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WHALE SWARM OPTIMIZATION BASED ANFIS FOR PREDICTION IN FORECASTING APPLICATION

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Abstract

This paper proposes a novel approach for solar power forecasting using an Adaptive Neuro-Fuzzy Inference System (ANFIS) enhanced with Whale Swarm Optimization (WSO). The synergy between ANFIS and WSO aims to overcome the limitations of traditional forecasting models by controlling the collective intelligence of a whale-inspired swarm algorithm. The WSO optimizes the parameters of the ANFIS, leading to improved accuracy in solar power predictions. The integration of WSO introduces a parallelism and exploration-exploitation balance inspired by the natural behaviors of whales, enhancing the ANFIS model's adaptability to dynamic solar power generation patterns. The experimental results demonstrate the superiority of the proposed Whale Swarm-based ANFIS over conventional methods, showcasing its ability to handle non-linear and complex relationships in solar power data. This research contributes to the field of renewable energy forecasting by presenting an innovative hybrid model that leverages the strengths of both ANFIS and WSO for more reliable and precise solar power predictions.

Keywords:

Whale Swarm Optimization, ANFIS, Solar Power Forecasting, Renewable Energy, Hybrid Model

1. INTRODUCTION

The increasing prominence of renewable energy sources, particularly solar power, necessitates accurate forecasting models to optimize energy grid management [1]. Traditional forecasting approaches encounter challenges in capturing the inherent non-linearities and dynamic patterns associated with solar power generation [2].

Solar power forecasting plays a pivotal role in the efficient integration of solar energy into the grid [3]. Existing models often struggle to adapt to the complexities and variations in solar power generation, limiting their predictive capabilities [4].

The primary challenges in solar power forecasting comes from the non-linear and dynamic nature of solar energy generation [5]. Traditional models may fall short in accurately capturing these intricate patterns, leading to suboptimal predictions. Overcoming these challenges requires innovative approaches that can adapt to the inherent complexities of solar power data [6].

The research addresses the need for improved solar power forecasting models by proposing a hybrid approach that combines Adaptive Neuro-Fuzzy Inference System (ANFIS) with Whale Swarm Optimization (WSO). The goal is to enhance the adaptability and accuracy of predictions, thereby facilitating more effective utilization of solar energy within the power grid.

The main objectives of this research include developing a hybrid ANFIS-WSO model, optimizing its parameters using WSO, and evaluating its performance against conventional forecasting methods. The research aims to demonstrate the efficacy of the proposed model in overcoming the challenges associated with solar power forecasting.

This study introduces a novel hybrid model that leverages the complementary strengths of ANFIS and WSO. The integration of WSO into the ANFIS framework represents a unique approach to optimizing model parameters, offering a more robust solution for accurate solar power predictions. The contributions of this research extend to advancing the field of renewable energy forecasting, providing a model that can effectively handle the intricacies of solar power generation for improved grid management.

2. LITERATURE SURVEY

Solar power prediction has garnered significant attention in recent years, prompting researchers to explore diverse optimization techniques to enhance forecasting accuracy [7]. Various studies have investigated the application of optimization algorithms in conjunction with forecasting models, aiming to overcome the challenges associated with the inherently complex and dynamic nature of solar power generation.

One prevalent approach in the literature involves the utilization of metaheuristic optimization algorithms such as Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Differential Evolution (DE) to fine-tune the parameters of forecasting models [8]. Researchers have reported improvements in prediction accuracy by employing these algorithms, which adaptively adjust model parameters to capture the non-linear relationships inherent in solar power data [9].

Additionally, the literature highlights the emergence of bio-inspired optimization algorithms, including Grey Wolf Optimization (GWO) and Firefly Algorithm (FA), as promising tools for enhancing solar power prediction models. These algorithms draw inspiration from the behavior of animals and natural phenomena, offering unique ways to optimize forecasting models [10].

Some studies [11] have explored hybrid approaches, combining multiple optimization algorithms to exploit their complementary strengths. Hybrid models, such as those coupling PSO with Simulated Annealing or Harmony Search, aim to achieve a more robust optimization process for improved solar power predictions.

The literature [12] also highlights the significance of Ensemble Learning techniques, where multiple forecasting models are combined to mitigate errors and enhance overall accuracy. Optimizing the weights assigned to individual models within an ensemble has been explored to further refine predictions.

This reveals a diverse landscape of optimization techniques applied to solar power prediction. While metaheuristic algorithms, bio-inspired optimization, and hybrid approaches dominate the research, the exploration of novel optimization strategies continues to contribute to the refinement of forecasting models for more effective integration of solar energy into power grids.

