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Enhanced the Maximum Power Point Tracking (MPPT) of Photovoltaic Systems Using the Flying Squirrel Search Optimization (FSSO) algorithm and Feed Forward Neural Network

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Abstract

In this current Investigation, a solar PV system is applied. The Flying Squirrel Search Optimization (FSSO) algorithm for Maximum Power Point Tracking (MPPT) is examined. The flying squirrel's movement serves as inspiration for the FSSO algorithm, which simulates their movements and evaluates fitness to find the optimal voltage and current levels for maximum power output. Through dynamic positioning of "squirrels" (potential solutions), the algorithm strives to find the optimal voltage and current combination, hence optimizing the PV system's total efficiency. The MATLAB script that is included demonstrates the unique optimization method of the FSSO algorithm for MPPT in a solar PV system. The parameters and movement rules of the script can be customized to match the unique features of the PV system, offering application versatility. In general, these methods raise. Before applying the FSSO algorithm, ANN was applied to aid in enhancing MPPT's performance by creating an input-output model. ANN results are based on 8761 datasets collected from (www.kaggle.com). ANN resulted in the best validation performance obtained at epoch 30, which is a total of 36 epochs. The coefficient of determination (R-squared) for the linear regression between the predictions of the neural network and the actual target values is displayed as a regression equal to 0.84666. The results concluded that the neural network has reasonably good predictive performance. Based on these results, applying FSSO using 100 iterations, the results concluded that the maximum power point of tracking was accurately determined based on photovoltaic resources.

Keywords—Maximum Power Point (MPP), Photovoltaic System, Artificial Intelligence, ANN, The Flying Squirrel Search Optimization (FSSO) algorithm

1 Introduction

One major application of artificial intelligence in photovoltaic systems is solar panel manufacturing and optimization. Artificial intelligence (AI) systems can analyze vast amounts of data, such as climatic trends, geographic data, and historical performance data. It utilizes to determine the optimal orientation, tilt, and position of solar panels (Alam, 2024) Solar panel installation may be optimized using artificial intelligence to increase solar absorption and boost total energy production. AI also has a big influence on maintenance scheduling and defect detection in solar energy systems. A few environmental factors that solar panels are exposed to and which may eventually reduce their efficacy are hotspots, shade, and dust accumulation (Kumar et al., 2021) (Ai et al., 2021). Artificial intelligence (AI) has emerged as a key driver of innovation and productivity increases in a number of industries, most notably the renewable energy sector. Artificial intelligence (AI)-based techniques have shown to be a promising field for improving the effectiveness, dependability, and overall efficiency of solar power plants when it comes to photovoltaic (PV), which is the process of converting light from

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the sun into electrical energy through the use of solar panels (Abubakar et al., 2021) (Kurukuru et al., 2021). The sporadic nature of power generation poses a challenge for renewable energy sources like solar energy. In order to maximize the efficiency of solar power plants, artificial intelligence (AI) algorithms can assess historical and present data on energy storage capacity, meteorology, and supply and demand for electricity (Feng et al., 2021) (Ai et al., 2021). The sensors incorporated in the panels may provide real-time data to artificial intelligence systems. Algorithms can be used to detect issues by employing machine learning techniques. Proactive maintenance can result in significantly reduced downtime and increased efficiency for solar systems. Integrating the solar energy into the current electrical system can be made easier with applying artificial intelligence techniques (Salim et al., 2021)) (Villegas-Mier et al., 2021). Artificial intelligence (AI) can dynamically modify the output of solar power plants, guaranteeing a steady and dependable supply of electricity by properly forecasting patterns of energy generation and demand. AI has the potential to improve energy storage devices' efficiency when utilized in conjunction with solar generators (Remoaldo & Jesus, 2021). In order to offset the intermittent nature of solar energy production, battery storage is required. AI systems that examine past data and present power usage can optimize battery charging and discharging cycles. By using AI algorithms and methodologies, solar power generation can be maximized. Additionally, Maintenance can be increased, and the overall performance of solar energy systems can be improved. Figure 1 illustrates AI approaches applied in the reviewed research, additionally shows which of the four main AI methods is most commonly used these days (Khan, 2021) (Khan & Pushparaj, 2021). This guarantees optimal utilization of stored energy, minimizes wastage, and facilitates effective energy administration. AI has the ability to progress solar energy research and development in addition to system optimization. Researchers can find and develop novel materials for solar panels more quickly because of AI's data analysis and pattern recognition skills. These materials include innovative solar cell designs and improved photovoltaic materials. In the end, artificial intelligence has enormous potential to improve solar energy systems' integration, efficiency, and dependability (Khan, 2021).

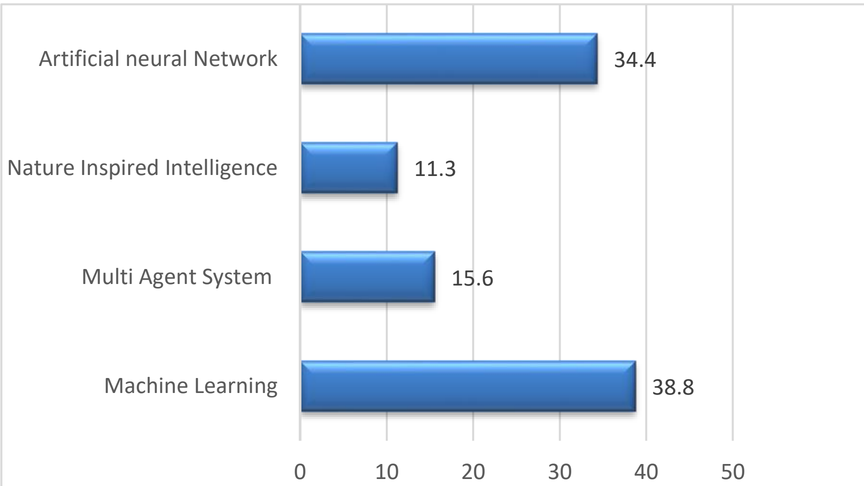

Figure 1: AI Methodologies Used in the Reviewed Research (Franki et al., 2023)

Artificial neural network (ANN) technology is regarded as one of the most sophisticated, cutting-edge, and successful techniques in data processing and prediction. The field of renewable energy, and solar photovoltaic (PV) systems in particular, is trending toward using artificial neural networks (ANN) to assist in determining maximum power point (MPPT), or the greatest production capacity that can be achieved from a PV system. ANN is a strong tool that can be used to calculate MPPT accurately since it can adapt and learn from past data. ANN may encounter several difficulties, such as building and training difficulties. ANN can be used with other optimization strategies, including FSSO algorithms, to overcome these obstacles and enhance MPPT determination performance. By optimizing the ANN construction and training settings, FSSO enhances both the overall system efficiency and MPPT recognition accuracy (refer to Figure 2)   (Zhao et al., 2023).

Because of its current significance, concentrating on the innovative and renewable energy sector is crucial. This study explores the use of artificial intelligence in the electrical industry, an important research area. This section aims to give readers a thorough understanding of the advancements and applications of artificial intelligence technologies to address opportunities and challenges in the electrical industry, particularly in relation to clean and sustainable energy sources, by reviewing these studies.

