Forecasting Inflation in Indonesia Using Hybrid ARIMA and Artificial Neural Networks Ensemble

by

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ABSTRACT

Hybrid autoregressive integrated moving average (ARIMA) and artificial neural networks (ANNs) ensemble is methodology which generating multi-model of hybrid ARIMA and ANNs then combining the output of each hybrid into single output. Meanwhile hybrid ARIMA and ANNs model is combination of ARIMA and ANNs which residual of ARIMA is used to input of ANNs. Hybrid ARIMA and ANNs ensemble are constructed to improve the performance of ARIMA for forecasting inflation in Indonesia. The architechture of ANNs in this research are feedforward neural network (FFNNs), recurrent neural network (RNNs), radial basis function neural network (RBFNNs) and generalized regression neural network (GRNNs) This research evaluates performance of hybrid ARIMA and ANNs ensemble based on root mean square error (RMSE), relative root mean square error (RelRMSE) and log mean square error ratio (LMR). This reserach use national inflation and seven cities in East Java as case study. The result show that, in the context of forecasting inflation, hybrid ARIMA and ANNs ensemble is better than ARIMA, particularly when the stacking hybrid ARIMA and GRNNs is used. Overall, stacking technique is better than averaging to combine ensemble member of hybrid ARIMA and ANNs.

Keyword : **ANNs, ARIMA, FFNNs, GRNNs, Hybrid, Inflation, LMR, RBFNNs, RelRMSE, RMSE, RNNs**

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CHAPTER 1
INTRODUCTION

1.1 Background

Inflation is an important element for the economy of country because inflation is a reflection of stability of the currency for goods and services. The importance of controlling inflation is based on the consideration that high and unstable inflation has negative impacts on socio-economic conditions such as high inflation will decrease purchasing power of people. Unstable inflation creates uncertainty for economist to make decisions. Communities will be inconvenient for consumption, investment, and production, so that will reduce economic growth, and when domestic inflation rate is higher than the rate of inflation in other countries, it can put pressure on its currency.

Bank Indonesia as a central bank in Indonesia has a single purpose to keep the stability of the rupiah which is reflected in inflation. Therefore, since 2005 Bank Indonesia applied the monetary policy as the main target by using Inflation Targeting Framework (ITF) (Bank Indonesia, 2013). ITF is adopted by Bank Indonesia to announce inflation target at a certain period. Bank Indonesia evaluates the estimation of future inflation is still in appropriate with the target set every period. This estimation is applied with several models and information which can reflect the conditions ahead.

Estimation of future inflation can use time series forecasting model, because time series forecasting is a method to forecast in which historical observations of the same variable are gathered and analyzed to construct model that seizes the underlying data generating process. Then the model is applied to estimate the future value (Khasei et al., 2009). ARIMA is the most widely used method for time series forecasting, especially since Box and Jenkins (1970) proposed a methodology for ARIMA modeling through three stages: identification, estimation and verification. ARIMA model is applied in various areas such as hydrodology, energy, economics, industrial and manufacturing (Vanipour et al. ,2013; Lee and Ko, 2011; Wijaya and Napitupulu, 2010; Chen, 2011; Liu et al., 2008). However, it has some limitations such as to construct the ARIMA model required a large number of past observations to generate forecasts with good accuracy and ARIMA is assumed as a linear function of several past observations with random errors (Khasei et al., 2009). Therefore, ARIMA can not seize nonlinear pattern in the real world problems (Zhang, 2003).

Several nonlinear models have been proposed to overcome the limitations of linear modeling in time series such as threshold autoregressive (TAR) (Tong and Lim, 1980; Davis et al., 2000), autoregressive conditional heteroscedastic (ARCH) (Engle, 1982; Gao et al., 2009), general autoregressive conditional heteroscedastic (GARCH) (Bollerslev, 1986; Kontonikas, 2004; Broto, 2011). However, these models only good in particular circumstances because they are constructed for a specific nonlinear model so that they are not able to model other types of nonlinear time series.One of the nonlinear model which is flexible and does not require certain information to construct the model is artificial neural networks (ANNs) (Donate et al., 2013). ANNs are often referred to as black box models which can seize the primary relationship between inputs and outputs (Zaier et al., 2010).

Recently, several studies about improvement forecasting performance has been developed. One of them is hybrid approach using ARIMA and ANN models. Hybrid ARIMA-ANN is obtained by modeling linear component using ARIMA, then modeling residuals from ARIMA using ANN.The main ideas by using hybrid approach are difficulty of determining the time series derived from the linear or nonlinear process, real world problems are seldom perfect linear or nonlinear and there is no single best method in every situation (Zhang, 2003). Combining several models which is often referred to ensemble approachis also quite popular for the past three decades (Gooijer and Hyndman, 2006). It became popular because ensemble approaches show great improvement to generalization prediction(Bates and Granger, 1969; Shu and Burn, 2004; Zaier et al. , 2010; Zheng and Zhong, 2011).

Therefore this study proposes a hybrid ARIMA-ANN ensemble to forecast future inflation in Indonesia. There are two steps to construct hybrid ARIMA-ANN ensemble. First, constructing several ensemble members by altering input and training algorithm in hybrid ARIMA-ANN while preserve the training data unchanged. Second, combining ensemble members by stacking and averaging to produce unique ensemble solution.

1.2 Statement of The Problems

The research questions in this research are

- How to construct model for forecasting inflation in Indonesia?
- How to construct a hybrid ARIMA-ANN model for forecasting inflation in Indonesia?
- What are the techniques used to create ensemble member from hybrid ARIMA-ANN model for forecasting inflation in Indonesia?
- How to create ensemble members from a hybrid ARIMA-ANN ensemble for forecasting inflation in Indonesia?
- What are the techniques used to combine ensemble members from a hybrid ARIMA-ANN model for forecasting inflation in Indonesia?
- How to combine ensemble members from a hybrid ARIMA-ANN for forecasting inflation in Indonesia?
- What are model selection criteria to determine the best model for forecasting inflation in Indonesia?
- How to calculate the model selection criteria for each method?
- How to calculate prediction of future inflation in Indonesia using a hybrid ARIMA-ANN ensemble?

1.3 Objectives

1.3.1 Overall Objective

- To obtain the best model, i.e.,a hybrid ARIMA-ANN ensemble,for forecasting inflation in Indonesia based on model selection criteria

1.3.2 Specific Objectives

- Presents methodology to construct a hybrid ARIMA-ANN
- Knowing the techniques to create ensemble member in hybrid ARIMA-ANN ensemble
- Knowing the techniques to combine ensemble member in hybrid ARIMA-ANN ensemble
- Presents methodology to construct hybrid ARIMA-ANN ensemble
- Presents model selection criteria to determine the best model for forecasting inflation in Indonesia

1.4 Scope

- ANN architecture will use FFNN, RBFNN, RNN and GRNN
- Applying monthly national inflation and seven cities in East Java in Indonesia from 1980 until 2013

CHAPTER 2
LITERATURE REVIEW

2.1 Inflation

Inflation is the increasing of price of goods and services in general where goods and services are basic needs of society or the declining purchasing power of currency of the country (BPS, 2013). Consumer Price Index (CPI) is an indicatoris often used to measure the rate of inflation. CPI changes from time to time shows the price movement of a package of goods and services consumed by the public (Bank Indonesia, 2013b).

Research about inflation particularly forecasting inflation has been studied for decades. A list of example of forecasting inflation is shown in Table 2.1

Table 2.1 A List of Example Forecasting Inflation

Case of Study	Benchmark	Reference
Quarterly consumer price index in United Kingdom	ARCH	Engle (1982)
Monthly inflation in US	Phillip-curve Model	Stock and Watson (1999)
Monthly inflation in US	Long memory regression (ARFIMAX)	Bos, Frances, and Ooms (2002)
Quarterly ECB case study	Fuzzy Approach	Kooths, Mitze, Ringhut (2003)
Monthly and quarterly inflation in United Kingdom	GARCH	Kartonikas (2004)
Monthly inflation in US, Europe area and Japan	ANN	McAdam and McNelis (2005)
Quarter GDP deflator in US	ANN	Nakamura (2005)
Monthly inflation in Brazil	Wavelet Approach	Tabak and Feitosa (2009)
Monthly inflation in Eight Latin American countries	GARCH	Broto (2011)
Monthly consumer price index in China	VAR	Ni (2011)
Monthly Inflation in Indonesia	Univariate ARIMA	Tarno, Suhartono, Subanar, Rosadi (2012)
Annual Inflation in Mexico	ANN	Hurtado, Luis, Fregoso, and Hector (2013)

Several research about comparison two or more methods for forecasting inflation also has been studied about such as comparison of principal component regression and principal covariate regression (Heij et al., 2007), comparison of time series modeling, Phillip-curve, linier regression and nonlinier regime switching regression (Ang et al. , 2007) and comparison of aggregate supply-demand supply and ANN (Wang and Wu, 2010). In addition, combination method for forecasting inflation also has been arisen such as combination random walk, SARIMA, VAR, m-VAR, BVAR by simple average, median, trimmed average, RMSE weight (Öğünç et al., 2013)

In Indonesia, research about forecasting inflation also has developed such as transfer function (Septiorini, 2009), ARIMAX and GARCH model (Rukini and Suhartono, 2013), and BPNN (Muqtasidah, 2009; Purnama, 2010), ensemble method by using ARIMA and ANN (Silfiani and Suhartono, 2012).

2.2 Summary of Methods

2.2.1 Autoregressive Integrated Moving Average

Autoregressive integrated moving average (ARIMA) is the most widely used method in time series forecasting for several decades. In ARIMA, future prediction is assumed to be linier function of several past observations. Formulation for general ARIMA (p,d,q) model as follows (Wei, 2006):

$$\phi_p(B)(1-B)^d Z_t = \theta_0 + \theta_q(B)a_t \qquad \text{(equation 2.1)}$$

where $\phi_p(B) = (1-\phi_1 B - \cdots - \phi_p B^p)$ and $\theta_q(B) = (1-\theta_1 B - \cdots - \theta_q B^q)$.

Box and Jenkins (1970) proposed methodology to create ARIMA (p,d,q) model. There are three phases i.e. identification model, parameter estimation and diagnostic checking. Identification model is a phase to identify the necessary of transformation such as transformation for stationary variance and transformation for stationary means(Wei, 2006). In addition, this phase is also used to determine ARIMA order based on pattern in autocorrelation function and partial autocorrelation. The next phase is parameter estimation. Parameter estimation is procedure to evaluate an appropriate parameter of model. There are several methods to estimate parameter of ARIMA such as moment, conditional least square, unconditional least square and full maximum likelihood (Cryer and Chan, 2008). The final phase is diagnostic checking. Diagnostic checking is a procedure to evaluate the fitted model by using residual analysis which includes two assumptions i.e. independent and normal distribution (Cryer and Chan, 2008).

2.2.2 Artificial Neural Networks

Artificial neural networks are a flexible nonlinier data-driven, self adaptive method and they do not the use of a priori knowledge (Khasei et al., 2009; Donate et al., 2013). ANNs are also part of machines learning algorithm. The fundamental in ANNs is that input or independent variables filtered through one or more hidden layers, which compose of node, before they reach the target or dependent variable (Gooijer and Hyndman, 2006). ANNs have been successfully applied to various area such as economics (McAdam and McNelis, 2005; Nakamura, 2005; Hurtado et al., 2013), hydrology (Shu and Burn, 2004; Zaier et al., 2010), short load forecasting demand (Sharaf et al., 1993; Methaprayoon et al., 2003). ANNs have several architectures such as feed forward neural networks, radial basis function neural networks, generalized regression neural networks and recurrent neural networks. Brief summary about each architecture as the following:

2.2.2.1 Feedforward Neural Networks

The most widely used ANN architecture in the field of time series forecasting is feedfordward neural networks (FFNN)as well as known multilayer perceptrons (MLPs). FFNN architecture is shown in Figure 2.1.In feedforward neural networks, the relationship between output Z_t and input $X_i (i = 1, 2, \ldots, p)$ where $X_i = Z_{t-i}$ has the following mathematical representation

$$\hat{Z}_t = w_0 + \sum_{j=1}^{q} w_j h_j \text{ and } h_j = \frac{1}{1+\exp\left(-\left(w_{0j} + \sum_{i=1}^{p} w_{ij} X_i\right)\right)} \qquad \text{(equation 2.2)}$$

where $w_{ij}\ (i=1, 2,\dots, p; j=1, 2,\dots, q)$ and $w_j\ (j=1, 2,\dots, q)$ areparameters model as referred to as weight, p is number of input neuron and q is number of hidden neuron. This study uses FFNN with one hidden layer, sigmoid logistic transfer function neuron in hidden layer and linier neuron in output layer. In addition, backpropagation algorithm is used to estimate weight and bias.

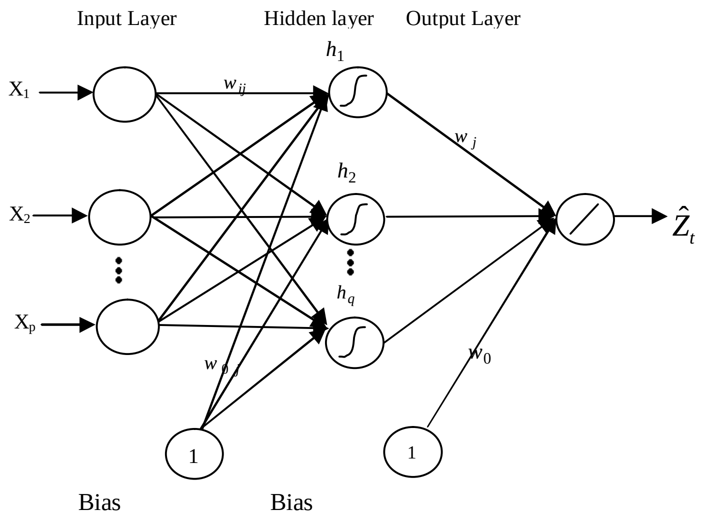


Figure 2.1 Feedforward Neural Networks Architecture

2.2.2.2Recurrent Neural Networks (RNN)

Recurrent neural networks are neural networks that have feedback. They have benefit over feedforward neural networks like that autoregressive moving average model has benefit over autoregressive model for certain types of time series because (Connor et al., 1994). The architecture of recurrent neural networks is similar feedforward neural networks because it has input layer, hidden layer and output layer however they have different input i.e. the error of the model.

Suppose ARMA(2,1) is represented in RNN with three unit neurons in hidden layer is shown in Figure 2.2 and the formulation of recurrent neural networks as follows

$$\hat{Z}_t = w_0 + \sum_{j=1}^{3} w_j h_j \text{ and } h_j = \frac{1}{1+\exp\left(-\left(w_{0j} + \sum_{i=1}^{3} w_{ij} X_i\right)\right)} \qquad \text{(equation 2.3)}$$

where $X_3=e_{t-1}$

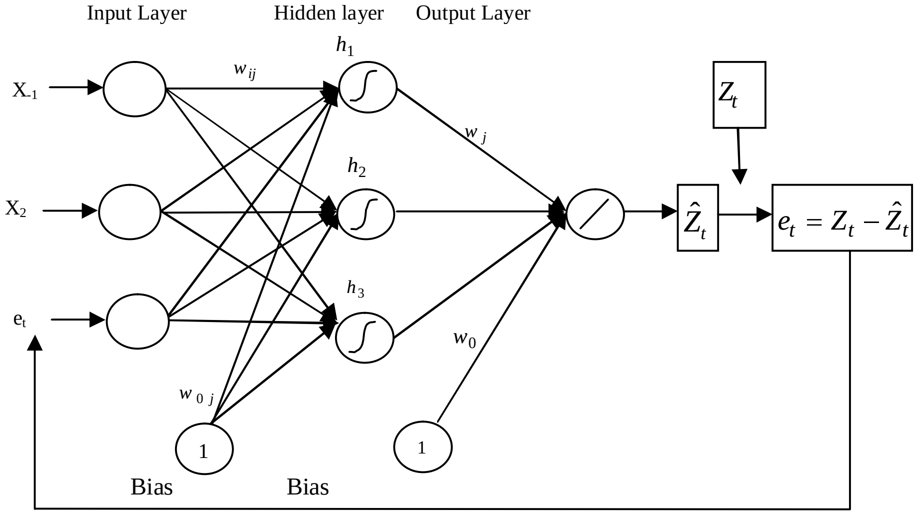


Figure 2.2 Recurrent Neural Networks Architecture

2.2.2.3 Radial Basis Function Neural Networks

Radial basis function neural networks (RBFNN) is neural networks which has similar architecture as feedforward neural networks consist of three layers i.e. input layer, hidden layer and output layer. The architecture of RBFNN is shown in Figure 2.3.

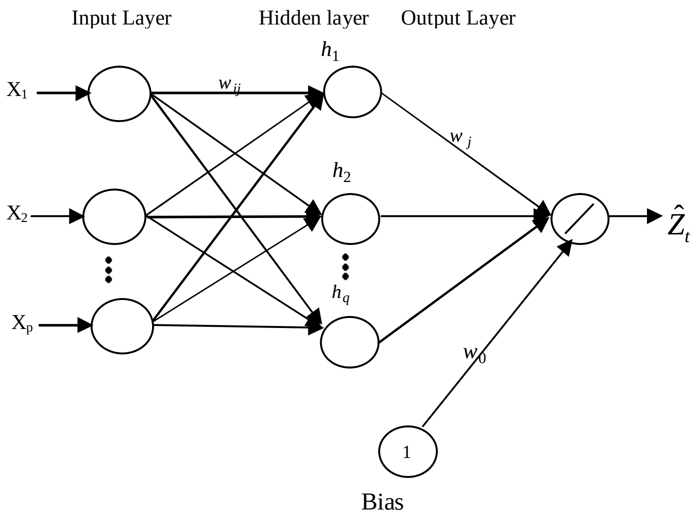


Figure 2.3 Radial Basis Function Neural Networks Architecture

RBFNN has more advantages than FFNN i.e. RBFNN is a forward networks model with good performance, global approximation, and is free from the local minima problems (Zheng and Zhong, 2011). RBFNN has the following mathematical representation

$$\hat{Z}_t = w_0 + \sum_{j=1}^{q} w_j h_j \text{ and } h_j = \exp\left(- \sum_{i=1}^{p} \left(X_i - c_{ij} \right) \Big/ \delta_j^2 \right) \quad \text{(equation 2.4)}$$

where $X_i(X_i = Z_{t-i}; i = 1, 2, \ldots, p)$ is the *i*th variable of input pattern, $c_{ij}(i = 1, 2, \ldots, p; j = 1, 2, \ldots, q)$ is the centre of *j*th RBF unit for variable *i*, δ_j is the width of *j*th RBF unit, w_j is the weight between *j*th RBF unit and output, w_0 is the biasing term at output node, *p* is the number of input nodes and *q* is the number of hidden layer nodes.

2.2.2.4 Generalized Regression Neural Networks

Generalized regression neural networks (GRNN) is used for estimation of continuous variables, as the standard regression techniques. It related to the RBFNN and based on standard statistical technique called kernel regression (Celikoglu, 2006). Its advantages are fast learning, consistency and optimal regression with large number of samples (Ren et al., 2010). GRNN has four layers i.e input layer, pattern layer, summation layer and output layer. The architecture of GRNN is as follows

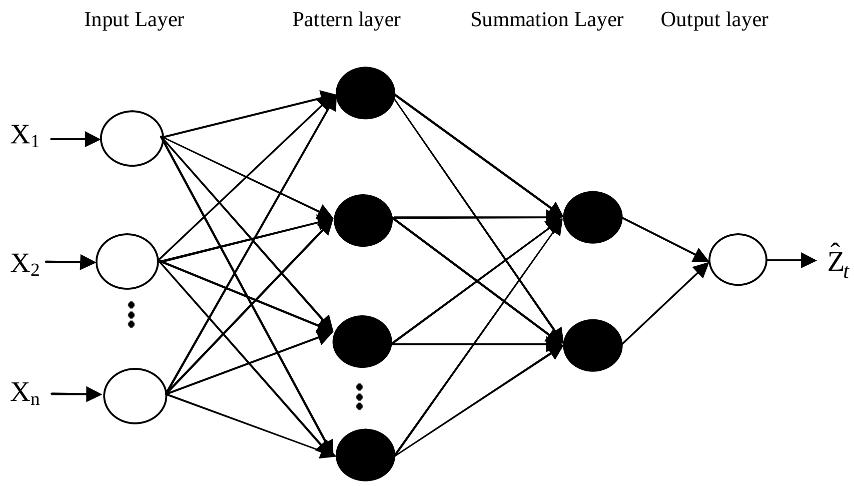


Figure 2.4 Generalized Regression Neural Networks Architecture

The following mathematical representation of GRNN is

$$\hat{Z}_i(x) = \frac{\sum_{i=1}^{n} Z_t \exp\left(-\frac{D_i}{2\sigma^2}\right)}{\sum_{i=1}^{n} \exp\left(-\frac{D_i}{2\sigma^2}\right)} \text{ and } D_i = \sum_{j=1}^{p}\left(X_j - X_{ij}\right)^2 \quad \text{(equation 2.5)}$$

where n indicates the number of training pattern, p indicates the number of elements of an input vector. The X_j and X_{ij} represent the *j*th element of X and X_i, respectively.

2.2.3 Hybrid Methodology

The fundamentals creating hybrid method are difficulty of determining the time series derived from the linear or nonlinear process, real world problems are seldom perfect linier or nonlinier and there is no single method is best in every situation (Zhang, 2003). Since it is difficult to completely know the characteristics of the data hybrid method that has both linier and nonlinier modeling has good performance for forecasting. When time series data considered have both linier and nonlinier, it can represent as

$$\hat{Z}_t = L_t + N_t \quad \text{(equation 2.6)}$$

where L_t indicates linier component and N_t indicates nonlinier component. These two components have to be predicted from the data. In this research, ARIMA is used to predict linier component and ANN is used to predict nonlinier component from residual of ARIMA.

2.2.4 Ensemble Approach

Combining several models is well-known as ensemble approach. There are two steps to create ensemble. First, creating several ensemble members by varying number of input and architecture of ANN while keeping the data training unchanged (Sharkey, 1999). Second,combining several predictions of ensemble members. Averaging and stacking are the most popular techniques to combine. Mathematical representation of averaging and stacking are as follow:
If k is number of ensemble members, then the solution of ensemble from averaging has the following mathematical representation:

$$\hat{Z}_t = \frac{1}{k}\sum_{i=1}^{k}\hat{Z}_t^{(i)}, i = 1, \ldots, k \qquad \text{(equation 2.7)}$$

where $\hat{Z}_t^{(i)}$ is prediction value in tth period and kth ensemble member.

Stacking is an approach to make linier combination of predictor to improve prediction accuracy. Stacking is produced by minimizing the least square from G function and it has constraint non-negative coefficient. Stacking has the following mathematical representation (Breimen, 1996)

$$G = \sum_{t=1}^{n}\left[Z_t - \sum_{i=1}^{k} c_i \hat{Z}_t^i\right], c_i > 0, \sum_{i=1}^{n} c_i = 1 \qquad \text{(equation 2.8)}$$

Coefficient $\hat{c}_1, \hat{c}_2, \cdots, \hat{c}_k$ is estimated to obtain the final output from ensemble

$$\hat{Z}_t = \sum_{i=1}^{k}\hat{c}_i \hat{Z}_t^{(i)} \qquad \text{(equation 2.9)}$$

CHAPTER 3
METHODOLOGY

3.1 Dataset

Dataset in this study use monthly inflation data since January 1980 until December 2013 periods. Dataset is available on Indonesia Central Bureau of Statistics (see www.bps.go.id) There are eight variables that represent about inflation in Indonesia, i.e., national inflation ($Z_{1,t}$), and seven cities in East Java : Surabaya inflation ($Z_{2,t}$), Malang inflation ($Z_{3,t}$), Jember inflation ($Z_{4,t}$), Kediriinflation ($Z_{5,t}$), Probolinggo inflation ($Z_{6,t}$), Madiun inflation ($Z_{7,t}$) and Sumenep inflation ($Z_{8,t}$). Before fitting the model, data are divided into two parts, i.e., in-sample and out-of-sample data. In-sample data is used to create the model and out-of-sample data is used to evaluate performance of model. Dataset for in-sample is January 1980 until December 2012 and the rest is for out-sample.

3.2 Hybrid ARIMA and ANN Ensemble Methodology

There are three steps to create hybrid ARIMA-ANN ensemble. First step is creating several ensemble members, second step is combining ensemble members and last step is selecting the best model. Further explanations about creating and combining ensemble member in hybrid ARIMA-ANN ensemble methodology are as follows:

3.2.1 Creating Ensemble Member

This study uses varying input to create several ensemble members. Ensemble members in this study are several hybrid ARIMA-ANNs. Generally, there are three steps to create hybrid ARIMA-ANN ensemble. First, modeling series data to ARIMA to obtain linear component. Second, estimating the residuals from series data and prediction value of ARIMA.Third, modeling the residuals to ANN to obtain nonlinear component. The detailed explanations of creating ensemble member are presented as follows

1. Constructing ARIMA based on Box and Jenkins (1970) methodology. SAS and Minitab software packages are applied to construct ARIMA Model.Three steps of Box and Jenkins (1970) methodology are as follows:
   a. Identification which is a phase to identify the necessary of transformation such as transformation for mean stationary and variance stationary (Wei, 2006). Non stationary process can be transformed to stationary process by using appropriate differencing. In other words, the series Z_t is not stationary but the dth differencing of series Z_t $\left\{(1-B)^d Z_t\right\}$ will be a stationary process. Differencing can only be used in homogenous time series. In the real world problems, many series are not homogenous. It is caused by time dependence in variance and autocovariance. This problem can be solved by Box-Cox transformation (Wei, 2006). Mathematical representation of Box-Cox transformation is as follows

   $$T(Z_t) = \frac{Z_t^{\lambda} - 1}{\lambda} \qquad \text{(equation 3.1)}$$

   where λ indicates transformation parameter.
   When a series has followed stationary process, the next step is determining the orders p and q in ARIMA (p,d,q) based on autocorrelation (ACF) and partial

autocorrelation (PACF). Bowerman et al. (2005) presented guidline to determine ARIMA order based on ACF and PACF pattern as follows

Table 3.1 Guideline to Determine Nonseasonal ARIMA Model

Sample ACF and Sample PACF Pattern	Nonseasonal Operator
Sample ACF has in lag 1, 2,…q and cut off after lag q and sample PACF has dies down pattern	Nonseasonal operator for model is *moving average*with q order $\theta_q(B)=(1-\theta_1 B-\theta_2 B^2-\cdots-\theta_q B^q)$
Sample ACF has dies down pattern and sample PACF has spikes in lag 1, 2,…p and cut off after lag p	Nonseasonal operator for model is *autoregressive*with p order $\phi_p(B)=(1-\phi_1 B-\phi_2 B^2-\cdots-\phi_p B^p)$
Sample ACF has spikes in lag 1, 2,…q and cut off after lag q, sample PACF has spikes in lag 1, 2,…p and cut off after lag p	$\theta_q(B)$ or $\phi_p(B)$
Sample ACF dan sample PACF do not have lag spikes	Model does not have nonseasonal operator
Sample ACF and PACF are dies down	Nonseasonal model $\theta_q(B)$ and $\phi_p(B)$

b. The next phase is parameter estimation. There are several methods to estimate parameter of ARIMA such as moment, conditional least square, unconditional least square and full maximum likelihood (Cryer and Chan, 2008). This study uses maximum likelihood to estimate parameter of ARIMA. The procedure to estimate parameter of ARIMA by using maximum likelihood is as follow:
Suppose the general ARMA(p,q) model has the following mathematical representation

$$\dot{Z}_t=\phi_1\dot{Z}_{t-1}+\cdots+\phi_p\dot{Z}_{t-p}+a_t-\theta_1 a_{t-1}-\cdots-\theta_q a_{t-q} \quad \text{(equation 3.2)}$$

where $\dot{Z}_t=Z_t-\mu$, a_t is i.i.d. $N\left(0,\sigma_{a_t}^2\right)$ and joint probability density function of $\mathbf{a}=\left(a_1,a_2,\ldots,a_n\right)'$ is as follows

$$P\left(\mathbf{a}\mid\boldsymbol{\varphi},\mu,\boldsymbol{\theta},\sigma_{a_t}^2\right)=\left(2\pi\sigma_{a_t}^2\right)^{-n/2}\exp\left[-\frac{1}{2\sigma_{a_t}^2}\sum_{t=1}^{n}a_t^2\right] \quad \text{(equation 3.3)}$$

Rewriting (equation 3.2)

$$a_t=\dot{Z}_t-\phi_1\dot{Z}_{t-1}-\cdots-\phi_p\dot{Z}_{t-p}+\theta_1 a_{t-1}+\cdots+\theta_q a_{t-q} \quad \text{(equation 3.4)}$$

Therefore

$$P\left(\mathbf{a}\mid\boldsymbol{\varphi},\mu,\boldsymbol{\theta},\sigma_{a_t}^2\right)=\left(2\pi\sigma_{a_t}^2\right)^{-n/2}\times$$
$$\exp\left[-\frac{1}{2\sigma_{a_t}^2}\sum_{t=1}^{n}\left(\dot{Z}_t-\phi_1\dot{Z}_{t-1}-\cdots-\phi_p\dot{Z}_{t-p}+\theta_1 a_{t-1}+\cdots+\theta_q a_{t-q}\right)^2\right] \quad \text{(equation 3.5)}$$

Let $\mathbf{Z}=\left(Z_1,Z_2,\ldots,Z_n\right)'$ and the log likelihood function

$$\ln L\left(\boldsymbol{\varphi},\mu,\boldsymbol{\theta},\sigma_{a_t}^2\mid\mathbf{Z}\right)=-\frac{n}{2}\ln\left(2\pi\sigma_{a_t}^2\right)-\frac{1}{2\sigma_{a_t}^2}S(\boldsymbol{\varphi},\mu,\boldsymbol{\theta},) \quad \text{(equation 3.6)}$$

where $S(\boldsymbol{\varphi}, \mu, \boldsymbol{\theta},) = \sum_{t=1}^{n} \left(\dot{Z}_t - \phi_1 \dot{Z}_{t-1} - \cdots - \phi_p \dot{Z}_{t-p} + \theta_1 a_{t-1} + \cdots + \theta_q a_{t-q}\right)^2$

To maximaze log likelihood function, taking the first derivatives of equation 3.6 over their parameters and then equating to zero.

$$\frac{\partial \ln L\left(\boldsymbol{\varphi}, \mu, \boldsymbol{\theta}, \sigma_{a_t}^2 \mid \mathbf{Z}\right)}{\partial \phi} = 0, \frac{\partial \ln L\left(\boldsymbol{\varphi}, \mu, \boldsymbol{\theta}, \sigma_{a_t}^2 \mid \mathbf{Z}\right)}{\partial \theta} = 0, \frac{\partial \ln L\left(\boldsymbol{\varphi}, \mu, \boldsymbol{\theta}, \sigma_{a_t}^2 \mid \mathbf{Z}\right)}{\partial \sigma_{a_t}^2} = 0,$$

To obtain parameter standard error by using maximum likelihood estimation, the information matrix $I(\phi, \theta)$ is used. Information matrix is obtained by second derivatives over parameters and it is denoted by l_{ij}

$$l_{ij} = \frac{\partial^2 \ln L\left(\boldsymbol{\beta}, \sigma_{a_t}^2 \mid \mathbf{Z}\right)}{\partial \beta_i \partial \beta_j} \text{ and } I(\phi, \theta) = -E\left(l_{ij}\right)$$

Variance and standard error of parameter are denoted by $V\left(\hat{\beta}\right) = [I(\phi, \theta)]^{-1}$ and $SE\left(\hat{\beta}\right) = \left[V\left(\hat{\beta}\right)\right]^{1/2}$

The next step after estimating parameter of ARIMA is evaluating the significance of parameter. Parameter evaluating procedure is as follows

$H_0 : \theta = 0$

$H_1 : \theta \neq 0$

$$\text{Statistics test } t = \frac{\hat{\theta}}{s_{\hat{\theta}}} \qquad \text{(equation 3.10)}$$

Critical area, reject H_0 if $|t| > t_{\left(\alpha/2, n-n_p\right)}$ where n indicates number of observations, $n_p$indicates number of estimation parameters

c. The final phase is diagnostic checking. Diagnostic checking is a procedure to evaluate the fitted model by using residual analysis which includes two assumptions, i.e., independent and normal distribution (Cryer and Chan, 2008). Residual independent evaluating is as follows

$H_0 : \rho_1 = \rho_2 = \cdots = \rho_K = 0$

H_1 :at least there is one $\rho_k \neq 0$ where k= 1, 2, …, K

Statistics test : $Q = n(n+2)\sum_{k=1}^{K}(n-k)^{-1}\hat{\rho}_k^2$ (equation 3.11)

where

n : number of residuals

$\hat{\rho}_k$: ACF residual *k*th estimation

Q can be approached by $\chi^2_{(K-m)}$ where $m = p + q$, p and q indicates order of ARIMA (p,d,q) and critical area is reject H_0 if $Q > \chi^2_{(K-p-q)}$.And normality distribution test for residual use Kolmogorov-Smirnov normality test as follows

H_0 : residual follows normal distribution

H_1 : residual does not follow normal distribution

Statistics test: $D = \sup\left|S(x) - F_0(x)\right|$ (equation 3.12) where $S(x)$ indicates cumulative probability function which is calculated in sample and $F_0(x)$ is cumulative probability function of normal distribution. Critical area, reject H_0 if D >Quantile $1-\alpha$ on Table A.17 (Daniel, 1989) or *p-value*< α .

The presence of outliers frequently causes the residuals of ARIMA model do not fulfill both assumptions, particularly normality distribution. Outlier detection is used to handle the ARIMA modeling with outlier data. There are many types of outlier, such as additive outlier (AO), innovational outlier (IO), temporary outlier (TO), and level shift outlier (LS). In this research, we consider only two kinds of outlier that already implemented in SAS package, i.e. AO and LS outliers. In general, ARIMA model with outlier can be formulated as

$$Z_t = \sum_{j=1}^{k} \varpi_j v_j(B) I_j^{(T_j)} + \frac{\theta(B)}{\phi(B)} a_t \qquad \text{(equation 3.13)}$$

where $I_j^{(T_j)}$ is variable that indicate the presence of outlier at T_j, period and $v_j(B)=1$ for AO, and $v_j(B)=\frac{1}{(1-B)}$ for LS.

2. Estimating residual from series dataset and prediction value of ARIMA
   Residual for ARIMA model is obtained by the following mathematical representation:
   $e_t = Z_t - \hat{L}_t$
   where Z_t is dataset, $\hat{L}_t$ is forecast value for time *t* from estimated ARIMA model.
3. The last step in creating ensemble member is modeling residual of ARIMA to ANN. R and Matlab are applied to build ANN model. This study uses four architecture of ANN. They are FFNN, RBFNN, GRNN, and RNN. The general methodology to build ANN which has the best predictive accuracy is as follows
   a. Determine the input of ANNs and their architectures.
      Selecting the number ofinput in ANN provide a greater effect than selecting the number of neurons in the hidden layer so many researchers pay more attention to the selection of input (Zhang et al., 2001). It is caused parameters are estimated on the ANN model provide nonlinear structure of autocorrelation in time series. Several studies regarding the selection of ANN input on modeling of time series (Crone and Kourentzes, 2009; Faraway and Chatfield, 1998) often follow Box-Jenkins methodology through the pattern of ACF and PACF. The methodology to select input of ANN is follow
      - ARIMA (p, 0,0). This model uses PACF pattern to determine the inputof ANN model.The input of this model is AR order, $Z_{t-1}, Z_{t-2}, \ldots, Z_{t-p}$
      - ARIMA (p, d, 0) and ARIMA (p, d, q). For nonstationary time series, there are many significant lag in ACF and PACF so it sould be differencing until it become stationary time series thereafter it can be determined its model. This model uses ACF and PACF pattern to determine the input. The inputs of this model are both AR order and its differencing order, $Z_{t-1}, Z_{t-2}, \ldots, Z_{t-p}, Z_{t-1-d}, Z_{t-2-d}, \ldots, Z_{t-p-d}$
      - ARIMA (0, d, 0). Input to the NN based model that is Z_{t-d}
      - ARIMA (0,0, q). When the time series have stucture of MA, RNN is the only one that can model use direct input from ACF pattern, whereas for the other ANN architecture keep use significant PACF patterns.
   b. Perform preprocessing of data

Several activation functions of neuron have a certainty range, for example. logistic sigmoid has range between 0 and 1, therefore, the data should be transformed as follows

$$Z_t^* = \frac{(Z_t - \min(Z_t))}{(\min(Z_t) - \min(Z_t))} \qquad \text{(equation 3.14)}$$

c. Training process

Training process is used to estimate the weights. The training process in this research use backpropogation algorithm. The following explanation is about example to estimate the weights of feedforward neural network by using backpropagation algorithm:

To update weights of neural networks we can use gradient descent optimization. Gradient descent use linear approach from error function to update weights. Error function formulation is as follows:

$$Q(\mathbf{w} + \Delta\mathbf{w}) \approx Q(\mathbf{w}) + \Delta\mathbf{w}^T Q'(\mathbf{w}) \qquad \text{(equation 3.15)}$$

Weights are updated by the following equation

$$\Delta\mathbf{w} = \eta Q'(\mathbf{w}), \eta > 0 \qquad \text{(equation 3.16)}$$

Q refer to sum square of error from training data and the formulation as follows

$$Q = \frac{1}{2}\sum_{t=1}^{n}(Z_t - \hat{Z}_t)^2 \qquad \text{(equation 3.17)}$$

where

Z_t = target

$\hat{Z}_t$ = expected value of the target

$$Q(\mathbf{w}) = \frac{1}{2}\sum_{t=1}^{n}\left(Z_t - g^o\left[w_0 + \sum_{j=1}^{q} w_j g_j^h\left(w_{0j} + \sum_{i=1}^{p} w_{ij} X_i\right)\right]\right)^2 \qquad \text{(equation 3.18)}$$

Completion of the above optimization problem will be done using a gradient algorithm, i.e.,

$$\Delta\mathbf{w} = \eta Q'(\mathbf{w}) \text{or} \, \mathbf{w}^{(m+1)} = \mathbf{w}^{(m)} - \eta \frac{\partial Q(\mathbf{w})^{(m)}}{d\mathbf{w}} \qquad \text{(equation 3.19)}$$

where η islearning rate, $0 < \eta < 1$.

To update weights we can use offline and online adaptation. Weights in offline adaptation are updated every input-output pair and weights in online adaptation are updated after all expected values from input and output are done. Online adaptation is well-known as batch mode. To simplify formulation 3.18, we define

$$v_j^h = w_{0j} + \sum_{i=1}^{p} w_{ij} X_i \qquad \text{(equation 3.20)}$$

$$a_j^h = f_j^h(v_j^h) = f_j^h\left(\beta_{0j} + \sum_{i=1}^{p} w_{ij} X_i\right) \qquad \text{(equation 3.21)}$$

$$v^o = w_0 + \sum_{j=1}^{q} w_j a_j^h \qquad \text{(equation 3.22)}$$

$$\hat{Z}_t = a^o = f^o(v^o) = f^o\left(w_0 + \sum_{j=1}^{q} w_j a_j^h\right) \qquad \text{(equation 3.23)}$$

To update weights, i.e., equation 3.19, we need partial derivative of Q on $\mathbf{w}$. First, we have to do partial derivative Q on $w_j$as follows:

$$\frac{\partial Q(\mathbf{w})}{\partial w_j} = \frac{\partial\left[\frac{1}{2}\sum_{t=1}^{n}\left(Z_t - f_t^o\left[w_0 + \sum_{j=1}^{q} w_j f_j^h\left(w_{0j} + \sum_{i=1}^{p} w_{ij} X_i\right)\right]\right)^2\right]}{\partial w_j} \qquad \text{(equation 3.24)}$$

$$\frac{\partial Q(\mathbf{w})}{\partial w_j} = \frac{\partial Q(\mathbf{w})}{\partial a^o}\frac{\partial a^o}{\partial v^o}\frac{\partial v^o}{\partial w_j} \qquad \text{(equation 3.25)}$$

$$\frac{\partial Q(\mathbf{w})}{\partial a^o} = \frac{\partial \frac{1}{2}\sum_{t=1}^{n}\left(Z_t - a^o\right)^2}{\partial a^o} = -\sum_{t=1}^{n}\left(Z_t - a^o\right) = -\sum_{t=1}^{n}\left(Z_t - \hat{Z}_t\right) \qquad \text{(equation 3.26)}$$

Because output layer use linier transfer function, therefore $f^o\left(v^o\right) = v^o$

$$\frac{\partial a^o}{\partial v^o} = \frac{\partial f^o\left(v^o\right)}{\partial v^o} = f^{o'}\left(v^o\right) = 1 \qquad \text{(equation 3.27)}$$

$$\frac{\partial v^o}{\partial w_j} = \frac{\partial\left(w_0 + \sum_{j=1}^{q} w_j a_j^h\right)}{\partial w_j} = a_j^h \qquad \text{(equation 3.28)}$$

$$\frac{\partial Q(\mathbf{w})}{\partial w_j} = \frac{\partial Q(\mathbf{w})}{\partial a^o}\frac{\partial a^o}{\partial v^o}\frac{\partial v^o}{\partial w_j} = -\sum_{t=1}^{n}\left(Z_t - \hat{Z}_t\right)a_j^h = -\sum_{t=1}^{n}\delta_t^o a_j^h \qquad \text{(equation 3.29)}$$

where, $\delta_t^o = \left(Z_t - \hat{Z}_t\right)$ (equation 3.30)

Second,perform partial derivative Qoverw_0, as follows:

$$\frac{\partial Q(\mathbf{w})}{\partial w_0} = \frac{\partial Q(\mathbf{w})}{\partial a^o}\frac{\partial a^o}{\partial v^o}\frac{\partial v^o}{\partial w_0} \qquad \text{(equation 3.31)}$$

$$\frac{\partial v^o}{\partial w_0} = \frac{\partial\left(w_0 + \sum_{j=1}^{q} w_j a_j^h\right)}{\partial w_0} = 1 \qquad \text{(equation 3.32)}$$

$$\frac{\partial Q(\mathbf{w})}{\partial w_0} = \frac{\partial Q(\mathbf{w})}{\partial a^o}\frac{\partial a^o}{\partial v^o}\frac{\partial v^o}{\partial w_0} = -\sum_{t=1}^{n}\left(Z_t - \hat{Z}_t\right) = -\sum_{t=1}^{n}\delta_t^o \qquad \text{(equation 3.33)}$$

where δ_t^o refer to equation 3.30.

Third, perform partial derivative Q over w_{ij}

$$\frac{\partial Q(\mathbf{w})}{\partial w_{ij}} = \frac{\partial Q(\mathbf{w})}{\partial a^o}\frac{\partial a^o}{\partial v^o}\frac{\partial v^o}{\partial a_j^h}\frac{\partial a_j^h}{\partial v_j^h}\frac{\partial v_j^h}{\partial w_{ij}} \qquad \text{(equation 3.34)}$$

and the solution is

$$\frac{\partial Q(\mathbf{w})}{\partial w_{ij}} = \frac{\partial Q(\mathbf{w})}{\partial a^o}\frac{\partial a^o}{\partial v^o}\frac{\partial v^o}{\partial a_j^h}\frac{\partial a_j^h}{\partial v_j^h}\frac{\partial v_j^h}{\partial w_{ij}} = -\sum_{t=1}^{n}\left(Z_t - \hat{Z}_t\right)a_j^h f_j^{h'}\left(v_j^h\right)X_i$$

because hidden layer use logistic sigmoid activation function, therefore $f_j^h\left(v_j^h\right) = \frac{1}{1+\exp\left(-v_j^h\right)}$

where, $\frac{\partial a_j^h}{\partial v_j^h} = \frac{\partial f_j^h\left(v_j^h\right)}{\partial v_j^h} = f_j^{h'}\left(v_j^h\right) = f_j^h\left(v_j^h\right)\left(1 - f_j^h\left(v_j^h\right)\right)$ (equation 3.35)

$$\frac{\partial v_j^h}{\partial w_{ij}} = \frac{\partial\left(w_{0j} + \sum_{i=1}^{p} w_{ij} X_i\right)}{\partial w_{ij}} = X_i \qquad \text{(equation 3.36)}$$

(equation 3.37)

To simplify equation equation 3.37, we can use δ_t^o as in equation 3.30,

$$\frac{\partial Q(\mathbf{w})}{\partial w_{ij}} = -\sum_{t=1}^{n} \delta_t^o a_j^h f_j^{h'}\left(v_j^h\right) X_i = -\sum_{t=1}^{n} \delta_{jt}^h X_i \qquad \text{(equation 3.38)}$$

where $\delta_{jt}^h = \delta_t^o a_j^h g_j^{h'}\left(v_j^h\right)$ (equation 3.39)

The last, perform derivative Q over w_{0j}

$$\frac{\partial Q(\mathbf{w})}{\partial w_{0j}} = \frac{\partial Q(\mathbf{w})}{\partial a^o} \frac{\partial a^o}{\partial v^o} \frac{\partial v^o}{\partial a_j^h} \frac{\partial a_j^h}{\partial v_j^h} \frac{\partial v_j^h}{\partial \beta_{0j}} \qquad \text{(equation 3.40)}$$

$$\frac{\partial Q(\mathbf{w})}{\partial \beta_{0j}} = \frac{\partial Q(\mathbf{w})}{\partial a^o} \frac{\partial a^o}{\partial v^o} \frac{\partial v^o}{\partial a_j^h} \frac{\partial a_j^h}{\partial v_j^h} \frac{\partial v_j^h}{\partial \beta_{0j}} = -\sum_{t=1}^{n}\left(Z_t - \hat{Z}_t\right) a_j^h g_j^{h'}\left(v_j^h\right) = -\sum_{t=1}^{n} \delta_{jt}^h \qquad \text{(equation3.41)}$$

where $\frac{\partial v_j^h}{\partial \beta_{0j}} = \frac{\partial\left(\beta_{0j} + \sum_{i=1}^{p} \beta_{ij} Z_{t-i}\right)}{\partial \beta_{0j}} = 1$ (equation 3.42)

Updating weights in output layer,

$$\alpha_j^{(m+1)} = \alpha_j^{(m)} + \eta \sum_{t=1}^{n} \delta_t^{o(m)} a_j^{h(m)} \qquad \text{(equation 3.43)}$$

$$\alpha_0^{(m+1)} = \alpha_0^{(m)} + \eta \sum_{t=1}^{n} \delta_t^{o(m)} \qquad \text{(equation 3.44)}$$

and updating weights in hidden layer

$$\beta_{ij}^{(m+1)} = \beta_{ij}^{(m)} + \eta \sum_{t=1}^{n} \delta_{jt}^{h(m)} Z_{t-i} \qquad \text{(equation 3.45)}$$

$$\beta_{0j}^{(m+1)} = \beta_{0j}^{(m)} + \eta \sum_{t=1}^{n} \delta_{jt}^{h(m)} \qquad \text{(equation 3.46)}$$

d. Predicting the testing data. Value prediction is done iteratively testing data.
e. Perform postprocessing of data

$$Z_t = \min\left(Z_t\right) + \left(Z_t^* \times \left(\min\left(Z_t\right) - \min\left(Z_t\right)\right)\right) \qquad \text{(equation 3.47)}$$

3.2.2 Combining Ensemble Member

When several ensemble members are available, the next step is combining several ensemble members to obtain unique solution of hybrid ARIMA-ANN ensemble. This study use averaging and stacking to combine several members. The unique solution of averaging hybrid ARIMA and ANN ensemble is presented in equation (2.7) and unique solution of stacking is presented in equation (2.9). To estimate parameter weight of stacking, SPSS is applied.

