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Performance of High-Order Chen Fuzzy Time Series Forecasting Method and Feedforward Backpropagation Neural Network Method in Forecasting Composite Stock Price Index

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Abstract The rapid development of time series data forecasting methods has resulted in many choices of methods that can be used to forecast according to the type of data. However, what needs to be considered in the selection of forecasting methods is whether the method used provides precise forecasting results or not. The high-order Chen fuzzy time series is a development of the fuzzy time series method with the determination of Fuzzy Logic Relations (FLR) which involves two or more historical data. The back propagation algorithm is one of the algorithms found in the artificial neural network method where this algorithm has a tendency to store experiential knowledge and make it ready for use. This study aims to compare the method of high-order Chen fuzzy time series and feedforward backpropagation neural network in forecasting the composite stock price index based on MSE and MAPE values. The results showed that feedforward backpropagation neural network predicts the composite stock price index better than high-order Chen fuzzy time series method with lower MSE and MAPE values.

Keywords High-order Chen fuzzy time series, Feedforward backpropagation neural network, MSE, MAPE

1. Introduction

Forecasting is a method for estimating a value in the future by paying attention to past data. The rapid development of time series data forecasting methods makes researchers have many choices of methods in forecasting data according to their needs.

Fuzzy time series is a forecasting method that is often used to predict time series data. This method is based on fuzzy logic [1,2]. High- order Chen fuzzy time series is the development of the fuzzy time series method with the determination of Fuzzy Logic Relations (FLR) which involves two or more historical data [3,4].

Artificial Neural Network (ANN) is an information processing system that has a characteristic appearance that is in accordance with biological neural networks [5]. Meanwhile, backpropagation algorithm is one of the algorithms found in the artificial neural network (ANN) method where this algorithm has a tendency to store experiential knowledge and make it ready to use [6]. The use of high-order fuzzy time series based on neural networks has been done by [7,8,9,10]. In this study, the researchers are interested in comparing high-order Chen Fuzzy Time Series method with the feedforward backpropagation neural network method in forecasting the composite stock price index.

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2. Materials and Methods

2.1. Fuzzy Time Series

The fuzzy time series data forecasting method is based on fuzzy logic as a basis. Future data projection with fuzzy time series is done by capturing patterns from past data. The process also does not require a learning system from a complicated system, as in genetic algorithms and neural networks so that it is easy to use and develop [1,2]. In fuzzy time series, several terms are used such as Fuzzy Logic Relations (FLR) and Fuzzy Logic Relations Group (FLRG). FLR is a fuzzy logic that has a relationship between the membership series that have been assigned to the data before and after it. FLRG is a grouping of FLRs based on the value of the previous period. To start forecasting using Chen's time series method, we first have to define a universal set (U) with:

$$U = [D_{min} - D_1; D_{max} + D_2] \quad (2.1)$$

where D_{min} and D_{max} are are the smallest and the largest data from historical data, respectively. D_1 and D_2 are constant values determined by the researcher. Next, select the classes using the Sturges formula Number of classes = $1 + 3{,}32\log(n)$ with Interval length $= \frac{D_{max} - D_{min}}{\text{Number of intervals}}$. This interval is used to form a number of linguistic values to represent the fuzzy set in the interval formed from the universal set $U = \{u_1, u_2, \ldots, u_n\}$ where U is the universal set and u_j is the number of classes with $j = 1,2,\ldots,n$. The average value of the universal set (U) is:

$$m_i = \frac{lower\ \ limit\ \ u_i - upper\ \ limit\ \ u_i}{2} \quad (2.2)$$

After that, the fuzzy set must be determined [11]. The fuzzy sets consist of objects in a group class with a continuum of membership degrees. Let U be the universal set, with $U = \{u_1, u_2, \ldots, u_n\}$ where u_i is the possible value of U, then variable A_i with respect to U can be formulated as:

$$A_i = \frac{\mu_{A_i(u_1)}}{u_1} + \frac{\mu_{A_i(u_2)}}{u_2} + \frac{\mu_{A_i(u_3)}}{u_3} + \cdots + \frac{\mu_{A_i(u_n)}}{u_n} \quad (2.3)$$

μ_{A_i} is a membership function of the fuzzy set A_i, such that $\mu_{A_i}: U \rightarrow [0,1]$. If u_j is membership of A_i, then $\mu_{A_i(u_j)}$ is the degree of membership of u_j to A_i. Then fuzzification is carried out on historical data to identify the data into fuzzy sets. If the historical data collected is included in the u_i interval, then the data will be fuzzified to A_i.

