Inflation forecasting by hybrid singular spectrum analysis – multilayer perceptrons neural network method, case of Indonesia

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INFLATION FORECASTING BY HYBRID SINGULAR SPECTRUM ANALYSIS – MULTILAYER PERCEPTRONS NEURAL NETWORK METHOD, CASE OF INDONESIA

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Abstract

Inflation is one of the most important macroeconomic indicators which affects the economic condition of a nation. Therefore, it is necessary to maintain its stability in order that it will not lead to a negative impact and an economic vulnerability. The drastic change in the rate of inflation is determined by the condition of the price of goods which is affected by the distribution and supply-demand factors of goods. As a consequence, it becomes a very important act of action to control inflation. This can be achieved by meeting the information needs of future inflation rates that is needed for the government and the policy of the monetary authority. Fulfillment of accurate and reliable future forecasts of future inflation estimates can be obtained through forecasting. This paper examines the application of the method of Hybrid singular spectrum analysis - a multilayer perceptions neural network to predict the inflation. The main data source used is monthly inflation (in percent) collected by BPS Statistics Indonesia. The result of the study found that the ability of SSA-MPNN Hybrid method is good enough in predicting monthly inflation, as it is provided by the MAPE value of 35.42 percent, without-sample of three observations.

(approximately 194 words)

Keywords: *inflation, forecasting, hybrid singular spectrum analysis-multilayer perceptions neutral network, Indonesia*

1. Introduction

Inflation is one of the economic phenomena in the form of increasing prices of goods and services in general and in a continuous way. Inflation can have both positive and negative impact on the economy. At the time the inflation is moderate, it has a positive impact such as raising national income and boosting people excited to work, saving and investing. On the contrary, if there is a high rate of inflation, when there is uncontrolled inflation (hyperinflation), the economic condition becomes sluggish, as a consequence of the weakening of people's purchasing power and can cripple production capability leading to economic crisis. Even if a high inflation outbreak occurs in many countries, it can drive a global economic crisis.

In this connection, it is worth noting that low and stable inflation is a prerequisite for realizing the people's welfare. Meanwhile, Indonesia's source of inflationary pressure is not only from demand side that can be managed by Bank Indonesia, but also from some research results. Inflation characteristic in Indonesia is still tended to fluctuate, mainly which is influenced by the supply side with regard to disturbance of production which is caused by climate change, the fail of harvest seasons, distribution and government policy. In addition, shocks to inflation may also come from government policies related to strategic commodity prices such as fuel and other energy commodities [3].

Therefore, inflation must be monitored and maintained for the stability in order not to have a negative impact on the economy. In this case, Indonesia Central Bank as the monetary authority for example, establishes and implements monetary policy to achieve and maintain the stability of the Rupiah value. The policy direction is based on the inflation rate target to be achieved by taking into account various other macroeconomic objectives, both in the short, medium and long term so that future inflation information is needed as an input in the formulation of macroeconomic policies and programs. Such information can be obtained through a statistical forecasting technique.

Furthermore, time series forecasting is a quantitative method for analyzing past data that has been collected regularly by using appropriate techniques. The results can be used as a reference for forecasting the specific of future value [9]. The development of forecasting methods are more rapid and complex as the development impact of computing technology progresses. The interesting thing about these developments is the reconstruction of hybrid time series forecasting methods [1], [6], [7], [12] and [13], meaning that a time series forecasting method is made up of two different types of forecasting methods, where the final forecasting value is derived from the sum of forecasting values of both methods.

In this study, forecasting is conducted by applying method of Hybrid Singular Spectrum Analysis (SSA) - MPNN [7] to forecast inflation on the grounds that the method is flexible to the data movement pattern, so it has excellent forecasting accuracy and is suitable for the case of stationary and non stationary data.

2. Data

The data used in the study are monthly inflation (%, in percentage) which is started from January 2003 to January 2018 and the source is originated from BPS Statistics Indonesia. The training data (the so-called as in sample data, which means that data has been used for model construction) including monthly inflation from January 2006 to October 2017, while testing data (Out of sample) including monthly inflation is started from November 2017 up to January 2018.

