Optimal allocation of PV units using metaheuristic optimization considering PEVs charging demand

A. Manjula, G. Yesuratnam
Department of Electrical Engineering, University College of Engineering, Osmania University, Hyderabad, India

Article Info

Article history:

Received Mar 25, 2024
Revised Aug 18, 2024
Accepted Oct 23, 2024

Keywords:

Distributed generators
Photovoltaic
Plug-in electric vehicles
Radial distribution system
WMODE
WMOEEFO
WMOGWO

ABSTRACT

The distribution system is seeing a dramatic shift as a result of the increasing use of distributed generators (DGs) and plug-in electric vehicles (PEVs), or plug-in hybrid electric cars. The research endeavors to optimize the allocation of photovoltaic (PV) based DGs within radial distribution systems (RDS) while accommodating the load demand stemming from PEVs. A weighted-sum based multiobjective (WMO) technique is employed in this study to optimize three fundamental technical metrics of the distribution network: achieving the best possible voltage stability index (VSI) while reducing real power loss and total voltage variation to a minimum. Initially, the study investigates the impact of both conventional and PEVs load demand, considering PEVs load demand on distribution system performance under three charging scenarios: a situation involving peak charging, scenario involving off-peak charging, and scene of random charging. Subsequently, PV units are strategically planned, taking into account the PEVs demand within the distribution system utilizing an innovative weighted multiobjective electric eel foraging optimization (WMOEEFO) algorithm, its effectuality is validated with weighted multiobjective differential evolutionary (WMODE) and weighted multiobjective grey wolf optimization (WMOGWO) algorithms on standard test system IEEE 33-bus.

Corresponding Author:

A. Manjula
Department of Electrical Engineering, University College of Engineering, Osmania University
Hyderabad-500007, Telangana, India
Email: manjulabanda89@gmail.com

1. INTRODUCTION

The demand for electricity is significant and is on the rise across the world. According to recent reports [1], traditional energy sources still maintain a dominant share of 62% in the global energy mix. However, the finite nature of fossil fuel resources coupled with their detrimental environmental impacts, such as pollution and climate-altering emissions leading to ecological imbalance, render them increasingly untenable as primary energy sources. As a result, the rapid incorporation of renewable energy sources (RESs) into distribution networks has intensified the need of decarbonizing the electrical energy industry. Solar photovoltaic (PV) units and wind turbines are the most well-known and fully functional examples of RESs among the many technologies [2] that may generate electricity from low-carbon sources. Among these renewable energy sources, solar-powered RESs have exploded in popularity during the last 18 years, outpacing all others. A notable jump of 24% in the global energy mix was seen in 2022 alone for solar-based energy systems.

Extensive literature documents the potential benefits of optimally allocating (sizing and siting) distributed generators (DGs) within the distribution system [3], including minimizing of energy loss [4], enhancement of the voltage profile [5], maximization of load ability [6], and augmentation of the voltage stability limit [7]. However, the optimal allocation of DGs presents a large-scale, nonlinear, and multi-objective optimization problem, often posing significant challenges in finding near-optimal solutions [8]. Consequently, nature-inspired metaheuristic algorithms have gained prominence as effective approaches for addressing this intricate optimization problem [9]. Electric vehicles (EVs) are becoming more common and are expected to play a big part in reducing carbon emissions from road travel, in addition to PV system integration [10]. Nonetheless, the inclusion of plug-in electric vehicle (PEV) charging loads remains largely unaddressed in the literature concerning DG allocation [11]. Various studies have incorporated different PEV charging profiles to evaluate the impact of PEV loads [12]. In [13], the application of a novel lightning search calculation is proposed to address the DG assignment issue. Nevertheless, the study [14] overlooks a crucial objective, namely, the voltage stability index (VSI), during DG allocation and confines its investigation to dispatchable DGs exclusively. In contrast, Sankar and Chatterjee [15] determine the placement and dimensions of DGs by use of the gorilla troops optimization technique.

The literature review underscores the necessity of considering plug-in electric vehicles (PEVs) charging demand when allocating PV units within the context of contemporary research. In this vein, we employ the weighted multiobjective electric eel foraging optimization (EEFO) algorithm to solve the PV unit allocation problem. The EEFO algorithm as detailed by [16], emulates the foraging behavior of electric eels and has been rigorously tested and compared with various renowned algorithms. This study contributes to the existing state-of-the-art in the following aspects:

- Incorporating PEVs charging demand in the allocation of PV units. Considering the stochastic modeling of the uncertain nature of PV generation.
- Comprehensive assessment of PEVs demand comprising off-peak charging scenario (OPCS), peak charging scenario (PCS), and stochastic charging scenario (SCS) scenarios on the distribution network. Distributing PV units while keeping in mind a number of important objectives such as power loss, voltage deviation, and stability index.
- Introducing a novel application of the weighted multiobjective electric eel foraging optimization (WMOEEFO) algorithm to address the complex PV allocation problem and comparing WMOEEFO with the weighted multiobjective grey wolf optimization (WMOGWO) [17] and weighted multiobjective differential evolutionary (WMODE) [18].
- Simulating numerous study scenarios to assess the impact of the number of PV units installed, and considering test cases to quantitatively evaluate the objectives in each scenario.

