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Research Article

A New Optimization Algorithm for Optimal Wind Turbine Location Problem in Constantine City Electric Distribution Network Based Active Power Loss Reduction

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Abstract

The wind turbine has grown out to be one of the most common Renewable Energy Sources (RES) around the world in recent years. This study was intended to position the Wind Turbine (WT) on a wind farm to achieve the highest performance possible in Electric Distribution Network (EDN). In this paper a new optimization algorithm namely Salp Swarm Algorithm (SSA) is applied to solve the problem of optimal integration of Distributed Generation (DG) based WT (location and sizing) in EDN. The proposed algorithm is applied on practical Algerian EDN in Constantine city 73-bus in presence single and multiple WT-DGs for reducing the total active power loss. The validity of the proposed algorithm is demonstrated by comparing the obtained results with those reported in literature using other optimization algorithms. A numerical simulation including comparative studies was presented to demonstrate the performance and applicability of the proposed algorithm.

Keywords: Distributed Generation (DG); Wind Turbine (WT); Optimal Placement; Active Power Loss; Electric Distribution Network (EDN); Salp Swarm Algorithm (SSA).

1. Introduction

Power systems have undergone major changes over the recent decades in the quest to provide reliable and economic electricity services in a way that benefits all associated parties. Achieving this goal involves the consideration of power industry regulations, and utilization of sustainable energies. Distributed Generation (DG) is expected to be a part of the solutions considered for the future (El-Khattam and Salama, 2004).

Today, producing energy from wind has become widespread thanks to the technological developments (Malen and Marcus, 2017; Wang and Huang, 2016). It is transformed into electricity through Wind Turbines (WTs); however, there are other methods to generate electricity (Omer, 2008).

The higher power losses in the transmission and distribution system also result in reducing efficiency of the existing system (Sultana *et al.*, 2016; Mehigan *et al.*, 2018).

The optimal site and size problems have a nonlinear nature. Therefore, the problem formulation of DG integration based WT source is modeled as a mixed integral nonlinear problem. Many researchers used multiples methods and algorithms: Probabilistic approach (Atwa and El-Saadany, 2011), Monte Carlo method (Marmidis *et al.*, 2008), Genetic algorithm (Grady *et al.*, 2005), Particle swarm optimization algorithm (Hou *et al.*, 2015), Gaussian particle swarm optimization (Song *et al.*, 2018), Evaluative algorithm (González *et al.*, 2010), Differential evolution algorithm (Biswas *et al.*, 2017), Adaptive differential evolution algorithm (Ramli *et al.*, 2018), Ant colony optimization (Eroğlu and Seçkiner, 2012), Greedy algorithm (Chen *et al.*, 2013), Harmony search algorithm (Kayalvizhi and Vinod Kumar, 2018), Artificial algae algorithm (Beşkirli *et al.*, 2018), Cuckoo search algorithm (Nadjemi *et al.*, 2017), Modified artificial bee colony (Zare *et al.*, 2017), Firefly Optimization algorithm (Hendrawati *et al.*, 2019), Pattern search method (Shin and Kim, 2016), and Water cycle optimization algorithm (Rezk *et al.*, 2019), Whale optimization algorithm (Settoul *et al.*, 2019a), and Moth-Flame Optimization Algorithm (Settoul *et al.*, 2019b).

In this paper, multiple WT-DG units are optimally integrated into practical EDN namely Constantine City 73-bus system by determining their optimal sizing and bus location using a novel bio-inspired algorithm called

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Salp Swarm Algorithm (SSA). To show the performance of the proposed algorithm the obtained results are compared with other powerful algorithms.

2. Problem Formulation and Constraints

2.1. Objective Function

In this work, the total active power losses are used as the principal Objective Function (*OF*) to be minimized (Settoul *et al.*, 2019a, 2019b, 2019c; Hassan and Zellagui, 2019; Lasmari *et al.*, 2020):

$$OF = \min \sum_{i=1}^{N_{bus}} \sum_{j=2}^{N_{bus}} P_{Loss}(i,j) \tag{1}$$

where,

$$P_{Loss}(i,j) = R_{ij} \frac{\left(P_{ij}^2 + Q_{ij}^2\right)}{V_i^2} \tag{2}$$

2.2. Distribution line constraints

Power conservation constraint: Equality constraints are represented by as follows (Settoul *et al.*, 2019a, 2019b, 2019c; Hassan and Zellagui, 2019; Lasmari *et al.*, 2020):

$$P_G + P_{WT-DG} = P_D + P_{Loss} \tag{3}$$

$$Q_G + Q_{WT-DG} = Q_D + Q_{Loss} \tag{4}$$

Bus voltage limits:

$$V_{\min} \leq |V_i| \leq V_{\max} \tag{5}$$

Voltage drop limit:

$$|V_1 - V_i| \leq \Delta V_{\max} \tag{6}$$

Line capacity constraint:

$$|S_{ij}| \leq |S_{\max}| \tag{7}$$

2.3. WT-DG constraints

Capacity limits:

$$P_{WT-DG}^{\min} \leq P_{WT-DG} \leq P_{WT-DG}^{\max} \tag{8}$$

$$Q_{WT-DG}^{\min} \leq Q_{WT-DG} \leq Q_{WT-DG}^{\max} \tag{9}$$

Position of units:

$$2 \leq WT - DG_{Position} \leq N_{bus} \tag{10}$$

Number of units:

$$N_{WT-DG} \leq N_{WT-DG.\max} \tag{11}$$

Location of units:

$$n_{WT-DG,i}/Location \leq 1 \tag{12}$$

3. Proposed Optimization Algorithm

The Salp Swarm Algorithm (SSA) a new modern metaheuristic algorithm that was introduced in 2017 by Mirjalil (Mirjalili *et al.*, 2017). The population of salps *X* consists of *N* agents with *d*-dimensions as described in the flowing equation:

$$X_i = \begin{bmatrix} x_1^1 & x_2^1 & \cdots & x_d^1 \\ x_1^2 & x_2^2 & \cdots & x_d^2 \\ \vdots & \vdots & \cdots & \vdots \\ x_1^N & x_2^N & \cdots & x_d^N \end{bmatrix} \tag{13}$$

