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Metaheuristic algorithm for optimal allocation of electric vehicles and photovoltaics in distribution grid

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ABSTRACT

Since electric vehicles (EVs) emit less carbon dioxide, their number is rapidly increasing. As the number of EVs grow, these added loads strain the distribution grid, introducing new challenges. Key concerns for network operators include voltage fluctuations and increased power losses. Properly deploying throughout the grid, photovoltaic (PV) systems and electric vehicle charging stations (EVCS) can assist in lowering power losses and improving the bus voltage profile. A MATLAB implementation of the metaheuristic algorithm called Harris Hawk optimization (HHO) algorithm is developed to select the best locations for integrating EVCSs and PVs, with the goals of enhancing the voltage profile and reducing power losses across buses. IEEE 12-bus and 14-bus systems and real-time distribution grid data were used to test the method. For the 26-bus real-time system, the results demonstrated a notable 24% decrease in overall power loss as compared to the base case and improved voltage regulation, as indicated by a lower average voltage deviation index (AVDI) value of 0.0929. A comparative analysis was performed between optimized and random placements of EVCSs and PVs, as well as against the grey wolf optimization (GWO) algorithm. The results provide a framework for implementing solar-powered EV charging infrastructure. This can reduce costs, enhance energy reliability, and contribute to a cleaner environment.

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1. INTRODUCTION

Distribution network becomes overloaded as a result of electric vehicle (EV) loads. An increase in EV loads can overload distribution transformers and feeders, thereby causing instability of the system This will result in increased loss of power and variation in bus voltages in the grid. This can ultimately lead to the tripping of the distribution network. To maintain stability in the grid, electric vehicle charging stations (EVCS) must be positioned in the distribution network as optimally as possible. Distributed generators (DGs) have been traditionally employed by researchers to achieve better voltage regulation at the buses and reduce associated power losses. Therefore, the problem identified is the optimal allocation of EVCS and PVs inside the distribution grid.

EV users should consider several factors such as, the availability of suitable charging infrastructure, charging time, and, most importantly, the size and location of charging stations (CSs). This is particularly important in urban areas where land costs and location play a significant role. It is also essential that the CS location is both cost-effective and easily accessible. Based on road network and geographic data, this study [1] presents an intelligent algorithm based planning system for EVCS.

A realistic hybrid grid-RES-based EV fast-CS can be analyzed by considering the characteristics of EV demand. This includes modeling factors such as the battery capacity, state of charge (SOC), arrival and departure timings, and the hourly distribution of EVs at the station. In this work [2], a hybrid genetic algorithm in conjunction with pattern search is used to improve the parameters for this precise modelling of EVs. The best place for EVCSs is a crucial factor in effectively serving EV users and maintaining a healthy power system. This study [3], [4] identifies the best locations by considering aspects such as power loss, voltage variation in the distribution network, and the land cost linked to each site in the road network. Inaccurate EVCS predictions will negatively impact the energy grid. To locate the best place for CSs within the grid, the Harris Hawk optimization (HHO) approach has been employed by [4]. The best location and capacity for DGs and PVs are found using the political optimization approach. Comparing the results with other optimization algorithms demonstrates minimized losses and more stable voltage [5].

It is necessary to go thorough research while charging EVs simultaneously in distribution networks in order to identify potential issues such as congestion, increased power losses, and voltage limit violations. To overcome these challenges, an optimal EV charging schedule is essential since it ensures that charging occurs between non-overlapping time slots and avoids overload scenarios that might compromise the distribution networks performance. To address this problem, a mixed-integer quadratic optimization model has been developed, which integrates photovoltaic (PV) system siting into the optimal framework [6].

Numerous advantages provided by DG units are thought to improve power distribution networks' security. However, by making sure that DG units are positioned and sized properly, these advantages may be further enhanced. Conversely, random placement of these units can adversely affect power systems by worsening the voltage profile and potentially increasing power losses. To address this, Jumaa *et al*. [7] utilize an artificial intelligence technique known as particle swarm optimization (PSO) to determine the optimal placement and sizing of DG units, aiming to minimize power losses and improve the voltage profile. PSO and Monte Carlo simulation are presented in this work, which takes in to account many goals [8]. Flattening the load curve is the main objective of peak shaving and valley filling procedures. Positive results are obtained when the suggested approach is used to a traditional system.

