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A Hybrid MODWT-ARIMA-FFNN Framework for Capturing Linear and Non-linear Patterns in ISSI Time Series

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Abstract. Time series forecasting plays a crucial role in data-driven decision-making, particularly in the financial context. Various forecasting methods, such as ARIMA, Neural Networks (NN), and Wavelet Transforms, have different advantages and limitations in handling linear and non-linear patterns. This study compares the forecasting performance of ARIMA, Feedforward Neural Network (FFNN), and the hybrid MODWT-ARIMA-FFNN model, referred to as MODWT, developed to enhance prediction accuracy. The novelty of the hybrid framework lies in its structure, where MODWT decomposes the time series into detail and smooth components, ARIMA forecasts the detail components, and FFNN models the smooth component before reconstructing the final forecast. The dataset consists of 237 observations from the Indonesian Sharia Stock Index (ISSI) between September 4, 2017, and September 19, 2018, divided into 225 training points and 12 testing points. Model performance is evaluated using Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE). The results indicate that the hybrid MODWT model outperforms ARIMA and FFNN individually, achieving the lowest testing errors with MSE equal to 2.3735 and MAPE equal to 0.0075. The model effectively captures both linear and non-linear patterns, making it particularly suitable for financial forecasting where data complexity and variability are high. Its performance demonstrates the potential of the hybrid MODWT framework for broader applications in forecasting financial markets and other sectors involving complex, non-linear time series data.

Keywords: Forecasting, ARIMA, FFNN, MODWT, Hybrid Model, Financial Time Series.

1 Introduction

Time series forecasting plays a crucial role across various sectors, particularly in economics, finance, and natural resource forecasting, as it enables data-driven decision-making with higher accuracy. Accurate predictions are vital for effective planning and management at both macro and micro levels. In the financial sector, precise forecasting helps investors make better-informed investment decisions, while in economics, accurate predictions facilitate more precise policy planning and response to economic changes. Therefore, the development of forecasting methods that can enhance prediction accuracy is of utmost importance, especially in dynamic sectors where market fluctuations and economic shifts require timely and accurate decisions for optimal resource management and strategic planning [1]–[3].

Despite the availability of numerous forecasting methods, significant challenges remain in selecting models that can effectively handle both linear and non-linear data patterns with high accuracy. Models like Autoregressive Integrated Moving Average (ARIMA) perform well with linear data but are less effective when dealing with non-linear patterns. Conversely, methods such as Neural Networks (NN) and Wavelet Transforms (WT) excel at capturing non-linear trends but face challenges in terms of accuracy and interpretability. The primary issue lies in integrating these methods to create a model that is better suited to forecast complex time series data, especially data with irregular patterns and high variability, which requires the flexibility and strength of multiple techniques [4]–[6].

Several previous studies have explored various approaches to time series forecasting, with many focusing on the application of ARIMA, Neural Networks, and Wavelet Transforms. ARIMA has long been used for forecasting linear data, as it captures linear relationships between data points effectively. However, for more complex, non-linear data, Neural Networks and Wavelet Transforms are often more suitable due to their ability to handle such complexities [7]. Despite the advantages of each method, significant limitations remain in terms of accuracy and generalization across different types of data. Past research has demonstrated promising results, yet there is still ample room for improvement in enhancing the forecasting accuracy, particularly in dealing with data that exhibits erratic or unpredictable patterns.

Although numerous studies have applied these forecasting methods, a notable gap remains in the literature regarding the application of hybrid methods that combine multiple forecasting models to address the weaknesses of each model simultaneously. Hybrid models can combine the strengths of ARIMA in handling linear data, the power of Neural Networks in dealing with non-linear patterns, and the flexibility of Wavelet Transforms in reducing noise and managing irregular data. However, the application and testing of hybrid models have not been widely discussed in existing research, presenting an important opportunity for further investigation. More specifically, previous studies have not sufficiently explained how different models can be assigned to different decomposed components of a time series after wavelet transformation, particularly by using ARIMA to model short-term fluctuation components and FFNN to model smooth non-linear components. This gap indicates the need for a more explicit hybrid framework that not only compares individual forecasting models but also integrates them systematically according to the characteristics of the decomposed data components. The development and validation of more effective and efficient hybrid models could potentially overcome the challenges faced by traditional methods and offer more accurate forecasting solutions for complex time series data [8], [9].

