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Forecasting Non-Metal and Rock Mineral (MBLB) Tax Revenue Using the Fuzzy Time Series Markov Chain Method in East Lombok Regency

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ABSTRACT

Indonesia is one of the countries that is included in a developing countries. Therefore, the Indonesian Goverment is trying to carry out various developments in various regions. Regional development is one of the Indonesian government's ways of achieving national goals. In carrying out regional development, of course funds are needed as the main source to support the achievement of national development. The main source of funds obtained by the Government comes from Regional Oroginal Income. One source of Regional Oroginal Income is tax. There are various types of taxes managed by the government in East Lombok Regency. One of them is the Non-Metal Minerals and Rocks, which is a tax on the extraction of non-metallic minerals and rock Tax, which is a tax on the extraction of of non-metallic minerals and rocks from natural sources within or on the surface of the earth for use. This Non-Metal and Rock Mineral tax provides quite large revenues for East Lombok district regional taxes. Non-Metal and Rock Mineral tax income is often not constant, meaning that there is an increases and there is a decreases in the amount of income. For this reason, it is necessary to forecast Non-Metal and Rock Mineral tax revenue to predict income in the future. The method used in this study is the FTS Markov Chain order 1 and order 2. Based on the MAPE indicator, the results of forecasting using the FTS Markov Chain method of order 1 amounted to Rp. 1.117.069.497 with an accuracy of 48,55% with a just good forecasting classification. While the results of forecasting using the FTS Markov Chain method of order 2 amounted to Rp.1.761.652.173 with an accuracy of 39,12% with a just good forecasting classification. If seen from the MAPE value obtained, the forecasting results using the 2nd order FTS Markov Chain are more accurate than using the 1st order Markov Chain FTS method.

Keywords: Fuzzy Time Series (FTS) Markov Chain order 1 and order 2, MAPE (Mean Absolute Percentage Error), Non-Metal and Rock Mineral tax, Regional development.

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1. Introduction

Indonesia is a country that is included in the developing country category. Therefore, the Indonesian Government is trying to develop infrastructure in various regions. Regional development is one way for the government to achieve national goals for the sake of common interests, welfare and prosperity. To make this happen, funds are needed as the main source to support regional development. One of the sources of funds obtained by the Indonesian Government to carry out regional development comes from Original Regional Income. Original Regional Income is revenue obtained by a region from sources within its own territory which is collected based on regional regulations in accordance with applicable laws and regulations (Halim, 2014).

One source of Original Regional Income is tax. The regional government of East Lombok district, West Nusa

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Tenggara province, has formed an institution or financial management body for tax revenues, namely the East Lombok Regional Revenue Agency. According to the official website (https://bapenda.lomboktimurkab.go.id, online edition), Regional Revenue Agency East Lombok is an institution that manages the amount of income or tax receipts. Tax on Non-Metal and Rock Mineral is a tax on the activity of extracting Non-Metal and Rock Mineral from natural sources within or on the surface of the earth for use.

Based on 2020 Non-Metal and Rock Mineral tax revenue data Sourced from the East Lombok Regency Regional Revenue Agency, Non-Metal and Rock Mineral tax provides revenue of 23% for East Lombok Regency regional taxes. Therefore, the Non-metal and Rock Mineral tax needs to be paid attention to by the government because the need for MBLB materials continues to increase as a basic material for industry and residential development in East Lombok Regency.

Non-Metal and Rock Mineral tax revenue data is data that includes time series data. This research analyzes Non-Metal and Rock Mineral tax revenue data to predict the estimated amount of tax revenue in the future. Predicting the amount of Non-Metal and Rock Mineral tax revenue can be done by forecasting.

The forecasting method used is the Fuzzy Times Series (FTS) Markov Chain method. Based on research conducted by Tsaur (2011), using a comparison of the FTS Markov Chain, ARIMA-GARCH and Gray model methods. This research shows that the FTS Markov Chain method is better than the two models. So this research will use the FTS Markov Chain method to be used in forecasting Non-Metal and Rock Mineral tax revenue data. FTS Markov Chain has the advantage of having a high level of accuracy and low error (Junaidi et al., 2015).

1.1. Types of research

The type of research used in this research is applied by applying the Fuzzy Time Series Markov Chain method. The steps for the FTS Markov Chain method are:

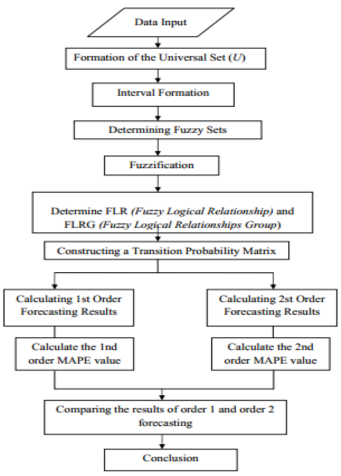

Figure 1. Research flow diagram

The subjects of this research are parties from the Regional Revenue Agency of East Lombok Regency using Non-Metal and Rock Mineral tax revenue data.

