Optimizing ANN with PSO and WIPSO for Solar Power Yield Prediction

1. Abstract

This research explores the application of Particle Swarm Optimization (PSO) and Weighted Improved Particle Swarm Optimization (WIPSO) techniques to optimize an Artificial Neural Network (ANN) for predicting the daily yield of inverters and the total yield over a specific period in solar power plants. The study leverages comprehensive datasets collected from two distinct solar power plants over 34 days, including power generation data from inverters and environmental data from strategically placed sensors. By enhancing the predictive capabilities of the ANN through PSO and WIPSO, this work aims to provide more accurate forecasts of solar power production, thus contributing to improved operational efficiency and strategic planning in solar energy management. The results demonstrate that the PSO-optimized ANN achieved an R-squared value between 72% and 88%, and WIPSO-optimized ANN achieved an R-squared value between 68% and 88%, indicating significant accuracy in predicting the AC power output for most inverters.

2. Introduction

The increasing adoption of renewable energy sources, particularly solar power, necessitates advancements in predictive analytics to optimize energy production and management. Solar power plants comprise multiple solar panels and inverters, which convert the generated direct current (DC) into usable alternating current (AC). The efficiency and reliability of these systems are influenced by various environmental factors such as temperature, sunlight intensity, and wind speed, monitored by an array of sensors distributed across the plant.

Accurate prediction of the daily and periodic yield of solar power is crucial for efficient energy management and strategic decision-making. Traditional forecasting methods often fall short in handling the nonlinear and dynamic nature of solar power generation. This research focuses on enhancing the prediction accuracy by optimizing an Artificial Neural Network (ANN) using Particle Swarm Optimization (PSO) and its variant, Weighted Improved Particle Swarm Optimization (WIPSO).

PSO is a computational method inspired by the social behavior of birds flocking, which is effective in solving complex optimization problems. WIPSO, an improved version of PSO, introduces weighted parameters to enhance convergence speed and accuracy. By integrating these optimization techniques with ANN, this study aims to improve the prediction of solar power yield, utilizing extensive datasets from two solar power plants over 34 days. The power generation data, sourced from inverters, and environmental data, collected by sensors, provide a robust foundation for developing a more accurate and efficient predictive model.

This paper presents the methodology, implementation, and evaluation of the optimized ANN models, highlighting the improvements in prediction accuracy and their implications for solar power plant management. The findings of this research are expected to contribute significantly to the field of renewable energy analytics, offering a practical approach to enhancing the efficiency and reliability of solar power generation.

3. Literature Review

Solar power plants convert sunlight into electricity using photovoltaic (PV) panels or concentrated solar power (CSP) systems. PV panels, consisting of semiconductor cells, generate direct current (DC) electricity when exposed to sunlight. Inverters convert this DC electricity into alternating current (AC) for the grid. Various types of inverters are used depending on the scale and configuration of the system.

To ensure reliability and manage the variability of solar energy, these plants often include energy storage systems such as lithium-ion batteries, flow batteries, and thermal storage systems. Continuous monitoring and control are crucial, with sensors collecting data on environmental conditions and system performance. This data helps optimize plant performance, identify maintenance needs, and ensure safe operation.

4. Data Collection and Preprocessing

4.1 Description of the Solar Power Plant Data

The datasets for this research were collected from two different solar power plants over a period of 34 days. These datasets include power generation data from inverters and environmental data from strategically placed sensors. The data is essential for analyzing and improving the performance and efficiency of solar power plants.

4.2 Power Generation Data from Inverters

The power generation data consists of AC power, DC power, daily yield, and total yield for each inverter in the solar power plants. The data is collected at regular intervals throughout the day, providing detailed insights into the performance of each inverter. Initial observations of the power generation data reveal the following:

The values of AC power and DC power of plant 1 are off by a scale of exactly one digit due to an error in the decimal point location as in figure (1).

