Metaheuristic optimization of wind turbine farm siting in power grids: a comparative study of PSO and GA

Taha Rachdi[1,2], Yahia Saoudi[3], Larbi Chrifi-Alaoui[2], Ayachi Errachdi[1]
[1]Laboratory of Research on Automatic (LARA), National Engineering School of Tunis (ENIT), Tunis El Manar University, Tunis, Tunisia
[2]Laboratory of Innovative Technology, Picardie Jules Verne University, Amiens, France
[3]Department of Electrical Engineering ENIS, Sfax University, Sfax, Tunisia

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ABSTRACT

This paper addresses the optimal integration of wind turbines into distribution networks with the aim of reducing active power losses and improving voltage stability. Two metaheuristic optimization methods genetic algorithm (GA) and particle swarm optimization (PSO) are applied to determine the optimal siting and sizing of wind turbines in the IEEE 14-bus system. The problem is formulated as a multi-objective function combining loss minimization and voltage profile enhancement under standard network constraints. Simulation results using MATLAB/PSAT show that both algorithms improve system performance compared to the base case, with PSO providing superior loss reduction and voltage stability. Wind variability is represented through a Weibull distribution to reflect realistic operating conditions. The study demonstrates the effectiveness of metaheuristic optimization for renewable integration and highlights PSO's stronger robustness. The work contributes a comparative evaluation of GA and PSO, supported by stability analysis and realistic wind modelling.

Corresponding Author:

Taha Rachdi
Laboratory of Research on Automatic (LARA), National Engineering School of Tunis (ENIT)
Tunis El Manar University
Tunis, Tunisia
Email: taha.rachdi@enit.utm.tn

1. INTRODUCTION

Wind energy has become a key component in modern power systems, supported by advances in power electronics and renewable technologies that facilitate its integration into existing grids [1]–[4]. As distributed energy resources continue to reshape traditional passive networks into dynamic and active systems, operators face increasing complexity in voltage regulation, power quality, protection coordination, and bidirectional power flow management [5]–[8]. Moreover, the intermittent and unpredictable nature of wind generation poses additional challenges for maintaining supply–demand balance, mitigating congestion, and ensuring frequency stability.

Although the benefits of wind integration such as reduced transmission losses, enhanced energy security, and reduced environmental impact are well acknowledged [9]–[11], their effectiveness strongly depends on appropriate siting and sizing. Inadequate placement or improper capacity selection may lead to higher losses, voltage deviations, and degraded system performance [10]–[12]. To address these concerns, several studies have applied metaheuristic methods such as genetic algorithms (GA) and particle swarm optimization (PSO), demonstrating notable improvements in loss minimization and voltage support on benchmark networks, particularly the IEEE 14-bus system [13]–[17].

However, despite this progress, two important gaps remain. First, most existing studies focus either on placement or on sizing, without treating both aspects simultaneously, which limits the practical applicability of their conclusions. Second, comparisons between GA and PSO are often qualitative or based on simplified stability indicators, failing to assess their performance under realistic operating conditions that account for wind variability and detailed voltage stability criteria.

This research addresses these shortcomings by providing a comparative and comprehensive analysis of GA and PSO for the simultaneous optimal siting and sizing of wind turbines in the IEEE 14-bus system. The study distinguishes itself from previous work by:

- Employing an advanced voltage stability index based on the reduced Q–V Jacobian [9],
- Integrating realistic wind variability through a Weibull distribution model, as recommended in wind modelling studies [18]–[25],
- In addition, validating the optimization results through both static and dynamic simulations, in alignment with recent recommendations in renewable energy integration research [11], [19]–[21].

Through this approach, the study aims to offer a more accurate, robust, and practically relevant evaluation of wind turbine integration strategies. The structure of this paper is as follows: Section 2 outlines the research problem, detailing the objective functions, decision variables, optimization criteria, and system constraints. Section 3 describes the methodological approach, offering background information on the GA and PSO techniques. Section 4 presents the results and discusses of the simulation outcomes. Finally, section 5 concludes the study and suggests avenues for future research.

2. THE PROBLEM STATMENT

This study addresses the optimization of wind turbine placement and sizing in a distribution grid. The objective is to minimize active power losses and improve the voltage profile through a multi-objective function. The decision variables are turbine location and capacity, while constraints include line limits, load flow equations, and bus voltage boundaries. The goal is to ensure reliable operation and enhance system performance with optimal renewable integration.

2.1. Objectives functions

The multi-objective optimization aims to minimize active power losses (F_1) and improve the voltage profile (F_2). Active power losses are calculated as the sum of the products of line resistances and the squares of the currents flowing through them. Voltage profile improvement is evaluated by measuring the deviation of bus voltages from the nominal value across the entire network. To balance these two criteria, a combined objective function (F) is defined as a weighted sum of F_1 and F_2, with respective coefficients of $w_1$and w_2. Each term is normalized by its maximum value to ensure comparable scales between the two objectives. The functions are given by the following equations:

To minimize the active power losses:

$$F_1 = \sum_i R_{kl} I_{kl}^2 \quad (1)$$

With:
R_{kl} : The line resistance through the line.
I_{kl} : The current passing between bus k and l.
In addition, improving voltage profile is given by the following equation:

$$F_2 = \sum_{i=1}^{B_{num}} (V_m(i) - 1)^2 \quad (2)$$

Where:
$V_m(i)$: Bus i magnitude voltage.
B_{num} : The number of bus in the network.
Lastly, the following statement provides the combined objective function.

$$F = w_1(F_1) + w_2(F_2) \quad (3)$$

Where: The weighted coefficients for (1) and (2) are denoted by $w_1$and w_2. In our case we take $w_1 = 0.4$ and$w_2 = 0.6$. The weighting factors were selected based on the relative importance of each objective. Voltage stability is the most critical criterion when integrating wind turbines, which justifies a higher weight (w2=0.6). Preliminary tests showed that moderate variations of the weights do not affect the optimal locations, indicating robustness of the solution.

