Optimal Sizing and Sitting of Distributed Generation in Distribution Network considering Power Generation Uncertainty

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Abstract. This paper presents an application of the recent metaheuristic Geometric Mean Optimizer (GMO) for the allocation of renewable energy sources (RES), including wind turbine (WT) and biomass-based Distributed Generation (DG) units in the distribution network (DN). The primary objective function is to minimize the total power and energy losses. The Weibull probability distribution function (PDF) is employed to describe the uncertainty of wind speed. The high penetration of RES with intermittent availability and demand variations has introduced many challenges to DN, such as power fluctuations, voltage rise, high losses, and low voltage stability. Therefore, the use of dispatchable biomass is considered to smooth out supply fluctuations and maintain supply continuity. A standard IEEE 69-bus test system is used to verify the performance of the proposed approach. The simulation results and comparison with other techniques demonstrate the significant energy loss reduction achieved by the proposed technique.

1. Introduction

There are three major components in a power system: generation, transmission, and distribution. Distribution networks (DNs) act as a connection between electric utilities and consumers. The primary objective of a power system is to provide users with electrical power efficiently and reliably. It is predicted that worldwide energy demand will increase by 50% by 2050, as stated in [1]. In the period between 2020 and 2050, residential and commercial power consumption will increase by 0.7% and 0.4%, respectively [2]. World's energy consumption is presented in Figure 1. This leads to overloaded distribution feeders and increased difficulties in operating the system [3]. Therefore, DNs need to be updated, maintained, and operated with more intelligent planning and incorporating cutting-edge technologies to fulfill load demand. Distributed generators (DGs) have become an essential component of today's power systems. There will be many benefits for the future smart-grid operations related to system stability, security, and efficiency as a result of the increased use of DGs.

Numerous social, economic, environmental, political, and technological issues are involved in the shift from conventional to "clean" energy power generation paradigms [4]. With these adjustments, developing a set of standards for environmental and renewable policies is necessary to develop a new value chain. Geopolitical shifts in the energy sector will result from the development of such initiatives [5]. Many electrical DNs have seen a steady rise in RES-based DG units. However, there are some difficulties with RES integration [6]. The nature of such resources is the biggest challenge. Power system operation, control, and planning are challenging since these resources are subject to natural volatility and partial unpredictability (uncertainty).

Additionally, the integration of RESs may present technical difficulties, including irregular current flows and voltage violations, congested networks, and rising losses. Various smart-grid-related technologies and concepts can be implemented in conjunction with variable energy sources to avoid or lessen the negative effects of RES integration in the DNs. Dispatchable Biomass is one of these technologies, which can potentially boost the penetration of RES-based DG units while reducing their negative consequences [7].

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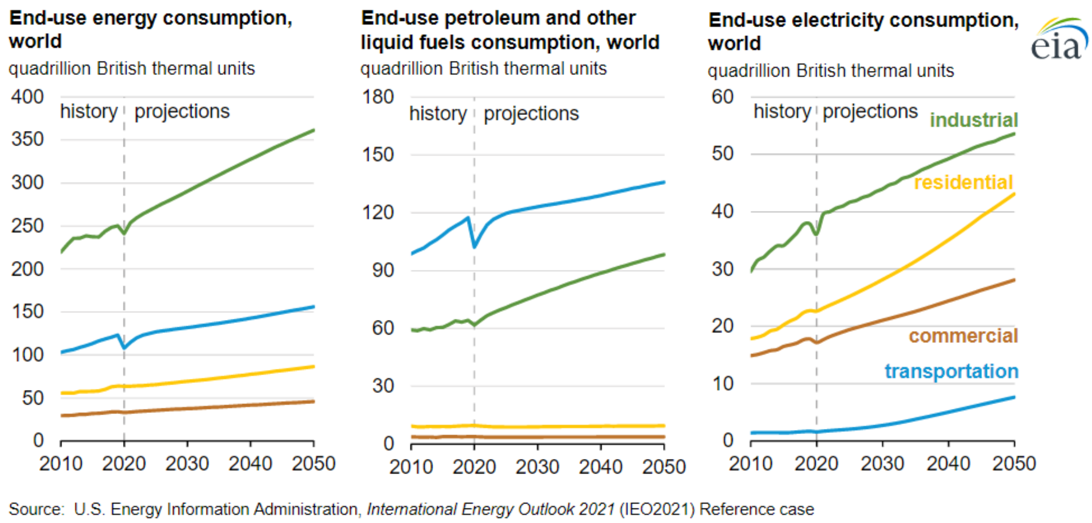

