OPTIMAL DESIGN OF WIND ENERGY GENERATION IN ELECTRICITY DISTRIBUTION NETWORK BASED ON TECHNICAL-ECONOMIC PARAMETERS

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Abstract:

In order to satisfy electricity customers and avoid some environmental constraints and problems, the transition to renewable energy sources has become increasingly important given their advantages and benefits, such as reducing pollution and improving the reliability of the targeted distribution system. In this paper, several state-of-the-art metaheuristic optimisation algorithms are used to investigate the optimal setting and sizing of wind turbines (WTs) when connected to the electricity distribution network (EDN). The selected algorithms were implemented to optimise and minimise a multi-objective function (MOF) considered as the sum of the techno-economic parameters of total active power loss (TAPL), total voltage deviation (TVD) and investment cost of the WTG (ICWTG) when the daily uncertainties and variations of the load-source powers are taken into account. The effectiveness of the selected algorithms was validated on the two standard test systems IEEE 33-bus and 69-bus. The simulation results in this paper showed the superiority of the Gorilla Troops Optimizer (GTO) algorithm compared to other new metaheuristic optimisation algorithms in terms of providing the best optimised results. Accordingly, the GTO algorithm showed excellent effectiveness and robustness in determining the optimal setting and sizing of the WTG units in EDN. Thus, the daily active power losses were reduced to 1,415 MWh for the first test system and 1,072 MWh for the second test system, while also improving the bus voltage profiles and favouring the investment costs of the installed WTG units, all with daily uncertainties in terms of load demand and WTG power variations.

1 Introduction

The increasing use of electricity, the increased cost of building large power generation plants and the significant pollution associated with electricity generation have led to decentralised generation (DG), based mainly on renewable energy sources (RES), representing a major shift in the power generation sector. In addition to providing affordable and clean energy, distributed generation based on wind turbines (WTG) offers numerous significant benefits, such as minimising electricity losses, purchasing electricity, reducing voltage deviations and improving power quality [1]. In the context of smart grids, optimal power flow and renewable energy planning in the electricity distribution network (EDN) are the most common optimisation tasks. On the other hand, metaheuristic methods are a subset of optimisation algorithms that are theoretically best able to address the challenges of smart grid optimisation and achieve higher quality results than conventional methods

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The challenge of optimal WT allocation is to calculate the best position and size of DG units to be installed in an existing EDN based on various technical constraints [3]. In [12], the Manta-Ray Foraging Optimisation (MRFO) algorithm was applied to reduce the total cost, pollutant emissions and voltage fluctuations, in [13] the Modified Equilibrium Algorithm (MEA) was applied to reduce the power generation cost and active power loss, and in [14] the Aquila Optimizer Algorithm (AOA) was applied to minimise the heat generation cost. The authors in [15] proposed a Modified Symbiotic Organisms Search (MSOS) algorithm based on several technical and economic objectives, the Chaotic Sequence Spotted Hyena Optimizer (CS-SHO) algorithm was used to minimise losses and improve the voltage age profile based on the voltage stability index in [16], the New Chaotic Stochastic Fractal Search (CSFS) algorithm was used to minimise power loss in [17], Quasi-Oppositional Grey Wolf Optimizer (QOGWO) algorithm to minimise the total annual economic losses with maximum techno-economic benefit in [18], Chaotic Differential Evolution (CDE) technique to reduce various technical and economic indices in [19], Artificial Electric Field Algorithm (AEFA) to reduce power loss and voltage deviation in [20]. Application of Salp Swarm Algorithm (SSA) to reduce active power losses in [21], Student Psychology-Based Optimisation (SPBO) algorithm with cost analysis considering load models in [22]. Chimp Optimisation Algorithm (COA) was used to reduce effective losses in chimpanzees in [23], and Grey Wolf Optimizer (GWO) algorithm was used to minimise simultaneous indices of different technical parameters considering seasonal uncertainties in [24]. Recently, an Adaptive PSO algorithm was developed to reduce the annual energy losses and voltage fluctuations in power lines [25], and Applied the Transient Search Optimisation (TSO) algorithm was used to minimise power losses and improve voltage stability [26]. In this work, the authors have applied numerous new nature-inspired metaheuristic algorithms that have been used to address nonlinear optimisation problems for the integration of WTG units in EDN: Dingo Optimization Algorithm (DOA) in [27], Archimedes Optimization Algorithm (AOA) in [28], Coot Optimization Algorithm (COA) in [29], Mayfly Optimization Algorithm (MOA) in [30], Smell Agent Optimization (SAO) algorithm in [31], Equilibrium Optimization Algorithm (EOA) in [32], African Vulture Optimization (AVO) algorithm in [33], Gorilla Troops Optimizer (GTO) algorithm in [34].