In SSA, the position of the leader is updated according to the follows (Mirjalili *et al.*, 2017; Faris *et al.*, 2020):

$$X_i^1 = \begin{cases} F_i + c_1[(ub_i - lb_i)c_2 + lb_i] & c_3 \geq 0 \\ F_i - c_1[(ub_i - lb_i)c_2 + lb_i] & c_3 < 0 \end{cases} \tag{14}$$

The first coefficient c_1 is introduced to make balance between the exploration and the exploitation (Mirjalili *et al.*, 2017) is defined in flowing equation:

$$c_1 = 2.e^{-\left(\frac{4t}{T_{\max}}\right)^2} \tag{15}$$

The follower salps update their positions based on Newton's law of motion using the following equation (Mirjalili *et al.*, 2017):

$$X_i^k = \frac{1}{2}\left(X_i^k + X_i^{k-1}\right) \qquad 2 \leq k \leq N \tag{16}$$

The pseudo-code of SSA is expressed in Algorithm 1 (Faris *et al.*, 2020).

Algorithm 1. Pseudo-code of the SSA

```
Initialize the salps positions x_i (i = 1, 2, . . . , N)
while (t < maximum iterations)
    Determinate the fitness of each salps
    Set F (best slap) as the leader salp
    Update the value of c1 using Eq. (15)
    for (every salp (x_i))
        if (i == 1)
            Update the position of leader by Eq. (14)
        else
            Update the position of followers by Eq. (16)
        end if
    end for
Update the population using the upper and lower limits of problem variables
Return back salps that violated the bounding restrictions.
Set t = t + 1
end while
Return F
```

Fig. 1. summarizes the above discussed elements forming a general mathematical optimization model of DGs in EDN.

4. Optimization Results and Discussions

4.1. Test System:

The proposed SSA algorithm is applied using MATLAB in a PC has processor Intel Core i5 with 2.7 GHz and 8 GB of RAM, the optimization process is done on a real practical EDN to evaluate the integration of WT-DG units. The case study is practical EDN of Constantine City (Algeria Company of Distribution) (Settoul *et al.*, 2019b), this EDN constituted of 72 distribution lines with nominal voltage 10 kV, and the total loads are 2.9375 MW and 1.6577 MVar. The single line diagram is represented in Figure 2.

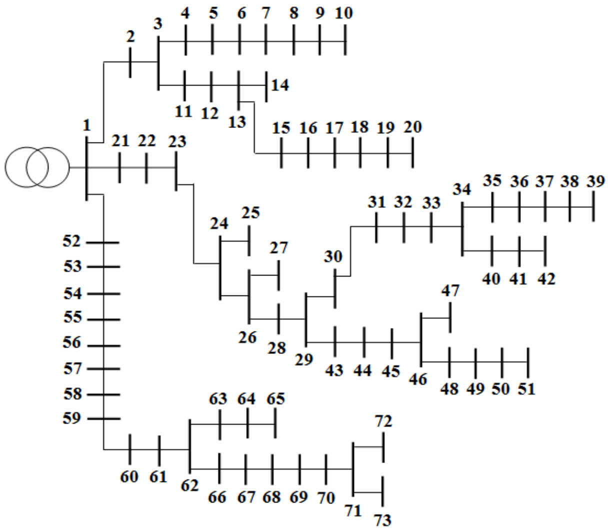


Fig. 2. Single line diagram of the EDN of Constantine city.

The following three cases studies are deployed to verify the effectiveness of the SSA algorithm:

- ➢ Case 1: EDN with one WT-DG,
- ➢ Case 2: EDN with two WT-DGs,
- ➢ Case 3: EDN with three WT-DGs.

4.2. Performance of SSA algorithm:

The convergence performance of the proposed SSA algorithm for optimal installation of WT- DG is illustrated in Figure 4.

From this figure, the proposed algorithm does not converge quickly, but it always achieved the better results compared to other algorithms, in the other hand, in the three cases, the optimal solution is obtained after 70 iterations from the first run.

