Optimal Placement of Electric Vehicle Charging Stations in a Distribution Network

Arindam Sadhukhan
Department of Electrical Engineering
Indian Institute of Technology Patna,
arindam.pee16@iitp.ac.in

S. Sivasubramani
Department of Electrical Engineering
Indian Institute of Technology Patna,
siva@iitp.ac.in

Md Samar Ahmad
Rolls-Royce@NTU Corporate Lab
NTU Singapore
samarahmad2008@gmail.com

***Abstract*—The rising popularity and improved environmental awareness are making the present transportation network move towards electric vehicles (EVs). With the increased number of grid-connected EVs, inappropriate placement of charging stations (CSs) will be injurious to city traffic layout and the power distribution network. It will also deprive the convenience of EV owners and increase distribution loss. Therefore, this paper proposes a new method for optimal allocation of CSs by minimizing distribution losses of the system and increasing the utilization factor of CSs. Since these two objectives are contradictory, non-dominated sorting genetic algorithm (NSGA-II) is used to solve them. A probabilistic load modelling method is employed to develop the charging demand of EVs. The proposed method is tested on a test system which is obtained by modifying the standard IEEE 33 bus system. Simulation results show that the proposed method is not only able to reduce the system loss but also achieve economical benefits while placing CSs in a network.**

***Index Terms*—Probabilistic load flow, electric vehicle integration, optimal allocation.**

I. Introduction

The rapid growing energy demand, the decreasing level of fossil fuels, and greenhouse gas (GHG) emissions are the major threats that the current generation is facing. The amount of oil consumption in the transport sector is expected to increase up to 54% by 2035. Specifically, 4.1% of the CO2 emission increased in road transport due to increase in diesel consumption in 2015. The transport sector is contributing about 23% of the global GHG emission, and therefore, a major contribution is required from the transport sector to restrict global warming within 2^{o}C [1]. The most efficient way to reduce GHG emission in the transportation sector is by replacing the internal combustion engine (ICE) vehicles with low-emission or zero-emission electric vehicles (EVs) [2]. EVs have the potential to control GHG emission, which is responsible for climate change and global warming. Other than the environmental aspects, lower operating cost, noise and maintenance are some of the additional benefits which influence many countries to convert their ICE vehicles with EVs [3].

Although the present growth rate of EVs is minimal due to battery technology and inadequate charging infrastructure. However, with favourable government policies and public interest, this rate is supposed to increase immediately [4]. A higher level of EV charging load addition to the present network without improving the charging infrastructure can create serious damage to the network features like; power loss, voltage deviation, power quality [5]. An effective way to add higher EV charging demand is by improving public charging stations with coordinated charging infrastructure.

Well-Planned distribution of charging station (CS) will lead towards an improved coordinated charging environment with the increase in EV integration [6]. The location of a CS plays an important role to affect various network aspects. Optimal placement of CSs can not only reduce power loss but also improve better accessibility [7]. Widespread adoption of EVs will increase the burden on public CSs. In such a scenario, the placement of CSs should assure that vehicles can easily roam in the whole city and still can access it [8].

In recent times, many research works have discussed the optimal location and sizing of CSs, majorly concentrating on economics and other utility grid-related issues. The stochastic characteristics of on-road EVs have been analysed to study the impact of EV penetration on the present distribution network considering possible congestion in the future distribution network [9].

Many have proposed a two-stage stochastic model, to simulate a probabilistic real-time coordinated charging environment in a CS [10], which have shown great effort in saving equivalent annual costs for CSs.

Authors in [11] have offered a smart load management scheme to control load dispatching, voltage profile improvement and distribution loss minimization for smart EV chargers. This method was tested on a 33 bus distribution system. Similarly, in [12], authors have presented a sizing model of CSs in terms of power loss in the network considering road traffic and distribution system. In both of these above discussed work, the authors mainly focused on grid loss but disregarded economical benefits.

A detailed cost function analysis on the distribution system for more realistic discussion on CS location is performed in [7]. On the other hand, a running cost analysis model for CS running expenses is considered in [13], where distribution loss and transformer capacity have been considered. This model has considered several constraints, such as sub-stations and EV's location distances, installation cost for CSs and the fleet size of an CS. However, the charging demand estimation was overlooked in the model.

