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Evaluating the Total Active Power Loss under Different Placement of Photovoltaic Power Plants Using an Effective Northern Goshawk Optimization

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ABSTRACT

This research presents a detailed evaluation of the total active power loss (TAPL) under different placements of photovoltaic power plants (PVPs) in the electric distribution network (EDN) IEEE 33-node. Three study cases have been conducted to serve the initial intention, including 1) optimizing both rated power and position of a PVP on selected EDN; 2) optimizing the positions of different quantities of PVPs independently to the grid with the same rated power, and 3) optimizing a sole PVP with a wide range of rated power. In all three study cases, northern goshawk optimization (NGO) is the primary search method for determining the essential results and data, especially in the last two cases, after proving its competitive performance in the first case compared to other methods. The results in study cases 2 and 3 indicated that for reaching the minimum value of TAPL, placing many PVPs independently on the grid simultaneously is the best implementation. Notably, the placement 7 PVPs with a total rated power of 2800kW has resulted in a significantly better TAPL than all the results in study case 3. However, for the situation where EDN can only adopt a sole PVP, all the data and results presented in study case 3 are also good academic material.

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1. Introduction

In power systems, distribution power grids (EDNs) receive electricity from transmission power grids and distribute the electricity to loads [1]. Nowadays, customers use more high power devices such as electric chargers for car, leading to high voltage drop and power loss [2]. So, solutions to the problem need to be found, and solar energy is one of the most effective solution [3]. Thanks to the benefits of economics and engineering, installing electric components in EDNs has become a hot trend [2], especially distributed generators (DGs) using solar radiation and wind speed. The added DGs can reduce power from the grid and current from the source to each load, leading to the reduction of voltage drop and power loss. Therefore, the paper focuses on the optimal placement of DGs based on solar radiation. The target is to improve the voltage and lessen the power loss based on the optimal determination of the location and power of photovoltaic power plants (PVPs) in EDNs.

Many previous studies have used different types of DGs for different purposes, such as general DGs [4]–[7], wind power plants (WPPs) [8]–[12], PVPs [13]–[16], and both WPPs and PVPs [17]–[21]. In a study [4], three standard IEEE EDNs with 33, 69, and 85 nodes were employed to find DGs' most suitable power and position to reduce the total power loss. In the study [5], only one standard IEEE EDN with 33 nodes was tested to simulate the impacts of injected active and reactive power from DGs. Another study [6] found other solutions with the combination of PVPs and WPPs in the standard IEEE 33-node EDN. in order to violate high voltage drop and reduce switching number when implementing network reconfiguration and using DGs in the IEEE 69-node configuration [7]. In the study [8], modern wind turbines based on Double Fed Induction Generator (DFIG) were connected to the EDNs to reduce loss and enhance voltage. In the study [9], high benefits of adding WPPs appropriately in EDNs were analyzed based on results from optimization tools' comparisons. In the study [10], the cutting-edges of energy storage system was applied in three unbalanced phase-EDNs. More specifically, the steady-state operation of DFIG has been analyzed in various conditions corresponding to several types of turbines were placed in the unbalance distribution network in [11]. In the study [12], DGs were integrated in combined heat and power systems, and the systems have reached a reduction of fuel cost of 8%, power loss of 5%. In addition, the voltage was improved by greater than 0.5% in an IEEE 33-node configuration. In [13], [14], small-power PVPs were applied to investigate the impact of these sources on load at peak hours. In the study [15], PVPs was proven to be very effective to reduce the investment cost of EDNs efficiently. The impact of placing PVPs on reactive and active power loss and node voltage amplitude has been investigated by using optimization algorithms and three benchmark EDNs with 33, 69 and 85 nodes. The study [16] considered two different single-objective functions: total installed PVPs and energy purchase cost at slack node.

In recent years, the combination of both PVPs and WPPs has become an interesting trend in EDNs. For instances, the two studies [17], [18] have applied the combination to solve the optimal load flow problem with two single-objective functions in the IEEE 33-node EDN. The studies [19], [20] have considered the uncertainty of wind and solar and demand side response with total power loss reduction, annual cost minimization and annual demand response compensation as well as voltage stability index improvement. Another trend of using both WPPs and PVPs to solve the reconfiguration issues for EDNs was tried in the study [21]. In the study, unpredictable load variation and the uncertainties of renewable generating sources were also considered simultaneously. Metaheuristic algorithms could solve complex optimization problems effectively and they should be applied for the considered problem [22]. Approximately all the mentioned studies have applied metaheuristic algorithms to get solutions for conclusions.

In the paper, a novel algorithm, which is Northern Goshawk Optimization (NGO) [23], is applied for simulating the placement of PVPs in the IEEE 33-node EDN. The algorithm is compared to two optimization tools, including Firefly algorithm [24] and configuration-based analysis method [25] for indicating the performance of the applied NGO. The contribution of the paper is summarized as follows:

- Testing different cases of placing PVPs in the IEEE 33-node EDN.
- Determine the best solution to place PVPs in EDNs.
- Reduce the power loss and improve the voltage effecitvely.

In addition to the Introduction, the rest of the paper is structured as follows: Section 2 will present the problem description, which features the main objective function and constraints; Section 3 briefly introduces the main applied method; Section 4 provides the results and related discussions; and finally, Section 5 reveals the crucial conclusions of the whole paper.

2. Problem description

In the study, objective function and constraints are presented in formulas. The objective function is used to evaluate obtained solutions and then the best solution of placing PVPs is determined. Constraints are operating condition of distribution lines and loads. The detail is expressed as follows.

2.1. Objective function

As loads are working, the transformer at the slack node is receiving from a higher voltage feeder and supplying electricity to the loads via distribution lines. The lines are conductors with resistance causing voltage drop and power loss; however, the power loss reduction is selected to be an objective function. On the other hand, voltage drop is imposed on constraints and voltage constraint must satisfy the operating condition of loads. The power loss is expressed as follows.

$$TAPL = 3\sum_{a=1}^{N_{li}}(I_a{}^2.R_a) \tag{1}$$

where $TAPL$ is the total active power loss in the whole grid; I_a and R_a are he current and resistance of the *ath* distribution line; N_{li} is the distribution line number.

