

COMPARATIVE ANALYSIS OF FTS METHOD WITH FTS MARKOV CHAIN ON RAINFALL FORECAST IN SOUTH KALIMANTAN

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Abstract

Time series data (TS) is a type of data that is collected according to the order of time within a certain time span. Time Series data analysis is one of the statistical procedures applied to predict the probability structure of future conditions for decision making. FTS (FTS) is a data forecasting method that uses fuzzy principles as its basis. Forecasting systems with FTS capture patterns from past data and then use them to project future data. FTS Markov Chain is a new concept that was first proposed by Tsaur, in his research to analyze the accuracy of the prediction of the Taiwan currency exchange rate with the US dollar. In his research, Tsaur combines the FTS method with Markov Chain, The merger aims to obtain the greatest probability using a transition probability matrix. The results obtained from this research are tests with the best number of presentation values from FTS Markov Chain with FTS, resulting in different accuracy values depending on the two methods. The best accuracy performance is obtained by the Markov Chain FTS method with an error value of 1.6% and an accuracy value of 98.4% and for FTS with an error value of 7.4% and an accuracy value of 92.6%. produce different accuracy values depending on the two methods. The best accuracy performance is obtained by the Markov Chain FTS method with an error value of 1.6% and an accuracy value of 98.4% and for FTS with an error value of 7.4% and an accuracy value of 92.6%. produce different accuracy values depending on the two methods. The best accuracy performance is obtained by the Markov Chain FTS method with an error value of 1.6% and an accuracy value of 98.4% and for FTS with an error value of 7.4% and an accuracy value of 92.6%.

Keywords: Forecasting, Time Series, Rainfall, FTS, FTS Markov Chain

1. INTRODUCTION

South Kalimantan is located in an area with rainfall which is influenced by wet and dry months. Wet month where the rainfall is more than 100 mm, while the dry month is a month where the rainfall is less than 60 mm. If there is rainfall between 60 mm - 100 mm then the rainfall is in a humid month. Serious impacts of climate change faced by the South Kalimantan region include changes in rainfall patterns, floods, droughts as well as sea level rise and changes in temperature. Changes in rainfall patterns will greatly affect the agriculture, plantation, and fisheries sectors^[1].

Time series data (TS) may be a style of information that's collected in keeping with the sequence of your time in an exceedingly bound time span. statistic information analysis is one amongst the applied mathematics procedures applied to predict the chance structure of future conditions for higher cognitive process. Fuzzy statistic (FTS) may be a information prediction methodology that uses fuzzy

principles as a basis. prediction systems with fuzzy times series capture patterns from past information so use them to project future information. A fuzzy set may be outlined as a category of numbers with imprecise boundaries. The values employed in prediction fuzzy statistic ar fuzzy sets of real numbers over a planned set of universes[2].

FTS Markov Chain is a new concept that was first proposed by Tsaur, in his analysis to research the accuracy of the prediction of the Taiwan currency rate of exchange with the US dollar. In his analysis, Tsaur combines the fuzzy statistic technique with Markov Chain, the merger aims to get the most important chance employing a transition chance matrix [4].

Based on the outline on top of, the authors have an interest in conducting analysis on Comparative Analysis of Fuzzy Time Series and FTS Markov Chain Methods in South Kalimantan Regional Rainfall Forecasting.

2. RESEARCH PROCEDURE

The research procedures carried out in this study are as follows:

