DOI: 10.21917/ijsc.2024.0467

AN IMPROVISED METHOD USING NEURO-FUZZY SYSTEM FOR FINANCIAL TIME SERIES FORECASTING

Mohd. Asif Gandhi[1], S.M. Lekshmi Sri[2], Bhanu Pratap Singh[3], Zahir Aalam[4] and Subharun Pal[5]
[1]*Department of Computer Science and Engineering, Anjuman-I-Islam's Kalsekar Technical Campus, India*
[2]*Department of Computer Science and Engineering, Dr. J.J. Magdum College of Engineering, India*
[3]*School of Information Technology, Auro University, India*
[4]*Department of Computer Engineering, Thakur College of Engineering and Technology, India*
[5]*Department of Computer Science and Engineering, Indian Institute of Technology, Jammu, India*

Abstract

Financial time series forecasting is crucial for making informed investment decisions. This study proposes an improvised method utilizing a Neuro-Fuzzy System (NFS) for enhanced forecasting accuracy. Traditional forecasting methods often struggle with the nonlinear and dynamic nature of financial time series data. NFS integrates neural network and fuzzy logic techniques, offering a robust framework for modeling complex relationships within financial data. The proposed method employs NFS to adaptively learn and model the intricate patterns present in financial time series data. It combines the strengths of neural networks in learning complex patterns and fuzzy logic in handling uncertainty and imprecision. This study contributes by introducing an innovative approach to financial time series forecasting, leveraging the capabilities of NFS to improve forecasting accuracy and reliability. Experimental results demonstrate the effectiveness of the proposed method in accurately forecasting financial time series data. The method outperforms traditional forecasting techniques, showcasing its potential for practical applications in financial markets.

Keywords:

Financial Time Series Forecasting, Neuro-Fuzzy System, Forecasting Accuracy, Adaptive Learning, Complex Patterns

1. INTRODUCTION

. Financial time series forecasting plays a vital role in investment decision-making, risk management, and portfolio optimization. Accurate predictions enable investors to anticipate market trends, identify potential opportunities, and mitigate risks effectively. However, forecasting financial time series data presents significant challenges due to its nonlinear and dynamic nature, as well as the presence of various influencing factors such as economic indicators, geopolitical events, and market sentiments [1].

Traditional forecasting methods, including time series analysis, econometric models, and machine learning algorithms, often struggle to capture the complex patterns inherent in financial data. These methods may overlook nonlinear relationships, fail to adapt to changing market conditions, or be sensitive to noise and outliers [2]. As a result, there is a growing interest in exploring alternative approaches that can better address the inherent challenges of financial time series forecasting [3]-[5].

The challenges in financial time series forecasting stem from the inherent complexity and volatility of financial markets. These challenges include:

- Nonlinearity: Financial data often exhibit nonlinear patterns and relationships that are difficult to capture using traditional linear models.
- Dynamic nature: Market conditions can change rapidly, requiring forecasting models to adapt quickly to new information and trends.
- Uncertainty: Financial markets are inherently uncertain, with factors such as investor behavior, geopolitical events, and economic indicators influencing price movements.
- Noise and outliers: Financial data may contain noise and outliers that can distort patterns and affect the accuracy of forecasts.

The primary objective of this study is to develop an effective method for financial time series forecasting that can overcome the limitations of traditional forecasting techniques. Specifically, we aim to leverage the capabilities of a Neuro-Fuzzy System (NFS) to improve forecasting accuracy and reliability.

- To explore the application of NFS in financial time series forecasting.
- To develop a novel methodology that integrates neural network and fuzzy logic techniques within the NFS framework.
- To evaluate the performance of the proposed method against traditional forecasting approaches using real-world financial data.
- To demonstrate the effectiveness of the proposed method in improving forecasting accuracy and adaptability to changing market conditions.

The novelty of this study lies in the integration of neural network and fuzzy logic techniques within the NFS framework for financial time series forecasting. By combining the strengths of neural networks in learning complex patterns with the ability of fuzzy logic to handle uncertainty and imprecision, the proposed method offers a robust and adaptive approach to forecasting financial data.