The following is an overview of the paper: i) Section 2 describes the PV modeling; ii) The multiobjective problem formulation is made in section 3; iii) In section 4, the EEFO algorithm is described in great length; iv) Section 5 delves the results and discussions; and v) In section 6 the final conclusion is summarized.

2. SOLAR PV UNCERTAINTY MODELLING

A beta probability density function (PDF) was utilized to depict the arbitrary behaving of sun-based illumination [19]. Within a designated time frame *t*, the beta PDF $f(z)$ supported by historical data used for assessing the probability of solar irradiation is expressed as (1) [20].

$$f(z) = \begin{cases} \frac{\Gamma(x+y)}{\Gamma(x)\Gamma(y)} z^{(a-1)}, & 0 \le z \le 1, x \ge 0, y \ge 0 \\ 0, & otherwise \end{cases} \tag{1}$$

Where z signifies the solar irradiance, x and y define the parameters that delineate the configuration of the PDF. Potential values of the solar irradiance state (z) at any given hour may be expressed as (2) [21].

$$P_z(H) = \int_{z_1}^{z_2} f(z).dz \tag{2}$$

PV module output power may be expressed as (3).

$$P_{pv0}(z) = N_m * FF_m * V_m * I_m \tag{3}$$

Where FF_M is the fill factor of PV module, N_M is no of modules, V_M is the voltage of the PV module, and I_M is the current of the PV module. Under varying solar irradiance conditions, the specific performance characteristics of PV panels output power are calculated as (4) [22].

$$P_{pv}(t) = P_z(H) * P_{pv0}(z) \tag{4}$$

3. MULTIOBJECTIVE FUNCTION FORMULATION

In this investigation, three pivotal boundaries of the distribution system have been meticulously examined to formulate the objective function. These parameters encompass energy loss (E_{loss}), total voltage deviation (TVD), and VSI. The objective function (OF) is calculated as (5) [15].

$$OF = \gamma_1 * \frac{(f_1)_{DG}}{(f_1)_{Without\ DG}} + \gamma_2 * \frac{(f_2)_{DG}}{(f_2)_{Without\ DG}} + \gamma_3 * \frac{1}{\frac{(f_3)_{DG}}{(f_3)_{Without\ DG}}} \tag{5}$$

Where γ_1, γ_2, and γ_3 denote the preference weights given to the objectives following $\sum_{i=1}^{3}\gamma_i = 1$ and γ_i for a given objective is decided based on the preference given to that objective and $\gamma_i \in [0,1]$. $(f)_{DG}$ and $(f)_{Without\ DG}$ denote the value of the parameter before and after the installation of the DG. Here OF is the overall objective function to be minimized. In this work, γ_1, γ_2, and γ_3 are assigned to 0.4, 0.3, and 0.3, respectively. The individual objectives are calculated as given in (6)-(9).

$$f_1 = E_{loss} = \sum_{t=1}^{24}\sum_{j=1}^{nbus-1} I_{t,j}^2 R_j \tag{6}$$

$$f_2 = TVD = \sum_{t=1}^{24}\sum_{m=1}^{nbus}\left(\left|1 - V_{t,m}\right|\right)^2 \tag{7}$$

$$f_3 = VSI = \sum_{t=1}^{24} \min\ \left(SI_{t,n}\right) \quad n = 2 \ldots\ldots n\ bus \tag{8}$$

$$SI_{t,n} = \left|V_{t,m}\right|^4 - 4\left[P_{t,n}X_{mn} - Q_{t,n}R_{mn}\right]^2 - 4\left[P_{t,n}R_{mn} + Q_{t,n}X_{mn}\right]\left|V_{t,m}\right|^2 \tag{9}$$

Where $I_{t,j}$, R_j, and $nbus$ respectively indicate the jth branch current, resistance of the branch j, and the total buses in the network. For a given bus m, $V_{t,m}$, $P_{t,n}$, X_{mn}, $Q_{t,n}$, and R_{mn} represent the bus voltage, injected real power, the reactance of the line between m and n buses, the injected reactive power injected, and the resistance of the line between m and n buses. The objective function framed in (5) is bound to the below constraints:

$$|V_{min}| \le |V_{t,m}| \le |V_{max}| \tag{10}$$

$$P_{t,ss} + P_{t,DG} = P_{t,D} + P_{t,loss} + P_{t,PEV} \tag{11}$$

$$P_{\ min,DG} \le P_{DG} \le P_{DGmax,DG} \tag{12}$$

Where V_{min} and V_{max} respectively define the minimum and maximum values of the bus voltage. $P_{t,ss}$, $P_{t,DG}$, $P_{t,D}$, $P_{t,loss}$, and $P_{t,PEV}$ respectively denote substation power, power injected by the DG, power demand of the network, power losses in the network, and demand due to PEVs. $P_{min,DG}$ and $P_{max,DG}$ indicate the minimum and maximum sizes of the DG rating.

