Jurnal
Teknologi

Full Paper

ANALYSIS OF NON-OPTIMAL PV SIZING AND PLACEMENT IN DISTRIBUTION NETWORKS WITH COMMERCIAL, INDUSTRIAL, AND RESIDENTIAL LOADS

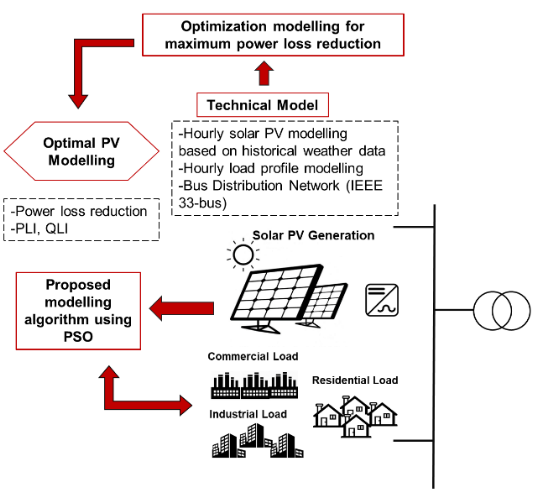
Hanis Farhah Jamahori[a*], Abid Ali[b], Siti Salwa Mat Isa[c]

[a]Electrical and Electronics Engineering Department, Faculty of Engineering, Universiti Teknologi Petronas, 32610 Seri Iskandar, Perak Darul Ridzuan, Malaysia
[b]Interdisciplinary Institute of Technological Innovation (3IT), Université de Sherbrooke, 3000 Boulevard
[c]Electrical Engineering Studies, College of Engineering, Universiti Teknologi MARA, Cawangan Pulau Pinang
13500 Permatang Pauh, Malaysia

Article history
Received
19 June 2024
Received in revised form
13 March 2025
Accepted
13 March 2025
Published Online
22 August 2025

*Corresponding author
hanis.jamahori@utp.edu.my

Graphical abstract



Abstract

The integration of Photovoltaic (PV)-based Distributed Generation (DG) into distribution networks is significantly influenced by varying load consumption patterns. Commercial, industrial, and residential users exhibit distinct consumption profiles, which impact the demand-supply dynamics within these networks. Therefore, implementing an effective optimization method to determine the optimal size and location of PV systems in the distribution network, while considering varying load patterns, is crucial for optimizing energy production, reducing dependence on the grid, and minimizing power losses. An optimization approach using Particle Swarm Optimization (PSO) is proposed to address this challenge effectively. To verify the effectiveness of the proposed method, simulation studies were conducted on IEEE 33 bus test distribution networks. Various test cases were examined to investigate the impacts of improper PV sizing and placement, and the results were compared with those of the proposed method. The findings revealed that the optimal placement and sizing of PV systems, as determined using PSO, achieved power loss reductions of 13.84%, 20.70%, and 32.71% for industrial, residential, and commercial loads, respectively, when located at bus 6. In contrast, improper PV installation resulted in either excess or insufficient power generation, leading to higher power losses and inefficiencies within the system.

Keywords: Photovoltaic (PV), solar irradiance, varied load, power loss, distribution network

Abstrak

Penyepaduan Penjanaan Teragih (DG) berasaskan Fotovoltaik (PV) ke dalam rangkaian pengagihan dipengaruhi secara signifikan oleh corak penggunaan beban yang berubah. Pengguna komersial, industri, dan kediaman mempunyai profil penggunaan yang berbeza, yang mempengaruhi dinamik permintaan dan bekalan dalam rangkaian tersebut. Oleh itu, pelaksanaan kaedah pengoptimuman yang berkesan untuk menentukan saiz dan lokasi optimum sistem PV dalam rangkaian pengagihan, dengan mengambil kira corak penggunaan beban yang berubah, adalah penting untuk mengoptimumkan pengeluaran tenaga, mengurangkan kebergantungan pada grid, dan meminimumkan kehilangan kuasa. Pendekatan pengoptimuman menggunakan Pengoptimuman Kawanan Zarah (PSO) dicadangkan untuk menangani cabaran ini secara berkesan. Untuk mengesahkan keberkesanan kaedah yang dicadangkan, kajian simulasi telah dijalankan pada rangkaian pengagihan ujian IEEE bas-33. Pelbagai kes ujian telah diuji untuk menyiasat kesan saiz dan lokasi PV yang tidak sesuai, dan hasilnya dibandingkan dengan kaedah yang dicadangkan. Dapatan kajian menunjukkan bahawa lokasi dan saiz sistem PV yang optimum, seperti yang ditentukan menggunakan PSO, mencapai pengurangan kehilangan kuasa sebanyak 13.84%, 20.70%, dan 32.71% masing-masing untuk beban industri, kediaman, dan komersial di bas 6. Sebaliknya, pemasangan PV yang tidak sesuai menyebabkan penjanaan kuasa yang berlebihan atau tidak mencukupi, mengakibatkan kehilangan kuasa yang lebih tinggi dan ketidakcekapan dalam sistem.

Kata kunci: Fotovoltaik (PV), sinaran suria, beban pelbagai, kehilangan kuasa, rangkaian pengedaran

© 2025 Penerbit UTM Press. All rights reserved

1.0 INTRODUCTION

The integration of Distributed Generation (DG) into distribution systems has various effects, which can be either advantageous or harmful depending on the DG's placement and capacity. A major impact of DG integration is its influence on power flow and line losses. In the traditional radial distribution system, power flow is unidirectional from generation to consumer point. DG implementation changes the distribution system structure because power flow is no longer unidirectional [1]. These changes impact grid losses since the power losses depend on the power flow. In addition, integrating DG into a distribution system can result in under-voltage or over-voltage issues. With Renewable Energy (RE)-based DG, the rapid penetration caused by the intermittent sources will impact network stability, and load balance. Sudden changes will induce large fluctuations in the output power and lead to high power losses in the distribution systems [2]. This amount of power loss in the distribution system greatly impacts the system's performance. Proper DG planning must be done early in the process to guarantee that DG is well optimized and helps to improve the load factors, voltage profiles, system security, and reliability. The efficiency of the distribution system also increases due to the reduction in power loss. The proper DG design, size, and location significantly impacted the distribution system [3-5].