Among the parameters in Equation (1), R_a and N_{li} are taken from input data of the considered EDNs; meanwhile, $I_a$is obtained by running forward/backward sweep technique [4]. Particularly, The forward-backward sweep technique is a powerful tool for analyzing power flow in radial distribution systems. It works in two iterative stages:

- A forward sweep calculates voltage at each bus, starting from the source and moving towards the loads.
- A backward sweep calculates current in each branch and power flow at each bus, starting from the loads and moving back to the source.

This back-and-forth process continues until voltage and current values converge to a stable solution. The method's efficiency and low computational cost make it ideal for radial systems. Variations of this technique exist, but all share the core principle of forward and backward sweeps. Ultimately, this technique helps engineers analyze voltage profiles, currents, power flows, and identify power losses within the distribution network.

2.2. Constraints

EDNs are comprised of distribution lines and loads at nodes. When the electric components are working within an allowable range, the EDNs are working stably. So, the operating conditions of the components are considered.

2.2.1. Voltage Magnitude limits

In the considered EDNs, loads are working and requiring a voltage value within a predetermined range, which is between the minimum and maximum limits. This is the voltage constraint shown in the following inequality:

$$V_{min} \le V_b \le V_{max}; b = 1, \dots, N_{bus} \tag{2}$$

where V_{min} and V_{max} are the minimum and maximum voltage limits; and V_b is the *bth* bus' voltage.

2.2.2. Conductor Current Limits

Unlike bus' voltages, the current of conductors is only restricted by its designed capability corresponding to the conductors' area and material. That parameter can be seen as the maximum current capability of the line without overload or damage. The constraint is expressed as follows.

$$I_b \le I_b^{Max}; b = 1, \dots, N_{li} \tag{3}$$

Where, I_b^{Max} is the maximum current that the conductor in the *bth* line can work stably.

2.2.3. PVP's Location limits

The locations to place PVPs are very imporant to cut the power loss and improving the voltage. The applied NGO is assigned to find the best locations for added PVPs, excluding bus 1 where the transformer is working. Particularly, the location constraint is formulated as follows

$$2 \le LSPVP_c \le N_{bus} \tag{4}$$

Where $LSPVP_c$ is the location of the *cth* added PVP.

3. The Northern goshawk optimization

3.1. The main foundations

Northern Goshawk Optimization (NGO) is proposed based on the hunting behavior of the Northern Goshawk science. There is a wide range of targets while a northern goshawk executes its hunting process. The target can sometimes be small rabbits, squirrels, or larger animals such as foxes or raccoons. In terms of methodology, NGO is classified as a population-based meta-heuristic algorithm. In the development of NGO, the algorithms were evaluated for performance by testing with different optimization problems, including theoretical and practical optimization problems. The results achieved by NGO are compared with other optimization methods proposed previously, such as marine predators' algorithm (MPA), tunicate swarm algorithm (TSA), whale optimization algorithm (WOA), gravitational search algorithm (GSA), teaching-learning based optimization (TLBO), particle swarm optimization (PSO), etc. [23]. In summary, the selection of an NGO to solve the considered problem is based on the following points:

- The NGO is a novel meta-heuristic algorithm when the research is conducted. Moreover, as mentioned above, NGOs have performed better than previous algorithms, especially while dealing with large-scale optimization problems.
- The literature has yet to use NGOs to solve the problem. Therefore, the application of NGOs in this research is considered a contribution in terms of the method applied to solving the optimization problem in a power system.
- By demonstrating NGOs' high capability in solving the considered problem, the research also paves the way for later studies applying NGOs to other problems in power system optimization.

3.2. The execution of NGO

As mentioned above, NGO is a population-based meta-heuristic algorithm. Therefore, a set of random populations is required at the beginning of the optimization process. Suppose that the space solution is limited by the two-boundary solution represented by X^{min} and X^{max}; other random individuals or solutions will be randomly produced within these boundaries. If the initial population size is N_{Po}, a set of solutions from 1 to N_{Po} will be produced. After that, all these solutions will be assessed for quality based on the given solution featured by the considered optimization problem. In addition, the quality of each solution is measured by its fitness value denoted by F_{Xi}, with i as the index of the solution in the initial population.

3.2.1. The update process

The update process for new soltuion is the key factor that differentiate a particular meta-heuristic algorihtm among many others. Therefore this section will focus on describing the update process of NGO which is executed subsequently by the identification and striking phase. The mathematical expression of the two phases will be given as follows.

The identification phase: This phase uses a mathematical model to describe how a northern goshawk identifies its target in the first phase of the hunting process. Then, the update process for new solutions of this phase is formulated by the following expression.

$$X_i^{new\_1} = \begin{cases} X_i + Rnd \times \left(SL - AF \times X_i\right), \text{if } \ F_{SL} < F_{X_i} \\ X_i + Rnd \times \left(X_i - SL\right), \qquad \text{otherwise} \end{cases} \tag{5}$$

Where, $X_i^{new\_1}$ is the new solution updated in the identification phase with $i = 1, 2, \ldots, N_{Po}$ and N_{Po} is the initial population size; X_i is the considered solution; Rnd is the random value between 0 and 1; SL is the random selected solution of the initial population; AF is the amplifying factor; F_{SL} and F_{X_i} are the fitness value of the selected solution and the considered solution.

While all the solutions complete their update process for new solutions, the refining procedure will be conducted to save the promising solutions for the next phase of the optimization process and remove the low. Besides, the ineffective solutions will be removed. The refining process is expressed using the following equation:

$$X_i = \begin{cases} X_i^{new_1} \text{ if } F_{X_i^{new_1}} < F_{X_i} \\ X_i, \qquad \text{otherwise} \end{cases} \tag{6}$$

The striking phase: This phase describes the variation in the location of the northern goshawks toward the target after the first phase. The location variation of the northern goshawks is formulated using the model below.

$$X_i^{new\_1} = X_i + SF \times \left(2Rnd - 1\right) \times X_i \tag{7}$$

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with

$$SF = 0.02 \times \left(1 - \frac{CI}{Maxiter}\right) \tag{8}$$

In the Equations (7) and (8), $X_i^{new\_2}$ is the new solution updated in the striking phase; SF is the space-shrinking factor; CI and $Maxiter$ are the number of the current iteration and the maximum number of iterations.