FLR $A_i \rightarrow A_j$ is determined based on the A_i value that has been determined in the previous step, where A_i is data in the previous period and A_j is data for next period. For example, if the FLR is in the form of $A_1 \rightarrow A_2$, $A_1 \rightarrow A_1$, $A_1 \rightarrow A_3$, $A_1 \rightarrow A_1$ then the best FLRG formed is $A_1 \rightarrow A_1, A_2, A_3$. After that, defuzzification is performed find the final forecast value using:

$$\hat{y}(t) = \frac{\sum_{i=1}^{n} m_i}{n} \quad (2.4)$$

where $\hat{y}(t)$ is defuzzification and m_i is the average of A_i. Finally, perform data forecasting with the following rules: f $(t-1) = A_i$ if FLR of A_i does not exist $(A_i \rightarrow \#)$, then $F(t) = A_i$. If there is only one FLR $A_i \rightarrow A_j$, then $F(t) = A_j$ and if $(A_i \rightarrow A_{j1}, A_{j2}, \ldots, A_{jk})$ then $F(t) = A_{j1}, A_{j2}, \ldots, A_{jk}$.

2.2. High-order Chen Fuzzy Time Series

To apply high-order Chen fuzzy time series, the calculation steps are identical to Chen's fuzzy time series. However, FLR for high-order is determined by involving two or more historical data [3]. For example, for the second-order it is necessary to involve two historical data, namely $F(t-2), F(t-1)$ so that FLRG is formed into groups based on the two data. For example if $F(t-2) = A_i, F(t-1) = A_j$ and $F(t) = A_k$, then the FLR formed is $A_i, A_j \rightarrow A_k$ which is a second-order of FLR.

2.3. Feedforward Backpropagation Neural Network

Artificial Neural Network (ANN) is a network designed to resemble the human brain that aims to carry out a specific task. This network is usually implemented using electronic components or simulated in computer applications. Neural networks are one of the methods used for pattern recognition, signal processing and forecasting, as are other methods found in neural networks. The model of the neural network consists of 3 layers, namely the input layer, the hidden layer and the output layer [6,7].

Backpropagation feedforward is a neural network model that can be used in forecasting. Backpropagation was formulated by [12] and popularized by [13] for use in neural networks.

The feedforward backpropagation algorithm is referred to as backpropagation because when the network is given an input pattern as a training pattern, the pattern goes to the units in the hidden layer to be forwarded to the output layer units [14]. Furthermore, the output layer units provide a response which is known as network output, when the network output is not the same as the expected output then the output will spread backward in the hidden layer forwarded to the units in the input layer.

To construct an artificial neural network using the feedforward backpropagation algorithm is to first determine the input based on the significant lags in Partial Autocorrelation Function Plot (PACF). Next, divide data into training and testing data. Percentage of Composition of training and testing data is open, can be 80-20 or 70-30 or 50-50. Before doing so, the data needs to be normalized. Normalization of data can be done with the following transformation formula:

$$x' = \frac{0.8(x-a)}{(b-a)} + 0.1 \quad (2.5)$$

where x' is normalized data and x is data to be normalized, respectively. a and b are the minimum and maximum values of the data.

Furthermore, the activation function and training algorithm have to be determined. The selection of the activation function must meet the conditions of being continuous, differentiable and not descending. The activation function is used in the first (hidden) and second (output) layers. While the training algorithm is used for the training stage. Next, the model is formed through the training stage by changing the number of hidden layers. Determination of the number of hidden layers is done by looking at the smallest error value. MAPE is used to measure the level of model reliability, while MSE is used to measure the accuracy of learning outcomes from the model. The best model obtained based on the smallest MAPE and MSE values at the training stage is used to form a model at the testing stage.

