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Optimization of Holt's Double Exponential Smoothing Model with Levenberg-Marquardt Algorithm for Forecasting Farmer Exchange Rate

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Abstract

The Farmer Exchange Rate (NTP) is an indicator of farmer welfare calculated from the ratio of prices received by farmers to costs incurred in farming. East Java is one of the provinces with the agricultural sector as the main pillar of the regional economy. However, the NTP in this region shows a fluctuating pattern with a certain trend that reflects the economic instability of the agricultural sector. This instability may lower farmers' purchasing power and threaten production sustainability. Therefore, accurate forecasting models are needed to support data-driven policy making. Holt's Double Exponential Smoothing (DES) is an effective method for analyzing trend-patterned data, as it captures both level and trend components through exponential smoothing. However, the model's accuracy heavily relies on selecting smoothing parameters, typically determined through a time-consuming trial-and-error process that may yield suboptimal results. This study proposes using the Levenberg-Marquardt algorithm to optimize parameter smoothing. The algorithm effectively combines the Gauss-Newton and Gradient Descent methods to minimize prediction error. The data included monthly NTP values in East Java from 2014 to 2024, sourced from BPS. The results showed that the model with optimized parameters has higher accuracy, with MAPE decreasing from 1.28% to 1.06%.

Keywords: *Farmer exchange rate, holt's DES, levenberg-marquardt, prediction.*

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1. INTRODUCTION

Farmer Exchange Rate (NTP) is one of the important indicators used to measure the welfare of farmers and evaluate their purchasing power in agricultural production activities [1]. This indicator is calculated by comparing the ratio between the price index obtained by farmers from the sale of their commodities and the price index paid to obtain goods and services needed in the farming process [2]. The disparity in the rate of change between the price index received and paid by farmers contributes to NTP fluctuations. These conditions reflect changes in the economic conditions of agricultural sector actors and provide an overview of the market dynamics that affect the sustainability of this sector.

East Java Province is known as one of the main agricultural centers in Indonesia and the third largest contributor to the Gross Regional Domestic Product (GRDP). However, the NTP value in this region shows a fluctuating pattern with a tendency to form a certain trend, which reflects instability in the economic conditions of the agricultural sector. This instability has the potential to reduce farmers' purchasing power and disrupt the sustainability of agricultural production, thus impacting the regional economy. Therefore, the dev elopment of a reliable forecasting model is necessary to provide a strong database for policy making. Forecasting is a process that is carried out systematically with the aim of estimating the likelihood of events that will occur in the future, based on data and information from the past and current conditions. This process is carried out to minimize prediction error, which is the difference between the forecast results and the reality that occurs. Although prediction cannot guarantee absolute accuracy of future events, this approach seeks to provide the most accurate estimate possible by considering patterns that have occurred previously [3].

One approach that is widely used in historical data-based forecasting is the time series method, which is a quantitative method that makes time the main basis in the analysis process. Time series data itself is data that is collected sequentially within a certain time interval, such as daily, monthly, or annually. The distinctive feature of this data lies in its chronological order, where each observation has a relationship with the observation at the previous time. Time series data is used to understand the dynamics of changes in a variable over time, and often shows certain patterns such as trends, seasonality, or random fluctuations that appear during the observation period [4].

Time series methods are widely applied in predicting economic indicators, including classical time series models and machine learning-based techniques. However, their accuracy and reliability are highly dependent on the characteristics of the data and the methods used. Time series approaches, such as Holt's Double Exponential Smoothing, have proven to be effective for handling trend patterns by considering the level and trend of the data in the forecasting process [5]. However, the accuracy of these methods is greatly affected by the selection of smoothing parameters (α and β), which are often determined manually or through a trial-and-error process.

Parameter selection by trial-and-error method in determining smoothing parameters is done through manual exploration to evaluate various combinations of alpha and beta values within a certain range, with the aim of obtaining the most optimal parameter combination [6]. This method generally requires a relatively long time and risks producing suboptimal parameter combinations. To improve efficiency and obtain more optimal parameterization results, an alternative approach that can be applied is the use of non-linear optimization algorithms that are more systematic and structured.

