

A New Electric EEL Foraging Optimization Technique for Multi-Objective PV Unit Allocation in the Context of PHEV Charging Demand

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ABSTRACT- The existing electric distribution system is under tremendous stress due to reasons like power efficacy & voltage profile, load growth, radial structure etc. Additionally, electric load demand due to PHEVs worsens the existing distribution system performance. Planning of DGs in distribution system is one of the potential solutions for improving existing distribution system performance without changing its infrastructure. Therefore, the primary objective of this research is to determine the optimal way to allocate photovoltaic (PV) based distributed generators (DGs) inside radial distribution networks while taking into account the load demands of both conventional and PHEVs. In the study, three key technical metrics of the distribution network are improved via optimal planning of PV units: maximizing the voltage stability index, minimizing total voltage variation, and minimizing energy loss. Mathematically, weighted objective function is formulated for dealing the above-cited technical metrics. The weighted objective function is optimized using recently developed robust electric eel foraging optimization (EEFO) algorithm. The study first looks into how PHEV load demand affects the technical aspects of the distribution system. Subsequently, improvement of distribution system (accommodating both conventional and PHEVs load demand) performance via optimal planning PV units is discussed. IEEE-69 bus system is considered as a test system in this study. In addition, simulations utilising the differential evolution (DE) and grey wolf optimisation (GWO) methods are carried out in order to examine the robustness of the EEFO approach. The results of these comparisons are described in detail.

Keywords: Distributed generators (DGs), Electric EEL foraging optimization (EEFO) algorithm, Plug-in hybrid electric vehicles (PHEVs), Photovoltaic (PV).

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1. INTRODUCTION

The demand for electricity is significant and still growing worldwide. Recent reports [1] state that conventional energy sources continue to have a commanding 62% share in the world's energy mix. Of the various technologies [2] that can be used to generate electricity from low-carbon sources, wind turbines and solar photovoltaic (PV) units have emerged as the most developed and widely accepted types of renewable energy sources (RESs). In particular, solar-based RESs have grown at an exceptional rate over the past 18 years, emerging as the energy source of the future [3].

Metaheuristic algorithms that draw inspiration from nature have become increasingly popular as efficient methods of solving this complex optimization problem. In order to incorporate PV units, [4] outlines a two-stage optimization strategy employing a genetic algorithm (GA). A GA-based method is presented in [5] for PV unit sizing and placement thus reducing system losses and raising the voltage stability limit. In a recent investigation in reference [6], a DE based approach is employed to optimally allocate PV-based DGs, accounting for various load models for minimization of network losses, total harmonic distortion and energy loss saving. A recent study [7] integrated the renowned DE algorithm with the grey wolf optimizer algorithm (GWO) to find the size and siting of PV-based DGs, aiming to improve the voltage profile and mitigate losses of the system.

To power a combustion-based engine, plug-in hybrid electric vehicles (PHEVs) are designed with a dual power system that consists of an electric motor powered by a battery and an additional fuel source [8]. However, when used in vehicle-to-grid mode, PHEVs have the ability to provide grid support services such peak shaving, phase balancing, voltage regulation, frequency regulation, and spinning reserve [9], [10]. The research on DG allocation has not addressed the addition of PHEV charging loads. Different PHEV charging profiles,

such as the off-peak charging scenario (OPCS), peak charging scenario (PCS), and stochastic charging scenario (SCS), have been included in numerous studies to assess the effects of PHEV loads [11]. In order to allocate PV units while taking PHEVs into account, this study includes three important objectives: power loss, voltage deviation, and voltage stability index. Addressing the PV unit allocation problem using the electric eel foraging optimization (EEFO) technique in RDS. The EEFO algorithm has undergone extensive testing and comparison with other well-known algorithms. It is based on the foraging behavior of electric eels, as described in detail by [12]. It is based on the foraging behavior of electric eels, as described in detail by [12]. The major contributions of this study are:

- (1) Incorporating the consideration of PHEV charging demand during the allocation of PV units in distribution system for improving its performance.
- (2) Thorough evaluation of the load demand required for PHEV charging using stochastic, peak, and off-peak charging scenarios (OPCS, PCS, SCS).
- (3) Presenting a novel use of the EEFO algorithm and contrasting it with the GWO and DE to handle the difficult PV allocation problem in radial distribution systems.
- (4) Developing a variety of research scenarios to evaluate the effect of the quantity of PV units deployed in the radial distribution system.

