Analysis of Financial Time Series Data Using Adaptive Neuro Fuzzy Inference System (ANFIS)

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Abstract

The aim of this research is to analyze ANFIS performance for prediction of financial time series data. Financial time series data is usually characterized by volatility clustering, persistence, and leptokurtic data behavior. The financial time series data are usually non-stationary and non-linear. ARIMA has a good performance to predict linear time series data, but its performance is decreasing when applied to predict non-linear times series data. ANFIS as one of hybrid models which composes neural network (NN) and fuzzy system is expected to be able to predict the financial time series data more accurate. Many research conclude that the effectiveness of ANFIS depend on the input selection, the membership function (MF) selection and the rule generation. In this study, the input variables of ANFIS are selected based on preprocessing of original data by using Subset ARIMA model. The rule bases of ANFIS are generated based on a linear Sugeno fuzzy model. The consequent parameters are identified by using least square method and premise parameters are adapted by using gradient descent. For practical assessment of ANFIS performance, ANFIS method is implemented to analyze the Indonesia inflation monthly data from January 1970 up to December 2012.

Keywords: *Financial Time Series, Fuzzy Logic, Neural Network, ANFIS.*

1. Introduction

Financial time series data is usually characterized by volatility clustering, persistence, and leptokurtic data behavior [2], [13], [14], [20]. The financial time series data is usually non-stationary and non-linear [22]. In financial time series research, ARIMA Box-Jenkins is one of popular mean models [4], [19], [26]. While Autoregressive Conditional Heteroscedasticity (ARCH) proposed by Engle [21] and Generalized Autoregressive Conditional Heteroscedasticity (GARCH) proposed by Bollerslev [25] are the popular variance models. Application of ARIMA-GARCH for modeling and forecasting financial time series data has been done by many researchers [22], [23]. Unfortunately, ARIMA-GARCH still has disadvantages when implemented for modeling and forecasting non-stationary and non-linear time series data.

In recent years, alternative models based on neural network (NN), fuzzy system and its hybrid have been improved to analyze non-stationary and non-linear time series data [7], [10], [24]. ANFIS method is one of the hybrid methods which combines neural network (NN) and fuzzy inference system (FIS) [6], [16]. The many examples of research on financial time series using ANFIS such as financial trading [1]; forecasting automobile sales [3]; prediction of stock market return [5], [11], [17]; prediction government bond yield [9]; forecasting EPS of leading industries [12]; financial volatility [13], [14] and exchange rate forecasting [15], [16], [23], conclude that the performance of ANFIS is better than the other methods.

The remaining parts of the article is organized as follows: Section 2 defines about ANFIS, types of membership function, reviews the architecture of ANFIS and learning algorithm in ANFIS. Section 3 describes the proposed procedure of ANFIS modeling. Section 4 discusses about results of empirical study. Section 5 summarizes the conclusion of the article.

2. Adaptive Neuro Fuzzy Inference System (ANFIS)

ANFIS is a multilayer feed forward network. This architecture has five layers such as fuzzy layer, product layer, normalized layer, de-fuzzy layer and total output layer [6], [7]. The fixed nodes are represented by circle and the nodes represented by square are the adapted nodes. ANFIS gives the advantages of the mixture of neural network and fuzzy logic. The aim of mixing fuzzy logic and neural networks is to design an architecture which uses a fuzzy logic to show knowledge in fantastic way, while the learning nature of neural network to maximize its parameters [18].

2.1 Membership Function in ANFIS

A membership function (MF) is a curve which explains how every point in the input space is mapped to a membership degree between 0 and 1 [16]. Here, four types of membership functions will be used to identify the fuzzy inference system (FIS) parameters, i.e. triangular MF (*trimf*), trapezoidal MF (*trapmf*), Generalized Bell MF (*gbellmf*) and Gaussian MF (*gaussmf*). The formula of each membership function is given in Table 1 below.

Table 1. Formula of fuzzy membership functions [7]

Membership function	***Formula***
Triangular MF(*trimf*)	$trimf(x;a,b,c) = \max\left(\min\left(\frac{x-1}{b-a},\frac{c-x}{c-b}\right),0\right)$
Trapezoidal MF(*trapmf*)	$trapmf(x;a,b,c,d) = \max\left(\min\left(\frac{x-1}{b-a},1,\frac{d-x}{d-c}\right),0\right)$
Generalized Bell MF (*gbellmf*)	$gbellmf(x;a,b,c) = \frac{1}{1+\left\lvert\frac{x-c}{a}\right\rvert^{2b}}$
Gaussian MF (*gaussmf*)	$gaussmf(x;c,\sigma) = \exp\left(-\frac{1}{2}\left(\frac{x-c}{\sigma}\right)^2\right)$

2.2 ANFIS Architecture

For simplicity, given two inputs of time series data $Z_{t,1}$, $Z_{t,2}$ and one output $\hat{Z}_t$. Assumed that rule-base of Sugeno order-one with two rules as follows.