To increase the system's dependability, supplementary power resources should be integrated. One approach is to utilize DGs, which provide both reactive and real power according to demand. The optimal incorporation of multiple DGs into the network boosts the system's reliability. The impact on the dependability of the 33-bus and 69-bus distribution systems is then analyzed after the DG units and EV charging loads are integrated optimally [9]. The artificial Hummingbird program is intended to determine the ideal location for wind and PV systems [10]. The placement of PV and EV is found using three metaheuristic methods. This study looks at particle swarm, and African vulture optimization strategies [11]. The aim is to reduce the expense of the system. Results from the simulation, which was performed on a few sample systems, showed reduced peak demand, less losses, and better voltage profiles. Sales of EVs have increased as a result of phase-out of older, petroleum-powered cars. However, as EVs gained popularity, so did the quantity of EV charge stations. The rapid installation of PVs and EVs has resulted in increased power losses. EV load models for power flow analysis may be developed using user-defined models. Through the use of programming using the power system analysis toolbox, a specific model has been developed for EVs designed as compact city cars for urban environments [12].

The optimal buses for PV and EV installation are found using the AI approach [13], [14]. A new method for figuring out the best place and size for EVCS and renewable energy sources using enhanced GA-PSO algorithm is done [15], [16]. In order to determine the highest levels of EV and renewable-based DG penetration that an electric distribution system can support, this work [17] proposes a method from the viewpoint of operator of the distribution system. Batteries can be used to control variations in PV production in order to fulfil energy demand and enhance the sustainability of CSs. A MATLAB simulation of a stand-alone PV-powered EVCS is shown in this paper [18]. Power quality issues and its mitigations are reviewed in this work [19]. The functionality of distribution grid is compromised by the increasing use of EVs. Consequently, the location of the EVCS affects the DS dependability. The DS's degradation as a result of an improper EVCS position is the main challenge. A novel algorithm is used to determine best location for DSTATCOM and EVCS allocation in DS is discussed [20]. Future research directions must include developing advanced optimization algorithms, exploring the integration of renewable energy sources into the charging infrastructure, investigating the potential of vehicle-to-grid (V2G) services, evaluating how EV charging affects the electrical infrastructure and developing plans for organizing and planning EV charging for sizable fleets [21].

Gaps found in the literature: i) the addition of EV loads increases power losses, but optimal EV placement can reduce these losses compared to random allocation. Scenarios not clearly addressed in existing literature, ii) although the optimal distribution of EVs has been examined, their integration with DGs has not [22], iii) this analysis only included PV CSs, not the combination of EVs and PV [23], iv) the analysis primarily focused on IEEE example systems, which is inadequate, as real-time data and various scenarios were not taken into account [24], and v) not more than 12.08% reduction in power losses was achieved utilizing the grey wolf optimization (GWO) method [25].

Significance of this study considering the limitations of the aforementioned studies, a novel optimization algorithm is proposed. Eight different scenarios involving EVCS and PV integration are analyzed. The key innovation of this paper lies in the application of the HHO algorithm to real-time data from a distribution grid in a small Indian town. Utilizing real-time data from a small town offers precise, location-specific insights that reflect the area's actual conditions and challenges. This improves the reliability of the research findings, ensuring the proposed solutions are both practical and directly applicable. Additionally, it reveals unique patterns and behaviors that might be overlooked in generic or simulated datasets.

This study suggests utilizing the HHO approach to plan an EVCS. The remainder of the paper is structured as follows. Method is in section 2. Results and discussions in section 3. While conclusions in section 4.

