Journal of Theoretical and Applied Information Technology
15th January 2021. Vol.99. No 1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

APPLICATION OF ENSEMBLE ARIMA, ANFIS FOR CONSTRUCTING MODEL OF GARLIC PRICE DATA IN SEMARANG

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ABSTRACT

This research was proposed for constructing the predictive model of commodity price data. The classical model such as Autoregressive Integrated Moving Average (ARIMA) and also machine learning model such Adaptive Neuro-Fuzzy Inference System (ANFIS) have been implemented in various field of time series analysis. This research is focused on constructing ARIMA, ANFIS and their combination or ensemble ARIMA-ANFIS. The main problem of combination is determining the weight of each vector predicted values which obtained from related models. In this research, the weight of each model were determined by variance-covariance approach and Lagrange Multiplier optimization, while in classical studies weight of each model was determined by averaging of predicted values. The main issue of this research is how to determine the weight of vector predicted values by using variance-covariance approach for constructing the ensemble ARIMA-ANFIS. The daily data of garlic price in Semarang collected from January 2019 to August 2019 were used as case studies. ARIMA, ANFIS and ensemble ARIMA-ANFIS were implemented for predicting data. ARIMA individual, ANFIS individual, ensemble model by averaging and ensemble model by weighting resulted high accuracy for predicting. The combination of ARIMA(1,0,0)-ARCH(1) and ANFIS (with lag-1, lag-2 as inputs and 2 MFs) is the best model for forecasting garlic price data in Semarang. The MAPE values of all models were less than 5% which had shown a good performance for forecasting.

Keywords: *ARIMA, ANFIS, Ensemble, Garlic Price Data*

1. INTRODUCTION

The classical model such as Autoregressive Integrated Moving Average (ARIMA) and also machine learning model such Adaptive Neuro-Fuzzy Inference System (ANFIS) have been implemented in various field of time series analysis. Time-series forecasting has been applied widely in many different fields such as economics, sociology, and science. Forecasting methods can be broadly divided into two categories: statistical and artificial intelligence (AI)-based techniques. Box-Jenkins or autoregressive integrated moving average (ARIMA), multiple regressions, and exponential smoothing are the examples of statistical methods, while AI paradigms include fuzzy inference systems, genetic algorithm, neural networks, machine-learning, and etc. [1].

ARIMA is one of the most intensive models which used for time series forecasting [2]. Autoregressive Conditional Heteroscedasticity (ARCH) model proposed by [3] and Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model that developed by [4] is the popular variance model. ARIMA-GARCH has been applied in a lot of research for forecasting nonlinear time series data.

In recent years, combination of neural networks (NN), fuzzy system and its hybrid have been developed for analyzing non-linear time series [5]. ANFIS model proposed by [6] has been implemented in many fields of time series research. There are many research which implemented ANFIS model for time series data such as [7] proposed statistical inference based on LM test for selecting optimal model in ANFIS inspired by [8]; Modeling minimum temperature using adaptive neuro-fuzzy inference system based on spectral analysis of climate indices: A case study in Iran [9]; Comparison of ANFIS, ANN, GARCH and ARIMA Techniques to Exchange Rate Forecasting [10]; Fuzzy time series forecasting based on fuzzy logical relationships and similarity measures [11]; The Prediction of Taiwan 10-Year Government Bond Yield [12]; A new hybrid enhanced local linear neuro-fuzzy model based on the optimized singular spectrum analysis and its application for nonlinear and chaotic time series forecasting [13]; Time-series prediction using adaptive neuro-fuzzy networks [14]; Time series forecasting for nonlinear and nonstationary processes: a review and comparative study [15]. Chaotic Time Series Prediction using Improved ANFIS with Imperialist Competitive Learning Algorithm [16]. The results of the most research concluded that ANFIS was better than the other methods.

