Inference Procedure Based on LM-Test in ANFIS for Constructing Time Series Model

by Tarno Tarno

2017 1st International Conference on Informatics and Computational Sciences (ICICoS)

Inference Procedure Based on LM-Test in ANFIS for Constructing Time Series Model

Tarno, Agus Rusgiyono, Sugito, Budi Warsito
Department of Statistics, Universitas Diponegoro
Semarang 50275, Indonesia
tarno.stat@gmail.com

***Abstract*—The aim of this study is to develop modeling procedure in Adaptive Neuro Fuzzy Inference System (ANFIS) for forecasting time series data. The focus of the development is selecting optimal ANFIS model by using the statistical inference based on Lagrange Multiplier (LM) test. To date, there are several methods for selecting optimal ANFIS model, but there is no research which applied LM-test procedure for selecting inputs, determining membership functions (clusters) and generating fuzzy rules, especially for forecasting time series data. Theoretical study related to the proposed procedure is supported by simulation study. The simulation datasets which generated based on Autoregressive Integrated Moving Average (ARIMA), ARIMA-Outlier and Seasonal ARIMA models are used for constructing ANFIS models and for evaluating the proposed algorithm. The performance of ANFIS models are evaluated by minimizing RMSE value.**

Keywords*—*time series, inference procedure, ANFIS, LM-test

I. INTRODUCTION

Neural network (NN), fuzzy inference system (FIS) and its hybrid have been developed to analyze non-stationary and non-linear time series data [1,2,3]. ANFIS model is one of the hybrid methods which combines NN and fuzzy system [4,5]. There are many investigations on time series by using ANFIS and NN such as: short-term wind-speed forecasting for Egypt's East-Coast [6]; forecasting gold price changes [7]; prediction of stock market return [8,9,10]; modeling hydrological time series [11]; forecasting EPS of leading industries [12]; constructing model of financial volatility [13,14,15]and exchange rate prediction [16,17]; electricity consumption [18]. All of those research concluded that the performance of ANFIS is better than the classical ARIMA model.

The crucial issues in time series data modeling using ANFIS are 1) How to identify and select the input variables; 2) How to determine the number of membership functions and 3) How to determine the numbers of fuzzy rules. To date, there is no researcher which develop the statistical inference using LM-test for selecting model in ANFIS. Based on selecting model in NN developed by White (see Unders and Korn [19]), this research is focused on procedure development of selecting model in ANFIS based on LM-test. Organization of the remaining parts of this article are as follows: Section 2 explain the definition of ANFIS architecture. Section 3 describes LM-test procedure for ANFIS modeling. Section 4 discusses simulation study. The conclusion of the research is summarized on section 5.

II. ANFIS ARCHITECTURE

An ANFIS architecture consists of fuzzification (layer-1), fuzzy inference system (layer-2 and layer-3), de-fuzzification (layer-4) and aggregation (layer-5). The NN architecture which used in the architecture has 5 fixed-layers [5]. Generally, the architecture for time series modeling with p input Z_{t-1}, Z_{t-2}, ..., Z_{t-p} and one output Z_t by assuming rule-bases of Sugeno order-one with m rules is as follow.

If Z_{t-1} *is* A_{11} *and* Z_{t-2} *is* A_{21} ... *and* Z_{t-p} *is* A_{p1} then

$Z_t^{(1)} = \theta_{11}Z_{t-1} + \theta_{12}Z_{t-2} + \cdots + \theta_{1p}Z_{t-p} + \theta_{10}$;

If Z_{t-1} *is* A_{12} *and* Z_{t-2} *is* A_{22} ... *and* Z_{t-p} *is* A_{p2} then

$Z_t^{(2)} = \theta_{21}Z_{t-1} + \theta_{22}Z_{t-2} + \cdots + \theta_{2p}Z_{t-p} + \theta_{20}$;

⋮

If Z_{t-1} *is* A_{1m} *and* Z_{t-2} *is* A_{2m} ... *and* Z_{t-p} *is* A_{pm} then