If $Z_{t,1}$ is A_1 and $Z_{t,2}$ is B_1, then $Z_t^{(1)} = p_1 Z_{t,1} + q_1 Z_{t,2} + r_1$.

If $Z_{t,1}$ is A_2 and $Z_{t,2}$ is B_2, then $Z_t^{(2)} = p_2 Z_{t,1} + q_2 Z_{t,2} + r_2$.

Here, $Z_{t,1}$ is A_1 and $Z_{t,2}$ is B_1 ; $Z_{t,1}$ is A_2 and $Z_{t,2}$ is B_2 are called as the premise section (nonlinear section), while $Z_t^{(1)} = p_1 Z_{t,1} + q_1 Z_{t,2} + r_1$ and $Z_t^{(2)} = p_2 Z_{t,1} + q_2 Z_{t,2} + r_2$ are called consequent (linear) section. p_1, p_2, q_1, q_2, r_1 and r_2 are linear parameters and A_1, B_1, A_2 and B_2 are called non-linear parameters. If the firing strength of each rules are w_1, w_2 for 2 values $Z_t^{(1)}$ and $Z_t^{(2)}$, then the output $\hat{Z}_t$ is computed as weighted mean

$$\hat{Z}_t = \frac{w_1 Z_t^{(1)} + w_2 Z_t^{(2)}}{w_1 + w_2} = \overline{w}_1 Z_t^{(1)} + \overline{w}_2 Z_t^{(2)}$$

Architecture of neuro-fuzzy with all fundamental layers is illustrated as Fig.1 [7].

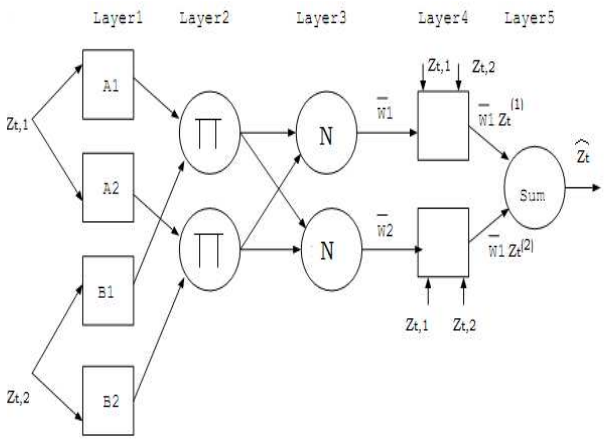

Fig. 1. Structure of Fundamental Neuro-Fuzzy Network

Neuro-fuzzy model as proposed by Jang [6] has 5 layers feed forward, which each layer is described as bellow.

Layer-1: Every node in the first layer is adaptive with one parametric activation function. The output is membership degree of given inputs which satisfy membership function $\mu_{A_1}(Z_{t,1})$, $\mu_{A_2}(Z_{t,1})$, $\mu_{B_1}(Z_{t,2})$ and $\mu_{B_2}(Z_{t,2})$. One example of fuzzy membership functions is generalized bell function *(gbellmf)*,

$$\mu_{A_i}(Z_{t,i}) = \frac{1}{1+\left\lvert\frac{Z_{t,i}-c_i}{a_i}\right\rvert^{2b}}, \; i=1,2;$$

$$\mu_{B_i}(Z_{t,i}) = \frac{1}{1+\left\lvert\frac{Z_{t,i}-c_i}{a_i}\right\rvert^{2b}}, \; i=1,2;$$

where c_i is the location parameter and a_i is the shape parameter. If the value of parameter is change then the shape of bell-function is also change. The parameters in this layer are called premise parameters.

Layer-2: Every node in the second layer is fixed node, which the output is product of incoming signal. Generally, it uses fuzzy operation AND. Output of each node represents firing strength w_i of i-th rule. $w_i = \mu_{A_i}(Z_{t,1}) * \mu_{B_i}(Z_{t,2})$, i=1,2.

Layer-3: Every node in the third layer is fixed node, which compute ratio of firing strength of i-th rule relative to sum of firing strengths of rules,

$$\overline{w}_i = \frac{w_i}{\sum_{i=1}^{2} w_i}, \quad i=1,2.$$

This result is a normalized firing strength.