The applied algorithms are tested and validated for two different standard EDNs, IEEE 33-bus and IEEE 69-bus. The proposed method is formulated in a Multi-Objective Function (MOF). The objectives of the study reflect the techno-economic aspects of total active power losses (TAPL), total voltage deviation (TVD) and investment costs for the WTGs installed in the tested distribution system (ICWTG) under the daily uncertainties of load-source powers.

2 Problem formulation and constraints

2.1 The multiple-objective functions

The multiple-objective functions (MOF) resolved in this paper were devoted to searching and identifying the optimal setting and size of multiple WTG units in an electricity distribution system. These equations show their mathematical formulation:

$$MOF = Minimize\sum_{i=1}^{N_{bus}}\sum_{j=2}^{N_{bus}}\sum_{i=1}^{N_{WTG}}\left[TAPL_{i,j} + TVD_j + IC_{WTG,i}\right] \tag{1}$$

The TAPL is formulated as follows [11-18], [35]:

$$TAPL_{i,j} = \sum_{i=1}^{N_{bus}}\sum_{j=2}^{N_{bus}} APL_{i,j} \tag{2}$$

$$APL_{i,j} = \alpha_{ij}\left(P_iP_j + Q_iQ_j\right) + \beta_{ij}\left(Q_iP_j + P_iQ_j\right) \tag{3}$$

$$\alpha_{ij} = \frac{R_{ij}}{V_i V_j} \cos\left(\delta_i - \delta_j\right) \tag{4}$$

$$\beta_{ij} = \frac{R_{ij}}{V_i V_j} \sin\left(\delta_i + \delta_j\right) \tag{5}$$

where, R_{ij} refers to the resistance in the distribution line, N_{bus} is the number of buses. (δ_i, δ_j). (P_i, P_j) and (Q_i, Q_j) is the active and reactive powers, respectively, and (V_i, V_j) is the bus voltages.
The TVD is formulated as in [36, 37]:

$$TVD_j = \sum_{j=2}^{N_{bus}} \left|1 - V_j\right| \tag{6}$$

The investment cost IC_{WTG} of WTG means the total capital, operating and maintenance cost, of the WTG's installed units [38]:, and is formulated as:

$$IC_{WTG} = \sum_{i=1}^{N_{WTG}} C_{WTG}.P_{WTG,i} \tag{7}$$

where, N_{WTG}, C_{WTG}, and P_{WTG} are the number of installed WTG units, the cost of one WTG in \$/kW, and the active injected power by WTG in kW, respectively.
The IC_{WTG} represents capital cost ($C^{WTG}{}_{Capital}$), operating, and maintenance cost ($C^{WTG}{}_{O\&M}$) [38]:

$$C_{WTG} = C^{WTG}_{Capital} + C^{WTG}_{O\&M} \qquad (\$/kW) \tag{8}$$

The capital cost ($C^{WGT}{}_{Capital}$) is 5800 \$/kW, comprising turbines, converters, transportation, and installation. The cost of maintenance ($C^{WTDG}{}_{O\&M}$) is 40 \$/kW.

