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Allocation of Photovoltaic and Wind Turbine Based DG Units Using the Energy Valley Optimizer (EVO) algorithm.

***Abstract**. In this paper, we introduce a novel meta-heuristic technique called the Energy Valley Optimizer (EVO) algorithm designed for the optimization of distributed generation (DG) allocation within distribution networks (DN). The proposed algorithm focuses on the efficient placement of DG units based on photovoltaic (PV) and wind turbine (WT) technologies. Drawing inspiration from advanced physics principles, particularly those related to stability and various modes of particle decay, the EVO algorithm seeks to minimize both total power and energy losses in the DN. To assess its efficacy, the presented technique is applied to problem instances aimed at minimizing power and energy losses, respectively. The evaluation of the proposed approach is conducted using the IEEE 33-bus test system as a case study. The effectiveness of the EVO method is substantiated through a comparative analysis, wherein simulation results are juxtaposed with those obtained from other optimization algorithms recently developed in the literature.*

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***Streszczenie.** W artykule przedstawiamy nowatorską technikę metaheurystyczną zwaną algorytmem Energy Valley Optimizer (EVO) zaprojektowaną w celu optymalizacji alokacji generacji rozproszonej (DG) w sieciach dystrybucyjnych (DN). Zaproponowany algorytm skupia się na efektywnym rozmieszczeniu jednostek DG w oparciu o technologie fotowoltaiczne (PV) i turbiny wiatrowe (WT). Czerpiąc inspirację z zaawansowanych zasad fizyki, szczególnie tych związanych ze stabilnością i różnymi trybami rozpadu cząstek, algorytm EVO stara się minimalizować zarówno całkowite straty mocy, jak i energii w DN. Aby ocenić skuteczność, przedstawioną technikę stosuje się do przypadków problemowych mających na celu minimalizację odpowiednio strat mocy i energii. Ocena proponowanego podejścia została przeprowadzona przy użyciu systemu testowego IEEE 33-bus jako studium przypadku. Skuteczność metody EVO potwierdzono analizą porównawczą, podczas której wyniki symulacji zestawiono z wynikami uzyskanymi z innych algorytmów optymalizacyjnych opracowanych ostatnio w literaturze.. (**Alokacja jednostek DG wykorzystujących fotowoltaikę i turbiny wiatrowe przy użyciu algorytmu Energy Valley Optimizer (EVO)**).*

Keywords: distribution system, Energy valley optimizer algorithm, uncertainties, Photovoltaic, wind turbine, Power Loss.
Słowa kluczowe: system dystrybucyjny, algorytm optymalizatora doliny energetycznej, niepewności, fotowoltaika, turbina wiatrowa, straty mocy.

Introduction

The electricity infrastructure deeply permeates every industry crucial for society's survival. Ensuring sufficient and reliable access to electricity is imperative for the endurance of contemporary civilization [1]. Renewable energy systems, increasingly cost-effective, now constitute a significant portion of the global power plant mix [2]. In recent years, Hybrid Re newable Energy Systems (HRES) have played a crucial role in boosting the penetration of renewable energy worldwide [3] , [4]. Configuring HRES with solar and wind energy has emerged as the preferred choice due to their complementary attributes, established technology, and widespread availability [5]. The effectiveness of such systems depends on the characteristics of Distributed Generator (DG) units, including photovoltaic panels, wind turbines, and reciprocating engines, as well as the features of loads, local renewable resources, and the layout of electrical distribution systems [6]. Integrating HRES into distribution systems presents both technical and economic implications. Photovoltaic and wind energy-based HRESs are extensively deployed and boast long lifespans [7]. A critical aspect of HRES operations lies in the energy management system. Addressing the crucial need for the correct sizing of HRES during the reinstallation stage underscores the importance of determining the optimal allocation (location and configuration) for HRES [8].

Generally, distribution network (DN) structures are radial due to their simplicity, consisting of main feeders and lateral distributors.

However, radial DNs often experience high power losses due to the high resistance to reactance ratio. To enhance overall system performance, the integration of Distributed Generation (DG) units is essential. Identifying the optimal location and size of DG units becomes crucial in mitigating power losses, avoiding grid reinforcement, improving voltage profiles and load factors, and enhancing system efficiency and reliability [9]. It is imperative to strategically install DG units in DNs to achieve these benefits. The improper integration of DG units in non-optimal locations and sizes can result in increased power losses, leading to higher costs and counteracting the desired positive effects. Furthermore, when multiple DG units are integrated, selecting the best allocation method becomes critical to maintaining system stability and reliability. The careful consideration of DG placement and sizing is pivotal in realizing the potential advantages of distributed generation while avoiding unintended consequences.

