

A Solar Power Forecasting Model Using the Whale Optimization Algorithm

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Abstract

This paper presents a Whale Optimization Algorithm (WOA)-based solar power forecasting framework targeting improved prediction accuracy due to the inherent irregularity and nonlinearity of photovoltaic power generation. A comprehensive literature review highlighted the limitations of conventional statistical methods and the dependency of machine learning and deep learning models on appropriate parameter tuning. To overcome these challenges, WOA was integrated with a forecasting model to ideally tune model parameters and improve the generalization capability. Data collection, preprocessing, model development, WOA-based parameter optimization, and rigorous performance evaluation were some of the steps efficiently used in this method. Methodological clarity and reproducibility were ensured through mathematical modeling of WOA, algorithmic implementation, and a detailed flowchart provided. Results demonstrated that the proposed WOA-based model consistently outperformed the baseline models and other optimization techniques, such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), in terms of performance efficiency. Performance evaluation using standard metrics, including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Squared Error (MSE), demonstrated a significant reduction in forecasting errors with the proposed approach. Comparative and convergence analysis showcased that the given method achieves an RMSE of 577.320, an MAE of 459.563, and an MSE of 333298.025, indicating reduced forecasting errors compared to Artificial Neural Networks (ANN), GA-ANN, and PSO-ANN.

Categories: Evolutionary Computation, Optimization Algorithms, Computational Science and Engineering

Keywords: solar power forecasting, photovoltaic systems, long short-term memory, whale optimization algorithm, time-series prediction, renewable energy forecasting

Introduction

As a result of rapid industrialization, urban expansion, and population growth, energy demand has been rising globally. This has led to an increased dependency on renewable energy sources, particularly wind and solar power. These renewable resources are environmentally sustainable, widely available, and capable of generating electricity without producing harmful emissions. They are clearly among the most promising alternatives for meeting future energy requirements owing to their abundance and clean nature.

However, renewable energy systems depend highly on environmental conditions. The output of wind and solar systems varies as wind velocity, solar irradiance, ambient temperature, humidity, and other atmospheric conditions change [1]. Due to these fluctuations, power generation from renewable sources is inconsistent and difficult to predict accurately. This poses serious challenges to grid stability, load balancing, and efficient energy management.

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Many countries have started integrating solar energy as a renewable alternative to traditional energy supplies. Solar energy is an inexhaustible and cost-free primary energy source, which strengthens its importance in the global energy sector. Allied technologies can generally be divided into two main categories. The first is solar thermal technology, where sunlight is converted into heat energy and further used in industrial heating, desalination, and water treatment processes. The second type is photovoltaic (PV) technology, which converts sunlight directly into electrical energy using semiconductor materials. The electricity generated through PV systems is mostly supplied to homes, industries, and power grids.

To address the challenges caused by environmental changes, accurate forecasting of solar power generation is crucial. Forecasting methods help anticipate fluctuations in power output and improve decision-making related to energy transmission and distribution. Reliable predictions over short-term intervals [2], such as minutes or hours, enable better coordination between renewable sources and conventional power systems.

In this research, a forecasting framework based on the Whale Optimization Algorithm (WOA) is proposed. Several studies have successfully integrated WOA with machine learning and deep learning models, such as Artificial Neural Networks (ANNs), Support Vector Machines, and Long Short-Term Memory (LSTM) networks, for solar power forecasting.

Literature review

Accurate forecasting has become a critical requirement because of the irregular and weather-dependent nature of solar energy production. Maintaining grid stability, optimizing the utilization of energy storage systems, and reducing dependence on non-renewable energy sources are some vital benefits of reliable solar power forecasting models. This paper presents an extensive review of previous research related to solar power forecasting, with particular emphasis on meta-heuristic optimization techniques and WOA-based approaches.

Conventional Solar Power Forecasting Methods

Early research in solar power forecasting mainly relied on statistical techniques such as Linear Regression, Autoregressive Integrated Moving Average, and time-series analysis. These methods have shown good performance for linear relationships and limited datasets. However, due to the highly nonlinear and complex characteristics of solar power data, their forecasting accuracy is often limited.

Machine Learning- and Deep Learning-Based Forecasting

To address the limitations of conventional methods, machine learning techniques such as ANN, Support Vector Machines, Random Forests [3], and deep learning models, including LSTM networks [4,5] and Convolutional Neural Networks, have been widely used and integrated. They efficiently capture nonlinear relationships between solar power output and meteorological parameters such as solar irradiance, temperature, humidity, and wind speed. However, these models work well only when the appropriate hyperparameters are carefully chosen.