3.2.3 Model Selection Criteria

Model selection criteria in this research use several forecast accuracy measurements such as root mean square error (RMSE), relative root mean square error (RelRMSE) and log mean squared error ratio (LMR). Mathematical representations of all model selection criteria are as follows (Gooijer and Hyndman, 2006)

$$\text{RMSE} = \sqrt{\frac{\sum_{t=1}^{n}\left(Z_t - \hat{Z}_t\right)^2}{n}} \qquad \text{(equation 3.48)}$$

$$\text{RelRMSE} = \text{RMSE}_a \big/ \text{RMSE}_b \qquad \text{(equation 3.49)}$$

$$\text{LMR} = \log\left(\text{MSE}_a \big/ \text{MSE}_b\right) \qquad \text{(equation 3.50)}$$

The flow chart of hybrid ARIMA and ANNs ensemble is shown in Figure 3.1.

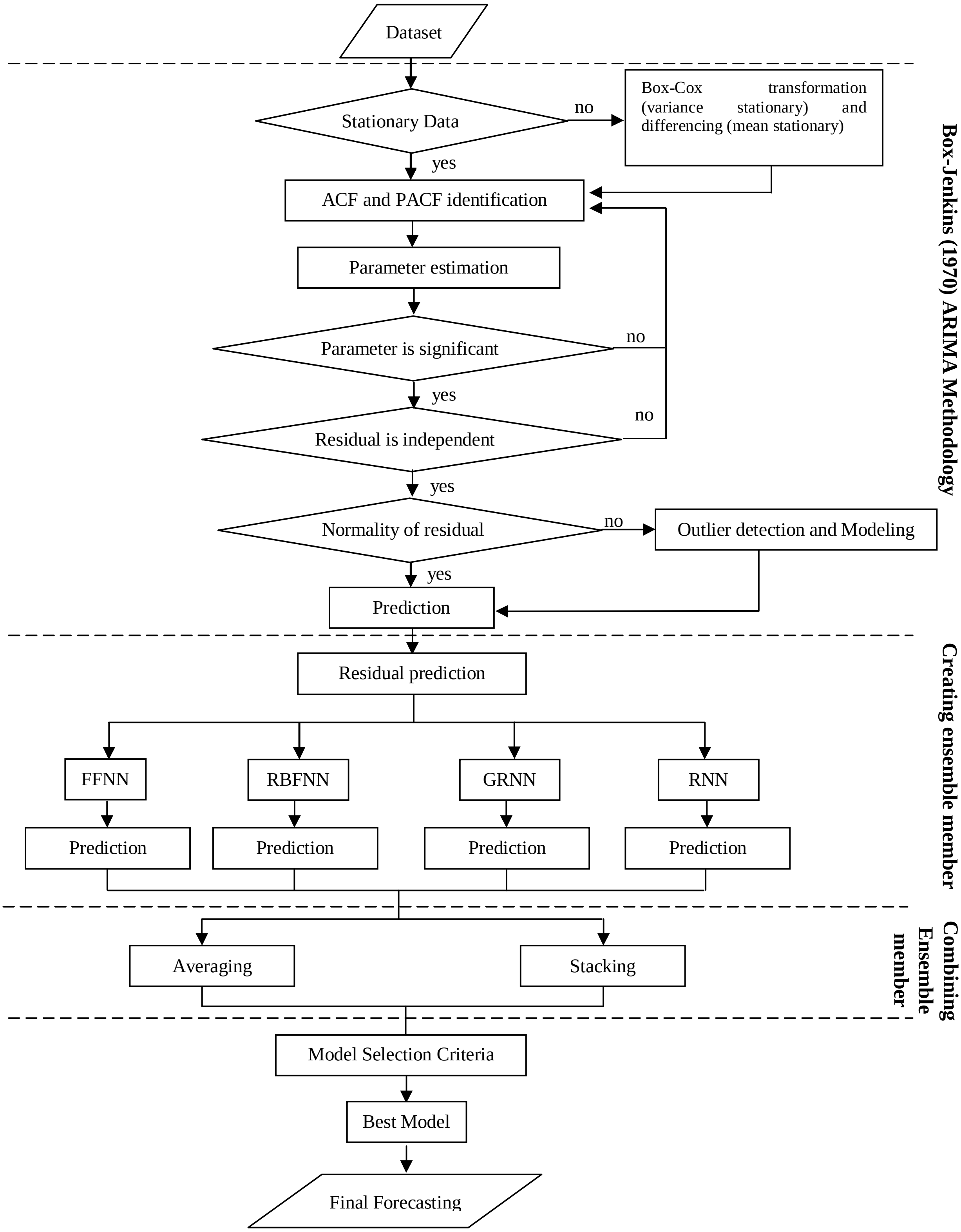


Figure 3.1 Flow Chart of Hybrid ARIMA and ANNs Ensemble Model

CHAPTER 4
RESULTS AND DISCUSSIONS

4.1 Inflation Characteristics

Time series patterns of national and seven cities inflation in East Java from January 1980 to December 2013 are showed in Figure 4.1. They have a pattern that tends to be relatively stable between 1 to 3, though there are some extreme points that reached more than 12, which was in 1998.

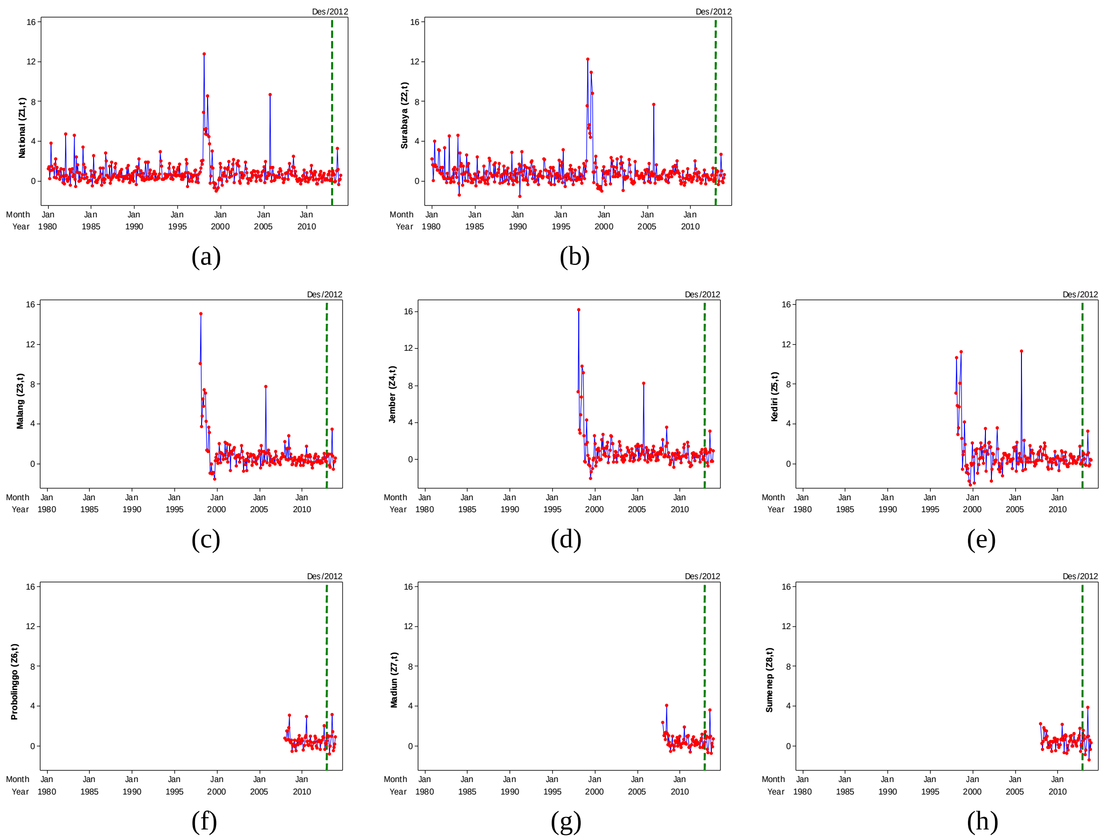
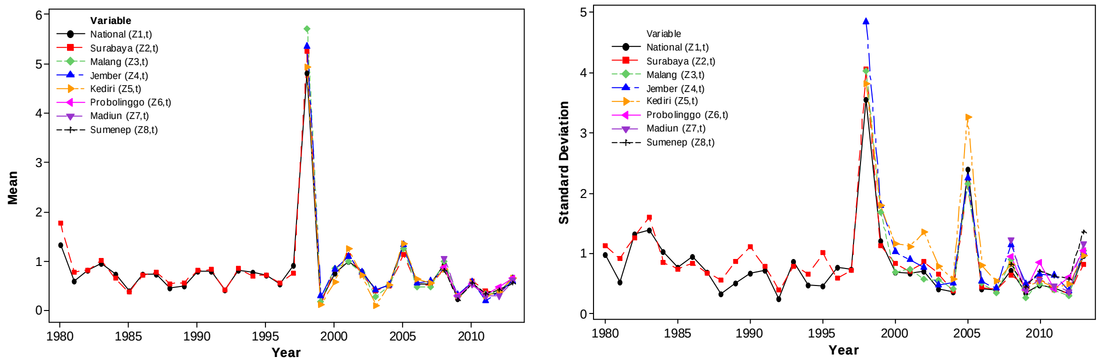


Figure 4.1 Time Series Plot of (a) National Inflation, (b) Surabaya Inflation, (c) Malang Inflation, (d) Jember Inflation, (e) Kediri Inflation, (f) Probolinggo Inflation, (g) Madiun Inflation, and (h) Sumenep Inflation from January 1980 until December 2013

Table 4.1 Descriptive Statistics of National Inflation and Seven Cities Inflation in East Java

Variable	N	Mean	StDev	Minimum	Maximum
$Z_{1,t}$	408	0.792	1.236	-1.050	12.760
$Z_{2,t}$	408	0.819	1.348	-1.590	12.280
$Z_{3,t}$	192	0.915	1.805	-1.570	15.080
$Z_{4,t}$	192	0.915	1.907	-2.040	16.200
$Z_{5,t}$	192	0.859	1.837	-2.150	11.350
$Z_{6,t}$	72	0.523	0.758	-0.820	3.130
$Z_{7,t}$	72	0.509	0.805	-0.750	4.050
$Z_{8,t}$	72	0.482	0.804	-1.440	3.840

Descriptive statistics of each variable can be seen in Table 4.1. It shows that data on each of variable is different, it happens due to policy changes for customer price index calculation. The average inflation in each variable are relatively stable because the inflation is less than1 while distribution of data indicated from standard deviation, the minimum and maximum shows that the variable $Z_{6,\ t}$ (Probolinggo) is the most homogeneous variableand has the smallest range while variables $Z_{4,\ t}$ (Kediri) is the most heterogeneous variableand has the largest range . In addition, the rate of mean and standard deviation annually for each variable can be shown in Figure 4.2.



(a) (b)

Figure 4.2 The Rate of Mean (a) and Standard Deviation (b) of Inflation

The annual mean rate of inflation for each of the variables has a similar pattern that fluctuates each year. The highest mean for each variable occurred in 1998 which reached over5, and for other mean is below 2. Meanwhile, the annual standard deviation rate of inflation for each of the variables has a variety of patterns and fluctuated. The highest standard deviation occurred in 1998 and the second highest in 2005. Mean and standard deviation were the highest in 1998 due to a weak banking system, the collapse of the rupiah over foreign currencies, and the main factor is political instability. In addition, the second highest standard deviation in 2005 is due to increase of fuel oil price.

4.2 Autoregressive Integrated Moving Average (ARIMA) Model for Inflation

ARIMA models are constructed from training data which consist inflation from January 1980 to December 2012, meanwhile testing data which consist January 2013 to December 2013 is used to evaluate the model. Time series plot of training data for each variable is shown in Figure 4.3.Figure 4.3 showed that National Inflation ($Z_{1,t}$) and inflation of Surabaya ($Z_{2,t}$)have 396 observations, inflation of Malang ($Z_{3,t}$), inflation of Jember ($Z_{4,t}$) and inflation of Kediri ($Z_{5,t}$)have 180 observations and inflation of Probolinggo ($Z_{6,t}$), inflation of Madiun ($Z_{7,t}$) and inflation of Sumenep ($Z_{8,t}$) have 60 observations.

Box Jenkins procedures to construct ARIMA modelsfor each variable arerelatively similar. Therefore, this discussion will only explain the Box Jenkins procedure on National inflation ($Z_{1,t}$). ARIMA models of the other variables are shown in the appendix.

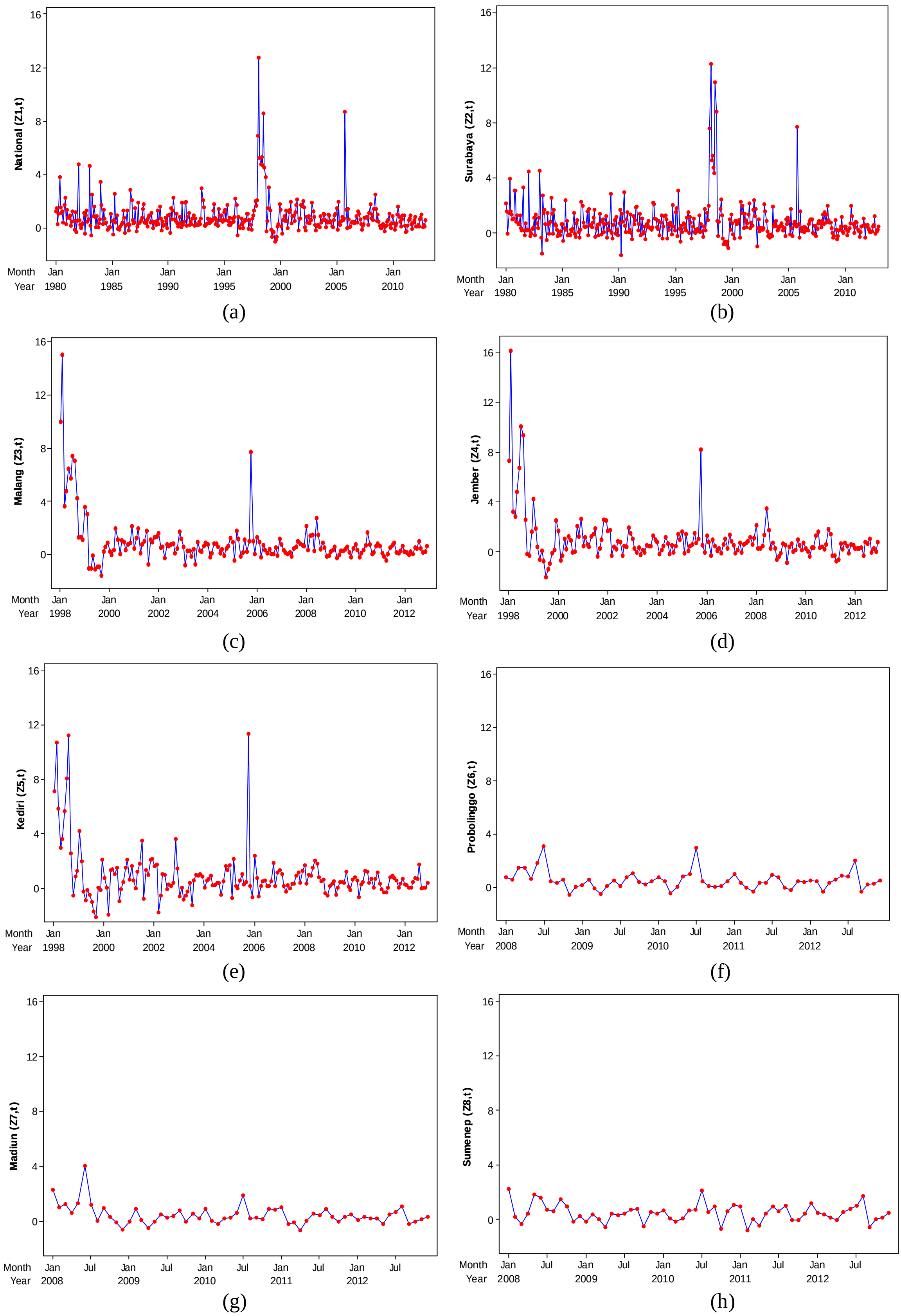


Figure 4.3 Time Series Plot of (a) National Inflation, (b) Surabaya Inflation, (c) Malang Inflation, (d) Jember Inflation, (e) Kediri Inflation, (f) Probolinggo Inflation, (g) Madiun Inflation, and (h) Sumenep Inflation from January 1980 until December 2012

The next step after creating time series plot is creating boxplot (Figure 4.4). Figure 4.4 shows that the boxplot of national inflation does not have seasonal pattern because the distribution of monthly inflation is relatively the same. In addition there are some extreme points which may eventually lead to the fact that the data do not follow normal distribution.

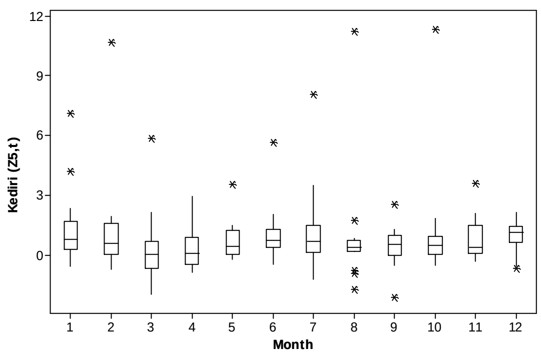
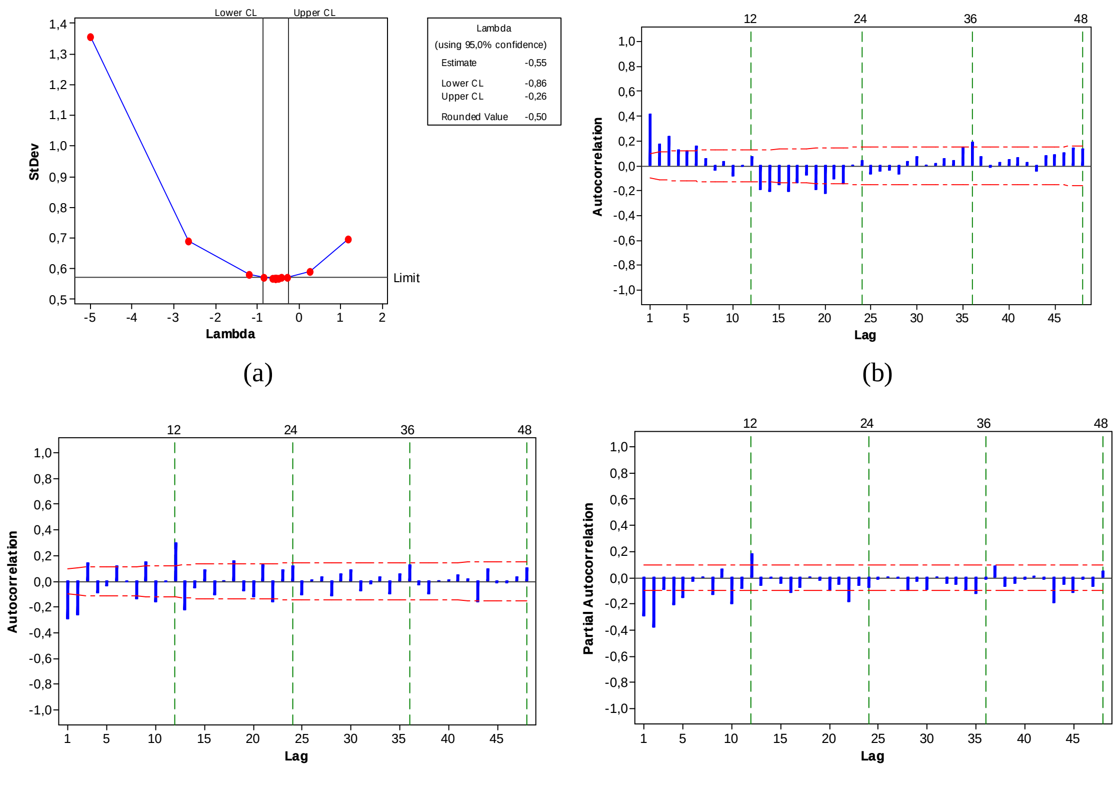


Figure 4.4 Box Plot of National Inflation ($Z_{1,t}$)



(a) (b)

(c) (d)

Figure 4.5 Identification Plot : (a) Box-Cox Transformation $Z_{1,t}$, (b) ACF plot of Transformation $Z_{1,t}$, (c) ACF plot of Transformation $Z_{1,t}$ with d=1, and (d) PACF plot of Transformation $Z_{1,t}$ with d=1

The next step is the evaluation data stationary (Figure 4.5). There are two kinds of stationary that should be evaluated are variance stationary and mean stationary. Evaluation of variance stationary can be evaluated by Box - Cox transformation plots in Figure 4.5a. Figure 4.5a shows that the data are not variance stationary due to lamnda=1 does not exist in range between lower CL and upper CL, so the data needs to be transformed. In this case, power -0.5 transformation is used because rounded lambda value equal to -0.5. The next step is the evaluation of mean stationary by evaluating the ACF pattern (Figure 4.5b) .

Figure 4.5b shows that the data are not mean stationary because there are many spikes outside the lower and upper CL so that the data need to be differencing with d = 1. After differencing with d = 1, spikes that are outside the lower and upper CL is reduced and ACF look dies down for a large lag so all stationary assumptions is satisfied. Therefore, it can be used to estimate ARMA(p,q) order. The ARMA (p,q) model of national inflation is constructed based on pattern of ACF and PACF (Figure 4.5c and Figure 4.5d) and order of ARMA (p,q) is presumed by using guideline in Table 3.1.

Table 4.2 Autoregressive Integrated Moving Average (ARIMA) Model for National Inflation

Model	Parameter Estimation			Diagnostic Checking of Residual	
	Parameter	Estimate	P-value	white noise*)	normality distribution*)
ARIMA ([1,12],1,[2,8,14,20])	θ_2	0.61056	<0.0001	satisfied	unsatisfied
	θ_8	0.13647	0.0104		
	θ_{14}	0.15583	0.0014		
	θ_{20}	0.08800	0.0479		
	ϕ_1	-0.57396	<0.0001		
	ϕ_{12}	0.26830	<0.0001		
ARIMA ([1,8,12],1,[2,20])	θ_2	0.51296	<0.0001	satisfied	unsatisfied
	θ_{20}	0.11572	0.0085		
	ϕ_1	-0.46265	<0.0001		
	ϕ_8	-0.13125	0.0028		
	ϕ_{12}	0.19808	<0.0001		
ARIMA ([1,12,20],1,[2,8,14])	θ_2	0.58754	<0.0001	satisfied	unsatisfied
	θ_8	0.12013	0.0067		
	ϕ_1	0.12810	0.0033		
	ϕ_{12}	-0.54423	<0.0001		
	ϕ_{20}	0.23315	<0.0001		
	θ_2	-0.09523	0.0285		
ARIMA ([1,12,14],1,[2,8,20])	θ_2	0.56306	<0.0001	satisfied	unsatisfied
	θ_8	0.15108	0.0005		
	θ_{14}	0.11161	0.0058		
	ϕ_1	-0.52071	<0.0001		
	ϕ_{12}	0.25455	<0.0001		
	ϕ_{20}	-0.11246	0.0131		
ARIMA ([1,8,12,14],1,[2,20])	θ_2	0.53775	<0.0001	satisfied	unsatisfied
	θ_{20}	0.11174	0.0094		
	ϕ_1	-0.49862	<0.0001		
	ϕ_8	-0.12515	0.0039		
	ϕ_{12}	0.22038	<0.0001		
	ϕ_{14}	-0.12694	0.0045		

***)**using α=5%

Table 4.3 Autoregressive Integrated Moving Average (ARIMA) with Outlier Analysis Model for National Inflation

Model	Parameter Estimation			Type of outlier	Diagnostic Checking of Residual	
	Parameter	Estimate	P-value		white noise lag to 30 (*)	normality distribution (*)
ARIMAX ([1,12],1,[2,8,20])	θ_2	0.59110	<0.0001	-	Satisfied	Satisfied
	θ_8	0.20921	<0.0001	-		
	θ_{20}	0.11726	0.0023	-		
	ϕ_1	-0.50636	<0.0001	-		
	ϕ_{12}	0.31332	<0.0001	-		
	ω_1	0.42226	<0.0001	additional outlier		
	ω_2	0.25775	<0.0001	additional outlier		
	ω_3	0.24837	<0.0001	additional outlier		
	ω_4	0.16792	0.0038	additional outlier		
	ω_5	-0.15264	0.0067	additional outlier		
	ω_6	-0.18539	0.0010	additional outlier		
	ω_7	0.20832	0.0002	additional outlier		
ARIMAX ([1,8,12],1,[2,20])	θ_2	0.48716	<0.0001	-	Satisfied	Satisfied
	θ_{20}	0.13297	0.0035	-		
	ϕ_1	-0.47243	<0.0001	-		
	ϕ_8	-0.09182	0.0378	-		
	ϕ_{12}	0.27058	<0.0001	-		
	ω_1	0.36159	<0.0001	additional outlier		
	ω_2	0.26380	<0.0001	additional outlier		
	ω_3	0.24708	0.0002	additional outlier		
	ω_4	-0.20531	0.0005	additional outlier		
	ω_5	0.21731	0.0003	additional outlier		
ARIMAX ([1,12,20],1,[2,8])	θ_2	0.59888	<0.0001	-	Satisfied	Satisfied
	θ_8	0.18795	<0.0001	-		
	ϕ_1	-0.49600	<0.0001	-		
	ϕ_{12}	0.26158	<0.0001	-		
	ϕ_{20}	-0.10415	0.0145	-		
	ω_1	0.26139	<0.0001	additional outlier		
	ω_2	0.28269	<0.0001	additional outlier		
	ω_3	0.20933	0.0004	additional outlier		
ARIMAX ([1,12,14],1,[2,8,20])	θ_2	0.56355	<0.0001	-	Satisfied	Satisfied
	θ_8	0.16263	0.0002	-		
	θ_{20}	0.10269	0.0117	-		
	ϕ_1	-0.52364	<0.0001	-		
	ϕ_{12}	0.29485	<0.0001	-		
	ϕ_{14}	-0.11751	0.0086	-		
	ω_1	0.28129	<0.0001	additional outlier		
	ω_2	0.26309	<0.0001	additional outlier		
ARIMAX ([1,3,12,14],1,[2])	θ_2	0.94807	<0.0001	-	Satisfied	Satisfied
	ϕ_1	-0.72058	<0.0001	-		
	ϕ_3	-0.13630	0.0006	-		
	ϕ_{12}	0.28597	<0.0001	-		
	ϕ_{14}	-0.19571	<0.0001	-		
	ω_1	0.18995	0.0029	additional outlier		
	δ_1	0.23259	<0.0001	level shift outlier		
	δ_2	-0.22046	<0.0001	level shift outlier		
	δ_3	-0.23161	<0.0001	level shift outlier		
	ω_2	0.18204	0.0024	additional outlier		
	δ_4	0.21369	<0.0001	level shift outlier		

*)Using α=5%

Table 4.2 shows that ARIMA (p,d,q) model for national inflation have five models. The next step after preassumed order of ARIMA (p,d,q) is parameter estimation and diagnostic checking. Parameter estimation is used to evaluate significance of parameter and diagnostic checking is used to evaluate independent and normal distribution of residuals. Table 4.2 shows that parameter of all models are significant because p-value < 0.05, and the residual of all models is independent but does not follow normal distribution. The cause of the fact that residuals does not follow normal distribution is the existence of outliers. Outliers are time series observations that are often influenced by interruptive events such as sudden political, economic crisis, and increased fuel price. These interruptive events create spurious observations that are inconsistent with the rest of data. In addition, the timing of interruptive event is sometimes unknown (Wei, 2006). To overcome this problem we can be used ARIMA model with outlier analysis (ARIMAX). ARIMA (p,d,q) model with outlier analysis is procedure that detects and removes the outlier effect in ARIMA (p,d,q) model (Wei, 2006).

The ARIMA (p,d,q) with outlier analysis for national inflation is shown in Table 4.3. Table 4.3 shows that some models have different order ARIMA (p,d,q) from the previous model (Table 4.2), for example ARIMA ([1,12],1,[2,8,14,20]) change into ARIMAX ([1,12],1,[2,8,20]) after using outlier analysis. All models have additional outliers meanwhile there is one model which exists level shift outlier. In addition, all models are satisfied both parameter significance test and diagnostic checking. Therefore, all models are satisfied all the assumptions and they can be used to predict the inflation.

Using the same Box-Jenkins procedure as it has been applied to the national inflation, the summary ARIMA (p,d,q) for national inflation and inflation of seven cities in East Java can be shown in Table 4.4.

Table 4.4 shows that all variables have five ARIMA (p,d,q) models except Malang inflation ($Z_{3,t}$) which has only four ARIMA (p,d,q) models. There are six variables which use ARIMA (p,d,q) with outlier analysis and another two variables use ARIMA (p,d,q) without outlier analysis. The two variables are Madiun inflation ($Z_{6,t}$) and Sumenep ($Z_{8,t}$). In addition, there are three variables (Probolinggo Inflation ($Z_{5,t}$), Madiun inflation ($Z_{6,t}$) and Sumenep ($Z_{8,t}$)) are already mean stationary because d=0 in the order of ARIMA(p,d,q) model. Moreover, every models in each variable has different number of parameters and number of outliers.

The next step after constructing the ARIMA (p,d,q) model is predicting the inflation then calculate the residual of ARIMA (p,d,q). The residual of ARIMA (p,d,q) is used to determine input of artificial neural networks (ANNs).

Table 4.4 Summary Autoregressive Integrated Moving Average (ARIMA) for National Inflation and Seven Cities Inflation in East Java

Variable	No. Ensemble Member	Model	No. of Parameters	No. of Outliers
$Z_{1,t}$	5	ARIMAX ([1,12],1,[2,8,20])	12	7
		ARIMAX ([1,8,12],1,[2,20])	10	5
		ARIMAX ([1,12,20],1,[2,8])	8	3
		ARIMAX ([1,12,14],1,[2,8,20])	8	2
		ARIMAX ([1,3,12,14],1,[2])	11	6
$Z_{2,t}$	5	ARIMAX([1,5,12,19],1,[2,14])	14	8
		ARIMAX([1,5,12],1,[2,20])	13	8
		ARIMAX([1,6,12,20],1,[2])	11	6
		ARIMAX([1,12,20],1,[2,6])	11	6
		ARIMAX([2,12],1,1)	11	8
$Z_{3,t}$	4	ARIMAX(1,1,[2])	8	6
		ARIMAX([1,2],1,[3])	7	4
		ARIMAX(0,1,1)	7	6
		ARIMAX([1,2,3],1,[4])	8	4
$Z_{4,t}$	5	ARIMA([1,7],1,2)	3	0
		ARIMAX([3,4],1,[1,11])	9	5
		ARIMAX([2,3],1,[1,4])	8	4
		ARIMAX([1,2,4],1,[3,12])	11	5
		ARIMAX(1,1,[2,3])	7	4
$Z_{5,t}$	5	ARIMAX([1,3],1,[2])	15	12
		ARIMAX(1,1,[2,3])	15	12
		ARIMAX(1,1,[2,7])	13	10
		ARIMAX([1,7],1,[2])	16	13
		ARIMAX([1,2],1,[3])	15	12
$Z_{6,t}$	5	ARIMAX(1,0,[9])	7	4
		ARIMAX([9],0,1)	7	4
		ARIMAX([9],0,0)	6	4
		ARIMAX(0,0,[9])	6	4
		ARIMAX([1,9],0,0)	7	4
$Z_{7,t}$	5	ARIMA(1,0,0)	2	0
		ARIMA(0,0,1)	2	0
		ARIMA([9],0,0)	2	0
		ARIMA(0,0,[9])	2	0
		ARIMA([1,9],0,0)	3	0
$Z_{8,t}$	5	ARIMA([3],0,0)	2	0
		ARIMA(0,0[3])	2	0
		ARIMA([9],0,0)	2	0
		ARIMA(0,0,[9])	2	0
		ARIMA([3,9],0,0)	3	0

Table 4.5 Member of Hybrid Autoregressive Integrated Moving Average (ARIMA) and Feedforward Neural Networks (FFNNs) Ensemble

Variable	Model	Input	FFNN Model
$Z_{1,t}$	ARIMAX ([1,12],1,[2,8,20])	Lag 14, Lag 19	NN(2,1,1)
	ARIMAX ([1,8,12],1,[2,20])	Lag 14, Lag 16	NN(2,2,1)
	ARIMAX ([1,12,20],1,[2,8])	Lag 14, Lag 19	NN(2,3,1)
	ARIMAX ([1,12,14],1,[2,8,20])	Lag 19	NN(1,1,1)
	ARIMAX ([1,3,12,14],1,[2])	Lag 20, Lag 22	NN(2,1,1)
$Z_{2,t}$	ARIMAX([1,5,12,19],1,[2,14])	Lag 19, Lag 20	NN(2,6,1)
	ARIMAX([1,5,12],1,[2,20])	Lag 16	NN(2,1,1)
	ARIMAX([1,6,12,20],1,[2])	Lag 16, Lag 22	NN(2,4,1)
	ARIMAX([1,12,20],1,[2,6])	Lag 16, Lag 22	NN(1,1,1)
	ARIMAX([2,12],1,1)	Lag 20, Lag 22	NN(2,6,1)
$Z_{3,t}$	ARIMAX(1,1,[2])	Lag 14, Lag 16	NN(2,1,1)
	ARIMAX([1,2],1,[3])	Lag 16, Lag 20	NN(2,8,1)
	ARIMAX(0,1,1)	Lag 16	NN(1,15,1)
	ARIMAX([1,2,3],1,[4])	Lag 16	NN(1,2,1)
$Z_{4,t}$	ARIMA([1,7],1,2)	Lag 3, Lag 20	NN(2,15,1)
	ARIMAX([3,4],1,[1,11])	Lag 2, Lag 13	NN(2,5,1)
	ARIMAX([2,3],1,[1,4])	Lag 6, Lag 15	NN(2,7,1)
	ARIMAX([1,2,4],1,[3,12])	Lag 13, Lag 20	NN(2,11,1)
	ARIMAX(1,1,[2,3])	Lag 20	NN(1,10,1)
$Z_{5,t}$	ARIMAX([1,3],1,[2])	Lag 9, Lag 11	NN(2,3,1)
	ARIMAX(1,1,[2,3])	Lag 22	NN(1,1,1)
	ARIMAX(1,1,[2,7])	Lag 8, Lag 22	NN(2,1,1)
	ARIMAX([1,7],1,[2])	Lag 15, Lag 22	NN(2,2,1)
	ARIMAX([1,2],1,[3])	Lag 9, Lag 15, Lag 22	NN(3,3,1)
$Z_{6,t}$	ARIMAX(1,0,[9])	Lag 11	NN(2,9,1)
	ARIMAX([9],0,1)	Lag 6, Lag 11	NN(2,1,1)
	ARIMAX([9],0,0)	Lag 1, Lag 11	NN(2,18,1)
	ARIMAX(0,0,[9])	Lag 1, Lag 11, Lag 12	NN(3,16,1)
	ARIMAX([1,9],0,0)	Lag 11	NN(1,13,1)
$Z_{7,t}$	ARIMA(1,0,0)	Lag 9, Lag 18	NN(2,14,1)
	ARIMA(0,0,1)	Lag 9	NN(1,5,1)
	ARIMA([9],0,0)	Lag 1, Lag 4	NN(2,1,1)
	ARIMA(0,0,[9])	Lag 1, Lag 2, Lag 4	NN(3,6,1)
	ARIMA([1,9],0,0)	Lag 4, Lag 8	NN(2,2,1)
$Z_{8,t}$	ARIMA([3],0,0)	Lag 9, Lag 11, Lag 17	NN(3,19,1)
	ARIMA(0,0[3])	Lag 9, Lag 17	NN(2,18,1)
	ARIMA([9],0,0)	Lag 11, Lag 17	NN(2,12,1)
	ARIMA(0,0,[9])	Lag 10, Lag 17	NN(2,3,1)
	ARIMA([3,9],0,0)	Lag 7, Lag 17	NN(2,7,1)

4.3 Hybrid Autoregressive Integrated Moving Average (ARIMA) and Feedforward Neural Networks (FFNNs) Ensemble Model for Inflation

Hybrid autoregressive integrated moving average (ARIMA) and feedforward neural networks (FFNNs) ensemble is a combination model from ARIMA and FFNNs, where the input of FFNNs is residual of ARIMA (p,d,q) model. Input of FFNNs is determined by PACF of Residual ARIMA and number of neuron in hidden layer of FFNNs is determined by the smallest mean square root error of in sample data. Number of neuron in hidden layer in this research is simulated from 1 to 20 (see appendix 5). The inputs and number of neuron in hidden layer of each model is shown in Table 4.5.

Table 4.5 showed that number of input for each model has variation from one input until three inputs and the majority number of input for each model is two inputs. Meanwhile, number of hidden layer has high variation and the majority number of neuron in hidden layer is 1 neuron. The next step after constructing hybrid ARIMA and FFNNs is combining each member by averaging and stacking techniques. Root mean square error of each member is shown in Figure 4.6

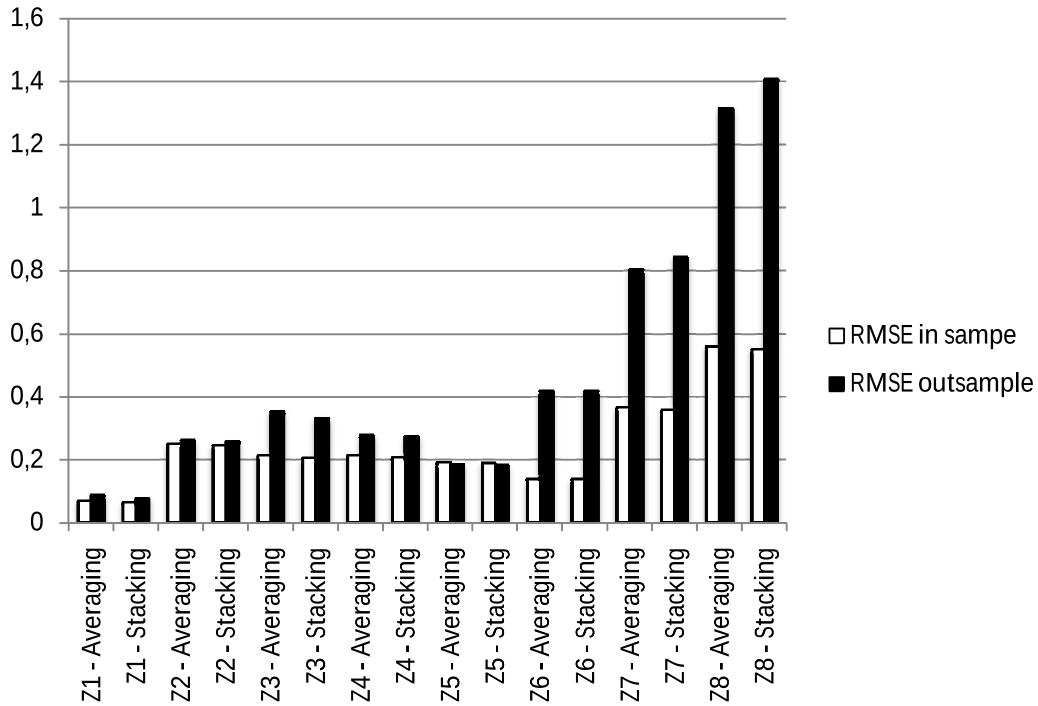


Figure 4.6 RMSE Hybrid ARIMA and FFNNs Ensemble

Figure 4.6 showed that in sample RMSE has smaller value than out sample RMSE. It happens because some data in out sample is expected to be positive but in reality the inflation is negative. Stacking has better performance than averaging in training data because all the in sample RMSE has less value than out sample RMSE. Meanwhile, in testing data stacking also take over averaging but in the last three models stacking have bigger RMSE than averaging.

Table 4.6 Member of Hybrid Autoregressive Integrated Moving Average (ARIMA) and Recurrent Neural Networks (RNNs) Ensemble

Variable	Model	Input	RNN Model
$Z_{1,t}$	ARIMAX ([1,12],1,[2,8,20])	Lag 14, Lag 19	NN(2,16,1)
	ARIMAX ([1,8,12],1,[2,20])	Lag 14, Lag 16	NN(2,20,1)
	ARIMAX ([1,12,20],1,[2,8])	Lag 14, Lag 19	NN(2,1,1)
	ARIMAX ([1,12,14],1,[2,8,20])	Lag 19	NN(1,7,1)
	ARIMAX ([1,3,12,14],1,[2])	Lag 20, Lag 22	NN(2,19,1)
$Z_{2,t}$	ARIMAX([1,5,12,19],1,[2,14])	Lag 19, Lag 20	NN(2,17,1)
	ARIMAX([1,5,12],1,[2,20])	Lag 16	NN(1,9,1)
	ARIMAX([1,6,12,20],1,[2])	Lag 16, Lag 22	NN(2,10,1)
	ARIMAX([1,12,20],1,[2,6])	Lag 16, Lag 22	NN(2,15,1)
	ARIMAX([2,12],1,1)	Lag 20, Lag 22	NN(2,2,1)
$Z_{3,t}$	ARIMAX(1,1,[2])	Lag 14, Lag 16	NN(2,7,1)
	ARIMAX([1,2],1,[3])	Lag 16, Lag 20	NN(2,1,1)
	ARIMAX(0,1,1)	Lag 16	NN(1,10,1)
	ARIMAX([1,2,3],1,[4])	Lag 16	NN(1,12,1)
$Z_{4,t}$	ARIMA([1,7],1,2)	Lag 3, Lag 20	NN(2,5,1)
	ARIMAX([3,4],1,[1,11])	Lag 2, Lag 13	NN(2,20,1)
	ARIMAX([2,3],1,[1,4])	Lag 6, Lag 15	NN(2,14,1)
	ARIMAX([1,2,4],1,[3,12])	Lag 13, Lag 20	NN(2,6,1)
	ARIMAX(1,1,[2,3])	Lag 20	NN(1,14,1)
$Z_{5,t}$	ARIMAX([1,3],1,[2])	Lag 9, Lag 11	NN(2,10,1)
	ARIMAX(1,1,[2,3])	Lag 22	NN(1,2,1)
	ARIMAX(1,1,[2,7])	Lag 8, Lag 22	NN(2,20,1)
	ARIMAX([1,7],1,[2])	Lag 15, Lag 22	NN(2,6,1)
	ARIMAX([1,2],1,[3])	Lag 9, Lag 15, Lag 22	NN(3,19,1)
$Z_{6,t}$	ARIMAX(1,0,[9])	Lag 11	NN(1,12,1)
	ARIMAX([9],0,1)	Lag 6, Lag 11	NN(2,6,1)
	ARIMAX([9],0,0)	Lag 1, Lag 11	NN(2,17,1)
	ARIMAX(0,0,[9])	Lag 1, Lag 11, Lag 12	NN(3,19,1)
	ARIMAX([1,9],0,0)	Lag 11	NN(1,2,1)
$Z_{7,t}$	ARIMA(1,0,0)	Lag 9, Lag 18	NN(2,19,1)
	ARIMA(0,0,1)	Lag 9	NN(1,16,1)
	ARIMA([9],0,0)	Lag 1, Lag 4	NN(2,15,1)
	ARIMA(0,0,[9])	Lag 1, Lag 2, Lag 4	NN(3,13,1)
	ARIMA([1,9],0,0)	Lag 4, Lag 8	NN(2,19,1)
$Z_{8,t}$	ARIMA([3],0,0)	Lag 9, Lag 11, Lag 17	NN(3,6,1)
	ARIMA(0,0[3])	Lag 9, Lag 17	NN(2,2,1)
	ARIMA([9],0,0)	Lag 11, Lag 17	NN(2,8,1)
	ARIMA(0,0,[9])	Lag 10, Lag 17	NN(2,3,1)
	ARIMA([3,9],0,0)	Lag 7, Lag 17	NN(2,20,1)

4.4 Hybrid Autoregressive Integrated Moving Average (ARIMA) and Recurrent Neural Networks (RNNs) Ensemble Model for Inflation

Hybrid autoregressive integrated moving average (ARIMA) and recurrent neural networks (RNNs) ensemble is a combination model from ARIMA and RNNs, where the input of RNNs is residual of ARIMA (p,d,q) model. Input of RNNs is determined by PACF of residual ARIMA and number of neuron in hidden layer of RNNs is determined by the smallest mean square root error (MSE) of in sample data. Number of neuron in hidden layer in this research is simulated from 1 to 20 (see appendix 7). The inputs and number of neuron in hidden layer of each model is shown in Table 4.6. This study use Matlab with newelm as function.

