Prediction of Photovoltaic Output Power using Hybrid Artificial Neural Network

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ABSTRACT
With the increasing adoption of rooftop photovoltaic (PV) systems, accurate power output forecasting has become essential for effective energy management and grid integration. This study proposes a hybrid Artificial Neural Network (ANN) model optimized using the Salp Swarm Algorithm (SSA) to enhance prediction accuracy for rooftop PV output. SSA was selected for its strong exploration and exploitation capabilities, which complement the ANN's learning strengths. Historical PV data from two university campuses in Malaysia, representing varied climatic conditions, were used over a one-year period to ensure model robustness. Key input variables influencing PV output were identified through correlation analysis, enabling more focused ANN training. SSA was used to optimize the ANN's initial weights and biases, accelerating convergence and improving accuracy. Across three test cases, the SSA-ANN model achieved Mean Squared Error (MSE) values as low as 0.0155 and correlation coefficients (R) up to 0.98069, significantly outperforming standalone ANN approaches. These results demonstrate the model's effectiveness in improving PV forecasting accuracy, offering practical benefits for urban energy planning and sustainable power systems.

KEYWORDS: Energy demand prediction, Hybrid optimization model, Salp Swarm Algorithm, Short-term load forecasting, University building

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1. INTRODUCTION

The global transition from fossil fuels to renewable energy sources is accelerating, driven by concerns over climate change, energy security, and rising costs of conventional energy. In Malaysia, solar energy is emerging as a key component of the country's renewable energy strategy, leveraging the nation's abundant sunlight (Fernandez et al., 2024). The rapid decline in photovoltaic (PV) panel costs and advancements in energy conversion efficiency are further propelling this shift. Solar PV systems, known for their affordability, scalability, and ease of deployment, now serve a wide range of applications, from large-scale solar farms to decentralized rooftop installations providing reliable, localized electricity to homes, commercial buildings, and educational institutions. Among these, rooftop PV systems are gaining popularity due to their efficient use of existing structures, eliminating the need for dedicated land, which is a key advantage in urban and institutional areas (Hassan et al., 2023). University campuses serve as optimal settings for the installation of rooftop photovoltaic systems. Universities, as autonomous communities with varied energy requirements encompassing residential, academic, and administrative loads, present a distinctive opportunity to model and enhance photovoltaic system efficiency. Campuses frequently possess extensive rooftop spaces ideal for solar systems and exhibit stable energy consumption patterns, rendering them optimal candidates for renewable energy implementation. This infrastructure not only fulfills the university's energy requirements but also functions as an active research facility for the advancement of solar energy research and energy management techniques (Maity et al., 2024).

Photovoltaic systems operate by converting sunlight into electricity through semiconductor materials. Their versatility supports installations ranging from residential rooftops to large-scale power plants. Additionally, they offer low maintenance, modularity, and high scalability, making them suitable for both on-grid and off-grid applications (Osman & Qureshi, 2025). Hybrid systems, which combine on-grid and off-grid features, are increasingly favored for their ability to store energy in batteries while still connecting to the main grid for backup supply (Falope et al., 2024).

However, PV systems remain vulnerable to performance fluctuations influenced by environmental factors such as module material, temperature, shading, dust accumulation, inverter efficiency, weather conditions, and geographic location (Okonkwo et al., 2025). Moreover, degradation effects like corrosion, micro-cracks, and humidity-induced losses can further reduce power output over time (Islam et al., 2024; Khan et al., 2024). These challenges underscore the importance of accurate output power forecasting to optimize energy management and grid reliability, especially in campus environments where energy demand fluctuates between peak academic hours and low-occupancy periods during holidays and semester breaks. Rooftop solar panels typically monocrystalline, polycrystalline, or bifacial dominate distributed solar generation worldwide, maximizing land use efficiency and minimizing environmental disruption (Kewte & Kewte, 2023; Reagan et al., 2025). In Malaysia, unpredictable weather patterns pose a significant hurdle to consistent energy output. Accurate forecasting models are crucial to mitigate this variability, ensuring a stable power supply and reducing reliance on conventional energy sources (Hasan et al., 2024). For universities, this becomes even more essential, as unreliable energy supply could disrupt research activities, essential campus operations, and student accommodations. Effective predictions allow for better grid balancing, preventing over-reliance on backup systems and supporting Malaysia's long-term sustainability goals (Kharrazi et al., 2020).

Artificial Intelligence (AI) techniques, particularly Artificial Neural Networks (ANNs), have demonstrated strong potential in modeling the nonlinear behavior of PV systems under diverse environmental conditions (Keddouda et al., 2023). ANNs, inspired by biological neural networks, map complex input-output relationships through interconnected neurons, weights, and bias adjustments. Backpropagation, one of the most common training methods, iteratively refines weights to minimize prediction errors (Zhang et al., 2025).

However, standard ANNs face challenges like slow convergence, getting trapped in local minima, and overfitting when trained on volatile weather data. Metaheuristic optimization algorithms, such as Genetic Algorithms (GA) (Han & Sun, 2024) and Particle Swarm Optimization (PSO) (Zoremsanga & Hussain, 2024) have emerged as effective solutions to enhance ANN performance by tuning initial weights and biases. Recent studies combining ANN with metaheuristics have shown significant improvements in PV power prediction accuracy (Hannan et al., 2021; Moreno et al., 2020). Nevertheless, balancing exploration (global search) and exploitation (local refinement) remains a persistent challenge in optimizing ANN parameters.