Optimization methods continually evolve to maximize the benefits of distributed generators, with metaheuristic optimization techniques standing out among top algorithms and various classifications for optimization. These techniques, known for their shorter execution times compared to alternative methods, find application in numerous optimization problems across various fields. Several studies have concentrated on minimizing system losses by optimizing the capacity and placement of Distributed Generators (DGs) using diverse methodologies

To address the optimal location and sizing problem of DGs, various metaheuristic methods have been proposed, including the Whale Optimization Algorithm (WOA) [10], the Invasive Weed Optimization Algorithm (IWO) [11], the Artificial Bee Colony algorithm (ABC) [12], and the Dragonfly Optimization Algorithm (DA) [13]. Additionally, the multiple objective particle swarm optimization algorithm (MOPSO) [14] is employed for the same purpose. A recommended approach to tackle the optimal location and sizing problem of DGs involves a hybrid strategy, as suggested in [15]. This hybrid methodology integrates analytical techniques with metaheuristic tools, providing a comprehensive and effective solution to the challenges associated with DG integration. The combined use of analytical and metaheuristic approaches enhances the robustness and efficiency of the methodology, offering a more holistic perspective in addressing the complexities of DG placement and sizing perspective in addressing the complexities of DG placement and sizing.

In this paper, we present the Energy Valley Optimizer (EVO) algorithm, proposed to minimize power losses and improve daily voltage profiles, considering different 24-hour loadings. The performance of the EVO algorithm is tested on a typical IEEE 33-node distribution network, demonstrating its efficiency compared to other optimization techniques described in the literature. The rest of this work is arranged as follows: Section II describes the mathematical formulation of the problem, while Section III explains PV, WIND, and Load models. In Section IV, the EVO method is discussed, and in Section V, the simulation results are presented and compared with other existing techniques in the literature. Finally, Section VI concludes the paper.

Problem Formulation

The objective of this article is to minimization the real power loss and improve the DN voltage [16,17].

Real power loss

The first term of the objective function is the real power loss, which is determined by equation (1)

(1) $$P_{LOSS} = \sum_{j=1}^{n_f}\sum_{k=1}^{n_s} R_k\left|I_k^2\right|$$

With: Ik − Is the current passing through line k; nf − Is the total number of branches; ns − Total number of sections in the system; Rk −Resistance of the line section between buses k and k +1

Accordingly, minimizing the total active power losses in the DS leads to reduce the total active energy losses $Eloss$ during 24 hrs as:

(2) $$\text{Fobj} = \frac{E_{loss}\ \text{after DG}}{E_{loss}\ \text{before DG}}$$

where, l is represents the total number of lines in DN, E_{loss} represents the total energy loss.

Voltage Profile improvement

The second goal of this work is to improve the VP, which is represented by the VP index in equation (3)

(3) $$VP = \sum_{j=1}^{n_f}\sum_{k\in lb}\left|V_k - V_{ref,k}\right|$$

With: lb − Collection of the load buses; $Vref$, k − Nominal voltage at load bus k.; Vk − Voltage amplitude at bus k.

PV, WIND and LOAD models

PV modeling

Power generation using PV unit is highly dependent on meteorological conditions, such as solar radiation, and ambient temperature. These conditions are directly related to geographic area. Hence, the effectiveness of the conditions of solar radiation in a certain area is usually analyzed at the initial stage for the effective use of PV panels. The standard deviation (SD) and mean of hourly solar radiation per day is calculated using collected historical data. Continuous PDF for an exact time interval is divided into stages, in each solar radiation within certain limits. The PV power generation is determined by all possible stages of probabilities in that hour.

In this study, the step for solar radiation is 0.05 kW/m^2.

The average value of each stage is used as output power calculation for this stage (i.e). if the first stage of solar irradiation, is between 0 kW/m2 and 0.05 kW/m^2, the average value of this stage is 0.025 kW/m^2).

Solar radiation model

It is considered that the probabilistic nature of solar radiation follows the Beta PDF [18,19]. The Beta PDF of solar radiation ‘s’(kW/m^2) in the time interval ‘t’ is defined as:

(4)
$$f_b(s^t) = \begin{cases} \frac{\Gamma(\alpha^t+\beta^t)}{\Gamma(\alpha^t)\Gamma(\beta^t)} s^{t(\alpha^t-1)}(1-s^t)^{(\beta^t-1)}, & 0 \le s^t \le 1,\ \alpha^t,\beta^t \ge 0 \\ 0, & \text{otherwise} \end{cases}$$

where, $f_b(s^t)$ is the Beta PDF of s^t; α^t and β^t are the shape rates of Beta PDF , Γ is depict Gamma function. The shape rates can be found based on the mean (μ) and SD (σ) of radiation for a suitable time interval.