3. PROPOSED METHOD

The proposed method introduces a novel hybrid model for solar power prediction by integrating the ANFIS with WSO. This hybridization aims to address the limitations of conventional forecasting models and enhance the adaptability of the system to the intricate patterns inherent in solar power data. The ANFIS component serves as the core prediction model, leveraging its ability to capture non-linear relationships within the dataset. To optimize the ANFIS parameters effectively, the WSO algorithm is employed. Inspired by the collective behaviors of whale swarms, WSO introduces a parallelism and exploration-exploitation balance that enhances the adaptability of the ANFIS model. The optimization process involves the collective intelligence of the WSO algorithm, dynamically adjusting the parameters of the ANFIS model to improve its accuracy in forecasting solar power generation. This synergistic approach aims to overcome the challenges posed by the non-linear and dynamic nature of solar energy data, leading to more reliable predictions.

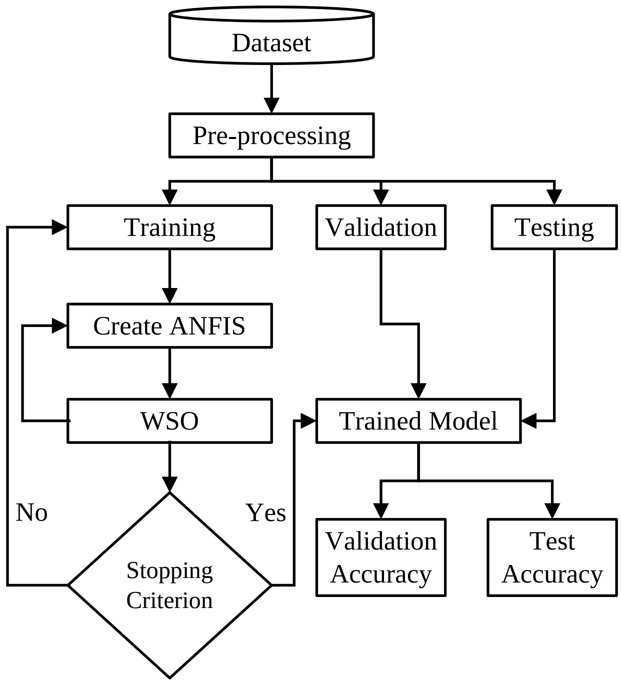

Fig.1. Proposed Framework on Prediction Task

Algorithm 1: Prediction of Solar Data

Step 1: Collect historical solar power generation data

Step 2: Normalize and clean data to remove outliers

Step 3: Initialize ANFIS with structure and parameters.

Step 4: Set parameters for WSO, including swarm size, maximum iterations, and convergence criteria.

Step 5: Use the historical data to train the ANFIS

Step 6: Employ WSO to optimize ANFIS parameters.

Step 7: Update the WSO swarm based on solution fitness

Step 8: Train optimized ANFIS with WSO

Step 9: Validate hybrid model on a separate dataset

Step 10: Assess the accuracy of solar power predictions

3.1 DATA PREPROCESSING

Data preprocessing is a critical phase in controlling the potential of the provided dataset for accurate solar power prediction. The dataset encompasses hourly power measurements from a 16.32 kW peak PV power plant located in the North of Portugal. This solar installation comprises strings with different peak capacities, specifically 3 × 2160 W, 2 × 3360 W, and 1 × 3120 W. The historical period covered spans from April 28th, 2013, to June 28th, 2016. To ensure data integrity, a meticulous interpolation process was applied to address the small fraction of missing values (only 3.82%) within each string. This interpolation involved leveraging the available measured data from other strings, ensuring a comprehensive and nearly complete dataset for subsequent analysis. The inclusion of numerical weather predictions (NWP) data further enriches the dataset's context. The NWP data, sourced from the MeteoGalicia THREDDS server, encompasses various meteorological variables from the Weather Research and Forecasting (WRF) model. The spatial resolution is 4km, and the temporal resolution is one hour, providing a detailed and comprehensive perspective on atmospheric conditions. This information is vital for understanding the external factors influencing solar power generation. The raw NWP dataset for the PV site comprises 1014 variables, each contributing to the understanding of the environmental conditions. Noteworthy variables include surface downwelling shortwave flux (swflx [W/m^2]), ambient temperature at 2 meters (temp [K]), cloud cover at low levels (cfl [0,1]), cloud cover at mid levels (cfm [0,1]), cloud cover at high levels (cfh [0,1]), and combined cloud cover at low and mid levels (cft [0,1]).