Solar PV energy is abundant and freely available across the world. The sun provides a substantial amount of energy every day, enough to meet global energy demands many times over if harnessed effectively. Unlike fossil fuels, which are finite and depleted over time, solar energy is a renewable resource that will be available, making it a sustainable energy solution. Additionally, PV systems generate electricity from converting sunlight directly into electricity using semiconductor materials. This process does not require any moving parts, significantly reducing the risk of mechanical failure and the need for frequent maintenance. In addition, no toxic gas emissions are produced during electricity generation, making it a source of green energy that benefits the environment [6-9]. PV offers several technical benefits when integrated into the distribution system. These benefits contribute to improved efficiency, reliability, and performance of the grid. Technical benefits of PV in the distribution system include but are not limited to loss minimizations, reliability improvement, loadability maximization, cost minimization, voltage profile improvement, and a hybrid system [10-12].

While PV systems offer many advantages, integrating them into a distribution system requires careful planning and consideration of several critical factors to maximize their benefits and avoid potential drawbacks. The effective planning and integration of PV systems into the distribution grid requires a comprehensive approach that considers load patterns, capacity planning, optimal location, network connection, and potential impacts on losses and costs. Proper planning ensures that the benefits of PV systems are fully realized while minimizing any negative impacts on the distribution system. The placement of PV units in non-optimal locations might increase system losses and costs and have the opposite of the desired impact [2, 13]. Different studies on optimal integration of PV have explored different technological issues to attain different benefits. In addition, selecting optimal installation locations and PV unit sizes in large distribution systems involves a difficult combination of the optimization problem. In developing countries, where utilities already face the problem of high-power losses and poor voltage profiles due to heavy loads, the PV must be properly integrated to take advantage of the benefits of improving loadability, lowering losses, and increasing supply reliability [14, 15].

Finding the optimal location and sizing of photovoltaic (PV) units in electrical power systems is a complex problem that has been approached using various methods. These methods range from analytical and numerical programming to heuristic and artificial intelligence-based optimization techniques, often referred to as meta-heuristic techniques. Among these, meta-heuristic techniques are particularly prevalent in electrical power applications due to their effectiveness in handling complex optimization problems. A Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Simulated Annealing (SA), Tabu Search (TS), Particle Swarm Optimization (PSO), Bat Algorithm (BA), Colony Optimization (ACO), and Grasshopper Optimization Algorithm (GOA) are some of the existing meta-heuristic techniques [16-21]. Most research used different optimization techniques for optimal DG size and location in a power system to reduce transmission power losses [22].

Some studies in DG planning considering time-varying DG generation and loads have been reported. In [23], Das. S *et al.* proposed GA to find the optimal DG size with a time-varying residential load. The optimal location for DG is determined based on network reconfiguration for loss reduction and voltage improvement using sensitivity analysis. The DG generation unit performed in this study was pre-defined. Hung *et al.* [24, 25] proposed an analytical method for DG integration with time-varying loads to minimize power loss and a multi-objective function to calculate the optimum PV penetration levels in distribution systems for different types of time-varying loads. However, the methodology followed in this study was limited due to pre-determined numbers of the combined DG and load model. Analytical methods provide the exact solution, but sometimes not always possible to achieve due to the long computation time. These methods are often based on numerical methods, which offer better computational time but can only approximate the exact solution. The solution approximation, in which the robustness depends on the numerical method, can produce non-realistic results.

Khan and Malik performed a comparative analysis of the impact of time-varying PV generation on the load model [26]. Three years of solar irradiance data were used to predict the hourly PV output through a novel probabilistic generation modelling approach to compute the hourly PV power. The optimal size and location are determined based on studies done in [27], which applied PSO to find the optimal location and the size of the PV unit. Another study proposed the Salp Swarm Algorithm (SSA) [28] in a 19-bus system to find the optimal location and size of wind-based DG on different time-varying loads based on multi-objective functions. However, the load model was pre-defined, and the use of historical weather data is not reported. Besides that, [24-28] proves that using a time-varying modelling approach significantly impacts the distribution systems and plays an imperative part in DG planning. A recent study in [29] has presented the analysis of the integration of PV with varying loads using PSO. While this research provides valuable analysis of PV performance on commercial users, it does not address the performance and challenges associated with residential and industrial load users. References to studies and literature indicate that most research focusing on optimal DG size and location employs different optimization techniques to achieve a high reduction in power losses. However, PSO stands out due to its consistent performance and efficiency in finding optimal solutions in DG planning scenarios.

Despite numerous studies addressing PV integration, the challenges of achieving optimal optimization for varied load profiles remain inadequately studied. The theoretical framework for this study is built on the principles of power systems optimization and renewable energy integration, focusing specifically on reducing power losses and improving grid efficiency through optimal PV system placement and sizing. While existing studies have addressed PV optimization, limited attention has been given to the effects of time-varying load profiles across industrial, residential, and commercial sectors. This study aims to address this gap by proposing an optimization framework to determine the optimal size and location of PV systems under varied load conditions. A review of existing literature reveals that most optimization studies primarily focus on generic load scenarios without adequately considering the characteristics of different load types. Furthermore, the connection between PV system sizing and location has often been analyzed in remote areas rather than as grid-connected. These gaps show the need for a more comprehensive approach to optimize PV integration in real-world grid distribution networks. The novelty of this study lies in its detailed analysis of the impacts of non-optimal PV sizing and placement for various load models, providing practical information for both grid operators and policymakers.

This study employs PSO method, which has proven effective for complex, multi-variable optimization problems. The methodology was applied to IEEE-33 bus of a distribution network, integrating time-varying load data to reflect real operational scenarios. The model not only extends prior research but also explores the consequences of non-optimal PV configurations, such as over-sizing or under-sizing systems. The results provide a detailed comparison of power loss reductions, voltage stability indices, and overall grid performance under optimal and non-optimal configurations. The findings contribute to the literature by suggesting a practical framework for optimizing PV systems, to show the critical balance between size and location.

2.0 METHODOLOGY

The system parameters employed in this study, consisting of load demand and PV profiles, are integrated with power flow formulation, power loss impact indices, and optimization techniques aimed at minimizing the objective function of reducing losses, as detailed below:

2.1 Load Demand Profile

Figure 1 illustrates the graphical representations of the electrical load (varying demand) patterns over 24 hours, normalized for different user categories of industrial, residential, and commercial [30].