$Z_t^{(m)} = \theta_{m1}Z_{t-1} + \theta_{m2}Z_{t-2} + \cdots + \theta_{mp}Z_{t-p} + \theta_{m0}$;

where Z_{t-k} is A_{kj} as premise (nonlinear) section, whereas $Z_t^{(j)} = \theta_{j0} + \sum_{k=1}^{p} \theta_{jk} Z_{t-k}$ as consequent (linear) section; θ_{jk}, θ_{j0} as linear parameters; A_{kj} as nonlinear parameters; $j = 1,2,...,m$; $k = 1,2,..., p$. If the firing strength for m values $Z_t^{(1)}$, $Z_t^{(2)}$, $\cdots$, $Z_t^{(m)}$ are $w_1, w_2, \ldots, w_m$ respectively then the output Z_t can be determined as:

$$Z_t = \frac{w_1 Z_t^{(1)} + w_2 Z_t^{(2)} + \cdots + w_m Z_t^{(m)}}{w_1 + w_2 + \cdots + w_m} \quad (1)$$

The architecture of ANFIS (see Fig.1) consist of 5 layers that can be described as follows [1].

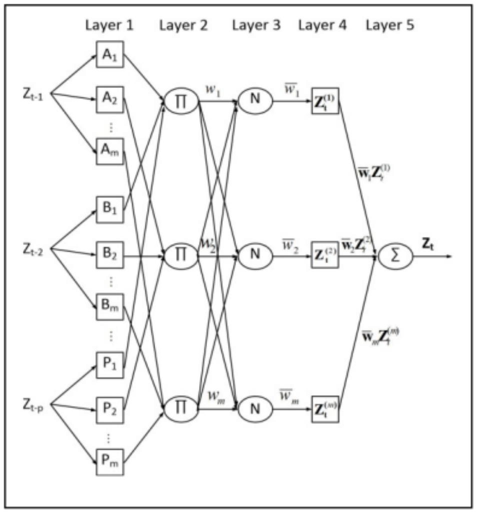

Fig. 1. Architecture ANFIS with p inputs, one output and m rules.

Layer-1: Each node in the first layer is adaptive with a parametric activation function. The output layer is membership degree of inputs: $\mu_{A_{11}}(Z_{t-1})$, $\mu_{A_{2}}(Z_{t-1})$, $\cdots$, $\mu_{A_{1m}}(Z_{t-1})$, $\mu_{A_{21}}(Z_{t-2})$, $\mu_{A_{22}}(Z_{t-2})$, $\cdots$, $\mu_{A_{2m}}(Z_{t-2})$, $\cdots$, $\mu_{A_{p1}}(Z_{t-p})$, $\mu_{A_{p2}}(Z_{t-p})$, $\cdots$, $\mu_{A_{pm}}(Z_{t-p})$.

For instance, Gaussian membership function (*gaussmf*) can be written as:

$$\mu_{A_{kj}}(Z_{t-k}) = \exp\left(-\frac{1}{2}\left(\frac{Z_{t-k}-c_{jk}}{a_{jk}}\right)^2\right),$$

$j=1,2,\cdots,m$, $k=1,2,\cdots,p$; c_{jk}: location parameters and a_{jk}: scaling parameters. The parameters are called as premise parameters.

Layer-2: Each node in second layer is fixed node and its output is the product of incoming signal that uses operation AND. The output of each node represents firing strength w_j.

$$w_j = \prod_{k=1}^{p} \mu_{A_{kj}}(Z_{t-k}),\ j=1,2,\cdots,m$$

Layer-3: Each node in the third layer is fixed node that computes ratio of firing strength of j-th rule relative to summation of firing strengths of rules.

$$\overline{w}_j = \frac{w_j}{\sum_{j=1}^{m} w_j}$$

Layer-4: Each node in the fourth layer is adaptive node and each node has output:

$$\overline{w}_j Z_t^{(j)} = \overline{w}_j(\theta_{j1}Z_{t-1} + \theta_{j2}Z_{t-2} + \cdots + \theta_{jp}Z_{t-p} + \theta_{j0})$$

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

$$Z_t = \sum_{j=1}^{m} \overline{w}_j(\theta_{j1}Z_{t-1} + \theta_{j2}Z_{t-2} + \cdots + \theta_{jp}Z_{t-p} + \theta_{j0}) \quad (2)$$

The general model of ANFIS is given as follow.

$$Z_t = \sum_{j=1}^{m}\sum_{k=1}^{p} \theta_{jk}(\overline{w}_j Z_{t-k}) + \sum_{j=1}^{m} \theta_{j0}\overline{w}_j \quad (3)$$

III. Proposed Procedure of Model Selection

The proposed procedure for selecting model in ANFIS using Lagrange Multiplier (LM) test are focused on selecting input variables, determining number of membership function sand deter mining number of fuzzy rules.

