FUZZY VECTOR AUTOREGRESSION FOR FORECASTING FARMER EXCHANGE RATE IN CENTRAL JAVA PROVINCE

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Abstract: Computer technology has developed to a very advanced measure. Calculations using complex formulas are no longer an obstacle for industry and researchers. Along with advances in computing technology, the development of fuzzy system models is also experiencing rapid progress. This paper proposes a fuzzy model combined with Vector Autoregression. The fuzzy membership function is built by selecting the median of each set to be the center of the fuzzy set. The function chosen as the membership function is Gaussian. The fuzzy Vector Autoregression model obtained was applied to the Farmer's Exchange Rate in Central Java Province. The accuracy of the model is measured based on the Mean Absolute Percentage Error. The results of model trials on FER Central Java in 2014-2020, show a pretty good forecast, namely forecasting with MAPE around 5%, and not exceeding 10%.

1. INTRODUCTION

Vector Autoregressive (VAR) is a time series multivariate statistical method that has more than one variable. Such multivariate processes arise when several time series processes are observed simultaneously over time. Applying a multivariate time series process to examine the movement of the economy in various fields such as economics, engineering, and agriculture becomes very interesting. For example, in agriculture, the yield of rice from time to time may be related simultaneously over time to the yield of other commodities such as plantations and fisheries.

Indonesia is an agricultural country where most of the people are farmers and fishermen (Murdianto, 2020). The agricultural sector is relied upon as a source of livelihood and as a support for development. As an agricultural country, national economic development in Indonesia needs to prioritize the agricultural sector, because most of Indonesia's population lives in rural areas with a livelihood as farmers.

The agricultural sector has an important role in absorbing labor and providing domestic food needs. In addition to making a very large contribution to meet national food needs, some agricultural products are also used as export commodities (Rosmayanti, 2019). In other words, agriculture is one of the largest sectors which support the economy in Indonesia. Therefore, to ensure the agricultural sector continues making a significant contribution to economic growth, the government's attention is always given to farmer

welfare (Dahiri, 2018). The higher the farming community level of welfare, the higher is the level of agricultural production.

One indicator used to measure the level of farmers'welfare is the Farmer's Exchange Rate (FER) (Trimono et al., 2020). Conceptually, FER appraises the pricing for goods (products) produced by farmers and the cost of goods or services needed to meet their own needs and for their agricultural production process. Farmer's Exchange Rate is formulated as a comparison between the price index received by farmers (It) and the price index paid by farmers (Ib) which is expressed as a percentage.

The income gap between urban and rural residents is still common (Han et al., 2021), as the welfare of farmers needs to be improved. In order to attend to the development of farmers' welfare, it is necessary to attend to the FER from time to time, as well as to predict FER in the future. Predictions can be made based on the availability of a number of historical data, especially strong forecasting techniques inferring a stochastic dependence between past and future values (Sagheer and Kotb, 2019). Based on correlation analysis (Trimono et al., 2020) the FER value of an agricultural sector in Central Java Province tends to be correlated with the FER of other agricultural sectors. This is because the harvest price for each sector is linked to the others. Given the correlation between various agricultural sectors, applying VAR processes to sector indices advances the prediction of FER behavior..

The development of computing technology is currently very advanced, allowing for statistical calculation methods to also progress. Complicated calculations are no longer an obstacle in processing statistical data, so sophisticated fuzzy models have lately been developed to handle information uncertainty in decision-making. Fuzzy models have been developed by several researchers for statistical data purposes (Chilwal and Mishra, 2020).

The use of fuzzy models in time series is also done by many researchers (Xie et al., 2021) to predict transportation use. Fuzzy models are also used for the diagnosis of brain cancer (Abadi et al., 2019). Prediction of exchange rates in modern financial markets using fuzzy models has been carried out by Reddy SK, (2015). Torbat et al., (2018) used the fuzzy ARIMA model for forecasting consumption in commodity markets.

Researchers also attempt to improve the fuzzy time series model performance for the purpose of forecasting. Giving weights to increase the accuracy of the fuzzy model for forecasting the Jakarta Composite Index was carried out by Abadi et al., (2017). Calculating with a scale factor also increases accuracy as evidenced by Nurhayadi et al. (2020). Cordón et al., 2000, improve accuracy by increasing cooperation between rules in Knowledge Base linguistic models.