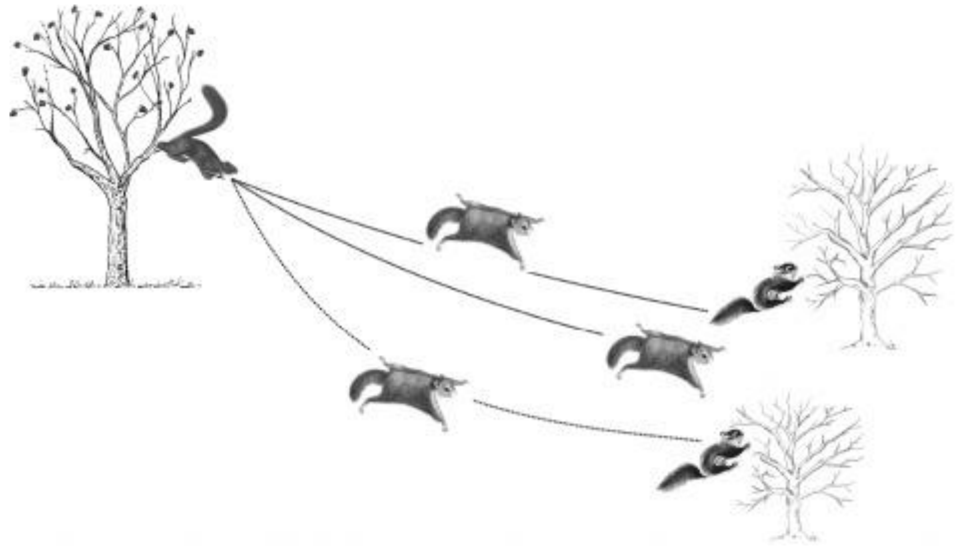

Figure 2: Squirrel Search Algorithm (Zhao et al., 2023)

2 Related Works

A lot of Research works has been done in the last few years to the application of artificial intelligence in renewable energy. For this regard, recently research aimed to develop a model that closely resembles the microgrid system, anticipates demand and supply, efficiently plans power distribution to meet demand, and provides useful insights into the SG system's performance. It also implemented the Demand Response Program (DRP), which comprises improved incentive-based payment options and cost-saving solutions. The test results were evaluated across multiple scenarios to improve operational expenses utilizing the multi-objective ant colony optimization method, without and with the DRP's input (Arumugham et al., 2023).

Another study examined and described several AI strategies for improving renewable energy-powered desalination systems. The use of several the models of forecasting, controlling systems, and algorithms utilized for optimization in developing and managing renewable energy-powered desalination systems was investigated and proved the artificial intelligence accurately in renewable energy field (Sayed et al., 2023).

Another assessment covered a variety of integrated systems, integration requirements, strategies, and issues related to microgrid communication and artificial intelligence integration. Additionally, the assessment included a thorough examination of the control mechanisms used in conjunction with renewable resource integration, as well as any prospective obstacles that may develop. The categorizations developed in this review made integration improvement easier. This study also examined several optimization strategies that are applied to reduce integrated energy sources' overall cost. Through the use of a case study, the consequences of integrating renewable energy sources (RESs) with artificial intelligence were assessed. The case study's findings demonstrated how the use of artificial intelligence increased system performance accuracy and enabled accurate and successful prediction of the integrated system. The optimal hybrid model was found by combining many optimization techniques with artificial neural networks (ANNs). Particle Swarm Optimization (PSO) took 3367.50 seconds to achieve the lowest error percentage (an NMSE of 1.10%) and the fastest rate of convergence out of all of these approaches (Talaat et al., 2023).

Another study employed the VOS viewer program to investigate and evaluate the use of machine learning and artificial intelligence in the electrical industry, identifying fascinating yet underutilized or unexplored areas where these concepts can be applied. The 2000 most recent publications and the 2000 most referenced articles in a variety of energy-related terms were examined in order to achieve this, and a correlation between them and keywords connected to AI and ML was demonstrated. The results revealed a number of current research trends in a wide range of subjects, from fundamental to innovative, as well as some interesting directions for further investigation. The results also showed a notable increase in the number of commercial patent applications for AI and machine learning in the energy sector (See Figure 3) (Entezari et al., 2023).

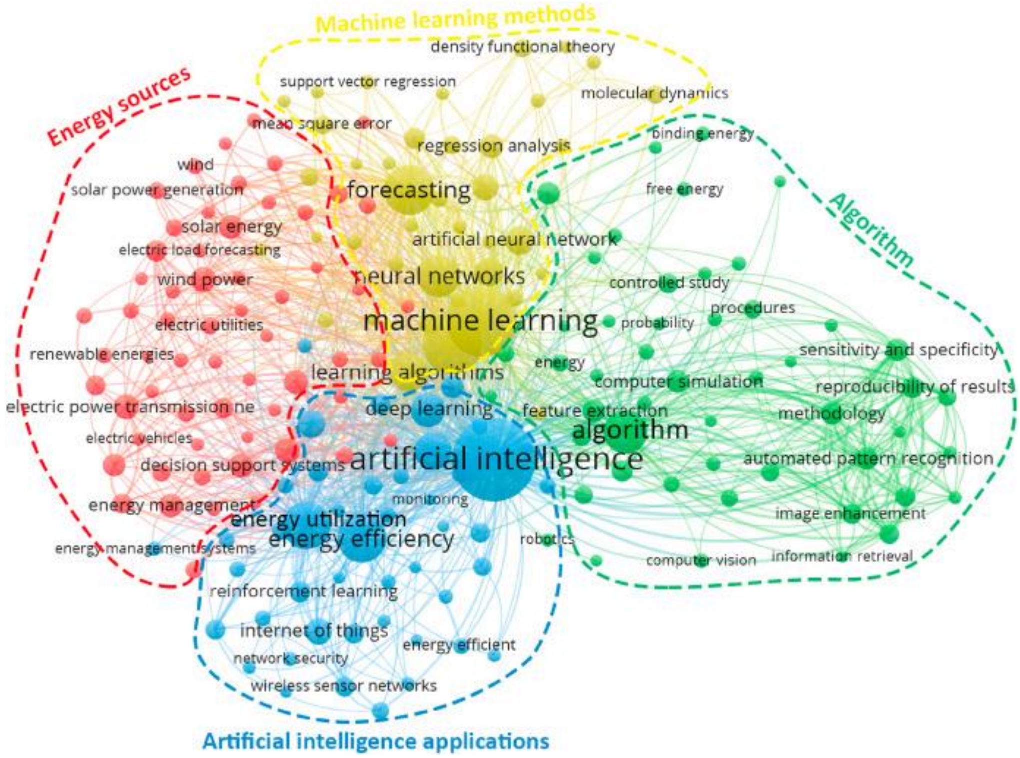

Figure 3: Application of Artificial Intelligence (Entezari et al., 2023)

Recently, an investigation was conducted to examine the possible roles that artificial intelligence and renewable energy could play in this endeavor. In light of this, a more recent study examined the processes that can enhance and boost energy consumption efficiency while lowering greenhouse gas emissions and advancing sustainable development. It is crucial to address the issue of setting high standards for renewable energy, passing legislation to support those standards, and utilizing artificial intelligence to enhance energy systems and facilitate smart grid management. By utilizing these techniques, we can accelerate the shift to a more ecologically friendly and sustainable future by realizing the full potential of renewable energy sources and artificial intelligence (Hassan et al., 2023).