This study aims to compare the accuracy of forecasts between three main forecasting models: ARIMA, Feedforward Neural Network (FFNN), and Maximal Overlap Discrete Wavelet Transform (MODWT), as well as to develop a hybrid model combining MODWT-ARIMA-FFNN to improve time series prediction accuracy. This research seeks to fill the gap in existing literature by developing a new approach that can optimize forecasting results by leveraging the strengths of these methods. The integration of ARIMA, FFNN, and MODWT in a hybrid model could provide a more robust and accurate solution for time series forecasting, especially in complex scenarios where linear and non-linear patterns co-exist, which are commonly found in financial data and other real-world applications [10]–[13].

The novelty of this study lies in the development of a MODWT-ARIMA-FFNN hybrid framework for forecasting the Indonesian Sharia Stock Index. In this framework, MODWT is used to decompose the original time series into detail and smooth components, ARIMA is applied to forecast the detail components that represent short-term fluctuations, and FFNN is employed to forecast the smooth component that represents broader non-linear movement. The forecasted components are then reconstructed to obtain the final hybrid forecast. Therefore, the main contribution of this study is not only the comparison of ARIMA, FFNN, and MODWT-based forecasting performance, but also the construction of an integrated hybrid model that assigns different forecasting techniques to different decomposed components of the time series.

The findings of this study are expected to make a significant contribution to the development of more effective hybrid forecasting models. By combining the strengths of various forecasting techniques, this research aims to provide new insights into the use of hybrid models to improve the accuracy of forecasts for complex time series data. The results will not only contribute to the field of time series forecasting but also provide a solid foundation for the application of hybrid models in various industries, particularly in financial forecasting. The research is anticipated to pave the way for the future development of more accurate and reliable forecasting techniques that can be applied in diverse sectors facing complex and dynamic data patterns [14]–[20].

This article begins by outlining the basic theories underlying each of the forecasting methods used in this study, followed by a discussion of the methodology applied to compare the three main forecasting models. The article then presents the results of the analysis and compares the accuracy of the ARIMA, FFNN, and MODWT models, along with the developed hybrid model. By comparing the performance of these models, this article aims to highlight the strengths and weaknesses of each method in forecasting complex time series data. Finally, the article concludes with recommendations for future research, focusing on the further application of hybrid models and the development of more accurate forecasting methods that could be applied across various fields, including finance, economics, and other sectors requiring precise data-driven predictions.

2 Research Methods

2.1 Research Design

The research employed a comparative computational approach and hybrid model development to evaluate the forecasting accuracy of three distinct models: ARIMA, FFNN, and MODWT, as well as to develop and evaluate the proposed MODWT-ARIMA-FFNN hybrid model. The primary objective of this study was to assess and compare the performance of these forecasting models in predicting time series data, particularly focusing on their ability to handle both linear and non-linear patterns. The models were applied to the Indeks Saham Syariah Indonesia (ISSI) dataset, which spans from September 4, 2017, to September 19, 2018.

2.2 Data Collection and Sources

The data used in this study were obtained from the ISSI daily closing index dataset, consisting of 237 observations between September 4, 2017, and September 19, 2018. The data were split into two distinct sets: a training set containing 225 data points, and a testing set with 12 data points, corresponding to the 12-step-ahead forecasting horizon. The training set was used to develop and calibrate the models, while the testing set was reserved for evaluating the models' forecasting accuracy. The data were sourced from the Indonesian Stock Exchange (IDX), ensuring their reliability and relevance for financial forecasting purposes.

2.3 Analytical Methods

This study compares three forecasting methods: ARIMA, FFNN, and MODWT. Each method was applied to the training and testing datasets, with performance metrics calculated to assess their accuracy.