Like the indentification phase, all the new solutions updated in the striking phase will be refined for saving the promissing solutions as follows:

$$X_i = \begin{cases} X_i^{new\_2} \text{ if } F_{X_i^{new\_2}} < F_{X_i} \\ X_i, \qquad \text{otherwise} \end{cases} \tag{9}$$

3.2.2. The stopping criterion

Generally, the optimization process of meta-heuristic algorithms, including NGO, is serial loops limited by the preset value of a maximum number of iterations. Therefore, when the serial loops reach the preset value of iterations, the optimization process will be stopped there, and the optimal solutions will be reported.

The whole searching process while using NGO to solve an optimization problem is described in Figure 1 below:

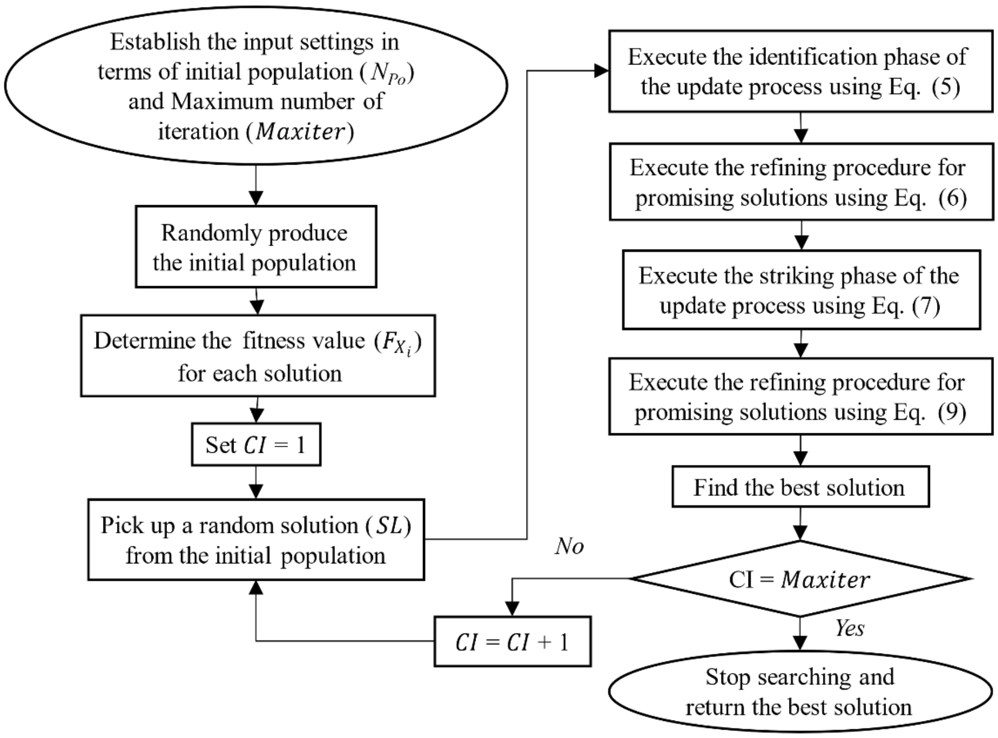

Figure 1. *The whole searching process of NGO*

4. Results and discussions

In this section, Northern goshawk optimization (NGO) is employed to optimize the placement of the distributed generators on the electric distribution network (EDN) to minimize the total active power loss (TAPL) of the whole grid. Besides, the performance of NGO is also evaluated in detail in different case studies as follows:

1. Investigating the stability of NGO while optimizing the placement of distributed generators on the grid using different settings in terms of the initial population size (N_{Po}) and maximum number

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of iterations (*Maxiter*). The TAPL values achieved by NGO is also compared to the previous methodsss for proving its effectiveness in solving the considered problem.

2. Examinate the TAPL value using different numbers of photovoltaic power plants (PVPs) on the grid. Note that the number of PVPs placed on the grid is varied from one to seven with the same rated power for each, which is 400 KW
3. Evaluate the TAPL under the placements of one PVP with different rated power and location on the grid. Note that the rated power of the sole PVP is varied from 0 to 3000kW

The standard configuration of IEEE 33-node EDN was selected to conduct the research, and the description of the selected EDN is presented in Figure 2. The primary data of the IEEE-33 node EDN is cited from [24], [25]. The selected EDN consists of 33 nodes linked by 32 branches. The operational voltage is 12.66 kV, and the total load demand for active and reactive power is 3715 kW and 2300 kVAR. Also, according to [24], [25], the TAPL value of the original EDN is 211 kW. Besides, codings and involved simulations are performed using Matlab programming language version R2015a installed on a personal computer with several specifications: the central processing unit (CPU) with 2.3 GHz of clock speed and 8 GB of random accessing memory (RAM). Additionally, the NGO has executed 100 testing runs for the best solution in each case study mentioned above

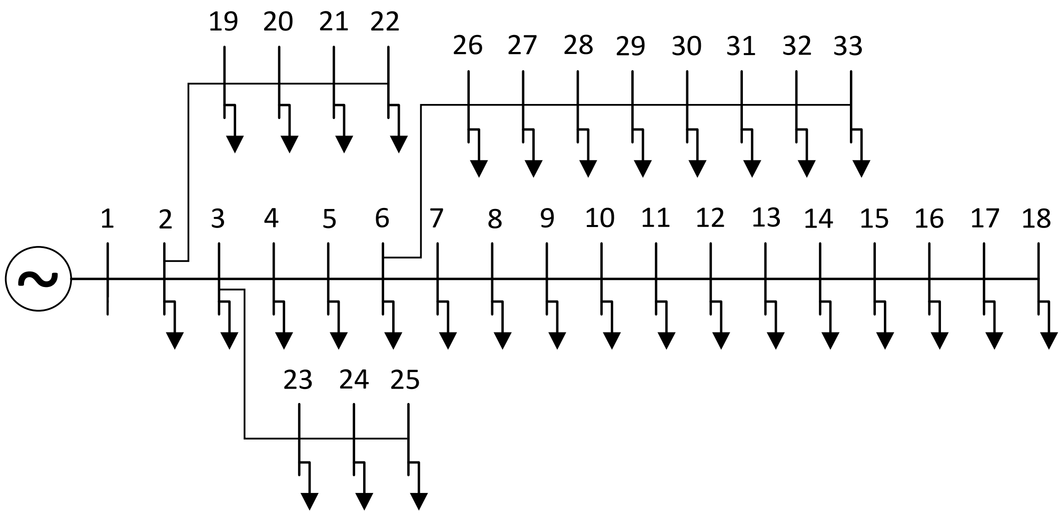

Figure 2. *The selected IEEE 33-node EDN*

Note that, all the PVPs used in the whole research can be stably operated with the following assumptions:

- Suppose that solar irradiation and the temperature at the site placing PVP are all sufficient to ensure the design capabilities of PVPs.
- The geographical locations and the specific nodes where PVPs are placed satisfy all the related standards required by the PVP's manufacturer to ensure the designed operation. In addition, the nodes where PVPs are connected can fully handle the amount of power injected by PVPs at any times.
- PVP systems can generate specific megawatt outputs to meet optimal solution requirements.