978-1-7281-4103-9/19/$31.00 ©2019 IEEE

There are various research works in the literature on finding the optimal sizing and location for EV CSs, with various aspects and challenges of EVs in [14]. Electric vehicles and their charging impact on a low voltage distribution system for different charger technologies have been shown in [15]. In [16], authors have discussed the uncertain driving nature of EVs considering a large fleet of plug-in vehicles (PEVs) with demand response program. But, the effect of a probabilistic load demand on a distribution network for loss analysis has not been addressed in the literature.

Impact of this work are as follows:

1) Modelling of EV charging demand using a probabilistic load model.
2) Improvement of the utilization of charging stations for economic benefits.

The rest of this paper is organized as follows. Section II presents the mathematical modelling of the work. Multi-objective problem formulation, is described in Section III, followed by Section IV introduces the charging demand simulation and test system. Section V discusses the case studies and their observed results. A detailed discussion on the result observed is presented in section VI. Finally, conclusion and future research are made in the last Section VII.

II. Mathematical Modelling

A. Single EV Charging Energy

The EV charging demand is evaluated based on some probabilistic parameters. First, the probabilistic driven distance of an EV is calculated from a lognormal distribution function [17], to generate the daily driven distance M_d.

$$M_d = e^{(\mu_m + \sigma_m * N)} \tag{1}$$

where, μ_m and σ_m are parameters of lognornal distribution, derived from the the mean (μ_{M_d}) and standard variation (σ_{M_d}) of the distribution of M_d [18]. N is the standard normal variate, calculated from U_1 and U_2. The lognormal random variable N is generated using the Box-Muller method [19].

$$N = \sqrt{-2.ln(U_1)} \times cos\,(2\Pi U_2) \tag{2}$$

Where U_1 and U_2 are independent random numbers, uniformly distributed over the range $[0, 1]$.

$$\left.\begin{aligned} \mu_m &= \ln\left(\frac{\mu_{M_d}^2}{\sqrt{\mu_{M_d}^2+\sigma_{M_d}^2}}\right) \\ \sigma_m &= \sqrt{\ln\left(1+\frac{\sigma_{M_d}^2}{\mu_{M_d}^2}\right)} \end{aligned}\right\} \tag{3}$$

Energy consumed by an EV to drive per mile E_m, is determined as a function of K_{EV}, depending on coefficients A_E and B_E for different EV types [17], [18].

As this work is concentrating on the electric demand of EV, K_{EV} is assumed to be one.

$$E_m = A_E \cdot (K_{EV})^{B_E} \tag{4}$$

After defining energy consumption per mile E_m, and the daily driven miles M_d of an EV, the recharge energy consumption per day denoted as D_E, is defined as follows:

$$D_E = \begin{cases} C_{Bat} & M_d \geq M_{d\ max} \\ M_d \cdot E_m & M_d < M_{d\ max} \end{cases} \tag{5}$$

Where C_{Bat} is the maximum battery capacity. $M_{d\ max}$ is the maximum driving distance of an EV when its battery is charged fully. It is calculated as follows:

$$M_{d\ max} = \frac{C_{Bat}}{E_m} \tag{6}$$

1) Charging Time Calculation: The charging time T for an EV follows the exponential distribution with mean T_μ, i.e.,

$$T = -T_\mu \cdot \ln(U) \tag{7}$$

Where, U is a uniform random number $U \in (0, 1)$.

According to the battery capacity and service restriction, the charging time T for an EV is restricted between an upper and lower limit $[T_{min}, T_{max}]$.

$$T = \begin{cases} T_{min} & T \leq T_{min} \\ -T_\mu \cdot \ln(U) & T_{min} < T < T_{max} \\ T_{max} & T \geq T_{max} \end{cases} \tag{8}$$

After selecting the charging power level [20], the average charging current is determined by the applied voltage V and maximum charging current I_{max} of selected power level

$$I = \min\left(\frac{D_E}{V \cdot T}, I_{max}\right) \tag{9}$$

The cumulative power demand P for n charging EVs is evaluated as

$$P = \sum_{q=1}^{n} V \cdot I_q \tag{10}$$

where I_q, is the charging current of the q^{th} EV obtained from Eq. (9).

