Journal of Mines, Metals and Fuels, *73(6): 1833-1838; 2025. DOI: 10.18311/jmmf/2025/49104*

Print ISSN : 0022-2755

Journal of Mines, Metals and Fuels

Contents available at: *www.informaticsjournals.co.in/index.php/jmmf*

The Hybrid PSO-ANN Methodology for Enhancing Net Load Prediction in Modern Power Systems

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Abstract

Accurately estimating the net load power needs is necessary for power networks to operate smoothly as the number of sufficient renewable energy sources increases. In this regard, our study adds to a novel PSO and ANN algorithm combination for net load prediction. To predict net load shortly, this study suggests a novel approach that blends Artificial Neural Networks (ANN) and Particle Swarm Optimisation (PSO). An ANN is employed to capture the nonlinear correlations in load data, while PSO is used to increase the network's weights and biases and forecasting accuracy. Weather, historical load data, and other pertinent factors are used to train and validate the model. The proposed ANN-PSO model considerably outperforms conventional forecasting methods in terms of prediction accuracy. This set of techniques aids in bettering operational decision-making and grid management. It also improves load forecast accuracy.

Major Findings: *The results demonstrate the effectiveness and dependability of the ANN-PSO strategy in addressing the difficulties related to net load forecasting in modern power systems.*

Keyword: *Artificial Neural Networks, Net Load Forecasting, Particle Swarm Optimisation, Prediction Accuracy, Renewable Energy*

Abbreviations

ANN = Artificial Neural Networks

PSO = Particle Swarm Optimisation

FSP = Forecasted Solar Power

FWP = Forecasted Wind Power

FLD = Forecasted Load Demand

FNL = Forecasted Net Load

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1.0 Introduction

The practice of estimating or predicting future patterns or events from past data, observations, and analysis is known as forecasting[1,2]. Forecasting is the process of estimating future values of a certain variable or combination of variables in a variety of domains. The intention is to provide insights into potential future events in order to decrease ambiguity and facilitate informed decision-making[3,4]. The prediction of the electrical power demand on the grid through net load forecasting takes into account both the conventional load, or consumer demand, and the contribution from variable renewable energy sources, such as solar and wind power[5,6]. The following are some forms of net load forecasting:

- Short-term load forecasting
- Medium-term load forecasting
- Long-term load forecasting

The subtraction between forecasted total load and forecasted renewable energy is known as netload forecasting[7,8]. It is becoming more and more important to integrate load forecasting with renewable energy forecasts for effective power system planning and operation. A thorough understanding of how renewable energy sources, like solar and wind, interact with traditional load patterns is becoming increasingly important as demand for these sources of energy grows[9,10]. By combining the advantages of different forecasting methods for load and renewable sources, these hybrid forecasting models hope to increase prediction accuracy and dependability overall. Accurate load and renewable energy forecasting is essential for projects like marketing plans, security system analysis, generator unit dispatch, and generation allocation[11,12]. Precise forecasts enable utility firms and grid operators to maximise resource usage, distribute generation capabilities effectively, and create strong plans for resilience and stability in the grid[13,14]. Additionally, the incorporation of renewable energy forecasts facilitates the smooth integration of these clean energy options into the electricity grid by accounting for the intermittent and fluctuating character of renewable sources[15,16]. The fact that renewable energy has recently been heavily incorporated into the electricity system cannot be ignored.

1.1 Literature Summary

Comparing renewable energy to other energy sources, it has been shown to be more affordable, environmentally friendly, and dependable. Despite the benefits of renewable energy, forecasting solar and wind power has proven difficult because of their erratic nature. Research on this topic is important since accurate renewable energy forecasting is essential for power system planning and operation. Figure 1 depicts the block diagram of net load forecasting[17,18].

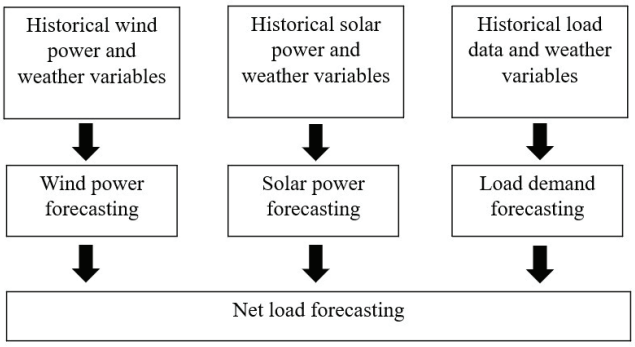


Figure 1. Diagram of net load forecasting[5].