Fig. 1. World's energy demand [2]

In this paper, an accurate technique for optimizing the placement and size of WT-based and Biomass-based DG units in DN is presented to minimize the total energy loss of the DN. Furthermore, win speed variability is characterized using the Weibull probability distribution function (PDF). In order to evaluate the effectiveness of the proposed technique, it is tested on an IEEE 69-bus system and compared to other approaches published in the literature to address the same problem it addresses.
The structure of the paper is as follows: Section 2 provides a detailed description of the probabilistic power generation model for WT-based DG unit, Biomass, and a load model. The problem formulation is presented in Section 3. The solution process of the proposed technique is presented in Section 4. Section 5 describes numerical results, and Section 6 concludes the paper with conclusions.

2. The probabilistic power generation of WT-based DG units, Biomass, and Load modelling

2.1. A WT model for generating power

Wind speed plays an essential role in determining WT power generation. To obtain reasonable solutions, it is necessary to model wind speed at a specific location accurately.
By analyzing collected historical data for hourly wind speed per day, we determine the standard deviation (SD) and mean. The continuous PDF of each WT-based DG unit is divided into states (periods), in each of which the wind speed lies within specified limits so that the output power of each WT-based DG unit can be taken into consideration as multistate variables in the planning formulation. Alternatively, the wind speed comprises several states for each time segment [8-9]. A wind speed state of 1 m/s is used in this paper. In this state, the output power is calculated based on the average value of each state (e.g., if the first state of wind speed falls between 1 and 2 m/s, the average value for this state is 1.5 m/s).

2.1.1 Modeling of wind speed: The Weibull PDF [8-10] describes the probabilistic nature of wind speed. Weibull PDF is defined as (1) for time interval t for wind speed v (m/s).

$$f_{weibull}(v^t) = \frac{K^t}{C^t} * \left(\frac{v^t}{C^t}\right)^{K^t-1} * \exp\left(-\left(\frac{v^t}{C^t}\right)^{K^t-1}\right) \quad for \quad C^t \succ 1; \quad K^t \succ 0 \tag{1}$$

where, $f_{weibull}(v^t)$ is the Weibull PDF of v^t, C^t and K^t are represents the Weibull PDF's shape and scale rates.
The Weibull PDF's shape and scale rates for a suitable time interval can be found using mean (μ) and SD (σ) of wind speed at time interval 't' and calculated as follows [8-10]:

$$K^t = \left(\frac{\sigma^t}{\mu_v^t}\right)^{-1.086} \tag{2.1}$$

$$C^t = \frac{\mu_v^t}{G(1+1/K^t)} \tag{2.2}$$

where, G represents a function of gamma.

2.1.2 Power generation from WT: An estimated WT hourly corresponds power output to a time interval 't' (P^t_{WT}), defined as (3). Figure 2 illustrates the average power generated for a day of 3 years in p.u.

$$P_{WT}^t = \sum_{m=1}^{N_s} P_{WT_o}(v_m^t) f_{weibull}(v_m^t) \tag{3}$$

where 'm' is the state factor and N_s is the total wind speed state number in the study period. v^t_m is represents speed of wind at t^{th} time interval and the m^{th} state.
A WT power output is primarily influenced by wind speed. Based on the average wind speed (v_{avm}) for the m^{th} state, it is estimated that WT power will be generated as follows [10]:

$$P_{WT_o} = \begin{cases} 0 & v_{avm} \prec v_{cin} \quad or \quad v_{avm} \succ v_{cout} \\ (A * v_{avm}^3 + B * P_r) & v_{cin} \le v_{avm} \le v_r \\ P_r & v_r \le v_{avm} \le v_{cout} \end{cases} \tag{4}$$

where P_r is the nominal installed WT power rate, v_{cout} is cut-out wind speed, v_{cin} and v_r represent cut-in and nominal wind speed, the constants A and B are obtained as follows [9]:

$$A = \frac{P_r}{(v_r^3 - v_{cin}^3)} \tag{5.1}$$

$$B = \frac{v_{cin}^3}{(v_r^3 - v_{cin}^3)} \tag{5.2}$$

2.2. Modeling of Biomass

The use of Biomass as an energy source has grown significantly over the years. In spite of the availability of a variety of biomass resources, the energy sector's production was not optimally improved by using this Biomass. Agriculture produces more waste than any other sector. Rural areas are increasingly using these wastes to generate biogas. A wide range of countries have developed conversion technology for generating electricity [11]. Pyrolysis, gasification, incineration, and digestion are currently the most common biomass processing technologies. Bulgur is used for anaerobic digestion, while dry feedstocks can be used for other processes. This type of renewable energy produces little emissions, which is one of the advantages of biomass-based DG units [11]. The following two types biomass-based DG units are commonly used in the energy sector.

2.2.1 Dispatchable source: In these case biomass-based DG units serve as synchronous generators. As well as that, biomass-based DG outputs can be dispatched according to the load curves in order to maximize efficiency. An integral characteristic of biomass-based DG units is their capacity factor (CF), which is defined as the ratio of the area under the power output curve in p.u. to the total period of operation [9].

$$CF = \sum_{t=1}^{24} \frac{p.u.DG\,output(t)}{24} \tag{6}$$

2.2.2 Nondispatchable source: Biomass-based DG can also be considered non-variable (constant) in that its output is maintained at a constant level for 24 hours a day at its nominal capacity. In other words, it has a CF of one.

2.3 Load modeling

As shown in Figure 2, the proposed load model uses a 24-hour daily load demand curve with a peak of 1 p.u. [10].
Load demand varies with time and voltage in a voltage-dependent model. In consequence, it can be calculated that the voltage-dependent time varying load model in [10], which includes variable loads at the time t, can be expressed as follows:

$$\begin{aligned} P_m(t) &= P_{om}(t) * V_m^{n_p} \\ Q_m(t) &= Q_{om}(t) * V_m^{n_q} \end{aligned} \tag{7}$$

where,Pm and Qm represent active and reactive power of bus m; P_{om} and Q_{om} are similarly base active and reactive load at bus m; V_m is the voltage at bus m, and n_p=1.51 and n_q=3.4 are voltage indexes [10].

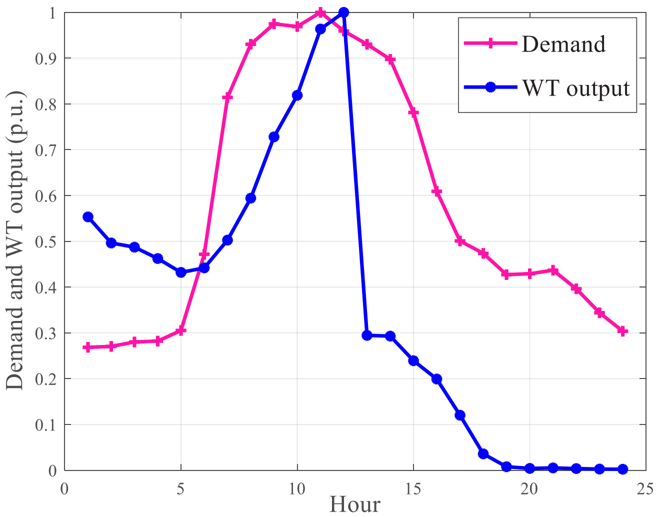

Figure 2. *Normalized WT output power and active load curves*

3. Problem formulation

Minimizing total energy losses in a DN can be achieved by integrating the WT and Biomass-based DG units at the optimal power factor (PF), locations, and sizes, considering the

The objective function is the energy loss (Eloss) during 24 hours can be expressed in the following formula:

$$F_{obj} = (minimize(P_{loss})) * \Delta t = minimize(E_{loss}) \tag{8}$$

where, Δt is time step, in this study (1 h). P_{loss} is active power loss of branches. To calculate the active power loss between buses n and m, the following formula is used:

$$P_{loss} = \frac{(P_m^2 + Q_m^2) * R_{nm}}{(V_m)^2} \tag{9}$$

where, Q_m and P_m are reactive and active power flows emanating from the bus *m*, V_m represents the voltage magnitude of bus m. R_{nm} is resistance of distribution line between bus *n* and *m*.