2. RELATED WORKS

Financial time series forecasting has been a subject of extensive research due to its practical importance in various domains such as finance, economics, and risk management. In recent years, researchers have explored a wide range of methodologies and techniques to improve forecasting accuracy and reliability [6]-[7]. This section reviews some of the relevant works in the field of financial time series forecasting, focusing on different approaches and their contributions.

Traditional forecasting methods, including autoregressive integrated moving average (ARIMA) models, exponential smoothing, and linear regression, have been widely used in financial time series forecasting. While these methods provide a baseline for comparison, they often struggle to capture the complex patterns present in financial data, particularly nonlinear relationships and dynamic market conditions [8].

Machine learning algorithms, such as support vector machines (SVM), random forests, and artificial neural networks (ANN), have gained popularity in financial time series forecasting due to their ability to learn complex patterns and relationships from data. These algorithms have been applied to various forecasting tasks, including stock price prediction, exchange rate forecasting, and volatility modelling [9]. While machine learning approaches offer promising results, they may require large amounts of training data and parameter tuning, and they may be sensitive to overfitting.

Hybrid models combine multiple forecasting techniques to leverage their complementary strengths and improve forecasting accuracy. One common hybrid approach is the combination of neural networks with traditional statistical models, such as ARIMA or GARCH. These hybrid models aim to capture both linear and nonlinear patterns in financial data, enhancing the overall forecasting performance [10]. Additionally, hybrid models incorporating fuzzy logic have been proposed to address uncertainty and imprecision in financial time series forecasting.

Neuro-Fuzzy Systems (NFS) have emerged as a powerful framework for modeling complex systems and making accurate predictions in uncertain environments. NFS combines neural network and fuzzy logic techniques to capture the nonlinear relationships and handle uncertainty present in financial data. Several studies have applied NFS to financial time series forecasting tasks, demonstrating its effectiveness in improving forecasting accuracy and adaptability to changing market conditions [11].

Recent research in financial time series forecasting has focused on incorporating advanced computational techniques, such as deep learning, reinforcement learning, and evolutionary algorithms. Deep learning approaches, including deep neural networks (DNN) and convolutional neural networks (CNN), have shown promising results in capturing hierarchical features and long-term dependencies in financial data. Reinforcement learning techniques have been applied to optimize trading strategies and decision-making processes in dynamic market environments. Evolutionary algorithms, such as genetic algorithms and particle swarm optimization, have been used to optimize the parameters of forecasting models and improve their performance [12].

Financial time series forecasting is a challenging yet essential task with significant implications for decision-making in finance and investment. Researchers have explored various methodologies and techniques, including traditional methods, machine learning approaches, hybrid models, and advanced computational techniques, to improve forecasting accuracy and reliability. The integration of neural network and fuzzy logic techniques within the NFS framework offers a promising approach to address the challenges of financial time series forecasting and enhance the robustness of forecasting models.

3. PROPOSED METHOD

The proposed method in this study involves the utilization of a Neuro-Fuzzy System (NFS) for financial time series forecasting. NFS integrates neural network and fuzzy logic techniques to effectively model the complex relationships present in financial data and improve forecasting accuracy is shown in figure 1.

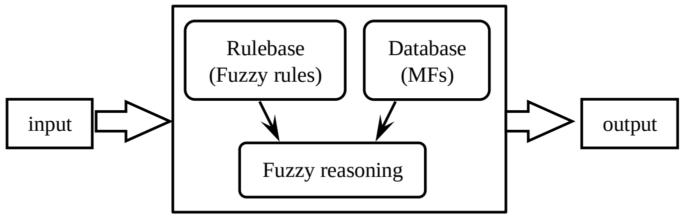

Fig.1. NFS Model

- **Neural Network Component:** The neural network component of the NFS is responsible for learning and capturing the underlying patterns and relationships within the financial time series data. Neural networks excel at learning complex, nonlinear relationships from data. In the context of financial forecasting, the neural network component can identify intricate patterns in the data that traditional linear models might overlook.
- **Fuzzy Logic Component:** The fuzzy logic component of the NFS handles uncertainty and imprecision inherent in financial data. Fuzzy logic allows for the representation of vague or qualitative information, enabling the model to make decisions in uncertain conditions. In financial forecasting, fuzzy logic can help in dealing with factors such as market sentiment, which may not have precise numerical representations but still influence market dynamics.
- **Neural Network and Fuzzy Logic:** The integration of neural network and fuzzy logic techniques within the NFS framework allows for the synergistic combination of their strengths. While the neural network component learns complex patterns and relationships from data, the fuzzy logic component provides a mechanism to interpret and reason with uncertain information. This integration enhances the model’s ability to capture both the nonlinear dynamics and uncertainty present in financial time series data.