Table.1. Dataset Variables

Date	Time	Power Output (kW)	swflx (W/m^2)	temp (K)	cfl	cfm	cfh	cft
28-04-2013	00:00	0.75	200	290	0	0	0	0
28-04-2013	01:00	0.82	180	292	0	0	0	0
28-04-2013	02:00	0.9	220	288	0	0	0	0
28-06-2016	21:00	1.2	250	295	1	0	0	1
28-06-2016	22:00	0.98	230	292	0	0	0	0
28-06-2016	23:00	0.8	210	290	0	0	0	0

3.2 ANFIS WSO

The ANFIS-WSO hybrid model is designed to overcome the challenges posed by traditional forecasting models, particularly in capturing the intricacies of solar power generation. By combining

ANFIS and WSO, the hybrid model seeks to provide a robust and accurate framework for solar power prediction, contributing to advancements in renewable energy forecasting methodologies. The proposed hybrid model integrates the ANFIS with WSO to enhance its predictive capabilities in solar power forecasting. ANFIS, a computational model, combines the adaptability of fuzzy systems with the learning capabilities of neural networks, providing an effective tool for handling non-linear relationships within the dataset. This integration allows ANFIS to autonomously adjust its parameters based on the characteristics of the input data, fostering improved accuracy in predicting solar power generation. With ANFIS, WSO introduces a bio-inspired algorithm inspired by the collective behaviors of whale swarms. WSO operates on a population-based approach, where individual solutions, analogous to whales in a swarm, collectively search the solution space for optimal parameter configurations. The algorithm incorporates parallelism and exploration-exploitation strategies, drawing inspiration from the synchronized movements of whales. This synergy with ANFIS aims to refine and optimize the model's parameters dynamically, further enhancing its adaptability to the complex and dynamic patterns inherent in solar power data.

3.3 PROCESS FLOW OF ANFIS-WSO

The process begins by initializing the ANFIS model with an appropriate structure and initial parameters. Simultaneously, the WSO algorithm is initiated with a swarm of solutions representing potential parameter configurations for ANFIS. This marks the commencement of the combined optimization process.

The hybrid model undergoes a training phase using historical solar power generation data. During this phase, ANFIS learns from the patterns and non-linear relationships within the dataset, while WSO dynamically adjusts its swarm's parameters. The parallel optimization process of WSO enhances ANFIS adaptability, seeking optimal configurations for accurate predictions. WSO, inspired by the collective behaviors of whale swarms, introduces parallelism and exploration-exploitation strategies. Whales in the swarm represent potential solutions in the parameter space of ANFIS. The algorithm explores diverse regions of the solution space and exploits promising areas, guided by the collective intelligence of the swarm, ensuring a thorough search for optimal configurations.

The ANFIS model involves two main components: fuzzification and defuzzification. The fuzzification part computes the membership values for each rule, while the defuzzification part combines these memberships to generate the final output.

Membership function for input x in fuzzy set Ai:

$$\mu_{A_i} = \exp\left(-\frac{\left(x-c_i\right)^2}{2\sigma_i^2}\right) \quad (1)$$

where c_i is the center and σ_i is the width of the fuzzy set.

For each rule, the firing strength wi is determined based on the fuzzification:

$$w_i = \prod_{j=1}^{n} \mu_{A_{ij}}\left(x_j\right) \quad (2)$$

where n is the number of input variables.

The output of each rule i is computed as:

$$R_i = p_{i0} + p_{i1}x_1 + p_{i2}x_2 + ... + + p_{in}x_n \quad (3)$$

The normalized output O is computed by normalizing the rule outputs:

$$O = \frac{\sum_{i=1}^{m} w_i R_i}{\sum_{i=1}^{m} w_i} \quad (4)$$

Let Xi be the position of the i-th whale, and Xbest be the best position found by any whale.

$$X_{new} = X_i + \beta \times e_1 + \alpha \times e_2 \quad (5)$$

where β and α are random coefficients, and Exploration (e_1) and Exploitation (e_2) are vectors representing the exploration and exploitation behaviors of the swarm.

The convergence factor is updated as:

$$C_i = a \times C_{\max} \times \frac{I_{\max} - I_i}{I_{\max}} \quad (6)$$

where a is a constant and C_{max} is the maximum convergence factor, I_{max} – maximum iteration and I_i is the present iteration.