3.1 Equality restrictions

In order to generate power, the following constraints must be met:

$$P_{sub} + \sum_{l=1}^{M_{DG}} P_{DG}(l) = \sum_{l=1}^{L} P_{Lineloss}(l) + \sum_{l=1}^{M} P_d(l) \tag{10.1.}$$

$$Q_{sub} + \sum_{l=1}^{M_{DG}} Q_{DG}(l) = \sum_{l=1}^{L} Q_{Lineloss}(l) + \sum_{l=1}^{M} Q_d(l) \tag{10.2.}$$

where, P_{sub} and Q_{sub} are the substation's active and reactive power. M_{DG} is the total DG number, M is the total line number in the system.

3.2 Inequality restrictions

Voltage restrictions:

There are certain voltage requirements between the lower and upper limits of the bus voltage. The requirements are as follows:

$$V_{\min} \leq |V_i| \leq V_{\max} \tag{11}$$

The power constraint of integrated DG units is as follows [9]:

$$P_{DG}^{\min} \leq P_{DG}(i) \leq P_{DG}^{\max} \tag{12.1}$$

$$Q_{DG}^{\min} \leq Q_{DG}(i) \leq Q_{DG}^{\max} \tag{12.2.}$$

here, the upper and lower active power limits of DG units are indicated as $P_{DG}^{\min}$ and $P_{DG}^{\max}$,similarly, the reactive power of DG units are indicated as $Q_{DG}^{\min}$ and $Q_{DG}^{\max}$, respectively.

The power factor limits of DG are as follows:

$$PF_{DG,\min} \leq PF_{DG,i} \leq PF_{DG,\max} \tag{13}$$

where, $PF_{DG,\min}$ and $PF_{DG,\max}$ are lower and upper limits of PF.

Line current limitation:
The line maximum current must meet the following limits:

$$I_{Li} \leq I_{Li(rated)} \tag{14}$$

3.3 In order to size a combined of WT&Biomass, we need to consider the following assumptions

It is assumed in this study that the WT-based DG is nondispatchable, it belongs to the owners of the DG, and it is owned by a utility company that manages the DG. Utility companies are responsible for dispatching, owning, and controlling biomass-based DG units that is dispatchable by them. The power output curve of the proposed combined WT and Biomass unit (WT+Biomass) is depicted in Figure 3 [9]. In order to decrease the power losses for a certain load level, non-dispatchable WT units outputs are combined with dispatchable biomass units [9]. For all the durations at bus k, the daily amount of energy of per WT&Biomass unit can be expressed as [10]:

$$E_{(WT\&Biomass)_m} = \sum_{t=1}^{24} P_{(WT\&Biomass)}(t) * \Delta t \tag{15}$$

where, $P_{(WT\&Biomass)}(t)$ is the combined WT&Biomass output power at bus m over a given period of time t.

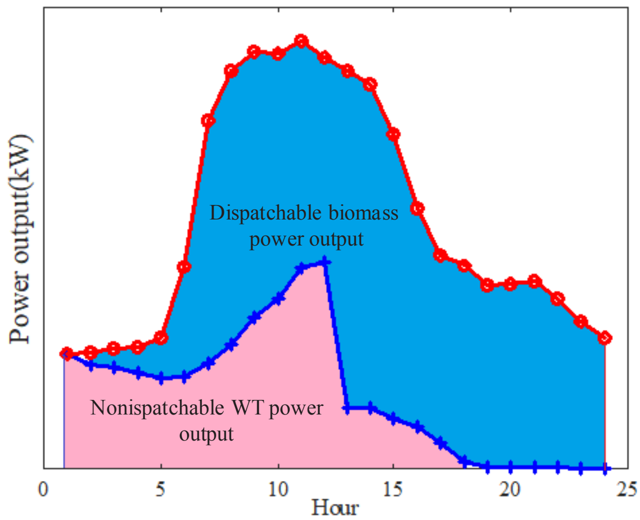

Fig. 3. Combined WT&Biomass based DG unit power generation

A description of the proposed procedure for the combination of WT& Bomass is as follows:

1. *A power flow is run for the initial step, and the WT&Biomass location, size, and power factor (PF) of the WT&Biomass are determined, taking into account the total lowest power loss over all the intervals taken into consideration.*
2. *Determine the optimal size or maximum output power ($P_{WT}^{\max}$)for each non-dispatchable WT unit over all the time intervals, provided that WT unit power output does not exceed WT&Biomass unit output as identified in Step 1.*

3. *According to (16), determine the WT unit that produces the optimal output power for time interval t [10].*

$$P_{WT}^{t} = P_{WT}^{\max} * (p.u.DG_{WT}\ output(t)) \tag{16}$$

where, *p.u.* DG_{WT}*output(t)* represents the WT power output in p.u. for time interval t.

