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COMPARISON OF PSO AND ABC IN CHENG FUZZY TIME SERIES FOR RICE PRICE FORECASTING

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ABSTRACT

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Rice prices as a primary food commodity in Indonesia play an important role in maintaining economic stability and public welfare, but tend to fluctuate, thus requiring accurate forecasting methods to support decision-making. Research on optimization in the Cheng Fuzzy Time Series (FTS Cheng) method remains limited, particularly in comparing the performance of Particle Swarm Optimization (PSO) and Artificial Bee Colony (ABC) in rice price forecasting. This study aims to compare the performance of PSO and ABC optimization in the FTS Cheng method using monthly data from January 2018 to October 2025, with accuracy evaluated using MAE, RMSE, and MAPE. The forecasting process is carried out through interval formation on training and testing data to obtain an optimal model. The results show that FTS Cheng-ABC performs better, with an MAE of 97.947, RMSE of 142.855, and MAPE of 0.633%, compared to FTS Cheng-PSO with an MAE of 118.579, RMSE of 153.354, and MAPE of 0.767%. However, this study is limited to the use of the Fuzzy Time Series Cheng method with two optimization algorithms, namely PSO and ABC, and does not incorporate adaptive parameter mechanisms or comparisons with more advanced methods. Therefore, the FTS Cheng-ABC method is more effective and can be used to support policy decision-making related to rice price stability. This study contributes by providing a comparative analysis of PSO and ABC optimization in improving the performance of the FTS Cheng method for rice price forecasting in Indonesia.

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1. INTRODUCTION

Food is a fundamental human need and an inseparable part of daily life, where food commodity prices in Indonesia frequently fluctuate due to market conditions, distribution, and government policies [1], [2]. As a basic necessity, food commodities are essential for community welfare, with rice as the main commodity in Indonesia [3]. Public consumption patterns show a high dependence on rice, with about 99.07% of households consuming it, making it the most widely consumed commodity [4]. This high dependency makes rice price changes a sensitive indicator that can trigger significant social and economic instability [5].

Based on PIHPS data, rice prices have shown significant fluctuations in recent years. The lowest price in 2023 was Rp12,850 per kilogram, surging to Rp15,950 in early 2024, slightly decreasing to the range of Rp15,300–Rp15,500 by mid-year, but rising again in 2025 [6]. Rice price fluctuations are influenced by several factors, such as natural conditions, distribution and infrastructure factors, as well as rice import and export policies [7]. Given its sensitive nature, price fluctuations can weaken people’s purchasing power and potentially lead to social unrest [5], [8].

Although various government policies have been implemented, rice prices remain volatile and difficult to predict [9]. Therefore, a forecasting approach is required to anticipate price changes and support accurate and sustainable decision-making based on historical data patterns [10]. This is because it helps reduce market risks, improve farmers’ income, and maintain price stability and purchasing power [11], [12]. Several traditional methods commonly used include MA, ARIMA, and Exponential Smoothing. However, these methods face constraints regarding additional tests, such as data stationarity. As an alternative, the Fuzzy Time Series (FTS) offers a more flexible approach as it does not require such assumptions, can handle non-stationary data, and manages uncertainty through fuzzy relationships [12]

FTS models such as Chen, Cheng, Singh, and Markov-Chain have been developed with different defuzzification approaches, namely averaging, supremum values, weighting, and probabilistic dynamics, respectively [13], [14]. Previous research indicates that the FTS Cheng model is more accurate compared to other models, such as ARIMA, Exponential Smoothing, MA, and FTS Chen, due to the application of a fuzzy relationship weighting system that is effective in identifying volatile price change patterns [12], [15], making it suitable for rice price forecasting. However, the forecasting performance of FTS Cheng is highly dependent on interval formation, where sub-optimal intervals can reduce accuracy because they affect subsequent calculation processes. Proper interval determination is also important because it directly influences forecasting results [16]. Therefore, optimization algorithms are required to determine optimal intervals and enhance the performance of the FTS Cheng model.

One of the popular optimization approaches is Swarm Intelligence (SI), which is inspired by the collective behavior of natural systems such as bees, ants, and bird flocks [17]. Among various SI algorithms, this study focuses on Particle Swarm Optimization (PSO) and Artificial Bee Colony (ABC). PSO holds an advantage in performing optimization through cooperative particle movements, though it is highly influenced by parameter settings and search strategies [18]. Meanwhile, ABC excels in exploring new candidate solutions while maintaining promising existing solutions, reducing the risk of being trapped in local optima [19].