3. Method

3.1 *Singular Spectrum Analysis* (SSA)

SSA is a nonparametric of time series technique based on the principle of multivariate statistics. SSA parses additive time series into independent components. These components can be identified as trending, periodic, quasi-periodic, and noise components. SSA procedure consists of four steps, namely as follows:

The 1st Step. *Embedding*

A *time series*$x_1, x_2, \ldots, x_T$, choose an integer L called window length, where the parameter determination L is in in $2 \leq L \leq T/2$, and set K = T-L + 1. Defined as a track matrix:

$$\boldsymbol{X} = (X_1, \dots, X_T) = \begin{pmatrix} x_1 & x_2 & \cdots & x_K \\ x_2 & x_3 & \cdots & x_{K+1} \\ \vdots & \vdots & \ddots & \vdots \\ x_L & x_{L+1} & \cdots & x_T \end{pmatrix}$$

It turns out that the track matrix is a Hankel matrix, which means that all the elements on the main anti-diagonal are equal. On the basis of that it can be considered **X** as a multivariate data with characteristic L and observation K so the covariance matrix is $\boldsymbol{S} = \boldsymbol{X}\boldsymbol{X}'$berdimensi $L \times L$.

The 2nd Step. ***Singular Value Decomposition*** **(SVD)**

At S having eigenvalues and eigenvectors respectively are $\lambda_1, \dots, \lambda_L$, where $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_L$ and $U_1, \dots, U_L$. SVD of $\boldsymbol{X}$ is obtained as follows:

$$\boldsymbol{X} = E_1 + E_2 + \cdots + E_d \tag{1}$$

With $E_i = \sqrt{\lambda_i} U_i V_i'$, $i = 1,2, \dots, d$, E_i is called the main component, d is the number of eigenvalues λ_i and $V_i = \boldsymbol{X}' \, U_i / \sqrt{\lambda_i}$.

The 3th Step. ***Grouping***

The grouping step is the stage of grouping $\boldsymbol{X}$ into subgroups based on time series forming patterns, i.e. trend components, periodic, quasi-periodic and noise additive. Partition the set of indices $\{1,2, \dots, d\}$ into groups $I_1, I_2, \dots, I_n$, then matrix $\boldsymbol{X}_I$ correspond on group $I = \{i_1, i_2, \dots, i_b\}$ defined:

$$\boldsymbol{X}_I = E_{i_1} + E_{i_2} + \cdots + E_{i_b} \tag{2}$$

So decomposition is represented:

$$X = X_{I_1} + X_{I_2} + \cdots + X_{I_n} \tag{3}$$

With $X_{I_j}\,(j = 1,2, \ldots, n)$ is called the reconstruction component (KR). The component contribution of X_I is measured by the corresponding share of eigenvalues: $\sum_{i\in I} \lambda_i / \sum_{i=1}^{d} \lambda_i$. In a grouping process research using auto grouping in reference [2] is based on the adjacent frequencies of the main components formed. If there are several major components that have relatively close relative frequencies, then one component of reconstruction is made and so on, until some reconstruction components are formed.

The 4th Step. Reconstruction

In this final step the transformation is done on X_{I_j} into a new time series of observational T numbers obtained by diagonal averaging or Hankelization. Let Y be a dimension matrix $L \times K$ of $y_{ij}, 1 \le i \le L, 1 \le j \le K$. Then $L^* = \min(L, K)\,, K^* = \max(L, K)$ dan $T = L + K - 1$. Then $y_{ij}^* = y_{ij}$ jika $L < K$ and $y_{ij}^* = y_{ji}$ jika $L > K$. The Y matrix is transferred into *series* $y_1, y_2, \ldots, y_T$ by using the formula:

$$y_k = \begin{cases} \dfrac{1}{k} \displaystyle\sum_{m=1}^{k} y_{m,k-m+1}^*\,, 1 \le k < L^* \\ \dfrac{1}{L^*} \displaystyle\sum_{m=1}^{L^*} y_{m,k-m+1}^*\,, L^* \le k \le K^* \\ \dfrac{1}{T-k+1} \displaystyle\sum_{m=k-K^*+1}^{T-K^*+1} y_{m,k-m+1}^*\,, K^* < k \le T \end{cases} \tag{4}$$

This corresponds to the averaging of matrix elements along with the antidiagonal $i + j = k + 1$ as an example supposed $k = 1$ to say

$y_1 = y_{1,1}$, untuk $k = 2$ menyatakan $y_2 = (y_{1,2} + y_{2,1})/2$. Note that if the Matrix $\boldsymbol{Y}$ is the path matrix of some series *series* $(z_1, \dots, z_T)$ then $y_i = z_i$ for all *i*.