One of the non-linear optimization approaches that can be applied is the Levenberg-Marquardt algorithm. This algorithm aims to determine the optimal combination of model parameters by minimizing the least squares residual function between the estimated results and the observed data. The optimization process is performed iteratively by utilizing information on the sensitivity of the model to parameter changes, represented through the Jacobian matrix. This approach allows adjusting the update step dynamically by balancing the Gauss-Newton method for fast convergence and Gradient Descent to maintain stability. Thus, the Levenberg-Marquardt algorithm can improve model accuracy more efficiently [7].

Previous research on the prediction of Farmer Exchange Rate has been researched by Zulfa Razi, et al [8] using the Double Exponential Smoothing method of two Holt parameters and Holt-Winter Additive. The results showed that the Holt DES method has better performance with RMSE 3.413201 and MAPE 2.85835 lower than Holt-Winter Additive. In addition, other studies have introduced the Brown's Weighted Exponential Moving Average (B-WEMA) method approach with Levenberg-Marquardt optimization. The results showed that optimization in the B-WEMA method resulted in more accurate stock price predictions with MSE 3.619 and MAPE 1.99%, compared to without optimization [7].

Based on the background description, this research aims to optimize the Holt's DES model parameters using the Levenberg-Marquardt algorithm. Although the Holt's DES is effective in handling trend-patterned data, the accuracy of this method is greatly influenced by the selection of smoothing parameters α and β which are generally determined through trial-and-error method with a long process. To overcome this, the Levenberg-Marquardt algorithm is used to iteratively optimize the parameters by minimizing the prediction error. The optimization process is carried out through parameter initialization, error calculation, and sensitivity evaluation using the Jacobian matrix until convergence is achieved. The results of this research are expected to improve the accuracy of NTP forecasting.

2. METHODOLOGY

This research was conducted through several systematically arranged stages. The initial step involves a literature review to understand relevant theories and methods. Subsequently, monthly Farmer Exchange Rate (NTP) data for East Java were collected and prepared, included an initial exploration to identify underlying patterns. The data was divided into training and testing sets. Modeling was carried out using the Holt's Double Exponential Smoothing (DES) method, optimized with the Levenberg-Marquardt algorithm to improve prediction accuracy. The resulting model was evaluated using the MAPE metric before being used for forecasting. The methodological flow of this study is illustrated in **Figure 1.**