There are also many research that combine statistical method (ARIMA) and AI paradigm (NN, ANFIS, machine learning) such as Time-series analysis with neural networks and ARIMA-neural network hybrid [17] with the results suggest that hybrids of the type proposed may yield better outcomes than either model by itself; The Construction and Application of a New Exchange Rate Forecast Model Combining ARIMA with a Chaotic BP Algorithm [18] with the result, the combination of an SARIMA and a chaotic BP algorithm outperforms all other models in terms of the statistical accuracy of short-term forecasts; Optimization of Ensemble Neural Networks with Type-2 Fuzzy Integration of Responses for the Dow Jones Time Series Prediction [19] with the simulation results show that the ensemble approach produces 99% prediction accuracy; Hybrid grey relational artificial neural network and auto regressive integrated moving average model for forecasting time-series data [1]. Uncertainty analysis for the forecast of lake level fluctuations using ensembles of ANN and ANFIS models [20]. The experiments have shown that the proposed model has outperformed other models with 99.5% forecasting accuracy for small-scale data and 99.84% for large-scale data. The obtained empirical results have proven that the GRANN-ARIMA model can provide a better alternative for time-series forecasting due to its promising performance and capability in handling time-series data for both small and large-scale data [1]. The averaging method was implemented to find an ensemble forecast from ANFIS and ARIMA models [21]. They concluded that the accuracy of the proposed method was lower than single ARIMA and ANFIS. The results of ensemble ARIMA-ANFIS that proposed hybrid patterns (AdaBoost) improve the accuracy of single ARIMA and ANFIS models in forecasting energy consumption [22]. The other study about implementation of ensemble method concludes that the ensemble of ANN and ANFIS model shows significant improvement in prediction performance as compared to the individual models [23].

Based on the results of previous research, this research is focused on constructing ARIMA, ANFIS and their combination (ensemble) ARIMA-ANFIS. The main problem of combination is determining the coefficient or weight of each vector predicted values which obtained from membership ensemble. In this research, weight of each model was determined by variance-covariance approach with Lagrange Multiplier (LM) optimization, while in classical studies weight of each model was determined by averaging of vector predicted values. The daily data of garlic price in Semarang collected from January 2019 to August 2019 are used as case studies. ARIMA, ANFIS and ensemble ARIMA-ANFIS are implemented for predicting data. ARIMA individual, ANFIS individual, ensemble model by averaging and ensemble model by variance-covariance approach were compared to each other. Organization of this paper is as follows: Section 2 discusses about material and methods; Section 3 describes about results and discussion; and conclusion is discussed in Section 4.

2. MANUSCRIPTS MATERIALS AND METHODS

2.1. ARIMA Model

Autoregressive integrated moving average (ARIMA) is the method proposed by Box-Jenkins [2,24]. ARIMA become the most intensive model for constructing univariate time series data. ARIMA(p, d, q) model can be formulated as [25].

$$\emptyset_p(B)(1-B)^d Z_t = \theta_q(B) a_t \qquad (1)$$

where $\emptyset_p(B) = 1 - \emptyset_1 B - \emptyset_2 B^2 - \cdots - \emptyset_p B^p$,

$\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$,

and B is backward shift operator, and a_t is a sequence of white noise with zero mean and constant variance, p: order of autoregressive and q: moving average order and d denotes differences order.

2.2. GARCH Model

Given stationary time series Z_t and there is no autocorrelation among Z_t itself, then Z_t can be

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

expressed as a summation of its mean and a white noise [26]. Z_t can be written as follow:

$$Z_t = \mu_t + a_t \quad (2)$$

where μ_t mean of process Z_t and $a_t = \sigma_t v_t$ with $v_t \sim N(0,1)$.

To investigate the volatility clustering or conditional heteroscedasticity, it is assumed that $Var_{t-1}(a_t) = \sigma_t^2$ where $Var_{t-1}(\bullet)$ express conditional variance given information at time (t-1), and

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \ldots + \alpha_p a_{t-p}^2 \quad (3)$$

Because mean a_t is equal to zero, $Var_{t-1}(a_t) = E_{t-1}(a_t^2) = \sigma_t^2$, so Equation 3 can be written as

$$a_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \ldots + \alpha_p a_{t-p}^2 + u_t \quad (4)$$

where $u_t = a_t^2 - E_{t-1}(a_t^2)$ is a white noise with mean zero. Model (2) and (3) are called ARCH model [3]. The parsimonious model to substitute model (4) proposed by [4] is formulated as:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i\, a_{t-i}^2 + \sum_{j=1}^{q} \beta_j\, \sigma_{t-j}^2 \quad (5)$$

where coefficients $\alpha_i > 0$ $(i = 0,1,\ldots,p)$ and $\beta_j > 0$ $(j = 1,\ldots,q)$ for guarantee that conditional variance σ_t^2 should be positive. Formula (5) together with (2) are called as generalized ARCH or GARCH(p,q). If q=0 then GARCH model become ARCH model.