Theoretically, ABC possesses adaptive exploration and exploitation capabilities that enable it to effectively explore different search landscapes while preserving promising solutions [20]. These characteristics are particularly relevant to interval optimization in the FTS Cheng model, where both the number and lengths of intervals must be determined simultaneously, resulting in a complex search space. Comparative studies have also reported that ABC often achieves better solution quality than PSO in various optimization problems, although it may require a longer convergence time [21]. Due to their different search mechanisms, both algorithms have the potential to produce different interval optimization performance in the FTS Cheng model.

Several studies on optimization in FTS models have been conducted by [16], [22], and [23]. The results show that the application of PSO and ABC optimization has a significant effect on forecasting accuracy, with error values decreasing from 2.2603% before optimization to 1.2551% after optimization. In addition, [24] applied Particle Swarm Optimization (PSO) to optimize the interval number and interval length in the FTS model, which further improved the accuracy of the forecasting results. The application of optimization algorithms enables the FTS model to capture data patterns more accurately, resulting in improved forecasting performance.

However, limited studies have compared the performance of PSO and ABC optimization within the FTS Cheng model for rice price forecasting in Indonesia, particularly in interval optimization. Both PSO and ABC exhibit different mechanisms in interval determination, making their comparative evaluation necessary for identifying the most effective optimization method. This highlights a research gap in determining the best optimization strategy. In this study, both PSO and ABC are specifically employed to optimize the interval parameters of the FTS Cheng model, which play a crucial role in determining forecasting accuracy. Therefore, this study aims to evaluate and compare the forecasting performance of PSO and ABC optimization in the FTS Cheng method for rice price prediction in Indonesia.

2. METHODS

Material and Data

Secondary data employed in this study were obtained from an official website of the Pusat Informasi Harga Pangan Strategis (PIHPS) by Bank Indonesia (www.bi.go.id/hargapangan). The dataset consists of monthly rice prices in Indonesia from January 2018 to October 2025. All available data are used as the research sample. The analysis is conducted using Python programming in Google Colaboratory.

Research Method

The analysis procedure of rice price data in this study was carried out with the following steps, as shown in **Figure 1**.