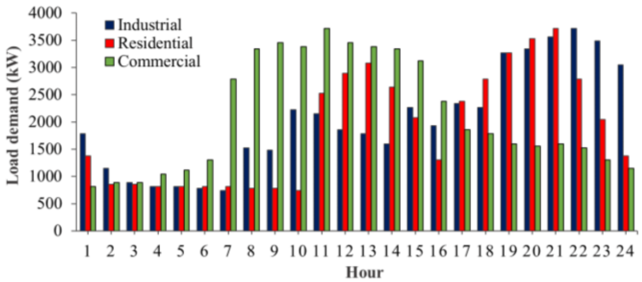


Figure 1 Industrial, residential, and commercial load demand consumption profile in 24 hours

2.2 Solar PV Profile

The Solar Probability Density Function is used to predict the output of PV following the methodology conducted in [31]. The solar PV curve is shown in Figure 2. The maximum irradiance collected from this site is 737 Wh/m^2.

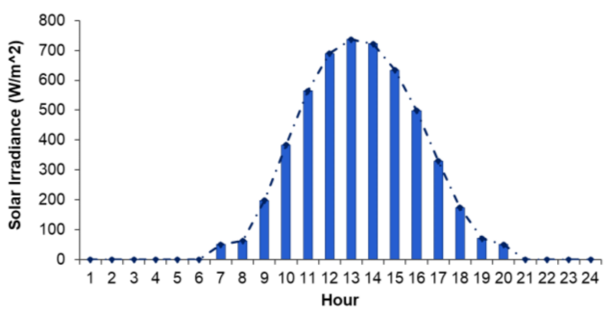


Figure 2 24-hour solar irradiance curve (Wh/m^2)

2.3 Power Flow

The active, $P_{Loss(i)}$ and reactive, $Q_{Loss(i)}$ power loss in any branches, *i* before and after PV is connected at $k+1$ bus can be calculated as follows [32]:

$$P_{Loss(i)} = R_i\left(\frac{{P_{k+1}}^2 + {Q_{k+1}}^2}{|V_{k+1}|^2}\right) \quad (1)$$

$$Q_{Loss(i)} = X_i\left(\frac{{P_{k+1}}^2 + {Q_{k+1}}^2}{|V_{k+1}|^2}\right) \quad (2)$$

$$P_{Loss,PV(i)} = R_i\left(\frac{(P_{(k+1)} - P_{PV})^2 + (Q_{(k+1)} - Q_{PV})^2}{|V_{k+1}|^2}\right) \quad (3)$$

$$Q_{Loss,PV(i)} = X_i\left(\frac{(P_{(k+1)} - P_{PV})^2 + (Q_{(k+1)} - Q_{PV})^2}{|V_{k+1}|^2}\right) \quad (4)$$

Similarly, the total losses in all branches before, $TP_{Loss(i)}$ and after PV, $TP_{Loss,PV(i)}$ is installed at $k+1$ bus are calculated as follows [33]:

$$TP_{Loss(i)} = \sum_{i=1}^{N_{branches}} (P_{Loss(i)} + jQ_{Loss(i)}) \quad (5)$$

$$TP_{Loss,PV(i)} = \sum_{i=1}^{N_{branches}} (P_{Loss,PV(i)} + jQ_{Loss,PV(i)}) \quad (6)$$

The objective function, *f* can be defined as the ratio of losses with PV to the base case power losses without PV [33]:

$$\text{Objective Function}, f = \text{minimize} \sum_{t=1}^{24} \frac{TP_{Loss,PV(i)}}{TP_{Loss(i)}} \quad (7)$$

2.4 Power Loss Index (Active, and Reactive)

The Active Power Loss Index (PLI) and Reactive Power Loss Index (QLI) are indices used to measure the impact of integrating photovoltaic (PV) systems on the power losses within the distribution grid. These indices compare the power losses in scenarios with PV integration to the base case scenario without PV integration [33]:

$$PLI = \sum_{t=1}^{t=24} \frac{PL_{PV}(t)}{PL\ (t)} \quad (8)$$

$$QLI = \sum_{t=1}^{t=24} \frac{QL_{PV}(t)}{QL\ (t)} \quad (9)$$

The impact values are as follows:

i. PLI and QLI < 1: Indicates a beneficial impact of PV integration on reducing power losses, leading to improved efficiency and potentially lower costs for maintaining the grid.
ii. PLI and QLI = 1: Indicates that PV integration does not significantly alter power losses, suggesting a neutral impact on the grid's performance in terms of power loss.
iii. PLI and QLI > 1: Indicates an increase in power losses due to PV integration, posing challenges that may need to be addressed through technical adjustments and improved grid management strategies.

3.0 OPTIMIZATION METHOD

3.1 IEEE 33-Bus Radial System

The process of identifying the optimal location and size for PV in the distribution system involves minimizing an objective function, f as in Equation (17). The IEEE 33 bus system, illustrated in Figure 3, is used as the test system. To find the ideal location, PV units of various sizes are placed on different buses, starting from the first to the last node. A load flow analysis is then conducted to compute the objective function at each bus. The optimal location and size, where f is minimized, are determined through this optimization process.

3.2 Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a stochastic, population-based optimization algorithm inspired by swarm intelligence. Developed by Dr. Eberhart and Dr. Kennedy in 1995, PSO addresses various combinatorial optimization problems, including those in power systems [34]. This iterative algorithm mimics the social behaviors of natural organisms like schooling fish and flocking birds. The flowchart illustrating the PSO process utilized in this study is presented in Figure 4.