Table 4.6 showed that number of input for each model has variation from one input until three inputs and the majority number of input for each model is two inputs. Meanwhile, number of hidden layer has high variation and the majority number of neuron in hidden layer is less than ten neuron. The next step after constructing hybrid ARIMA and RNNs is combining each member by averaging and stacking techniques. Root mean square error of each member is shown in Figure 4.6.

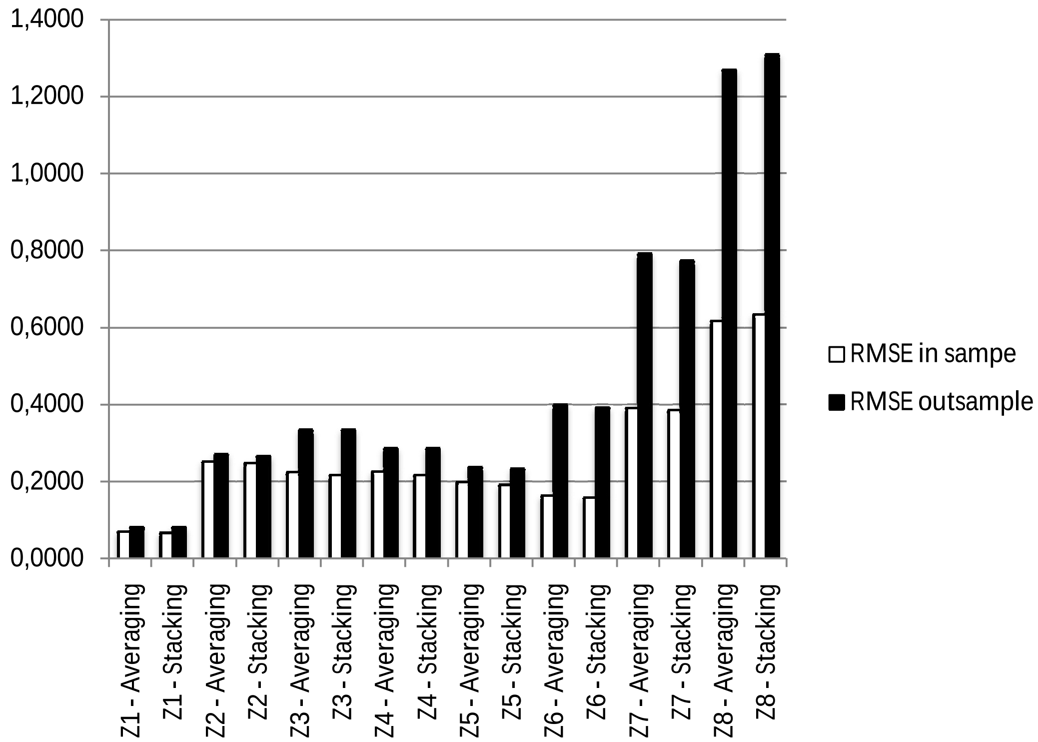


Figure 4.7 RMSE Hybrid ARIMA and RNNs Ensemble

Figure 4.7 showed that RMSE in sample is smaller than RMSE out sample and almost all stacking hybrid ARIMA and RNNs ensemble have smaller RMSE than averaging hybrid ARIMA and RNNs ensemble except sumenep inflation ($Z_{8,t}$) which has smaller RMSE in averaging hybrid ARIMA and RNNs ensemble. Therefore, hybrid ARIMA and RNNs stacking has higher performance to combining ensemble member than averaging.

Table 4.7 Member of Hybrid Autoregressive Integrated Moving Average (ARIMA) and Radial Basis Function Neural Networks (RBFNNs) Ensemble

Variable	Model	Input	SPREAD
$Z_{1,t}$	ARIMAX ([1,12],1,[2,8,20])	Lag 14, Lag 19	0.1
	ARIMAX ([1,8,12],1,[2,20])	Lag 14, Lag 16	0.1
	ARIMAX ([1,12,20],1,[2,8])	Lag 14, Lag 19	0.1
	ARIMAX ([1,12,14],1,[2,8,20])	Lag 19	0.1
	ARIMAX ([1,3,12,14],1,[2])	Lag 20, Lag 22	0.1
$Z_{2,t}$	ARIMAX([1,5,12,19],1,[2,14])	Lag 19, Lag 20	0.1
	ARIMAX([1,5,12],1,[2,20])	Lag 16	0.3
	ARIMAX([1,6,12,20],1,[2])	Lag 16, Lag 22	2.6
	ARIMAX([1,12,20],1,[2,6])	Lag 16, Lag 22	2.2
	ARIMAX([2,12],1,1)	Lag 20, Lag 22	1.2
$Z_{3,t}$	ARIMAX(1,1,[2])	Lag 14, Lag 16	1.7
	ARIMAX([1,2],1,[3])	Lag 16, Lag 20	0.4
	ARIMAX(0,1,1)	Lag 16	0.1
	ARIMAX([1,2,3],1,[4])	Lag 16	0.1
$Z_{4,t}$	ARIMA([1,7],1,2)	Lag 3, Lag 20	0.9
	ARIMAX([3,4],1,[1,11])	Lag 2, Lag 13	0.6
	ARIMAX([2,3],1,[1,4])	Lag 6, Lag 15	0.4
	ARIMAX([1,2,4],1,[3,12])	Lag 13, Lag 20	0.7
	ARIMAX(1,1,[2,3])	Lag 20	0.3
$Z_{5,t}$	ARIMAX([1,3],1,[2])	Lag 9, Lag 11	0.5
	ARIMAX(1,1,[2,3])	Lag 22	0.7
	ARIMAX(1,1,[2,7])	Lag 8, Lag 22	0.4
	ARIMAX([1,7],1,[2])	Lag 15, Lag 22	0.6
	ARIMAX([1,2],1,[3])	Lag 9, Lag 15, Lag 22	1.5
$Z_{6,t}$	ARIMAX(1,0,[9])	Lag 11	0.8
	ARIMAX([9],0,1)	Lag 6, Lag 11	5.1
	ARIMAX([9],0,0)	Lag 1, Lag 11	0.005
	ARIMAX(0,0,[9])	Lag 1, Lag 11, Lag 12	10.6
	ARIMAX([1,9],0,0)	Lag 11	1.4
$Z_{7,t}$	ARIMA(1,0,0)	Lag 9, Lag 18	0.1
	ARIMA(0,0,1)	Lag 9	1.2
	ARIMA([9],0,0)	Lag 1, Lag 4	3.3
	ARIMA(0,0,[9])	Lag 1, Lag 2, Lag 4	0.2
	ARIMA([1,9],0,0)	Lag 4, Lag 8	9.8
$Z_{8,t}$	ARIMA([3],0,0)	Lag 9, Lag 11, Lag 17	0.1
	ARIMA(0,0[3])	Lag 9, Lag 17	16.6
	ARIMA([9],0,0)	Lag 11, Lag 17	10.1
	ARIMA(0,0,[9])	Lag 10, Lag 17	8.2
	ARIMA([3,9],0,0)	Lag 7, Lag 17	0.053

4.5 Hybrid Autoregressive Integrated Moving Average (ARIMA) and Radial Basis Function Neural Networks (RBFNNs) Ensemble Model for Inflation

Hybrid autoregressive integrated moving average (ARIMA) and radial basis function neural networks (RBFNNs) ensemble is a combination model from ARIMA and RBFNNs, where the input of RBFNNs is residual of ARIMA (p,d,q) model. Input of RBFNNs is the same with input of FFNNs which determined by PACF of residual ARIMA. This study use Matlab with newrbe as function because it has advantages that can produce a network with zero error on training vector. Number of neuron in hidden layer is the same length asoutput of training data. Constant spread is simulated from 0.1 until 5 with increment 0.1 and some models have larger and smaller spread (see Appendix 9). The hybrid ARIMA and RBFNNs model is shown in Table 4.7.

Table 4.7 showed that the majority of RBFNNs have spread between 0.1 and 0.5. There are only two models that have constant spread less than 0.1 and twelve models that have constant spread larger than 0.5. The next step after constructing hybrid ARIMA and RBFNNs is combining each member by averaging and stacking techniques. Root mean square error of each member is shown in Figure 4.8.

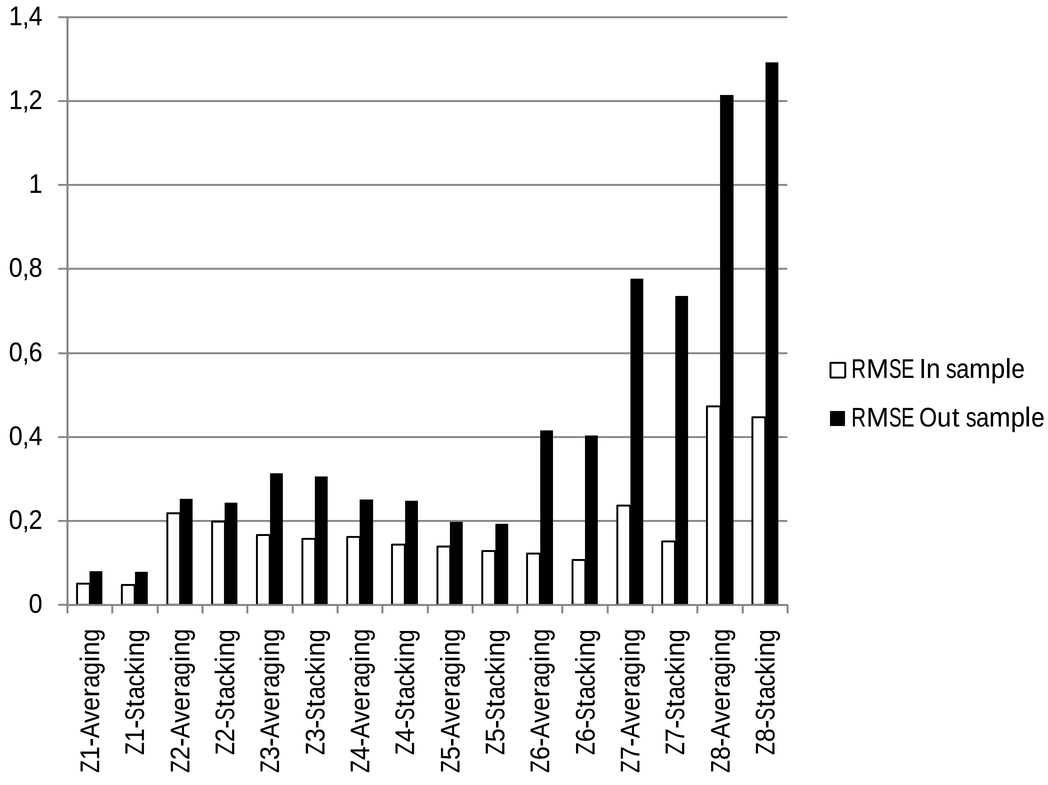


Figure 4.8 RMSE Hybrid ARIMA and RBFNNs Ensemble

Figure 4.8 showed that RMSE in sample is smaller than RMSE out sample and almost all stacking hybrid ARIMA and RBFNNs ensemble have smaller RMSE than averaging hybrid ARIMA and RBFNNs ensemble except sumenep inflation ($Z_{8,t}$) which has smaller RMSE in averaging hybrid ARIMA and RBFNNs ensemble in out sample. Therefore, stacking in hybrid ARIMA and RBFNNs ensemble has high performance to combining ensemble member.

Table 4.8 Member of Hybrid Autoregressive Integrated Moving Average (ARIMA) and Generalized Regression Neural Networks (GRNNs) Ensemble

Variable	Model	Input	SPREAD
$Z_{1,t}$	ARIMAX ([1,12],1,[2,8,20])	Lag 14, Lag 19	0.02
	ARIMAX ([1,8,12],1,[2,20])	Lag 14, Lag 16	0.01
	ARIMAX ([1,12,20],1,[2,8])	Lag 14, Lag 19	0.02
	ARIMAX ([1,12,14],1,[2,8,20])	Lag 19	0.02
	ARIMAX ([1,3,12,14],1,[2])	Lag 20, Lag 22	0.04
$Z_{2.t}$	ARIMAX([1,5,12,19],1,[2,14])	Lag 19, Lag 20	0.08
	ARIMAX([1,5,12],1,[2,20])	Lag 16	0.01
	ARIMAX([1,6,12,20],1,[2])	Lag 16, Lag 22	0.09
	ARIMAX([1,12,20],1,[2,6])	Lag 16, Lag 22	0.06
	ARIMAX([2,12],1,1)	Lag 20, Lag 22	0.06
$Z_{3.t}$	ARIMAX(1,1,[2])	Lag 14, Lag 16	0.1
	ARIMAX([1,2],1,[3])	Lag 16, Lag 20	0.07
	ARIMAX(0,1,1)	Lag 16	0.01
	ARIMAX([1,2,3],1,[4])	Lag 16	0.06
$Z_{4.t}$	ARIMA([1,7],1,2)	Lag 3, Lag 20	0.03
	ARIMAX([3,4],1,[1,11])	Lag 2, Lag 13	0.02
	ARIMAX([2,3],1,[1,4])	Lag 6, Lag 15	0.05
	ARIMAX([1,2,4],1,[3,12])	Lag 13, Lag 20	0.04
	ARIMAX(1,1,[2,3])	Lag 20	0.04
$Z_{5.t}$	ARIMAX([1,3],1,[2])	Lag 9, Lag 11	0.07
	ARIMAX(1,1,[2,3])	Lag 22	0.09
	ARIMAX(1,1,[2,7])	Lag 8, Lag 22	0.05
	ARIMAX([1,7],1,[2])	Lag 15, Lag 22	0.03
	ARIMAX([1,2],1,[3])	Lag 9, Lag 15, Lag 22	0.09
$Z_{6.t}$	ARIMAX(1,0,[9])	Lag 11	0.2
	ARIMAX([9],0,1)	Lag 6, Lag 11	0.15
	ARIMAX([9],0,0)	Lag 1, Lag 11	0.2
	ARIMAX(0,0,[9])	Lag 1, Lag 11, Lag 12	0.01
	ARIMAX([1,9],0,0)	Lag 11	0.3
$Z_{7.t}$	ARIMA(1,0,0)	Lag 9, Lag 18	0.18
	ARIMA(0,0,1)	Lag 9	0.09
	ARIMA([9],0,0)	Lag 1, Lag 4	0.04
	ARIMA(0,0,[9])	Lag 1, Lag 2, Lag 4	0.06
	ARIMA([1,9],0,0)	Lag 4, Lag 8	0.05
$Z_{8.t}$	ARIMA([3],0,0)	Lag 9, Lag 11, Lag 17	0.35
	ARIMA(0,0[3])	Lag 9, Lag 17	0.02
	ARIMA([9],0,0)	Lag 11, Lag 17	0.3
	ARIMA(0,0,[9])	Lag 10, Lag 17	0.15
	ARIMA([3,9],0,0)	Lag 7, Lag 17	0.1

4.6 Hybrid Autoregressive Integrated Moving Average (ARIMA) and Generalized Regression Neural Networks (GRNNs) Ensemble Model for Inflation

Hybrid autoregressive integrated moving average (ARIMA) and generalized regression neural networks (GRNNs) ensemble is a combination model from ARIMA and GRNNs. where the input of GRNNs is residual of ARIMA (p.d.q) model. Input of GRNNs is the same with input of FFNNs which determined by PACF of residual ARIMA. This study use Matlab with newgrnn as function. Number of neuron in hidden layer is the same length as output of training data. Constant spread is simulated from 0.01 until 0.5 with increment 0.01 (see Appendix 11). The hybrid ARIMA and GRNNs model is shown in Table 4.8.

Table 4.8 showed that the majority of GRNNs have spread less than 0.1. There are only nine models that have constant spread more than 0.1. The next step after constructing hybrid ARIMA and GRNNs is combining each member by averaging and stacking techniques. Root mean square error of each member is shown in Figure 4.9.

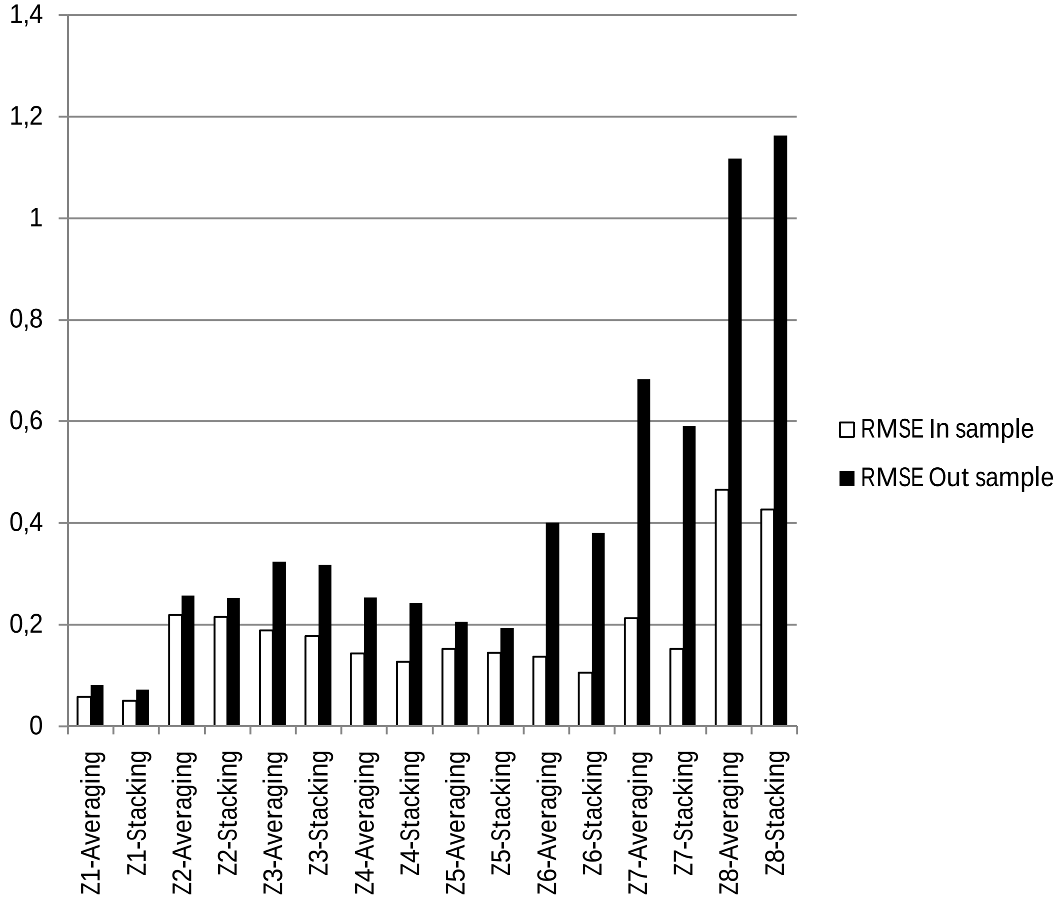


Figure 4.9 RMSE Hybrid ARIMA and GRNNs Ensemble

Figure 4.9 showed that RMSE in sample is less than RMSE out sample and almost all stacking hybrid ARIMA and GRNNs ensemble have smaller RMSE than averaging hybrid ARIMA and RBFNNs ensemble except sumenep inflation ($Z_{8.t}$) which has smaller RMSE in averaging hybrid ARIMA and GRNNs ensemble in out sample. Therefore. stacking hybrid ARIMA and GRNNs ensemble has higher performance to combining ensemble member than averaging hybrid ARIMA and GRNNs ensemble.

Table 4.9 RMSE of Autoregressive Integrated Moving Average (ARIMA) for National Inflation and Seven Cities in East Java

Variable	Model	RMSE Training	RMSE Testing
$Z_{1.t}$	**ARIMAX ([1,12],1,[2,8,20])***	**0.071**	**0.078**
	ARIMAX ([1,8,12],1,[2,20])	0.073	0.082
	ARIMAX ([1,12,20],1,[2,8])	0.075	0.083
	ARIMAX ([1,12,14],1,[2,8,20])	0.075	0.081
	ARIMAX ([1,3,12,14],1,[2])	0.068	0.083
$Z_{2.t}$	**ARIMAX([1,5,12,19],1,[2,14])***	**0.257**	**0.263**
	ARIMAX([1,5,12],1,[2,20])	0.258	0.264
	ARIMAX([1,6,12,20],1,[2])	0.273	0.283
	ARIMAX([1,12,20],1,[2,6])	0.275	0.280
	ARIMAX([2,12],1,1)	0.263	0.267
$Z_{3.t}$	ARIMAX(1,1,[2])	0.224	0.336
	ARIMAX([1,2],1,[3])	0.255	0.336
	ARIMAX(0,1,1)	0.225	0.338
	ARIMAX([1,2,3],1,[4])*	**0.268**	**0.334**
$Z_{4.t}$	ARIMA([1,7],1,2)	0.318	0.289
	ARIMAX([3,4],1,[1,11])	0.240	0.300
	ARIMAX([2,3],1,[1,4])*	**0.258**	**0.283**
	ARIMAX([1,2,4],1,[3,12])	0.225	0.286
	ARIMAX(1,1,[2,3])	0.243	0.297
$Z_{5.t}$	ARIMAX([1,3],1,[2])	0.212	0.229
	ARIMAX(1,1,[2,3])	0.201	0.225
	ARIMAX(1,1,[2,7])*	**0.233**	**0.223**
	ARIMAX([1,7],1,[2])	0.225	0.234
	ARIMAX([1,2],1,[3])	0.209	0.231
$Z_{6.t}$	ARIMAX(1,0,[9])	0.167	0.407
	ARIMAX([9],0,1)	0.161	0.396
	ARIMAX([9],0,0)	0.180	0.388
	ARIMAX(0,0,[9])	0.182	0.403
	ARIMAX([1,9],0,0)*	**0.164**	**0.372**
$Z_{7.t}$	ARIMA(1,0,0)	0.410	0.830
	ARIMA(0,0,1)	0.410	0.829
	ARIMA([9],0,0)	0.419	0.764
	ARIMA(0,0,[9])*	**0.417**	**0.756**
	ARIMA([1,9],0,0)	0.393	0.769
$Z_{8.t}$	ARIMA([3],0,0)	0.632	1.290
	ARIMA(0,0[3])	0.633	1.300
	ARIMA([9],0,0)	0.632	1.224
	ARIMA(0,0,[9])	0.629	1.216
	ARIMA([3,9],0,0)*	**0.618**	**1.191**

*) ARIMA model which has the smallest RMSE

4.7 Comparison between Hybrid Autoregressive Integrated Moving Average (ARIMA) and Artificial Neural Networks (ANNs) Ensemble Model and Autoregressive Integrated Moving Average (ARIMA) Model

Comparison between hybrid autoregressive integrated moving average (ARIMA) and artificial neural networks ensemble and autoregressive integrated moving average (ARIMA) is used to know does complicated model (in this case is hybrid ARIMA and ANN ensemble) have higher performance than simple method (in this case is ARIMA). To know that. this study using relative root mean square error (RelRMSE) and log mean square error ratio (LMR). All hybrid ARIMA and ANNsensemblemodels for each variable are compared by ARIMA which have the smallest RMSE in testing data. The RMSE of ARIMA is shown in Table 4.9. meanwhile RelRMSE and LMR of hybrid ARIMA and ANNs ensemble is shown in Table 4.10.

Table 4.10 RelRMSE and LMR Hybrid Autoregressive Integrated Moving Average (ARIMA) and Artificial Neural Networks (ANNs) Ensemble for National Inflation and Seven Cities in East Java

Variable	Method	RelRMSE		LMR	
		Training	Testing	Training	Testing
Z1	Hybrid ARIMA-FFNN Averaging	0.971	1.108	-0.058	0.204
	Hybrid ARIMA-FFNN Stacking	0.917	**0.984**	-0.173	**-0.033**
	Hybrid ARIMA-RNN Averaging	0.971	1.029	-0.058	0.058
	Hybrid ARIMA-RNN Stacking	0.923	1.029	-0.161	0.057
	Hybrid ARIMA-RBFNN Averaging	0.717	1.029	-0.665	0.057
	Hybrid ARIMA-RBFNN Stacking	0.663	1.020	-0.822	0.040
	Hybrid ARIMA-GRNN Averaging	0.815	1.029	-0.409	0.057
	Hybrid ARIMA-GRNN Stacking	0.708	**0.913**	-0.690	**-0.183**
Z2	Hybrid ARIMA-FFNN Averaging	0.970	**0.998**	-0.062	**-0.004**
	Hybrid ARIMA-FFNN Stacking	0.959	**0.981**	-0.085	**-0.038**
	Hybrid ARIMA-RNN Averaging	0.977	1.033	-0.046	0.064
	Hybrid ARIMA-RNN Stacking	0.964	1.010	-0.072	0.020
	Hybrid ARIMA-RBFNN Averaging	0.846	**0.959**	-0.335	**-0.084**
	Hybrid ARIMA-RBFNN Stacking	0.768	**0.928**	-0.528	**-0.149**
	Hybrid ARIMA-GRNN Averaging	0.853	**0.976**	-0.319	**-0.049**
	Hybrid ARIMA-GRNN Stacking	0.835	**0.959**	-0.361	**-0.083**
Z3	Hybrid ARIMA-FFNN Averaging	0.801	1.058	-0.445	0.113
	Hybrid ARIMA-FFNN Stacking	0.764	**0.994**	-0.538	**-0.013**
	Hybrid ARIMA-RNN Averaging	0.836	1.000	-0.359	0.001
	Hybrid ARIMA-RNN Stacking	0.807	1.000	-0.428	**-0.001**
	Hybrid ARIMA-RBFNN Averaging	0.622	**0.938**	-0.950	**-0.128**
	Hybrid ARIMA-RBFNN Stacking	0.584	**0.916**	-1.076	**-0.175**
	Hybrid ARIMA-GRNN Averaging	0.706	**0.970**	-0.696	**-0.061**
	Hybrid ARIMA-GRNN Stacking	0.664	**0.951**	-0.820	**-0.100**

Table 4.10 RelRMSE and LMR of Hybrid Autoregressive Integrated Moving Average (ARIMA) and Artificial Neural Networks (ANNs) (continue)

Variable	Method	RelRMSE		LMR	
		Training	Testing	Training	Testing
Z4	Hybrid ARIMA-FFNN Averaging	0.826	**0.983**	-0.382	**-0.034**
	Hybrid ARIMA-FFNN Stacking	0.805	**0.968**	-0.435	**-0.065**
	Hybrid ARIMA-RNN Averaging	0.875	1.009	-0.266	0.018
	Hybrid ARIMA-RNN Stacking	0.835	1.008	-0.360	0.016
	Hybrid ARIMA-RBFNN Averaging	0.625	**0.889**	-0.939	**-0.235**
	Hybrid ARIMA-RBFNN Stacking	0.555	**0.874**	-1.177	**-0.268**
	Hybrid ARIMA-GRNN Averaging	0.557	**0.892**	-1.169	**-0.228**
	Hybrid ARIMA-GRNN Stacking	0.491	**0.854**	-1.423	**-0.315**
Z5	Hybrid ARIMA-FFNN Averaging	0.824	**0.833**	-0.387	**-0.365**
	Hybrid ARIMA-FFNN Stacking	0.812	**0.820**	-0.416	**-0.397**
	Hybrid ARIMA-RNN Averaging	0.852	1.065	-0.321	0.126
	Hybrid ARIMA-RNN Stacking	0.819	1.044	-0.400	0.086
	Hybrid ARIMA-RBFNN Averaging	0.594	**0.890**	-1.041	**-0.234**
	Hybrid ARIMA-RBFNN Stacking	0.552	**0.869**	-1.187	**-0.281**
	Hybrid ARIMA-GRNN Averaging	0.651	**0.923**	-0.858	**-0.161**
	Hybrid ARIMA-GRNN Stacking	0.621	**0.862**	-0.952	**-0.296**
Z6	Hybrid ARIMA-FFNN Averaging	0.846	1.123	-0.168	0.116
	Hybrid ARIMA-FFNN Stacking	0.841	1.126	-0.173	0.118
	Hybrid ARIMA-RNN Averaging	0.994	1.072	-0.006	0.070
	Hybrid ARIMA-RNN Stacking	0.968	1.052	-0.033	0.051
	Hybrid ARIMA-RBFNN Averaging	0.742	1.117	-0.298	0.110
	Hybrid ARIMA-RBFNN Stacking	0.650	1.086	-0.431	0.082
	Hybrid ARIMA-GRNN Averaging	0.839	1.077	-0.176	0.074
	Hybrid ARIMA-GRNN Stacking	0.643	1.023	-0.441	0.023
Z7	Hybrid ARIMA-FFNN Averaging	0.876	1.064	-0.132	0.062
	Hybrid ARIMA-FFNN Stacking	0.857	1.117	-0.155	0.110
	Hybrid ARIMA-RNN Averaging	0.938	1.047	-0.064	0.046
	Hybrid ARIMA-RNN Stacking	0.925	1.023	-0.078	0.022
	Hybrid ARIMA-RBFNN Averaging	0.568	1.029	-0.566	0.028
	Hybrid ARIMA-RBFNN Stacking	0.361	**0.974**	-1.019	**-0.026**
	Hybrid ARIMA-GRNN Averaging	0.510	**0.904**	-0.672	**-0.101**
	Hybrid ARIMA-GRNN Stacking	0.365	**0.781**	-1.009	**-0.247**
Z8	Hybrid ARIMA-FFNN Averaging	0.905	1.104	-0.099	0.099
	Hybrid ARIMA-FFNN Stacking	0.893	1.182	-0.114	0.167
	Hybrid ARIMA-RNN Averaging	0.998	1.066	-0.002	0.064
	Hybrid ARIMA-RNN Stacking	1.024	1.100	0.024	0.095
	Hybrid ARIMA-RBFNN Averaging	0.765	1.020	-0.267	0.020
	Hybrid ARIMA-RBFNN Stacking	0.723	1.085	-0.325	0.081
	Hybrid ARIMA-GRNN Averaging	0.754	**0.938**	-0.283	**-0.064**
	Hybrid ARIMA-GRNN Stacking	0.690	**0.976**	-0.371	**-0.024**

Performance of forecasting model is evaluation in testing data. because it shows how model generate forecasting value for future. Eventhough. overall hybrid ARIMA and ANNs ensemble has much higher performance than ARIMA model in training but in testing only some hybrid ARIMA and ANNs have higher performance than ARIMA for each variable because RelRMSE has less than 1 and LMR has less than 0 (Table 4.10). However. hybrid ARIMA and ANNs ensemble in Probolinggo inflation ($Z_{6.t}$) has lower performance than ARIMA because RelRMSE has more than 1 and LMR has more than 0. Overall. stacking technique has higher performance than averaging to combine the hybrid ARIMA and ANNs ensemble. In addition. hybrid ARIMA and GRNNs ensemble has higher performance than the rest of other hybrid ARIMA and ANNs.

Summary of the best models which have the smallest RMSE, RelRMSE which less than 1 and LMR which less than 0 is shown in Table 4.11

Table 4.11 The Best Model for National Inflation and Seven Cities in East Java

Variable	Method	RMSE	RelRMSE	LMR
Z1	Hybrid ARIMA-GRNN Stacking	0.072	0.913	-0.183
Z2	Hybrid ARIMA-RBFNN Stacking	0.244	0.928	-0.149
Z3	Hybrid ARIMA-RBFNN Stacking	0.306	0.916	-0.175
Z4	Hybrid ARIMA-GRNN Stacking	0.242	0.854	-0.315
Z5	Hybrid ARIMA-GRNN Stacking	0.192	0.862	-0.296
Z6	ARIMAX([1,9],0,0)	0.372	1.000	0.000
Z7	Hybrid ARIMA-GRNN Stacking	0.590	0.781	-0.247
Z8	Hybrid ARIMA-GRNN Averaging	1.116	0.938	-0.064

CHAPTER 5
CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

In this research hybrid autoregressive integrated moving average (ARIMA) and artificial neural networks (ANNs) are used with varying input while the training data unchanged to create ensemble members for forecasting purpose. Meanwhile, averaging and stacking techniques are used to combine the ensemble members. The networks of ANNs in this study are feedforward neural networks (FFNNs), recurrent neural networks (RNNs), radial basis function neural networks (RBFNNs) and generalized regression neural networks (GRNNs). There are five ensemble members for each variable except Malang inflation ($Z_{3.t}$)which has only four ensemble members. The input of ANNs is PACF of residual ARIMA. The best network in hybrid ARIMA and ANNs is determined by the best root mean square error of training data. Meanwhile, the best model is determined by the smallest RMSE, RelRMSE less than 1 and LMR more than 0 in testing data. In general,hybrid ARIMA and ANNs gives better performance than ARIMA for each variable.Also, stacking technique give better performance than averaging to combine the hybrid ARIMA and ANNs ensembles. In addition, hybrid ARIMA and GRNNs ensemble gives higher performance than the other hybrid ARIMA and ANNs.

5.2 Recommendations

To improve forecasting accuracy in this research, future research can be done in the following directions:

1. Create ensemble members of hybrid ARIMA and ANNsensemble usingother data training methodologies such as bootstrap and boosting.
2. Stepwise regression can be used to determine inputs of ANNs in hybrid ARIMA and ANNs ensemble

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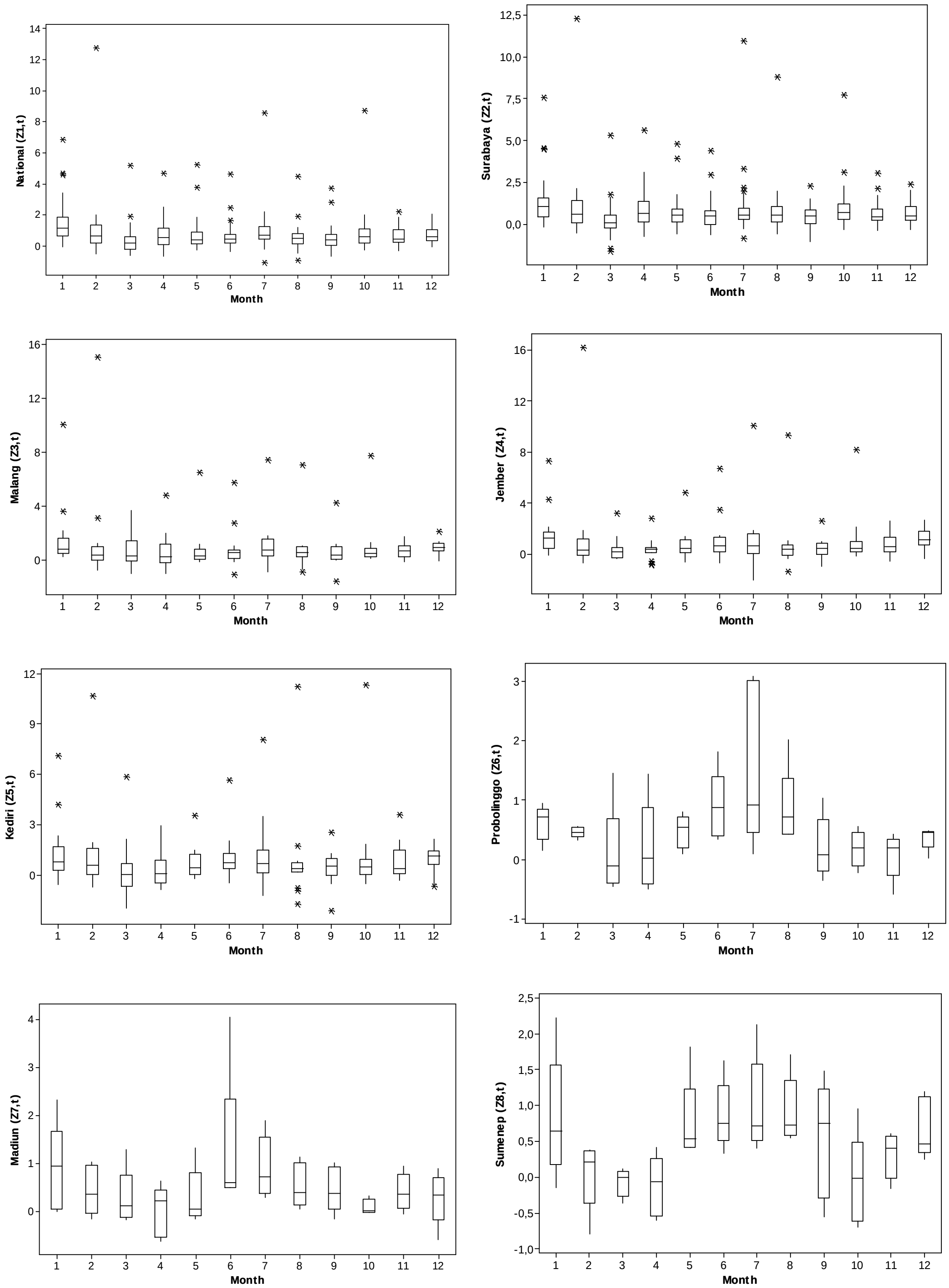
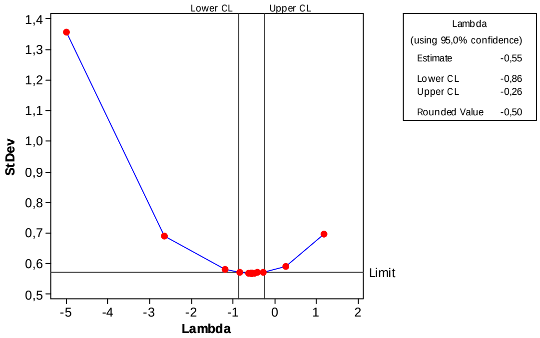
APPENDICES

Appendix 1: Box Plot for Inflation of Seven Cities in East Java

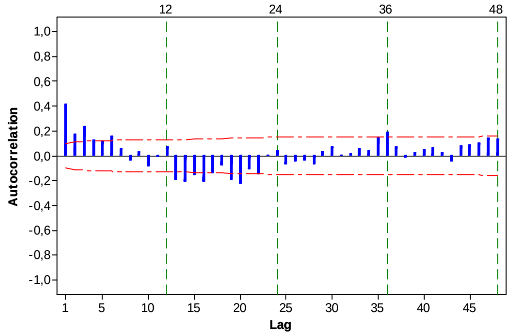


Appendix 2: Box-Cox Transformation. ACF and PACF Graph for Inflation of Seven Cities in East Java

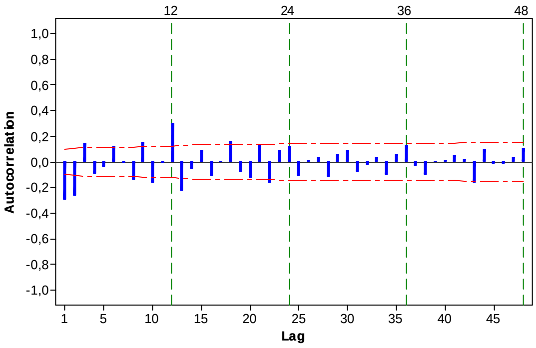
- National Infation ($Z_{1.t}$)



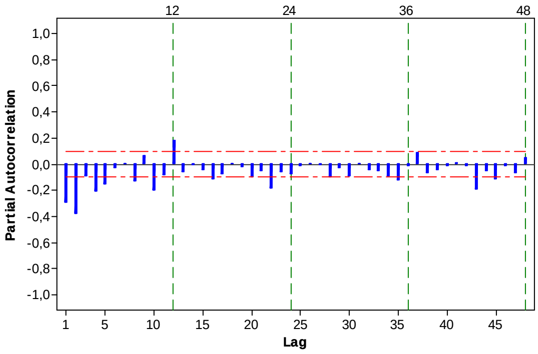
(a) Box-Cox Transformation of $Z_{1.t}$



(b) ACF of transformation $Z_{1.t}$

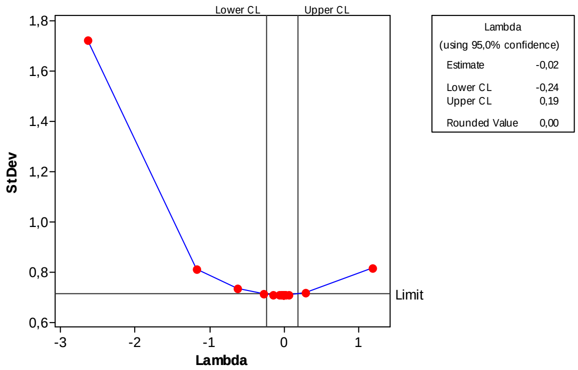


(c) ACF of $Z_{1.t}$ with d=1

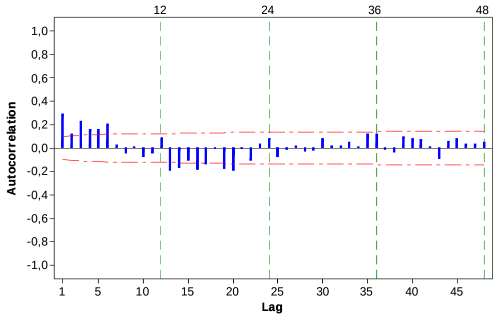


(d) PACF of $Z_{1.t}$ with d=1

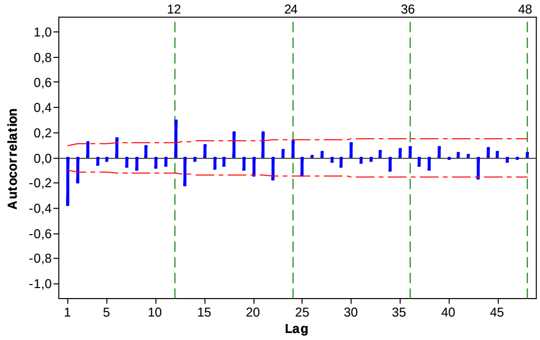
- Surabaya Inflation ($Z_{2.t}$)



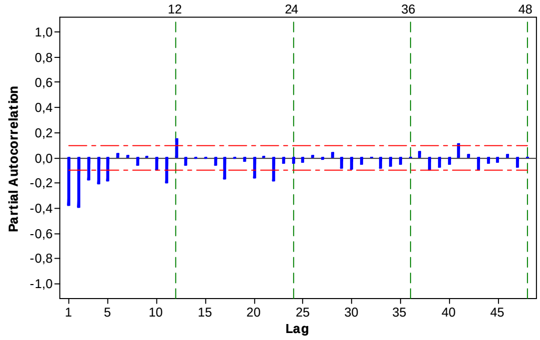
(a) Box-Cox Transformation of $Z_{2.t}$



(b) ACF of transformation $Z_{2.t}$

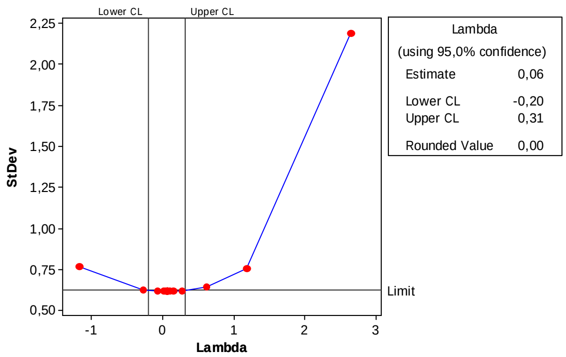


(c) ACF of $Z_{2.t}$ with d=1

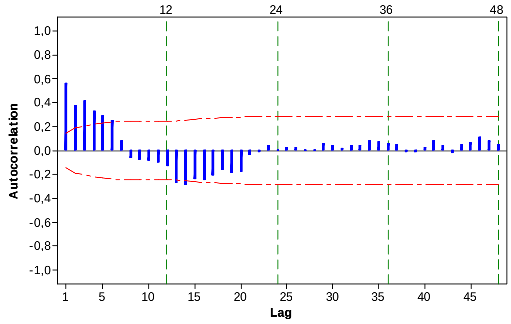


(d) PACF of $Z_{2.t}$ with d=1

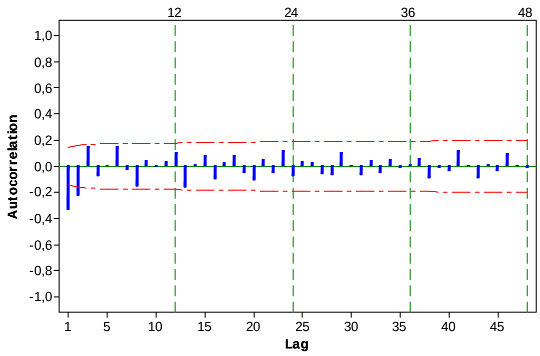
- Malang Inflation ($Z_{3.t}$)