2.3. ANFIS Architecture

The ANFIS architecture consists of fuzzyfication (layer-1), fuzzy inference system (layer-2 and layer-3), defuzzyfication (layer-4) and aggregation (layer-5). The NN architecture which used in ANFIS architecture has 5 fixed-layers [5]. Generally, the architecture of ANFIS for time series modeling with p input variables Z_{t-1}, $Z_{t-2}, \cdots$, Z_{t-p} and one output variable Z_t by assuming rule-base 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; $j = 1,2,\ldots,m$; $k = 1,2,\ldots,p$. 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:

$$Z_t = \frac{w_1 Z_t^{(1)} + w_2 Z_t^{(2)} + \cdots + w_m Z_t^{(m)}}{w_1 + w_2 + \cdots + w_m} \quad (6)$$

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

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 $\mu_{A_{11}}(Z_{t-1})$, $\mu_{A_{12}}(Z_{t-1})$, $\cdots$, $\mu_{A_{1m}}(Z_{t-1})$, $\mu_{A_{21}}(Z_{t-2}), \mu_{A_{22}}(Z_{t-2}), \cdots, \mu_{A_{2m}}(Z_{t-2}), \cdots, \mu_{A_{p1}}(Z_{t-p}), \mu_{A_{p2}}(Z_{t-p}), \cdots, \mu_{A_{pm}}(Z_{t-p})$. One example of membershipfunction is Gaussian membership function (gaussmf) which 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: Every node in the second layer is fixed node which the output of this layer is the product of incoming signal. Generally, it uses fuzzy operation AND. The output of each node represents firing strength w_j of the j-th rule.

$$w_j = \prod_{k=1}^{p} \mu_{A_{kj}}(Z_{t-k}), j = 1,2,\cdots,m. \quad (7)$$

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

$$\bar{w}_j = \frac{w_j}{\sum_{j=1}^{m} w_j} \quad (8)$$

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

$$\bar{w}_j Z_t^{(j)} = \bar{w}_j(\theta_{j1}Z_{t-1} + \theta_{j2}Z_{t-2} + \cdots + \theta_{jp}Z_{t-p} + \theta_{j0}) \quad (9)$$

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.

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

The general model of ANFIS is given as follow.

$$Z_t = \sum_{j=1}^{m} \sum_{k=1}^{p} \theta_{jk}\, (\bar{w}_j Z_{t-k}) + \sum_{j=1}^{m} \theta_{j0}\, \bar{w}_j \quad (10)$$

Figure 1. ANFIS Architecture for Time Series Modeling [7]

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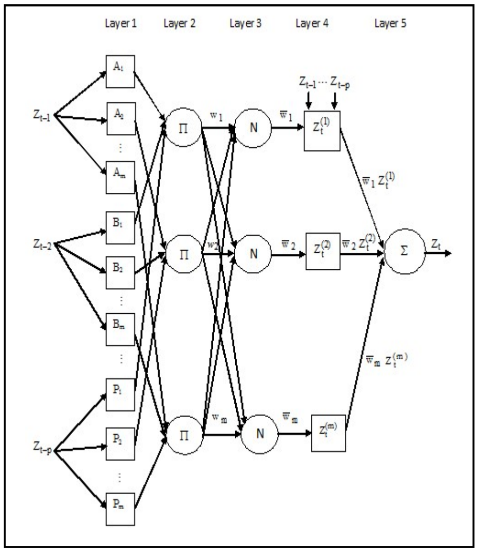

2.4. Ensemble Method

There are two methods usually be used for combining the difference outputs from membership ensemble, i.e. averaging and stacking [21]. The Architecture of ensemble is shown in Figure 2.