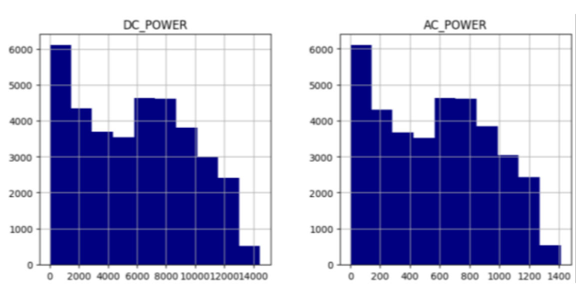


Figure (1)

Distorted waveforms suggest the presence of anomalies or missing values. Daily yield data shows inconsistencies, with some entries dropping to zero at different times. Total yield data indicates cumulative energy produced over time for inverter 1 which is shown in figure (2).

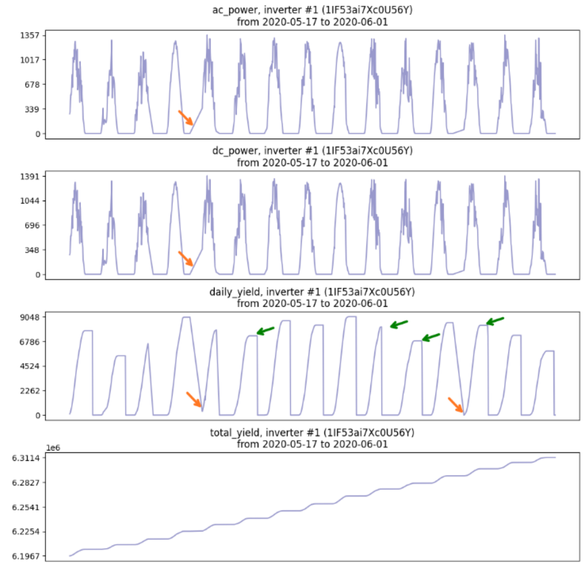


Figure (2)

To address these issues, we performed data cleaning and preprocessing, including:

- Filling missing timestamps with zero values.

- Standardizing daily yield to be zero when AC power is zero.

- Filtering out anomalies in total yield and daily yield data.

Results after preprocessing the data for inverter 11 in figure (3).

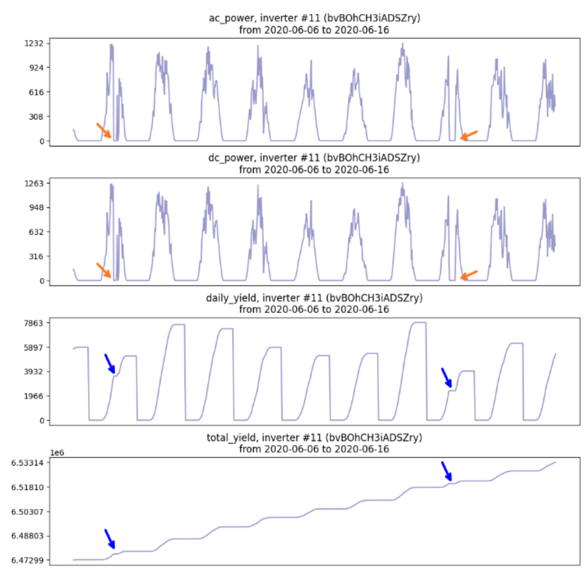


Figure (3)

4.3 Environmental Sensor Data

Environmental sensor data includes measurements of ambient temperature, sunlight intensity (irradiance), and other relevant factors affecting solar panel performance. This data is collected by sensors strategically placed around the plant. Key observations from the sensor data include:

There is a clear positive relationship between irradiance and Ambient temperature verses AC power also between Ambient temperature verses AC power only as shown in figure 4.

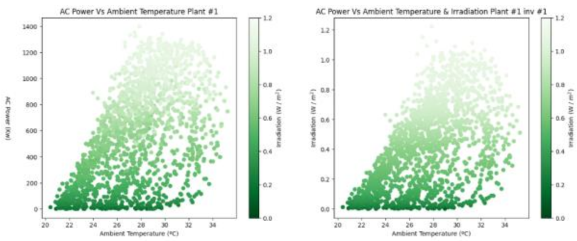


Figure (4)

Irradiance values are greater than zero from 05:45 to 18:45, indicating daylight hours.