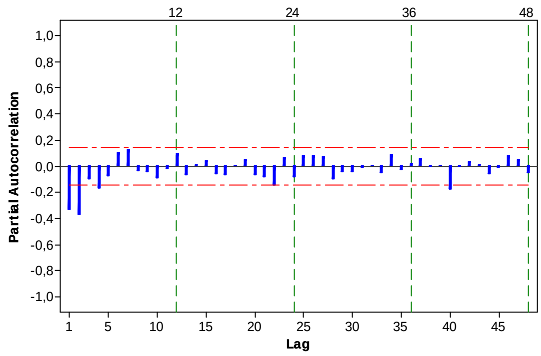
(a) Box-Cox Transformation of $Z_{3.t}$



(b) ACF of transformation $Z_{3.t}$

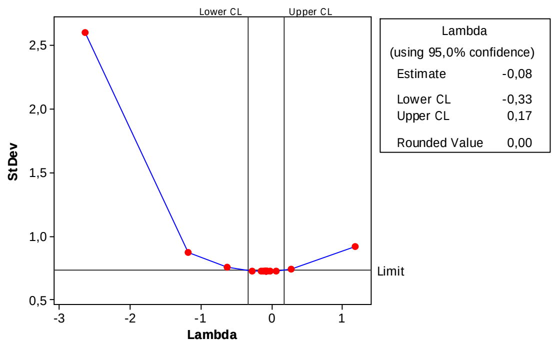


(c) ACF of $Z_{3.t}$ with d=1

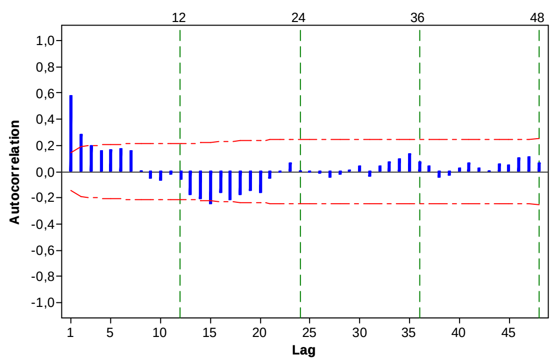


(d) PACF of $Z_{3.t}$ with d=1

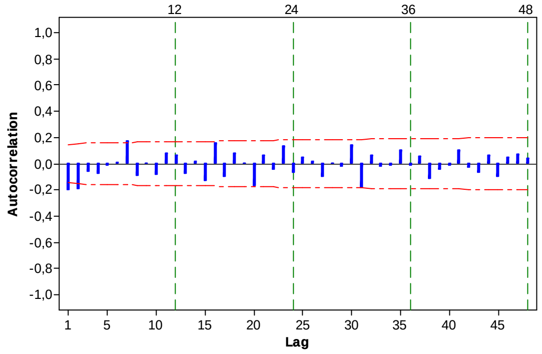
- Jember Inflation ($Z_{4.t}$)



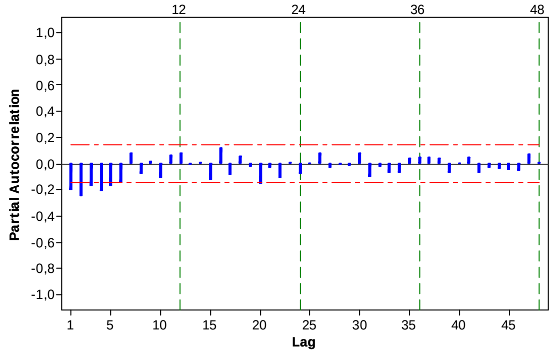
(a) Box-Cox Transformation of $Z_{4.t}$



(b) ACF of transformation $Z_{4.t}$

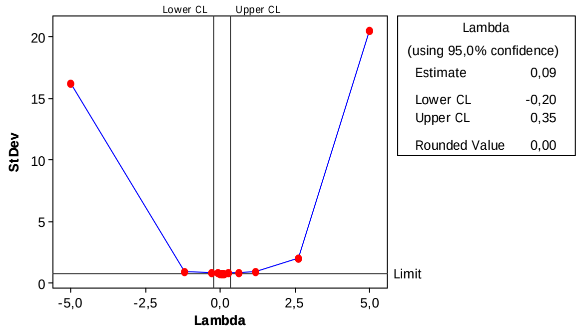


(c) ACF of $Z_{4,t}$ with d=1

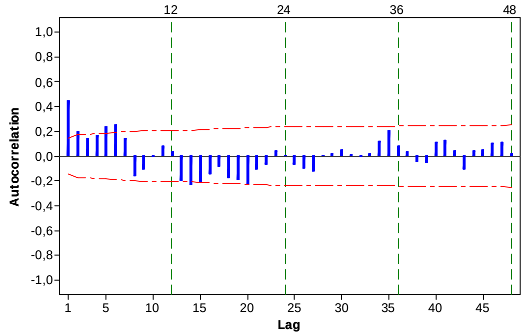


(d) PACF of $Z_{4,t}$ with d=1

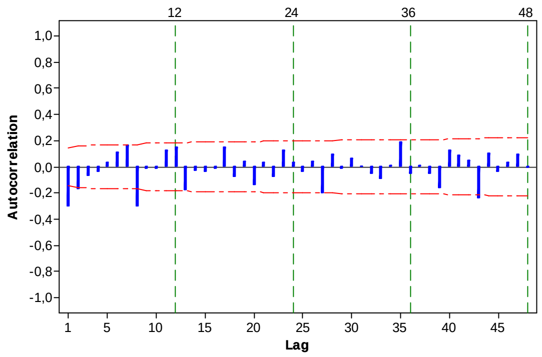
- Kediri Inflation ($Z_{5,t}$)



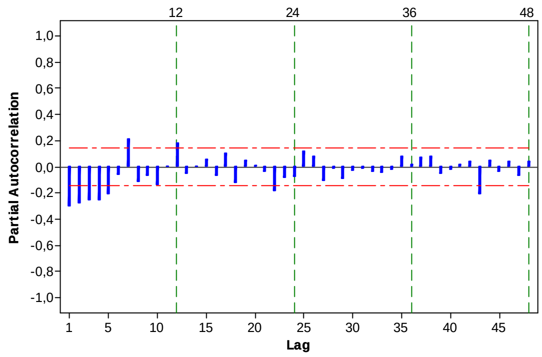
(a) Box-Cox Transformation of $Z_{5,t}$



(b) ACF of transformation $Z_{5,t}$

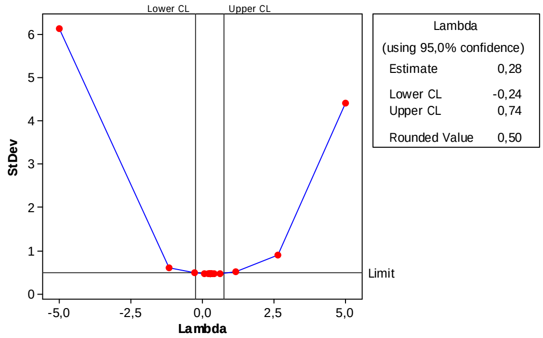


(c) ACF of $Z_{5,t}$ with d=1

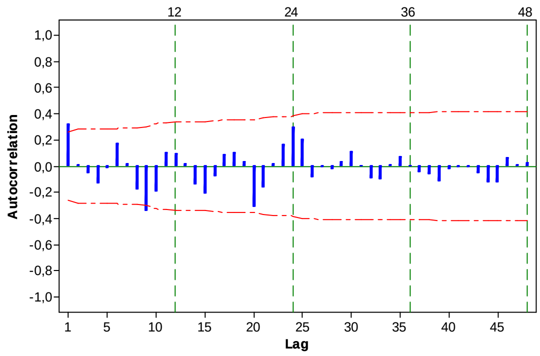


(d) PACF of $Z_{5,t}$ with d=1

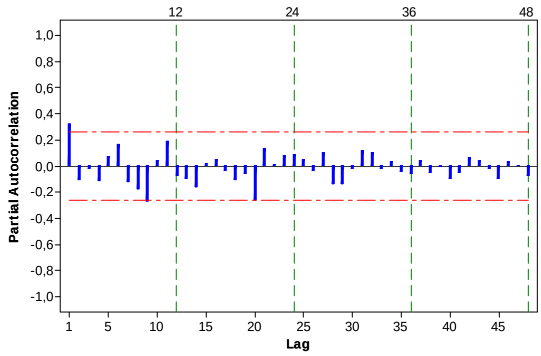
- Probolinggo Inflation ($Z_{6.t}$)



(a) Box-Cox Transformati$_{on}$ of $Z_{6.t}$

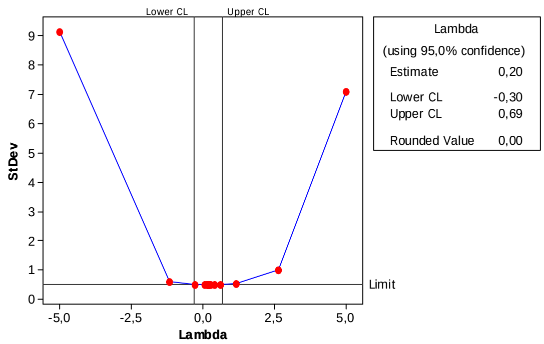


(b) ACF of transformation $Z_{6.t}$

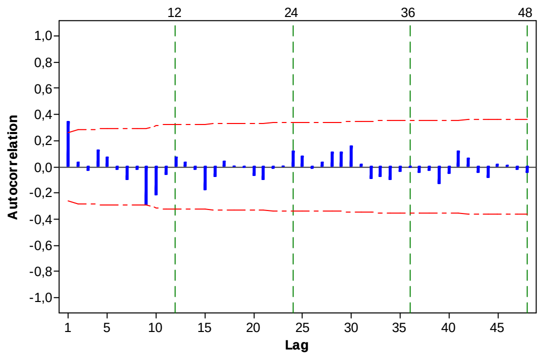


(c) PACF of transformation $Z_{6.t}$

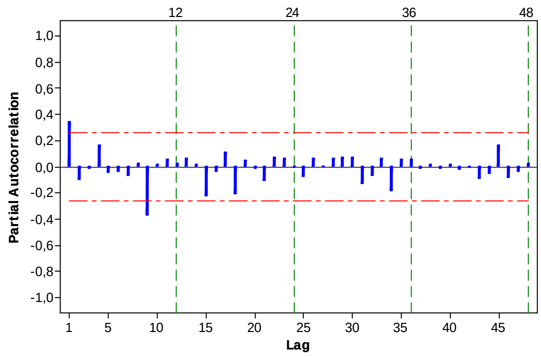
- Madiun Inflation ($Z_{7.t}$)



(a) Box-Cox Transformation of $Z_{6.t}$

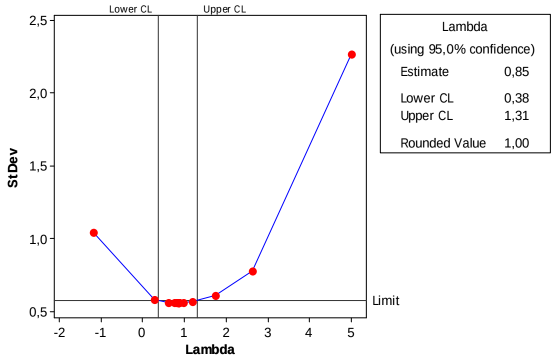


(b) ACF of transformation $Z_{7.t}$

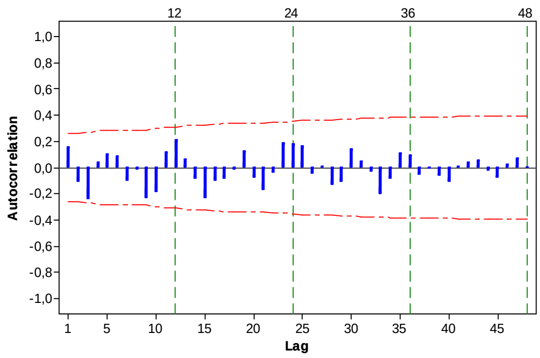


(c) PACF of transformation $Z_{7.t}$

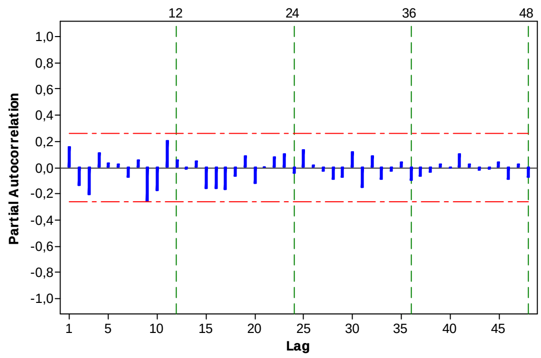
- Sumenep Inflation ($Z_{8.t}$)



(a) Box-Cox Transformation of $Z_{8.t}$



(b) ACF of transformation $Z_{8.t}$



(c) PACF of transformation $Z_{8.t}$

Appendix 3: SAS Output ARIMA Model for Inflation

- National Inflation ($Z_{1,t}$)

The ARIMA Procedure
Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MA1.1	0.59110	0.04610	12.82	<.0001	2	z1	0
MA1.2	0.20921	0.04242	4.93	<.0001	8	z1	0
MA1.3	0.11726	0.03847	3.05	0.0023	20	z1	0
AR1.1	-0.50636	0.04635	-10.93	<.0001	1	z1	0
AR1.2	0.31332	0.04456	7.03	<.0001	12	z1	0
NUM1	0.42226	0.06547	6.45	<.0001	0	aonum235	0
NUM2	0.25775	0.05727	4.50	<.0001	0	aonum226	0
NUM3	0.24837	0.06356	3.91	<.0001	0	aonum236	0
NUM4	0.16792	0.05802	2.89	0.0038	0	aonum232	0
NUM5	-0.15264	0.05630	-2.71	0.0067	0	aonum081	0
NUM6	-0.18539	0.05630	-3.29	0.0010	0	aonum303	0
NUM7	0.20832	0.05645	3.69	0.0002	0	aonum195	0

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	3.78	1	0.0519	0.007	-0.002	-0.053	0.000	-0.076	0.027
12	6.50	7	0.4825	-0.047	0.027	0.022	0.001	-0.030	-0.049
18	19.42	13	0.1108	-0.060	-0.135	-0.048	-0.044	-0.056	0.047
24	29.00	19	0.0659	-0.079	-0.040	-0.059	-0.008	0.071	0.080
30	36.37	25	0.0662	-0.034	0.050	0.014	-0.079	0.066	0.053

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.993485	Pr < W	0.0865
Kolmogorov-Smirnov	D	0.038409	Pr > D	>0.1500
Cramer-von Mises	W-Sq	0.143923	Pr > W-Sq	0.0294
Anderson-Darling	A-Sq	0.821899	Pr > A-Sq	0.0352

The ARIMA Procedure
Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MA1.1	0.48716	0.05002	9.74	<.0001	2	z1	0
MA1.2	0.13297	0.04547	2.92	0.0035	20	z1	0
AR1.1	-0.47243	0.04695	-10.06	<.0001	1	z1	0
AR1.2	-0.09182	0.04421	-2.08	0.0378	8	z1	0
AR1.3	0.27058	0.04242	6.38	<.0001	12	z1	0
NUM1	0.36159	0.06550	5.52	<.0001	0	aonum235	0
NUM2	0.26380	0.05922	4.45	<.0001	0	aonum226	0
NUM3	0.24708	0.06588	3.75	0.0002	0	aonum236	0
NUM4	-0.20531	0.05925	-3.46	0.0005	0	aonum310	0
NUM5	0.21731	0.06073	3.58	0.0003	0	aonum039	0

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	1.85	1	0.1743	-0.019	-0.013	-0.034	-0.006	-0.009	0.053
12	8.09	7	0.3251	-0.076	-0.013	-0.073	-0.045	-0.021	-0.040
18	21.09	13	0.0712	-0.078	-0.122	-0.015	-0.100	-0.006	0.018
24	28.31	19	0.0776	-0.051	-0.027	0.014	-0.023	0.078	0.084
30	34.41	25	0.0994	-0.004	0.008	-0.005	-0.078	0.087	0.024

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.989125	Pr < W	0.0049
Kolmogorov-Smirnov	D	0.0462	Pr > D	0.0397
Cramer-von Mises	W-Sq	0.193644	Pr > W-Sq	0.0065
Anderson-Darling	A-Sq	1.14207	Pr > A-Sq	0.0056

The ARIMA Procedure
Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MA1.1	0.59888	0.04550	13.16	<.0001	2	z1	0
MA1.2	0.18795	0.04268	4.40	<.0001	8	z1	0
AR1.1	-0.49600	0.04661	-10.64	<.0001	1	z1	0
AR1.2	0.26158	0.04475	5.84	<.0001	12	z1	0
AR1.3	-0.10415	0.04261	-2.44	0.0145	20	z1	0
NUM1	0.26139	0.05974	4.38	<.0001	0	aonum235	0
NUM2	0.28269	0.05987	4.72	<.0001	0	aonum226	0
NUM3	0.20933	0.05942	3.52	0.0004	0	aonum195	0

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	--------------------Autocorrelations--------------------					
6	2.87	1	0.0902	0.015	0.027	-0.047	0.012	-0.062	-0.003
12	4.73	7	0.6934	-0.024	0.046	-0.004	-0.002	-0.027	-0.034
18	20.34	13	0.0870	-0.083	-0.146	-0.050	-0.074	-0.028	0.031
24	29.58	19	0.0575	-0.087	-0.046	-0.057	-0.052	0.040	0.070
30	34.23	25	0.1030	-0.038	0.050	-0.016	-0.051	0.059	0.026

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.990065	Pr < W	0.0090
Kolmogorov-Smirnov	D	0.041889	Pr > D	0.0902
Cramer-von Mises	W-Sq	0.168752	Pr > W-Sq	0.0145
Anderson-Darling	A-Sq	1.033132	Pr > A-Sq	0.0100

The ARIMA Procedure
Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MA1.1	0.56355	0.04718	11.95	<.0001	2	z1	0
MA1.2	0.16263	0.04378	3.71	0.0002	8	z1	0
MA1.3	0.10269	0.04073	2.52	0.0117	20	z1	0
AR1.1	-0.52364	0.04843	-10.81	<.0001	1	z1	0
AR1.2	0.29485	0.04445	6.63	<.0001	12	z1	0
AR1.3	-0.11751	0.04469	-2.63	0.0086	14	z1	0
NUM1	0.28129	0.06165	4.56	<.0001	0	aonum235	0
NUM2	0.26309	0.06208	4.24	<.0001	0	aonum226	0

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	--------------------Autocorrelations--------------------					
6	.	0	.	0.026	-0.016	-0.048	0.012	-0.064	-0.008
12	6.28	6	0.3921	-0.017	0.015	-0.016	-0.002	-0.049	-0.070
18	13.83	12	0.3116	-0.053	-0.063	-0.076	-0.050	-0.047	0.034
24	24.45	18	0.1409	-0.108	-0.060	-0.008	-0.015	0.069	0.072
30	30.26	24	0.1762	-0.035	0.073	-0.051	-0.046	0.019	0.044

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.990347	Pr < W	0.0108
Kolmogorov-Smirnov	D	0.043019	Pr > D	0.0754
Cramer-von Mises	W-Sq	0.193342	Pr > W-Sq	0.0066
Anderson-Darling	A-Sq	1.087892	Pr > A-Sq	0.0078

The ARIMA Procedure
Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MA1.1	0.94807	0.02756	34.40	<.0001	2	z1	0
AR1.1	-0.72058	0.04152	-17.35	<.0001	1	z1	0
AR1.2	-0.13630	0.03958	-3.44	0.0006	3	z1	0
AR1.3	0.28597	0.03927	7.28	<.0001	12	z1	0
AR1.4	-0.19571	0.03926	-4.99	<.0001	14	z1	0
NUM1	0.18995	0.06368	2.98	0.0029	0	aonum235	0
NUM2	0.23259	0.04317	5.39	<.0001	0	lsnum232	0
NUM3	-0.22046	0.03367	-6.55	<.0001	0	lsnum238	0
NUM4	-0.23161	0.02433	-9.52	<.0001	0	lsnum214	0
NUM5	0.18204	0.05997	3.04	0.0024	0	aonum032	0
NUM6	0.21369	0.03532	6.05	<.0001	0	lsnum226	0

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	1.61	1	0.2051	0.030	0.024	0.004	-0.012	-0.032	0.036
12	2.71	7	0.9104	-0.009	-0.013	-0.026	0.033	0.000	0.027
18	7.17	13	0.8933	0.055	0.016	-0.005	-0.041	0.015	0.074
24	25.47	19	0.1458	-0.067	-0.156	0.018	-0.098	0.070	0.006
30	32.53	25	0.1431	-0.051	0.006	-0.018	-0.051	0.090	0.053

Tests for Normality

Test	Statistic		p Value	
Shapiro-Wilk	W	0.992323	Pr < W	0.0398
Kolmogorov-Smirnov	D	0.044498	Pr > D	0.0560
Cramer-von Mises	W-Sq	0.140863	Pr > W-Sq	0.0329
Anderson-Darling	A-Sq	0.753787	Pr > A-Sq	0.0493

- Surabaya Inflation ($Z_{2.t}$)

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MA1.1	0.84943	0.09092	9.34	<.0001	2	z2	0
MA1.2	0.14636	0.05171	2.83	0.0046	14	z2	0
AR1.1	-0.76046	0.06739	-11.28	<.0001	1	z2	0
AR1.2	-0.14142	0.04179	-3.38	0.0007	5	z2	0
AR1.3	0.18808	0.03157	5.96	<.0001	12	z2	0
AR1.4	0.09194	0.02930	3.14	0.0017	19	z2	0
NUM1	-1.79872	0.23344	-7.71	<.0001	0	aonum123	0
NUM2	-1.53414	0.23490	-6.53	<.0001	0	aonum39	0
NUM3	-1.15142	0.11231	-10.25	<.0001	0	lsnum226	0
NUM4	1.07392	0.11216	9.57	<.0001	0	lsnum217	0
NUM5	1.06851	0.23268	4.59	<.0001	0	aonum310	0
NUM6	-0.89737	0.23447	-3.83	0.0001	0	aonum267	0
NUM7	0.88792	0.24098	3.68	0.0002	0	aonum25	0
NUM8	0.87527	0.24338	3.60	0.0003	0	aonum37	0

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	.	0	.	0.047	0.010	-0.023	0.028	0.016	0.017
12	7.09	6	0.3125	-0.061	-0.073	-0.060	0.021	-0.017	-0.004
18	9.09	12	0.6954	-0.022	0.030	-0.008	-0.031	0.035	0.034
24	24.10	18	0.1518	-0.110	-0.113	0.044	-0.064	0.061	0.034
30	27.67	24	0.2743	-0.034	-0.037	-0.035	-0.034	-0.036	0.046

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.99451	Pr < W	0.1697
Kolmogorov-Smirnov	D	0.037076	Pr > D	>0.1500
Cramer-von Mises	W-Sq	0.073756	Pr > W-Sq	>0.2500
Anderson-Darling	A-Sq	0.549801	Pr > A-Sq	0.1612

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MA1.1	0.74269	0.04673	15.89	<.0001	2	z2	0
MA1.2	0.19737	0.03978	4.96	<.0001	20	z2	0
AR1.1	-0.66553	0.04320	-15.41	<.0001	1	z2	0
AR1.2	-0.13045	0.03674	-3.55	0.0004	5	z2	0
AR1.3	0.18460	0.03638	5.07	<.0001	12	z2	0
NUM1	-1.86761	0.21650	-8.63	<.0001	0	aonum123	0
NUM2	-1.48054	0.22844	-6.48	<.0001	0	aonum39	0
NUM3	-1.29518	0.12448	-10.40	<.0001	0	lsnum226	0
NUM4	1.22664	0.12379	9.91	<.0001	0	lsnum217	0
NUM5	1.00507	0.21740	4.62	<.0001	0	aonum310	0
NUM6	-0.81355	0.21768	-3.74	0.0002	0	aonum267	0
NUM7	0.85738	0.23285	3.68	0.0002	0	aonum25	0
NUM8	0.89985	0.23169	3.88	0.0001	0	aonum37	0

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	--------------------Autocorrelations--------------------					
6	1.52	1	0.2171	-0.026	-0.002	-0.055	-0.010	-0.001	-0.001
12	9.19	7	0.2390	-0.080	-0.074	-0.063	0.040	-0.005	0.037
18	15.31	13	0.2883	-0.034	-0.044	-0.009	-0.102	0.012	-0.034
24	24.38	19	0.1819	-0.053	-0.045	0.062	-0.004	0.068	0.090
30	27.54	25	0.3296	-0.010	-0.002	-0.043	-0.031	-0.052	0.041

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.991341	Pr < W	0.0207
Kolmogorov-Smirnov	D	0.035992	Pr > D	>0.1500
Cramer-von Mises	W-Sq	0.074192	Pr > W-Sq	0.2483
Anderson-Darling	A-Sq	0.620486	Pr > A-Sq	0.1067

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MA1.1	0.56461	0.05079	11.12	<.0001	2	z2	0
AR1.1	-0.58169	0.04356	-13.35	<.0001	1	z2	0
AR1.2	0.13010	0.04082	3.19	0.0014	6	z2	0
AR1.3	0.16185	0.04017	4.03	<.0001	12	z2	0
AR1.4	-0.18495	0.03782	-4.89	<.0001	20	z2	0
NUM1	-1.73970	0.22867	-7.61	<.0001	0	aonum123	0
NUM2	-1.04859	0.19832	-5.29	<.0001	0	lsnum225	0
NUM3	1.12521	0.22986	4.90	<.0001	0	aonum310	0
NUM4	-1.50465	0.23304	-6.46	<.0001	0	aonum039	0
NUM5	-0.92865	0.22926	-4.05	<.0001	0	aonum267	0
NUM6	0.80190	0.19970	4.02	<.0001	0	lsnum238	0

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	--------------------Autocorrelations--------------------					
6	1.57	1	0.2100	-0.034	-0.015	0.014	0.044	-0.014	0.015
12	3.38	7	0.8480	-0.013	-0.050	-0.034	-0.016	0.018	0.008
18	13.71	13	0.3947	-0.046	-0.076	-0.038	-0.117	-0.025	-0.037
24	20.49	19	0.3655	-0.065	-0.019	-0.002	-0.091	0.044	0.036
30	22.15	25	0.6272	-0.013	-0.006	-0.007	0.018	-0.036	0.044

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.988492	Pr < W	0.0033
Kolmogorov-Smirnov	D	0.038916	Pr > D	>0.1500
Cramer-von Mises	W-Sq	0.072913	Pr > W-Sq	>0.2500
Anderson-Darling	A-Sq	0.57654	Pr > A-Sq	0.1381

The ARIMA Procedure
Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MA1.1	0.54957	0.05080	10.82	<.0001	2	z2	0
MA1.2	-0.11297	0.04723	-2.39	0.0168	6	z2	0
AR1.1	-0.58302	0.04427	-13.17	<.0001	1	z2	0
AR1.2	0.17386	0.04008	4.34	<.0001	12	z2	0
AR1.3	-0.16684	0.03949	-4.22	<.0001	20	z2	0
NUM1	-1.73451	0.23124	-7.50	<.0001	0	aonum123	0
NUM2	-1.10631	0.20204	-5.48	<.0001	0	lsnum225	0
NUM3	1.10611	0.23150	4.78	<.0001	0	aonum310	0
NUM4	-1.46673	0.23661	-6.20	<.0001	0	aonum039	0
NUM5	-0.96247	0.23172	-4.15	<.0001	0	aonum267	0
NUM6	0.84388	0.20450	4.13	<.0001	0	lsnum238	0

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	--------------------Autocorrelations--------------------					
6	1.83	1	0.1755	-0.025	-0.031	0.026	0.031	-0.004	0.036
12	6.48	7	0.4850	-0.068	-0.064	-0.035	-0.032	0.009	0.020
18	15.55	13	0.2741	-0.056	-0.066	-0.037	-0.112	-0.022	-0.001
24	23.62	19	0.2113	-0.088	-0.015	-0.003	-0.083	0.048	0.044
30	24.79	25	0.4741	-0.017	-0.015	0.014	-0.002	-0.019	0.041

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.988016	Pr < W	0.0025
Kolmogorov-Smirnov	D	0.037247	Pr > D	>0.1500
Cramer-von Mises	W-Sq	0.074457	Pr > W-Sq	0.2468
Anderson-Darling	A-Sq	0.590197	Pr > A-Sq	0.1283

The ARIMA Procedure
Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MA1.1	0.81371	0.03383	24.06	<.0001	1	z2	0
AR1.1	-0.12113	0.05498	-2.20	0.0276	2	z2	0
AR1.2	0.25736	0.04950	5.20	<.0001	12	z2	0
NUM1	-1.75221	0.24386	-7.19	<.0001	0	aonum123	0
NUM2	-1.22899	0.14736	-8.34	<.0001	0	lsnum225	0
NUM3	1.24606	0.24405	5.11	<.0001	0	aonum310	0
NUM4	-0.66788	0.14719	-4.54	<.0001	0	lsnum231	0
NUM5	1.11109	0.14535	7.64	<.0001	0	lsnum217	0
NUM6	-1.43886	0.24712	-5.82	<.0001	0	aonum039	0
NUM7	-0.93270	0.24446	-3.82	0.0001	0	aonum267	0
NUM8	0.76741	0.24524	3.13	0.0018	0	aonum184	0

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	--------------------Autocorrelations--------------------					
6	4.35	3	0.2262	0.046	-0.023	0.039	-0.041	-0.045	0.055
12	6.94	9	0.6429	-0.059	-0.042	-0.001	-0.029	0.014	-0.009
18	15.30	15	0.4302	-0.086	0.052	0.036	-0.061	0.032	0.065
24	31.53	21	0.0652	-0.092	-0.093	0.070	-0.111	0.066	0.010
30	33.51	27	0.1808	-0.003	-0.005	-0.019	-0.051	-0.034	0.020
36	42.70	33	0.1202	0.034	-0.013	-0.026	0.044	0.075	0.108

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.989746	Pr < W	0.0073
Kolmogorov-Smirnov	D	0.04337	Pr > D	0.0708
Cramer-von Mises	W-Sq	0.104388	Pr > W-Sq	0.0988
Anderson-Darling	A-Sq	0.720236	Pr > A-Sq	0.0626

- Malang Inflation ($Z_{3,t}$)

The ARIMA Procedure
Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MA1.1	0.88557	0.04469	19.81	<.0001	2	z3	0
AR1.1	-0.79299	0.05786	-13.70	<.0001	1	z3	0
NUM1	-1.37040	0.13622	-10.06	<.0001	0	lsnum15	0
NUM2	1.00857	0.10774	9.36	<.0001	0	lsnum22	0
NUM3	1.13393	0.21144	5.36	<.0001	0	aonum94	0
NUM4	-0.64820	0.13674	-4.74	<.0001	0	lsnum10	0
NUM5	-0.98854	0.20819	-4.75	<.0001	0	aonum44	0
NUM6	-0.64999	0.18993	-3.42	0.0006	0	lsnum03	0

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	--------------------Autocorrelations--------------------					
6	2.61	4	0.6248	0.040	0.036	0.036	0.037	0.049	0.078
12	9.75	10	0.4626	-0.044	-0.086	-0.091	0.027	0.075	0.115
18	19.62	16	0.2381	-0.073	-0.151	0.006	-0.123	-0.039	-0.072
24	27.68	22	0.1866	-0.059	-0.169	-0.044	-0.050	-0.044	0.032
30	31.99	28	0.2749	0.030	-0.043	-0.028	-0.000	0.105	0.074

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.975698	Pr < W	0.0032
Kolmogorov-Smirnov	D	0.056124	Pr > D	>0.1500
Cramer-von Mises	W-Sq	0.09576	Pr > W-Sq	0.1307
Anderson-Darling	A-Sq	0.796585	Pr > A-Sq	0.0401

The ARIMA Procedure
Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MA1.1	0.39925	0.09975	4.00	<.0001	3	z3	0
AR1.1	-0.69370	0.07051	-9.84	<.0001	1	z3	0
AR1.2	-0.60365	0.08476	-7.12	<.0001	2	z3	0
NUM1	-1.38483	0.24470	-5.66	<.0001	0	aonum21	0
NUM2	-1.16576	0.18039	-6.46	<.0001	0	lsnum15	0
NUM3	1.19334	0.23990	4.97	<.0001	0	aonum94	0
NUM4	-0.76114	0.17987	-4.23	<.0001	0	lsnum10	0

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	--------------------Autocorrelations--------------------					
6	1.57	3	0.6670	-0.001	-0.008	-0.010	-0.022	0.069	0.055
12	7.65	9	0.5697	0.066	-0.026	-0.105	0.026	0.091	0.083
18	13.72	15	0.5470	-0.024	-0.079	0.040	-0.149	-0.001	0.006
24	22.57	21	0.3671	-0.100	-0.172	-0.038	-0.026	0.030	0.030
30	25.15	27	0.5663	0.021	-0.002	-0.087	-0.047	0.043	0.009

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.969471	Pr < W	0.0006
Kolmogorov-Smirnov	D	0.062983	Pr > D	0.0822
Cramer-von Mises	W-Sq	0.144451	Pr > W-Sq	0.0286
Anderson-Darling	A-Sq	1.025227	Pr > A-Sq	0.0105

The ARIMA Procedure
Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MA1.1	0.96397	0.02307	41.79	<.0001	1	z3	0
NUM1	-1.24550	0.13533	-9.20	<.0001	0	lsnum15	0
NUM2	0.83635	0.10112	8.27	<.0001	0	lsnum22	0
NUM3	1.35647	0.22403	6.05	<.0001	0	aonum94	0
NUM4	-0.63637	0.13098	-4.86	<.0001	0	lsnum10	0
NUM5	-0.98331	0.24006	-4.10	<.0001	0	aonum21	0
NUM6	-0.64610	0.17852	-3.62	0.0003	0	lsnum03	0

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	--------------------Autocorrelations--------------------					
6	3.03	5	0.6956	0.069	-0.047	0.068	0.050	0.025	0.042
12	10.49	11	0.4868	0.073	-0.035	-0.133	0.018	0.099	0.069
18	20.89	17	0.2312	-0.049	-0.103	-0.018	-0.184	-0.041	0.061
24	27.45	23	0.2374	-0.060	-0.163	-0.031	0.000	0.024	0.023
30	32.20	29	0.3110	0.039	-0.014	-0.091	-0.001	0.100	0.045

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.983485	Pr < W	0.0327
Kolmogorov-Smirnov	D	0.045893	Pr > D	>0.1500
Cramer-von Mises	W-Sq	0.061651	Pr > W-Sq	>0.2500
Anderson-Darling	A-Sq	0.512888	Pr > A-Sq	0.2005

The ARIMA Procedure
Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MA1.1	0.36394	0.09905	3.67	0.0002	4	z3	0
AR1.1	-0.68134	0.07403	-9.20	<.0001	1	z3	0
AR1.2	-0.56867	0.08801	-6.46	<.0001	2	z3	0
AR1.3	-0.37789	0.09807	-3.85	0.0001	3	z3	0
NUM1	-1.21046	0.19159	-6.32	<.0001	0	lsnum15	0
NUM2	1.23418	0.25676	4.81	<.0001	0	aonum94	0
NUM3	-0.67991	0.19260	-3.53	0.0004	0	lsnum10	0
NUM4	-0.70500	0.22767	-3.10	0.0020	0	lsnum03	0

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	--------------------Autocorrelations--------------------					
6	2.51	2	0.2850	-0.016	-0.034	-0.003	0.019	0.061	0.089
12	7.61	8	0.4720	-0.016	-0.067	-0.011	0.048	0.096	0.100
18	11.61	14	0.6378	-0.042	-0.061	-0.005	-0.107	0.027	0.049
24	19.27	20	0.5044	0.004	-0.105	0.027	-0.049	0.151	0.014
30	23.75	26	0.5902	0.071	-0.023	-0.089	-0.058	0.064	0.009

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.966575	Pr < W	0.0003
Kolmogorov-Smirnov	D	0.058696	Pr > D	0.1347
Cramer-von Mises	W-Sq	0.181437	Pr > W-Sq	0.0091
Anderson-Darling	A-Sq	1.29288	Pr > A-Sq	<0.0050

- Jember Inflation ($Z_{4.t}$)

The ARIMA Procedure
Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MA1.1	0.45293	0.07326	6.18	<.0001	2
AR1.1	-0.36435	0.07356	-4.95	<.0001	1
AR1.2	0.18121	0.07035	2.58	0.0100	7

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	--------------------Autocorrelations--------------------					
6	6.72	3	0.0815	0.026	0.032	-0.151	-0.077	-0.066	0.041
12	8.79	9	0.4572	-0.013	0.045	-0.020	-0.011	0.065	0.062
18	15.05	15	0.4480	-0.058	-0.026	-0.119	0.089	-0.072	0.019
24	22.46	21	0.3735	-0.065	-0.148	0.016	-0.007	0.091	0.037
30	26.24	27	0.5051	0.037	0.012	-0.084	-0.034	-0.050	0.073

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.957552	Pr < W	<0.0001
Kolmogorov-Smirnov	D	0.065994	Pr > D	0.0556
Cramer-von Mises	W-Sq	0.224256	Pr > W-Sq	<0.0050
Anderson-Darling	A-Sq	1.388472	Pr > A-Sq	<0.0050

The ARIMA Procedure
Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MA1.1	0.60203	0.05975	10.08	<.0001	1	z4	0
MA1.2	-0.26932	0.06305	-4.27	<.0001	11	z4	0
AR1.1	-0.29603	0.06864	-4.31	<.0001	3	z4	0
AR1.2	-0.29201	0.07185	-4.06	<.0001	4	z4	0
NUM1	-1.61341	0.20283	-7.95	<.0001	0	aonum19	0
NUM2	1.37258	0.19666	6.98	<.0001	0	aonum94	0
NUM3	-1.03984	0.15764	-6.60	<.0001	0	lsnum10	0
NUM4	-0.54942	0.14801	-3.71	0.0002	0	lsnum16	0
NUM5	-0.79499	0.19881	-4.00	<.0001	0	aonum136	0

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	--------------------Autocorrelations--------------------					
6	4.12	2	0.1275	-0.003	-0.140	0.006	-0.029	0.007	0.043
12	8.44	8	0.3916	-0.067	-0.041	0.009	-0.086	0.035	0.087
18	15.20	14	0.3645	-0.157	-0.074	0.021	-0.041	0.045	0.009
24	21.17	20	0.3870	-0.100	-0.064	0.017	-0.090	0.080	0.013
30	34.02	26	0.1346	0.020	0.114	-0.158	-0.000	0.072	0.128

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.9815	Pr < W	0.0178
Kolmogorov-Smirnov	D	0.061454	Pr > D	0.0957
Cramer-von Mises	W-Sq	0.137281	Pr > W-Sq	0.0367
Anderson-Darling	A-Sq	0.804066	Pr > A-Sq	0.0385

The ARIMA Procedure
Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MA1.1	0.57270	0.06776	8.45	<.0001	1	z4	0
MA1.2	0.39111	0.06875	5.69	<.0001	4	z4	0
AR1.1	-0.26464	0.08551	-3.09	0.0020	2	z4	0
AR1.2	-0.26733	0.07177	-3.72	0.0002	3	z4	0
NUM1	1.19767	0.23664	5.06	<.0001	0	aonum94	0
NUM2	0.88512	0.23987	3.69	0.0002	0	aonum02	0
NUM3	0.35408	0.11008	3.22	0.0013	0	lsnum24	0
NUM4	-1.24694	0.15161	-8.22	<.0001	0	lsnum10	0

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	4.66	2	0.0974	0.028	-0.020	-0.046	-0.006	-0.046	-0.140
12	8.35	8	0.3999	0.078	0.007	-0.082	-0.026	0.018	0.074
18	13.57	14	0.4825	-0.015	0.009	-0.140	0.041	-0.004	0.068
24	20.75	20	0.4121	-0.084	-0.116	0.056	-0.080	0.065	0.032
30	31.82	26	0.1991	0.125	0.030	-0.136	-0.003	0.008	0.129

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.925028	Pr < W	<0.0001
Kolmogorov-Smirnov	D	0.065137	Pr > D	0.0632
Cramer-von Mises	W-Sq	0.168325	Pr > W-Sq	0.0146
Anderson-Darling	A-Sq	1.16393	Pr > A-Sq	<0.0050

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MA1.1	0.65516	0.07674	8.54	<.0001	3	z4	0
MA1.2	-0.17035	0.06478	-2.63	0.0085	12	z4	0
AR1.1	-0.54458	0.07305	-7.45	<.0001	1	z4	0
AR1.2	-0.53930	0.07836	-6.88	<.0001	2	z4	0
AR1.3	-0.31233	0.06306	-4.95	<.0001	4	z4	0
NUM1	-1.95629	0.20910	-9.36	<.0001	0	aonum19	0
NUM2	1.49100	0.19602	7.61	<.0001	0	aonum94	0
NUM3	0.76246	0.21255	3.59	0.0003	0	aonum02	0
NUM4	-0.97752	0.13744	-7.11	<.0001	0	lsnum10	0
NUM5	-0.67490	0.19077	-3.54	0.0004	0	aonum136	0
NUM6	-0.93142	0.21076	-4.42	<.0001	0	aonum20	0

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	2.62	1	0.1055	-0.047	0.050	-0.050	-0.070	-0.037	0.028
12	10.12	7	0.1821	0.086	-0.096	0.009	-0.119	0.057	0.073
18	14.86	13	0.3160	-0.112	-0.018	-0.089	-0.057	-0.014	-0.011
24	28.36	19	0.0768	-0.051	-0.163	0.035	-0.142	0.122	0.010
30	41.30	25	0.0214	-0.044	0.055	-0.130	0.074	-0.010	0.181

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.989599	Pr < W	0.2163
Kolmogorov-Smirnov	D	0.059553	Pr > D	0.1216
Cramer-von Mises	W-Sq	0.069413	Pr > W-Sq	>0.2500
Anderson-Darling	A-Sq	0.462357	Pr > A-Sq	>0.2500

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MA1.1	0.66919	0.16035	4.17	<.0001	2	z4	0
MA1.2	0.32306	0.08807	3.67	0.0002	3	z4	0
AR1.1	-0.56640	0.11538	-4.91	<.0001	1	z4	0
NUM1	-1.33709	0.22336	-5.99	<.0001	0	aonum19	0
NUM2	1.20336	0.22062	5.45	<.0001	0	aonum94	0
NUM3	-1.00073	0.12398	-8.07	<.0001	0	lsnum09	0
NUM4	0.87900	0.22472	3.91	<.0001	0	aonum02	0

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	4.80	3	0.1873	0.017	0.063	-0.038	-0.121	0.072	0.023
12	12.94	9	0.1655	0.051	-0.068	-0.054	-0.127	0.065	0.109
18	17.08	15	0.3140	-0.048	-0.039	-0.114	0.047	-0.013	0.042
24	31.44	21	0.0666	0.004	-0.214	0.036	-0.101	0.102	0.049
30	40.67	27	0.0443	0.068	-0.034	-0.126	-0.003	-0.008	0.145

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.994968	Pr < W	0.8096
Kolmogorov-Smirnov	D	0.059642	Pr > D	0.1203
Cramer-von Mises	W-Sq	0.065832	Pr > W-Sq	>0.2500
Anderson-Darling	A-Sq	0.33753	Pr > A-Sq	>0.2500

- Kediri Inflation ($Z_{5.t}$)

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MA1.1	0.58470	0.08102	7.22	<.0001	2	z5	0
AR1.1	-0.50528	0.08377	-6.03	<.0001	1	z5	0
AR1.2	-0.21979	0.06962	-3.16	0.0016	3	z5	0
NUM1	1.39700	0.19306	7.24	<.0001	0	aonum94	0
NUM2	-1.18474	0.19419	-6.10	<.0001	0	aonum27	0
NUM3	-0.75565	0.15450	-4.89	<.0001	0	lsnum09	0
NUM4	-1.04269	0.19445	-5.36	<.0001	0	aonum51	0
NUM5	-1.00796	0.20409	-4.94	<.0001	0	aonum21	0
NUM6	0.61006	0.19356	3.15	0.0016	0	aonum59	0
NUM7	-0.60325	0.19287	-3.13	0.0018	0	aonum32	0
NUM8	-0.68370	0.19269	-3.55	0.0004	0	aonum86	0
NUM9	-0.66632	0.19414	-3.43	0.0006	0	aonum67	0
NUM10	0.50709	0.19469	2.60	0.0092	0	aonum97	0
NUM11	-0.43700	0.19409	-2.25	0.0243	0	aonum61	0
NUM12	-0.58018	0.15394	-3.77	0.0002	0	lsnum15	0

