trav,e}$	Travelled distance by electric vehicle e

I. INTRODUCTION

Economic and environmental problems of fossil fuel transportation have motivated the electrification of vehicles worldwide. The market share of electric vehicles (EV) has already reached 28.8% in Norway, 6.4% in the Netherlands and 1.4% in China, whereas many countries have set targets to reach 100% EV penetration in the foreseeable future [1]. By 2022, the number of EVs is expected to surpass 35 million globally [2]. The growing EV industry implies a potential of zero-emissions when powered by renewable energy. In fact, it is necessary to power these EVs by renewable energy as much as possible because these high charging loads will have adverse effects on the environment if powered by fossil fuel power plants [3].

In context of above mentioned framework, need of optimal planning for EV charging stations has been significantly increased. It is important to analyze the impacts of EV on power system as EV integration increases the demand of system. For a typical distribution system, 10% penetration of EVs has proved to increase peak load by 17.9% while 20% penetration increases peak load by 35.8% [4]. The impact of plug-in hybrid EVs on grid load is studied and analyzed in [5] and EV load was measured and used in this study. Higher peak load caused by EV increases power losses and voltage deviations. It can also cause thermal limit violations of transformers and lines [8], [9]. A solution is proposed in [8] to lower distribution system losses by coordinated charging scheme. Calculations are based on an assumed EV load model. In [9], coordinated charging is proved to achieve a smooth voltage profile while also reducing power losses. It is also proved to avoid the overloading of the distribution system in [10]. When vehicles are charged in a coordinated manner, peak load can be managed to remain within allowable limits. However, the uncertain behavior of the vehicle owner can make it difficult to implement coordinated charging. To overcome these problems, optimal placement and sizing of charging station were proposed in [11] where a probability distribution was used to model EV load and a heuristic algorithm was employed to solve the siting and sizing problem.

Optimal planning of EV charging stations has been done with different approaches and objectives. The usage of EVs as a spinning reserve to supply peak load and enhance system performance can contribute to optimal planning of charging stations. Therefore, EVs can help us in achieving better economics and critical parameter improvement such as loss reduction and voltage deviation minimization [12]. Particle swarm optimization is used in [13] to solve location problem of charging stations. CO_2 emission has been incorporated by authors in [14] for planning of EV charging stations. Profit maximization of a parking lot owner is achieved in [15] by optimizing interaction among parking lots using K-means clustering technique. Moreover, minimization of power loss and voltage deviation as well as maximization of network reliability is achieved by optimally allocating parking lots with charging stations. An interesting approach in [16] is to mitigate negative effects of high photovoltaic penetration and charging stations by optimal siting and sizing of both. Similarly, the ability of solar photovoltaic generation to improve voltage profile has been used to reduce negative impacts of EV parking in [17].

A well-planned charging infrastructure is therefore required to facilitate users in order to increase penetration of EVs. The three types of chargers used to recharge EVs are given in Table 1. Level 1 chargers are low power chargers and are usually used in residential areas. To reduce charging time, level 2 chargers are preferable than level 1 chargers. However, level 2 chargers require protection upgrade if used inside a residential house [18]. For use at the commercial-level, level 3 chargers are designed that can fully charge an EV battery within one hour. Because of their reduced charging time, these fast-charging stations are getting more attention. Nevertheless, their cost is very high and if proper planning is neglected, then they can overload the electrical power system [1]. In [19], fast-charging station planning is done considering cost and traffic in a distribution network. Nash bargaining theory is used to optimize the profit of operators by optimally placing and sizing fast-charging stations in [20]. A comprehensive plan for optimally locating and sizing fast-charging stations on urban roads is presented in [21]. It includes EV and power grid loss in planning and identifies them as important factors for determining siting and sizing of charging stations.

TABLE 1. Charger types [5].

Type of Charger	Suitable Location	Charging Power	Charging Time
Level 1	Residential	1.9 kW	11+ hours
Level 2	Residential/Commercial	4 kW	6-8 hours
Level 3	Commercial	Up to 100 kW	0.5-1 hour

Nevertheless, none of the reviewed papers has considered optimizing and analyzing the benefits of using more than one type of charging station. Significant effect of level 3 chargers on increased system losses and loading of distribution transformers is also not studied in detail in reviewed papers. In addition, the benefit of photovoltaic (PV) generation in maintaining voltage of the distribution system in the presence of charging stations is not fully explored.

In this paper, placement and number of all three different types of charging stations are optimized and analyzed in an active distribution system. Extensive planning is done to satisfactorily charge EVs while minimizing the installation cost of charging stations and system losses. Capital costs of level 1 and level 2 chargers are less than the cost of level 3 chargers. However, level 1 and level 2 chargers take a longer time to charge EVs. An optimized mix of these types of chargers can meet EV load with reduced installation costs. To the best of the authors' knowledge, this aspect has not attracted sufficient attention in the past. In addition, the impact of level 3 chargers on system losses and transformer utilization is presented in detail. The effect of PV on the voltage profile of the distribution system in the presence of a charging load is also studied. A stochastic model is developed to estimate hourly EV load from arrival time, departure time and distance traveled. In contrast to many other studies that use a general probability distribution model, input data of this model is gathered by a survey in the test case system to include the real behavior of vehicle owners. Simulations are done considering dynamic generation and load unlike many studies that assume only static generation and load. This paper presents a more realistic and comprehensive planning for the integration of EV charging stations in an active distribution system keeping in view electrical and geographic constraints.