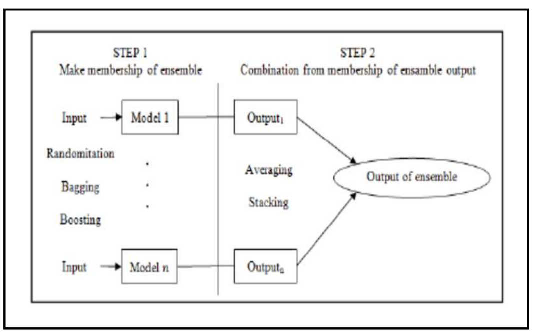

Figure 2. Architecture of ensemble [21]

By using averaging method, the output of ensemble is obtained by computing the mean of output of the number of networks [21]. If given k vector predicted values $\hat{Z}_t^{(1)}, \hat{Z}_t^{(2)}, \dots, \hat{Z}_t^{(k)}$, then to obtain combination of k vector predicted values $\hat{Z}_t$ can be done by summation of product $\hat{Z}_t^{(i)}$ with its weight. Summation of product $\hat{Z}_t^{(i)}$ with each weight can be expressed as:

$$\hat{Z}_t = \sum_{i=1}^{k} w_i \hat{Z}_t^{(i)} \quad (11)$$

By averaging formula (10) can be written as:

$$\hat{Z}_t = \frac{1}{k} \sum_{i=1}^{k} \hat{Z}_t^{(i)} \quad (12)$$

Stacking is a general methods of using the combination of in order too achieve a greater predictive accuracy [21]. The general formula of stacking can be written as:

$$\hat{Z}_t = \sum_{i=1}^{k} w_i \hat{Z}_t^{(i)} \quad (13)$$

In order to obtain the coefficient/weight w_i of each output of the membership ensemble by minimizing:

$$G = \left[\hat{Z}_t - \sum_{i=1}^{k} w_i \hat{Z}_t^{(i)}\right]^2, w_i > 0 \quad (14)$$

In this research, the weight w_i of vector predicted values $\hat{Z}_t^{(1)}, \hat{Z}_t^{(2)}, \dots, \hat{Z}_t^{(k)}$ was proposed by variance-covariance approach with Lagrange multiplier (LM) optimization. The LM optimization method of variance-covariance approach can be determined by minimizing the Lagrange function:

$$L = \mathbf{w}^T \mathbf{\Sigma} \mathbf{w} + \lambda(1 - \mathbf{w}^T \mathbf{1}_N) \quad (15)$$

where, L is Lagrange function, λ = Lagrange multiplier factor, and $\sum_{i=1}^{k} w_i = 1$.

For the case of ensemble method with efficient variance, the weighting of $\hat{Z}_t^{(i)} \sim Norm_N(0, \mathbf{\Sigma})$ is

$$\mathbf{w} = \frac{\mathbf{\Sigma}^{-1}\mathbf{1}_N}{\mathbf{1}_N{}^T \mathbf{\Sigma}^{-1}\mathbf{1}_N} \quad (16)$$

where $\mathbf{\Sigma}^{-1}$ is the inverse of variance-covariance matrix.

3. RESULTS AND DISCUSSION

3.1. Analysis of Garlic price Data Using ARIMA

The data used for ARIMA modeling is the garlic price data in Semarang from January 2019 to August 2019, amounting to 155 observations (www.hargajateng.org). The plot of garlic price data is presented in Figure 2. In Figure 2 shows that the data are not stationary because the data visually fluctuations are not constant. The data are then performed unit root testing using the Augmented Dickey-Fuller (ADF) testing procedure to test stationarity. ADF test results concluded that data are not stationary.

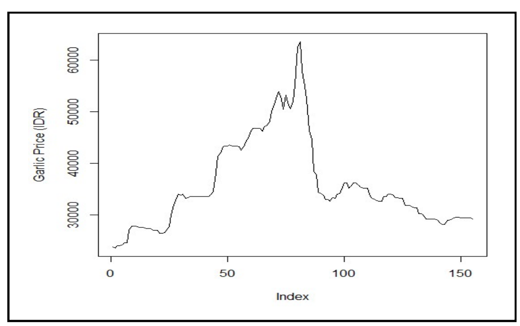

Figure 3. Time Series Plot for Garlic Prices Data of Semarang

The determination of the order in ARIMA seen based on the plot of the Partial Autocorrelation Function (PACF) and Auto Correlation Function (ACF) is shown in Figure 4.