(5) $$\beta^t = (1-\mu^t)\left(\frac{\mu^t(1+\mu^t)}{\sigma^{t2}} - 1\right),\ \alpha^t = \frac{\mu^t * \beta^t}{1-\mu^t}$$

PV array power generation

The PV array hourly average power output corresponding to an exact time interval ‘t’ (P^t PV) is expressed as (6). A typical day for three years is generated in p.u., as shown in Fig .1

(6) $$P_{PV}^t = \sum_{g=1}^{n_s} P_{PV_o}(s_g^t) f_b(s_g^t)$$

where ‘g’ denotes a stage factor and ns is the solar radiation discrete stage number. Stg is the gth stage of solar radiation at tth time interval.

Solar radiation and ambient temperature are the basic dominant factors that affect the PV array power output. The PV power generation with average solar radiation (s_ag) for the gth stage is estimated as [18,19]:

(7) $$P_{PV_o}(s_{ag}) = N_{PV\mathrm{mod}} * FF * V_g * I_g$$

Where

(8) $$FF = \frac{V_{MPP} * I_{MPP}}{V_{OC} * I_{SC}};\ V_g = V_{OC} - K_v * T_{cg};\ I_g = S_{ag}[I_{SC} + K_i(T_C - 25)];\ T_{cg} = T_A + s_{ag}\left(\frac{N_{OT}-20}{0.8}\right)$$

Here, $N_{PV\mathrm{mod}}$ is the PV modules total number; T_A (°C) is ambient temperature; V_{MPP} and I_{MPP} are maximum power tracing voltage (V) and current(A), respectively; V_OC and I_SC are voltage of open-circuit and current of short circuit, respectively; Ki and Kv are the current and voltage temperature coefficients (A/°C and V/°C), respectively; FF is the fill factor; Tcg is PV module temperature at gth stage (°C).

WT MODEL

Wind speed modeling

Weibull was chosen to evaluate the stochastic behavior of wind speed at a predetermined duration of time [18]. Weibull for wind speed vt (m/s) at the tth time interval can be calculated as:

(9) $$f_v(v^t) = \frac{k^t}{c^t} * \left(\frac{v^t}{c^t}\right)^{k^t-1} * \exp\left(-\left(\frac{v^t}{c^t}\right)^{k^t-1}\right)$$

for $c^t > 1;\ k^t > 0$

The shaping rate (k^t) and scale rate (c^t) at tth time interval are expressed as [18]:

(10) $$k^t = \left(\frac{\sigma^t}{\mu_v^t}\right)^{-1.086}$$

(11) $$c^t = \frac{\mu_v^t}{\Gamma(1+1/k^t)}$$

where, μ_v^t and σ^t are mean and Sd of wind speed at time interval 't'.

WT power generation

The hourly WT average output power corresponds to a specific time interval 't' (P_{WT}^t) can be expressed as (1). A typical day for three years is generated in p.u., as shown in Fig. 1

(12) $$P_{WT}^t = \sum_{g=1}^{n_s} P_{WT_o}(v_g^t) f_b(v_g^t)$$

where 'g' denotes a stage factor and ns is the number of wind speed discrete stage. v_g^t is the gth stage of wind speed at tth time interval. The WT power generation [19] with an average wind speed (v_{ag}) for stage "g" is expressed as :

(13) $$P_{WT_o} = \begin{cases} 0 & v_{ag} < v_{cin} \text{ or } v_{ag} > v_{cout} \\ (A^* v_{ag}^3 + B * P_r) & v_{cin} \le v_{ag} \le v_r \\ P_r & v_r \le v_{ag} \le v_{cout} \end{cases}$$

where Pr is the nominal power rate that WT can be generated v_{cout} is cut-out; cut-in (v_{cin}) and nominal (v_r) wind speed, respectively, constants A and B are achieved as [19]:

(14) $$A = \frac{P_r}{(v_r^3 - v_{cin}^3)}$$

(15) $$B = \frac{v_{cin}^3}{(v_r^3 - v_{cin}^3)}$$

Load model

The load demand for the system is modelled corresponding to the normalized daily 24- hours load curve with a peak of 1 pu, as shown in Fig. 1 [20, 21]. The load factor (LF) can determine as the field beneath the load curve, the load curve in p.u. subdivide by the sum of time interval [21].