Layer-4: Every node in the fourth layer is adaptive node, the output of each node is

$$\overline{w}_i Z_t^{(i)} = \overline{w}_i (p_i Z_{t,1} + q_i Z_{t,2} + r_i)\ .$$

$\overline{w}_i$ is a normalized firing strength of the third layer and $\{p_i, q_i, r_i\}$ is a set of this node parameters. Parameters in this layer are called consequent parameters (forward parameters).

Layer-5: Every node in the fifth layer is a fixed node which adds all of incoming signal. The output of fifth layer is the output of the whole network.

$$\hat{Z}_t = \sum_{i=1}^{2} \overline{w}_i Z_t^{(i)}$$

$$\hat{Z}_t = \sum_{i=1}^{2} \overline{w}_i (p_i Z_{t,1} + q_i Z_{t,2} + r_i)$$

$$\hat{Z}_t = \overline{w}_1 (p_1 Z_{t,1} + q_1 Z_{t,2} + r_1) + \overline{w}_2 (p_2 Z_{t,1} + q_2 Z_{t,2} + r_2)$$

$$\hat{Z}_t = p_1(\overline{w}_1 Z_{t,1}) + q_1(\overline{w}_1 Z_{t,2}) + r_1\overline{w}_1 + p_2(\overline{w}_2 Z_{t,1}) + q_2(\overline{w}_2 Z_{t,2}) + r_2\overline{w}_2 \qquad (1)$$

2.3 Learning Algorithm of ANFIS

The ANFIS parameters related to membership functions change through the learning process of neural network. If the premise parameters are fixed, the whole output of ANFIS is a linearly combination of consequent parameters as Eq. (1). ANFIS is optimized by adapting the premise and consequent parameters. The parameters are adjusted to minimize the error objective function defined by the sum of the squared difference between the model output and the actual. Hybrid algorithm justifies consequent parameters by using forward step and premise parameters (location parameter and shape parameter) in backward step. In forward step, inputs of network are passed into layer-4, with consequent parameters are identified by using least square method. Whereas in backward step, signal error are feed backward and premise parameters adapted by using *gradient descent* [7], [8].

3. The Proposed Procedure of ANFIS Modeling

This proposed procedure is extended based on the procedure which proposed by Wei et al. [12]. There are three basic step blocks of ANFIS modeling, those are preprocessing of data, rule generation and performance evaluation. These steps can be described completely as follows.

(1) Collecting the financial time series data
The financial time series data are collected.

(2) Preprocessing original data
The original data are preprocessed by using ARIMA method. The ARIMA models are constructed based on significant lags of ACF and PACF. The best model is selected by minimizing the root mean square of error (RMSE), AIC or SBC criterion.

(3) Non-linearity test
Non-linearity test is needed to determine the non-linearity properties of data.

(4) Determining the input variables
The input variables of ANFIS can be selected based on significant lag periods of ARIMA or Subset ARIMA. The all possible of significant lags yielded from informal preprocessing are selected as input variables of ANFIS.

(5) Defining and partitioning the input variables
The selected input variables are classified into some clusters using Fuzzy C-means (FCM).

(6) Setting the type of membership functions for input variables
We can set a membership function which can be applied to input variables. In this study, we use four types of membership functions such as triangular function (*trimf*), trapezoidal function (*trapmf*), generalized bell function (*gbellmf*), Gaussian function (*gaussmf*).

(7) Generating the fuzzy If-Then rules
The output variables are associated with each input cluster based on the degree of possibility [16]. The fuzzy i*f-then* rules are constructed using a linear Sugeno fuzzy model.

(8) Training the parameters of fuzzy inference system (FIS)
FIS parameters are identified from training datasets. Fuzzy reasoning is used to infer new knowledge from identified base [16]. Consequent parameters are estimated using recursive least square method and premise parameters are adapted using back-propagation gradient descent.

(9) Forecasting the training data and calculating RMSE value
After the significant models are constructed based on training data, we determine the predicted values and

calculate the RMSE values. The best model is selected by minimizing RMSE.

(10) *Forecasting the checking data and calculating RMSE value*
For assessment of ANFIS performance, the model result from previous steps is applied to forecast checking datasets and then calculate the RMSE values. The best model can be determined based on both RMSE values of training and checking data.

4. Results and Discussion

4.1 Results

For practical implementation of proposed ANFIS model for forecasting financial time series data, Indonesia inflation data are used as case study. The proposed procedure of ANFIS modeling for forecasting the Indonesia inflation data are summarized as below.