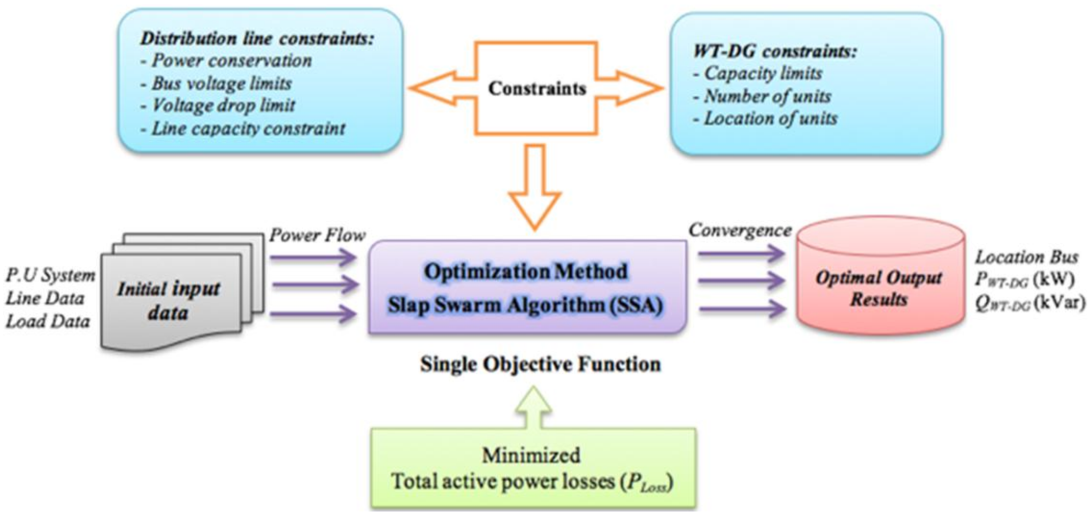
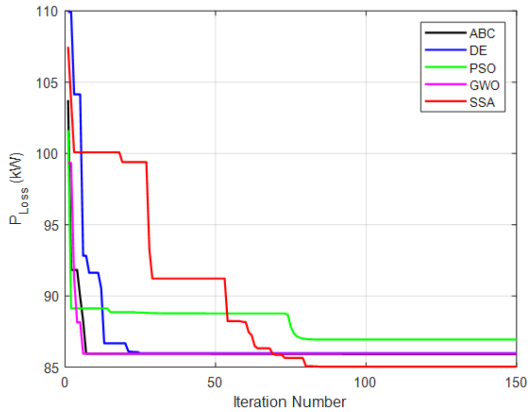
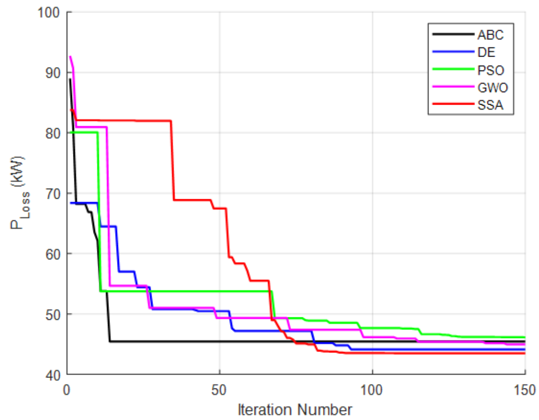


Fig. 3. Summary of the optimization process.



(a)



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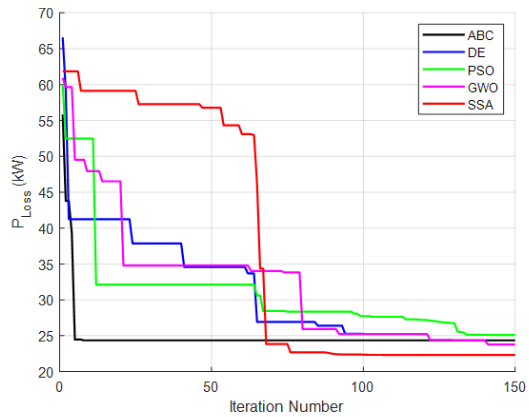


(c)

Fig. 4. The Convergence characteristics of various algorithms.
a). 1 WT-DG, b). 2 WT-DGs, c). 3 WT-DGs,

Figure 5 indicates the CPU time of each algorithm for the three cases studies, from the figure it clearly shows that the worst CPU time is for the ABC algorithm, while the best are recorded by GWO, but it can be said that SSA has a good CPU time in case three which has the second-best CPU time after GWO, another observation that in the three cases the proposed SSA algorithm has close CPU time which means that it's can deal with the augmentation in the number of WT-DGs with a short CPU time, unlike the other algorithms which in their cases the CPU time is augmented in case three.

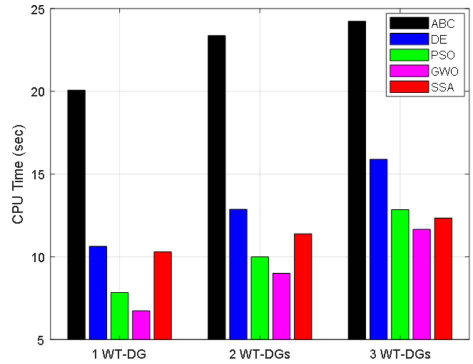
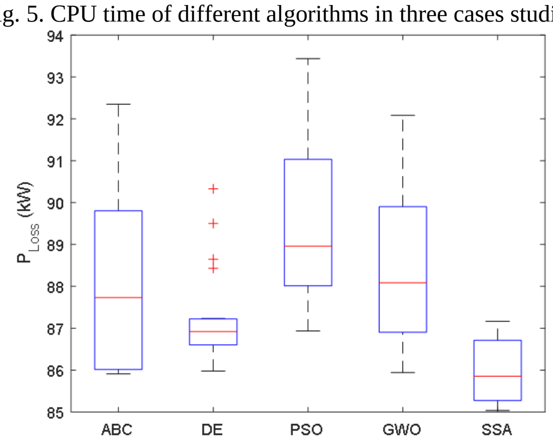
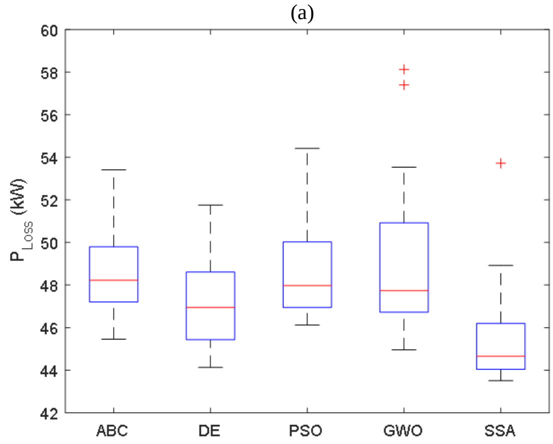


Fig. 5. CPU time of different algorithms in three cases studies.



