Technical/economic/environmental optimal wind generation allocation in power systems

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ABSTRACT

This paper proposes an optimization technique to find the optimal allocation of wind farms (WFs) in a transmission network considering several objectives associated with economic, losses, voltage profile, and environmental impact represented in the reduction of carbon emissions. The problem is solved on the basis of maintaining three constraints which are transmission line power limits, active/reactive power constrain, and bus voltage limits. The particle swarm optimization (PSO) algorithm and Newton-Raphson method for load flow analysis are utilized to solve the optimization problem as a whole. In this context, there are two wind turbines added to the transmission network and a matrix laboratory (MATLAB) has been devised to evaluate their performance with varying capacities at different locations in the system. The proposed approach has been validated on the modified IEEE 14-bus transmission system.

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1. INTRODUCTION

With the growing concerns about the need of reducing emissions of greenhouse gas and climate change, wind power has emerged as a clean and renewable source of energy. Unlike fossil fuels, wind energy does not produce any harmful emissions or pollutants, making it a much more environmentally friendly option. Additionally, wind power is a domestic resource that can help countries reduce their dependence on imported oil and gas [1]. Furthermore, the cost of wind energy is gradually becoming more competitive with that of fossil fuels, rendering it a desirable choice for both consumers and utility companies. Wind power integration has grown rapidly in recent decades as a result of continued attempts to reduce reliance on fossil fuel resources. As of the end of 2021, the worldwide cumulative installed capacity of wind energy had reached 837 GW [2]. Increased wind power penetration poses several obstacles to the energy grid's functioning, spanning from stability to dependability of the system.

Some of the most important problems with grid functioning are directly associated with the growing use of wind energy in distribution systems, especially radial distribution networks (RDNs). With the help of competent policymaking and updated regulations, distributed energy resources (DERs) that have a maximum capacity of 50 MW have acquired a lot of traction in power networks as replacements or complementary options to traditional energy sources. The location and sizing of DERs in a distribution network are critical, as failure to do so can result in significant voltage instability, power losses, reliability concerns, financial losses, and increased harmonics [3]. Obtaining the desired interconnection of a WF in an RDNs frequently necessitates a complex analysis that includes network data and WF operational capability, as well as other relevant factors such as reverse power flow, frequency regulation, voltage regulation, islanding protection,

protection schemes, and harmonics [4]. DERs were only recognized as active power sources until recently, and they were not required to participate in voltage regulation. As rapid growth and quick-power electronic interfaces have emerged, the ability of DERs to provide voltage support has become an increasingly important requirement. Transmission system operator (TSOs) have been continuously revising their grid codes to prescribe the working features of DERs and make them conform with many functional and technical standards related to the frequency and voltage regulation, in line with the rise of WFs in low-voltage grids [5]. Most grid-integration challenges with wind farms (WFs) can be solved by applying optimal location and sizing processes, strategic planning, imposing various operational, technical, and reliability limitations, and fitting computational approaches to generate the best available solution.

Many authors have presented studies of the optimal allocation of distributed generators (DG). In 2012, Grillo *et al.* [6] presented a dynamic programming-based algorithm that is able to suggest the optimal management strategies that combine wind power generation and storage. The system was created to tackle the challenge of integrating renewable generation into the power grid. The model is used to utilized to establish the profile of optimal generation for the entire power generation. This allows for more effective utilization of wind power generation, which is naturally intermittent.

In 2013, a framework for planning with multiple objectives namely improved multi-objective harmony search (IMOHS) was presented in [7] and it was able to estimate the impact of DG location for the optimal planning in a distribution system. Non-dominated sorting genetic algorithm II (NSGA-II) was used in this work, which was carried out on two distribution networks. Siano and Mokryaniin [8] focused on finding the optimal allocation of WT and maximizing the net present value (NPV) associated with the investment of WTs in the environment of the distribution market. This work used the hybrid optimization method that is used for choosing the optimal size while a market-based optimal power flow (OPF) is used for determining the optimal WTs number at each candidate bus and the PSO optimization method [9]. The efficiency of the technique is illustrated using a radial distribution system with 84 buses and a voltage of 11.4 kV. A probabilistic methodology was presented in [10] that allowed the evaluation of the wind power`s amount that can be integrated into the power grid and the effect of wind power on the reliability of the network. This methodology considered the uncertainties associated with the production of wind power and load demand, and the results were obtained through Monte Carlo simulations (MCS). The suggested methodology was applied to a 33 kV distribution network in the UK. Lee and Park [11] proposed a method for determining the optimal location and size of DGs in a distribution system by using the Kalman filter algorithm.