2.0 Methodology

This section shows the methodology used to forecast load demand, solar power, wind power, and net load in a microgrid system. Figure 2 shows the layers of the feed-forward ANN algorithm. Following the literature review and problem formulation stages, this chapter focuses on the implemented techniques. The methodology discussion covers data selection, preparation, model building through coding, and simulation using Artificial Neural Networks (ANN) and Particle Swarm Optimisation (PSO) techniques within MATLAB 2021a software.

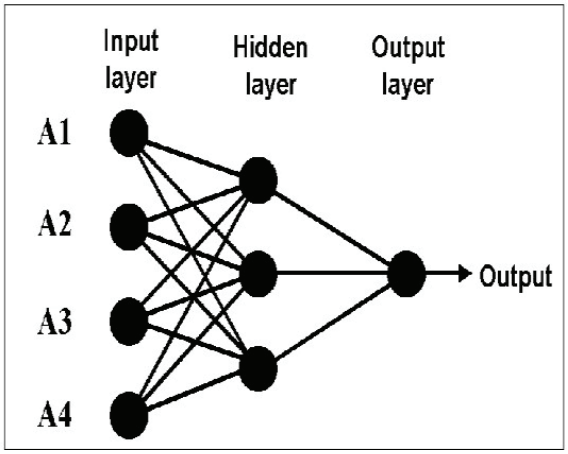


Figure 2. Feed-forward neural network[7].

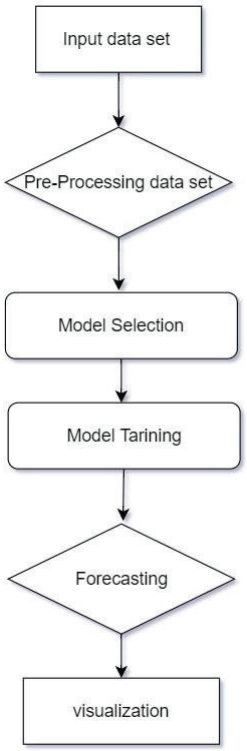


Figure 3. Flow chart of ANN-PSO Method[9].

Artificial Neural Networks (ANNs) are inspired by the brain's structure and excel at learning through experience. They consist of interconnected nodes (neurons) that mimic the brain's parallel processing and feedback mechanisms. Each node receives input from other nodes, applies a weight to it, and transforms it using an activation function. These weighted sums are then used to calculate an output value. By adjusting the weights, ANNs can learn complex relationships within data.

There are two main ANN structures: Feedforward Neural Networks (FFNNs) and Feedback Neural Networks (FBNNs). FFNNs are ideal for forecasting problems as information flows unidirectionally, preventing feedback loops. FBNNs, on the other hand, incorporate feedback loops within their architecture.

Figure 3 gives the flow chart of ANN–PSO hybrid methodology used to predict the net load power forecasting based on the fed data sets. Particle Swarm Optimisation (PSO) is a swarm intelligence-based optimisation technique inspired by the behaviour of bird flocks searching for food. It overcomes limitations of local minima convergence by iteratively updating a population of particles (potential solutions) based on their positions and velocities. Each particle adjusts its position towards the one with the best value (closest to the food source), mimicking the flock's collective movement. This process continues until an optimal solution is found. In PSO, particles represent potential solutions, velocities represent movement directions, and positions indicate coordinates of the solution space.

3.0 Analysis Result and Discussion

Table 1 summarises the forecasted values of renewable energy production, load demand, and net load within the microgrid. These forecasts were generated using MATLAB code and demonstrate a high degree of accuracy when compared to the actual data. This successful implementation highlights the effectiveness of the MATLAB-based forecasting approach.

3.1 Solar Generation Power Forecasting Graph using ANN-PSO

Figure 4 presents a comprehensive graphical analysis of the forecasting models' performance for solar power generation. The graphs depict a close correspondence between the predicted and actual values, signifying the models' high accuracy and precision. This alignment reflects the models' ability to effectively capture the underlying trends and variations in solar power output

Table 1. Forecasting the value of renewable energy, load demand and net load[3]

Hours	FSP (KW)	FWP (KW)	FLD (KW)	FNL (KW)
1	21.67	4652.7	8904.3	4231
2	34.00	4380.7	8168.8	3754.1
3	1068.61	3072.6	7150	3008.8
4	2019.00	2674	7359.6	2666.6
5	3197.00	2590.9	6556.3	768.4
6	3885.00	2938.8	6354.2	-469.59
7	1467.00	2685.5	4607.1	454.62
8	404.00	2791.1	8730.6	5535.5
9	100.00	2911	8973.4	5963.4
10	60.67	2812.5	5431.8	2559.7
11	2.64	2426.1	6198.9	3769.2
12	1.00	1358.5	9041.4	7684