To address this, the Salp Swarm Algorithm (SSA) has gained attention for its ability to dynamically balance exploration and exploitation during optimization (Mirjalili et al., 2017). Inspired by the swarming behavior of salps in ocean currents, SSA efficiently navigates the search space to escape local minima and accelerate convergence. This study proposes a novel hybrid SSA-ANN model for rooftop PV power prediction, leveraging SSA's adaptive capabilities to fine-tune ANN weights and biases. The model is trained and validated using historical data from two university campuses representing different geographical and meteorological conditions to ensure robustness. By using university campuses as the testbed, this study not only enhances prediction accuracy for campus energy systems but also provides a scalable, data-driven approach that can be replicated in other educational institutions or urban environments with similar energy profiles.

The significance of this study extends beyond improved prediction accuracy. University campuses, as energy-intensive microgrids, represent a strategic opportunity for accelerating the adoption of renewable energy. Accurate forecasting supports smarter energy planning, helping campuses reduce operational costs, lower carbon footprints, and improve energy self-sufficiency. Moreover, the research strengthens the role of universities as innovation hubs, integrating sustainable technologies into real-world systems while training future engineers and energy managers to tackle global energy challenges.

2. METHODOLOGY

The paper utilizes data collected from two university campuses in Malaysia: Campus 1, located on Malaysia's East Coast, and Campus 2, situated in the southern region. These campuses were strategically selected due to their operational rooftop photovoltaic (PV) systems and distinct geographical locations, providing a diverse dataset that captures varying climatic conditions. The dataset includes key parameters such as Global Horizontal Irradiation, Date and Time, Ambient Temperature, Wind Speed, PV Module Temperature, and Average PV Output Power, all recorded at five-minute intervals. Data for this study were collected from 1 February 2022 to 30 September 2023. Measurements were recorded at 5-minute intervals daily, between 7:30 AM and 7:30 PM, to capture the full range of daylight hours relevant for photovoltaic (PV) power generation. This consistent data logging resulted in 144 data points per day, totaling 87,408 data points over the entire collection period. The extensive dataset supports robust training and evaluation of the artificial neural network (ANN) models for accurate PV output prediction. The data from two campuses are used to evaluate rooftop PV power production. In the first scenario, the Artificial Neural Network (ANN) model is trained and tested on a single day. The second scenario extends the testing period to one month. The third scenario involves a more extensive training period of one year, followed by a three-month testing phase. This multi-scenario approach is designed to comprehensively assess the model's performance across different training and testing durations, ensuring the reliability and robustness of the predictions.

2.1 Correlation Analysis

Correlation analysis is a vital statistical technique used to evaluate the relationship between input and output variables, determining both the existence and strength of these associations. This analysis helps uncover patterns within the dataset, providing insights into whether the relationships are advantageous or detrimental. A positive correlation indicates that the input and output variables increase together, while a negative correlation implies that one variable increases as the other decreases. To quantify these relationships, this study employs the Pearson correlation coefficient that is widely used to measure the linear correlation. The coefficient is calculated using the equation. (1).

$$r = \frac{\sum(X-\hat{X})(Y-\hat{Y})}{\sqrt{\sum(X-\hat{X})^2}\sqrt{(Y-\hat{Y})^2}} \qquad (1)$$

Where X is the input variables, Y is the output variables, $\hat{X}$ is the mean of the input variables and $\hat{Y}$ is the mean of the output variables.

2.2 Artificial Neural Networks (ANN)

Artificial Neural Networks (ANN) offer a powerful approach for predicting rooftop photovoltaic (PV) output power, especially when paired with supervised learning techniques. The training process utilizes the backpropagation algorithm, which iteratively adjusts weights and biases across network layers to enhance model performance. This algorithm operates in two stages: first, it forwards inputs from the input layer through the hidden layers to the output layer; then, it backpropagates errors, refining the connections to minimize prediction inaccuracies. The ANN architecture consists of input, hidden, and output layers, incorporating key variables such as solar irradiance, ambient temperature, and historical PV output data to generate accurate predictions.

The ANN model was configured and tested multiple times to determine the optimal setup. A two-hidden-layer architecture was employed, with the number of neurons in each hidden layer varied heuristically from 1 to 20. Additionally, the learning rate and momentum rate were adjusted between 0 and 1 to explore different training behaviors and improve convergence. Simulations were conducted for all case studies at both campuses to ensure the robustness and generalizability of the model across different climate conditions. The model's performance is assessed using the Mean Square Error (MSE), a standard metric that measures the average squared difference between predicted and actual outputs. The MSE is calculated using the equation. (2).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \qquad (2)$$

where, *MSE* is mean squared error, *n* is the number of data points, Y_i is the observed values and $\hat{Y}_i$ is the predicted values.

2.3 Development of SSA-ANN

The hybridization of the Salp Swarm Algorithm (SSA) with Artificial Neural Networks (ANN) is proposed to enhance the accuracy and efficiency of rooftop photovoltaic (PV) power output predictions. SSA, a bio-inspired metaheuristic algorithm that mimics the swarming behavior of salps in the ocean, is employed to optimize the weights and biases of the ANN, thereby improving its predictive performance. Traditional training methods, such as gradient descent, often suffer from slow convergence and the risk of getting trapped in local minima. The SSA-ANN framework overcomes these limitations by leveraging SSA's strong global search capability, ensuring optimal weight selection for more accurate and robust predictions.