Because rural areas have a high potential for renewable energy, recent research looked at the application of the analytic hierarchy process (AHP) to pick alternative energy sources based on financial, environmental, social, and physical variables using integer linear programming to size generation systems. Finally, it demonstrated how to train an artificial neural network (ANN) to improve processes while accounting for farm agroeconomic characteristics. The proposed methodology was implemented on farms in São Francisco do Glória in Brazil. The AHP advised that wind, solar and biomass systems be implemented in 22.52%, 62.16%, and 15.32% of the farms, respectively. The improved ANN configuration achieved a maximum precision of 81.80 ± 3.36 percent (Oliveira et al., 2023).

Another study suggested a modified multi-step constant current technique for solar systems. The proposed technique provided a multi-step continuous current to the wolf pack while monitoring the hierarchy's interior and outside movements. The proposed technique accurately tracks the highest power point of solar systems under different partial shadowing scenarios (PSCs) (Dagal et al., 2024).

The deficiency in current study pertains to the restricted investigation of hybrid methodologies that merge artificial intelligence with efficient MPPT algorithms. Improved maximum power point tracking of PV systems is clearly needed, since current solutions struggle to remain efficient under changing climatic conditions. Although

ANNs have been used to determine MPPT in PV systems, there are challenges in effectively constructing and training ANNs to achieve improved performance. The majority of earlier research concentrated on determining MPPT solely using ANN, ignoring the use of other optimization strategies. To maximize the ANN's construction and training in order to calculate MPPT in solar systems, this work integrated the ANN with the (FSSO) technique. The emphasis was on creating and honing an efficient ANN before applying (FSSO), which raises the system's overall efficiency and MPPT determination accuracy. To demonstrate the efficacy of the suggested approach, the performance of the suggested system (ANN-FSSO) was compared with that of conventional techniques for calculating MPPT. Because ANN and FSSO can handle non-linearities and optimize, these algorithms were utilized in MPPT instead of more conventional algorithms like Perturb and Observe, which offer lower accuracy and less efficiency. By creating an ANN-based system backed by hybrid optimization techniques to calculate MPPT in PV systems with high accuracy, this study aims to close the research gap. The methods used in this research are predicated on meteorological variables such radiation, temperature, humidity, wind speed, and solar power generation calculations. Through the application of artificial intelligence, primarily artificial neural networks, to historical data analysis, the goal of this competition is to develop a relationship between solar system (ANN) outputs and climate conditions. The ANN model estimates PV system production based on weather forecast data, allowing operators to take necessary action to enhance system performance and make well-informed judgments. A predicted link between the ideal MPPT control parameters and the PV system inputs (temperature and irradiance) was established using the ANN model. Next, the ANN model's presented MPPT control parameters were further optimized using the FSSO. Overall, based on ANN results, the maximum power point tracking (MPPT) (FSSO) technique in solar PV systems is also examined.

3 Methodology

3.1 Photovoltaic System

One category for solar panels is semiconductors. A direct electric current is produced via the solar panels when sunlight enters the outer layer of photovoltaic cells (Kumar et al., 2021). This is seen using a comparable circuit in Figure 4. The single diode model is made up of two resistors, a current source, and a single diode (Hajjaj et al., 2022).

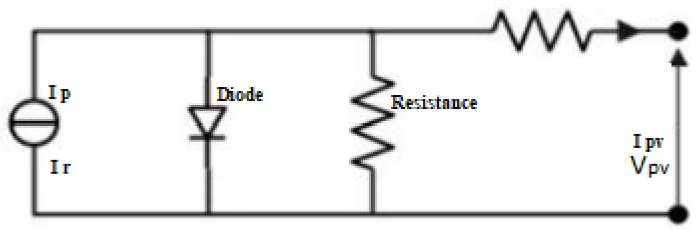

Figure 4: Schematic Diagram of PV Cell (Belhaouas et al., 2021) (Feng et al., 2021) (Khan & Pushparaj, 2021), (Zhao et al., 2023)

The sun photo produced the current I_p based on the irradiance I_r and the temperature T as in Equation (1). The photocurrent can be determined according to Equation (1) (Belhaouas et al., 2021) (Franki et al., 2023).

$$photo\ current\ (I_p) = \frac{G}{1000} \times [K_i(T - 298) + I_{sc}] \tag{1}$$

Where $I_p$the photo current, solar irradiation is is referred by G, I_{sc} is the short circuit current at 1000W/m2 and 25°C, and K_i is the temperature coefficient of I_{sc}. Accordingly, the PV current can be determined according to Equation (2) (Belhaouas et al., 2021) (Kurukuru et al., 2021) (Franki et al., 2023).

$$PV\ current = I_p - \frac{V_{pv} + R_S \times I_{pv}}{R_{Sh}} - I_0 \times (-1 + e^{\frac{q\ (V_{pv} + R_S \times I_{pv})}{KTn}}) \tag{2}$$

Temperature and irradiation have a considerable impact on a PV system's voltage and current production. Higher temperatures tend to reduce voltage output while boosting current output. In contrast, rising irradiance often results in higher voltage and current output until the system approaches saturation. Considering these interactions is critical for creating and optimizing solar systems. Figure 5 shows the effect of Temperature and irradiation on the photovoltaic current and voltage (Abo-Khalil et al., 2023).

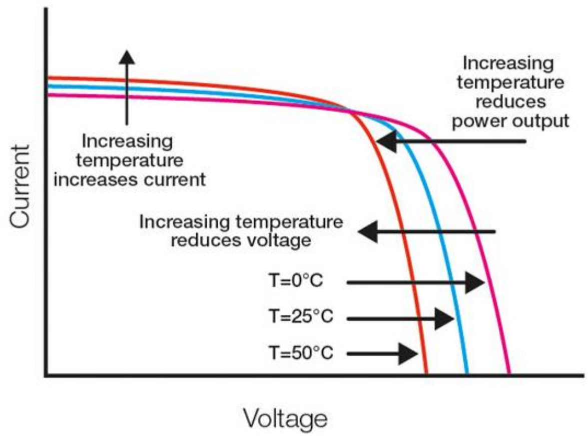

Figure 5: Relation Between Temperature and V-I Characteristics (Hajjaj et al., 2022) (Abo-Khalil et al., 2023).

The maximum power point (MPP) is the single point at which the power reaches its peak. Weather conditions affect the location of this point: power grows as irradiance rises, and a PV panel performs better for low temperatures than a high temperature (Abo-Elnour et al., 2023).