4. *A dispatchable biomass-based DG unit's output power is calculated in step. The optimal size or maximum power output of Biomass-based DG units is equal to the combination of WT & Biomass units in Step 1, minus the WT-based DG unit power output in Step 3, for every time interval t.*

As shown in Figure 3, the output power of WT-based DG unit follows the expected WT-based DG unit power production curve, as seen in Figure 2. There is a maximum penetration of wind power in this case. As an additional dispatchable biomass-based DG units can be used to fill in some of the energy that the WT-based DG units could not supply due to their size.

4. Overview of Geometric mean optimizer (GMO)

The Geometric mean optimizer (GMO) is an entirely newly developed metaheuristic optimization technique that utilizes the unique mathematical properties of the geometric mean operator in order to optimize mathematical functions. Using this operator, the fitness and diversity of search agents can be evaluated simultaneously. GMO considers the geometric mean of the scaled objective values (OVs) of each agent's opposites to be its weight, indicating that the agent is appropriately regarded to guide the other agents toward solving an optimization problem by guiding their search process based on the geometric mean of their scaled OVs. This technique consists of the following steps:

1. At first, the positions and velocity of search agents were generated randomly.

$$\begin{aligned} x_i^0 &\quad U(x_{\min}, x_{\max}) \\ v_i^0 &\quad U(v_{\min}, v_{\max}) \end{aligned} \tag{17}$$

where, $x_{\min,j}$, $v_{\min,j}$ and $x_{\max,j}$, $v_{\max,j}$ are the lower and upper limits of the dimension j.

2. Find the personal best position of all search agents by calculating the fitness function values of all search agents.

$$fit(x_i) \tag{18}$$

3. After that, the fuzzy membership function (MF) is calculated for all opposite agents of a certain agent by multiplying the OVs:

$$MF_j^t = \frac{1}{1+\exp\left[-\frac{4}{\sigma^t\sqrt{e}} * (Z_{best,j}^t - \mu^t\right]}; j = 1,2,...N \tag{19}$$

where $Z_{best,j}^t$ represents the personal best agent's objective value's at the *t*th iteration; μ^t and σ^t are the mean and SD of the fitness function values of all personal best agents, MF_j^t is the MF value of the *j*th personal best agent , *e* is Napier's constant and *N* is the total search agents number.

4. In this step, to calculate a new index, called the dual-fitness index (DFI) for a search agent the following formula can be used:

$$DFI_i^t = MF_1^t * ... * MF_{i-1}^t * MF_{i+1}^t * ... * MF_N^t = \prod_{\substack{j=1 \\ j\neq i}}^{N} MF_j^t \tag{20}$$

5. Sorting DFI indexes in descending order to choose the first Nbest elite agents.
6. The guide agents calculate as follows:

$$Y_i^t = \frac{\sum_{j\in Nbest, j\neq i} DFI_j^t * X_j^{best}}{\sum_{j\in Nbest} DFI_j^t + \varepsilon} \tag{21}$$

where Y_i^t is the vector of the position of the unique global guide agent calculated at iteration t for the agent i, X_j^{best} represents the personal best position vector of the jth search agent, and ε is a very small positive number it added to avoid singularity.

7. In order for this Y_i^t to be more stochastic due to the nature of the guide agents (i.e. to better preserve the diversity of these agents), the guide agents are then mutated in a GMO process. Gaussian mutations are considered in this mutation scheme. For this type of mutation to be imposed on the guide agents, the following equation must be followed:

$$Y_{i,mut}^t = Y_i^t + w * randn * (SD_{\max}^t - SD^t) \tag{22}$$

where $randn$ is a random number from the standard normal distribution, SD^t is the SD vector calculated for the personal best agents at the tth iteration, $SD_{\max}^t$ is a vector consisting of the maximum SD values of the personal best agents' dimensions, and w is step size of mutation by lapse of iterations and calculated as follows:

$$w = 1 - \frac{t}{T_{\max}} \tag{23}$$

where, t is the present iteration number and $T_{\max}$ is the maximum seted iteration numbers.