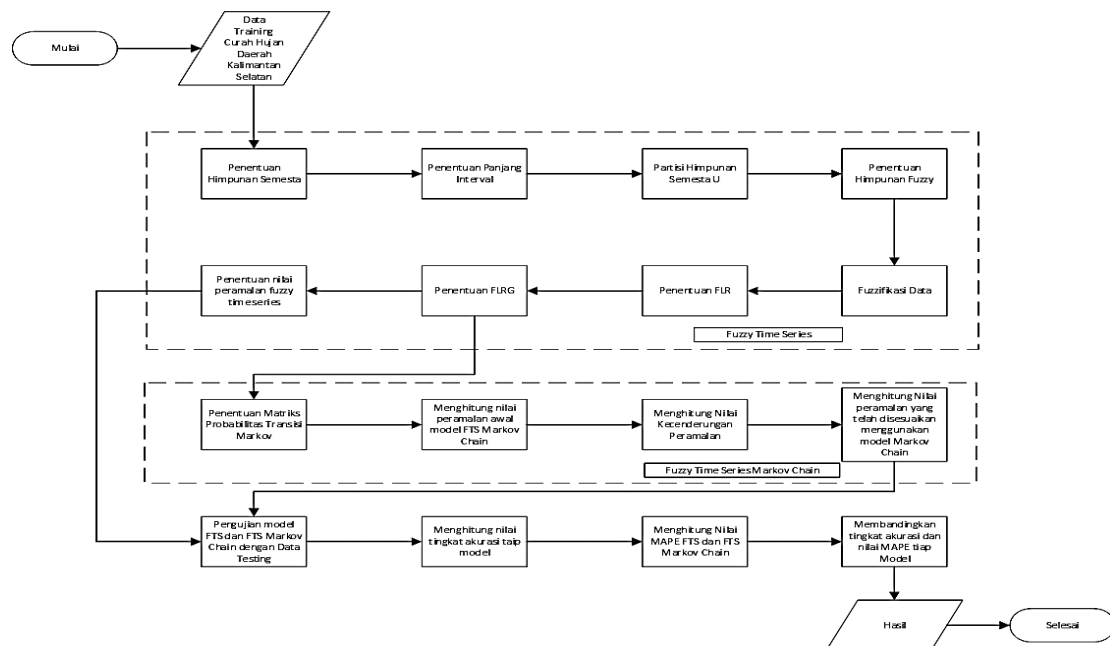


Figure 1. Research Flow

2.1 Training Data

Training data is data used to train the method that will be used in prediction. Data collection was obtained through the official website of the Central Statistics Agency of South Kalimantan Province. In this study, 75% of rainfall data will be used starting from 2003 – 2011 in South Kalimantan.

2.2 Fuzzy Time Series

The steps used to get the results of the Markov chain FTS method are the same as the steps in the FTS[3]

2.2.1 Determining the Universal Set

Define the universal set U , with U is historical information. when measure the universe set, the base and most data from the given recorded data will be will be data. basically the universe set U are often outlined with $[U_{min}; U_{max}] = [D_{min} - D1; D_{max} + D2]$ where $D1$ and $D2$ could be a corresponding positive range.

2.2.2 Dividing the Universal Set

Divide the set of universes U into elements with intervals (n) that is that the same by mistreatment the subsequent Sturges equation:

$$n = 1 + 3.322 \log N$$

With N is a lot of authentic information. The distinction between two successive spans can be characterized by l as follows :

$$l = U_{max} - U_{min} \quad n = [(D_{max} + D2) - (D_{min} - D1)] / n$$

Then each interval is obtained, namely:

$$\begin{aligned} u_1 &= [D_{min} - D1; D_{min} - D1 + l] \\ u_2 &= [D_{min} - D1 + l; D_{min} - D1 + 2l] \\ &\vdots \\ u_n &= [D_{min} - D1 + (n-1)l; D_{min} - D1 + nl] \\ u_n &= [d_n; d_{n+1}] \end{aligned}$$

2.2.3 Determining the Fuzzy Set

Determine the fuzzy set for the entire universe set U . Every fuzzy set A_i ($i = 1, 2, 3, \dots, n$) is defined in terms of n intervals, that is $u_1 = [d_1 ; d_2]$, $u_2 = [d_2 ; d_3]$, $u_3 = [d_3 ; d_4]$, ..., $u_n = [d_n ; d_{n+1}]$. Fuzzy set A_i can be obtained through:

$$A_i = \sum_{j=1}^n \mu_{ij}$$

With μ_{ij} is the level of enrollment which can be resolved as follows

$$\mu = \begin{cases} 1 & ; i = l \\ 0.5 & ; j = i - 1 \text{ or } i = j - 1 \\ 0 & ; \text{etc} \end{cases}$$

The equation can be explained by several rules, namely:

1. If historical data Y_j is u_i then the degree of membership u_i is 1, u_{i+1} is 0.5, and for others is 0.
2. If historical data Y_j is u_i with $1 < i < n$ then the degree of membership u_i is 1, u_{i+1} is 0.5, and for others is 0.
3. If historical data Y_j is u_n then the degree of membership u_n is 1, u_{i+1} is 0.5, and for others is 0.

Therefore, based on the equation, the fuzzy set of A_1, A_2, \dots, A_n can be defined as follows:

$$\begin{aligned} A_1 &= \{1/u_1 + 0.5/u_2 + 0/u_3 + \dots + 0/u_n\} \\ A_2 &= \{0.5/u_1 + 1/u_2 + 0.5/u_3 + \dots + 0/u_n\} \\ &\vdots \\ A_n &= \{0/u_1 + 0/u_2 + 0/u_3 + \dots + 0.5/u_n + 1/u_n\} \end{aligned}$$

2.2.4 Determining Fuzzification of Historical Data.

This progression expects to track down the proper fluffy set for every information..

