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OPTIMIZATION OF AVERAGE RICE PRICE FORECASTING IN EAST JAVA USING DECOMPOSITION-WEIGHTED FUZZY TIME SERIES WITH LAGRANGE AND DIFFERENTIAL EVOLUTION

Alya Fitri Syalsabilla[1], Agus Fachrur Rozy[2]

[1]Department of Statistics, Institut Teknologi Sepuluh Nopember, Surabaya, Indonesia, alyaaaaasy@gmail.com
[2]Department of Statistics, University Brawijaya, Malang, Indonesia, agus.rozy@yahoo.com

Abstract

Accurate rice price forecasting is crucial for East Java's economic stability. East Java stands as Indonesia's top rice-producing province, supported by data from Badan Pusat Statistik (BPS) published in October 2024, which highlights an impressive production volume of 9 million tons, outperforming all other provinces in the country. Using the Weighted Fuzzy Time Series (WFTS) model combined with Lagrange Quadratic Programming (LQP) and Differential Evolution (DE), this study forecasts rice prices from January to July 2024 using data from https://panelharga.badanpangan.go.id. The WFTS-LQP-DE model enhances accuracy by refining forecasts through DE, showing improvements over the WFTS-LQP model with lower Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). Recommendations include integrating WFTS-LQP-DE forecasts into planning, improving supply chain management, and establishing a price stabilisation fund.

Keywords: *Weighted Fuzzy Time Series; Lagrange Quadratic Programming; Differential Evolution; Rice Price.*
JEL Classification: C53; Q11.

INTRODUCTION

Rice price forecasting is crucial in maintaining economic stability and food security in Indonesia, particularly in East Java, a major rice-producing region. East Java is supported by data from Badan Pusat Statistik (BPS) published in October 2024, which highlights an impressive production volume of 9 million tons, outperforming all other provinces in the country. Fluctuating rice prices can impact the well-being of the general population, especially those in economically vulnerable groups. (Rozaki, 2021). One of the main causes of these issues includes variable climate and weather conditions, compounded by pest disturbances leading to crop failures, w hich frequently result in rising rice prices. If not addressed promptly, these fluctuations can lead to more severe consequences, such as inflation. (Fitri, 2022). T herefore, accurately forecasting rice prices is essential for the government and other stakeholders to anticipate market volatility and develop effective policies.

The research conducted by Sukmaningtyas et al. (2023) demonstrates that price prediction technology is crucial for preparing for price increases at specific times and serves as a basis for various policies to address unavoidable future rice price surges. Various rice price forecasting techniques have been employed, including the Weighted Fuzzy Time Series, which represents a novel concept in forecasting methods. Over time, the Weighted Fuzzy Integrated Time Series (WFITS) emerged, introducing weighted differences in relationships and the use of higher-order sequences. In the study by Rahmawan et al. (2019), first-order and higher-order WFITS methods were applied to forecast rice prices in Indonesia based on data from January

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2011 to December 2017. This applicatio n yielded RMSE and MAPE values of 69.898 and 0.47% for test data, respectively, and RMSE and MAPE values of 70.4039 and 0.54% for training data, respectively.

Although the Weighted Fuzzy Time Series method improves accuracy by assigning weights to each relationship, it has certain limitations. One of these is the complexity involved in determining the appropriate weights for each relationship, which can impact the prediction results. Additionally, this method may not effectively capture sudden changes or unexpected patterns in the data due to its reliance on available historical data. Research by Rozy et al. (2023) addresses these limitations by adjusting the prediction values using Lagrange Quadratic Programming (LQP). This approach enhances the WFTS model and evaluates its accuracy with MAPE, which showed a value of 0.61% for the monthly closing prices of the IHSG from January 2017 to January 2023. The model's effectiveness in forecasting is demonstrated by its low MAPE value, achieved through a deterministic approach and weight adjustment during fuzzification.

The decomposition process is used in the Weighted Fuzzy Time Series (WFTS) method to enhance prediction accuracy by breaking down the data into simpler components: trend, seasonal, and residual. By separating the data into these parts, the forecasting process can focus more precisely on each element individually, allowing for more accurate adjustments and improving the model's ability to capture the underlying patterns in rice prices. (Lehmann & Romano, 2022). This decomposition approach enables the forecasting model to handle each aspect of the data separately, which aids in better identifying and modelling the underlying patterns, thereby increasing prediction accuracy (Samari et al., 2022). For example, the model can specifically address long-term trends, adjust for seasonal patterns, and reduce noise in the residuals to produce more precise predictions.