The hybrid approach follows a structured optimization process, as illustrated in **Figure 1**. First, the SSA parameters, including population size and maximum iterations, are initialized to guide the search for optimal solutions. Simultaneously, ANN parameters such as the number of neurons in each layer, learning rate, and momentum constant are set to ensure compatibility with the initial network configuration. The optimization process begins with SSA randomly generating initial positions of salps, representing candidate solutions for the ANN's weight and bias values. An objective function, typically based on the Mean Square Error (MSE), evaluates the fitness of each solution by measuring the discrepancy between predicted and actual PV output. During the iterative optimization process, the leader salp directs the swarm's movement based on the best-found solution, while follower salps adjust their positions dynamically to balance exploration and exploitation. This adaptive movement prevents premature convergence and ensures the discovery of an optimal set of ANN weights. The optimization continues until the convergence criteria are met, either when the objective function stabilizes or the maximum iteration count is reached.

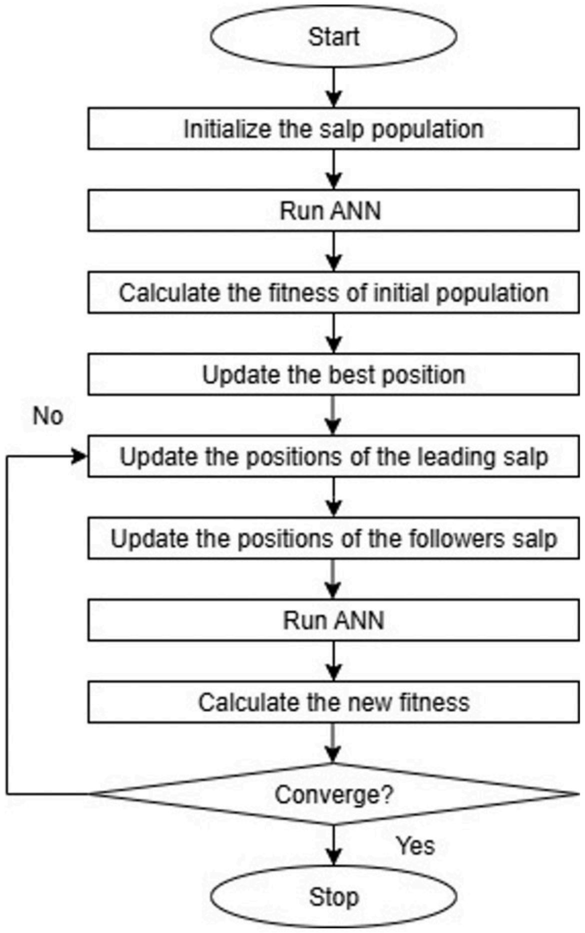


Figure 1: *Flowchart of SSA-ANN*

The final optimized weights and biases are then applied to the ANN model, significantly improving its predictive accuracy. This hybrid SSA-ANN approach not only enhances ANN training efficiency but also ensures reliable PV power predictions across varying environmental conditions. Future enhancements could include adaptive SSA parameter tuning, integration with other metaheuristic algorithms, or application to multi-objective optimization scenarios for further performance improvements.

3. RESULTS AND DISCUSSION

This section presents a comprehensive analysis of the proposed hybrid SSA-ANN model's performance in predicting rooftop photovoltaic (PV) output power. The results are evaluated based on different training and testing scenarios, considering diverse environmental conditions from two distinct campuses. Key performance indicators, including Mean Square Error (MSE) and correlation analysis, are used to assess prediction accuracy and model reliability. Comparisons are made between the baseline ANN model and the SSA-optimized ANN to highlight improvements in prediction precision and convergence efficiency. The discussion interprets the results, focusing on how SSA optimization enhances ANN's ability to generalize under varying climatic conditions, ensuring robust and accurate PV power forecasts. All tables and figures must have a corresponding caption.

3.1 Results of Correlation Analysis

A heatmap in **Figure 2** was generated to evaluate the strength of the linear correlation between environmental variables and the average PV output power for Campus 1. The correlation coefficients range from 0 (no correlation) to 1 (perfect correlation), as indicated by the color bar on the right side of the figure.

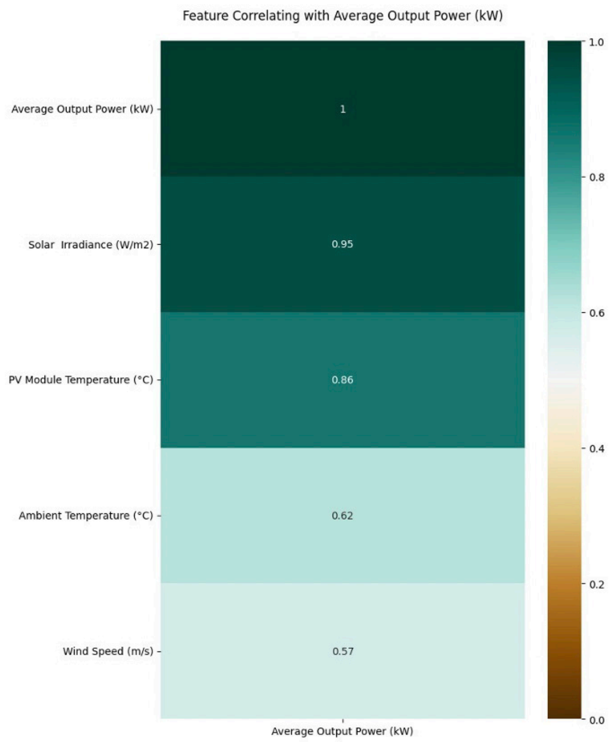


Figure 2: *Results of correlation analysis for Campus 1*

The feature most strongly correlated with the average output power is Solar Irradiance (W/m²), with a coefficient of 0.95. This result is expected and consistent with established PV performance models, as solar irradiance directly influences the amount of energy that can be harvested by the photovoltaic panels. It confirms that irradiance is the most critical input feature when predicting PV output using artificial neural networks or any other machine learning-based models. PV Module Temperature (°C) also shows a strong positive correlation of 0.86. While an increase in temperature generally reduces the efficiency of PV modules due to thermal losses, the high correlation suggests that the temperature rise is largely driven by high irradiance conditions—hence, it indirectly correlates with higher power output. This underscores the importance of including module temperature as a secondary feature in predictive models. Ambient Temperature (°C) and Wind Speed (m/s) show moderate correlations of 0.62