2.2.5 Determining FLR and FLRG

2.2.6 Calculating the Forecasted Output Value

If $F(t-1) = A_j$, forecasting from $F(t)$ can be determined by the following basic rules:

Rule 1 : If the FLRG of A_j is that the empty set ($A_j \rightarrow \emptyset$), then the prediction of $F(t)$ is m_j , wherever is that the center of the interval u_j is

$$F(t) = m_j$$

Rule 2: If FLRG of A_j is a one - to - one set ($A_j \rightarrow A_k, j, k = 1, 2, \dots, n$), then the prediction of $F(t)$ is m_k , wherever is that the center of the interval u_k is

$$F(t) = m_k$$

Rule 3: If FLRG of A_j may be a one - to - many set ($A_j \rightarrow A_1, A_3, A_5, j = 1, 2, \dots, n$), then the prediction of $F(t)$ is m_1, m_2, m_3 , wherever is that the center of the interval u_1, u_3, u_5 is

$$F(t) = (m_1 + m_3 + m_5)/3$$

2.3 Markov Chain

Markov analysis is a technique of analyzing this behavior of many variables, with the aim of predicting traveller behavior towards elector transfer. Thus, the Markov process can explain the movements of many variables in an exceedingly amount of your time within the future supported the movements of those variables within the present^[3].

2.4 FTS Markov Chain

In every FLRG of FTS, there's a relationship between 2 states referred to as the present state and therefore the next state. the present state is that the worth that may be calculated because the forecast worth. whereas future satay is that the knowledge that's used as a condition to get the worth within the current state. Therefore, the connection between the present state and therefore the next state in every of those FLRGs may be thought of as a conditional method that is in line with the essential principles of the Markov chain method. Markov chain is a stochastic

process, wherever future events solely rely on today's events and don't rely on past conditions. the connection between the FTS and Markov Chain forecasting methods was first used by [3] with the subject of prediction the worth of the Taiwanese currency against the USA dollar. The steps of this model in steps one to six are constant because the Fuzzy statistic (FTS) model. However, the distinction between the FTS model and therefore the FTS - Markov Chain is in steps six to eight [4]. The following is an explanation of steps 6 to 8 of the FTS-Markov Chain

2.4.1 Calculating Initial Forecasting Output

In the time series data, the Fuzzy Logical Relationship Group (FLRG) is employed to get the chance of successive state, so a transition matrix for mathematician is obtained with the size of the transition matrix, specifically $n \times n$. moreover, the worth of the chance matrix that has been obtained is calculated by the subsequent rules:

Rule 1: If the FLRG of A_j is that the empty set ($A_j \rightarrow \emptyset$), then the prognostication of $F(t)$ is m_j , wherever is that the center of the interval u_j is

$$F(t) = m_j$$

Rule 2: If FLRG of A_j may be a matched set ($A_j \rightarrow A_l$) with $P_{jk} = \text{zero}$ and $P_{jl} = \text{one}$, $k \neq l$, then the prognostication of $F(t)$ is m_l , wherever is that the center of the interval u_k is

$$F(t) = m_l p_{jl} = m_l$$

Rule 3: If FLRG of A_j may be a one-to-many set ($A_j \rightarrow A_1, A_2, \dots, A_n$, $j = 1, 2, \dots, n$), if the information set $Y(t-1)$ at the instant that is in state A_j , then the prognostication of $F(t)$ is as follows:

$$F(t) = m_1 P_{j1} + m_2 P_{j2} + \dots + m_j P_{jj} + Y(t-1) P_{j+1} + m_{j+1} P_{j+1} + \dots + m_n P_{jn}$$

With $m_1, m_2, \dots, m_j, m_{j+1}, \dots, m_n$ is that the center of $u_1, u_2, \dots, u_j, u_{j+1}, \dots, u_n$ and m_j substituted for $Y(-1)$ so as to get data from the state A_j moment $t-1$.

2.4.2 Completing the Forecasting Value Trend

In time series tests, enormous examples square measure persistently required. Consequently, the little example size once sculptural with the FTS-Markov Chain model consistently winds up in a one-sided Markov chain framework, and a couple of changes to estimate esteems square measure prescribed to survey the gauge mistake.

