OPTIMAL PLACEMENT IDENTIFICATION OF MULTIPLE DG TYPES USING OPTIMIZATION TECHNIQUE

Mounika S[1], *Dr.R.Narmatha Banu*[2], *Dr.B.Kiruthiga*[3]

[1,2,3]Department of EEE, Velammal college of Engineering and technology, Madurai-9

Abstract. In this paper, a combination algorithm called GAIPSO, which combines GA and a better version of the classic particle swarm optimization process, is used. In order to calculate the data enhancement in voltage profile, this study uses the GWO algorithm. The ideal position for the proposed charging points inside the distribution system is the goal. The received comment thread solution (site & station size) is further re-optimized by PSO, improving both the functionality and outcome overall. Studies based on simulations show that the above mentioned technique outperforms GA, GWO, and PSO in respect of an improved voltage profiles as well as the quality of the solution found for the objective function. Optimum planning for the charging station's location and size. the IEEE 33 bus system. The suggested approach takes into consideration the IEEE 33 bus service. The received thread solutions (site and station size) is further re-optimized by PSO, improving both the performance and outcome overall.

Keywords: PSO, GWO, GA, HYBRID OPTIMIZATION,DG LOCATION

1. Introduction

India's market for electric vehicles (EVs) and plug-in hybrid electric vehicles (PHEVs) has grown significantly in recent years. The public's mindset is profoundly altered by the Indian government's incentives, financial savings from using liquid fuel, and growing environmental awareness of the negative effects of greenhouse gas emissions [1]. In 2013, the Indian government proposed the National Electric Mobility Mission Plan (NEMMP) 2020, which outlined goals, incentives, and strategies for increasing sales of hybrid and electric vehicles to 7 million by 2020 [2]. The biggest challenge facing the electric vehicle industry right now is putting in place charging stations of the right size and location. Over the past few years, the issue of where to put electric vehicle charging stations (EVCS) in the best possible location has been studied [3-7]. In [3,] the size and location of EVCS were addressed separately, while in [4,] a combined optimization joint approach was used to minimize the objective function using Particle Swarm Optimization (PSO). The

-Corresponding author – mouni0305@gmail.com

environmental factors (such as a dependable power supply, the cost of the land, the location of the loads, etc.) that were used in the initial screening of the charging station candidate sites. and the EVCS's attainable radius. The EVCS placement objective function was obtained using a method that was followed in [5] and provided four distinct approaches to its solution. It made use of the fundamental ideas of graph theory to accomplish this. The difficulty of the problem was rated as NP (Nondeterministic Polynomial Time). Another study in Canada's Ontario region looked at the zonal model of Ontario's transmission network to find the best locations for EVs and PHEVs while maintaining an acceptable penetration level. This paper proposes a novel CS deployment method using the same framework as in [12]. In this paper, GAIPSO was used to find the best locations and sizes for electric vehicle charging stations in Allahabad, India. The first population needed to set up the charging station is made. For each selected CS, GA generates a suboptimal size and site for the given objective function, which is then passed on to the PSO. IPSO is the name given to the PSO algorithm because the initial particles are semi-optimized as opposed to random as used in conventional PSO. As a result, the dual task of optimization results in better solutions for PSO and GA and requires fewer iterations per experiment. The proposed work's block diagram can be seen in Figure 1.

2. IMPLEMENTATION OF THE PROPOSED WORK

IEEE 33 bus system was considered for the proposed research work.GWO GA and PSO algorithm were used for implementation