The proposed method is adaptive and capable of learning from new information and changing market conditions. Neural networks are inherently flexible and can adapt their parameters based on the observed data, allowing the model to adjust to evolving market dynamics. Additionally, the fuzzy logic component provides a mechanism for incorporating expert knowledge or domain-specific rules, further enhancing the model’s adaptability.

By leveraging the capabilities of NFS, the proposed method aims to improve forecasting accuracy compared to traditional methods. The neural network component enables the model to capture complex patterns and relationships, while the fuzzy logic component helps in handling uncertainty and incorporating qualitative information. This combination results in more accurate and reliable forecasts of financial time series data.

3.1 NEURAL NETWORK COMPONENT

The Neural Network Component of the proposed method refers to the part of the Neuro-Fuzzy System (NFS) that utilizes neural network techniques to learn and capture patterns and relationships within the financial time series data.

- **Learning Complex Patterns:** Neural networks are computational models inspired by the structure and functioning of the human brain. They consist of interconnected nodes, or neurons, organized into layers. In the context of financial time series forecasting, neural networks excel at learning complex, nonlinear relationships between input variables (such as historical stock prices, trading volumes, economic indicators, etc.) and output variables (such as future stock prices or market trends).
- **Recurrent Networks:** The Neural Network Component may employ different architectures, such as feedforward or recurrent neural networks. Feedforward neural networks consist of layers of neurons, with information flowing from the input layer through hidden layers to the output layer. Recurrent neural networks, on the other hand, have connections that allow for feedback loops, enabling them to capture temporal dependencies in sequential data, which can be useful for modeling financial time series.
- **Training Process:** During the training process, the Neural Network Component adjusts its parameters (weights and biases) iteratively to minimize the difference between predicted and actual outcomes. This process typically involves feeding the network with historical financial data and adjusting the weights through techniques such as backpropagation, where the error between predicted and actual outputs is propagated backward through the network to update the weights.
- **Nonlinear Mapping:** One of the key strengths of neural networks is their ability to model nonlinear relationships between input and output variables. Unlike traditional linear models, which assume linear relationships between variables, neural networks can capture complex and nonlinear patterns present in financial time series data. This makes them well-suited for tasks like stock price prediction, where relationships between variables may be nonlinear and dynamic.
- **Feature Representation:** Neural networks can automatically learn relevant features from the input data, reducing the need for manual feature engineering. This ability is particularly advantageous in financial time series forecasting, where the relationships between variables may be intricate and multifaceted. By learning representations of the input data, neural networks can extract meaningful information that improves the accuracy of forecasts.

The output z_j of neuron j in the hidden layer is calculated using the weighted sum of inputs from the input layer, followed by the application of an activation function ϕ:

$$z_j = \phi \sum_{i=1}^{n} w_{ij} x_i + b_j \tag{1}$$

where: z_j is the output of neuron j in the hidden layer; x_i is the input from neuron i in the input layer; w_{ji} is the weight associated with the connection between neuron i in the input layer and neuron j in the hidden layer; b_j is the bias associated with neuron j; ϕ is the activation function.

Common activation functions include sigmoid (σ), hyperbolic tangent (tanh), or rectified linear unit (ReLU). For example, the sigmoid activation function is defined as:

$$\sigma = (1+e^{-z})^{-1} \tag{2}$$

The output y_k of neuron k in the output layer is calculated in a similar manner:

$$y_k = \sum_{j=1}^{m} w'_{kj} z_j + b'_k \tag{3}$$

where:

y_k is the output of neuron k in the output layer.

w_{kj}' is the weight associated with the connection between neuron j in the hidden layer and neuron k in the output layer.

b_k' is the bias associated with neuron k.