2. METHOD

In India, the establishment of EVCS and solar-powered EV charging infrastructure is still at a nascent stage. Solar EVCS are increasingly recognized as a sustainable solution, capitalizing on the country's abundant solar energy resources. However, the overall infrastructure and technology are still evolving, which emphasizes the importance of this study. The systematic approach and techniques employed in this paper are as follows:

- Implementation of HHO algorithm for ideal positioning of PVs and EVs on the IEEE 12 bus, 15 bus example systems.
- The use of real-world data from a distribution grid of a small town in India.
- Comprehensive studies are conducted across various scenarios.
- DGs such as PV generation are included in the analysis.
- Percentage reduction in losses is tabulated and compared with GWO method.
- The HHO algorithm results are compared with other algorithms from the literature and analyzed.

With inspiration from the EVCS planning research publications mentioned above, a novel optimization technique called Harris Hawk is considered to locate optimal places for EVCS in the distribution grid. PV generation is considered as DG sources. The algorithm is initially tested for IEEE-12 and 15 bus systems. By examining a broad range of scenarios, potential risks and vulnerabilities that could arise in real-world usage can be identified. This helps mitigate performance, reliability, and security risks, ensuring the system meets its requirements and performs optimally in various situations.

To validate the proposed HHO algorithm, simulations are conducted also on the real distribution grid data of the Hiremagaluru express feeder in Chikkamagaluru, Karnataka, India.

2.1. Goal function

To increase the distribution network's performance, placement of EVs and PVs in the network is optimized. The goals of the study stabilize the bus voltage and reduce loss in power. The goal function of the system for power losses is given by (1):

$$F_1(n) = MIN \sum_{i=1}^{e} R_i * I_i^2 \tag{1}$$

where e is the total quantity of elements and i is their number. The resistance of the i^{th} element is Ri and I_i the current in the i^{th} element. Average voltage deviation index (AVDI) is the variation of voltage from 1 pu of reference voltage considered is given by (2):

$$F_2(n) = \frac{1}{b} MIN \sum_{n=1}^{b} |1 - V_n|^2 \tag{2}$$

where n is the bus number, V_n is the voltage at n^{th} bus, b represents number of buses.

The stability of the system can be determined by looking at the value of VSI that is lowest. In order to lower loss of power, average potential difference deviation, the absolute objective function is created. Mathematically it is represented as (3):

$$F(n) = MIN[W_1F_1(n) + W_2F_2(n)] \tag{3}$$

weights W_1 and W_2 are assumed equal weights and assumed as (1).

2.2. Constraints

The limitations on the needs for power balance:

$$\sum_{n=1}^{b} PG_n - P_L = P_D \tag{4}$$

$$\sum_{n=1}^{b} QG_n - Q_L = Q_D \tag{5}$$

where P_L, Q_L, P_D, Q_D are loads and demands for both real and reactive power respectively.

The highest allowable generated power by DGs must not exceed the acceptable limit of distribution systems. Additionally, voltage deviation must not exceed 5%.

$$PG_n^{Min} \leq PG_n \leq PG_n^{Max} \tag{6}$$

$$QG_n^{Min} \leq QG_n \leq QG_n^{Max} \tag{7}$$

$$0.95 \leq V_n \leq 1.05 \tag{8}$$

PG_n is real power generation and QG_n is reactive power generation at the n^{th} bus.

2.3. Harris Hawk optimization algorithm workflow

The HHO algorithm is developed to achieve the goals while considering the aforementioned constraints. The workflow is displayed in Figure 1.

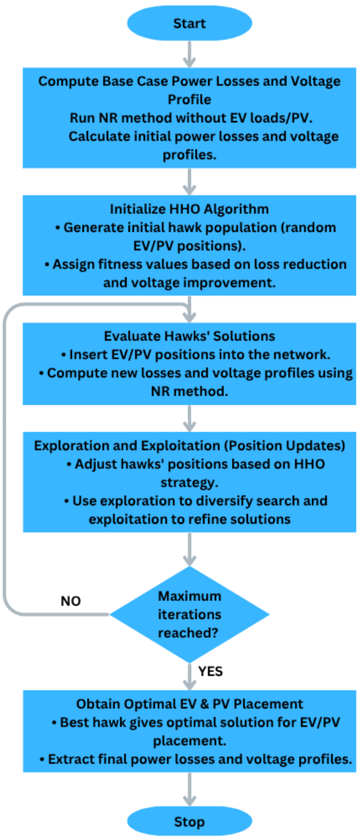


Figure 1. HHO work flow diagram

2.4. Cases under consideration

EVs and PV systems introduce uncertainty due to charging demand variation, solar fluctuations, and grid impacts like voltage stability and power loss. Simulating different scenarios helps analyze grid behavior and optimize EV/PV placement. Hence various cases are taken in to consideration.