This paper proposes the idea of a new multiple input and multiple output fuzzy model, namely VAR fuzzy inference. As an empirical comparison of forecast results, the model will be applied to data on the agricultural sector of rice & secondary crops, horticulture, and fisheries in Central Java Province, as has been studied by Trimono et al., (2020).

2.   LITERATURE REVIEW

The literature review provides a brief and straightforward overview of theories, statements or anything related to and supports the problem posed either from formal literature (books, journals, written scientific reports) or real conditions that can be proven/observed.

In this section, some basic definitions of fuzzy and time series will be explained which will be used for modeling. A fuzzy set is a collection of elements with a range of membership grades. Let U be the universe of discourse with $U = \{u_1, u_2, u_3, \ldots, u_n\}$ where u_j, j=1, 2, …, n is the linguistic value that can be assigned to U. The fuzzy set A_i of U is defined by

$$A_i = \sum_{j=1}^{n} \mu_{Ai} \ (u_j)/u_j \tag{1}$$

Where μ_{Ai} is the membership function of the fuzzy set A_i, such that $\mu_{Ai}: U \rightarrow [0,1]$, and u_j where $1 \le j \le n$ are elements of set U and $\mu_{Ai}(u_j) \in [0,1]$ u is the degree of membership of u_j to A_i

Let series $\{y_t\}$ where $t = (\ldots, 0, 1, 2, 3, \ldots)$ is subset of R, and R be the universe of discourse defined by the fuzzy sets $f_i(t)$. If $F(t)$ consists of $f_i(t)$ where $i = (1, 2, 3, \ldots)$, then $F(t)$ is defined as a fuzzy time series on $\{y_t\}$.

Suppose that $F(t)$ is caused only by $F(t-k)$ and is denoted by $F(t-k) \rightarrow F(t)$; then there is a fuzzy causal relationship between $F(t)$ and $F(t-k)$ that can be expressed as the fuzzy relational equation $F(t) = F(t-k) \circ R(t, t-k)$ where $\circ$ is a max-min composition operator. Further, $F(t)$ is called a time-invariant fuzzy time series, if the fuzzy relation $R(t, t-k)$ of $F(t)$ is independent of time t, that is for $t_1 \ne t_2$, $R(t_1, t_1 - k) = R(t_2, t_2 - k)$.

The time series invariant Takagi-Sugeno-Kang (TSK) fuzzy model is defined as follows. If $F(t)$ is caused only by $F(t-1)$, the fuzzy relationship $F(t-1) \rightarrow F(t)$ is called a first-order model of $F(t)$. If $F(t)$ is given a constant value c, where c is a crisp number, the fuzzy relationship is called a fuzzy model Takagi-Sugeno-Kang relationship.

3. MATERIAL AND METHOD

This study aims to develop a fuzzy model combined with VAR. The optimal input variable is selected. The obtained model was applied to FER data in Central Java for the rice and secondary crops, horticulture and fishery sectors. The data obtained is data from January 1, 2014 to December 2021, from Badan Pusat Statistik (Adhi, 2022).

The fuzzy time series model is applied to each agricultural sector. The data is divided into two parts, the first 79 data sets are used as training data, and the last data is used for testing. Various numbers were tried to determine the number of fuzzy sets to construct three fuzzy rule bases, and several other numbers were trialed to determine the scale parameters of the Gaussian fuzzy membership function. Furthermore, the Fuzzy VAR model is compiled by combining the three fuzzy time series models using a weighted average formula. Mean Absolute Error is calculated to determine the accuracy of the model.

4. RESULTS AND DISCUSSION
4.1. Model Fuzzy Formation

This paper proposes an alternative forecasting method using a fuzzy system which is applied to an autoregressive vector model. Given m time series, $y_{i,1}, y_{i,2}, \ldots, y_{i,n}$ where i = 1, 2, …, m and a relationship is made between the current data and the past data.

$$Y_{i,(t-1)} \rightarrow Y_{i,t} \tag{2}$$

For each series, a universe of discourse, or scope, is built $U_i = [\min(y_{i,j}), \max(y_{i,j})]$, with $j = , 1, 2, ..., n$, where $\min(y_{i,j})$ and $\max(y_{i,j})$ are minimum score and maximum on series $y_{i1}, y_{i2}, ..., y_{in}$. Partition then, each universe of discourse into several length intervals: $u_{i,1}, u_{i,2}, ..., u_{i,p_i}$. The number of intervals will be in accordance with the number of linguistic variables fuzzy sets $A_{i,1}, A_{i,2}, ..., A_{i,p_i}$, to be considered.