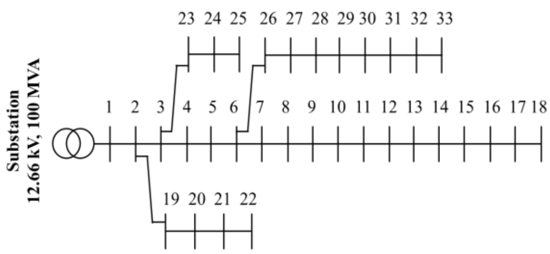


Figure 3 IEEE 33-bus distribution test system

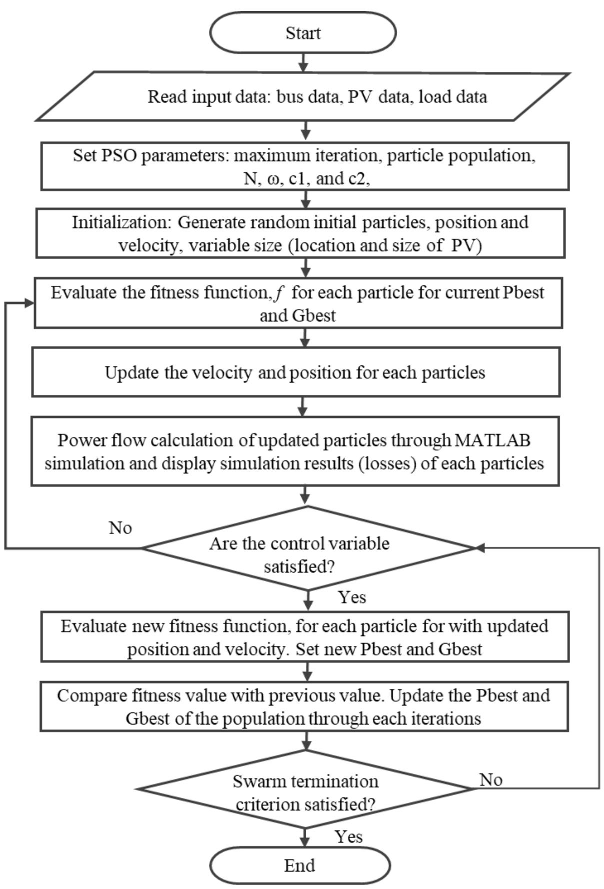


Figure 4 PSO optimization flowchart

4.0 RESULTS AND DISCUSSION

The findings of PV integration determined by PSO for different users in the IEEE 33-Bus test system are performed using different test cases to determine the different impacts of PV on the distribution system. The PSO results with six case studies listed below are considered for the analysis of the results for three different users:

PSO : The result obtained through the optimization for optimal PV size and location.
Case 1: Increase the PV size determined by PSO by 10%, connected to the same optimal bus, bus No. 6.
Case 2: Reduce the PV size determined by PSO by 10%, connected to the same optimal bus, bus No. 6.
Case 3: Connect the same optimal PV size determined by PSO to bus No. 5 instead of bus No. 6.
Case 4: Connect the same optimal PV size determined by PSO to bus No. 7 instead of bus No. 6.
Case 5: Increase the PV size determined by PSO by 10%, connected to bus No. 5 instead of bus No. 6.
Case 6: Reduce the PV size determined by PSO by 10%, connected to bus No. 7 instead of bus No. 6.

4.1 Simulation Results

Table 1, 2 and 3 shows the optimization results for the optimal size and location of PV to reduce the power loss in the distribution system for all load models using different case tests. The analysis result elaborates on the findings for all cases (Case 1 through Case 6), focusing on how deviations in location and size affect power loss reduction (ΔP_{Loss}), reactive power loss reduction (ΔQ_{Loss}), Active Power Loss Index (PLI), and Reactive Power Loss Index (QLI).

Table 1 Optimization results for industrial load

Parameters	Industrial Load						
	PSO	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
Bus No.	6	6	6	5	7	5	7
PV size (MW)	2.90	3.19	2.61	2.90	2.90	3.19	2.61
ΔP_{Loss}, %	13.84	13.70	13.71	10.23	13.67	10.31	13.68
ΔQ_{Loss}, %	12.41	12.21	12.36	7.87	11.63	7.95	12.17
PLI	0.8616	0.8630	0.8629	0.8977	0.8631	0.8968	0.8632
QLI	0.8759	0.8779	0.8764	0.9213	0.8837	0.9205	0.8782

Table 2 Optimization results for residential load

Parameters	Residential Load						
	PSO	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
Bus No.	6	6	6	5	7	5	7
PV size (MW)	3.34	3.68	3.01	3.34	3.34	3.68	3.01
ΔP_{Loss}, %	20.70	20.50	20.51	15.32	20.47	15.46	20.47
ΔQ_{Loss}, %	18.63	18.33	18.55	11.86	17.44	12.00	18.25
PLI	0.7930	0.7950	0.7949	0.8468	0.7953	0.8454	0.7953
QLI	0.8137	0.8167	0.8145	0.8814	0.8256	0.8800	0.8175

Table 3 Optimization results for commercial load

Parameters	Commercial Load						
	PSO	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
Bus No.	6	6	6	5	7	5	7
PV size (MW)	4.58	5.04	4.12	4.58	4.58	5.04	4.12
ΔP_{Loss}, %	32.71	32.43	32.39	24.25	32.33	24.51	32.32
ΔQ_{Loss}, %	29.54	29.12	29.39	18.92	27.66	19.18	28.89
PLI	0.6729	0.6757	0.6761	0.7575	0.6767	0.7549	0.6768
QLI	0.7046	0.7088	0.7061	0.8108	0.7234	0.8082	0.7111

From the results shown, the optimal location of PV is found to be at bus number 6 for all load models with PV sizes of 2.90MW, 3.34MW, and 4.58MW and power losses of 13.84%, 20.70%, and 32.71%, for industrial, residential, and commercial load, respectively. Based on the findings, the results determined through PSO were the most optimum for power loss reduction, PLI, and QLI based on the location and sizing of PV for different load models. Inaccurate placement and sizing of PV have contributed to low power loss reduction and high PLI and QLI indices.

4.2 Analysis of Non-Optimal Sizing in Case 1 and Case 2

In Case 1 and Case 2, PV units are installed at the optimal location (Bus 6) but with oversized (Case 1) and undersized (Case 2). As seen in commercial load, the results in ΔP_{Loss} decreased marginally from 32.71% (PSO) to 32.43%, despite the PV size increasing to 5.04 MW from the optimal 4.58 MW. Similarly, ΔQ_{Loss} reduces from 29.54% to 29.12%. This demonstrates declining returns, where the added capacity fails to contribute proportionally to loss reduction. In Case 2, the PV system is undersized to 4.12 MW, leading to ΔP_{Loss} dropping further to 32.39% and ΔQ_{Loss} to 29.19%. The industrial load follows the same trend as seen in Case 1, oversizing to 3.19 MW achieves negligible improvements in ΔP_{Loss} (13.70%) compared to PSO (13.84%), while undersizing in Case 2 to 2.61 MW slightly worsens ΔP_{Loss} at 13.71%. In the residential load, oversizing to 3.68 MW in Case 1 results in ΔP_{Loss} decreasing only slightly from 20.70% (PSO) to 20.51%. Similarly, ΔQ_{Loss} drops marginally from 18.63% to 18.33%, showing that the system cannot fully utilize the additional capacity. Moreover, in all cases, indices such as PLI and QLI increase compared to PSO, showing poorer performance in reducing power and reactive power losses. The analysis for Cases 1 and 2 revealed that non-optimal sizing results in reduced system efficiency, even when the PV is placed at the optimal bus. Oversizing offers negligible benefits and increases costs, while undersizing leads to underutilization of the PV system.