The remaining part of the paper is organized as follows. Methodology is explained in section II, results are presented in section III and research is concluded in section IV.

II. METHODOLOGY

Methodology is elaborated by introducing stochastic EV load modeling in subsection A, PV generation modeling in subsection B, overall formulation of stochastic non-linear problem by PSO using MATLAB in subsection C and modeling of distribution system for power flow analysis using OpenDSS in subsection D.

A. EVs LOAD MODELING

Most of the power systems in developing countries lack EV load data. It is really important to model this load for the planning of EV integration. EV load depends on number of EVs, arrival and departure times at particular stations, charging characteristics, and traveling distance. These are probabilistic variables which can be used to estimate EV load [16]. A survey is conducted with a 300 sample size to gather information about behavior of vehicle owner. Questions were asked about their daily routine including arrival time, departure time and traveled distance. MATLAB was used to find the best fitting probabilistic distribution for this survey data. The resulting probability distribution functions and selected parameters are listed in Table 2. Two probability distributions are used to represent the arrival and departure of vehicles in the commercial feeder to incorporate morning and evening shifts. The EV load estimation approach is depicted in Figure 1.

The arrival time of EVs determines the starting time of charging. From the probabilistic distribution, the number of EVs arriving every hour can be inferred. Traveled distance indicates an initial state of charge of EV's batteries. This variable directly affects the amount of energy required to charge EV. Initial state of charge (SOC_{init}) is related to traveled distance as [22]:

$$SOC_{init,e} = 1 - \left(\frac{dist_{trav,e}}{d_{\max}}\right) \quad \forall e \in E \tag{1}$$

where $dist_{trav,e}$ is the traveled distance by vehicle and d_{max} is the range of particular EV, i.e. maximum distance it can cover when fully charged.

TABLE 2. Vehicle user data and fitted probability distribution parameters.

Data	Fitted Distribution	Parameters
	Commercial feeders	
Morning arrival	Generalized extreme value	$\xi = 0.0629$ $\sigma = 0.5492$ $\mu = 8.9068$
Evening arrival	Weibull distribution	$\lambda = 16.0386$ $k = 18.0225$
Evening departure	Generalized extreme value	$\xi = -0.2821$ $\sigma = 1.1106$ $\mu = 16.4070$
Night departure	Generalized extreme value	$\xi = -0.2779$ $\sigma = 0.5369$ $\mu = 20.5495$
	Residential feeder	
Evening arrival	Generalized extreme value	$\xi = 0.0631$ $\sigma = 0.5129$ $\mu = 18.7393$
Morning departure	Generalized extreme value	$\xi = -0.2532$ $\sigma = 1.1832$ $\mu = 7.0910$
	Commercial and residential feeder	
Traveled distance	Generalized extreme value	$\xi = 0.0474$ $\sigma = 7.9015$ $\mu = 12.8820$

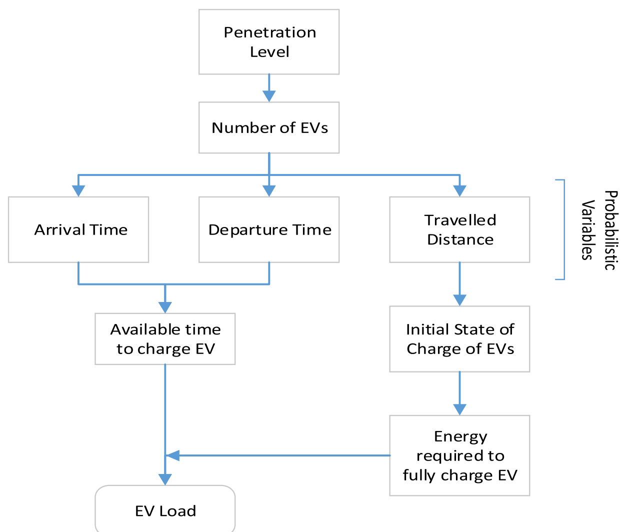


FIGURE 1. EV load estimation.

Arrival and departure times of vehicles determine available time to charge EVs. Most of the users would like to fully charge their vehicles in minimum time. However, this is limited by technical and economic constraints. The time of charging varies according to the charging level being used to charge a vehicle.