and 0.57, respectively. These features may influence system performance by affecting the operating temperature of the PV modules (e.g., wind providing a cooling effect), but their relatively lower correlation indicates they are not as directly impactful as irradiance or module temperature. Nevertheless, their inclusion may help improve the model's ability to generalize under different environmental conditions. The perfect correlation value of 1.0 for Average Output Power (kW) with itself serves as a reference and validation of the heatmap structure.

The heatmap for Campus 2 in **Figure 3** presents the Pearson correlation coefficients between environmental parameters and the average output power (kW) of the PV system. This analysis aims to identify the most relevant features for predicting PV performance in a hybrid ANN model. The most influential feature, as expected, is Solar Irradiance (W/m²), showing a very strong positive correlation of 0.97 with average output power. This aligns with physical principles, as solar irradiance represents the energy input directly converted to electrical power by the PV system.

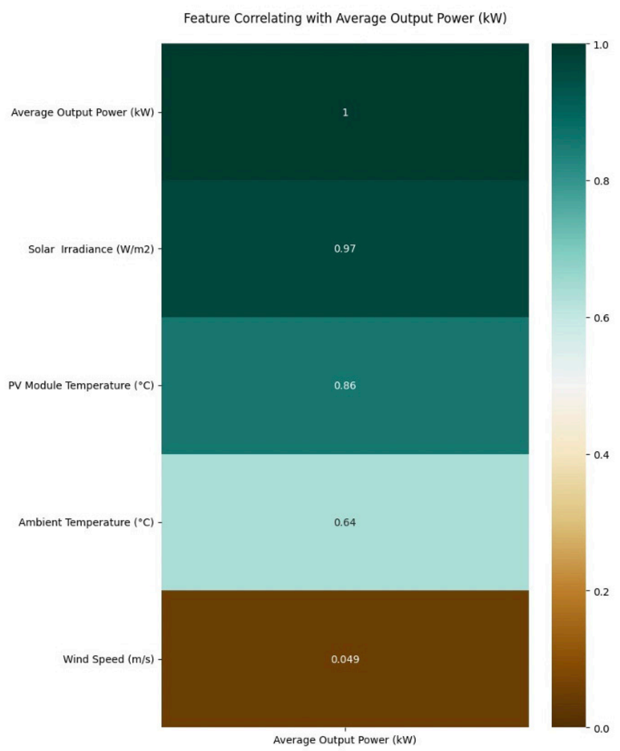


Figure 3: *Results of correlation analysis for Campus 2*

The high correlation reinforces the importance of irradiance as the primary driver of PV output and its essential role as a key input feature in the prediction model. PV Module Temperature (°C) also demonstrates a strong positive correlation of 0.86. This indicates that as module temperature rises, the average output power also tends to increase. However, it's important to note that while irradiance typically causes this increase in temperature, higher temperatures can lead to efficiency losses in PV modules. Despite this, the positive correlation highlights the temperature's relevance in model training, particularly in environments where irradiance and heat levels closely track each other. Ambient Temperature (°C) shows a moderate correlation of 0.64, suggesting it contributes to PV performance but is not as dominant. It may influence the module temperature indirectly and can affect cooling rates and system efficiency, thus playing a supporting role in prediction accuracy. The most notable deviation from Campus 1 is observed in Wind Speed (m/s), which exhibits a very weak correlation of 0.049 with the average output power. This near-zero correlation indicates that wind speed has a negligible linear influence on power output in Campus 2's environment. While wind can help cool PV modules and potentially improve efficiency, this effect appears to be minimal or inconsistent in this dataset. The self-correlation of 1.0 for average output power acts as a benchmark reference for comparison.

The study of both campuses consistently identifies solar irradiation as the predominant factor, exhibiting a robust positive association with electricity generation. Conversely, ambient temperature and photovoltaic module temperature demonstrated fewer correlations, suggesting that while temperature influences performance, particularly via module heating, the effects are less predictable and vary by location. Wind speed, while aiding in module cooling, demonstrated an inconsequential association and was hence omitted from further simulations. The study discovered three essential factors for forecasting photovoltaic output: ambient temperature, solar irradiation, and photovoltaic module temperature. The findings emphasize the necessity of prioritizing sun irradiance as the principal input for ANN models, whereas temperature-related variables operate as supplementary factors to account for performance variations. This methodology balances model complexity with predictive accuracy, ensuring flexibility to various geographical and climatic situations, as evidenced in the Campus 1 and Campus 2 campuses.

3.2 Results of ANN

The heuristic approach to configuring the Artificial Neural Network (ANN) was conducted systematically by first determining the optimal number of neurons in the first hidden layer (H1). During this stage, other parameters, including the second hidden layer (H2), learning rate (LR) and momentum constant (MC) were randomly selected to allow a focus on fine-tuning H1. Once the best-performing H1 configuration was identified, the ANN was rerun multiple times to optimize H2, following the same heuristic trial-and-error approach. After identifying the optimal hidden layers, the process was repeated to tune the learning rate and momentum constant, ensuring the model achieved both fast convergence and stability. This iterative process resulted in progressively lower error rates, as seen in **Figure 4** and **Figure 5** for Campus 1.