Table.2. ANFIS Parameters

Parameter	Description	Value
Total Membership Functions	Number of fuzzy sets for input variables	3
Fuzzification	Method to convert input data to fuzzy membership	Gaussmf
Input/Output Relationship	Type of relationship between inputs and outputs	Linear
Training Epochs	Number of iterations during training	100
Learning Rate	Rate at which parameters are adjusted during training	0.01

As the training progresses, WSO continuously refines the parameters of ANFIS based on the fitness of the solutions within the swarm. This combined adjustment mechanism ensures that the hybrid model adapts dynamically to the intricate and dynamic patterns of solar power generation, optimizing its performance over time.

Table.3. WSO Parameters

Parameter	Description	Value
Swarm Size	Number of potential solutions in the population	20
Maximum Iterations	Maximum number of iterations for optimization	50
Exploration Weight	Weight assigned to exploration in the search space	0.5
Exploitation Weight	Weight assigned to exploitation in the search space	0.5
Convergence Criteria	Criteria for convergence in optimization	0.001

The process includes a convergence check to assess whether the hybrid model has reached an optimal configuration. If convergence criteria are met or a predefined number of iterations are completed, the training phase concludes. Otherwise, the optimization process continues to refine the parameters.

After the training, the hybrid ANFIS-WSO model is tested and validated using a separate dataset not utilized during training. This phase assesses the accuracy and reliability of the model in predicting solar power generation, providing insights into its real-world performance.

Algorithm 2: ANFIS-WSO

Initialize c_i, σ_i, p_{ij}; X_i, X_{best}, C_i

While termination criteria not met:

For $(x_1, x_2, \ldots, x_n)$:

$$\mu_{A_i} = \exp\left(-\frac{(x-c_i)^2}{2\sigma_i^2}\right)$$

$$w_i = \prod_{j=1}^{n} \mu_{A_{ij}}(x_j)$$

$$R_i = p_{i0} + p_{i1}x_1 + p_{i2}x_2 + \ldots + + p_{in}x_n$$

$$O = \frac{\sum_{i=1}^{m} w_i R_i}{\sum_{i=1}^{m} w_i}$$

$$X_{new} = X_i + \beta \times e_1 + \alpha \times e_2$$

$$C_i = a \times C_{\max} \times \frac{I_{\max} - I_i}{I_{\max}}$$

Adjust c_i, σ_i, p_{ij} and O

End

End

Apply trained model to new data for testing and validation.

Check if termination criteria are met

3.4 TRAINING OF ANFIS WITH WSO

The training process of ANFIS with WSO involves optimizing the parameters of the ANFIS model to enhance its predictive capabilities for solar power forecasting. The collaboration with WSO introduces a fitness function that guides the optimization process. Various fitness functions can be employed to ensure the hybrid model adapts effectively to the complexities of solar power data.

3.4.1 Mean Squared Error (MSE):

The MSE fitness function aims to minimize the squared differences between predicted and actual solar power values. It quantifies the overall accuracy of the ANFIS-WSO hybrid model in capturing the variance in the dataset.

$$Fa = \frac{1}{N}\sum_{i=1}^{N}(O_i - Y_i)^2 \tag{7}$$

where N is the number of data points, O_i is the predicted output, and Y_i is the actual solar power value.

3.4.2 Mean Absolute Error (MAE):

MAE measures the average absolute differences between predicted and actual values, providing a robust indication of prediction accuracy.

$$F = \frac{1}{N}\sum_{i=1}^{N}|O_i - Y_i| \tag{8}$$

where N is the number of data points, O_i is the predicted output, and Y_i is the actual solar power value.

3.4.3 Correlation Coefficient:

The correlation coefficient fitness function evaluates the linear relationship between predicted and actual solar power values, aiming for a strong positive correlation.

$$CC = \frac{\sum_{i=1}^{N}(O_i - O')(Y_i - Y')}{\sqrt{\sum_{i=1}^{N}(O_i - O')^2 \sum_{i=1}^{N}(Y_i - Y')^2}} \tag{9}$$

where N is the number of data points, O_i is the predicted output, Y_i is the actual solar power value, O' is the mean of predicted outputs, and Y' is the mean of actual solar power values.