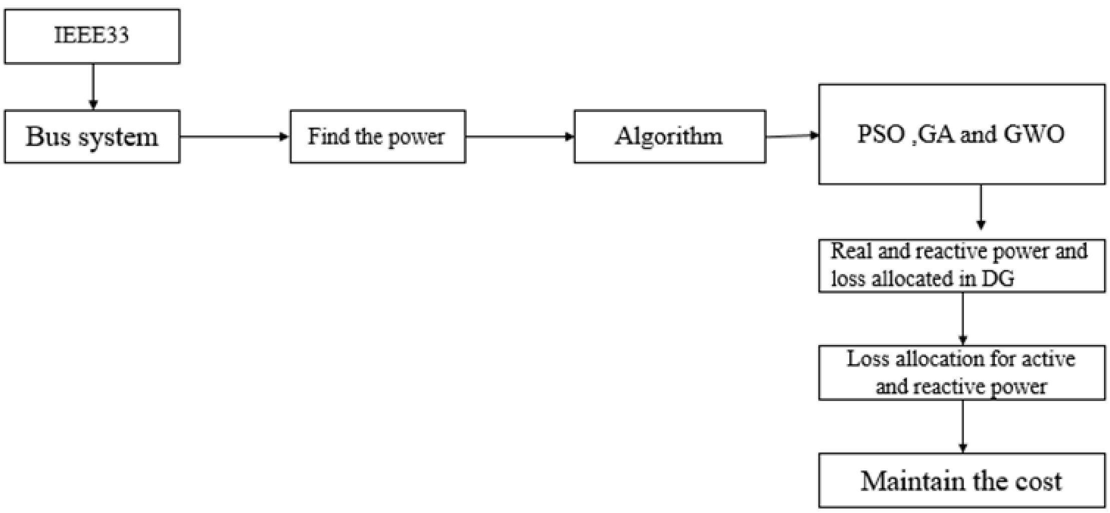

Figure. 1 Block Diagram of Proposed Work

a) IEEE 33 bus system :

 https://doi.org/10.1051/e3sconf/202338701009

A medium-sized network that addresses the cost system's fundamental issues is the IEEE-33 bus system in Figure 2.. The IEEE 33 Bus Test Case serves as a partial representation of the American Electric Cost System in the US Midwest as of December 1961. Based on the model, these buses actually have base voltage of either 132 or 33KV, which are my best guesses. The 33 bus test scenario does not have any line restrictions.

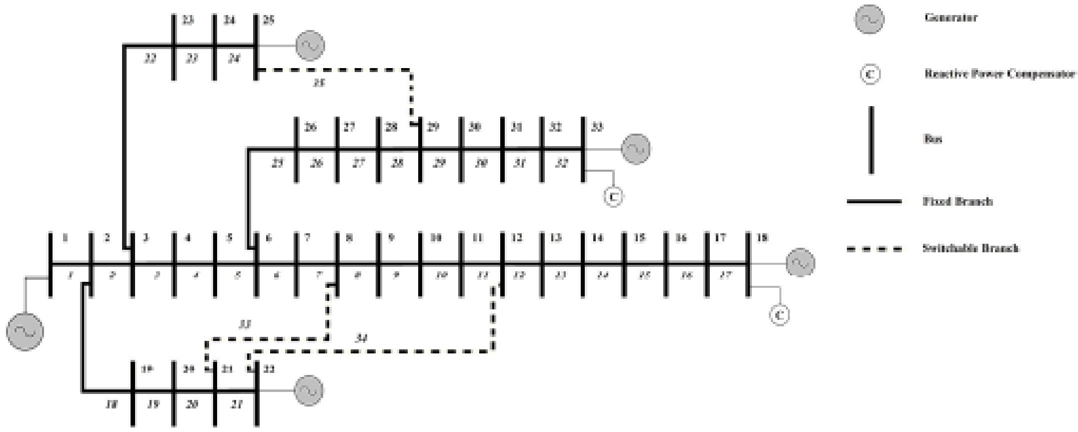

Figure 2. IEEE 33 bus system

b) GWO ,GA and PSO algorithm:

It is clear from the objective function that has been proposed that the issue at hand is a constrained Mixed Integer Non-Linear Problem (MINLP), which was solved through PSO, GA, and GWO optimization under the given constraints. In this paper, the only reason evolutionary algorithms are used is that traditional mathematical programming methods are hard to use in practice in Figure 3.