4.1. The results achieved in case study 1

In this subsection, NGO is executed to reach the best value of TAPL by optimizing the placement in terms of rated power and location of PVPs on the grid. Note PVP used in this case can only supply active power to grid. Suppose that rated power of the PVP used in the first case study can varied between 0 to 3000 KW. NGO had been tested with different settings of *Maxiter* which is varied from 50 to 200 with step of 50 each change. Additionally, the value of N_{Po} is fixed at 10 for all values of *Maxiter*. Figure 3 shows the results qualitatively achieved by NGO with different settings of *Maxiter* where *Maxiter* = 200 is the only option achieving the best stability of power loss throughout 100 testing runs.

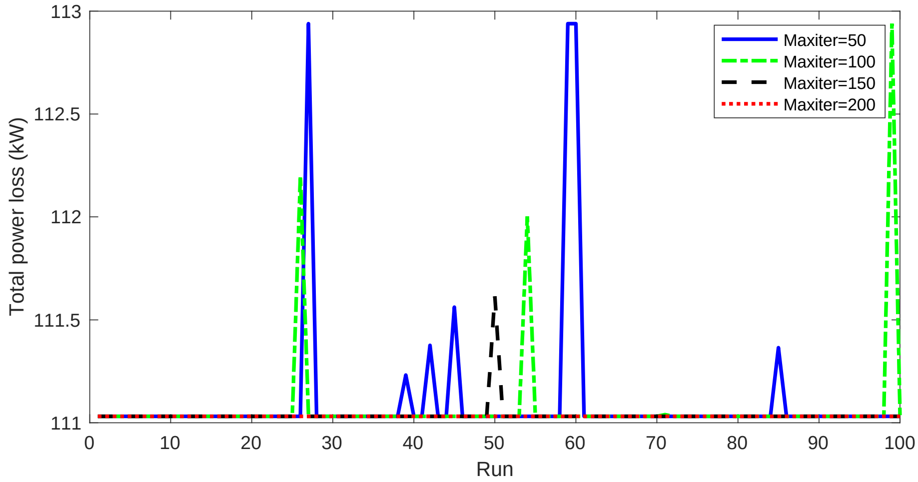

Figure 3. *The results obtained by NGO after 100 testing runs with different setting of MI*

Figure 4 provides quantitative results while executing NGO various settings of *Maxiter*. These settings reach a similar value to TAPL, which is 111.0311 kW. However, the observation of the STD value reveals a vast difference. Notably, while the STD value resulting from *Maxiter* = 50 is up to 0.3328, that of *Maxiter* = 200 is zero, meaning that the TAPL values throughout 100 testing runs are the same. The conclusion needed to be made is with N_{Po} is fixed at 10, the *Maxiter* = 200 is the best setting for achieving best mimium value of TAPL and also zero value of STD. The best convergence of *Maxiter* = 200 is displayed in Figure 5.

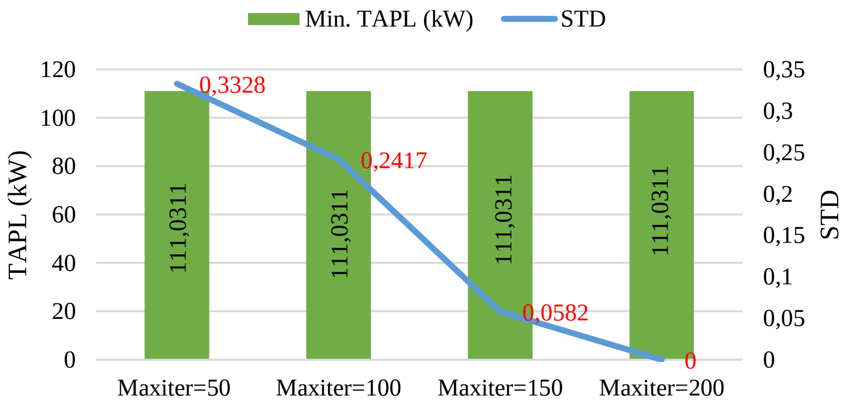

Figure 4. *The suvery on the stability achieved by NGO with different settings of Maxiter = 200*