4. ELECTRIC EEL FORAGING OPTIMIZATION ALGORITHM

A metaheuristic approach based on natural processes, the EEFO [16] takes its cues from the foraging tactics used by electric eels. The algorithm aims to emulate the complex foraging behaviors displayed by electric eels within their ecological environment. Notably, electric eels demonstrate four key foraging behaviors: interaction, idling, resettlement, and hunting. In Figure 1, we can see the whole process flowchart.

4.1. Interaction

This behavior, also termed churning, occurs among eels as they engage in hunting fish. Throughout this activity, eels exchange information by maneuvering randomly in various directions. In the framework of EEFO, each eel represents a potential solution, with the most optimal solution identified thus far serving as the target prey. The interacting phase can be modeled as (13) [16].

$$\begin{bmatrix} \left\{\begin{array}{l} v_i(t+1) = x_j(t) + C \times \left(\bar{x}(t) - x_i(t)\right) q_1 > 0.5 \\ v_i(t+1) = x_j(t) + C \times \left(x_r(t) - x_i(t)\right) q_1 \le 0.5 \end{array}\right\} fit\left(x_j(t)\right) < fit\left(x_i(t)\right) \\ \left\{\begin{array}{l} v_i(t+1) = x_i(t) + C \times \left(\bar{x}(t) - x_j(t)\right) q_2 > 0.5 \\ v_i(t+1) = x_i(t) + C \times \left(x_r(t) - x_j(t)\right) q_2 \le 0.5 \end{array}\right\} fit\left(x_j(t)\right) \ge fit\left(x_i(t)\right) \end{bmatrix} \tag{13}$$

Where q_1 and q_2 represent random numbers between (0, 1), $fit\left(x_j(t)\right)$, $x_j(t)$, and n respectively represent candidate fitness, eel position, population size, and a random number between (0, 1).

4.2. Idling

Idling characterizes the behavior of an eel as it rests within an idling zone distinct from the interaction zone. The idling zone is defined in EEFO by projecting an arbitrary eel position dimension onto the search region's diagonal and then normalizing it within the range of 0 to 1, which enhances exploring capabilities. The eels will modify their position for idling, which is modeled as (14) [16].

$$v_i(t+1) = R_i(t+1) + n \times \left(R_i(t+1) round(rand) \times x_i(t)\right); n \sim N(0.1) \tag{14}$$

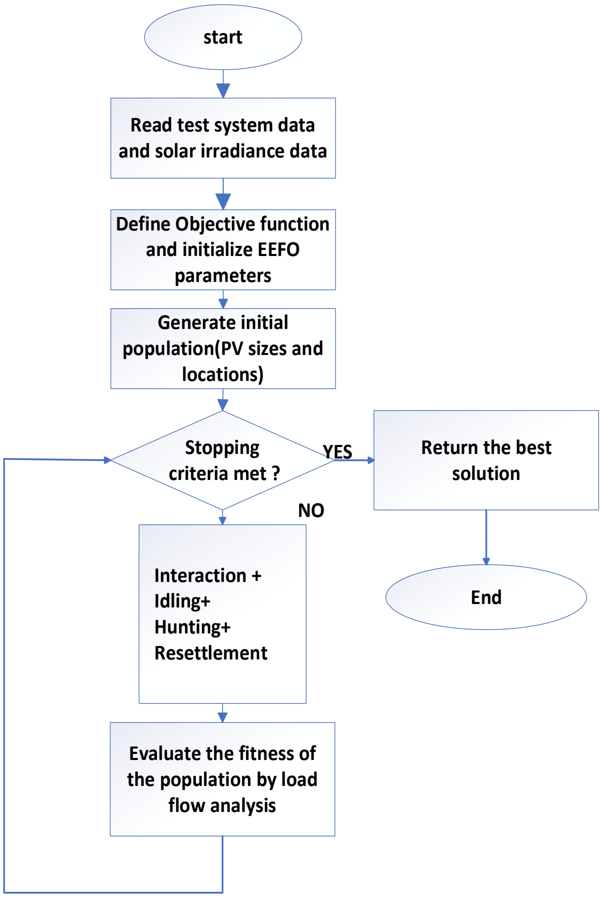

Figure 1. EEFO algorithm flowchart

4.3. Hunting

During prey hunting, electric eels create an electric communication circle around the target. They encircle the prey and communicate with each other through organ electric discharges, thereby forming an electric circle that delineates the hunting zone. This hunting behavior in electric eels entails a curling movement, which is represented as (15) [16], where η denote curling parameter.

$$v_i\,(t+1) = H_{prey}(t+1) + \eta \times (H_{prey}(t+1) - round(rand) \times x_i(t)) \tag{15}$$

4.4. Resettlement

Resettlement is a migratory behavior observed in electric eels, wherein they transition from the idling zone to the hunting zone. The (16) delineate the resettlement trait in EEFO [13].

$$v_i(t+1) = -r_1 \times R_i(t+1) + r_2 \times H_r(t+1) - L \times \left(H_r(t+1) - x_i(t)\right) \tag{16}$$

Where H_r denotes any position within the hunting zone, r_1 and r_2 represent randomly selected values within the interval (0.1).