Case 1 : base case load flow studies without connecting any PVs and EVs. Power losses are lower compared to all other scenarios.

Case 2 : a bus recommended by the HHO algorithm is chosen to connect one EV.

Case 3 : buses recommended by the HHO algorithm are chosen to connect two EVs.

Case 4 : buses recommended by the HHO algorithm are chosen to connect three EVs. Each additional EV load increases power losses. Bus voltages to fluctuate.

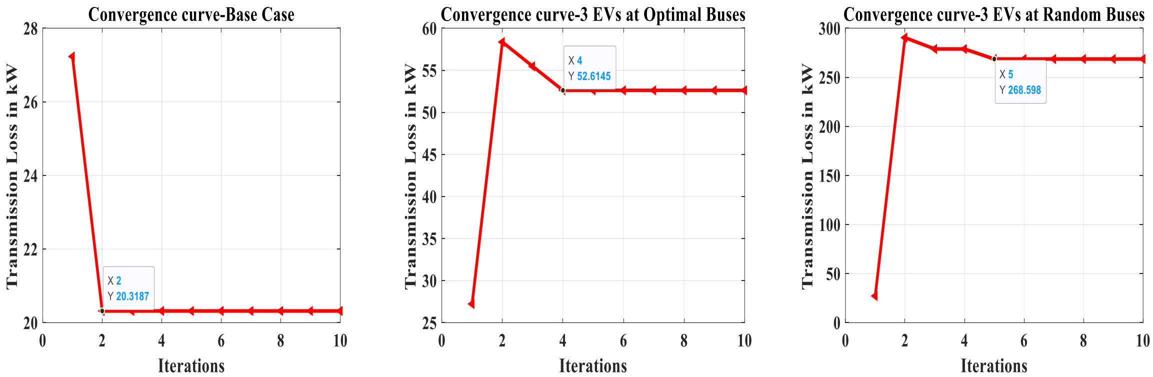
Case 5 : buses recommended by the HHO algorithm are chosen to connect three EVs and three PVs. Power losses will reduce because of PVs. Better Voltage deviation index.

Case 6 : three EVs are connected at randomly selected the buses. The increase in power losses is significantly higher compared to the HHO-based optimal location, as seen in Case 4.

3. RESULTS AND DISCUSSION

HHO algorithm was run in MATLAB. The solution in terms of ideal locations is obtained. The analysis assumes a 250-kW CS with 5 connectors for simultaneous charging of five EVs. The potential for a 150-kW solar-powered CS is considered. The convergence curves for IEEE 12-bus, 15-Bus and real time 26-Bus system for cases 1, 3, and 6 are presented accordingly in Figures 2 to 4. Convergence is achieved within 10 iterations when applying the NR method.

From Figure 2(a), it is evident that in the base case load flow study (Case 1) for the IEEE 12-bus system, the solution converged in 4 iterations. The active power loss (Ploss) was found to be 17.2313 kW, and the reactive power loss (Qloss) was 10.2512 kVAr, which are the minimum values due to the absence of additional EV loads. In Figure 2(b), the solution converged in 3 iterations when 3 EVs were connected at optimal bus locations 2 to 4. The corresponding Ploss and Qloss increased to 46.227 kW and 23.7843 kVAr, respectively, indicating that power losses rise with the inclusion of EV loads. Figure 2(c) shows that when the 3 EVs were connected at random bus locations 10, 11, and 12, the solution required 7 iterations to converge. The losses increased significantly, with Ploss reaching 270.117 kW and Qloss rising to 119.28 kVAr, as observed in Case 6.