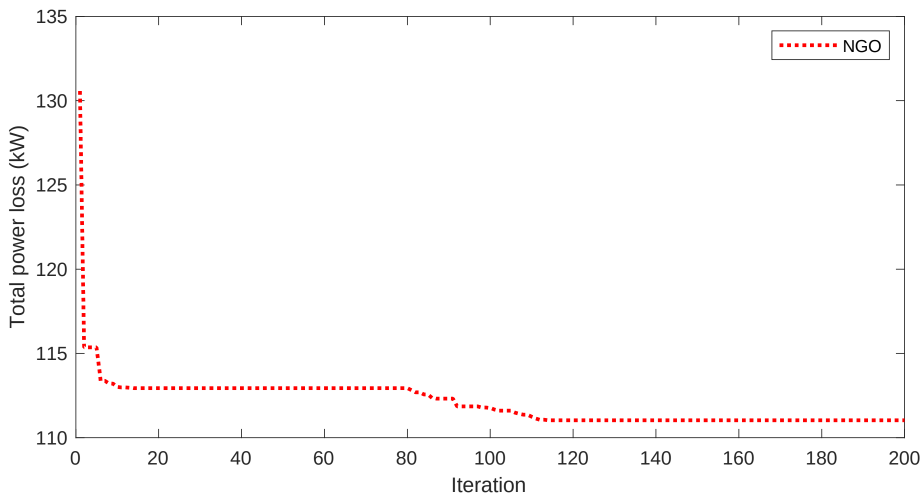

Figure 5. *The best convergence resulted by the Maxiter = 200*

Table 1 compares NGO and other previous methods in terms of different criteria. Notably, the result from the NGO on the TAPL value is compared to 6 other methods, including IA [24], INPS [25], WIPSO [26], SADE [26], ALO [27], and MFO [28]. In the table, only WIPS and SADE found the same installed bus for PVP placement, which is at bus 30, while others placed PVPs at bus 6. On the other hand, the differences in the PVP's rated power are also spotted. The top three largest values of PVP's rated power are IA with 2601 MW and NGO and INPS with 2590 MW and 2474 MW, respectively. More importantly, the values of TAPL recorded by the methods should be paid more attention to because TAPL is the key factor indicating the performance of the compared method in the table. Notably, the TAPL value achieved by NGO is better than all the meta-heuristic algorithms in the table except for INPS, which is not a meta-heuristic algorithm. For instance, when compared with WIPSO and SADE, the difference between NGOs and these two methods is significant, at 125.267 kW compared to only 111.03 kW by NGOs. In addition, NGO is also better than IA and ALO, with the TAPL results from these two methods being 111.1 kW and 111.302 kW, respectively. Finally, in comparison with the last meta-heuristic algorithm considered, MFO, the TAPL value achieved by NGO is also slightly better. However, the difference is not as great as that between the other methods in the same class mentioned above.

Table 1. *The comparison on the results achived by NGO and previous methods*

	IA [24]	INPS [25]	WIPSO [26]	SADE [26]	ALO [27]	MFO [28]	NGO
Original TAPL (kW)	211	211	211	211	211	211	211
Installed bus	6	6	30	30	6	6	6
PVP's rated power (kW)	2601	2474	1600	1600	2450	2560	2590
TAPL with PVP (kW)	111.1	110.142	125.267	125,267	111.302	111.042	111.03
TAPL reduction (%)	47.39	47.8	40.63	40.63	47.25	47.37	47.38

4.2. Determine the optimial locations for placing different number of PVP on grid.

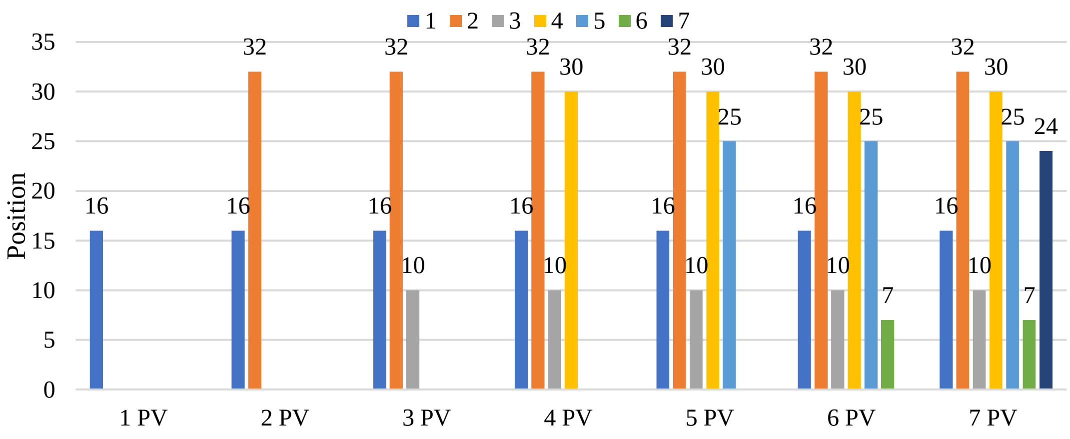

Figure 6. *Different number and position of PVPs placed in grid*

In this subsection, different numbers of PVP placed in the grid will be examined to evaluate the effect of PVP numbers on the TAPL. Specifically, the number of PVPs placed in the grid varies from 1 to 7, and the NGO is in charge of finding the optimal position of the PVPs on the grid and the TAPL value corresponding with each case of PVP number. Note that the rated power of each PVP used in this section is the same and is fixed at 400 kW. This rated power is achieved using ten solar panels of the JAM54S30-400/MR model from JA Solar. This Chinese manufacturer is also known as one of the top solar power companies in the Chinese mainland while considering their cost-effective and efficient solar solutions. The detailed specifications of the selected solar panel can be learned at [29]. The specific positions corresponding to different numbers of PVPs are presented in Figure 6. Next, the TAPL values resulting

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from different numbers of PVPs are given in Figure 7. The observation in Figure 7 reveals that the more PVPs penetrate the grid, the more TAPL is decreased.

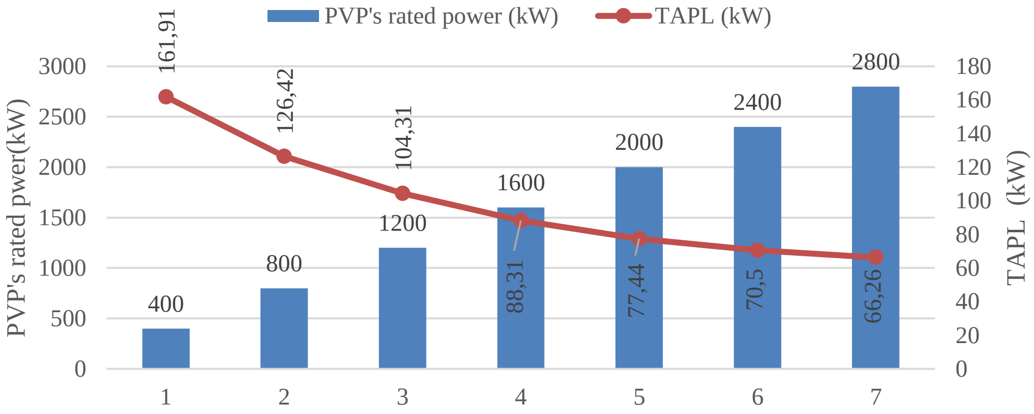

Figure 7. *The TAPL values corresponding to the number of PVPs placed on grid*

4.3. Determine the optimal position of placing PVP with different values of rated power.

In this subsection, a sole PVP with a different rated power output varying from 100 to 4000 kW is placed on the grid to evaluate the variation on TAPL. Like the above subsections, NGO is also applied to determine the optimal position of PVP on the grid for achieving the best value of TAPL. The results achieved by the NGO are shown in Figure 8. The figure indicates that while the rated power of the PVP is increased from 100 to 1300 kW, the value of TAPL becomes smaller, and the position to place the PVP is also changed. However, while the rated power is increased from 1300 to 1800 kW, the exact position of PVP on the grid is found with a slight reduction of TAPL. A similar phenomenon also happens with the rated power between 1900 and 2100 kW with the optimal position on the grid in bus 7. The consideration of TAPL on the last range of rated power from 2200 to 4000 kW of PVP can be divided into two stages, including stage 1, where TAPL kept reducing, and stage 2, where the TAPL started increasing again regardless of the similar position of PVP on the grid is found. Stage 1 lasts from the rated power output of 2200 kW to 2600 kW. The values of TAPL are reduced from 112.2 kW and reach the minimum value of 111 kW. In stage 2, while the rated power continuously increases from 2700 kW onward, the value of TAPL also increases reverently compared to stage 1 and reaches the top value of 137.5 kW.