A. Inference Procedure for Selecting Input Variable

Given p input variables Z_{t-1}, Z_{t-2}, ..., Z_{t-p} with m number of membership functions, then the restricted model for this case is as follow.

$$Z_t = \sum_{j=1}^{m}\sum_{k=1}^{p} \theta_{jk}(\overline{w}_j Z_{t-k}) + \sum_{j=1}^{m} \theta_{j0}\overline{w}_j + \varepsilon_t \quad (4)$$

where $\varepsilon_t \sim N(0,\sigma_\varepsilon^2)$, and unrestricted model for one input addition $Z_{t-(p+1)}$ is:

$$Z_t = \sum_{j=1}^{m}\sum_{k=1}^{p+1} \theta_{jk}(\overline{w}_j Z_{t-k}) + \sum_{j=1}^{m} \theta_{j0}\overline{w}_j + \upsilon_t \quad (5)$$

where $\upsilon_t \sim N(0,\sigma_\upsilon^2)$.

The formulation of null hypothesis of adding variables test can be written as:

$$H_0: \theta_{1(p+1)} = \theta_{2(p+1)} = \cdots = \theta_{m(p+1)} = 0$$

The steps of hypothesis test are as follows:

Step-1: Estimate the parameters of restricted model $\hat{\theta}_{11},\hat{\theta}_{12},...,\hat{\theta}_{1p},\hat{\theta}_{10},\hat{\theta}_{21},\hat{\theta}_{22},...,\hat{\theta}_{2p},\hat{\theta}_{20},...,\hat{\theta}_{m1},\hat{\theta}_{m2},...,\hat{\theta}_{mp},\hat{\theta}_{m0}$.

Step-2: Determining residual:

$$\hat{\varepsilon}_t = Z_t - \sum_{j=1}^{m}\sum_{k=1}^{p} \hat{\theta}_{jk}(\overline{w}_j Z_{t-k}) - \sum_{j=1}^{m} \hat{\theta}_{j0}\overline{w}_j$$

Step-3: Regress $\hat{\varepsilon}_t$ with: a constant, $(\overline{w}_1 Z_{t-1})$, $(\overline{w}_1 Z_{t-2})$, … , $(\overline{w}_1 Z_{t-p})$, $(\overline{w}_1 Z_{t-p-1})$, $\overline{w}_1$, $(\overline{w}_2 Z_{t-1})$, $(\overline{w}_2 Z_{t-2})$, … , $(\overline{w}_2 Z_{t-p})$, $(\overline{w}_2 Z_{t-p-1})$, $\overline{w}_2$, … , $(\overline{w}_m Z_{t-1})$, $(\overline{w}_m Z_{t-2})$, … , $(\overline{w}_m Z_{t-p})$, $(\overline{w}_m Z_{t-p-1})$, $\overline{w}_m$ and calculate $nR_{\hat{\varepsilon}}^2$. It was known that $LM = nR_{\hat{\varepsilon}}^2 \sim \chi_m^2$ [15]. Ho is rejected when $nR_{\hat{\varepsilon}}^2 > \chi_m^2(\alpha)$.

B. Determining Number of Membership Functions (MFs)

When the ANFIS model with optimal inputs have been established, adding number of clusters can be executed using LM-test to get a model with optimal number of clusters. If given p input Z_{t-1}, Z_{t-2}, ..., Z_{t-p} the unrestricted model for adding one membership function is

$$Z_t = \sum_{j=1}^{m+1}\sum_{k=1}^{p}\theta_{jk}(\overline{w}_j Z_{t-k}) + \sum_{j=1}^{m}\theta_{j0}\overline{w}_j + \upsilon_t \quad (6)$$

Where $\upsilon_t \sim N(0,\sigma_\upsilon^2)$ .The null hypothesis for adding variables $(\overline{w}_{m+1}Z_{t-1})$, $(\overline{w}_{m+1}Z_{t-2})$, …, $(\overline{w}_{m+1}Z_{t-p})$ can be formulated as follows:

$H_0 : \theta_{(m+1)1} = \theta_{(m+1)2} = \cdots = \theta_{(m+1)p} = 0$.

Hypothesis test algorithm based on LM-test are as follows.