2.2. Decision variables and decision vector

In the optimization process, two main decision variables are considered: the placement of wind turbines within the distribution grid (WT_{site}) and the generation capacity or size of each installed unit (WT_{size}). These variables directly influence network performance by affecting power losses and voltage stability. To formalize the optimization problem, a decision vector X is defined, combining both parameters. Thus, the vector is expressed as:

$$X = [WT_{site}, WT_{size}] \tag{4}$$

it represents simultaneously the optimal locations and the corresponding sizes of wind turbines in the distribution system.

2.3. Constraints

The optimization of the placement and operation of wind turbine generation units within a distribution network must comply with several technical constraints to ensure voltage stability and minimize power losses. Firstly, the active power flowing between two buses on the same line must not exceed the line's thermal power limit. Secondly, load flow equations must be satisfied, accounting for the injected active and reactive powers at each bus, as well as the voltage magnitudes, phase angles, conductance, and susceptance of the lines.

$$P_{ij} = V_i \sum_j V_j\big(G_{ij}\cos(\theta_{ij} - \delta_i + \delta_j)\big) + B_{ij} sin(\theta_{ij} - \delta_i + \delta_j) \tag{5}$$

$$Q_{ij} = V_i \sum_j V_j\big(G_{ij}\sin(\theta_{ij} - \delta_i + \delta_j)\big) - B_{ij} cos(\theta_{ij} - \delta_i + \delta_j) \tag{6}$$

where: P_{ij} and Q_{ij} are the injected active and reactive powers, the voltage value is presented by Vi and the angle value is presented byδ_i at i-bus. Also B_{ij} and G_{ij} are the susceptance and conductance. Finally, the voltage at each bus must remain within specified limits to ensure the safe and reliable operation of the grid.

$$V_{min} \leq V_i \leq V_{max} \tag{7}$$

Where Vi is the i-bus magnitude voltage, Vmax and Vmin are the voltage limite maximum and minimum. In addition to the network operating limits, constraints related to the wind turbine units are also imposed in order to ensure realistic and technically feasible operating conditions. The active power injected by each wind turbine must remain within its rated capacity limits, which can be expressed as:

$$0 \leq P_{WT,i} \leq P_{WT,i}^{max}, \quad i = 1 \ldots N_{WT} \tag{8}$$

where $P_{WT,i}$ is the active power generated by the i-th wind turbine and $P_{WT,i}^{max}$ denotes its maximum admissible capacity. Wind turbines must also comply with reactive power capability curves. Their reactive power injection or absorption is bounded by:

$$0 \leq Q_{WT,i} \leq Q_{WT,i}^{max}, \quad i = 1 \ldots N_{WT} \tag{9}$$

These constraints ensure that the optimization process does not select infeasible turbine sizes or unrealistic penetration levels, and that the resulting solutions remain compatible with practical design and operational requirements. In our work, the "stability index" is derived from the reduced Q–V Jacobian of the Newton–Raphson power flow. After forming the reduced Jacobian J_R ,we compute its eigenvalues λ_k and define the stability index as:

$$\lambda_k = \sum_{k=1}^{N_{PQ}} \frac{1}{\lambda_k(J_R)} \tag{10}$$

this scalar indicator measures the proximity of the system to voltage instability: when the system approaches a voltage collapse point, one of the eigenvalues of J_R tends to zero, which causes the inverse λ_k (and thus SI) to grow very large. Conversely, smaller values of SI indicate a more stable operating condition with a healthier voltage profile [26] and [27].

3. METHODOLOGY-GA AND PSO OPTIMIZATION THEORY

The goal is to determine the optimal location and size of wind turbines in a distribution network to minimize active power losses and enhance the voltage profile.

3.1. Genetic algorithm

GA are inspired by Darwin's theory of evolution and the principle of the "survival of the fittest." They simulate the natural processes of selection, crossover, and mutation to evolve optimal solutions. Each chromosome represents a potential solution. The GA steps for this work are organized as follows; population initialization: Random generation of an initial population of size Npop, where each chromosome represents a bus location.

- Fitness function evaluation: two objectives are considered: Reduction of active power losses F1 and improvement of voltage profile F2.
- Parent selection: using methods such as roulette wheel or tournament selection.
- Crossover: new offspring are generated from selected parents.
- Mutation: random gene modifications to maintain diversity and prevent local optima.
- Next generation: offspring are included in the new population.
- Stopping iteration: the process stops when the maximum number of iterations niter is reached or convergence is achieved.