(16) $$LF = \sum_{t=1}^{24} \frac{\text{per.unit. Demand } (t)}{24}$$

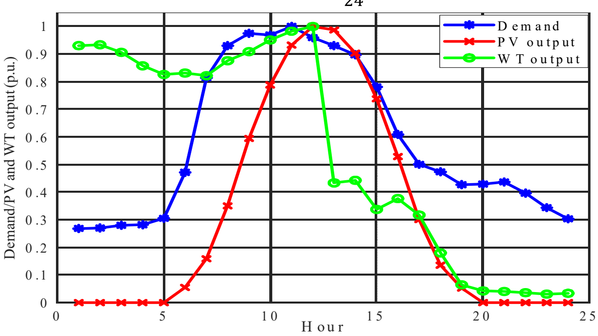


Fig 1: Normalized daily active load curve, PV and WT output

The voltage-dependent load demand model, which includes variable load over time, can be calculated as [20, 21]:

(17) $$P_k(t) = P_{ok}(t) * V_k^{n_p}$$

(18) $$Q_k(t) = Q_{ok}(t)^* V_k^{n_q}$$

where, P_k and Q_k represent active and reactive power injected at node k. P_{ok} and Q_{ok} represent the active and reactive power loads injected at nodes k. Vk represents the voltage value at node k, and np and nq represent active and reactive load demand voltage indexes, where np = 1.51 and nq = 3.4.

Energy valley optimizer Algorithm

In this section, the Energy Valley Optimizer (EVO) algorithm is detailed, employing principles of physics for optimization [22]. The algorithm begins with an initialization process, treating solution candidates as particles in a specific part of the universe. The candidates' positions are determined within defined bounds using random numbers [0,1]

(19) $$X = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_i \\ \vdots \\ X_n \end{bmatrix} = \begin{bmatrix} x_1^1 x_1^2 \cdots x_1^j \cdots x_1^d \\ x_2^1 x_2^2 \cdots x_2^j \cdots x_2^d \\ \cdots \ddots \vdots \\ x_i^1 x_i^2 \cdots x_i^j \cdots x_i^d \\ \cdots \\ \cdots \\ x_n^1 x_n^2 \cdots x_n^j \cdots x_n^d \end{bmatrix}, \begin{cases} i = 1,2,\dots,n. \\ j = 1,2,\dots,d. \end{cases}$$

$$x_i^j = x_{i,\min}^j + \mathrm{rand} \cdot (x_{i,\max}^j - x_{i,\min}^j), \begin{cases} i = 1,2,\dots,n. \\ j = 1,2,\dots,d. \end{cases}$$

The second step calculates the Enrichment Bound (EB) based on Neutron Enrichment Levels (NEL) of particles

(20) $$\mathrm{EB} = \frac{\sum_{i=1}^n \mathrm{NEL}_i}{n}, i = 1,2,\dots,n$$

Stability levels are then determined, considering the best (BS) and worst (WS) stability levels in the universe

(21) $$\mathrm{SL}_i = \frac{\mathrm{NEL}_i - \mathrm{BS}}{\mathrm{WS} - \mathrm{BS}}, i = 1,2,\dots,n$$

The main search loop of EVO involves decisions based on neutron enrichment levels and stability bounds. If NEL exceeds EB, decay processes are considered. Alpha and gamma decay occur for particles with high stability levels, and new candidates are generated accordingly

(22) $$X_i^{New1} = X_i\left(X_{BS}\left(x_i^j\right)\right), \begin{cases} i = 1,2,\dots,n. \\ j = \text{ Alpha Index II.} \end{cases}$$

(23) $$X_i^{New2} = X_i\left(X_{Ng}\left(x_i^j\right)\right), \begin{cases} i = 1,2,\dots,n. \\ j = \text{ GammaIndex II.} \end{cases}$$

For lower stability levels, beta decay is applied, causing particles to move towards the best stability level and the center of particles

(24) $$X_{CP} = \frac{\sum_{i=1}^n X_i}{n}, i = 1,2,\dots,n.$$
$$X_i^{New1} = X_i + \frac{(r_1 \times X_{BS} - r_2 \times X_{CP})}{SL_i}, i = 1,2,\dots,n.$$

Additionally, a controlled movement is conducted toward the best stability level and a neighboring particle for exploration

(25) $$X_i^{New2} = X_i + (r_3 \times X_{BS} - r_4 \times X_{Ng}), i = 1,2,\dots,n.$$

If NEL is below EB, random movements are made to simulate electron capture or positron emission

(26) $$X_i^{New} = X_i + r, i = 1,2,\dots,n.$$

At the end of each loop, newly generated vectors are merged with the current population. The algorithm utilizes boundary violation flags and a termination criterion based on the maximum number of evaluations or iterations. This algorithm introduces three position updating processes in its main loop, balancing exploration and exploitation for improved candidate performance. The unique aspect lies in deriving inspiration from particle decay processes for optimization.