4.4 Data Cleaning and Preprocessing Techniques

Data cleaning and preprocessing involved several steps to ensure data quality and consistency:

- Handling Missing Values:

Missing timestamps during night hours (18:45 to 05:45) were filled with zeros, as there is no power production during these hours.

Daytime missing entries were carefully reviewed and filled or removed as needed.

- Standardizing Data:

The daily yield was standardized to zero when AC power was zero.

Total yield anomalies, appearing as pronounced peaks, were filtered out.

- Feature Engineering:

New features were generated from the sensor data, including cubic and quadratic terms of irradiance and ambient temperature, and their interaction terms.

These preprocessing steps significantly reduced the memory footprint of the data and improved its quality for analysis.

Results in Numbers

- Memory footprint reduction for Plant 1 Power Production Data: 77.84%

- Memory footprint reduction for Plant 2 Power Production Data: 78.19%

- Memory footprint reduction for Plant 1 Weather Sensor Data: 82.16%

- Memory footprint reduction for Plant 2 Weather Sensor Data: 82.16%

- Reduction in total missing entries for Plant 1: from 115 (3.52%) to 87 (2.67%)

- Reduction in total missing entries for Plant 2: from 1505 (46.11%) to 1122 (34.38%)

5. Methodology

5.1 Artificial Neural Network (ANN) Architecture

Artificial Neural Networks (ANNs) are computational models inspired by the human brain's neural networks. An ANN typically consists of three types of layers: input, hidden, and output layers. The input layer receives the initial data, the hidden layers process the data, and the output layer produces the final prediction. Each layer contains neurons, which are interconnected with weights and biases that are adjusted during the training process to minimize prediction error as shown in figure (5).

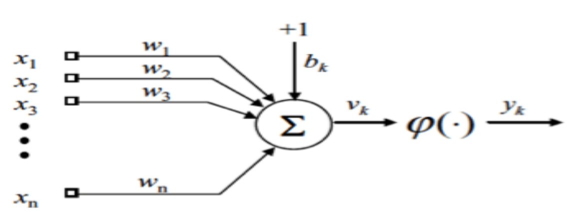


Figure (5)

The mathematical representation of a neuron's output in an ANN is given by:

$$Z = f\left(\sum_{i=1}^{n} x_i . w_i + b\right)$$

where xi are the input features, wi are the weights, b is the bias, and f is the activation function. Common activation functions include the sigmoid, hyperbolic tangent, and ReLU functions.

5.2 Introduction to Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is a global optimization algorithm inspired by the social behavior of birds flocking or fish schooling. Each particle in the swarm represents a potential solution to the optimization problem and moves through the solution space by updating its velocity and position based on its own experience and the experience of its neighbors as shown in figure (6).

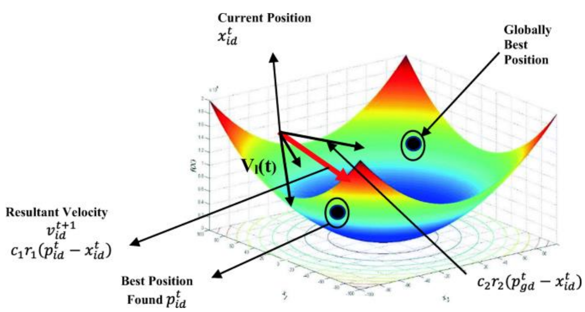


Figure (6)

Mathematical Formulation

The velocity and position update equations for a particle given by:

$$V_{i+1} = \omega V_i + c_1 r_1 (p_i - x_i) + c_2 r_2 (p_g - x_i)$$
$$x_{i+1} = x_i + V_{i+1}$$