4.3 Analysis of Non-Optimal Location in Case 3 and Case 5

n Case 3 and Case 5, the PV system is placed at bus 5 and bus 7, respectively, resulting in non-optimal configurations for all load models. For the commercial load, Case 3 (bus 5) shows reduced ΔP_{Loss} from the PSO-optimal value of 32.71% to 24.51%, and ΔQ_{Loss} declined from 29.54% to 19.18%. Similarly, Case 5 (bus 7) sees a drop in ΔP_{Los} to 24.51% and ΔQ_{Loss} to 19.18%, show how improper placement drastically impacts system performance. In both cases, PLI values increased as seen in Case 3: 0.7575, and Case 5: 0.7549, indicating inefficiencies caused by placing the PV system away from the optimal node. Similarly, in the industrial load model, Case 3 shows ΔP_{Loss} reduced from 13.84% to 10.23%, while Case 5 lowers it further to 10.31%. Both cases revealed poorer voltage stability due to lower reactive power compensation, ΔQ_{Loss}. The residential load demonstrated similar trends where Case 3 reduced ΔP_{Loss} from 20.70% (PSO) to 15.32%, while Case 5 resulted in marginally better ΔP_{Loss} at 15.46% but lost ΔQ_{Loss} stability.

Despite the optimal sizing, placing PV on a non-optimal bus led to significantly reduced power loss and worsened PLI and QLI. This is because these locations may not align with the load centers, causing higher transmission losses. Furthermore, non-optimal locations affect voltage stability issues, especially in industrial and residential load models, where load profiles are more sensitive to location mismatches. The findings indicate that even an optimal-sized PV system cannot achieve its full potential unless it is installed at the optimal bus, as non-optimal locations affect the balance between generation and demand patterns in the network. Even with optimal sizing, improper placement led to significant power loss and voltage stability issues. When sizing deviates from the ideal, these inefficiencies increase, as seen in the increase of PLI and QLI values.

4.4 Analysis of Non-Optimal Location and Sizing in Case 4 and Case 6

Case 4 and Case 6 show the impact of both non-optimal sizing and location of PV in the distribution network. In Case 4, the PV system is installed at a non-optimal bus while maintaining the optimal size determined by the PSO algorithm. This configuration reduces effectiveness to minimize power and reactive power losses across all load models. For the commercial load model, placing the PV from the optimal bus (bus 6) to bus 5 reduces active power loss reduction ΔP_{Loss} from 32.71% to 24.51% and reactive power loss reduction ΔQ_{Loss} from 29.54% to 22.98%. Similarly, the residential load model exhibits a drop in ΔP_{Loss} from 20.70% to 15.46%, and ΔQ_{Loss} from 19.92% to 14.35%, highlighting the impact of location on system performance. The industrial load model follows a comparable trend, where non-optimal placement causes a drop in ΔP_{Loss} from 13.84% to 10.73% and ΔQ_{Loss} from 12.41% to 9.81%.

In Case 6, the PV system is placed at a non-optimal bus, with an oversized capacity. This scenario worsens inefficiencies as both location and size deviate from the optimal configuration. For the commercial load model, placing the PV at bus 5 with an oversized capacity of 5.04 MW reduces ΔP_{Loss} to 24.28% and

ΔQ_{Loss} to 22.36%, further worsening performance compared to Case 4. Similarly, for the residential load model, ΔP_{Loss} declines from 20.51% to 15.31%, and ΔQ_{Loss} drops from 19.64% to 14.22%. The industrial load model exhibits even more obvious losses, where ΔP_{Loss} decreases from 13.71% to 10.31%, and ΔQ_{Loss} drops to 8.15%. Oversizing the PV system increases costs without providing proportional benefits in power loss reduction. Furthermore, the mismatch between the oversized generation and the system's actual demand can lead to operational inefficiencies, further increasing PLI and QLI values. These results show the negative effects of poor placement and overestimated sizing on system efficiency.

4.5 Summary of Simulation Results Analysis

The location and sizing of a PV system plays a critical role in determining how effectively it can reduce active power loss, ΔP_{Loss} and reactive power loss, ΔQ_{Loss} Incorrect placement and sizing impacts the network's ability to control the PV system's power injection to reduce losses effectively. When the PV is not placed at the optimal bus with the right sizing as determined by PSO, the reduction in ΔP_{Loss} and ΔQ_{Loss} decreases significantly. This is because increasing or decreasing the PV size impacts the amount of power generated injected into the grid. However, if the size is not optimal, the PV system might produce either too much or too little power relative to the grid's needs, leading to non-optimal power loss reduction. The location of the PV system affects how effectively the generated power is utilized. Optimal locations are typically chosen based on the generation distance to loads and other factors influencing power flow and losses. Even if a PV system is installed at an optimal location, an incorrect size might not interact efficiently with the grid, thereby failing to minimize losses. Therefore, the connection between size and location is crucial. Maximum power loss reduction is achieved only when the PV system's size is perfectly matched to the demand at the optimal location. This balance ensures that the generated power is fully utilized without causing excess losses due to over- or under-production. Case 1 and Case 2 demonstrate scenarios where either the size or location, or both, are not optimized. These cases showed that only the optimal combination of size and location leads to the highest reduction in power losses, emphasizing the importance of comprehensive optimization while Case 3 and Case 5 have the lowest power loss reductions attained as the installed PV location deviated from the optimal location.

In summary, the analysis for all six cases proves the critical need for both optimal sizing and location of PV systems to maximize power loss reduction and ensure efficient grid operation. Non-optimal sizing, whether oversized or undersized, coupled with non-optimal location, leads to high inefficiencies, including higher transmission losses, reduced voltage stability, and degraded power quality. The main idea is that both the location and the size of the PV system need to be precisely optimized to achieve the highest reduction in power losses.

4.6 PLI and QLI

The PLI and QLI for all load models are depicted in Figure 5. These indices are calculated both with and without PV integration, considering active and reactive power losses using Equation (8)-(9). These indices are influenced by the presence of PV systems, which generate electricity and thus affect the overall power loss in the network. The results indicate that a high PLI and QLI contributed to a negligible impact of PV integration on reducing power losses, while a low index indicates a significant loss reduction. Both indices are relatively low for commercial load but high for industrial load demand. The indices are low for commercial loads, indicating a significant reduction in power losses due to PV integration. Commercial loads typically consume electricity during the daytime, matching the peak generation period of PV systems. Since both generation and consumption occur simultaneously, the electricity generated by the PV systems is immediately utilized by the commercial loads, reducing the need to draw power from the grid, hence reducing losses.

