MATHunesa
Jurnal Ilmiah Matematika
e-ISSN : 2716-506X | p-ISSN : 2301-9115

Volume 14 No 02
Tahun 2026

COMPARATIVE ANALYSIS OF FUZZY TIME SERIES MARKOV CHAIN AND FUZZY TIME SERIES CHENG MODELS IN INFLATION PREDICTION KUDUS REGENCY

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Abstrak

Inflasi merupakan salah satu indikator ekonomi penting yang mencerminkan stabilitas harga dan daya beli masyarakat. Fluktuasi inflasi yang tidak menentu menuntut adanya metode peramalan yang akurat guna mendukung perencanaan dan pengambilan kebijakan, khususnya di tingkat daerah. Penelitian ini bertujuan untuk membandingkan kinerja Fuzzy Time Series (FTS) Markov Chain dan FTS Cheng dalam memprediksi inflasi di Kabupaten Kudus serta menentukan model yang paling efektif dan efisien. Data yang digunakan berupa data inflasi bulanan Kabupaten Kudus, yang dianalisis melalui tahapan penentuan semesta pembicaraan, pembentukan interval, fuzzifikasi, pembentukan hubungan logika fuzzy, hingga proses defuzzifikasi. Tingkat akurasi model dievaluasi menggunakan Mean Absolute Error (MAE) dan Root Mean Square Error (RMSE). Hasil penelitian menunjukkan bahwa model FTS Markov Chain memiliki performa yang lebih baik dibandingkan FTS Cheng. FTS Markov Chain menghasilkan nilai MAE sebesar 0,1811 dan RMSE sebesar 0,2371, lebih kecil dibandingkan FTS Cheng yang menghasilkan MAE 0,2659 dan RMSE 0,3656. Keunggulan ini disebabkan oleh kemampuan FTS Markov Chain dalam memanfaatkan penyesuaian transisi antar state, sehingga lebih adaptif terhadap dinamika perubahan data. Dengan demikian, dapat disimpulkan bahwa FTS Markov Chain merupakan model yang paling efektif dan efisien untuk memprediksi inflasi di Kabupaten Kudus.

Kata Kunci: Fluktuasi, Fuzzy Time Series, Markov chain, MAE, RMSE.

Abstract

Inflation is one of the important economic indicators that reflects price stability and people's purchasing power. Unpredictable inflation fluctuations require accurate forecasting methods to support planning and policy-making, especially at the regional level. This study aims to compare the performance of Markov Chain Fuzzy Time Series (FTS) and Cheng FTS in predicting inflation in Kudus Regency and to determine the most effective and efficient model. The data used is monthly inflation data for Kudus Regency, which is analyzed through the stages of determining the universe of discourse, interval formation, fuzzification, fuzzy logic relationship formation, and defuzzification. The accuracy level of the model is evaluated using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). The results showed that the Markov Chain FTS model performed better than the Cheng FTS model. The Markov Chain FTS produced an MAE value of 0.1811 and an RMSE of 0.2371, which were smaller than those of the Cheng FTS, which produced an MAE of 0.2659 and an RMSE of 0.3656. This advantage is due to the Markov Chain FTS's ability to utilize transition adjustments between states, making it more adaptive to data dynamics. Thus, it can be concluded that the Markov Chain FTS is the most effective and efficient model for predicting inflation in Kudus Regency.

Keywords: *Fluctuations, Fuzzy Time Series, Markov chain, MAE, RMSE.*

INTRODUCTION

Inflation is a key indicator in macroeconomic analysis, as it reflects the overall increase in the prices of goods and services (Mankiw, 2018). In Kudus Regency, Central Java Province, inflation shows fluctuations influenced by various factors, such as food prices, fuel prices, and transportation and education services (BPS, 2024). Therefore, this nonlinear pattern and uncertainty require a forecasting approach such as fuzzy logic (Amalani et al., 2024).

Fuzzy Time Series (FTS), introduced by Song and Chissom in 1993, is capable of handling data ambiguity (Vianita et al., 2025). Furthermore, variants such as FTS Markov Chain integrate fuzzy theory with Markov transition probabilities to capture changes in fuzzy status between periods more realistically (Sunusi et al., 2025). On the other hand, Cheng's FTS, developed by Cheng in 1999, simplifies fuzzy relations and defuzzification, making calculations more efficient (Husain et al., 2021).