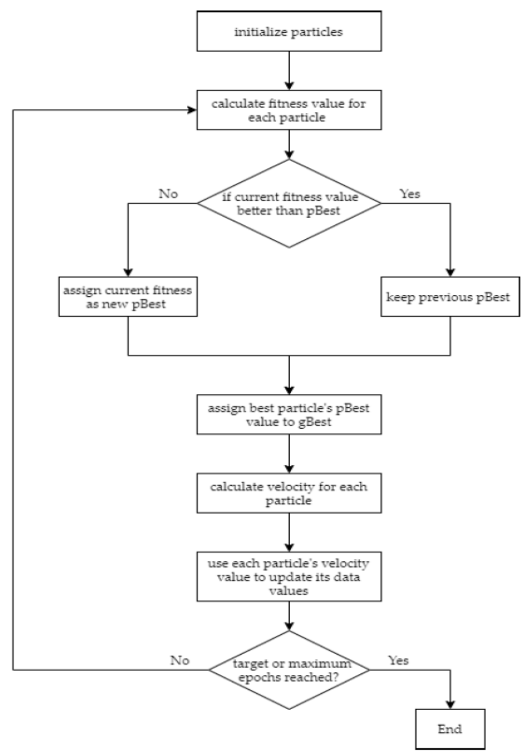
Where x_i is the current position of particle i. V_i is the particle's velocity at time i. ω is positive constants, called inertia factor which is linearly reducing with iteration. c_1 and c_2 are non- negative constants, called cognitive learning rate. r_1 and r_2 are random numbers in range [0,1]. p_i is the particle's individual best solution as of time i. p_g is the swarm's best solution. $r1$ and $r2$ are random numbers between 0 and 1.

Pseudo code

```
P=Particle_Initialization();
for i=1 to it-max
   for each particle p in P do
      fp = f(p)
      if fp is better than f(pBest)
         pBest = p;
      end
   end

   gBest=best p in P;
   for each particle p in P do
      v = v + c1*r1*(pBest - p) + c2*r2*(gBest - p)
      p =p + v
   end
end
```

Flowchart



5.3 Weighted Improved Particle Swarm Optimization (WIPSO)

Weighted Improved Particle Swarm Optimization (WIPSO) introduces enhancements to the standard PSO by dynamically adjusting the inertia weight to balance exploration and exploitation. This improves the convergence rate and helps avoid local minima.

Mathematical Formulation

$$V_{i+1} = W_{new}V_i + C_1r_1(P_{best_i} - S_i) + C_2r_2(g_{best_i} - S_i)$$
$$W_{new} = W_{min} + wr_1$$

the WIPSO algorithm finds the answer with less iteration and with higher speed convergence among the proposed methods. WIPSO algorithms have lower iteration numbers than PSO algorithm. In the WIPSO algorithm, in order to improve the global search quality of standard PSO, the inertia weight factor and the cognitive and social components ($C1$, $C2$)

5.4 Integration of PSO and WIPSO with ANN

The integration of PSO and WIPSO with ANN involves using these optimization algorithms to train the neural network by finding the optimal weights and biases that minimize the error function. The training process starts with initializing the network's weights and biases, followed by optimizing these parameters using PSO or WIPSO to improve the network's performance.

Figure (7) shows how to train ANN with PSO.

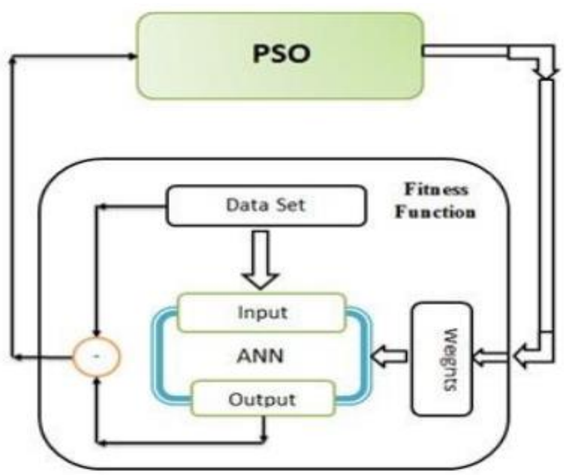


Figure (7)