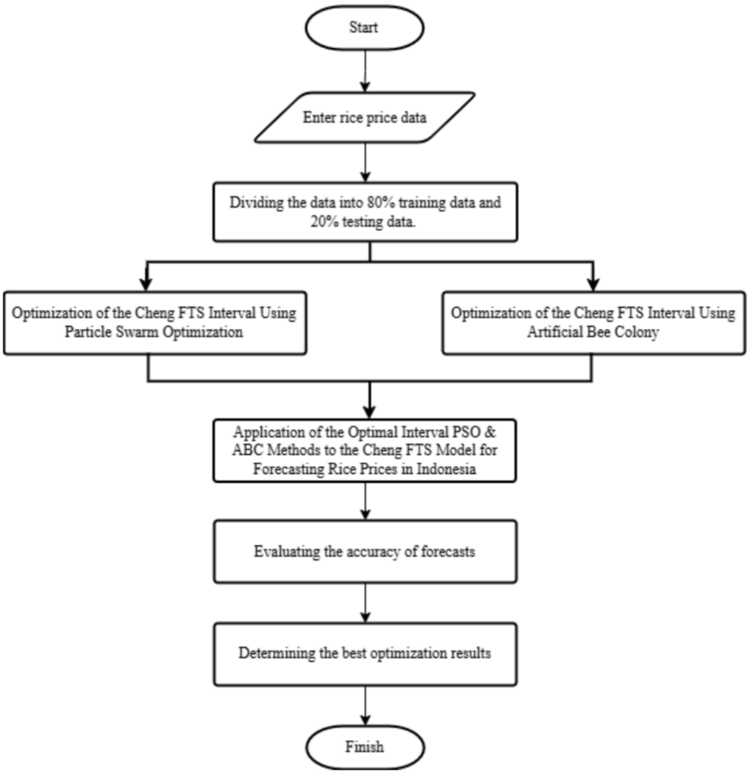

Figure 1. Research Procedure

Fuzzy Time Series Cheng

The Fuzzy Time Series Cheng (FTS Cheng) method is used to model time series data using a fuzzy relationship approach. This stage supports the fuzzification process, which transforms numerical data into fuzzy sets based on the defined intervals. After fuzzification, Fuzzy Logical Relationships (FLR) are formed from relationships between consecutive observations expressed as $A_i \to A_j$. FLRs that share the same current state are then organized into Fuzzy Logical Relationship Groups (FLRG), which represent fuzzy relationships with the same initial condition (current state) and various possible subsequent conditions (next state) to capture the data transition patterns in a more structured way. The relationships in FLRG are then represented in a weighting matrix $W = [w_{ij}]$, where each element indicates the frequency of transitions between fuzzy sets. The standardized weights are calculated using:

$$W_{ij}^{\,*} = \frac{w_{ij}}{\sum_{j=1}^{p} w_{ij}} \tag{1}$$

Forecast values are obtained through defuzzification by multiplying the normalized weight matrix by the interval midpoints. If no relationship exists (i.e., the s ($A_i \to \emptyset$), the forecast value is taken as the midpoint of the corresponding interval [25].

$$F_i = W_{i1}^{\,*}(m_1) + W_{i2}^{\,*}(m_2) + \cdots + W_{ip}^{\,*}(m_p) \tag{2}$$

Particle Swarm Optimization (PSO)

PSO is an optimization method motivated by the collective movement patterns of bird groups and fish schools. Within PSO, each particle represents a candidate solution that updates its position based on its personal best experience (Pbest) and the global best solution found by the swarm (Gbest) [23]. The optimization process begins by initializing particles with random positions and zero velocity. Each particle's fitness value is assessed using the Mean Squared Error (MSE), and the initial values of *Pbest* and *Gbest* are determined. The velocity and position of particles are then revised using the following equation [26].

$$v_{i,j}^{\,t+1} = \omega v_{i,j}^{\,t} + c_1 r_1 (Pbest_{i,j}^{\,t} - x_{i,j}^{\,t}) + c_2 r_2 (Gbest_j^{\,t} - x_{i,j}^{\,t}) \tag{3}$$

$$x_{i,j}^{\,t+1} = x_{i,j}^{\,t} + v_{i,j}^{\,t+1} \tag{4}$$

Here, ω denotes the inertia weight, c_1 and c_2 represent acceleration constants, and r_1 and r_2 are randomly generated values within the interval [0,1]. Once the position is updated, the fitness value of each particle is recalculated. The value of Pbest is updated if the updated fitness value shows improvement compared to the previous result, while Gbest is determined as the best solution among all particles. This iterative procedure is repeated until the stopping condition or the maximum iteration limit is achieved.

Artificial Bee Colony (ABC)

Inspired by the foraging behavior of honey bee colonies, ABC is a population-based optimization method that consists of three categories of bees, namely employed bees, onlooker bees, and scout bees [27], [28], each of which plays a role in exploring and exploiting potential solutions. The optimization process begins by initializing employed bees through random generation of food source positions, followed by evaluating the fitness of each food source using Mean Squared Error (MSE). The positions of employed bees are then updated using the following equation [28]:

$$x_{ij}^{new} = x_{ij} + \phi[-1,1]\,(x_{ij} - x_{kj}) \tag{5}$$

If the new solution yields a better fitness value, it replaces the previous one; otherwise, the trial counter is increased. Onlooker bees choose food sources according to a probability value determined as follows:

$$P_i = \frac{fitness_i}{\sum_{i=1}^{m} fitness_i} \tag{6}$$

Food sources are then selected using a roulette wheel mechanism and updated similarly to the employed bee phase. Meanwhile, scout bees monitor the trial value of each food source; if it exceeds a predetermined limit, the corresponding food source is abandoned and replaced with a new randomly generated solution. The optimal solution obtained during the search process is continuously recorded. This iterative procedure is repeated until the maximum iteration limit is reached or the convergence condition is met.