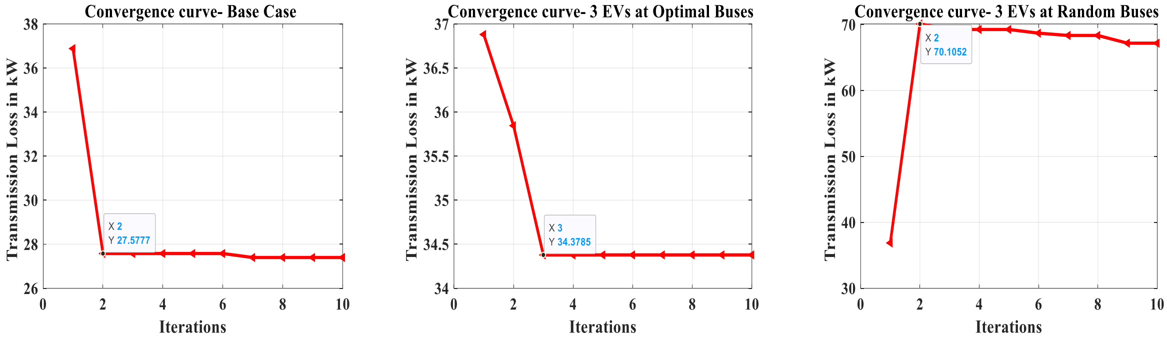


(a) (b) (c)

Figure 2. Convergence curves for 12 bus system; (a) base case, (b) 3 EV at optimal buses, and (c) 3 EV at random buses

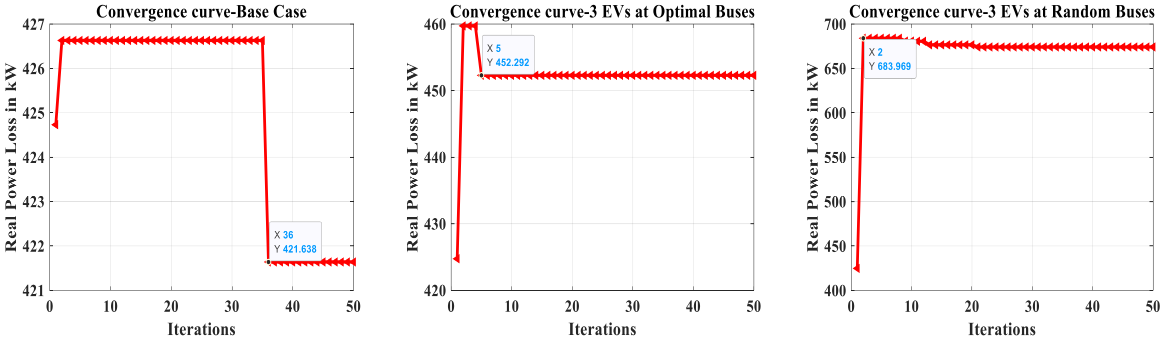
Moreover, sequentially connecting EVCSs at optimal locations (Cases 2 to 4) results in a gradual increase in both Ploss and Qloss. In contrast, the integration of PV systems (Case 5) results in a minor decrease in power losses.

Comparable results were observed for both the IEEE 15-bus system and the real-time 26-bus system, as illustrated in Figures 3(a)-(c) and 4(a)-(c), respectively. These outcomes highlight the efficiency of the HHO algorithm in substantially minimizing power losses and improving grid stability. A consolidated summary of the results is presented in Table 1.



(a) (b) (c)

Figure 3. Convergence curves for 15 bus system; (a) base case, (b) 3 EV at optimal buses, and (c) 3 EV at random buses



(a) (b) (c)

Figure 4. Convergence curves for 26 bus system; (a) base case, (b) 3 EV at optimal buses, and (c) 3 EV at random buses

Table 1. Actual and reactive loss of power for different cases

Type of system	Nature of loss	Cases 1	2	3	4	5	6
IEEE 12-bus	Ploss in kW	17.2313	22.453	29.827	46.227	31.2889	270.117
	Qloss in kVAr	10.2512	12.439	18.962	23.7843	15.3551	119.28
IEEE 15-bus	Ploss in kW	26.887	34.043	33.96	34.344	27.949	55.547
	Qloss in kVAr	63.93	71.83	72.80	69.42	61.58	90.94
Real time data of 26-bus	Ploss in kW	425.931	424.569	424.636	467.688	442.968	620.211
	Qloss in kVAr	192.72	198.22	185.62	230.69	223.0	290.36