The data obtained for this research is documentation data of the monthly income from Non-Metal and Rock Mineral tax which has been listed in the form of an income table in accordance with existing data.

The analytical method used in this research is a quantitative method using descriptive data analysis techniques and the FTS Markov Chain forecasting method.

1.2. Data source and Research variable

Research data and variables used in this research is secondary data regarding monthly tax income data in East Lombok Regency for 2017 - 2020. The secondary data comes from the tax revenue agency of East Lombok Regency.

1.3. Work procedures

The research steps carried out in this research are starting with preparation, data collection, descriptive data, forecasting using the FTS Markov Chain method of order 1 and order 2, forecasting results and conclusions.

1.4. Data analysis

The data analysis method used is forecasting using the FTS Markov Chain method. The FTS Markov Chain forecasting method is a combination of the FTS method with a Markov Chain. Where FTS is a relatively new concept proposed by Song and Chissom (1993) based on Fuzzy Time Series set theory (fuzzy sets) and the concept of linguistic variables. So, The FTS Markov Chain forecasting method is a forecasting method using linguistic variables added with the use of a Markov Chain probability matrix. The FTS Markov Chain method begins with the following steps:

1. Formation of a universal set

$$U = [D_{min} - D_1, D_{max} + D_2] \tag{1}$$

with D_{min} is the minimum data, D_{max} is the maximum data and D_1 and D_2 is an arbitrary positive number determined by the researcher.

2. Formation of intervals

Determine the interval width using a frequency distribution, with the following steps :

a. Determine the range using the following formula :

$$R = (D_{max} + D_2) - (D_{min} - D_1) \tag{2}$$

with D_{min} is the minimum data / smallest data whereas, D_{max} is the maximum data / largest data

b. Determine the number of class intervals / number of classes using the Sturgess formula. The formula is as follows:

$$i = 1 + 3{,}3 \log n \tag{3}$$

with i is the number of classes or class intervals and n is a lot of data

c. Specifies the width of the interval.

To determine the length of the class interval, use the formula as below:

$$l = \frac{R}{i} \tag{4}$$

with l is the class inteval lenght, R is the range of data while i is the number of classes or class intevals.

d. Create a table based on steps a,b and c with the following formula:

$$\begin{aligned} U_1 &= [D_{min} - D_1, D_{min} - 1 + l) \\ U_2 &= [D_{min} - D_1 + l, D_{min} - D_1 + 2l) \\ U_n &= [D_{min} - D_1 + (n-1)l, D_{min} - D_1 + nl] \end{aligned} \tag{5}$$

and find the midpoint with the formula below:

$$m_i = \frac{Upper\ limit + Lower\ limit}{2} \tag{6}$$

3. Define Fuzzy Sets

Defines a fuzzy set on U. For example $A_1, A_2, A_3, \dots, A_n$ is fuzzy set that has a linguistic value from a linguistic variable, defining a fuzzy set $A_1, A_2, A_3, \dots, A_n$ in the universe of speech U is a follows:

$$A_i = \left\{\frac{\mu_{Ai}(u_1)}{u_1}, \frac{\mu_{Ai}(u_2)}{u_2}, \frac{\mu_{Ai}(u_3)}{u_3}, \dots \frac{\mu_{Ai}(u_n)}{u_n}\right\} \tag{7}$$

with $\mu(u_1)$ is a degree of membership that has a range [0,1] and $1 \le i \le n$.

4. Fuzzification

Furthermore, the fuzzification process is carried out, namely the process of mapping the input data into Fuzzy sets by building membership functions.

5. Determine Fuzzy Logical Relationship (FLR) dan Fuzzy Logical Relationship Groups (FLRG)

a. Create a Fuzzy Logical Relationship (FLR) table based on actual data. FLR can be symbolized by $A_i \to A_j$. with A_i is called the current state and A_j called the next state.

b. Determining Fuzzy Logical Relationship Groups (FLRG)

If the results of the i-th period fuzzification are Ai, and Ai do not have FLR on FLRG with conditions $A_i \to \emptyset$, where the maximum value of membership degree is u, then the forecasting value (Fi) is the middle value of u_1 or is defined by m_i.

6. Compiling a Probability Matrix

Based on the group of Fuzzy Logic Relations that have been determined in the previous step. This Markov transition probability matrix has dimensions $p \times p$, with p is the number of Fuzzy sets. The state transition probability can be formulated as follows:

$$p_{ij} = \frac{r_{ij}}{r_i} \tag{8}$$

with p_{ij} is the transition probability of the state A_i to A_j, r_{ij} is the number of state transitions A_i to A_j and r_i is a lot of data included in the state A_i. Transition probability matrix P can be written as follows:

$$P = \begin{bmatrix} p_{11} & p_{12} & p_{13} & \cdots & p_{1j} \\ p_{21} & p_{22} & p_{23} & \cdots & p_{2j} \\ p_{31} & p_{32} & p_{33} & \cdots & p_{3j} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ p_{i1} & p_{i2} & p_{i3} & \cdots & p_{ij} \end{bmatrix}$$