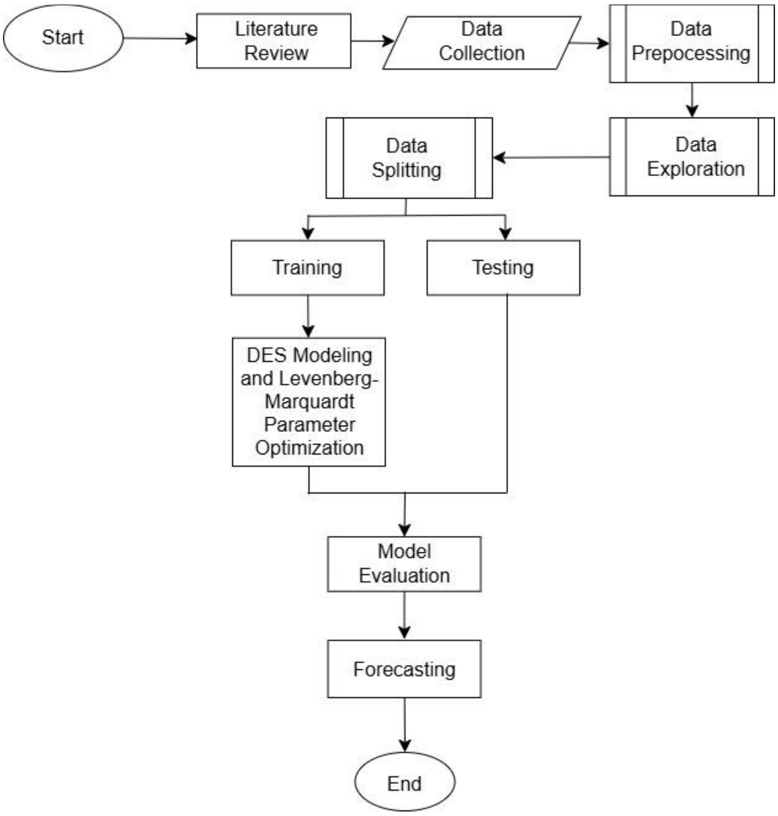

Figure 1. Research Flow

2.1. Literature Review

In this literature study, researchers searched various sources, including books, journals, and research reports to find research related to Farmer Exchange Rate (NTP) prediction analysis. The **focus** of this research is on the use of the Holt Double Exponential Smoothing (DES) forecasting method whose parameters are optimized using the Levenberg-Marquardt Algorithm. Based on previous research, the DES method optimized using this algorithm has proven effective, especially in the application of Brown's DES and Brown's Weighted Exponential Moving Average variations. The results of this previous research show that Levenberg-Marquardt optimization can reduce the error rate in prediction and improve the accuracy of forecasting results.

2.2. Data Collection

This research utilized a monthly time series dataset on the Farmer Exchange Rate (NTP) in East Java Province, sourced from official website of BPS-Statistics Indonesia at https://jatim.bps.go.id. The data covered the period from January 2014 to December 2024. NTP was chosen as main variable because it reflects economic condition of farmers in the region, which became focus of this study. This data is published periodically through the agricultural economic survey. Moreover, the period 2014-2024 was chosen because that period is considered representative to describe the dynamics of agricultural economy in East Java in recent years.

2.3. Data Preprocessing

To ensure the suitability of the data prior to analysis, a data preparation phase was conducted, which involved transforming date formats and normalizing variable values.

Since a wide range of values can adversely impact the accuracy of the prediction model, normalization is necessary to standardize the scale across variables while preserving the essential information contained within them [9]. This research used the Min-Max method, which is a linear transformation technique that transforms data into a range of 0 to 1 to reduce dominance of certain variables and improve model performance [10]. The Min-Max normalization process is expressed as:

$$x' = \frac{x_i - \min(x)}{\max(x) - \min(x)} \tag{1}$$

Based on Equation (1), $\boldsymbol{x_i}$ represents data value before normalization, $\boldsymbol{x'}$ is normalization result, $\mathbf{min}(\boldsymbol{x})$ is minimum value of a feature, and $\max(x)$ indicates maximum value of **a** feature.

2.4. Data Exploration

Once data has been prepared, the next process is data exploration stage which aims to understand basic patterns and characteristics of the NTP time series. Initial analysis is done through visualization of those time series data to observe long-term trends as well as seasonal fluctuations. In addition, time series decomposition is also conducted to separate the main components such as trend, seasonality, and residuals. This step is important so that structure of those data can be analyzed more deeply, thus supporting selection of most suitable forecasting method.

2.5. Data Splitting

After data exploration, the next process is data splitting using the walk-forward validation method with an expanding window approach. This technique was selected for its capacity to reflect practical forecasting scenarios, in which model is trained using historical observations and evaluated incrementally on future data [11]. At each iteration, training data is expanded by continuously adding new data to that data series without removing previous data, so that size of training data increases over time. This approach facilitates more accurate model evaluation and demonstrates adaptability to evolving data patterns [12].