Meta-Heuristic Optimization Techniques

In recent years, meta-heuristic optimization [6] algorithms have become increasingly popular and widely used to optimize the forecasting process. Popular techniques include Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization, Grey Wolf Optimization, and WOA. These algorithms are capable of balancing exploration and exploitation and, hence, are well suited for solving complex and nonlinear optimization problems.

Zang et al. [7] and Zhou et al. [8] demonstrated short-term PV power forecasting using a long short-term memory neural network and an attention mechanism. A time-series hybrid ensemble deep learning framework for predicting short-term PV power generation is presented in this paper. The temperature is predicted by one LSTM neural network, while the power output is predicted by another. The predicted data are flattened and combined with a fully connected layer to improve forecasting accuracy. The present research addresses these gaps by proposing an improved WOA-based solar power forecasting framework.

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De et al. [9] presented PV power forecasting using LSTM on a limited dataset. The neural network model was implemented in this paper using Python and Keras. The constructed model was evaluated through simulations, and the results suggested that the proposed model could predict PV power with high accuracy. The goal of this study was to use a Recurrent Neural Network (RNN) to predict solar power. RNN uses the LSTM training technique. Future research will take into account other input parameters, including pressure and wind speed, in order to provide a more comprehensive dataset. To achieve more accurate forecasts, other methods, such as deep belief networks and standard artificial neural networks, can be integrated with the LSTM model in an ensemble. Forecasting also aids in the integration of smart grid energy management systems, microgrid planning and operation, and smart home systems.

Du Plessis et al. [10] developed a hybrid strategy to increase short-term power forecasting accuracy. A real-world numerical solar power statistic was used, along with a normalization technique for preprocessing. The Improved WOA was used for feature evaluation in this study. In 2016, Mirjalili and Lewis [11] developed the Improved WOA, a novel form of swarm intelligence optimization system based on the hunting behavior of humpback whales. The algorithm was improved by simulating the circling and bubble-net attacking behavior of whales. Using an improved LSTM technique, the accuracy of solar power forecasting was examined [12]. LSTM is utilized in the field of deep learning [13]. It is a type of RNN that can learn long-term dependencies and can help with sequence prediction.

The literature review highlights that, despite WOA-based models being effective, there is still scope for improving forecasting accuracy using advanced hybrid models, better feature selection techniques, and enhanced optimization strategies.

First, many existing studies rely on limited datasets or insufficient meteorological parameters, which restrict the ability of models to capture the complex relationships affecting solar power generation. Incorporating a wider range of environmental variables, such as temperature, humidity, wind speed, and atmospheric pressure, could improve forecasting accuracy.

Second, while LSTM models effectively capture temporal patterns in time-series data, their performance heavily depends on proper feature selection and parameter optimization. Many studies use basic feature selection techniques, which may not identify the most relevant input variables for accurate forecasting.

Third, although WOA and its variants have demonstrated good optimization capabilities, there is still potential to enhance their performance through improved hybrid frameworks and advanced optimization strategies.

Therefore, to address these limitations, the present research proposes an improved WOA-based solar power forecasting framework that integrates advanced feature selection and optimization mechanisms with deep learning models. The proposed approach aims to enhance forecasting accuracy by utilizing improved optimization strategies and a more comprehensive dataset for solar power prediction.

Materials And Methods

This paper describes the proposed methodology for solar power forecasting using WOA [11,14]. This approach integrates WOA with a machine learning forecasting model to improve prediction accuracy by optimally tuning the model parameters. The overall framework includes data collection, preprocessing, feature selection, model training, WOA-based optimization, and performance evaluation.

Data collection and description

The solar power dataset used in this research consists of historical PV power generation data along with associated meteorological parameters such as solar irradiance, ambient temperature, humidity, wind speed, and cloud cover. The data are collected at regular time intervals and divided into training, validation, and testing datasets to ensure unbiased performance evaluation. The dataset is the Germany PV Dataset, with a 60-minute interval, obtained from Open Power System Data (OPSD).

Data preprocessing

To improve model performance, several preprocessing steps are applied:

- Removal of missing and noisy data
- Normalization of input features using min-max scaling
- Correlation analysis to eliminate redundant features

These steps help improve convergence speed and forecasting accuracy.