(1) *Collecting financial time series data*
These data are observed monthly from January 1970 up to February 2012 and obtained from the Indonesia Central Bureau of Statistics (see www.bps.go.id).

(2) *Preprocessing original data*
Before ANFIS method is employed to forecast the monthly Indonesia inflation data. The original data is preprocessed using ARIMA method. Based on significant lags of autocorrelation function (ACF) and partial autocorrelation function (PACF), we can identify the tentative models such as ARIMA ([1,3],0,[2,7,12,24]), ARIMA ([1,3,12],0,[2,7,19,24]) and ARIMA ([1,3],0,[2,7,19])$(1,0,0)^{12}$. When the residuals of fitted models are verified, all of the models contain ARCH effect and normality assumption of residuals are not satisfied. Based on non-linearity test using RESET test, the inflation data satisfy nonlinear properties. By RMSE, AIC or SBC criterion, ARIMA ([1,3],0,[2,7,12,24]) is the best model among the tentative models yielded from preprocessing. Furthermore, the significant lags of ARIMA ([1,3],0,[2,7,12,24]) are considered for determining input variables of ANFIS.

(3) *Defining and partitioning of input variables*
Based on ARIMA ([1,3],0,[2,7,12,24]) result from preprocessing data, the lag-1 and lag-3 of AR term can be selected as input variables of ANFIS. Besides, by invertibility properties of ARIMA, lag-1, lag-3, lag-2, lag-7, lag-12 or lag-24 or it combinations can also be considered as input variables. In this study, the combination of significant lags, such as lag-1 and lag-3 (Z_{t-1}, Z_{t-3}); lag-1, lag-2 and lag-3 ($Z_{t-1}, Z_{t-2}, Z_{t-3}$); lag-1, lag-3 and lag-12 ($Z_{t-1}, Z_{t-3}, Z_{t-12}$) and lag-1, lag-3, lag-7 and lag-12 ($Z_{t-1}, Z_{t-3}, Z_{t-7}, Z_{t-12}$) are selected as inputs variables of ANFIS. The selected input variables are classified into 2, 3 or 4 clusters using FCM. The degree of membership function of input variables are determined by using four types of membership functions, such as triangular function (*trimf*), trapezoidal function (*trapmf*), generalized bell function (*gbellmf*), Gaussian function (*gaussmf*).

(4) *Setting the type of membership function for output variables*
A linear type of Sugeno fuzzy model is used to set the membership for output variables. For example,
If $Z_{t,1}$ is A_i and $Z_{t,2}$ is B_i, then $Z_t^{(i)} = p_i Z_{t,1} + q_i Z_{t,2} + r_i$, i =1, 2;
where $Z_{t,1}$ and $Z_{t,2}$ are linguistic variables, while A_i and B_i are linguistic values, $Z_t^{(i)}$ denotes the i-th output value.

(5) *Generating the fuzzy If-Then rules*
Fuzzy inference system is generated by using a linear Sugeno fuzzy model. This step is done for four types of membership functions respectively.

(6) *Training parameters of fuzzy inference system (FIS)*
In this step, the parameters of Fuzzy Inference System for training models are optimized by using recursive least square method and back-propagation gradient descent.

(7) *Forecasting the training and the checking data and calculating RMSE values.*
The predicted values are obtained using 48 types of models and RMSE values are calculated based on training data. These models are verified by using the checking data. The optimal model is selected by minimizing RMSE value of both training and checking data. The results of empirical study of Indonesia inflation data are shown in Table 2.

Table 2. Empirical Results

Input	***MFs***	***Cluster***	***RMSE***	
			Training	***Checking***
(Z_{t-1}, Z_{t-3})	trimf	[2,2]	1.3425	35.3753
		[3,3]	1.2772	31. 7801
		[4,4]	1.2484	97.9147
	trapmf	[2,2]	1.3107	2.3659
		[3,3]	1.3020	2.8290
		[4,4]	1.2676	9.4467
	gbellmf	[2,2]	1.3233	3.0806
		[3,3]	1.2688	38.6644
		[4,4]	1.2589	55.1295
	Gaussmf	[2,2]	1.3259	2.8368
		[3,3]	1.2759	15.3602
		[4,4]	1.2574	95.2298

(a)