2.6. Holt Double Exponential Smoothing Modeling

In Holt's Double Exponential Smoothing (DES) method, two main components are calculated, namely the exponential smoothing of data and the trend estimation. The update process of each component is determined by two different parameters, namely α (alpha) to update the level and β (beta) to update the trend. Both parameters have values between 0 and 1 and serve as weights to historical data [13]. The level component update is determined through following equation:

$$S'_t = aX_t + (1 - \alpha)(S'_{t-1} + b_{t-1}) \tag{2}$$

Based on Equation (2), the exponential smoothing value $\boldsymbol{S'_t}$ is calculated by combining the actual value $\boldsymbol{X_t}$ and the adjustment of the previous level $\boldsymbol{S'_{t-1}}$ as well as the previous trend $\boldsymbol{b_{t-1}}$. The trend estimate is also updated through following equation:

$$b_t = \beta\,(S'_t - S'_{t-1}) + (1-\beta)b_{t-1} \tag{3}$$

Based on **Equation (3),** this equation allows the trend to adjust to changes in the growth or decline rate of the data. Once the level and trend components are obtained, the forecasting value for the future period $t + m$ is calculated using following equation:

$$F_{t+m} = S'_t + b_t m \tag{4}$$

Based on **Equation (4),** $\boldsymbol{F_{t+m}}$ is forecasted value for the period $\boldsymbol{t+m}$, with $\boldsymbol{m}$ indicates number of steps ahead. This model requires initialization at an early stage, where $\boldsymbol{S_1}$ is set equal to value of first observation $\boldsymbol{X_1}$, and initial estimate of the trend $\boldsymbol{b_1}$ is obtained from difference between first two observations $\boldsymbol{X_2 - X_1}$.

2.7. Levenberg Marquardt Optimization

To improve accuracy, parameter values are optimized using the Levenberg-Marquardt algorithm. This algorithm is used to find optimal value of smoothing parameters α and β, by minimizing difference between predicted results and actual data **[14].** Calculation those parameters of this algorithm is based on following equation:

$$x^2(\beta) = \left(y - \hat{y}(\beta)\right)^T W\left(y - \hat{y}(\beta)\right) \tag{5}$$

Based on **Equation (5),** the Least Squares / Chi-Squared function is used to measure difference between observed data $\boldsymbol{y(t_i)}$ and model results $\boldsymbol{\hat{y}(t_i;\beta)}$, with $\boldsymbol{\beta}$ is parameter vector to be optimized. The weight matrix W is a diagonal matrix with entries $\boldsymbol{\frac{1}{m}}$, used to normalize the contribution of each observation to total error. The value of $\boldsymbol{x^2(\beta)}$ is minimized through an iterative process.

$$\boldsymbol{\frac{\partial}{\partial_\beta} x^2 = -2(y-\hat{y})^T W J} \tag{6}$$

Equation (6) represents derivative of the error function with respect to parameter, which is used in the Gradient Descent method. The matrix $\boldsymbol{J} = \frac{\partial \hat{y}}{\partial_\beta}$ is Jacobian Matrix, which expresses model sensitivity to parameter changes. The parameter update step in the Gradient Descent approach is:

$$\boldsymbol{h_{gd} = \alpha J^T W(y-\hat{y})} \tag{7}$$

With $\boldsymbol{\alpha}$ being the learning rate, and $\boldsymbol{h_{gd}}$ being the update direction vector.

$$\boldsymbol{[J^T W J]h_{gn} = J^T W(y-\hat{y})} \tag{8}$$

Based on **Equation (8)**, the parameter update using the Gauss-Newton method involves a linear quadratic approximation that provides a faster estimation of the optimization solution compared to the Gradient Descent method when applied to a quadratic error function. The value $\boldsymbol{h_{gn}}$ is a vector of parameter correction steps to be added to $\boldsymbol{\beta}$.

$$\boldsymbol{[J^T W J + \lambda I]h_{lm} = J^T W(y-\hat{y})} \tag{9}$$

Based on **Equation (9),** the parameter update process of the Levenberg-Marquardt algorithm that combines the Gradient Descent and Gauss-Newton methods determined by the damping parameter $\boldsymbol{\lambda} \geq \mathbf{0}$. When $\boldsymbol{\lambda}$ is small it approaches to the Gauss-Newton method. Conversely, when $\boldsymbol{\lambda}$ is large it approaches to the Gradient Descent Method. This allows adaptive flexibility to error function conditions.