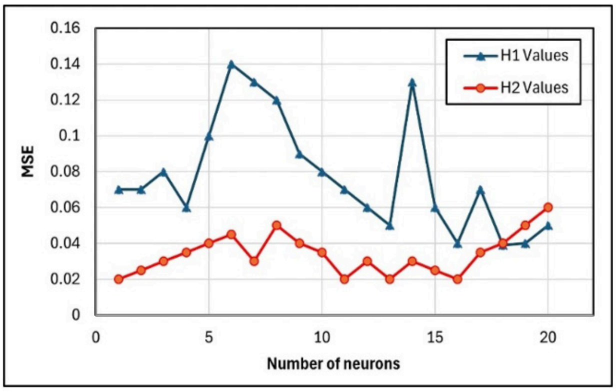


Figure 4: *Best number of neurons for Case 1 (daily prediction)*

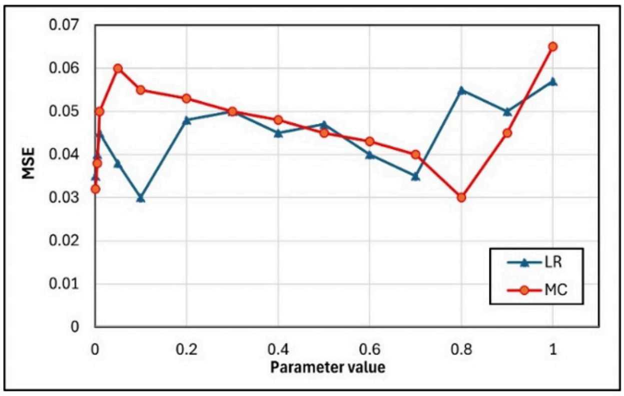


Figure 5: *Best number of learning rate and momentum constant for Case 1 (daily prediction)*

These figures present the results of the heuristic method for daily prediction in Case 1. The fluctuations in H1 reflect the model's sensitivity to initial configurations, highlighting the importance of careful tuning. H2, in comparison, showed more stable behavior, suggesting its role in refining the network's performance rather than driving major changes. The gradual reduction in error across iterations confirms that the heuristic approach successfully narrowed down the best combination of parameters, balancing model complexity and predictive accuracy. This method, while time-intensive, ensures a tailored network configuration that adapts to the specific characteristics of the dataset, leading to more reliable photovoltaic (PV) power output predictions.

Similar analysis is also carried out using other prediction categories, such as weekly prediction (Case 2) and monthly prediction (Case 3) for Campus 2. The best configuration for all cases is tabulated in **Table 1**. For Campus 1, the artificial neural network (ANN) performance varied noticeably across different parameter settings. Case 2, with 10 neurons in H1, 4 in H2, a learning rate of 0.1, and a momentum coefficient of 0.8, achieved the lowest mean squared error (MSE) of 0.0163. This indicates that moderate network size and a conservative learning rate contributed to stable learning and effective generalization. In contrast, Case 1 with a larger architecture (H1=18, H2=10) and a higher learning rate (0.2) produced a higher MSE of 0.0281, suggesting possible overfitting or instability. Case 3, with a smaller network and a low learning rate (0.001), performed better than Case 1 but was not as optimal as Case 2. For Campus 2, the best result was obtained in Case 2, where a higher learning rate of 1.0 combined with a moderately sized H1 (10 neurons) and a small H2 (2 neurons) yielded the lowest MSE of 0.0157. Interestingly, this configuration outperformed the smaller networks in Cases 1 and 3, both of which used H1=3, H2=2 and a learning rate of 0.5, resulting in higher MSEs of 0.0312 and 0.0196, respectively. This suggests that the dataset characteristics for Campus 2 allowed the ANN to benefit from a more aggressive learning strategy without sacrificing accuracy. Overall, these results highlight that ANN parameters, specifically the number of hidden neurons, learning rate, and momentum coefficient, play a critical role in achieving accurate PV output predictions. Proper tuning of these parameters is essential for model performance, and optimal settings may vary depending on the data characteristics of each location.

Table 1: *Results of using ANN for all cases*

Campus	Case	H1	H2	LR	MC	MSE
	1	18	10	0.2	0.8	0.0281
Campus 1	2	10	4	0.1	0.8	0.0163
	3	5	5	0.001	0.3	0.0208
	1	3	2	0.5	0.7	0.0312
Campus 2	2	10	2	1	0.8	0.0157
	3	3	2	0.5	0.7	0.0196

3.3 Results of SSA-ANN

The integration of the Salp Swarm Algorithm (SSA) with Artificial Neural Networks (ANN) plays a significant role in enhancing prediction accuracy. SSA optimizes key ANN parameters, including the number of neurons in the first and second hidden layers (H1 and H2), learning rate (LR), and momentum constant (MC). For this study, SSA was configured with 20 search agents and 50 iterations. The primary objective of the SSA-ANN hybrid model is to minimize the Mean Squared Error (MSE) during ANN training and prediction.