The following is a summary of the upcoming sections of this paper: *Section 2* delves the modeling of PV and PHEV. The multi-objective function's formulation is presented in *Section 3*. A thorough explanation of the EEFO algorithm is provided in *section 4*. The results and discussions that followed are expounded upon in *section 5*. An overview of the concluding remarks is provided in *section 6*.

2. UNCERTAINTY MODELING FOR SOLAR PHOTOVOLTAICS

The Beta probability density function (PDF) is used to describe the stochastic behavior of solar irradiation during a specified time interval t , is expressed as [13]:

$$f_s(s^t) = \begin{cases} \frac{r(\alpha^t + \beta^t)}{r(\alpha^t)r(\beta^t)} s^{t\alpha^t+1} (1-s^t)^{\beta^t+1}, & 0 \leq s^t \leq 1, \alpha^t \geq 0, \beta^t \geq 0 \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

where s^t is the sun irradiation, α^t and β^t specify the parameters that outline the PDF's configuration. The following formula is used to calculate the output power (P_{PV}^t) of a photovoltaic (PV) module over time t that takes into account the random nature of solar radiation:

$$P_{PV}^t = \frac{\sum_{q=1}^{N_s} P_{PV0q} f_s(s_q^t)}{\sum_{q=1}^{N_s} f_s(s_q^t)} \quad (2)$$

where P_{PV0q} indicates the power produced by the module for a specific state q and time interval t , and N_s indicates the number of states.

3. FORMULATION OF MULTI-OBJECTIVE FUNCTIONS

To develop the objective function, three critical parameters of variables include voltage stability index (VSI), total voltage deviation (TVD), and energy loss (E_{loss}). The objective function (OF) is computed as follows [13]:

$$OF = \gamma_1 * \frac{(f_1)_{DG}}{(f_1)_{NODG}} + \gamma_2 * \frac{(f_2)_{DG}}{(f_2)_{NODG}} + \gamma_3 * \frac{1}{\frac{(f_3)_{DG}}{(f_3)_{NODG}}} \quad (3)$$

where γ_1, γ_2 and γ_3 indicate the preference weights. $(f)_{DG}$ and $(f)_{NODG}$ are parameter's value both before and after the DG was installed. The objective function is to be reduced and γ_1, γ_2 & γ_3 are allocated to 0.4, 0.3, and 0.3, accordingly. The following formula is used to determine each individual objective:

$$f_1 = E_{loss} = \sum_{t=1}^{24} \sum_{j=1}^{nbus-1} I_{t,j}^2 R_j \quad (4)$$

$$f_2 = TVD = \sum_{t=1}^{24} \sum_{m=1}^{nbus} (|1 - V_{t,m}|)^2 \quad (5)$$

$$f_3 = VSI = \sum_{t=1}^{24} \min (SI_{t,n}) \quad n = 1 \dots nbus \quad (6)$$

$$SI_{t,n} = |V_{t,m}|^4 - 4[P_{t,m}X_{mn} - Q_{t,m}R_{mn}]^2 - 4[P_{t,m}R_{mn} + Q_{t,m}X_{mn}]|V_{t,m}|^2 \quad (7)$$

Where $R_j, nbus$ and I denote, respectively, the branch resistance, total number of buses in the network, and the branch current. The symbols $V_{t,m}, P_{t,m}, X_{mn}, Q_{t,m}$ and R_{mn} and indicate the voltage at the bus, real power injected, reactance of the connecting buses, reactive power injected and resistance of the line connecting buses m and n , respectively, for a given bus. Eq. 6 frames the objective function is restricted by the following:

$$|V_{LB}| \leq |V_{t,m}| \leq |V_{UB}| \quad (8)$$

$$P_{t,ss} + P_{t,DG} = P_{t,D} + P_{t,loss} + P_{t,PHEV} \quad (9)$$

$$P_{DG,LB} \leq P_{DG} \leq P_{DG,UB} \quad (10)$$

where $P_{t,ss}, P_{t,DG}, P_{t,D}, P_{t,loss}$ and $P_{t,PHEV}$ denotes slack bus power, power injected by the DG, network power demand, power losses in the network, and demand due to PHEVs; $P_{DG,LB}$ and $P_{DG,UB}$ indicate the lower and upper bounds of the DG rating. V_{LB} and V_{UB} , on the other hand, define the lower and higher bounds of the bus voltage.