Step-1: Estimate the parameters of restricted model:

$$\hat{\theta}_{11},\hat{\theta}_{12},...,\hat{\theta}_{1p},\hat{\theta}_{10},\hat{\theta}_{21},\hat{\theta}_{22},...,\hat{\theta}_{2p},\hat{\theta}_{20},...,\hat{\theta}_{m1},\hat{\theta}_{m2},...,\hat{\theta}_{mp},\hat{\theta}_{m0}.$$

Step-2: Determine the estimate of residual:

$$\hat{\varepsilon}_t = Z_t - \sum_{j=1}^{m}\sum_{k=1}^{p}\hat{\theta}_{jk}(\overline{w}_j Z_{t-k}) + \sum_{j=1}^{m}\hat{\theta}_{j0}\overline{w}_j$$

Step-3:Regress the residual $\hat{\varepsilon}_t$ with a constant, $(\overline{w}_j Z_{t-k})$, $\overline{w}_j$; $j = 1,2,\cdots,m$; $k = 1,2,\cdots,p$, and calculate $LM = nR^2_{\hat{\varepsilon}}$. It is known that $LM = nR^2_{\hat{\varepsilon}} \sim \chi^2_p$. Null hypothesis Ho is rejected when $nR^2_{\hat{\varepsilon}} > \chi^2_p(\alpha)$.

C. Determining Number of Fuzzy Rules

In general, if given Z_{t-1} , Z_{t-2} ,..., Z_{t-p} as inputs, and m MFs, then minimum number of rules is m and the maximum number of rules is m^p . In this research genfis3 method is used for modeling, the number of rules are given based on the number of optimal MFs. So, the number of rules are equal to the number of optimal MFs.

IV. Simulation Study

The aim of this simulation study is to prove that LM-test procedure for selecting inputs, determining number of membership functions and number of fuzzy rules in constructing optimal model can work well. In this part, three types of data are generated for constructing ANFIS model and selecting the optimal model using LM-test procedure. Three types dataset are generated based on AR(2), AR(2)-Outlier and seasonal models. Input variables are selected based on LM-test procedure. The significant inputs are selected based on LM statistics or p-value. For simulated AR(2) data resulted lag-1(Z_{t-1}) and lag-2(Z_{t-2}) are selected as input ANFIS because p-value is less than significance level α =0.05 (5%) . By using the same procedure AR(2)-O data resulted lag-1 (Z_{t-1}), lag-2 (Z_{t-2}) and for seasonal data resulted lag-2 (Z_{t-2}), lag-4 (Z_{t-4}) as significant inputs (see TABLE I).

The estimated models of simulated datasets can be written LM-test procedure is also applied to determine the number of membership functions of the datasets. For AR(2) simulated data, this test resulted two membership functions because LM statistics is less then significance level. Whereas for AR(2)-O data have two membership functions and for each input of seasonal data divided into three membership functions.

TABLE I. Results of LM-test for determining input

Model	Input	$R^2_{Z_t}$	$R^2_{\varepsilon_t}$	LM	p-value
AR(2)	Z_{t-1}	0.561	-		
	Z_{t-2}	0.149	-		
	Z_{t-3}	0.001	-		
	Z_{t-1} , Z_{t-2}	-	0.171	27.915	0.00
AR(2)-O	Z_{t-1}	0.939	-		
	Z_{t-2}	0.863	-		
	Z_{t-3}	0.792	-		
	Z_{t-1} , Z_{t-2}	-	0.066	11.947	0.00
	Z_{t-1} , Z_{t-3}	-	0.012	2.131	0.34
SARIMA	Z_{t-1}	2.1×10^{-5}	-	-	
	Z_{t-2}	0.90	-	-	
	Z_{t-3}	0.79	-	-	
	Z_{t-4}	0.91	-	-	
	Z_{t-2} , Z_{t-4}	-	0.32	57.29	0.00

TABLE II. Results of LM-test for determining number of membership functions

Model	Input	Number of MFs	$R^2_{\varepsilon_t}$	LM	p-value
AR(2)	Z_{t-1} , Z_{t-2}	2	0.171	27.915	0.00
		3	1.22×10^{-30}	2.16×10^{-28}	1
AR(2)-O	Z_{t-1} ,Z_{t-2}	2	0.066	11.947	0.00
		3	6.67×10^{-6}	0.001	1
SARIMA	Z_{t-2} ,Z_{t-4}	2	0.219	39.52	0.00
		3	0.298	53.68	0.00