2.2 Equality constraints

$$P_G + P_{WTG} = P_D + P_{Loss} \tag{9}$$

$$Q_G + Q_{WTG} = Q_D + Q_{Loss} \tag{10}$$

where, P_G and Q_G are the generator powers; P_{WTG} *and* Q_{WTG} are the total powers of WTG. P_D and Q_D are total load powers. P_{Loss} and Q_{Loss} are the total active and reactive losses.

2.3 Inequality constraints of distribution line

$$V_{\min} \le \left|V_i\right| \le V_{\max} \tag{11}$$

$$\left|1 - V_j\right| \le \Delta V_{\max} \tag{12}$$

$$\left|S_{ij}\right| \le S_{\max} \tag{13}$$

where, V_{max} *and* V_{min} are the maximum and minimum specified voltages; ΔV_{max} is the maximum voltage drop. V_1 is sub-stations voltage =1.0 p.u. S_{ij} is the apparent power in *ij*. S_{max} is the maximum apparent power.

2.4 Inequality constraints of WTG units

$$P_{WTG}^{\min} \leq P_{WTG} \leq P_{WTG}^{\max} \tag{14}$$

$$Q_{WTG}^{\min} \leq Q_{WTG} \leq Q_{WTG}^{\max} \tag{15}$$

$$\sum_{i=1}^{N_{WTG}} P_{WTG}(i) \leq \sum_{i=1}^{N_{bus}} P_D(i) \tag{16}$$

$$\sum_{i=1}^{N_{WTG}} Q_{WTG}(i) \leq \sum_{i=1}^{N_{bus}} Q_D(i) \tag{17}$$

$$2 \leq WTG_{Position} \leq N_{Bus} \tag{18}$$

$$N_{WTG} \leq N_{WTG.\max} \tag{19}$$

$$n_{WTG,i} / Location \leq 1 \tag{20}$$

$$PF_{WTG}^{\min} \leq PF_{WTG} \leq PF_{WTG}^{\max} \tag{21}$$

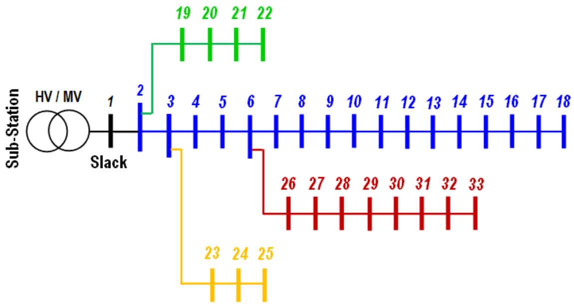
$$PF_{WTG} = \frac{P_{WTG}}{\sqrt{P_{WTG}{}^2 + Q_{WTG}{}^2}} \tag{22}$$

where, (P_{WTG}^{min}, Q_{WTG}^{min}, P_{WTG}^{max}, Q_{WTG}^{max}) are limits of WTG powers. ($WTG_{Position}$, N_{WTG}, $N_{WTG.max}$) are the WTG position, number, and maximum units per location at bus *i*, respectively. PF_{WTG} is the power factor of WTG.

3 Test networks, comparisons, and results

3.1 Test networks

The chosen meta-heuristic algorithms were validated and applied on the two standards IEEE 33-bus, and IEEE 69-bus using the MATLAB software (version 2020b) with a PC containing a processor of Intel Core i5, 3.4 GHz, and 8 GB of RAM. The two standard test systems are demonstrated using their line diagrams in Figure 1, where the applied base voltage is 12.66 kV in both of them. The IEEE 33-bus comprised 33 buses and 32 branches, including a total load of 3715.00 kW and 2300.00 kVar, while the IEEE 69-bus comprised 69 buses and 68 branches, including a total load of 3790.00 kW, 2690.00 kVar [39, 40].