4. FORAGING OPTIMIZATION ALGORITHM FOR ELECTRIC EELS

Inspired by the foraging behaviors of electric eels, the electric eel foraging optimization algorithm (EEFO) [12] is a metaheuristic method based on natural processes. The program seeks to mimic the intricate foraging behaviors found in the natural habitat of electric eels. The four primary foraging activities that electric eels exhibit are interaction, idling,

resettlement, and hunting. Because of the robust four foraging strategies during EEFO algorithm is giving best results in comparison to other algorithms during optimization process [12]. Due to the above cited advantage, in this work EEFO was chosen for optimal allocation of PV units' problem in RDS. Fig.1 shows the process flow chart in its entirety.

4.1 Interaction

When eels seek fish, they exhibit this behavior, which is also known as churning. Eels move erratically in different directions to exchange information during this action. Each eel in the EEFO framework represents a potential solution, and the target prey is the best solution found so far. One way to model the interaction phase is as [12]:

$$\left\{ \begin{array}{l} v_i(t+1) = x_j(t) + C \times (\bar{x}(t) - x_i(t)) \quad q_1 > 0.5 \\ v_i(t+1) = x_j(t) + C \times (x_r(t) - x_i(t)) \quad q_1 \leq 0.5 \end{array} \right\} \text{fit}(x_j(t)) < \text{fit}(x_i(t))$$

$$\left\{ \begin{array}{l} v_i(t+1) = x_i(t) + C \times (\bar{x}(t) - x_j(t)) \quad q_2 > 0.5 \\ v_i(t+1) = x_i(t) + C \times (x_r(t) - x_j(t)) \quad q_2 \leq 0.5 \end{array} \right\} \text{fit}(x_j(t)) \geq \text{fit}(x_i(t))$$
(11)

where q_1 and q_2 are the random values between (0,1), $\text{fit}(x_j(t))$, $x_j(t)$, n stand for candidate fitness, eel position, population size.

4.2 Idling

To improve the exploration capabilities in EEFO, an idle zone is constructed by projecting any arbitrary dimension of the eel's position onto the search region's diagonal and then normalizing it between 0 and 1. The following can be used to symbolize this [12]:

$$\{X|X - Z(t)| \leq \alpha_0 \times |Z(t) - x_{prey}(t)|\} \quad (12)$$

where the terms best solution position, starting idling zone scale, idling zone range represented, respectively by x_{prey} , α_0 , $\alpha_0 \times |Z(t) - x_{prey}(t)|$.

4.3 Hunting

electric eels surround their prey by creating an electric communication circle. They use organ electric discharges to communicate with one another, creating an electric circle that marks the hunting area. The mathematical model for this phenomenon is as follows [12]:

$$\{X|X - x_{prey}(t)| \leq \beta_0 \times |x(t) - x_{prey}(t)|\} \quad (13)$$

where β_0 and $\beta_0 \times |x(t) - x_{prey}(t)|$ denotes the initial scale of the hunting zone and the term that determines the hunting zone's range, respectively.