$$\boldsymbol{p_i}(\boldsymbol{h_{lm}}) = \frac{\boldsymbol{x^2}(\boldsymbol{\beta}) - \boldsymbol{x^2}(\boldsymbol{\beta} + \boldsymbol{h_{lm}})}{\boldsymbol{h^t_{lm}}(\boldsymbol{\lambda i h_{lm}} + \boldsymbol{J^T W}(\boldsymbol{y} - \widehat{\boldsymbol{y}}(\boldsymbol{\beta})))} \tag{10}$$

Based on **Equation (10),** the ratio used to evaluate success of $\boldsymbol{h_{lm}}$ step in reducing error function value. If $\boldsymbol{p_i} > \boldsymbol{\varepsilon}$ (where is the tolerance threshold), then parameter update is accepted and $\boldsymbol{\lambda}$ is minimized. Otherwise, then the update step is rejected and $\boldsymbol{\lambda}$ is enlarged to minimize in next step to make process more stable.

2.8. Model Evaluation

After modeling process is complete, the next process is to evaluate accuracy of forecasting results. The Mean Absolute Percentage Error (MAPE) is among the frequently applied metrics in time series analysis, assessing prediction performance by averaging the absolute deviations between predicted and actual data, scaled relative to the actual values **[15]**. A low MAPE value indicates that model has a high level of accuracy. In general, a model is categorized as "excellent" if the MAPE is <10%, "good" if it is between 10%-20%, "fair" if it is between 20%-50%, and "poor" if it is more than 50% **[16]**. That evaluation is important for assessment whether model needs to be readjusted to improve prediction performance. The MAPE formula is written as follows:

$$MAPE = \left(\frac{1}{n}\sum_{i=1}^{n}\left|\frac{\varepsilon_i}{Y_i}\right|\right) \times 100\% \tag{11}$$

with ε_i is difference between actual value Y_i and predicted value $\hat{Y}_i$ also n is total number of observations.

3. RESULT AND DISCUSSION

3.1. Data Collection

Monthly data on Farmer Exchange Rate (NTP) in East Java Province was collected from official website of BPS-Statistics Indonesia (link: https://jatim.bps.go.id). **Table 1** presented data during the period 2014 to 2024 with a total of 132 observations.

Table 1. East Java Province NTP Data

No.	Year	Month	NTP
1.	2014	January	104.84
2.	2014	February	104.67
3.	2014	March	104.07
4.	2014	April	104.19
5.	2014	May	104.32
…	...	...	...
128.	2024	August	111.98
129.	2024	September	111.61
130.	2024	October	111.32
131.	2024	November	110.20
132.	2024	December	111.96

(BPS: 2024)

3.2. Data Preprocessing

Before process of time series analysis was carried out, the East Java Province NTP data, originally presented in 'Year' and 'Month' column formats, were first converted into datetime-type variables. The initial step involved transforming month names from text format to numerical values. Subsequently, the 'Year' and 'Month' columns were merged into a single 'Date' column, which was employed as index for time series analysis.

Table 2. Data Transformation

No.	Date	NTP
1.	2014-01-01	104.84
2.	2014-02-01	104.67
3.	2014-03-01	104.07
4.	2014-04-01	104.19
5.	2014-05-01	104.32
…	…	…
128.	2024-08-01	111.98
129.	2024-09-01	111.61
130.	2024-10-01	111.32
131.	2024-11-01	110.20
132.	2024-12-01	111.96

Table 2 showed that data were already organized in a time series, allowed application of forecasting models to identify historical patterns and project future values. Next, normalization of the transformed data was performed to equalize scale of values.

Table 3. Data Normalization

No.	Date	NTP
1.	2014-01-01	0.303157
2.	2014-02-01	0.295265
3.	2014-03-01	0.267409
4.	2014-04-01	0.272981
5.	2014-05-01	0.279016
...	...	...
128.	2024-08-01	0.634633
129.	2024-09-01	0.617456
130.	2024-10-01	0.603993
131.	2024-11-01	0.551996
132.	2024-12-01	0.633705

Table 3 showed that data has been normalized to a uniform scale (between 0 and 1) to improve stability of calculations, also facilitate the application of time series forecasting method in next stage of analysis.

