JTAM (Jurnal Teori dan Aplikasi Matematika)
http://journal.ummat.ac.id/index.php/jtam
p-ISSN 2597-7512 | e-ISSN 2614-1175
Vol. 10, No. 2, April 2026, pp. 559-575

Forecasting Rice Prices in Indonesia Using a Hybrid HWES-MLP Time Series Prediction Model

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Article History:
Received : 06-10-2025
Revised : 05-12-2025
Accepted : 11-12-2025
Online : 01-04-2026

Keywords:
Multilayer Perceptron;
Holt-Winters Exponential Smoothing;
Rice Prices in Indonesia;
Forecasting.

ABSTRACT

Rice is the main staple food for the majority of the Indonesian population. However, the fluctuation in rice prices and future uncertainty emphasize the importance of forecasting rice prices, thus requiring a forecasting model capable of providing accurate predictions. Various previous forecasting methods have been limited in capturing the combination of linear and non-linear patterns in rice price data, spurring the need for a more comprehensive hybrid approach. This research applies a quantitative approach by utilizing secondary data sourced from publications of the Central Statistics Agency (BPS) of Indonesia. This study aims to forecast rice prices in Indonesia using a hybrid approach combining Holt–Winters Exponential Smoothing (HWES) with Multilayer Perceptron (MLP). The hybrid model is designed to overcome the limitations of the Holt-Winters Exponential Smoothing method, which can only capture linear patterns such as trend and seasonality, by adding the Multilayer Perceptron method to capture non-linear patterns that cannot be handled by the linear approach. The dataset comprises monthly rice prices in Indonesia from January 2010 to December 2024, while the period of January–December 2025 is used as the prediction period. The data analysis process was carried out using the software R-Studio and Minitab, which provide a variety of features to support time series modeling. The results indicate that the most effective method for forecasting rice prices in Indonesia is the Hybrid Holt Winters Exponential Smoothing (α = 0.5; β = 0.3; γ = 0.3)-Multilayer Perceptron (12-12-1), which achieved the highest accuracy with a MSE of 9666.12, a RMSE of 310.9117, and a MAPE of 1.9949%. This finding indicates that the Hybrid HWES-MLP approach is highly capable of capturing rice price data patterns. Thus, this model holds significant potential to be utilized as a benchmark supporting government policy in maintaining rice price stability, market intervention, and optimizing the management of national rice reserves stock.

https://doi.org/10.31764/jtam.v10i2.35445
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A. INTRODUCTION

Indonesia has a total land area of 1.9 million square kilometres. It is recognised as an agrarian country, as the majority of its population is employed in the agricultural sector. This sector plays a crucial role in meeting the nation's primary food needs (Handani et al., 2021; Virgiani et al., 2023). Rice is one of the primary agricultural commodities (Juniarsih et al., 2025). It serves as the staple food for Indonesians from Sabang to Merauke (Susanti et al., 2023). Around 78% of the Indonesian population relies on rice as their main energy source, mainly carbohydrates. According to data from the United States Department of Agriculture (USDA) for 2020–2024, Indonesia ranks as the world's third-largest rice producer after China and India, with an annual output of 752 million tons. Per capita rice consumption in Indonesia grew by 3.16% between 2019 and 2023, based on Food Consumption Statistics. It increased from 78.429 kg/capita/year in 2019 to 80.905 kg/capita/year in 2023 (Sabarella, 2024).

The government continuously monitors and regulates rice prices, as rice is a staple food commodity. This is necessary because rice prices have a large impact on food security, poverty reduction, macroeconomic stability, and national economic growth (Bairagi et al., 2022; Lestari & Saidah, 2023; Mujihartono et al., 2023; Putra et al., 2021; Sari & Hariyanto, 2023). According to Statistics Indonesia (*Badan Pusat Statistik*/BPS), the price of rice at the milling level experienced a significant increase from January 2020 to December 2023, with a particularly sharp upward trend observed in 2023 (Aulia & Pratama, 2024). This condition indicates that the most contentious issue in rice pricing is the occurrence of price fluctuations (Feryanto et al., 2023; Matondang et al., 2024). The existence of such fluctuations, coupled with future uncertainties, underscores the importance of rice price forecasting (Putra et al., 2021; Song & Kang, 2020). Price fluctuations must be managed through policies aimed at stabilizing prices to safeguard national stability and public welfare (Balié & Valera, 2020).

The information obtained from rice price forecasting can be utilised by the government to take anticipatory measures in maintaining price stability. If rice prices increase, the National Logistics Agency (*Badan Urusan Logistik*/BULOG) can provide subsidies or reduce prices to alleviate the burden on the public (Amri et al., 2025; Utami et al., 2024; Yulianti et al., 2024; Lathifah & Agustina, 2024). However, most time series data do not only exhibit linear patterns but also contain nonlinear patterns that cannot be optimally captured by methods focusing solely on linear trends, such as Holt-Winters Exponential Smoothing. Although the Holt-Winters Exponential Smoothing method is widely used, its limitation in capturing non-linear patterns justifies the need for a hybrid approach. One method that can be employed to overcome this limitation is the Multilayer Perceptron (Haris et al., 2023). The Multilayer Perceptron is chosen for its flexible structure and effectiveness in modelling data characteristics that do not follow linear patterns (Sumayli & Alshahrani, 2023). Therefore, this research offers a novelty element in the form of applying the hybrid Holt-Winters Exponential Smoothing–Multilayer Perceptron (HWES-MLP) model to improve the accuracy of rice price forecasting (Chaudhuri & Alkan, 2022).