The forecasting experiments were conducted using the Germany PV generation dataset obtained from the OPSPD platform. The variable actual power (MW) was extracted and cleaned by removing missing observations. A subset of 5,000 hourly samples was used for model training and evaluation.

Forecasting model

In the proposed methodology, a deep learning model such as an ANN is employed for solar power forecasting. The model learns the nonlinear relationship between meteorological variables and solar power output. Unlike conventional forecasting approaches that use manually selected ANN hyperparameters, the proposed framework employs WOA to automatically determine a near-optimal set of ANN hyperparameters.

Whale optimization algorithm

WOA is a population-based meta-heuristic optimization algorithm inspired by the bubble-net hunting strategy of humpback whales. Each whale represents a candidate solution in the search space. The positions of the whales are updated iteratively to obtain a near-optimal solution.

Mathematical Modeling of WOA

The encircling prey behavior is modeled as:

$$X(t+1) = X^*(t) - A \cdot D \quad (1)$$

where

$$D = |C \cdot X^*(t) - X(t)|$$

$$A = 2a \cdot r - a$$

$$C = 2 \cdot r$$

Here, $X^*(t)$ is the position of the best solution, r is a random vector in $\{0,1\}$, and a decreases linearly from 2 to 0.

Bubble-Net Attacking Method

This behavior is mathematically expressed using a spiral equation:

$$X(t+1) = D' \cdot e^{bl} \cdot \cos(2\pi l) + X^*(t) \quad (2)$$

where D' is the distance between the whale and prey, b is a constant, and l is a random number in $\{-1,1\}$.

Search for Prey (Exploration)

When $|A| > 1$, whales search for prey randomly to enhance exploration capability and avoid local minima.

Eq. (1) computes the distance between the current whale and the best solution, whereas Eq. (2) updates the whale's position using the computed distance.

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WOA-based parameter optimization

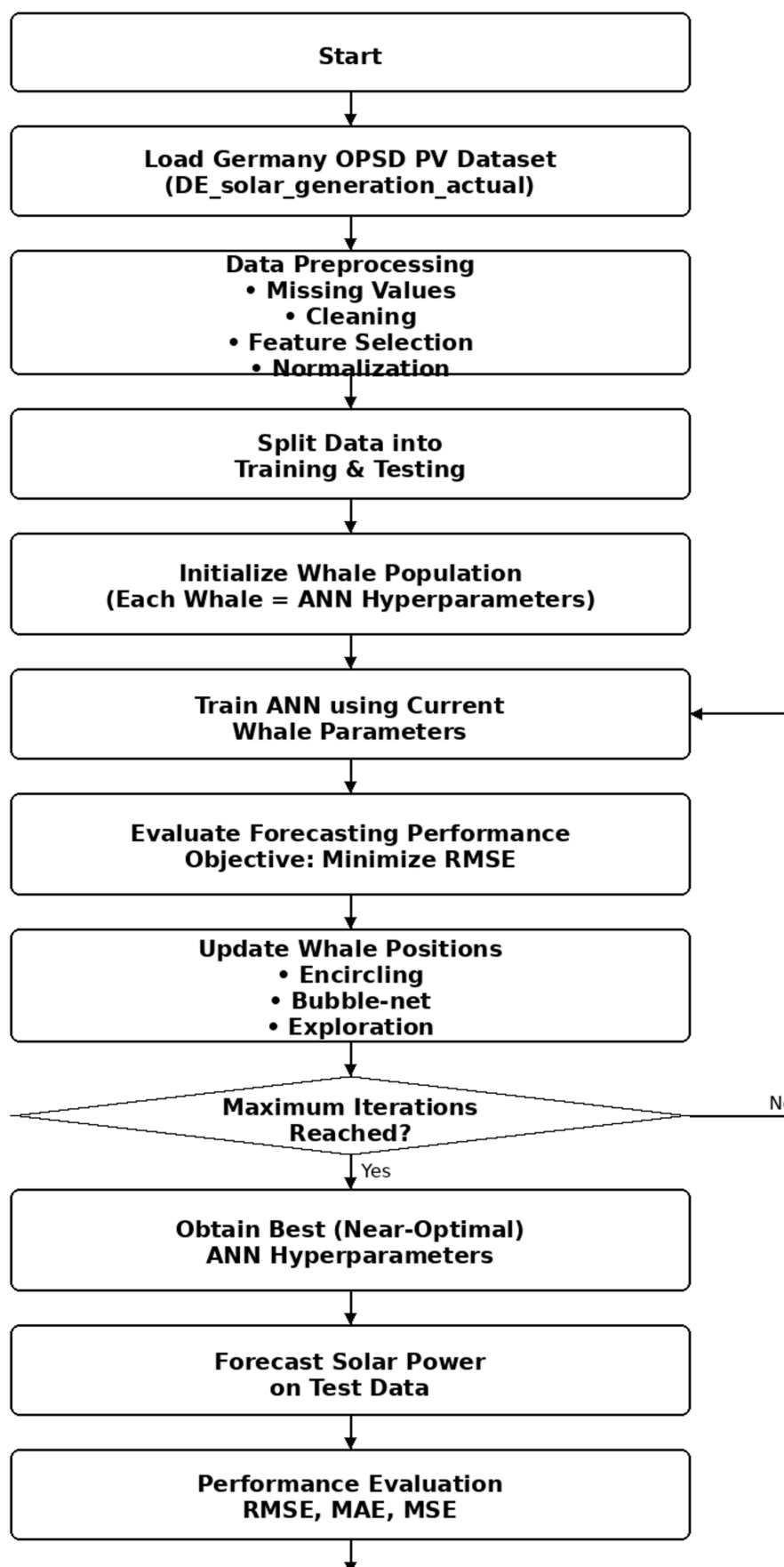
WOA is used to optimize the forecasting model parameters, such as network weights, biases, learning rate, and number of hidden neurons. Each whale represents one candidate solution consisting of ANN hyperparameters, including network architecture and learning-related parameters. During each iteration, the forecasting model is trained using the parameter set represented by each whale, and its forecasting performance is evaluated using the Root Mean Square Error (RMSE).