The index representing average voltage deviation known as AVDI, is a measure of deviation of bus voltages from the reference value of 1 pu. Table 2 presents the AVDI values for different scenarios. A lower AVDI signifies smaller voltage fluctuations. For the 26-bus system, the lowest AVDI of 0.0929 is achieved when EVs are allocated to optimal buses 3, 4, and 7, indicating improved voltage stability compared to a higher AVDI of 0.1032 observed with random EV placements at 12, 18, and 25. Similar trends are observed across the IEEE test systems.

Table 2. AVDI for various cases

Type of system	Base case	EVs at optimal buses	EVs at random buses
12 bus	0.0430	0.0605	0.0979
15 bus	0.0392	0.0588	0.0668
26 bus	0.0863	0.0929	0.1032

Percentage reduction in power losses is analyzed for optimal and random EV bus placement. Both HHO and GWO algorithms were employed to identify optimal locations. As shown in Table 3, the proposed HHO algorithm achieved greater reductions in both Ploss and Qloss compared to the GWO method. The comparison of the proposed HHO algorithm with other algorithms from various literatures is presented in Table 4. It is observed that the HHO method achieves a with a lower AVDI value 0.0605, which indicates reduced voltage fluctuations compared to GWO, PSO, hybrid GWOPSO, African vultures, and salp swarm methods.

Table 3. Comparison of HHO with GWO algorithm for P_{loss} & Q_{loss}

Method	% Reduction in P_{loss}			% Reduction in Q_{loss}		
	12 bus	15 bus	26 bus	12 bus	15 bus	26 bus
GWO	74.16	32.83	17.8	73.29	19.90	16.21
HHO	83.44	39.77	24.59	80.06	23.66	20.55

Table 4. Comparison of HHO with other algorithms

Algorithm	AVDI	References
GWO	0.648	[9]
PSO	0.6358	[9]
Hybrid GWOPSO	0.661	[9]
African vultures optimization	1.99	[11]
Salp swarm	1.97	[11]
Bacterial foraging optimization	0.01702	[26]
Hybrid PFOA & PSO	0.01271	[26]
Proposed HHO	0.0605	-

4. CONCLUSION

The growth of EVCS and solar-powered EV charging infrastructure in India is still in its early phases. As such, this research aims to develop metaheuristic algorithm to identify the best location for EVs and PV systems, which is essential for maintaining the stability of the distribution grid. IEEE 12 and 15 bus distribution networks are two widely recognized IEEE standard example networks on which the suggested HHO method was tested. Later the method is implemented for real time 26 bus power distribution system. It was discovered that the HHO is more efficient compared to GWO method. PVs in the grid will improve voltage levels and reduce power losses. The aforementioned findings support this.

This work provides practical solutions to real-world challenges, benefiting both the academic community and the broader society working towards sustainable energy solutions. The above results offer a data-driven approach to guide policymakers and grid planners in making informed decisions about the design and expansion of EV and PV infrastructure. The proposed bus locations 3, 4, and 7 for EV and PV placement have been suggested to the Mangalore electricity supply company (MESCOM) for consideration in future implementation. Additionally, future research could evaluate the potential cost savings resulting from reduced power losses in the distribution grid.

The transportation industry and the power utility firm should work together to efficiently plan EVCS in order to serve EV consumers. In addition to determining the best locations for EVCS's, this study should eventually examine the daytime fluctuations in PV power production, EV owner's driving habits, unpredictable parameters of distribution network, and times of EV charging in future.

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Magge Subbaraya Raviprakasha					✓	✓				✓	✓	✓		
Haleyur Lakshmegowda Suresh					✓	✓				✓	✓	✓		

C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT
Authors state no conflict of interest.

DATA AVAILABILITY
Data availability is not applicable to this paper as no new data were created or analyzed in this study.