(a)



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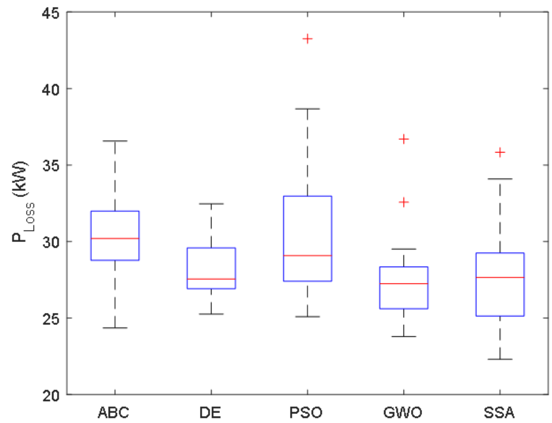


(c)

Fig. 6. Boxplot off different optimization algorithms.
a). Before WT-DG, b). After 1 WT-DG, c). After 2 WT-DG, d). After 3 WT-DG

Figure 6 indicates the boxplot of P_{Loss} (objective function) for different algorithm applied after 20 runs by using the same number of iterations to show the performance of each algorithm after this number of runs, the proposed SSA show a good performance for the three cases studies compared with the other algorithms.

4.3. Optimization results

The optimization results after installation of multiple WT-DGs in EDN are tabulated in Table 1.

Table 1
Performance analysis of the proposed SSA algorithm.

Parameters	**P_{Loss} (kW)**	**Q_{Loss} (kVar)**	**V_{min} (p.u.) @ Bus**	**P_{WT-DG} (kW) / Q_{WT-DG} (kVar) Bus**
Before WT-DG	204.1259	101.3120	0.8779 @ 39	-----
1 WT-DG	85.0321	42.5802	0.9232 @ 73	1075.6 / 528.2 (34)
2 WT-DGs	43.5043	24.6370	0.9599 @ 51	1087.6 / 514.4 (34) 572.4 / 251.1 (62)
3 WT-DGs	22.3059	12.1958	0.9801@ 39	794.8 / 321.5 (34) 569.2 / 281.6 (48) 579.9 / 341.5 (66)

In the basic case before WT-DG installation, which is performed using the Newton-Raphson method. The P_{Loss} is 204.1259 kW, and the Q_{Loss} in EDN is 101.3120 kVar. The bus voltage varies between 0.8779 p.u. and 1.0000 p.u.

After the installation of one WT-DG, the power losses in EDN are reduced to 85.0321 kW and 42.5802 kVar. The minimum voltage has become 0.9232 p.u. at bus number 73 using the proposed SSA algorithm.

In the case of installing two WT-DGs, the SSA identified buses 34 and 62, his has resulted the active and reactive power losses minimized to 43.5043 kW and 24.6370 kVar, respectively.

This observation is still valid for the last case studies with installation three WT-DGs when comparing the improvement in the P_{Loss}, and Q_{Loss} which have become 22.3059 kW and 12.1958 kVar, respectively. The minimum voltage has increased from 0.8779 p.u. to 0.9801 p.u.

Figure 7 indicates the bus voltage profiles for different case studies performed for EDN. The voltages of all the buses are within allowable limits, after single or multiple WT-DGs installations in EDN, and the best voltage profile is justifiably obtained compared with the basic case.

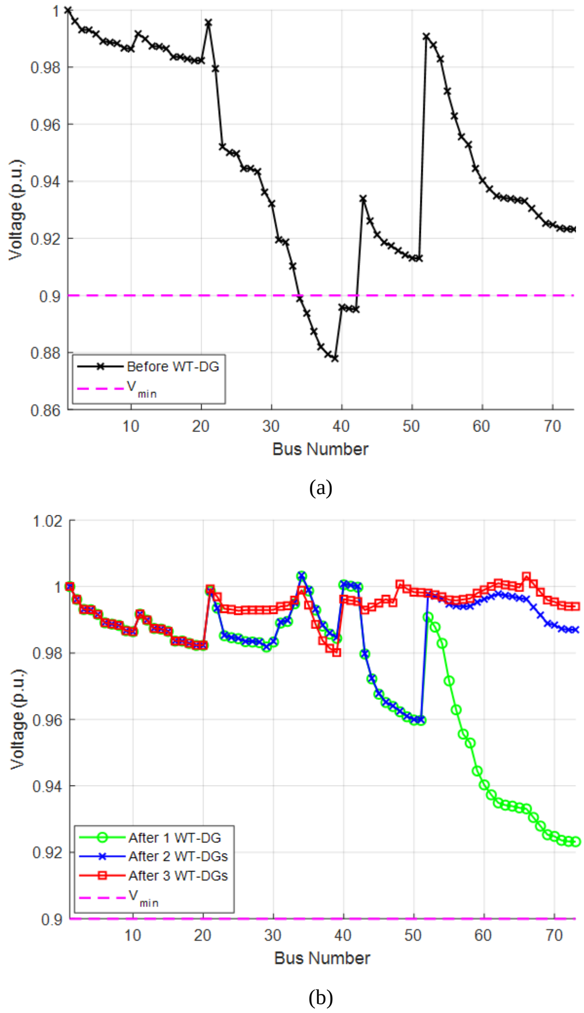
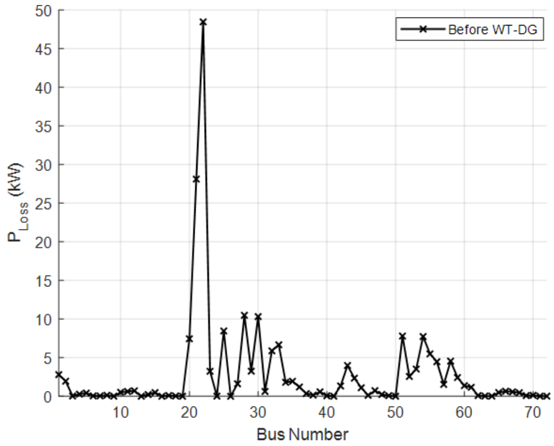
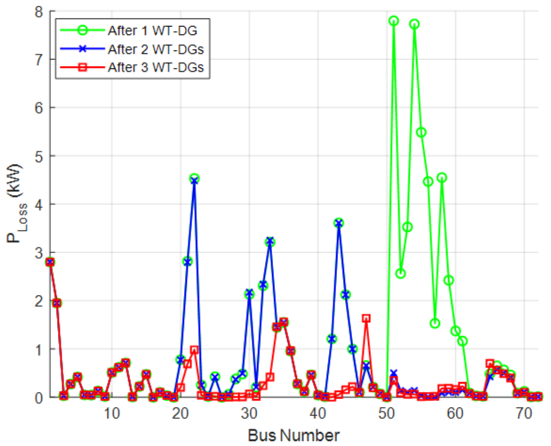