The adjustment rules for prognostication values square measure delineated as follows:

Rule 1: If state A_j communicate with A_j , starting from state A_j When $t-1$ as $F(t-1) = A_j$ and there's a transition up to state A_j once once, ($i < j$), then the adjustment worth worth outlined as:

$$D_{t1} = \binom{l}{2}$$

Rule 2: If state A_j communicate with A_j , starting from state A_j When t_1 as $F(t_1) = A_j$ and there's a transition all the way down to all the way down to all the way down to, ($i > j$), then the adjustment worth outlined as:

$$D_{t1} = -\binom{l}{2}$$

Rule 3: If state A_j When t_1 as $F(t_1) = A_j$ and there is a forward transition to state A_{j+s} once, ($1 \leq s \leq n-j$), then the adjustment worth outlined as:

$$D_{t2} = \binom{l}{2} s, (i \leq s \leq n-1)$$

Where s is the number of displacements of the forward transition.

Rule 4: If state A_j When t_1 as $F(t_1) = A_j$ and there is a backward transition to state A_{j-v} once, ($1 \leq v \leq n-j$), then the adjustment worth outlined as:

$$D_{t2} = -\binom{l}{2} v, (i \leq v \leq j)$$

Where v is the number of reverse transition displacements.

2.5 Error Calculation

Error calculation is a way to determine the accuracy of the model that has been obtained. By calculative this error, it are often seen however correct the foretelling knowledge from the model has been with the particular knowledge. For the utilization of foretelling techniques with the littlest error rate is that the best foretelling technique. One methodology of calculative this error is to use the Mean Absolute proportion Error (MAPE) and Mean Sqaure Error (MSE), for MAPE itself are often obtained by the subsequent formula [4]:

$$MAPE = \frac{1}{n} \sum_{t=1}^n \frac{|Y(t) - F'(t)|}{Y(t)} \times 100\%$$

Where :

$Y(t)$ = Actual Data

$F'(t)$ = Forecasting Data

3. Results and Discussion

3.1 Results

The data used in this study is the rainfall data for the area of South Kalimantan from 2003 to 2014. Data collection was carried out by accessing the website of the Central Statistics Agency of South Kalimantan Province and obtained 144 monthly rainfall data every year.

Table 1. Amount of Data Obtained

Month	Year						
	2003	2004	2005	:	2012	2013	2014
January.	395.2	626.1	286.9	:	223.7	355.2	443
February.	547.5	375.1	271.8	:	258.4	414.6	220
March.	150.0	303.0	332.5	:	313.0	308.3	332
April.	197.1	126.9	129.5	:	319.1	305.5	223
May.	50.3	228.0	230.4	:	149.1	346.5	159
June.	115.8	80.0	49.7	:	58.4	140.7	221
July.	47.0	90.1	18.8	:	193.5	125.7	113
August.	41.6	0.0	49.3	:	70.3	81.5	53
September.	110.0	32.6	36.1	:	58.2	33.6	5
October.	171.1	51.7	176.5	:	157.0	106.0	16
November.	263.4	289.6	203.2	:	297.8	439.1	199
December.	680.0	415.0	284.4	:	409.8	349.4	387

The data will be divided into 75% training data and 25% testing data. The distribution started from January 2003 to December 2011 for training data and January 2012 to December 2014 for testing data.

Table 2. Training Data

Month	Year									
	2003	2004	2005	2006	2007	2008	2009	2010	2011	
January	395.2	626.1	286.9	362.6	240.6	221.7	384.0	324.3	418.9	
February	547.5	375.1	271.8	345.9	239.0	242.0	148.0	320.6	211.8	
March	150.0	303.0	332.5	294.8	482.7	419.4	212.0	285.1	337.1	
April	197.1	126.9	129.5	219.3	325.6	228.5	279.0	243.0	250.8	
May	50.3	228.0	230.4	72.5	235.3	140.2	237.0	171.0	210.5	
June	115.8	80.0	49.7	188.2	170.9	170.1	22.0	365.7	83.1	
July	47.0	90.1	18.8	24.7	229.3	225.1	73.0	171.7	21.3	
August	41.6	0.0	49.3	4.6	54.8	157.6	25.0	240.4	26.8	
September	110.0	32.6	36.1	2.9	30.1	127.5	21.0	338.2	77.3	
October	171.1	51.7	176.5	16.5	62.4	208.8	189.0	256.5	133.5	
November	263.4	289.6	203.2	115.6	1641.9	300.2	292.0	317.5	276.4	
December	680.0	415.0	284.4	408.4	255.2	427.2	287.0	354.7	856.4	

Table 3. Testing Data

Month	Year		
	2012	2013	2014
January	223.7	355.2	443
February	258.4	414.6	220
March	313.0	308.3	332
April	319.1	305.5	223
May	149.1	346.5	159

June	58.4	140.7	221
July	193.5	125.7	113
August	70.3	81.5	53
September	58.2	33.6	5
October	157.0	106.0	16
November	297.8	439.1	199
December	409.8	349.4	387