The complete results of determining number of membership functions can be seen in TABLE II.

as follows:

1) Estimated model for AR(2) dataset

$$Z_t = 0.9176\,\overline{w}_{1,t}Z_{t-1} - 0.3033\,\overline{w}_{1,t}Z_{t-2} - 0.24337\,\overline{w}_{1,t} + 1.3522\,\overline{w}_{2,t}Z_{t-1} - 0.6701\,\overline{w}_{2,t}Z_{t-2} + 0.1937\,\overline{w}_{2,t} \quad (7)$$

where

$$\overline{w}_{j,t} = \frac{w_{j,t}}{\sum_{j=1}^{2} w_{j,t}}$$

$$w_{1,t} = \exp\left[-\frac{1}{2}\left\{\left(\frac{Z_{t-1}+3.2680}{3.2986}\right)^2 + \left(\frac{Z_{t-2}+2.7831}{3.4977}\right)^2\right\}\right],$$

$$w_{2,t} = \exp\left[-\frac{1}{2}\left\{\left(\frac{Z_{t-1}-2.7744}{3.2674}\right)^2 + \left(\frac{Z_{t-2}-2.2708}{3.3071}\right)^2\right\}\right].$$

The root mean squares error (RMSE) value based on (7) is 4.965.

2) Estimated model for AR(2)-O dataset

$$Z_t = 0.8077\,\overline{w}_{1,t}Z_{t-1} - 0.1797\,\overline{w}_{1,t}Z_{t-2} + 4.6323\,\overline{w}_{1,t} + 0.9711\,\overline{w}_{2,t}Z_{t-1} - 0.3775\,\overline{w}_{2,t}Z_{t-2} + 0.0099\,\overline{w}_{2,t} \quad (8)$$

where

$$\overline{w}_{j,t} = \frac{w_{j,t}}{\sum_{j=1}^{2} w_{j,t}}$$

$$w_{1,t} = \exp\left[-\frac{1}{2}\left\{\left(\frac{Z_{t-1}-12.6403}{5.5438}\right)^2 + \left(\frac{Z_{t-2}-12.5196}{5.7711}\right)^2\right\}\right]$$

$$w_{2,t} = \exp\left[-\frac{1}{2}\left\{\left(\frac{Z_{t-1}+0.2505}{6.7046}\right)^2 + \left(\frac{Z_{t-2}+0.2313}{6.8907}\right)^2\right\}\right].$$

By using (8), the value of root mean squares Error (RMSE) is 2.262.

3) *Estimated model for seasonal dataset*

$$\begin{aligned} Z_t = {} & 0.8289\,\overline{w}_{1,t}Z_{t-2} - 0.2143\,\overline{w}_{1,t}Z_{t-4} + 161.4606\,\overline{w}_{1,t} + \\ & 0.1333\,\overline{w}_{2,t}Z_{t-2} - 0.11075\,\overline{w}_{2,t}Z_{t-4} + 524.0359\,\overline{w}_{2,t} + \\ & 0.1253\,\overline{w}_{3,t}Z_{t-2} - 0.2434\,\overline{w}_{3,t}Z_{t-4} + 307.7296\,\overline{w}_{3,t} \end{aligned} \tag{9}$$

where

$$\overline{w}_{j,t} = \frac{w_{j,t}}{\sum_{j=1}^{3} w_{j,t}}$$

$$w_{1,t} = \exp\left[-\frac{1}{2}\left\{\left(\frac{Z_{t-2}-401.0901}{40.0353}\right)^2 + \left(\frac{Z_{t-4}-401.0128}{40.3605}\right)^2\right\}\right],$$

$$w_{2,t} = \exp\left[-\frac{1}{2}\left\{\left(\frac{Z_{t-2}-298.7588}{43.1570}\right)^2 + \left(\frac{Z_{t-4}-504.8368}{49.4041}\right)^2\right\}\right],$$

$$w_{3,t} = \exp\left[-\frac{1}{2}\left\{\left(\frac{Z_{t-2}-504.7904}{53.7904}\right)^2 + \left(\frac{Z_{t-4}-298.6950}{45.7326}\right)^2\right\}\right].$$

Based on (9), the value of root mean squares error (RMSE) is 250.393.

Performance of the optimal model for forecasting *in sample data* are given as Fig. 2.

The optimal model gave the accurate result of prediction, because the predicted value are very close to data.