4.4 Resettlement

Electric eels exhibit a migratory behavior known as "resettlement," in which they move from the idle zone to the hunting zone. The resettlement feature in EEFO is defined by the following equations [12]:

$$v_i(t+1) = -r_1 \times R_i(t+1) + r_2 \times H_r(t+1) - L \times (H_r(t+1) - x_i(t)) \quad (14)$$

where H_r indicates any location inside the hunting zone, r_1 and r_2 stands for values chosen at random from the range of (0,1)

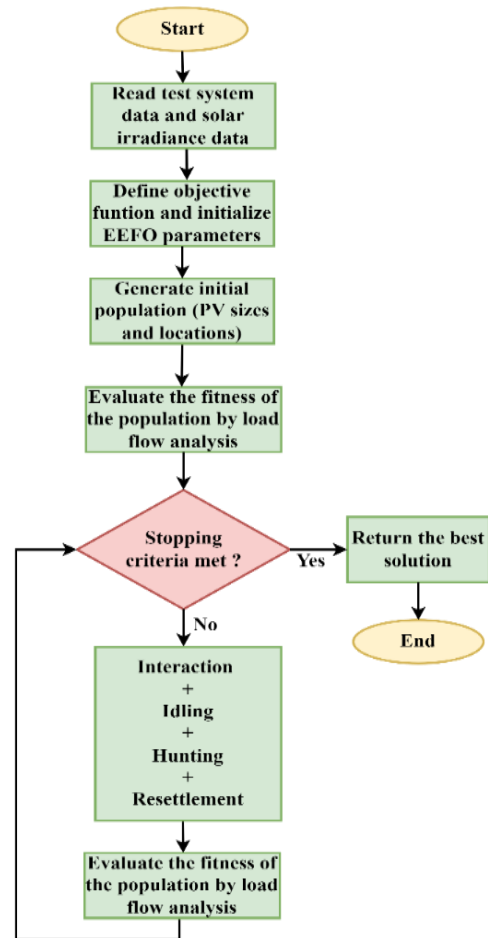


Figure 1. Flowchart of EEFO algorithm

5. RESULTS AND DISCUSSION

The IEEE 69-bus radial distribution system (RDS) test system is used in the study. Line and bus data of the IEEE-69 bus test system is taken from [13],[14]. The base voltage and base MVA of the 69-bus RDS shown in fig.2 are 12.66 and 100, respectively. Peak true and reactive power demands for the 69-bus network are 3.801 MW and 2.693 MVAR, respectively. The normal daily load pattern shown in fig.3 [16] is where the hourly power needs for each bus during the day for test system are taken. The p.u. PV unit output power is depicted in Fig 4 was taken from [16]. The study incorporates, a population size of 200 and a maximum of 100 iterations have been considered for all algorithms. Maximum and minimum PV unit sizes are set to 100 kW and 3000 kW. In DE, crossover and mutation rates are set to 0.7, GWO & EEFO are parameter-free optimization algorithms. All algorithms undergo 30 independent runs, and the best values are chosen. A PC with 8 GB of RAM and an Intel(R) Core (TM) i5-7200U 2.50GHz CPU was used to perform all of the simulations, which were created in MATLAB.