3.1.1 FTS Modeling

Based on the steps that have been discussed in the previous chapter, the following results are obtained:

$$1. \quad U = [D_{\min} - D1, D_{\max} + D2] \\ = [0 - 0, 1641,9+8,1] = [0,1650]$$

Divide the universal set U into several parts based on intervals with the sturges formula as follows

$$n = 1 + 3.322 \log N \\ = 1 + 3,322 \log_8 (144) \\ = 8.170 \approx 8$$

2. Suppose U will be divided into 8 intervals, then the length of the interval is

$$l = \frac{[1650-0]}{8} = 206$$

3. The resulting 8 intervals in the division of the universal set U for each data are $u_1, u_2, u_3, u_4, u_5, u_6, u_7, u_8$ with bulk values can be seen in the following table.

Table 4. Grade Value

Class	Lower limit	Upper limit
u_1	0	206.3
u_2	206.3	412.5
u_3	412.5	618.8
u_4	618.8	825.0
u_5	825.0	1031.3
u_6	1031.3	1237.5
u_7	1237.5	1443.8
u_8	1443.8	1650,0

Then the calculation is carried out to get the middle value, the results can be seen in the following table

Table 5. Middle Value

Class	Middle value
u_1	103.1
u_2	309.4
u_3	515.6
u_4	721.9
u_5	928.1
u_6	1134.4
u_7	1340.6
u_8	1546.9

4. Determine the fuzzy set and perform fuzzification on the actual observed data.

$$A1 = \{1 / u_1 + 0.5 / u_2 + 0 / u_3 + 0 / u_4 + 0 / u_5 + 0 / u_6 + 0 / u_7 + 0 / u_8\}$$

$$A2 = \{0.5 / u_1 + 1 / u_2 + 0.5 / u_3 + 0 / u_4 + 0 / u_5 + 0 / u_6 + 0 / u_7 + 0 / u_8\}$$

$$A3 = \{0 / u_1 + 0.5 / u_2 + 1 / u_3 + 0.5 / u_4 + 0 / u_5 + 0 / u_6 + 0 / u_7 + 0 / u_8\}$$

$$A4 = \{0 / u_1 + 0 / u_2 + 0.5 / u_3 + 1 / u_4 + 0.5 / u_5 + 0 / u_6 + 0 / u_7 + 0 / u_8\}$$

$$A5 = \{0 / u_1 + 0 / u_2 + 0 / u_3 + 0.5 / u_4 + 1 / u_5 + 0.5 / u_6 + 0 / u_7 + 0 / u_8\}$$

$$A6 = \{0 / u_1 + 0 / u_2 + 0 / u_3 + 0 / u_4 + 0.5 / u_5 + 1 / u_6 + 0.5 / u_7 + 0 / u_8\}$$

$$A7 = \{0 / u_1 + 0.5 / u_2 + 0 / u_3 + 0 / u_4 + 0 / u_5 + 0.5 / u_6 + 1 / u_7 + 0.5 / u_8\}$$

$$A8 = \{0 / u_1 + 0.5 / u_2 + 0 / u_3 + 0 / u_4 + 0 / u_5 + 0 / u_6 + 0.5 / u_7 + 1 / u_8\}$$

5. fuzzification, Perform fuzzification on each historical data based on the fuzzy set that has been formed

Table 6 Fuzzification Value

Period	Actual Value	Fuzzification
January 2003	395.2	A2
February 2003	547.5	A3
⋮	⋮	⋮
November 2011	276.4	A2

December 2011	856.4	A5
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6. Define FLR and FLRG, Because FLR is a relationship between data sequences, then FLR can be determined based on Table 6 in the form of a fuzzy set.

Table 7. Sample FLR

Period	Actual Value	Fuzzification	FLR1
January 2003	395.2	A2	-
February 2003	547.5	A3	A2->A3
⋮	⋮	⋮	⋮
November 2011	276.4	A2	A1->A2
December 2011	856.4	A5	A2->A5

After getting the FLR value, the FLRG value will then be determined based on Table 11. FLRG itself is a grouping of FLR based on the relationship between the state transfer from the current state to the next state..

Table 8. FLRG

Current State	Next State
A1	(49)A1,(17) A2,(1) A3,(1) A8
A2	(18)A1,(42) A2,(4) A3,(1) A4,(1) A5
A3	(1)A1,(5) A2
A4	A3
A5	A2
A6	-
A7	-
A8	A2

3.1.2 FTS Markov Chain Modeling

In the FTS Markov Chain modeling, additional steps are used to get more accurate forecasting results, so the additional steps that will be used are as follows.