3.2. Particle swarm optimization

PSO is inspired by the social behaviour of birds or fish. Each particle represents a potential solution and adjusts its position based on: Its personal best position ($P_{best,i}$) and the global best position ($G_{best,i}$). The PSO update equations are given in the following equations:
velocity update:

$$v_i(t+1) = \omega.V_i(t) + c_1.r_1.\left(P_{best,i} - x_i(t)\right) + c_2.r_2.(G_{best,i} - x_i(t)) \quad (11)$$

Position update:

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (12)$$

Inertia weight adaptation:

$$\omega = \omega_{max} - \left(\frac{\omega_{max}-\omega_{min}}{iter_{max}}\right).iter \quad (13)$$

The PSO steps for the proposed algorithm are organized as follows:

- Load system data and set maximum iterations.
- Identify the substation bus and perform load flow analysis.
- Calculate active power lossesP_{loss}.
- Initialize a swarm of particles representing bus positions.
- Evaluate fitness (losses) of each particle.
- Update personal best (P_{best}) if current fitness is better.
- Update global best (G_{best}) across the swarm.
- Update velocities and positions using equations (9) and (10).
- Repeat until convergence or $iter_{max}$ is reached.
- Select the best particle as the optimal placement for the wind turbine.

4. RESULTS AND DISCUSSION

In this research, The GA and the PSO were applied to determine the most effective locations for integrating wind turbines into the IEEE 14-bus power system. The simulation work was conducted using MATLAB R2010a. The main goal was to minimize active power losses, improve the voltage profile, and enhance the overall power factor of the system. The power network was modelled with a base value of 100 MVA, with voltage levels of 69 kV in certain sections and 13.8 kV in others. Prior to the integration of wind energy units, the system experienced a total active power loss of 10.5990 kW.

Table 1 provides a side-by-side comparison of the GA and PSO techniques. It illustrates the extent of power loss reduction and the corresponding voltage stability indices resulting from wind turbine placement at various bus locations. Additionally, the table indicates the optimal sites determined by each algorithm, highlighting substantial improvements in power loss mitigation and system stability. These findings demonstrate the effectiveness of strategically incorporating wind energy to enhance the performance and reliability of electrical power networks.

Table 1. Effect of wind turbine location on system power

	Using genetic algorithm	Using PSO algorithm
The proper location of wind turbines	3, 5, 8 and 13	3, 6, 7 and 9
The WT size [MW]	[6 8 2 2.6]	[5 3.9 5 5]
Total initially power losses [KW]	10.5990	10.5990
Power losses using algorithm [KW]	3.4925	1.6251
Power savings [kW]	7.1065	8.9739
Initially stability index	2.0477	2.0477
With wind stability index	0.9577	0.6384

The outcomes from the PSO algorithm and GA algorithm are summarized:
PSO execution result:
Turbine sizes (MW): 5.0000, 5.0000, 5.0000, 3.91168
Wind turbine locations: Buses 3, 6, 7 and 9
GA execution result:
Turbine sizes (MW): 6.0460, 8.07518, 2.1010, 2.6910
Wind turbine locations: Buses 3, 5, 8, and 13

To account for the stochastic nature of GA and PSO, several independent runs were carried out during the experimentation phase. The resulting optimal locations exhibited very small variability from one run to another, demonstrating the robustness and repeatability of the solutions. For the sake of clarity and to avoid redundancy, only the most representative (best) run is reported in the main text. The corresponding convergence curves are provided in the following Figure 1.

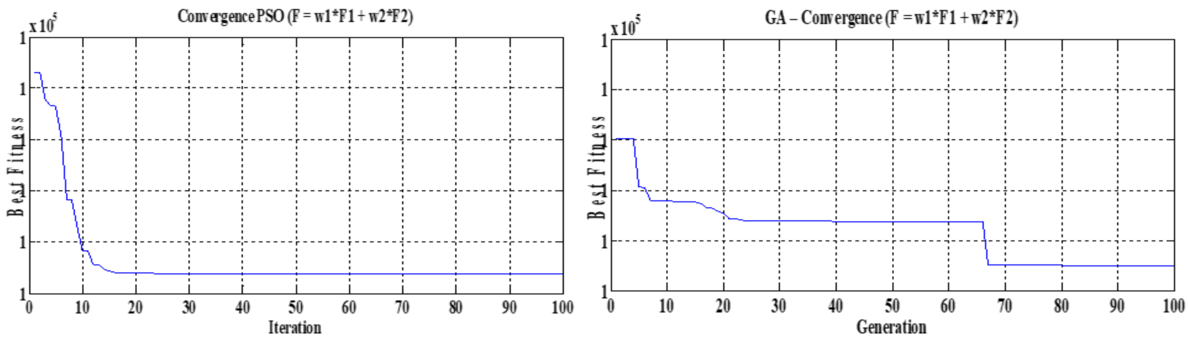


Figure 1. Convergence curve of the PSO and GA algorithm for WT placement optimization

The Figure 2 presented in the form of a radar chart, illustrates the impact of various wind turbine placement strategies on two key performance indicators in a distribution network: power losses and the stability index. Three scenarios are compared: the base case without optimization IEEE 14 bus, optimization using the GA, and optimization using the PSO algorithm. The base case exhibits the highest power losses, reaching 10.5990 kW, which highlights the need for effective optimization methods. Among the approaches, the PSO algorithm demonstrates superior performance by reducing power losses significantly to 1.6251 kW and improving the system stability index to 0.6384. Although the GA also proves effective, its performance is slightly inferior to that of PSO in this configuration. This comparison emphasizes the importance of selecting an appropriate optimization technique to ensure efficient integration of wind turbines into power distribution systems, both in terms of energy efficiency and network stability.

