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OPTIMAL PLACEMENT OF CHARGING STATION IN OM DISTRIBUTION FEEDER OF NEW CHABIL SUBSTATION CONSIDERING DYNAMIC NATURE OF ELECTRIC VEHICLE LOAD

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ABSTRACT

One of the major contributors of global warming and environmental changes which is considered as global problem is fossil operated internal combustion engines vehicles. To sort out this problem, enhanced battery technology and subsidies provided by the Government has caused rapid increase in number of electric vehicles (EVs) which requires charging station (CS) to connect the power grid and the transport network. The behaviour of EV is uncertain and CS random placement affects both the network simultaneously. So, in this paper demand of CS is obtained by Monte Carlo simulation (MCS) with the help of queuing theory for taking the dynamic characteristics of a CS serviceability into account. Optimal placement of CSs is structured as a multi-objective optimization problem, which is solved by non-dominated sorting genetic algorithm-II (NSGA-II) to obtain a set of compromised solutions from which best compromised solution is obtained by Fuzzy optimization technique. The objective functions to be optimized are minimization of electrical distribution loss, minimization of power loss occurring in EVs' when travel towards CS location and maximization of utilization factor (UF). UF value provides an insight on how well the CS infrastructure is utilized and helps in determining the number of CSs required in a network. The proposed method is simulated on a real 12kV OM feeder of Nepal to show various results. Results show best location of CSs and parameters like voltage profile, CS utilization and demand uncertainty of CS are analyzed and presented.

Keywords: *Queuing theory, utilization factor, NSGA-II, electric vehicle, charging station, Monte Carlo simulation, Fuzzy optimization.*

INTRODUCTION

The risks to present era are greenhouse gas (GHG) emissions, the rapidly increasing demand for energy, while the depletion of petroleum and natural gas. Since the transportation sector (Internal combustion engine) is responsible for 23% of the GHG emissions in the world, it must play a significant role in keeping temperatures rising to less than 2^0C [1]. Electric vehicles (EVs) possess the ability to reduce greenhouse gas emissions, which are the cause of rising temperatures and environmental damage. Besides to the benefits for the environment, other benefits that encourage many nations to switch from internal combustion engines to electric vehicles include reduced maintenance costs, noise levels, and operating costs. Many countries have stated that their entire transportation system will be electrified by 2030 [2]. The Nepal government also intends to increase the percentage of electric vehicles driven up to 25% by 2025 and up to 90% by 2030. Electric power is required for charging EVs. EVs have become incredibly popular in recent years, and it appears that this trend will continue until the transportation sector adopts a maximum of EVs, in accordance with new policies implemented by several governments across the globe. The selection of EVs is growing due to advancements in power electronics and battery technologies.

A higher level of integrating plug-in electric vehicles (PEVs) can have both positive and negative effects for the electrical system operator. The unfortunate thing is that an increase in the number of electric vehicles on the road can lead to problems such as voltage drop, overloaded power transformers, overloaded low voltage lines, increased energy loss, and harmonic currents [3]. In order to prevent these issues, grid managers and electric vehicle users must collaborate and develop a plan for energy-efficient use of electricity and locate charging station required for EVs optimally. The charging demand behaviour of plug-in electric vehicles considering the different factors such as inter-arrival time and service time duration, charging voltage level and current level, the number of plug-in hybrid electric vehicles beings charged [4], energy consumption per mile, total battery capacity and start or end status [5], daily driven distance pattern and daily recharge energy [6] , type of electric vehicles and presence of percentage of electric vehicles in the CS [7] has been determined. Establishing public charging stations presents a problem since it needs integration of two distinct systems: the transportation and electricity system. If we only think about what the electrical system needs and don't consider how people travel and where they need to charge their electric vehicles, we might put charging stations in places that are good for the electrical system but not easy for drivers to reach. This means the solution won't be good for the people who drive electric cars and need to charge them. Similarly, if we only think about where people drive and put charging stations in those places, it might be hard for the electrical system to handle all the electric cars charging there.

The previous studies did not to consider into account the uncertainty of electric vehicles and charging stations, distance travel of EV to arrive at CS nor it examined the charging capability of charging stations. In this work distribution losses and the capital cost of the charging stations are taken into account when placing charging stations in addition to consumer comfort or reduce the traveling loss. M/M/s queuing models is selected to obtain power demands of a charging station and stochastic load models for the EV propelling system. Monte Carlo Simulation (MCS) technique [8] is employed to examine load demand of the charging station. Multi-objective function considering utilization factor to measure the effective utilization of charging station infrastructure is solved with the help of Non-sorted Genetic algorithm (NSGA-II).