B. PHOTOVOLTAIC (PV) GENERATION INTEGRATION

Planned and installed PV at different nodes of the distribution system are also considered. PV in the distribution system is proved to reduce system losses and to improve voltage profile. Real insolation and temperature data obtained from high precision measurement system [23], installed at the same location as case study system, is used to estimate PV generation. It can be related as:

$$P_{PV} = 0.995 \times \eta \times A \times I \times (T_m - T_{\text{Ref}}) \tag{2}$$

where

η = Panels efficiency
A = Area of panel (m^2)
I = Irradiance (kW/m^2)
T_m = Measured temperature in degree Celsius
T_{Ref} = 25°C

Per kW solar panels' generation is based on real data and is presented in Figure 2.

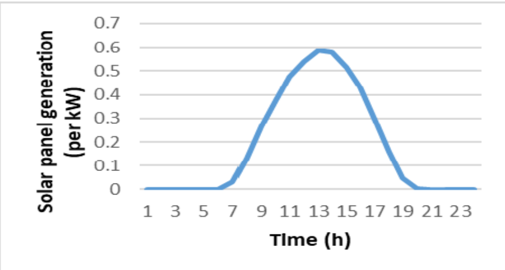


FIGURE 2. Per kW solar panels generation.

C. PROBLEM FORMULATION

To optimally locate different numbers of level 1, level 2, and level 3 chargers while reducing installation cost and cost of power losses in the distribution system, the following objective function is devised:

$$f = \min_{n_{1,i},n_{2,i},n_{3,i}} \left[\sum_{i=1}^{N} \left\{ \begin{array}{l} (n_{1,i}c_1 + n_{2,i}c_2 + n_{3,i}c_3) \\ + \left(Sgn(n_{1,i})|| \left(Sgn(n_{2,i})\right) \right. \\ \left. || \left(Sgn(n_{3,i})\right)\right) c_{p,i} \end{array} \right\} + c_{p.l} \sum_{t=1}^{T} \sum_{j=1}^{M} P_{j,loss} \right] \tag{3}$$

where optimization variables $n_{1,i}$, $n_{2,i}$ and $n_{3,i}$ are number of level 1, level 2 and level 3 chargers respectively at node i, N is the total number of nodes in the system while c_1, c_2 and c_3 are total cost coefficients (hardware cost + installation cost) as given in [24]. Sgn is signum function, || is or operator and $c_{p,i}$ is the parking availability coefficient to include geographic constraint. Its value is 0 when parking is available at an electrical node and a penalty cost when there is no parking available at the node. The cost of power loss per kWh is $c_{p,l}$ and its value is \$0.092/kWh [25] while M represents total number of lines in the distribution system. T is the total number of hours for which the system is simulated. Time step of optimization is 1 hour. The first part of the objective function calculates the total cost of installation of different types of chargers and includes parking availability cost. The second part calculates losses of all elements for the total time of the simulation. Losses are calculated by the difference of power in and out of each element. As the number and location of different types of chargers are changed, the current through and the voltage across an element can change resulting in a different value of loss. This provides one of the criteria on which optimizer finalizes its solution containing location, number and type of chargers.

The above-mentioned objective function is subjected to the following constraints:

$$V_{\min} \leq V_{i,t} \leq V_{\max} \quad \forall i \in N,\ \forall t \in T \tag{4}$$

The maximum and minimum voltage limit constraint ensures voltage lies within permissible limits (±10%) [9]. Any combination of charging stations resulting in voltage violating this range is rejected by the optimizer.

$$S_{j,t} \leq S_{j,\max} \quad \forall j \in M,\ \forall t \in T \tag{5}$$

The thermal limit constraint makes sure that line flows are not exceeding allowable thermal limits of conductors. High penetration of EV load may increase line flows which might otherwise violate thermal limits of conductors.

$$0 < n_{1,i}C_1 + n_{2,i}C_2 + n_{3,i}C_3 \leq C_{1,i}^{\max} + C_{2,i}^{\max} + C_{3,i}^{\max} \quad \forall\, i \in N \tag{6}$$

Limited charging capacity constraint ensures that the charging capacity of all levels of charger at a node should be less than aggregated maximum capacity. Besides this, it makes sure energy is being transferred to vehicles only as vehicle to grid (V2G) option is not considered in this paper. Maximum capacity refers to maximum power a specific type of charger can provide as presented in Table 1.

$$n_{1,i} + n_{2,i} + n_{2,i} \leq n_{\max,i} \quad \forall i \in N \tag{7}$$

The limited charger number constraint ensures that total number of chargers at a node is less than the pre-determined feasible charging slots available for EV in a given location.

$$0 \leq n_{l,i} \leq 3 \quad \forall l \in O,\ \forall i \in N \tag{8}$$

Constraint 8 is based on the physical limits of allowable parking slots in any location (assumed to be 3 in this study). This may vary according to available parking slots for EVs in any location.

$$n_{l,i} \in I \quad \forall l \in O,\ \forall i \in N \tag{9}$$

Constraint 9 ensures that number of chargers of level 1, level 2, and level 3 can only be integer numbers.

$$\Sigma\,(\eta_{ch}C_e)\,\Delta t_{ch} + SOC_{init} \geq SOC_{\max} \quad \forall e \in E \tag{10}$$

η_{ch} is charging efficiency (92%) [26], C_{ev} is EV charging power which is determined by the type of charger, SOC_{init} is the initial state of charge which can be in the range of 0-1 and Δt_{ch} is available time of charging. This constraint caters to customer satisfaction by ensuring that EV gets charged to above 80% level within the available time.