REFERENCES

[1] M. Bilal and M. Rizwan, "Intelligent algorithm-based efficient planning of electric vehicle charging station: a case study of metropolitan city of India," *Scientia Iranica*, vol. 30, no. 2, pp. 559–576, Apr. 2023, doi: 10.24200/sci.2021.57433.5238.

[2] P. Ray, N. R. Babu, P. K. Khushwaha, C. Bhattacharjee, and D. K. Raju, "Optimal parameter allocation in renewable energy sources integrated fast charging ev station considering hgps algorithm," *Journal of Engineering Research (Kuwait)*, vol. 11, no. 1, pp. 198–211, Feb. 2023, doi: 10.36909/jer.12737.

[3] A. Pal, A. Bhattacharya, and A. K. Chakraborty, "Placement of electric vehicle charging station and solar distributed generation in distribution system considering uncertainties," *Scientia Iranica*, vol. 30, no. 1, pp. 183–206, Feb. 2023, doi: 10.24200/sci.2021.56782.4908.

[4] N. K. Golla, S. K. Sudabattula, and V. Suresh, "Optimal placement of charging station and distributed generator along with scheduling in distribution system using arithmetic optimization algorithm," *International Journal of Renewable Energy Research*, vol. 12, no. 2, pp. 970–980, 2022, doi: 10.20508/ijrer.v12i2.12964.g8480.

[5] N. Dharavat *et al.*, "Optimal allocation of renewable distributed generators and electric vehicles in a distribution system using the political optimization algorithm," *Energies*, vol. 15, no. 18, pp. 1-25, Sep. 2022, doi: 10.3390/en15186698.

[6] C. V. Grammenou, M. Dragatsika, and A. S. Bouhouras, "Optimal EV charging and PV siting in prosumers towards loss reduction and voltage profile improvement in distribution networks," *World Electric Vehicle Journal*, vol. 15, no. 10, pp. 1-20, Oct. 2024, doi: 10.3390/wevj15100462.

[7] F. A. Jumaa, O. M. Neda, and M. A. Mhawesh, "Optimal distributed generation placement using artificial intelligence for improving active radial distribution system," *Bulletin of Electrical Engineering and Informatics*, vol. 10, no. 5, pp. 2345–2354, Oct. 2021, doi: 10.11591/eei.v10i5.2949.

[8] E. Hadian, H. Akbari, M. Farzinfar, and S. Saeed, "Optimal allocation of electric vehicle charging stations with adopted smart charging/discharging schedule," *IEEE Access*, vol. 8, pp. 196908–196919, 2020, doi: 10.1109/ACCESS.2020.3033662.

[9] M. Bilal, M. Rizwan, I. Alsaidan, and F. M. Almasoudi, "AI-Based approach for optimal placement of EVCS and DG with reliability analysis," *IEEE Access*, vol. 9, pp. 154204–154224, 2021, doi: 10.1109/ACCESS.2021.3125135.

[10] M. S. Abid, H. J. Apon, K. A. Morshed, and A. Ahmed, "Optimal planning of multiple renewable energy-integrated distribution system with uncertainties using artificial hummingbird algorithm," *IEEE Access*, vol. 10, pp. 40716–40730, 2022, doi: 10.1109/ACCESS.2022.3167395.

[11] N. Pompern, S. Premrudeepreechacharn, A. Siritaratiwat, and S. Khunkitti, "Optimal placement and capacity of battery energy storage system in distribution networks integrated with PV and EVs using metaheuristic algorithms," *IEEE Access*, vol. 11, pp. 68379–68394, 2023, doi: 10.1109/ACCESS.2023.3291590.

[12] Y. Kongjeen and K. Bhumkittipich, "Modeling of electric vehicle loads for power flow analysis based on PSAT," in *2016 13th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology, ECTI-CON 2016*, Jun. 2016, pp. 1–6, doi: 10.1109/ECTICon.2016.7561430.

[13] M. Abbas, M. A. Alshehri, and A. B. Barnawi, "Potential contribution of the grey wolf optimization algorithm in reducing active power losses in electrical power systems," *Applied Sciences*, vol. 12, no. 12, pp. 1-22, Jun. 2022, doi: 10.3390/app12126177.