The relation in (2) is used as the basis for forming a fuzzy relationship

$$F_i(Y_{i(t-1)}) \rightarrow Y_{it} \tag{3}$$

to be applied to each series. Let each $y_{i,t-1}$, $i = 1, 2, ...m$, be selected $A_{i,k}$ where $k = 1, 2, ..., p_i$ which has the highest degree. To determine the degree of membership, this paper uses the Gaussian function:

$$\mu_{A_{ik}}(y_{ij}) = \exp\left(-\frac{(y_{ij} - c_{ik})^2}{\sigma_i^2}\right) \tag{4}$$

where $i = 1, 2, ...n$, and $k = 1, 2, ..., p_i$

Takaki-Sugeno-Kang relation is created, if A_{ij} has a relation with some crisp number $y_{ij_1}, y_{ij_2}, ..., y_{ij_n}$ then A_{ij} related to the median $\tilde{y}_{ij}$; $j = 1, 2, ...n$ in the hope of obtaining a time series forecast with the smallest absolute error (Nurhayadi et al., 2014), so that for each j, $y_{i,t}$ can be calculated:

$$\hat{y}_{i,t} = \frac{\sum_{k=1}^{p_i} \tilde{y}_{i,t}\, \mu_{A_{ik}}(y_{i,t-1})}{\sum_{k=1}^{p_i} \mu_{A_{ik}}(y_{i,t-1})} \tag{5}$$

4.2. Application of Fuzzy Model on VAR

Suppose the VAR model for the three series is:

$$
\begin{aligned}
y_{1,t} &= c_1 + a_{1,1}y_{1,t-1} + a_{1,2}y_{2,t-1} + a_{1,3}y_{3,t-1} + e_{1,t}\\
y_{2,t} &= c_2 + a_{2,1}y_{1,t-1} + a_{2,2}y_{2,t-1} + a_{2,3}y_{3,t-1} + e_{2,t}\\
y_{3,t} &= c_3 + a_{3,1}y_{1,t-1} + a_{3,2}y_{2,t-1} + a_{3,3}y_{3,t-1} + e_{3,t}
\end{aligned} \tag{6}
$$

and given the correlation of the three time series $Y_{1,t}$, $Y_{2,t}$, $Y_{3,t}$ as shown in Table 1. The fuzzy VAR model is prepared by substituting equation (5) in equation (6), using a fuzzy approach.

Table 1. The Correlation Value Between Series

	Series-1	Series-2	Series-3
Series-1	1	r_{12}	r_{13}
Series-2	r_{12}	1	r_{23}
Series-3	r_{13}	r_{23}	1

The correlation coefficient of the three series is quite reasonable if it is used as a weight on the fuzzy model, so that the prediction of $\hat{y}^*_{i,t}$ obtained from the weighted average of the three forecasts:

$$\hat{y}^*_{1,t} = \frac{r_{1,1}\,\hat{y}_{1t} + r_{1,2}\hat{y}_{2,t} + r_{1,3}\hat{y}_{3t}}{r_{1,1} + r_{1,2} + r_{1,3}}$$

$$\hat{y}^*_{2,t} = \frac{r_{2,1}\,\hat{y}_{1t} + r_{2,2}\hat{y}_{2,t} + r_{2,3}\hat{y}_{3t}}{r_{2,1} + r_{2,2} + r_{2,3}} \tag{7}$$

$$\hat{y}^*_{3,t} = \frac{r_{3,1}\,\hat{y}_{1t} + r_{3,2}\hat{y}_{2,t} + r_{3,3}\hat{y}_{3t}}{r_{3,1} + r_{3,2} + r_{3,3}}$$