MATHEMATICAL FORMULATION

1. Modelling of PEV Recharging Energy

In the M/M/s queuing theory [9], the first M means the exponential distribution of incoming for charging PEVs customer with a mean of average arrival time 1/λ, the second M means of exponential distribution of a PEV customer’s average service time 1/μ, and s represents the maximum number of CP for parallel charging PEVs in the same instant [10]. The following steps are used for the random simulation process to determine the total charging demand samples of EV:

a. The number of PEVs (n) being charged at the same instant is randomly generated using this equation for charging station:

$$P(n) = \begin{cases} \frac{\alpha^n}{n!} p_0; n = 1,2,3, \dots. \\ \frac{\alpha^n}{s! s^{n-s}} p_0; n = s+1, \dots\dots \infty \end{cases} \quad \text{where} \quad p_0 = \frac{1}{\left(\sum_{i=0}^{s-1} \frac{(s\alpha)^i}{i!} + \frac{(s\alpha)^s}{s!} \cdot \frac{1}{1-\alpha}\right)} \quad (1)$$

b. Randomly select PEV as per their market share.

c. Randomly generate PEV daily driven distance (M_d) parameters for selected market share [11].

$$M_d = e^{\mu_m + \sigma_m * N} \quad (2)$$

d. Calculate electrical energy consumed per km by a PEV (EK).

e. Calculate daily recharge energy requirement of a PEV, (D_E) [4] using this equation:

$$D_E = \begin{cases} C_{Bat} M_d \geq M_E \\ E_K . M_d M_d < M_E \end{cases} \quad (3)$$

f. Charging time (T_C) is generated randomly with a mean T_μ using this equation. T_C is truncated inside a certain range [T_{min}, T_{max}] due to the battery capacity or service restrictions [4].

$$T_C = \begin{cases} T_{min} T_C \leq T_{min} \\ T_\mu . \in (U) T_{min} < T_C < T_{max} \\ T_{max} T_C \geq T_{max} \end{cases} \quad (4)$$

g. Charging current (I_i is calculated by the applied voltage V and maximum charging current I_{max} of selected power level [4] using this equation.

$$I_i = min\left(\frac{D_E}{V.T_C}, I_{max}\right) \quad (5)$$

h. Overall charging demand P of a CS for charging n EV [4] is calculated using this equation.

$$P = \sum_{i=1}^{n} V . I_i \quad (6)$$

The previously mentioned process is carried out till sufficient samples are generated to perform further static evaluation.

2. Formulation of objective function

A) Minimization of Distribution Loss

When the distance between the distribution transformer and the charging station location is increased then the distribution loss will increase. So, it is important to evaluate the network loss correctly.

$$f_{obj1} = min(P_{Loss}) = \sum_{b=1}^{n_{max}} \sum_{b=1}^{n_{max}} (I_b)^2 . R_b \quad \forall b \in n_{max} \quad (7)$$

Where, $n_{max}$is the number of branches in the network, R_b is the branch resistance and I_b is the branch current.

B) Minimization of Travelling Loss

The minimum travelling distance L_{min} from currently situated spot at jth bus to the candidate CS spot at ith bus [12] is calculated as

$$L_{i,j} = Z_{i,j} . x_i ; \forall i, j i \neq j ; L_{i,j}^{min} = min(L_{i,j})$$

Where, $Z_{i,j}$ is node bus connectivity matrix and x_i is binary variable denoting CS availability at bus i.

The power required$(E_{i,j})$ for an EV to travel $L_{i,j}^{min}$ is determined as,

$$E_{i,j} = \sum_{s=1}^{M_{i,j}^{ev}} E_{K,s} . L_{i,j}^{min} \quad (8)$$

The travelling loss of total EV population in the system [12] is evaluate using this equation.

$$f_{obj2} = min(L_{Travel}) = \sum_{i=2}^{N_{Bus}} . \sum_{j=2}^{N_{Bus}} E_{i,j} ; \forall i, j, \{i, j\} \in N_{Bus} \quad (9)$$

C) Maximization of Utilization Factor

Utilization factor is the percentage of the number of charging ports that are active to the total number of charging ports in the CS [12] & [13]. It makes the CS investor able to evaluate the exact usage of CS infrastructure.