The Figure 3 illustrates the voltage profiles across different buses under two distinct scenarios. The first scenario, shown in red, represents the network without any optimization. In this case, the voltages at buses 9 and 10 are 1.04 [p.u.] and 1.038 [p.u.], respectively. In contrast, the second scenario depicted in green reflects the using of the PSO algorithm. Under this configuration, a slight improvement in voltage levels is observed at the same buses, increasing to 1.05 and 1.048 [p.u.], respectively.

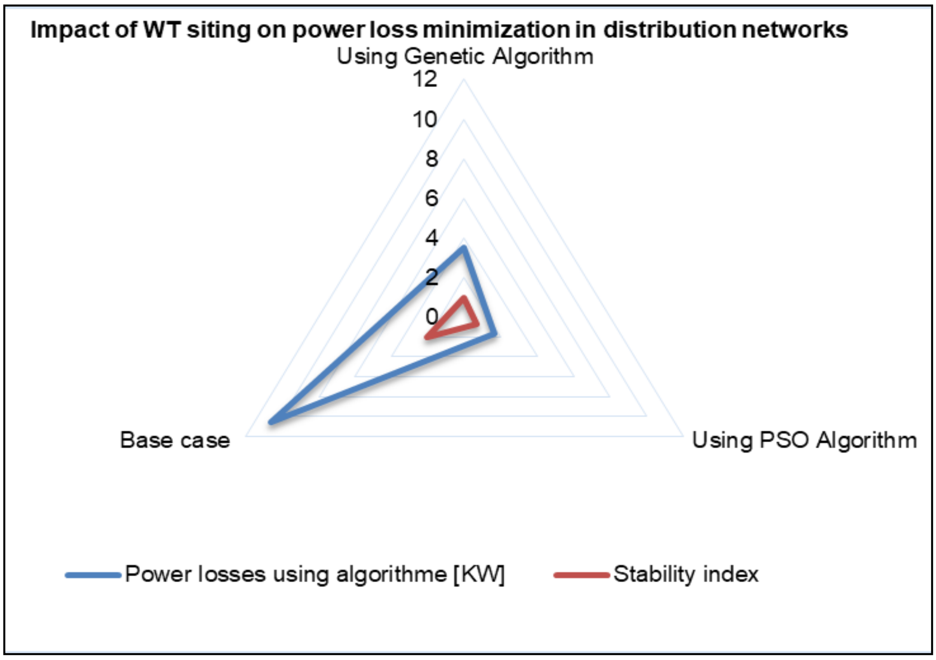


Figure 2. Comparative analysis of WT placement impact on power losses and network stability using GA and PSO algorithms

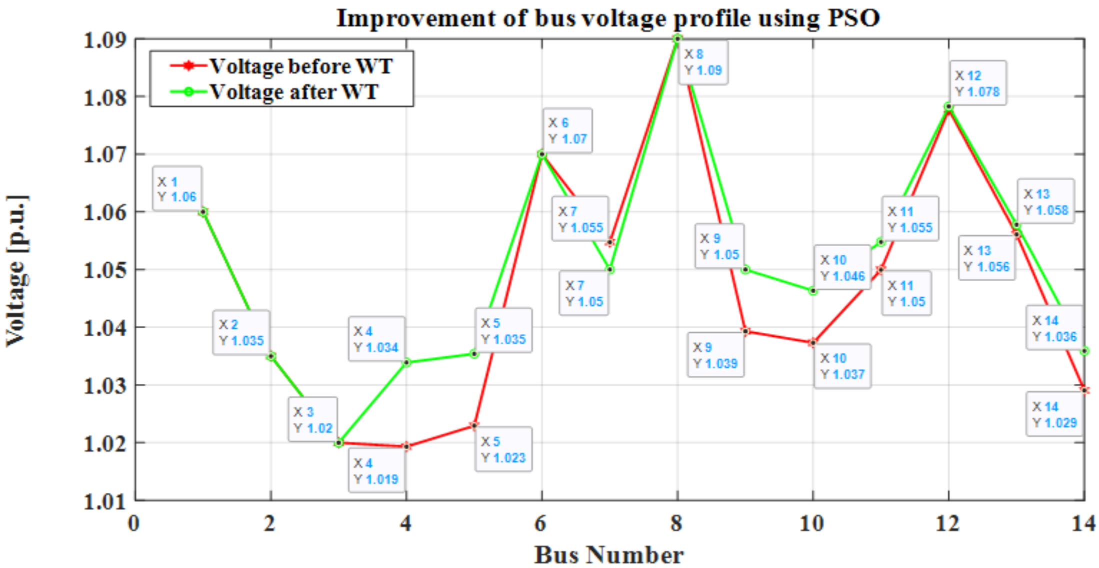


Figure 3. Voltage profile analysis of IEEE 14-bus system with optimal wind turbine placement via PSO

The Figure 4 illustrates the second scenario, where the GA was applied. The voltage levels, displayed in green, reflect the system response following the placement of the wind turbine at its optimal location. In the base case, the voltages at buses 4 and 5 were initially 1.02 and 1.025 [p.u.], respectively. Following optimization, these values increased slightly to 1.03 and 1.035 [p.u.].