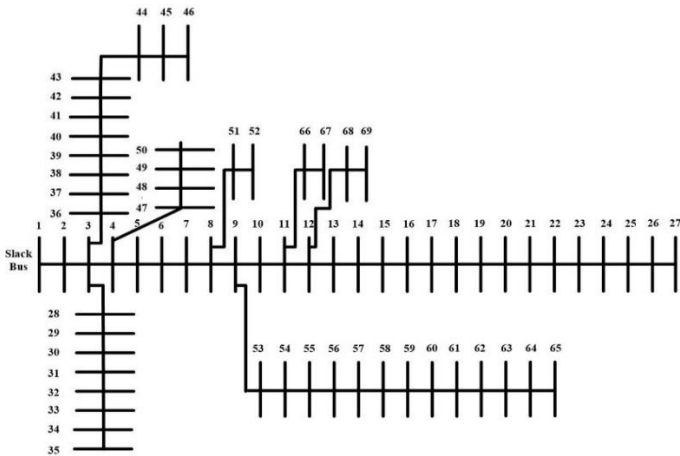


Figure 2: IEEE 69 bus system single diagram

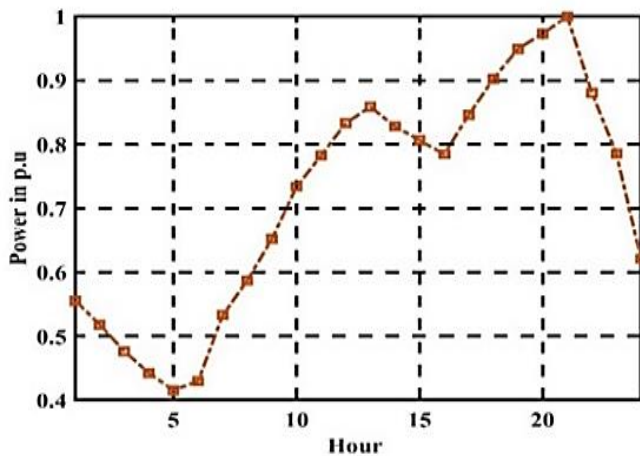


Figure 3. P.U normalized load curve

This study examines the following scenarios. In each scenario distribution system performance is analyzed.

Scenario 0: without PHEVs electric demand and PV units in RDS.

Scenario 1: with PHEVs electric demand and without PV units in RDS.

Scenario 2: The optimal placement to install a single PV unit in in an RDS that is hosting PHEV load demand.

Scenario 3: The optimal placement of two photovoltaic units in an RDS that is hosting a PHEV load demand.

Scenario 4: The optimal placement of three photovoltaic units in an RDS that is hosting a PHEV load demand.

In scenario-0, the load flow method is applied to a distribution system devoid of PV units & PHEVs to acquire an overview of the technical metrics of the system. In scenario-1, the load flow technique is used to investigate the effects of PHEV load demand on system technical metrics by adding PHEV load to the conventional load demand. The optimal placement of one, two, and three PV units in RDS to accommodate PHEV load demand for network curtailment and system enhancement is shown in scenario 2, 3, and 4.

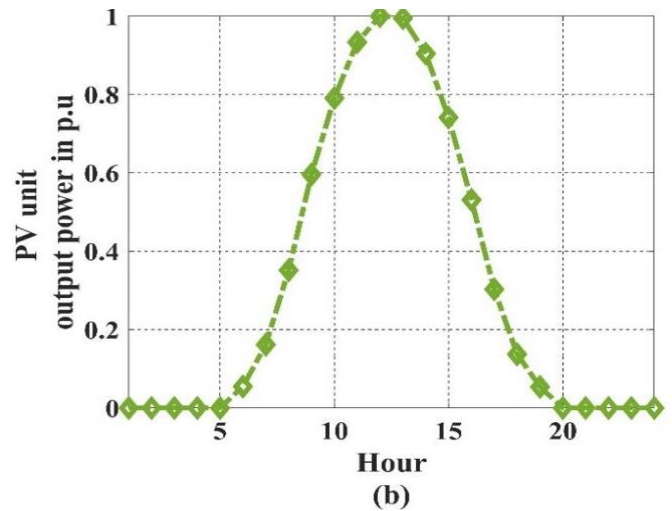


Figure 4. Normalized PV unit out power curve

In Scenario-0, load flow study is performed and the results show an E_{loss} of 2844 kWh, TVD of 1.2569 p.u. and VSI of 18.4902 p.u. In Scenario-1, to investigate the PHEVs demand on the electric distribution system, 9 PHEVs per bus with a total of 432 PHEVs are considered in 69-bus system. It is presupposed that all PHEVs are equipped with 25 kWh batteries and all PHEVs come to home with an SOC of 50%. The total electrical energy needed for charging of 432 PHEVs per day is $432 * 25 * 0.5 = 5400$ kWh. Fig.5 depicts the three charging scenarios of PHEVs: PCS, OPCS, and SCS. In the study, it was assumed that one-third of PHEVs charge under PCS, another one-third of PHEVs charge under OPCS and remaining one third PHEVs charge under SCS. The 24-hour electric power demand needed for charging of PHEVs is generated using PCS, OPCS and SCS charging scenarios and imposed on the distribution system, and the load flow algorithm is executed in scenario-2. Fig.6 illustrates the hourly variation of slack bus power in scenarios-0 & 1 shows an increment in slack bus power due to PHEVs load demand on the system. As a result, E_{loss} of system worsened to 3031 kWh, accounts 6.1% enhancement, TVD deteriorated to 1.3849 p.u. and VSI is worsened to 18.3505 p.u. shows a worsening of three technical metrics.