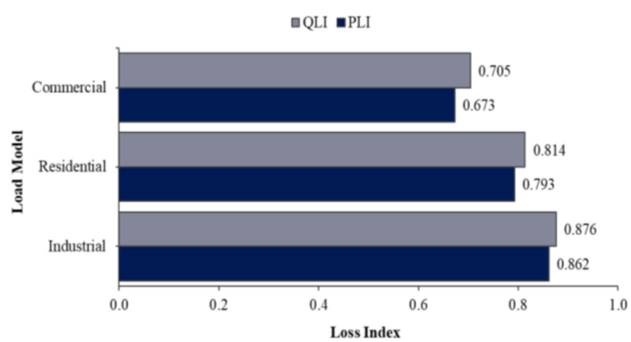


Figure 5 The PLI and QLI after PV integration for all load models (Industrial, Residential, and Commercial)

On the other hand, the indices are high for industrial loads, indicating a negligible reduction in power losses with PV integration. Industrial operations often run 24 hours a day, with significant power consumption occurring during night shifts. Since PV systems generate power during the day and industrial loads consume a huge amount of power at night, the generated power cannot be directly used by the industrial loads. Instead, it must be stored or sent back to the grid, which is less efficient and leads to higher losses. Hence, PV has a more significant effect on commercial load users, while its impact on industrial loads is nearly negligible.

4.7 Optimization Convergence

Figure 6 shows the fitness value computed by PSO in MATLAB. In the early iterations, the mean best fitness starts high and drops sharply.

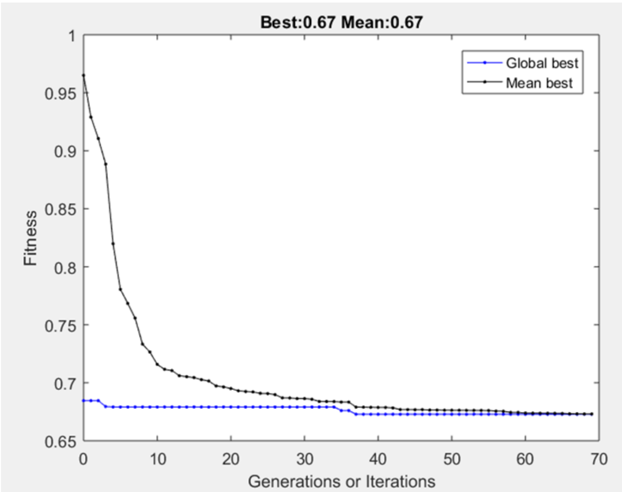


Figure 6 PSO convergence performance

This indicates that the swarm is quickly finding better solutions. The global best fitness also drops rapidly as the best particles quickly converge towards good solutions. The optimization shows that PSO gives the best performance regarding power loss reduction, fast convergence characteristics, and fast computation time. Throughout the iteration, the rate of improvement in fitness slows down. The mean best fitness continues to decrease but at a slower rate. The global best fitness also shows some improvement but at a much slower pace. After Both curves start to flatten out, indicating that the swarm is converging to a solution. The global best fitness remains constant after a certain point, indicating that the best solution found by the swarm is not improving further. The mean best fitness also stabilizes, showing that the particles in the swarm are converging toward this best solution. The best fitness value achieved by the PSO algorithm is 0.67. It demonstrates that the PSO algorithm converges quickly towards an optimal solution. Fast convergence indicates that the algorithm efficiently explores the search space and converges to a near-optimal solution within a reasonable number of iterations.

4.8 PV Output and Load Demand

Figure 7 illustrates the optimized PV output across different load models, while Figure 8 presents the hourly power loss results for all load models, both with and without PV integration, within the 33-bus test system. Based on the optimized PV size for each load model, the commercial load shows the most significant reduction in power loss. Conversely, the industrial load demonstrates the least reduction in power loss. This minimal reduction occurs when PV generation cannot meet the load demand, which peaks at night, particularly for industrial and residential loads. Additionally, there is excess PV output at noon that neither industrial nor residential models fully utilize. In contrast, the commercial load benefits from a better match between PV production and demand throughout the day. This leads to the highest power loss reduction, especially during peak hours at noon.

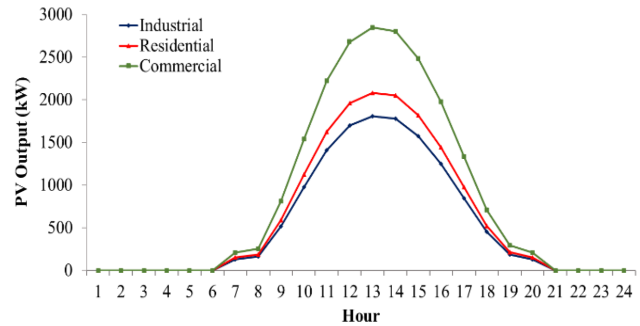
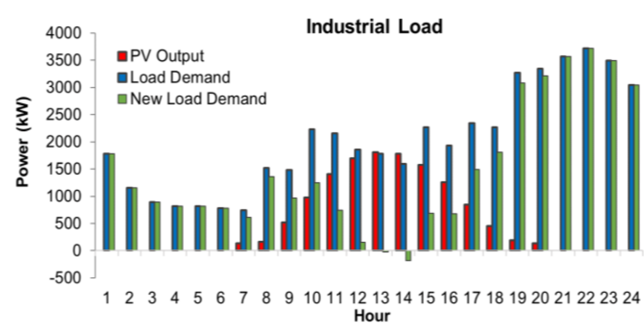
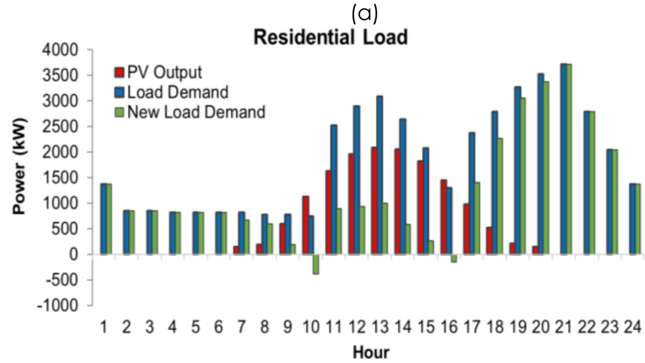


Figure 7 The PV output power (kW) for different load models (Industrial Residential, and Commercial)