8. Finally, the search agents' velocity and positions update using the following formula:

$$V_i^{t+1} = w * V_i^t + \varphi * (Y_{i,mut}^t - X_i^t); f = 1 + (2 * rand - 1) * w \tag{24}$$

$$X_i^{t+1} = X_i^t + V_i^{t+1} \tag{25}$$

where, V_i^t is ith search agent's velocity at the tth iteration, V_i^{t+1} is the velocity at $(t + 1)$th iteration, $Y_{i,mut}^t$ is unique global guide position for the agent i and X_i^t is a position of the ith agent's, f is a scaling parameter, and $rand$ is a random number within (0, 1).

Table 1. Used parameters and operational constraints

Parameters	Values
Number of search agents	50
Number of iterations	500
ε	0
Bus system voltage constraints	$0.9 p.u. \le V_i \le 1.05 p.u.$
DG power generation constraints	$0.2MW \le P_{DG,m} \le 3MW$
DG's power factor constraints	$0.7 \le PF_{DG,i} \le 1$

5. Results and Discussion

This section uses a standard 69-bus test system to evaluate the proposed approach. The simulation has been carried out using MATLAB R2021b software. The following scenarios are considered in order to check the performance of the proposed approach:

First scenario: The goal of this scenario is to determine the most efficient WT unit's allocation at optimal power factor in order to minimize power losses without taking into account voltage-dependent time-varying loads.

Second scenario: To minimize energy losses, the probabilistic power generation model is utilized with daily commercial load demands.

Third scenario: Optimal sizing of the combined WT&Biomass unit for minimize energy loss model is carry out.

An illustration of a single line diagram of a test system can be found in Figure 4. The system has a base kV and MVA of 12.66 kV and 100 MVA for 69-bus DN. The test system has 3.802MW and 2.695 MVAr active and reactive power loads. There is an initial active power loss of 224.98 kW and a minimum voltage of 0.90919 p.u. for the test system. In [13] provides additional information for the test system.

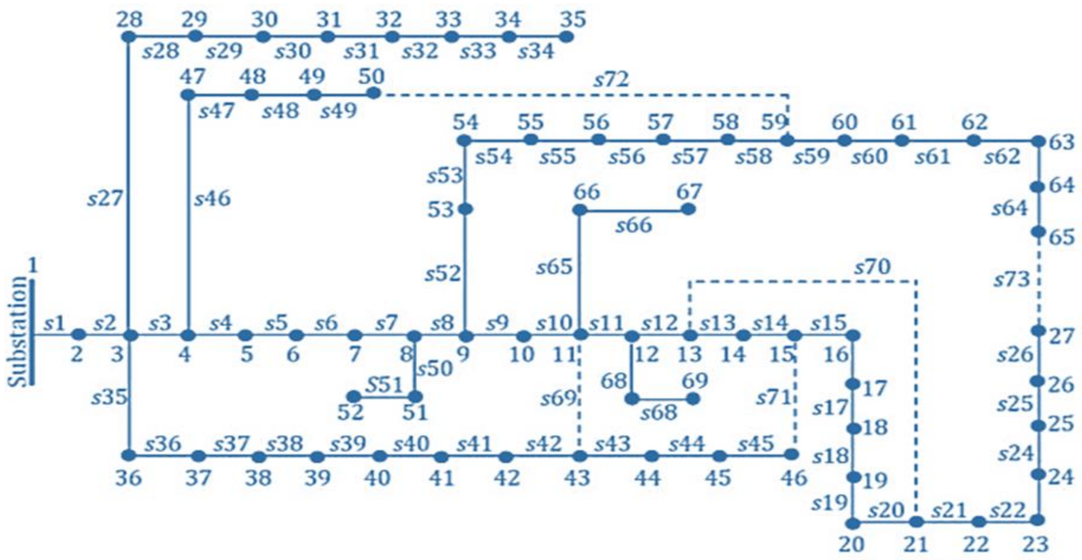

Fig. 4. The line diagram of the IEEE 69-bus system

Scenario 1: Table 2 summarizes the results of the proposed method for scenario 1 for determining the optimal size and location of WT-based DG units with optimal PF in the 69-bus system to minimize power loss. It can be seen from the table that for integrating 1, 2 and 3 WT-based DG units in DN, the percentages of power loss reduction were 89.7016 %,96.5243 %, and 98.0998 %. Based on the analysis of Table 2, it appears that the proposed algorithm is capable of providing the least amount of power loss when it comes to WT-based DG units both in case of one and multiple units' integration, in comparison to EA, BA, PSO, and HHO.