The hybrid Holt-Winters Exponential Smoothing–Multilayer Perceptron (HWES-MLP) approach was chosen because single forecasting methods are often unable to capture time series patterns that are mixed, namely linear and non-linear (Ahmadpour et al., 2023; Chen et al., 2023; Adeyinka & Muhajarine, 2020). The Holt-Winters Exponential Smoothing method is effective in identifying linear patterns such as trends and seasonality, while the Multilayer Perceptron excels at modeling more complex, non-linear (Montano & Moyon, 2024; Mathonsi & van Zyl, 2022)

Previous studies relevant to this research have been conducted by Septiana (2024), who applied the Holt-Winters Exponential Smoothing method to forecast the average wholesale rice prices in Indonesia from 2014 to 2023. The evaluation results indicated that the additive method produced the lowest Mean Absolute Percentage Error (MAPE) of 0.954%. Furthermore, Damaliana et al. (2023) developed a hybrid Holt–Winters and Prophet method to forecast the number of international tourist arrivals to Bali via Ngurah Rai International Airport. Their findings demonstrated that the hybrid method achieved higher accuracy compared to the single method. The Holt–Winters method yielded a MAPE of 6.0350%, whereas the hybrid Holt–Winters–Prophet method produced a substantially lower MAPE of 2.5880%. Another study by Zhang et al. (2021) compared five machine learning methods for forecasting monthly copper prices from January 1990 to December 2019, namely the Multilayer Perceptron (MLP), K-Nearest Neighbours (KNN), Support Vector Machine (SVM), Gradient Boosting Tree (GBT), and Random Forest (RF). The evaluation results revealed that the Multilayer Perceptron (MLP) was the best-performing method, with a Mean Absolute Error (MAE) of 228.617. In contrast, other methods such as KNN, SVM, GBT, and RF produced higher errors, with MAE values ranging from 308.691 to 453.147. Based on this background, the present study aims to forecast rice prices in Indonesia by applying a hybrid HWES-MLP approach.

B. METHODS

1. Data Source

The dataset employed in this study consists of monthly wholesale rice prices in Indonesia, sourced from the official publications of Statistics Indonesia (*Badan Pusat Statistik*/BPS) through its official website (www.bps.go.id). The dataset covers the period from January 2010 to December 2024, encompassing a total of 180 monthly observations. The data analysis process was carried out using the software R-Studio and Minitab, which provide a variety of features to support time series modeling.

2. Research Procedures

The data analysis process was conducted through the following steps:

a. Descriptive Analysis
   Descriptive analysis is performed on the Indonesian rice price data for the period of January 2010 to December 2024. This stage aims to provide an initial overview of the data to be analyzed.
b. Data Splitting
   Splitting the dataset into training and testing subsets with a composition of 85% and 15%, respectively (Du et al., 2024; Haris et al., 2023; Xue et al., 2024).
c. Holt-Winters Exponential Smoothing Modeling
   Applying the HWES method for modeling and forecasting through the following stages:
   1) Determining the smoothing parameters for level (α), trend (β), and seasonal pattern (γ) using a trial and error approach for both Additive and Multiplicative Holt–Winters models (Wasono et al., 2024; Haris et al., 2023; Djakaria & Saleh, 2021).
   2) Establishing the initial values for level smoothing (L_t), trend smoothing (T_t) and seasonal smoothing (S_t).
   3) Calculating the smoothed values for level (L_t), trend (T_t), and seasonality (S_t) using the optimal model.
   4) Generating forecasts for the next 12 periods.

5) Evaluating the forecasting accuracy for Indonesian rice price data using the Mean Absolute Percentage Error (MAPE).

d. Calculating the Residual Value of Holt-Winters Exponential Smoothing
The HWES residual is calculated as the difference between the actual data and the HWES forecast result.
e. Normalization of Holt-Winters Exponential Smoothing Residuals
Performing data normalization on the residuals to standardize the scale and reduce bias in the calculation (Haris et al., 2023; Kim et al., 2025; Wasono et al., 2024).
f. Hybrid Holt-Winters Exponential Smoothing-Multilayer Perceptron (HWES-MLP) Modeling
Implementing the Hybrid HWES–MLP model for modeling and forecasting through the following stage:
1) Utilizing the residual data from the HWES model as input.
2) Defining the input and target data. The input data consist of residual values from January to December of the first year, while the target data correspond to the values for January of the subsequent year, and so forth, continuing until the final year of the dataset.
3) Designing the network architecture by setting the input layer to 12 neurons, the hidden layer was tested from 1 to 12 neurons $z_j(j = 1,2,3 \dots ,12)$, output layer consists of 1 neuron, target error of 0.0001, a learning rate of 0.001, 1.000 epochs, a momentum constant of 0.95, and a Binary Sigmoid activation function. These parameters were chosen based on previous studies that demonstrated the configuration is stable and effective in learning the non-linear patterns of time series residuals (Mou et al., 2025; Haris et al., 2023; Wang et al., 2022).
4) Applying the Backpropagation algorithm to train the Multilayer Perceptron using the training dataset.
5) Testing the network with the testing dataset based on the Mean Absolute Percentage Error (MAPE) value.
6) Data denormalization.

g. Forecasting
The forecasting of rice prices in Indonesia was conducted for the period from January 2025 to December 2025 using the optimal model architecture.
h. Interpretation
Conclusions were drawn, and the results were interpreted.