4 Artificial Neural Network

Kalaiarasi et al. provided an introduction to artificial intelligence in electric sector. Because of its importance in this field of electrical engineering, artificial neural networks (ANN) are being widely explored in the renewable energy sector especially photovoltaic systems to predict weather conditions such as temperature and radiation, hence controlling and optimizing the maximum power point (MPP). This study proposes an optimal irradiance and temperature controller for use in solar systems based on neural network-based artificial intelligence technology. Figure 6 shows artificial Neural Network Structure. It is made up of many neurons, which are identical to brain biological cells. The neurons in question are structured in layers, with a large number of connections that are weighted to neurons at higher levels. Each input layer neuron takes data from entering variables and provides it to the layer's hidden neurons that integrate the inputs to generate a single result that is then communicated to its results via a function of activation (Kalaiarasi et al., 2023).
Ultimately, each neuron in the results layer integrates the outputs from the hidden layer with the bias before sending the result to the activation function, which produces the final output. The weights and biases (w), output (y), and input (x) the ANN are displayed in Figure 6. As demonstrated in Figure 6, the ultimate outcome can be attained by giving neurons in the input and output layers linear activation and neurons in the hidden layer sigmoidal activation functions.

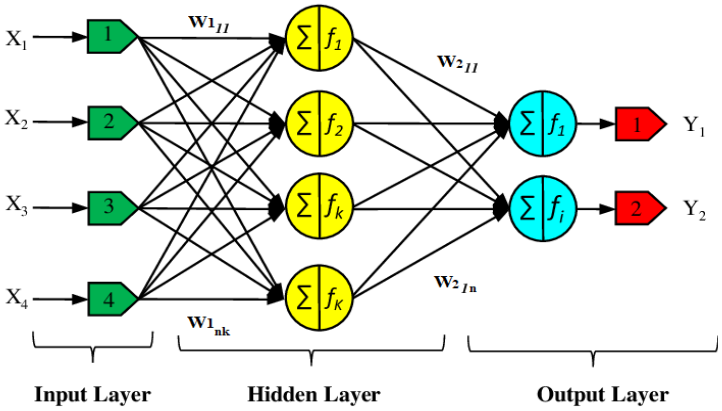

Figure 6: Artificial Neural Network Structure (Arumugham et al., 2023) (Abo-Khalil et al., 2023).

The output function can be determined according to Equation (3) (Hichem et al., 2023):

$$(y_n) = W2_{10}X_0 + \cdots + W2_{1n}X_n + \quad (3)$$

Where W is the weights of the layers, Y is the output function, and X is the input. The weights of the layers of a neural network are changed during trained to minimize errors between the target and output values.

Equation (4) defines the mean square error (MSE) as the performance function of the ANN network.

$$E_{mse} = \frac{1}{n}\sum_{i=0}^{i=n}(t_i - y_i)^2 \quad (4)$$

Where, n indicates the number of trained models, t_i represents the target at sample i, and y_i represents the output signal at sample i.

In this study, 8761 datasets are applied on ANN – MATLAB Simulink. The number of inputs, hidden layers and output are 2, 10, and 1 respectively. The datasets percentage of training, validation, and testing are 75, 5, and 20 % respectively. Figure 7 shows the construction of ANN on the MATLAB software as showing in Table 1. Applying ANN prior to calculating MPPT with the Flying Squirrel Search Optimization (FSSO) algorithm allows one to learn from past data and create an input-output model. This aids in enhancing MPPT's performance.

Table 1: The Datasets Utilizing in ANN software

Datasets	Number	Percentage (%)
Training	6570	75
Validation	438	5
Testing	1752	20
Total	8761	100

4.1 The Flying Squirrel Search Optimization (FSSO) algorithm

The Flying Squirrel Search Optimization (FSSO) algorithm is a nature-inspired optimization technique that resembles flying squirrels' foraging behavior. FSSO divides the search space into regions and use both exploration and exploitation tactics to find optimal solutions.

The FSSO algorithm comprises of two major operators: soaring and gliding. These operators imitate squirrels' flying and gliding behaviors, allowing the algorithm to explore varied regions and focus on promising places.

To locate all flying squirrels, the grid provided is utilized as in Equation (5)

$$FS_{nt}^{t+1} = \begin{cases} Random & Otherwise \\ G_c \times D_g \times (FS_{at}^{t} - FS_{nt}^{t}) + FS_{nt}^{t} & at\ R_2 \geq P_{dp} \end{cases} \quad (5)$$

Where R_2 is a random number in the range [0, 1].

$$fs = \begin{vmatrix} FS_{1,1} & \dots & FS_{1,n} \\ & . & \\ & . & \\ FS_{k,1} & \dots & FS_{k,n} \end{vmatrix} \quad (6)$$

The Fitness can be evaluated according to Equation (7). The region's soundness for each flying squirrel is determined using the upsides of choice variables (Mazumdar et al., 2023) (John et al., 2023).

$$f = \begin{vmatrix} f1([FS_{1,1} \ \dots \ FS_{1,n}] \\ . \\ . \\ fn([FS_{k,1} \ \dots \ FS_{k,n}]) \end{vmatrix} \quad (7)$$

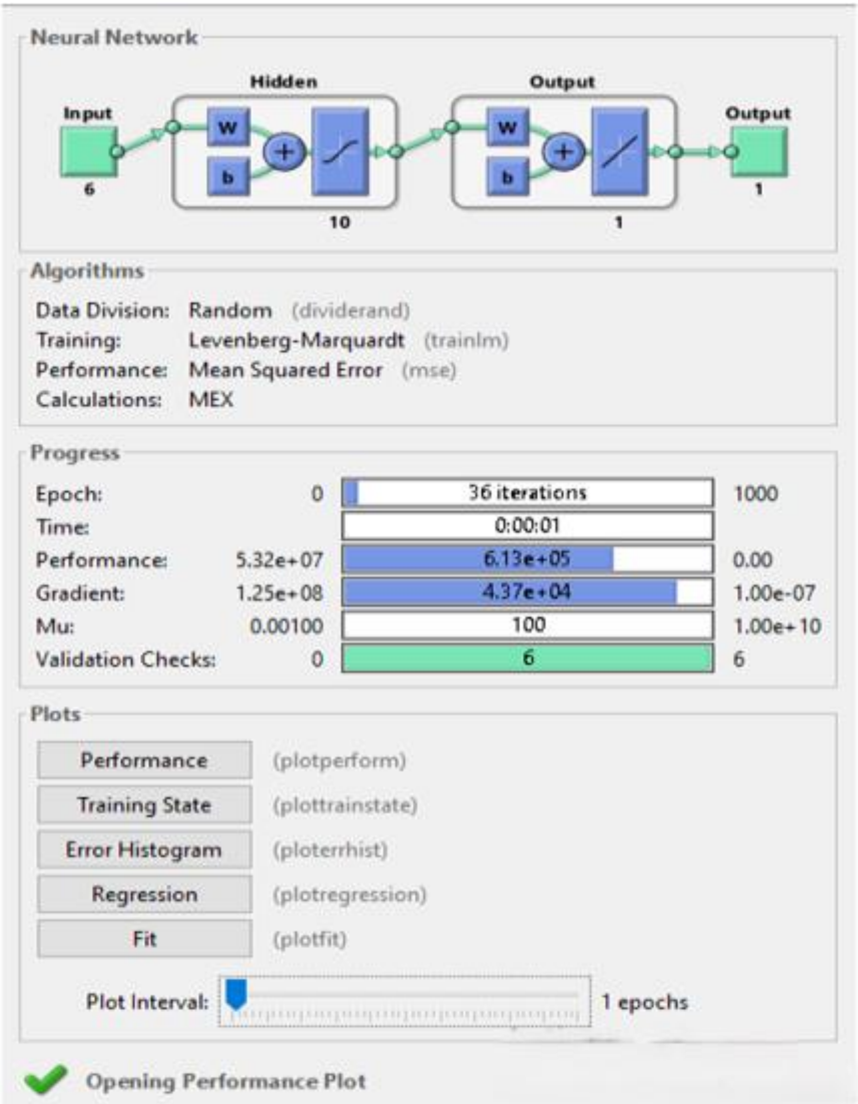

Figure 7: The ANN Construction on MATLAB Software.