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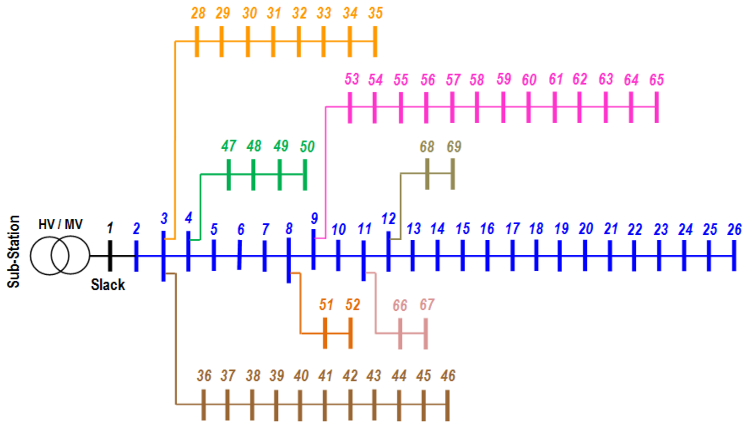

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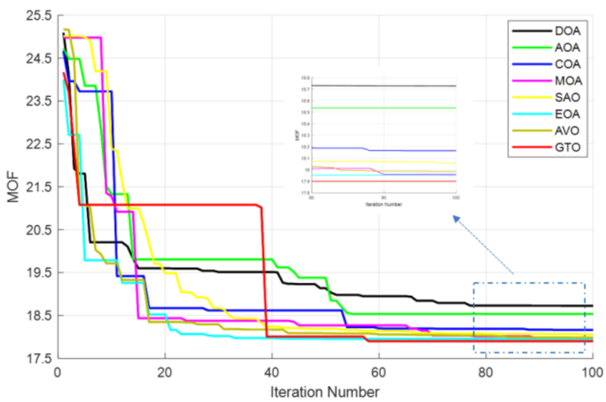
Figure 1. Single line diagram of tested EDN:
a - IEEE 33-bus; b - IEEE 69-bus

3.2 Assessment of the applied algorithms

Figure 2 represents the convergence curves of the applied algorithms for both test systems EDNs while optimally integrating the WTG units. From Figure 2, it is remarkable that in terms of analyzing the results, the GTO algorithm provided the best convergence curves. Notably, the GTO algorithm needs more than 50 iterations to converge. On the other hand, the MOA algorithm provided the best curves regarding the convergence speed for both cases which can obtain a solution near its best solution after only 20 iterations. The DOA and AOA algorithms are the worst regarding MOF results and convergence speed. In addition, the EOA and AVO algorithms show an excellent convergence speed, and their results are close to the optimal values obtained by the GTO algorithm.



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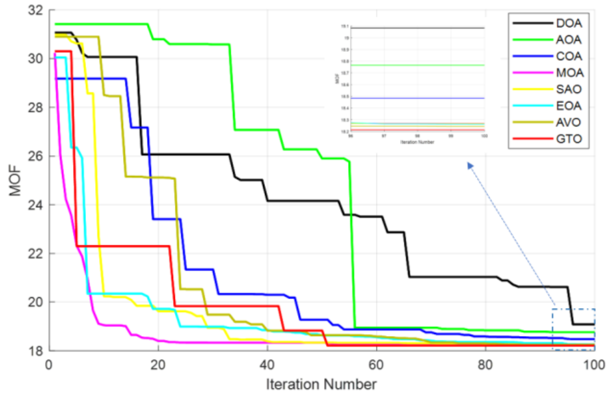

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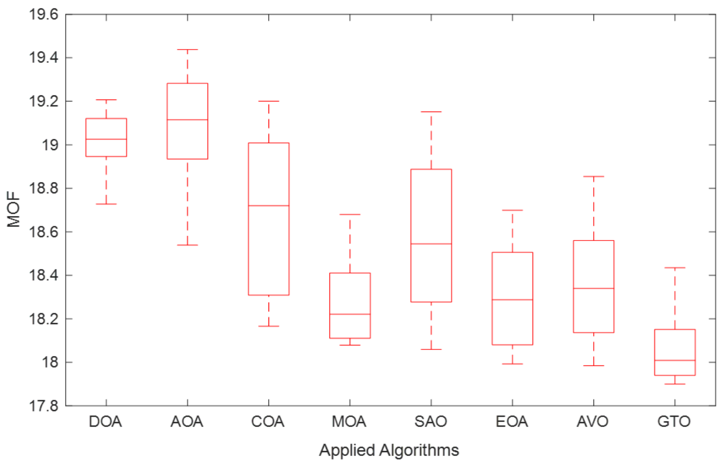
Figure 2. The convergence curves of the applied algorithms :
a - IEEE 33-bus; b - IEEE 69-bus