Using the PSAT/MATLAB platform, the wind turbines were successfully integrated into the IEEE 14-bus network, as illustrated in Figure 4. The installed wind parks are shown in Figure 5. The wind parks connected to buses 3, 6, and 7 each have an apparent power rating of 5 MVA, while the park located at bus 9 has an apparent power of 3.9 MVA. In order to meet standard requirements, the connection between buses 03 and 17 was made using identical step-down transformers. Their technical specifications are detailed in the Figure 6.

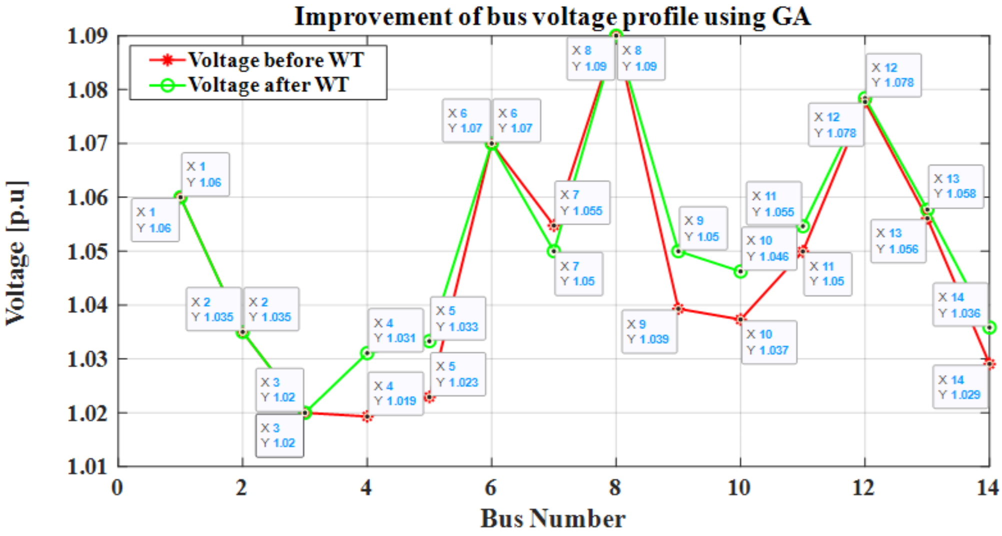


Figure 4. Voltage profile analysis of IEEE 14-bus system with optimal wind turbine placement via GA