 https://doi.org/10.1051/e3sconf/202338701009

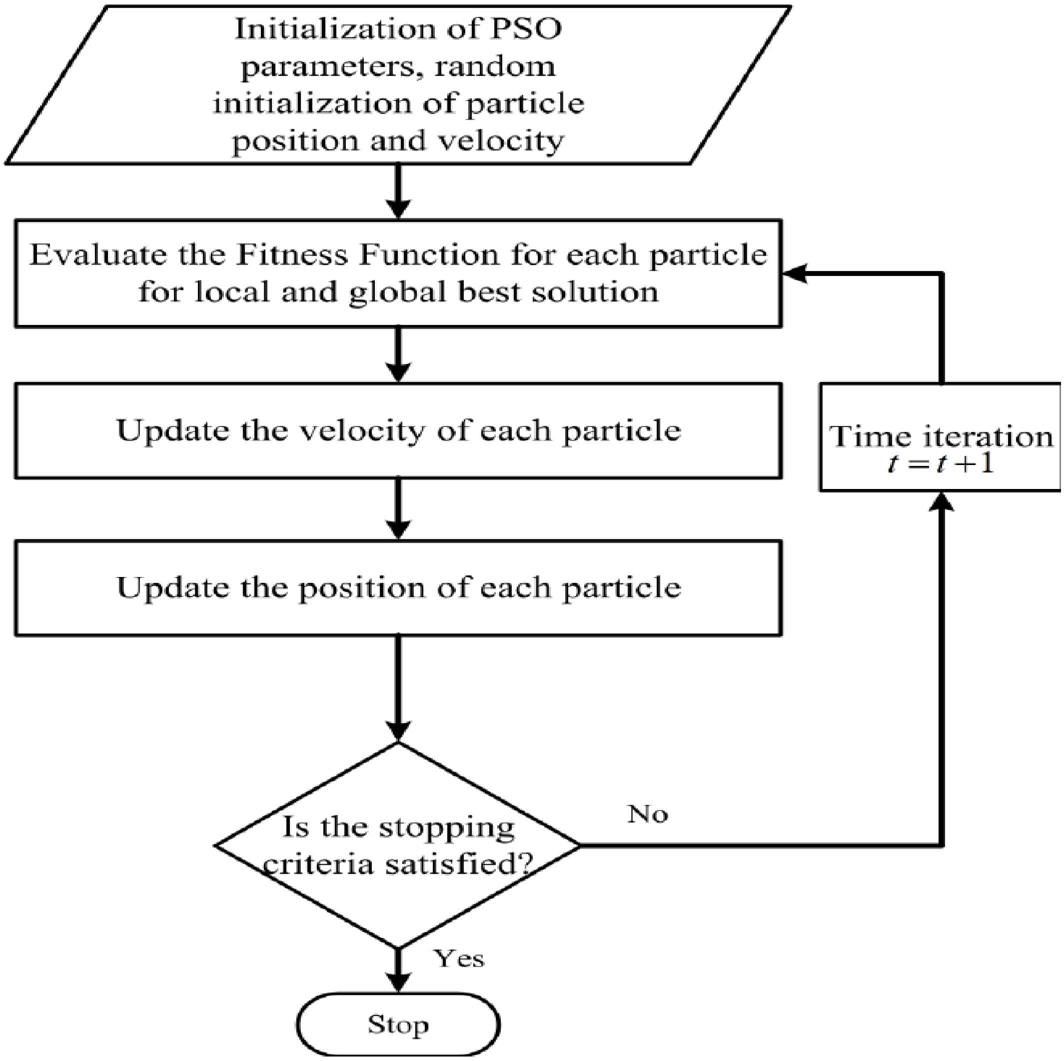

Figure 3. Flow Chart

C) DG Location:

. The optimum location for the DG should be determined first, and then the best size should be determined second. These two subproblems make up the optimal DG location and sizing problem. Numerous research suggested different solutions to the issue, including analytical techniques, deterministic approaches, and heuristic ways. The optimal DG sizing in the Irish system was solved for using a constrained linear programming (LP) technique, which forms the basis of the study. Their suggested strategy was to generate as much DG as feasible. They were loosened up to take advantage of the nonlinear limitations in the LP approach. On the basis of a power loss sensitivity study, an analytical method for determining the ideal DG sizing was suggested.This approach makes use of a search strategy created for the ideal DG seating and sizing. Each of the system buses had a DG unit attached, and the candidate buses were ranked in accordance with their ideal objective function values. In particular, this strategy produces a condensed search space and a narrow distribution of results. The search is carried out using the GA technique, an integer-based optimization algorithm, as the position is represented by a discrete variable (the bus number, which is an integer from 1 to 69). The PSO algorithm then uses the result of the GA approach to optimise the DG sizing.