Figure 3 illustrates the Boxplot of the applied algorithms after 20 executions for both test systems while integrating the WTG units.



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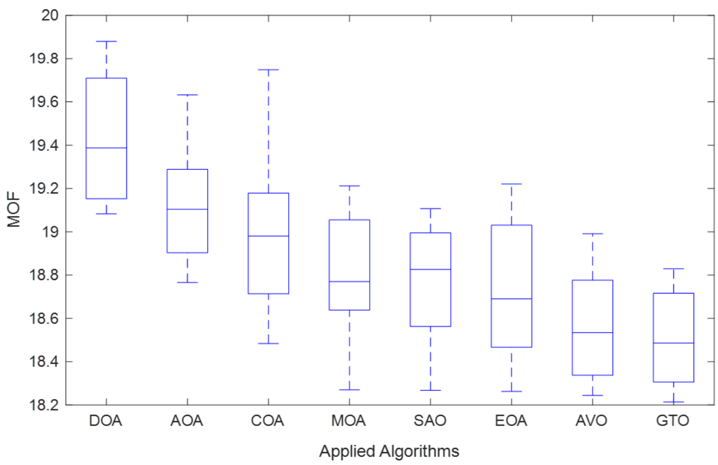


(b)

Figure 3. Boxplot of MOF using applied algorithms:
a - IEEE 33-bus; b - IEEE 69-bus

The analysis of Figure 3 reveals that the results of 20 runs of the GTO algorithm are very close, one to the other. The DOA algorithm results for IEEE 33-bus are also close to each other, but in terms of quality, they seem the worst. The results whose far from each other in the IEEE 33-bus are obtained by applying the COA and then ASO algorithms. On the other hand, for IEEE 69-bus, the results of COA and EOA algorithms are also the most distant from each other. Tables 1 and 2 show the statistical analysis for the selected metaheuristic algorithms applied for the optimal placement of the WTG units into both test systems EDNs. As mentioned in the tables, the statistical analysis was carried out after 20 executions for each applied algorithm to validate their efficiency and effectiveness. Hence, based on the selected indices: Best, Worst, Mean, Standard Deviation (SD), and CPU Time. The analysis summary shows that the GTO algorithm was superior and showed the best efficiency in all statistical analysis sides for both systems EDNs. The GTO algorithm provided and delivered the best and the smallest values of MOF by 18.214 and 18.829, respectively. Also, the minimum Mean and SD values of 18.515 and 0.207, including the second quickest CPU Time of 166.04 seconds after the SAO algorithm reached its optimal solution only after 164.33 seconds.

Table 1. Analysis of the algorithms results for IEEE 33-bus

Applied Algorithm	***Worst***	***Mean***	***Best***	***SD***	***CPU Time (sec)***
DOA	19.207	19.018	18.727	0.131	90.22
AOA	19.438	19.092	18.538	0.258	93.28
COA	19.200	18.685	18.166	0.363	91.80
MOA	18.679	18.279	18.079	0.177	82.42
SAO	19.151	18.581	18.059	0.349	99.30
EOA	18.699	18.295	17.992	0.231	89.89
AVO	18.854	18.366	17.984	0.260	93.28
GTO	18.434	18.064	17.900	0.152	86.88