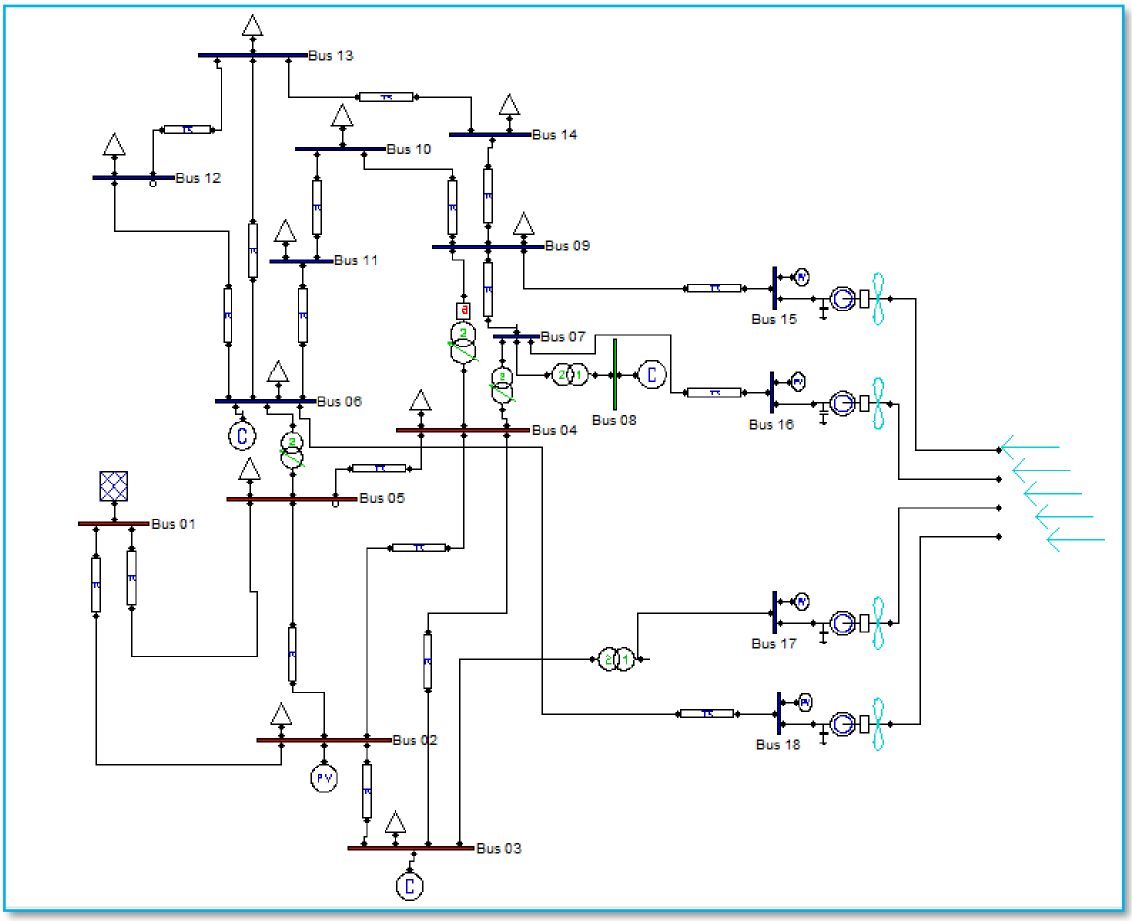


Figure 5. Configuration of the IEEE 14-bus system with four integrated wind parks

To closely reflect real-world conditions, the Weibull distribution was employed in this study using the PSAT tool [18]–[20]. This distribution is widely used to statistically model wind speed variability and is defined by the following:

$$f(v) = \frac{k}{c}(\frac{k}{c})^{k-1}e^{-(\frac{v}{c})^{k}} \quad (14)$$

with: $f(v)$: the probability density function of wind speed v, k is the shape parameter and c is the scale parameter [21]–[25].

To validate the performance of the PSO algorithm, a realistic wind speed evolution was generated using the PSAT environment in MATLAB. As illustrated in Figure 7, the wind speed profile obtained from the Weibull probability distribution adopted in this study. A nominal wind speed of 14 m/s was assumed, meaning that a per-unit (p.u.) value of 1 corresponds to 14 m/s. The resulting profile exhibits significant short-term fluctuations, which are characteristic of natural wind variability. Such temporal variations play a crucial role, as they directly influence the dynamic behavior of wind energy conversion systems and, consequently, impact both the transient and steady-state performance of the electrical network. Incorporating these realistic wind patterns is therefore essential to accurately assess the robustness of the power system under renewable energy penetration.