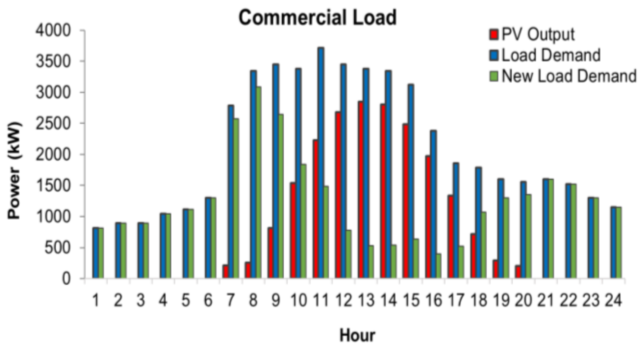
Based on the results presented, the impact of different load models on PV planning studies yielded different outcomes in several aspects. Through a detailed comparative analysis of the reduction in power losses, and different impact indices, the results demonstrate the importance of considering a variation of load models in PV planning studies. It is shown that conducting PV planning using improper sizing and location can give misleading results if implemented in practical distribution systems. The PV sizing based on fixed load is not ideal in both bus distribution systems compared to varying loads.



(a)



(b)



(c)

Figure 8 The load demand curve before and after PV integration for (a) Industrial (b) Residential (c) Commercial loads

Typically, the generation size greatly impacts the technical aspects of the grid systems, especially the power loss in the distribution system. In addition, a large generator will result in a high penetration level as seen in Figure 7 in the distribution systems. However, improper placement and sizing could lead to inappropriate results and more adverse impacts than before the PV integration. The power loss reduction for an optimal system must be the highest, while the impact indices PLI, and QLI must be the lowest. The graph illustrates the hourly distribution of residential load demand and the impact of photovoltaic (PV) integration on this demand over 24 hours. In the early hours (01:00-06:00), there is no PV output as it is nighttime, resulting in the new load demand being almost identical to the original load demand. As the day progresses and the sun rises, the PV output increases, particularly noticeably from 07:00 to 17:00. During this period, the PV generation offsets a significant portion of the load demand, leading to a noticeable reduction in the new load demand, which is evident from the shorter green bars compared to the blue ones. During peak sunlight hours (12:00-15:00), PV output reaches its maximum, considerably reducing the new load demand. This is where the new load demand is significantly reduced than the actual demand, indicating the significant contribution of PV systems in reducing the overall energy requirement from the grid. In the evening hours (18:00-24:00), as the sun sets, the PV output decreases and eventually ends, which causes the new load demand to again align closely with the original load demand. The graph effectively demonstrates the significant role of PV systems in reducing the load demand during daylight hours, particularly during peak generation times, thus highlighting the potential of PV integration in mitigating energy consumption and reducing dependency on grid power in residential settings.

5.0 CONCLUSION AND RECOMMENDATION

In conclusion, the integration of photovoltaic (PV) systems with time-varying load models has demonstrated significant impacts on distribution systems. The findings indicate that the sizing of PV installations greatly influenced load variations, with optimal PV sizes corresponding to specific load profiles. Notably, the reduction in power losses was most significant when integrating PV with commercial load models, resulting in minimized impact indices compared to other load models. Moreover, the study shows the importance of matching the PV generation with fluctuating load demands, particularly seen in the commercial sector where higher PV levels were observed during periods of matching between generation and demand patterns. This stresses the need to accurately size PV systems based on load requirements to mitigate mismatches between generation and demand profiles. Practically, considering the variability of loads throughout the day is essential for effective PV integration. By optimizing PV sizes according to load demands, potential mismatches can be minimized, enhanced efficiency, and improved reliability of PV-integrated distribution systems.

The novelty of this study lies in the detailed analysis of time-varying load profiles for industrial, residential, and commercial consumers, demonstrating how optimal PV sizing and placement significantly influence power loss reduction and grid efficiency, compared to existing literature that often overlooks the interplay between the load variations and PV system performance. Finally, policymakers are urged to prioritize initiatives that encourage the deployment of PV systems to match load-specific needs. This includes subsidizing solar PV installations for sectors with high load variability, such as industrial and commercial consumers, where optimized PV systems can significantly reduce operational costs and enhance grid performance. Furthermore, policies should mandate the integration of energy storage systems in large-scale renewable projects to address mismatches between peak generation and demand. These steps will ensure a more efficient, reliable, and sustainable energy future while supporting national and global decarbonization goals.

5.1 Future work and Recommendation

To enhance the effectiveness of PV placement and sizing, future research could focus on several areas. First, exploring hybrid optimization techniques, such as combining PSO with machine learning or other metaheuristic algorithms, could potentially yield better performance by addressing the limitations of single-method approaches. Second, integrating real-weather conditions and real-time load variations into the optimization process would provide a more accurate representation of practical scenarios, therefore, ensuring solutions remain effective under varying conditions. Last, testing the proposed methodology on larger or more complex distribution systems with multiple interconnected networks could validate its scalability and robustness, paving the way for broader real-world applications.

Acknowledgement

The authors would like to acknowledge the support from Universiti Teknologi PETRONAS (UTP) for fuding this research through the Short-Term Internal Research Funding (STIRF) research grant, under Cost Center: 015LA0-093.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

References

[1] Takele, H. 2022. Distributed Generation Adverse Impact on the Distribution Networks Protection and Its Mitigation. *Heliyon*. 8(6): e09624.

[2] Shivashankar, S., et al. 2016. Mitigating Methods of Power Fluctuation of Photovoltaic (PV) Sources – A Review. *Renewable and Sustainable Energy Reviews*. 59: 1170–1184.

[3] Ali, A., *et al*. 2023. Multi-objective Optimal Siting and Sizing of Distributed Generators and Shunt Capacitors Considering the Effect of Voltage-dependent Nonlinear Load Models. *IEEE Access*. 11: 21465–21487.

[4] Gümüş, T. E., S. Emiroglu, and M. A. Yalcin. 2023. Optimal DG Allocation and Sizing in Distribution Systems with Thevenin based Impedance Stability Index. *International Journal of Electrical Power & Energy Systems*. 144: 108555.

[5] Salimon, S.A., *et al*. 2023. Impact of Distributed Generators Penetration Level on the Power Loss and Voltage Profile of Radial Distribution Networks. *Energies*. 16(4): 1943.

[6] Adeosun, T., *et al*. 2023. Renewable Energy for Sustainable Development in Developing Countries: Benefits to the Environment. *Journal of Energy Research and Reviews*. 13(3): 1–25.

[7] Algarni, S., *et al*. 2023. Contribution of Renewable Energy Sources to the Environmental Impacts and Economic Benefits for Sustainable Development. *Sustainable Energy Technologies and Assessments*. 56: 103098.