B. Objective Functions

1) Distribution Loss: Current flowing through any conductor produces power loss because of its resistive nature. Line resistance is proportional to the length of the line conductor. With an increase in line length the loss in power transmission will also increase. The load demand of a charging station is a cumulative charging demand of EVs. With the addition of a CS in the electric network, this cumulative load demand is added to the present distribution network, and the charging power has to be transferred to the CS. In such a situation distribution loss will increase with the increase in distance between CS and distribution transformer bus. Backward Forward method has evaluated different load flow aspects. The branch parameters of 33 bus are received from [21]. The objective function minimizes the total network loss in the distribution grid.

$$P_{loss\ br} = (i_{br})^2 \cdot R_{br} \tag{11}$$

Where, i_{br} and R_{br} are the branch current and branch resistance of the br^{th} line.

$$\min f_{\text{obj}_1} = \left(\sum_{br=1}^{n_{max}} P_{loss\ br} \right), br = 1, 2, ..., n_{max} \quad (12)$$

Where, $P_{loss\ br}$ is the power loss in br^{th} branch and n_{max} is the number of branches in the network. Total power loss for all branches in the distribution network is taken for cumulative loss calculation.

2) Utilization Factor: The utilization factor of a CS is measured as the number of charging points (CPs) serving to the EVs at any moment of time. EVs can't connect them directly to the grid. They need an intermediate conversion device and after that a connecting port or charging point. Therefore one CP can connect to one EV at a time.

The ratio of the number EVs connected to the CS to the maximum number of EVs that can be connected to the CS is called the utility factor of the CS at that moment [22].

It denotes how many CPs of the CS are currently utilized at any moment of time. In the above definition Eq (13), CPs are the servers of the CS, and the number of vehicles connected to that CS for that moment is the CS fleet size .

$$\max f_{\text{obj}_2} = UF = \frac{N_{\text{fleet}}}{N_{CP}} \quad (13)$$

Where, N_{fleet} is the fleet size of the CS at that moment and N_{CP} is the Number of CPs or servers in the CS.

C. Constraints

1) Charging Station Location Restriction: Charging stations play an essential role to serve the local traffic network. They should be placed to help a vast area in the distribution network. When more than one charging stations are needed to put in the system, it should not be in the same place. To improve their service area, they should serve a different set of EV drivers so that everyone will get one charging station nearer. Placing two or more CSs in a single bus location is equivalent of placing one CS with fleet size sum of two CSs. In that scenario, it would not be economically beneficial to place them together, as the installation cost of an EV CS is much higher than their CPs. Therefore, two or more CSs cannot be placed on a single bus location. The objective function maximizes the least usage of the infrastructure set-up there in a charging station.

$$-\left| l_p^{CS} - l_q^{CS} \right| + 1 \leq 0 \quad (14)$$

Subject to

$$p \neq q$$

Where, l_p^{CS}, l_q^{CS} is the bus location of the p, q th bus in the electrical network.

2) Voltage Limit: To maintain quality power supply, voltage of each bus should be maintained within it's maximum and minimum limits at each bus (i.e., V_i^{Min} and V_i^{Max}).

$$V_i^{Min} \leq V_i \leq V_i^{Max} \quad (i = 1, 2, ..., N_{Bus}) \quad (15)$$

3) Current Limit: The current is each feeder should be less than its maximum limit I_{ij}^{Max}.

$$|I_{ij}| \leq I_{ij}^{Max} \quad (16)$$

Where, I_{ij} is the current in the feeder between node bus i and j.

4) Charging Power Limit: The charging power requirement of i^{th} EV CS should be within its limits (i.e., P_{EVCSi}^{Min} and P_{EVCSi}^{Max})

$$P_{EVCSi}^{Min} \leq P_{EVCSi} \leq P_{EVCSi}^{Max} \quad (i = 1, 2, ..., N_{EVCS}) \quad (17)$$

Where P_{EVCSi} is the charging power requirement of the i^{th} EV charging station. This constraint reflects the supply capabilities limitations of the distributed system associated.

$$P_{EVCSi} = \sum_{j=1}^{n_i} P_{CE_{ij}} \quad (18)$$

Where $P_{CE_{ij}}$ is the charging power requirement of the j^{th} CP of the i^{th} charging station.

5) Power Balance Constraint: Load flow constraints of radial distribution networks are considered here.