Table 2. Comparison of GMO simulation results of 69-bus system

Type and number of DG		HHO [9]	BA [15]	EA [14]	PSO [14]	**Proposed GMO**
One WT	Bus (Size (KW /P.F))	61(1879.41 /0.82)	61(2100/0.98)	61(2290/0.82)	61(2100/0.98)	**61 (1828.47/ 0.814)**
	Power loss (KW)	34.65	52.5	23.26	52.5	**23.1682**
Two WT	Bus (Sizes (KW /P.F))	60(1678.5 /0.82)	61(2000/0.98)	61(2189, 0.82)	61(2200/0.98)	**61(1750.06/0.819)**
		11(898.19 /0.7)	17(600/0.98)	17(643/0.83)	18(600/0.98)	**17 (432.371/0.7)**
	Power loss (KW)	22.97	38.7	7.35	41.1	**7.19**
Three WT	Bus (Sizes (KW /P.F))	61(1412.4/0.766)	61(2000/0.98)	61(2113/0.82)	61(1500/0.98)	**18(370.25/ 0.819)**
		16(796.43/0.875)	49 (800/0.98)	18(458/0.83)	59(600/0.98)	**11(508.44/0.836)**
		47(1.0493/0.995)	19 (600/0.98)	11(668/0.82)	16 (500/0.98)	**61(1670.84/0.810)**
	Power loss (KW)	12.526	37.1	4.48	39.2	**4.21**

Scenario 2: In Scenario 2, the power generation uncertainty model of WT is addressed by using the optimal locations and sizes that have been determined in Scenario 1, as well as the time-varying daily commercial load demand, which can be seen in Figure 2.

It is shown in Figure 5 that three WT units have been installed in buses 18, 11 and 61 and are capable of generating power 24 hours a day. It is shown in Figure 7 that a 69-bus DN is conducted in a base case and the potential impact of the installation of WT based DG units with optimal PF on energy losses. As compared to base case, there is a significant decrease in energy loss. Integrating WT-based DG units leads to a decline in the highest energy loss. Table 4 presents the total energy loss and the reduction of that loss on a particular day. The energy loss reduction in this scenario is 70%.

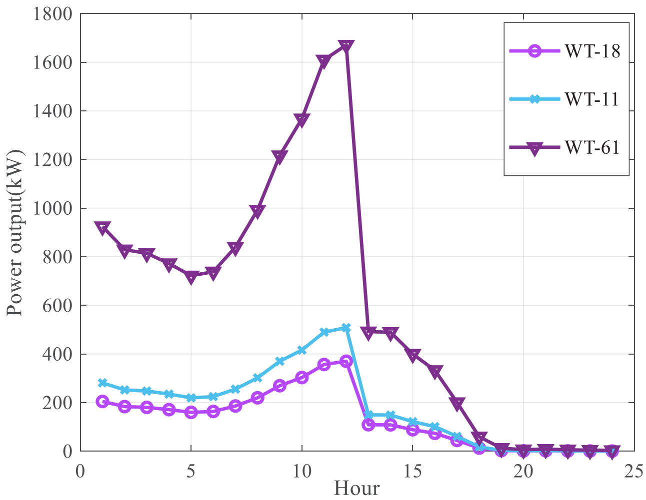

Fig. 5. Daily power generation curve for three WT based DGs on test system

Scenario 3: optimizing the power generation from WT&biomass units to minimize the total energy losses.

WT&Biomass power output curves are shown in Figure 6 for bus 18. According to Figure 6, the total power generation of WT& Biomass based DG unit in each time interval follows the load demand curve in Figure 2. In the same way, the wind power output corresponds to that indicated in Figure 2, in case the WT unit power penetration is at its maximum. Biomass-based DG units, which have also been mentioned above, have been used as an alternative to WT-based DG units to fill some of the energy gaps. According to Figure 6, the WT-based DG units are not able to handle the load demand as shown in Figure 2. Based on the maximum output power difference found at hour 13, we can determine the maximum output power or the biomass-based DG unit's nominal power rating ($P_{Biomass}$). A similar result was obtained for the WT&Biomass units in bus 18 as well as bus 61. Detailed results of the simulations performed in Scenario 3 for 69 bus test systems are shown in Table 3. The table includes the type of DG unit, its size, location, and the power factor of DG unit.