$$Utilization\ Factor\ (UF) = \frac{Total\ amount\ of\ energy\ sold}{CS's\ Power\ capacity * CS's\ total\ working\ time(T_w)}$$

$$f_{obj3} = max\big(min(UF_r)\big) = \frac{\sum_{t_{unit}} P_r}{\sum_{t_{unit}} P_{CS}^r} ; \forall t_{unit} \in T_w ; \forall r \in N_{CS} ; P_{CS}^r = P_{CP}^q . k_{cp} \quad (10)$$

D) Constraints

i. *Charging Station Location Restriction:* Placing two or more than one CS in a one location, it would not be beneficial as installation cost of EVCS is much higher than their charging ports. It also reduces the service area because EV not able to select nearby CS, and wasted investment in CS.

$$-\left|l_i^{CS} - l_j^{CS}\right| + 1 \leq 0; \text{Subject to: } i \neq j \quad (11)$$

where, l_i^{CS}, l_j^{CS} is the bus location of the i^th^, j^th^ bus in the electrical system.

ii. *Charging Power Limit:* The charging power requirements$(P|i)$ of i^th^ CS must be within its limits ($P_i^{min} \wedge P_i^{max}$) and the charging power requirements ($P_{i,q}^{CP}$) of the q^th^ CP of the i^th^ CS.

$$P_i^{min} \leq P_i \leq P_i^{max} ; \forall i \epsilon \varphi^{dn} where, P_i = \sum_{q=1}^{k_{cp}} P_{i,q}^{CP} \quad (12)$$

iii. *Voltage Limit:* The voltage of each bus should be kept within its maximum and minimum limits (i.e., V_i^{Min} and V_i^{Max}) in order to maintain a high-quality power supply.

$$V_i^{Min} \leq V_i \leq V_i^{Max} (i = 1,2,3, \ldots\ldots\ldots, N_{Bus}) \quad (13)$$

RESULTS AND DISCUSSION

A) Simulation of CS Load Demand

CS load demand is obtained by mathematical framework as explained above. For this total EVs currently available and running in Kathmandu valley are grouped into four different classes as per their battery capacity namely class-1 (Tigor / E-pres-t, CITROEN and NEXON Prime), class-2 (NETA, KONA and NEXON Max), class-3 (ORA and MG ZS) and class-4 (BYD car). Battery capacity of each EV of a class is averaged to obtain class-wise capacity and 90% of total kWh is considered here because battery won't be fully discharged before going to charging station. Different required data of each class is as shown in table-1.

Table 1: Class-wise EVs parameters

Description	Class-1	Class-2	Class-3	Class-4
Market share in %	25.29	29.91	30.32	14.48
Battery capacity in kWh	25.62	35.46	44.45	64.53
Energy consumption in kWh/km	0.0902	0.0954	0.1395	0.1728

For this study, arrival time and service time of a vehicle is taken as 75 minute and 56 minutes respectively. Voltage of charging station is taken as 420V and maximum charging current limit of a charging port is taken as 150 A. Limiting value of charging time is taken as 10 minute and 120 minutes. Mean and standard deviation of daily driven distance of a vehicle inside Kathmandu valley is obtained to be 40.26 km and 19.45 km respectively. Total EVs population is taken as 63 and total number of charging port 4. The number of EVs in any CS is generated using M/M/c queuing theory and Monte Carlo simulation technique is employed to obtain demand of CS. With 25000 iteration PDF with different fitting obtained for CS demand simulation is as shown in figure 1.