5. RESULTS AND DISCUSSION

Using the IEEE 33-bus radial distribution systems (RDS), a standard test system, this research validates the appropriate deployment of PV units in a distribution system that supports PEVs. Reference [23] is used to get data of bus and line information for the 33-bus test system. Figure 2 shows a 33-bus RDS with a base voltage of 12.66 KV and a base of 100 MVA; the peak values of real power demand of 3.715 MW, and reactive power demand are 2.300 MVAR. The test systems' hourly power needs for each bus are derived from the normal daily load pattern [24] shown in Figure 3. A PV unit with a maximum capacity of 3200 kW and a minimum capacity of 100 kW is considered [25]. A total of 100 iterations were taken into account for all algorithms in this research, with a population size of 200. The parameter-free optimization methods WMOGWO and WMOEEFO are used in WMODE with mutation rates and crossover rates set at 0.7. The optimal values are selected after each algorithm undergoes 30 separate runs. The MATLAB simulations were performed on a computer with 8 GB of RAM and an Intel(R) Core (TM) i5-7200U 2.50 GHz CPU. This research analyses the distribution system's performance in each of the following scenarios:

- Scenario 0: without PV units and without PEVs load demand, only conventional load demand in RDS.
- Scenario 1: without PV units and with PEVs, load demand and conventional load in RDS.
- Scenario 2: optimal deployment of one PV unit in RDS hosting PEVs' load demand and conventional load.
- Scenario 3: optimal deployment of two PV units in RDS hosting PEVs' load demand and conventional load.
- Scenario 4: optimal deployment of three PV units in RDS hosting PEVs' load demand and conventional load.

Scenario 0 involves a distribution system subjected to a load flow algorithm without PV units to get a high-level picture of the system's technical parameters. In scenario 1, the load flow algorithm is utilized to dissect the influence on system technical metrics caused by the addition of PEVs to the traditional load demand. For scenarios 2, 3, and 4, the best way to meet the load demand of PEVs is to use one, two, or three PV units in an RDS. This will reduce the network E_{loss}, TVD, and improve the system VSI.

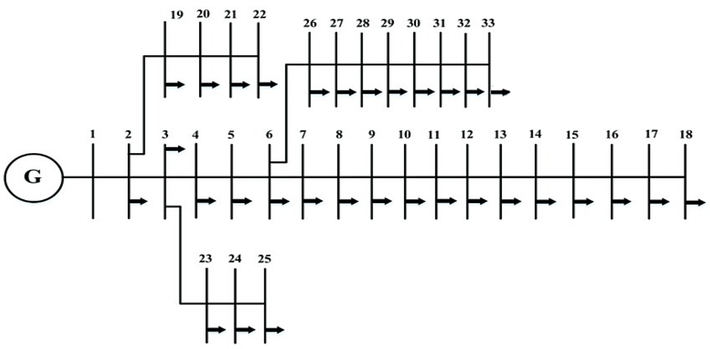

Figure 2. IEEE 33-bus system single line diagram

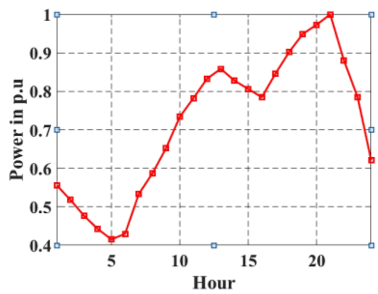

Figure 3. Load curve in p.u.