As the objective function uses power flow to calculate losses, it becomes a nonlinear function. Moreover, constraints involve an initial state of charge SOC_{init} and available time (Δt) variables which are modeled as probabilistic as explained in section A. For this nonlinear and stochastic problem, heuristic techniques are well suited. In this paper, a well-known heuristic technique particle swarm optimization (PSO) is used. PSO was originally developed by Kennedy and Eberhart in 1995 [24]. It is a metaheuristic and population-based technique that simulates the social behavior of a flock of birds. It starts its search by randomly generating candidate solutions in a large search space and narrows down to the best solution by iteratively updating its candidate solutions. This improvement in candidate solutions is guided by the quality of solutions in each iteration.

D. MODELING OF TEST SYSTEM IN OpenDSS

The distribution system is usually a radial or weak meshed network having high R/X ratio [27]. Further, the presence of an unbalanced load makes its behavior different from the transmission network. As such, conventional power flow techniques, such as Gauss-Seidel and Newton Raphson, become slow or may even diverge [27], [28]. For this reason, many authors prefer techniques based on the application of Kirchhoff's current law (KCL) and Kirchhoff's voltage law (KVL) for load flow in the distribution system. These include Forward/Backward sweep method and its variants [29], [30] and some novel techniques as presented in [27], [28], [31]. In this paper, a test case system is modeled in OpenDSS environment. OpenDSS is developed to simulate active distribution systems and uses a normal circuit solution technique which can be written as a fixed-point iterative method:

$$V_{n+1} = \left[Y_{system}\right]' I_{PC} V_n \quad \text{where n} = 0, 1, 2, 3 \ldots\ldots \tag{11}$$

All elements except loads are represented by their primitive nodal admittance matrix. Loads are modeled by Norton equivalent which includes constant and linear Norton admittance. This technique builds system primitive admittance matrix (Y_{system}) and starts the process by a random system voltage vector V_o to calculate compensation currents from each power conversion element in the circuit to populate I_{PC} vector. The new V_{n+1} is computed using the above equation. This is an iterative process and repeated until a convergence criterion is met [32]. Optimizer code based on PSO is developed in MATLAB and a MATLAB-OpenDSS interface is created. Based on EV charging placement of a particular number and type of chargers at different nodes, electrical loads of nodes are changed, and this data is sent from MATLAB to OpenDSS. Power flow of distribution system is done in OpenDSS and results are imported back in MATLAB to be processed by the optimizer. This process is repeated iteratively until the optimizer reaches to a converged solution. PSO is a heuristic technique and can get stuck in local optima. To overcome this problem, PSO is run multiple times and the results are analyzed statistically. Although, computational burden increases with an increase in the number of PSO runs, chances to hit global optima also increase. The optimization algorithm is illustrated by a flow chart in Figure 3.

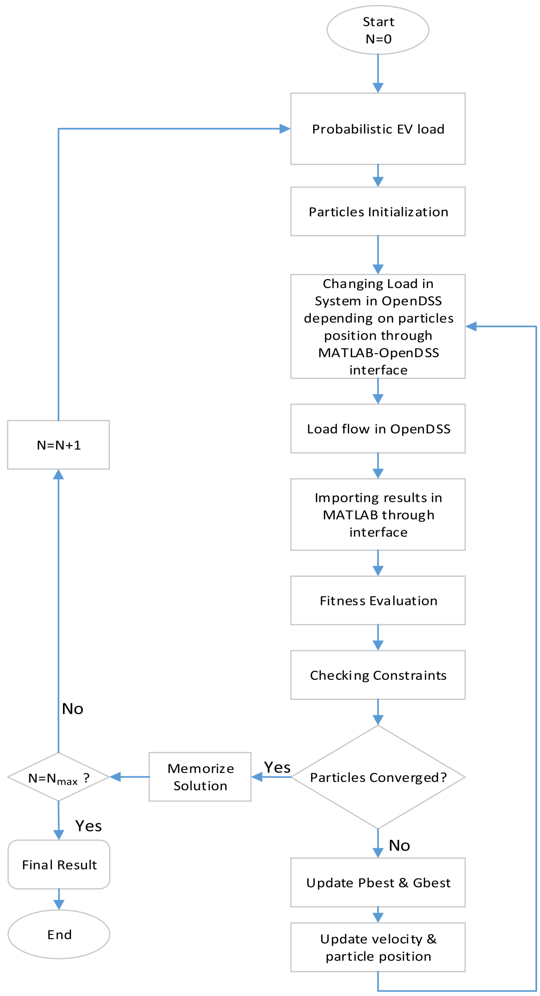


FIGURE 3. **Flow chart of the optimization algorithm.**

III. RESULTS

In order to validate the proposed idea, it is simulated on the real distribution network of the National University of Sciences and Technology (NUST), Islamabad, Pakistan. It is an 11/0.4kV radial distribution system where LV side of network is considered for placement of EV charging stations. It has three distribution feeders which have many laterals as shown in Figure 4. Feeders 1 and 2 are commercial whereas feeder 3 is residential. Loads are modeled as unbalanced while PV generation is also taken into consideration. The EV selected for simulation is Nissan Altra with Li-ion battery of capacity 29.07 kWh. When fully charged, its maximum range is around 80 miles [4]. Characteristics of this battery are similar to typical EVs which use Li-ion battery.