The convergence curve for Case 1 in **Figure 6**, representing daily prediction performance using SSA-ANN at Campus 1 and Campus 2, demonstrates the effectiveness of the SSA in optimizing ANN parameters. For Case 1, the curve shows a consistent and steady decline in MSE across the 50 iterations, reflecting an efficient search for the optimal configuration. The MSE starts around 0.032 and gradually decreases, eventually stabilizing just below 0.024. This steady reduction indicates that SSA continuously refines the ANN's weights and biases, improving prediction accuracy with each iteration. Notably, the final sharp drop near the end suggests that SSA discovered a better set of parameters in the later stages, reinforcing its exploratory strength. In contrast, the Campus 2 campus curve starts similarly but quickly flattens after a few iterations, stabilizing at approximately 0.03. This behavior implies that the search space may have reached a local minimum earlier, or the dataset characteristics for this campus yield less variation in error reduction. The plateau indicates that further iterations do not significantly improve the model's performance, suggesting that the initial parameter set for this campus might be closer to optimal from the beginning. Overall, the convergence trends show that SSA-ANN effectively minimizes MSE, with Campus 1 achieving more significant improvements compared to Campus 2. This could be due to differences in environmental factors or data variability between the two campuses, influencing how SSA explores and exploits potential solutions.

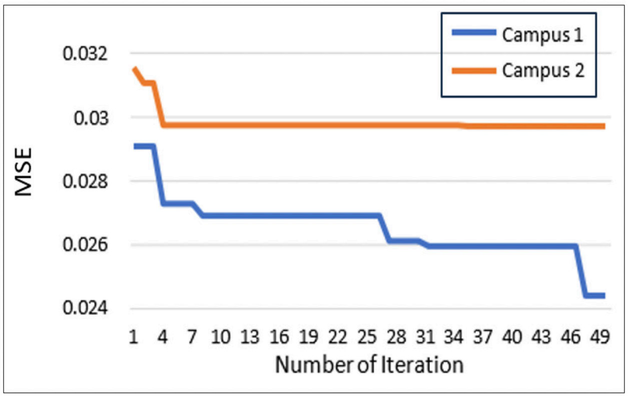


Figure 6: *Convergence curve for Case 1*

Figure 7 presents a convergence curve for Case 2. For Case 2, the weekly prediction convergence curves for both campuses show a steady decline in Mean Squared Error (MSE) as the iterations progress. The Campus 2 campus demonstrates a slightly faster reduction in MSE early on, stabilizing around iteration 19, indicating that the Salp Swarm Algorithm (SSA) quickly identified a near-optimal solution. Campus 1 campus, on the other hand, maintains a more gradual decline and stabilizes later around iteration 34. This difference in convergence behavior suggests that the dataset from Campus 2 may have fewer complexities or variations, enabling faster optimization. Despite the slower reduction in MSE for Campus 1, both curves ultimately achieve low error values, confirming that the SSA-ANN combination effectively enhances prediction accuracy over weekly intervals.

The convergence curve for Case 3 is presented in **Figure 8**. For Case 3, the monthly prediction results reveal a similar trend, though with more gradual improvement.

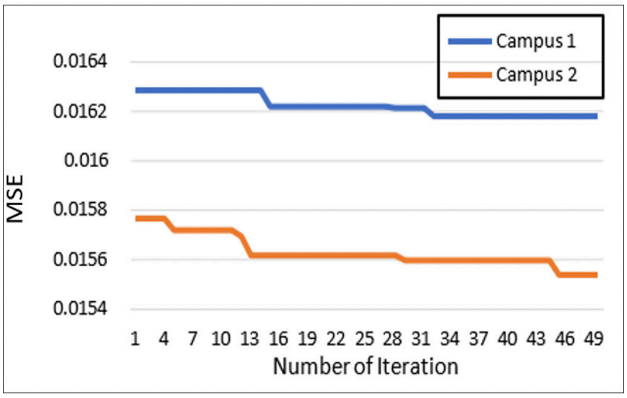


Figure 7: *Convergence curve for Case 2*

The MSE for Campus 2 exhibits an early decrease and stabilizes around iteration 22, maintaining a consistently lower error compared to Campus 1. Campus 1 shows a clear downward trend, stabilizes later and at a slightly higher error rate. This slower convergence might indicate that the monthly data for Campus 1 has more variability, requiring more iterations for SSA to refine the ANN parameters. However, both campuses achieved near-optimal results by the final iterations, with Campus 2 maintaining a marginally better performance. This highlights the SSA-ANN model's robustness in handling longer prediction horizons, though convergence speed and final error rates remain sensitive to site-specific data patterns.

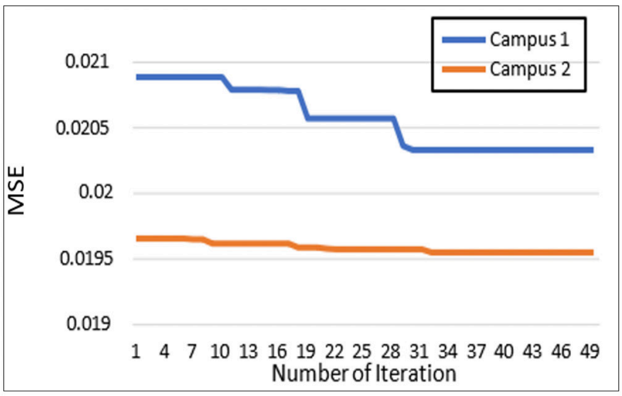


Figure 8: *Convergence curve for Case 3*

The results in **Table 2** present the optimized parameters for all case studies using the Salp Swarm Algorithm combined with Artificial Neural Networks (SSA-ANN). The table highlights the fine-tuned values for key ANN parameters, specifically H1 (first hidden layer neurons), H2 (second hidden layer neurons), Learning Rate (LR), and Momentum Rate (MR) that were determined through the iterative SSA optimization process. Across all cases (daily, weekly, and monthly predictions), the values of H1 and H2 show variation, indicating that different prediction horizons require different network architectures to balance model complexity and performance. For example, daily predictions tend to have a larger number of neurons in the hidden layers to capture short-term fluctuations, while weekly and monthly cases typically require fewer neurons due to smoother data trends.