3. Holt–Winters Exponential Smoothing Method

The HWES method is a combination of the Holt and Winters approaches, applied to data exhibiting both trend and seasonal patterns. This method employs three smoothing parameters: alpha (α) for the level component, beta (β) for the trend component, and gamma (γ) for the seasonal component, with each parameter value ranging between 0 and 1 (Wasono et al., 2024).

The initial values for the level, trend, and seasonal components can be initialized using the following equations (Lathifah & Agustina, 2024):

Initial level value: $L_t = \frac{1}{l}\,[Z_1 + Z_2 + \cdots + Z_n]$ (1)

Initial trend value: $T_t = \frac{1}{l}\left[\frac{Z_{t+1} - Z_1}{l} + \frac{Z_{t+2} - Z_2}{l} + \cdots + \frac{Z_{t+t} - Z_t}{l}\right]$ (2)

Initial Additive seasonal component: $S_t = Z_1 - L_t, S_1 = Z_2 - L_t, \ldots, Z_t - L_t$ (3)

Initial Multiplicative seasonal component: $S_t = \frac{Z_1}{L_t}, S_2 = \frac{Z_2}{L_t}, \ldots, S_t = \frac{Z_t}{L_t}$ (4)

The HWES method consists of two types based on the seasonal pattern: the Multiplicative model and the Additive model. The calculation of the HWES model with an Additive seasonal pattern is performed using the following equations (Septiana, 2024):

Level smoothing : $A_t = \alpha\,(Z_t - S_{t-s}) + (1-\alpha)(A_{t-1} + T_{t-1})$ (5)

Trend smoothing : $T_t = \beta\,(A_t - A_{t-1}) + (1-\beta)T_{t-1}$ (6)

Seasonal smoothing : $S_t = \gamma\,(Z_t - A_t) + (1-\gamma)S_{t-s}$ (7)

Forecasting : $F_{t+m} = A_t + T_t m + S_{t-s+m}$ (8)

The calculation of the HWES model with a Multiplicative seasonal pattern is carried out using the following equations (Amri et al., 2025):

Level smoothing : $A_t = \alpha\left(\frac{Z_t}{(S_{t-s})}\right) + (1-\alpha)\,(A_{t-1} + T_{t-1})$ (9)

Trend smoothing : $T_t = \beta\,(A_t - A_{t-1}) + (1-\beta)T_{t-1}$ (10)

Seasonal smoothing : $S_t = \gamma\left(\frac{Z_t}{A_t}\right) + (1-\gamma)\,S_{t-s}$ (11)

Forecasting : $F_{t+m} = A_t + T_t m + S_{t-s+m}$ (12)

with:

A_t : Represents the smoothing level at time period t.
T_t : Represents the smoothed trend component at time period t.
S_t : Represents the smoothed seasonal component at time period t.
Z_t : Denotes the observed data value at time period t.
F_{t+m} : Indicates the forecasted value for the future time period t + m.
α, β, γ : Smoothing parameters ranging between 0 and 1.
m : Refers to the number of periods ahead to be forecasted.
l : Denotes the number of periods in one seasonal cycle.

4. Data Normalization

In this study, data normalization was performed to convert the research dataset from an unbounded range to a bounded range between 0 and 1. This transformation was undertaken to ensure compatibility with the binary sigmoid activation function employed in the Multilayer Perceptron method, thereby improving data stability and facilitating a more efficient computational process during modeling (Kim et al., 2025; Wasono et al., 2024). The normalization equation is defined as follows:

$$X' = \frac{X_t - X_{min}}{X_{max} - X_{min}} + (X_{maxb} - X_{minb}) + X_{minb} \quad (13)$$

5. Multilayer Perceptron

The Multilayer Perceptron (MLP) is a type of Artificial Neural Network (ANN) consisting of three primary layers: the input layer, the hidden layer, and the output layer (Sumayli & Alshahrani, 2023). ANN operates by mimicking the mechanisms of the human neural system, where each neuron within these layers is interconnected through weights that are continuously updated during the training process to ensure that the predicted output closely approximates the desired target. The input layer receives the input data and transmits it to the hidden layer, which then processes the information using activation functions. The result of this processing is forwarded to the output layer to generate the final prediction (Safar et al., 2023).

6. Backpropagation in Multilayer Perceptron

The backpropagation algorithm is named for its learning process, which flows backward from the output layer to the hidden layer, and ultimately to the input layer, whenever the predicted output does not match the target. One of the key advantages of this algorithm is its ability to adapt to the given data and produce low prediction error. The training process of the backpropagation algorithm involves the following steps (Haris et al., 2023):

Step 0: Initialize all weights with small random values.

Step 1: If the stopping criterion has not been met, proceed to Steps 2 through 8.

Step 2: For each training data pair, execute Steps 3 through 8.