In 2014, Lamaina *et al.* [12] presented a probabilistic technique for wind-based DG which aims to maximize NPV related to the investment of WTs developers, who participate in the market of electricity distribution. This method combined MCS and market-based OPF. The effectiveness of the presented method was demonstrated with a radial distribution system 84-bus 11.4 kV. Das *et al.* [13] introduced a comprehensive model for generation expansion planning (GEP), which allows the central planning authority (CPA) for creating the optimal incentive rates for renewable energy integration and targets of energy conservation, while also taking into account the interests and limitations of investors. The model determines the appropriate location, scale, time, and technology needed to meet the anticipated demand over the planning period. MCS was used in this study, and the suggested model was implemented on an actual scenario using data that is currently available for Ontario, Canada.

In 2015, Alnaser and Ochoa [14] developed a method to determine the minimum power and energy storage capacities required at various locations in distribution networks for decreasing curtailment of DG, specifically WFs, while controlling congestion and voltage levels. The framework utilized a two-stage iterative process. A multi-period AC to OPF was used for obtaining the initial storage sizes using wind and load patterns that change every hour as a basis for the entire studied planning horizon in the first stage. Actual curtailment data was used to adjust the storage sizes obtained in the first stage, using a precise minute-by-minute control strategy guided by a single-period, two-level AC OPF in the second stage. The planning framework was tested on a real 33 kV electric network located in the North of England for one week.

In 2016, Santos *et al.* [15] introduced a model that involves multiple stages and incorporates randomness and uncertainty to optimize the implementation of advanced power grid systems and technologies that facilitate the incorporation of renewable energy sources on a significant scale. The model incorporated various technologies such as energy storage systems (ESS), network switching, sources of reactive power, reinforcement, and expansion. To solve the optimization problem, the authors utilized the mixed integer linear programming (MILP) technique. This study focused on the IEEE 41-bus radial distribution network systems (DNS) for testing the proposed model.

In 2017, a risk assessment tool was introduced by Al-Saadi *et al.* [16] to estimate the network hosting capacity (HC) while taking into account the uncertainties associated with PV, WT, and loads. The tool utilized the likelihood approximation approach and also suggested the use of a clearness index for the prediction of localized solar irradiance for PV. The study employed MCS and was conducted on two actual distribution networks, an 11-bus network and a large feeder in South Australia. A planning framework was recommended for the optimal size and placement of ESS in the distribution networks [17]. This framework aimed for minimizing the total cost of energy supply while ensuring network reliability, using the MILP model to optimize DGs placement and sizing. The suggested model was tested on a real 33 kV distribution network in the UK. Similarly in [18], a planning framework was introduced for the optimal size and placement of renewable DG in the distribution networks. The framework aimed for minimizing the total cost of energy supply while ensuring network reliability, also utilizing the MILP model to optimize the placement and sizing of renewable DGs. The study was conducted on a real 33 kV distribution network in the UK.

In 2018, Abad *et al.* [19] presented an optimization approach for the optimal location and sizing of multiple DGs and ESS in the distribution networks. The approach used the MILP model to minimize the total cost of energy supply while ensuring the reliability of the network. The suggested approach was implemented for a real 33-kV distribution network in the UK. A stochastic optimization approach was proposed in [20] for the optimal placement of multiple DGs in a radial distribution system. The approach was designed to consider uncertainties in load demand and renewable energy generation, and it used the MCS method to generate stochastic scenarios. The optimal placement and size of DGs were obtained through the MILP model. The implemented method was applied in a 69-bus distribution system.

In 2020, Jafari *et al.* [21] proposed a method for determining the optimal size and placement of switched capacitors which are using the hybrid optimization algorithm. The algorithm consisted of two inner and one outer optimization layer. The outer layer was implemented by a genetic algorithm (GA), while the inner layer was performed by either a GA, PSO, or exchange market algorithm (EMA). The study utilized IEEE 33-bus and 69-bus networks. Jafari *et al.* [22], an approach was introduced for determining the optimal capacity type and capacity of generation resources for microgrids (MGs) that incorporated renewable energy sources (RESs) such as WTs and photovoltaics (PVs), as well as diesel generators at each bus of the MG. The optimization problem was solved using EMA in MATLAB, with 200 iterations. The mean time for one iteration was approximately 10 seconds, and the overall time averaged around 30 minutes over the course of the study in 2020.