III. Multi-objective Problem Solving Approach

A constrained, non-linear, general multi-objective optimization problem is described as below:

$$\min \left[f_{obj\,1}(\mathbf{x}), f_{obj\,2}(\mathbf{x}), ..., f_{obj\,N_f}(\mathbf{x}) \right] \quad (19)$$

subjecte to;

$$g_k(\mathbf{x}) = 0, k = 1, 2, ..., N_{eq} \quad (20)$$

$$h_l(\mathbf{x}) \leq 0, l = 1, 2, ..., N_{ieq} \quad (21)$$

where objective functions are described as $f_{obj\,1}(\mathbf{x}), f_{obj\,2}(\mathbf{x}), ..., f_{obj\,N}(\mathbf{x})$, total number of objective functions N_f, and function variable $\mathbf{x}$ is the optimization variable vector. The equality and inequality constraints are $g_k(\mathbf{x})$ and $h_l(\mathbf{x})$, respectively. N_{eq} is the number of equality constraints and N_{ieq} is the number of inequality constraints.

Non-dominated sorting genetic algorithm II (NSGA-II) [23] is used to solve the objectives simultaneously. Unlike single objective optimization problems, multi-objective problems have many solutions. NSGA-II gives a set of non-dominated solutions, where each solution is equally important. The charging station location bus is the control variable or optimization variable here. The number of variables depends on the number of charging stations present in the distribution network.

A. Fuzzy Optimization Technique

This technique is a tool for selecting the best solution from all compromised non-dominated solutions from the set of N_D, of a multi-objective problem [24]. It normalizes the solution values and model them by a membership function to choose the best compromised solution from the set. The fuzzy optimization function is described as follows:

$$\mu_r = \begin{cases} 1 & \text{if } F_r(\mathbf{x}) \leq F_r^{Min} \\ \frac{F_r^{Max} - F_r(\mathbf{x})}{F_r(\mathbf{x}) - F_r^{Min}} & \text{if } F_r^{Min} < F_r(\mathbf{x}) < F_r^{Max} \\ 0 & \text{if } F_r(\mathbf{x}) \leq F_r^{Max} \end{cases} \quad (22)$$

F_r^{Min} is the minimum and and F_r^{Max} is the maximum value of the r^{th} objective function $F_r(x)$, and its membership value is μ_r.

$$N_{\mu_q} = \frac{\sum_{r=1}^{N_{obj}} \mu_r(q)}{\sum_{q=1}^{N_{nd}} \sum_{r=1}^{N_{obj}} \mu_r(q)} \quad (23)$$

N_{μ_q} is the normalized value of the membership function for q^{th} non-dominated solution. N_{obj} is the number of objective functions and N_{nd} is the number of non-dominated solutions present. The best solution from all N_{nd} compromised non-dominated solutions of the multi-objective problem is selected by the maximum N_{μ_q} value of all.

IV. SIMULATION DATA AND TEST SYSTEM

The distance travelled by an EV per day is evaluated using a lognormal distribution parameter $\mu_d = 40$ and $\sigma_d = 20$ [18]. The total PHEVs population is divided in 4 classes; Micro EV 20%, Economy EV 30%, Mid-size 30% and Light truck/SUV 20%, [25]. The Maximum travelling distance of a PHEV in battery mode is generated using $A_E = 0.3790, 0.4288, 0.5740, 0.8180$ and $B_E = 0.4541, 0.4179, 0.4040, 0.4802$, sequentially for four vehicle classes [17], [18].

A. EV Charging Load Demand Simulation

After building the associations of the different parameters and variables that determine the charging behaviour of EVs model, the charging load demand in an EV charging station is obtained as follows:

1) Generate the number of EVs charging at the same time, considering the number of vehicles in present, coming from different resident bus location. After that for each one from n selected EVs, proceed through the following Steps of evaluation:
2) Generate EV parameters for selected market shares [20];
3) Calculate E_m, energy consumption per mile;
4) Randomly generate M_d, EV driven miles;
5) Calculate D_E, recharge energy;
6) Generate charging time T, randomly;
7) Evaluate charging current I;
8) sum up total charging demand according to Eq. (10).

The above steps have to be repeated for each EV.

B. Test System

IEEE 33 Bus distribution system is used to demonstrate the city traffic layout and network planning. The line length data is shown in Table III. Original load data and line parameters for 33 Bus distribution system are selected form [26]. The number of vehicles for each residential bus is presented in Table I.