Step 3: Each input unit X_i $(i = 1, .., n)$ receives a signal and transmits it to the hidden units.

Step 4: Each unit in the hidden layer Z_j $(j = 1,2.., p)$ computes the weighted input signal using the following equation:

$$z\_net_j = v_{0j} \sum_{i=1}^{n} x_i \, v_{ij} \quad (14)$$

Next, the output layer is computed using an activation function.

$$z_j = f(z\_net_j) = \frac{1}{1+e^{-z\_net_j}} \quad (15)$$

Step 5: Each unit in the output layer Y_k $(k = 1,2.., m)$ calculates the total weighted input signal it receives using the following equation:

$$y\_net_k = w_{k0} \sum_{i=1}^{n} w_{kj} \quad (16)$$

Then, the activation function is applied to compute the output signal as follows:

$$y_k = f\,(y\_net_k) = \frac{1}{1+e^{-z\_net_j}} \quad (17)$$

Step 6: Each unit in the output layer Y_k (k = 1,2.., m) receives the corresponding input from the training pattern and calculates the error using the following equation:

$$\delta = (t_k - y_k)\left(y_{net_k}\right) f'\ y\_net_k \tag{18}$$

Then, compute the weight correction to update W_{kj}

$$\Delta W_{kj} = \alpha \delta_k Z_j \tag{19}$$

The bias correction for w_{k0} is calculated as:

$$\Delta W_{k0} = \alpha \delta_k \tag{20}$$

The value of δ_k is then propagated back to the units in the preceding layer.

Step 7: Each unit in the hidden layer Z_j (j = 1,2.., p) computes the net delta value received from the units in the subsequent layer:

$$\delta\_net_j = \sum_{k=1}^{m} \delta_k\, w_{kj} \tag{21}$$

This value is multiplied by the derivative of the activation function to calculate the error.

$$\delta_j = \delta\_net_j\, f'\left(Z_{net_j}\right) = \delta_{net_j} Z_j (1 - Z_j) \tag{22}$$

The weight correction to update v_{ij} is computed as:

$$\Delta v_{ji} = \alpha \delta_j\, x_i \tag{23}$$

The biased correction for v_{0j} is calculated as:

$$\Delta v_{0j} = \alpha \delta_j \tag{24}$$

Step 8: Each unit in the output layer Y_k (k = 1,2.., m) updates its bias and weights (j = 1, 2.., p).

$$W_{kj}(new) = W_{kj}(old) + \Delta W_{kj} \tag{25}$$

Each hidden unit Z_j (j = 1,2.., p) updates its bias and weights.

$$V_{ji}(new) = V_{ji}\,(old) + \Delta v_{ji} \tag{26}$$

Step 9: Check whether the stopping condition has been met.

7. Data Denormalization

Data denormalization is done to return the data to its original scale (Sudiatmika et al., 2024). Data denormalization can be calculated using the following equation:

$$X = X'(X_{max} - X_{min}) + X_{min} \tag{27}$$

8. Hybrid Holt-Winters Exponential Smoothing–Multilayer Perceptron (HWES-MLP)

In the Hybrid HWES-MLP approach, the forecasting process is carried out in sequential stages. First, the Holt-Winters Exponential Smoothing method is used to capture the linear components, such as trend and seasonality. Subsequently, the remaining error (residual) from the Holt-Winters Exponential Smoothing forecast is modeled using a Multilayer Perceptron to identify the residual non-linear patterns in the data (Damaliana et al., 2023). The HWES-MLP model can be expressed through the following equation:

$$\hat{y}_{t+1} = \hat{y}_{t+1}^{HWES} + \hat{r}_{t+1}^{MLP} \tag{28}$$

The final forecast value is obtained by summing the linear forecast produced by the HWES method and the non-linear forecast of the residuals generated by the MLP.

9. Forecasting Model Accuracy

a. Mean Square Error (MSE)

The Mean Squared Error (MSE) is calculated by summing the squared differences between the actual data and the predicted values, and then dividing the result by the total number of data points. It is obtained using the following formula (Haris et al., 2023):

$$MSE = \sum \frac{(Y_t - \hat{Y}_t)^2}{n} \tag{29}$$

b. Root Mean Squared Error (RMSE)

The Root Mean Squared Error (RMSE) is the square root of the MSE and is used to measure the average magnitude of prediction errors in a model. It is obtained using the following formula (Septiana, 2024):

$$RMSE = \sqrt{\sum \frac{(Y_t - \hat{Y}_t)^2}{n}} \tag{30}$$

c. Mean Absolute Percentage Error (MAPE)

The Mean Absolute Percentage Error (MAPE) indicates the average percentage error between the predicted values and the actual data. It is obtained using the following formula (Lathifah & Agustina, 2024):

$$\text{MAPE} = \frac{\sum_{i=1}^{n} \left| \frac{Y_t - \hat{Y}_t}{Y_t} \right|}{n} \text{ x } 100\% \qquad (31)$$

n represents the total number of observations, Y_t is the actual data value at period t, while $\hat{Y}_t$ is the value generated through the forecasting process. The MAPE accuracy level categories are presented in Table 1.