However, decomposition alone is not always sufficient to optimise prediction outcomes. Therefore, additional optimisation techniques such as Differential Evolution (DE) are needed to enhance forecasting results. Differential Evolution is an optimisation algorithm used to find the best solution within a model's parameter space (Ahmad et al., 2022). In the context of WFTS, DE is employed to more effectively adjust the weights and parameters of the model, leading to more accurate predictions. Differential Evolution works by iteratively modifying existing solutions to identify the optimal parameters that improve model performance. (Arung-Laby & Huda, 2022). This algorithm explores and exploits the parameter space to find the optimal combination of weights that will enhance forecasting accuracy. The process involves creating an initial population of solutions, evaluating these solutions based on an objective function, and updating the solutions through mutation and crossover mechanisms. By applying Differential Evolution to the WFTS model, the model parameters can be fine-tuned more precisely, thereby improving the forecasting results. This algorithm helps in optimising weights and other parameters that affect prediction accuracy, leading to more reliable and accurate outcomes.

The integration of WFTS with LQP and DE is expected to enhance prediction accuracy by combining the strengths of each method in handling uncertainty and optimising model parameters. With a more accurate and stable prediction model, this research aims to make a significant contribution to food planning and policy in East Java. Specifically, the model can assist policymakers and other stakeholders in making better decisions regarding rice stock management, pricing, and distribution strategies. Additionally, with more reliable rice price predictions, it is hoped that price stability can be achieved, thereby improving food security in the region. Thus, this research has the potential to provide widespread benefits by boosting economic well-being and ensuring more sustainable food security in East Java.

RESEARCH METHOD

A. Data set

The data utilised in this research consists of the National Average Rice Prices per month, covering the period from January 1, 2024, to July 1, 2024, specifically for East Java. The data is sourced from the platform https://panelharga.badanpangan.go.id/harga-eceran, which is widely recognised for providing accurate and up-to-date information on various economic indicators and commodity prices in Indonesia, including rice. This data offers in-depth insights into the dynamics of the rice market in Indonesia, enabling researchers to comprehend the factors influencing price changes during the specified period.

The study's use of daily average rice prices as a variable allows it to effectively track and analyse price movements and fluctuations within East Java. This analysis helps in understanding how rice prices evolve, identifying any underlying trends, and providing insights into factors influencing these changes. By focusing on this variable, the research aims to develop a detailed understanding of price dynamics and make informed policy recommendations.

B. Methodology

In this study, the methodology employs a comprehensive approach to enhance predictive patterns for average rice prices in East Java. The first step involves generating time series data that captures the complexities of rice prices. Using a decomposition method, the data is carefully processed to separate key components, such as trends, seasonal effects, and random variations. The decomposition process is integrated into the Weighted Fuzzy Time Series algorithm, starting with the creation of the universe as follows (Zamelina et al., 2024):

$$\mathrm{U} = [\mathrm{D}_{\min} - \mathrm{B}_1, \mathrm{D}_{\max} + \mathrm{B}_2] \quad (1)$$

The creation of the universe in Equation (1) aims to fuzzify the actual data. Additionally, in this study, the fuzzified data is further decomposed to obtain a detailed breakdown of the time series components, which is formulated as follows. (Husain & Amran, 2023):

$$Y_t = I_t . T_t . C_t . E_t \quad (2)$$

Based on Equation (2), the actual data is subsequently grouped into each decomposition component, which has different fuzzy membership values ranging from 1 to others. The next transformation process involves estimating the weighted fuzzy Time Series weights using Lagrange Quadratic Programming (LQP), which is defined as (Rozy et al., 2023):

$$L(w_{j,i}, \lambda_i) = \sum_{j=1}^{n} w_{j,i}^2 u_{j,i} + 2\lambda_i \left(\sum_{j=1}^{n} w_{j,i} - 1\right) \quad \text{with} \quad i = 1,2,3,\dots,n \quad (3)$$

Next, fuzzy logic relationships are iteratively built to construct a weight matrix for forecasting rice prices in East Java. The subsequent step is to optimise the prediction results using Differential Evolution (DE). Differential Evolution enhances the optimisation process through population-based search strategies, starting with initialisation, which involves generating initial values for the generation variable set to 0, variable j, and vector i, As represented by the following notation (Zhao et al., 2022):

$$x_{j,i,0} = rand_j(0,1).\left(b_{j,U} - b_{j,L}\right) + b_{j,L} \quad (4)$$

Following initialisation, DE will mutate and combine the initial population to produce a population with N trial vectors. In DE, mutation is performed by adding the difference between two vectors to a third vector using the following approach (Maruhawa et al., 2023):

$$v_{i,g} = x_{r0,g} + F.(x_{r1,g} - x_{r2,g}) \quad (5)$$

The term "crossover" here is distinct from the crossover in Genetic Algorithms. In this stage, DE performs the crossover of each vector, x_i, g, with the mutant, v_i, g, to create the resulting crossover vector, u_i, g, using the formula (Paillin et al., 2019).