TABLE I
RESIDENTIAL VEHICLE POPULATION DATA

Node Bus	Number of Vehicles
1	0
2	10
3	20
4	30
5	30
6	40
7	40
8	50
9	50
10	50
11	50
12	60
13	80
14	100
15	120
16	150
17	170
18	200
19	30
20	20
21	20
22	10
23	10
24	10
25	10
26	30
27	30
28	20
29	20
30	20
31	20
32	10
33	10

V. CASE STUDY AND RESULTS

Two cases such as single charging station allocation and two charging station allocation operation are considered in this paper.

A. Single Charging Station Placement

When working with a single charging station in the network, the system operator tries to reduce installation cost by allocating only one CS for all EVs. An additional charging demand from EVs' will add an extra peak demand in the system, which increases the network losses. With some wrong selection of sitting location, the distribution loss can increase up to 737.68 kW, for placing charging station in bus 18.

In this method, all EVs have to go for the only CS in the network, so the utilization factor will not play a major role in this scenario.

1) Network Loss Minimization: In the case of network loss investigation in a distribution network, its reduction depends on the length of power transmission. The loss decreases with a reduction in power transmission length. With an increase of length for power to travel, system loss increases.

After analysing the distribution loss for all 32 load buses in the network, it is found that minimum network loss of 290.12 kW can be achieved by placing the CS at Bus 2.

B. Double Charging Station Placement

When a charging station is integrated in a distribution network, it is considered sufficient to serve all the vehicles in the network. But with an increase in demand from a vast network, the number of service providers should also be increased gradually. To serve a large network, number of CSs should be increased, but with their proper utilization. Then the installation of a new CS will be economically beneficial for the system operator.

The loss minimization strategy needs to include more than one charging station in the distribution network with improved utilization.

TABLE II
NON-DOMINATED SOLUTION SET FOR 2 CHARGING STATION SOLUTION

1st CS Location	2nd CS Location	Power Loss kW	Utilization Factor
13	**33**	**665.25**	**0.5133**
22	**32**	**577.95**	**0.44**
25	**32**	**398.49**	**0.42**
19	**33**	**303.23**	**0.4133**
19	**2**	**289.55**	**0.0493**

1) Network Loss Minimization: With the reduction in line length between CS and distribution station, the distribution loss reduces. Network loss is directly proportional to the branch length, from the substation to the load. It is found that the minimum network loss of 289.58 kW can be attained by selecting two CSs at bus 2 and bus 19.

2) Network Loss Minimization and Maximization Utilization Factor: When considering more than one CS in the network, the economic benefit should also be considered. Because the infrastructure cost of a CS is high, which has to be borne by the network operator [27]. In the case of multiple CS installation, the utilization factor plays a key role to analyse the effective usage of the charging stations. Proper utilization of these charging stations will increase the infrastructure usefulness for the charging station. As it is a multi-objective scenario with two contradictory objectives, one fitness function has to be decreased for an increment of others. The contradictory behaviour of the fitness functions for selecting charging station locations is described in Fig 1. With the compromised set of values for both objectives described in Table II, it is found that all values are equally significant.

The best solution from the compromised non-dominated set of values is selected using fuzzy optimization technique, described in Table II. The critical optimal value of network loss is 303.23 kW with a utilization factor of 0.413 , when the charging stations are placed in bus 19 and bus 33.

TABLE III
BUS DISTANCE DATA

Line number	Sending node	Receiving node	Distance (KM)
1	1	2	0.3745
2	2	3	2.0018
3	3	4	1.4861
4	4	5	1.5475
4	5	6	3.9147
6	6	7	2.3392
7	7	8	2.7109
8	8	9	4.5889
9	9	10	4.6301
10	10	11	0.7492
11	11	12	1.4268
12	12	13	6.7585
13	13	14	3.2394
14	14	15	2.8627
15	15	16	3.3437
16	16	17	7.7799
17	17	18	3.3657
18	2	19	0.8202
19	19	20	7.3261
20	20	21	2.2785
21	21	22	4.2521
22	3	23	1.9773
23	23	24	4.1400
24	24	25	4.1165
25	6	26	0.8243
26	26	27	1.1539
27	27	28	5.1084
28	28	29	3.8591
29	29	30	2.0607
30	30	31	4.9569
31	31	32	1.7253
32	32	33	2.2809