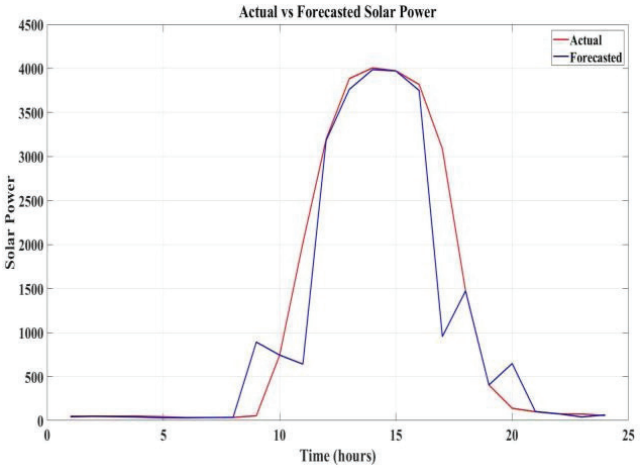


Figure 4. Solar generation power forecasting graph using ANN-PSO[11].

throughout 24 hours. In simpler terms, the forecasts closely match real-world observations, demonstrating the models' success in predicting solar power generation.

The accurate solar power generation forecasts from this research hold significant weight for future grid integration of renewable energy sources. By mitigating the operational challenges caused by solar variability, these models pave the way for a more seamless shift towards a renewable-based power grid. This translates to reduced greenhouse gas emissions and a more sustainable energy landscape, directly aligning with global efforts to combat climate change. In essence, the successful validation of the forecasting models, as evidenced by the close correlation between predicted and actual solar power generation, underlines their critical role in optimising solar energy management and integration. These models transcend operational decision support, ultimately serving as key drivers for broader renewable energy adoption and the pursuit of sustainability objectives.

3.2 Wind Generation Power Forecasting Graph using ANN-PSO

Our wind power generation forecasting models achieved high accuracy, as evidenced by the close correspondence between predicted and actual values in the generated graphs. This visual representation demonstrates that the forecasted curves (predicted values) closely track the patterns observed in the actual wind power generation data. This strong correlation signifies the model's ability

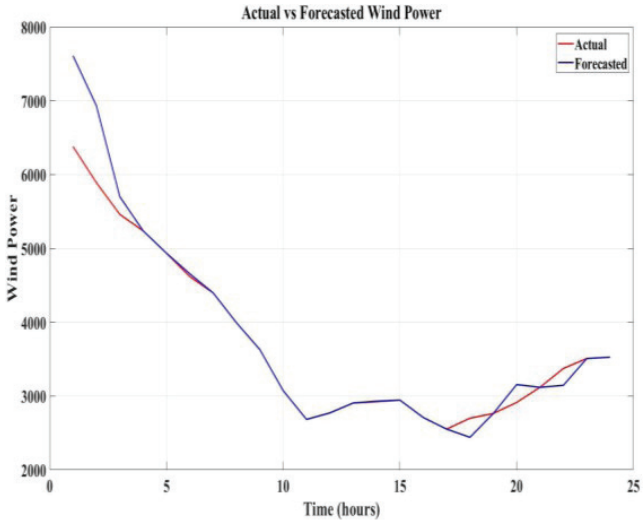


Figure 5. Wind generation power forecasting graph using ANN-PSO[13].

to effectively capture the inherent trends and variations characteristic of wind power generation.

The close correspondence between predicted and actual wind power generation curves validates the efficacy of the implemented forecasting models. This success signifies their potential as crucial instruments for facilitating the shift towards a more sustainable, renewable energy-powered future. The models' strong performance underscores the critical role advanced forecasting plays in achieving efficient and dependable renewable energy integration, ultimately promoting both environmental sustainability and energy security, as shown in Figure 5.