4.2 Utilizing ANN and Flying Squirrel Search Optimization (FSSO) algorithm in PV System

The proposed technique based on artificial neural network in training the input factors as temperature and irradiation intensity to optimizes the system production. Thus, Flying Squirrel Search Optimization (FSSO) algorithm utilized to determine the Maximum power point for the solar cell. Figure 8.a shows the Flowchart of FSSO algorithm. Figure 8.b illustrates the proposed approach based on artificial intelligence algorithms. The procedures of these approaches as following: -

1. Insert the maximum number of iterations and squirrels; in this case, they are equal to 20 and 100, respectively .
2. Determine each squirrel's fitness value by calculating its position.
3. Arrange the squirrels according to their fitness levels.
4. Use the soaring operation to search through additional areas of the search space by doing the following:
    - Determine each squirrel's exploration probability by grading its fitness.
    - Assign each squirrel a random number.

- Update the squirrel's position at random if the random number is less than or equal to the exploration probability.
- If not, use the best position to update the squirrel's location.

5. Execute the gliding operation to take advantage of promising regions: Determine the gliding distance for each squirrel by comparing its fitness value with the best fitness value discovered thus far. Then, update the squirrel's position by moving it in the direction of the best position.
6. Using the squirrels' fitness values as a guide, update the best location thus far.

Continue steps 2-4 until the termination requirement is satisfied.

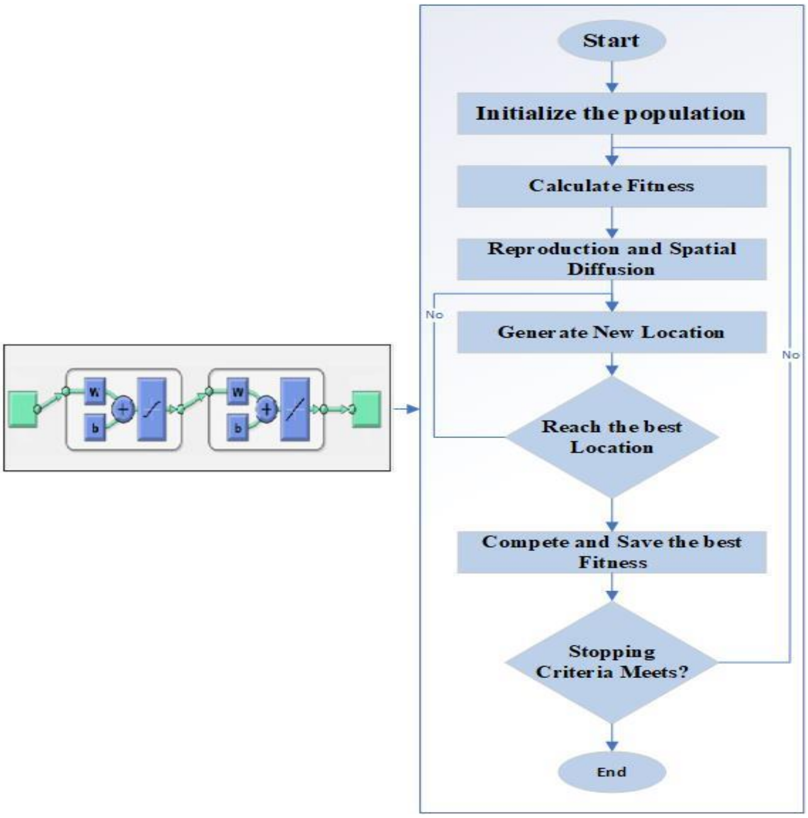

Figure 8: The Flowchart of The Proposed Approach for PV System.

5 Results and Discussion

An ANN model in MATLAB/Simulink is constructed with a three-layer feed-back ANN structure. The ANN's inputs are temperature and irradiance; its output is system productivity. Two neurons make up the input layer, ten neurons make up the hidden layer, and one neuron makes up the output layer of this model's brain structure. The artificial neural network (ANN) model operates in two stages. Firstly, it is trained using a database of inputs (temperature and radiation) in order to apply the Levenberg-Marquardt technique to establish the optimal target values (system production). Using this perfect ANN model, the FSSO approach is then applied to monitor the MPP. Figure 9 displays the ANN network's performance. The objective of Mean Squared Error (MSE) is used to gauge the model's performance. The discrepancy between the actual or observed values and the expected or estimated values is measured using the widely used MSE metric. The best validation performance is 618255.5074 at epoch 30 of total 36 epochs. The purpose of the AAN's training state is to give a visual depiction of the artificial neural network's performance and training progress (See Figure 10). It shows the training state, where gradient is 43703.7981, Mu is 100, and validation checks are 6 at epoch 36. The data shows that, out of the 36 epochs, epoch 30 produced the best validation performance of 618,255.5074. This indicates that the model's performance got better during the initial epochs, peaking at epoch thirty.

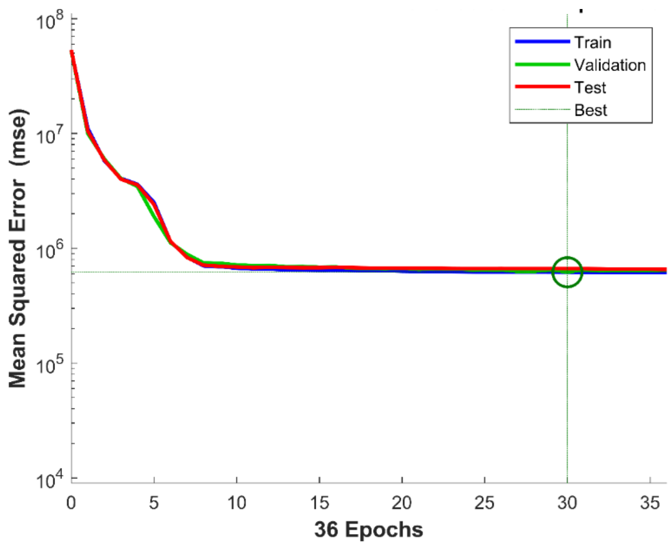

Figure 9: The Best Validation Performance.