7. Calculate the Results of Order 1 and Order 2 Forecasting

Rule 1

If there is a Fuzzy set that does not have Fuzzy Logical Relations, for example if $A_i \to \emptyset$, and then there is data in the 2nd period $(t-1)$ get inside $A_{i,}$ then the forecasting value F_t is $m_{i(t-i)}$ is the middle value of the interval u_i on the group of Fuzzy Logic Relations formed on the data to $(t-1)$

Rule 2

If the logic relation group is fuzzy A_i is a one to one relationship (eg $A_i \to A_p$ where p_{ip} = 1 and p_{ij} = 0, $j \ne p$, where the data is taken Y_{t-1} at time $(t-1)$ enter the state A_i, then the forecasting value F_t is $m_{p(t-1)}$, with $(t-1)$ is the middle value of u_p on the group of fuzzy logic relations formed on the data to $(t-1)$

Rule 3

If the logic relation group is fuzzy A_j is a one to many relationship $\left(A_j \to A_1, A_2, A_3, \dots, A_q, j = 1,2,\dots,q\right)$, where data is taken Y_{t-1} at time $(t-1)$ enter the state A_j, hence forecasting F_t is :

$$\begin{aligned} F_t = {} & m_{1(t-1)} + m_{2(t-1)}P_{j2} + \dots + m_{j-1(t-1)}P_{j(j-1)} \\ & + Y_{(t-1)}P_{jj} + m_{j+1(t-1)}P_{j(j+1)} + \cdots \\ & + m_{t-1}P_{jq} \end{aligned} \tag{9}$$

8. Calculate MAPE Values of Order 1 and Order 2.

To find the level of forecasting accuracy in conducting this research, researchers used MAPE (Mean Absolute Percentage Error) calculations with the formula:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \times 100\% \tag{10}$$

9. Comparing the Results of Order 1 and Order 2 Forecasting.

2. Result

2.1. Descriptive Analysis Results

Based on the Non-Metal and Rock Mineral tax revenue data used, the average value (mean) of the data is IDR Rp.1.122.516.397,31; the minimum data value is RP. 253.062.925; maxmum value is Rp. 4.870.923.220 and the variant value is 648.385.809.121.660.290.000. The following is a figure plotting the total monthly income of Non-Metal and Rock Mineral Taxes.

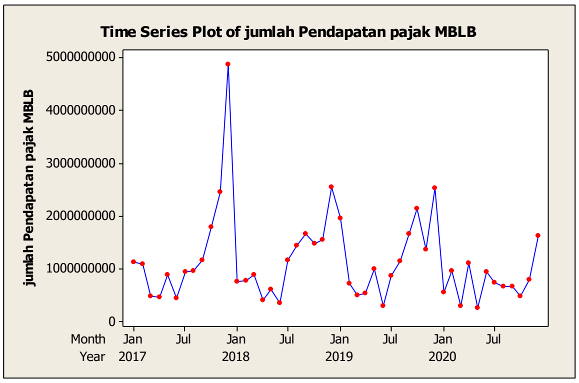

Figure 2. Time series plot of revenue Non-Metal and Rock Mineral tax.

Based on graphic Figure 2, it can be seen that the amount of monthly Non-Metal and Rock Mineral tax income from January 2017 to November 2017 moved between IDR 400.000.000 to IDR 2.000.000.000, then jumped up in December 2017 to IDR 4.870.923.220. The data decreased drastically from January 2018 to December 2020 starting from the range of IDR 250.000.000 to IDR 2.500.000.000.

2.2. Fuzzy Time Series Markov Chain Order 1

1. The Universal Set

$$U = [D_{min} - D_1, D_{max} - D_2]$$
$$U = [253.602.925 - 2,\ \ 4.870.923.220 + 5]$$
$$U = [\mathbf{253.602.923},\ \ \mathbf{4.870.923.225}]$$

2. Formation of intervals

To form an interval, this is done by finding the range of data, the number of intervals, the length of the interval and finding the middle value. The following are the results of forming intervals :

Table 1. Classification of Distric Non-Metal and Rock Mineral Tax Data. East Lombok

Intervals	Lower limit	Upper limit	Middle value(m_i)
u_1	253.602.923	913.220.109	583.411.516
u_2	913.220.109	1.572.837.295	1.243.028.702
u_3	1.572.837.295	2.232.454.481	1.902.645.888
u_4	2.232.454.481	2.892.071.667	2.562.263.074
u_5	2.892.071.667	3.551.688.853	3.221.880.260
u_6	3.551.688.853	4.211.306.039	3.881.497.446
u_7	4.211.306.039	4.870.923.225	4.541.114.632