After getting the best model from the training stage, the next step is to carry out the testing stage to determine the accuracy or error rate of the model obtained at the training stage and carry out the forecasting process. In the forecasting process, all the data used to get the forecasting process for the next period is still in the form of normalized data. Forecasting results in the form of normalized data must be denormalized in order to obtain the original value data from the forecasting results. Forecasting results can be denormalized using formula:

$$x = \frac{(x' - 0.1)(x_{max} - x_{\min})}{0.8} + x_{min} \quad (2.6)$$

with x' is normalize values in the dataset, x_{min} and x_{max} are the minimum and maximum values, respectively.

2.4. Forecasting Accuracy Measure

In order to produce optimal forecasting with a small error rate, Mean Square Error (MSE) and Mean Absolute Percentage Error (MAPE) are calculated and compared from both methods with the following formula:

$$MSE = \sum_{t=1}^{n} \frac{(y_t - \hat{y}_t)^2}{n} \quad (2.7)$$

where y_t and $\hat{y}_t$ are the actual values in the ke-t period and the forecasted values in the ke-t periods, respectively.

$$MAPE = \frac{1}{n} \sum_{t=1}^{n} |PE_t| \quad (2.8)$$

with $PE_t = \left(\frac{y_t - \hat{y}_t}{y_t}\right) \times 100\%$.

3. Results and Discussion

The composite stock price index data from the period September 2021 to February 2022 obtained from https://finance.yahoo.com/quote/%5EJKSE/history/ was analyzed using high-order Chen time series fuzzy method and feedforward backpropagation neural network method using R-Studio software and Matlab R2013a.

The first step was to predict the data using a high-order fuzzy Chen time series method. To forecast using this method, we must first determine the universal set (U) according to the definition in equation (2.1) and we obtained U = [6060,76;6844,61]. Then the universal set U is divided into classes to look for the average value in each class. The resulting classes of the universe set is:

Table 1. The Universal Set (U)

Class	Interval (u)	Average (m)
1	$u_1 = [6060{,}760; 6158{,}741]$	$m_1 = 6109{,}751$
2	$u_2 = [6158{,}741; 6256{,}722]$	$m_2 = 6207{,}732$
3	$u_3 = [6256{,}722; 6354{,}704]$	$m_3 = 6305{,}713$
4	$u_4 = [6354{,}704; 6452{,}685]$	$m_4 = 6403{,}694$
5	$u_5 = [6452{,}685; 6550{,}666]$	$m_5 = 6501{,}676$
6	$u_6 = [6550{,}666; 6648{,}648]$	$m_6 = 6599{,}657$
7	$u_7 = [6648{,}648; 6746{,}629]$	$m_7 = 6697{,}638$
8	$u_8 = [6746{,}629; 6844{,}610]$	$m_8 = 6795{,}619$

Based on the rules of determining the degree of membership of the fuzzy set formed are as follows:

$$A_1 = \frac{1}{u_1} + \frac{0{,}5}{u_2} + \frac{0}{u_3} + \frac{0}{u_4} + \frac{0}{u_5} + \frac{0}{u_6} + \frac{0}{u_7} + \frac{0}{u_8}$$

$$A_2 = \frac{0{,}5}{u_1} + \frac{1}{u_2} + \frac{0{,}5}{u_3} + \frac{0}{u_4} + \frac{0}{u_5} + \frac{0}{u_6} + \frac{0}{u_7} + \frac{0}{u_8}$$

$$A_3 = \frac{0}{u_1} + \frac{0{,}5}{u_2} + \frac{1}{u_3} + \frac{0{,}5}{u_4} + \frac{0}{u_5} + \frac{0}{u_6} + \frac{0}{u_7} + \frac{0}{u_8}$$

$$A_4 = \frac{0}{u_1} + \frac{0}{u_2} + \frac{0{,}5}{u_3} + \frac{1}{u_4} + \frac{0{,}5}{u_5} + \frac{0}{u_6} + \frac{0}{u_7} + \frac{0}{u_8}$$

$$A_5 = \frac{0}{u_1} + \frac{0}{u_2} + \frac{0}{u_3} + \frac{0{,}5}{u_4} + \frac{1}{u_5} + \frac{0{,}5}{u_6} + \frac{0}{u_7} + \frac{0}{u_8}$$

$$A_6 = \frac{0}{u_1} + \frac{0}{u_2} + \frac{0}{u_3} + \frac{0}{u_4} + \frac{0{,}5}{u_5} + \frac{1}{u_6} + \frac{0{,}5}{u_7} + \frac{0}{u_8}$$

$$A_7 = \frac{0}{u_1} + \frac{0}{u_2} + \frac{0}{u_3} + \frac{0}{u_4} + \frac{0}{u_5} + \frac{0{,}5}{u_6} + \frac{1}{u_7} + \frac{0{,}5}{u_8}$$

$$A_8 = \frac{0}{u_1} + \frac{0}{u_2} + \frac{0}{u_3} + \frac{0}{u_4} + \frac{0}{u_5} + \frac{0}{u_6} + \frac{0{,}5}{u_7} + \frac{1}{u_8}$$

Next, fuzzification was carried out on the data and the results are obtained in Table 2.