$$u_{i,g} = u_{j,i,g} = \begin{cases} v_{j,i,g};\ j,i,g \le Cr \\ v_{j,i,g};\ j,i,g\ for\ others \end{cases} \quad (6)$$

The selection process here involves choosing between two vectors. If the trial vector, ui,g, has a smaller objective function value than the objective function value of its target vector, xi,g, then ui,g will replace the position of xi,g in the population in the next generation. If the opposite occurs, the target vector will remain in its position within the population. In the final stage, a robustness check is performed using three indicators.

The Mean Absolute Error (MAE) is a commonly used metric for assessing the accuracy of a predictive model. It measures the average magnitude of errors in a set of predictions, without considering their direction. In other words, MAE calculates the average absolute difference between the predicted values and the actual values, providing a straightforward measure of how well the model's predictions match the observed data (Robeson & Willmott, 2023).

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|Y_t - \widehat{Y}_t\right| \quad (7)$$

Where Y_t represents the actual value of Y at time t, $\widehat{Y}_t$ represents the predicted value at the time t, and n Denotes the number of observations. Root Mean Square Error (RMSE) is a widely used metric for evaluating the accuracy of predictive models. It quantifies the average magnitude of prediction errors by taking the square root of the average of the squared differences between predicted values and actual values. Unlike Mean Absolute Error (MAE), RMSE emphasises larger errors more than smaller ones due to the squaring of differences. (Hodson, 2022).

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(Y_t - \widehat{Y}_t\right)^2} \quad (8)$$

Where Y_t represents the actual value of Y at time t, $\widehat{Y}_t$ represents the predicted value at the time t, and n denotes the number of observations.

Mean Square Error (MSE) is a fundamental metric used to evaluate the performance of predictive models by quantifying the average squared difference between predicted values and actual values. It provides a measure of how well a model's predictions approximate the actual data, with larger errors contributing more significantly due to the squaring operation. (Ito & Kubokawa, 2020).

$$MSE = \frac{1}{n}\sum_{t=1}^{n}\left(Y_t - \widehat{Y}_t\right)^2 \quad (9)$$

Where Y_t represents the actual value of Y at time t, $\widehat{Y}_t$ represents the predicted value at the time t, and n Denotes the number of observations interpretation and provides policy recommendations based on the prediction results.

RESULTS AND DISCUSSION

This section is divided into seven subsections. The first subsection covers key aspects of the WFTS-LQP algorithm and its optimisation process using Differential Evolution (DE). The second subsection presents the primary predictability results. Finally, the last subsection addresses the robustness checks and provides policy recommendations for the East Java government.

Preliminary Result

This study's descriptive analysis aimed to examine the variations in the Average Rice Price in East Java over the period from January 1, 2024, to July 1, 2024. The findings were illustrated through a series of visualisations, including:

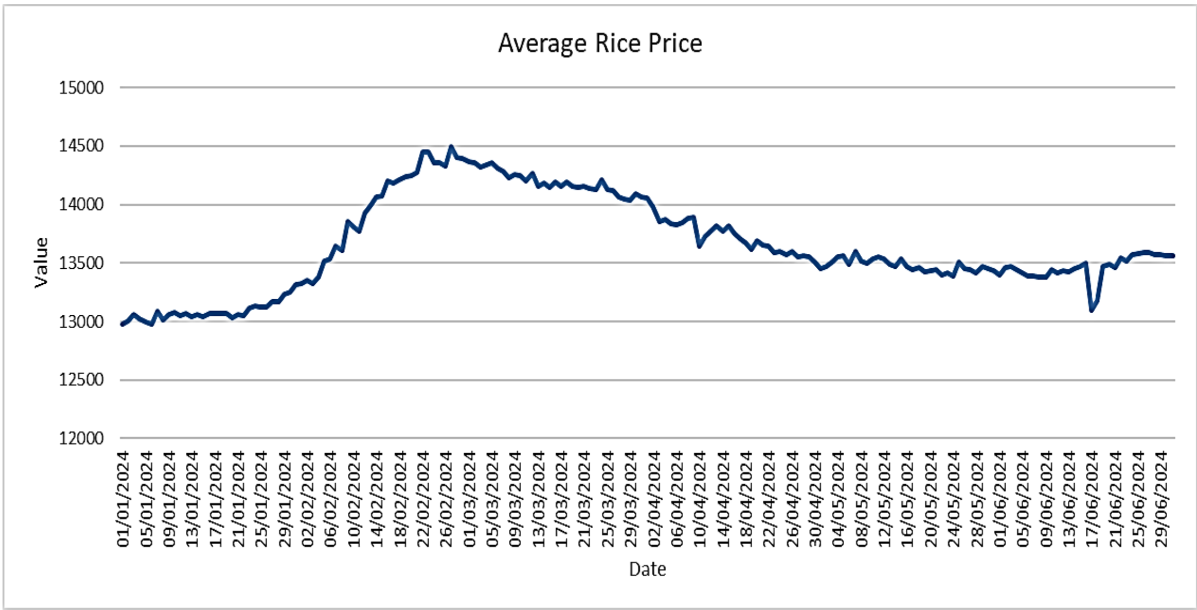

Figure 1. Actual Average Rice Price
Source: Badan Pangan Nasional (2024)
Notes: This figure illustrates the actual average rice prices in East Java from January 1, 2024, to July 1, 2024. It provides a visual representation of the price fluctuations over this timeframe, highlighting trends and variations in the market.

From January 1, 2024, to July 1, 2024, the average rice price in East Java displayed a notable upward trend. Starting at 12,980 IDR on January 1, the price increased steadily, peaking at 14,205 IDR by February 16. This early surge was followed by a period of fluctuation, where the price reached a high of 14,060 IDR by March 31 but then exhibited some volatility with periodic declines and recoveries. In April, the price fell to as low as 13,510 IDR but showed signs of recovery in May, closing at 13,550 IDR. The trend continued into June with relative stability, with the price hovering around 13,500 IDR and ending at 13,565 IDR on July 1. The data reflects both seasonal patterns and market dynamics, with periods of significant price changes and stabilisation, suggesting ongoing shifts in the rice market throughout the first half of 2024.

Preprocessing Data

In the next stage, data preprocessing involves dividing the dataset into training and testing sets. The training set includes data on the average rice price in East Java from January 1, 2024, to May 31, 2024, while the testing set covers the period from June 1, 2024, to July 1, 2024. This division is designed to validate the model, mitigate overfitting, and provide an impartial evaluation of its performance. By assessing the model on a separate dataset from the training period, we can gauge its ability to predict and adjust to variations that were not present during training.

This separation also helps in detecting overfitting, where the model becomes excessively adapted to the training data and performs poorly on new, unseen data. The method offers a realistic view of the model's effectiveness in real-world scenarios. Insights gained from testing can inform further adjustments, such as applying regularisation techniques or altering model parameters. Additionally, by dividing the data temporally, the model is evaluated on its ability to handle changes in trends and patterns over time, which is crucial for accurate time series analysis.

Build Decomposition

The process of decomposing time series data serves as an initial analysis step to identify patterns of change within the data. This technique involves breaking down the data into its main components, such as trend, seasonal, and residual. The phrase "used as an initial analysis to identify patterns of change in the data" underscores the primary goal of decomposition, which is to provide preliminary insights into how the data changes over time.

In this study, the decomposition process is conducted during the fuzzification stage, laying the groundwork for the creation of a quadratic Lagrange function that subsequently generates predictive values. The outcomes of the decomposition are expressed through the sequence of linguistic variables between observations from 1 January 2024 to 31 May 2024 for the average rice price, using equation (11) as follows:

Table 1. Decomposition of Linguistic Variable

Date	Fuzzyfikasi Trend	Fuzzyfikasi Season	Fuzzyfikasi random
01/01/2024	A1	A1	A5
02/01/2024	A1	A2	A5
03/01/2024	A1	A4	A6
...	...	...	...
30/05/2024	A3	A7	A5
31/05/2024	A3	A7	A5

Source: Data processing

Notes: This table describes the decomposition process for linguistic variables in each observation of the average rice price in East Java from January 1, 2024, to May 31, 2024.

The table illustrates the decomposition process for linguistic variables in each observation of the average rice price in East Java from January 1, 2024, to May 31, 2024. It breaks down the average rice prices into three primary components: trend, seasonality, and randomness, with each date corresponding to a specific fuzzy linguistic variable for each element.

For instance, the trend component shows a stable trend categorised as "A1" from January 1 to January 3, 2024, which shifts to "A3" towards the end of May, indicating a change in trend behaviour. The seasonal component progresses from "A1" on January 1, moving through different stages such as "A2" and "A4", and reaches "A7" by May 30 and 31, marking the culmination of the seasonal cycle.