Fig. 7. Bus voltages profile of EDN.
a). Before WT-DG, b). After WT-DG.

Figure 8 shows the line P_{Loss} of every individual branch for each of the three case studies in the presence of one, two, and three WT-DGs in EDN. Analysis of results reveals that after the integration of WT-DG units, a significant minimization of the P_{Loss} in all buses in EDN is observed.



(a)



(b)

Fig. 8. Active power loss of EDN.
a). Before WT-DG, b). After WT-DG.

Table 2 represents the optimal results achieved by the applied SSA algorithm and different optimization algorithms.
As shown in Tables 2, ΔP_{Loss} and ΔQ_{Loss} percentage obtained by using SSA algorithm are less than those obtained with the other algorithms in all case studies.

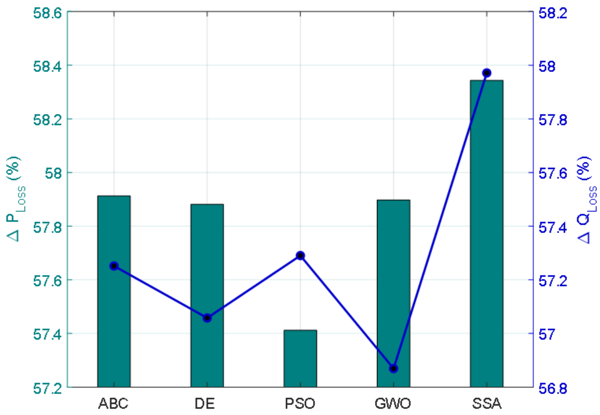
In order to show the performance of the SSA algorithm, as pre-mentioned, we compared it with ABC, DE, PSO, and GWO algorithms, in terms of active power loss minimization the compared algorithms minimize the power losses respectively by 57.9128 %, 57.8814 %, 57.4119 %, and 57.8976 % as shown in Table 2 in the presence single WT-DG in EDN.

This observation is still valid for the case installation of multiple WT-DGs units (two and three) while comparing the optimal results of applying the SSA with alternative algorithms. In all case studies, the proposed SSA algorithm performs outstandingly in minimizing the ΔP_{Loss} and ΔQ_{Loss} reduction percentage and improving the voltage profile.

Figure 9 indicates the graphical comparison of ΔP_{Loss} and ΔQ_{Loss} percentage obtained by different algorithms of the three case studies. The analysis of the results shows the superiority of the proposed SSA algorithms in terms of both P_{Loss} and Q_{Loss} for the different installation number of WT-DGs in EDN, the worst ΔP_{Loss} is obtained by PSO while the worst ΔQ_{Loss} in case one is obtained by GWO and in case two is obtained by ABC, in case three the worst ΔP_{Loss} is obtained by DE and the worst ΔQ_{Loss} is obtained by PSO algorithm.

Table 2.
Comparison of optimal results in the presence WT-DGs.

Case Studies	**Algorithms Applied**	**P_{Loss} (kW)**	**Q_{Loss} (kVar)**	**V_{min} (p.u.)**	**ΔP_{Loss} (%)**	**ΔQ_{Loss} (%)**
1 WT-DG	ABC	85.9109	43.3093	0.9232	57.9128	57.2516
	DE	85.9749	42.4925	0.9232	57.8814	57.0578
	PSO	86.9333	43.2700	0.9232	57.4119	57.2904
	GWO	85.9420	43.6966	0.9232	57.8976	56.8693
	SSA	85.0321	42.5802	0.9232	58.3433	57.9712
2 WT-DGs	ABC	45.4574	26.2372	0.9644	77.7307	74.1026
	DE	44.1326	25.2010	0.9613	78.3797	75.1254
	PSO	46.1259	25.7852	0.9592	77.4032	74.5487
	GWO	44.5816	25.8226	0.9633	78.1598	74.5118
	SSA	43.5043	24.6370	0.9599	78.6875	75.6821
3 WT-DGs	ABC	24.3498	13.6285	0.9823	88.0712	86.5480
	DE	25.2660	13.4288	0.9804	87.6223	86.7451
	PSO	25.0892	13.7100	0.9807	87.7090	86.4675
	GWO	23.7862	13.1634	0.9823	88.3473	87.0071
	SSA	22.3059	12.1958	0.9801	89.0725	87.9621