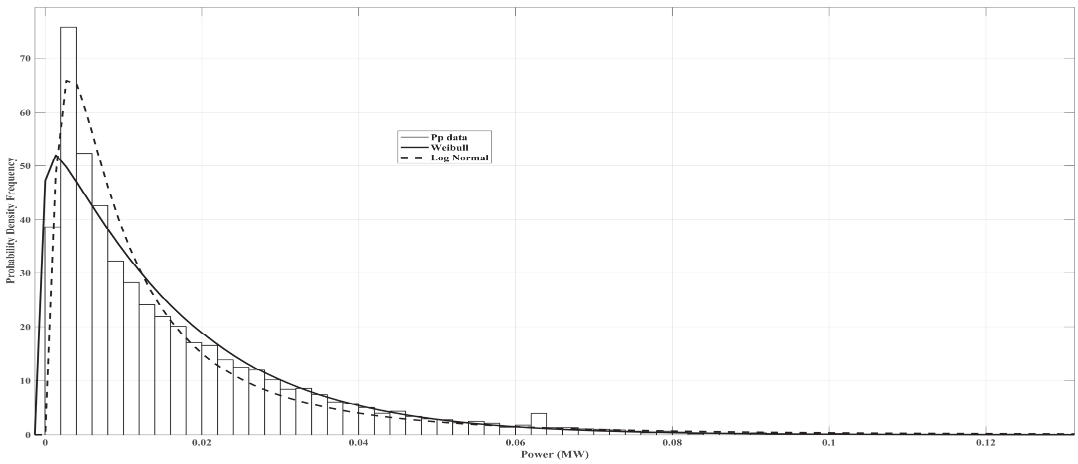

Figure 1: PDF fitting on CS demand distribution functions

From figure 1, it can be observed that Weibull distribution best fits on the sample of charging station demand in case of single CS with 4 number of ports. Weibull distribution parameters are A= 0.0166289, B = 1.04722 and Log-likelihood of 41060.5. Mean and variance of fitting are 0.0163257 and 0.000243179 respectively with error in parameter A and B of 0.0146463% and 0.694882% respectively. Parameters of the fitted distribution function can be used in case of probabilistic load flow for real time placement of charging station and continuous demand of charging station can be obtained as per the requirement

B) Test System

A real 12kV distribution feeder namely OM feeder of new Chabil substation of Maharajgung distribution center (DCS), Nepal Electricity Authority (NEA) is considered for implementing the considered concept in context of Nepal and single line diagram of the considered network is as shown in figure 2. It has one feeder with 16 different laterals, 80 buses including substation and 79 branches. The selected network is considered to be balanced system and it’s per phase total active and reactive peak load of the system considering total installed capacity of transformer is 3936.00 kW and 1924.50 kVAr respectively. With the coded backward/forward sweep method taking base power 100 MVA, and base voltage 12.00 kV, the total per phase power loss for base configuration obtained is 63.0516 kW with minimum voltage of 0.96871 p.u. at bus number 58 and current in branch-1 is 371.773 Amp.

C) Single CS Placement

In case of single CS placement, the selected network can have only one charging station and all the EVs owner should come to that location. The distribution losses rise when electric vehicle charging load demands grow because it creates extra load in the network's infrastructure. Random placement of CS (which is one load) will create unwanted disturbances in the electrical network as well increases losses by large amount. So, to have minimum effect in the distribution network optimal allocation of the charging station is done considering following three different scenarios of objective functions. In case of single objective function Genetic Algorithm (GA) is used to obtain optimal location satisfying different constraints.

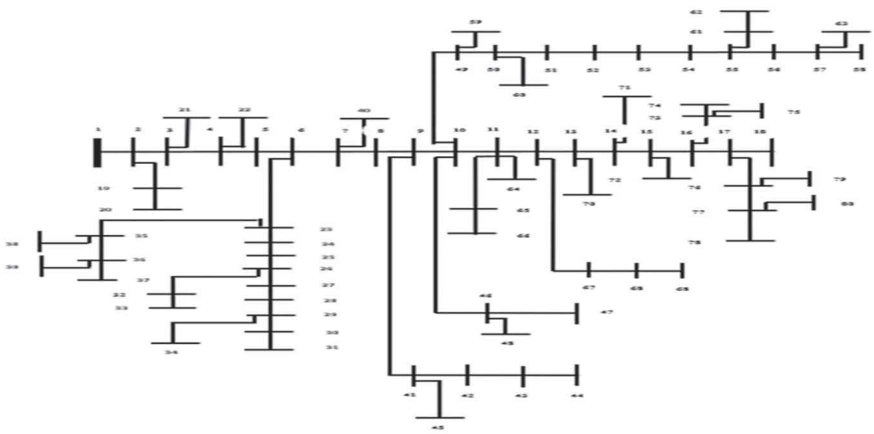

Figure 2: SLD of OM 80-Bus Radial Distribution Network

1) Distribution Loss Minimization

In this case best location of charging station is selected for given demand of CS in such a way that total loss in the selected distribution network will be minimum and all the constraints are within the limit. Simulation done with help of GA in case of 80 bus OM feeder, it is found that optimal location of CS is at bus no. 2 having distribution power loss of 63.2197kW with minimum voltage of 0.96869 p.u. At this location travel loss is found to be equal to 0.5097kW.