Overall, these studies demonstrate the growing interest in the optimal strategizing and operation of DG and systems of energy in distribution networks. The studies use a variety of optimization techniques, including PSO, MCS, evolutionary algorithms, and MILP. The results show that these approaches can help to improve the reliability and efficiency of distribution networks while promoting the integration of renewable energy sources. In Table 1 compares the mentioned methods according to the objectives and functions that are taken into account.

Table 1. Comparative analysis of different methodologies related to optimal location and sizing of wind turbine

Reference	Economic issues	EVI	Voltage profile	Losses
[6], [12], [13], [18], [21]	✓	×	×	✓
[16], [19]	×	×	✓	×
[8], [10]	✓	×	✓	×
Proposed method	✓	✓	✓	✓

This paper managed to find the optimal allocation of a WF consisting of two WTs in a transmission network taking into account several objectives associated with economic, losses, voltage profile, and environmental impact represented in the reduction of carbon emissions and maintains four constraints which are transmission line power limits, power flow equations, active power constrain, and bus voltage limits, which to the author's knowledge have not been combined all together on one optimization problem in the literature before. To tackle the optimization problem in its entirety, the PSO algorithm and Newton Raphson method for load flow analysis are employed. In this context, there are two WTs added to the transmission network and a MATLAB was created to assess their performance under different capacities and locations within the system. The validity of the proposed approach was confirmed using the IEEE 14-bus transmission system. The paper is structured as follows: i) Section 2 outlines the problem being addressed; ii) Section 3 describes the methodology used; iii) Section 4 presents the results and discussions; and iv) Section 5 concludes the paper and suggests directions for future research.

2. PROBLEM STATEMENT

The location of WTs in the electrical grid is a critical and important aspect that should be taken into consideration during the setup of any WF. There are many problems faced the integration of wind energy in the grid when wind turbines are not optimally allocated such as reduced energy production, increased costs, environmental impacts, and community opposition. The annual wind speed variation is represented using the Weibull distribution [23]. The probability density function $f_v(v)$ and the cumulative distribution function $F_v(v)$ of the Weibull distribution are defined as (1) and (2).

$$f_v(v) = ba^{-b}v^{b-1}e^{-\left(\frac{v}{a}\right)^b} \tag{1}$$

$$F_v(v) = 1 - e^{-\left(\frac{v}{a}\right)^b} \tag{2}$$

In the formula, where a represents the scale parameter, b represents the shape parameter, and v represents the Weibull random variable (wind speed) [23]. Characteristics of wind speed vary depending on wind direction, according to measurements. These equations explain how the probabilistic wind speed model integrates the correlation between the speed and direction of the wind. Annual wind data (typically collected hourly) at a single location is divided into N_d intervals according to ongoing direction. Afterward, a Weibull distribution is applied to represent the values of wind speed grouped for each interval, along with a frequency measure that indicates the proportion of the ten wind directions in this interval concerning all intervals [24], [25]. Consequently, the model defines the probability density function of the speed of wind for a specific location as (3).

$$f_v(v) = \sum_{i=1}^{N_d} f_{V_i}(v)\, W_i \tag{3}$$

Where N_d is the overall number of direction intervals, and W_i is the frequency of i^{th} interval.

There are various factors, including wind speed, rotor blade size and shape, and generator efficiency, that affect the amount of energy that can be harnessed by a WT and converted into electrical energy. Usually, the amount of energy that a WT can capture increases as wind speed increases, but there is a limit to how much energy a WT can capture based on the maximum output of the generator and the rotor blades design. If the wind speed is too low, the WT may not generate enough energy to be economically feasible, while if the wind speed is too high, the WT may need to be shut down to prevent damage to the equipment. Thus, WT operators continuously monitor wind speed and alter the rotor blades direction to optimize energy generation while maintaining safe operating conditions. The energy available in the wind is transformed into a practical type of energy by WTs. The power output of a WT based on wind speed is given as (4).