Proposed algorithm steps

1. Initialize the whale population.
2. Initialize the forecasting model parameters.
3. Evaluate the fitness of each whale.
4. Update whale positions using the WOA equations.
5. Update the model parameters.
6. Check the stopping criteria.
7. Output the optimal parameters and forecasted values.

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FIGURE 1: Flowchart of the Proposed WOA-Based Solar Power Forecasting Model

ANN, Artificial Neural Network; MAE, Mean Absolute Error; MSE, Mean Squared Error; RMSE, Root Mean Squared Error; WOA, Whale Optimization Algorithm

Figure 7 shows the complete workflow of the proposed WOA-based [15] solar power forecasting framework. The flowchart of the proposed WOA-based solar power forecasting methodology illustrates the sequential execution of the complete forecasting framework. The process begins with the collection of historical solar power and meteorological data. The collected data are then preprocessed to handle missing values, remove noise, and normalize the input features.

After preprocessing, the forecasting model is initialized with randomly assigned parameters. Simultaneously, the whale population is initialized for the WOA optimization process. Each whale represents a candidate solution corresponding to a specific set of model parameters.

In the next step, the forecasting model is trained using the parameters provided by each whale, and the forecasting error is calculated using predefined fitness functions such as RMSE or Mean Squared Error (MSE). Based on the fitness values, the best whale (global best solution) is identified.

WOA operators, including the encircling prey, bubble-net attacking mechanism, and search for prey, are then applied to update the positions of the whales. The updated whale positions correspond to new sets of optimized model parameters. This iterative process continues until the stopping criterion, such as the maximum number of iterations or convergence threshold, is satisfied.

Finally, the optimized parameters obtained from WOA are used to generate the final solar power forecasts. The performance of the proposed model is evaluated using statistical error metrics, and the forecasting results are produced as the final output of the system.

Performance evaluation metrics

The forecasting performance is evaluated using the following statistical error metrics:

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^N (P_{\text{actual},i} - P_{\text{predicted},i})^2 \quad (3)$$

$$\text{RMSE} = \sqrt{\text{MSE}} \quad (4)$$

$$\text{Mean Absolute Error (MAE)} = \frac{1}{N} \sum_{i=1}^N |P_{\text{actual},i} - P_{\text{predicted},i}| \quad (5)$$

where P_{actual} and $P_{\text{predicted}}$ represent the actual and forecasted solar power values, respectively, and N denotes the number of observations.