Table 3 and Table 4 show the type, location and number of chargers selected by the optimizer for different penetration level of EVs for commercial and residential feeders, respectively. Moreover, the tables give the minimum cost of the

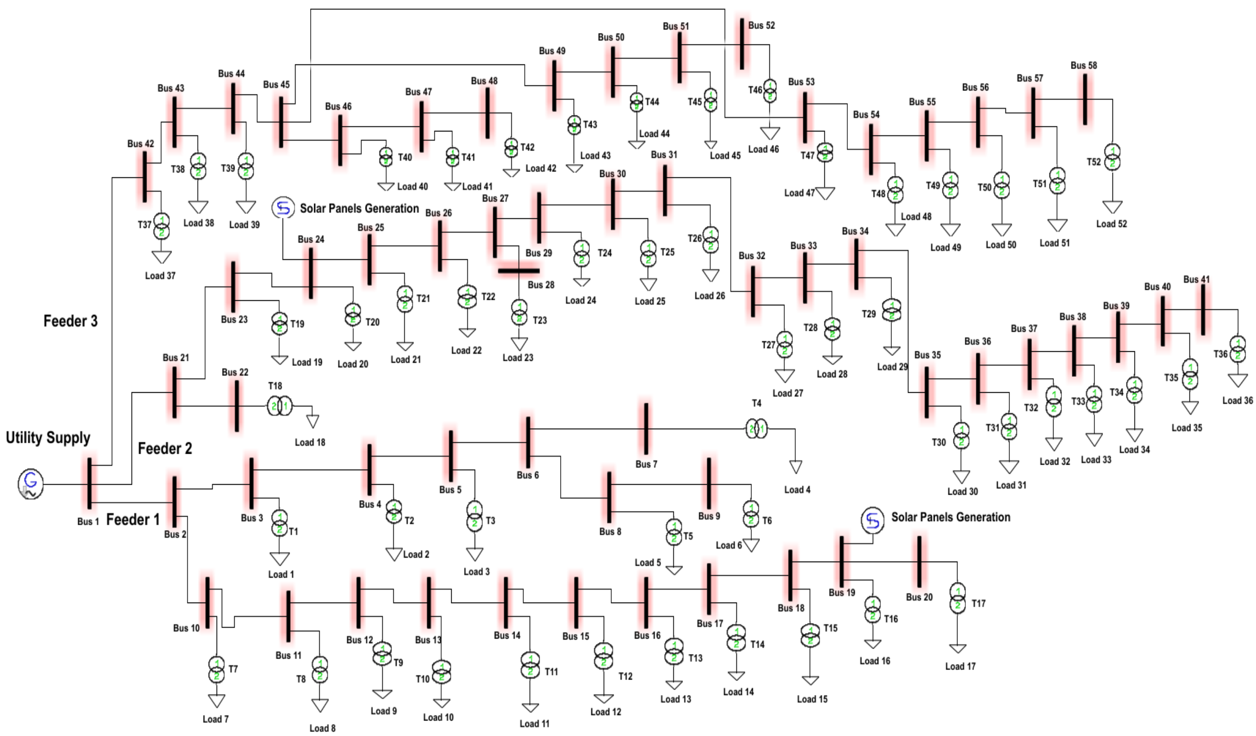


FIGURE 4. Single line diagram of simulated distribution system.

TABLE 3. Simulation results for commercial distribution feeders.

Type of Charger	Placement	Objective Function (million $)	System Status	Daily System Loss (kWh)	Maximum Transformer Utilization
Only level 1 charger	Maximum allowable chargers at each available parking	0.13	11% of EVs have not got a chance to charge. On average, 32% have to wait longer in rush hours 7 am-12 pm	265	21%
Only level 2 chargers	Maximum allowable chargers at each available parking	0.33	9% EVs are not charged at all On average 25% EVs have to wait longer in rush hours 7 am-12 pm	272	22%
Optimized solution for level 3 chargers (5% penetration level)	8, 12, 16, 23, 26, 29, 32, 35, 38	1.63	EV load satisfied, Higher cost	407	58%
10% penetration level	5, 8, 12, 14, 16, 19, 23, 26, 29, 32, 35, 38, 40, 41	2.53		611	58%
20% penetration level	5, 8, 12, 13, 14, 17, 18, 19, 22, 23, 25, 26, 29, 30, 31, 32, 35, 39, 40, 41	3.55		787	58%
Our optimized solution (5% Penetration level)	Level 1: 5,8, 12, 25 Level 2: 5,14,30,32,40 Level 3: 14,26,30	0.60	EV load satisfied, Lower cost	256	22%
10% penetration level	Level 1: 8, 16, 25,39, 40, Level 2: 5, 13, 14,16, 17, 18, 19, 22,23, 25, 30, 31, 38, 39, 41 Level 3: 5,8, 16, 18, 25,40	1.22	EV load satisfied	279	22%
20% penetration level	Level 1: 8, 13 Level 2: 5, 12,13, 14, 18, 19, 22, 25, 40, 41 Level 3: 13, 17, 19, 22, 25, 26, 29, 32, 35, 39, 41	1.99	EV load satisfied	286	22%