Table 3. Optimized location and size of WT and Biomass in the test system

Location	11th bus	18th bus	61st bus	Total sizes
WT- based DG unit size (MW)	0.2395	0.1835	0.8108	1.2337
Biomass-based DG unit size (MW)	0.3889	0.2981	1.3164	2.0033
Optimal PF	0.81	0.83	0.82	

As compared to base case, there is a noticeable decrease in energy loss in scenario 3. Integrating WT-based DG units with optimal PF leads to the highest energy loss decline. Table 4 presents the total energy loss and the reduction of that loss on a particular day. The energy loss reduction in this scenario is 98%.

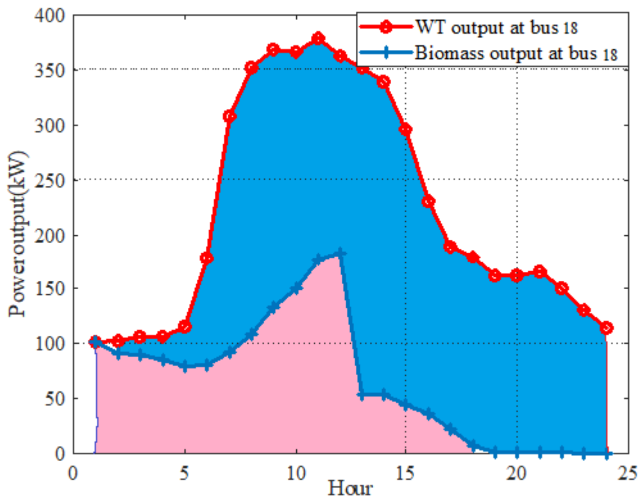

Fig. 6. WT&Biomass DG units power generation curves in test system at bus 18

Table 4. Daily energy losses of test system

Scenarios	Energy losses (kW h)	Reduction %
Base case	2173.9	-
With only three WT	647.5	70
With three WT +Biomass	42.50	98

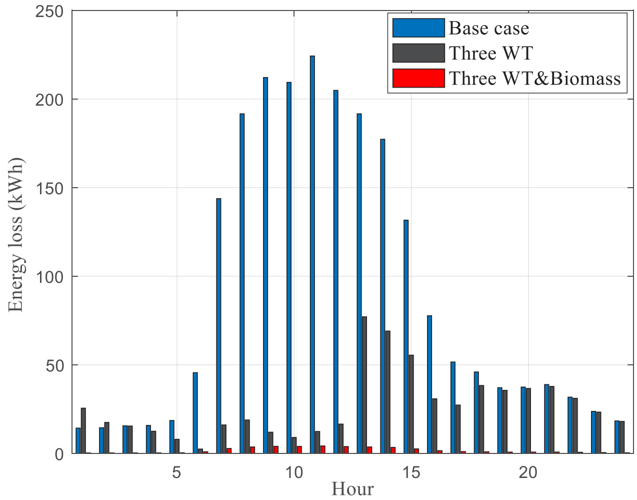

Fig. 7. Three WT and WT&Biomass based DG units' integration effect on active energy losses

6. Conclusions

In this paper, a new metaheuristic GMO technique has been proposed and employed to calculate optimal allocations of 1,2 and 3 WT and Biomass-based DG units, considering the time-varying voltage-dependent load demand and the WT based DG units probabilistic power generation. The Weibull PDF model has been used to illustrate the uncertainty nature of wind speed. The minimization the active energy loss of DNs is has been considered as main objective function of this study. In order to demonstrate the effectiveness of the proposed method, a standard IEEE 69-bus system has been used. Three WT and three WT&Biomass-based DG units have been taken into account to test the feasibility of the proposed method on minimize active energy loss. A comparison has been made between the proposed method's performance and the performance of other algorithms used for the same problem in the literature. Furthermore, the results indicate that integrating three WT-based and three WT&Biomass-based DG units into the IEEE 69-bus system can minimize energy losses by 70% and 98% compared to the base case.

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