Forecasting Accuracy Evaluation

Forecasting accuracy is evaluated by measuring the deviation between actual values and predicted results. In this study, three evaluation metrics, namely Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE), are used to deliver a thorough evaluation of model performance.[29], [30]:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{7}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \tag{8}$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n} \left|\frac{X_t - F_t}{X_t}\right| \times 100 \tag{9}$$

3. RESULTS

Descriptive Analysis

Descriptive analysis is used as an initial basis to understand the characteristics of the data and a general overview related to monthly rice price data in Indonesia from January 2018 to October 2025, obtained from PIHPS. The outcomes of the descriptive analysis are shown in **Table 1**.

Table 1. Descriptive Analysis

N	Mean	Min	Median	Max	Std. Dev
94	12,915	11,500	11,875	15,950	1,569

As shown in **Table 1**, the rice price data during the study period consist of 94 observations. The rice prices range from 11,500 as the lowest value to 15,950 as the highest value. The gap between the lowest and highest values indicates that there were relatively wide price changes during the observation period. The mean value is recorded at 12,915, while the median value is 11,875, and the standard deviation is 1,569, indicating that the data have relatively high variance with diverse data distribution. This condition indicates that there were price increases during certain periods, causing rice prices to fluctuate over time. This is also supported by **Figure 2.**

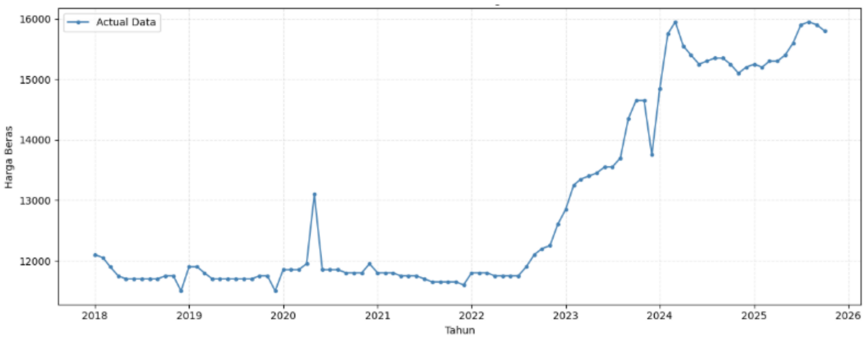

Figure 2. Research Data Visualization

Based on **Figure 2**, the rice price data during the study period consist of 94 observations. The rice prices range from 11,500 as the lowest value to 15,950 as the highest value. The rice price data show changes over time with an increasing trend and fluctuating pattern.

Data Splitting

Data splitting is performed in this study by dividing the data into 80% as training data and 20% as testing data. This proportion is selected to divide the data proportionally between the training and testing processes. The accuracy level of forecasting methods often records the highest percentage under the 80% and 20% data splitting scheme [31]. The proportion of 80% training data is used so that the model can recognize the characteristics of rice price fluctuations. Meanwhile, 20% testing data function as an evaluation to test the accuracy of the model in predicting new data that are not included in the training process. Based on the 94 observations, the training data consist of 75 observations, namely rice price data from January 2018 to March 2024. Meanwhile, the testing data consist of 19 observations, namely rice price data from April 2024 to October 2025.

Interval Optimization Using PSO and ABC

After dividing the training and testing data, interval optimization of FTS Cheng is then carried out using PSO and ABC, which are tested separately. The solutions to be searched by PSO and ABC are the number of intervals and the interval lengths of FTS Cheng in the form of interval cut points within the range of the minimum and maximum data values, namely 11,500 and 15,950. These solutions are searched within a wide solution search space, allowing PSO and ABC to determine various interval boundaries. Before performing interval optimization, the initial parameters of the PSO and ABC algorithms were specified. The parameter settings used in this study are presented in **Table 2**.

Table 2. Parameters of the PSO And ABC Algorithms

PSO Parameter	Value	ABC Parameter	Value
Number of particles	40	Number of food sources	20
Maximum iterations	400	Maximum iterations	400
Inertia weight (w)	0.3	Limit value	70
Cognitive coefficient (c_1)	1.5		
Social coefficient (c_2)	1.5		

In the optimization process, each candidate solution generated by PSO and ABC represents a set of interval cut points used to construct the FTS Cheng model. The quality of each solution is evaluated using the Mean Squared Error (MSE). The interval configuration with the minimum MSE is selected as the optimal solution. The results of the FTS Cheng interval optimization are presented in **Table 3**.