The Learning Rate (LR) values remain within a moderate range, ensuring a balance between convergence speed and model stability. A higher LR might speed up learning but risks overshooting the optimal solution, while a lower LR ensures steady, stable convergence. The Momentum Rate (MR) helps prevent the model from getting stuck in local minima, and the optimized values in Table 2 reflect this balance, providing enough inertia for the model to escape suboptimal points while maintaining steady progress toward the global minimum. The variation in parameters between Campus 1 and Campus 2 campuses further supports the idea that site-specific data patterns influence ANN structure. For instance, Campus 2, with a more stable weather pattern, might achieve optimal results with fewer neurons, while Campus 1's more fluctuating climate may require a more complex network. In summary, **Table 2** demonstrates that SSA effectively tailors ANN configurations to each prediction scenario, ensuring lower MSE and higher accuracy. This adaptability is crucial when applying ANN models to diverse environments and prediction timeframes.

The testing results of SSA-ANN for campus 1 and campus 2 are presented in **Figure 9** and **Figure 10**, respectively. These figures demonstrate strong predictive performance across all three cases: daily, weekly, and monthly predictions. Each plot compares the ANN outputs against the actual targets, accompanied by a linear fit line and a reference line (Y = T) representing perfect prediction. For Campus 1, the results show impressive accuracy across all cases. In Case 1 (daily prediction), the correlation coefficient (R = 0.98069) indicates an excellent fit, with data points closely following the linear fit line and minimal deviation. Case 2 (weekly prediction) maintains a high correlation (R = 0.97151), though a slight increase in spread is observed, reflecting the added challenge of predicting weekly trends. Case 3 (monthly prediction) yields a slightly lower correlation (R = 0.9634), with a more noticeable spread around the linear fit, which is expected as longer-term predictions introduce more variability. Despite this, the model continues to capture the overall trend effectively.

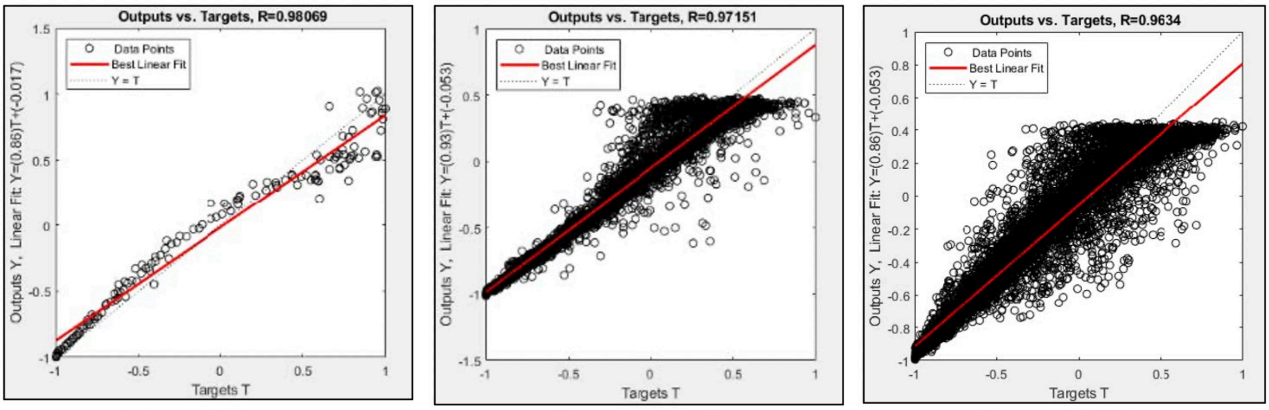
For Campus 2, the SSA-ANN model similarly shows strong performance. Case 1 (daily prediction) achieves R = 0.96485, slightly lower than Campus 1's daily results but still indicating high accuracy. The spread is modest, and the linear fit remains strong. Case 2 (weekly prediction) demonstrates consistency with R = 0.97029, showing that the model generalizes well to weekly data, with points remaining densely clustered around the fit line. In Case 3 (monthly prediction), the model maintains a robust correlation of R = 0.96268, similar to Campus 1's performance. While the spread increases, the linear fit still captures the overall relationship accurately, proving the model's stability.

Overall, the results across both campuses validate the effectiveness of the SSA-ANN approach. With R values consistently above 0.96 in all cases, the model demonstrates reliable predictive capability. Campus 1 consistently achieves slightly better correlations, which may indicate more stable data or less environmental variability compared to Campus 2.

The increasing spread from daily to monthly predictions reflects the natural challenge of long-term forecasting due to external influences, but the SSA-ANN model's performance remains strong, showcasing its adaptability to different timescales and environments. Daily predictions consistently yield higher correlation coefficients and tighter clustering around the linear fit line. This is expected because daily data provides more granular information, allowing the ANN to adapt and adjust more frequently, leading to better performance. Weekly predictions, while still highly accurate, face greater challenges due to the reduced data frequency and the increased influence of unpredictable factors that SSA may not fully optimize within the ANN structure.