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	--------------------Autocorrelations--------------------					
6	3.60	3	0.3085	0.000	0.076	-0.081	-0.055	-0.032	-0.056
12	13.19	9	0.1542	0.081	-0.069	-0.146	-0.062	0.118	-0.003
18	16.99	15	0.3194	-0.014	-0.054	0.103	-0.037	0.056	0.031
24	22.60	21	0.3657	0.064	-0.125	-0.018	-0.049	0.062	0.036
30	31.10	27	0.2669	-0.045	0.009	-0.156	-0.112	-0.020	0.023

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.975138	Pr < W	0.0027
Kolmogorov-Smirnov	D	0.059432	Pr > D	0.1235
Cramer-von Mises	W-Sq	0.170282	Pr > W-Sq	0.0136
Anderson-Darling	A-Sq	1.097578	Pr > A-Sq	0.0073

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MA1.1	0.64426	0.06959	9.26	<.0001	2	z5	0
MA1.2	0.30915	0.06510	4.75	<.0001	3	z5	0
AR1.1	-0.61142	0.08027	-7.62	<.0001	1	z5	0
NUM1	1.45706	0.18962	7.68	<.0001	0	aonum94	0
NUM2	-1.25481	0.19263	-6.51	<.0001	0	aonum27	0
NUM3	-0.77379	0.14242	-5.43	<.0001	0	lsnum09	0
NUM4	-1.03801	0.19079	-5.44	<.0001	0	aonum51	0
NUM5	-0.87491	0.19726	-4.44	<.0001	0	aonum21	0
NUM6	0.58201	0.19041	3.06	0.0022	0	aonum59	0
NUM7	-0.59806	0.19080	-3.13	0.0017	0	aonum32	0
NUM8	-0.67906	0.19001	-3.57	0.0004	0	aonum86	0
NUM9	-0.69827	0.19009	-3.67	0.0002	0	aonum67	0
NUM10	-0.43326	0.19032	-2.28	0.0228	0	aonum61	0
NUM11	-0.66055	0.13979	-4.73	<.0001	0	lsnum15	0
NUM12	0.48782	0.10264	4.75	<.0001	0	lsnum24	0

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	3.22	3	0.3592	-0.021	-0.063	-0.102	-0.036	0.038	0.011
12	12.48	9	0.1876	0.112	-0.038	-0.126	-0.039	0.129	0.019
18	15.18	15	0.4385	-0.045	-0.026	0.082	-0.051	-0.016	0.036
24	19.79	21	0.5346	0.027	-0.063	-0.005	-0.081	0.097	0.042
30	25.83	27	0.5278	-0.026	0.050	-0.123	-0.057	0.028	0.077

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.983069	Pr < W	0.0287
Kolmogorov-Smirnov	D	0.058383	Pr > D	0.1395
Cramer-von Mises	W-Sq	0.114825	Pr > W-Sq	0.0747
Anderson-Darling	A-Sq	0.733452	Pr > A-Sq	0.0564

The ARIMA Procedure
Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MA1.1	0.80619	0.06432	12.53	<.0001	2	z5	0
MA1.2	-0.18078	0.06201	-2.92	0.0036	7	z5	0
AR1.1	-0.49943	0.07427	-6.72	<.0001	1	z5	0
NUM1	-1.07588	0.20254	-5.31	<.0001	0	aonum27	0
NUM2	-0.87487	0.15255	-5.74	<.0001	0	lsnum09	0
NUM3	-0.99190	0.18912	-5.24	<.0001	0	aonum51	0
NUM4	-1.02756	0.20835	-4.93	<.0001	0	aonum21	0
NUM5	-0.57490	0.19342	-2.97	0.0030	0	aonum32	0
NUM6	-0.81397	0.19270	-4.22	<.0001	0	aonum44	0
NUM7	-0.81050	0.15271	-5.31	<.0001	0	aonum67	0
NUM8	0.83108	0.19620	4.24	<.0001	0	aonum13	0
NUM9	0.38193	0.11758	3.25	0.0012	0	aonum106	0
NUM10	-0.54507	0.15011	-3.63	0.0003	0	lsnum15	0

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	1.51	3	0.6793	0.025	0.068	0.028	-0.026	-0.036	0.018
12	7.98	9	0.5358	0.063	-0.151	-0.081	-0.007	-0.016	0.022
18	10.06	15	0.8159	-0.043	-0.054	0.059	-0.008	0.040	-0.025
24	14.29	21	0.8568	-0.015	-0.074	-0.014	-0.090	0.080	0.006
30	15.15	27	0.9673	0.017	-0.007	-0.042	-0.042	-0.010	-0.006

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.971011	Pr < W	0.0009
Kolmogorov-Smirnov	D	0.052507	Pr > D	>0.1500
Cramer-von Mises	W-Sq	0.079478	Pr > W-Sq	0.2165
Anderson-Darling	A-Sq	0.661776	Pr > A-Sq	0.0861

The ARIMA Procedure
Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MA1.1	0.72811	0.06322	11.52	<.0001	2	z5	0
AR1.1	-0.48881	0.07337	-6.66	<.0001	1	z5	0
AR1.2	0.16577	0.07190	2.31	0.0211	7	z5	0
NUM1	-1.16973	0.19695	-5.94	<.0001	0	aonum27	0
NUM2	-0.81580	0.16340	-4.99	<.0001	0	lsnum09	0
NUM3	-1.05355	0.19672	-5.36	<.0001	0	aonum51	0
NUM4	-1.04966	0.19641	-5.34	<.0001	0	aonum21	0
NUM5	0.35020	0.18818	1.86	0.0627	0	aonum59	0
NUM6	-0.50349	0.18594	-2.71	0.0068	0	aonum32	0
NUM7	-0.39255	0.16580	-2.37	0.0179	0	aonum86	0
NUM8	-0.86882	0.18835	-4.61	<.0001	0	aonum44	0
NUM9	-0.98536	0.18453	-5.34	<.0001	0	aonum67	0
NUM10	0.86167	0.18527	4.65	<.0001	0	aonum13	0
NUM11	0.49704	0.17249	2.88	0.0040	0	aonum106	0
NUM12	0.39108	0.19081	2.05	0.0404	0	aonum176	0
NUM13	-0.44184	0.15825	-2.79	0.0052	0	lsnum15	0

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	2.42	3	0.4906	0.003	0.037	0.002	-0.047	-0.096	0.013
12	4.18	9	0.8989	0.033	-0.028	-0.078	0.017	0.022	0.023
18	7.16	15	0.9531	-0.054	-0.057	0.086	0.003	0.032	-0.023
24	11.23	21	0.9580	-0.019	-0.079	-0.070	-0.076	0.044	0.025
30	13.71	27	0.9840	-0.010	-0.013	0.017	-0.097	-0.015	-0.035

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.951014	Pr < W	<0.0001
Kolmogorov-Smirnov	D	0.058723	Pr > D	0.1343
Cramer-von Mises	W-Sq	0.130792	Pr > W-Sq	0.0441
Anderson-Darling	A-Sq	1.090972	Pr > A-Sq	0.0076

The ARIMA Procedure
Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MA1.1	0.60792	0.07948	7.65	<.0001	3	z5	0
AR1.1	-0.50568	0.07982	-6.34	<.0001	1	z5	0
AR1.2	-0.49304	0.08015	-6.15	<.0001	2	z5	0
NUM1	1.44316	0.18838	7.66	<.0001	0	aonum94	0
NUM2	-1.08159	0.18795	-5.75	<.0001	0	aonum27	0
NUM3	-0.78383	0.15549	-5.04	<.0001	0	lsnum09	0
NUM4	-0.90692	0.18697	-4.85	<.0001	0	aonum51	0
NUM5	-0.90800	0.19228	-4.72	<.0001	0	aonum21	0
NUM6	0.69604	0.18321	3.80	0.0001	0	aonum59	0
NUM7	-0.64410	0.18295	-3.52	0.0004	0	aonum32	0
NUM8	-0.64003	0.18321	-3.49	0.0005	0	aonum86	0
NUM9	-0.71721	0.18483	-3.88	0.0001	0	aonum67	0
NUM10	0.59673	0.19042	3.13	0.0017	0	aonum97	0
NUM11	-0.47926	0.18647	-2.57	0.0102	0	aonum61	0
NUM12	-0.52027	0.15203	-3.42	0.0006	0	lsnum15	0

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	2.88	3	0.4113	0.021	-0.009	-0.000	-0.108	-0.000	0.058
12	11.63	9	0.2350	0.048	-0.067	-0.134	-0.079	0.120	0.021
18	16.68	15	0.3381	-0.033	-0.056	0.097	-0.053	0.071	0.064
24	22.18	21	0.3894	0.019	-0.107	-0.029	-0.080	0.074	0.046
30	33.95	27	0.1676	-0.072	0.015	-0.164	-0.147	0.031	0.012

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.980125	Pr < W	0.0117
Kolmogorov-Smirnov	D	0.051998	Pr > D	>0.1500
Cramer-von Mises	W-Sq	0.120842	Pr > W-Sq	0.0610
Anderson-Darling	A-Sq	0.780527	Pr > A-Sq	0.0434

- Probolinggo Inflation ($Z_{6.t}$)

The ARIMA Procedure
Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MU	1.16491	0.02587	45.02	<.0001	0	z6	0
MA1.1	0.39098	0.14816	2.64	0.0083	9	z6	0
AR1.1	0.41708	0.13058	3.19	0.0014	1	z6	0
NUM1	0.60550	0.14902	4.06	<.0001	0	aonum31	0
NUM2	0.54737	0.16414	3.33	0.0009	0	aonum07	0
NUM3	0.68715	0.16191	4.24	<.0001	0	aonum56	0
NUM4	-0.46982	0.14888	-3.16	0.0016	0	aonum11	0

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	5.88	4	0.2084	0.083	-0.186	-0.005	-0.093	0.008	0.196
12	13.79	10	0.1829	-0.012	0.019	-0.015	-0.187	0.248	0.087
18	20.76	16	0.1879	-0.141	-0.107	-0.002	-0.054	0.163	0.148
24	30.64	22	0.1038	-0.007	-0.095	-0.186	-0.030	0.177	0.155

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.973344	Pr < W	0.2121
Kolmogorov-Smirnov	D	0.103017	Pr > D	0.1122
Cramer-von Mises	W-Sq	0.088428	Pr > W-Sq	0.1608
Anderson-Darling	A-Sq	0.599536	Pr > A-Sq	0.1169

The ARIMA Procedure
Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MU	1.16631	0.02452	47.56	<.0001	0	z6	0
MA1.1	-0.56078	0.12249	-4.58	<.0001	1	z6	0
AR1.1	-0.41226	0.12982	-3.18	0.0015	9	z6	0
NUM1	0.57973	0.12718	4.56	<.0001	0	aonum31	0
NUM2	0.44820	0.14243	3.15	0.0017	0	aonum07	0
NUM3	0.76965	0.13807	5.57	<.0001	0	aonum56	0
NUM4	-0.51107	0.12689	-4.03	<.0001	0	aonum11	0

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	2.57	4	0.6316	0.000	0.022	0.044	-0.045	0.001	0.182
12	10.23	10	0.4207	-0.040	0.066	0.073	-0.172	0.246	-0.025
18	13.71	16	0.6203	-0.053	-0.100	0.031	-0.072	0.149	0.012
24	20.65	22	0.5427	-0.005	-0.084	-0.132	-0.016	0.136	0.162

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.969223	Pr < W	0.1337
Kolmogorov-Smirnov	D	0.101176	Pr > D	0.1286
Cramer-von Mises	W-Sq	0.109916	Pr > W-Sq	0.0845
Anderson-Darling	A-Sq	0.662516	Pr > A-Sq	0.0834

The ARIMA Procedure
Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MU	1.16021	0.01724	67.30	<.0001	0	z6	0
AR1.1	-0.48294	0.11950	-4.04	<.0001	9	z6	0
NUM1	0.69167	0.16347	4.23	<.0001	0	aonum31	0
NUM2	0.64102	0.17993	3.56	0.0004	0	aonum07	0
NUM3	0.59193	0.17999	3.29	0.0010	0	aonum56	0
NUM4	-0.41965	0.16339	-2.57	0.0102	0	aonum11	0

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	8.84	5	0.1156	0.340	0.024	0.008	-0.060	-0.005	0.136
12	13.86	11	0.2409	0.041	0.116	0.126	-0.100	0.154	0.054
18	18.98	17	0.3297	-0.143	-0.140	-0.009	0.005	0.133	0.066
24	31.03	23	0.1220	-0.056	-0.090	-0.199	-0.065	0.161	0.202

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.969958	Pr < W	0.1452
Kolmogorov-Smirnov	D	0.093023	Pr > D	>0.1500
Cramer-von Mises	W-Sq	0.082086	Pr > W-Sq	0.1984
Anderson-Darling	A-Sq	0.614066	Pr > A-Sq	0.1063

The ARIMA Procedure
Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MU	1.16017	0.01731	67.00	<.0001	0	z6	0
MA1.1	0.38923	0.14316	2.72	0.0066	9	z6	0
NUM1	0.70799	0.17548	4.03	<.0001	0	aonum31	0
NUM2	0.70184	0.18786	3.74	0.0002	0	aonum07	0
NUM3	0.60048	0.18866	3.18	0.0015	0	aonum56	0
NUM4	-0.39671	0.17645	-2.25	0.0246	0	aonum11	0

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	--------------------Autocorrelations--------------------					
6	10.13	5	0.0717	0.354	-0.000	-0.053	-0.075	0.016	0.156
12	14.39	11	0.2120	0.048	0.028	0.004	-0.142	0.167	0.074
18	24.17	17	0.1149	-0.146	-0.164	-0.035	0.007	0.185	0.179
24	34.93	23	0.0529	0.000	-0.083	-0.203	-0.053	0.154	0.184

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.965902	Pr < W	0.0918
Kolmogorov-Smirnov	D	0.09926	Pr > D	0.1457
Cramer-von Mises	W-Sq	0.111064	Pr > W-Sq	0.0818
Anderson-Darling	A-Sq	0.742352	Pr > A-Sq	0.0500

The ARIMA Procedure
Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MU	1.16043	0.02133	54.41	<.0001	0	z6	0
AR1.1	0.35021	0.11151	3.14	0.0017	1	z6	0
AR1.2	-0.43629	0.11146	-3.91	<.0001	9	z6	0
NUM1	0.66708	0.14599	4.57	<.0001	0	aonum31	0
NUM2	0.54017	0.15921	3.39	0.0007	0	aonum07	0
NUM3	0.63677	0.15790	4.03	<.0001	0	aonum56	0
NUM4	-0.45107	0.14540	-3.10	0.0019	0	aonum11	0

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	--------------------Autocorrelations--------------------					
6	5.14	4	0.2736	0.106	-0.150	-0.013	-0.089	-0.014	0.188
12	12.21	10	0.2715	-0.008	0.052	0.081	-0.107	0.257	0.083
18	16.66	16	0.4080	-0.109	-0.092	0.007	-0.046	0.158	0.074
24	27.92	22	0.1783	-0.059	-0.092	-0.193	-0.045	0.178	0.177

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.973395	Pr < W	0.2132
Kolmogorov-Smirnov	D	0.108935	Pr > D	0.0765
Cramer-von Mises	W-Sq	0.109	Pr > W-Sq	0.0866
Anderson-Darling	A-Sq	0.665513	Pr > A-Sq	0.0821

- Madiun Inflation ($Z_{7,t}$)

The ARIMA Procedure
Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.30993	0.08391	3.69	0.0002	0
AR1.1	0.36802	0.12163	3.03	0.0025	1

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	--------------------Autocorrelations--------------------					
6	2.85	5	0.7232	0.017	-0.093	-0.105	0.145	0.044	-0.014
12	12.84	11	0.3041	-0.105	0.139	-0.277	-0.132	-0.006	0.110
18	16.33	17	0.5006	0.017	0.034	-0.182	-0.035	0.079	-0.005
24	18.95	23	0.7041	0.016	-0.042	-0.091	0.024	-0.041	0.117

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.973771	Pr < W	0.2223
Kolmogorov-Smirnov	D	0.083987	Pr > D	>0.1500
Cramer-von Mises	W-Sq	0.078112	Pr > W-Sq	0.2220
Anderson-Darling	A-Sq	0.53441	Pr > A-Sq	0.1715

The ARIMA Procedure
Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.30644	0.07230	4.24	<.0001	0
MA1.1	-0.35615	0.12364	-2.88	0.0040	1

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	--------------------Autocorrelations--------------------					
6	2.47	5	0.7810	0.022	0.056	-0.096	0.155	0.017	0.018
12	13.10	11	0.2870	-0.137	0.119	-0.298	-0.110	-0.047	0.100
18	16.12	17	0.5153	-0.011	0.037	-0.175	-0.032	0.056	-0.014
24	18.79	23	0.7134	0.012	-0.042	-0.095	0.031	-0.043	0.114

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.970708	Pr < W	0.1580
Kolmogorov-Smirnov	D	0.069209	Pr > D	>0.1500
Cramer-von Mises	W-Sq	0.087715	Pr > W-Sq	0.1650
Anderson-Darling	A-Sq	0.577719	Pr > A-Sq	0.1326

The ARIMA Procedure
Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.28157	0.03936	7.15	<.0001	0
AR1.1	-0.39863	0.12075	-3.30	0.0010	9

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	--------------------Autocorrelations--------------------					
6	10.71	5	0.0575	0.321	-0.047	-0.038	0.182	0.119	-0.109
12	15.27	11	0.1703	-0.138	0.134	0.038	-0.127	-0.077	0.052
18	20.04	17	0.2722	0.081	0.005	-0.177	-0.086	0.030	-0.103
24	21.37	23	0.5587	-0.062	-0.066	-0.028	0.004	-0.033	0.060

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.981113	Pr < W	0.4774
Kolmogorov-Smirnov	D	0.081281	Pr > D	>0.1500
Cramer-von Mises	W-Sq	0.055353	Pr > W-Sq	>0.2500
Anderson-Darling	A-Sq	0.35172	Pr > A-Sq	>0.2500

The ARIMA Procedure
Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.27956	0.03306	8.46	<.0001	0
MA1.1	0.44515	0.14210	3.13	0.0017	9

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	--------------------Autocorrelations--------------------					
6	11.82	5	0.0374	0.329	-0.070	-0.074	0.189	0.135	-0.103
12	16.15	11	0.1355	-0.159	0.106	0.065	-0.095	-0.090	0.045
18	22.25	17	0.1753	0.110	0.028	-0.196	-0.127	0.063	0.048
24	23.69	23	0.4213	-0.012	-0.083	-0.058	0.041	0.025	0.049

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.98152	Pr < W	0.4961
Kolmogorov-Smirnov	D	0.067317	Pr > D	>0.1500
Cramer-von Mises	W-Sq	0.039304	Pr > W-Sq	>0.2500
Anderson-Darling	A-Sq	0.299706	Pr > A-Sq	>0.2500

The ARIMA Procedure
Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	0.28654	0.05148	5.57	<.0001	0
MA1.1	-0.36090	0.12355	-2.92	0.0035	1
AR1.1	-0.37115	0.12554	-2.96	0.0031	9

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	--------------------Autocorrelations--------------------					
6	3.61	4	0.4610	0.014	-0.017	-0.087	0.186	0.084	-0.068
12	9.69	10	0.4684	-0.174	0.186	-0.004	-0.116	-0.054	0.060
18	14.82	16	0.5378	0.037	0.047	-0.174	-0.056	0.084	-0.128
24	16.16	22	0.8081	0.002	-0.062	-0.018	0.032	-0.063	0.065

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.972937	Pr < W	0.2027
Kolmogorov-Smirnov	D	0.11329	Pr > D	0.0541
Cramer-von Mises	W-Sq	0.131349	Pr > W-Sq	0.0427
Anderson-Darling	A-Sq	0.70588	Pr > A-Sq	0.0652

- Sumenep Inflation ($Z_{8.t}$)

The ARIMA Procedure
Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	1.46983	0.06562	22.40	<.0001	0
AR1.1	-0.26986	0.12658	-2.13	0.0330	3

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	2.81	5	0.7290	0.170	-0.039	0.038	0.062	0.085	-0.029
12	12.63	11	0.3180	-0.147	0.052	-0.181	-0.223	0.114	0.116
18	19.68	17	0.2911	-0.000	-0.074	-0.204	-0.058	-0.133	-0.124
24	29.18	23	0.1744	0.110	-0.056	-0.148	0.043	0.180	0.158

Tests for Normality

Test	Statistic		p Value	
Shapiro-Wilk	W	0.965397	Pr < W	0.0866
Kolmogorov-Smirnov	D	0.101159	Pr > D	0.1288
Cramer-von Mises	W-Sq	0.096809	Pr > W-Sq	0.1246
Anderson-Darling	A-Sq	0.64636	Pr > A-Sq	0.0901

The ARIMA Procedure
Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	1.46539	0.06080	24.10	<.0001	0
MA1.1	0.27742	0.12911	2.15	0.0316	3

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	2.86	5	0.7214	0.166	-0.031	0.029	0.045	0.105	0.042
12	12.50	11	0.3274	-0.135	0.046	-0.193	-0.222	0.111	0.108
18	19.77	17	0.2863	-0.005	-0.079	-0.226	-0.069	-0.114	-0.108
24	29.21	23	0.1735	0.122	-0.065	-0.154	0.037	0.161	0.161

Tests for Normality

Test	Statistic		p Value	
Shapiro-Wilk	W	0.967653	Pr < W	0.1119
Kolmogorov-Smirnov	D	0.085688	Pr > D	>0.1500
Cramer-von Mises	W-Sq	0.085013	Pr > W-Sq	0.1811
Anderson-Darling	A-Sq	0.587327	Pr > A-Sq	0.1257

The ARIMA Procedure
Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	1.44988	0.06274	23.11	<.0001	0
AR1.1	-0.33702	0.13062	-2.58	0.0099	9

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	5.49	5	0.3594	0.113	-0.111	-0.179	0.104	0.116	-0.052
12	10.75	11	0.4642	-0.184	0.005	0.029	-0.118	0.092	0.122
18	16.88	17	0.4625	0.108	0.007	-0.184	-0.092	-0.117	-0.075
24	22.53	23	0.4884	0.046	-0.095	-0.091	0.005	0.178	0.078

Tests for Normality

Test	Statistic		p Value	
Shapiro-Wilk	W	0.969886	Pr < W	0.1441
Kolmogorov-Smirnov	D	0.08925	Pr > D	>0.1500
Cramer-von Mises	W-Sq	0.08479	Pr > W-Sq	0.1824
Anderson-Darling	A-Sq	0.582536	Pr > A-Sq	0.129

The ARIMA Procedure
Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	1.44782	0.05460	26.52	<.0001	0
MA1.1	0.38198	0.13933	2.74	0.0061	9

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	7.31	5	0.1987	0.099	-0.132	-0.212	0.111	0.158	-0.045
12	12.26	11	0.3444	-0.159	-0.018	0.067	-0.140	0.048	0.124
18	20.17	17	0.2657	0.129	0.037	-0.230	-0.115	-0.097	0.046
24	27.22	23	0.2468	0.046	-0.111	-0.113	0.017	0.201	0.063

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.978427	Pr < W	0.3657
Kolmogorov-Smirnov	D	0.079678	Pr > D	>0.1500
Cramer-von Mises	W-Sq	0.058514	Pr > W-Sq	>0.2500
Anderson-Darling	A-Sq	0.409729	Pr > A-Sq	>0.2500

The ARIMA Procedure
Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	1.45450	0.05369	27.09	<.0001	0
AR1.1	-0.22963	0.11493	-2.00	0.0457	3
AR1.2	-0.30219	0.12856	-2.35	0.0187	9

Autocorrelation Check of Residuals

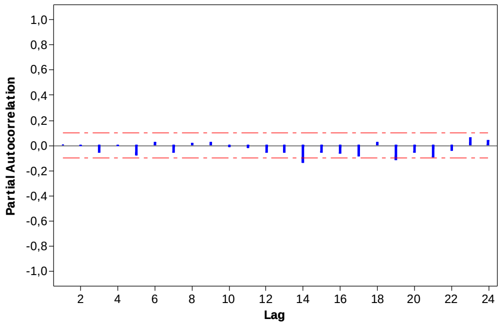
To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	3.29	4	0.5111	0.115	-0.056	0.039	0.104	0.125	-0.073
12	9.06	10	0.5267	-0.215	0.050	0.037	-0.148	0.084	0.030
18	16.14	16	0.4434	0.033	-0.005	-0.181	-0.069	-0.140	-0.157
24	20.66	22	0.5416	0.050	-0.078	-0.078	0.067	0.150	0.065

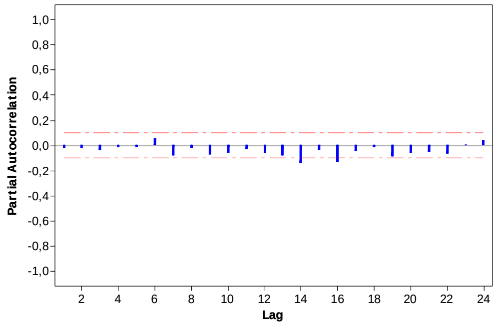
Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.955601	Pr < W	0.0288
Kolmogorov-Smirnov	D	0.132176	Pr > D	<0.0100
Cramer-von Mises	W-Sq	0.157574	Pr > W-Sq	0.0196
Anderson-Darling	A-Sq	0.970543	Pr > A-Sq	0.0148

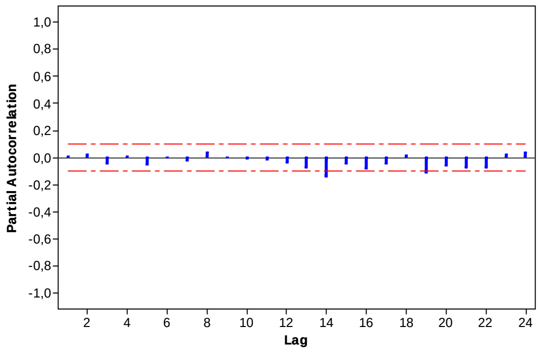
Appendix 4: Partial Autocorrelation (PACF) residual of ARIMA

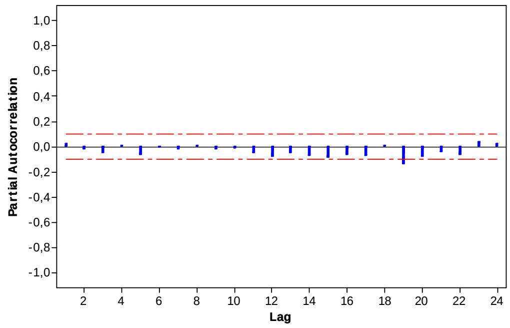
- National Inflation ($Z_{1,t}$)



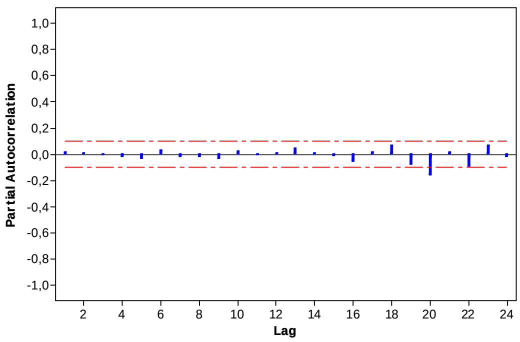


(a) PACF of ResidualARIMAX ([1,12],1,[2,8,20]) (b) PACF of ResidualARIMAX ([1,8,12],1,[2,20])



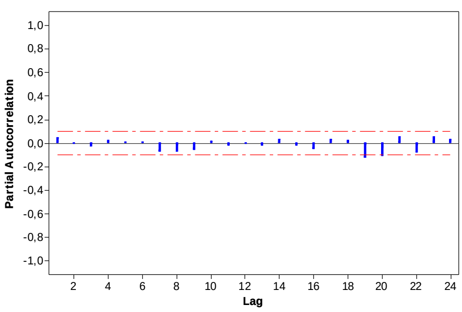


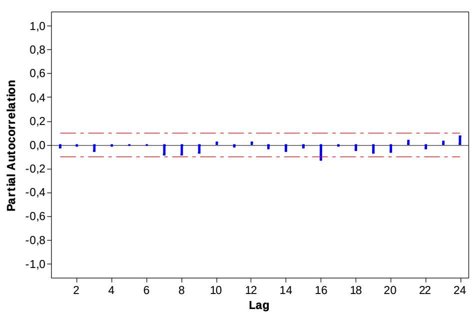
(a)PACF of ResidualARIMAX ([1,12,20],1,[2,8]) (b) PACF of ResidualARIMAX([1,12,14],1,[2,8,20])



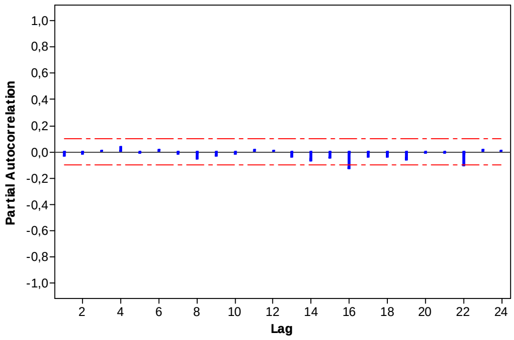
(e) PACF of ResidualARIMAX ([1,3,12,14],1,[2])

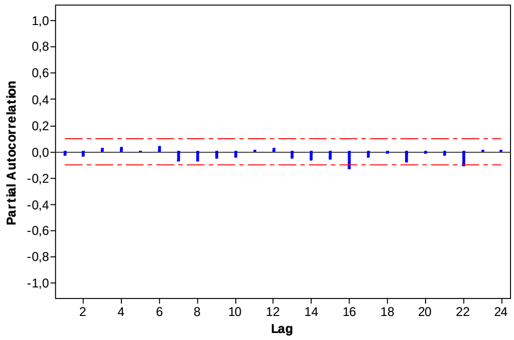
- Surabaya Inflation ($Z_{2,t}$)



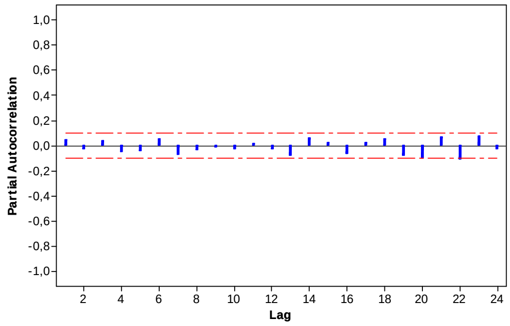


(a) PACF of ResidualARIMAX([1,5,12,19],1,[2,14]) (b) PACF of ResidualARIMAX([1,5,12],1,[2,20])



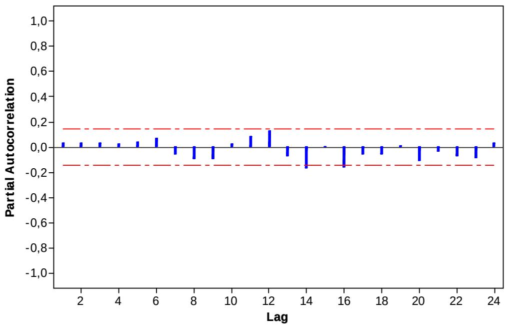


(c) PACF of ResidualARIMAX([1,6,12,20],1,[2])(d) PACF of ResidualARIMAX([1,12,20],1,[2,6])

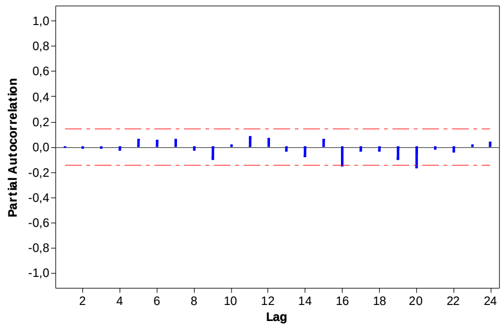


(e) PACF of ResidualARIMAX([2,12],1,1)

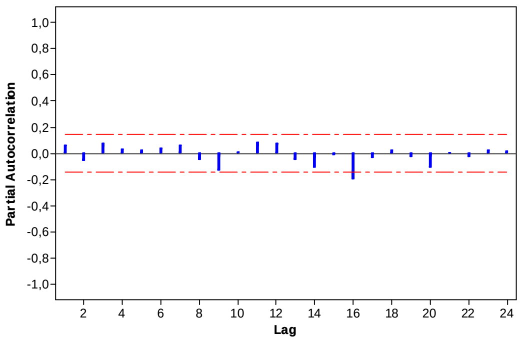
- Malang Inflation ($Z_{3,t}$)



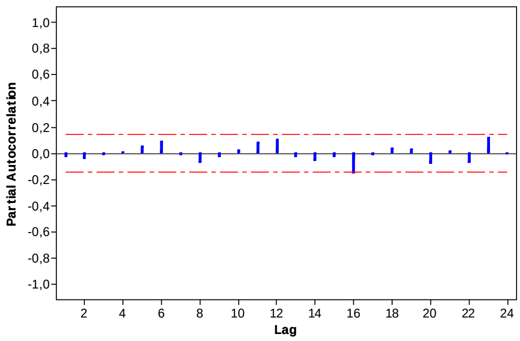
(a) PACF of ResidualARIMAX(1,1,[2])



(b) PACF of ResidualARIMAX([1,2],1,[3])

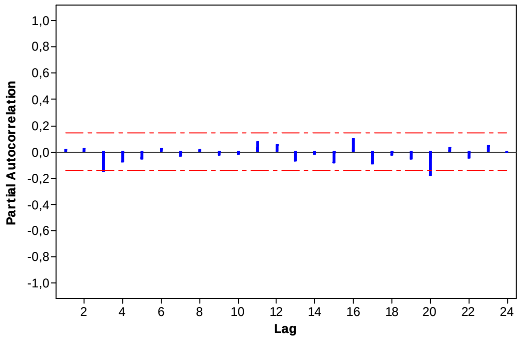


(c) ACF ARIMAX(0,1,1)

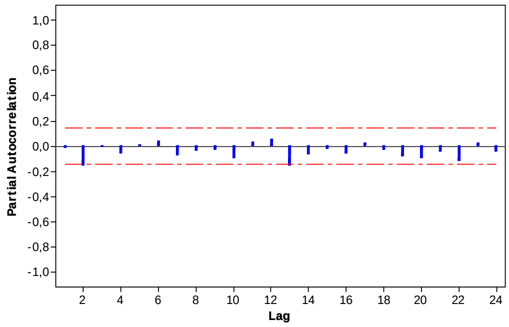


(d) PACFARIMAX([1,2,3],1,[4])

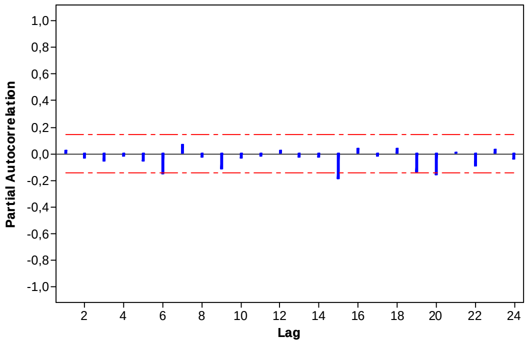
- Jember Inflation ($Z_{4,t}$)



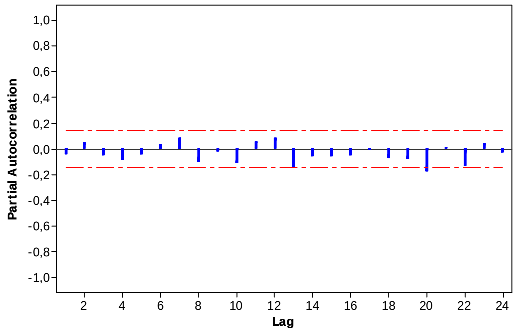
(a) PACF of ResidualARIMA([1,7],1,2)



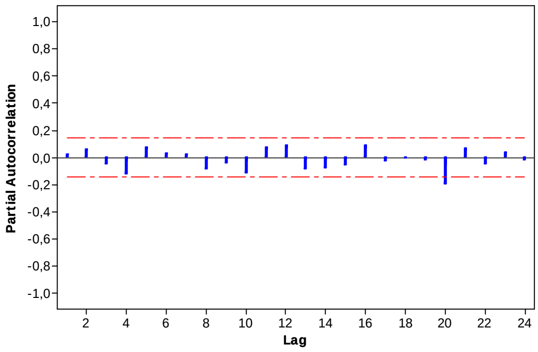
(b) PACF of ResidualARIMAX([3,4],1,[1,11])



(a) PACF of ResidualARIMAX([2,3],1,[1,4])

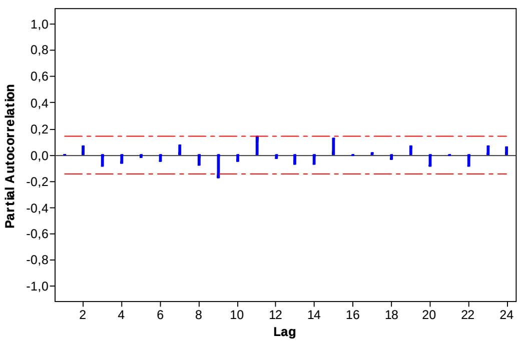


(b) PACF of ResidualARIMAX([1,2,4],1,[3,12])

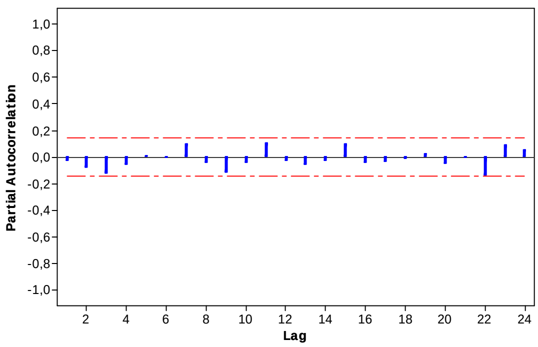


(e) PACF of Residual ARIMAX(1,1,[2,3])

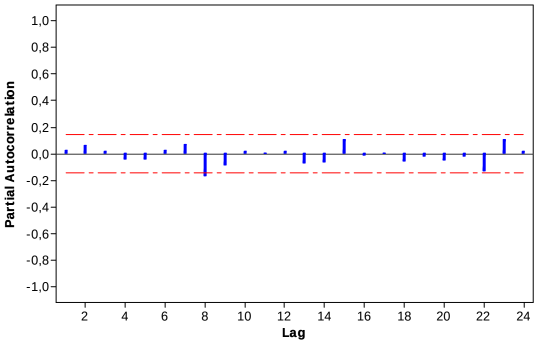
- Kediri Inflation ($Z_{5,t}$)



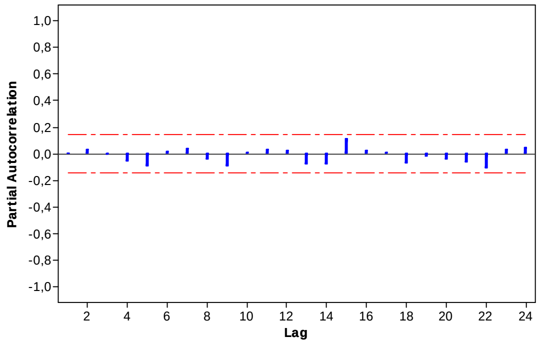
(a) PACF of Residual ARIMAX([1,3],1,[2])



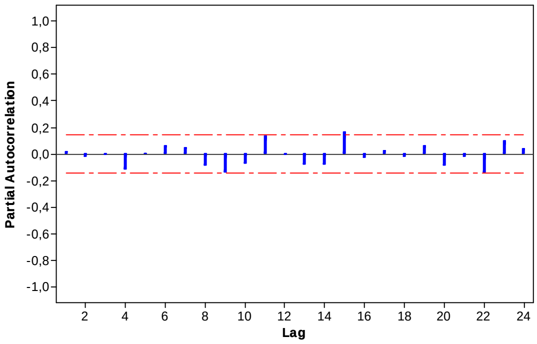
(b) PACF of Residual ARIMA(1,1,[2,3])



(c) PACF of Residual ARIMA(1,1,[2,7])

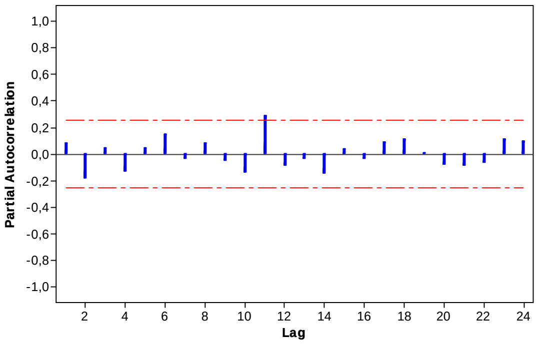


(d) PACF of Residual ARIMA([1,7],1,[2])

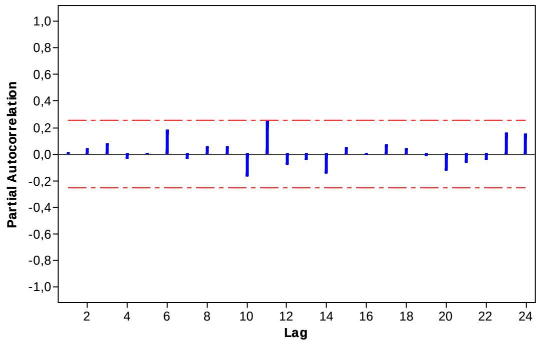


(e) PACF of Residual ARIMA([1,2],1,[3])

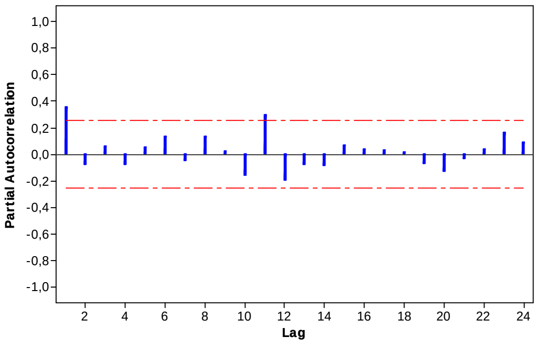
- Probolinggo Inflation ($Z_{6,t}$)



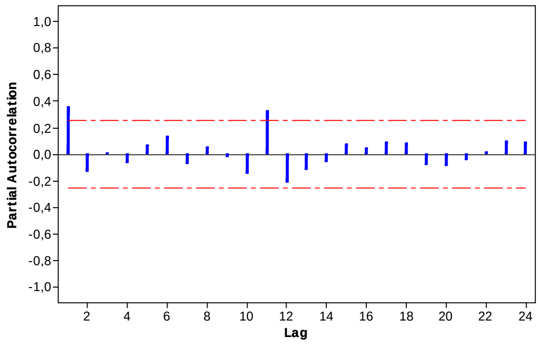
(a) PACF of Residual ARIMA(1,0,[9])



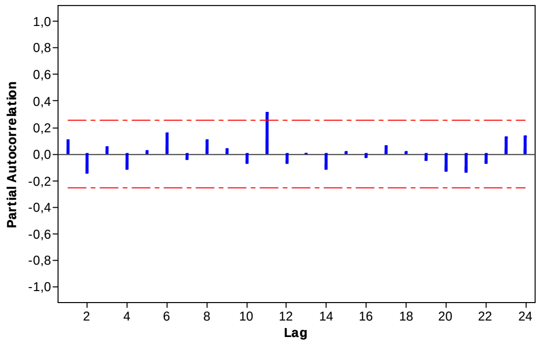
(b) PACF of Residual ARIMA([9],0,1)



(c) PACF of Residual ARIMA([9],0,0)

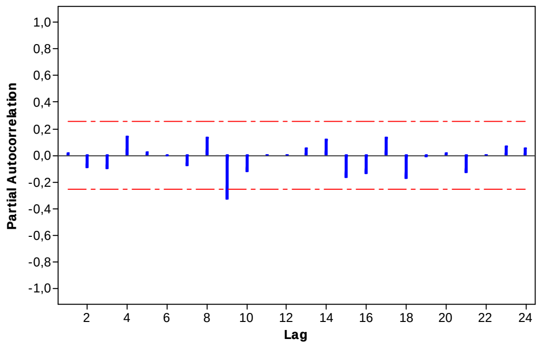


(d) PACF of Residual ARIMA(0,0,[9])

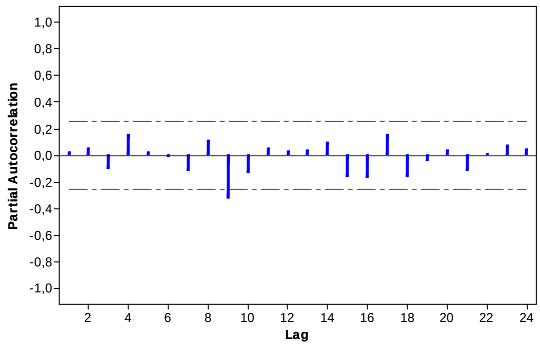


(e) PACF of Residual ARIMA([1,9],0,0)

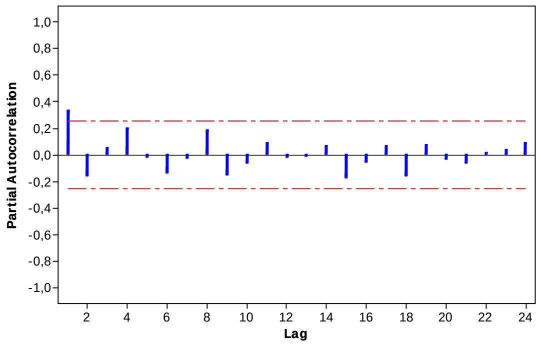
- Madiun Inflation ($Z_{7,t}$)