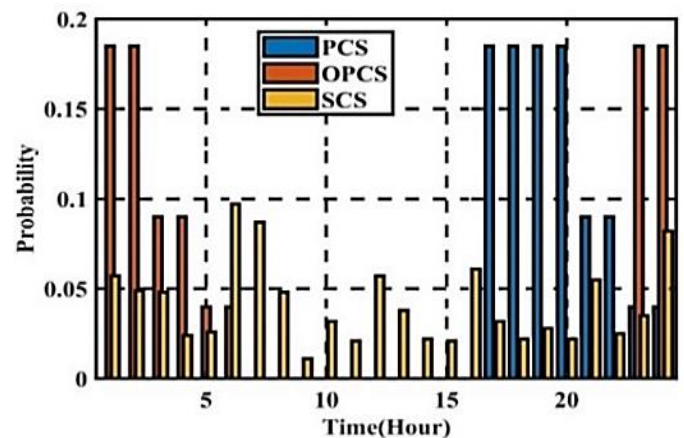


Figure 5. Probability distribution of PHEVs PCS, OPCS and SCS scenarios

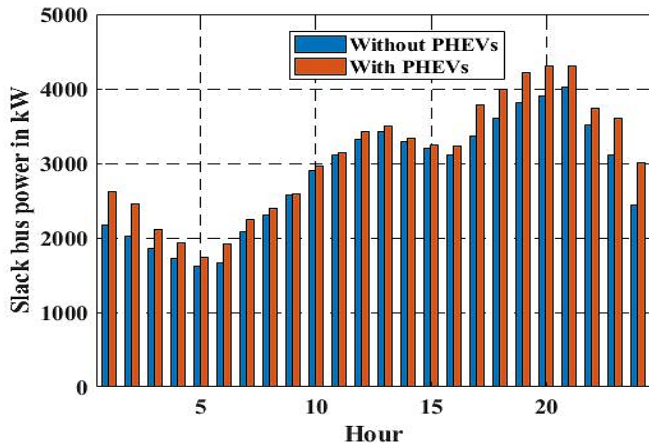


Figure 6. 69-bus system's hourly slack bus power with and without PHEVs

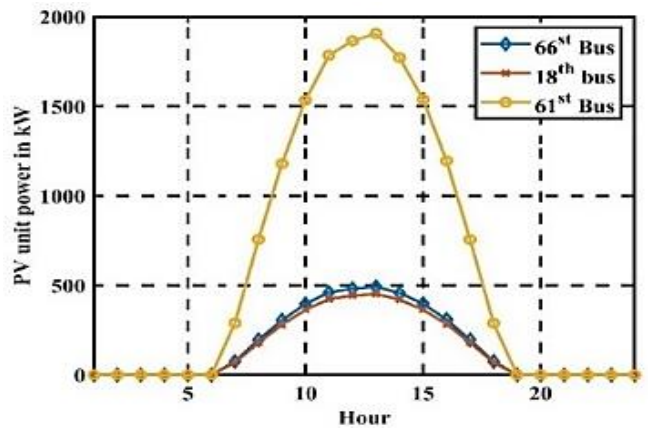


Figure 7. PV unit output curves for the 69-bus system's scenario-4

Table 1 presents the summary of outcomes generated by EEFO in scenarios 2-4 scenarios. In scenario-2, due to the optimal connection of a single PV unit at 61st bus of size 2187 kW, E_{loss} of system is curtailed to 1860 kWh accounts 38.63% reduction, TVD is improved to 0.8494 p.u. and VSI is maximized to 20.0891 p.u. In scenario-3, due to optimal connection of two PV units at 13th & 61st buses with sizes of 608 kW, 1976 kW, E_{loss} of the system is curtailed to 1051 kWh, accounts 42.63% reduction, TVD is improved to 0.7803 p.u. and VSI is maximized to 20.5465 p.u. The hourly PV units power output curves generated for scenario-4 are depicted in fig.7.