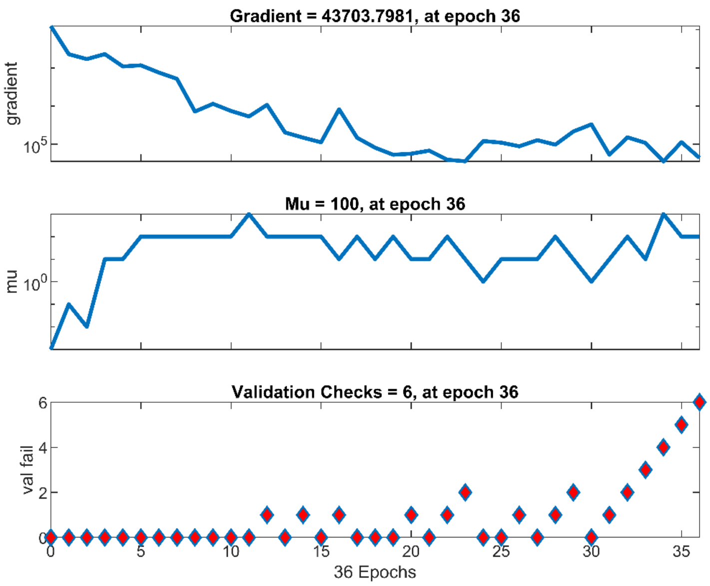

Figure 10: The Training State Result

The purpose of the error histogram is to show the distribution of residuals, or errors, between the actual target values and the predictions made by the neural network as showing in Figure 11. It is evident that the performance, which contains error, is acceptable as showing in Figure 11. Table 2 shows the MSE and R results for training, Validation, and testing samples. According to this table, the precision and applicability of the model in the estimate process are indicated by the average MSE value of 633148.62067. Regression-related issues benefit greatly from the visual depiction of the relationship that the regression result offers between the actual target values and the predictions made by the neural network as showing in Figure 12. It shows that the output for all training, testing, and valuation samples equals 0.71 * target + 1.8e+02. This equation depicts the linear regression line that was fitted to the scatter plot of the neural network's predictions against the actual target values.

The regression line has a slope of 0.71, indicating that the neural network's expected output changes by 0.71 units for every unit change in the goal value. 180 is the value of the regression line's intercept, 1.8e+02. The coefficient of determination (R-squared) for the linear regression between neural network predictions and actual target values is shown as regression = 0.84666. When the R-squared value is nearer 1, there is a stronger match between the expected and actual numbers.

Table 2: Error and Regression Results

Datasets	Number	MSE	Regression
Training	6570	617484.38367e-0	8.48182e-1
Validation	438	618255.50737e-0	8.48404e-1
Testing	1752	663705.97097e-0	8.40670e-1
Total	8761	-	8.48666e-1

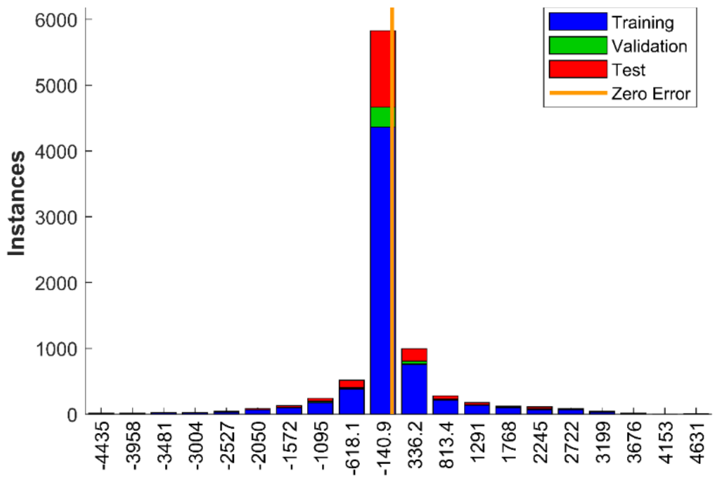

Figure 11: The Mean Squared Error Result

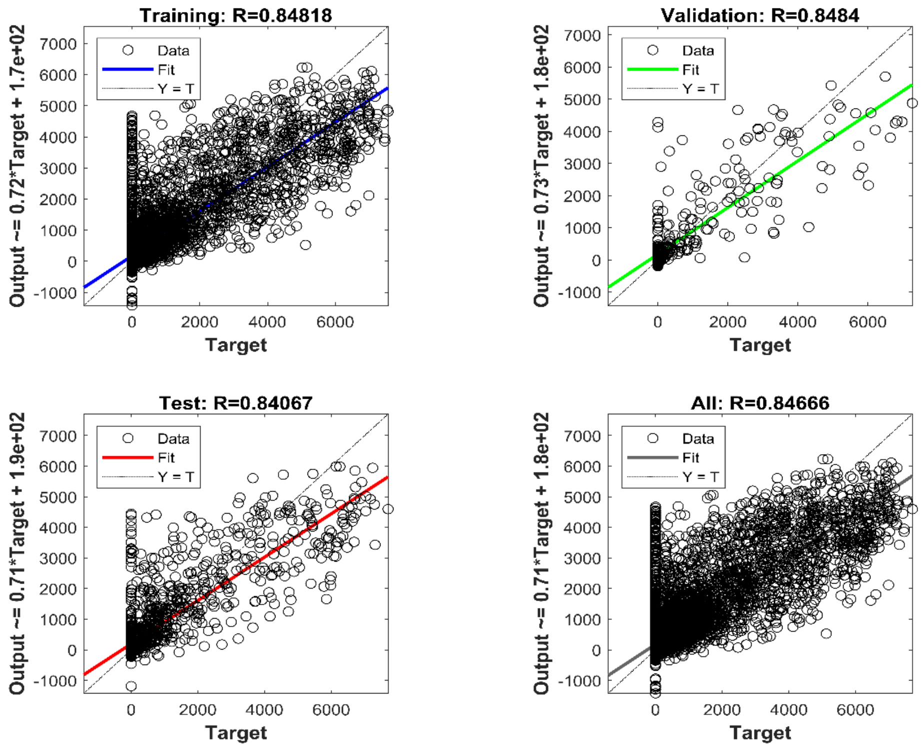

Figure 12: The Regression Result.

The value of R-squared falls between 0 and 1. In this case, the neural network's predictions account for approximately 84.7% of the variance in the target values, according to the R-squared value of 0.84666. This implies that there is a persistent bias and offset in the neural network's predictions. With an R-squared value of 0.84666 and a linear relationship between the predictions and the actual target values, these findings imply that the neural network performs quite well in terms of prediction. An R-squared value of 0.84666 indicates that the model is a strong fit. it suggests that the model captures a significant portion of the variability in the data. The remaining 15.3% of variance indicates the Factors outside the model's scope, measurement Errors, and non-linear Relationships. Overall, these results indicate to the higher performance of the proposed model.

The maximum power point can be determined for iterations 1, 18, 34, 51, 67, 84, and 100 by applying the ANN result in the FSSO method. The highest power for iterations 1, 18, 34, and 51 is 0.89399, 1.2392, 1.4011, and 1.7724 (volt ampere), as shown in Figure 13. For the relevant iterations, these figures represent the highest power output in terms of voltage and current.