3. Determine the Fuzzy Set

Determine the fuzzy set in the speech universe U which is based on partition re-division. Fuzzy sets are denoted in linguistic variables based on the state of the universal set $u_1, u_2, u_3, u_4, u_5, u_6, u_{7.}$ Based on the partition results, a fuzzy set A from U can be formed as follows : $A_1 =$ Very low, $A_2 =$ Low , $A_3 =$ Preety low, $A_4 =$ currently, $A_5 =$ High enough , $A_6 =$ High , $A_7 =$ Very high. The following is a fuzzy set:

$$\begin{aligned}
A_1 &= \left\{\frac{1}{u_1}, \frac{0,5}{u_2}, \frac{0}{u_3}, \frac{0}{u_4}, \frac{0}{u_5}, \frac{0}{u_6}, \frac{0}{u_7}\right\} \\
A_2 &= \left\{\frac{0,5}{u_1}, \frac{1}{u_2}, \frac{0,5}{u_3}, \frac{0}{u_4}, \frac{0}{u_5}, \frac{0}{u_6}, \frac{0}{u_7}\right\} \\
A_3 &= \left\{\frac{0}{u_1}, \frac{0,5}{u_2}, \frac{1}{u_3}, \frac{0,5}{u_4}, \frac{0}{u_5}, \frac{0}{u_6}, \frac{0}{u_7}\right\} \\
A_4 &= \left\{\frac{0}{u_1}, \frac{0}{u_2}, \frac{0,5}{u_3}, \frac{1}{u_4}, \frac{0,5}{u_5}, \frac{0}{u_6}, \frac{0}{u_7}\right\} \\
A_5 &= \left\{\frac{0}{u_1}, \frac{0}{u_2}, \frac{0}{u_3}, \frac{0,5}{u_4}, \frac{1}{u_5}, \frac{0,5}{u_6}, \frac{0}{u_7}\right\} \\
A_6 &= \left\{\frac{0}{u_1}, \frac{0}{u_2}, \frac{0}{u_3}, \frac{0}{u_4}, \frac{0,5}{u_5}, \frac{1}{u_6}, \frac{0,5}{u_7}\right\} \\
A_7 &= \left\{\frac{0}{u_1}, \frac{0}{u_2}, \frac{0}{u_3}, \frac{0}{u_4}, \frac{0}{u_5}, \frac{0,5}{u_6}, \frac{1}{u_7}\right\}
\end{aligned} \tag{11}$$

4. Fuzzification

Fuzzification is the process of identifying historical data into fuzzy sets. If F_t is in the fuzzy set A_k so F_t will be fuzzified as A_k. For example, For January 2017 with historical data of 1.122.133.535 which is in the fuzzy set A_2 then fuzzified as A_2. In the same way for other Non-Metal and Rock Mineral tax income data. The fuzzification of each historical data can be seen in Table 2 below :

Table 2. Fuzzification of Actual Data.

No	Mounth	Actual Data (x_t)	Fuzzification
1	Jan – 2017	1.122.133.535	A_2
2	Feb – 2017	1.096.132.611	A_2
. . .	...	...	...
47	Nov – 2020	795.487.998	A_1
48	Des – 2020	1.620.658.457	A_3

5. Determine Fuzzy Logical Relationship (FLR) and Determine Fuzzy Logical Relationship Group (FLRG)

a. Determine *Fuzzy Logical Relatioship* (FLR)

Relationship is determined based on the fuzzification value of historical data if F_{t-1} fuzzified as A_t and F_t as A_j, so A_i relate to $A_{j.}$ For example, in January 2017 it was fuzzified A_2 and February 2017 its fuzzification A_2 so the FLR from January 2017 to February 2017 is $A_2 \to A_2$. Overall, the FLR formed based on 48 months of historical data for monthly Non Metal and Rock Mineral tax income data is presented in Table 5.6 below. The FLR that was formed was immediately carried out in February 2017 with F_{t-1} was fuzzified in January 2017 and F_t is February 2017.

Table 3. Fuzzy Logical Relationship (FLR) Order 1.

No	Mounth	Data order	FLR	No. FLR
1	Jan – 2017			
2	Feb – 2017	1 – 2	$A_2 \to A_2$	1
3	Mar – 2017	2 – 3	$A_2 \to A_1$	2

No	Mounth	Data order	FLR	No. FLR
4	Apr – 2017	3 – 4	$A_1 \to A_1$	3
. . .	. . .	. . .	. . .	...
48	Des – 2020	47 – 48	$A_1 \to A_3$	47
49	Jan – 2021	48 – 1	$A_3 \to A_2$	48

b. Classifying FLR into Groups to Form a Fuzzy Logical Relationship Group (FLRG)

Next, after getting the FLR, then determine the FLRG. FLRG is carried out by grouping fuzzy sets that have the same Current state or left state of the FLR which is formed from Table 3. For example for relationships A_1 which is the left state or current state, namely each is related to $A_1 \to A_1$, $A_1 \to A_2$, $A_1 \to A_3$ then the FLRG formed is $A_1 \to A_1, A_2, A_3$. Overall, The FLRG obtained based on the FLR formed is presented in Table 4 below. When determining FLRG, even if there is a repetition of the relationship, it is still counted once. FLRG is a grouping of each state shift which aims to simplify calculations of existing FLRG and is in line with the basic principles of Markov chains. Below is the FLRG of all the data.