The results produced by WMOEEFO for scenarios 2-4, are summarized in Table 1, are as follows. A total of 2677 kW of P_{loss}, 1.6931 p.u. of TVD, and 0.757 p.u. of VSI were recorded in scenario 0 load flow results. Scenario 1 considers a 33-bus system with a total load of 288 PEVs, PEVs of 9 per bus as shown in Figure 2, to concentrate on the interest on the electric circulation framework brought about by PEVs. It is assumed that the state of charge (SOC) of PEVs is 50%, and all PEVs use 25 kWh batteries [15]. The daily charging of 288 PEVs requires a total of 3600 kW of electrical power, calculated as 288*25*0.5. Three different scenarios for charging PEVs are shown in Figure 4: PCS, OPCS, and SCS. This research considers that PEVs charge equally under PCS, OPCS, and SCS. Scenarios PCS, OPCS, and SCS are used to calculate the electric power needed to charge PEVs in a day. Scenario 2 involves the execution of the load flow algorithm. Figure 5 displays the hourly variation of substation power in scenarios 0 and 1, indicating that the system's load demand from PEVs causes an increase in substation power. Three technical measures have deteriorated subsequently: P_{loss} of system has deteriorated to 2913 kW, which accounts for an 8.1% improvement; TVD has deteriorated to 1.8581 p.u., and VSI has further aggravated to 0.745 p.u. In scenario 2, a single 3194 kW PV unit is optimally connected to the 7th bus, reducing the system's P_{loss} to 2106 kW (a 27.70% decrease), improving TVD to 1.0837 p.u., and maximizing VSI to 0.824 p.u. Scenario 3's efficient linking of two 932 kW and 1424 kW PV units at the 13th and 30th buses reduces the system's P_{loss} to 1845 kW, which is a 36.36% improvement; it also improves TVD to 1.0481 p.u. and maximizes VSI to 0.831 p.u. As a result of connecting three PV units at the 14th, 24th, and 30th buses, with a capacity of 844 kW, 992 kW, and 1313 kW, respectively, in scenario 4, the system's P_{loss} is reduced to 1742 kW, accounting for 40.19%, the

TVD is enhanced to 1.0437 p.u, and the VSI is maximized to 0.842 p.u. Figure 6 shows the power production curves for the hourly PV units produced for scenario 4 of the 33-bus system.

Table 1. Summary of outcomes generated by WMOEEFO for scenarios 0-4 of 33-bus system for 24 hours

S.L.	Technical metrics	Scenario 0	Scenario 1	Scenario 2	Scenario 3	Scenario 4
1	PV loc's/PV sizes (kW)	-	-	7/3194	13/0932 30/1424	14/0844 24/0992 30/1313
2	Substation power (kVA)	78351	81813	53365	60201	53250
3	Objective function (OF)	-	-	0.7356	0.6916	0.6733
4	Real power loss (P_{loss}) in kW	2677	2913	2106	1845	1742
5	Total voltage deviation (TVD) in p.u.	1.6931	1.8581	1.0837	1.0481	1.0437
6	Voltage stability index (VSI) in p.u.	0.757	0.745	0.824	0.831	0.842
7	% P_{loss} reduction	-	-	27.70	36.36	40.19

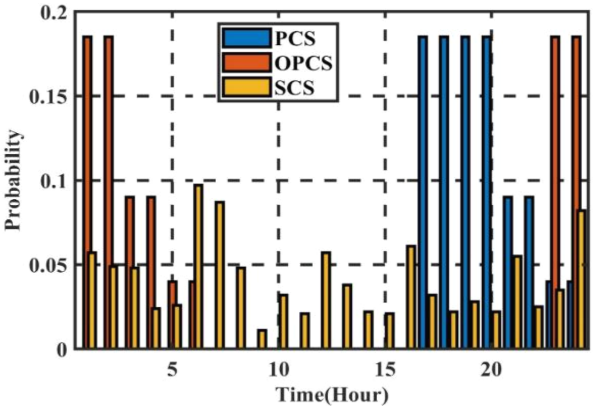

Figure 4. Distribution of probabilities for the PEVs in PCS, OPCS, and SCS scenarios

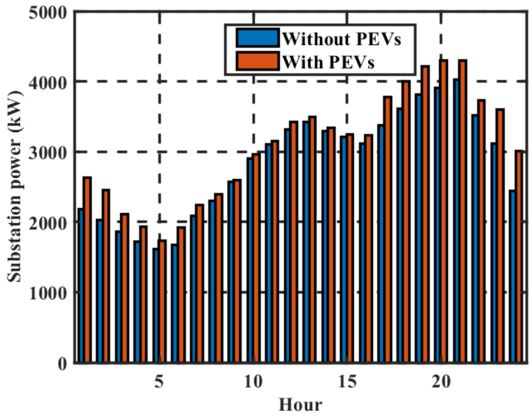

Figure 5. Hourly substation power of 33-bus system without and with PEVs

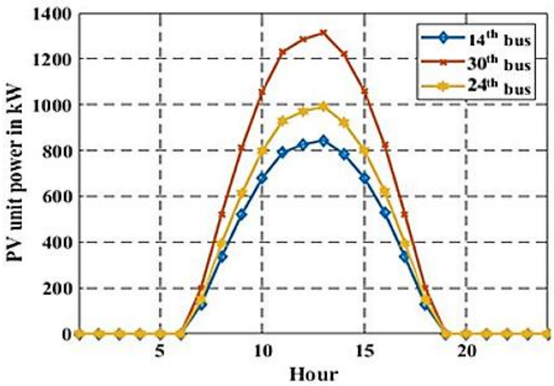

Figure 6. PV unit output curves for scenario 4 of the 33-bus system

In Figure 7, we can see the 33-bus system average voltage profile for scenarios 0–4. Figure 7 further demonstrates that, in scenario 1, the load demand of PEVs worsens the system voltage, while the optimal possible deployment of PV units further develops the voltage profile of the system. Figure 8 shows the hourly loss of the system for scenarios 0–4. In order to determine the WMOEEFO algorithm's effectiveness using the WMODE and WMOGWO algorithms to run in scenarios involving the fourth scenario of the 33-bus test system. The summary of outcomes by comparing different methods is illustrated in Table 2. Figure 9 also shows how the WMOEEFO, WMODE, and WMOGWO algorithms converge for the test system of scenario 4. The WMOEEFO algorithm outperforms WMODE and WMOGWO in achieving optimal results.