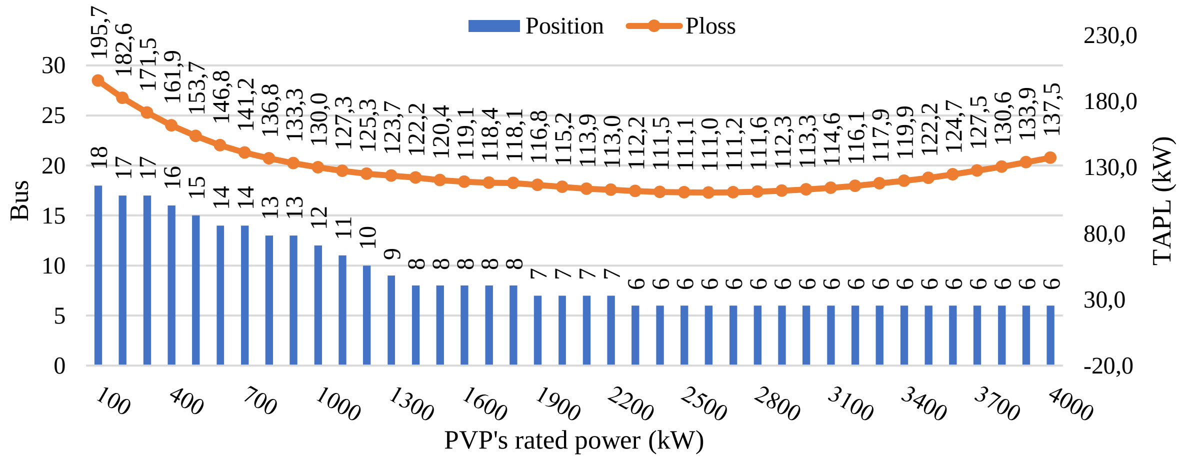

Figure 8. *The position on grid and the values of TAPL corressponding to different rated power of the sole PVP.*

Through the results described in Figure 8, the conclusion is that if the rated power of PVP is between 100 and 700 kW, a PVP should be placed at one of the buses 18, 17, 16, and 15 to achieve the best

TAPL. On the other hand, if PVP's rated power is more significant than 2200 kW, bus 6 is the best position to place PVP for a minimum value of TAPL.

Figure 9 presents the grid's highest and lowest voltage values for each value of PVP's rated power between 100 to 4000kW. The figure shows that the lowest voltage value gradually increases while PVP's rated powers become larger from 100 to 1800kW and from 2300 to 4000kW. At the time the PVP's rated power reaches 1900 kW, the lowest value of voltage is sharply decreased; however, while PVP's rated power is continuously increased by 100 kW more, the lowest value of voltage has moved up again and slightly decreases after PVP's rated power reaches 2200 kW. On the contrary, with the voltage's lowest values, the highest ones almost remain the same except in cases where PVP's rated power reaches 3600 kW onward. However, the higher voltage value increase is not dramatic compared to the lowest one following the variation of PVP's rated power.

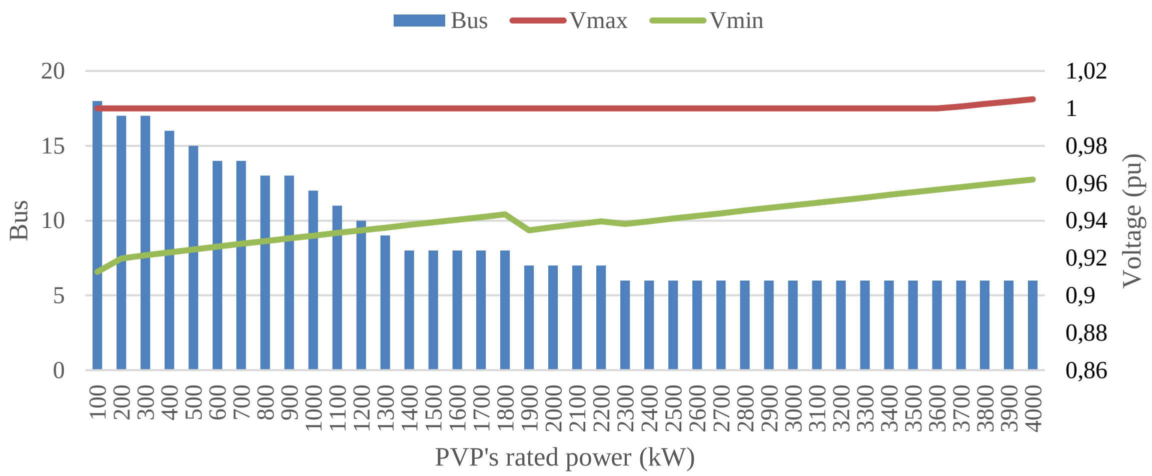

Figure 9. *The voltage profiles corresponding to different values of PVP's rated power placed on grid..*

4.4. The discussion on the rated installed power of the PVP using the previous sections

Choosing the right size for a grid-connected PV system requires a multi-step approach. Analyze sunlight data and available installed space to understand potential energy generation. Investigate the adaptability of the power grid at the location where the PV system will be placed and connected to the grid. This step is necessary because if PVP injects more power than the value needed at the specific point, this will negatively influence dynamic stability, resulting in the unstable operation of electrical devices and causing economic damage. Next, a detailed analysis of the electricity demand must be conducted to accompany the expandability factor in the future. The selection of the correct expandability factor will later benefit while demand increases, leading to a larger power supply. Finally, financials are key – compare system costs with projected energy savings and available incentives to find the most cost-effective size. In this last step, optimization methods are applied to establish an optimal solution that best balances engineering and economic considerations.