Table 2. Analysis of the algorithms results for IEEE 69-bus

Applied Algorithm	***Worst***	***Mean***	***Best***	***SD***	***CPU Time (sec)***
DOA	19.879	19.430	19.082	0.282	162.19
AOA	19.631	19.115	18.765	0.250	158.48
COA	19.748	18.970	18.483	0.321	172.30
MOA	19.212	18.802	18.269	0.272	174.03
SAO	19.107	18.763	18.267	0.275	164.33
EOA	19.221	18.739	18.262	0.316	169.84
AVO	18.991	18.575	18.244	0.240	189.43
GTO	18.829	18.515	18.214	0.207	166.04

Tables 3 and 4 illustrate the optimal results after applying the different metaheuristic algorithms to integrate multiple WTG units in both EDNs. Both results from Tables 3 and 4 revealed the effectiveness and robustness of all the applied and selected metaheuristic algorithms in providing perfect results of MOF minimization for both test systems EDNs. Hence, the comparison clearly shows that the GTO algorithm represents the best technique that delivered the minimum MOF of 17.900 for the IEEE 33-bus and 18.214 for the IEEE 69-bus optimally integrated with the WTG units.

Table 3. Optimal results using the IEEE 33-bus

Applied Algorithm	***Bus***	***P_{WTG}* (MW)**	***Q_{WTG}* (MVar)**	***APL* (MWh)**	***ΔAPL* (%)**	***VD* (p.u.)**	***IC_{WTG}* (M$)**	***MOF***
DOA	2	0.0134	0.0101	1.483	58.30	20.388	9.009	18.727
	13	0.7277	0.5457					
	33	0.8017	0.5092					
AOA	2	0.0132	0.0099	1.493	58.02	20.581	9.169	18.538
	17	0.6091	0.3750					
	29	0.9478	0.7109					
COA	15	0.5554	0.3418	1.459	58.98	19.860	9.649	18.166
	17	0.1035	0.0381					
	30	0.9934	0.7451					
MOA	12	0.1062	0.0500	1.449	59.26	20.168	8.906	18.079
	15	0.6544	0.4131					
	31	0.7645	0.5734					
SAO	15	0.6114	0.4333	1.421	60.05	20.111	9.147	18.059
	18	0.0950	0.0101					
	30	0.8598	0.6449					
EOA	10	0.0139	0.0100	1.458	59.01	20.159	8.845	17.992
	15	0.7301	0.4487					
	31	0.7707	0.5781					
AVO	15	0.7346	0.4529	1.453	59.15	20.127	8.894	17.984
	31	0.7336	0.5502					
	33	0.0549	0.0333					
GTO	11	0.4486	0.3365	1.415	60.21	19.830	9.157	17.900
	17	0.3874	0.1973					
	32	0.7320	0.5490					

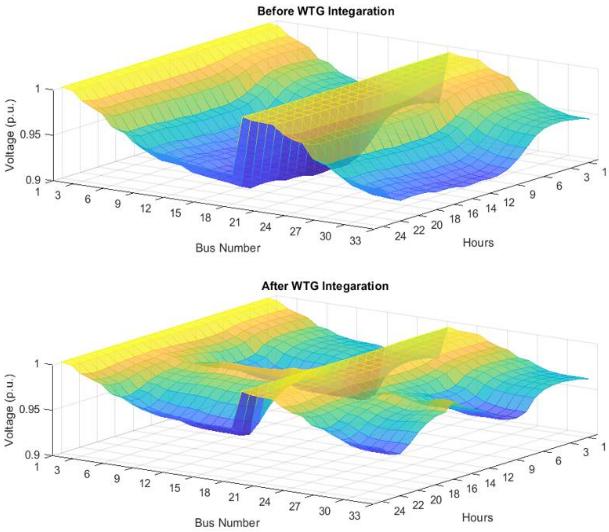
Table 4. Optimal results using the IEEE 69-bus