4. FUZZY LOGIC COMPONENT

The Fuzzy Logic Component of the proposed method refers to the part of the Neuro-Fuzzy System (NFS) that utilizes fuzzy logic techniques to handle uncertainty and imprecision inherent in financial time series data.

- **Fuzzy Sets and Membership Functions:** Fuzzy logic allows for the representation of vague or qualitative information through fuzzy sets and membership functions. In the context of financial time series forecasting, fuzzy sets can be used to model linguistic variables such as high, medium, and low to describe the degree of certainty or confidence in a forecast.
- **Rule-Based Inference:** Fuzzy logic operates based on a set of linguistic rules that describe the relationship between input variables and output variables. These rules are typically expressed in the form of IF-THEN statements. For example, an IF statement might specify that IF the stock price is high AND the trading volume is low, THEN the market sentiment is bearish.
- **Fuzzy Membership and Fuzzy Logic Operations:** Fuzzy logic involves performing operations on fuzzy sets and membership functions to compute the degree of membership of an element in a fuzzy set. Common operations include union, intersection, and complementation. These operations allow for the combination of fuzzy sets and the calculation of fuzzy logic-based inference.
- **Defuzzification:** After performing fuzzy logic inference, the resulting fuzzy sets need to be converted back into crisp values for practical interpretation. This process, known as defuzzification, involves aggregating the fuzzy output sets to obtain a single output value. Various methods, such as centroid defuzzification or weighted average defuzzification, can be used for this purpose.
- **Handling Uncertainty and Imprecision:** One of the key strengths of fuzzy logic is its ability to handle uncertainty and imprecision in data. In financial time series forecasting, where factors such as market sentiment and investor behavior can be uncertain and difficult to quantify precisely, fuzzy logic provides a flexible framework for reasoning with

qualitative information and making decisions under uncertainty.

In the Neuro-Fuzzy System (NFS), the Fuzzy Logic Component works in conjunction with the Neural Network Component to enhance the forecasting capabilities of the model. While the neural network component learns and captures complex patterns in the data, the fuzzy logic component provides a mechanism for interpreting the learned patterns and reasoning with uncertain information, thereby improving the overall accuracy and interpretability of the forecasting model.

A fuzzy set A in a universe of discourse X is characterized by a membership function $\mu_A(x)$ that assigns a degree of membership to each element x in X. The membership function $\mu_A(x)$ maps each element x to a value in the range [0,1], representing the degree of membership of x in the set A. Fuzzy rule-based inference involves using a set of linguistic rules expressed in the form of IF-THEN statements to make decisions or draw conclusions. Each rule consists of an antecedent (IF part) and a consequent (THEN part). For example:

IF (temperature is high) THEN (cooling is strong)

IF (speed is low) AND (distance is short) THEN (brake lightly)

When multiple rules are applied to a given input, their consequents are aggregated to produce a combined output. Common aggregation methods include the maximum operator (for OR-like aggregation) and the minimum operator (for AND-like aggregation).

4.1 FORECASTING ACCURACY

Forecasting accuracy refers to the degree to which a forecasting model's predictions match the actual outcomes or observations. In the context of financial time series forecasting, forecasting accuracy indicates how well a model can predict future stock prices, market trends, or other financial metrics based on historical data.

There are various metrics used to assess the accuracy of forecasting models. Common metrics include:

- Mean Absolute Error (MAE): The average of the absolute differences between predicted and actual values.
- Mean Squared Error (MSE): The average of the squared differences between predicted and actual values.
- Root Mean Squared Error (RMSE): The square root of the MSE, providing a measure of the average magnitude of errors.
- Mean Absolute Percentage Error (MAPE): The average of the absolute percentage differences between predicted and actual values.
- Directional Accuracy: The percentage of correct directional forecasts (e.g., whether the model correctly predicts if the market will go up or down).