stated objective function. It is clearly depicted in Table 3 and Table 4 that level 1 and level 2 chargers are insufficient to satisfy EV load at 5% penetration level. To charge EVs using level 1 and level 2 chargers, the number of chargers needed is approximately equal to the number of vehicles to be charged daily. This is due to the fact that these low power

TABLE 4. Simulation results for residential feeder.

Type of Charger	Placement	Objective Function (million $)	System Status	Daily System Loss (kWh)	Maximum Transformer Utilization
Only level 1 charger	Maximum allowable chargers at each available parking	0.08	29% not charged at all, 45% have to wait longer in rush hours	371	11%
Only level 2 chargers	Maximum allowable chargers at each available parking	0.16	13% EV not charged, 36% have to wait longer	383	14%
Optimized solution for level 3 chargers (5% penetration level)	42, 47, 53, 57	0.77	EV load satisfied, Higher cost	682	34%
10% penetration level	42, 43, 48, 53, 57, 58	1.15		977	60%
20% penetration level	42 (6), 43, 47 (6), 48 (6), 49, 53 (6), 57 (6), 58	2.50		2167	106%
Our optimized solution 5% penetration level	Level 1: 43 Level 2: 42, 57 Level 3: 48	0.25	EV load satisfied, Lower cost	373	11%
10% penetration level	Level 1: 43, 49, 53, 57 Level 2: 42,48, 49, 53, 58 Level 3: 47	0.29		379	13%
20% penetration level	Level 1: 42, 48, 53, 58 Level 2: 43, 47, 48, 49, 53, 57,58 Level 3: 43, 47, 53, 58	0.81		398	14%

chargers need 6-12 hours to charge an EV and once a vehicle is plugged in, it may remain connected for most of the time it is in the parking lot. Therefore, a large number of chargers are needed to satisfy all EV in limited time available in the commercial and residential feeder for level 1 and level 2 chargers. It can be a challenge to deploy such a huge number of level 1 and level 2 chargers in parking lots. This challenge can be responded by deploying level 3 chargers. As shown in the table, a lesser number of level 3 chargers can fully satisfy vehicle load. However, there are certain negative impacts of level 3 chargers on system parameters. System losses increase significantly due to high power level 3 chargers. Moreover, maximum transformation utilization increases by a large percentage as compared to level 1 and level 2 chargers. This reduces the spare capacity of system transformers which may lead to the replacement of existing transformers with larger capacity transformers. Regarding the type of feeder, level 3 chargers are proved more uneconomical and technically infeasible for residential feeders than commercial feeders. This is because residential feeders are low power feeders and level 3 chargers can increase its losses significantly and may overload certain transformers. Comparing the proposed solution of using all types of chargers instead of a single-type of charger, it is proved that the former satisfies EV load with minimum cost.

In addition, the losses are around 37% (45%) less than level 3 chargers in commercial (residential) feeder for 5% penetration level of EV, as shown in Figure 7. With an increase of penetration level of EV to 10% (20%), losses for proposed solutions are 54% (63%) less than system losses for

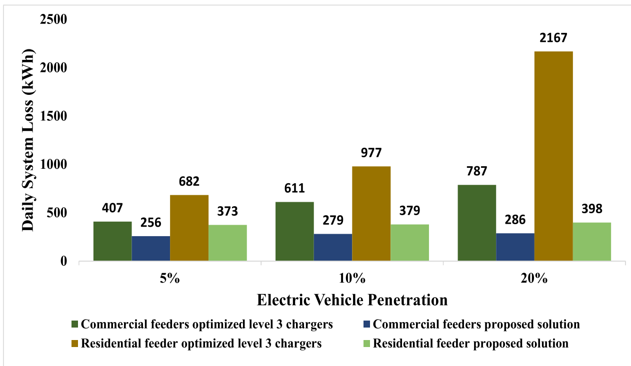


FIGURE 5. Daily system losses for level 3 chargers and proposed solution.

optimized level 3 chargers for commercial feeders. In case of residential feeder, the proposed solutions offer 61% (82%) less losses than level 3 chargers for 10% (20%) penetration. In case of commercial feeders, maximum transformer utilization is 22% for proposed solution as compared to 58% for level 3 chargers for all 3 penetration levels that were studied. In residential feeder, maximum transformer utilization for 5%, 10%, and 20% penetration levels is 34%, 60%, and 106% for level 3 chargers as compared to 11%, 13%, and 14% for proposed solution, as presented in Figure 6. These statistics clearly show that the significance of the proposed solution increases as penetration level of EV increases in the system.