Applied Algorithm	Bus	P_{WTG} (MW)	Q_{WTG} (MVar)	APL (MWh)	ΔAPL (%)	VD (p.u.)	IC_{WTG} (M$)	MOF
	15	0.5972	0.3998					
DOA	61	0.3127	0.2001	1.329	64.88	19.841	11.027	19.082
	65	0.9783	0.6403					
	26	0.3274	0.2313					
AOA	60	0.3569	0.2487	1.104	70.08	19.980	10.981	18.765
	60	1.1960	0.8945					
	13	0.0155	0.0116					
COA	21	0.4063	0.2597	1.275	66.31	21.042	10.145	18.483
	63	1.3155	0.9276					
	20	0.4819	0.3170					
MOA	58	0.0113	0.0085	1.273	66.36	20.611	10.183	18.269
	62	1.2506	0.9379					
	23	0.4525	0.2925					
SAO	62	1.2661	0.9496	1.273	66.36	20.663	10.154	18.267
	69	0.0201	0.0143					
	21	0.4157	0.2826					
EOA	61	1.1485	0.8613	1.228	67.55	20.812	10.122	18.262
	65	0.1691	0.1222					
	21	0.4003	0.2817					
AVO	24	0.0704	0.0338	1.281	66.15	20.641	10.075	18.244
	62	1.2545	0.9409					
	24	0.4394	0.2865					
GTO	61	0.4865	0.3649	1.072	71.67	20.690	10.010	18.214
	64	0.7882	0.5912					

Also, the GTO revealed excellent efficiency in providing even the minimum of each parameter on its own. Where minimized the APL and VD until 1.415 MWh and 19.830 p.u. for the first test system, besides the APL and IC_{WTG} until 1.072 MWh and 10.01 M$ for the second test system. Another remark is that the EOA and DOA algorithms delivered the minimum values of IC_{WTG} and VD until 8.845 M$ and until 19.84 p.u. for the first and the second test systems, respectively.

3.3 Analysis of the voltage efficiency using the GTO algorithm

Figure 4 represents the daily voltage profile variation for both cases, before and after the optimal integration of WTG units into both EDNs using the GTO algorithm. From both Figures 4, it is evident that the daily values of the voltage profiles have been enhanced directly after the installation of WTG units in the two test systems EDNs. The injection of both reactive and active powers in different optimal locations based on the GTO algorithm was the reason for those exemplary achievements. The improvement of voltage profiles was reversed to the daily depreciation of the voltage deviation values, which was until 19.830 p.u. for IEEE 33-bus and until 20.69 p.u. for IEEE 69-bus.



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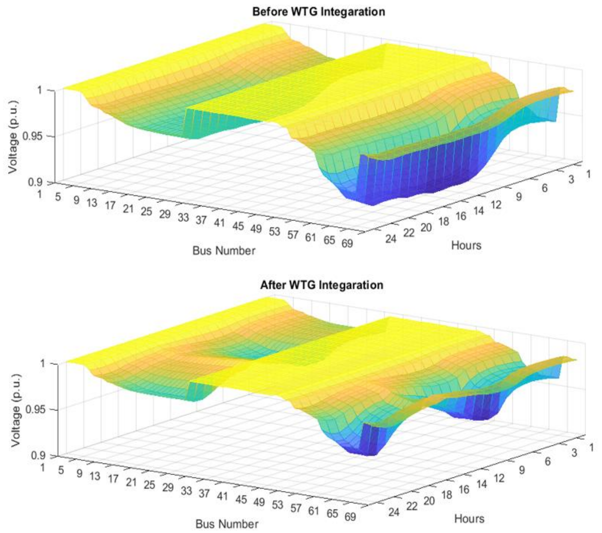
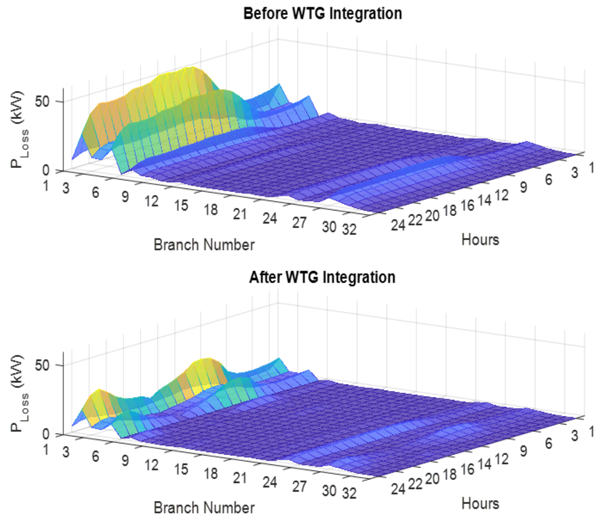