Stopping Condition

The purpose of training artificial neural networks using PSO is to get a balance between the correct responses to training samples as well as good responses for new entry samples (i.e. the balance between remembering and forecasting). This training process is not supposed to continue until we get to the smallest value of MSE, but it can be determined by a stopping condition. So, the data were randomly split into two groups during the training process (training group and testing group), these two groups are independent and there is no correlation between them. The algorithm will continue in training and improving the weights, it depends choose weights on the output of the use of the test set error, in each iteration, the error value of the square of the group training and a test account and as long as the error to set the test decreases the training process will continue, and when it begins to increase the network remembering the training samples and after so it will lose its ability to predict, and at this point ends the training process. Figure (8) shows the best time to stop the training process.

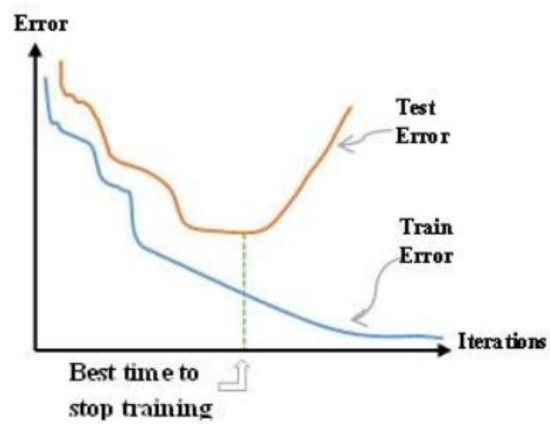


Figure (8)

6. Experimental Setup

6.1 Training and Testing Data

The dataset used for the experiments was divided into training and testing sets to evaluate the performance of the ANN model. The data was split using an 80-20 ratio, where 80% of the data was used for training, and 20% was used for testing.

6.2 Performance Metrics

The performance of the ANN model optimized with PSO and WIPSO with 10 particles and 10 maximum iterations was evaluated using the following metrics.

Root Mean Squared Error (RMSE): Measures the average magnitude of the error between the predicted and actual values. It is calculated as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (Predicted_i - Actual_i)^2}{N}}$$

R-squared (R^2): Represents the proportion of the variance in the dependent variable that is predictable from the independent variables. It is calculated as:

$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}}$$

7. Results and Discussion

7.1 Prediction Results for Daily Yield

The results for daily yield prediction using PSO and WIPSO-optimized ANN models are shown in the following figures. The predictions closely follow the actual daily yield values, indicating the models' effectiveness in capturing the underlying patterns in the data.

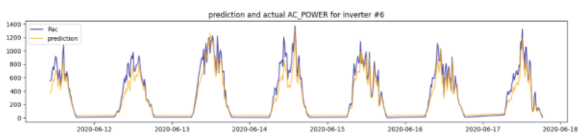


Figure (9) PSO Prediction Results

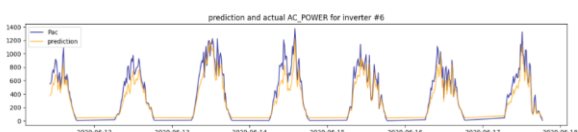


Figure (10) WIPSO Prediction Results

7.2 Prediction Results for Total Yield

The total yield predictions show the cumulative energy produced over time. Both PSO and WIPSO-optimized ANN models demonstrate strong performance in predicting the total yield.