Table 1. MAPE Evaluation Criteria

MAPE	Interpretation
<10%	Very Good Forecasting
10%-20%	Good Forecasting
21%-50%	Fair Forecasting
>50%	Poor Forecasting

C. RESULT AND DISCUSSION

1. Descriptive Statistics

The movement of rice prices in Indonesia from January 2010 to December 2024 was analyzed descriptively to provide a general overview of the data characteristics. Figure 1 presents a time series visualization of rice prices in Indonesia.

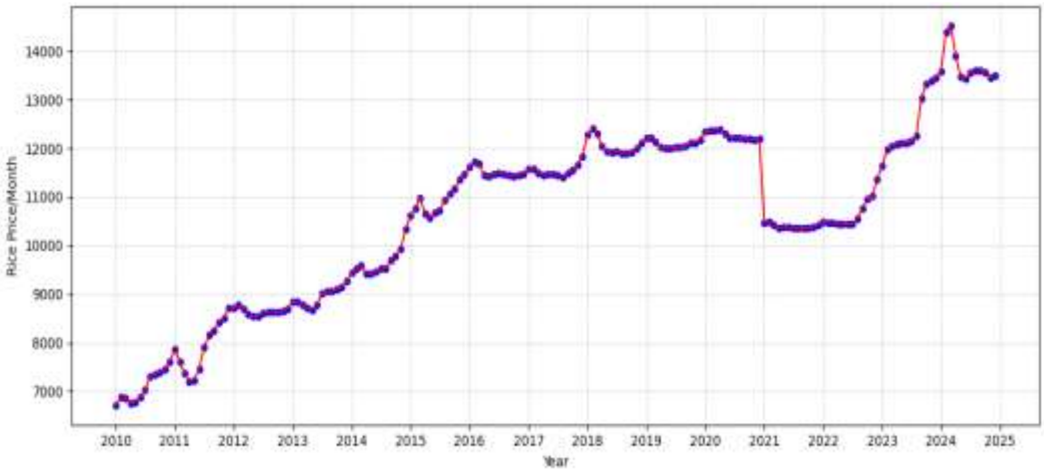

Figure 1. Rice price movements in Indonesia from January 2010 to December 2024

Based on Figure 1, rice prices in Indonesia generally exhibited an upward trend from 2010 to the end of 2024, with a fluctuating movement pattern. This pattern indicates the presence of both trend and seasonal components in the time series data. Therefore, it can be concluded that the rice price data are non-stationary. The descriptive analysis shows that the highest rice price in Indonesia occurred in March 2024, amounting to IDR 14,528, while the lowest price was recorded in January 2010 at IDR 6,702.49. Over the past 15 years of observation, the average rice price in Indonesia was IDR 10,653.13, with a standard deviation of IDR 1,839.87.

2. Holt-Winters Exponential Smoothing Method

The smoothing parameters for level (α), trend (β), and seasonality (γ) were determined through a trial and error process for each composition of training and testing data. The estimated smoothing parameters of the HWES method for rice price data in Indonesia are presented in Table 2.

Table 2. Smoothing parameters for level (α), trend (β), and seasonality (γ)

α	β	γ	MAPE
0.1	0.9	0.7	60.6700
0.2	0.8	0.4	22.7054
0.3	0.4	0.2	5.4747
0.4	0.3	0.2	4.7635
0.5	**0.3**	**0.3**	**2.6443**
⋮	⋮	⋮	⋮
0.8	0.8	0.1	20.6878
0.9	0.9	0.1	5.6417
1.0	1.0	0.9	9.4215

Based on Table 2, the optimal parameters for the additive HWES model were obtained with a level (α) value of 0.5, a trend (β) value of 0.3, and a seasonal (γ) value of 0.3, as this combination produced the lowest MAPE value of 2.6443. The smoothing values are calculated using the best parameters obtained, so the smoothing values for the level, trend, seasonal, and the forecast in the Additive model can be calculated based on equations (5), (6), (7), and (8). The calculation results show that the level smoothing value (A_t) = 7693.35, the trend smoothing value (T_t) = 229.71, the seasonal smoothing value (S_t) = -219.22, and the Additive model forecast value (F_{t+m}) = 6769.62. The calculations for the level, trend, and seasonal parameters, as well as the forecast for the subsequent period, were performed using the above equations. The forecast results for rice prices in Indonesia for the year 2025 covering the next 12 months, are presented in Figure 2.