The EVO flowchart is illustrated in figure 2

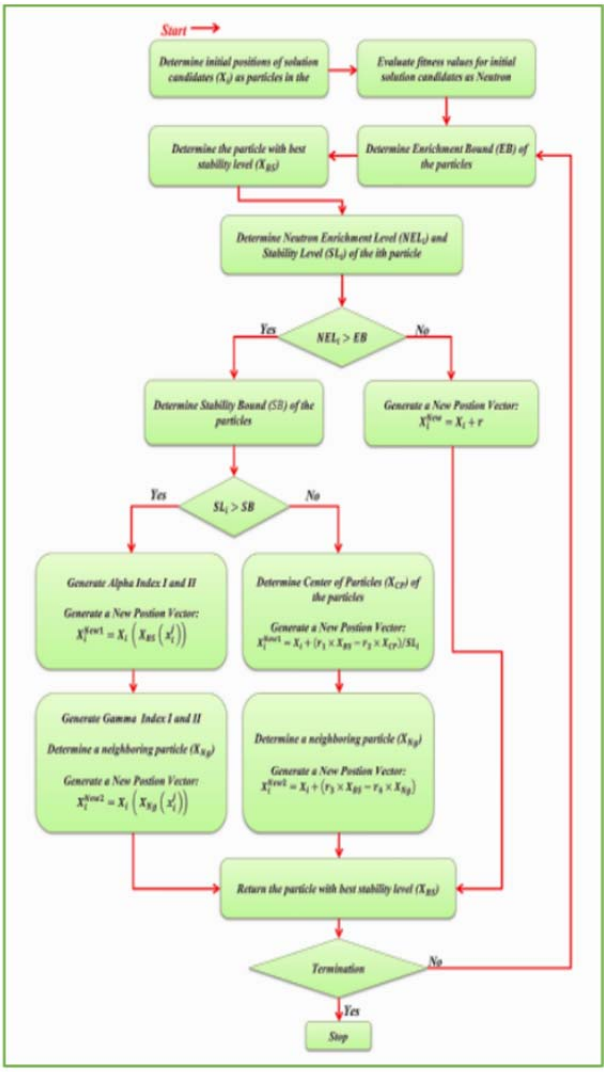


Fig 2: Flowchart of the EVO.

Results and simulation

To elucidate the characteristics of the proposed Evolutionary Optimization (EVO) approach and assess its performance, we opted for a standard 33-bus Radial Distribution Network (RDN). The line and load data for the tested system were sourced from [23]. The one-line diagrams of the analyzed systems are depicted in Fig. 3. The developed technique was implemented using MATLAB 2021b and executed on an Intel Core i5-7500, CPU@3.4GHz, with 8 GB of RAM.
The power flow calculations were solved using the backward/forward sweep algorithm [24].
The 33-bus system comprises total real and reactive power loads of 3.715 MW and 2.3 MVAr, respectively. When DG integration is not considered, the power flow analysis is conducted with Sbase = 100 MVA and Vbase = 12.66 kV. In the base case, the power losses amount to 210.986 kW, and the VP index is 0.90378 pu.
Upon integration, it is determined that the overall losses amount to 111.02707 kW and 67.8678 kW when single Photovoltaic (PV)-based and Wind Turbine (WT)-based Distributed Generation (DG) units are incorporated at bus 6. The PV-based DG operates at unity Power Factor (PF), while the WT-based DG operates at a lagging PF of 0.85.
Furthermore, when two PV-based and WT-based DG units are introduced at buses 13 and 30, the total losses are reduced to 87.1664 kW and 28.6336 kW. The PV-based DG at bus 13 operates at unity PF, and the WT-based DG at bus 30 operates at a lagging PF of 0.85, while the WT-based DG at bus 13 operates at a lagging PF of 0.864.
Similarly, with the integration of three PV-based and WT-based DG units at buses 24, 13, and 30 for PV type and at buses 24, 13, and 30 for WT type, the impact on overall losses can be assessed.
In the integration scenario, where Photovoltaic (PV)-based DG operates at unity Power Factor (PF) and Wind Turbine (WT)-based DG operates at PFs of 0.878, 0.864, and 0.85 (lag), it has been established that the total losses are 72.79 kW, 72.7861 kW, and 11.7410 kW, respectively. The corresponding results are presented in Table 1 and Table 2, utilizing the proposed approach as well as other methods. Notably, the proposed approach demonstrates the lowest power losses and notable voltage profile enhancement.
The impact of single, two, and three integrations of DG units on the voltage profile, as well as the convergence characteristics for single, two, and three installations of both PV-based and WT-based DG units, is illustrated in Figures 4, 5 respectively. Furthermore, it is worth noting that the results obtained by considering reactive power outperform those obtained with DGs operating at unity PF.