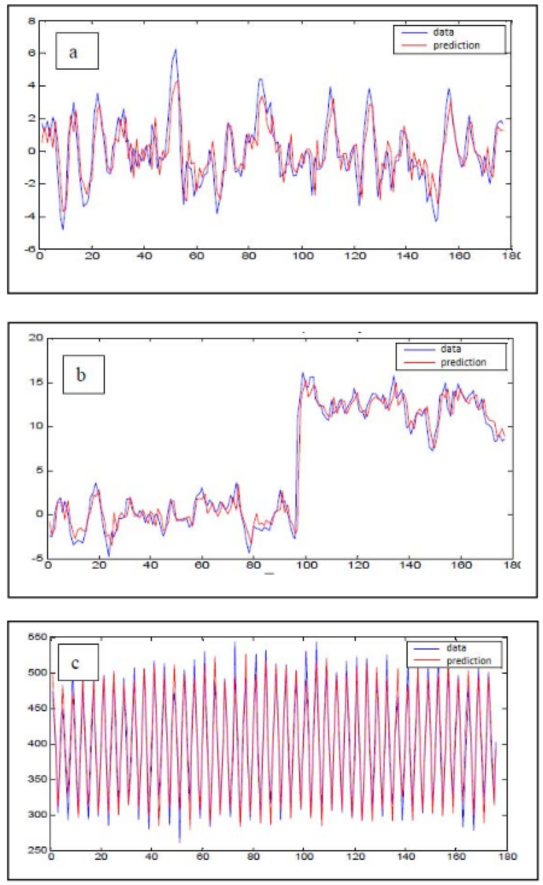

Fig. 2. Prediction of *in sample*simulated data; (a) AR(2), (b) AR(2)-O, (c) SARIMA

I. CONCLUSION

Based on simulation study, LM-test procedure can be applied for selecting input, determining number of membership functions and number of fuzzy rules in ANFIS for forecasting time series data. So the proposed procedure can work well for selecting model in ANFIS.

ACKNOWLEDGMENT

This research supported by Research Grant from Directorate of Research and Publics Services, Ministry of Research, Technology and Higher Education, Republics of Indonesia.

REFERENCES

[1] J.-S.R., Jang, C.–T. Sun, E. Mizutani, Neuro-Fuzzy and Soft Computing: A computational Approach to Learning and Machine Intelligent. Prentice Hall International, 1997.

[2] L. Fausset, Fundamental of Neural Networks: Architectures, Algorithms and Aplications, Prentice Hall, Englewood Cliffs, New Jersey, 1994.

[3] S. Haykin, Neural Networks: A Comprehensive Foundation, Second Edition, Prentice Hall International, Inc., 1999.

[4] J. -S. R. Jang, ANFIS: Adaptive-Network-Based Fuzzy Inference System, IEEE Transactions on Systems, Man, and Cybernetics, Vol. 23, No.3, 1993, pp.665-685.

[5] M. Alizadeh, R. Rada, A.K.G. Balagh, M.M.S. Esfahani, Forecasting Exchange Rates: A Neuro-Fuzzy Approach, IFSA-EUSFLAT, 2009, pp.1745-1750.

[6] O. M. Salim, M. A. Zohdy, H. T. Dorrah & A. M. Kamel, Adaptiveneuro-fuzzy short-term wind-speed forecasting for Egypt's East-Coast, International Journal ofSustainable Energy, 33:1, 2014, 16-34

[7] A. Yazdani-Chamzini, S. H. Yakhchali, D. Volungevičienė& E. K. Zavadskas, Forecasting gold price changes by using adaptivenetwork fuzzy inference system, Journal of Business Economics and Management, 13:5, 2012, 994-1010.

[8] J-C. Hung, A Fuzzy Asymmetric GARCH model applied to stock markets, Information Sciences 179, 2009, pp.3930-3943.

[9] L. Y. Wei, T. L. Chen & T. H. Ho, A hybrid model based on adaptive-networkbased fuzzy inference system to forecast Taiwan stock market. Expert Systems with Applications, 38, 2011, pp.13625-13631.

[10] M.A. Boyacioglu and D. Avci, An Adaptive Network-Based Fuzzy Inference System (ANFIS) for the prediction of stock market return: The case of the Istanbul Stock Exchange. Expert Systems with Applications, 37, 2010, pp.7908-7912.