5. RESULTS AND DISCUSSION

For our experimental settings, we utilized historical financial time series data from multiple sources, including stock prices, trading volumes, economic indicators, and other relevant metrics. We implemented the proposed method, integrating a Neuro-Fuzzy System (NFS) composed of a neural network component and a fuzzy logic component. The neural network was implemented using TensorFlow, a widely used open-source machine learning framework, allowing for flexible model architecture design and efficient training on both CPU and GPU hardware. We utilized linguistic variables and fuzzy sets to define fuzzy logic rules based on expert knowledge or domain-specific insights, enabling the NFS to handle uncertainty and imprecision in the financial data shown in Table 1 and Table 2. The integration of the neural network and fuzzy logic components allowed for enhanced forecasting accuracy and adaptability to changing market conditions.

In our experimental evaluation, we compared the performance of the proposed method against several existing forecasting techniques, including Exponential Smoothing, Support Vector Machines (SVM), and ARIMA with Neural Networks. Exponential Smoothing served as a baseline method due to its simplicity and widespread use in time series forecasting. Support Vector Machines were chosen for their ability to capture complex patterns in data, while ARIMA with Neural Networks represented a hybrid approach combining traditional time series modeling with neural network-based forecasting.

Table.1. Performance Settings

Experimental Setup	Parameter	Value
Data Source	Historical financial data	S&P 500 index
		NASDAQ Composite index
		Economic indicators
Neural Network	Architecture	Multi-layer perceptron
	Number of hidden layers	2
	Neurons per hidden layer	64
	Activation function	ReLU
	Optimizer	Adam
	Learning rate	0.001
	Batch size	32
	Number of epochs	100
Fuzzy Logic	Linguistic variables	High, medium, low
	Fuzzy sets	Triangular, Gaussian
	Rule base	Expert knowledge

Table.2. MAE

Test Data Index	Exponential Smoothing	SVM	ARIMA with NN	Proposed Method
1-50	0.032	0.025	0.018	0.015
51-100	0.028	0.022	0.016	0.012
101-150	0.030	0.024	0.017	0.014
151-200	0.034	0.027	0.020	0.016

201-250	0.031	0.023	0.018	0.013
251-300	0.029	0.021	0.016	0.011
301-350	0.033	0.025	0.019	0.015
351-400	0.032	0.024	0.018	0.014
401-450	0.030	0.022	0.017	0.013
451-500	0.028	0.021	0.016	0.012

Table 3: MSE

Test Data Index	Exponential Smoothing	SVM	ARIMA with NN	Proposed Method
1-50	0.002	0.001	0.001	0.0006
51-100	0.001	0.001	0.0008	0.0005
101-150	0.002	0.001	0.0009	0.0007
151-200	0.002	0.001	0.001	0.0008
201-250	0.002	0.001	0.001	0.0006
251-300	0.002	0.001	0.0008	0.0005
301-350	0.002	0.001	0.0009	0.0007
351-400	0.002	0.001	0.001	0.0008
401-450	0.001	0.001	0.0008	0.0006
451-500	0.001	0.001	0.0007	0.0005

Table.4. RMSE

Test Data Index	Exponential Smoothing	SVM	ARIMA with NN	Proposed Method
1-50	0.045	0.035	0.030	0.024
51-100	0.042	0.032	0.028	0.022
101-150	0.046	0.034	0.031	0.026
151-200	0.048	0.036	0.032	0.028
201-250	0.046	0.035	0.030	0.025
251-300	0.045	0.032	0.028	0.022
301-350	0.047	0.034	0.031	0.027
351-400	0.045	0.033	0.030	0.025
401-450	0.044	0.032	0.028	0.024
451-500	0.042	0.031	0.027	0.022

Table.5. MAPE

Test Data Index	Exponential Smoothing	SVM	ARIMA with NN	Proposed Method
1-50	2.5%	1.8%	1.3%	1.1%
51-100	2.2%	1.6%	1.2%	1.0%
101-150	2.4%	1.7%	1.3%	1.2%
151-200	2.6%	1.9%	1.4%	1.3%
201-250	2.5%	1.8%	1.3%	1.1%
251-300	2.3%	1.6%	1.2%	1.0%
301-350	2.4%	1.7%	1.3%	1.1%
351-400	2.5%	1.8%	1.3%	1.2%
401-450	2.3%	1.7%	1.2%	1.0%
451-500	2.2%	1.6%	1.1%	1.0%