The random component, indicating irregular variations, starts with "A5" on January 1 and 2, changes to "A6" on January 3, and returns to "A5" by the end of May, reflecting consistent random fluctuations similar to the beginning of the year. This detailed breakdown aids in understanding and predicting future rice price trends based on historical data.

Formulation Lagrange Quadratic Programming

The Lagrange equation model is derived from the membership levels in the training data, which are then distributed to each linguistic variable for each decomposition component as shown below: During the process of predicting the price of rice per kg, each value generated through the decomposition process is employed. The prediction is assessed by considering the trend condition, where the linguistic variable relationship between $t-1$ and t is utilised. Simultaneously, for the seasonal effect, the six previous periods are employed to forecast the current period ($t-6$ to t). The random effect is calculated by combining the effects of both trend and seasonality. Additionally, it is necessary to formulate using the Lagrange equation in equation (3), which can be expressed as follows:

$$L(w_{j,1},\lambda_1) = \sum_{j=1}^{20} w_{j,1}^2 u_{j,1} + 2\lambda_1(\sum_{j=1}^{20} w_{j,1} - 1)$$
$$L(w_{j,2},\lambda_2) = \sum_{j=1}^{5} w_{j,2}^2 u_{j,2} + 2\lambda_2(\sum_{j=1}^{5} w_{j,2} - 1)$$
$$L(w_{j,3},\lambda_3) = \sum_{j=1}^{22} w_{j,3}^2 u_{j,3} + 2\lambda_3(\sum_{j=1}^{22} w_{j,3} - 1)$$
$$L(w_{j,4},\lambda_4) = \sum_{j=1}^{16} w_{j,4}^2 u_{j,4} + 2\lambda_4(\sum_{j=1}^{16} w_{j,4} - 1)$$
$$L(w_{j,5},\lambda_5) = \sum_{j=1}^{13} w_{j,5}^2 u_{j,5} + 2\lambda_5(\sum_{j=1}^{13} w_{j,5} - 1)$$
$$L(w_{j,6},\lambda_6) = \sum_{j=1}^{9} w_{j,6}^2 u_{j,6} + 2\lambda_6(\sum_{j=1}^{9} w_{j,6} - 1)$$
$$L(w_{j,7},\lambda_7) = \sum_{j=1}^{19} w_{j,7}^2 u_{j,7} + 2\lambda_7(\sum_{j=1}^{19} w_{j,7} - 1)$$
$$L(w_{j,8},\lambda_8) = \sum_{j=1}^{11} w_{j,8}^2 u_{j,8} + 2\lambda_8(\sum_{j=1}^{11} w_{j,8} - 1)$$

The formulation of the equation is developed based on the number of members in the actual data values for each interval class within the linguistic variables. The WFTS-LQP equation integrates the fuzzy time series approach with Lagrange multipliers to handle the optimisation problem, providing a robust framework for making predictions. The equation is solved using partial derivatives, which involves calculating the derivatives with respect to each variable and setting them to zero. This process helps in finding the optimal values that minimise the error in predictions. The solution of the WFTS-LQP equation through partial derivatives yields the predicted values, reflecting the expected future values based on the trends, seasonality, and randomness observed in the historical data. This structured and optimised method ensures accurate forecasting by considering the membership distribution of actual data values in linguistic intervals.

Forecast Result

In the following subsection, forecasts for the WFTS-LQP model are calculated based on the established weights. The results are obtained by multiplying each estimated weight with the actual average rice price values corresponding to each membership in the linguistic variable. The figure below illustrates the forecasting results using the WFTS-LQP model:

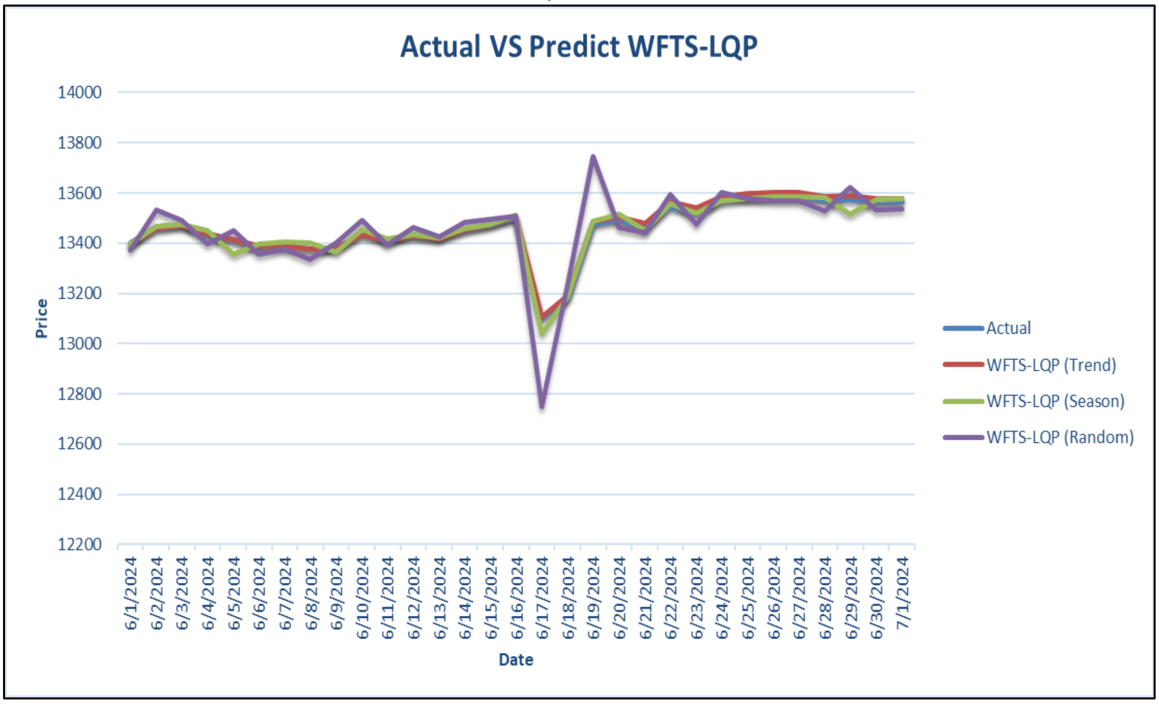

Figure 2. Forecasting using Model WFTS-LQP
Source: Data processing

Notes: This figure illustrates the prediction of average rice prices in East Java using the Weighted Fuzzy Time Series Lagrange Quadratic Programming model. The predictions are based on testing data from June 1, 2024, to July 1, 2024.

The figure provides a comparative analysis of the actual average rice prices in East Java from June 1, 2024, to July 1, 2024, against the predictions generated by the Weighted Fuzzy Time Series Lagrange Quadratic Programming (WFTS-LQP) model, including its trend, seasonal, and random components. The actual average rice prices, represented in blue, show daily fluctuations with values ranging from 13,400 IDR on June 1, 2024, to 13,565 IDR on July 1, 2024. The WFTS-LQP (Trend) predictions, shown in red, follow a smooth trajectory reflecting the long-term trend. For instance, on June 1, 2024, the trend prediction was 13,396.89 IDR, and by July 1, 2024, it was 13,579.18 IDR. The WFTS-LQP (Seasonal) predictions, displayed in green, capture seasonal variations. On June 1, 2024, the seasonal prediction was 13,396.59 IDR, and by July 1, 2024, it reached 13,579.04 IDR. The WFTS-LQP (Random) predictions, illustrated in purple, account for unpredictable changes. On June 1, 2024, the random prediction was 13,371.52 IDR, increasing to 13,536.78 IDR by July 1, 2024.

The figure demonstrates how these components combine to form the final prediction, providing a comprehensive view of how each aspect contributes to the model's overall forecast. For example, the WFTS-LQP model's predictions closely align with actual prices, with the trend component providing a steady forecast, the seasonal component adjusting for periodic changes, and the random component capturing irregular fluctuations. This detailed breakdown helps assess the model's effectiveness in reflecting the complexities of rice price movements.

In the subsequent analysis, the predictions obtained from the Weighted Fuzzy Time Series Lagrange Quadratic Programming (WFTS-LQP) model are further refined using the Differential Evolution (DE) algorithm. This optimisation process is critical for improving the accuracy and reliability of the forecasting results. The primary goal of applying DE in this context is to enhance the model's performance by fine-tuning its parameters to minimise prediction errors. DE operates through an iterative process that generates new candidate solutions based on existing ones, using mechanisms of mutation, crossover, and selection. This approach allows DE to explore a wide range of potential solutions and converge towards an optimal set of parameters that best fit the data. By incorporating DE into the optimisation phase, the model’s predictions are adjusted to better align with the actual data, thereby increasing forecasting precision. The optimisation process focuses on reducing discrepancies between predicted and actual values, ensuring that the model can effectively capture underlying trends and patterns. This refinement is crucial for improving the model's generalisation capability, enabling it to perform robustly not only on historical data but also on new, unseen datasets.