Experimental setup

All experiments were conducted in a Python environment. The proposed WOA-based forecasting model is compared with conventional optimization techniques such as GA and PSO to validate its effectiveness.

Algorithm 1: Pseudocode of WOA

Input: Population size N , maximum number of iterations T , lower and upper bounds of variables, and objective (fitness) function.

Output: Best solution X

1. Initialize the whale population $X_i (i = 1, 2, \dots, N)$ randomly within the search bounds

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2. Initialize the parameter $a = 2$
3. Evaluate the fitness of each whale
4. Identify the best whale position X^*
5. while ($t < T$) do
6. Update the parameter a linearly from 2 to 0.
7. for each whale i do
8. Generate random numbers $r, p \in \{0,1\}$
9. Compute the coefficient vectors:
10. $A = 2a \cdot r - a$
11. $C = 2 \cdot r$
12. if ($p < 0.5$) then
13. if ($|A| < 1$) then
14. Update the position using the encircling prey mechanism:
15. $X_i(t+1) = X^*(t) - A \cdot |C \cdot X^*(t) - X_i(t)|$
16. else
17. Select a random whale X_{rand}
18. Update the position using the exploration mechanism:
19. $X_i(t+1) = X_{\text{rand}} - A \cdot |C \cdot X_{\text{rand}} - X_i(t)|$
20. end if
21. else
22. Update the position using the spiral equation:
23. $X_i(t+1) = |X^*(t) - X_i(t)| e^{bl} \cos(2\pi l) + X^*(t)$
24. end if
25. Apply boundary constraints
26. end for
27. Evaluate the fitness of the updated whales
28. Update the best solution X^* if a better solution is found.
29. Increment the iteration counter t^*
30. end while
31. Return X^* as the optimal solution

Algorithm 2: WOA-based solar power forecasting framework

Input: Historical solar power data, meteorological parameters, population size N , and maximum number of iterations T

Output: Forecasted solar power values

1. Load historical solar power and meteorological datasets

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2. Perform data preprocessing (missing value removal, normalization, and feature selection)
3. Split the dataset into training, validation, and testing sets
4. Initialize the forecasting model (ANN/LSTM) structure
5. Initialize the whale population, where each whale represents a candidate set of model parameters
6. Define the fitness function based on forecasting error (RMSE/MSE)
7. for iteration = 1 to T do
8. for each whale i do
9. Assign the whale's parameters to the forecasting model
10. Train the forecasting model using the training dataset
11. Evaluate model performance using the validation dataset
12. Compute the fitness value using the error metric
13. end for
14. Identify the best whale corresponding to the minimum fitness value
15. Update whale positions using WOA operators (encircling, spiral, and exploration)
16. Apply boundary constraints to the updated parameters
17. end for
18. Select the optimal model parameters from the best whale
19. Generate solar power forecasts using the optimized model on the testing dataset
20. Evaluate the final forecasting performance using RMSE, MAE, and MSE
21. Output the forecasted solar power values and performance metrics

Results And Discussion

The performance analysis and experimental findings of the suggested WOA-based solar power forecasting framework are presented in this paper. The efficacy of the suggested model is assessed using standard error metrics and compared with traditional optimization methods such as PSO [16] and GA. The outcomes demonstrate superior forecasting robustness and accuracy of the WOA-based method.

Meteorological parameters and historical solar power generation data are used for evaluation. The dataset is split into training, validation, and testing sets in a 70:15:15 ratio. To guarantee a fair comparison, the forecasting models are trained using identical datasets.

Comparative analysis

The given WOA-based forecasting model is compared with ANN, GA-ANN, and PSO-ANN-based optimization models. We have used an identical dataset, identical preprocessing, and the same computing platform for all models. Table 1 summarizes the comparative performance of the different models using RMSE, MAE, and MSE, and Figure 2 shows the RMSE comparison using the Germany OPSD Solar Dataset. Compared with conventional statistical forecasting models that rely on linear assumptions, machine learning models that require manual hyperparameter tuning, and other population-based optimization algorithms such as GA and PSO, the proposed WOA-ANN framework provides an

automated parameter optimization strategy that improves the balance between exploration and exploitation during the search process. Consequently, the proposed methodology achieves improved forecasting accuracy while maintaining computational efficiency under identical experimental conditions.