Table 4. Fuzzy Logical Relationship Group (FLRG) Order 1 and FLR Number

Fuzzy Logic Relations	FLR Number
$\mathbf{A_1 \to A_1, A_2, A_3}$	3,4,5,6,13,14,15,16,17,18,26, 27,28,30,31,37,39,41,43,44,4 5,46,47.
$\mathbf{A_2 \to A_1, A_2, A_3, A_4}$	1,2,7,8,9,19,20,22,23,24,29,3 2,35,38,40,42
$\mathbf{A_3 \to A_1, A_2, A_3, A_4}$	10,21,25,33,34
$\mathbf{A_4 \to A_1, A_3, A_7}$	11,24,36
$\mathbf{A_5 \to \emptyset}$	-
$\mathbf{A_6 \to \emptyset}$	-
$\mathbf{A_7 \to A_1}$	12

For other interval classes, each has a FLRG according to table 4 above. For more clarity regarding the number of states from Left Hand Side (LHS) and Right Hand Side (RHS) in Table 5 below.

Table 5. Fuzzy Logical Relationship Groups (FLRG) Order 1

Current state **(LHS)**	***Next state*** **(RHS)**
$\mathbf{A_1}$	$15(A_1), 7(A_2), A_3$
$\mathbf{A_2}$	$5(A_1), 5(A_2), 3(A_3), 2(A_4)$
$\mathbf{A_3}$	$A_1, 2(A_2), A_3, A_4$
$\mathbf{A_4}$	A_1, A_3, A_7
$\mathbf{A_5}$	$\emptyset$
$\mathbf{A_6}$	$\emptyset$
$\mathbf{A_7}$	A_1

Based on Table 5, it shows the number of next states for each existing current state. For example, in the current state A_1 has a next state that is transitioning to A_1 15 times, transitioning to state A_2 7 times and transitions to state A_3 1 time. In the same way, the explanation of the next state is also the same as the state A_1, so that by obtaining transitions from each state, it makes it easier to determine the Markov transition matrix that will be used to determine the forecasting value. The following is the forecasting transition process presented in Figure 3 below:

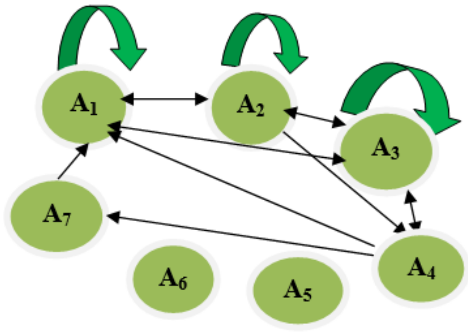

Figure 3. 1st Order Forecasting Transition Process

6. Determining the Markov Transition Probability Matrix

Determining the Markov transition probability matrix can be determined by looking at the state transition probability with the size of the matrix $p \times p$. By using monthly Non-Metal and Rock Mineral tax income data, we get 7 class intervals so that the size of the matrix formed is a matrix of size 7×7. To determine the Markov Chain transition probability matrix, look at the FLRG that is formed, for example in the first row of the matrix is the third state A_1 where A_1 transition to state A_1 15 times, state A_2 7 times, and state A_3 1 times and the number of states is 23. So that each of them has a probability of successive transition matrisks $\frac{15}{23}, \frac{7}{23}, \frac{1}{23}$. In the same way, other matrix formation results are obtained as below

$$P = \begin{bmatrix} 15/23 & 7/23 & 1/23 & 0 & 0 & 0 & 0 \\ 5/15 & 5/15 & 3/15 & 2/15 & 0 & 0 & 0 \\ 1/5 & 2/5 & 1/5 & 1/5 & 0 & 0 & 0 \\ 1/3 & 0 & 1/3 & 0 & 0 & 0 & 1/3 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

7. Determining Forecasting Results

After getting the Markov transition probability matrix, forecasting will be carried out. For example, forecasting calculations for February 2017 (2nd data) are transitioning from state $A_2 \to A_2$ Calculations are made by looking at previous data. The following are forecasting calculations for February 2017:

$$\begin{aligned} F_{(1)} &= m_1 p_{11} + m_2 p_{22} + m_3 p_{23} + m_4 p_{24} + m_5 p_{25} \\ &\quad + m_6 p_{26} + m_7 p_{27} \\ &= (583.411.516) \times \frac{5}{15} + (1.122.133.535) \times \frac{5}{15} \\ &\quad + (1.902.645.888) \times \frac{3}{15} \\ &\quad + (2.562.263.074) \times \frac{2}{15} + 0 + 0 + 0 \end{aligned}$$

$$= 194.470.506{,}333 + 374.044.511{,}667 + 380.529.177{,}6 + 341.635.076{,}533$$
$$= 1.290.679.271{,}13$$