3. RESULTS AND DISCUSSIONS

The programme was created using MATLAB software, and the outcomes are contrasted with those of alternative approaches. Table 1 and Figure 4 compare the DG sizes of the PSO, GA, and GWO algorithms.

Table 1. Compare the DG sizes of the PSO, GA, and GWO algorithms

	DG1	DG2	DG3	DG SIZE
PSO	0.0811	0.0031	1.0237	0.8849
GA	0.089	0.0012	1.0303	0.9297
GWO	0.0832	0.0049	1.0335	1.1998

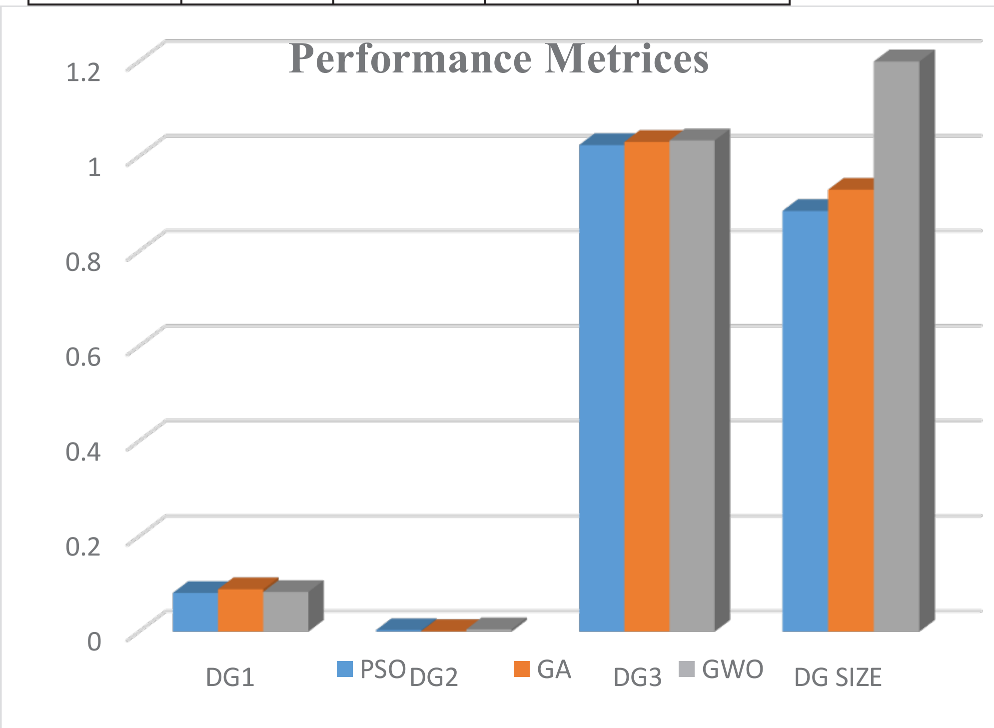

Figure 4. Performance Matrices of PSO, GA, GWO

The objective function variation is depicted. For the fifty initial populations, the variance is calculated. GA and PSO have output variances of 0.0986 and 0.02134, respectively; however, the combined method has been found to have output variances that are nearly zero. This indicates that the combined method produces uniform results while the other methods do not. Zero variance indicates that the combined method is preferable to the other two options. A combined approach was proposed to address DG's capacity and location issues. The GA and PSO methods were utilized in this approach to calculate DG's capacity and location, respectively.

The voltage levels for a 33-bus radial distribution system are as follows: DG size (MW) GWO 0.0811 0.0031 1.0237 63 0.8849 61 1.1926 21 0.9105 GA 0.089 0.0012 1.0303 21 0.9297 62 1.0752 64 0.9848 PSO 0.0832 0.0049 1.0335 61 1.1998 63 0.7956 17 0.9925

The benefits and drawbacks of the combined method were contrasted with those of the other two methods. The outcomes indicated that the proposed method is superior; The uniform responses and negligible variances are one of its benefits.