Moreover, the selection of 3000kW or 4000kW rated power of the PV system in the manuscript is based on the following reasons:

- The PV systems with rated power ranging from 3000 to 4000 kW, which we have chosen for our research, are not just theoretical concepts. They are already installed and connected to the distribution power grid in real-world applications. For instance, further information about the supplier providing a 3MW PV system can be found at [30] and [31] for a 4000kW PV system. This practical application underscores the relevance and importance of our research.
- Previous studies [32], [33] have also evaluated the PVP's rated power output of 3000 to 4000kW. These studies also claim that these rated powers are practically and economically suited to small and medium-scale distribution networks.

- Compared to the load demand of the considered EDN, which has active and reactive power demands of 3750 kW and 2300 kVar, the placement of PVPs with a total rated power greater than 4000 kW is not really essential.

5. Conclusions

In this research, an effective search method called the Northern Goshawk Optimization (NGO) is employed to optimize the placement of the photovoltaic power plants (PVPs) on the IEEE 33-bus for minimum total active power loss (TAPL). Three study cases have been conducted to assess the actual effectiveness of NGO and also evaluate the variation of TAPL in different implementations of PVP on the grid. Mainly, NGO is applied to optimize the placement for a sole PVP on a grid using different settings of a maximum number of iterations (*Maxiter*) and a constant value of the initial population size (N_{Po}). The results achieved by the best optimal settings of NGO are compared to previous meta-heuristic algorithms, and the NGO has proven its competitive capability in the first case. In the second study case, the placement of PVPs on the grid is executed with different quantities from 1 to 7 using the same rated power for each PVP. Finally, a PVP with different rated power from 100 to 4000kW has been optimized for placement on the grid. The comparison of TAPL resulting in the last two cases reveals that the placement of PVPs independently in study case 2 achieves the highest efficiency regarding TAPL reduction and total rated power of all PVPs. However, the results in the third study case also provide valuable references for the cases in which EDNs in practice can only place a sole PVP with different rated power due to some reasons both in engineering and non-engineering.

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Conflict of Interest

The authors declare no conflict of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

REFERENCES

[1] T. T. Nguyen and F. Mohammadi, “Optimal Placement of TCSC for Congestion Management and Power Loss Reduction Using Multi-Objective Genetic Algorithm,” *Sustainability*, vol. 12, no. 7, p. 2813, Apr. 2020, doi: 10.3390/su12072813.

[2] F. Mohammadi and M. Saif, “A comprehensive overview of electric vehicle batteries market,” *e-Prime - Adv. Electr. Eng. Electron. Energy*, vol. 3, p. 100127, Mar. 2023, doi: 10.1016/j.prime.2023.100127.

[3] F. Mohammadi, “Design, Analysis, and Electrification of a Solar-Powered Electric Vehicle,” *J. Sol. Energy Res.*, vol. 3, no. 4, pp. 293–299, 2018, [Online]. Available: www.jser.ut.ac.ir

[4] M. G. Hemeida, A. A. Ibrahim, A. A. A. Mohamed, S. Alkhalaf, and A. M. B. El-Dine, “Optimal allocation of distributed generators DG based Manta Ray Foraging Optimization algorithm (MRFO),” *Ain Shams Eng. J.*, vol. 12, no. 1, pp. 609–619, 2021, doi: 10.1016/j.asej.2020.07.009.

[5] T. T. The, S. N. Quoc, and D. V. Ngoc, “Symbiotic Organism Search Algorithm for Power Loss Minimization in Radial Distribution Systems by Network Reconfiguration and Distributed Generation Placement,” *Math. Probl. Eng.*, vol. 2020, pp. 1–22, Jun. 2020, doi: 10.1155/2020/1615792.

[6] B. Sun, Y. Li, Y. Zeng, J. Chen, and J. Shi, “Optimization planning method of distributed generation based on steady-state security region of distribution network,” *Energy Reports*, vol. 8, pp. 4209–4222, Nov. 2022, doi: 10.1016/j.egyr.2022.03.078.

[7] A. Asrari, T. Wu, and S. Lotfifard, “The Impacts of Distributed Energy Sources on Distribution Network Reconfiguration,” *IEEE Trans. Energy Convers.*, vol. 31, no. 2, pp. 606–613, 2016, doi: 10.1109/TEC.2015.2514191.

[8] X. Hao, C. Jiang, L. Wu, and L. Zhang, “Based on the power factors of dfig wind farm for power flow optimization,” *Lect. Notes Electr. Eng.*, vol. 334, pp. 157–165, 2015, doi: 10.1007/978-3-319-13707-0_18.

[9] P. Siano and G. Mokryani, “Evaluating the Benefits of Optimal Allocation of Wind Turbines for Distribution Network Operators,” *IEEE Syst. J.*, vol. 9, no. 2, pp. 629–638, Jun. 2015, doi: 10.1109/JSYST.2013.2279733.

[10] M. R. Nayak, D. Behura, and K. Kasturi, “Optimal allocation of energy storage system and its benefit analysis for unbalanced distribution network with wind generation,” *J. Comput. Sci.*, vol. 51, p. 101319, Apr. 2021, doi: 10.1016/j.jocs.2021.101319.

[11] T. Datta and P. Bajpai, “Steady-State Modeling of DFIG-Based Wind Energy System for Unbalanced Operation,” in *Handbook of Renewable Energy Technology & Systems*, WORLD SCIENTIFIC (EUROPE), 2021, pp. 3–35. doi: 10.1142/9781786349033_0001.

[12] S. Pazouki, A. Mohsenzadeh, M. R. Haghifam, and M. E. Talebian, “Optimal allocation of wind turbine in multi carrier energy networks improving loss and voltage profile,” *ELECO 2013 - 8th Int. Conf. Electr. Electron. Eng.*, pp. 67–71, 2013, doi: 10.1109/eleco.2013.6713805.

[13] I. Calero, C. A. Canizares, K. Bhattacharya, and R. Baldick, “Duck-Curve Mitigation in Power Grids With High Penetration of PV Generation,” *IEEE Trans. Smart Grid*, vol. 13, no. 1, pp. 314–329, Jan. 2022, doi: 10.1109/TSG.2021.3122398.