Table 2. Fuzzification of Composite Stock Price Index Data

No	Period	Price	Fuzzification
1	14/9/2021	6129,10	A_1
2	15/9/2021	6110,23	A_1
3	16/9/2021	6109,94	A_1
4	17/9/2021	6133,25	A_1
⋮	⋮	⋮	⋮
103	8/2/2022	6789,52	A_8
104	9/2/2022	6834,61	A_8
105	10/2/2022	6730,64	A_7
106	11/2/2022	6815,61	A_8

Then the next step was to define the Fuzzy Logic Relations (FLR) and Fuzzy Logic Relations Group (FLRG) and defuzzification. The results are shown in Table 3-6.

Table 3. FLR Composite Stock Price Index Data

No	Period	Price	FLR
1	14/9/2021	6129,10	
2	15/9/2021	6110,23	$A_1 \to A_1$
3	16/9/2021	6109,94	$A_1 \to A_1$
4	17/9/2021	6133,25	$A_1 \to A_1$
⋮	⋮	⋮	⋮
103	8/2/2022	6789,52	$A_8 \to A_8$
104	9/2/2022	6834,61	$A_8 \to A_8$
105	10/2/2022	6730,64	$A_8 \to A_7$
106	11/2/2022	6815,61	$A_7 \to A_8$

Table 4. FLRG Composite Stock Price Index Data

Grup	FLRG
A_1	$A_1 \to A_1, A_2$
A_2	$A_2 \to A_3$
A_3	$A_3 \to A_2, A_3, A_4$
A_4	$A_4 \to A_4, A_5$
A_5	$A_5 \to A_5, A_6$
A_6	$A_6 \to A_5, A_6, A_7$
A_7	$A_7 \to A_6, A_7, A_8$
A_8	$A_8 \to A_7, A_8$

Table 5. FLRG Defuzzification

Group	FLRG	Defuzzification Formula ($\hat{y}(t)$)	Defuzzification Value
A_1	$A_1 \to A_1, A_2$	$\frac{m_1 + m_2}{2}$	6158,74
A_2	$A_2 \to A_3$	m_3	6305,71
A_3	$A_3 \to A_2, A_3, A_4$	$\frac{m_2 + m_3 + m_4}{3}$	6305,71
A_4	$A_4 \to A_4, A_5$	$\frac{m_4 + m_5}{2}$	6452.68
A_5	$A_5 \to A_5, A_6$	$\frac{m_5 + m_6}{2}$	6550,67
A_6	$A_6 \to A_5, A_6, A_7$	$\frac{m_5 + m_6 + m_7}{3}$	6599.66
A_7	$A_7 \to A_6, A_7, A_8$	$\frac{m_6 + m_7 + m_8}{3}$	6697.64
A_8	$A_8 \to A_7, A_8$	$\frac{m_7 + m_8}{2}$	6746.63

Table 6. Defuzzification of Composite Stock Price Index Data

No	Period	Price	Fuzzifikasi	Defuzzification Value
1	14/9/2021	6129,10	A_1	6158,74
2	15/9/2021	6110,23	A_1	6158,74
3	16/9/2021	6109,94	A_1	6158,74
4	17/9/2021	6133,25	A_1	6158,74
⋮	⋮	⋮	⋮	⋮
103	8/2/2022	6789,52	A_8	6746.63
104	9/2/2022	6834,61	A_8	6746.63
105	10/2/2022	6730,64	A_7	6697.64
106	11/2/2022	6815,61	A_8	6746.63

Next, forecasting was carried out in the first-order and the results are as presented in Table 7.