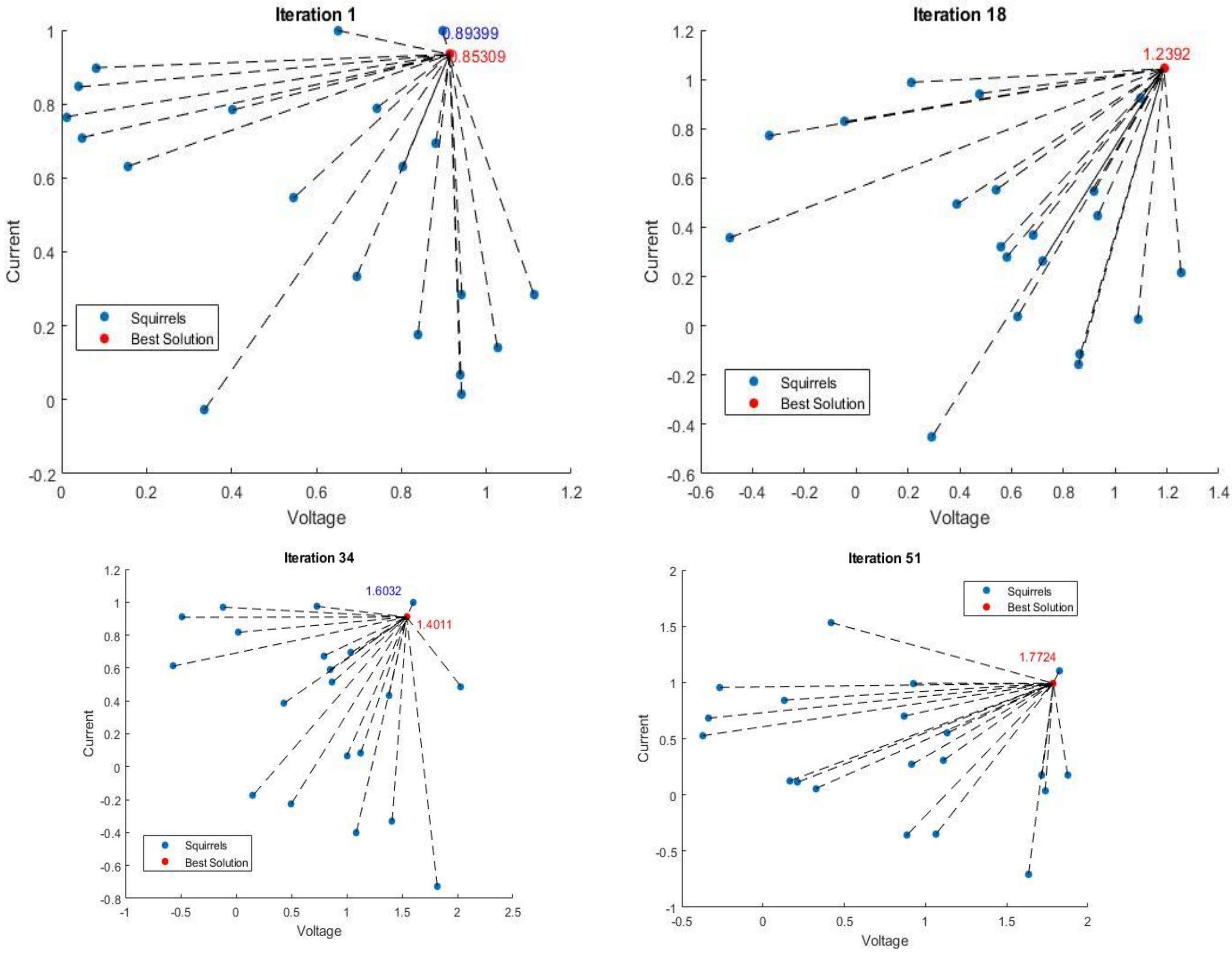

Figure 13: The Max Power Point Technique (MPP) Results of Iterations 1, 18, 34, and 51.

Figure 14 shows the max power (VI) for iterations 67, 84, and 100. The max power for these iterations are 2.2734, 2.3572, and 2.3572 (volt ampere), as shown in Figure 14. Table 3 shows the volt and current results at max power point for each iteration.

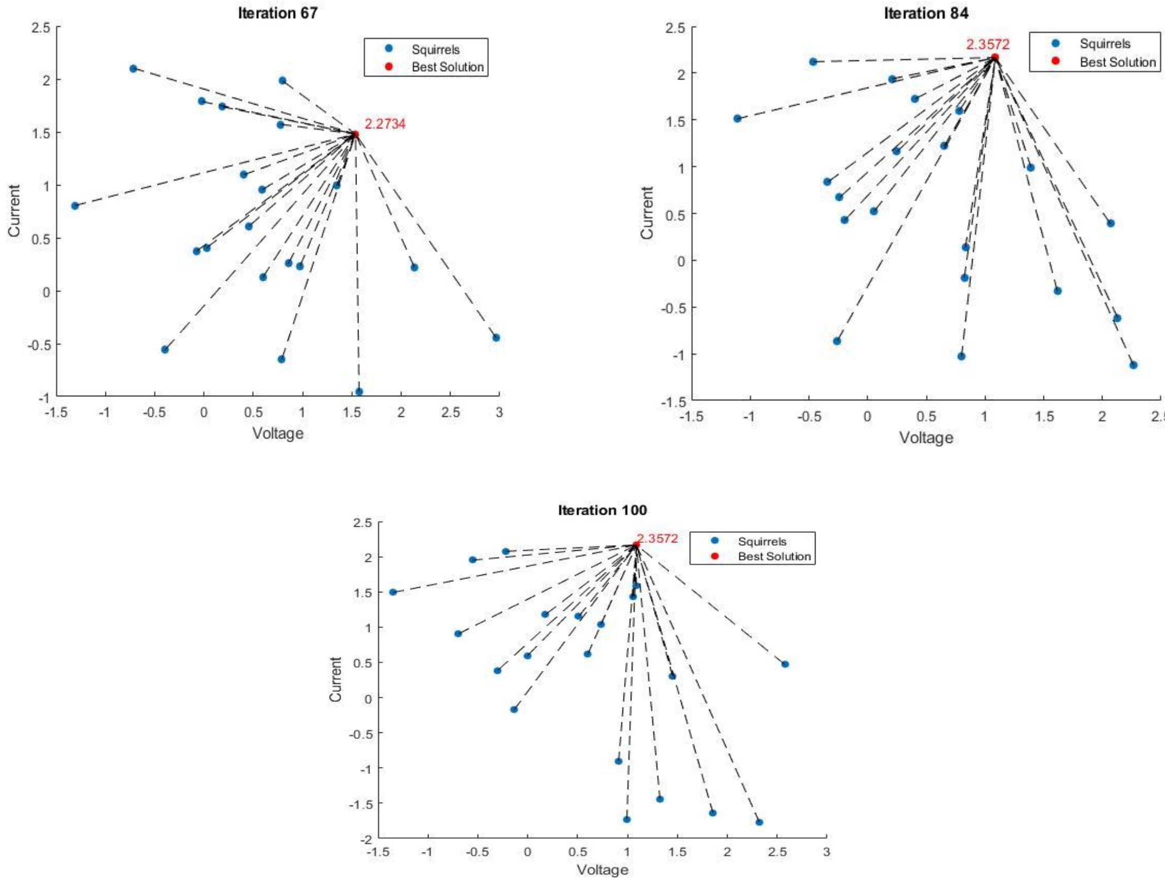

Figure 14: The Max Power Point Technique (MPP) Results of Iterations 67, 84, and 100.