[11] M. E. Keskin, D. Taylan& Ö. Terzi, Adaptiveneural-based fuzzy inference system (ANFIS) approach for modelling hydrological time series,Hydrological Sciences Journal, 51:4, 2006, 588-598,.

[12] L. Y. Wei, C. H. Cheng & H. H. Wu, Fusion ANFIS Model Based on AR for Forecasting EPS of Leading Industries. International Journal of Innovative Computing Information and Control, 7, 2011, pp.5445-5458.

[13] L.S. Maciel, A Hybrid Fuzzy GJR-GARCH Modeling Approach for Stock Market Volatility Forecasting, Rev. Bras. Financas, Rio de Janeiro, Vol. 10, No.3, 2012, pp.337-367.

[14] L.Y. Wei, An Adaptive Expectation GeneticAlgorithm Based on ANFIS and Multinational Stock Market VolatilityCausality For Taiex Forecasting, Cybernetics And Systems, 43:5, 2012, 410-425.

[15] R. F. Engle, Autoregressive Conditional Heteroscedasticity with Estimates of Variance United Kingdom Inflation, Econometrica, Vol. 50, No.4, 1982, pp. 987-1007.

[16] M.N.Y. Alakhras, Neural Network-based Fuzzy Inference System for Exchange Rate Prediction, Journal of Computer Science (Special Issue), Science Publications, 2005, pp. 112-120.

[17] S. M. Fahimifard, M. Homayounifar, M. Sabouhi and A.R. Moghaddamnia, Comparison of ANFIS, ANN, GARCH and ARIMA Techniques to Exchange Rate Forecasting, Journal of Applied Sceinces 9 (20), 2009, pp.3641-3651.

[18] R. Abiyev, V. H. Abiyev and C. Ardil., Electricity Consumption Prediction Model using Neuro-Fuzzy System, World Academy of Science, Engineering and Technology 8, 2005.

[19] U. Anders and O. Korn, Model selection in Neural Networks. Neural Networks, 12, 1999, 309-323

Inference Procedure Based on LM-Test in ANFIS for Constructing Time Series Model

ORIGINALITY REPORT

7%	5%	4%	1%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	etd.repository.ugm.ac.id Internet Source	2%
2	schwert.ssb.rochester.edu Internet Source	1%
3	downloads.hindawi.com Internet Source	1%
4	Submitted to SASTRA University Student Paper	<1%
5	Jan G. De Gooijer, Ali Gannoun, Dawit Zerom. "A Multivariate Quantile Predictor", Communications in Statistics - Theory and Methods, 2006 Publication	<1%
6	Naoki Doteguchi, Naoyuki Kubota. "Chapter 2 Topological Tracking for Mobility Support Robots Based on Multi-scale Batch Learning Growing Neural Gas", Springer Science and Business Media LLC, 2022 Publication	<1%

7	Submitted to Ashesi University Student Paper	<1%
8	Donghai Li, Xiaoyu Liu, Yumei Wang, Yu Liu. "Importance-Driven Downlink Resource Scheduling for Video Transmission over LTE", 2018 International Conference on Network Infrastructure and Digital Content (IC-NIDC), 2018 Publication	<1%
9	www.coursehero.com Internet Source	<1%
10	Yong Wang, Yuanyuan Ding, Yongjian He, Qilong Miao. "Realization of HHT Method to Solar Irradiance Data in MATLAB", 2010 Second World Congress on Software Engineering, 2010 Publication	<1%
11	Tineo, A.. "Existence of global attractors for a class of periodic Kolmogorov systems", Journal of Mathematical Analysis and Applications, 20030315 Publication	<1%
12	www.econstor.eu Internet Source	<1%
13	Manuel A. Domínguez, Ignacio N. Lobato. "Testing the Martingale Difference Hypothesis", Econometric Reviews, 2003	<1%

Publication

14	JOON-HO HAHM, JINHO KIM. "COST-AT-RISK AND BENCHMARK GOVERNMENT DEBT PORTFOLIO IN KOREA", International Economic Journal, 2003 Publication	<1%

Exclude quotes	Off	Exclude matches	Off
Exclude bibliography	Off		

Inference Procedure Based on LM-Test in ANFIS for Constructing Time Series Model

GRADEMARK REPORT

FINAL GRADE

/0

GENERAL COMMENTS

Instructor

PAGE 1

PAGE 2

PAGE 3

PAGE 4

PAGE 5

PAGE 6