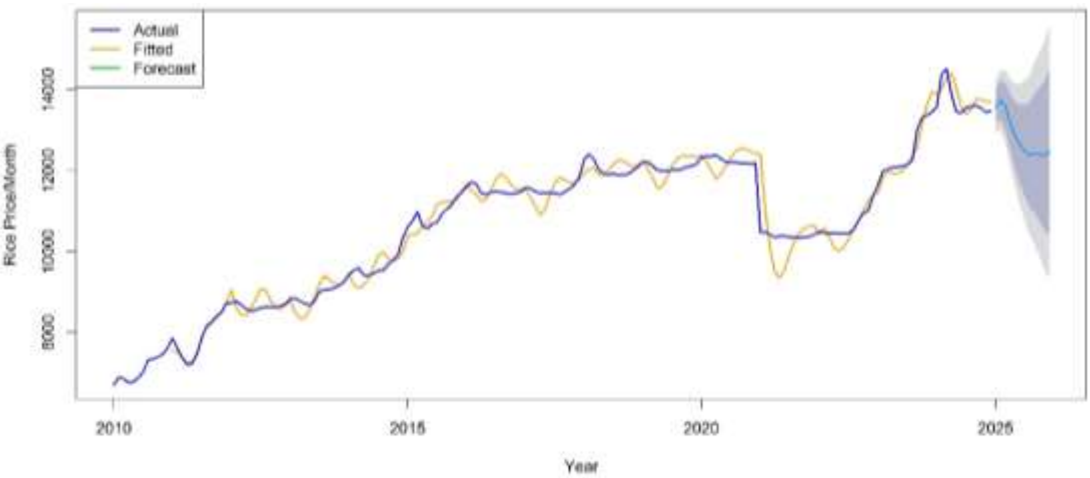

Figure 2. Forecast graph of rice prices in Indonesia using the HWES method

Based on Figure 2, the forecasting results show that the highest rice price is estimated to occur in February 2025, reaching IDR 13,759.51, while the lowest price is estimated to occur in

November 2025, at IDR 12,378.56. The price movement pattern from January to February 2025 indicates an upward trend, which may be caused by various factors such as post-year-end holiday adjustments and scarcity due to increased rice demand during the month of Ramadan. Subsequently, from March to November 2025, the rice price is predicted to experience a gradual decline, which is influenced by the main harvest season leading to increased supply and stable rice distribution post-harvest. In December 2025, the price slightly increases again to IDR 12,478.80, caused by several factors such as the long Christmas and New Year Holidays.

3. Data Normalization

After obtaining the rice price forecasts in Indonesia using the HWES method (α = 0.5; β = 0.3; dan γ = 0.3), the next step was to calculate the residuals by subtracting the predicted values from the actual data. The residual values were then normalized before being processed using the Multilayer Perceptron method. Before modeling, the rice price data in Indonesia were normalized according to equation (13). The normalized residual values were then processed using the Multilayer Perceptron method with the Backpropagation algorithm to find the optimal architecture for forecasting Indonesian rice prices in the subsequent period. The normalized residual values are presented in Table 3.

Table 3. Normalized residual values using the Holt-Winters Exponential Smoothing method

Year	January	February	March	...	December
2011	0.698756	0.651851	0.624354	...	0.621179
2012	0.535347	0.669101	0.688191	...	0.629634
2013	0.631597	0.714452	0.738291	...	0.622458
⋮	⋮	⋮	⋮	⋮	⋮
2022	0.640259	0.591365	0.642498	...	0.612292
2023	0.671305	0.668324	0.632990	...	0.487336
2024	0.536491	0.725574	0.678215	...	0.560108

4. Hybrid Holt-Winters Exponential Smoothing and Multilayer Perceptron (HWES-MLP)

The implementation of the Hybrid Holt-Winters Exponential Smoothing–Multilayer Perceptron method began by dividing the residual data obtained from the Holt-Winters Exponential Smoothing forecasts into training and testing datasets, with a composition of 85% and 15%, respectively. The next step was to define the input and target variables for the network. This study employed 12 input variables representing the residual values from the first to the twelfth month of the initial year, and one target variable representing the residual value of the thirteenth month, or the first month of the following year. The selection of 12 input variables was based on the monthly nature of the data, with the expectation that a full 12-month cycle would adequately capture the variability patterns within one annual cycle. The input and target data used in constructing the Multilayer Perceptron network are presented in Table 4.

Table 4. Input and target data for the Multilayer Perceptron network

Observation	Input					Target
	X_1	X_2	...	X_{11}	X_{12}	
1	0.698756	0.651851	...	0.615217	0.621179	0.535347
2	0.651851	0.624354	...	0.621179	0.535347	0.669101
3	0.624354	0.612475	...	0.535347	0.669101	0.688191
4	0.612475	0.609563	...	0.669101	0.688191	0.665379
5	0.609563	0.610999	...	0.688191	0.665379	0.607894
⋮	⋮	⋮	⋮	⋮	⋮	⋮
153	0.746936	0.660804	...	0.66712	0.645316	0.579266
154	0.660804	0.552793	...	0.645316	0.579266	0.563582
155	0.552793	0.487336	...	0.579266	0.563582	0.549390
156	0.487336	0.536491	...	0.563582	0.549390	0.560108

The architecture of the MLP network using the Backpropagation algorithm was constructed by setting a target error of 0.0001, a learning rate of 0.001, 1.000 epochs, and a momentum constant of 0.95. As a result, a comparison of forecasting accuracy between the training and testing datasets was obtained and is presented in Table 5.