2) Travelling Loss Minimization

In this case, total travelling loss that occurs when all EVs travel from the bus where they are located to the bus where CS is placed, is minimized to get optimal position of CS in the network. From the solution obtained after running GA, minimum value of travelling loss is found to be 0.3081kW when CS is placed at bus 10. At this location, distribution power loss is 64.3199kW and minimum voltage of the system is 0.96849 p.u.

3) Distribution Loss and Travelling Loss Minimization

In this scenario, both distribution loss of the network and travelling loss occurring in the system are minimized simultaneously with help of NSGA-II optimization algorithm [14]. A set of compromised solutions by considering both the functions or losses present in pareto front-1 of NSGA-II algorithm for the case of one CS are as shown in table 2.

From the table 2, it is seen that both the objective functions are contradictory in nature, so the best compromised solution among the set of compromised solutions is obtained with the help of Fuzzy optimization technique [15]. The best compromised value of the distribution loss and travelling loss are 63.7658kW and 0.2982kW respectively with minimum voltage of 0.96860 p.u. for location of a CS at bus no. 7.

Table 2: Pareto set considering network loss and travel loss in case of one CS

Pareto Set Number	1	2	3	4	5	6	7	8	9
Bus No.	2	3	4	5	6	7	9	10	11
Distribution Loss in kW	63.22	63.411	63.501	63.565	63.624	63.766	63.834	64.32	64.323
Travelling Loss in kW	0.4699	0.3966	0.3596	0.3454	0.3309	0.2982	0.2916	0.2725	0.2723

D) Multiple CS Placement

In this case, more than one CS are taken considering the above-mentioned objective functions individually and simultaneously. In case of a large system, system operator is motivated to have more than one CS if the CSs are utilized efficiently. So, here the third objective functions namely utilization factor is also calculated. The policy maker is assured to have high return when the CSs are utilized adequately and hence, the investment on CSs will be worthy. During selection of number of CSs, utilization factor plays a vital role. Different scenario of objective function considered are as follows.

1) Distribution Loss Minimization

Considering distribution loss as minimization function, GA gives bus 2 & 19 for locating the charging station in the OM feeder with distribution loss 63.2217kW and minimum voltage of 0.968687p.u. For these locations travelling loss is found to be 0.4885kW. Similarly, location and other parameters can be obtained for 3, 4, etc number of CSs as per the requirement.

2) Travelling Loss Minimization

In this case, the traveling loss of all EVs is only minimized to find the optimal location of the two CS in the network by using GA. It is found that minimum value of travelling loss is 0.2138kW for location of CSs at bus 46 and 57 of the considered OM feeder. For these locations distribution loss is 64.7708kW and minimum voltage of the network is 0.96819 p.u.

3) Distribution Loss and Travelling Loss Minimization

Optimal placement of the two-charging station in the OM feeder network by simultaneously minimizing both distribution loss and travelling loss is carried with help of NSGA-II optimization algorithm [14]. Figure 3 shows plot of distribution loss and travelling loss corresponding to pareto set number present in a set of compromised solution of pareto front-1 in case two charging stations.

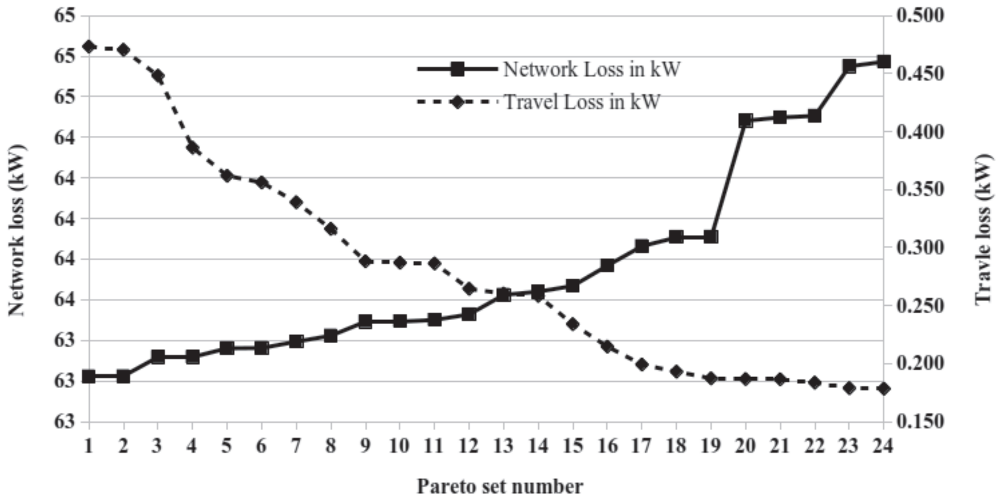

Figure 3: Network loss and travel loss for pareto set number for two CSs.