$$P_w(v) = \begin{cases} 0 & 0 \le v \le v_{ci} \\ P_{wr} * \frac{v - v_{ci}}{v_r - v_{ci}} & v_{ci} \le v \le v_r \\ P_{wr} & v_r \le v \le v_{co} \\ 0 & v_{co} \le v \end{cases} \tag{4}$$

The formula includes the parameters P_w, P_{wr}, and v_r which represent the output power, rated power, and rated speed of the wind turbine, respectively. To initiate power generation, the wind velocity must exceed the critical cut-in speed v_{ci}, and the turbine will discontinue its operation at wind speeds that exceed the cut-off speed v_{co} to avoid damage and stop power production [25]. The probability of zero output power can be evaluated as the total probability of wind speeds being either below the cut-in speed or above the cut-off speed [26]. Where ε is a small positive number.

$$F_P(0) = F_V(v_{ci} - \varepsilon) + 1 - F_V(v_{co} + \varepsilon) \tag{5}$$

3. METHOD

This study primarily aims to find the optimal location and size of WF consisting of two WTs in a power system, considering several technical objectives. The objectives that this work takes into account are operation cost, power losses, voltage profile, and environmental impact. Newton Raphson method is used for load flow analysis and PSO is used for solving optimization problems. The PSO algorithm [9] is a method of population-based optimization that utilizes a group of particles to find the optimal solution. Each particle represents an individual and the clusters of particles are known as a swarm. One of the advantages of PSO is that it is easy to implement and does not require knowledge of gradients. The problem's solution space is transformed into a search space in PSO, with each point in the search space representing a potential solution.

The particles work together to locate the best position (optimal solution) within the search space (solution space). Each particle's movement is determined by its velocity [27].

PSO is an optimization algorithm, that differs from MFO, GWO, and WOA even enough all of them are metaheuristic optimization methods [28]–[33]. PSO uses a velocity-based search strategy, where each particle's velocity is updated based on its own position and the swarm's best position. PSO uses a set of empirically determined equations to update the particle velocities and positions. The PSO algorithm can have a variable number of iterations depending on the problem being solved, the size of the search space, and the convergence criteria. In general, PSO iterations continue until a stopping criterion is met, such as a maximum number of iterations being reached, a minimum error threshold being achieved, or the fitness value no longer improving. A typical number of iterations for PSO can range from a few hundred to several thousand. However, the optimal number of iterations for a given problem can be determined through experimentation and tuning until we get to the best values of hyperparameters [34]. The PSO parameters used in training our model were as follows: a maximum number of iterations = 1000, population size (swarm size) = 100, inertia weight W = 0.8, inertia weight damping ratio (w_{damp}) = 0.9, personal learning coefficient c_1 = 1.5, global learning coefficient c_2 = 2, number of WFs = 2, WFs _max. Size = [300, 250], and WFs _min. Size = [10, 40].

3.1. The objectives

In general, objectives refer to specific goals or targets that an individual, organization, or project aims to achieve. Objectives provide a clear and measurable direction for action and help to focus efforts toward a desired outcome. The objectives that this paper takes into account are mentioned below.

3.1.1. Operation costs

The operation cost of generators is a critical objective that must be taken into account. The generation cost of thermal generators is expressed as in (6).

$$GC = \sum_{t=1}^{T} \sum_{i=1}^{N_g} \left(a_i P_g^2 + b_i P_g + c_i \right) \tag{6}$$

Where: a_i, b_i, and c_i are the thermal generation cost coefficient. The used generation cost coefficients of five generators are illustrated in Table 2.

Table 2. Generation cost coefficients of five generators

Unit N	P_i^{min}	P_i^{max}	a_i	b_i	c_i
1	50	500	0.007	7	240
2	20	200	0.0095	10	200
3	20	300	0.009	8.5	220
4	20	150	0.009	11	200
5	20	200	0.008	10.5	220