The diagonal averaging of equation (4) which is applied to all matrix components $\boldsymbol{X}_{I_j}$ in equation (3) produces a series $\widetilde{\boldsymbol{X}}^{(k)} = \left(\breve{x}_1^{(k)}, \breve{x}_2^{(k)}, \dots, \breve{x}_T^{(k)}\right)$, so the series $x_1, x_2, \dots, x_T$ decomposes into a summation of the reconstruction of m series:

$$x_t = \sum_{k=1}^{m} \breve{x}_t^{(k)}, t = 1,2, \dots, T \qquad (5)$$

3.2 Multilayer Perceptrons Neural Network (MPNN)

The most common form of NN (Neural Network) used for forecasting is the multilayer perceptron's feed forward. The multilayer perceptron architecture is visually presented in Figure 3.1

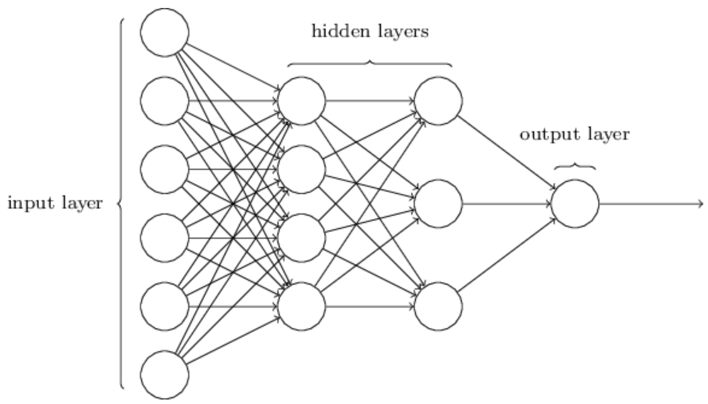

Figure 3.1 Architecture of *Multilayer Perceptrons*

Figure 3.1 explains that in a forecasting, the result of output is only one value by using two hidden layers (hidden layer can be more than one hidden layer) in which consists of 4 nodes on the first hidden layer and 3 nodes on the second hidden layer. Meanwhile, the input layer on forecasting one step ahead, $\hat{x}_{t+1}$, is calculated by using inputs derived from the lag variables k studied (x_{t-k}) and / or other exogenous variables. Then the input of neural network p_r as much as *R*, then time series of forecasting with multilayer perceptrons [8]:

$$\hat{x}_{t+1} = \beta_0 + \sum_{h=1}^{H} \beta_h g\left(\gamma_{0i} + \sum_{r=1}^{R} \gamma_{hr} p_r\right) \quad (6)$$

In equation (3), the $\boldsymbol{w} = (\boldsymbol{\beta}, \boldsymbol{\gamma})$ is weighed with $\boldsymbol{\beta} = [\beta_0, \dots, \beta_0], \boldsymbol{\gamma} = [\gamma_{11}, \dots, \gamma_{HR}]$ each for output and hidden layers. H is the number of hidden nodes in the network and $g(.)$ is the activation of function which is used to limit the output being produced by neurons. The activation of function often used in this research is: binary sigmoid function. Determination of hidden node in MPNN by using 5-fold cross validation and set by set.seed (1986-2018) to generate initial value.

3.3 *Hybrid Singular Spectrum Analysis* – **Multilayer Perceptrons Neural Network** (SSA-MPNN)

This section contains some stages of the proposed *SSA - MPNN* hybrid forecasting method as follows:

1. The original time series is decomposed into the main component by using SSA.
2. The main component results in the (1^{st}) step can be determined to be the trend components, periodic components, quasi-periodic components and noise.
3. The reconstruction component is formed from the sum of several major components based on the proximity of the frequency.
4. MPNN is applied to each of the reconstruction component, so that the MPNN architecture is different for each component of its reconstruction.
5. The final forecasting result by the SSA-MPNN Hybrid is the sum of the forecasting results by of some MPNN architecture at (6).

Visually, the above stages are presented in Figure 3.2. SSA-MPNN hybrid prediction results can be directly used does not require residual examination whether pure random or not pure random as in SSA-ARIMA Hybrid [13].