From figure 3, it can be observed that for same location i.e., same pareto set number value of distribution loss decreases while value of travelling loss increases, which clearly shows that both the objective functions are contradictory in nature. When distribution loss is plotted against travelling loss obtained in set of compromised solution of pareto front-1, then graph as shown in figure 4 is obtained.

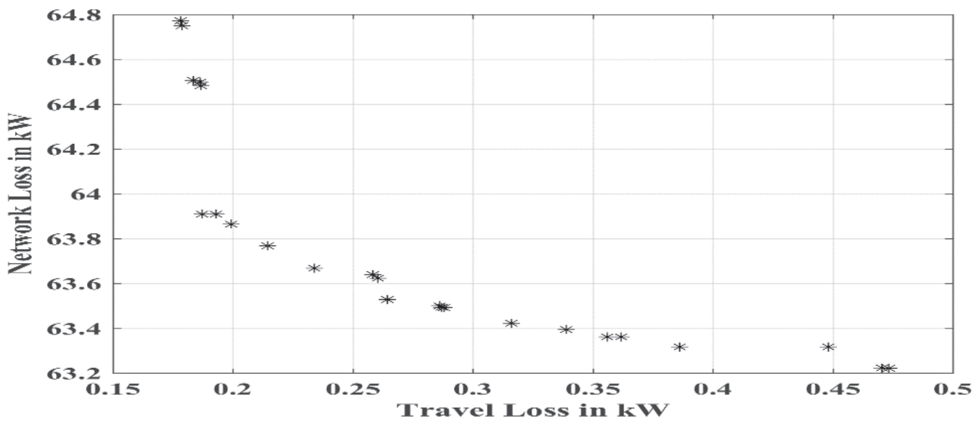

Figure 4: Network loss and travel loss of pareto set in case of two CS

Using Fuzzy optimization technique [15]. best compromised solution from a set of compromised solution is obtained and best compromised value of the distribution loss and travelling loss are 63.9095kW and 0.1872kW respectively with minimum voltage of 0.96857 p.u. for location of CSs at the bus 10 and 22.

4) Distribution Loss and Travelling Loss Minimization with Maximization of Utilization Factor

In this case, optimal placement of the more than one charging station in the OM feeder network by simultaneously minimizing both distribution loss and travelling loss with maximization of utilization factor is carried with help of NSGA-II optimization algorithm [14]. Table 3 shows a set of compromised solutions by considering all objective functions or distribution loss, travelling loss and utilization factor present in pareto front-1 of NSGA-II algorithm for the case of two CS. Figure 5 shows plot of distribution loss and utilization factor corresponding to pareto set number present in a set of compromised solution of pareto front-1 in case two charging stations.

Table 3: Pareto set considering three objectives in case of two CS

PSN	Bus No.		Distr. Loss	Trav. Loss	Max. UF	PSN	Bus No.		Distr. Loss	Trav. Loss	Max. UF
1	19	2	63.222	0.564	16.2	24	9	36	63.676	0.243	6.4
2	20	2	63.222	0.523	14.2	25	9	38	63.678	0.265	12.3
3	2	3	63.315	0.43	15.8	26	25	9	63.762	0.284	12.8
4	19	3	63.317	0.425	13.5	27	2	10	63.768	0.235	12.7
5	2	4	63.36	0.394	15.7	28	19	10	63.77	0.248	14.4
6	19	4	63.362	0.382	13.8	29	3	10	63.864	0.211	11.8
7	20	4	63.363	0.383	17.4	30	3	11	63.865	0.21	10
8	2	5	63.392	0.372	14.3	31	4	10	63.909	0.219	13.3
9	19	5	63.394	0.349	13.3	32	22	10	63.91	0.211	11.3
10	2	6	63.421	0.363	15.2	33	4	11	63.911	0.19	7.38
11	19	6	63.423	0.33	8.86	34	6	53	64.366	0.229	15.5
12	20	6	63.424	0.331	9.71	35	8	53	64.443	0.206	13.2
13	2	7	63.492	0.32	14.5	36	7	54	64.448	0.209	14.2
14	19	7	63.494	0.296	11.8	37	8	54	64.454	0.207	13.4
15	20	7	63.495	0.316	14.9	38	9	53	64.471	0.202	14.3
16	2	8	63.498	0.312	14.7	39	8	55	64.477	0.19	11.5
17	19	8	63.5	0.318	15.1	40	7	56	64.481	0.189	5.67
18	2	9	63.526	0.293	12.2	41	8	56	64.487	0.202	11.9
19	19	9	63.528	0.299	15.6	42	8	57	64.498	0.187	9.81
20	3	9	63.622	0.279	12.6	43	9	55	64.506	0.199	12.2
21	4	8	63.639	0.277	11.7	44	9	56	64.515	0.199	13.4
22	4	9	63.667	0.28	12.6	45	9	57	64.526	0.186	12.4
23	22	9	63.668	0.255	11.7	46	10	55	64.75	0.194	12.6