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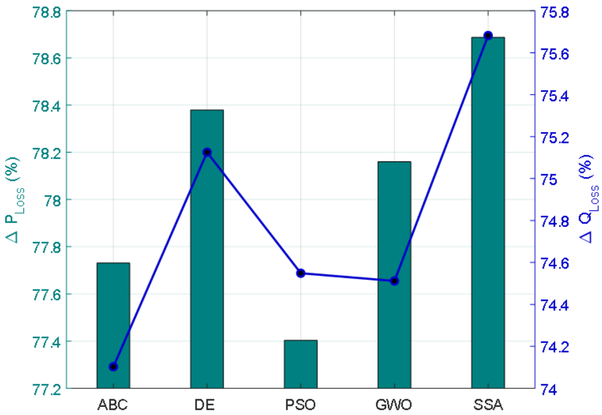

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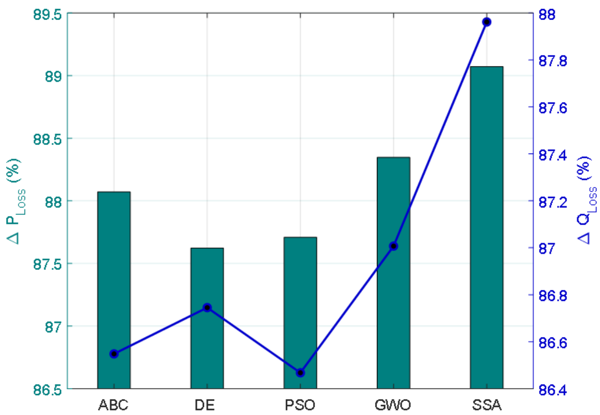
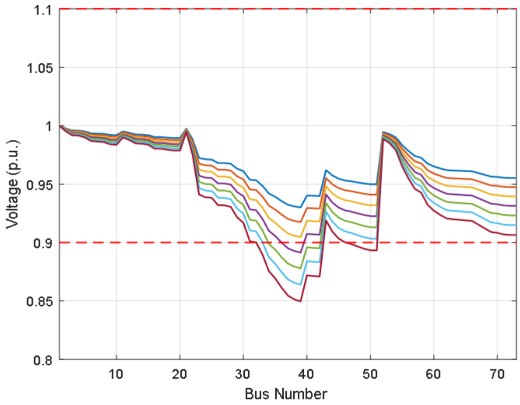


(c)

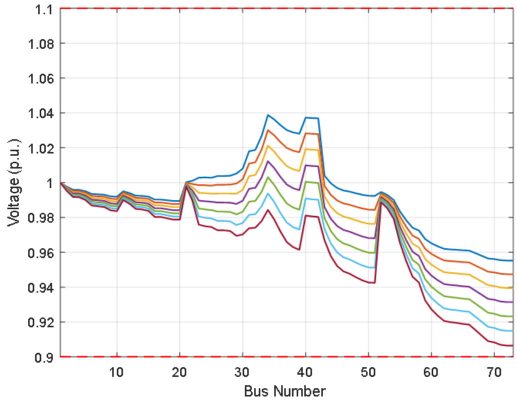
Fig. 9. Comparison of SSA with other algorithms.
a). 1 WT-DG, b). 2 WT-DG, c). 3 WT-DG.

4.4. Impact of load demand variation

Figure 10 shows the voltage profile under different load demand level before and after WT-DG installations, the load has a linear variation between 60% and 120%, and to show the improvement according to the allowable voltage limits. The minimum and maximum voltages limits are plotted with dashed red lines which are 0.9 and 1.1 p.u., respectively.



(a)



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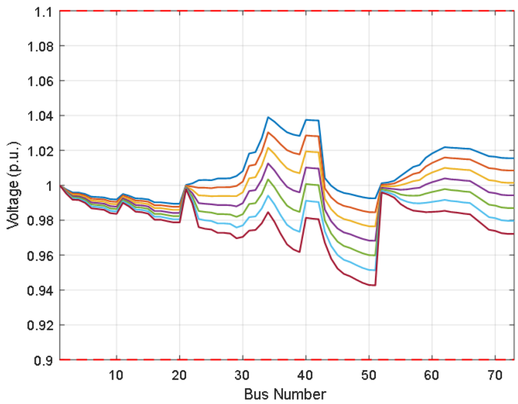

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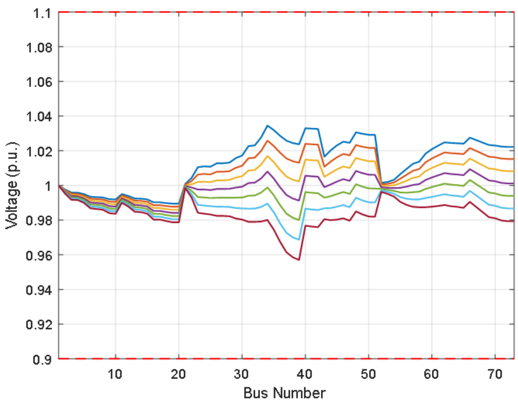

(d)

Fig. 10. Voltage profile under different load variation.
a). Before WT-DG, b). After 1 WT-DG, c). After 2 WT-DGs,
d). After 3 WT-DGs.

In Figure 10. a. it clearly shows that is the voltage before WT-DG is less than the minimum limit in busses between 30 and 42, and also between 47 and 51. After WT-DG integration, the bus voltage is improved and become between the allowed limits, by taking a look at Figure 9. b., it observed that one WT-DG installation improved the voltage and affect the busses between 30 and 42. But two and three WT-DG as shown in Figures 9.c. and 9.d, respectively are affecting almost all busses, another observation that three WT-DG makes voltage profiles for different loads close to each other and almost flat.