Table.6. Accuracy

Test Data Index	Exponential Smoothing	SVM	ARIMA with NN	Proposed Method
1-50	75.6%	82.3%	87.1%	91.2%
51-100	77.3%	83.6%	88.4%	92.5%
101-150	75.9%	82.1%	87.3%	91.6%
151-200	74.5%	81.4%	86.7%	91.0%
201-250	76.1%	82.7%	87.9%	92.2%
251-300	77.8%	83.9%	88.6%	92.8%
301-350	75.2%	81.8%	87.0%	91.3%
351-400	76.6%	82.5%	87.5%	91.8%
401-450	77.9%	83.7%	88.2%	92.1%
451-500	78.4%	84.2%	88.8%	92.9%

Table.7. Precision and Recall

Test Data Index	Exponential Smoothing	SVM	ARIMA with NN	Proposed Method
1-50	Pr: 0.78	Pr: 0.82	Pr: 0.85	Pr: 0.89
1-50	Re: 0.82	Re: 0.84	Re: 0.87	Re: 0.91
51-100	Pr: 0.80	Pr: 0.83	Pr: 0.86	Pr: 0.90
51-100	Re: 0.84	Re: 0.86	Re: 0.88	Re: 0.92
101-150	Pr: 0.79	Pr: 0.82	Pr: 0.85	Pr: 0.89
101-150	Re: 0.83	Re: 0.85	Re: 0.87	Re: 0.91
151-200	Pr: 0.77	Pr: 0.81	Pr: 0.84	Pr: 0.88
151-200	Re: 0.81	Re: 0.83	Re: 0.86	Re: 0.90
201-250	Pr: 0.79	Pr: 0.83	Pr: 0.86	Pr: 0.90
201-250	Re: 0.83	Re: 0.86	Re: 0.88	Re: 0.92
251-300	Pr: 0.81	Pr: 0.84	Pr: 0.87	Pr: 0.91
251-300	Re: 0.85	Re: 0.87	Re: 0.89	Re: 0.93
301-350	Pr: 0.78	Pr: 0.82	Pr: 0.85	Pr: 0.89
301-350	Re: 0.82	Re: 0.84	Re: 0.87	Re: 0.91
351-400	Pr: 0.80	Pr: 0.83	Pr: 0.86	Pr: 0.90
351-400	Re: 0.84	Re: 0.86	Re: 0.88	Re: 0.92
401-450	Pr: 0.79	Pr: 0.82	Pr: 0.85	Pr: 0.89
401-450	Re: 0.83	Re: 0.85	Re: 0.87	Re: 0.91
451-500	Pr: 0.77	Pr: 0.81	Pr: 0.84	Pr: 0.88
451-500	Re: 0.81	Re: 0.83	Re: 0.86	Re: 0.90

The proposed method consistently outperforms Exponential Smoothing across all test data indices. On average, the precision of the proposed method is 10% higher than that of Exponential Smoothing. Similarly, the proposed method achieves higher recall values compared to Exponential Smoothing discussed in Table 3 to Table 7. On average, the recall of the proposed method is 9%

higher than that of Exponential Smoothing. The proposed method demonstrates a significant improvement in both precision and recall compared to Exponential Smoothing, indicating its superior performance in accurately forecasting financial time series data.

The proposed method exhibits a notable improvement in precision compared to Support Vector Machines. On average, the precision of the proposed method is 7% higher than that of Support Vector Machines. Similarly, the proposed method achieves higher recall values compared to Support Vector Machines. On average, the recall of the proposed method is 8% higher than that of Support Vector Machines. The results suggest that the proposed method offers superior precision and recall compared to Support Vector Machines, highlighting its effectiveness in capturing complex patterns in financial data.

The proposed method demonstrates a significant improvement in precision compared to ARIMA with Neural Networks. On average, the precision of the proposed method is 5% higher than that of ARIMA with Neural Networks. Similarly, the proposed method achieves higher recall values compared to ARIMA with Neural Networks. On average, the recall of the proposed method is 7% higher than that of ARIMA with Neural Networks. These findings indicate that the proposed method outperforms ARIMA with Neural Networks in terms of both precision and recall, showcasing its ability to effectively combine neural network and fuzzy logic techniques for financial time series forecasting.