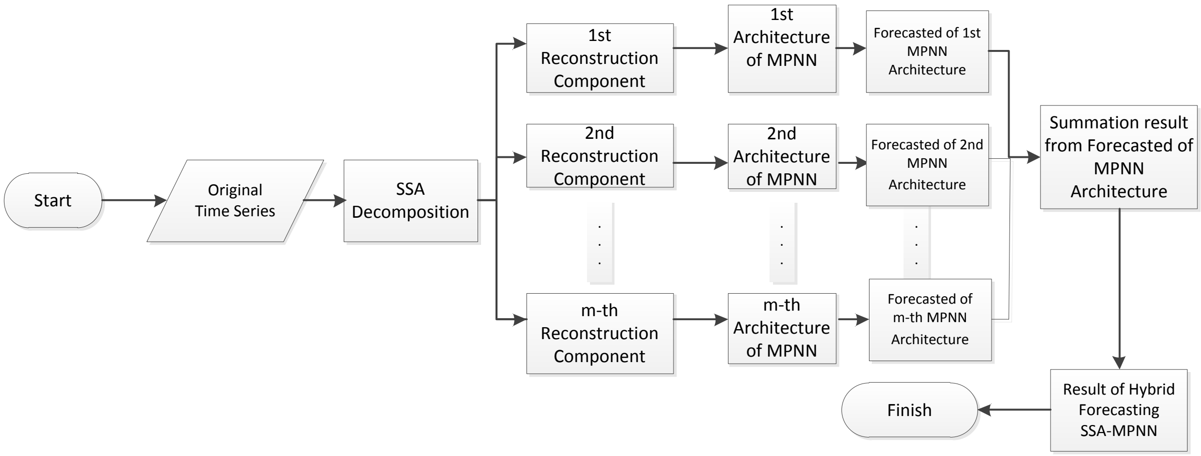

Figure 3.2 Framework of *Hybrid* Forecasting SSA – MPNN Method

3.4 Forecasting Accuracy

Forecasting accuracy in testing data (out sample) in this study using MAPE (Mean Absolute Percentage Error) to formulate as follows:

$$MSFE = \frac{1}{v-T}\sum_{t=T+1}^{v}\left|\frac{\hat{x}_t - x_t}{x_t} \times 100\%\right| \tag{7}$$

There are four criterias of MAPE value [4], namely: (a) If MAPE value <10%, then the ability of SSA-MPNN Hybrid method forecasting is very good. (b) If the MAPE value is 10% - 20%, then the forecasting ability of SSA - MPNN Hybrid method. (3) If the MAPE value is at 20% -50%, then the forecasting ability of the SSA-MPNN Hybrid method is quite good; and (4) If the MAPE value is> 50%, then the forecasting ability of the SSA-MPNN Hybrid method is bad. When the MAPE value is bad, it means that this method cannot be adopted for doing forecasting in the certain data and or region.

4. **Discussion**

In the process of forecasting SSA Hybrid - MPNN, the first step is to decompose data with SSA. In the SSA the determination of *L* in this study is the amount of training data divided by two, so *L* is 89. Based on the SVD of the training data obtained 89 main components, but only 50 main components are recommended for further analysis.

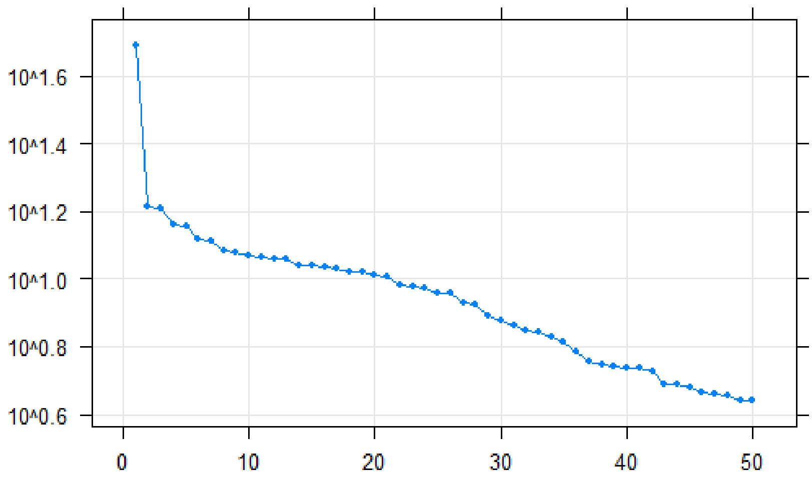

Figure 4.1 Number of Main Components Recommended

From the auto grouping process based on the reference [1] two reconstructing components are produced, in which the first reconstruction component is formed from the 1st, 2nd 3th, 4th, 5th, 6th, 7th, 8th, 9th, 12th, 13th, 14 th, 23 th, 24 th, 25 th, 26 th, 27 th, 28th, 34th, 36th, 38th, 39th, 40th, 41th, 42 th, 45 th, 46 th, 47 th, and 48 th, then the 2nd reconstructed are formed from the major components of the 10th, 11th, 16th, 17 th, 18 th, 19 th, 20 th, 21th, 22 th, 29 th, 30th , 31st, 32nd, 33 th, 35th, 37 th, 43 th, 44 th, 49 th, and 50th. The following visuals of the two reconstruction components presented in Figure 4.2.