In the same way, the final forecasting results are obtained as below:

Table 6. Final Forecasting Results of Order 1

No	Actual Data (x_t)	Adjustment Value (D_t)	Early Forecasting (F_t)	Final Forecasting (F'_t)
1	1.122.133.535	-	-	-
2	1.096.132.611	0	1.290.679.271,13	1.290.679.271,13
⋮	⋮	⋮	⋮	⋮
25	1.958.770.262	-329.808.593	2.342.390.678,67	2.012.582.085,67
26	721.662.049	-659.617.186	1.518.100.451,2	858.483.265,2
⋮	⋮	⋮	⋮	⋮
48	1.620.658.457	659.617.186	979.833.337,913	1.639.450.523,91
49		-329.808.593	1.446.878.090,2	1.117.069.497,2

Based on Table 6, the final forecast value for January 2021 is 1.117.069.497. Next, after getting the forecasting value for the next period, look for the MAPE (Mean Absolute Percentage Error) value to determine the level of accuracy of the forecasting that has been done.

8. Determining MAPE For 1st Order FTS Markov Chain Forecasting

$$\mathrm{MAPE} = \frac{1}{\mathrm{n}}\sum_{\mathrm{t}=1}^{\mathrm{n}}\left|\frac{\mathrm{A_t} - \mathrm{F_t}}{\mathrm{A_t}}\right| \times 100\%$$
$$= \frac{1}{48} \times (22{,}30380908) \times 100\%$$
$$= 48{,}54960226$$
$$\cong 48{,}541\%$$

By using the formula above, the forecasting accuracy is 48,541%. For this reason, by obtaining a MAPE value of 48,541%, using the FTS Markov Chain method of order 1, it was found that the forecasting model's capabilities were suitable for use for monthly tax revenue data for Non-Metal and Rock Mineral taxes for 2017 - 2020 in East Lombok Regency.

2.3. Fuzzy Time Series Markov Chain Order 2

Forecasting using FTS Markov Chain Order 2 has four steps at the beginning, the process is the same as FTS Markov Chain order 1. The following are the steps using the FTS markov chain order 2 method, namely as follows:

1. Determine the fuzzy logical relationship (FLR) and determine the fuzzy logical relationship group (FLRG)

Table 7. Fuzzy Logical Relationship (FLR) Order 2

No. FLR	FLR
1	$(\mathrm{A_2}, \mathrm{A_2}) \rightarrow \mathrm{A_1}$
2	$(\mathrm{A_2}, \mathrm{A_1}) \rightarrow \mathrm{A_1}$
⋮	⋮
46	$(\mathrm{A_1}, \mathrm{A_1}) \rightarrow \mathrm{A_3}$
47	$(\mathrm{A_3}, \mathrm{A_2}) \rightarrow \mathrm{A_2}$

Table 8. Fuzzy Logical Relationship Group (FLRG) and 2nd Order FLR Data Sequence

No. FLR	FLR
1	$(\mathrm{A_2}, \mathrm{A_2}) \rightarrow \mathrm{A_1}$
2	$(\mathrm{A_2}, \mathrm{A_1}) \rightarrow \mathrm{A_1}$
⋮	⋮
46	$(\mathrm{A_1}, \mathrm{A_1}) \rightarrow \mathrm{A_3}$
47	$(\mathrm{A_3}, \mathrm{A_2}) \rightarrow \mathrm{A_2}$

Based on Table 8. 2nd order FLR which is formed from several sub intervals where there are interval classes A_5 and A_6 which do not have FLRG meaning the interval class A_5 and A_6 is an empty set because nothing transitions between these two states. For example, for state $(A_1, A_1) \rightarrow A_1, A_2, A_3$ transition with the FLR number as in the table above. In the same way the FLR and the corresponding FLR number are obtained.

Table 9. Table of Current state and Next State Order 2

Current State (LHS)	Next State (RHS)
$(\boldsymbol{A_1}, \boldsymbol{A_1})$	$10(A_1), 4(A_2), A_3$
$(\boldsymbol{A_1}, \boldsymbol{A_2})$	$4(A_1), 2(A_2), A_3$
⋮	⋮
$(\boldsymbol{A_4}, \boldsymbol{A_7})$	A_1
⋮	⋮
$(\boldsymbol{A_7}, \boldsymbol{A_1})$	A_1
⋮	⋮

Table 9. shows the number of transitions from the current state and next state. For example, for state $(A_1, A_1) \rightarrow A_1, A_2, A_3$ make the transition to A_1 10 times, transition to A_2 4 times, and transition to A_3 1 times. This applies to the next state with the same transition to the next state as seen from the number of each transition. The following is the forecasting transition process using the 2nd order FTS markov chain method:

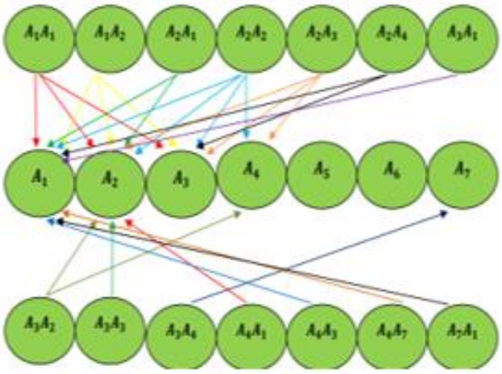

Figure 4. 2nd Order Forecasting Transition Process

2. Determine the Markov Transition Probability Matrix

Determining the Markov transition probability matrix can be determined by looking at the state transition probability with the size of the matrix $p^r \times p$, where r is the order of the FTS markov chain method. Using monthly MBLB tax income data, we get 7 class intervals and the number of second order states is 49, so the size of the matrix formed is a matrix of size 49×7. The results of matrix formation are as below:

$$P = \begin{bmatrix} 10/15 & 4/15 & 1/15 & 0 & 0 & 0 & 0 \\ 4/7 & 2/7 & 1/7 & 0 & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 3/5 & 2/5 & 0 & 0 & 0 & 0 & 0 \\ 1/5 & 1/5 & 2/5 & 1/5 & 0 & 0 & 0 \\ 0 & 1/3 & 1/3 & 1/3 & 0 & 0 & 0 \\ 1/2 & 0 & 1/2 & 0 & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1/2 & 0 & 1/2 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

3. Calculating Forecasting Results

The following are the forecasting results using the 2nd order FTS Markov Chain method which starts using February data with calculations as below:

Forecast for March 2017 which transitions from state $(A_2, A_2) \rightarrow A_1$:

$$\begin{aligned} F_{(2)} &= m_1 p_{221} + x_2 p_{222} + m_3 p_{223} + m_4 p_{224} + m_5 p_{225} \\ &\quad + m_6 p_{226} + m_7 p_{227} \\ &= 583.411.516 \times 1/5 + 1.906.132.611 \times 1/5 \\ &\quad + 1.902.645.888 \times 2/5 \\ &\quad + 2.562.263.074 \times 1/5 + 0 + 0 + 0 \\ &= 116.682.303{,}2 + 219.226.522{,}2 + 761.058.355{,}2 \\ &\quad + 512.452.614{,}8 \\ &= 1.609.419.795{,}4 \end{aligned}$$

In the same way, initial forecasting results were obtained using the FTS markov chain method of order 2 as shown in Table 10 below.

Table 10. Final Forecasting Results of Order 2

No	Actual Data(x_t)	Adjustment Value (D_t)	Early Forecasting (F_t)	Final Forecasting (F'_t)
1	1.122.133.535	-	-	-
2	1.096.132.611	-	-	-
3	488.364.110	-329.808.593	1.609.419.795,4	1.279.611.202,4
4	457.076.969	-329.808.593	790.229.946,8	460.421.353,8
⋮	⋮	⋮	⋮	⋮
36	2.523.608.876	659.617.186	1.961.465.289,5	2.621.082.475,5
37	556.727.383	-989.425.779	1.243.028.702	253.602.923
⋮	⋮	⋮	⋮	⋮
46	485.517.302	0	899.282.901,733	899.282.901,733
47	795.487.998	0	781.995.581,066	781.995.581,066
48	1.620.658.457	659.617.186	998.642.711,733	1.648.259.897,73
49		-329.808.593	2.091.460.765,5	1.761.652.172,5

Based on Table 10, The forecast results for the next period, namely January 2021, are 1.761.652.173. The next step is to look for the MAPE value to see the percentage of error in forecasting.

4. Determining the MAPE value in the 2nd order FTS Markov Chain method

$$\begin{aligned} MAPE &= \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \times 100\% \\ &= \frac{1}{48}(18{,}77685409) \times 100\% \\ &= 39{,}11844601 \\ &\cong 39{,}118\% \end{aligned}$$

By using the formula above, the forecasting accuracy is 39,118%. For this reason, by obtaining a MAPE value of

39.118%, using the 2nd order FTS markov chain method, it is found that the forecasting model's capabilities are suitable for use for monthly tax revenue data for Non-Metal and Rock Mineral taxes for 2017 - 2020 in East Lombok Regency.

3. Discussion

This research uses the FTS Markov Chain forecasting method, namely a combination of the FTS method and the Markov Chain. Based on previous research conducted by Tsaur (2011), using the FTS Markov Chain forecasting method is better than using the ARIMA-GARCH and Gray model methods. This is because the level of accuracy of the FTS Markov Chain method is higher and has a low error. The following are the results of forecasting calculations using the FTS Markov Chain method of order 1 and order 2 as well as the MAPE values of each order as follows.

Table 11. Comparison of 1st Order and 2nd Order Forecasting Results.