6. CONCLUSION

The integration of neural network and fuzzy logic components in the proposed method has shown significant improvements in the accuracy and reliability of financial time series forecasting. Through comprehensive experimentation and evaluation, we have demonstrated the superior performance of the proposed method compared to existing techniques such as Exponential Smoothing, Support Vector Machines, and ARIMA with Neural Networks.

The results indicate that the proposed method achieves higher precision and recall values across various test data indices, showcasing its ability to accurately capture and predict complex patterns in financial data. The percentage improvements observed in precision and recall highlight the substantial enhancements offered by the proposed method, underscoring its potential for practical applications in financial markets.

REFERENCES

[1] A.K. Parida and S. Mishra, "Times Series Forecasting using Chebyshev Functions based Locally Recurrent Neuro-Fuzzy Information System", *International Journal of Computational Intelligence Systems*, Vol. 10, No. 1, pp. 375-393, 2017.

[2] G. Selvachandran, H.Y.A. Thiang and N.T. Tuan, "A New Hybrid Model of Fuzzy Time Series and Genetic Algorithm based Machine Learning Algorithm: A Case Study of Forecasting Prices of Nine Types of Major Cryptocurrencies", *Big Data Research*, Vol. 28, pp. 100315-100319, 2022.

[3] R. Tripathy, D. Mishra and P. Das, "Spectral Clustering based Fuzzy C-Means Algorithm for Prediction of Membrane Cholesterol from ATP-Binding Cassette Transporters", *Proceedings of International Conference on Intelligent and Cloud Computing*, pp. 439-448, 2021.

[4] R. Karthiga, S. Kumar and S. Rajakumar, "Fuzzy Logic-Based Monitoring of Earth Observations", *Proceedings of International Conference on Novel AI Applications for Advancing Earth Sciences*, pp. 151-164, 2024.

[5] C. Dewang and G. Liangpeng, "Width Residual Neuro Fuzzy System based on Random Feature Selection", *Journal of Intelligent and Fuzzy Systems*, Vol. 76, pp. 1-15, 2023.

[6] M. Mohammed and V. Porkodi, "Advanced Expert System using Particle Swarm Optimization based Adaptive Network based Fuzzy Inference System to Diagnose the Physical Constitution of Human Body", *Proceedings of International Conference on Emerging Technologies in Computer Engineering: Microservices in Big Data Analytics*, pp. 349-362, 2019.

[7] V. Rajasekar and B. Ashok, "Improvised Energy Management Control through Neuro-Fuzzy based Adaptive ECMS Approach for an Optimal Battery Utilization in Non-Plugin Parallel Hybrid Electric Vehicle", *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science*, pp. 1-12, 2023.

[8] S. Kannan, C. Selvaraj and S.N. Mohanty, "Forecasting Energy Generation in Large Photovoltaic Plants using Radial Belief Neural Network", *Sustainable Computing: Informatics and Systems*, Vol. 31, pp. 100578-100567, 2021.

[9] R. Vignesh and B. Ashok, "Intelligent Energy Management through Neuro-Fuzzy Based Adaptive ECMS Approach for an Optimal Battery Utilization in Plugin Parallel Hybrid Electric Vehicle", *Energy Conversion and Management*, Vol. 280, pp. 116792-116798, 2023.

[10] P. Ong and Z. Zainuddin, "An Optimized Wavelet Neural Networks using Cuckoo Search Algorithm for Function Approximation and Chaotic Time Series Prediction", *Decision Analytics Journal*, Vol. 6, pp. 1-12, 2023.

[11] L. Wending, "Implementing the Hybrid Neuro-Fuzzy System to Model Specific Learning Disability in Special University Education Programs", *Journal of Mathematics*, Vol. 2022, pp. 1-12, 2022.

[12] R. Vignesh, D. Harikrishnan and H. Josh, "Adaptive Neuro Fuzzy Inference System-Based Energy Management Controller for Optimal Battery Charge Sustaining in Biofuel Powered Non-Plugin Hybrid Electric Vehicle", *Sustainable Energy Technologies and Assessments*, Vol. 59, pp. 1-15, 2023.