[8] Hamid, A. K., *et al*. 2023. A Systematic Review of Grid-connected Photovoltaic and Photovoltaic/Thermal Systems: Benefits, Challenges And Mitigation. *Energy & Environment*. 34(7): 2775-2814.

[9] Hossain, M. S. *et al*. 2023. High Penetration of Solar Photovoltaic Structure on the Grid System Disruption: An Overview of Technology Advancement. *Sustainability*. 15(2): 1174.

[10] Lupangu, C. and R.C. Bansal. 2017. A Review of Technical Issues on the Development of Solar Photovoltaic Systems. *Renewable and Sustainable Energy Reviews*. 73: 950–965.

[11] Zhao, L., *et al*. 2021. Sizing Renewable Energy Systems with Energy Storage Systems based Microgrids for Cost Minimization using Hybrid Shuffled Frog-leaping and Pattern Search Algorithm. *Sustainable Cities and Society*. 73: 103124.

[12] Aman, M. M., *et al*. 2014. A New Approach for Optimum Simultaneous Multi-DG Distributed Generation Units Placement and Sizing based on Maximization of System Loadability using HPSO (Hybrid Particle Swarm Optimization) Algorithm. *Energy*. 66: 202–215.

[13] Shawon, S. M. R. H., X. Liang, and M. Janbakhsh. 2023. Optimal Placement of Distributed Generation Units for Microgrid Planning in Distribution Networks. *IEEE Transactions on Industry Applications*. 59(3): 2785–2795.

[14] Allouhi, A., *et al*. 2023. Recent Technical Approaches for Improving Energy Efficiency and Sustainability of PV and PV-T Systems: A Comprehensive Review. *Sustainable Energy Technologies and Assessments*. 56: 103026.

[15] Kumar, A., *et al*. 2023. Impact of Demand Side Management Approaches for the Enhancement of Voltage Stability Loadability and Customer Satisfaction *index*. *Applied Energy*. 339: 120949.

[16] Fesanghary, M. and M. M. Ardehali. 2009. A Novel Meta-Heuristic Optimization Methodology for Solving Various Types of Economic Dispatch Problem. *Energy*. 34: 757–766.

[17] Lakshmi, G. V. N., A. Jayalaxmi, and V. Veeramsetty. 2023. Optimal Placement of Distributed Generation based on DISCO's Financial Benefit with Loss and Emission Reduction using Hybrid Jaya–Red Deer Optimizer. *Electrical Engineering*. 105: 965–977.

[18] Radosavljević, J., *et al*. 2020. Optimal Placement and Sizing of Renewable Distributed Generation Using Hybrid Metaheuristic Algorithm. *Journal of Modern Power Systems and Clean Energy*. 8(3): 499–510.

[19] Sireesha, R., S. R. Coppisetty, and M. Vijay Kumar. 2023. Hybrid Optimization to Enhance Power System Reliability using GA, GWO, and PSO. *Paladyn, Journal of Behavioral Robotics*. 14(1): 20220119.

[20] Alyu, A. B., *et al*. 2023. Hybrid GWO-PSO based Optimal Placement and Sizing of Multiple PV-DG Units for Power Loss Reduction and Voltage Profile Improvement. *Scientific Reports*. 13(1): 6903.

[21] Prakash, R. and B.C. Sujatha. 2016. Optimal Placement and Sizing of DG for Power Loss Minimization and VSI Improvement using Bat Algorithm. *2016 National Power Systems Conference (NPSC)*.

[22] Fu, J., *et al*. 2023. A Novel Optimization Strategy for Line Loss Reduction in Distribution Networks with Large Penetration of Distributed Generation. *International Journal of Electrical Power & Energy Systems*. 150: 109112.

[23] Das, S., D. Das, and A. Patra. 2016. Distribution Network Reconfiguration using Distributed Generation Unit Considering Variations of Load. *2016 IEEE 1st International Conference on Power Electronics, Intelligent Control and Energy Systems (ICPEICES)*.

[24] Hung, D. Q., N. Mithulananthan, and R. C. Bansal. 2013. Analytical Strategies for Renewable Distributed Generation Integration Considering Energy Loss Minimization. *Applied Energy*. 105: 75–85.

[25] Hung, D. Q., N. Mithulananthan, and K. Y. Lee. 2014. Determining PV Penetration for Distribution Systems With Time-Varying Load Models. *IEEE Transactions on Power Systems*. 29(6): 3048–3057.

[26] Khan, M. F. N., T. N. Malik, and I. A. Sajjad. 2018. Impact of Time Varying Load Models on PV DG Planning. Journal of Renewable and Sustainable Energy. 10(3): 035501.

[27] Khan, M. F. N. and T. N. Malik. 2017. Probablistic Generation Model for Optimal Allocation of PV DG in Distribution System with Time-varying Load Models. *Journal of Renewable and Sustainable Energy*. 9(6): 065503.

[28] Ahmed, A., *et al*. Optimal Allocation of Wind DG with Time Varying Voltage Dependent Loads Using Bio-Inspired: Salp Swarm Algorithm. *2020 3rd International Conference on Computing, Mathematics and Engineering Technologies (iCoMET)*. 2020.

[29] Jamahori, H. F., *et al*. 2024. Optimal Design and Performance Analysis of Multiple Photovoltaic with Grid-Connected Commercial Load. *International Journal of Technology*. 15(4).

[30] Hung, D., M. Nadarajah, and K. Lee. 2014. Determining PV Penetration for Distribution Systems With Time-Varying Load Models. *IEEE Transactions on Power Systems*.

[31] Jamahori, H. F., M. P. Abdullah, and A. Ali. 2021. Integration of PV Distributed Renewable Energy Generation into Distribution System using Time-Varying Weather and Load Data. *2021 IEEE 19th Student Conference on Research and Development (SCOReD)*.

[32] Ali, A., *et al*. 2018. Sizing and Placement of Solar Photovoltaic Plants by Using Time-series Historical Weather Data. *Journal of Renewable and Sustainable Energy*. 10(2): 023702.

[33] Jamahori, H. F., M. P. Abdullah, and A. Ali. 2023. Impact and Evaluation of Optimized PV Generation in the Distribution System with Varying Load Demands. *Jurnal Teknologi*. 85(3): 61–73.

[34] Papazoglou, G. and P. Biskas. 2023. Review and Comparison of Genetic Algorithm and Particle Swarm Optimization in the Optimal Power Flow Problem. *Energies*. 16(3): 1152.