Table.1 EEFO's summary of results for the 69 bus system's scenarios 2-4

Technical Metrics	Scenario -0	Scenario-1	Scenario -2	Scenario -3	Scenario -4
PVloc's/PV Sizes (kW)	-----	-----	61/2187	10/0608 61/1976	18/0452 61/1906 66/0492
Substation power (kVAh)	83100	87587	67831	64324	62035
Objective Function (OF)	-----	-----	0.7035	0.6681	0.6657
E_{loss} in kWh	2844	3031	1860	1051	1035
TVD in p.u	1.2569	1.3849	0.8494	0.7803	0.7791

VSI in p.u	18.4902	18.3505	20.0891	20.5465	20.5467
% E_{loss} reduction	-----	-----	38.63	42.33	42.7600
Minimum Voltage in p.u	0.9092	0.9070	0.9070	0.9070	0.9070

Fig. 8 depicts the hourly system loss for scenarios 0-4. The mean voltage profile of the 69-bus for scenarios 0-4 is illustrated in fig. 9.

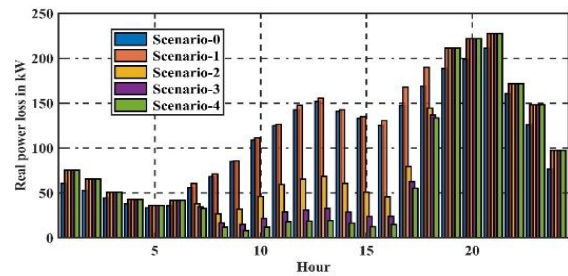


Figure 8. Hourly 69-bus system power loss in scenarios 0-4

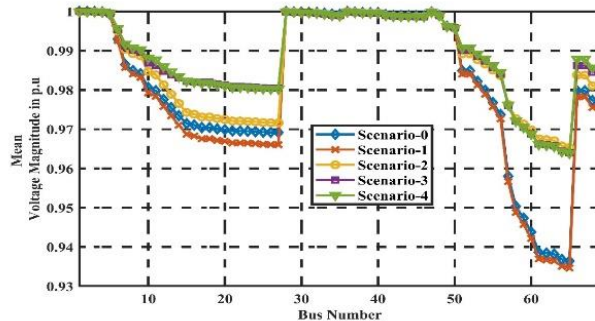


Figure 9. Mean voltage profile of 69-bus system power for scenarios 0-4

Scenarios involving scenario-4 of 69-bus test system were run using the DE and GWO algorithms to evaluate the efficacy of the EEFO method. Table 2 displays the comparison results of different algorithms. Fig. 10 shows how the EEFO, DE, and GWO algorithms converge for scenario-4 outcomes. The EEFO algorithm achieves optimal outcomes i.e. EEFO minimizes the objective function value to 0.6657 but DE [6] and GWO [7] reduces to 0.662 and 0.6679 only.

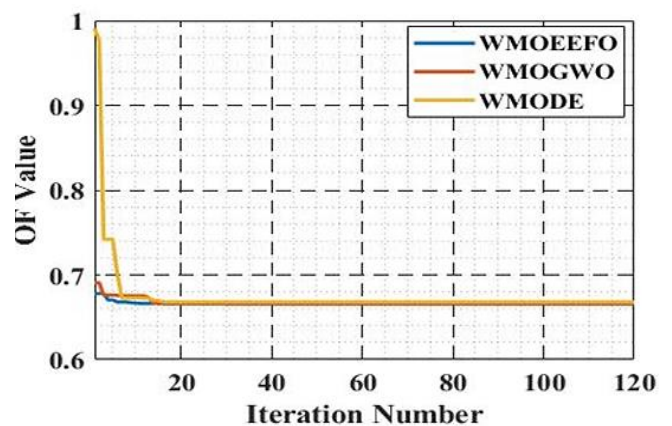


Figure 10. EEFO, DE, and GWO algorithms' convergence graphs of 69-bus system

Table 2. EEFO, GWO, and DE's outcomes for the scenario 4

Optimization Technique	PVloc's/P V Sizes (kW)	OF value	E_{loss} in kWh	TVD in p.u	VSI in p.u
EEFO	18/0452 61/1906 66/0492	0.6657	1035	0.7791	20.54 67
GWO [7]	10/0457 61/1907 68/0389	0.6662	1038	0.7792	20.53 92
DE [6]	9/0662 16/0571 62/1053	0.6679	1049	0.7795	20.52 31