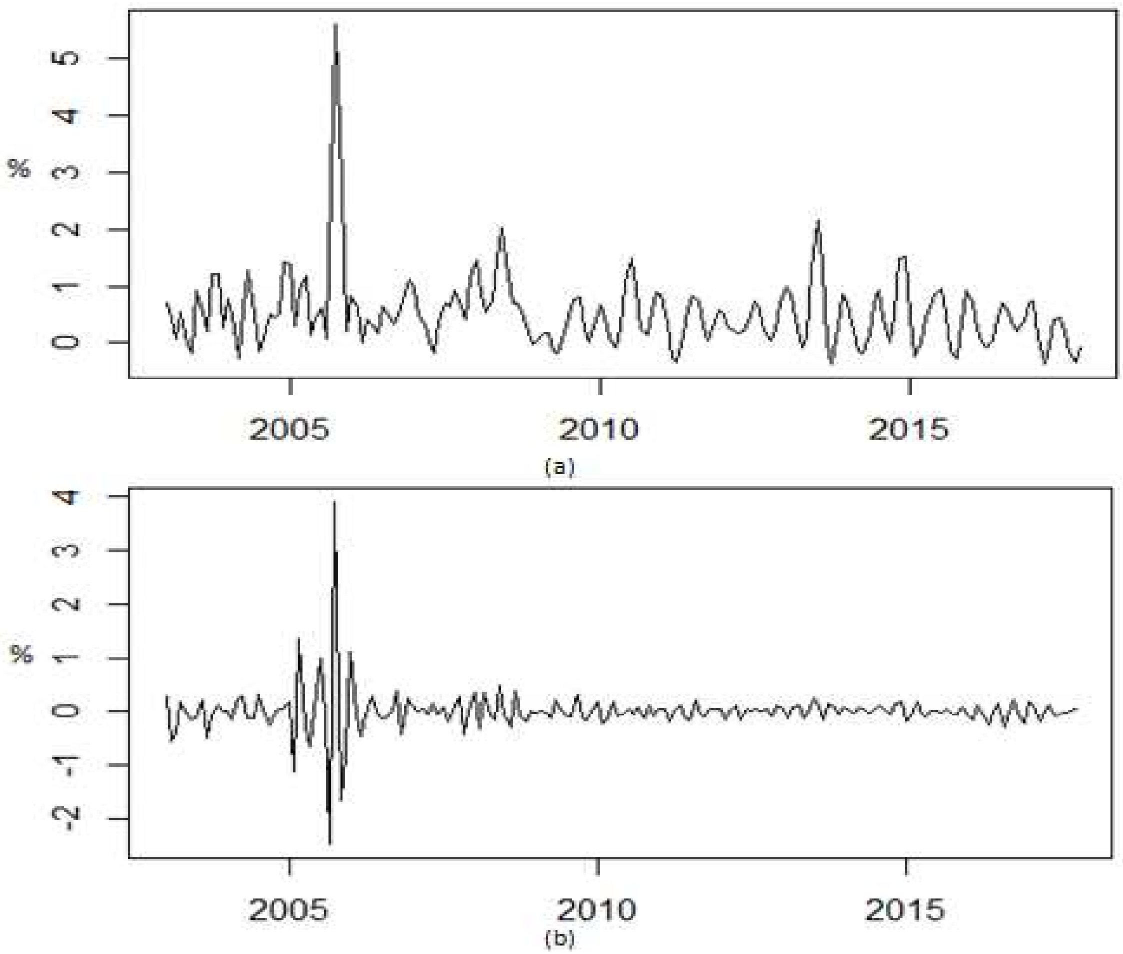

Figure 4.2 (a) The first Reconstruction Component, (b) The Second Reconstruction Component.