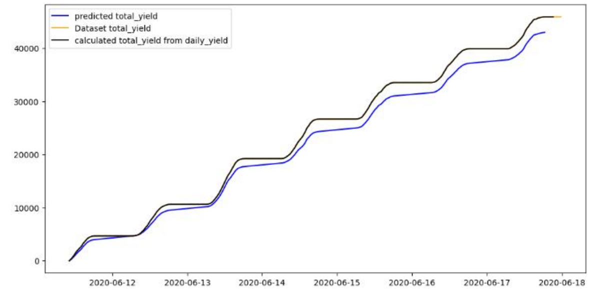


Figure (11) PSO Total Yield Prediction

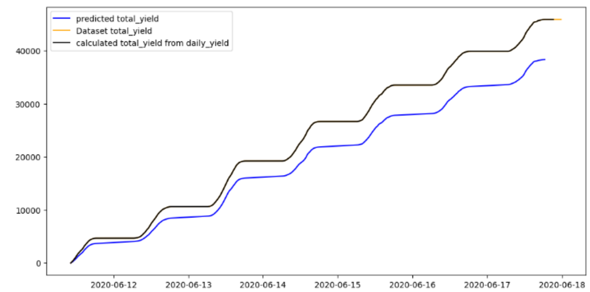


Figure (12) WIPSO Total Yield Prediction

7.3 Comparison between PSO-Optimized ANN and WIPSO-Optimized ANN

The performance metrics for both optimization techniques are summarized below:

PSO:

RMSE (Root Mean Squared Error): The RMSE values range from 115 to 181, indicating the model's average error in predicting the AC power output.

R-squared (Coefficient of Determination): The R-squared values range from 72% to 88%, indicating the proportion of variance in the dependent variable (AC power output) that is predictable from the independent variables.

WIPSO:

RMSE (Root Mean Squared Error): The RMSE values range from 116 to 192.

R-squared (Coefficient of Determination): The R-squared values range from 68% to 88%.

7.4 Analysis of Results

The results indicate that both PSO and WIPSO-optimized ANN models perform well in predicting the daily and total yield of solar power plants. The RMSE values for both models suggest that they have a relatively low average prediction error. The R-squared values indicate that a significant proportion of the variance in the AC power output is predictable from the independent variables.

7.5 Discussion on the Efficiency and Accuracy of the Methods

The PSO-optimized ANN demonstrated slightly better performance in terms of RMSE and R-squared values compared to the WIPSO-optimized ANN. However, the WIPSO-optimized ANN showed competitive performance and is effective in scenarios where dynamic adjustment of inertia weight is crucial for avoiding local minima and improving convergence rates.

Overall, the integration of PSO and WIPSO with ANN significantly enhances the predictive capabilities of the models, providing reliable forecasts for solar power plant yields and contributing to improved operational efficiency and strategic planning in solar energy management.

8. Conclusion and Future Work

8.1 Summary of Findings

This research explored the optimization of Artificial Neural Networks (ANNs) using Particle Swarm Optimization (PSO) and Weighted Improved Particle Swarm Optimization (WIPSO) to predict the daily and total yield of solar power plants. The study demonstrated that both PSO and WIPSO-optimized ANN models performed well in predicting solar power plant yields. The PSO-optimized ANN model achieved RMSE values ranging from 115 to 181 and R-squared values between 72% and 88%, indicating a high level of prediction accuracy. Similarly, the WIPSO-optimized ANN model achieved RMSE values ranging from 116 to 192 and R-squared values between 68% and 88%, showing competitive performance. The integration of PSO and WIPSO with ANN significantly enhanced the predictive capabilities of the models, providing reliable forecasts for solar power plant yields.

8.2 Implications for Solar Power Plant Management

The findings of this research have important implications for the management and operation of solar power plants. The optimized ANN models provide accurate predictions of daily and total yield, enabling better planning and decision-making for solar power plant operations. Accurate yield predictions allow for more efficient management of energy resources, reducing wastage and maximizing energy production. Furthermore, the models can be used to forecast future energy production, aiding in strategic planning and investment decisions for solar power plants. Additionally, predictive models can help identify potential issues and maintenance needs, improving the reliability and longevity of solar power systems.

8.3 Future Work

Future research can build on these findings by exploring other optimization algorithms and advanced neural network architectures to further improve prediction accuracy. Developing real-time predictive models to provide immediate insights and responses to changing environmental conditions is another area of interest. Testing the models on larger datasets and different types of solar power plants will ensure scalability and generalizability. Integrating the predictive models with Internet of Things (IoT) devices for continuous monitoring and data collection can enhance the real-time capabilities of the models, providing more dynamic and responsive solutions for solar power plant management.

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