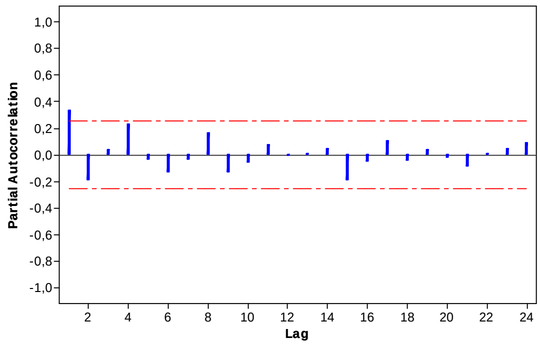
(a) PACF of Residual ARIMA(1,0,0)



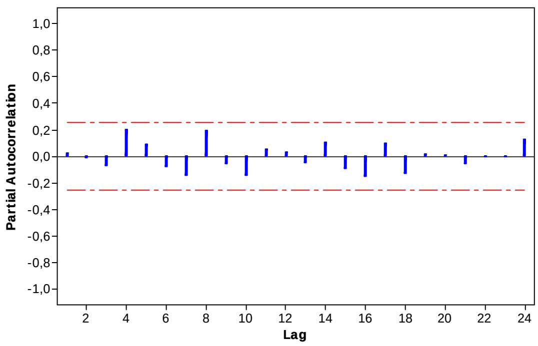
(b) PACF of Residual ARIMA(0,0,1)



(c) PACF of Residual ARIMA([9],0,0)

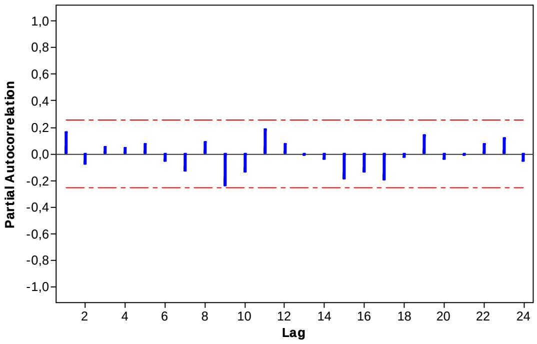


(d) PACF of Residual ARIMA(0,0,[9])

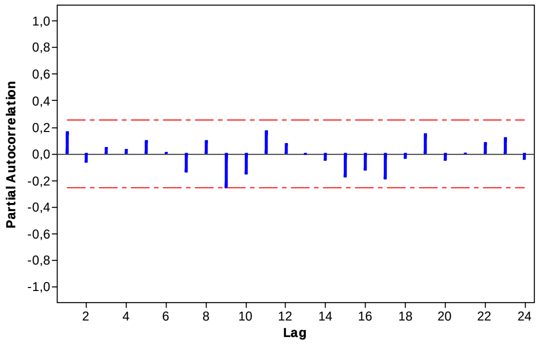


(e) PACF of Residual ARIMA([1,9],0,0)

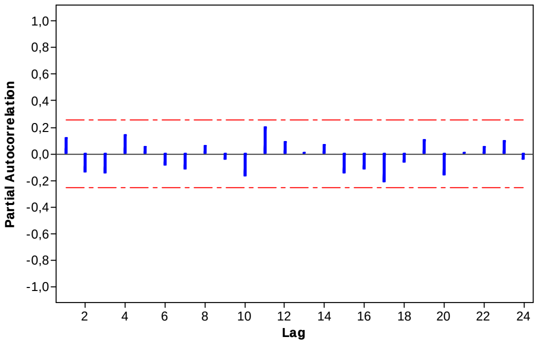
- Sumenep Inflation ($Z_{8,t}$)



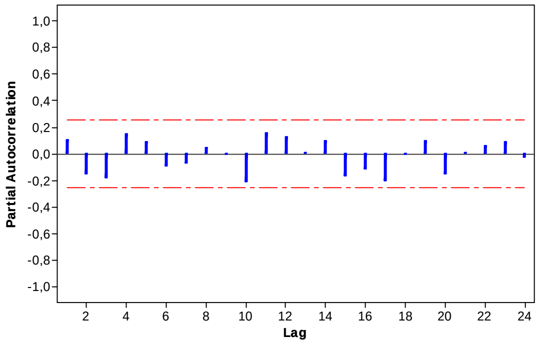
(a) PACF of ResidualARIMA([3],0,0)



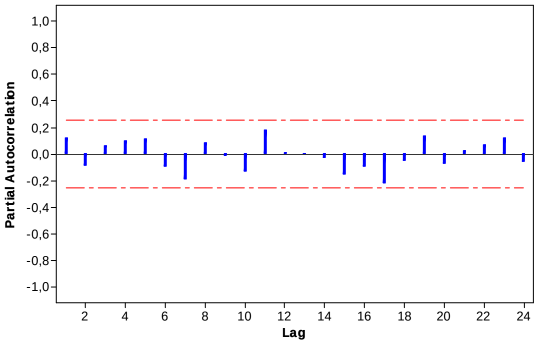
(b) PACF of Residual ARIMA(0,0[3])



(c) PACF of Residual ARIMA([9],0,0)



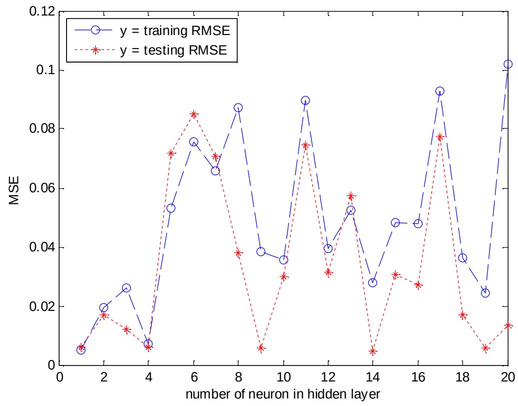
(d) PACF of Residual ARIMA(0,0,[9])

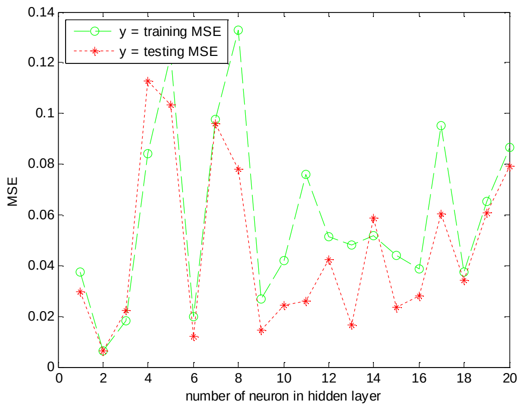


(e) PACF of Residual ARIMA([3,9],0,0)

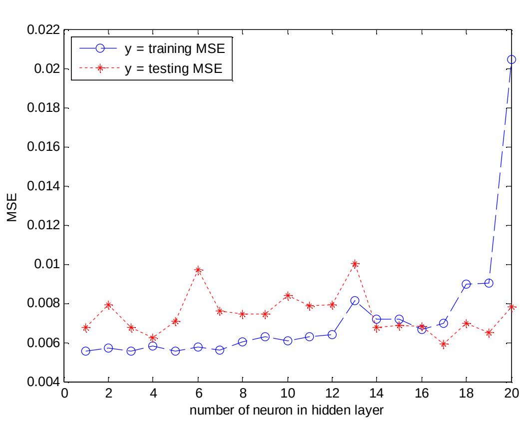
Appendix 5: Root Mean Square Error of Hybrid Autoregressive Integrated Moving Average (ARIMA) and Feedforward Neural Networks (FFNNs)

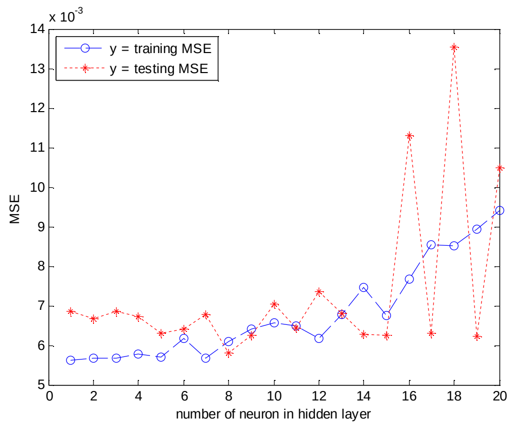
- National Inflation ($Z_{1,t}$)



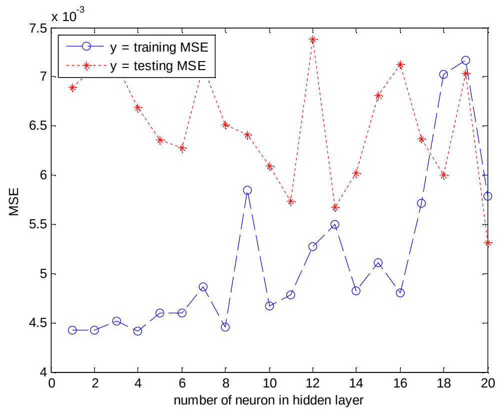


(a) RMSE of Hybrid ARIMAX ([1,12],1,[2,8,20]) and FFNNs(b) RMSE of Hybrid ARIMAX ([1,8,12],1,[2,20]) and FFNNs



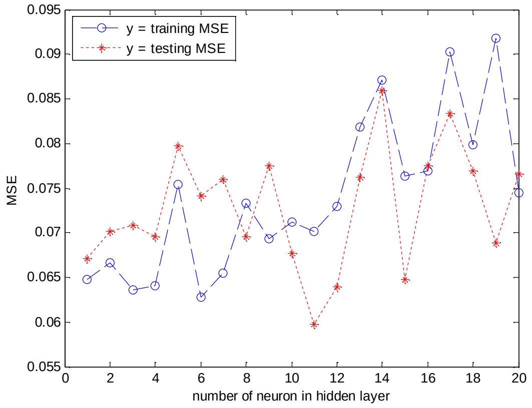


(a) RMSE of Hybrid ARIMAX ([1,12,20],1,[2,8]) and FFNNs (b) RMSE of Hybrid ARIMAX([1,12,14],1,[2,8,20]) and FFNNs

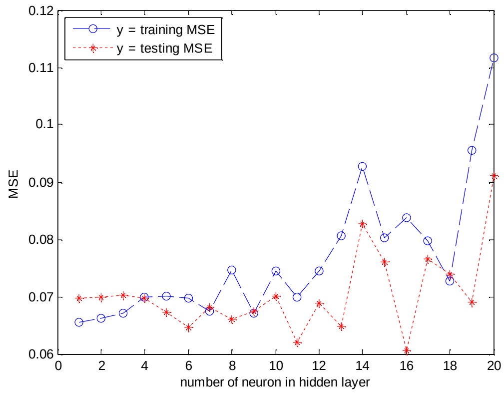


(e) RMSE of Hybrid ARIMAX ([1,3,12,14],1,[2]) and FFNNs

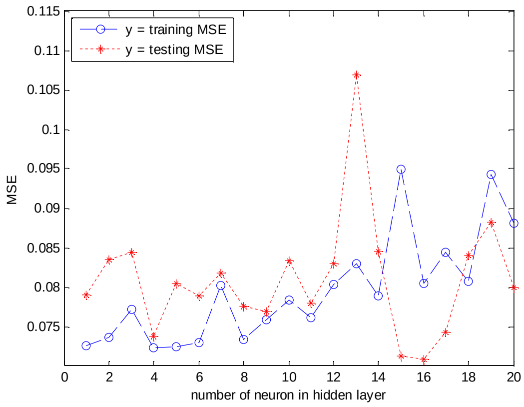
- Surabaya Inflation ($Z_{2,t}$)



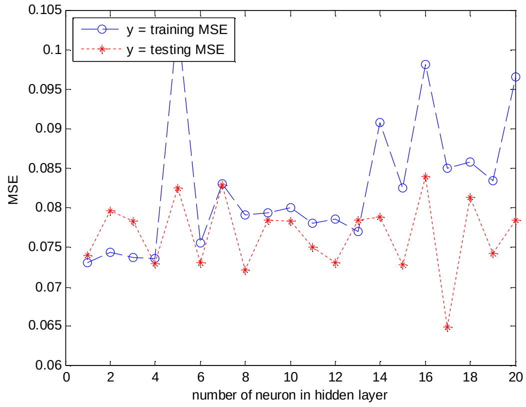
(a) RMSE of Hybrid ARIMAX([1,5,12,19],1,[2,14]) and FFNNs



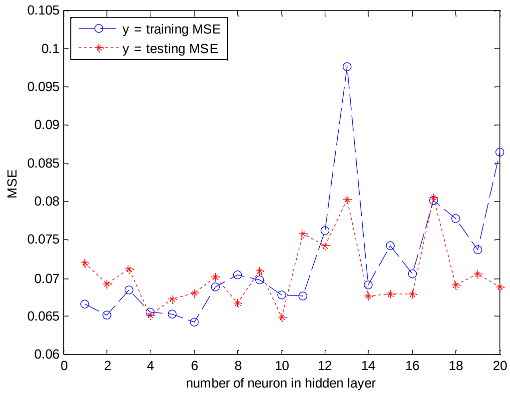
(b) RMSE of Hybrid ARIMAX([1,5,12],1,[2,20]) and FFNNs



(c) RMSE of Hybrid ARIMAX([1,6,12,20],1,[2]) and FFNNs

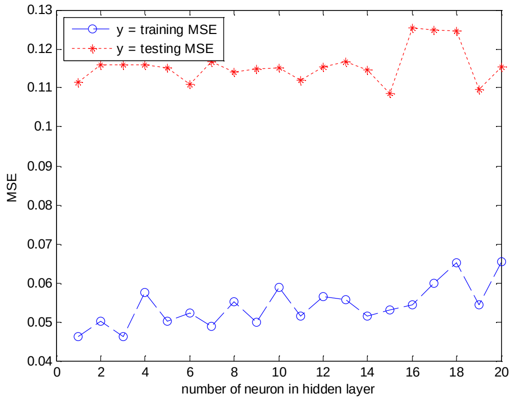


(d) RMSE of Hybrid ARIMAX([1,12,20],1,[2,6]) and FFNNs

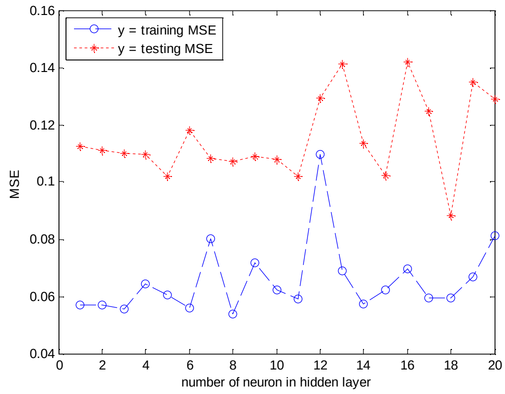


(e) RMSE of Hybrid ARIMAX([2,12],1,1) and FFNNs

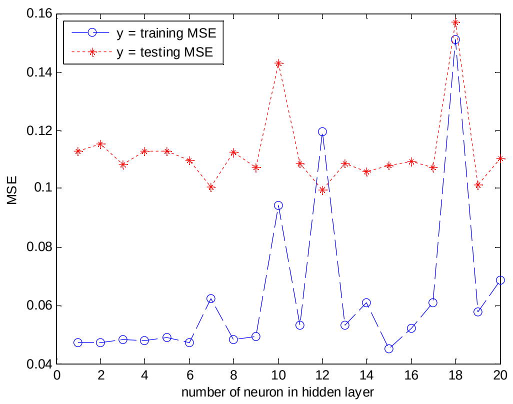
- Malang Inflation ($Z_{3,t}$)



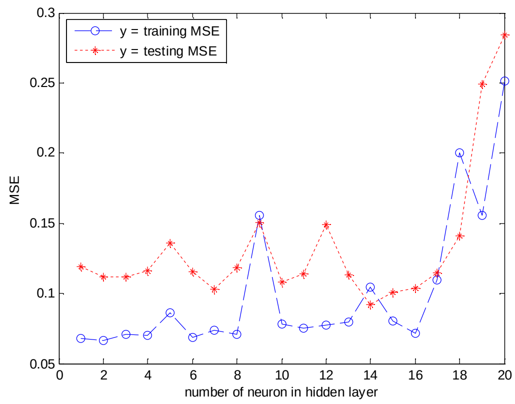
(a) RMSE of Hybrid ARIMAX(1,1,[2]) and FFNNs



(b) RMSE of Hybrid ARIMAX([1,2],1,[3]) and FFNNs

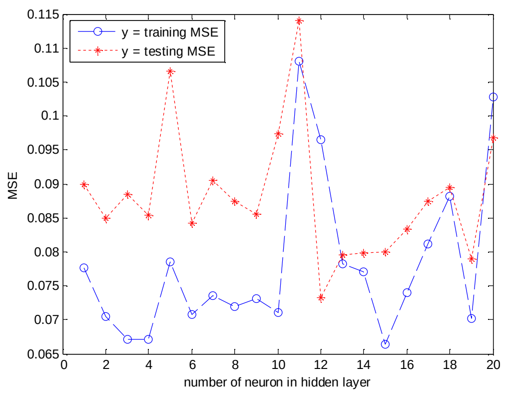


(c) RMSE of Hybrid ARIMAX(0,1,1)and FFNNs

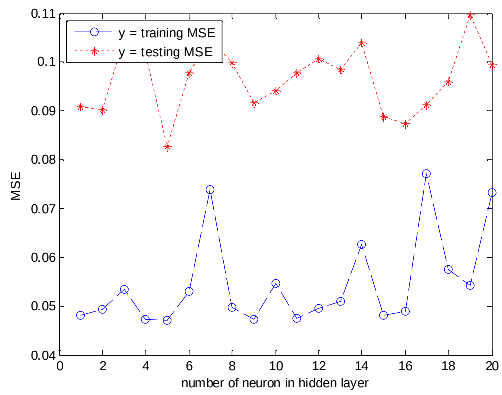


(d) RMSE of Hybrid ARIMAX([1,2,3],1,[4]) and FFNNs

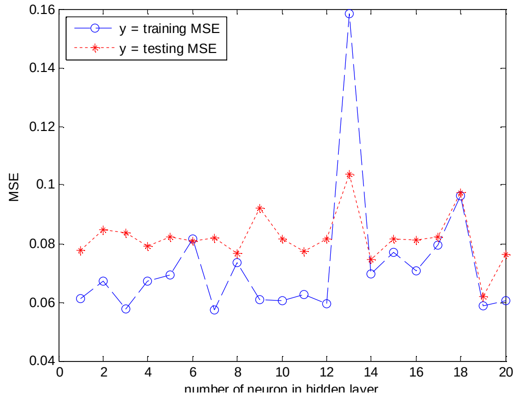
- Jember Inflation ($Z_{4,t}$)



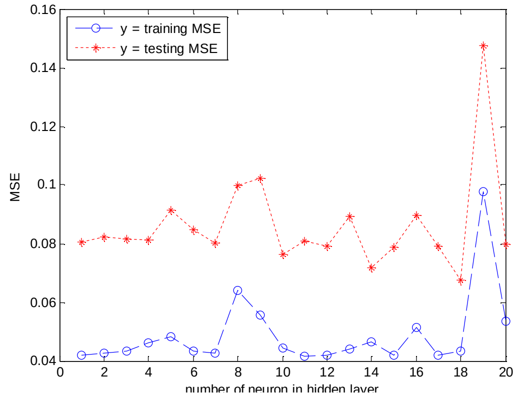
(a) RMSE of Hybrid ARIMA([1,7],1,2) and FFNNs



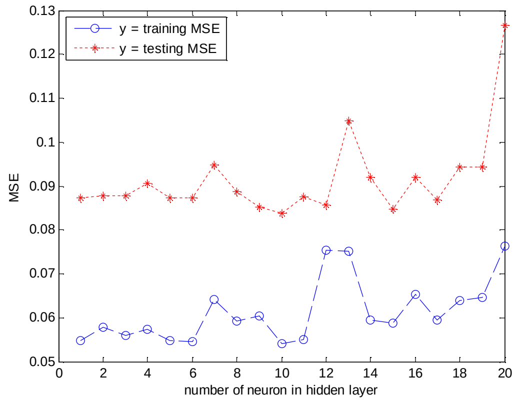
(b) RMSE of Hybrid ARIMAX([3,4],1,[1,11]) and FFNNs



(c) RMSE of Hybrid ARIMAX([2,3],1,[1,4]) and FFNNs

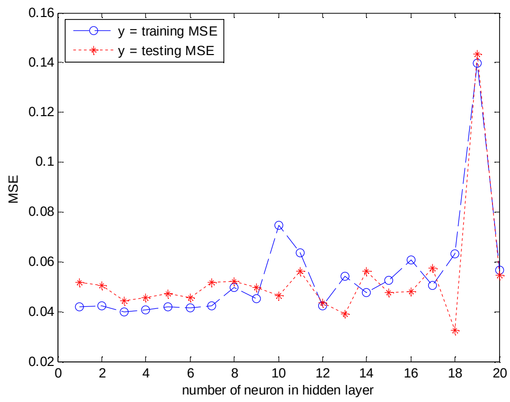


(d) RMSE of Hybrid ARIMAX([1,2,4],1,[3,12]) and FFNNs

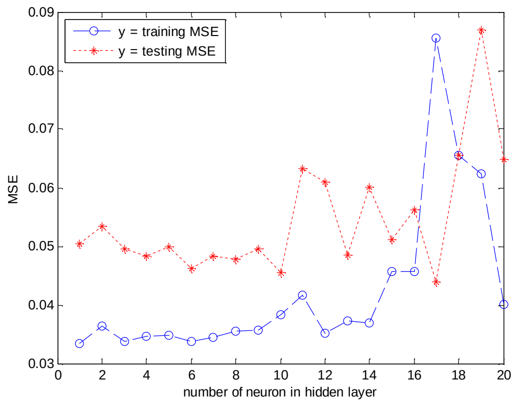


(e) RMSE of Hybrid ARIMAX(1,1,[2,3]) and FFNNs

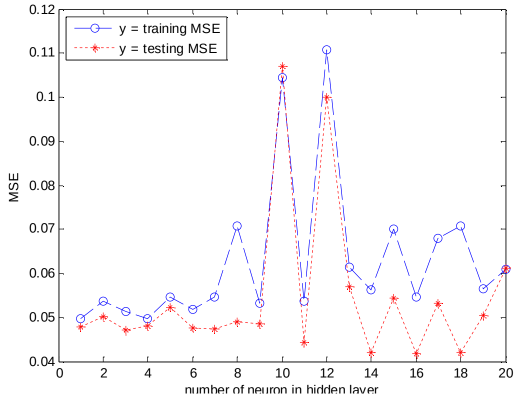
- Kediri Inflation ($Z_{5,t}$)



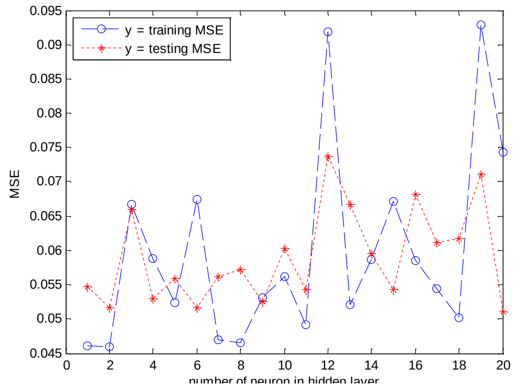
(a) RMSE of Hybrid ARIMAX([1,3],1,[2]) and FFNNs



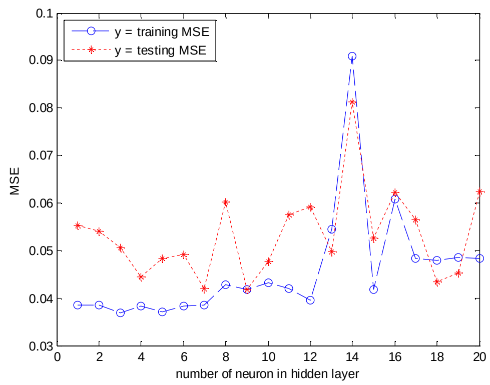
(b) RMSE of Hybrid ARIMA(1,1,[2,3]) and FFNNs



(c) RMSE of Hybrid ARIMA(1,1,[2,7]) and FFNNs

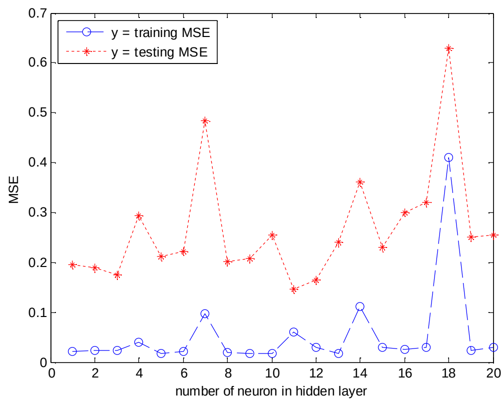


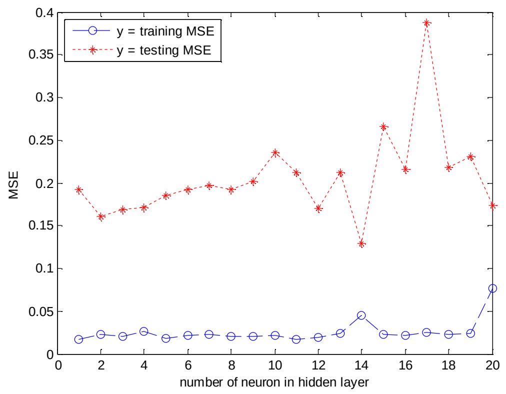
(d) RMSE of Hybrid ARIMA([1,7],1,[2]) and FFNNs



(e) RMSE of Hybrid ARIMA([1,2],1,[3]) and FFNNs

- Probolinggo Inflation ($Z_{6,t}$)

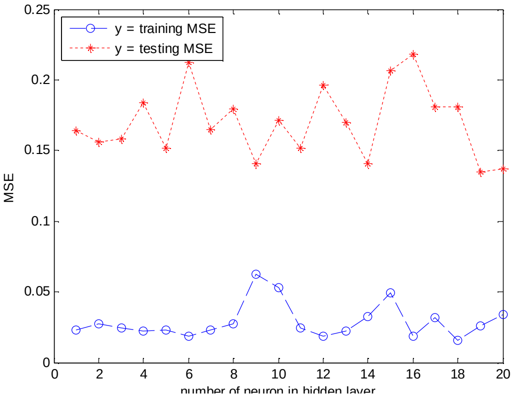




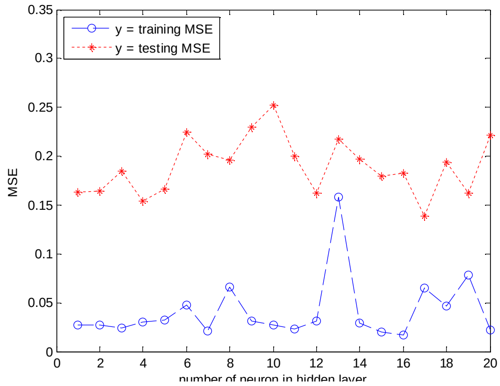
(a)

RMSE of Hybrid ARIMA(1,0,[9]) and FFNNs

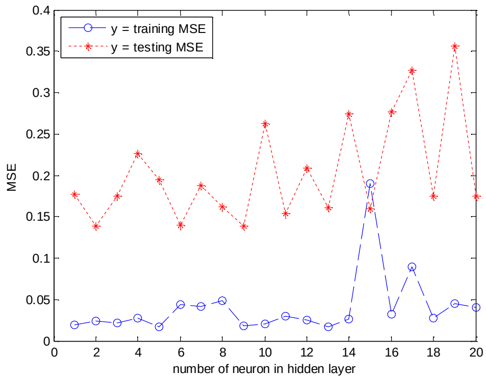
(b) RMSE of Hybrid ARIMA([9],0,1) and FFNNs



(c) RMSE of Hybrid ARIMA([9],0,0) and FFNNs

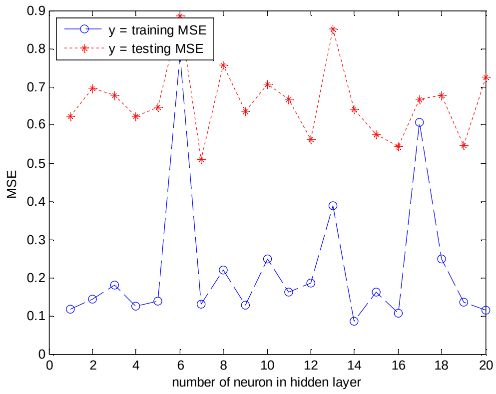


(d) RMSE of Hybrid ARIMA(0,0,[9]) and FFNNs

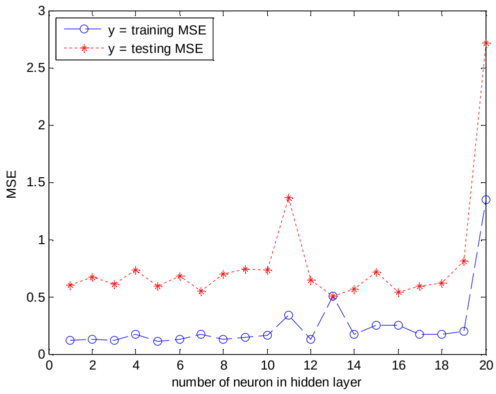


(e) RMSE of Hybrid ARIMA([1,9],0,0) and FFNNs

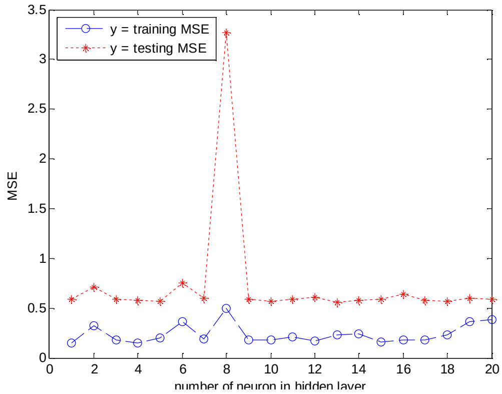
- MadiunInflation ($Z_{7,t}$)



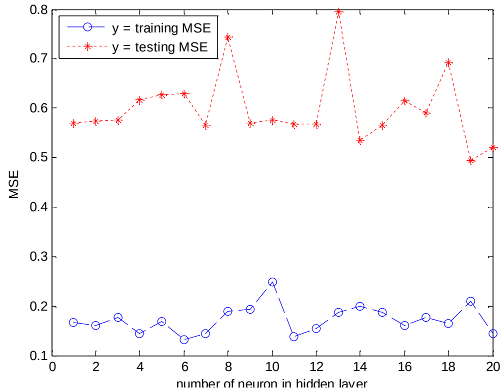
(a) RMSE of Hybrid ARIMA(1,0,0) and FFNNs



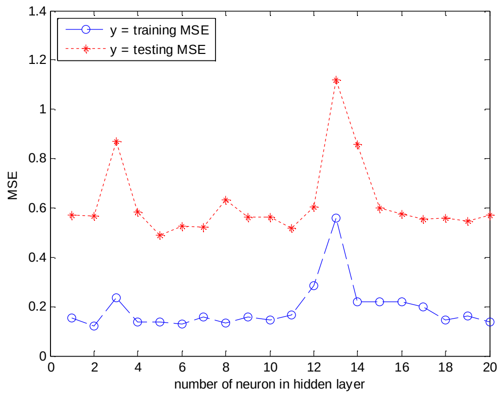
(b) RMSE of Hybrid ARIMA(0,0,1) and FFNNs



(c) RMSE of Hybrid ARIMA([9],0,0) and FFNNs

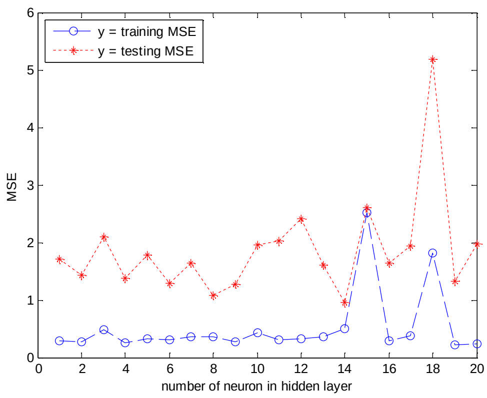


(d) RMSE of Hybrid ARIMA(0,0,[9]) and FFNNs

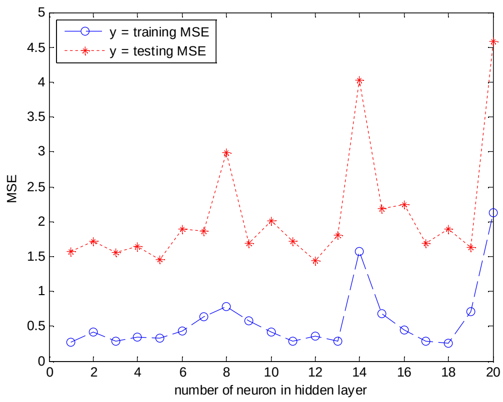


(e) RMSE of Hybrid ARIMA([1,9],0,0) and FFNNs

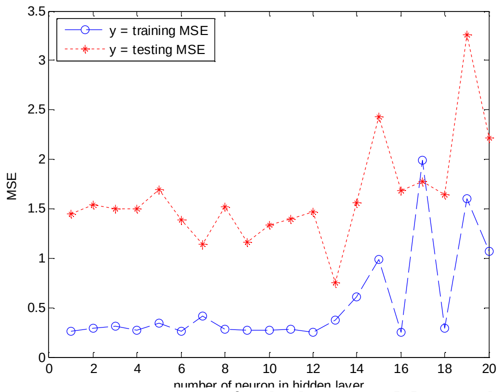
- SumenepInflation ($Z_{8,t}$)



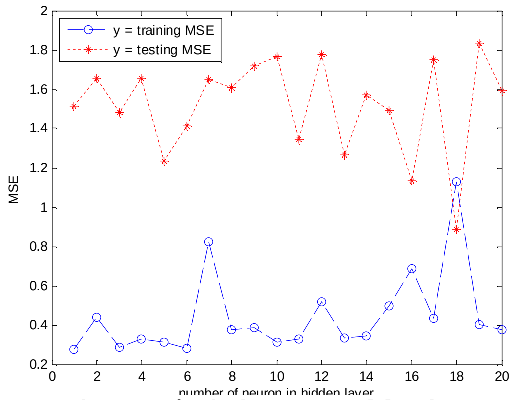
(a) RMSE of Hybrid ARIMA([3],0,0) and FFNNs



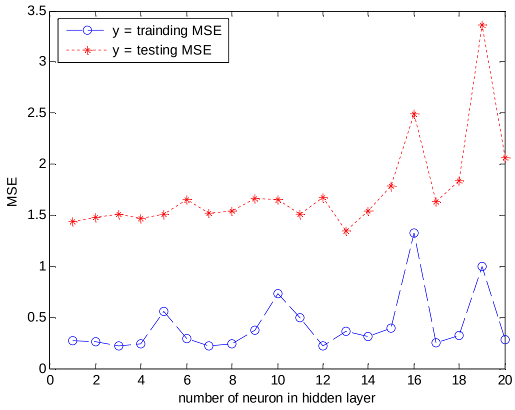
(b) RMSE of Hybrid ARIMA(0,0[3]) and FFNNs



(c) RMSE of Hybrid ARIMA([9],0,0) and FFNNs



(d) RMSE of Hybrid ARIMA(0,0,[9]) and FFNNs



(e) RMSE of Hybrid ARIMA([3,9],0,0) and FFNNs

Appendix 6: Output SPSS for Coeffient of Stacking of Hybrid Autoregressive Integrated Moving Average (ARIMA) and Feedforward Neural Networks (FFNNs)

- National Inflation ($Z_{1.t}$)

Parameter	Estimate	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
c1	.347	.156	.041	.654
c2	.049	.112	-.171	.269
c3	.000	.225	-.442	.442
c4	.000	.227	-.447	.447
c5	.604	.086	.434	.773

- Surabaya ($Z_{2.t}$)

Parameter	Estimate	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
c1	.360	.202	-.037	.757
c2	.123	.196	-.262	.507
c3	.146	.229	-.304	.597
c4	.000	.236	-.464	.464
c5	.371	.109	.156	.586

- Malang ($Z_{3.t}$)

Parameter	Estimate	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
c1	.407	.128	.155	.660
c2	.128	.116	-.101	.356
c3	.465	.118	.232	.697
c4	.000	.113	-.223	.223

- Kediri ($Z_{5.t}$)

Parameter	Estimate	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
c1	.176	.196	-.211	.563
c2	.503	.170	.167	.838
c3	.000	.184	-.363	.363
c4	.305	.185	-.059	.670
c5	.015	.225	-.428	.459

- Jember ($Z_{4.t}$)

Parameter	Estimate	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
c1	.026	.069	-.111	.162
c2	.226	.111	.007	.446
c3	.184	.106	-.024	.393
c4	.374	.131	.115	.632
c5	.190	.108	-.022	.403

- Probolinggo ($Z_{6.t}$)

Parameter	Estimate	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
c1	.247	.419	-.593	1.087
c2	.327	.268	-.211	.865
c3	.301	.191	-.081	.684
c4	.081	.242	-.403	.566
c5	.044	.424	-.807	.894

- Madiun ($Z_{7.t}$)

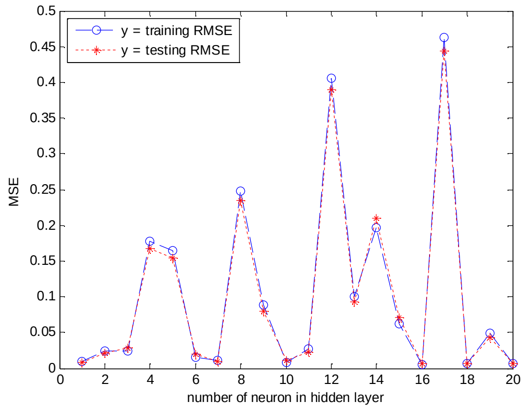
Parameter	Estimate	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
c1	.360	.251	-.143	.863
c2	.278	.295	-.314	.869
c3	.000	.512	-1.027	1.027
c4	.363	.401	-.442	1.167
c5	.000	.448	-.897	.897

- Sumenep ($Z_{8.t}$)

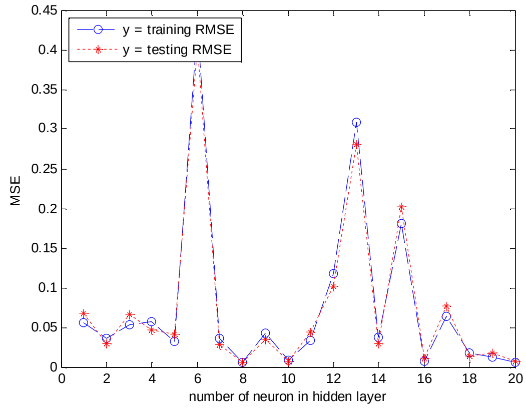
Parameter	Estimate	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
c1	.297	.274	-.253	.847
c2	.321	.210	-.100	.742
c3	.136	.293	-.452	.724
c4	.000	.318	-.637	.637
c5	.246	.276	-.307	.799

Appendix 7: Root Means Square Error of Hybrid Autoregressive Integrated Moving Average (ARIMA) and Recurrent Neural Network (RNNs)

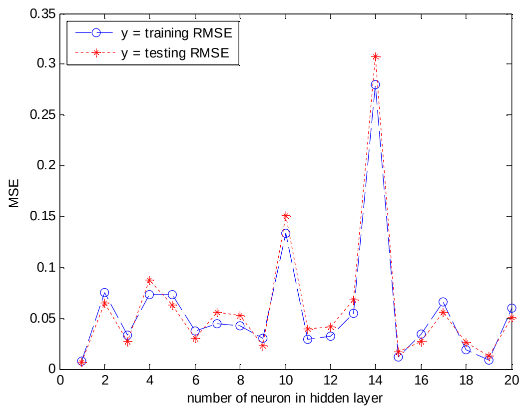
- National Inflation ($Z_{1,t}$)



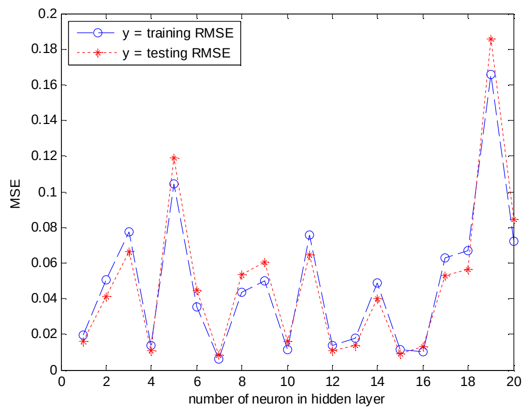
(a) RMSE of Hybrid ARIMAX ([1,12],1,[2,8,20]) and RNNs



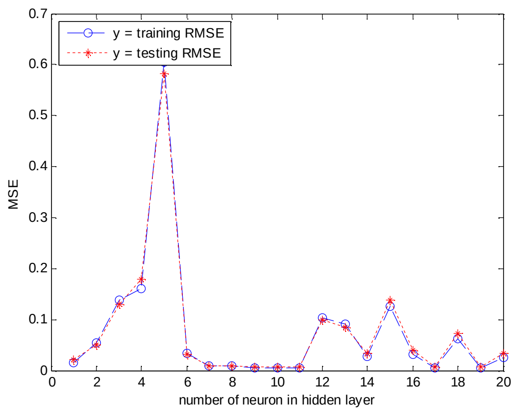
(b) RMSE of Hybrid ARIMAX ([1,8,12],1,[2,20]) and RNNs



(c) RMSE of Hybrid ARIMAX ([1,12,20],1,[2,8]) and RNNs

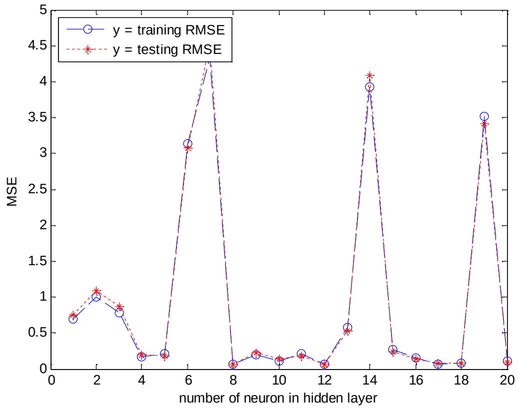


(d) RMSE of Hybrid ARIMAX([1,12,14],1,[2,8,20]) and RNNs

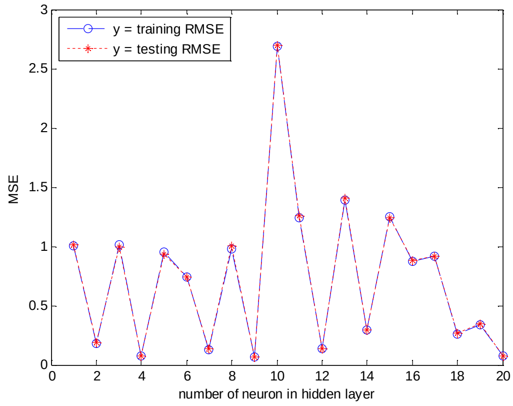


(e) RMSE of Hybrid ARIMAX ([1,3,12,14],1,[2]) and RNNs

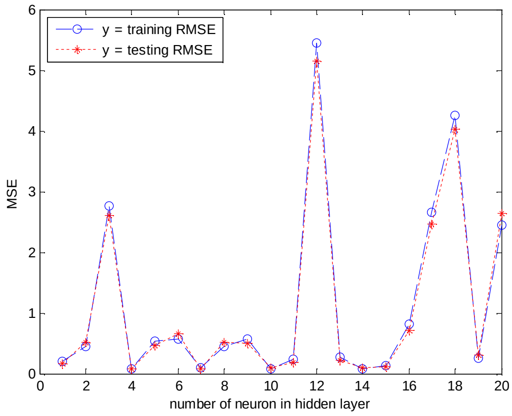
- Surabaya Inflation ($Z_{2,t}$)



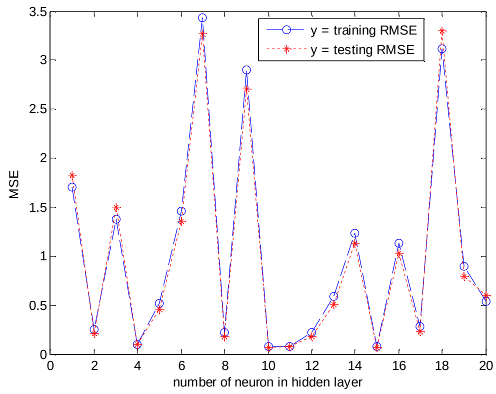
(a) RMSE of Hybrid ARIMAX([1,5,12,19],1,[2,14]) and RNNs



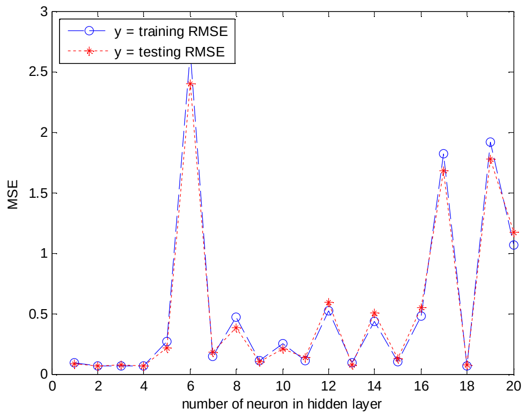
(b) RMSE of Hybrid ARIMAX([1,5,12],1,[2,20]) and RNNs