(b)

Figure 4. The daily bus voltages profile variation:
a - IEEE 33-bus; b - IEEE 69-bus

Another remark is that the voltage profiles ameliorating was registered almost along the days' hours, as long as the WT provides their power generation for 24 hours and with no interruptions. Besides, after the optimal integration of the WTG units, the voltage profiles got raised above the value of 0.95 p.u. in all buses for the two test systems EDNs. For the reason that the voltage value of 0.95 p.u. represents one of the voltage constraints that have been respected while optimising the GTO algorithm. Figure 5 represents the daily variation of active power loss in both studied network branches for the WTG units' optimal integration.



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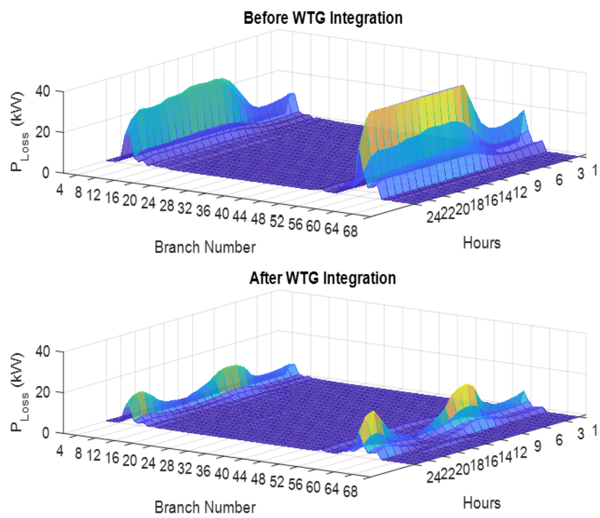

(b)

Figure 5. The daily active power loss variation in branches:
a - IEEE 33-bus; b - IEEE 69-bus

The optimal presence of the WTG units affected the technical parameters of the two test systems. Meanwhile, mentioning the 3D graphics in Figure 5 of the daily active power loss in all branches. The daily active power loss in all branches significantly minimises the two test systems after optimal installation of the WTG units along all the day's hours. The WTG units caused a depreciation in the total value of daily active power loss from 3557.02 kWh to 1415.50 kWh, including a rate of reduction of 60.21 % for the first EDN, also from 3785.31 kWh until 1072.00 kWh, including a rate of reduction of 71.67 % for the second EDN. That minimization impact was related to the WTG units' production of both reactive and active generated powers for both EDNs, almost throughout the day.

4 Conclusion

In this work, the application of various new metaheuristic optimisation algorithms to solve the problem of optimal integration of WTs into two standard EDNs was investigated. The optimisation was performed by minimising several objective functions, which were considered as total techno-economic parameters, taking into account the daily uncertainties of the load demand and the source power fluctuations. Among the applied algorithms, the GTO algorithm proved to be the most reliable and effective, as it provided the best results for both EDNs, including a demanding behaviour and fast convergence properties when reaching the optimal solutions. The results also highlight the efficiency of the optimal presence of WEA, which provides a noticeable performance improvement for both test systems. This is because WTG generation is present for most of the day and is dependent on wind speed. They also provide both reactive and active power. However, the optimisation led to an improvement in voltage and a minimisation of active power losses, while at the same time the investment costs for the WTG systems were favourable. At least, the GTO algorithm was a perfect choice that reached the optimal solutions quickly and converged after a small number of iterations, which is recommended when solving the problem of optimal integration of different renewable energy sources in practical electrical distribution systems.

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