Table 3. Optimal Interval Results of PSO and ABC

PSO Lower Bound	PSO Upper Bound	ABC Lower Bound	ABC Upper Bound
11,500	11,638	11,500	11,562
11,638	11,693	11,562	11,637
11,693	11,702	11,637	11,661
17,702	11,774	11,661	11,731
17,774	11,829	11,731	11,763
⋮	⋮	⋮	⋮
15,510	15,716	15,514	15576
15,716	15,895	15576	15,934
15,895	15,950	15,934	15,950

Based on **Table 3**, the PSO testing results produced 32 intervals forming 31 interval cut points, while the ABC testing results produced 35 intervals forming 34 interval cut points. The generated intervals are located between the minimum and maximum data values and are arranged sequentially to form structured and systematic intervals. The optimal intervals obtained through the PSO and ABC optimization processes were then applied to the FTS Cheng method.

Application of Optimal PSO and ABC Intervals in Fuzzy Time Series Cheng

The optimal intervals that have been obtained are then used to construct fuzzy set intervals, and the midpoint values of each interval are calculated. The application of the optimal intervals in the FTS Cheng method is carried out through data fuzzification based on the obtained intervals, where the data are transformed into the form of A_i according to the obtained intervals and assigned to the corresponding fuzzy set intervals. A summary of the fuzzification results is presented in **Table 4**.

Table 4. Fuzzification of FTS Cheng using PSO and ABC

Period	Data	PSO Fuzzification	ABC Fuzzification
Jan 2018	12,100	A_{10}	A_{11}
Feb 2018	12,050	A_{10}	A_{10}
Mar 2018	11,900	A_7	A_8
Apr 2018	11,750	A_4	A_5
May 2018	11,700	A_3	A_4
⋮	⋮	⋮	⋮
Jan 2024	14,850	A_{25}	A_{29}
Feb 2024	15,750	A_{31}	A_{34}
Mar 2024	15,950	A_{32}	A_{35}

Based on **Table 4**, FLR is formed from the fuzzification process to identify the relationship between fuzzy states in two consecutive periods. For example, if the sequential fuzzification results are A_{10}, A_{10}, A_7, then the resulting FLRs are $A_{10} \rightarrow A_{10}$ and $A_{10} \rightarrow A_7$. After obtaining the FLR results, FLRG is then formed by grouping FLRs that have the same current state, as presented in **Table 5**.

Table 5. FLRG of FTS Cheng using PSO and ABC

Group	PSO FLRG	Group	ABC FLRG
A_{10}	$A_{10}(1), A_7(1), A_{11}(1)$	A_{11}	$A_{10}(1), A_{12}(1)$
A_7	$A_4(1), A_7(1), A_5(1), A_{10}(1)$	A_{10}	$A_8(1)$
A_4	$A_3(2), A_4(7), A_1(2), A_7(1)$	A_8	$A_5(1), A_8(1), A_6(1), A_{11}(1)$
A_3	$A_3(9), A_4(2), A_2(1)$	A_5	$A_4(2), A_5(7), A_1(2), A_8(1)$
A_1	$A_7(1), A_6(1), A_5(1)$	A_4	$A_4(9), A_5(2), A_3(1)$
⋮	⋮	⋮	⋮
A_{24}	$A_{24}(1), A_{22}(1)$	A_{25}	$A_{29}(1)$

A_{25}	$A_{31}(1)$	A_{29}	$A_{34}(1)$
A_{31}	$A_{32}(1)$	A_{34}	$A_{35}(1)$

Based on **Table 5**, the obtained FLRG refers to the relationships generated from the FLR results. For example, from the FLR results $A_{10} \rightarrow A_{10}$ dan $A_{10} \rightarrow A_7$ the FLRG formed is FLRG $A_{10} \rightarrow A_{10}, A_7$ and so on. The FLRG results are then used in the weighted matrix stage, with matrix dimensions adjusted according to the number of FLRGs in PSO and ABC. However, before being entered into the weighted matrix, the values are calculated first. The following is the calculation for the current state A_{10} with the next state A_{10} in PSO.