6. CONCLUSION

The main objective of this study was to locate PV units in an RDS as optimally as possible including PHEV load demands. The IEEE-69 bus RDS were used to evaluate the proposed technique. The three main technical measures of the system that needed to be optimized were maximizing VSI, minimizing TVD, and E_{loss} minimizing. To minimize the weighted-based multi-objective function, the EEFO algorithm was used. The study was conducted in two phases: first, to examine how PHEV load demand affected the operation of the distribution system; second, to propose the best way to distribute PV units within the system accommodating PHEV load demand. Three charging scenarios (PCS, OPCS, and SCS) were used to simulate the hourly electrical power demand of PHEVs. The best arrangement of three PV units in 69 distribution system led to the greatest improvements in all three technical measures. In system, energy loss was decreased by about 40–42%. In terms of optimization of the objective function, the EEFO algorithm outperformed DE and GWO in reaching the best possible solution.

REFERENCES

- [1] M. Zieliński *et al.*, "Global Electricity Review 2022," no. March, p. 23, 2022.
- [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," *Appl. Energy*, vol. 278, no. August, p. 115723, 2020.
- [3] "Global Electricity Review 2023," 2023.
- [4] O. Babacan, W. Torre, and J. Kleissl, "Siting and sizing of distributed energy storage to mitigate voltage impact by solar PV in distribution systems," *Sol. Energy*, vol. 146, pp. 199–208, 2010.
- [5] M. A. Rasheed and R. Verayah, "Investigation of Optimal PV Allocation to Minimize System Losses and Improve Voltage Stability for Distribution and Transmission Networks" *Front. Energy Res.*, vol. 9, no. October, pp. 1–13, 2021.
- [6] S. S. Parihar and N. Malik, "Analysing the impact of optimally allocated solar PV-based DG in harmonics polluted distribution network," *Sustain. Energy Technol. Assessments*, vol. 49, no. November 2021, p. 101784, 2022.
- [7] 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," *Sci. Rep.*, vol. 13, no. 1, pp. 1–17, 2023.
- [8] S. Nakayama, S. Oie, A. Shiota, Y. Mitani, and M. Watanabe, "Construction of PHEV driving support system using GIS for optimal operation," *Energy Reports*, vol. 9, pp. 533–542, 2023.

- [9] F. Erden, M. C. Kisacikoglu, and N. Erdogan, "Adaptive V2G Peak Shaving and Smart Charging Control for Grid Integration of PEVs," *Electr. Power Components Syst.*, vol. 46, no. 13, pp. 1494–1508, 2018.
- [10] M. Mani and K. Chatterjee, "A posteriori multiobjective approach for techno-economic allocation of PV and BES units in a distribution system hosting PHEVs," *Appl. Energy*, vol. 351, no. August, p. 121851, 2023.
- [11] 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.
- [12] W. Zhao *et al.*, "Electric eel foraging optimization: A new bio-inspired optimizer for engineering applications," *Expert Syst. Appl.*, vol. 238, no. PF, p. 122200, 2024.
- [13] Karupiah, N. (2021). 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)*, 12(2), 1140-1146.
- [14] Karupiah, N., S. Muthubalaji, S. Ravivarman, Md Asif, and Abhishek Mandal. "Enhancing the performance of Transmission Lines by FACTS Devices using GSA and BFOA Algorithms." *Int. J. Engin. Technol. (UAE)* 7, no. 4.6 (2018): 203-208.
- [15] V. K. Thunuguntla and S. K. Injeti, "E-constraint multiobjective approach for optimal network reconfiguration and optimal allocation of DGs in radial distribution systems using the butterfly optimizer," *Int. Trans. Electr. Energy Syst.*, vol. 30, no. 11, pp. 1–20, 2020.
- [16] 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 ICREEDCON*, 2023, pp. 368–373.



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