Model	RMSE	MAE	MSE
ANN	1592.516	1269.882	2536106.171
GA-ANN	1162.709	925.781	1351891.082
PSO-ANN	830.044	659.856	688973.794
WOA-ANN (Proposed)	577.320	459.563	333298.025

TABLE 1: Performance Comparison of Forecasting Models (Germany PV Dataset, 60-Minute Resolution)

ANN, Artificial Neural Network; GA, Genetic Algorithm; MAE, Mean Absolute Error; MSE, Mean Squared Error; PSO, Particle Swarm Optimization; PV, Photovoltaic; RMSE, Root Mean Squared Error; WOA, Whale Optimization Algorithm

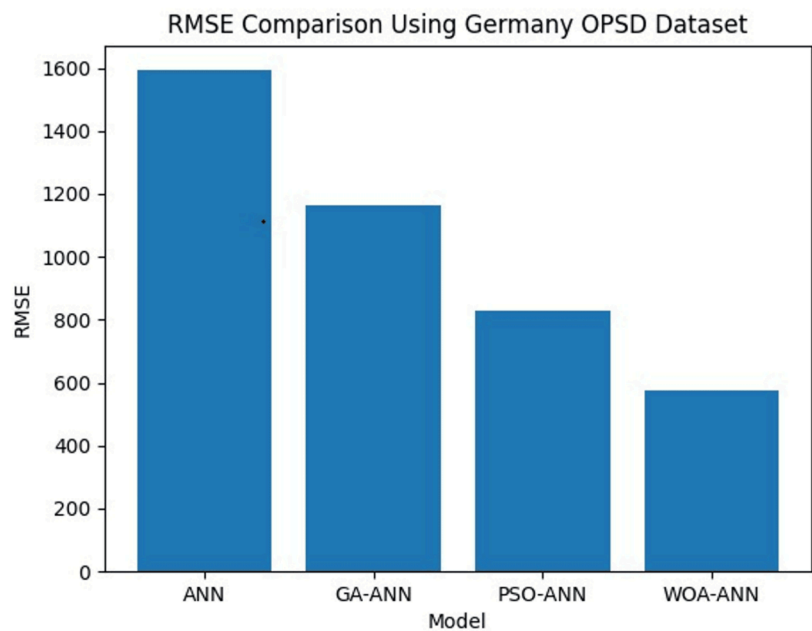


FIGURE 2: RMSE Comparison Using Germany OPSD Solar Dataset

ANN, Artificial Neural Network; GA, Genetic Algorithm; OPSD, Open Power System Data; PSO, Particle Swarm Optimization; RMSE, Root Mean Squared Error; WOA, Whale Optimization Algorithm