Fuzzy Time Series Markov Chain Method	FTS Markov Chain Order 1	FTS Markov Chain Order 2
Forecasting results	1.117.069.497	1.761.652.173
MAPE value	48,541 %	39,118 %

Based on Table 11 above, it shows that by using the 2nd order FTS Markov Chain method, the forecasting value for the next period is higher compared to the 1st order FTS Markov Chain method with a difference in forecasting results of 644.582.676. The forecasting results using the 2nd order FTS Markov Chain method are more accurate than the 1st order FTS Markov Chain. This can be seen from the MAPE value of each forecasting method, namely for the 1st order FTS Markov Chain it is 48,541 % and the 2nd order MAPE is 39,118 %.

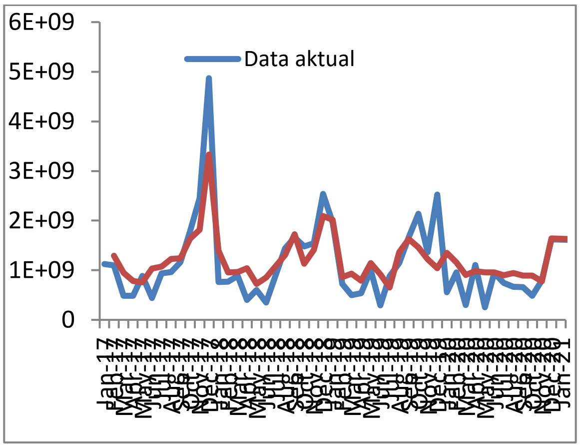

Figure 5. Comparison graph of actual data and 1st order forecasting

Based on Figure 5 above, it shows a comparison of the forecasting results of the FTS Markov Chain method with actual data from Non-Metal and Rock Mineral tax revenue data from January 2017 to January 2021 in East Lombok Regency. The red graph shows data from 1st order forecasting results and the blue graph shows actual data. The forecast graph above the average is above the actual data pattern. However, there are also FTS Markov Chain forecasting data patterns that have forecasting results that are close to the actual data.

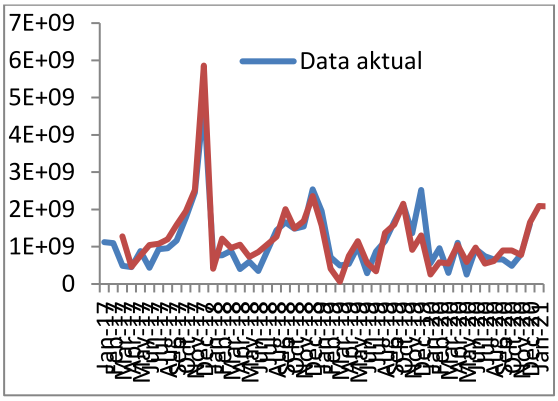

Figure 6. Comparison graph of actual data and 2nd order forecasting.

Based on Figure 6 above, it shows a graph comparing actual data with forecast data for Non-Metal and Rock Mineral tax data from January 2017 to January 2021 in East Lombok Regency. The actual data forecasting pattern graph in the image above is blue and the 2nd order forecasting is red. Based on the picture above, it can be seen that second order forecasting tends to be close to the actual data even though there are second order forecasting data results that exceed the actual data.

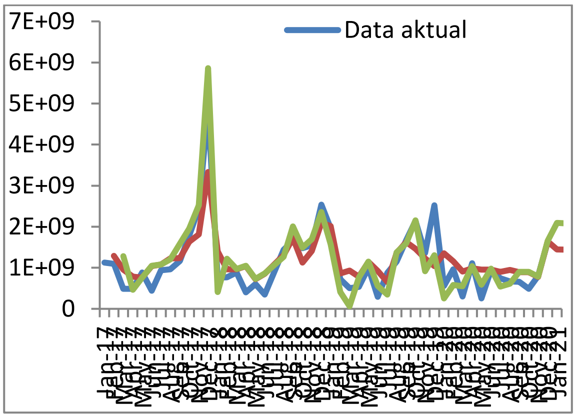

Figure 7. Comparison graph of actual data with 1st order and 2nd order forecasting

Based on Figure 7, it shows the graph for actual data, namely the graph is blue, while the graph for the 1st order FTS Markov Chain method is red and the graph for the 2nd order FTS Markov Chain method is green. From the graph, it can be seen that the average forecasting result that is closer is the forecasting result of the 2nd order FTS Markov Chain method, which on average moves closer to the actual data graph. This is made clear by the MAPE value resulting from the order of each method, where the FTS Markov Chain method of order 2 has a smaller MAPE value compared to the MAPE value of the FTS Markov Chain method of order 2.

4. Conclusion

Based on the research results that have been obtained, it can be concluded that the results of forecasting Non-Metal and Rock Mineral tax revenue using the FTS Markov Chain order 1 method is IDR 1.117.069.497 with a MAPE value of 48.541 %. Meanwhile, the forecasting results using the 2nd order FTS Markov Chain method were IDR 1.761.652.173 with a MAPE value of 39,118 %. Therefore, if we look at the MAPE values obtained, it can be concluded that the FTS Markov Chain method of order 2 is more accurate and more feasible than the FTS Markov Chain method of order 1.

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