Considering this complexity, a comparative analysis between the two models is important to identify the most accurate one in predicting Kudus inflation, using metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). FTS is effective for fluctuating and non-stationary data without requiring specific distribution assumptions (Fikri et al., 2023).

Previous research, such as that conducted by Hidayat et al. (2023), shows that the Markov Chain FTS is more accurate (MAPE 6.97%) than the Cheng FTS (11.39%) on Indonesian inflation data for the 2019–2022 period (Arnita et al., 2020). Similarly, Putra and Rahayu (2022) found that sMAPE was lower for Markov Chain (2.11%) versus Cheng (2.98%) on the Composite Stock Price Index (IHSG) (Anwar et al., 2024). However, the Cheng model can excel in repetitive patterns due to the weighting of frequency relations. Furthermore, compared to ARIMA, FTS is more effective for nonlinear or non-stationary data (Park et al., 2022), although the majority of studies are still focused on the national or financial scale, not regional ones such as Kudus.

Therefore, this study, entitled "Comparative Analysis of Fuzzy Time Series Markov Chain and Fuzzy Time Series Cheng Models in Inflation Prediction in Kudus Regency," aims to determine the most effective fuzzy model based on local economic characteristics and provide a scientific basis for regional economic policies based on modern analytical data

LITERATURE REVIEW

In this study, two developments of fuzzy time series were applied, namely FTS Markov chain and FTS Cheng. The stages of the FTS Markov Chain method are generally as follows (Telaumbanua et al., 2023):

a. Determining the Universe , defined as

$$U = [\min(X_t) - D_1, \max(X_t)\, D_2]$$

b. Forming the Interval Class, calculating the number of classes with $K = 1 + 3{,}322 log N$
Next, the length of the interval is defined:

$$l = \frac{[(max(X_t) + D_2\,) - (min(X_t) - D_1)]}{K}$$

Then, each interval is obtained using the following equation:

$$\begin{gathered} u_1 = [min(X_t) - D_1, min(X_t) - D_1 + l] \\ u_2 = [min(X_t) - D_1 + l, min(X_t) - D_1 + 2l] \\ \vdots \\ u_n = [min(X_t) - D_1 + (n-1), min(X_t) - D_1 \\ + nl] \end{gathered}$$

c. Determining the Fuzzy SetA_i on the Universe$U$ and Performing Fuzzification
The fuzzy set $A_1, A_2, \dots, A_n$ can be defined as follows:

$$\begin{gathered} A_1 = \left\{\frac{1}{u_1} + \frac{0{,}5}{u_2} + \frac{0}{u_3} + \dots + \frac{0}{u_n}\right\} \\ A_2 = \left\{\frac{0{,}5}{u_1} + \frac{1}{u_2} + \frac{0{,}5}{u_3} + \dots + \frac{0}{u_n}\right\} \\ \vdots \\ A_n = \left\{\frac{0}{u_1} + \frac{0}{u_2} + \dots + \frac{0{,}5}{u_{i-1}} + \frac{1}{u_n}\right\} \end{gathered}$$

d. Determining *the Fuzzy Logical Relationship* (FLR) will form the relationship:$A_i \rightarrow A_j$ and the *Fuzzy Logical Relationship Group* (FLRG) will form the relationship:$A_i \rightarrow A_{j1}, A_{j2}, \dots, A_{jn}$
e. Determining the Markov Transition Probability Matrix

The one-step transition probability fromA_i to A_j is defined as: $P_{ij} = \frac{M_{ij}}{M_i}$; $i, j, = 1,2, \dots, n$

The Markov transition matrix is as follows:

$$P = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1n} \\ P_{21} & P_{22} & \cdots & P_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ P_{n1} & P_{n2} & \cdots & P_{nn} \end{bmatrix}$$

f. Defuzzification to Obtain the Initial Forecast Value.
g. Calculating the Adjustment Value (D_t) to review the prediction error.
h. Calculating the Final Prediction Result (($F'_{(t)}$).