[14] E. S. Eid, M. Saeed, and M. El-Saadawi, "Optimal location of EV-PV charging stations in a radial distribution system (Dept.E)," *MEJ. Mansoura Engineering Journal*, vol. 45, no. 4, pp. 45–52, Dec. 2020, doi: 10.21608/bfemu.2020.127211.

[15] M. R. Mozafar, M. H. Moradi, and M. H. Amini, "A simultaneous approach for optimal allocation of renewable energy sources and electric vehicle charging stations in smart grids based on improved GA-PSO algorithm," *Sustainable Cities and Society*, vol. 32, pp. 627–637, Jul. 2017, doi: 10.1016/j.scs.2017.05.007.

[16] N. Das, A. Haque, H. Zaman, S. Morsalin, and S. Islam, "Domestic load management with coordinated photovoltaics, battery storage and electric vehicle operation," *IEEE Access*, vol. 11, pp. 12075–12087, 2023, doi: 10.1109/ACCESS.2023.3241244.

[17] E. C. D. Silva, O. D. M. Dominguez, and R. Romero, "Simultaneous distributed generation and electric vehicles hosting capacity assessment in electric distribution systems," *IEEE Access*, vol. 9, pp. 110927–110939, 2021, doi: 10.1109/ACCESS.2021.3102684.

[18] E. Abdulrahman *et al.*, "MATLAB simulation of an electric vehicle charging station supplied by photovoltaic energy," *International Journal of Applied Engineering Research*, vol. 17, no. 3, pp. 283–289, 2022.

[19] L. Wang, Z. Qin, T. Slangen, P. Bauer, and T. V. Wijk, "Grid impact of electric vehicle fast charging stations: trends, standards, issues and mitigation measures - an overview," *IEEE Open Journal of Power Electronics*, vol. 2, pp. 56–74, 2021, doi: 10.1109/OJPEL.2021.3054601.

[20] T. Yuvaraj, K. R. Devabalaji, S. B. Thanikanti, V. B. Pamshetti, and N. I. Nwulu, "Integration of electric vehicle charging stations and DSTATCOM in practical indian distribution systems using bald eagle search algorithm," *IEEE Access*, vol. 11, pp. 55149–55168, 2023, doi: 10.1109/ACCESS.2023.3280607.

[21] M. R. Fauzi, A. A. Zakri, and Syafii, "Recent trend and future prospect in optimization of electric vehicle charging: a systematic review," *Bulletin of Electrical Engineering and Informatics*, vol. 13, no. 4, pp. 2289–2297, Aug. 2024, doi: 10.11591/eei.v13i4.8017.

[22] H. U. R. Habib *et al.*, "Analysis of optimal integration of EVs and DGs Into CIGRE's MV benchmark model," *IEEE Access*, vol. 10, pp. 95949–95969, 2022, doi: 10.1109/ACCESS.2022.3204311.

[23] E. A. Rene, W. S. T. Fokui, and P. K. N. Kouonchie, "Optimal allocation of plug-in electric vehicle charging stations in the distribution network with distributed generation," *Green Energy and Intelligent Transportation*, vol. 2, no. 3, pp. 1-12, Jun. 2023, doi: 10.1016/j.geits.2023.100094.

[24] A. Pal, A. Bhattacharya, and A. K. Chakraborty, "Allocation of EV public charging station in renewable based distribution network using HHO considering uncertainties and traffic congestion," *Research Square*, pp. 1–10, 2021.

[25] F. Ahmad, M. Marzband, A. Iqbal, I. Ashraf, and I. Khan, "Placement of electric vehicle fast charging stations using grey wolf optimization in electrical distribution network," in *PESGRE 2022 - IEEE International Conference on "Power Electronics, Smart Grid, and Renewable Energy,"* Jan. 2022, pp. 1–6, doi: 10.1109/PESGRE52268.2022.9715842.

[26] W. S. T. Fokui, M. J. Saulo, and L. Ngoo, "Optimal placement of electric vehicle charging stations in a distribution network with randomly distributed rooftop photovoltaic systems," *IEEE Access*, vol. 9, pp. 132397–132411, 2021, doi: 10.1109/ACCESS.2021.3112847.

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