Constant maximum transformer utilization for commercial feeders is due to the fact that chargers are distributed across feeders rather than increasing the number of chargers at

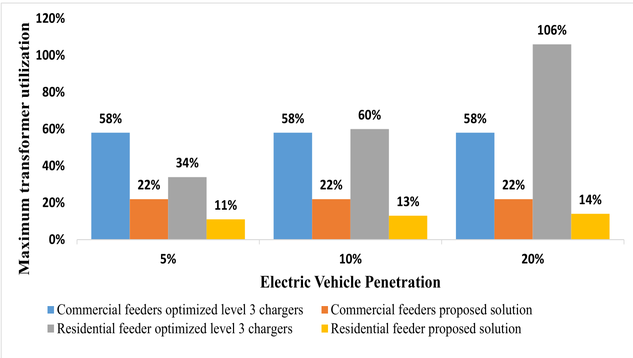


FIGURE 6. **Maximum transformer utilization for level 3 chargers and proposed solution.**

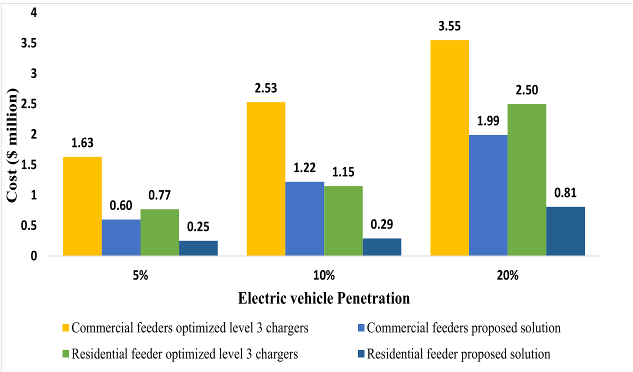
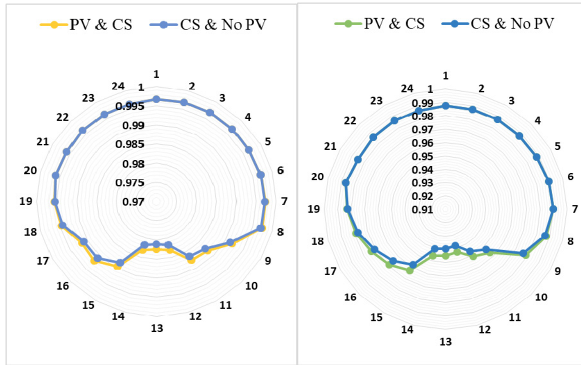


FIGURE 7. **Cost of installation of charging stations for level 3 chargers and proposed solution.**



(a) (b)

FIGURE 8. **Daily voltage profile of commercial feeder (a) Daily voltage profile of commercial feeder node 20 (b) Daily voltage profile of commercial feeder node 41.**

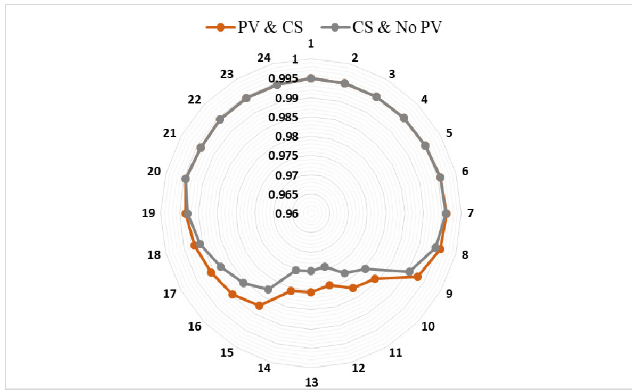


FIGURE 9. **Daily voltage profile of commercial feeder node 24.**

particular nodes. However, this cannot be done in every scenario especially when limited parking is available or penetration increases to such an extent that number of chargers have to be increased at most of the system nodes to satisfy EV load. Figure 7 shows the importance of the proposed solution in terms of cost. A solution involving the use of only level 3 chargers is costly while the proposed solution can meet the requirement in less cost for both commercial and residential feeders.