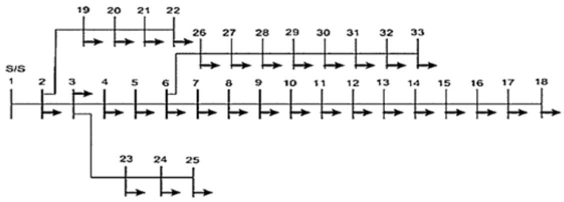
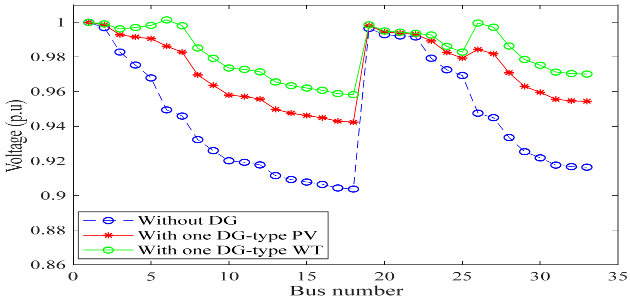


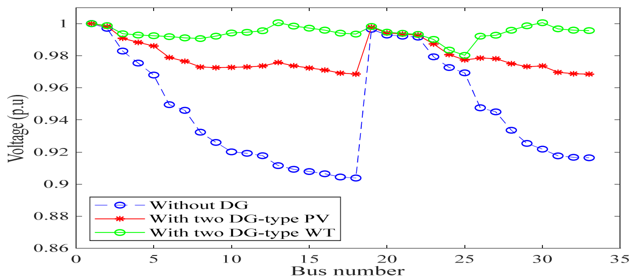
Fig 3: The standard 33-bus distribution system

Table 1. Simulation Results of the studied system

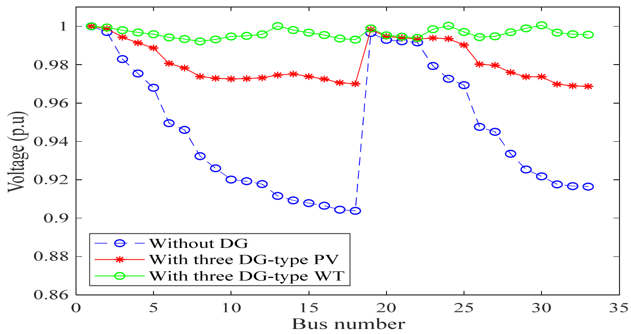
DG number and type		EVO
One PV	Bus (Size (kW /PF))	6 (2590.217/1)
	Power loss (kW)	111.02707
	Minimum voltage/Bus	0.94237 @ bus 18
Two PV	Bus (Size (kW /PF))	30 (1157.6/1) 13(851.51/1)
	Power loss (kW)	87.1664
	Minimum voltage/Bus	0.96851@ bus 33
Three PV	Bus (Size (kW /PF))	24(1091.3/1) 13(801.7058/1) 30(1053.6/1)
	Power loss (kW)	72.7861
	Minimum voltage/Bus	0.96868 @ bus33
One WT	Bus (Size (kW /PF))	6(2558.5/0.8236)
	Power loss (kW)	67.8678
	Minimum voltage/Bus	0.95835 @ bus 18
Two WT	Bus (Sizes (kW /PF))	13(858.4383/0.911) 30 (1089.1/0.7)
	Power loss (kW)	28.6336
	Minimum voltage/Bus	0.98025 @ bus 25
Three WT	Bus (Sizes (kW /PF))	24(1070.0/0.90) 13(793.7976/0.9048) 30 (1029.8/0.7134)
	Power loss (kW)	11.7410
	Minimum voltage/Bus	0.99212 @ bus 8