3.3. Data Exploration

A time series visualization of the Farmer Exchange Rate (NTP) in East Java Province as shown in **Figure 2.**

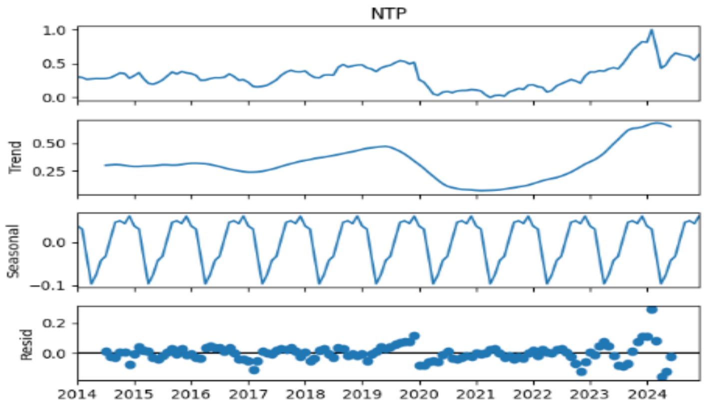

Figure 2. Time Series Decomposition

Figure 2. showed that the trend component was more dominant than seasonal component in those data. The trend at the beginning of period showed stability, then experienced a sharp decline in 2020, and began to increase in 2022. The seasonal pattern appeared consistent every year, but its contribution was relatively small compared to long-term changes shown by the trend pattern. At the beginning of period, residual points were around zero, indicated that data variability was relatively low. However, after 2022, residuals began to deviate from zero, reflecting heightened variability in data and implying potential nonlinearity in time series.

3.4. Data Splitting

The normalized Farmer Exchange Rate (NTP) data was divided by expanding window approach, where a certain amount of initial data used as training data to predict one test data point, then the testing data was added to the training data in next iteration until all data is used.

Table 4. Data Splitting

Split	Train (truncated)	Test
1	[0.3032, 0.2953, 0.2630, ...]	0.3524
2	[0.3032, 0.2953, 0.2630, ...]	0.3254
3	[0.3032, 0.2953, 0.2630, ...]	0.2530
4	[0.3032, 0.2953, 0.2630, ...]	0.2563
5	[0.3032, 0.2953, 0.2630, ...]	0.2772
...	...	...
104	[0.3032, 0.2953, 0.2630, ...]	0.6346
105	[0.3032, 0.2953, 0.2630, ...]	0.6715
106	[0.3032, 0.2953, 0.2630, ...]	0.6039
107	[0.3032, 0.2953, 0.2630, ...]	0.5520
108	[0.3032, 0.2953, 0.2630, ...]	0.6337

Table 5. shown data division using the expanding window approach with 108 iterations. In first iteration, an initial set of data (first 24 months) was used as training data to predict one test data point (25th month). The test data was then added to the training data in the next iteration, so that in second iteration the training data consists of 25 months, thus the model is tested again to predict the 26th month. This process continued until all data was used to ensure the model continues to learn and adapt to the evolving data over time.

3.5. Modeling

In modeling stage, the Holt's DES method is used by setting the parameters $\boldsymbol{\alpha} = \mathbf{0.5}$ and $\boldsymbol{\beta} = \mathbf{0.5}$. The calculation process produced a level component ($\boldsymbol{S'_t}$), a trend component ($\boldsymbol{b_t}$), and a one-step ahead forecasting value ($\boldsymbol{F_{t+1}}$) at each point in time.