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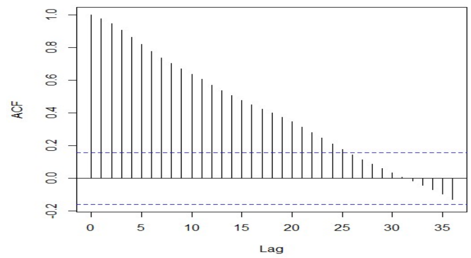
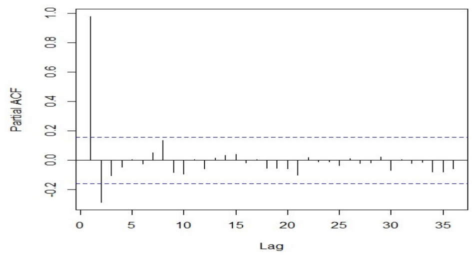


(a)



(b)

Figure 4. (a) Plot of ACF Garlic Price Data (b) Plot of PACF Garlic Price Data

The plot of ACF shows that visually the data are not stationary, the plot of PACF the cut-off after lag-1 (Figure 4). By first level differencing, stationary assumption of data is satisfied. There are several identified ARIMA models based on the plots of ACF and PACF. Table 1 shows a summary of the identified ARIMA models.

Table 1. Significance Test of Parameters and Diagnostics Check of Identified ARIMA Models

Identified Model	Parameter Significance	Independence Assumption	Normality Assumption	Homoscedasticity Assumption
ARIMA(1,0,0)	√	√	×	×
ARIMA([2],0,0)	√	√	×	×
ARIMA([3],0,,0)	√	√	×	×
ARIMA([1,3],0,0)	√	√	×	×
ARIMA(1,0,1)	√	√	×	×

Based on the constructed models (see table 1), there is no model that fulfill normality and homoscedasticity assumptions. Furthermore identified ARIMA models should be tested to prove the homoscedasticity assumption. The results of testing show that all models have ARCH/GARCH effect. The significance test of parameters and diagnostics check for each model is shown in Table 2.

Table 2. Significance Test of Parameters and Verification of ARIMA-GARCH Models

Identified Model	Significance of Parameter	Independence Assumption	Normality Assumption	Homoscedasticity Assumption
ARIMA(1,0,0)-ARCH(1)	√	√	×	√
ARIMA([2],0,0)-GARCH(1,1)	√	√	×	√
ARIMA([3],0,0)-ARCH(1)	√	√	×	√
ARIMA(1,0,1)-ARCH(1)	√	√	×	√

The RMSE and MAPE values of the four ARIMA models are presented in Table 3.

Table 3. The RMSE and MAPE values for the identified ARIMA models

Model	RMSE	MAPE (%)
ARIMA (1,0,0)-ARCH(1)	1390	1.80
ARIMA ([2],0,0)-GARCH(1,1)	2631	3.22
ARIMA([3],0,0)-ARCH(1)	3264	4.89
ARIMA (1,0,1)-ARCH(1)	1314	1.89

By considering MAPE, RMSE values and also parsimonious principles, model ARIMA(1,0,0)-ARCH(1) is selected as the optimal model (see Table 3). The ARIMA(1,0,0)-ARCH(1) was expressed as follow:

$$Z_t = 24287 + 0.994Z_{t-1} + a_t \quad (17)$$

where $a_t \sim N(0, \sigma_t^2)$ and $\sigma_t^2 = 24287 + 1.904a_{t-1}^2$. By using model (17), the predicted values of garlic price data are presented as Figure 5.

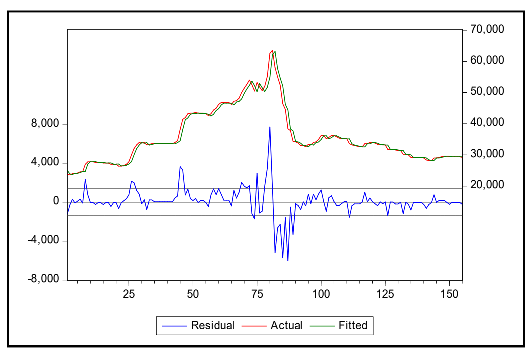


Figure 5. Time Series Plot and Prediction for Garlic Prices Data in Semarang Using ARIMA(1,0,0)-ARCH(1)