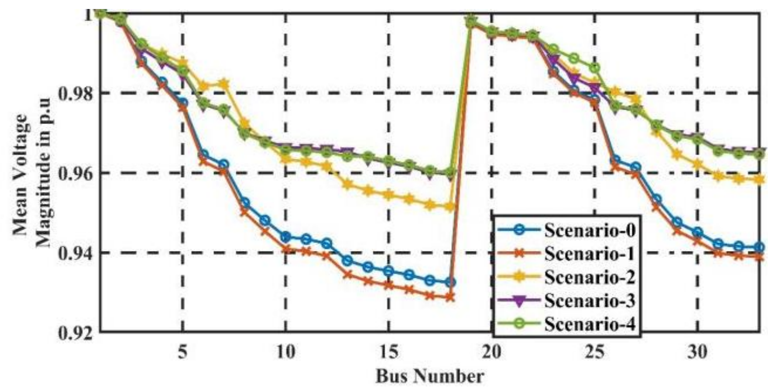

Figure 7. 33-bus system mean voltage profile for scenarios 0–4

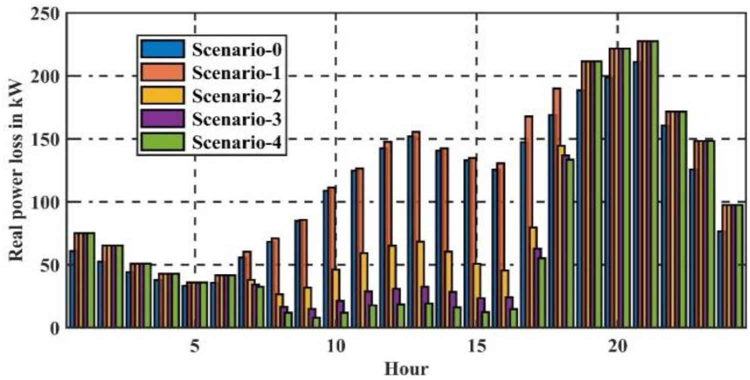

Figure 8. Power loss in the 33-bus system for scenarios 0-4 on an hourly basis

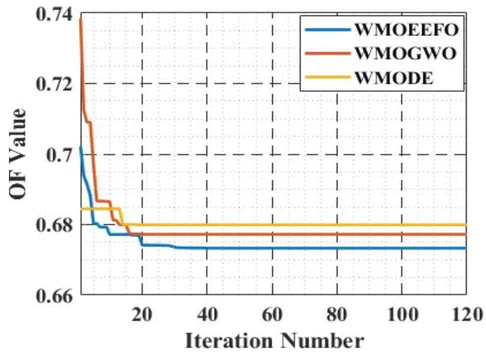

Figure 9. Convergence of WMOEEFO, WMODE, and WMOGWO algorithms for 33-bus system

Table 2. Summary of outcomes generated by WMOEEFO, WMOGWO, and WMODE for scenario 4 of the 33-bus system

S.No	System	Optimization technique	PV loc's/PV sizes (kW)	OF value	P_{loss} (kW)	TVD (p.u.)	VSI (p.u.)
1	33-bus	WMOEEFO	14/0844, 24/0992, 30/1313	0.6733	1742	1.0437	0.842
		WMOGWO	10/1074, 25/0649, 30/1209	0.6772	1758	1.0463	0.839
		WMODE	10/1272, 25/0667, 30/1010	0.6799	1788	1.0481	0.834

6. CONCLUSION

This research focused on optimizing the placement of PV units in an RDS that caters to the load demand of PEVs. An evaluation of the suggested approach was carried out utilizing the IEEE 33-bus RDS. The study aimed at optimizing three key technical metrics of the system: maximizing VSI, minimizing TVD, and minimizing P_{loss}. In order to achieve these objectives, a weighted-based multiobjective approach was developed and used the EEFO algorithm to minimize its corresponding function. The study was considered into two parts. The first part looked at how PEVs' load demand affected the operation of the distribution system. The second part showed how to best allocate PV units in the system to accommodate PEVs' load demand. Three different charging scenarios (PCS, OPCS, and SCS) were used to model the electrical power requirement of PEVs on an hourly basis. Research showed that the load demand from PEVs degraded the test system's performance. Maximal gains in all three technical parameters were achieved by strategically placing three PV units in the 33-bus distribution system. Real power loss in 33-bus system was reduced by approximately 40-42%. Nevertheless, the minimum voltage of the system did not improve due to the absence of PV unit power during peak load times. Further enhancements in loss reduction and minimum voltage were observed through dispatchable DGs, suggesting a potential future avenue for this research. Comparing optimization algorithms, the WMOEEFO algorithm demonstrated superior performance in achieving the optimal solution when contrasted with WMODE and WMOGWO.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
A. Manjula		✓	✓		✓	✓		✓	✓					
G. Yesuratnam	✓	✓		✓	✓	✓	✓	✓		✓	✓	✓	✓	

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

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Derived data supporting the findings of this study are available from the corresponding author [AM], on request.