4.3. Test model

The obtained formula (7), will be applied to the Farmer's Exchange Rate in Central Java Province. The commodities selected for the formula trial were the rice & secondary crops, horticulture, and fisheries sectors. The data was selected from January 2014 to December 2021, because all of the data used the same standard, namely the 2012 standard. The numerical calculations in this paper were carried out using the native R language computer program. The agricultural exchange rate plot data for rice and secondary crops, horticulture and fisheries is shown in Figure 1.
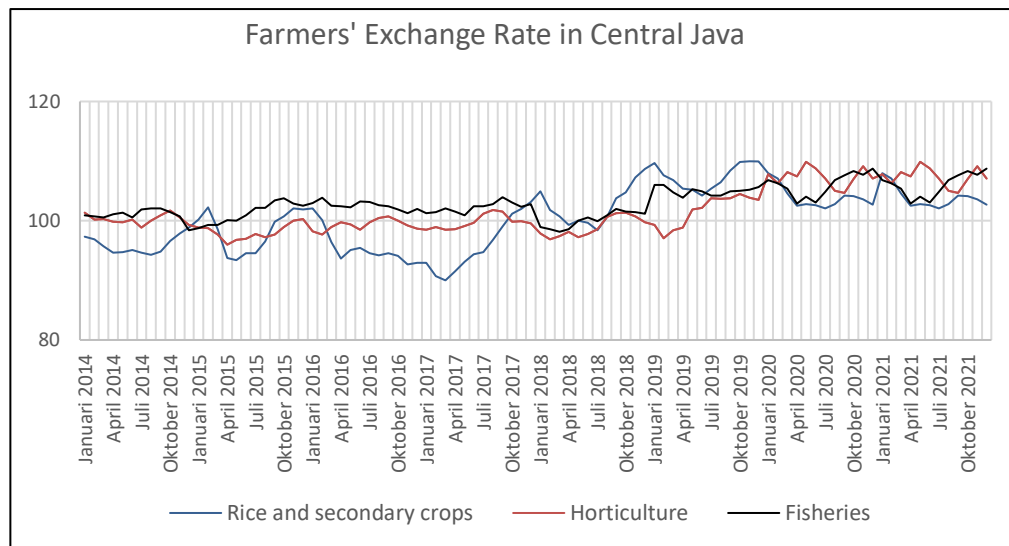

Figure 1. Farm Exchange Rate in Central Java Province

The available data is 96, of which 79 are used as in-sample or training data and the rest are used as out-sample or test data.

In order to facilitate the computer program preparation to calculate the fuzzy model, the data is transformed into intervals [0,1] using the following formula

$$y_t = \frac{z_t - \min\left(z_{sample}\right)}{\max\left(z_{sample}\right) - \min\left(z_{sample}\right)} \tag{7}$$

From the sample data, a fuzzy rule base was built for each of the three time series data, with the same number of sets, namely six fuzzy sets. The relation (3) along with the Gaussian fuzzy membership function (4) with $\sigma = 0.6$ is used to construct the fuzzy rule base. This parameter σ is obtained from empirical experiments with several numbers that give the smallest error.

         Nurhayadi (Fuzzy Vector Autoregression)

The normalized plot of the data together with the Gaussian fuzzy membership function is presented in the same graph, to provide intuition about the fuzzy rule base data points. **Error! Reference source not found.** illustrates the membership function of the fuzzy rule base for the fuzzy VAR model for (a) rice and secondary crops, (b) for horticulture, and (c) for fisheries.
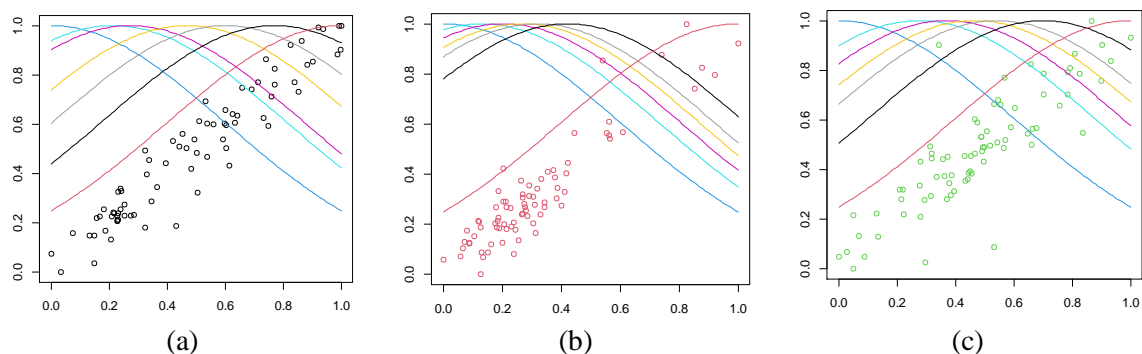

(a)   (b)   (c)

Figure 2. Fuzzy Rule Based System

Forecasting each time series is carried out using formula (5), and VAR predictions are calculated using equation (7) with the weight r_{ij} taken from the correlation coefficient in *Table 2* below.