1. Determination of the initial forecast on the FTS-Markov Chain method using previous data and a transition probability matrix. The transition probability matrix is based on FLRG. The transition probability matrix for each data has the order of 8 x 8 according to the interval obtained previously. The transition probability matrix for each data can be seen in table 9.

Table 9. Probability Matrix

P _{ij}	A1	A2	A3	A4	A5	A6	A7	A8
A1	0.7	0.3	0.01	0	0	0	0	0.01
A2	0.3	0.6	0.1	0.02	0.02	0	0	0
A3	0.2	0.8	0	0	0	0	0	0
A4	0	0	1	0	0	0	0	0
A5	0	1	0	0	0	0	0	0
A6	0	0	0	0	0	0	0	0
A7	0	0	0	0	0	0	0	0
A8	0	1	0	0	0	0	0	0

Based on the probability values contained in each transition probability matrix in table 9, the initial forecast values in historical data can be calculated. This calculation uses previous historical data, so the initial forecasting calculation starts from $t = 2$. For example, the rainfall data for $t = 2$ has a value of 547.5 and $t = 1$ has a value of 395.2 where in this $t = 1$ data has FLR A2 \rightarrow A3 which means it transitions from A2 to A3, so the forecasting calculation is

$$\begin{aligned}
 F2 &= m_1p_{21} + Y_2p_{22} + m_3p_{23} + m_4p_{24} + m_5p_{25} \\
 &= (103.1)(0.3) + (395.2)(0.6) + (515.6)(0.1) + (721.9)(0.02) + (928.1)(0.02) \\
 &= 335.9
 \end{aligned}$$

Where is the middle value of the value of each FLRG class which can be seen in the following table 10:

Table 10 Table of Middle Value

Class	Middle value
G1	103.1
G2	309.4
G3	515.6
G4	721.9
G5	928.1
G6	1134.4
G7	1340.6
G8	1546.9

In the same way, the results of the sample for each data can be seen in table 11.

Table 11 FTS Markov Chain Preliminary Forecasting Results Data

Period	Actual Value	Forecasting Value (F)
January 2003	395.2	
February 2003	547.5	335.9
⋮	⋮	⋮

November 2011	276.4	203.9
December 2011	856.4	260.3

2. Completing Preliminary Forecasting Value Trends, Suppose the rainfall for $t = 1$ based on table 14 can be seen that the next state is A3 and the current state is A2. With $s = \text{next state order} - \text{current state order} = 3 - 2 = 1$, then we get

$$D_{t1} = \binom{l}{-} s = \binom{206}{-} 1 = 103,1$$

2 2

So based on the equation, the results of the calculation of the adjustment value of the sample data are located in table 12.

Table 12 Adjustment Value

Period	Actual Value	Forecasting Value (F)	Adjustment Value
January 2003	395.2	0	0
February 2003	547.5	335.9	103.1
⋮	⋮	⋮	⋮
November 2011	276.4	203.9	103.1
December 2011	856.4	260.3	309.4

3. Determine the final forecasting result. To solve the final forecasting results, the following equation can be used

$$F'(t) = F(t) \pm_{t1} D \pm_{t2} D = F(t) \pm_{-} \binom{l}{-} \pm_{-} \binom{l}{-} v$$

2 2

This equation uses the adjustment value that has been obtained in Step 2. For example, in rainfall data which has an adjustment value of 103.1 and an initial forecast value of 335.9 so that

$$F'_2 = F_2 \pm D_{t1} = 335,9 + (103,1) = 439,0$$

For the final forecasting results the data sample can be presented in table 13

Table 13 Final Forecasting Sample Data

Period	Actual Value	Final Forecast (Markov Chain)
January 2003	395.2	
February 2003	547.5	439.0
⋮	⋮	⋮
November 2011	276.4	307.0
December 2011	856.4	569.6

3.1.3 FTS-Markov Chain Model Testing

The test is carried out using testing data, which is 25% of the actual data from the rainfall data, which amounts to 36 data. Using the same determination as the training data, the following is table 14 which is a sample of the forecasting results on the test data.