Table 6. Holt's DES Modeling

No.	t	X_t	S_t	b_t	F_{t+1}	Split
0	1	0.303157	0.30	-0.01	NaN	1
1	2	0.295265	0.30	-0.01	0.29	1
2	3	0.267409	0.28	-0.01	0.26	1
3	4	0.272981	0.27	-0.01	0.26	1
4	5	0.279016	0.27	-0.01	0.26	1
...	...	...	...	...	...	...
8365	127	0.655525	0.53	-0.02	0.52	108
8366	128	0.634633	0.58	0.01	0.59	108
8367	129	0.617456	0.60	0.02	0.62	108
8368	130	0.603993	0.61	0.02	0.63	108
8369	131	0.551996	0.59	-0.00	0.59	108

Based on **Table 6** it showed that the Holt DES method was able to capture the up-and-down trend pattern in data. However, the small value of $\boldsymbol{b_t}$ (close to zero) indicated that the trend was not too sharp, so the model produced smoother and more stable forecasts. Nevertheless, stability of the level component and the direction of change in $\boldsymbol{b_t}$ still provided a clear picture of the pattern of NTP movement in long term, although it was less responsive to sudden changes in data. Therefore, parameter optimization using the Levenberg-Marquardt algorithm was conducted to improve forecasting accuracy.

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Best Alpha (Optimasi): 0.95
Best Beta (Optimasi): 0.5
Best Average MAPE (Optimasi): 0.14%
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Figure 3. Optimized Parameter Result

Figure 3. showed results of the Holt's DES parameter optimization using the Levenberg-Marquardt algorithm. The value of $\alpha = 0.95$ and $\beta = 0.5$ was obtained with an average MAPE of 0.14%. High alpha value made model quickly adjust to latest data, while the beta value of 0.5 indicated that the trend was updated in a balanced manner.

Table 7. Holt's DES Modeling With Optimization

No.	t	X_t	S_t	b_t	F_{t+1}	Split
0	1	0.303157	0.30	-0.01	NaN	1
1	2	0.295265	0.30	-0.01	0.29	1
2	3	0.267409	0.27	-0.02	0.25	1
3	4	0.272981	0.27	-0.01	0.27	1
4	5	0.279016	0.28	-0.00	0.28	1
...	...	...	...	...	...	...
8365	127	0.655525	0.66	0.04	0.70	108
8366	128	0.634633	0.63	0.01	0.65	108
8367	129	0.617456	0.62	-0.00	0.61	108
8368	130	0.603993	0.60	-0.01	0.60	108
8369	131	0.551996	0.55	-0.03	0.52	108

Table 7 showed that the obtained values of S_t' and b_t were adaptive to changes in actual data (X_t). At beginning, the value of b_t was quite small close to zero, indicated a weak or stable trend. However, at certain points, b_t showed more pronounced positive or negative values, reflected the change in trend direction detected by model. For example, at $t = 127$, the b_t value of 0.04 indicated an increasing trend. Conversely, at $t = 131$, b_t value of -0.03 indicated a downward trend. This result showed that application of optimal parameters could capture trend dynamics more responsively.