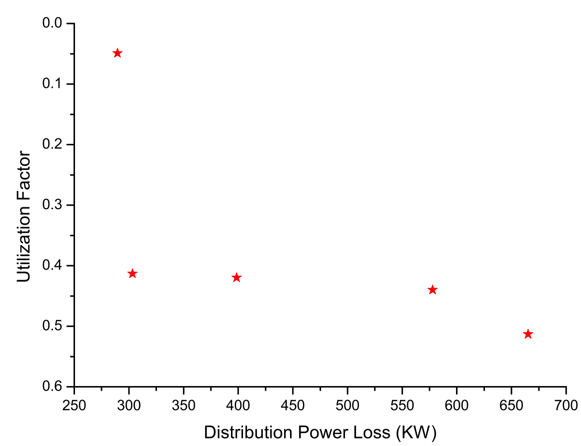

Fig. 1. Pareto-Optimal Set

VI. DISCUSSION

It is observed from the case studies that power loss reduces in two charging stations case compared to a single charging station case, in the network. It shows the fact that, increase in the number of charging stations can reduce the power loss with optimally allocating them in the network.

But while considering the utilization factor, it is observed that the power loss increases in search for better utilization. Better utilization factor indicates better effectiveness of the charging stations to serve those vehicles. It means the optimal location for loss minimization may not favour the vehicle's accessibility or effective utilization of CSs. However, improved utilization of the charging stations can not reduce system losses. Better utilization factor makes charging stations more economically beneficial. Optimal charging location is a compromised solution of these two objectives, where both these fitness functions are satisfied.

VII. Conclusion

A new strategy has been introduced to describe the effect of multiple charging stations in a distribution network. This method estimates the optimal location of charging stations giving equal priority to the power system loss and effective usage of charging stations. The problem was structured by modelling the total charging power requirement of several EVs for calculating PPF, and modelling the total charging load requirement of EVs at a charging station.

The proposed method has been tested on the 33-bus test system for allocating charging stations. It is clear that an increase in number of charging stations will reduce loss in the network. However, the best compromised solution describes that optimal location should be chosen depending on a trade-off between the two objectives. In future, the uncertain charging demand will be considered with random arrival of vehicles.

VIII. Acknowledgment

This research work is funded by project under the **Visvesvaraya PhD Scheme of Ministry of Electronics & Information Technology, Government of India**, being implemented by Digital India Corporation.

References

[1] Global ev outlook 2016, int. energy agency, paris, france, may 2016. [Online]. Available: https://www.iea.org/publications/freepublications/publication/Global_EV_Outlook_2016.pdf

[2] E. Graham-Rowe, B. Gardner, C. Abraham, S. Skippon, H. Dittmar, R. Hutchins, and J. Stannard, "Mainstream consumers driving plug-in battery-electric and plug-in hybrid electric cars: A qualitative analysis of responses and evaluations," *Transportation Research Part A: Policy and Practice*, vol. 46, no. 1, pp. 140–153, 2012.

[3] A. C. R. Teixeira and J. R. Sodré, "Simulation of the impacts on carbon dioxide emissions from replacement of a conventional brazilian taxi fleet by electric vehicles," *Energy*, vol. 115, pp. 1617–1622, 2016.

[4] J. C. Mukherjee and A. Gupta, "A review of charge scheduling of electric vehicles in smart grid," *IEEE Systems Journal*, vol. 9, no. 4, pp. 1541–1553, 2014.

[5] R. C. Green II, L. Wang, and M. Alam, "The impact of plug-in hybrid electric vehicles on distribution networks: A review and outlook," *Renewable and sustainable energy reviews*, vol. 15, no. 1, pp. 544–553, 2011.

[6] R. B. Chinnam, A. E. Murat *et al.*, "Community-aware charging station network design for electrified vehicles in urban areas: reducing congestion, emissions, improving accessibility, and promoting walking, bicycling, and use of public transportation." Western Michigan University. Transportation Research Center for Livable . . . , Tech. Rep., 2016.

[7] M. M. Islam, A. Mohamed, and H. Shareef, "Optimal allocation of rapid charging stations for electric vehicles," in *2015 IEEE Student Conference on Research and Development (SCOReD)*. IEEE, 2015, pp. 378–383.

[8] M. M. Islam, H. Shareef, and A. Mohamed, "Optimal location and sizing of fast charging stations for electric vehicles by incorporating traffic and power networks," *IET Intelligent Transport Systems*, vol. 12, no. 8, pp. 947–957, 2018.