Autoregressive Integrated Moving Average (ARIMA)

The ARIMA model, a classical time series forecasting method, was used to model the time-dependent structure of ISSI data. Stationarity of the series was first tested using the Augmented Dickey-Fuller (ADF) test, and differencing was applied to achieve stationarity. Autocorrelation (ACF) and partial autocorrelation (PACF) functions were then examined to determine candidate p and q values. The optimal parameters (p, d, q) were selected through iterative fitting based on the lowest AIC and BIC values, as well as the lowest MSE and MAPE on the training set. This process resulted in the ARIMA (3,1,0) model as the best-performing configuration. This modeling strategy is consistent with previous studies that applied ARIMA or ARIMA-based comparisons in inflation, health arrears, and extreme weather forecasting [2], [7], [21].

Feedforward Neural Network (FFNN)

The FFNN model was implemented using a three-layer architecture consisting of an input layer, a hidden layer, and an output layer. The input features were derived from lagged observations, and the optimal number of neurons in the hidden layer was determined through grid search and trial-and-error testing. The selected architecture included 4 neurons in the input layer, 7 neurons in the hidden layer, and 1 neuron in the output layer. The activation function was logistics, and training was performed using backpropagation with a learning rate of 0.01 and 1e+05 epochs. Early stopping was applied to prevent overfitting. The Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE) were calculated during both training and testing to evaluate model performance. The use of neural-network-based forecasting architectures and the tuning of input structure and activation behavior have been widely discussed in prior studies [14]–[20], [22].

Maximal Overlap Discrete Wavelet Transform (MODWT)

MODWT was utilized for its ability to perform multi-resolution analysis and data denoising. The wavelet transform decomposed the ISSI time series into detail and smooth components. The detail coefficients were forecasted using the ARIMA model identified above, while the smooth components were predicted using the FFNN architecture specified earlier. The predicted components were then reconstructed to form the hybrid MODWT-ARIMA-FFNN model. This systematic integration ensures that the hybrid model leverages the strengths of both wavelet transformation and neural networks, while maintaining reproducibility of the forecasting process. This approach aligns with recent wavelet-based and wavelet-enhanced forecasting studies [10]–[13], [23]–[25].

2.4 Tools and Software

The analysis was conducted using R Studio (version 4.1.0), a comprehensive software environment for statistical computing and data visualization. R Studio was chosen for its compatibility with the ARIMA and FFNN models, as well as for its flexibility in handling time series data. MATLAB was used for implementing wavelet transformation, as it provides robust functionality for signal processing and time series analysis. The combination of these tools allowed for seamless integration of statistical and machine learning models.

2.5 Procedures

The study followed a rigorous procedure for model application and evaluation. Initially, the ISSI dataset was preprocessed by normalizing the data and splitting it into training and testing subsets. Stationarity of the series was verified using the ADF test before applying the ARIMA model, and differencing was performed as needed. Candidate ARIMA parameters (p, d, q) were determined using ACF and PACF analyses and selected based on the lowest AIC, BIC, MSE, and MAPE values.

The FFNN model was trained on the same dataset, and the optimal network configuration was determined by minimizing error metrics. Input features were derived from lagged observations, and the hidden layer neurons were tuned through grid search and trial-and-error, with early stopping applied using a validation split of 10% to prevent overfitting.

The MODWT-ARIMA-FFNN hybrid model was then applied, with the detail and smooth coefficients predicted separately: detail coefficients were forecasted using the optimized ARIMA model, while smooth components were predicted using the tuned FFNN architecture. The predicted components were then reconstructed to produce the final hybrid forecast, ensuring systematic integration for reproducibility.

For each model, forecasting accuracy was evaluated using two primary metrics: MSE (Mean Squared Error) and MAPE (Mean Absolute Percentage Error). These metrics were calculated for both the training and testing sets to assess the predictive performance of the models. The MAPE was particularly important for this study as it provides a clear measure of percentage error, making it easier to interpret the accuracy of the forecasts.

2.6 Validation and Testing

The performance of each model was evaluated on the testing dataset, which was kept separate from the training data to ensure the validity of the results. The models were validated using MAPE and MSE values, with the best-performing model selected based on the lowest error metrics. Statistical significance was not assessed, as this study focuses on comparative performance based on error metrics. The results from ARIMA, FFNN, and MODWT-ARIMA-FFNN were compared to determine which model provided the most accurate forecast.