REFERENCES

[1] A. Lebsir and T. Benamimour, “Renewable energies in the twenty-first century: a global-view,” *2023 Second International Conference on Energy Transition and Security (ICETS)*, 2023, pp. 1-6, doi: 10.1109/ICETS60996.2023.10410757.

[2] P. Singh, N. K. Meena, J. Yang, E. Vega-Fuentes, and S. K. Bishnoi, “Multi-criteria decision making monarch butterfly optimization for optimal distributed energy resources mix in distribution networks,” *Applied Energy*, vol. 278, p. 115723, Nov. 2020, doi: 10.1016/j.apenergy.2020.115723.

[3] M. M. Sankar and K. Chatterjee, “A posteriori multiobjective approach for techno-economic allocation of PV and BES units in a distribution system hosting PHEVs,” *Applied Energy*, vol. 351, p. 121851, Dec. 2023, doi: 10.1016/j.apenergy.2023.121851.

[4] B. Ahmadi, O. Ceylan, A. Ozdemir, and M. Fotuhi-Firuzabad, “A multi-objective framework for distributed energy resources planning and storage management,” *Applied Energy*, vol. 314, p. 118887, May 2022, doi: 10.1016/j.apenergy.2022.118887.

[5] S. K. Injeti and V. K. Thunuguntla, “Optimal integration of DGs into radial distribution network in the presence of plug-in electric vehicles to minimize daily active power losses and to improve the voltage profile of the system using bio-inspired optimization algorithms,” *Protection and Control of Modern Power Systems*, vol. 5, no. 1, p. 3, Dec. 2020, doi: 10.1186/s41601-019-0149-x.

[6] V. K. Thunuguntla and S. K. Injeti, “Butterfly optimizer assisted max–min based multi-objective approach for optimal connection of DGs and optimal network reconfiguration of distribution networks,” *Journal of Electrical Systems and Information Technology*, vol. 9, no. 1, p. 8, Dec. 2022, doi: 10.1186/s43067-022-00049-y.

[7] A. Fathy, “A novel artificial hummingbird algorithm for integrating renewable based biomass distributed generators in radial distribution systems,” *Applied Energy*, vol. 323, p. 119605, Oct. 2022, doi: 10.1016/j.apenergy.2022.119605.

[8] P. Singh, N. K. Meena, S. K. Bishnoi, B. Singh, and M. Bhadu, “Hybrid elephant herding and particle swarm optimizations for optimal DG integration in distribution networks,” *Electric Power Components and Systems*, vol. 48, no. 6–7, pp. 727–741, Apr. 2020, doi: 10.1080/15325008.2020.1797931.

[9] R. O. Bawazir and N. S. Cetin, “Comprehensive overview of optimizing PV-DG allocation in power system and solar energy resource potential assessments,” *Energy Reports*, vol. 6, pp. 173–208, Nov. 2020, doi: 10.1016/j.egyr.2019.12.010.

[10] N. Jabalameli and A. Ghosh, "Online centralized coordination of charging and phase switching of PEVs in unbalanced LV networks with high PV penetrations," *IEEE Systems Journal*, vol. 15, no. 1, pp. 1015–1025, 2021, doi: 10.1109/JSYST.2020.3000504.

[11] A. Selim, S. Kamel, A. A. Mohamed, and E. E. Elattar, "Optimal allocation of multiple types of distributed generations in radial distribution systems using a hybrid technique," *Sustainability*, vol. 13, no. 12, p. 6644, Jun. 2021, doi: 10.3390/su13126644.

[12] H. Ma, Z. Yang, P. You, and M. Fei, "Multi-objective biogeography-based optimization for dynamic economic emission load dispatch considering plug-in electric vehicles charging," *Energy*, vol. 135, pp. 101–111, 2017, doi: 10.1016/j.energy.2017.06.102.

[13] Y. Thangaraj and R. Kuppan, "Multi-objective simultaneous placement of DG and DSTATCOM using novel lightning search algorithm," *Journal of Applied Research and Technology*, vol. 15, no. 5, pp. 477–491, Oct. 2017, doi: 10.1016/j.jart.2017.05.008.