The main steps in the Cheng FTS method are as follows (Sofhya, 2022):

a. Defining *the universe of discourse*(U)
b. Forming intervals.
c. Forming fuzzy sets in the universe (U) and fuzzification.
d. Determining FLR and FLRG.
e. Establishing a normalized weighting matrix, with the following equation. Suppose there is a sequence of FLRs, for example: $W_{ij}{}^* = \frac{W_{ij}}{\sum_{j=1}^{n} W_{ij}}$

   The weighting matrix(W) is written as follows:

$$W = \begin{bmatrix} W_{11} & W_{12} & \cdots & W_{1n} \\ W_{21} & W_{22} & \cdots & W_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ W_{n1} & W_{n2} & \cdots & W_{nn} \end{bmatrix}$$

f. Calculating the Prediction Value (F_i)

Cheng's FTS analysis has several steps that are similar to those in Markov Chain FTS analysis. In Markov Chain FTS, the defuzzification value is used as the initial prediction value, whereas in Cheng FTS, the defuzzification prediction value is the final prediction value (Fikri et al., 2023). Then, *Mean Absolute Error* (MAE) and *Root Mean Square Error* (RMSE) are used to measure the accuracy of the errors in both models.

METHODE

The research was conducted in Kudus Regency, Central Java Province, due to its fluctuating economic dynamics. Secondary data in the form of monthly inflation was obtained from the official publication of the Central Statistics Agency (BPS) of Kudus Regency through the website kuduskab.bps.go.id, covering the period from January 2015 to December 2025.

RESULT AND DISCUSSION

Data Description

In this study, the *Fuzzy Time Series* Markov Chain and *Fuzzy Time Series* Cheng models were applied to inflation data for Kudus Regency from January 2015 to December 2025. The following is a time series graph of inflation data in Kudus Regency:

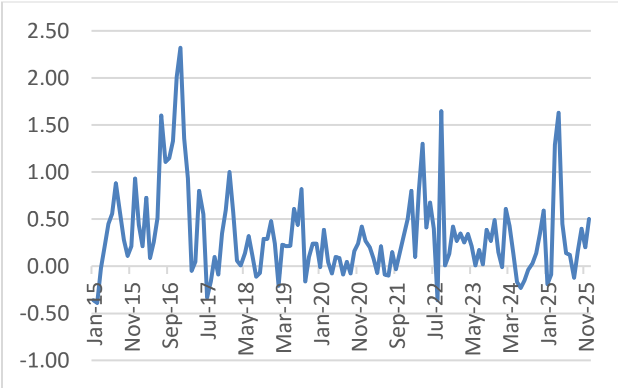

Figure 1. Inflation Graph for the Period January 2015 - December 2025

Based on Figure 1, monthly inflation from January 2015 to July 2025 fluctuated quite sharply, with several significant spikes during certain periods. At the beginning of the period (2015–2017), there was a fairly high increase, including a peak around early 2017 that approached 2.3%, followed by a decline to near or even slightly below 0. In the 2018–2020 period, inflation tended to be more stable with small fluctuations around 0–0.8%. Entering 2021–2022, there was another spike, especially around mid-2022, which reached more than 1.5%, then declined again and fluctuated moderately throughout 2023–2024. In early 2025, there was another sharp increase to around 1.6% before declining and stabilizing in the range of 0–0.5% until mid-2025, indicating an unstable but generally controlled inflation pattern in the long term.

Fuzzy Time Series Markov Chain Modeling

Fuzzy Time Series (FTS) Markov Chain is an integration model between the FTS approach and Markov chain theory. The basic concept is to utilize the transition probability between fuzzy sets to strengthen prediction accuracy.

Step 1. Determine *the Universe of Discourse* (U) from actual data for the period January 2015 - December 2025. The minimum value $(min(X_t))$) was obtained in February 2015 as$min(X_t) = -0.3900$ and the maximum value $(max(X_t))$) was obtained in December 2016 as$max(X_t) = 2.3200$, with a value ofD_1dan $D_2 = 0.0001$. Using equation , the universe of discourse U is obtained as follows: $U = [-0.3901; 2.3201]$

Step 2. Determining the interval length with a total of 132 data points(N)

1. Using the Struges formula in equation to calculate the number of classes:
   $K = 1 + 3.322 \times \log(132) = 8.0445 \approx 8$
2. Dividing the speaker universe U into interval classes using equation as follows:
   $$l = \frac{[(2.32 + 0.0001) - (-0.39 - 0.0001)]}{8}$$
   $= 0.3388$

There are 8 intervals in the universe U , namely u_1, u_2, u_3 , u_4, u_5, u_6, u_7, , and u_8 , obtained based on equation as an exampleu_1 , as follows: $u_1 = [-0.3900 - 0.0001, -0.3900 - 0.0001 + 0.3388] = [-0.3901, -0.0513]$

The values for each interval are as follows: $u_1 = [-0.3901, -0.0513)$, $u_2 = [-0.0513, 0.2875)$, $u_3 = [0.2875, 0.6262)$,..., $u_8 = [1.9813, 2.3201)$. Next, calculate the midpoints$m$ of each universe(U) . The midpoints for each interval are as follows: $m_1 = [-0.2207]$, $m_2 = [0.1181]$, $m_3 = [0.4568]$,..., $m_8 = [2.1507]$.