[9] Z. Liu, Q. Wu, S. S. Oren, S. Huang, R. Li, and L. Cheng, "Distribution locational marginal pricing for optimal electric vehicle charging through chance constrained mixed-integer programming," *IEEE Transactions on Smart Grid*, vol. 9, no. 2, pp. 644–654, 2016.

[10] H. Zhang, Z. Hu, Z. Xu, and Y. Song, "Optimal planning of pev charging station with single output multiple cables charging spots," *IEEE Transactions on Smart Grid*, vol. 8, no. 5, pp. 2119–2128, 2016.

[11] A. S. Masoum, S. Deilami, P. Moses, M. Masoum, and A. Abu-Siada, "Smart load management of plug-in electric vehicles in distribution and residential networks with charging stations for peak shaving and loss minimisation considering voltage regulation," *IET generation, transmission & distribution*, vol. 5, no. 8, pp. 877–888, 2011.

[12] S. Pazouki, A. Mohsenzadeh, and M.-R. Haghifam, "Optimal planning of pevs charging stations and demand response programs considering distribution and traffic networks," in *2013 Smart Grid Conference (SGC)*. IEEE, 2013, pp. 90–95.

[13] K. Lingfeng, L. Zifa, and Z. Huan, "Modeling algorithm of charging station planning for regional electric vehicle," *Modern Electric Power*, vol. 27, no. 4, pp. 44–48, 2010.

[14] M. ISLAM, H. Shareef, A. Mohamed *et al.*, "Optimal siting and sizing of rapid charging station for electric vehicles considering bangi city road network in malaysia." *Turkish Journal of Electrical Engineering & Computer Sciences*, vol. 24, no. 5, 2016.

[15] N. R. Watson, J. D. Watson, R. M. Watson, K. Sharma, and A. Miller, "Impact of electric vehicle chargers on a low voltage distribution system," 2015.

[16] J. Aghaei, A. E. Nezhad, A. Rabiee, and E. Rahimi, "Contribution of plug-in hybrid electric vehicles in power system uncertainty management," *Renewable and Sustainable Energy Reviews*, vol. 59, pp. 450–458, 2016.

[17] S. Meliopoulos, J. Meisel, G. Cokkinides, and T. Overbye, "Power system level impacts of plug-in hybrid vehicles," *Power Systems Engineering Research Center (PSERC)*, vol. 32, 2009.

[18] P. Sharer, R. Leydier, and A. Rousseau, "Impact of drive cycle aggressiveness and speed on hevs fuel consumption sensitivity," SAE Technical Paper, Tech. Rep., 2007.

[19] P. M. Subcommittee, "Ieee reliability test system," *IEEE Transactions on power apparatus and systems*, no. 6, pp. 2047–2054, 1979.

[20] M. H. Amini and A. Islam, "Allocation of electric vehicles' parking lots in distribution network," in *ISGT 2014*. IEEE, 2014, pp. 1–5.

[21] V. Vita, "Development of a decision-making algorithm for the optimum size and placement of distributed generation units in distribution networks," *Energies*, vol. 10, no. 9, p. 1433, 2017.

[22] F. N. Lee, "The application of commitment utilization factor (cuf) to thermal unit commitment," *IEEE Transactions on Power Systems*, vol. 6, no. 2, pp. 691–698, 1991.

[23] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: Nsga-ii," *IEEE transactions on evolutionary computation*, vol. 6, no. 2, pp. 182–197, 2002.

[24] T. Niknam, M. Narimani, J. Aghaei, and R. Azizipanah-Abarghooee, "Improved particle swarm optimisation for multi-objective optimal power flow considering the cost, loss, emission and voltage stability index," *IET generation, transmission & distribution*, vol. 6, no. 6, pp. 515–527, 2012.

[25] M. S. Ahmad and S. Sivasubramani, "Optimal number of evs for existing networks considering economic and emission dispatch," *IEEE Transactions on Industrial Informatics*, 2018.

[26] R. Ranjan and DAS, "Simple and efficient computer algorithm to solve radial distribution networks," *Electric power components and systems*, vol. 31, no. 1, pp. 95–107, 2003.

[27] Q. Cui, Y. Weng, and C.-W. Tan, "Electric vehicle charging station placement method for urban areas," *IEEE Transactions on Smart Grid*, 2019.