(c) RMSE of Hybrid ARIMAX([1,6,12,20],1,[2]) and RNNs

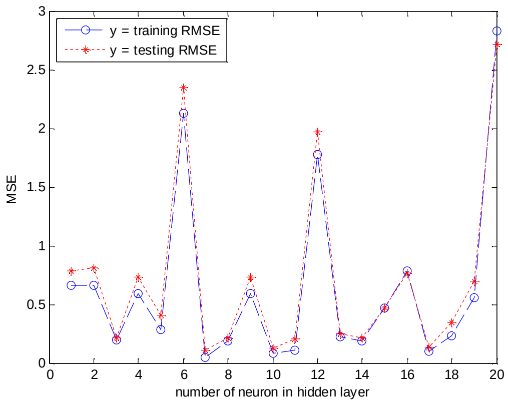


(d) RMSE of Hybrid ARIMAX([1,12,20],1,[2,6]) and RNNs

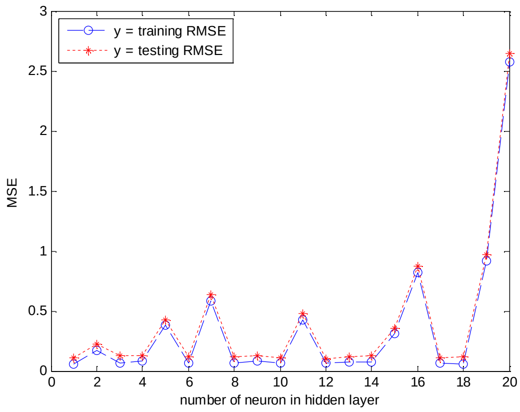


(e) RMSE of Hybrid ARIMAX([2,12],1,1) and RNNs

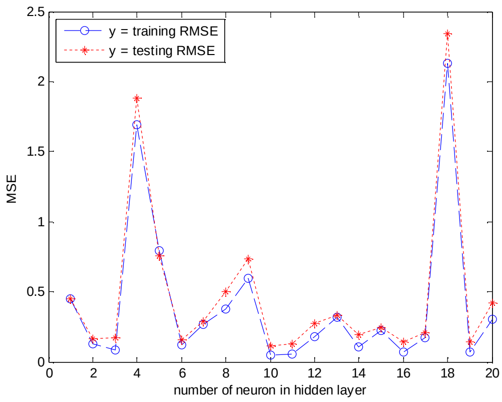
- Malang Inflation ($Z_{3,t}$)



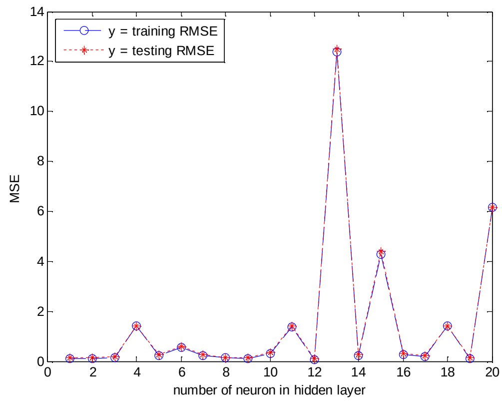
(a) RMSE of Hybrid ARIMAX(1,1,[2]) and RNNs



(b) RMSE of Hybrid ARIMAX([1,2],1,[3]) and RNNs

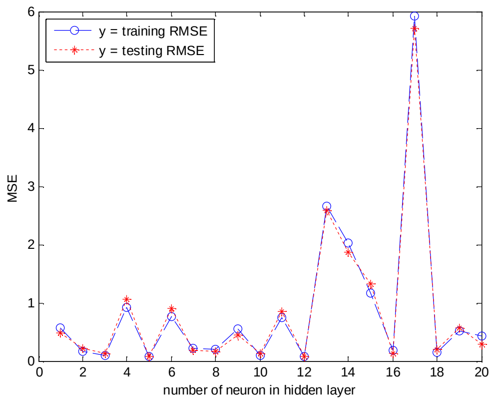


(c) RMSE of Hybrid ARIMAX(0,1,1)and RNNs

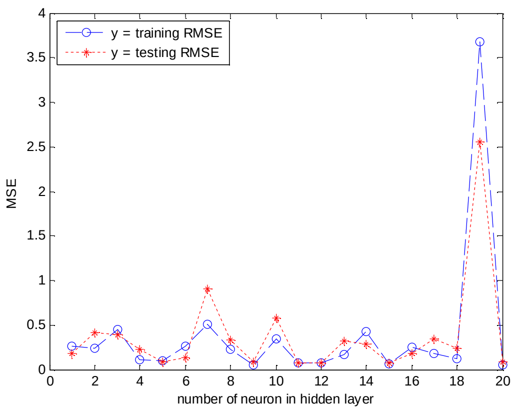


(d) RMSE of Hybrid ARIMAX([1,2,3],1,[4]) and RNNs

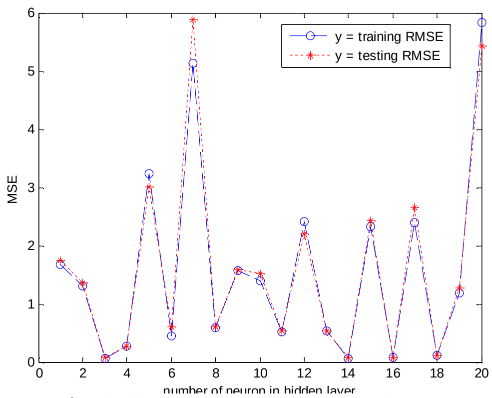
- Jember Inflation ($Z_{4,t}$)



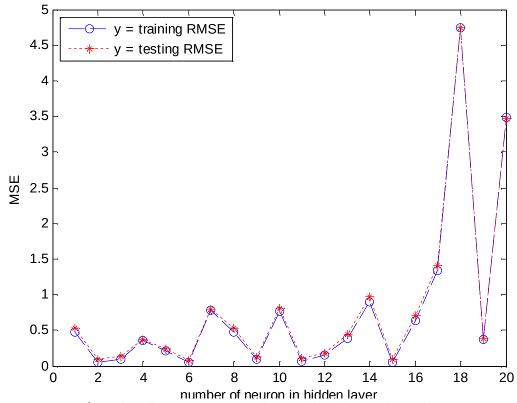
(a) RMSE of Hybrid ARIMA([1,7],1,2) and RNNs



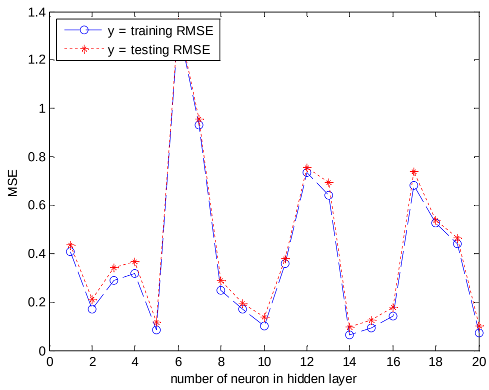
(b) RMSE of Hybrid ARIMAX([3,4],1,[1,11]) and RNNs



(c) RMSE of Hybrid ARIMAX([2,3],1,[1,4]) and RNNs

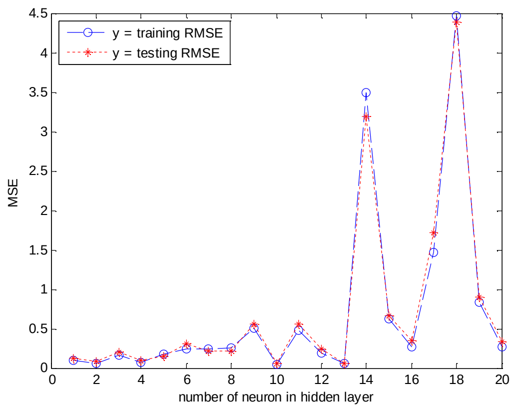


(d) RMSE of Hybrid ARIMAX([1,2,4],1,[3,12]) and RNNs

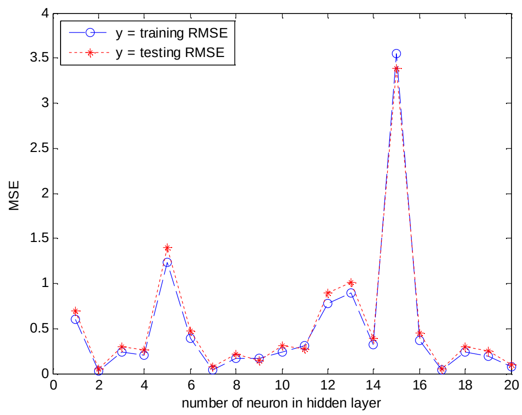


(e) RMSE of Hybrid ARIMAX(1,1,[2,3]) and RNNs

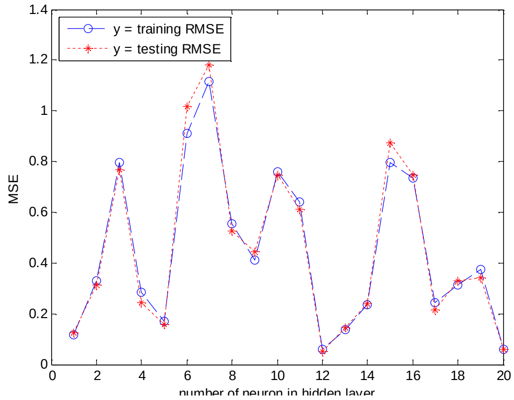
- Kediri Inflation ($Z_{5,t}$)



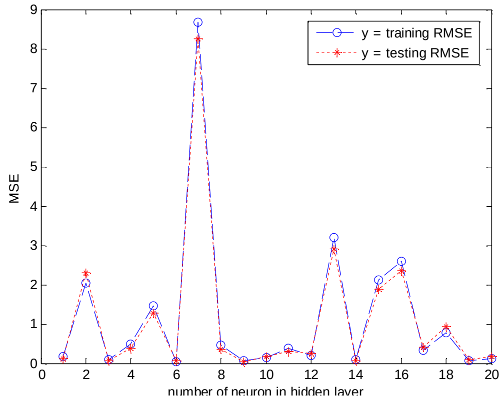
(a) RMSE of Hybrid ARIMAX([1,3],1,[2]) and RNNs



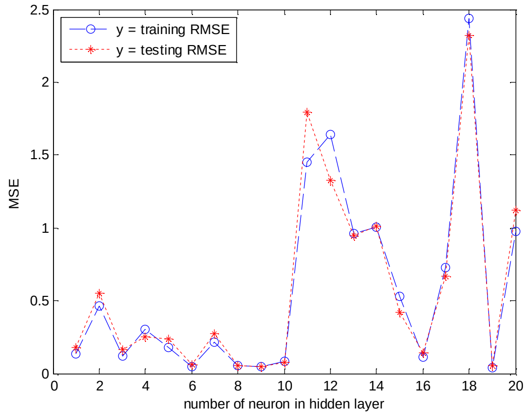
(b) RMSE of Hybrid ARIMA(1,1,[2,3]) and RNNs



(c) RMSE of Hybrid ARIMA(1,1,[2,7]) and RNNs

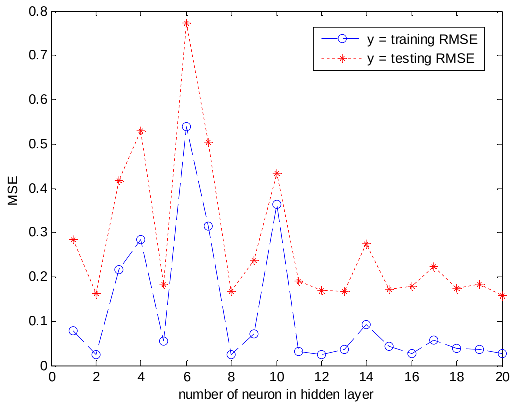


(d) RMSE of Hybrid ARIMA([1,7],1,[2]) and RNNs

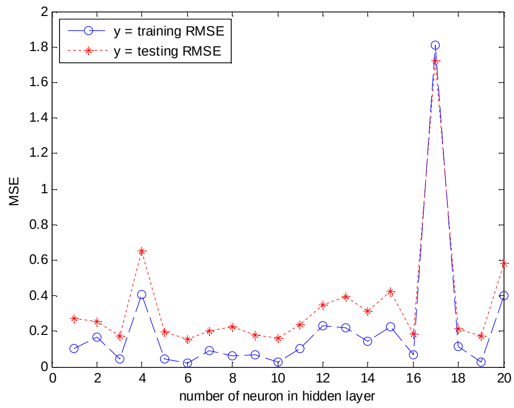


(e) RMSE of Hybrid ARIMA([1,2],1,[3]) and RNNs

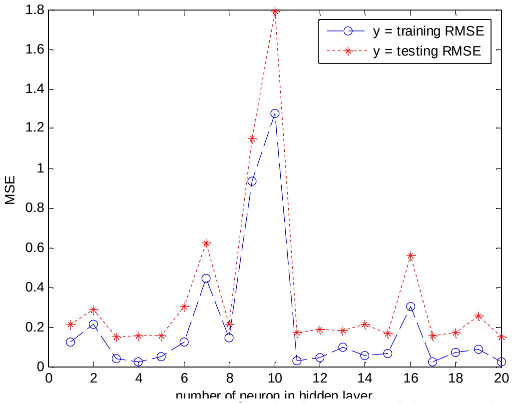
- Probolinggo Inflation ($Z_{6,t}$)



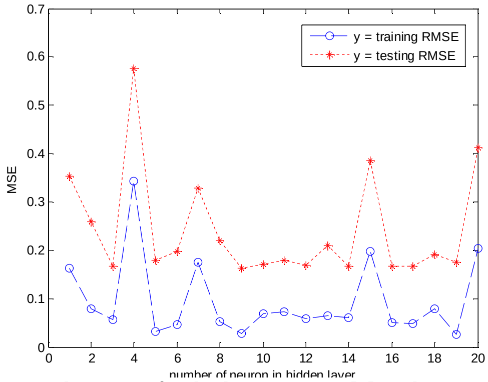
(a) RMSE of Hybrid ARIMA(1,0,[9]) and RNNs



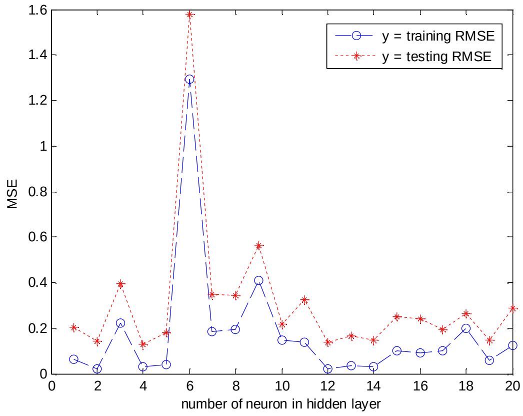
(b) RMSE of Hybrid ARIMA([9],0,1) and RNNs



(c) RMSE of Hybrid ARIMA([9],0,0) and RNNs

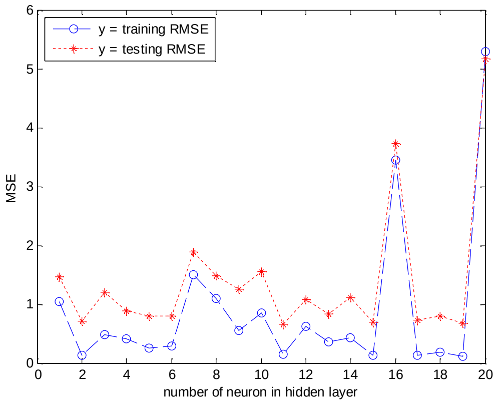


(d) RMSE of Hybrid ARIMA(0,0,[9]) and RNNs

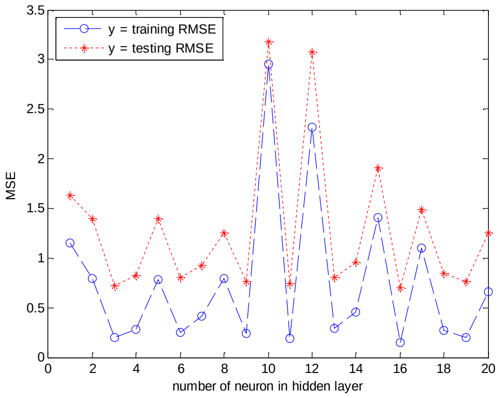


(e) RMSE of Hybrid ARIMA([1,9],0,0) and RNNs

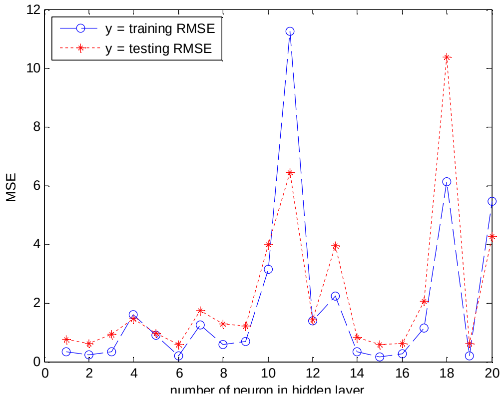
- Madiun Inflation ($Z_{7,t}$)



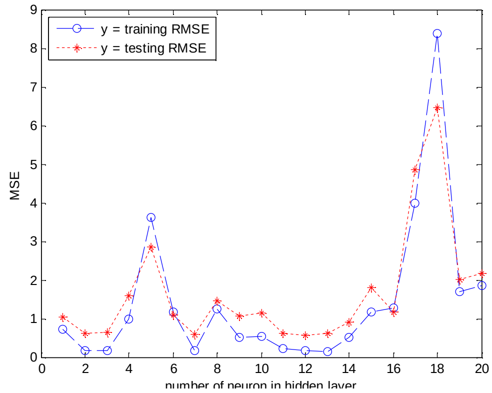
(a) RMSE of Hybrid ARIMA(1,0,0) and RNNs



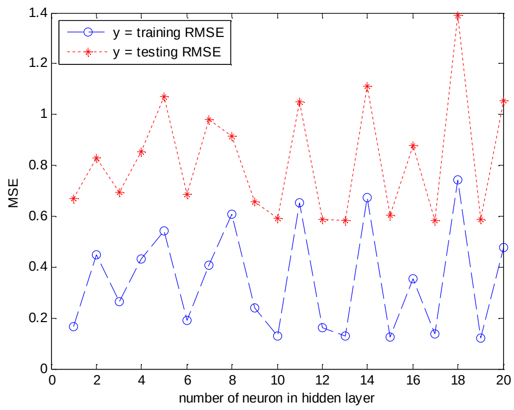
(b) RMSE of Hybrid ARIMA(0,0,1) and RNNs



(c) RMSE of Hybrid ARIMA([9],0,0) and RNNs

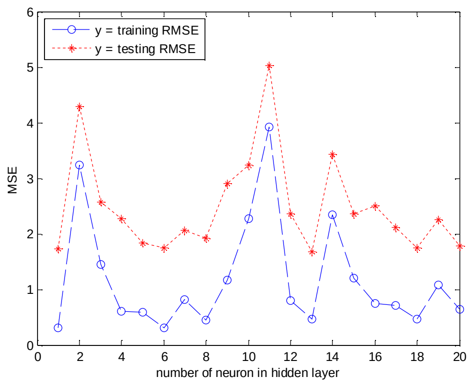


(d) RMSE of Hybrid ARIMA(0,0,[9]) and RNNs

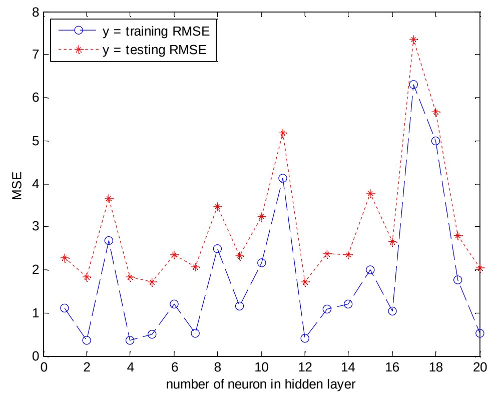


(e) RMSE of Hybrid ARIMA([1,9],0,0) and RNNs

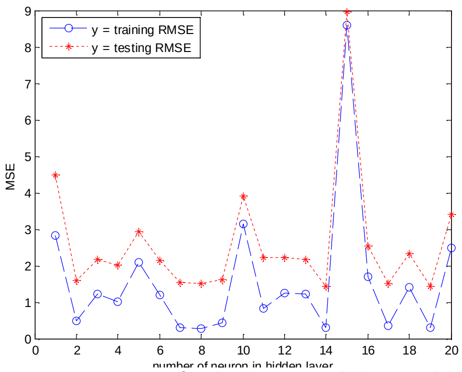
- Sumenep Inflation ($Z_{8,t}$)



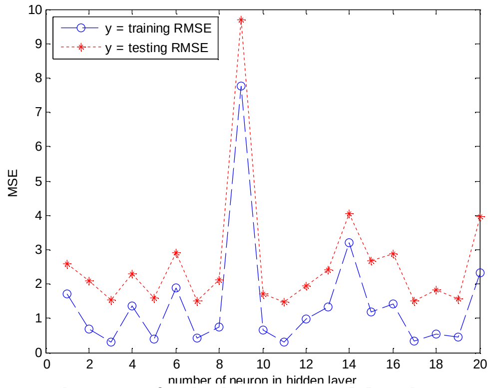
(a) RMSE of Hybrid ARIMA([3],0,0) and RNNs



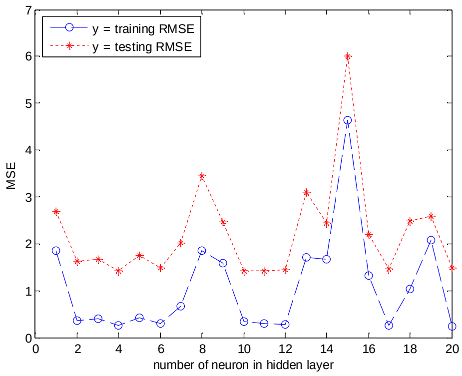
(b) RMSE of Hybrid ARIMA(0,0[3]) and RNNs



(c) RMSE of Hybrid ARIMA([9],0,0) and RNNs



(d) RMSE of Hybrid ARIMA(0,0,[9]) and RNNs



(e) RMSE of Hybrid ARIMA([3,9],0,0) and RNNs

Appendix 8: Coeffient of Stacking of Hybrid Autoregressive Integrated Moving Average (ARIMA) and Recurrent Neural Networks (RNNs)

- National Inflation ($Z_{1.t}$)

Parameter	Estimate	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
c1	.354	.146	.066	.642
c2	.098	.128	-.154	.350
c3	.000	.172	-.338	.338
c4	.000	.180	-.355	.355
c5	.547	.079	.392	.703

- Surabaya Inflation ($Z_{2.t}$)

Parameter	Estimate	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
c1	.347	.212	-.070	.764
c2	.187	.200	-.205	.580
c3	.000	.157	-.309	.309
c4	.134	.141	-.143	.411
c5	.332	.104	.127	.537

- Malang Inflation ($Z_{3.t}$)

Parameter	Estimate	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
c1	.394	.143	.113	.676
c2	.049	.178	-.302	.401
c3	.530	.203	.130	.930
c4	.027	.143	-.255	.308

- Jember Inflation ($Z_{4.t}$)

Parameter	Estimate	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
c1	.000	.080	-.159	.159
c2	.322	.120	.086	.558
c3	.110	.123	-.132	.353
c4	.375	.144	.092	.659
c5	.192	.122	-.048	.432

- Kediri Inflation ($Z_{5.t}$)

Parameter	Estimate	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
c1	.000	.281	-.555	.555
c2	.533	.190	.157	.908
c3	.000	.183	-.361	.361
c4	.328	.184	-.036	.691
c5	.140	.262	-.377	.657

- Probolinggo Inflation ($Z_{6.t}$)

Parameter	Estimate	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
c1	.000	.851	-1.706	1.706
c2	.475	.437	-.402	1.351
c3	.000	.665	-1.332	1.332
c4	.134	.560	-.989	1.257
c5	.392	.875	-1.362	2.146

- Madiun Inflation ($Z_{7.t}$)

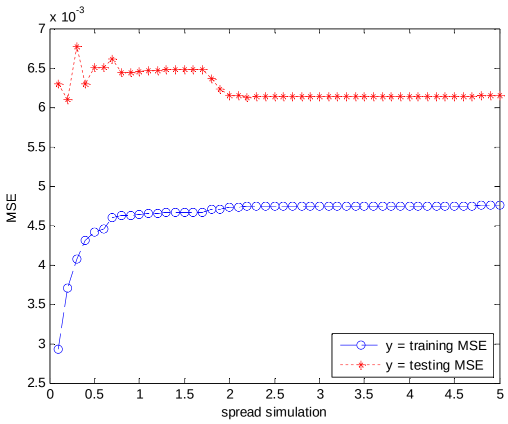
Parameter	Estimate	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
c1	.072	.889	-1.709	1.853
c2	.000	.764	-1.532	1.532
c3	.000	1.098	-2.201	2.201
c4	.208	.601	-.996	1.411
c5	.720	.856	-.996	2.437

- Sumenep Inflation ($Z_{8.t}$)

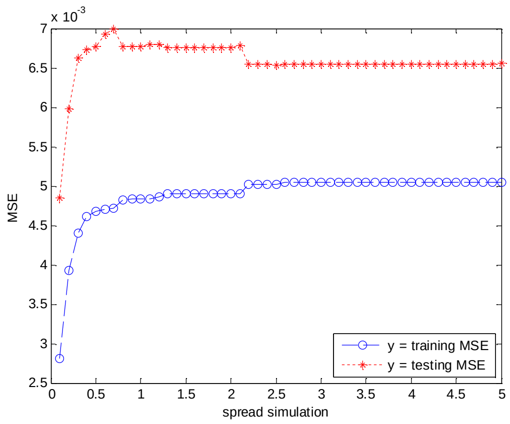
Parameter	Estimate	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
c1	.911	.265	.380	1.442
c2	.000	.231	-.462	.462
c3	.012	.190	-.370	.393
c4	.000	.175	-.351	.351
c5	.077	.113	-.149	.303

Appendix 9: Root Means Square Error of Hybrid Autoregressive Integrated Moving Average (ARIMA) and Radial Basis Function Neural Networks (RBFNNs)

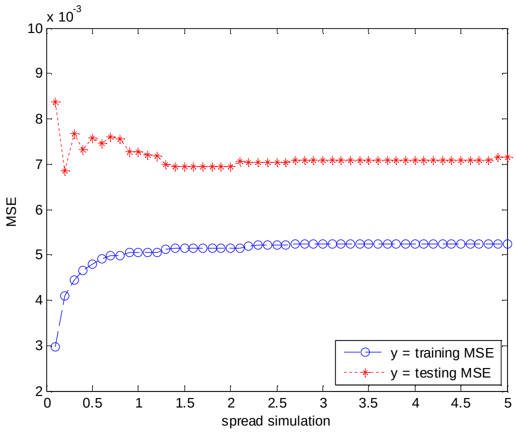
- National Inflation ($Z_{1.t}$)



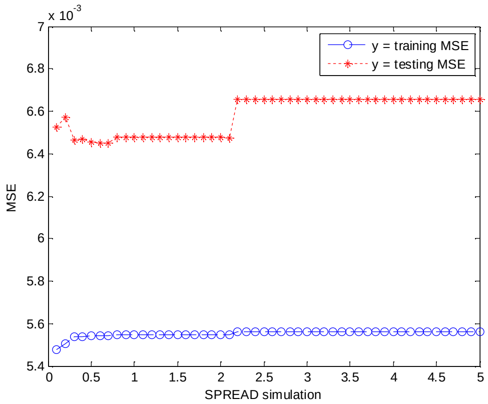
(a) RMSE of Hybrid ARIMAX ([1,12],1,[2,8,20]) and RBFNNs



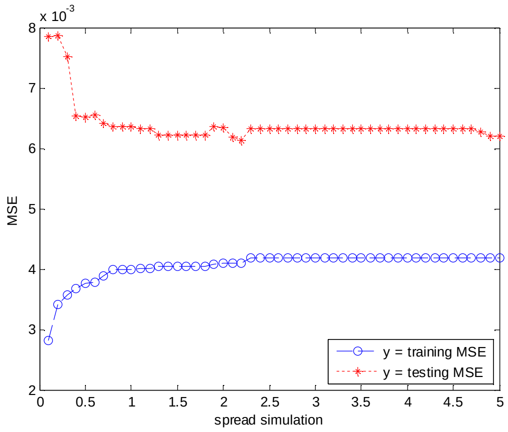
(b) RMSE of Hybrid ARIMAX ([1,8,12],1,[2,20]) and RBFNNs



(c) RMSE of Hybrid ARIMAX ([1,12,20],1,[2,8]) and RBFNNs

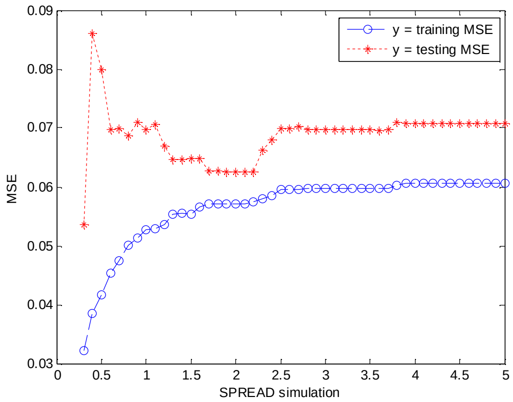


(d) RMSE of Hybrid ARIMAX([1,12,14],1,[2,8,20]) and RBFNNs

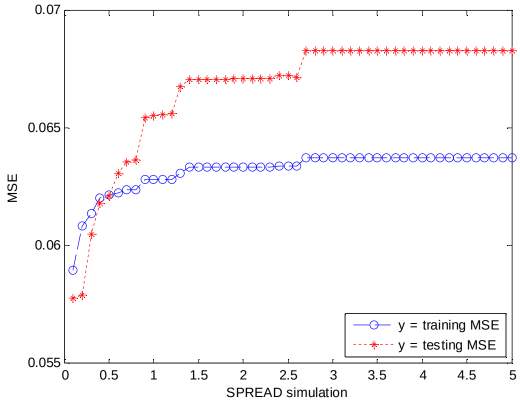


e) RMSE of Hybrid ARIMAX ([1,3,12,14],1,[2]) and RBFNNs

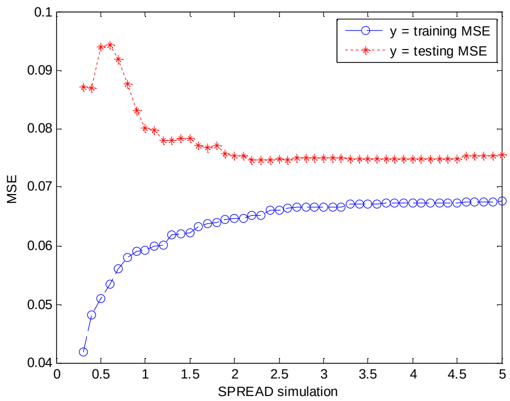
- Surabaya Inflation ($Z_{2,t}$)



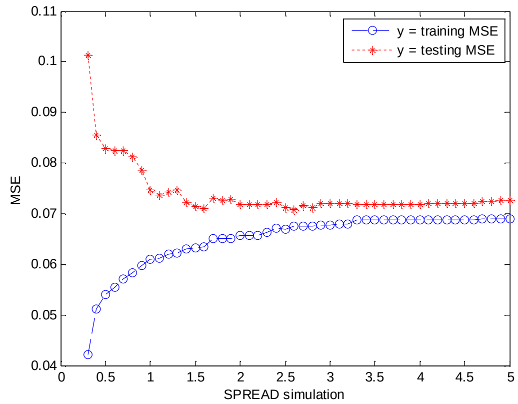
(a) RMSE of Hybrid ARIMAX([1,5,12,19],1,[2,14]) and RBFNNs



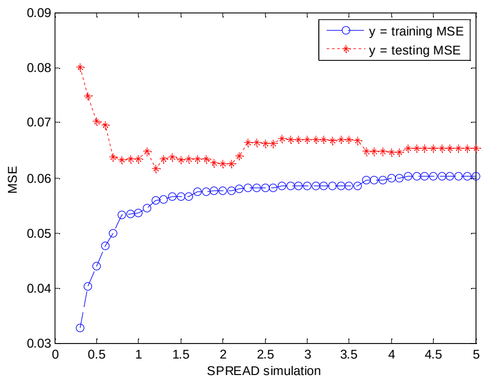
(b) RMSE of Hybrid ARIMAX([1,5,12],1,[2,20]) and RBFNNs



(c) RMSE of Hybrid ARIMAX([1,6,12,20],1,[2]) and RBFNNs

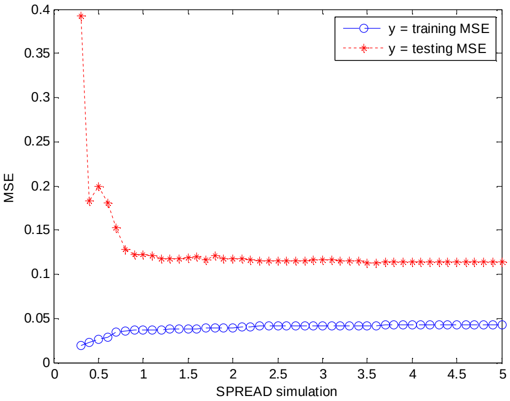


(d) RMSE of Hybrid ARIMAX([1,12,20],1,[2,6]) and RBFNNs

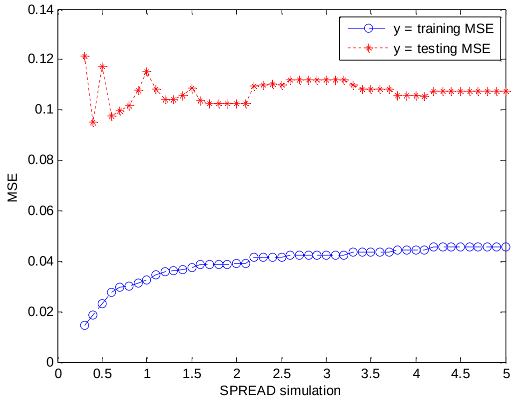


(e) RMSE of Hybrid ARIMAX([2,12],1,1) and RBFNNs

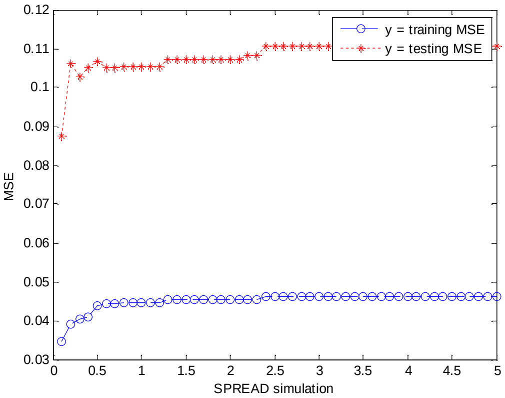
- Malang Inflation ($Z_{3,t}$)



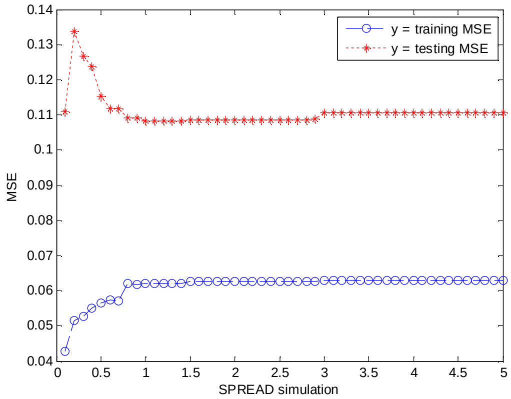
(a) RMSE of Hybrid ARIMAX(1,1,[2]) and RBFNNs



(b) RMSE of Hybrid ARIMAX([1,2],1,[3]) and RBFNNs

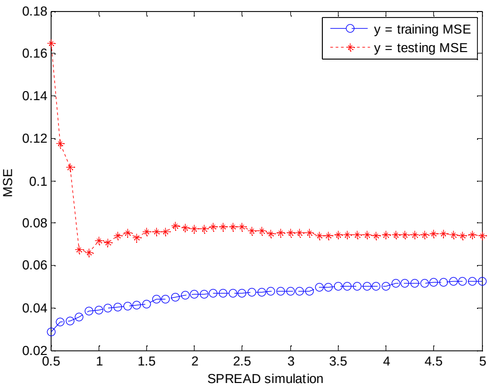


(c) RMSE of Hybrid ARIMAX(0,1,1)and RBFNNs

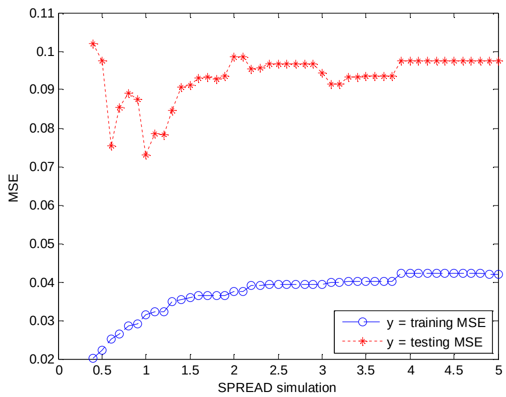


(d) RMSE of Hybrid ARIMAX([1,2,3],1,[4]) and RBFNNs

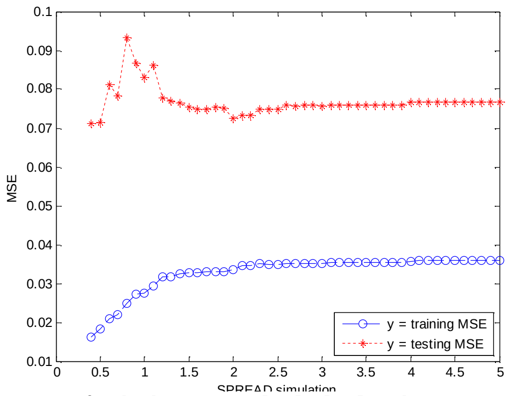
- Jember Inflation ($Z_{4,t}$)



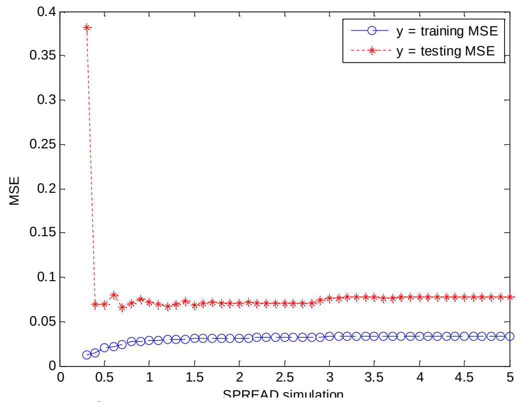
(a) RMSE of Hybrid ARIMA([1,7],1,2) and RBFNNs



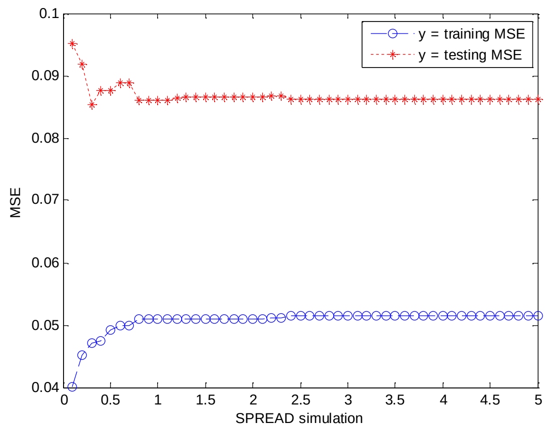
(b) RMSE of Hybrid ARIMAX([3,4],1,[1,11]) and RBFNNs



(c) RMSE of Hybrid ARIMAX([2,3],1,[1,4]) and RBFNNs

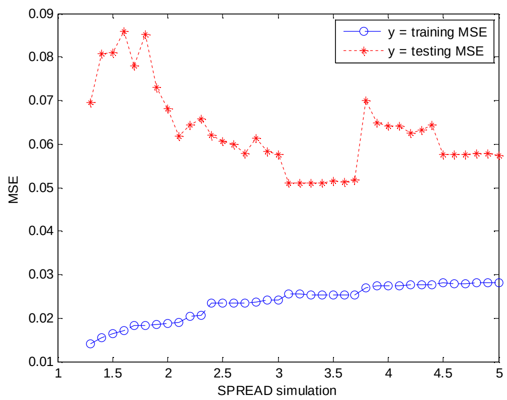


(d) RMSE of Hybrid ARIMAX([1,2,4],1,[3,12]) and RBFNNs

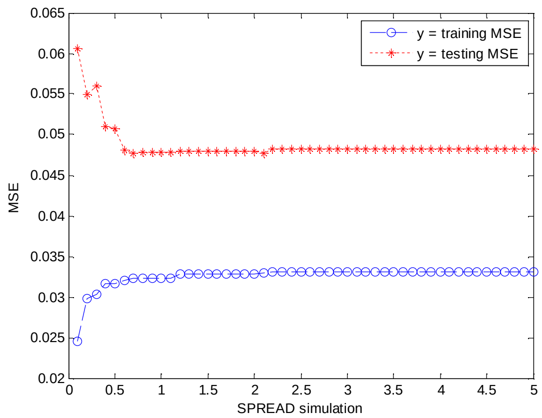


(e) RMSE of Hybrid ARIMAX(1,1,[2,3]) and RBFNNs

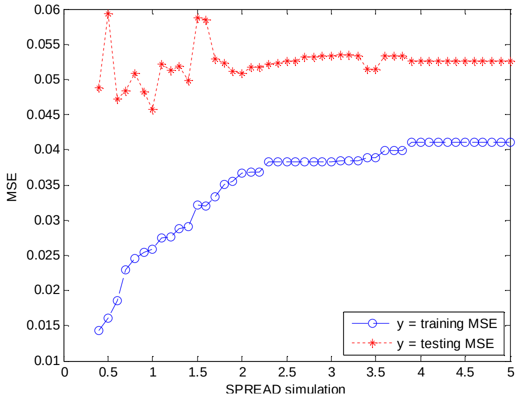
- Kediri Inflation ($Z_{5,t}$)



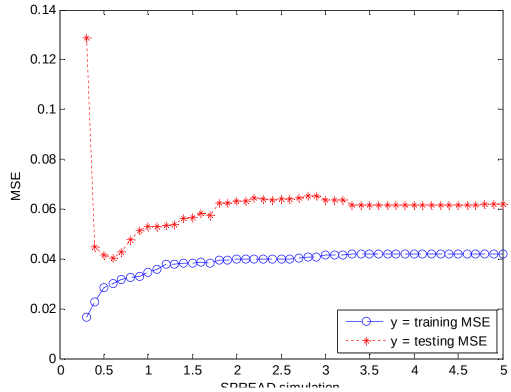
(a) RMSE of Hybrid ARIMAX([1,3],1,[2]) and RBFNNs



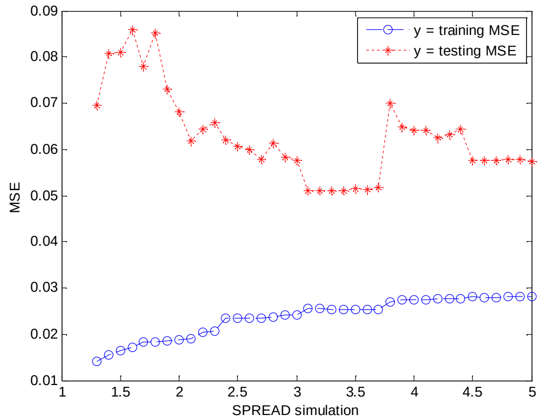
(b) RMSE of Hybrid ARIMA(1,1,[2,3]) and RBFNNs



(c) RMSE of Hybrid ARIMA(1,1,[2,7]) and RBFNNs

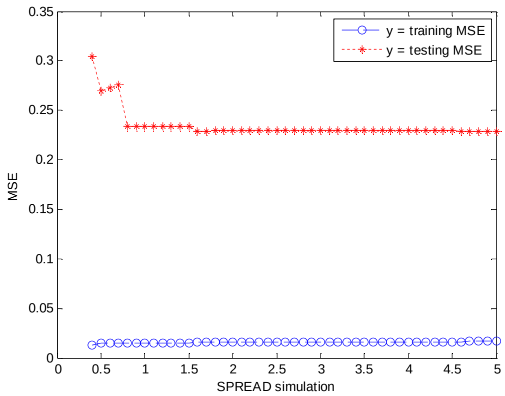


(d) RMSE of Hybrid ARIMA([1,7],1,[2]) and RBFNNs

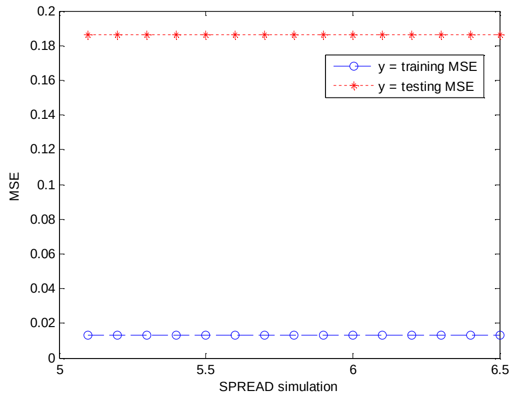


(e) RMSE of Hybrid ARIMA([1,2],1,[3]) and RBFNNs

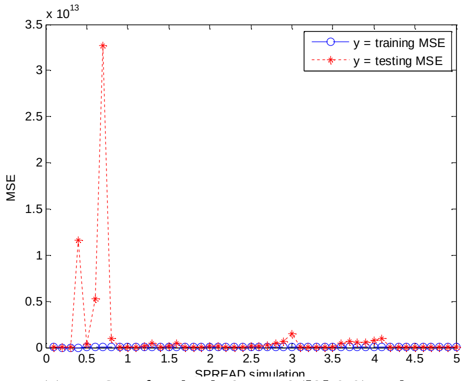
- Probolinggo Inflation ($Z_{6,t}$)