[14] J. N. Nweke, A. O. Salau, and C. U. Eya, "Headroom-based optimization for placement of distributed generation in a distribution substation," *Engineering review*, vol. 42, no. 1, pp. 109–120, 2022, doi: 10.30765/er.1748.

[15] M. M. Sankar and K. Chatterjee, "Optimal accommodation of renewable DGs in distribution system considering plug-in electric vehicles using gorilla troops optimizer," in *2023 International Conference on Recent Advances in Electrical, Electronics & Digital Healthcare Technologies (REEDCON)*, May 2023, pp. 368–373, doi: 10.1109/REEDCON57544.2023.10151205.

[16] W. Zhao *et al.*, "Electric eel foraging optimization: A new bio-inspired optimizer for engineering applications," *Expert Systems with Applications*, vol. 238, p. 122200, Mar. 2024, doi: 10.1016/j.eswa.2023.122200.

[17] A. B. Alyu, A. O. Salau, B. Khan, and J. N. Eneh, "Hybrid GWO-PSO based optimal placement and sizing of multiple PV-DG units for power loss reduction and voltage profile improvement," *Scientific Reports*, vol. 13, no. 1, p. 6903, Apr. 2023, doi: 10.1038/s41598-023-34057-3.

[18] N. Karuppiah, "Optimal siting and sizing of multiple type DGs for the performance enhancement of distribution system using Differential Evolution Algorithm," *Turkish Journal of Computer and Mathematics Education (TURCOMAT)*, vol. 12, no. 2, pp. 1140–1146, 2021.

[19] J. Radosavljevic, N. Arsic, M. Milovanovic, and A. Ktena, "Optimal placement and sizing of renewable distributed generation using hybrid metaheuristic algorithm," *Journal of Modern Power Systems and Clean Energy*, vol. 8, no. 3, pp. 499–510, 2020, doi: 10.35833/MPCE.2019.000259.

[20] K. Fettah, T. Guia, A. Salhi, S. Mouassa, A. Bosisio, and R. Shirvani, "Optimal allocation of capacitor banks and distributed Generation: A comparison of recently developed metaheuristic optimization techniques on the real distribution networks of ALG-AB-Hassi Sida, Algeria," *Sustainability*, vol. 16, no. 11, p. 4419, May 2024, doi: 10.3390/su16114419.

[21] K. N. Maya and E. A. Jasmin, "Optimal integration of distributed generation (DG) resources in unbalanced distribution system considering uncertainty modelling," *International Transactions on Electrical Energy Systems*, vol. 27, no. 1, p. e2248, Jan. 2017, doi: 10.1002/etep.2248.

[22] A. Soroudi, M. Aien, and M. Ehsan, "A probabilistic modeling of photo voltaic modules and wind power generation impact on distribution networks," *IEEE Systems Journal*, vol. 6, no. 2, pp. 254–259, Jun. 2012, doi: 10.1109/JSYST.2011.2162994.

[23] A. Hamouda and K. Zehar, "Efficient load flow method for radial distribution feeders," *Journal of Applied Sciences*, vol. 6, no. 13, pp. 2741–2748, Jun. 2006, doi: 10.3923/jas.2006.2741.2748.

[24] T. Gu *et al.*, "Placement and capacity selection of battery energy storage system in the distributed generation integrated distribution network based on improved NSGA-II optimization," *Journal of Energy Storage*, vol. 52, p. 104716, Aug. 2022, doi: 10.1016/j.est.2022.104716.

[25] V. K. Thunuguntla and S. K. Injeti, "Ɛ-constraint multiobjective approach for optimal network reconfiguration and optimal allocation of DGs in radial distribution systems using the butterfly optimizer," *International Transactions on Electrical Energy Systems*, vol. 30, no. 11, p. e12613, Nov. 2020, doi: 10.1002/2050-7038.12613.

BIOGRAPHIES OF AUTHORS

A. Manjula received her B.Tech. in Electrical and Electronics Engineering from the JNTU, Hyderabad in 2010 and M.Tech. from JNTU, Hyderabad in Electrical Power Engineering in 2012. She is currently a Ph.D. student at Osmania University, Hyderabad. Her research interests include renewable energy sources and power system analysis. She can be contacted at email: manjulabanda89@gmail.com.

G. Yesuratnam completed his B.Tech. from JNTU, Hyderabad in 1995 and M.Tech. in Power Systems Engineering, Regional Engineering College, Warangal in 1997. He was awarded a Ph.D. in Electrical Engineering from the Indian Institute of Science, Bangalore in 2007. Currently, he is working as a Sr. professor in the Department of Electrical Engineering at Osmania University, Hyderabad. His research interests include computer-aided power system analysis, reactive power optimization, power system security, voltage stability, AI applications in power systems, and gas-insulated substations. He is serving as a peer reviewer of international journals. Throughout his career, he has supervised Ph.D. students as well as published many papers in IEEE as well as international conference proceedings and journals. He can be contacted at email: ratnamgy2003@gmail.com.