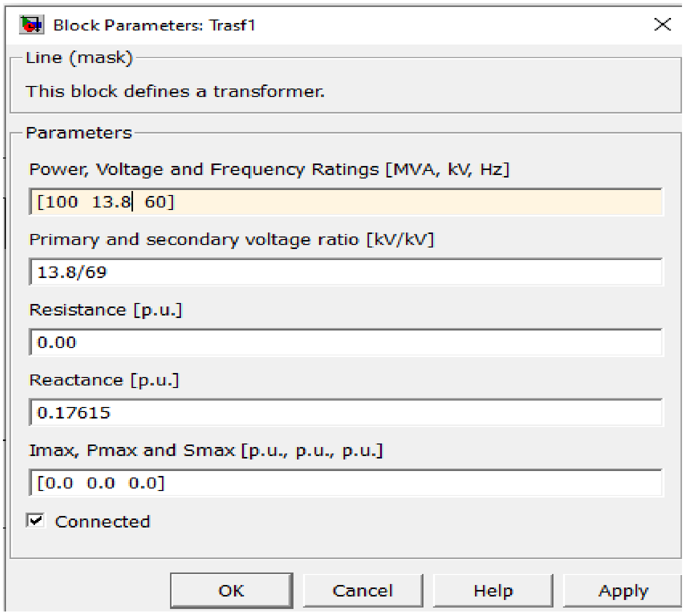


Figure 6. Step-down transformer characteristics

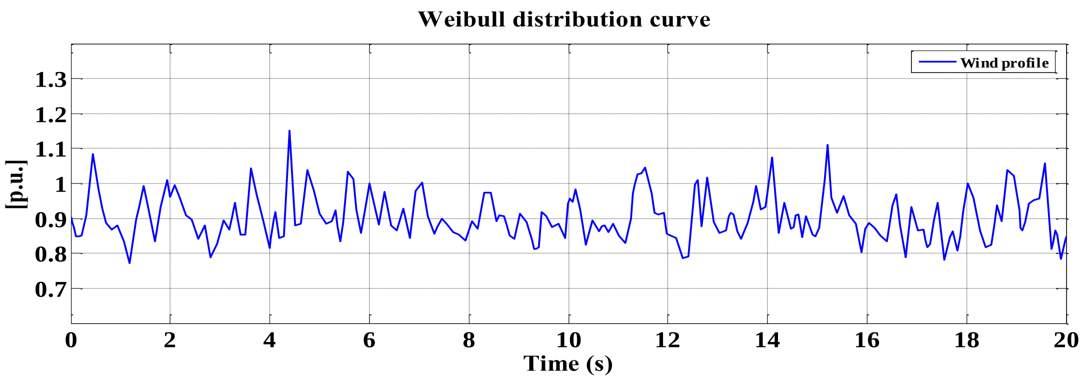
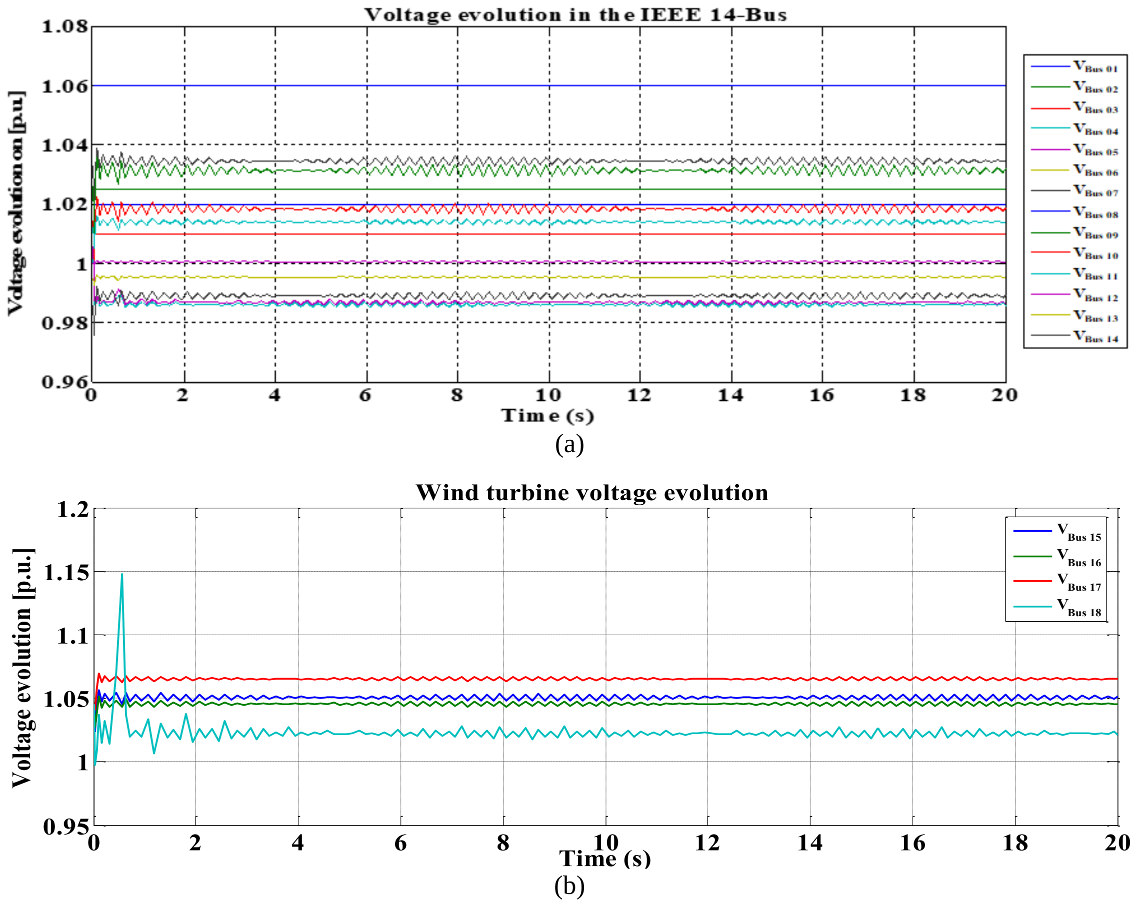


Figure 7. Wind speed profile generated using the Weibull istribution

Figure 8 illustrates the dynamic voltage response of the IEEE 14-bus system over a 20-second simulation horizon. Figure 8(a) shows the dynamic evolution of voltage magnitudes at the 14 buses of the IEEE 14-bus benchmark system over a simulation horizon of 20 seconds. The network demonstrates a globally stable behavior, with voltages contained within a relatively narrow band, typically between 0.98 p.u.

and 1.04 p.u., which falls within acceptable operational limits for distribution systems. An initial transient response is observed during the first instants of the simulation, corresponding to the establishment of the steady-state operating point. Among the buses, Bus 7 reaches the highest voltage level, approximately 1.035 p.u., a phenomenon that can be attributed to its proximity to a generation source or favorable network topology. In contrast, buses 10, 11, and 14 exhibit the lowest voltage amplitudes, close to 0.99 p.u., a behavior commonly associated with peripheral buses subjected to higher load or longer electrical distances from generator nodes. Despite these variations, the overall voltage profile remains well regulated, confirming that the network maintains satisfactory static and dynamic stability under the studied conditions.

Figure 8(b) depicts the voltage trajectories at buses 15, 16, 17, and 18, which correspond to the terminals of the integrated wind turbine units. The curves reveal a more pronounced transient period at the onset of the simulation, particularly noticeable at bus 15, where a significant initial fluctuation occurs before stabilization. As the system evolves, the voltages at all four buses gradually converge towards steady-state values. Bus 17 consistently maintains the highest and most stable voltage level, around 1.05 p.u., indicating a favorable electrical environment or strong coupling with the main grid. Conversely, bus 15 stabilizes at the lowest voltage level, approximately 1.01 p.u. The remaining buses, 16 and 18, display intermediate behaviors with limited oscillatory content. The collective trends observed in these voltage trajectories demonstrate that despite the inherent variability of the wind resource the integrated network is capable of maintaining reliable voltage levels and achieving a stable operating condition.