Where, PSN: Pareto Set Number, Distr. Loss: Distribution Lossin kW and Trav. Loss: Travelling Loss in kW.

From figure 5 & 6 and table 3, it can be observed that value of distribution loss decreases while value of utilization factor increases but value of travelling loss increases, which clearly shows that all these objective functions are contradictory in nature. When distribution loss is plotted against travel loss obtained in set of compromised solution of pareto front-1, then graph as shown in figure 6 is obtained. So, using Fuzzy optimization technique [15] best compromised solution from a set of compromised solution is obtained and best compromised value of the distribution loss, travelling loss and utilization factor with minimum voltage for different number of charging station are shown in table 4.

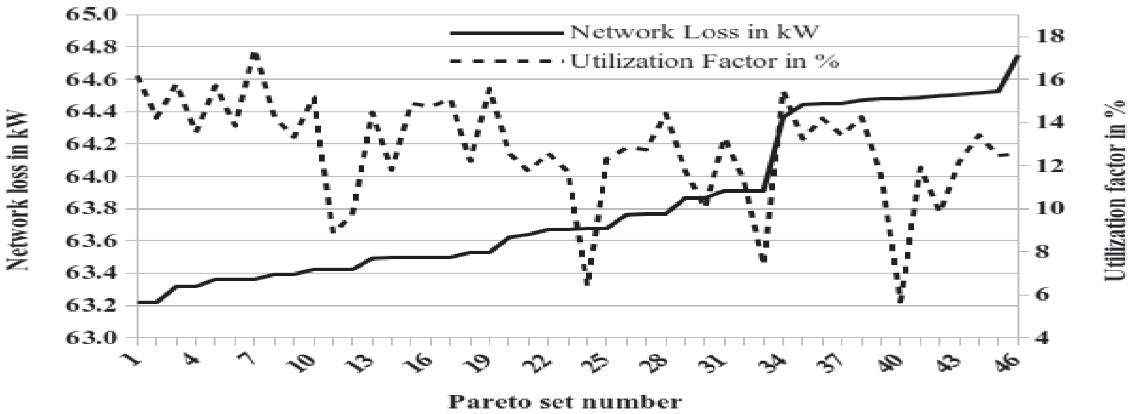

Figure 5: Network loss and utilization factor for each pareto set number.

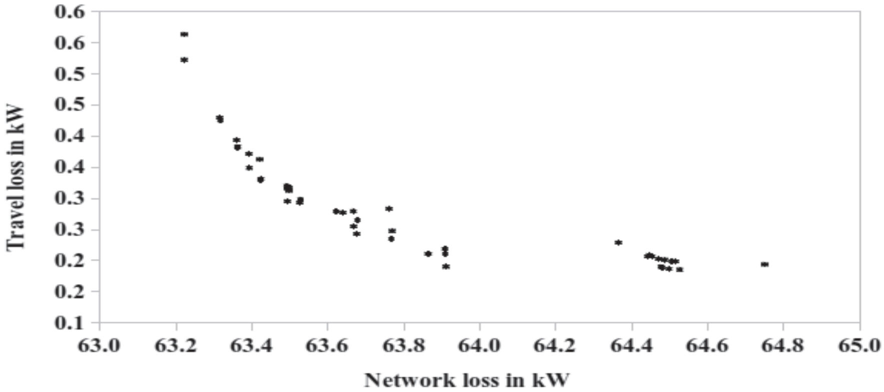

Figure 6: Travel loss versus network loss in case of three objective function.