It was able to find the best system-optimized solution simultaneously. The characteristics of convergence are shown in Figure 5. Power Loss Before and afterusing PSO Algorithm and comparison shown in table 2,3 &4.

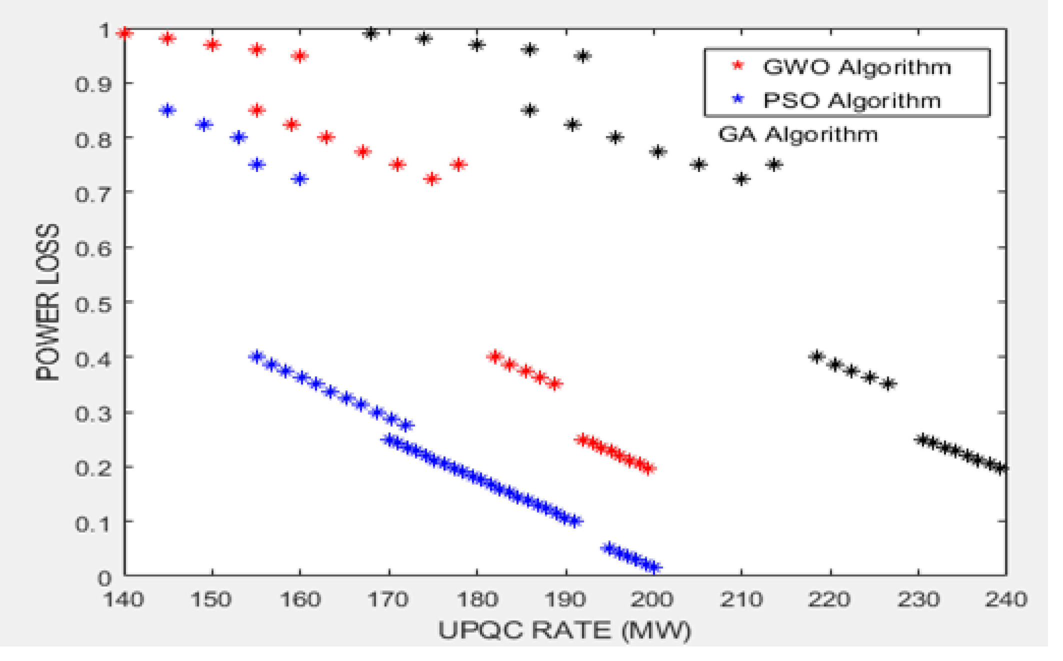

Figure 5. Convergence characteristics

Table.2Power Loss Before using PSO Algorithm

BUS	VOLTAGE (pu)	ANGLE	INJECTION_P (MW)	INJECTION_Q(MW)
1	1.0600	0	260.9280	-17
2	1.0430	-5.3474	18.3000	35
3	1.0217	-7.5448	-2.4000	-12

4	1.0129	-9.2989	-7.6000	-11
5	1.0100	-14.152	-94.2000	16
6	1.0121	-11.0880	3.0127e – 12	4.547
7	1.0035	-12.8734	-22.8000	-10
8	1.0100	-11.8039	-30.0000	0
9	1.0507	-14.1363	-22.8000	4.547
10	1.0438	-15.731	3.3751e – 13	0
11	1.0820	-14.1363	-5.8000	16
12	1.0576	-14.9461	0	-7
13	1.0710	-14.9461	-11.2000	10
14	1.0438	-15.8244	0	-11
15	1.0384	-15.9101	-6.2000	-2
16	1.0445	-15.5487	-8.2000	-1
17	1.0387	-15.8856	-3.5000	-5
18	1.0282	-16.5425	-9.0000	0
19	1.0252	-16.7273	-3.2000	-3
20	1.0291	-16.5363	-9.5000	0
21	1.0293	-16.0738	-2.2000	-11
22	1.0353	-16.2528	-17.5000	-1.705