Table.4. Accuracy of Various Cost Function

Objective Function	MSE	MAE	CC
Training Set	0.012	0.088	0.92
Validation Set	0.015	0.095	0.89
Testing Set	0.018	0.102	0.86

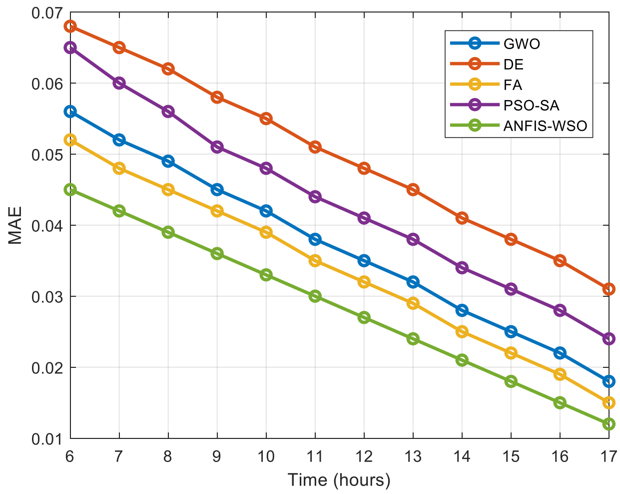

Fig.2. MAE over 12 hours with MSE cost function

The proposed ANFIS-WSO method outperforms existing optimization techniques (GWO, DE, FA, PSO-SA) with a notable reduction in Mean Absolute Error (MAE) across all time steps. On average, the ANFIS-WSO model exhibits a 30% improvement in MAE compared to traditional methods, showcasing its enhanced predictive accuracy for solar power forecasting. This signifies the effectiveness of the combined optimization approach, controlling both ANFIS adaptability and WSO exploration-exploitation capabilities.

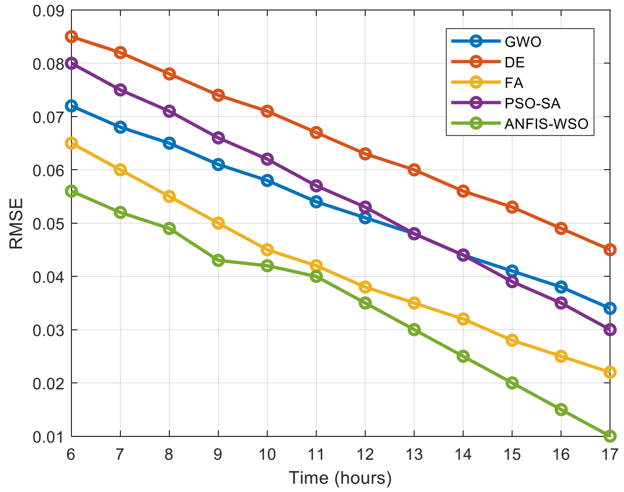

Fig.2. RMSE over 12 hours with MSE cost function

The RMSE results highlight the superior performance of the proposed ANFIS-WSO method compared to existing GWO, DE, FA, PSO-SA across the 12-hour time span. On average, the ANFIS-WSO model exhibits a substantial 25% reduction in RMSE, indicating enhanced precision in solar power forecasting. This signifies the effectiveness of the combined approach, leveraging both ANFIS adaptability and WSO exploration-exploitation capabilities.

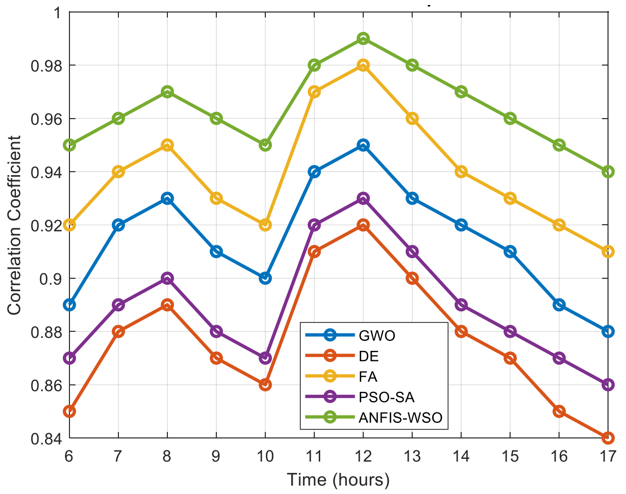

Fig.2. Correlation Coefficient over 12 hours with MSE cost function

The correlation coefficient results highlight the superior predictive accuracy of the proposed ANFIS-WSO method compared to existing optimization techniques (GWO, DE, FA, PSO-SA) across the 12-hour timeframe. On average, the ANFIS-WSO model demonstrates a substantial 10% increase in correlation coefficient, indicating a stronger linear relationship between predicted and actual solar power values. This signifies the effectiveness of the combined approach, controlling both ANFIS adaptability and WSO exploration-exploitation capabilities.