Table 2. The Correlation Value Between Series

Sector	Rice and secondary crops	Horticulture	Fisheries
Rice and Secondary crops	1	0.441	0.500
Horticulture	0.441	1	0.553
Fisheries	0.500	0. 553	1

Forecasting results using an autoregressive fuzzy vector model with a Gaussian membership function are shown in Table 3.

Table 3. Forecasting Farmer Exchange Rate

	Rice and Palawija		Horticulture		Fisheries	
Series	$Y_{1,t}$	$\widehat{Y}_{1,t}$	$Y_{2,t}$	$\widehat{Y}_{2,t}$	$Y_{3,t}$	$\widehat{Y}_{3,t}$
1	97.31	90.00	101.33	95.99	100.89	98.15
2	96.91	98.04	100.22	100.92	100.71	101.67
3	95.73	97.92	100.31	100.88	100.55	101.63
4	94.61	97.65	99.86	100.85	101.06	101.59
5	94.77	97.44	99.72	100.84	101.37	101.64
6	95.07	97.50	100.23	100.85	100.59	101.68
7	94.60	97.50	98.82	100.84	101.90	101.58
8	94.27	97.48	100.02	100.80	102.09	101.72
9	94.81	97.46	100.91	100.88	102.10	101.75
10	96.58	97.61	101.69	100.92	101.48	101.76
11	97.89	97.97	100.58	100.94	100.73	101.74
12	98.82	98.12	99.30	100.91	98.39	101.65
13	100.18	97.88	98.87	100.67	98.75	101.18

14	102.26	98.10	98.79	100.68	99.31	101.27
15	98.62	98.34	97.73	100.73	99.28	101.39
16	93.72	97.91	95.99	100.59	100.08	101.35
17	93.36	96.87	96.80	100.28	100.05	101.37
18	94.53	96.83	96.99	100.41	100.91	101.39
19	94.59	97.25	97.80	100.52	102.19	101.56
20	96.49	97.44	97.20	100.70	102.19	101.72
21	99.87	97.84	97.68	100.66	103.39	101.74
22	100.72	98.49	98.92	100.79	103.77	101.83
23	102.05	98.66	100.02	100.93	102.87	101.85
24	101.93	98.78	100.32	101.01	102.56	101.88
25	102.04	98.76	98.26	101.01	102.97	101.87
26	100.07	98.70	97.65	100.87	103.89	101.85
27	96.45	98.52	98.95	100.78	102.49	101.82
28	93.64	97.95	99.72	100.87	102.41	101.80
29	95.07	97.31	99.37	100.86	102.27	101.75
30	95.47	97.64	98.46	100.87	103.26	101.77
31	94.58	97.74	99.71	100.81	103.11	101.79
32	94.18	97.58	100.42	100.89	102.65	101.80
33	94.53	97.49	100.76	100.91	102.45	101.78
34	94.1	97.57	99.97	100.92	101.91	101.78
35	92.65	97.40	99.21	100.87	101.24	101.73
36	92.98	96.93	98.63	100.75	101.98	101.62
37	92.95	97.06	98.53	100.74	101.29	101.69
38	90.69	96.99	98.97	100.70	101.40	101.62
39	90.00	96.41	98.50	100.68	102.06	101.59
40	91.51	96.26	98.60	100.64	101.57	101.63
41	93.13	96.63	99.14	100.68	100.87	101.62
42	94.36	97.01	99.66	100.74	102.44	101.58
43	94.76	97.49	101.19	100.87	102.39	101.77
44	96.75	97.63	101.78	100.93	102.78	101.78
45	99.05	98.10	101.57	100.98	103.91	101.84
46	101.20	98.53	99.82	101.02	103.06	101.87
47	101.98	98.72	99.88	101.00	102.38	101.88
48	103.14	98.74	99.54	100.99	102.77	101.85
49	104.96	98.79	97.87	100.98	98.92	101.87
50	101.83	98.23	96.92	100.58	98.58	101.28
51	100.72	98.10	97.43	100.43	98.15	101.19
52	99.32	97.97	98.10	100.46	98.58	101.10
53	100.05	97.92	97.20	100.58	100.02	101.20
54	99.67	98.18	97.74	100.59	100.59	101.49
55	98.39	98.25	98.57	100.70	99.96	101.60
56	100.62	98.02	100.61	100.74	100.92	101.50
57	103.81	98.52	101.27	100.95	102.02	101.70
58	104.78	98.79	101.36	101.01	101.50	101.83
59	107.23	98.72	100.77	100.98	101.43	101.78
60	108.71	98.50	99.70	100.94	101.14	101.74