Table 14 FTS Markov Chain Forecasting Results

Period	Actual Value	Final Forecasting (Markov Chain)
January 2012	223.7	0.0
February 2012	258.4	226.7
March 2012	313.0	251.9
April 2012	319.1	289.8
May 2012	149.1	193.7
June 2012	58.4	215.1
July 2012	193.5	149.8
August 2012	70.3	247.1
September 2012	58.2	158.3
October 2012	157.0	149.6
November 2012	158.0	220.8
December 2012	409.8	324.7
January 2013	355.2	354.5
February 2013	414.6	399.5
March 2013	308.3	171.9
April 2013	305.5	266.5
May 2013	346.5	264.7
June 2013	140.7	187.7
July 2013	125.7	209.1
August 2013	81.5	198.3
September 2013	33.6	166.4
October 2013	106.0	131.9
November 2013	439.1	390,3
December 2013	349.4	171.9
January 2014	443.0	228.2
February 2014	220.0	171.9
March 2014	332.0	233.8
April 2014	223.0	281.6
May 2014	159.0	109.1
June 2014	221.0	325.4
July 2014	113.0	107.8
August 2014	53.0	189.1
September 2014	5.0	145.9
October 2014	16	111.3
November 2014	199	119.2
December 2014	387.0	354.2

Based on the results of the FTS Markov chain modeling method, the following is a graph of the results of the FTS Markov Chain forecasting

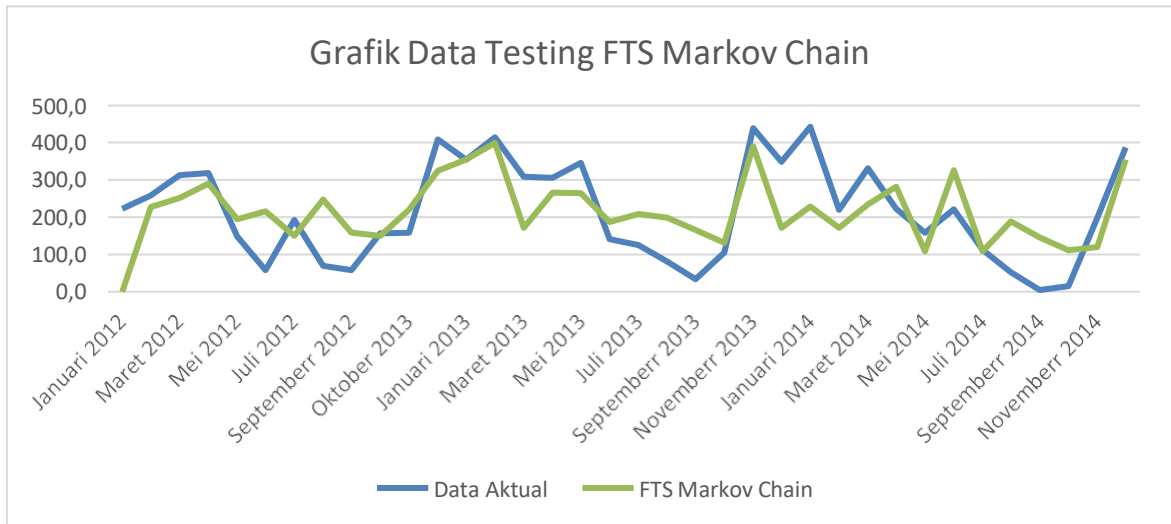


Figure 2 Forecasting Graph using FTS Markov Chain

3.1.4 Fuzzy Time Series Model Testing for Comparison

The formation of the FTS model is carried out to obtain an appropriate comparison model. The steps to get the forecast results are the same as Steps 1 to 6 For example, for rainfall data it has FLR from A2 to A3 with FLRG rainfall data from A2 to many are (18)A1,(42)A2,(4)A3 ,(1)A4,(1)A5, then the calculation of the forecasting results is as follows:

$$F(2) = \frac{m_1 + m_2 + m_3 + m_4 + m_5}{5}$$

$$= \frac{103,1 + 309,4 + 515,6 + 721,9 + 928,1}{5}$$

Where m is the symbol of the mean value of each FLRG which is used as the forecast value. For samples of test data forecasting results from FTS can be seen in table 15.

Table 15 Samples of FTS Forecasting Data

Period	Actual Value	Fuzzy Time Series
January 2012	223.7	515.6
February 2012	258.4	515.6
March 2012	313.0	515.6
April 2012	319.1	515.6
May 2012	149.1	618.8
June 2012	58.4	618.8
July 2012	193.5	618.8
August 2012	70.3	618.8

September 2012	58.2	618.8
October 2012	157.0	618.8
November 2013	158.0	618.8
December 2012	409.8	515.6
January 2013	355.2	515.6
February 2013	414.6	206.3
March 2013	308.3	515.6
April 2013	305.5	515.6
May 2013	346.5	515.6
June 2013	140.7	618.8
July 2013	125.7	618.8
August 2013	81.5	618.8
September 2013	33.6	618.8
October 2013	106.0	618.8
November 2013	439.1	206.3
December 2013	349.4	515.6
January 2014	443.0	206.3
February 2014	220.0	515.6
March 2014	332.0	515.6
April 2014	223.0	515.6
May 2014	159.0	618.8
June 2014	221.0	515.6
July 2014	113.0	618.8
August 2014	53.0	618.8
September 2014	5.0	618.8
October 2014	16	618.8
November 2014	199	618.8
December 2014	387.0	515.6

Based on the data in the table, the following is a graph of the actual data with FTS forecasting.