In addition to the error metrics, a white noise test was conducted on the residuals of each model to ensure that no patterns remained in the forecast errors. Autocorrelation and partial autocorrelation functions (ACF and PACF) of the residuals were inspected to confirm the adequacy of the models and to check for any remaining serial correlation in the forecast errors.

3 Results and Discussion

The performance of ARIMA, FFNN, and MODWT was evaluated using the daily Indonesia Sharia Stock Index (ISSI) data from September 4, 2017, to September 19, 2018. The data set consisted of 237 observations, with 225 points used for training and 12 points for testing. Forecasting accuracy was measured using Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE) for both training and testing sets.

The best ARIMA model was obtained with ARIMA (3,1,0), and the best FFNN architecture had 4 neurons in the input layer, 7 neurons in the hidden layer, and 1 neuron in the output layer. The MODWT-ARIMA-FFNN hybrid model used the detailed coefficients predicted by ARIMA and the smooth coefficients predicted by FFNN, which were then reconstructed to produce the final forecast. Table 1 presents the comparison of forecasting accuracy for the three models.

Table 1. Comparison of forecasting accuracy for ISSI data using ARIMA, FFNN, and MODWT-ARIMA-FFNN

Forecasting Method	ARIMA	FFNN	MODWT-ARIMA-FFNN
MSE Training	1.5395	1.2639	0.5743
MAPE Training	0.0051	0.0046	0.0032
MSE Testing	4.8462	38.620	2.3735
MAPE Testing	0.0112	0.0328	0.0075

Based on Table 1, the hybrid MODWT-ARIMA-FFNN model produced the smallest errors for both training and testing forecasts, indicating superior predictive performance compared with the individual ARIMA and FFNN models. ARIMA performed moderately well on linear patterns but was limited in capturing the non-linear characteristics of the ISSI data. FFNN demonstrated lower errors on the training set, yet its testing performance was the least accurate among the models, reflecting challenges in generalization.

MODWT preprocessing effectively decomposed the series into detail and smooth components, which enhanced model performance when combined in the hybrid framework. The hybrid MODWT-ARIMA-FFNN model leveraged the linear modeling strength of ARIMA for the detail components and the non-linear modeling capability of FFNN for the smooth components, producing a more robust forecast. By reducing noise and capturing patterns at multiple resolutions, the hybrid model addressed both linear and non-linear aspects of the financial time series, providing improved accuracy compared with the standalone models.

Residual analysis confirmed the adequacy of the models, with white noise tests and ACF/PACF inspections indicating no significant autocorrelation in the forecast errors for the hybrid model. These results demonstrate that combining traditional statistical methods with modern machine learning techniques can produce a more reliable forecasting tool for financial time series data, especially in cases with complex non-linear patterns and noise.

The findings highlight that while ARIMA remains useful for linear trend modeling and FFNN provides potential for non-linear pattern extraction, the integration of these methods with MODWT in a hybrid model enhances predictive performance. This approach can be applied to other types of time series data in finance, economics, energy, and health sectors, where non-linear and noisy data are prevalent. Future research could explore additional hybrid configurations and improvements in interpretability for complex forecasting models.

4 Conclusion

This study compared the forecasting accuracy of three models: ARIMA, Feedforward Neural Network (FFNN), and Maximal Overlap Discrete Wavelet Transform (MODWT), using the ISSI dataset. The results revealed that the hybrid MODWT-ARIMA-FFNN model outperformed the other models, achieving the lowest Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE). While ARIMA effectively captured linear trends, the FFNN model contributed to modeling non-linear relationships, particularly when combined with MODWT for data preprocessing. The superior performance of the hybrid model suggests that combining wavelet transformations for data decomposition with machine learning for forecasting can enhance prediction accuracy, especially when dealing with complex, noisy data such as financial time series. These findings offer practical insights for improving time series forecasting, particularly in financial applications, where both linear and non-linear components coexist. However, the study's limitations include the specific ISSI dataset, and the limited scope of time series features explored. Furthermore, the computational complexity of the hybrid model may require further optimization for large-scale applications. Future research could extend the application of the hybrid model to other financial datasets or time series from different industries, such as climate data or healthcare analytics, and experiment with different wavelet types or machine learning architectures to further enhance model performance and efficiency.

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