Figure 11 shows the total P_{Loss} and Q_{Loss} with the same linear variation of load demand between 60% and 120%, the figure reveals that after integration of WT-DG reduces P_{Loss} and Q_{Loss} for different load level, that means that locations and sizes obtained are optimal to integrate WT-DG, it is logical that the number of WT-DG integrated has a positive effect on P_{Loss} and Q_{Loss} due to the WT-DG powers injected in different buses in EDN.

For example in the installation of three WT-DG units with 120% of load demand, the value of P_{Loss} reduced to 38 kW which were more than 300 kW this reduction represents 87 %, while Q_{Loss} reduced from 150 kVar to 20 kVar which represent 86 %, the previous values reveal that WT-DG injected in the locations and sizes obtained by the proposed SSA algorithm can deal with load demand variation.

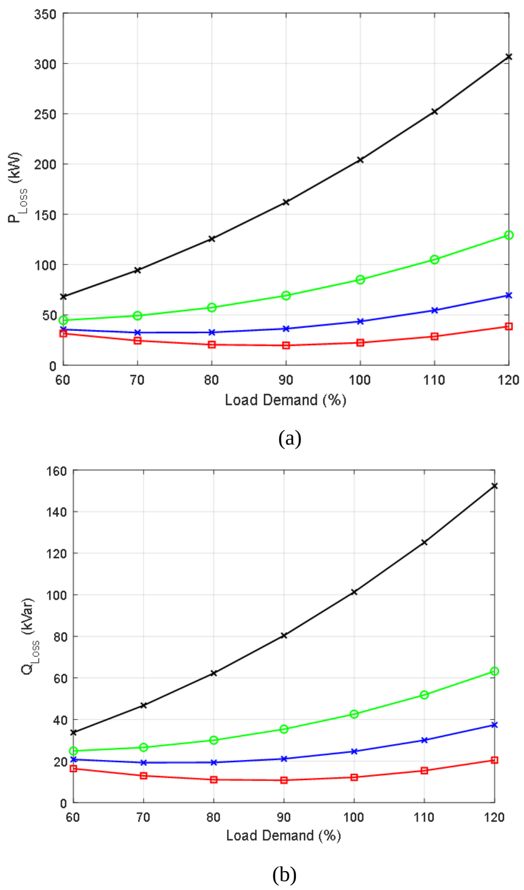

Fig. 11. The power losses variation under different load demand. a). P_{Loss}, b). Q_{Loss}.

5. Conclusion

In this paper, the SSA algorithm was used to obtain the optimal location and size of single and multiple WT-DGs units in practical EDN based total active power loss reduction.

The results obtained were satisfying as they demonstrated that the proposed algorithm provided improved results than other existing algorithms through better prediction of the best location of WT-DG units. The SSA algorithm reduced the active and reactive power losses and the voltage profile is ameliorated in all buses with the WT-DG installations in EDN.

It can be concluded that the SSA algorithm is a robust and reliable technique for solving the optimization objective function problems in power systems.

In future, authors are planning to include a specified WT-DG cost value, different load models, and optimal number of WT-DGs to connect in a large practical electric distribution network.

References

Atwa, Y. M., & El-Saadany, E. F. (2011). Probabilistic approach for optimal allocation of wind-based distributed generation in distribution systems. IET Renewable Power Generation, 5(1), 79-88.

Beşkirli, M., Koç, İ., Haklı, H., & Kodaz, H. (2018). A new optimization algorithm for solving wind turbine placement problem: Binary artificial algae algorithm. Renewable energy, 121, 301-308.

Biswas, P. P., Suganthan, P. N., & Amaratunga, G. A. (2017, June). Optimal placement of wind turbines in a windfarm using L-SHADE algorithm. In IEEE Congress on Evolutionary Computation (CEC) (pp. 83-88). IEEE.

Chen, K., Song, M. X., He, Z. Y., & Zhang, X. (2013). Wind turbine positioning optimization of wind farm using greedy algorithm. Journal of Renewable and Sustainable Energy, 5(2), 023128.

El-Khattam, W., & Salama, M. M. (2004). Distributed generation technologies, definitions and benefits. Electric power systems research, 71(2), 119-128.

Eroğlu, Y., & Seçkiner, S. U. (2012). Design of wind farm layout using ant colony algorithm. Renewable Energy, 44, 53-62.

Faris, H., Mirjalili, S., Aljarah, I., Mafarja, M., & Heidari, A. A. (2020). Salp swarm algorithm: theory, literature review, and application in extreme learning machines. In Nature-Inspired Optimizers (pp. 185-199). Springer, Cham.

González, J. S., Rodriguez, A. G. G., Mora, J. C., Santos, J. R., & Payan, M. B. (2010). Optimization of wind farm turbines layout using an evolutive algorithm. Renewable energy, 35(8), 1671-1681.

Grady, S. A., Hussaini, M. Y., & Abdullah, M. M. (2005). Placement of wind turbines using genetic algorithms. Renewable energy, 30(2), 259-270.

Hassan, H. A., & Zellagui, M. (2019, December). MVO Algorithm for Optimal Simultaneous Integration of DG and DSTATCOM in Standard Radial Distribution Systems Based on Technical-Economic Indices. In 2019 21st International Middle East Power Systems Conference (MEPCON), Cairo, Egypt, 277-282.

Hendrawati, D., Soeprijanto, A., & Ashari, M., (2019). Turbine wind placement with staggered layout as a strategy to maximize annual energy production in onshore wind farms. International Journal of Energy Economics and Policy. 9(2), 334-340.

Hou, P., Hu, W., Soltani, M., & Chen, Z. (2015). Optimized placement of wind turbines in large-scale offshore wind farm using particle swarm optimization algorithm. IEEE Transactions on Sustainable Energy, 6(4), 1272-1282.