Table.3 Power Loss After using PSO Algorithm

Line .No	FROM	TO	P (MW)	Q (MW)	FROM
1	1	2	173.143	-18.1076	2
2	1	3	87.7849	6.2478	3
3	2	4	43.6185	5.1943	4
4	3	4	82.2620	-3.7720	4
5	2	5	60.3529	4.0325	5
6	2	6	72.2720	1.4034	6
7	4	6	-14.8525	-17.5214	6
8	5	7	38.1954	11.7958	7
9	6	7	29.4897	-1.2007	7
10	6	8	27.7995	-3.2137	8

11	6	9	15.8822	-18.4846	9
12	6	10	1.0408 e –	-5.3058	10
13	9	11	27.7995	-15.7993	11
14	9	12	7.7900	7.0412	12

.

15	4	12	44.1470	-16.7948	12
16	12	13	-2.047e – 14	-10.1193	13
17	12	14	7.7900	2.3896	14
18	12	15	17.6368	6.7049	15
19	12	16	7.5176	3.4205	16
20	14	15	1.5176	0.6377	15
21	16	17	3.9600	1.4993	17
22	15	18	6.2913	1.8291	18
23	18	19	3.0486	0.8422	19

Total Loss before optimization : 43.208

Total Loss after using PSO optimization :10.8287

Table 4. Comparison table

	Proposed	**Existing ATGA**	**Existing 1KHA**	**Existing 2 SKHA2**	**Existing PPSO-GSA**
Location	28	18	10	19	19
Size	1667.9	1395.04	955.10	575.71	1467.9
Ploss (KW)	10.23	73.03	74.42	73.10	72.93
LR%	79.87	82.3	79.49	79.85	79.9

The multi-objective problem of minimizing power loss and maximizing VSI is solved. As can be seen, the VSI rises from 0.6672 put to 0.9667 p.u., and the power loss decreases to 12.53 kW. The maximum loadability is also raised to 4.4134. The distribution of DG units of various types results in a significant increase in voltage.

Utilizing the proposed ATGA and other optimization methods, the ideal location and capacities for multiple DG types in the IEEE 69-bus distribution system are determined. When three DG type I with optimal sizes of 509.08, 382.73, and 723.20 kWs are installed into buses 11, 17, and 61, the ATGA achieves the highest LR, which is 69.14 percent. In addition, the proposed ATGA yields LR superior to that of TGA, PSO, SKHA, Hybrid, and IA in comparison to the other optimization methods. In case 4, the injected active and reactive power of DG type III reduces the losses to 4.27 kW, resulting in a significant LR. where the losses in TGA, Hybrid, and PSO are 9.17 kW, 4.3 kW, and 4.61 kW, respectively. Figure 5 depicts the performance of the proposed ATGA in comparison to the original TGA for each case study. In terms of the rate at which the gained result converges, the figure demonstrates that the ATGA is superior. In addition, the hybridization of the analytical method improves the proposed method, as shown by the boxplot for the 30 runs. PSO , GA and GWO algorithm parameters are given in tables 5-7.

Table 5. PSO Algorithm parameters

Parameter	Scheduling with user preface	Optimal scheduling
Wmin	0.4	0.4
Wmax	0.9	0.9
C1	1.2	1.2
C2	1.2	1.2
Lower bound	[120, 261, 192]	[0,0,0]
Upper bound	[144, 26, 216]	[288,288,288]
Population	10	10

Table 6. GA algorithm parameters

Parameter	Scheduling withuser preference	Optimal scheduling
Wmin	0.4	0.4
Wmax	0.9	0.9
C1	1.2	1.2
C2	1.2	1.2
Lower bound	[120,216,192]	[0,0,0]
Upper bound	[144,264,216]	[288,288,288]
Population	10	10

Table 7. GWO Algorithm parameters

Parameters	GWO
Number of search agents	30
Maximum iteration	100
Dimension	5
Best_score	Alpha_score
Best_pos	Destination_position

Fluctuation for the goal capabilities is outlined. The fluctuation is determined for the fifty starting populaces. The result changes for GA and PSO are at 0.0986 and 0.02134 separately, yet it has viewed as nearly at zero for the joined strategy. This means that yield consistency for the consolidated strategy and non-consistency for the others. Having zero change is exhibiting that the joined strategy is liked in correlation with the other two. Voltage solidness file in transport 18 from the main framework and transport 61 from the second were low before DG establishment. This could cause shakiness in the organizations within the sight of aggravations.