A. IMPACT OF PHOTOVOLTAIC (PV) GENERATION ON VOLTAGE PROFILE

Figure 8 and Figure 9 show the impact of PV on voltage profile of different nodes at 5% penetration level. 200kW PV is located at node 19 of feeder 1 whereas 1MW PV is installed at node 24 of feeder 2. Moreover, node 20 and 41 are end nodes of commercial feeder 1 and 2, respectively. The graphs clearly show the importance of PV generation in improving the voltage profile. At peak load, improvement in voltage at node 20 is 0.001 per unit while it is 0.005 per unit at node 24 regardless of more charging stations (CS) near node 24. This is because of the size difference of the PVs in both feeders. Note that 1MW PV capacity at node 24 is 5 times larger than the 200kW PV installation at node 19 which is right next to node 20. Node 41 is the far end of commercial feeder 2 and voltage drops much lower to 0.93 per unit without PV. Since the charging load may drop the voltage below the acceptable level, PV generation can be crucial in improving the voltage profile of system.

B. IMPACT OF PENETRATION LEVEL OF LEVEL 3 CHARGERS AND PROPOSED SOLUTION ON VOLTAGE PROFILE

Figure 10 and Figure 11 show the significance of the proposed solution for voltage under different penetration levels of EVs in the commercial and residential feeders. An increase in penetration level causes more charging load and therefore decreases voltage. Especially, deployment of level 3 chargers causes a significant decrease in voltage for different penetration levels. The proposed solution is helpful in maintaining the voltage profile even for the increased penetration level of EVs. Differences in voltage dips for 24 hours can be seen in graphs for the commercial and residential feeder. Residential feeder experiences EV charging load during night whereas EVs usually remain plugged in during daytime in commercial feeders. Voltage in commercial feeder drops to less than 0.92 per unit for a 20% penetration level while the proposed solution maintains it above 0.94 per unit for all penetration levels. In residential feeder, the proposed solution maintains voltage at 0.99 per unit while suffering a voltage drop to less than 0.975 per unit at peak times for a 20% penetration level.

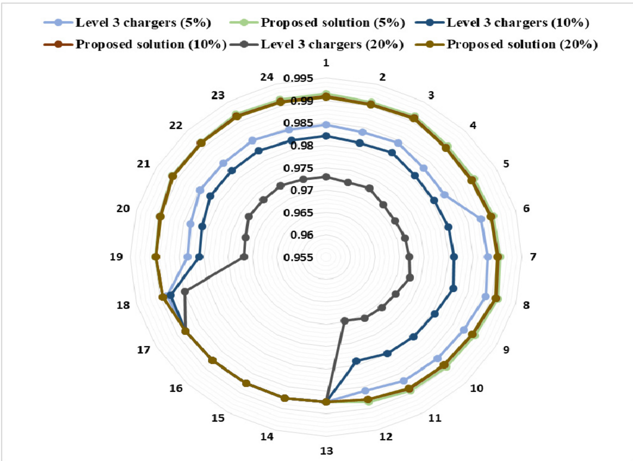


FIGURE 10. Daily voltage profile of residential feeder node 58 for level 3 chargers and proposed solution.

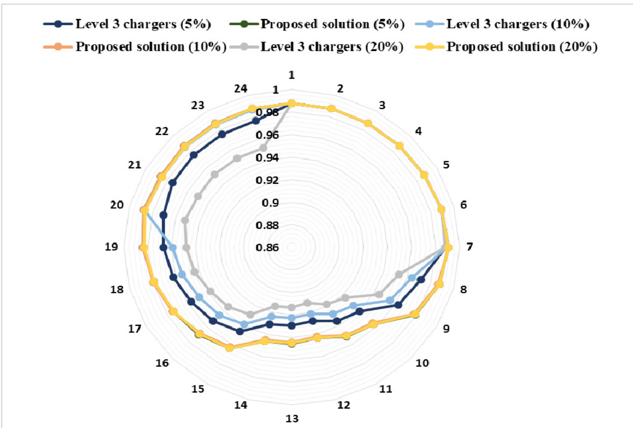


FIGURE 11. Daily voltage profile of commercial feeder node 41 for level 3 chargers and proposed solution.

A higher voltage drop in the commercial feeder is because of higher and concurrent building loads and EV charging. In residential feeder, most of the household load is off at late night and only vehicles are plugged in for charging. The demand of the residential colony is also smaller than the rest of the university campus that makes up the commercial area. Therefore, voltage drop in the residential feeder is less in comparison to the commercial feeder.

IV. CONCLUSION

In this paper, a novel strategy was presented for optimal sizing and siting of different types of EV charging stations in the active distribution system of commercial and residential buildings including offices and homes. In addition, the uncertain behavior of the vehicle owner was modeled using probabilistic distributions fitted on real data and geographic constraints of parking were taken into consideration. PSO was used to solve the resulting stochastic nonlinear problem. The results have demonstrated that proposed optimized solution reduced the cost of EV charging infrastructure by 75% and distribution system losses by 82% as compared to level 3 charging station, whereas the optimized solution enabled higher EV load satisfaction when compared with level 1 and level 2 charging station scenarios. The proposed solution also ensured that loading on commercial and residential transformers was minimum and therefore need to install new transformers was deferred. Furthermore, analysis of the impact of PV on the voltage profile revealed that distributed PV generation can support voltage profile despite EV charging stations in commercial feeders of the distribution system.

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