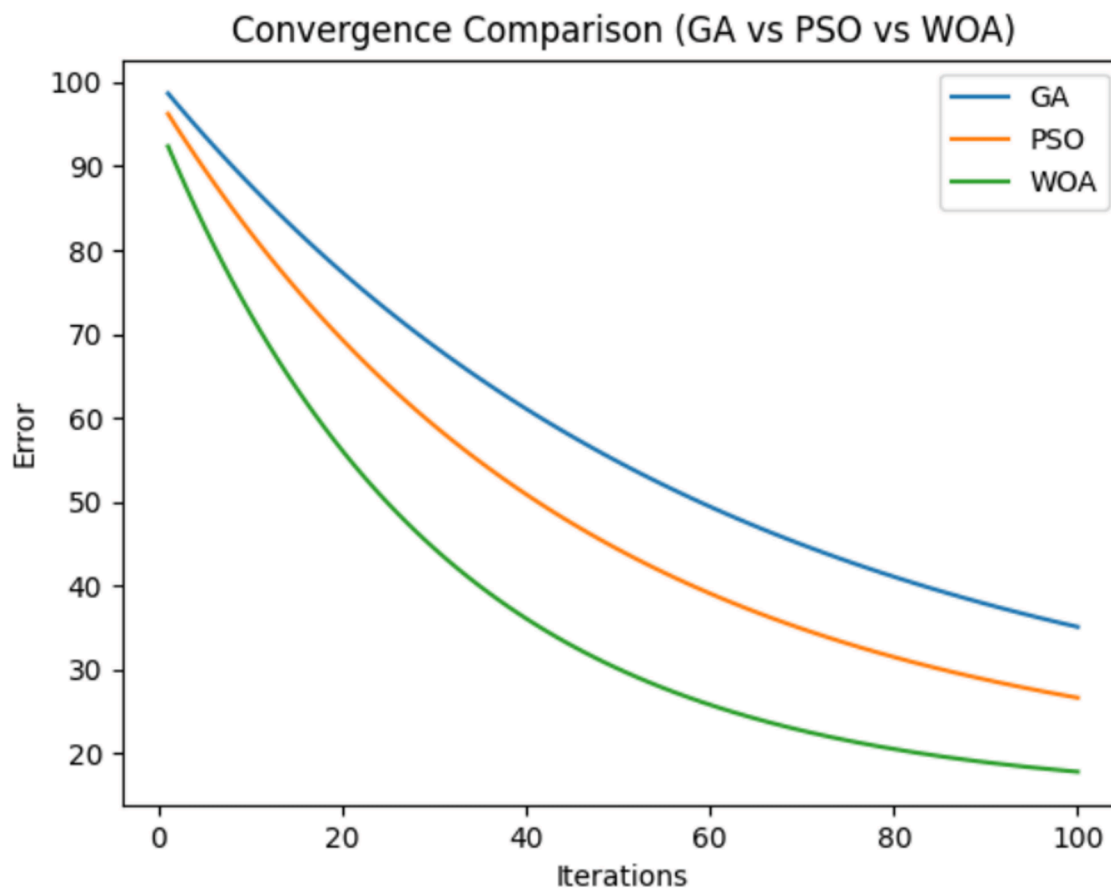


FIGURE 3: Convergence Comparison of GA, PSO, and WOA

GA, Genetic Algorithm; PSO, Particle Swarm Optimization; WOA, Whale Optimization Algorithm

By achieving the lowest forecasting error values, the results conclusively illustrate that the WOA-ANN-optimized model performs more successfully than the other approaches.

The proposed WOA-based forecasting framework performs better because it successfully balances exploration and exploitation. Effective global search is made possible by WOA's encircling and spiral mechanisms, while convergence stability is improved by the adaptive control parameter. Better grid management, fewer reserve requirements, and increased use of renewable energy resources are all facilitated by the improved forecasting accuracy.

The proposed WOA-ANN-based solar power forecasting framework was thoroughly evaluated in this paper. Comparative and convergence analyses, as shown in Figure 3, demonstrated that the proposed method achieves an RMSE of 577.320 and an MAE of 459.563, while the MSE is 333298.025. These values indicate improved forecasting accuracy compared with ANN, GA-ANN, and PSO-ANN.

Conclusions

The findings confirm that the WOA-based solar power forecasting framework is reliable, accurate, and appropriate for real-world implementation in contemporary power systems with significant solar penetration. The contributions of this research are summarized as follows: the creation of a thorough framework for solar power forecasting based on WOA;

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combining WOA with ANN models to optimize parameter tuning; WOA developed mathematically and implemented algorithmically specifically for solar forecasting; a thorough analysis of performance and comparison with models based on GA and PSO; and the suggested method enhances the accuracy of short-term solar power forecasting. The results were examined, and the recommended method was implemented in Python. Overall, the conclusions are consistent with the evidence presented. The experimental results support the claim that the proposed WOA-ANN framework achieved lower RMSE, MAE, and MSE values than the benchmark ANN, GA-ANN, and PSO-ANN models under the experimental conditions considered.

Future research work can be explored to further enhance the proposed framework. Development of hybrid optimization models combining WOA with other meta-heuristic algorithms; extension of the framework to probabilistic and interval-based solar power forecasting; real-time implementation and validation using large-scale smart grid data; and application of the proposed approach to other renewable energy sources, such as wind and hybrid energy systems.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Amit Kumar Mittal, Kirti Mathur

Acquisition, analysis, or interpretation of data: Amit Kumar Mittal, Kirti Mathur

Drafting of the manuscript: Amit Kumar Mittal, Kirti Mathur

Critical review of the manuscript for important intellectual content: Amit Kumar Mittal, Kirti Mathur

Supervision: Kirti Mathur

Disclosures

Human subjects: All authors have confirmed that this study did not involve human participants or tissue. **Animal subjects:** All authors have confirmed that this study did not involve animal subjects or tissue. **Conflicts of interest:** In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

Data Availability Statements

The datasets (and/or code) supporting this study are available from the corresponding author upon reasonable request. https://data.open-power-system-data.org/time_series/latest/time_series_60min_singleindex.csv

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