Input	MFs	Cluster	RMSE	
			Training	Checking
(Z_{t-1}, Z_{t-3}, Z_{t-12})	trimf	[2,2,2]	1.10590	17.9494
		[3,3,3]	0.96717	32.0057
		[4,4,4]	0.65487	19.7370
	trapmf	[2,2,2]	0.95464	20.3815
		[3,3,3]	0.99922	2.44670
		[4,4,4]	0.78331	82.0337
	gbellmf	[2,2,2]	0.95460	13.1610
		[3,3,3]	0.78693	62.5988
		[4,4,4]	0.72207	84,9292
	Gaussmf	[2,2,2]	0.97910	10.8220
		[3,3,3]	0.78728	36.4362
		[4,4,4]	0.71839	119.0773

(b)

Input	MFs	Cluster	RMSE	
			Training	Checking
(Z_{t-1}, Z_{t-2}, Z_{t-3})	trimf	[2,2,2]	1.2306	16.6616
		[3,3,3]	1.1110	18.0150
		[4,4,4]	0.8258	243.6845
	trapmf	[2,2,2]	1.1227	148.8850
		[3,3,3]	1.1454	1.4679
		[4,4,4]	0.8614	11.9678
	gbellmf	[2,2,2]	1.1270	20.0157
		[3,3,3]	0.9024	234.8535
		[4,4,4]	0.8050	181.4140
	Gaussmf	[2,2,2]	1.1443	12.3128
		[3,3,3]	0.9154	211.9401
		[4,4,4]	0.7916	201.5126

(c)

Input	MFs	Cluster	RMSE	
			Training	Checking
(Z_{t-1}, Z_{t-3}, Z_{t-7} Z_{t-12})	trimf	[2,2,2,2]	0.84854	9.5150
		[3,3,3,3]	0.72032	25.6660
		[4,4,4,4]	0.53881	82.8281
	trapmf	[2,2,2,2]	0.77921	108.2097
		[3,3,3,3]	0.72396	4.99610
		[4,4,4,4]	0.61412	11.1981
	gbellmf	[2,2,2,2]	0.77593	34.2834
		[3,3,3,3]	0.60507	55.5389
		[4,4,4,4]	0.50233	141.1441
	Gaussmf	[2,2,2,2]	0.77959	37.9520
		[3,3,3,3]	0.61909	75.1578
		[4,4,4,4]	0.49641	85.9995

(d)

4.2 Discussion

In this study, we set four combinations of input variables lag-1 and lag-3 (Z_{t-1}, Z_{t-3}); lag-1, lag-2 and lag-3 (Z_{t-1}, Z_{t-2}, Z_{t-3}); lag-1, lag-3 and lag-12 (Z_{t-1}, Z_{t-3}, Z_{t-12}) and lag-1, lag-3, lag-7 and lag-12 (Z_{t-1}, Z_{t-3}, Z_{t-7}, Z_{t-12}). Every input variable is classified into 2, 3 or 4 clusters. Four types of membership functions are applied to each combination of input. So, we have 48 types of ANFIS models which should be evaluated. The evaluation to these models are classified into four groups based on the combination of inputs. It can be summarized as follows.

- Corresponding to input variables (Z_{t-1}, Z_{t-3}), optimal RMSE are 1.3020 for training data and 2.8290 for checking data. These values related to the number of clusters [3,3] and trapezoidal membership function.
- Corresponding to input variables (Z_{t-1}, Z_{t-2}, Z_{t-3}), optimal RMSE are 1.1454 for training data and 1.4679 for checking data. These values related to the number of clusters [3,3,3] and trapezoidal membership function.
- Corresponding to input variables (Z_{t-1}, Z_{t-3}, Z_{t-12}), optimal RMSE are 0.99922 for training data and 2.4467 for checking data. These values related to the number of clusters [3,3,3] and trapezoidal membership function.
- Corresponding to input variables (Z_{t-1}, Z_{t-3}, Z_{t-7}, Z_{t-12}), optimal RMSE are 0.72396 for training data and 4.9961 for checking data. These values related to the number of clusters [3,3,3] and trapezoidal membership function.

If we compare among minimal RMSE values of 4 groups, we obtain the optimal RMSE are 1.1454 for training data and 1.4679 for checking data related to input variables (Z_{t-1}, Z_{t-2}, Z_{t-3}), the number of clusters [3,3,3] and the type of membership function is trapezoidal MF.

5. Conclusion

The accuracy of ANFIS model depends on many factors. There are three important roles which can determine the accurate model, i.e. selection of input variables, determining the number of clusters and selection of membership function. Based on the results of empirical study of Indonesia inflation data, we can obtain the optimal ANFIS model with three input variables (Z_{t-1}, Z_{t-2}, Z_{t-3}), the number of clusters [3,3,3] and trapezoidal membership function. Using this model, Indonesia inflation data can be predicted accurately.

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