Table 5. Training and testing architecture of the MLP network using the Backpropagation algorithm

Category	Network Architecture	Epoch	Time	MSE	RMSE	MAPE
Training	12-1-1	75	00:00:00	0.002761	0.052541	0.073161
	12-2-1	368	00:00:00	0.002258	0.047513	0.066499
	⋮	⋮	⋮	⋮	⋮	⋮
	12-9-1	1000	00:00:00	0.000025	0.004989	0.006069
	12-10-1	1000	00:00:00	0.000019	0.004322	0.004247
	12-11-1	1000	00:00:00	0.000011	0.003254	0.003255
	12-12-1	**1000**	**00:00:00**	**0.000003**	**0.001779**	**0.001525**
Testing	12-1-1	75	00:00:00	0.005901	0.076818	0.092719
	12-2-1	368	00:00:00	0.004473	0.066878	0.077711
	⋮	⋮	⋮	⋮	⋮	⋮
	12-9-1	1000	00:00:00	0.039638	0.199093	0.252693
	12-10-1	1000	00:00:00	0.040924	0.202297	0.272427
	12-11-1	1000	00:00:00	0.050063	0.223748	0.253260
	12-12-1	**1000**	**00:00:00**	**0.018890**	**0.137441**	**0.185899**

Based on Table 5, the selection of the network architecture was guided by the lowest values of MSE, RMSE, and MAPE obtained during the testing phase, in order to minimize the risk of overfitting. Accordingly, the 12-12-1 network architecture was identified as the optimal configuration for both training and testing datasets, with an MSE of 0.018890, an RMSE of 0.137441, and a MAPE of 18.5899%. The significantly large difference in MAPE between the training and testing data indicates the presence of overfitting. However, this condition is still acceptable because the degree of overfitting remains within the tolerance limit, as the testing MAPE of 18.5899% is still categorized as good according to Lewis (1982). Furthermore, the performance of the 12-12-1 testing architecture is still better compared to other architectures within the model group tested. The visualization of the best performing Multilayer Perceptron architecture using the Backpropagation algorithm developed during the training phase of the rice price residual data in Indonesia is presented in Figure 3.

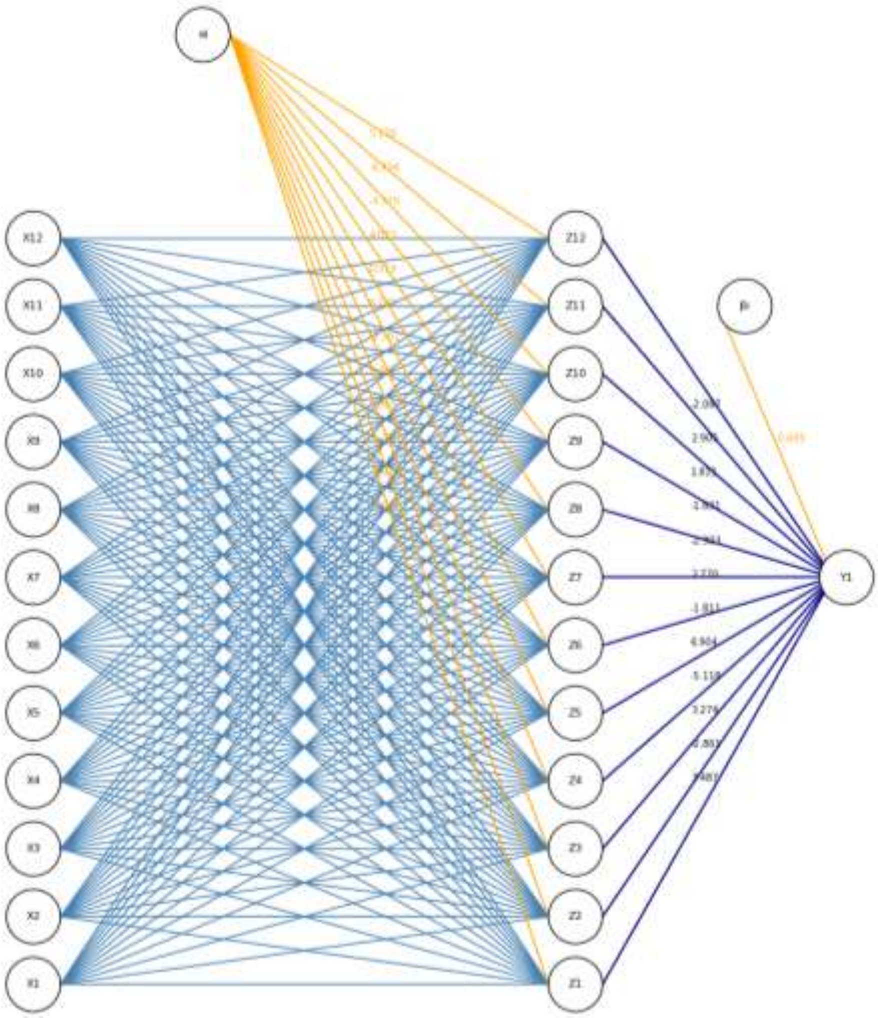

Figure 3. Optimal architecture of the 12-12-1 Multilayer Perceptron network

5. Comparison of Forecasting Method Performance

After the denormalization and forecasting process was carried out on the normalized data using the Hybrid Holt-Winters Exponential Smoothing (α = 0.5; β = 0.3; γ = 0.3)–Multilayer Perceptron (12-12-1) method calculated using equations (27) and (28), a comparative analysis was conducted to determine the method with the best level of accuracy in predicting rice prices in Indonesia. The forecasting accuracy values can be seen in Table 6.