Step 3. Determine the fuzzy sets A_i in the universe U and perform fuzzification. There are 8 fuzzy sets that can be formed based on the number of intervals u . Based on equation (7) and the membership degree determination rule, the fuzzy sets formed are as follows:

$$A_1 = \left\{\frac{1}{u_1} + \frac{0{,}5}{u_2} + \frac{0}{u_3} + \frac{0}{u_4} + \frac{0}{u_5} + \frac{0}{u_6} + \frac{0}{u_7} + \frac{0}{u_8}\right\}$$
$$A_2 = \left\{\frac{0{,}5}{u_1} + \frac{1}{u_2} + \frac{0{,}5}{u_3} + \frac{0}{u_4} + \frac{0}{u_5} + \frac{0}{u_6} + \frac{0}{u_7} + \frac{0}{u_8}\right\}$$
$$A_3 = \left\{\frac{0}{u_1} + \frac{0{,}5}{u_2} + \frac{1}{u_3} + \frac{0{,}5}{u_4} + \frac{0}{u_5} + \frac{0}{u_6} + \frac{0}{u_7} + \frac{0}{u_8}\right\}$$
$$\vdots$$
$$A_8 = \left\{\frac{0}{u_1} + \frac{0}{u_2} + \frac{0}{u_3} + \frac{0}{u_4} + \frac{0}{u_5} + \frac{0}{u_6} + \frac{0{,}5}{u_7} + \frac{1}{u_8}\right\}$$

Next, determine the fuzzification of historical data. Based on the fuzzy sets formed, fuzzy sets can be determined for each inflation value. The results of fuzzification of several inflation data noted in linguistic numbers can be seen in Table 1 below:

Table 1. Fuzzified Data

t	Month	Actual Data	Fuzzy Data
1	Jan-15	-0.3600	A_1
2	Feb-15	-0.3900	A_1
3	Mar-15	-0.0200	A_2
4	Apr-15	0.2100	A_2
5	May-15	0.4500	A_3
⋮	⋮	⋮	⋮
128	Aug-25	-0.1200	A_1
129	Sep-25	0.1600	A_2
130	Oct-25	0.4000	A_3
131	Nov-25	0.2000	A_2
132	Dec-25	0.5000	A_3

Step 4. Determining *the Fuzzy Logical Relationship* (FLR). Based on the fuzzification results of the data Y_t , denoted by the fuzzy sets A_i . The FLR results for several inflation data can be seen in Table 2 below:

Table 2. *Fuzzy Logical Relationship* (FLR)

t	Actual Data	Fuzzy Data	FLR
1	-0.3600	A_1	-
2	-0.3900	A_1	$A_1 \rightarrow A_1$
3	-0.0200	A_2	$A_1 \rightarrow A_2$
4	0.2100	A_2	$A_2 \rightarrow A_2$
5	0.4500	A_3	$A_2 \rightarrow A_3$
⋮	⋮	⋮	⋮
128	-0.1200	A_1	$A_2 \rightarrow A_1$
129	0.1600	A_2	$A_1 \rightarrow A_2$
130	0.4000	A_3	$A_2 \rightarrow A_3$
131	0.2000	A_2	$A_3 \rightarrow A_2$
132	0.5000	A_3	$A_2 \rightarrow A_3$

Next, form *a Fuzzy Logical Relationship Group* (FLRG) based on the FLR in Table 2. Table 3 below shows the complete FLRG results from inflation data for January 2015 – December 2025 in Kudus Regency.