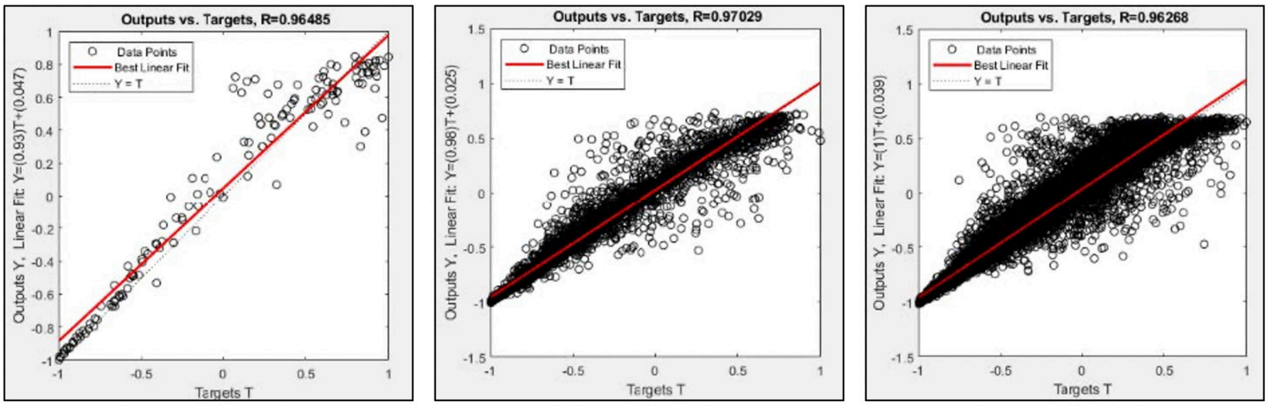
Table 2: *Parameters obtained using SSA-ANN for all cases*

Campus	Case	H1	H2	LR	MC	MSE	R
	1	14	1	0.9999	0.5951	0.0195	0.98069
Campus 1	2	3	8	0.2564	0.7404	0.0162	0.97151
	3	2	1	0.5941	0.5888	0.0206	0.9634
	1	20	1	0.9997	0.1002	0.0296	0.96485
Campus 2	2	9	2	0.6495	0.9942	0.0155	0.97029
	3	2	11	0.9357	0.285	0.0195	0.96268



(a) Case 1 (b) Case 2 (c) Case 3

Figure 9: *Testing results of SSA-ANN for Campus 1*



(a) Case 1 (b) Case 2 (c) Case 3

Figure 10: *Testing results of SSA-ANN for Campus 2*

In conclusion, SSA-ANN demonstrates strong predictive capabilities in both daily and weekly cases. Daily predictions outperform weekly ones in terms of correlation and data fit, reflecting the advantage of more frequent data inputs. Weekly predictions remain reliable, though with a slightly higher spread, which is reasonable given the longer prediction interval. The consistent performance across campuses and time scales validates the SSA-ANN model's adaptability and robustness, making it a powerful tool for short-term and medium-term forecasting alike.

4. CONCLUSION

This paper offers a hybrid Artificial Neural Network (ANN) model that incorporates the Salp Swarm Algorithm (SSA) to improve the accuracy of photovoltaic (PV) power production prediction. Accurate prediction of PV generation in campuses brings several significant benefits. First, it supports better energy management by allowing campus facilities to balance supply and demand more efficiently, reducing reliance on grid electricity and lowering energy costs. This enables campuses to maximize self-consumption of solar power, minimizing excess energy wastage or the need for expensive energy storage solutions. Additionally, accurate forecasting helps improve the stability of the local grid by providing reliable estimates of energy output, which is crucial when integrating renewable sources that are naturally intermittent. It also supports long-term sustainability goals by empowering campuses to track and optimize their renewable energy usage, contributing to carbon reduction initiatives. Furthermore, precise predictions enable more effective maintenance scheduling, as sudden drops in output can signal performance issues, allowing for proactive interventions that extend the lifespan of the PV system. Finally, accurate generation data enhances research and educational opportunities, providing real-world datasets for students and researchers to analyze energy systems, smart grids, and renewable integration strategies, fostering a more informed and energy-conscious campus community.

In this paper, the prediction of SSA-ANN is conducted using real data from two campuses, demonstrated that SSA-ANN effectively optimizes key ANN parameters, enhancing prediction performance. Daily predictions exhibited higher accuracy, indicated by stronger correlation coefficients and tighter clustering around the regression line, while weekly predictions maintained commendable performance despite increased data variability. The model's consistent performance across both campuses highlights its robustness and adaptability, validating SSA-ANN as a reliable hybrid tool for complex prediction tasks.

Future improvements to the SSA-ANN model could further enhance its performance and versatility. Integrating SSA with other metaheuristic algorithms, such as Particle Swarm Optimization (PSO) or Genetic Algorithm (GA), may improve convergence speed and prevent the model from getting stuck in local minima. Additionally, dynamic parameter tuning, where learning rates and momentum coefficients adapt throughout the training process, could improve responsiveness to evolving data patterns. Incorporating external factors like weather conditions and operational schedules would enable the model to capture more complex relationships, leading to greater accuracy. Moreover, applying transfer learning by training the model on one campus and fine-tuning it for another could enhance scalability and efficiency, particularly for data-limited sites. Finally, deploying SSA-ANN in a real-time forecasting setup would allow continuous learning and adaptation to live data streams, ensuring more dynamic and resilient predictions. Future work will also explore benchmarking SSA-ANN against other hybrid optimization techniques such as ANN-PSO and ANN-GA to further validate the model's optimization efficiency and comparative performance. By extending the SSA-ANN framework with these enhancements, future studies can push the boundaries of predictive accuracy and generalizability, making this approach applicable to a broader range of industries and scenarios. By extending the SSA-ANN framework with these enhancements, future studies can push the boundaries of predictive accuracy and generalizability, making this approach applicable to a broader range of industries and scenarios.

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