Table 6. Comparative Analysis of forecasting accuracy the HWES and Hybrid HWES-MLP methods

Method	MSE	RMSE	MAPE
The HWES (α = 0.5; β = 0.3; γ = 0.3)	8523732.6	923.4532	6.2987
The Hybrid HWES (α = 0.5; β = 0.3; γ = 0.3)-MLP (12-12-1)	**9666.12**	**310.9117**	**1.9949**

Based on Table 6, it can be observed that both the HWES method (α = 0.5; β = 0.3; γ = 0.3) and the Hybrid HWES–MLP (12-12-1) demonstrate better forecasting performance compared to the HWES method alone in predicting rice prices in Indonesia. This is evidenced by the forecasting error evaluation results, which show an MSE of 9666.12, an RMSE of 310.9117, and a MAPE of 1.9949%. A comparison graph between the HWES method and the Hybrid HWES–MLP against the actual data is illustrated in Figure 4.

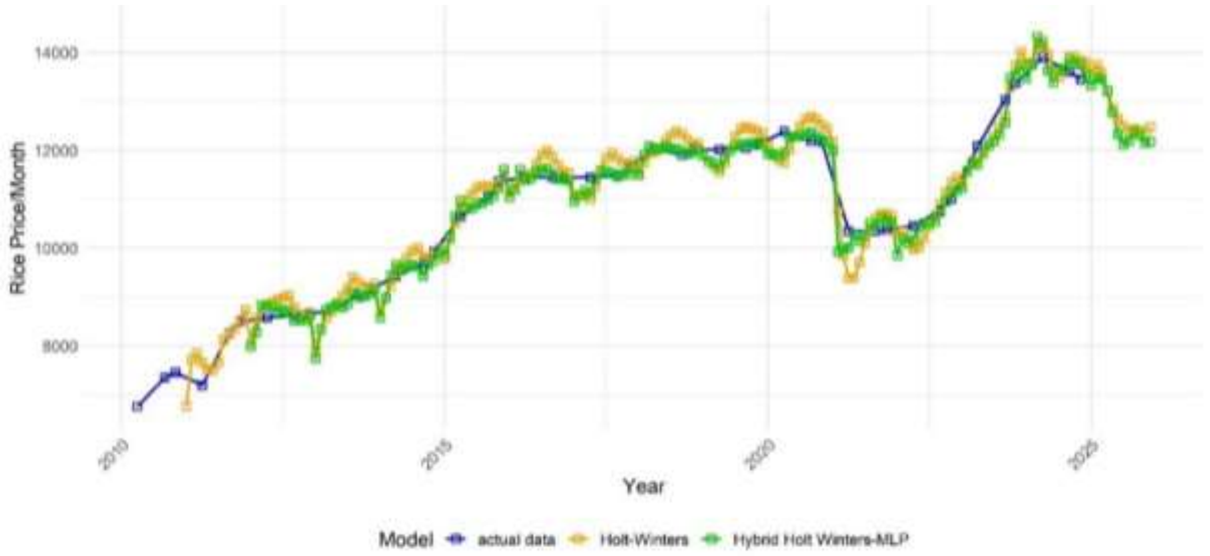

Figure 4. Comparison graph of rice price forecasting results in Indonesia using the HWES method and the Hybrid HWES-MLP

Based on the analysis results, the best method for forecasting rice prices in Indonesia is the Hybrid Holt-Winters Exponential Smoothing–Multilayer Perceptron (HWES-MLP). This hybrid approach is proven to provide higher accuracy compared to single models. This finding is consistent with research conducted by (Haris et al., 2023; Damaliana et al., 2023) which shows that hybrid models are capable of improving forecasting accuracy. Therefore, the Hybrid HWES–MLP model deserves to be used as a benchmark supporting government decision-making in national food price policy, in line with the research results by (Ruspayandi et al., 2022; Khairunnisa et al., 2022) who emphasized the importance of maintaining rice price stability, market intervention, and more timely and data-driven management of rice reserves stock.

D. CONCLUSION AND SUGGESTIONS

Based on the analysis results, the most effective method for forecasting rice prices in Indonesia is the Hybrid HWES ($\alpha = 0.5$; $\beta = 0.3$; $\gamma = 0.3$)–MLP (12-12-1). This hybrid approach proved to provide the highest accuracy with an MSE of 9.666.12, an RMSE of 310.9117, and a MAPE of 1.9949%, making it superior to using a single model. This research contributes by combining the strengths of the classical time series method and artificial neural networks, where HWES (Holt-Winters Exponential Smoothing) is effective in capturing linear patterns such as trend and seasonality, while MLP (Multilayer Perceptron) is capable of learning non-linear residual patterns that cannot be captured by the classical model. The results of the rice price forecasting in Indonesia using the Hybrid HWES-MLP method for the period of January to December 2025 show fluctuations in each month. The highest rice price is predicted to occur in February 2025, amounting to IDR 13,491.26, while the lowest price is predicted in July 2025, amounting to IDR 12,122.65. This information has significant implications as an early warning system for the government in anticipating potential price increases, allowing rice price stabilization strategies to be planned more effectively. The limitation of this study lies in the use of univariate data, meaning external factors such as climate, production costs, and import policies have not been included in the model. Therefore, future research is suggested to integrate more comprehensive external variables, as well as to develop the Holt-Winters method with other advanced development methods, such as Hybrid Holt-Winters Exponential Smoothing–Radial Basis Function Neural Network (HWES-RBFNN) and Hybrid Holt-Winters Exponential Smoothing-Long Short-Term Memory (HWES-LSTM).

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