Due to the variability of available RES at any given point in time, the model should account for factors that may cause overestimation or underestimation of their availability. The reason for the overestimation factor is straightforward: if the model assumes a particular amount of renewable energy power will be available at a specific time, but it is not, alternative sources of power must be utilized or the demand for power must be reduced. In the case of an underestimation penalty, if more renewable energy power is available than expected, the surplus energy may go to waste, and the system operator may charge the RES power product for the loss of capacity. Typically, excess renewable energy is sold to neighboring utilities or quickly redistributed. If neither of these options is feasible, load resistors may be connected to "consume" the excess power. A clearly, a straightforward minimization penalty cost function may be used to model these activities as shown in [23]:

$$C_W(P_W) = d_W f_W(P_{W_{av}}) P_W + c_{p.W}(P_{W_{av}} - P_W) + c_{r.W}(P_W - P_{W_{av}}) \tag{7}$$

where C_W is the total cost of WF generators ($), d_W is the cost coefficient of WF generators ($/MW), $f_W(P_W)$ is the Weibull pdf of WF generator, $c_{p.W}$ is the cost coefficient of WF generators because of over-generation ($/MW), P_W is the scheduled output of WT generators, and $c_{r.W}$ is the cost coefficient of WF generators because of under-generation ($/MW). The cost coefficients of WF are calculated as (8) and (9) [23]:

$$c_{p.W}(P_{W_{av}} - P_W) = c_{p.W} \int_{P_W}^{P_{W_r}} (P_{W_{av}} - P_W) f_W(P_{W_{av}}) dP_W \tag{8}$$

$$c_{r.W}\left(P_W - P_{W_{av}}\right) = c_{r.W} \int_0^{P_W} \left(P_W - P_{W_{av}}\right) f_W\left(P_{W_{av}}\right) dP_W \tag{9}$$

3.1.2. Maximizing annual WT generation

The relation in (10) presents an optimization problem aimed at identifying the optimal solution for the WF allocation issue. The goal is to maximize the total annual power generation expected from the chosen locations while complying with the regulations set by the transmission system operator. As a result, the objective function $f(S_k)$ to be maximized is defined as (10) [35].

$$f(S_k) = \sum_{k=1}^{N} \int_0^{S_k} (1 - F_n(n))dp \times 8760 \tag{10}$$

In the context of the optimization problem, $f(S_k)$ denotes the total annual power generation from the WFs, while N represents the total number of possible WF locations that meet the established criteria. $F_n(n)$ is the cumulative distribution function (CDF) of the power output for the WF at the K^{th} site, and S_k represents the capacity of the WF at the K^{th} site.

3.1.3. Reducing total losses

Either the load flow software running on the system or using the B-coefficient method can be used to calculate the transmission losses. The first one is used in this study based on the following expression of transmission losses as (11) [23].

$$P_{Li} = \sum_{j=1}^{N_l} G_{ij}(V_i^2 + V_j^2 - 2V_iV_j \cos\theta_{ij}) \tag{11}$$

Where G_{ij} is the conductance of the transmission line that connects bus *i* and bus *j*. V_i, V_j are the voltage levels of bus *i* and bus *j*, respectively θ_{ij} is the difference in voltage phase angle between bus *i* and bus *j*.

3.1.4. Improving voltage profile

The voltage constraints will be as follows: In order to achieve the desired voltage level at a particular bus in the network, automatic voltage regulation is employed, which involves controlling multiple components in the system, such as the reactive power generation in synchronous generators. This control is achieved through the use of complementary constraints that generate a discrete function as described in [36]. To obtain a continuous approximation of this behaviour, a sigmoid function is used, which has been fine-tuned for this purpose.

$$0.95 \leq V \leq 1.1 \tag{12}$$

$$\Gamma(V) = \frac{2}{\pi} \arctan\left\{\frac{\pi}{2}\rho\left(V - V_{sp}\right)\right\} \tag{13}$$

Where V_{sp} and ρ are the voltage set point and a tuning parameter that determines the sensitivity of the control function, are both used in the process [37]. Also mentions the use of the sigmoid function for voltage regulation. The following are the required limitations for generator voltage control:

$$\beta_1 \frac{Q^{max} + Q^{min} - 2Q}{Q^{max} - Q^{min}} \leq \Gamma(V) \tag{14}$$

$$\beta_2 \frac{Q^{max} + Q^{min} - 2Q}{Q^{max} - Q^{min}} \geq \Gamma(V) \tag{15}$$

where β_1 and β_2 are two auxiliary variables with the continuous interval [0 1] as their bounds. Given that the generator's reactive power output is restricted by Q^{max} and Q^{min}, the reactive power produced by the generator will be constrained and eventually reach one of the following states.