$$W_{10,10}{}^{*} = \frac{1}{3} = 0.333$$

The calculation is performed for each current state with every next state contained in the FLRG results, both in PSO and ABC. After the weighting process, the next step is calculating defuzzification, which produces the forecasting values. As an example, the following calculation is used to obtain the defuzzification value of FTS Cheng-PSO. The complete defuzzification results are presented in **Table 6.**

$$F_{10} = 0.333(12{,}125) + 0.333(11{,}888) + 0.333(12{,}360) = 12{,}112.209$$

Table 6. Defuzzification of FTS Cheng using PSO and ABC

State	PSO Defuzzification	State	ABC Defuzzification
A_{10}	12,112.209	A_{11}	12,115.500
A_7	11,888.250	A_{10}	11,886
A_4	11,715.547	A_8	11,879.250
A_3	11,702.024	A_5	11,713.948
A_1	11,834.487	A_4	11,700.616
⋮	⋮	⋮	⋮
A_{24}	14,264	A_{25}	14,858
A_{25}	15,806	A_{29}	15,755
A_{31}	15,922	A_{34}	15,942

In **Table 6**, the defuzzification results obtained for each state are then applied to the data. The model, which was previously constructed using the training data, was subsequently applied to the testing data, as shown in **Figure 3**.

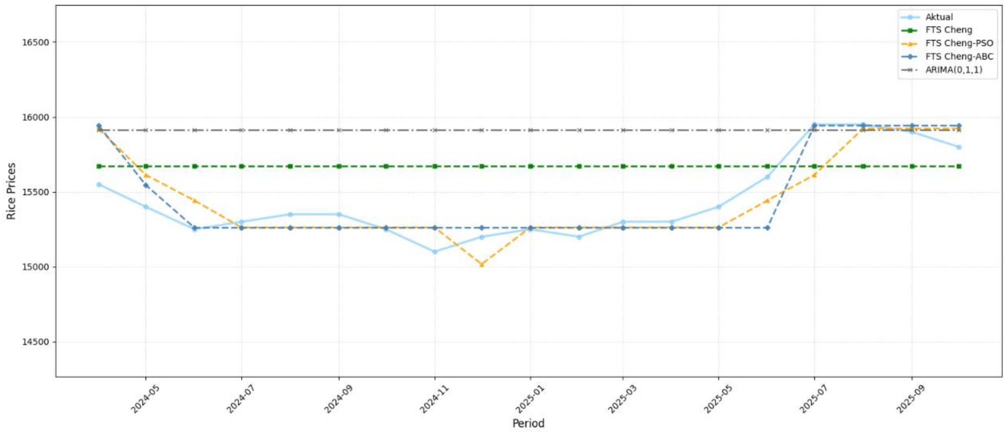

Figure 3. Comparison of Forecasting Results on Testing Data

Based on **Figure 3**, the forecasting results on the testing data show a pattern that follows the actual data. Several forecasting values have the same value. These identical forecasting values are caused by data that fall within the same interval range, resulting in the same fuzzification state and consequently producing the same forecasting values. However, the forecasting results are still not significantly different from the actual testing data. This indicates that the model is able to follow the pattern of data changes quite well during the testing period. In addition, the visualization of forecasting results includes the FTS Cheng model without optimization and the ARIMA model to provide a broader comparison of model performance. The FTS Cheng model without optimization shows noticeable deviations from the actual data, while the ARIMA model exhibits larger deviations in comparison. These results highlight that the optimized FTS Cheng models are able to provide more accurate forecasting results.

Overall, the FTS Cheng models with optimization (PSO and ABC) demonstrate superior performance compared to the non-optimized FTS Cheng model and ARIMA, indicating the effectiveness of swarm intelligence-based optimization in improving forecasting accuracy. Furthermore, forecasting accuracy evaluation is conducted by comparing the actual and forecasted values using MAE, RMSE, and MAPE.