61	109.72	98.23	99.31	100.85	105.98	101.67
62	107.62	98.09	97.10	100.76	105.97	101.54
63	106.77	98.31	98.42	100.56	104.72	101.54
64	105.41	98.58	98.83	100.81	103.87	101.75
65	105.16	98.73	101.87	100.90	105.32	101.83
66	104.22	98.78	102.17	100.96	104.97	101.73
67	105.40	98.84	103.81	100.98	104.24	101.78
68	106.47	98.80	103.68	100.89	104.24	101.82
69	108.39	98.72	103.81	100.89	104.97	101.81
70	109.83	98.45	104.46	100.81	105.04	101.71
71	109.97	98.17	103.85	100.71	105.17	101.66
72	109.95	98.15	103.50	100.76	105.68	101.65
73	108.00	98.13	107.83	100.76	106.83	101.59
74	107.06	98.17	106.28	100.13	106.24	101.30
75	104.61	98.44	108.18	100.46	105.42	101.48
76	102.50	98.59	107.46	100.22	102.90	101.58
77	102.81	98.67	109.88	100.42	104.04	101.77
78	102.65	98.54	108.80	99.96	103.07	101.66
79	102.07	98.60	107.05	100.18	104.83	101.72
80	102.78	98.67	105.00	100.46	106.79	101.70
81	104.24	98.63	104.69	100.64	107.64	101.44
82	104.17	98.53	106.96	100.59	108.34	101.26
83	103.57	98.32	109.10	100.20	107.75	101.03
84	102.72	98.28	107.06	99.87	108.74	101.10
85	108.00	98.25	107.83	100.16	106.83	100.93
86	107.06	98.17	106.28	100.13	106.24	101.30
87	104.61	98.44	108.18	100.46	105.42	101.48
88	102.50	98.59	107.46	100.22	102.90	101.58
89	102.81	98.67	109.88	100.42	104.04	101.77
90	102.65	98.54	108.80	99.96	103.07	101.66
91	102.07	98.60	107.05	100.18	104.83	101.72
92	102.78	98.67	105.00	100.46	106.79	101.70
93	104.24	98.63	104.69	100.64	107.64	101.44
94	104.17	98.53	106.96	100.59	108.34	101.26
95	103.57	98.32	109.10	100.20	107.75	101.03
96	102.72	98.28	107.06	99.87	108.74	101.10

To measure forecasting accuracy using the introduced model, the mean absolute percentage error of each forecast is calculated and presented in Table 4.

Table 4. Mean Absolute Percentage Error

Agricultural sector	MAPE	
	in-sample	out-sample
Rice and Secondary crops	4.16	5.11
Horticulture	2.29	6.35
Fisheries	1.54	4.84

Every forecast using calculated information must contain errors, the smaller the error that occurs, it can be interpreted that the better is the forecasting method. The model that we introduce gives MAPE in the range of 5%, so this fuzzy VAR model can be considered for valid use to forecast various time series.

Trimono (2020) has made predictions in the same agricultural sector using a vector integrated moving average (VIMA). Although the amount of data used in the VAR study byTrimono (2020) is not the same as the data in this paper, the comparison of prediction accuracy can provide a general view. The comparison of MAPE on predictions using VIMA and predictions using Fuzzy VAR is presented in Table 5.

Table 5. Perbandingan Mean Absolute Percentage Error

Agricultural sector	VIMA	Fuzzy VAR
Rice and Secondary crops	1.91	5.11
Horticulture	2.44	6.35
Fisheries	2.18	4.84

The data in Table 5 shows that the Fuzzy VAR model has a larger error than the VIMA model. I hope the Fuzzy researchers' model can improve the accuracy of the Fuzzy VAR model.

5. CONCLUSION

The TSK fuzzy system applied to VAR was introduced to increase the diversity of forecasting models. The basis of the fuzzy rules for the three time series are made identical, each using six fuzzy sets and the membership function used is Gaussian with a scale parameter of $\sigma=0.6$. The data that lies on the median in each interval is chosen as the center of the fuzzy set, which is used as the location parameter in the Gaussian function. The incorporation of the fuzzy model into a fuzzy VAR form is done by calculating the weighted average, using the correlation coefficient as the weight.

The results of model trials on FER Central Java in 2014-2020, show a pretty good forecast, namely forecasting with MAPE around 5%, and not exceeding 10%. We hope the paper we submit can be useful for the general public and for education.

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