Table 7. First-order forecasting on composite stock price index data

No	Period	Price	Fuzzifikasi	Forecasting Value
1	14/9/2021	6129,10	A_1	
2	15/9/2021	6110,23	A_1	6158,74
3	16/9/2021	6109,94	A_1	6158,74
4	17/9/2021	6133,25	A_1	6158,74
⋮	⋮	⋮	⋮	⋮
103	8/2/2022	6789,52	A_8	6746.63
104	9/2/2022	6834,61	A_8	6746.63
105	10/2/2022	6730,64	A_7	6746.63
106	11/2/2022	6815,61	A_8	6697.64

The next step was to forecast the second and third-order using the same universe set. In this high-order forecasting method, it starts with determining the Fuzzy Logic Relations (FLR) and the Fuzzy Logic Relations Group (FLRG). The results of forecasting the composite stock price index data using a high-order Chen fuzzy time series can be seen in Table 8-9.

Table 8. Second-order forecasting on composite stock price index data

No	Period	Price	Fuzzifikasi	Forecasting Value
1	14/9/2021	6129,10	A_1	
2	15/9/2021	6110,23	A_1	
3	16/9/2021	6109,94	A_1	6158,74
4	17/9/2021	6133,25	A_1	6158,74
⋮	⋮	⋮	⋮	⋮
103	8/2/2022	6789,52	A_8	6795,62
104	9/2/2022	6834,61	A_8	6746,63
105	10/2/2022	6730,64	A_7	6746,63
106	11/2/2022	6815,61	A_8	6795,62

Table 9. Third- order forecasting on composite stock price index data

No	Period	Price	Fuzzifikasi	Forecasting Value
1	14/9/2021	6129,10	A_1	
2	15/9/2021	6110,23	A_1	
3	16/9/2021	6109,94	A_1	
4	17/9/2021	6133,25	A_1	6158,74
⋮	⋮	⋮	⋮	⋮
103	8/2/2022	6789,52	A_8	6795,62
104	9/2/2022	6834,61	A_8	6795,62
105	10/2/2022	6730,64	A_7	6697,64
106	11/2/2022	6815,61	A_8	6795,62

The predicting data was obtained by looking at the FLR in the previous period and match it with FLRG. For example, in the period of February 11, 2022, we had FLR $A_7 \to A_8$, so that in the period of February 12, 2022, the forecasting value used is in Group A_8 with the relation $A_8 \to A_7, A_8$. In the second-order, the determination of the forecasting value for the future period is done by looking at the FLR in the previous period. Meanwhile, the determination of the forecast value for the next period in the third-order is carried out in the same way but by using two data from the previous period. The following are the results of data forecasting using a high-order Chen fuzzy time series.

Based on Table 10, it can be seen that the third order produces forecasting values with the smallest MSE and MAPE. However, it cannot predict the data for the next period which is denoted by (#) because the resulting relation in the next period does not exist in the predefined group or groups in the third-order FLRG. Therefore, forecasting stops in the second-order.

Table 10. Composite stock price index forecast results on high-order

Order	No	Period	Price	FLR	Forecasting Value	MSE	MAPE
First-order	106	11/2/2022	6815,61	$A_7 \rightarrow A_8$	6697.64	3001,39	0,65%
	107	12/2/2022		$A_8 \rightarrow A_7, A_8$	6746,63		
Second-order	106	11/2/2022	6815,61	$A_8, A_7 \rightarrow A_8$	6795,62	2603,55	0,61%
	107	12/2/2022		$A_7, A_8 \rightarrow A_8$	6795,62		
Third-order	106	11/2/2022	6815,61	$A_8, A_8, A_7 \rightarrow A_8$	6795,62	2054,95	0,52%
	107	12/2/2022		$A_8, A_8, A_7 \rightarrow$ #	-		

Furthermore, the data were analyzed using the feedforward backpropagation neural network method. The first step is to determine the network input by looking at the significant lag in PACF plot. Figure 1 shows that the significant PACF plot is at lag 1 and the network input is at X_1. Based on this, the network input was defined as seen in Table 11.