$$\text{voltage control}\begin{cases} Q = Q^{max} & V \leq V_{sp} \\ Q^{min} \leq Q \leq Q^{max} & V = V_{sp} \\ Q = Q^{min} & V \geq V_{sp} \end{cases} \tag{16}$$

3.1.5. Maximization of the environmental index (EVI)

Evi is a parameter that measures environmental considerations proposed in [38] and expressed as (17).

$$EVI = 0.93 \times \frac{Total\ energy\ generated\ in\ a\ year}{Wind\ farm\ rating} \tag{17}$$

It is assumed that producing 1 MWh of energy from fossil fuels releases around 0.93 metric tons of greenhouse gases.

3.2. Solution space constraints

3.2.1. Transmission line power limits

According to (18), where $\left|P_{ij}^{line}\right|$ and $P_{ij,max}^{line}$ are the absolute and maximum power transmitted through the distribution line connecting nodes i and j, respectively. It`s one of the primary factors that limit transmission line power is the maximum current that the line can handle. The amount of current that can flow through a given transmission line is limited by the line's physical characteristics, as well as the surrounding environment, including temperature, humidity, and wind speed.

$$\left|P_{ij}^{line}\right| < P_{ij,max}^{line} \tag{18}$$

3.2.2. Power flow equations

According to (19) and (20), where P_i and Q_i represented the active and reactive powers that are injected, V_i and δ_i are the voltage magnitude and phase angle at i^{th} bus. Also, Y_{ij} and θ_{ij} are the magnitude and phase angle of the branch admittance connecting i^{th} and j^{th} buses. Power flow analysis is essential for power system planning and operation. By analyzing the power flow in a network, potential problems can be identified, such as overloaded transmission lines or voltage instability, and take corrective actions to ensure that the power system remains stable and reliable.

$$P_i = \sum_{i=1}^{N_{bus}} V_i V_j Y_{ij} \cos\left(\theta_{ij} - \delta_i + \delta_j\right) \tag{19}$$

$$Q_i = \sum_{i=1}^{N_{bus}} V_i V_j Y_{ij} \sin\left(\theta_{ij} - \delta_i + \delta_j\right) \tag{20}$$

3.2.3. Active power constraints of the WPG

According to (21), where $P_{min,w,i}$ and $P_{max,w,i}$ are the minimum and maximum permissible power of the i^{th} WTG. Active power constraints are typically implemented to ensure that the power system remains stable and reliable. When the amount of active power being generated or consumed exceeds the system's capacity, it can lead to voltage instability, frequency fluctuations, and even power outages.

$$P_{min,w,i} \leq P_{w,i} \leq P_{max,w,i} \tag{21}$$

3.2.4. Bus voltage limits

According to (22), where V_{min} and V_{max} are the minimum and maximum allowable magnitudes for the bus voltage. Bus voltage limits are important because excessive voltage can damage equipment, while low voltage can cause equipment to malfunction or even fail. In addition, voltage levels that are too high or too low can lead to instability in the power system, which can cause power outages and other problems.

$$V_{min} \leq V_i \leq V_{max} \tag{22}$$

4. RESULTS AND DISCUSSION

The proposed method has been tested on the modified IEEE 14-bus transmission system [38]. The data for a system based on 100 MVA. The range of acceptable voltage magnitude and phase angle is between 0.95 p.u. and 1.05 p.u. The discussion can be made in several sub-sections. The wind speed is unstable and changes throughout the day, Figure 1 shows minimum, maximum, and mean speed all day long.

4.1. Cost

After optimization, the optimal costs of five generators are 630.14, 472.33, 393.6, 423.6, and 748,236$. So it can be said the total cost of generators improved from 13,300$ to 2,668$. Figure 2 shows the improvement that occurred in the cost of generators after optimization.

4.2. Power losses

By using Newton Raphson load flow analysis, without optimization real and reactive losses respectively are 7.6011 MW and 29.5488 MW and total losses are 30.75125 MW. After running 50 iterations and optimization by PSO real and reactive losses respectively become 6.0005 MW, 23.4639 MW, and total losses are 24.390863 MW. In summary, optimization has minimized total losses, and the minimum achievable loss is 24.390863 MW. This occurs when the optimal location and size of the two WTs at bus 3 and bus 14 and the optimal size are 300 MW and 250 MW respectively. Figure 3 shows the total losses of the system before and after optimization, and Figure 4 shows the active power of the turbine during the day.