Kayalvizhi, S., & Vinod Kumar, D. M. (2018). Optimal planning of active distribution networks with hybrid distributed energy resources using grid-based multi-objective harmony search algorithm. Applied Soft Computing, 67, 387-398.

Lasmari, A., Zellagui, M., Chenni, R., Semaoui, S., El-Bayeh, C. Z., & Hassan, H. A. (2020). Optimal energy management system for distribution systems using simultaneous integration of PV-based DG and DSTATCOM units. Energetika, 66(1), 1-14.

Malen, J., & Marcus, A. A. (2017). Promoting clean energy technology entrepreneurship: The role of external context. Energy Policy, 102, 7-15.

Marmidis, G., Lazarou, S., & Pyrgioti, E. (2008). Optimal placement of wind turbines in a wind park using Monte Carlo simulation. Renewable energy, 33(7), 1455-1460.

Mehigan, L., Deane, J. P., Gallachóir, B. Ó., & Bertsch, V. (2018). A review of the role of distributed generation (DG) in future electricity systems. Energy, 163, 822-836.

Mirjalili, S., Gandomi, A. H., Mirjalili, S. Z., Saremi, S., Faris, H., & Mirjalili, S. M. (2017). Salp swarm algorithm: a bio-inspired optimizer for engineering design problems. Advances in Engineering Software, 114, 163-191.

Nadjemi, O., Nacer, T., Hamidat, A., & Salhi, H. (2017). Optimal hybrid PV/wind energy system sizing: Application of cuckoo search algorithm for Algerian dairy farms. Renewable and Sustainable Energy Reviews, 70, 1352-1365.

Omer, A. M. (2008). Energy, environment and sustainable development. Renewable and sustainable energy reviews, 12(9), 2265-2300.

Ramli, M. A., Bouchekara, H. R. E. H., & Alghamdi, A. S. (2018). Optimal sizing of PV/wind/diesel hybrid microgrid system using multi-objective self-adaptive differential evolution algorithm. Renewable energy, 121, 400-411.

Rezk, H., Fathy, A., Diab, A. A. Z., & Al-Dhaifallah, M. (2019). The application of water cycle optimization algorithm for optimal placement of wind turbines in wind farms. Energies, 12(22), 4335.

Settoul, S., Chenni, R., Hasan, H. A., Zellagui, M., & Kraimia, M. N. (2019, November). MFO Algorithm for Optimal Location and Sizing of Multiple Photovoltaic Distributed Generations Units for Loss Reduction in Distribution Systems. In 2019 7th International Renewable and Sustainable Energy Conference (IRSEC), Agadir, Morocco, 1-6

Settoul, S., Chenni, R., Zellagui, M., Nouri, H. (2019, December). Optimal integration of renewable distributed generation using the whale optimization algorithm for techno-economic analysis. 4th International Conference on Electrical Engineering and Control Applications (ICEECA), Constantine, Algeria 513-532

Settoul, S., Zellagui, M., Abdelaziz, A.Y., & Chenni, R. (2019, November). optimal integration of renewable distributed generation in practical distribution grids based on moth-flame optimization algorithm. International Conference on Advanced Electrical Engineering (ICAEE), Algiers, Algeria 1-6.

Shin, J. S., & Kim, J. O. (2016). Optimal design for offshore wind farm considering inner grid layout and offshore substation location. IEEE Transactions on Power Systems, 32(3), 2041-2048.

Song, M., Chen, K., & Wang, J. (2018). Three-dimensional wind turbine positioning using Gaussian particle swarm optimization with differential evolution. Journal of Wind Engineering and Industrial Aerodynamics, 172, 317-324.

Sultana, U., Khairuddin, A. B., Aman, M. M., Mokhtar, A. S., & Zareen, N. (2016). A review of optimum DG placement based on minimization of power losses and voltage stability enhancement of distribution system. Renewable and Sustainable Energy Reviews, 63, 363-378.

Wang, H., & Huang, J. (2016). Cooperative planning of renewable generations for interconnected microgrids. IEEE Transactions on Smart Grid, 7(5), 2486-2496.

Zare, M., Azizipanah-Abarghooee, R., Hooshmand, R. A., & Malekpour, M. (2017). Optimal reconfigurattion of distribution systems by considering switch and wind turbine placements to enhance reliability and efficiency. IET Generation, Transmission & Distribution, 12(6), 1271-1284.

Nomenclature

A. EDN parameters	
N_{bus}	Number of buses
R_{ij}	Resistance of distribution line
V_i	Bus voltage
P_{ij}, Q_{ij}	Active and reactive powers in line
P_G, Q_G	Total active and reactive power of generator
P_D, Q_D	Total active and reactive power of load
P_{Loss}, Q_{Loss}	Total active and reactive power losses
$V_{\min}$, $V_{\max}$	Minimum and maximum bus voltage
$\Delta V_{\max}$	Maximum voltage drops
S_{ij}	Apparent power in distribution line
S_{max}	Maximum of apparent power
B. WT-DG	
$P_{WT\text{-}DG}^{min}$, $Q_{WT\text{-}DG}^{min}$	Minimum powers output limits of WT-DG
$P_{WT\text{-}DG}^{max}$, $Q_{WT\text{-}DG}^{max}$	Maximum powers output limits of WT-DG
$P_{WT\text{-}DG}$, $Q_{WT\text{-}DG}$	Powers outputs of WT-DG
C. SSA algorithm	
X_i^1	Leader’s position
F_i	Place of food source
c_1	First balance coefficient
c_2 , c_3	Random numbers
ub_i, lb_i	Upper and lower bounds
t	Current iteration
T_{max}	Maximum number of iterations
X_i^k	Position of salp
N	Number of salp particles

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http://www.qjie.ir/article_677886.html

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