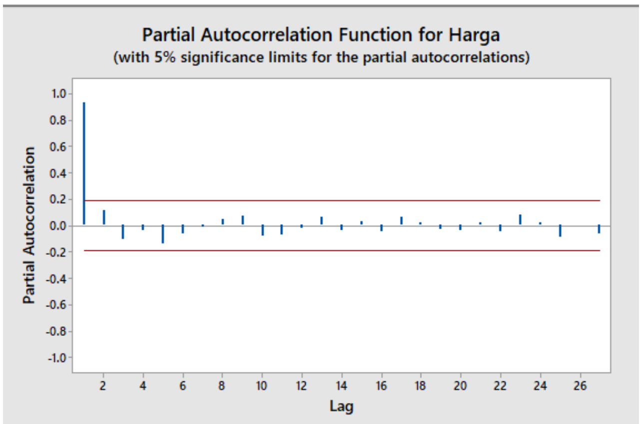

Figure 1. Plot of PACF Composite Stock Price Index Data

Table 11. Network Input

No	Input (X_1)	Target
1	6129,10	6110,23
2	6110,23	6109,94
3	6109,94	6133,25
⋮	⋮	⋮
103	6789,52	6834,61
104	6834,61	6730,64
105	6730,64	6815,61

After that, the data were analyzed using a feedforward backpropagation neural network method. The first thing to do was divide the data into training data and test data with a percentage of 70% training data and 30% test data. Then normalization was carried out on the two data as shown in Table 12.

After the normalization process is carried out, the next step was to define the activation function and training algorithm. The activation function used in the hidden layer was binary sigmoid (tansig) and the output layer used an identity or linear (purelin) activation function. Meanwhile, the training algorithm used trainlm. Next was the formation and selection of models based on the MSE and MAPE values at the hidden neurons training stage. The following are some of the models built as presented in Table 13.

Table 12. Normalization Results

	Training Data		Testing Data	
No	Input (X_1)	Target	Input (X_1)	Target
1	0,17065	0,15114	0,65575	0,65817
2	0,15114	0,15084	0,65817	0,63832
3	0,15084	0,17494	0,63832	0,72498
⋮	⋮	⋮	⋮	⋮
72	0,61151	0,61911	0,85339	0,90000
73	0,61911	0,63207	0,90000	0,79252
74	0,63207	0,65575	0,79252	0,88036

Table 13. MSE and MAPE Values on Hidden Neurons Training Stage

Hidden Neurons	MSE	MAPE
1	0,00216	9,27166
2	0,00221	9,55709
3	0,00211	8,93961
4	0,00232	10,47245
5	0,00204	8,45593
6	0,00236	9,74444
7	0,00190	8,21880
8	0,00200	8,24316
9	0,00179	7,46082
10	0,00241	9,02242
15	0,00239	7,59897
20	0,00391	7,56510

Table 13 shows that the smallest MSE and MAPE values in 9 hidden neurons. Therefore, feedforward backpropagation neural network model was formed using 1 input layer, 9 hidden layers and 1 output layer.

After getting the best model at the training stage, the next step was to calculate the weight of maximum epoch value (iteration) of the model at the training data using the parameters obtained. The resulting weight was 1000 and shows 25 with a performance goal of 0.001, a learning rate of 0.01 and a momentum constant of 0.9. Table 14 gives the results of the weight values obtained using these parameters.

The next stage of testing was carried out to determine the accuracy or error rate of the best model obtained at the training stage by looking at the forecasting data at the resulting test stage. Forecasting calculations at the testing stage are carried out using 31 data with weights that have been obtained from the training stage as seen in Figure 2.

Table 14. The Weight values

No	Hidden Weight	Hidden Bias	Output Weight	Output Bias
1	-67,4586	86,6305	0,0341	0,514883
2	82,7159	-123,0306	-0,0378	
3	26,7825	-46,9707	2,3482	
4	-25,7617	45,2362	2,4072	
5	12,3145	-32,6463	-3,4373	
6	14,6709	-38,7444	3,2524	
7	-3,8939	19,4148	-5,4481	
8	-4,6745	23,0820	5,0735	
9	6,1105	-43,2832	-0,3217	