(a)

(b)

Figure 8. Dynamic voltage response of the system: (a) voltage profiles of the IEEE 14-bus dystem and (b) wind turbine bus

5. CONCLUSION

In summary, this study demonstrates that the optimal integration of wind turbines into distribution networks significantly enhances system performance by reducing active power losses and improving voltage stability. Through a comparative application of GA and PSO, the results confirm the superiority of metaheuristic methods over conventional analytical approaches, with PSO offering greater robustness and faster convergence. The work introduces several key contributions, including a simultaneous siting-and-sizing optimization framework and the use of an advanced voltage stability index based on the reduced Q–V Jacobian. These findings are directly relevant to electrical engineering practice, as they support improved network reliability, reduced component stress, and more efficient smart grid planning. Finally, the study highlights the potential of extending this approach by coordinating renewable integration with FACTS devices such as STATCOM or UPFC to further strengthen voltage control, reactive power support, and overall grid flexibility in future intelligent power systems. In summary, this study has shown that the optimal integration of wind turbines into distribution networks can significantly enhance system performance by reducing active power losses and improving voltage stability. Through the application of two metaheuristic optimization methods GA and PSO the results demonstrate the advantage of heuristic-based techniques over conventional analytical approaches, with PSO providing superior robustness and faster convergence.

This work contributes several scientific advances: a simultaneous siting-and-sizing optimization framework for wind turbines, the use of an advanced stability index derived from the reduced Q–V Jacobian and a quantitative comparison of GA and PSO on the IEEE 14-bus system. The findings have clear relevance for electrical engineering practice. Loss reduction and improved voltage stability directly enhance network reliability and power quality, while the proposed optimization strategy supports smarter planning of renewable integration in future distribution networks. Looking ahead, combining renewable energy units with FACTS devices such as STATCOM or UPFC represents a promising direction for strengthening voltage control, power flow regulation, and overall smart grid flexibility.

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BIOGRAPHIES OF AUTHORS

Taha Rachdi is currently pursuing a Ph.D. in Electrical Engineering at the University of Tunis El Manar, Tunisia. An active member of the Research Laboratory in Automation (LARA) at the National Engineering School of Tunis, he has also contributed to research at the Laboratory of Innovative Technologies at the University of Picardie Jules Verne, France. Graduating as an electrical engineer from the National Engineering School of Monastir in 2015, Taha has gained valuable experience by holding several industrial positions in the fields of electrical engineering and industrial maintenance. Over the years, he has led projects focused on innovative technologies, particularly in the renewable energy sector, delivering practical solutions to the challenges of industrial maintenance and sustainable development. With his strong technical skills, Taha combines in-depth knowledge of electrical engineering with research expertise, enabling him to make significant contributions to cutting-edge projects. His research interests include smart grid, power system, wind turbine optimization power losses, methaheuristic optimization approachs. He can be contacted at email: taha.rachdi@enit.utm.tn.

Yahia Saoudi is a Doctor-Engineer with extensive experience in project management, particularly in electrotechnics and industrial systems. His expertise encompasses energy systems, including distribution networks (LV, MV), transmission networks (HV, EHV), energy dispatching, and Smart Grids. He focuses on optimization and efficiency, working on reducing losses in electrical networks and optimizing multi-source renewable energy. Yahia is well-versed in advanced technologies such as multi-level inverters, HVDC & HVAC systems, reactive power compensation, and synchronous compensation systems (FACTS). His work in renewable energy includes studying onshore and offshore wind turbines, solar panels, and energy storage systems. Additionally, he specializes in system analysis, modeling, and control of electrical systems, with a focus on harmonic reduction and dynamic performance of networks. He has developed algorithms for electrical management and data processing in microgrids. From September 2010 to June 2022, he supervised academic projects at the Institute of Applied Sciences and Technology in Sousse, Tunisia, while also engaging in industrial interventions and purely industrial projects. He can be contacted at email: saoudi.yahia@gmail.com.

Larbi Chrifi-Alaoui currently works at Université de Picardie Jules Verne, where he serves as the Head of the Department of Electrical Engineering and Industrial Computing. Larbi Chrifi-Alaoui received the Ph.D. degree in automatic control from the Ecole Centrale de Lyon, Ecully, France, in 1994. Since 1999, he has held a teaching position in automatic control at the Aisne University Institute of Technology, Université de Picardie Jules Verne, Cuffies-Soissons, France, where, from 2004 to 2010, he was the Head of the Department of Electrical Engineering and Industrial Informatics. His research interests include linear and nonlinear control theory, including sliding mode control, adaptive control, and robust control, with applications to electric drive and mechatronics systems. He can be contacted at email: larbi.alaoui@u-picardie.fr.

Ayachi Errachdi is currently an Associate Professor of Electrical Engineering at the University of Kairouan, Tunisia. He holds the position of Director at the Higher Institute of Applied Sciences and Technology of Kairouan (ISSATK). His scientific interests are related to artificial neural network models, direct and indirect adaptive control, and nonlinear observers. He has published numerous articles in international journals. He can be contacted at email: errachdi_ayachi@yahoo.fr.