Table 7. Forecast Accuracy Evaluation

Method	MAE	RMSE	MAPE (%)
FTS Cheng	322.684	346.894	2.101%
FTS Cheng-PSO	118.579	153.354	0.767%
FTS Cheng-ABC	97.947	142.855	0.633%
ARIMA	477.819	539.796	3.122%

Based on **Table 7**, all forecasting models show different levels of performance. The optimized models, namely FTS Cheng-PSO and FTS Cheng-ABC, generally produce lower error values compared to the non-optimized FTS Cheng model and the ARIMA model. In detail, the FTS Cheng-ABC model achieves the best performance with an MAE of 97.947, RMSE of 142.855, and MAPE of 0.633%, followed by the FTS Cheng-PSO model with an MAE of 118.579, RMSE of 153.354, and MAPE of 0.767%. Meanwhile, the non-optimized FTS Cheng model produces an MAE of 322.684, RMSE of 346.894, and MAPE of 2.101%, while the ARIMA model produces an MAE of 477.819, RMSE of 539.796, and MAPE of 3.122%. Overall, the FTS Cheng-ABC model shows the best performance among all evaluated methods, followed by the FTS Cheng-PSO model.

4. DISCUSSIONS

As shown by the result of this study, different forecasting accuracy evaluation values were obtained between the implementation of FTS Cheng-PSO and FTS Cheng-ABC. The FTS Cheng-ABC method showed better accuracy, indicating that FTS Cheng-ABC produced forecasting values that were closer to the actual data compared to FTS Cheng-PSO. This indicates that the FTS Cheng-ABC method has a better ability to capture data patterns, resulting in more accurate forecasting performance in this study. The superiority of FTS Cheng-ABC is based on the gradual solution-searching capability of the ABC method in optimizing FTS Cheng intervals. ABC has a broad solution-search mechanism through gradual improvement, allowing less optimal solutions to be replaced with better solutions during the iteration process. The superior performance of the ABC algorithm compared to PSO can be attributed to its stronger balance between exploration and exploitation, which enables a more effective search of the solution space and reduces the risk of premature convergence in optimization.

In addition, the comparison with the non-optimized FTS Cheng model and the ARIMA model shows that both methods produce higher forecasting errors compared to the optimized approaches. This indicates that both the non-optimized FTS Cheng model and the classical statistical approach, such as ARIMA, exhibit higher error values relative to the optimized models, resulting in lower forecasting accuracy. In particular, the FTS Cheng-ABC method consistently achieves the lowest error values across all evaluation metrics compared to the other methods, demonstrating its superior forecasting capability. This is followed by the FTS Cheng-PSO model, which also shows improved performance relative to the non-optimized approach, further indicating that the use of optimization techniques enhances the accuracy of the FTS Cheng forecasting model.

When compared with several previous studies, namely [16], [22], [23], this study shows differences in terms of model accuracy and the optimization approaches used. These differences may be caused by the characteristics of the data and the research cases used in each study. In addition, previous studies generally focused only on optimizing the number of intervals or interval lengths, whereas this study simultaneously optimizes both the number and length of FTS Cheng intervals. Previous studies have also not directly compared the application of PSO and ABC algorithms in the FTS Cheng method. Therefore, this study is expected to contribute as an additional reference in the development of PSO and ABC optimization in the FTS Cheng method for forecasting rice prices in Indonesia.

The findings of this study are anticipated to provide an overview for decision-making processes related to rice price forecasting in Indonesia. In addition, this study may serve as a consideration for the government in estimating changes in rice prices, so that anticipatory measures can be taken to maintain price stability and improve public welfare. For upcoming studies, it is suggested to further develop optimization algorithms by implementing an adaptive parameter system, allowing parameter values to adjust automatically during the iteration process, which is expected to improve the performance of optimal solution searching.

5. CONCLUSION

The implementation of FTS Cheng optimized using PSO produced a good forecasting model with an MAE value of 118.579, an RMSE value of 153.354, and an MAPE value of 0.767% on the testing data. Meanwhile, FTS Cheng optimized using ABC produced an MAE value of 97.947, an RMSE value of 142.855, and a MAPE value of 0.633% on the testing data, indicating that both methods showed very good forecasting accuracy. In addition, the non-optimized FTS Cheng model and ARIMA also show higher error values compared to the optimized approaches. Based on these evaluation results, it can be concluded that FTS Cheng optimized using ABC provides better performance compared to PSO.

Therefore, the FTS Cheng method with ABC is better in determining FTS Cheng intervals, resulting in more accurate forecasting of rice prices in Indonesia. For upcoming studies, it is recommended to develop an adaptive parameter system for the optimization method used. In addition, comparisons between the FTS Cheng method and Deep Learning-based approaches can also be conducted to evaluate forecasting accuracy in capturing more complex data patterns.

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