3.2. Analysis of Garlic Price Data Using ANFIS

Based on partial autocorrelation function (PACF) plot, the input ANFIS is difficult to select because the data are non-stationary (Figure 3). In this study, input variables in ANFIS will be selected by using LM test. Firstly, variables lag-1, lag-2, lag-3 with 2 clusters (membership functions) and its combination are selected as inputs. The results of input selection are shown in Table 4.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table 4. Result of LM test for input selection

Input	R_Z^2	R_e^2	LM	p-value
Z_{t-1}	0.972	-	-	-
Z_{t-2}	0.929	-	-	-
Z_{t-3}	0.880	-	-	-
Z_{t-1}, Z_{t-2}	0.978	0.230	35.690	0.0
Z_{t-1}, Z_{t-3}	0.979	0.231	35.765	0.0

Based on Table 4, variables lag-1 and lag-3 with 2 membership functions (MFs) are considered as inputs ANFIS. The optimal input will be evaluated for determining the optimal number of membership functions by using LM test. The result of membership functions selection was shown on Table 5.

Table 5. Result of LM test for membership functions selection

Input	MFs	R_e^2	LM	p-value
$Z_{t-1,}Z_{t-3}$	3	0.009	1.364	0.094

According to the results on Table 5 variable input lag-1with 3 membership functions can not be selected as input of ANFIS because p-value of result test is greater than level of significant 0.05. So the variables lag-1 and lag-3 with 2 clusters were selected as optimal inputs of ANFIS. If given two inputs Z_{t-1}, Z_{t-3} with 2 number of clusters, and one output Z_t by assuming first order Sugeno, the rules of fuzzy system can be expressed as follows:

Rule-1: If Z_{t-1} *is* A_{11} and Z_{t-3} *is* A_{13}

then $Z_t^{(1)} = \theta_{11}Z_{t-1} + \theta_{13}Z_{t-3} + \theta_{10}$,

Rule-2: If Z_{t-1} *is* A_{21} *and* Z_{t-3} *is* A_{23}

then $Z_t^{(2)} = \theta_{21}Z_{t-1} + \theta_{22}Z_{t-3} + \theta_{20}$.

The result of optimal model is as follow.

$$Z_t = 1.236\overline{w}_{1,t}Z_{t-1} - 0.289\overline{w}_{1,t}Z_{t-3} + 1682\overline{w}_{1,t} + 1.145\overline{w}_{2,t}Z_{t-1} - 0.319\overline{w}_{2,t}Z_{t-3} + 8516\overline{w}_{2,t} \quad (18)$$

where

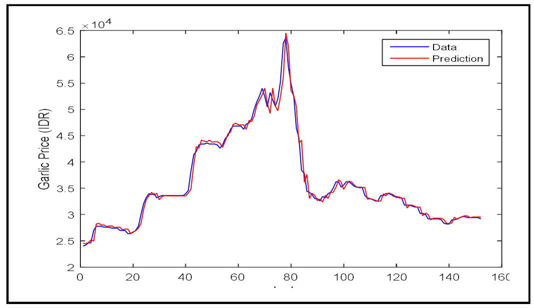
$$\overline{w}_{1,t} = \frac{w_{1,t}}{w_{1,t}+w_{2,t}},$$

$$\overline{w}_{2,t} = \frac{w_{2,t}}{w_{1,t}+w_{2,t}},$$

$$w_{1,t} = exp\left[-\frac{1}{2}\left(\frac{Z_{t-1}-31369}{10331}\right)^2 - \frac{1}{2}\left(\frac{Z_{t-3}-31321}{10956}\right)^2\right],$$

$$w_{2,t} = exp\left[-\frac{1}{2}\left(\frac{Z_{t-1}-48436}{7707}\right)^2 - \frac{1}{2}\left(\frac{Z_{t-3}-48261}{7858}\right)^2\right].$$

The MAPE and RMSE values of forecasting for data using Eq.18 are 1.69% and 1222 respectively. The predicted value of garlic price data based on model



(18) can be seen as Figure 6.