Table 3. Fuzzy Logical Relationship Group (FLRG)

current state		*Next state*
A_1	$\rightarrow$	$7(A_1), 11(A_2), 2\ (A_3), A_5\ , A_7$
A_2	$\rightarrow$	$10(A_1), 26(A_2), 16(A_3), 4(A_4)$
A_3	$\rightarrow$	$3(A_1), 15(A_2), 8(A_3), 4(A_4), A_5, A_6$
A_4	$\rightarrow$	$A_1, 3(A_2\ ), 4(A_3), A_5$
A_5	$\rightarrow$	$2(A_3\ ),\ A_5, 2(A_6)$
A_6	$\rightarrow$	$A_3, A_4,\ A_5, A_8$
A_7	$\rightarrow$	A_2
A_8	$\rightarrow$	A_6, A_8

Step 5. Determine the Markov Transition Probability Matrix based on the obtained FLRG. Thus, the *state* transition probability matrix of order 8×8 with elements $P_{ij} = \frac{M_{ij}}{M_i}$ is presented as follows:

$$P = \begin{bmatrix} \frac{7}{22} & \frac{11}{22} & \frac{2}{22} & 0 & \frac{1}{22} & 0 & \frac{1}{22} & 0 \\ \frac{10}{56} & \frac{26}{56} & \frac{16}{56} & \frac{4}{56} & 0 & 0 & 0 & 0 \\ \frac{3}{32} & \frac{15}{32} & \frac{8}{32} & \frac{4}{32} & \frac{1}{32} & \frac{1}{32} & 0 & 0 \\ \frac{1}{9} & \frac{3}{9} & \frac{4}{9} & 0 & \frac{1}{9} & 0 & 0 & 0 \\ 0 & 0 & \frac{2}{5} & 0 & \frac{1}{5} & \frac{2}{5} & 0 & 0 \\ 0 & 0 & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} & 0 & 0 & \frac{1}{4} \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \frac{1}{2} & 0 & \frac{1}{2} \end{bmatrix}$$

Defuzzifying the forecast values, based on the obtained probability values, the initial forecast values can be calculated. Some of the initial forecast values are available in Table 4 below:

Table 4. Prediction results before data adjustment

t	Month	Actual Data	Initial Forecast
1	Jan-15	-0.3600	
2	Feb-15	-0.3900	0.1643
3	Mar-15	-0.0200	0.1643
4	Apr-15	0.2100	0.2028
5	May-15	0.4500	0.2028
⋮	⋮	⋮	⋮
128	Aug-25	-0.1200	0.2028
129	Sep-25	0.1600	0.1643
130	Oct-25	0.4000	0.2028
131	Nov-25	0.2000	0.3298
132	Dec-25	0.5000	0.2028

Step 7. Calculating the Adjustment Value, the Markov Chain FTS has a step to adjust the forecasting value trend as a stage to reduce the magnitude of the forecasting result deviation with a class length of (l) .

Table 5. Adjustment Values for Forecasting Results

t	Actual Data	FLR	Adjustment Value
1	-0.3600	-	
2	-0.3900	$A_1 \rightarrow A_1$	0
3	-0.0200	$A_1 \rightarrow A_2$	0.1694
4	0.2100	$A_2 \rightarrow A_2$	0
5	0.4500	$A_2 \rightarrow A_3$	0.1694
⋮	⋮	⋮	⋮
128	-0.1200	$A_2 \rightarrow A_1$	-0.1694
129	0.1600	$A_1 \rightarrow A_2$	0.1694
130	0.4000	$A_2 \rightarrow A_3$	0.1694
131	0.2000	$A_3 \rightarrow A_2$	-0.1694
132	0.5000	$A_2 \rightarrow A_3$	0.1694

Step 8. Determine the final forecast result, which is the sum of the initial forecast and the adjustment value. Some of the data based on the calculation results are available in Table 6 below:

Table 6. Final FTS Markov Chain Forecast Results

t	Actual Data	Final Forecast
1	-0.3600	
2	-0.3900	0.1643
3	-0.0200	0.3336
4	0.2100	0.2028
5	0.4500	0.3721
⋮	⋮	⋮
128	-0.1200	0.0334
129	0.1600	0.3336
130	0.4000	0.3721
131	0.2000	0.1604
132	0.5000	0.3721

Calculations were also performed using MATLAB software to support and verify the results of the analysis calculated previously. The calculations showed the same and consistent results as those obtained using Microsoft Excel. A graphical visualization of the comparison between actual data and forecast values using the FTS Markov Chain with MATLAB can be seen in the graph below:

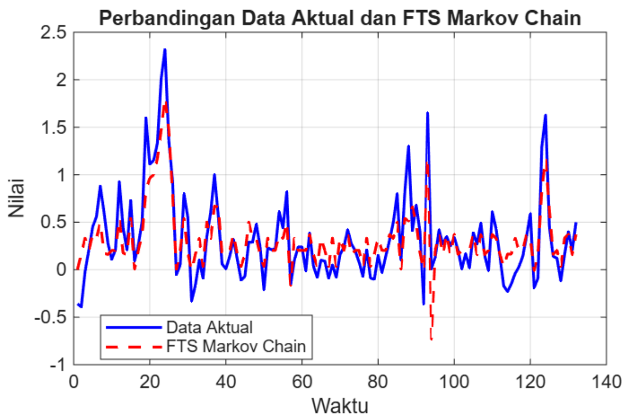

Figure 2. Actual Data and Markov Chain FTS Graph using MATLAB

Based on Figure 2, the actual data line (blue) fluctuates following the dynamics of values over time, while the Markov Chain FTS line (dashed red in MATLAB and solid red in Excel) attempts to follow the direction of the actual data movement. It can be seen that the Markov Chain FTS model is quite good at capturing the general trends and ups and downs of the data, although at some extreme points (peaks and troughs) there are still differences between the actual values and the forecast results. This indicates that the model is capable of representing data patterns globally, but still has limitations in following very sharp changes. The difference in appearance between the two graphs is more due to the difference in visualization styles between MATLAB and Excel, rather than a difference in calculation results.

Cheng's Fuzzy Time Series Modeling

Forecasting using Cheng's *Fuzzy Time Series* (FTS) was performed to obtain an appropriate comparison model. The difference between the Markov Chain FTS model and the Cheng FST model lies in steps 5 and 6.

Step 5. Determine the weights for each fuzzy set entered into the weighting matrix (W). Then, the normalized weighting matrix (W^*) is as follows:

$$W = \begin{bmatrix} \frac{7}{22} & \frac{11}{22} & \frac{2}{22} & 0 & \frac{1}{22} & 0 & \frac{1}{22} & 0 \\ \frac{10}{56} & \frac{26}{56} & \frac{16}{56} & \frac{4}{56} & 0 & 0 & 0 & 0 \\ \frac{3}{32} & \frac{15}{32} & \frac{8}{32} & \frac{4}{32} & \frac{1}{32} & \frac{1}{32} & 0 & 0 \\ \frac{1}{9} & \frac{3}{9} & \frac{4}{9} & 0 & \frac{1}{9} & 0 & 0 & 0 \\ 0 & 0 & \frac{2}{5} & 0 & \frac{1}{5} & \frac{2}{5} & 0 & 0 \\ 0 & 0 & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} & 0 & 0 & \frac{1}{4} \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \frac{1}{2} & 0 & \frac{1}{2} \end{bmatrix}$$

Step 6. Calculate the prediction value by multiplying the normalized weighting matrix (W^*) and the mean value (m_i). Some of the data based on the calculation results are available in Table 7 below:

Table 7. Final FTS Cheng Prediction Results

t	Actual Data	Final Forecast
1	-0.3600	
2	-0.3900	0.1643
3	-0.0200	0.1643
4	0.2100	0.2028
5	0.4500	0.2028
⋮	⋮	⋮
128	-0.1200	0.2028
129	0.1600	0.1643
130	0.4000	0.2028
131	0.2000	0.3298
132	0.5000	0.2028

A graphical visualization comparing actual data and forecast values using FTS Cheng using MATLAB can be seen in the graph below:

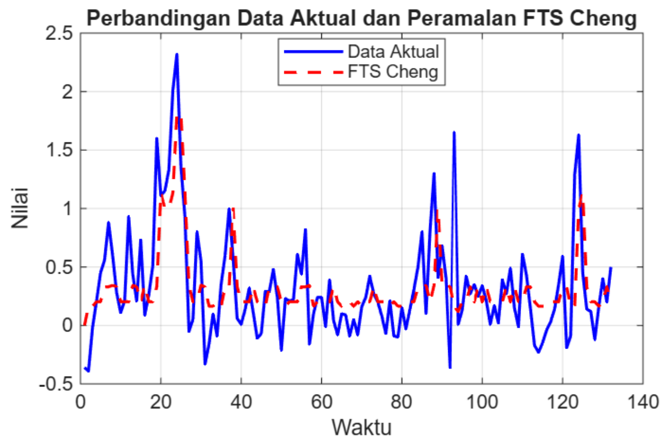

Figure 3. Actual Data and FTS Cheng Graph using MATLAB

Based on Figure 3, which shows a comparison between actual data and Fuzzy Time Series (FTS) Cheng prediction results, there is a consistent graph pattern, namely the actual data line (blue) fluctuates quite sharply in certain periods, especially at peak values, while the FTS Cheng line (red) follows the direction of data movement with a smoother pattern. This indicates that the Cheng FTS method is capable of capturing general trends and data change dynamics, although at some extreme points there is still a difference between the actual values and the forecast results. The apparent difference between the two figures is more due to differences in display and visualization styles between MATLAB and Excel, rather than differences in model calculation results.