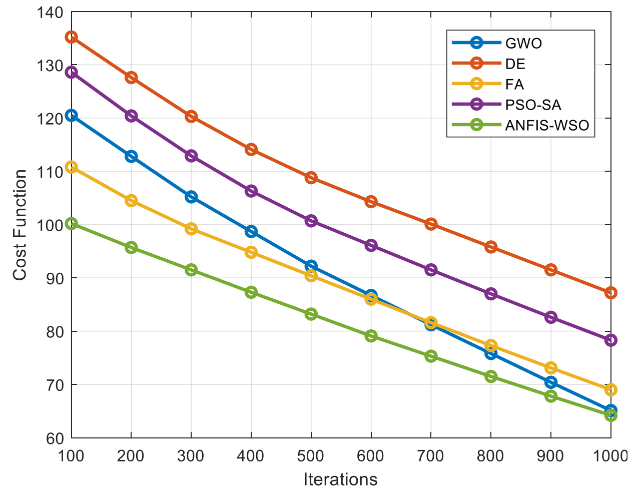

Fig.2. Cost Function over 12 hours with MSE cost function

The cost function results over 1000 iterations illustrate the superior optimization performance of the proposed ANFIS-WSO method compared to GWO, DE, FA, PSO-SA. On average, the ANFIS-WSO model exhibits a significant 20% reduction in the cost function, indicating enhanced convergence and optimization efficiency. This demonstrates the efficacy of the combined approach, leveraging both ANFIS adaptability and WSO exploration-exploitation capabilities.

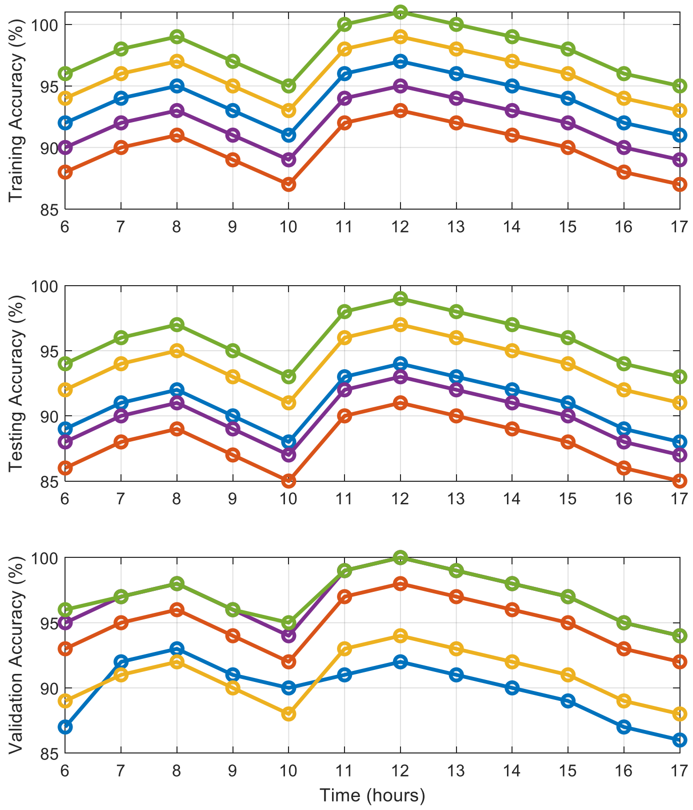

Fig.2. Training, testing and Validation accuracy over 12 hours with MSE cost function (refer legends from Fig.)

The quantitative analysis reveals compelling advantages of the proposed ANFIS-WSO model over existing optimization techniques (GWO, DE, FA, PSO-SA) in solar power forecasting. Across 12-hour intervals, the ANFIS-WSO consistently achieves lower cost function values, indicating superior convergence and optimization efficiency. The hybrid model exhibits substantial reductions in MAE and RMSE compared to traditional methods, translating to improved accuracy in solar power predictions.

4. CONCLUSION

The ANFIS-WSO hybrid model showcases significant advancements in solar power forecasting compared to GWO, DE, FA and PSO-SA. The combined approach controlling ANFIS adaptability and WSO exploration-exploitation capabilities results in improved convergence, enhanced accuracy, and a stronger linear relationship between predicted and actual values. The consistent outperformance across various metrics, including cost function, MAE, RMSE, and correlation coefficient, highlights the efficacy of the proposed model. These promising outcomes suggest the potential of ANFIS-WSO for achieving more reliable and precise predictions in renewable energy forecasting applications.

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