Figure 6. Time Series Plot and Prediction for Garlic Prices Data in Semarang Using ANFIS with 2 input and 2 MFs

3.3. Analysis of Garlic Price Data Using Ensemble ARIMA and ANFIS

Based on the analysis using ARIMA in the previous section, ARIMA(1,0,0)-ARCH(1) was selected as optimal model. While the ANFIS model that involve 2 input (lag-1 and lag-3) with 2 clusters is selected as the best model. In this section, the two optimal models will be combined to get the new predicted values. The combination of predicted values will be done using ensemble method by averaging and also by determining the weight of the predicted values. From the two models can be determined forecast values from each period of each model. The next step is to combine forecasting values obtained from the ARIMA and ANFIS through the averaging method, which is to average the forecast results for each period. Mathematically the ARIMA and ANFIS model with a combination of averaging is formulated:

$$\hat{Z}_t = \frac{1}{2}\sum_{i=1}^{2} \hat{Z}_t^{(i)}$$

where $\hat{Z}_t^{(1)}$is the forecast value of ARIMA(1,0,0)-ARCH(1) and $\hat{Z}_t^{(2)}$is the forecast value of ANFIS (with inputs lag-1, lag-2 and 2 MFs).

The second ensemble method is determined by giving the weight of ARIMA and ANFIS models. Determining the weight of each model is performed using Lagrange Multiplier (LM) optimization. The general formula of combination is as follow:

$$\hat{Z}_t = \sum_{i=1}^{2} w_i \hat{Z}_t^{(i)}$$

where w_i: weight of vector predicted values $\hat{Z}_t^{(i)}$ should be positive number and satisfy $\sum_{i=1}^{2} w_i = 1$, and $\hat{Z}_t^{(1)}$is the forecast values of ARIMA(1,0,0)-ARCH(1) and $\hat{Z}_t^{(2)}$ is the forecast values of ANFIS (with inputs lag-1, lag-2 and 2 MFs).

Matrix variance-covariance of $\hat{Z}_t^{(1)}$ and $\hat{Z}_t^{(2)}$ is:

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

$$\mathbf{\Sigma} = \begin{pmatrix} 71833415.5 & 711123022.4 \\ 71123022.4 & 71475101.1 \end{pmatrix}$$

So inverse of matrix variance-covariance $\mathbf{\Sigma}$ is:

$$\mathbf{\Sigma}^{-1} = \begin{pmatrix} 9.4274E-07 & -9.381E-07 \\ -9.38096E-07 & 9.47466E-07 \end{pmatrix}$$

By applying formula (16) we get the weight of $\hat{Z}_t^{(1)}$ and $\hat{Z}_t^{(2)}$ $are\ as\ follows$:

$$\begin{pmatrix} w_1 \\ w_2 \end{pmatrix} = \begin{pmatrix} 0.33 \\ 0.67 \end{pmatrix}$$

Based on LM optimization, the ARIMA weight of 33% and ANFIS weight of 67%. The predicted values by ensemble (ARIMA-ANFIS) give MAPE value as presented in Table 6.

Table 6. The Value of MAPE for ARIMA, ANFIS and Ensemble Method

Model	MAPE
Single ARIMA (1,0,0)-ARCH(1)	1.80 %
Single ANFIS (Z_{t-1}, Z_{t-3} with 2 MFs)	1.69 %
ARIMA-ANFIS *by Averaging*	1.64 %
ARIMA-ANFIS *by var-covar approach*	1.65 %

Table 6 shows that the combination of AR(1)-ARCH(1) and ANFIS (Z_{t-1}, Z_{t-3} with 2 MFs) is better than the others based on MAPE values, but generally the all models resulted high accuracy for forecasting.

4. CONCLUSION

Based on results and discussion on previous section, the ARIMA individual, ANFIS individual, ensemble model by averaging and ensemble model by using variance-covariance approach resulted high accuracy for predicting data. The combination of ARIMA(1,0,0)-ARCH(1) and ANFIS (with Z_{t-1}, Z_{t-3} as inputs and 2 MFs) is the best model for forecasting garlic price data in Semarang. The MAPE value of individual model or ensemble model were less than 5% which had already shown a good performance for forecasting.

ACKNOWLEDGMENTS

We would like to thank to Rector of Universitas Diponegoro, Directorate Research and Public Services Ministry of Research, Technology and Higher Education Republics of Indonesia for their supports to this research.

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