3.3 Load Demand Forecasting Graph using ANN-PSO

Figure 6 presents the resulting graphs, which visually confirm the efficacy of the proposed forecasting models for load demand estimation. The curves representing the predicted values closely track those of the actual values, signifying the model's ability to capture the underlying data patterns and trends. This strong visual agreement between the forecasted and actual load demand curves underscores the precision of the forecasting approach. It demonstrates that the models can effectively predict future load demands based on the provided historical data, temperature, and day of the week parameters. The observed consistency in the curves suggests a high

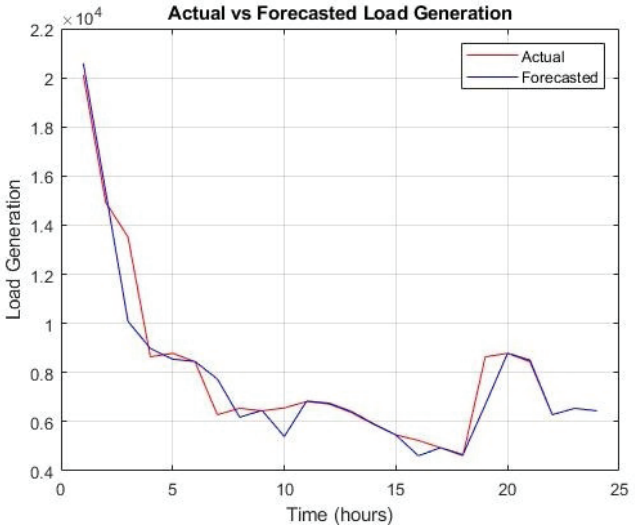


Figure 6. Load demand forecasting graph using ANN-PSO[15].

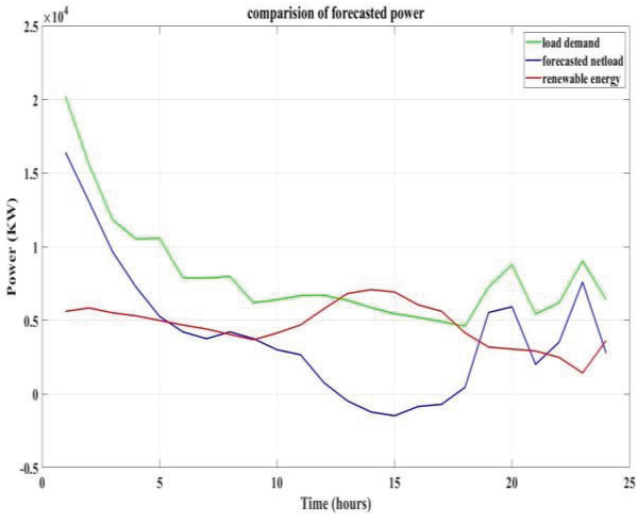


Figure 7. Comparison of total renewable energy, total load demand and net-load[17].

degree of accuracy in the predictions, a critical aspect for efficient energy management and planning within the microgrid.

The implemented validation approach goes beyond simply verifying the models' functionality. By visually comparing predicted and actual data, the process strengthens our trust in the models' ability to translate to real-world applications, such as energy forecasting. This level of accurate load demand prediction empowers us to optimise energy distribution strategies. The benefits are two-fold: reduced operational costs and increased stability within the energy supply system. Furthermore, performance metrics like MAPE (Mean Absolute Percentage Error) and MSE (Mean Squared Error) offer a quantifiable measure of this accuracy, providing a more rigorous assessment of the models' forecasting competence.

3.4 Comparison of Total Renewable Energy, Total Load Demand and Net Load

The provided Figure 7 depicts the forecasted net load in relation to projected load demand and total projected renewable energy generation. A negative net load signifies an excess of renewable energy production compared to the expected demand. Conversely, a positive net load indicates insufficient renewable generation to meet the anticipated demand. During positive net load periods, the system must draw additional power from the grid or other sources to maintain grid stability. This graph offers a vital tool for analysing net load behaviour within the next 24 hours. It allows for pinpointing instances of both positive and negative net load, enabling informed decisions regarding excess energy management. Surplus energy can be either stored for later use or sold back to the grid, promoting efficient energy utilisation as depicted in Figure 7.

4.0 Conclusion

In this study, a combined approach is presented that utilises MATLAB software for precise forecasting of Load requirements. ANN-PSO techniques were implemented to forecast short-term load demand, solar power, and wind power in a hybrid microgrid. The developed models give successful predictions of net load patterns, enhancing understanding of microgrid performance. The research demonstrates the effectiveness of this method for renewable energy microgrids. The comparison between the load demanded and forecasted is almost the same as depicted in Figure 7. Future work focuses on improving accuracy through advanced machine learning and algorithm optimisation. Exploration of hybrid models with techniques like fuzzy logic and genetic algorithms is promising for broader applicability. Additionally, researchers aim to reduce computational complexity and enhance real-time processing for large-scale data and diverse applications.

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