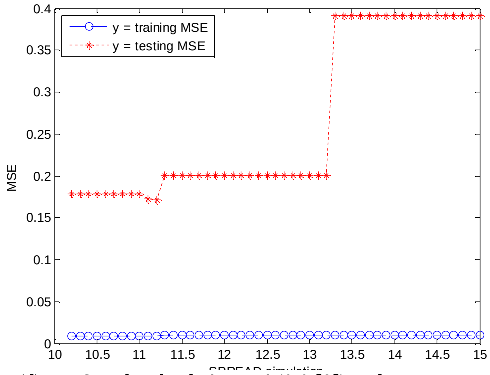
(a) RMSE of Hybrid ARIMA(1,0,[9]) and RBFNNs



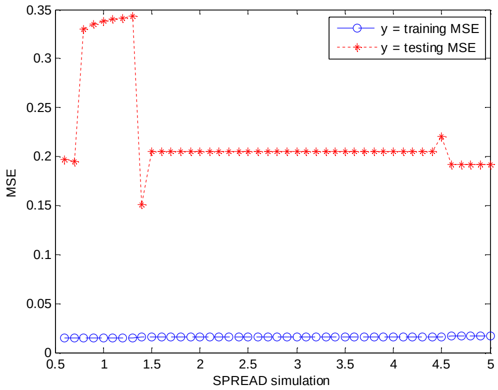
(b) RMSE of Hybrid ARIMA([9],0,1) and RBFNNs



(c) RMSE of Hybrid ARIMA([9],0,0) and RBFNNs

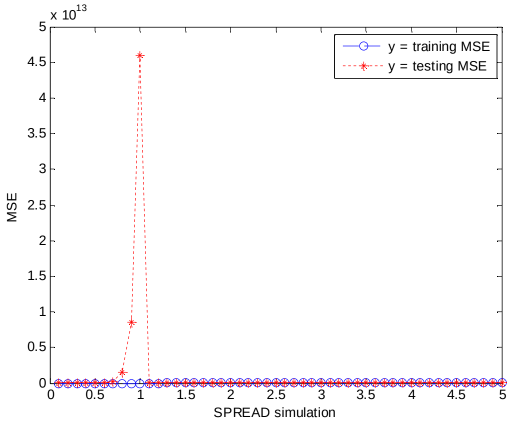


(d) RMSE of Hybrid ARIMA(0,0,[9]) and RBFNNs

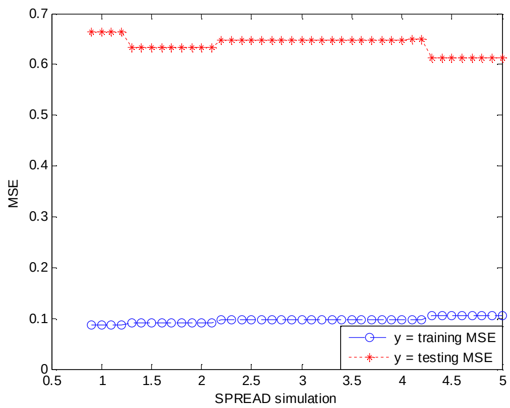


(e) RMSE of Hybrid ARIMA([1,9],0,0) and RBFNNs

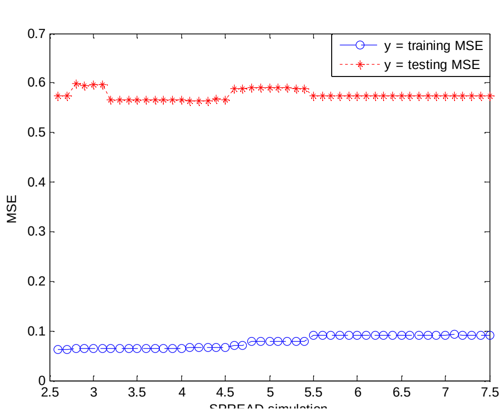
- Madiun Inflation ($Z_{7,t}$)



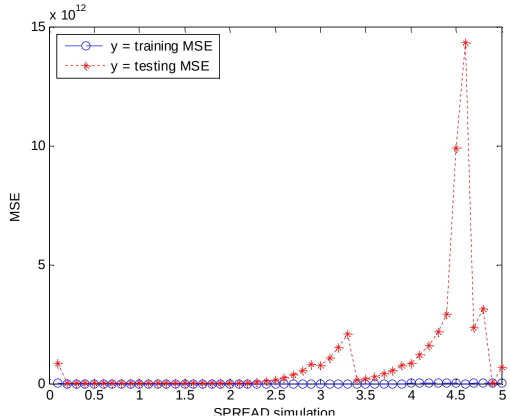
(a) RMSE of Hybrid ARIMA(1,0,0) and RBFNNs



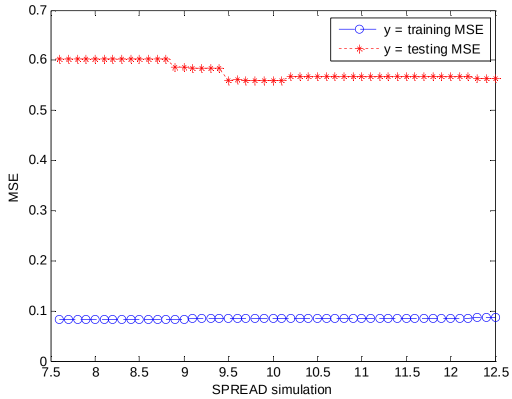
(b) RMSE of Hybrid ARIMA(0,0,1) and RBFNNs



(c) RMSE of Hybrid ARIMA([9],0,0) and RBFNNs

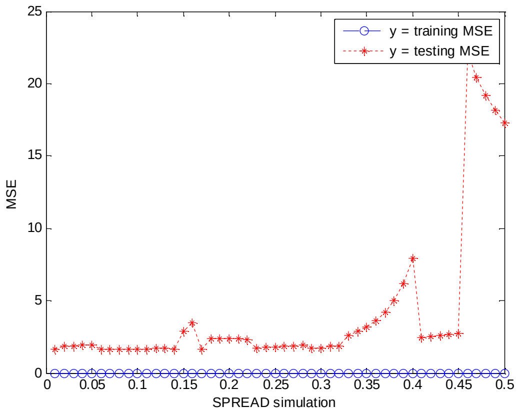


(d) RMSE of Hybrid ARIMA(0,0,[9]) and RBFNNs

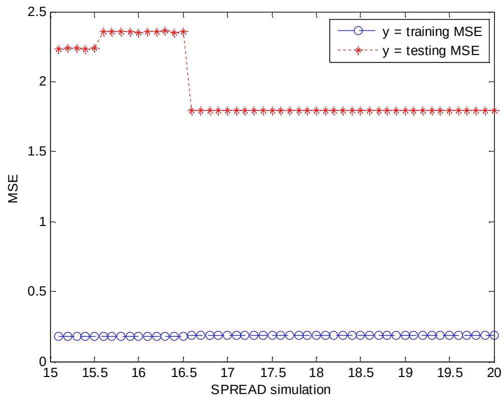


(e) RMSE of Hybrid ARIMA([1,9],0,0) and RBFNNs

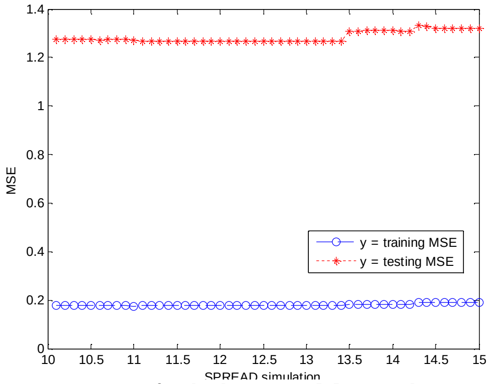
- Sumenep Inflation ($Z_{8,t}$)



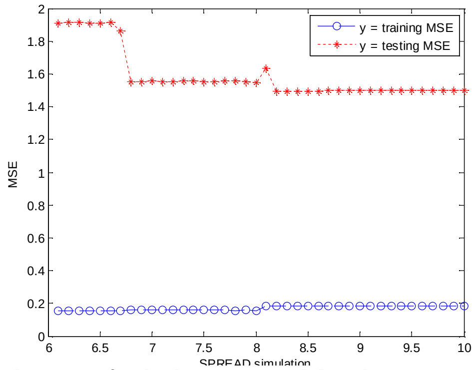
(a) RMSE of Hybrid ARIMA([3],0,0) and RBFNNs



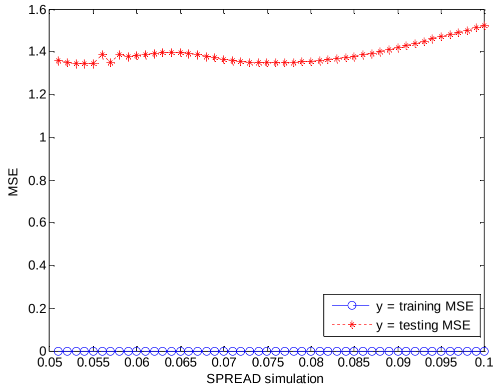
(b) RMSE of Hybrid ARIMA(0,0[3]) and RBFNNs



(c) RMSE of Hybrid ARIMA([9],0,0) and RBFNNs



(d) RMSE of Hybrid ARIMA(0,0,[9]) and RBFNNs



(e) RMSE of Hybrid ARIMA([3,9],0,0) and RBFNNs

Appendix 10: Output SPSS Stacking Coefficient of Hybrid Autoregressive Integrated Moving Average (ARIMA) and Radial Basis Function Neural Networks (RBFNNs)

- National Inflation ($Z_{1.t}$)

Parameter	Estimate	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
c1	.216	.088	.043	.388
c2	.304	.065	.176	.431
c3	.133	.089	-.042	.308
c4	.000	.055	-.108	.108
c5	.348	.055	.239	.456

- Surabaya Inflation ($Z_{2.t}$)

Parameter	Estimate	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
c1	.539	.196	.154	.923
c2	.034	.381	-.715	.783
c3	.348	1.014	-1.645	2.342
c4	.000	1.009	-1.983	1.983
c5	.079	.377	-.662	.820

- Malang Inflation ($Z_{3.t}$)

Parameter	Estimate	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
c1	.074	.107	-.137	.286
c2	.584	.074	.437	.731
c3	.196	.104	-.008	.401
c4	.145	.075	-.003	.293

- Jember Inflation ($Z_{4.t}$)

Parameter	Estimate	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
c1	.030	.051	-.071	.130
c2	.243	.073	.099	.386
c3	.564	.075	.417	.711
c4	.159	.088	-.016	.333
c5	.005	.069	-.132	.142

- Kediri Inflation ($Z_{5.t}$)

Parameter	Estimate	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
c1	.321	.086	.151	.491
c2	.000	.082	-.163	.163
c3	.401	.081	.241	.560
c4	.053	.066	-.077	.182
c5	.225	.089	.050	.400

- Probolinggo Inflation ($Z_{6.t}$)

Parameter	Estimate	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
c1	.072	.346	-.622	.766
c2	.082	.216	-.352	.515
c3	.774	.172	.430	1.118
c4	.000	.232	-.465	.465
c5	.072	.343	-.614	.759

- Madiun Inflation ($Z_{7.t}$)

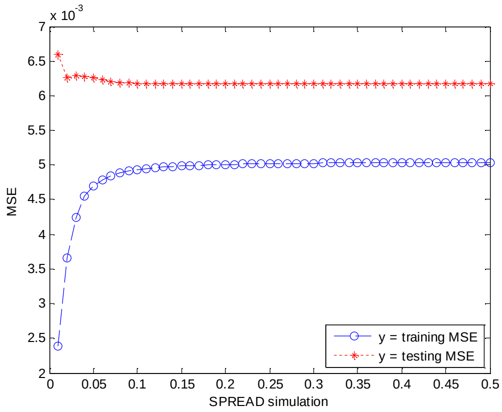
Parameter	Estimate	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
c1	.072	.116	-.161	.305
c2	.000	.135	-.270	.270
c3	.000	.108	-.217	.217
c4	.928	.104	.720	1.135
c5	.000	.112	-.224	.224

- Sumenep Inflation ($Z_{8.t}$)

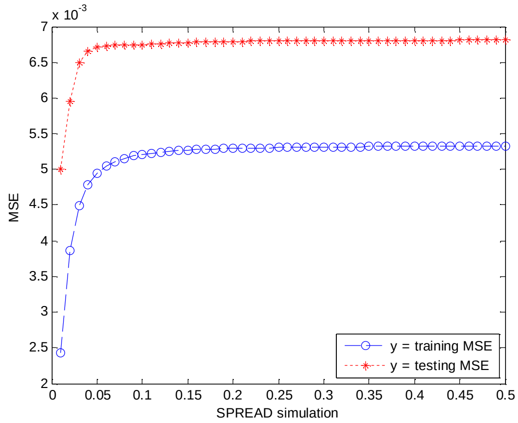
Parameter	Estimate	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
c1	.916	.581	-.248	2.080
c2	.000	.221	-.443	.443
c3	.050	.307	-.566	.666
c4	.034	.302	-.571	.639
c5	.000	.588	-1.178	1.178

Appendix 11: Root Means Square Error of Hybrid Autoregressive Integrated Moving Average (ARIMA and) Generalized Regression Neural Networks (GRNNs)

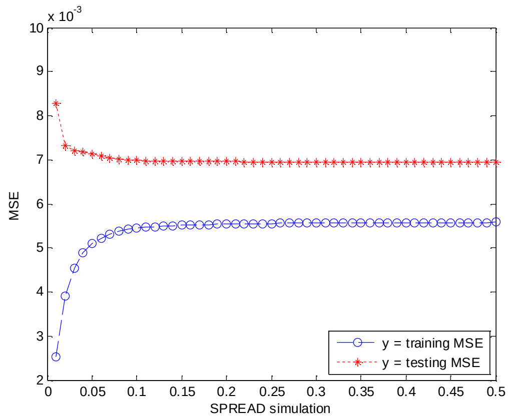
- National Inflation ($Z_{1.t}$)



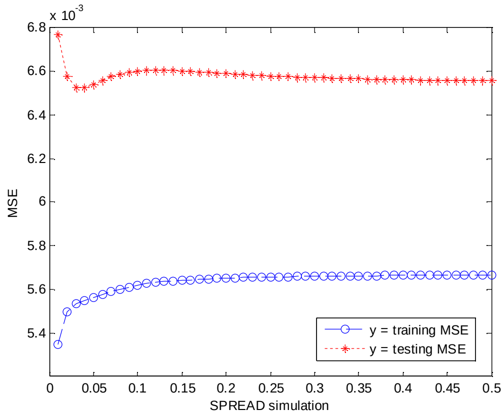
(a) RMSE of Hybrid ARIMAX ([1,12],1,[2,8,20]) and GRNNs



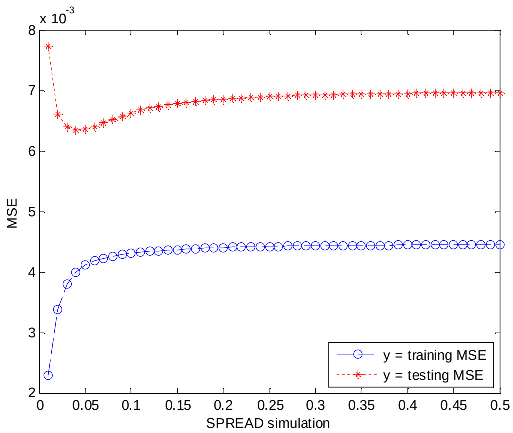
(b) RMSE of Hybrid ARIMAX ([1,8,12],1,[2,20]) and GRNNs



(c) RMSE of Hybrid ARIMAX ([1,12,20],1,[2,8]) and GRNNs

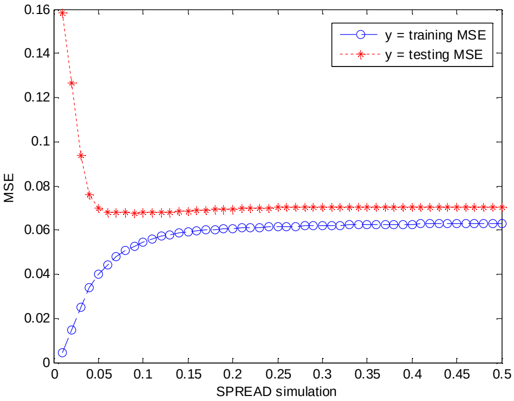


(d) RMSE of Hybrid ARIMAX([1,12,14],1,[2,8,20]) and GRNNs

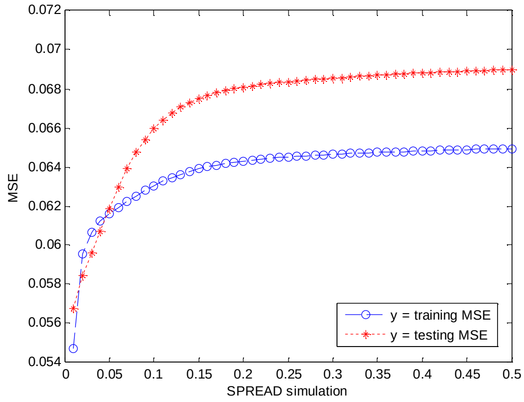


(e) RMSE of Hybrid ARIMAX ([1,3,12,14],1,[2]) and GRNNs

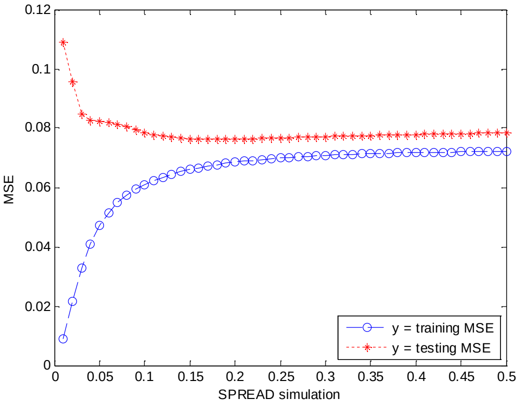
- Surabaya Inflation ($Z_{2,t}$)

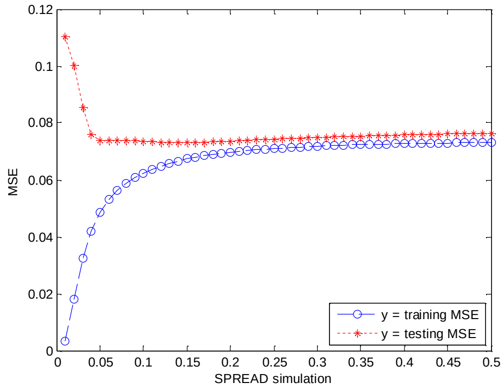


(a) RMSE of Hybrid ARIMAX([1,5,12,19],1,[2,14]) and GRNNs

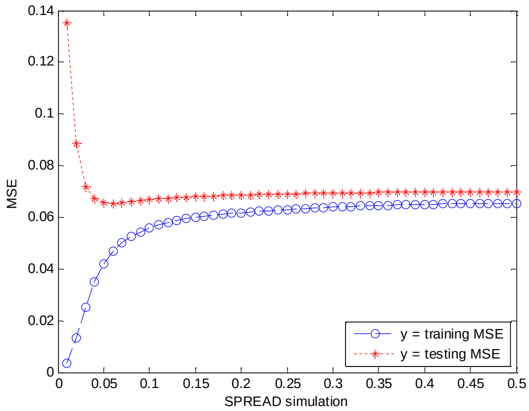


(b) RMSE of Hybrid ARIMAX([1,5,12],1,[2,20]) and GRNNs



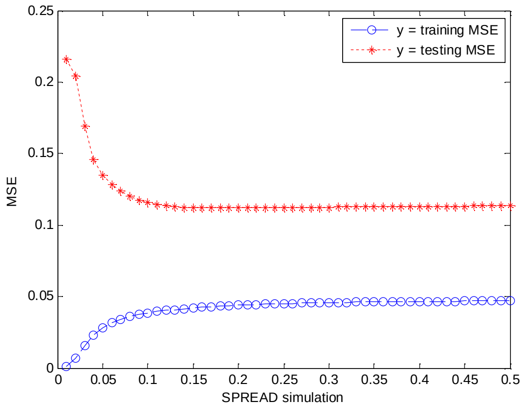


(c) RMSE of Hybrid ARIMAX([1,6,12,20],1,[2]) and GRNNs(d) RMSE of Hybrid ARIMAX([1,12,20],1,[2,6]) and GRNNs

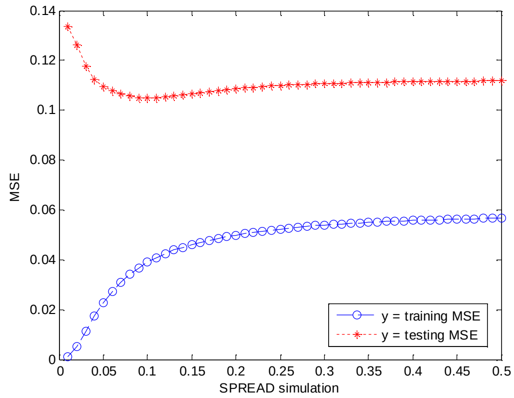


(e) RMSE of Hybrid ARIMAX([2,12],1,1) and GRNNs

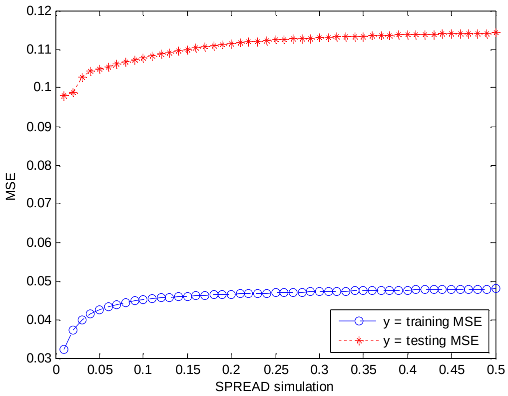
- Malang Inflation ($Z_{3,t}$)



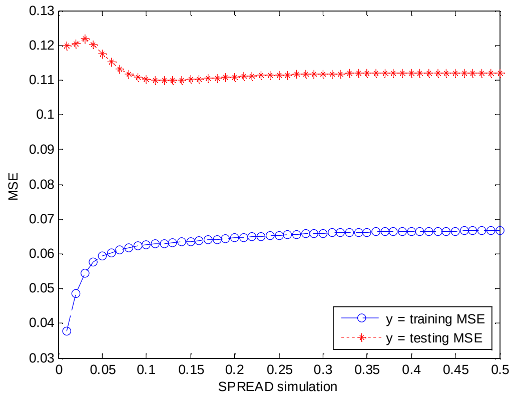
(a) RMSE of Hybrid ARIMAX(1,1,[2]) and GRNNs



(b) RMSE of Hybrid ARIMAX([1,2],1,[3]) and GRNNs

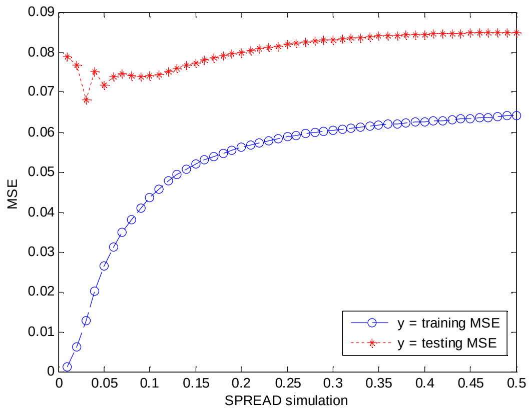


(c) RMSE of Hybrid ARIMAX(0,1,1)and GRNNs

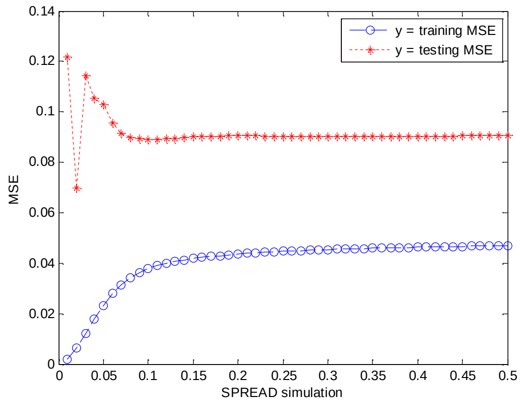


(d) RMSE of Hybrid ARIMAX([1,2,3],1,[4]) and GRNNs

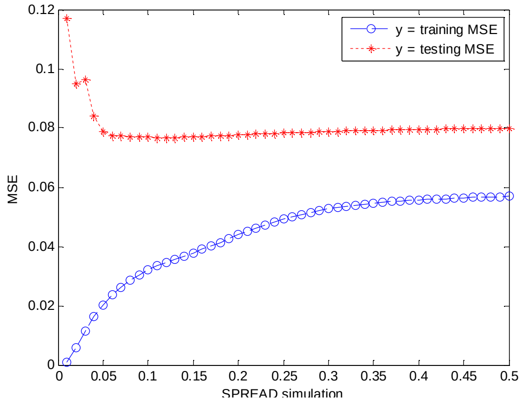
- Jember Inflation ($Z_{4,t}$)



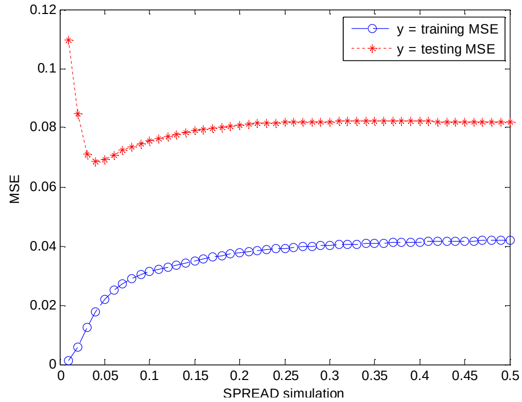
(a) RMSE of Hybrid ARIMA([1,7],1,2) and GRNNs



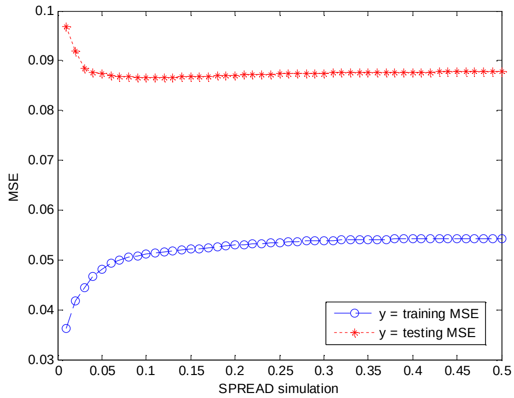
(b) RMSE of Hybrid ARIMAX([3,4],1,[1,11]) and GRNNs



(c) RMSE of Hybrid ARIMAX([2,3],1,[1,4]) and GRNNs

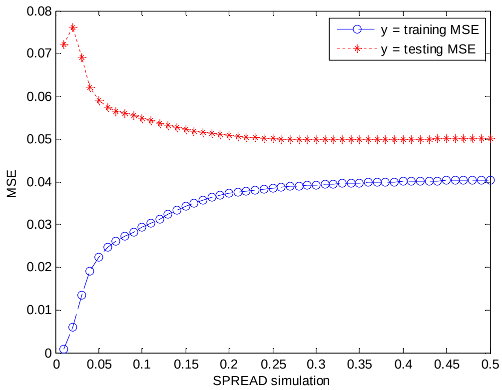


(d) RMSE of Hybrid ARIMAX([1,2,4],1,[3,12]) and GRNNs

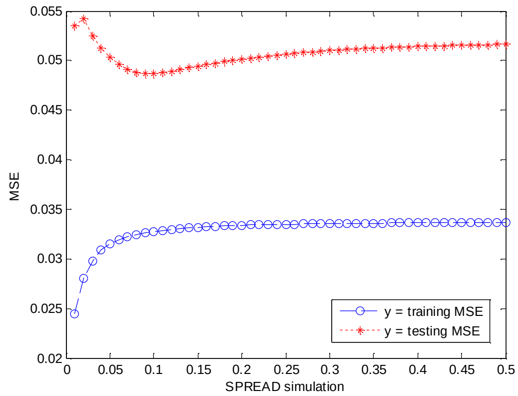


(e) RMSE of Hybrid ARIMAX(1,1,[2,3]) and GRNNs

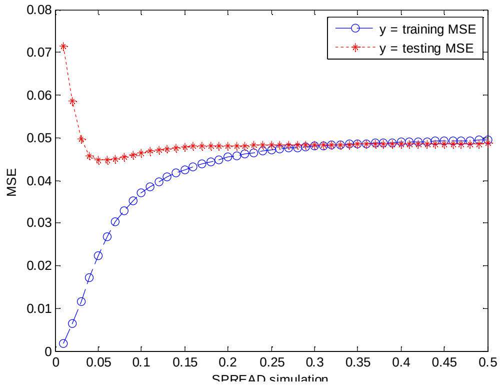
- Kediri Inflation ($Z_{5,t}$)



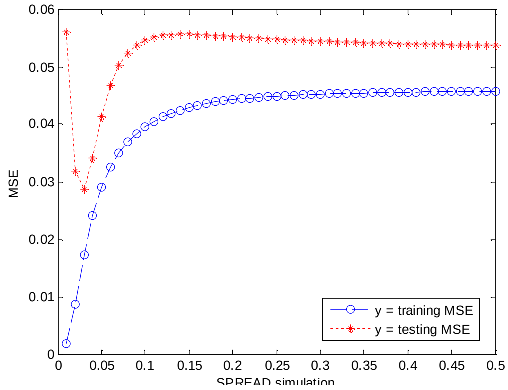
(a) RMSE of Hybrid ARIMAX([1,3],1,[2]) and GRNNs



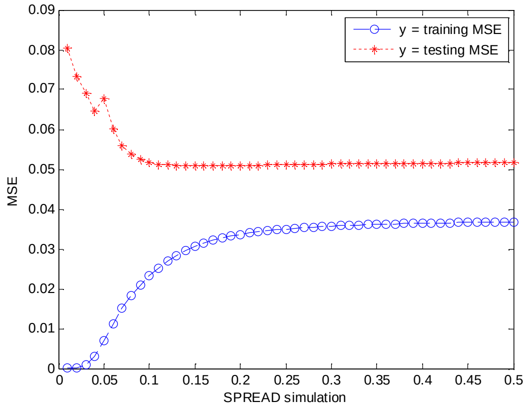
(b) RMSE of Hybrid ARIMA(1,1,[2,3]) and GRNNs



(c) RMSE of Hybrid ARIMA(1,1,[2,7]) and GRNNs

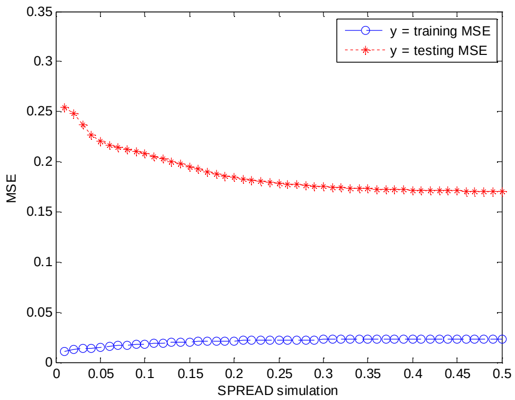


(d) RMSE of Hybrid ARIMA([1,7],1,[2]) and GRNNs

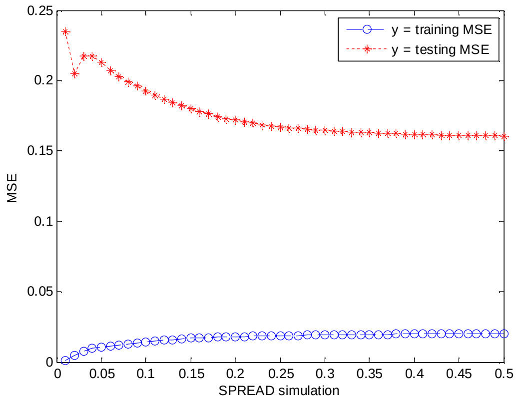


(e) RMSE of Hybrid ARIMA([1,2],1,[3]) and GRNNs

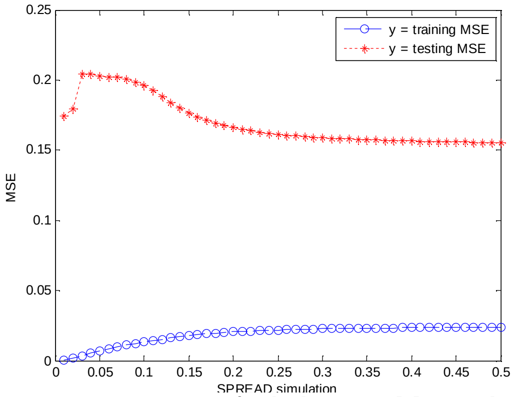
- Probolinggo Inflation ($Z_{6,t}$)



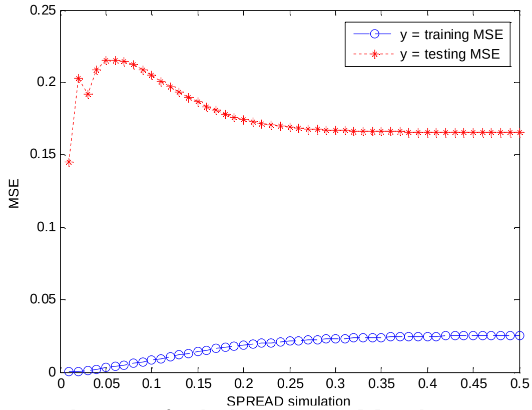
(a) RMSE of Hybrid ARIMA(1,0,[9]) and GRNNs



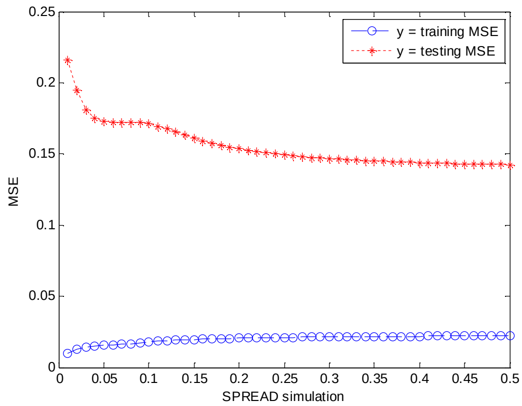
(b) RMSE of Hybrid ARIMA([9],0,1) and GRNNs



(c) RMSE of Hybrid ARIMA([9],0,0) and GRNNs

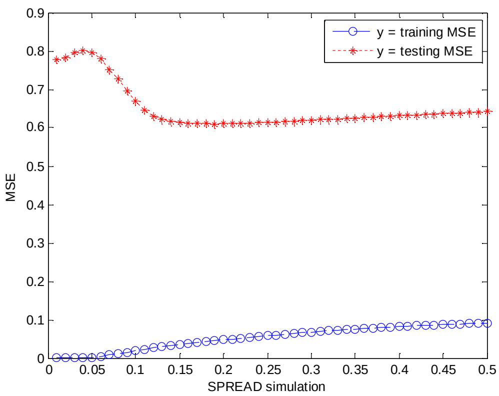


(d) RMSE of Hybrid ARIMA(0,0,[9]) and GRNNs

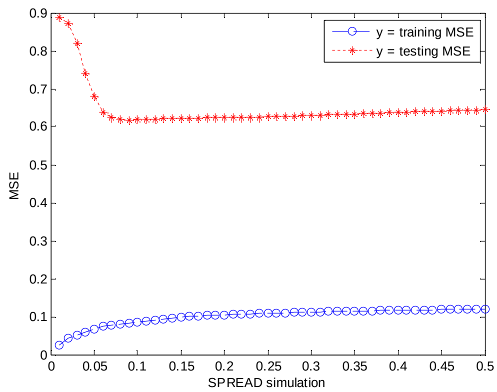


(e) RMSE of Hybrid ARIMA([1,9],0,0) and GRNNs

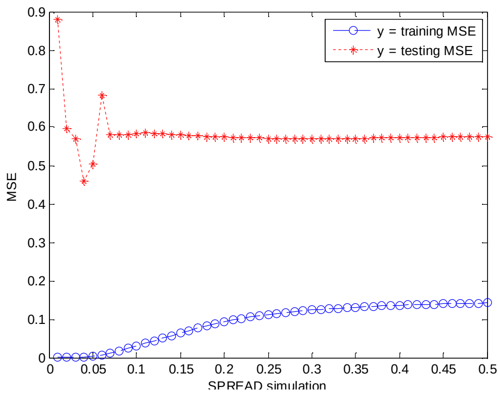
- Madiun Inflation ($Z_{7,t}$)



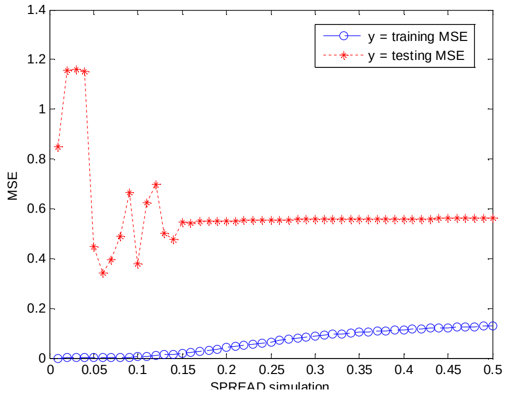
(a) RMSE of Hybrid ARIMA(1,0,0) and GRNNs



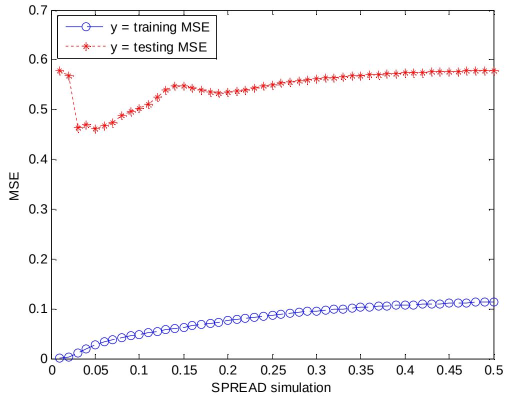
(b) RMSE of Hybrid ARIMA(0,0,1) and GRNNs



(c) RMSE of Hybrid ARIMA([9],0,0) and GRNNs

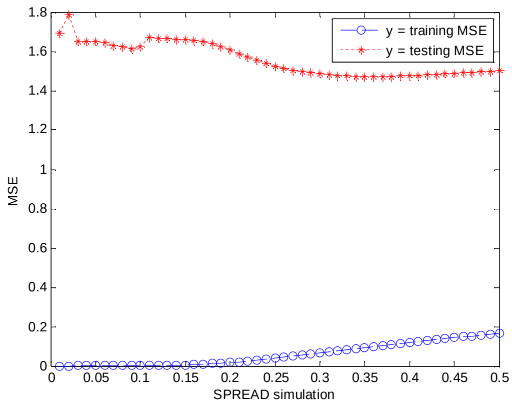


(d) RMSE of Hybrid ARIMA(0,0,[9]) and GRNNs

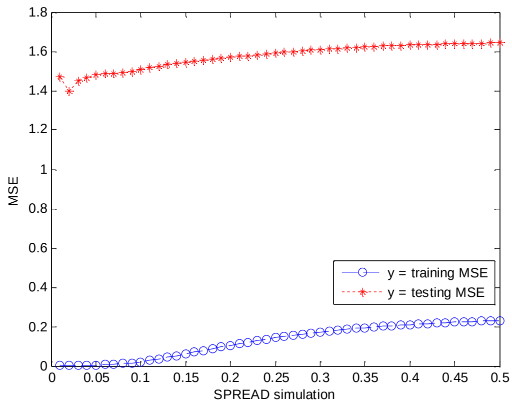


(e) RMSE of Hybrid ARIMA([1,9],0,0) and GRNNs

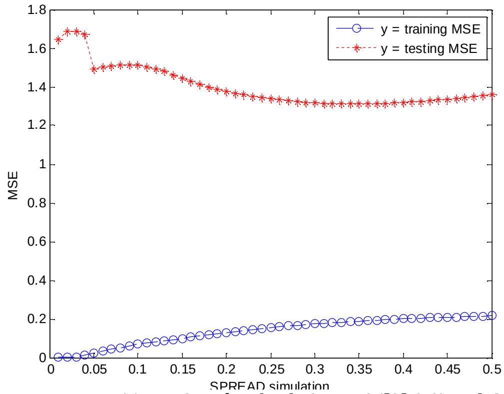
- Madiun Inflation ($Z_{7,t}$)



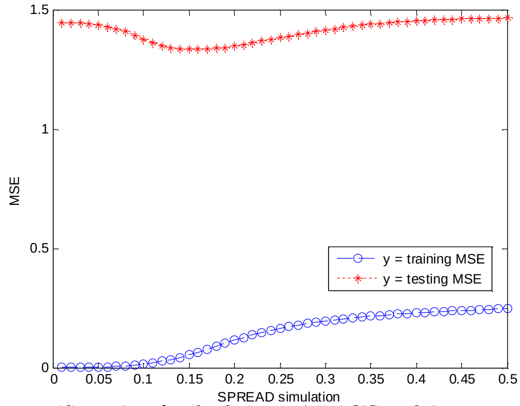
(a) RMSE of Hybrid ARIMA([3],0,0) and GRNNs



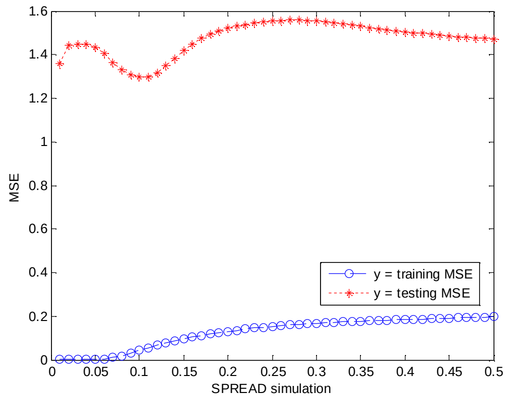
(b) RMSE of Hybrid ARIMA(0,0[3]) and GRNNs



(c) RMSE of Hybrid ARIMA([9],0,0) and GRNNs



(d) RMSE of Hybrid ARIMA(0,0,[9]) and GRNNs



(e) RMSE of Hybrid ARIMA([3,9],0,0) and GRNNs

Appendix 12: Coeffient of Stacking of Hybrid Autoregressive Integrated Moving Average (ARIMA) and Generalized Regression Neural Networks (GRNNs)

- National Inflation ($Z_{1.t}$)

Parameter	Estimate	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
c1	.027	.136	-.240	.293
c2	.838	.072	.696	.979
c3	.000	.148	-.291	.291
c4	.000	.087	-.171	.171
c5	.135	.068	.002	.269

- Surabaya Inflation ($Z_{2.t}$)

Parameter	Estimate	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
c1	.145	.131	-.112	.402
c2	.172	.115	-.054	.398
c3	.000	.210	-.413	.413
c4	.238	.206	-.166	.642
c5	.445	.096	.255	.634

- Malang Inflation ($Z_{3.t}$)

Parameter	Estimate	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
c1	.170	.124	-.076	.416
c2	.353	.106	.143	.563
c3	.477	.126	.228	.726
c4	.000	.089	-.176	.176

- Jember Inflation ($Z_{4.t}$)

Parameter	Estimate	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
c1	.040	.053	-.064	.144
c2	.590	.076	.440	.740
c3	.161	.085	-.007	.329
c4	.209	.086	.039	.379
c5	.000	.064	-.126	.126

- Kediri Inflation ($Z_{5.t}$)

Parameter	Estimate	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
c1	.172	.124	-.072	.416
c2	.000	.127	-.250	.250
c3	.123	.110	-.093	.339
c4	.454	.109	.239	.669
c5	.250	.132	-.009	.510

- Probolinggo Inflation ($Z_{6.t}$)

Parameter	Estimate	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
c1	.008	.404	-.802	.818
c2	.051	.280	-.510	.611
c3	.000	.252	-.505	.505
c4	.855	.124	.606	1.103
c5	.087	.387	-.689	.862

- Madiun Inflation ($Z_{7.t}$)

Parameter	Estimate	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
c1	.035	.186	-.339	.408
c2	.000	.220	-.442	.442
c3	.066	.467	-.870	1.002
c4	.866	.456	-.049	1.781
c5	.034	.123	-.212	.279

- Sumenep Inflation ($Z_{8.t}$)

Parameter	Estimate	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
c1	.000	.377	-.756	.756
c2	.866	.402	.060	1.672
c3	.000	.409	-.820	.820
c4	.134	.462	-.793	1.061
c5	.000	.386	-.773	.773