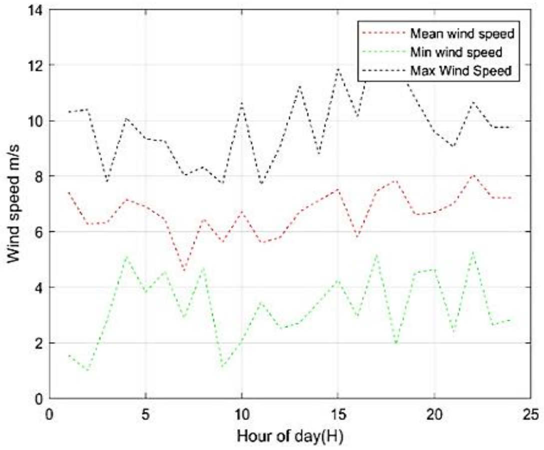

Figure 1. Minimum, maximum, and mean speed during the day

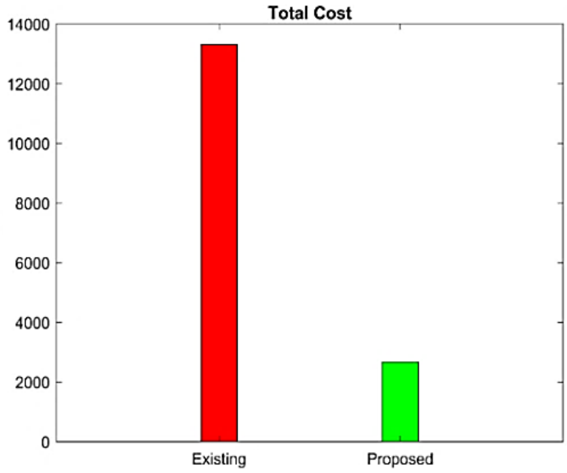

Figure 2. Cost of generators in the system before and after optimization

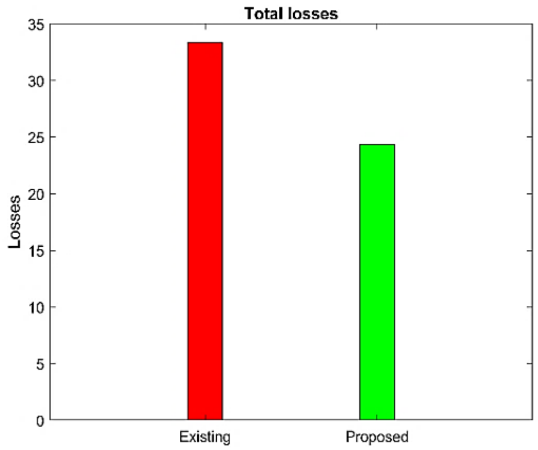

Figure 3. Total losses of the system before and after optimization

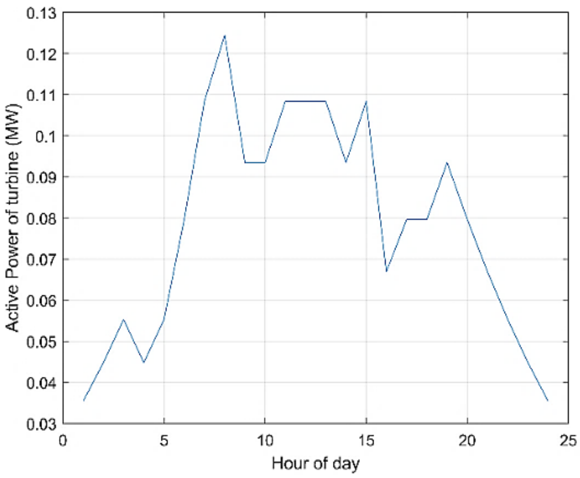

Figure 4. The active power of the turbine all day long

4.3. Voltage profile

The voltage profile improved in the system after PSO optimization generally and especially at bus 3 from 1.01 to 1.03 p.u. and bus 14 from 1.017 to 1.05 p.u. Bus 3 and bus 14 have been identified as the optimal locations based on the voltage profile analysis. Figure 5 shows the improvement of the voltage profile and active power.