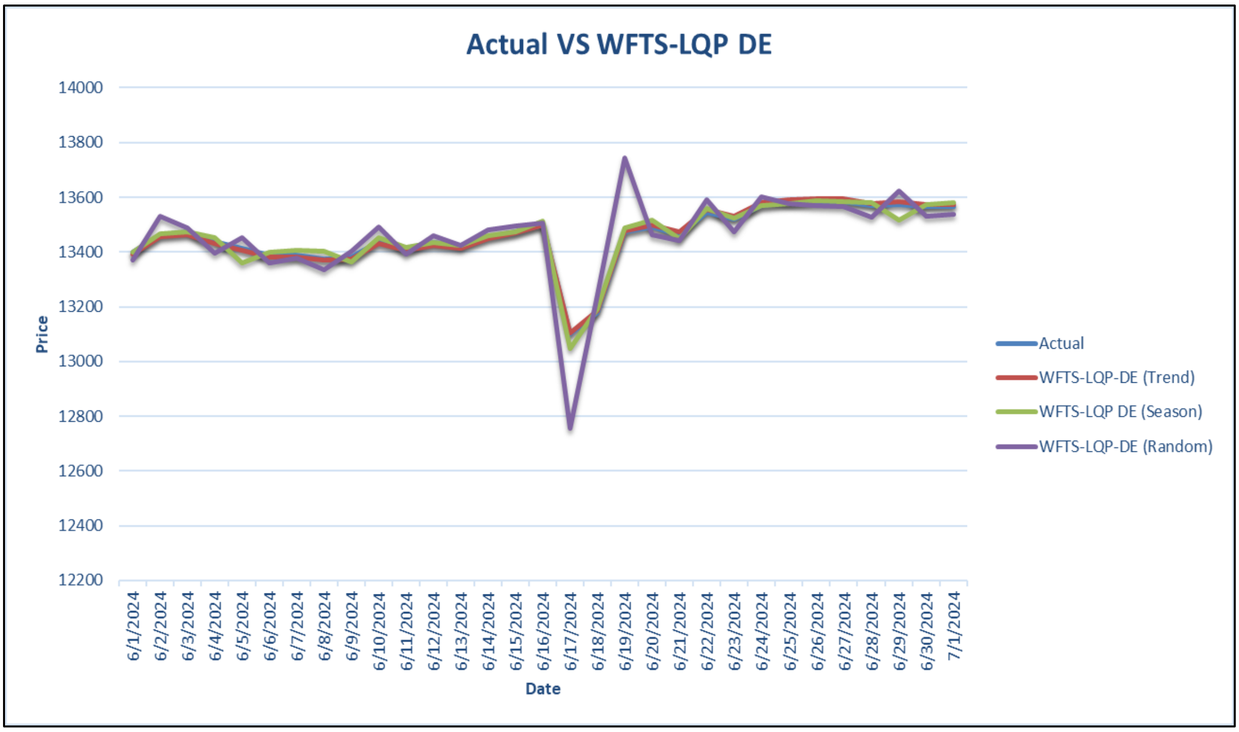

Figure 3. Forecasting using Model WFTS-LQP DE
Source: Data processing
Notes: This figure illustrates the prediction of average rice prices in East Java using the Weighted Fuzzy Time Series Lagrange Quadratic Programming model. The projections are based on testing data from June 1, 2024, to July 1, 2024. Additionally, the prediction results have been optimised using the Differential Evolution algorithm for improved accuracy.

The figure presents the forecasting results for the average rice prices in East Java, using the Weighted Fuzzy Time Series Lagrange Quadratic Programming with Differential Evolution (WFTS-LQP-DE) model. This model refines predictions by incorporating trend, seasonal, and random components, with the Differential Evolution algorithm optimising the forecasts. In the figure, the actual average rice prices are depicted in blue. The trend component predictions are shown in red, reflecting the model's ability to capture the overall price trajectory. For instance, on June 1, 2024, the actual price was 13,400, while the trend prediction was 13,391.39, indicating minimal deviation.

The seasonal component predictions are illustrated in green, representing the model's effectiveness in accounting for regular seasonal fluctuations. On June 6, 2024, the actual price was 13,390, and the seasonal prediction was 13,400.19, demonstrating a good fit for seasonal patterns. The random component predictions are presented in purple, addressing irregular variations not captured by trend or seasonality. For example, on June 16, 2024, the actual price was 13,500, and the random prediction was 13,506.05, showing close alignment.

Overall, the WFTS-LQP-DE model offers a comprehensive forecasting approach, integrating trend, seasonal, and random elements to accurately predict future rice prices. The figure, with actual prices in blue and forecasted values in red, green, and purple, illustrates the model's precision and reliability in predicting the dynamic price movements of rice in East Java.