4. CONCLUSION

An exhaustive correlation between the proposed Hereditary Calculation and further developed rendition of ordinary Molecule Multitude Streamlining (GAIPSO) and GWO calculation and other improvement strategies has been done. Results obtained show the productivity of the proposed strategy contrasted and the cutthroat advancement procedures utilized in the issue. The outcomes demonstrated that DG type gives the most elevated loadability because of its infused dynamic and receptive powers.

REFERENCES

1. Z. Liu, F. Wen, and G. Ledwich, “Optimal planning of electric-vehicle
2. charging stations in distribution systems,” *IEEE Trans. Power Del* vol. 28, no. 1, pp. 102–110, Jan. 2013.
3. Z. F. Liu, W. Zhang, X. Ji, and L. Ke, “Optimal planning of chargingstation for electric vehicle based on particle swarm optimization,”in*Proc. IEEE Innov. Smart Grid Technol. Asia*, Tianjin, China, pp. 1–5, May 2012
4. A. Y. S. Lam, Y.-W. Leung, and X. Chu, “Electric vehicle chargingstation placement: Formulation, complexity, and solutions,”*IEEETrans.Smart Grid*, vol. 5, no. 6, pp. 2846–2856, Nov. 2014.
5. A. H. Hajimiragha, C. A. Canizares, M. W. Fowler, and A. Elkamel,“Optimal transition to plug-in hybrid electric vehicles in Ontario,Canada, considering the electricity-grid limitations,” *IEEE Trans. Ind.Electon.,* vol. 57, no. 2, pp. 690–701, Feb. 2010.
6. W. Guibin, X. Zhao, W. Fushuan, and P. W. Kit, “Traffic-constrainedmultiobjective planning of electric-vehicle charging stations,” *IEEETrans. Power Del.*, vol. 28, no. 4, pp. 2363–2372, Oct. 2013.
7. P. Sadeghi-Barzani, A. Rajabi-Ghananieh, and H. Kazemi-Karegar,“Optimal fast charging station placing and sizing,”Appl. Energy,vol.125, pp. 289–299, Jul. 2014.
8. L. Jia, Z. Hu, Y. Song, and Z. Luo, “Optimal siting and sizing ofelectric vehicle charging stations,” in *Proc. IEEE Int. Elect. VehConf.*, Greenville, SC, USA, pp. 1–6, Mar. 2012

9. S. Mehar and S. M. Senouci, "An optimization location scheme forelectric charging stations," in *Proc. Int. Conf. Smart Commun. Netw.Technol.*, 2013, vol. 1, pp. 1–5.
10. C.J. Kilonzi, "System Loss Reduction And Voltage ProfileImprovement By Optimal Placement And Sizing Of DistributedGeneration (Dg) Using A Hybrid Of Genetic Algorithm (GA) AndImproved Particle Swarm Optimization (PSO)", M.Sc. Thesis,University Of Nairobi, Nairobi, Kenya, 2014.
11. C. L. Su, R. C. Leou, J. C. Yang, and C. N. Lu, "Optimal electricvehicle charging stations placement in distribution systems,"Proceedings of the 39th Annual Conference of the IEEE IndustrialElectronics Society, Vienna, Austria,pp. 10-13,Nov.2013.
12. FareedAhmad, AtifIqbal, ImtiazAshraf, MousaMarzband and Irfankhan, " Optimal location of electric vehicle charging station and its impact on distribution network: A review" ,Energy Reports, Elsevier , November 2022, Pages 2314-2333.
13. Ali Selim, Salah Kamel, Francisco Jurado, "Voltage stability analysis based on optimal placement of multiple DG types using hybrid optimization technique",Wiley Online Library, Aug 2020.