Accuracy Level

Accuracy level testing of the predictions using the *Fuzzy time series* Markov Chain and *Fuzzy time series Cheng* models was conducted to determine how well the models performed in predicting inflation values. The complete accuracy levels are presented in the table below:

Table 8. Forecasting Accuracy Level

Fuzzy Markov Chain Time Series		***Fuzzy time series Cheng***	
MAE	**RMSE**	**MAE**	**RMSE**
0.1811	0.2371	0.2659	0.3656

A graphical visualization comparing actual data and final forecast values using the FTS Markov Chain and FTS Cheng can be seen in the graph below:

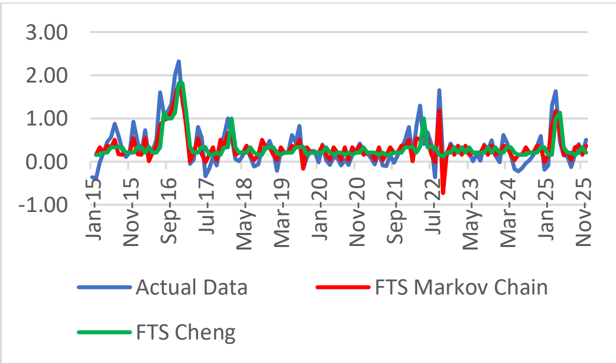

Figure 4. Actual Data, FTS Markov Chain, and FTS Cheng Graph

Based on Figure 4, it can be seen that the FTS Markov Chain model is better able to follow the upward and downward patterns of actual inflation data. This is shown by the FTS Markov Chain forecast line, which is more responsive to spikes and declines in inflation, especially during periods of significant change. This advantage is also quantitatively proven through the accuracy measurement values of MAE of 0.1811 and RMSE of 0.2371, which are smaller than MAE of 0.2659 and RMSE of 0.3656 in FTS Cheng. Lower error values indicate that the Markov Chain FTS has better accuracy and is more stable in representing inflation patterns in Kudus Regency.

CONCLUTION

Based on the results of research on the application of the Markov Chain *Fuzzy Time Series* (FTS) and Cheng FTS models in predicting inflation in Kudus Regency, it can be concluded that both models can be used to forecast inflation using a fuzzy-based approach. The process of applying both methods begins with determining the universe of discourse, forming intervals, fuzzifying data, forming fuzzy logic relationships, to the defuzzification process to produce forecast values. However, visually and numerically, the Markov Chain FTS shows better ability in following the fluctuation patterns of actual inflation data in Kudus Regency compared to the Cheng FTS, especially during periods of significant inflation spikes or declines.

The difference in accuracy between the two models is clearly seen from the accuracy error values produced. The Markov Chain FTS model produced an MAE value of 0.1811 and an RMSE of 0.2371, while the Cheng FTS model produced an MAE value of 0.2659 and an RMSE of 0.3656. The smaller MAE and RMSE values in the Markov Chain FTS indicate that the forecasting error is lower and the prediction results are closer to the actual data. This difference occurs because the Markov Chain FTS considers the transition probability between states, so it is able to capture the dynamics of inflation changes in more detail than the Cheng FTS, which only relies on direct fuzzy relationships.

Thus, it can be concluded that the Markov Chain FTS model is the most effective and efficient fuzzy model for predicting inflation in Kudus Regency. This model not only provides a higher level of accuracy but is also more adaptive to changes in data patterns, making it more appropriate for use as an inflation forecasting tool for relevant parties in regional economic planning and policy-making.

RECOMMENDATION

Overall, this study successfully answered the research question by demonstrating the superiority of the Markov Chain FTS model in predicting inflation in Kudus Regency. These findings are expected to contribute to the development of knowledge and practice in the field of economics, as well as encourage innovation in *fuzzy logic-based* prediction methods. Thus, this study paves the way for more adaptive fuzzy model applications in the era of economic data digitalization.

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