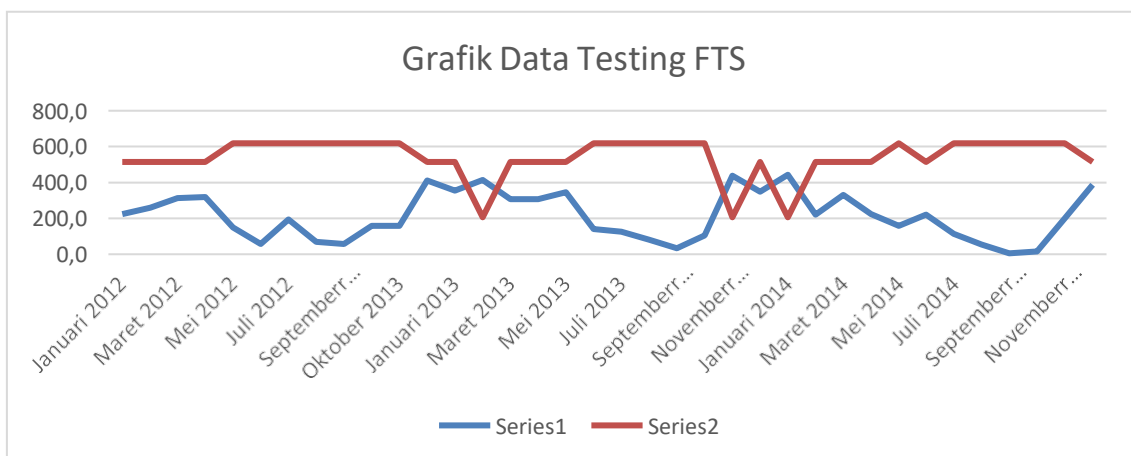


Figure 3 Forecasting Graph using FTS

3.1.5 Error Calculation

This error calculation is dispensed to check the accuracy of the FTS - Markov Chain model. As a comparison model, the FTS method is used. Testing the extent of accuracy during this study victimisation Mean Absolute share Error (MAPE). MAPE Calculation Results is seen in Table 16.

Table 16 Results of MAPE FTS Markov Chain and FTS

Data	MAPE FTS Markov Chain	MAPE Fuzzy Time Series
Rainfall	1.6%	7.4%

In table 16 it can be seen that the FTS-Markov Chain method has a smaller MAPE value than the FTS method. This can be seen in the rainfall data which has a MAPE FTS-Markov Chain value of 1.6% compared to the MAPE FTS of 7.4%. Thus the FTS-Markov Chain model is better than the FTS model in predicting rainfall in the South Kalimantan area because it has a MAPE value of 1.6% and an accuracy rate of 98.4%.

3.2 Discussion

In this study, the data used is data that has been processed by the Central Static Agency. The amount of data in this research is 144 data based on monthly data from 2003 - 2014 that will be divided into training data by 75% starting in January 2003 to December 2011 and testing data by 25% starting in January 2012 to December 2014. The data is divided into 75% and 25% due to the training methods used, namely FTS and FTS Markov chain and to see the performance of each method used. In January 2012 there was a decrease in rainfall from the same month but in a different year that is January 2011 so the testing data was taken in January 2012. The results showed that markov chain's FTS method was more accurate with an error rate of 1.6% and an accuracy score of 98.4% compared to FTS with an error rate of 7.4% and an accuracy value of 92.6%.

The distance of the comparison of MAPE between FTS and FTS Markov chain is caused by actual data processed has a value that experienced a drastic increase and decrease. And in november 2007 data has a considerable influence as the data that has the highest value of 1641.9. With the high value of the data, it will have a huge effect on the FTS method that only uses the middle value as the overall result of the data usage for the method. As for fuzzy time Markov chain uses probability matrix. To determine the final forecasting value is used the value of each actual data and the adjustment value of the initial forecasting. So that results are closer to the actual value.

1. Conclusion

From the description that has been discussed in the previous chapter, it can be concluded that the FTS markov chain method in South Kalimantan Regional Rainfall data for the period 2003 to 2014 obtained an error value of 1.6% so that it obtained an accuracy result of 98.4% and the method FTS which produces an error value of 7.4% to obtain an accuracy of 92.6%. From the results of the accuracy values of the two methods, it can be seen that the FTS Markov Chain method is better than the FTS accuracy level.

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