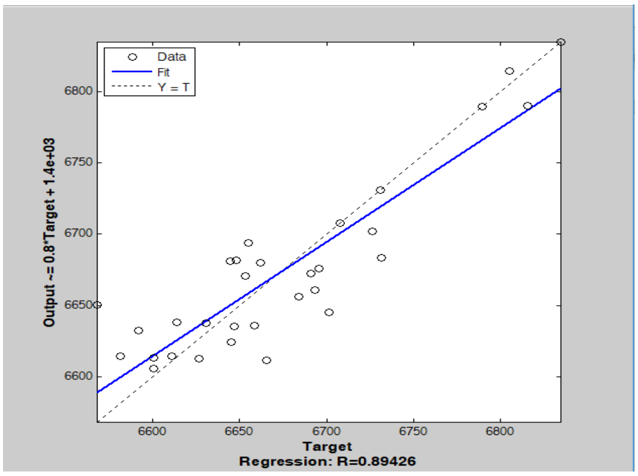

Figure 2. Correlation in testing stage

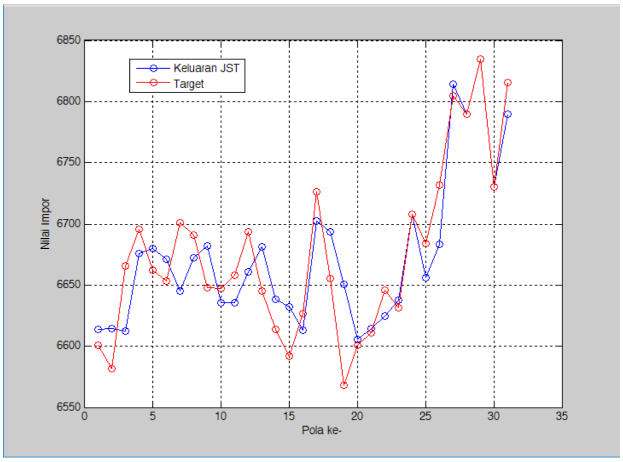

Figure 3. Comparison of target data with test results at the testing stage

Figure 2 shows that the correlation is 0.89426. It means that the target data and the test results data at the testing stage have a good correlation. It also indicates that the accuracy between the target data and the test result data is high. While Figure 3 shows that there is no significant difference between the target data and the test result data. Table 15 presents a comparison between the target data and the test results at the testing stage. In addition, we can see MAPE's value is 3.448222%. This shows that the level of accuracy is quite high because it is below 10%.

Table 15. Comparison of Target Data with Test Results at the Testing Stage

No	Target	Test results	Error	Abs PE
1	0,65817	0,67176	-0,01359	2,065511
2	0,63832	0,67244	-0,03412	5,345141
3	0,72498	0,66995	0,05503	7,590498
⋮	⋮	⋮	⋮	⋮
29	0,90000	0,90009	-0,00009	0,009518
30	0,79252	0,79253	-0,00001	0,001138
31	0,88036	0,85382	0,02654	3,014823
		MAPE		3,448222

After the training and testing stages are carried out, forecasting is carried out for the period 12 February 2022. Forecasting value for this period is 6048.15. This forecast uses the overall data using the best model and the parameters obtained.

Finally, we compared the forecasting accuracy between high-order Chen fuzzy time series and a feed-forward propagation neural network based on MSE and MAPE as presented in Table 16.

Table 16. Forecasting value comparison

Period	Forecast Value	
	high order chen fuzzy time series	feedforward backpropagation neural network
12/2/2022	6795,62	6048,15
MSE	2603,551	1314,41
MAPE	0,6054%	0,4168%

Table 16 shows that feedforward backpropagation method has MAPE = 0.4168% and MSE = 1314.41 and high-order Chen fuzzy time series has MAPE = 0,6054% and MSE = 2603,551, respectively. This shows that feedforward backpropagation neural network method performs better than high-order Chen fuzzy time series with smaller MAPE and MSE. Therefore, what we use to estimate the composite stock price index for the next period is based on feedforward backpropagation, which is 6048.15.

4. Conclusions

Based on the results of the analysis of the two methods used, it can be concluded that the feedforward backpropagation forecasting method has better performance than the high-order fuzzy Chen time series forecasting method. The error values of Mean Square Error (MSE) and Mean Absolute Percentage Error (MAPE) of the feedforward backpropagation method are lower than the high-order Chen fuzzy time series forecasting method. This method produces MSE = 1314.41 and MAPE = 0.4168% with the forecast value in the next period is 6048.15. Meanwhile, in the high-order Chen fuzzy time series forecasting method, MSE = 2603.551 and MAPE = 0.6054% with a forecasting value of 6795.62.

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