By tracking the voltage and current values, it is shown that the algorithm is able to reach points close to MPP after a limited number of iterations. The PV system's final voltage and current levels are near to its optimal MPP. This suggests that the SSA algorithm can accurately identify MPP. The number of iterations required to obtain MPP varies; in some cases, it is achieved after only one iteration, while in others it takes 100 iterations. This indicates that the convergence speed of the algorithm using MPP varies according to the optical system's operating parameters. Improving convergence speed may be a future improvement to the algorithm. By tracking these numbers, it is obvious that the SSA algorithm can retain consistent performance at the MPP. The voltage and current readings at the endpoint show no discernible variations, indicating steady performance. Overall, these findings show that the FSSO algorithm performs well in identifying the optical system's maximum performance point, with excellent accuracy and a respectable convergence speed. In contrast to references (Talaat et al., 2023), where particle swarm optimization (PSO) took 3367.50 s to obtain the optimum solution (NMSE 1.10%), there is still opportunity for improvement to improve the convergence speed and stability. In contrast, the Squirrel Flying algorithm took between one and one hundred iterations to achieve a location that was nearly at maximum performance (MPP). This suggests that the PSO method was substantially slower than the SSA approach in locating the best solutions to the issue. Consequently, the maximum performance point (MPP) of the PV system may be accurately determined with a good degree of precision using the algorithm suggested in this study.

The study's limitations include the number of datasets employed, which should be raised in further research to produce conclusions with more accuracy. In addition, the study relies solely on simulated or theoretical outcomes rather than experimental validation under real-world situations. In order to confirm the efficacy of the ANN and FSSO algorithms in real MPPT settings, future research might address this by conducting field experiments. This would allow for the consideration of a variety of environmental conditions for more reliable and applicable results.

Table 3: The (volt and current) result to obtain the maximum power

Iterations	Current (y- axis)	Volt (x- axis)
[1]	0.9759	0.9088
[18]	0.9286	1.361
[34]	1.775	1.364
[51]	1.977	1.869
[67]	2.9	1.63
[84]	2.687	1.88
[100]	1.765	2.238

6 Conclusion

By dynamically adjusting ANN, the FSSO algorithm tries to converge on the best combination of voltage and current, enhancing the overall efficiency of the PV system. Prior to using the FSSO approach, an input-output model was created using ANN to help improve the performance of MPPT. Results of the ANN derived from 8761 datasets gathered from (www.kaggle.com). This competition intends to establish a relationship between climate conditions and PV system output (ANN) by utilizing artificial intelligence (more particularly, artificial neural networks) to analyze historical data. The ANN model anticipates PV system production based on anticipated meteorological data, allowing operators to take appropriate action to enhance system performance and make well-informed decisions. According to the results of the ANN, epoch 30 out of the 36 epochs yielded the best validation performance. Regression equal to 0.84666 represents the coefficient of determination (R-squared) for the linear regression between the neural network's predictions and the actual target values. This study came to the conclusion that the neural network performs reasonably well in terms of prediction. Building on the findings of the ANN in control and predict the system production based on the temperature and irradiance, the study additionally investigated the FSSO method for MPPT in a Solar PV System. The flying squirrel movement serves as an inspiration for the FSSO algorithm, which used this behavior to optimize the voltage and current levels in order to produce the maximum amount of electricity. The ANN's predictions can be used into the FSSO algorithm to determine the greatest power point. The outputs of the FSSO algorithm showed which specific iterations generated the highest power points. The accompanying voltage and current values for these iterations revealed the optimal operating points for power output optimization. Taking everything into account, this study demonstrates how effectively the ANN model predicts PV system production and how it works with the FSSO method for MPPT. Overall, a strongly fit of the suggested model was guaranteed by the higher R-squared value, which reached 0.84666. It implies that a sizable amount of the data's variability is captured by the model. These outcomes show that the suggested approach performs better. The highest power point needs to be precisely defined in order to maximize the efficiency of solar cells. The effective application of artificial intelligence in the renewable energy and electric utility sectors demonstrates that it is a valuable tool for increasing the efficacy and efficiency of systems. Future work will be applying the same model with a higher dataset than these used in this study with different inputs included all weather parameters.

7 Appendix

The FSSO algorithm, which uses MATLAB software to calculate the Maximum power point (MPP) for photovoltaic radiation, is represented by the code below.

```
% Define parameters
num_squirrels = 20;
max_iterations = 100;
Tem;
Irr;
dimension = 2;  % Number of optimization variables
squirrels = rand(num_squirrels, dimension);  % Random initial positions
best_solution = zeros(1, dimension);          % Initialize the best solution
best_fitness = Inf;                          % Initialize best fitness value
figure_intervals = round(linspace(1, max_iterations, 7));
for iteration = 1:max_iterations
    for squirrel = 1:num_squirrels
        % Calculate fitness value for the current squirrel's position
        fitness = calculate_fitness(squirrels(squirrel, :));
        % Update the best solution if the current fitness is better
        if fitness < best_fitness
            best_fitness = fitness;
            best_solution = squirrels(squirrel, :);
        end
        squirrels(squirrel, :) = update_position(squirrels(squirrel, :), best_solution);
    end
    % Produce output figures at predetermined intervals of iteration
    if ismember(iteration, figure_intervals)
        figure;
        scatter(squirrels(:, 1), squirrels(:, 2), 'filled');
        hold on;
        scatter(best_solution(1), best_solution(2), 'r', 'filled');
        xlabel('Voltage');
        ylabel('Current');
        title(['Iteration ', num2str(iteration)]);
        legend('Squirrels', 'Best Solution');
        for i = 1:num_squirrels
            plot([squirrels(i, 1), best_solution(1)], [squirrels(i, 2), best_solution(2)], 'k--');
        end
        power_outputs = zeros(num_squirrels, 1);
        for i = 1:num_squirrels
            power_outputs(i) = calculate_power_output(squirrels(i, :));
        end
        for i = 1:num_squirrels
            text(squirrels(i, 1), squirrels(i, 2), num2str(power_outputs(i)), 'Color', 'b');
        end
        text(best_solution(1), best_solution(2), num2str(calculate_power_output(best_solution)), 'Color', 'r');
    end
end
fprintf('Optimal Voltage: %.2f V\n', best_solution(1));
fprintf('Optimal Current: %.2f A\n', best_solution(2));
fprintf('Optimal Power Output: %.2f W\n', calculate_power_output(best_solution));
function fitness = calculate_fitness(position)
    % Implement fitness calculation using the position (voltage and current)
    % Replace with your actual fitness calculation logic
    % For MPPT, the fitness function typically evaluates power output
    voltage = position(1);
    current = position(2);
    power_output = calculate_power_output(position);
    fitness = -power_output;  % Minimize negative power output
end

% FSSO movement rule
function new_position = update_position(current_position, best_solution)
    % Implement FSSO movement rule to update squirrel's position
    % Adjust the current_position based on best_solution and other parameters
    % Replace with your actual movement rule implementation
    new_position = current_position + randn(size(current_position)) * 0.1;
end

% Power calculation function (replace with your specific PV system's power calculation)
function power_output = calculate_power_output(position)
    % Implement power calculation using the position (voltage and current)
    % Replace with your actual power calculation logic
    voltage = position(1);
    current = position(2);
    power_output = voltage * current;
end
```

Figure a.1: MATLAB Code

8 References

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