(a) Voltage profile with one DG

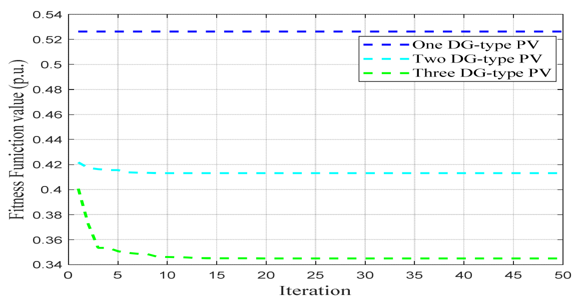


(b) Voltage profile with two DG

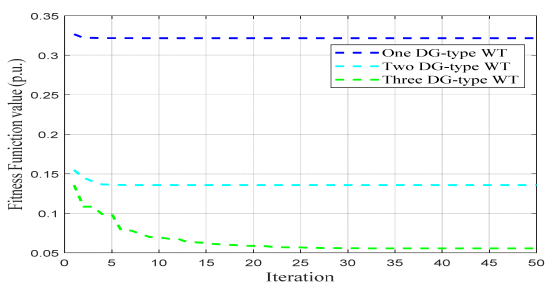


(c) Voltage profile with three DG

Fig 4: The voltage profile of studied system (a): with integration one DG units and (b): with integration two DG units. and (c): system with integration three DG units.



(a) Convergance curve of DG type PV



(b) Convergance curve of DG type WT

Fig 5: Convergence curve of one and two and three PV and WT based DG unit's integration.

The Table 2 And Table 3 chow the results of EVO with Comparison with WOA, IWO ALO, and EVO methods respectively. EVO results are much better.
It can be seen from the results that the integration three PV and three WT based DG units improve DN performance.

Table 2. Comparative Analysis of the Evolutionary Optimization (EVO) Method with Previous Literature (PV)

Methods	DG		Power Loss (KW)
	Size (KW)	Bus	
WOA [25]	1072.83 772.488 856.678	30 25 13	73.75
IWO [26]	624.7 104.9 1056	14 18 32	90.69
ABC [27]	1750 570 780	6 15 25	79.25
ALO [28]	1500 750 250	32 5 18	75.26
AEO[29]	755.7328 1031.13 961.193	14 30 24	73.13
EVO	1091.3 801.758 1053.6	24 13 30	72.78

Table 3. Comparative Analysis of the Evolutionary Optimization (EVO) Method with Previous Literature (WT)

Methods	DG Size and location			Power Loss (KW)
	$PDG(KW)$	$QDG(KVar)$	Bus	
WOA [25]	1171.38 881.88 953.62	602.811 644.027 750	24 13 30	16.28
IWO [26]	1098 1098 768	766.26 766.26 535.96	30 30 14	22.29
ABC [27]	1014 960 1363	628.21 594.76 844.43	12 25 30	15.91
AEO[29]	798.54 1039.2 1106.4	371.94 1008.2 504.537	13 30 24	11.76
EVO	1070 793.79 1029.8	1070 793.79 1029.8	24 13 30	11.74

In the described scenario, the system underwent comprehensive adjustments aimed at introducing variability to both solar power capacity and wind power throughout a 24-hour period. Simultaneously, modifications were applied to the load, causing it to exhibit variations over the entire day. The details of these changes are visually presented in Figure 1, 6 providing a clear representation of how the solar and wind power capacities, along with the load, evolve over the specified time frame.

The impact of these adjustments on the voltage profile (VP) is highlighted in Figure 7. In the base case, the VP was measured at 0.90378 per unit (pu). However, with the incorporation of three Photovoltaic (PV) units, the VP improved to 0.933 pu. Furthermore, the VP increased even further to 0.954 pu with the integration of three Wind Turbine (WT) units. This demonstrates a positive correlation between the number of renewable energy units and the enhancement of the voltage profile.

Additionally, noteworthy improvements were observed in terms of energy losses. In the initial state, energy losses were recorded at 2044.79 kWh. Following the integration of PV units, the losses significantly reduced to 1036.10 kWh. Furthermore, with the addition of WT units, the losses decreased even more, reaching 748.75 kWh. These quantitative results are systematically presented in Table 4, offering a comprehensive overview of the positive impact of the introduced adjustments on both voltage profile and energy efficiency.