4.4. EVI

Figure 6 shows that EVI without PSO optimization is 531.7 and after optimization 639.4. So, it can be said that EVI is improved and the optimal EVI is 639.4. Although the model is active, it has also limitations. It may be inefficient to find the global optima if the search space gets enamors or is very complicated that is why we choose to optimize a selected number of objectives and we applied the complete iteration for each objective separately. Also, the PSO algorithm suffers from a major limitation regarding finding the global optimum solution, it is known that PSO like other population-based optimization techniques, is susceptible to premature convergence, which can result in suboptimal solutions and to overcome this limitation we were careful to initialize the PSO hyperparameters with values that were proven to perform ideally in previous work [34]. Also, the model was very consuming regarding computational resources and memory requirements. And we do not believe that the model could be scalable to larger populations. Table 3 presents the improvement achieved in each objective before and after optimization.

Table 3. Comparison of objectives before and after optimization

Objective	Optimal location	Before optimization	After optimization	percentage of improvement
Generation cost of generators	Bus 3, bus 14	13300$	2668$	79.94%
Reducing total losses	Bus 3, bus 14	30.75125 MW	24.390863 MW	20.68%
Improving voltage profile	Bus 3, bus 14	1.01 p.u.	1.03 p.u.	2%
		1.017	1.05 p.u.	3.2%
EVI	Bus 3, bus 14	531.7	639.4	20.26%

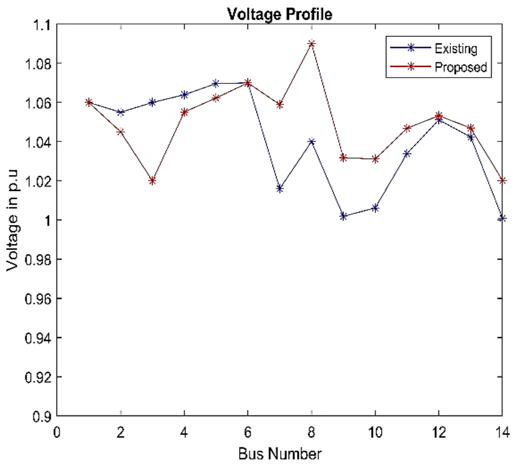

Figure 5. Voltage profile of the system before and after optimization

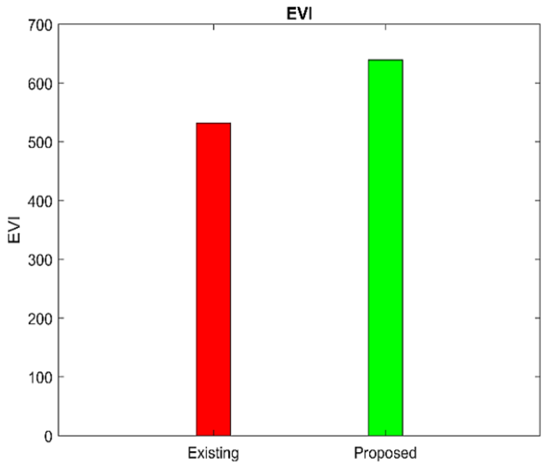

Figure 6. Environmental index before and after optimization

5. CONCLUSION

An innovative multi-objective planning methodology for identifying the optimal location and size of a WF consisting of two WTs in a transmission system based on operation cost, losses, voltage profile, and the environmental index has been proposed in this work. The used optimization method is PSO and Newton Raphson method for load flow analysis. The total cost improved from 13300$ to 2668$, so the percentage of improvement is 79.94%. Total losses improved from 30.75125 MW to 24.390863 MW, and the percentage of improvement is 20.68%. The voltage profile improved at bus 3 from 1.01 to 1.03 p.u., and at bus 14 from 1.017 to 1.05 p.u. EVI is improved from 531.7 to 639.4, and the percentage of the environment is 20.26%. So it can be said that the optimal allocation of two WTs is at bus 3 and bus 14 where optimization of all objectives occurs on it. These results are shown in Table 3. Future research should consider extending this study to various WTs. Additionally, it might be explored whether adding energy storage would have any effects on the dependability and financial aspects.

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