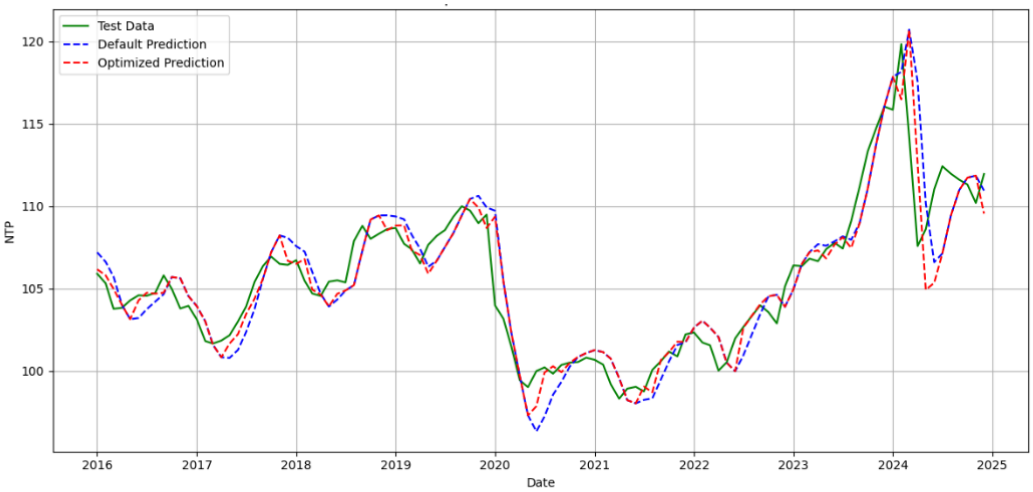

Figure 4. Visualization of prediction comparison plots using holt DES

The graph in Figure 4. showed that prediction using Holt's DES method with optimized parameters ($\alpha = 0.95, \beta = 0.5$) was more accurate in following the actual NTP data pattern compared to default parameters ($\alpha = 0.5, \beta = 0.5$). The prediction line generated using optimized parameters demonstrated greater responsiveness to trend fluctuations, particularly during periods of abrupt spikes and declines, resulting in forecasts that more closely approximated the actual values.

3.6. Model Evaluation

The evaluation results showed that optimizing the parameters α and β using the Levenberg-Marquardt algorithm has improved the accuracy of the model. Before optimization, the MAPE value was 1.28%, while after optimization the MAPE value dropped to 1.06%. This decrease indicated that the model with optimized parameters could produce predictions that are closer to actual values compared to the model before optimization.

Forecasting the Farmer Exchange Rate (NTP) was carried out for the next 3 months, namely the period January to March 2025. The forecasting results using the Holt's DES method are shown in **Table 8.**

Table 8. Forecasting Result

No.	Month	Forecasting	Actual
1.	January 2025	112.324013	113.26
2.	February 2025	112.805267	110.90
3.	March 2025	113.286522	111.61

The prediction results of the Farmer Exchange Rate (NTP) from January to March 2025 showed gradual upward trend every month. The NTP value was projected to increase from 112.32 in January 2025 to 113.28 in March 2025. This increase reflected positive trend pattern captured by the model, which indicated potential for strengthening farmer exchange rates in the first semester period of 2025 if the historical pattern continues. When compared to actual values, the forecasting results exhibited a relatively small deviation, with absolute errors of 0.94, 1.91, and 1.68 for January, February, and March, respectively. These differences indicated that the model captures the direction and magnitude of the trend effectively.

The closeness between predicted and actual values further demonstrated the contribution of parameter optimization using the Levenberg-Marquardt algorithm in enhancing forecasting accuracy. For instance, Deswita et al. **[14]** implemented Levenberg-Marquardt optimization in Brown's DES and B-WEMA models to forecast tourist arrivals in Central Java, resulting in improved prediction performance with MAPE values around 16.26%. Likewise, Putri et al. **[7]** applied the same optimization to the B-WEMA method for stock price forecasting, where the MAPE decreased from 3.02% to 1.99%. Thus, this study supports the conclusion that Levenberg-Marquardt optimization not only enhances model performance but also improves sensitivity in detecting trend changes in economic indicators like the Farmer Exchange Rate.

4. CONCLUSION

Drawing from the preceding analysis, it can be inferred that implementing Holt's Double Exponential Smoothing (DES) method, enhanced by the Levenberg-Marquardt optimization algorithm, successfully identifies trend patterns within East Java's Farmer Exchange Rate (NTP) data. This approach yields reasonably accurate short-term forecasts. Although the model demonstrates solid performance in reducing prediction errors, minor seasonal components remain partially unaccounted for. Future research may focus on improving the model's ability to capture such seasonal fluctuations by employing Triple Exponential Smoothing.

AUTHOR CONTRIBUTIONS STATEMENT

Author	Contribution Roles
Lisa Dama Yanti	Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Visualization, Writing – original draft, Writing – review & editing, Project administration, Resources
Wahyu Syaifullah J. S.	Supervision, Validation, Writing – review & editing
Aviolla Terza Damaliana	Supervision, Validation, Writing – review & editing

DATA AVAILABILITY

The data that support the findings of this study are openly available from BPS-Statistics Indonesia at https://www.bps.go.id/.

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