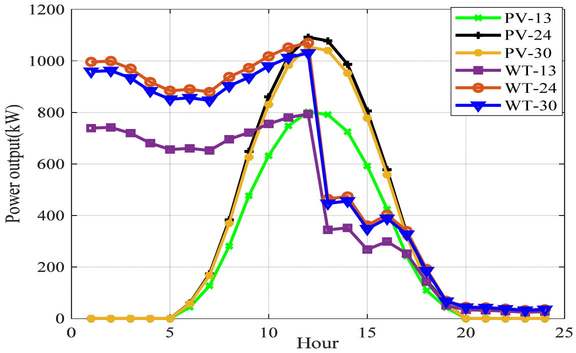
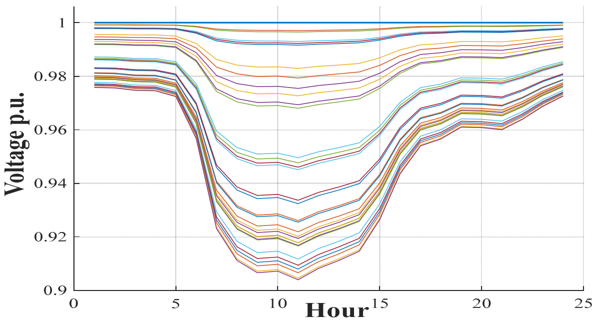
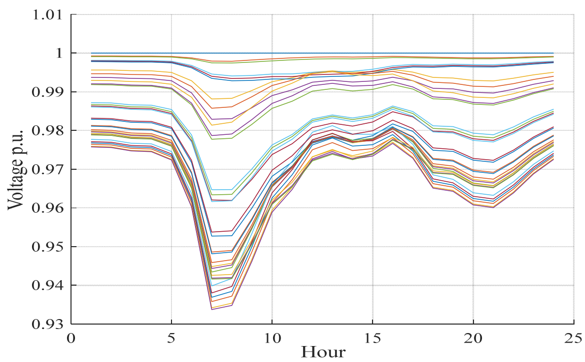


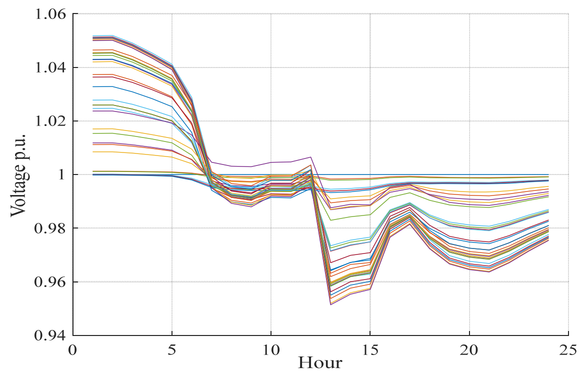
Fig 6: Daily power generation curve for 3 PV and 3 WT DGs on studied test system.



(a) Base case



(b) With Three PV



(a) with three WT

Fig 7: The voltage profile of studied system (a): base case and (b): with three PV based DG and (c): with three WT based DG

Table 4. Daily energy loss for studied test system

Scenario	Energy loss (kW h)	Loss reduction %
Base case	2044.79	-
With 3 PV	1036.10	50.70
With 3 WT	748.75	63.31

Conclusion

In conclusion, this study leverages the Evolutionary Optimization (EVO) approach to identify optimal locations and sizes for Distributed Generators (DGs), specifically Photovoltaic (PV) and Wind Turbine (WT) units, within a radial distribution network. The overarching objective is to minimize power losses, decrease energy loss, and enhance the voltage profile (VP). The application of the EVO method is demonstrated through simulations on the IEEE-33 bus test system, encompassing two distinct scenarios based on the injected power's nature.

In the first scenario, focusing on the injection of only real power (PV), our findings reveal a substantial reduction in the objective function (active power losses) from 210.986 kW to 72.78 kW. Additionally, the voltage profile experiences a significant improvement, rising from 0.90 per unit (pu) to 0.96 pu. Moving to the second scenario, involving the injection of both real and reactive power (WT), our results demonstrate a noteworthy decrease in the objective function (active power losses) from 210.98 kW to 11.74 kW. Crucially, the voltage profile undergoes a remarkable enhancement, reaching 0.99 pu from the initial 0.90 pu.

To validate the efficacy of the EVO method, a comprehensive comparative analysis with other algorithms, including WOA, IWO, ABC, AEO, and ALO, was conducted. The results affirm that the EVO algorithm surpasses recent algorithms, demonstrating superior optimization in terms of power loss and voltage profile. Notably, the EVO method achieves a 50% reduction in energy losses with PV and a 63% reduction with WT. Furthermore, the voltage profile performance exhibits substantial improvement over the base system. In summary, our findings underscore the superiority of the EVO algorithm in delivering optimal solutions for power distribution systems.

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