[14] A. P. Adeagbo, F. K. Ariyo, K. A. Makinde, S. A. Salimon, O. B. Adewuyi, and O. K. Akinde, “Integration of Solar Photovoltaic Distributed Generators in Distribution Networks Based on Site’s Condition,” *Solar*, vol. 2, no. 1, pp. 52–63, 2022, doi: 10.3390/solar2010004.

[15] O. D. Montoya, L. F. Grisales-Noreña, L. Alvarado-Barrios, A. Arias-Londoño, and C. Álvarez-Arroyo, “Efficient Reduction in the Annual Investment Costs in AC Distribution Networks via Optimal Integration of Solar PV Sources Using the Newton Metaheuristic Algorithm,” *Appl. Sci.*, vol. 11, no. 23, p. 11525, Dec. 2021, doi: 10.3390/app112311525.

[16] O. D. Montoya, L. F. Grisales-Noreña, and D. A. Giral-Ramírez, “Optimal Placement and Sizing of PV Sources in Distribution Grids Using a Modified Gradient-Based Metaheuristic Optimizer,” *Sustainability*, vol. 14, no. 6, p. 3318, Mar. 2022, doi: 10.3390/su14063318.

[17] R. K. Samala and K. Mercy Rosalina, “Optimal Allocation of Multiple Photo-Voltaic and/or Wind-Turbine Based Distributed Generations in Radial Distribution System Using Hybrid Technique with Fuzzy Logic Controller,” *J. Electr. Eng. Technol.*, vol. 16, no. 1, pp. 101–113, 2021, doi: 10.1007/s42835-020-00577-5.

[18] A. Arasteh, P. Alemi, and M. Beiraghi, “Optimal allocation of photovoltaic/wind energy system in distribution network using meta-heuristic algorithm,” *Appl. Soft Comput.*, vol. 109, p. 107594, Sep. 2021, doi: 10.1016/j.asoc.2021.107594.

[19] T. Rawat, K. R. Niazi, N. Gupta, and S. Sharma, “Impact analysis of demand response on optimal allocation of wind and solar based distributed generations in distribution system,” *Energy Sources, Part B Econ. Planning, Policy*, vol. 16, no. 1, pp. 75–90, Jan. 2021, doi: 10.1080/15567249.2020.1844346.

[20] H. A. Taha, M. H. Alham, and H. K. M. Youssef, “Multi-Objective Optimization for Optimal Allocation and Coordination of Wind and Solar DGs, BESSs and Capacitors in Presence of Demand Response,” *IEEE Access*, vol. 10, pp. 16225–16241, 2022, doi: 10.1109/ACCESS.2022.3149135.

[21] R. Fathi, B. Tousi, and S. Galvani, “A new approach for optimal allocation of photovoltaic and wind clean energy resources in distribution networks with reconfiguration considering uncertainty based on info-gap decision theory with risk aversion strategy,” *J. Clean. Prod.*, vol. 295, p. 125984, May 2021, doi: 10.1016/j.jclepro.2021.125984.

[22] T. T. Nguyen, L. H. Pham, F. Mohammadi, and L. C. Kien, “Optimal Scheduling of Large-Scale Wind-Hydro-Thermal Systems with Fixed-Head Short-Term Model,” *Appl. Sci.*, vol. 10, no. 8, p. 2964, Apr. 2020, doi: 10.3390/app10082964.

[23] M. Dehghani, S. Hubalovsky, and P. Trojovsky, “Northern Goshawk Optimization: A New Swarm-Based Algorithm for Solving Optimization Problems,” *IEEE Access*, vol. 9, pp. 162059–162080, 2021, doi: 10.1109/ACCESS.2021.3133286.

[24] K. Nadhir, D. Chabane, and B. Tarek, “Firefly algorithm based energy loss minimization approach for optimal sizing & placement of distributed generation,” in *2013 5th International Conference on Modeling, Simulation and Applied Optimization (ICMSAO)*, Apr. 2013, pp. 1–5. doi: 10.1109/ICMSAO.2013.6552580.

[25] S. Dahal, A. K. Jha, N. Bhattarai, and A. K. Panjiyar, “Determining the Hosting Capacity of Solar Photovoltaic in a Radial Distribution Network Using an Analytical Approach,” *J. Adv. Coll. Eng. Manag.*, vol. 5, pp. 15–25, 2019, doi: 10.3126/jacem.v5i0.26673.

[26] S. Rajeswaran, and K. Nagappan, “Optimum simultaneous allocation of renewable energy DG and capacitor banks in radial distribution network,” *Circuits Syst*, vol.7. *no*. 11, pp. 3556-3564, 2016, doi: 10.4236/cs.2016.711302.

[27] E. S. Ali, S. M. Abd Elazim, and A. Y. Abdelaziz, “Ant Lion Optimization Algorithm for optimal location and sizing of renewable distributed generations,” *Renew. Energ.*, vol. 101, pp. 1311-1324, 2017, doi: 10.1016/j.renene.2016.09.023.

[28] M. A. Tolba, A. A. Z. Diab, V. N. Tulsky, and A. Y. Abdelaziz, “LVCI approach for optimal allocation of distributed generations and capacitor banks in distribution grids based on moth–flame optimization algorithm,” *Electr. Eng.*, vol. 100, pp. 2059-2084, 2018, doi: 10.1007/s00202-018-0684-x.

[29] https://www.jasolar.com: https://www.jasolar.com/uploadfile/2022/0511/20220511060029354.pdf

[30] 3MW PV system solution from Bluesun. https://www.bluesunpv.com/3mw-grid-tied-solar-system-power-plant-commercial-solution_p273.html

[31] 4MW PV system solution from Nidec. https://www.nidec-industrial.com/document/solar-production-energy-storage-system-case-study/

[32] F. U. H. Faiz, R. Shakoor, A. Raheem, F. Umer, N. Rasheed, , and M. Farhan, “Modeling and analysis of 3 MW solar photovoltaic plant using PVSyst at Islamia University of Bahawalpur, Pakistan,” *Int. J. Photoenergy*, vol. 2021, pp. 1-14, 2021, doi: 10.1155/2021/6673448.

[33] J. Sreedevi, N. Ashwin, and M. N. Raju, “A study on grid connected PV system,” In *2016 National Power Systems Conference (NPSC)* (pp. 1-6). IEEE, December 2016, doi: 10.1109/NPSC.2016.7858870.

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