Table 4: Results considering three objective functions

No. of CSs	Location	Distribution Loss in kW	Travelling Loss in kW	Utilization Factor in %	Min. Voltage in p.u.
2	4 & 20	63.3627	0.3829	17.40	0.9687
3	4, 9 & 55	64.1685	0.1556	6.22	0.9684
4	5, 10, 38 & 61	64.1443	0.1137	5.05	0.9684

From table 5, it can be observed that when the number of CS is increased from 2 to 3 then utilization factor decreases by around 3 times and when increased from 3 to 4 then utilization factor further decreases. So, in this case we can see that when the number of CS increases then utilization factor decreases. So, it is better to have 2 number of CS instead of 3 and 4 number from policy maker’s or system operator perspective. But from EV’s owner perspective a greater number of CS in the system is better option. When the EVs population is increased from current EVs population and then utilization factor is also increased during keeping the CS capacity constant as shown in table 5.

From the table 5, it can be observed that when EVs population increases then travelling loss, distribution loss and utilization factor also increases in comparison to present population of EV in the system. So, during planning stage near future EVs population can be considered to decide the number of CSs because utilization of CS will get increased in near future and system operator will have more revenue.

Table 5: Results for varying EVs population

EV Population	Location	Total 1 phase Demand of CS in kW	Network Loss in kW	Travel Loss in kW	Utilization Factor in %
63	4 & 20	129.759	63.3627	0.3829	17.40
126	2 & 7	187.143	63.6877	0.6314	22.13
189	9 & 19	175.223	63.6957	0.9199	26.88

The voltage magnitude for different case of objective function is almost same when charging station is placed optimally in the existing distribution network. Since position of charging station only varies and total capacity is same so there is only slight variation in voltage magnitude as shown in figure 7. The variation in voltage at each bus for different number of charging station is minor and there is no violation of voltage limit also.

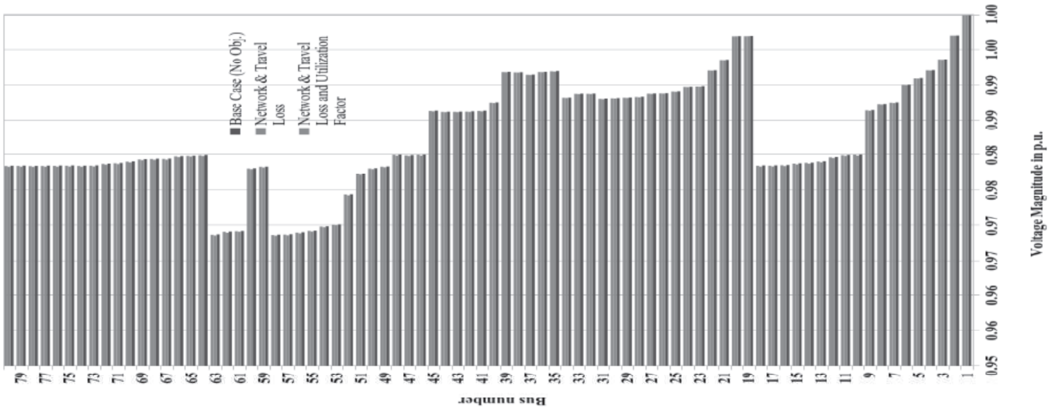

Figure 7: Voltage magnitude of OM feeder in case of various objective function.

CONCLUSION

This paper has introduced a strategy to study the impacts of CS placement in the existing distribution network. Monte Carlo simulation (MCS) is used to take into account the dynamic behaviour of EVs load with the help of queuing theory for taking the dynamic characteristics of a CS serviceability. This method finds the optimal allocation of CS by simultaneously minimizing electrical distribution loss which benefits the system operator, minimizing travelling loss of EVs when traveling to the location of CS benefiting the EVs owner and maximizing the utilization factor which confirms economical utilization of charging station infrastructure thus benefiting the charging station investor. This method is tested on the 80-bus OM feeder network for optimal placement of CS. The results of this study indicate very clear that while an increase in number of CS will increase the distribution loss but decrease in travelling loss of EVs as well as utilization of CS. The impact of charging station location on the network voltage profile is minor and there is no violation of voltage limit also.

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