Robustness Check

In the evaluation and validation phase of forecasting models, robustness checks utilizing metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) are crucial for confirming the models' reliability and stability. The results of these robustness checks are presented in the following table:

Table 2. Robustness Check

Evaluate	WFTS-LQP			WFTS-LQP-DE		
	Trend	Seasonal	Random	Trend	Seasonal	Random
MSE	117.6	437.48	7373.3	73.86	422.71	7210.99
RMSE	10.84	20.92	85.87	8.59	20.56	20.56
MAE	8.77	13.22	48.04	8.19	13.31	47.69

Source: Data processing

Notes: The robustness checks are summarized in the following table, which compares the performance of the WFTS-LQP and WFTS-LQP-DE models using evaluation metrics. The robustness check results across different components (Trend, Seasonal, Random) for each model.

Robustness Check presents a detailed comparison of the performance between the WFTS-LQP and WFTS-LQP-DE models using evaluation metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). The results show that the WFTS-LQP-DE model generally outperforms the WFTS-LQP model across all components. Specifically, the MSE values for the Trend component are reduced from 117.6 in the WFTS-LQP model to 73.86 in the WFTS-LQP-DE model, indicating improved accuracy. Similarly, the RMSE for the Trend component decreases from 10.84 to 8.59, and for the Random component, it drops significantly from 85.87 to 20.56, reflecting a substantial improvement in error reduction. The MAE results also show a slight advantage for the WFTS-LQP-DE model, with the Trend MAE decreasing from 8.77 to 8.19. Overall, these findings suggest that the WFTS-LQP-DE model provides more reliable and stable forecasts, effectively minimizing errors and enhancing the accuracy of predictions for average rice prices in East Java.

CONCLUSION AND RECOMMENDATION

Conclusion

Based on the results and discussions, the following conclusions can be made about the performance of the WFTS-LQP-DE Model: The WFTS-LQP-DE model exhibits outstanding accuracy in forecasting average rice prices in East Java. By incorporating trend, seasonal, and random components, and optimizing predictions with the Differential Evolution algorithm, the model effectively captures the dynamic nature of rice prices. The close alignment between the model's forecasts and actual prices underscores its reliability. For instance, predictions for specific dates closely match observed prices, highlighting the model's precision in accounting for both regular patterns and unexpected fluctuations.

Comparison of Forecasting Models: Comparative analysis reveals that the WFTS-LQP-DE model significantly outperforms the traditional WFTS-LQP model. Evaluation metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) show substantial improvements in forecasting accuracy with the WFTS-LQP-DE model. The reduction in error metrics across trend, seasonal, and random components highlights the enhanced performance of this model. This indicates that the WFTS-LQP-DE model provides more accurate and stable predictions, making it a more effective tool for forecasting rice price movements.

Recommended Policy

Based on the advanced forecasting capabilities of the Weighted Fuzzy Time Series Lagrange Quadratic Programming with Differential Evolution (WFTS-LQP-DE) model, several targeted policy recommendations can help the East Java government maintain rice price stability. The model's precision in capturing trends, seasonal patterns, and random variations enables a proactive approach to managing rice prices. By incorporating these forecasts into planning and decision-making, the government can better anticipate price fluctuations and implement timely interventions.

First, the government should integrate the WFTS-LQP-DE model into its price forecasting and planning processes. Regularly updated forecasts will provide valuable insights into future price movements, helping to anticipate and mitigate potential price spikes or drops. By monitoring the predicted trends, seasonal variations, and random fluctuations, the government can adjust its procurement and distribution strategies accordingly. This proactive approach ensures that interventions are based on reliable data, reducing the impact of unforeseen price volatility on both consumers and producers.

Enhancing supply chain management is crucial in addition to forecasting. The government should use the model's predictions to adjust procurement strategies and manage buffer stocks effectively. For instance, during predicted high-price periods, increasing buffer stocks can stabilize supply and prevent sharp price increases. Improved storage and logistics infrastructure will also help manage seasonal surpluses and shortages, minimising the impact of price fluctuations. These measures will ensure a steady supply of rice and help maintain price stability in the market.

Lastly, implementing a price stabilization fund can provide a financial safety net during periods of price volatility. This fund, informed by the model's forecasts, can subsidize rice prices or guarantee minimum prices to support both consumers and producers. Additionally, investing in research and development to refine forecasting models and enhance rice production efficiency will further support long-term price stability. Engaging stakeholders through transparent communication and regular policy reviews will also ensure that strategies remain effective and adaptable to changing market conditions.

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