Subsequently, MPNN is applied to both components of the reconstruction for each forecasting. The final forecasting is the sum up of the forecasting results of both components of the reconstruction. In MPNN's forecasting, the first reconstruction component with 3000 times of iteration is obtained by MPNN architecture, i.e. 12 - 3 - 1, meaning 12 node input layer, 1 hidden layer consisting 3 nodes, and 1 output and MSE (mean squared error) in the data training results SSA grouping of 0.05. Then, forecasting MPNN on the second reconstruction component with 3000 times iteration obtained by MPNN architecture is 8 - 4 - 1, which means that the input layer as 8 node, 1 hidden layer consisting of 4 nodes, and produce 1 output and MSE in data training is as a result of grouping SSA of 0.02. Here are the results of forecasting of both reconstruction components with MPNN.

Table 4.1 Forecasting Results of Out Sample of Singular Spectrum Analysis

Year	Month	Reconstruction Component (%)	Reconstruction Component II (%)	Final Value of Forecasting *Hybrid* SSA – MPNN (%)	Actual Inflation (%)
(1)	(2)	(3)	(4)	(5) = (3)+(4)	(6)
2017	11	0.47	-0.07	0.40	0.20
2017	12	0.74	0.04	0.70	0.71
2018	1	0.52	0.07	0.59	0.62

Source: Calculated from inflation series data, derived from BPS Statistics Indonesia

Based on the results of the SSA-MPNN Hybrid forecasting shown in Table 4.1, it can be seen that the inflation forecast for November 2017 is quite wide compared to the actual value. However, inflation forecast in December 2017 and January 2018 is not significantly different from the actual value. On the average, the absolute difference in forecasting values to their actual value is indicated by the MAPE value of 35.42 percent, which means that the ability of the SSA-MPNN Hybrid method is good enough to predict inflation in the next three months.

5. Conclusion

Based on the analysis that has been done, it can be concluded that the ability of SSA-MPNN Hybrid method is good enough to forecast monthly inflation. This can be proven by the fact that the results obtained from the MAPE value of 35.42 percent with out-sample of three observations. In further perspective, this research results for policy formulation support to decision maker and data producer, It can be suggested that other developing countries that have a similarities trend inflation statistics data characteristics to Indonesia data and economic condition should have trial and or adopt this SSA-MPNN Hybrid method.

6. References

[1] Aladag, C.H., Egrioglu, E, & Kadilar, C. ,2012, Improvement in forecasting accuracy using the *Hybrid* Model of ARFIMA and Feed Forward Neural Network. American Journal of Intelligent Systems 2 (2), p 12-17.

[2] Alexandrov, Th., Golyandina, N. , 2005, Automatic extraction and forecast of time series cyclic components within the framework of SSA. In Proceedings of the 5th St.Petersburg Workshop on Simulation, June 26 – July 2, 2005, St.Petersburg State University, St.Petersburg: pp. 45–50

[3] *Bank Indonesia* [Central Bank of Indonesia], 2012, *Koordinasi Pengendalian Inflasi* [Coordination of Inflation Control], dated 18th February 2018, can be downloaded from http://www.bi.go.id/id/moneter/koordinasi-pengendalian-inflasi/Contents/Default.aspx

[4] Chang, P-C., Wang, Y-W., & Liu, C-H., 2007, The development of a weighted evolving fuzzy neural network for PCB sales forecasting. Expert Systems with Applications 32, p 86–96.

[5] Cryer, J.D., & Chan, K.S., 2008, Time series analysis: with application in R. Second Edition. USA: Spinger Science and Businiess Media, LLC.

[6] Fajar, M., 2016, *Perbandingan Kinerja Peramalan Pertumbuhan Ekonomi Indonesia Antara ARMA, FFNN dan Hybrid ARMA-FFNN.* [Performance comparison of Indonesia economic growth-forecast among ARMA, FFNN and Hybrid ARMA-FFNN]. DOI: 10.13140/RG.2.2.34924.36483

[7] Fajar, M., 2018, *Meningkatkan Akurasi Peramalan dengan Menggunakan Metode Hybrid Singular Spectrum Analysis-Multilayer Perceptron Neural Networks* [Improving the forecasting accuracy by Hybrid Method Singular Spectrum Analysis-Multylayer Perceptron Neural Networks]. DOI: 10.13140/RG.2.2.32839.60320.

[8] Kourentzes,N, Barrow, D. K., & Crone, S.F., 2014, Neural network ensemble operators for time *series* forecasting. Expert Systems with Applications 41, p 4235–4244.

[9] Makridakis, W., & Mac Gee, 1999, *Metode dan Aplikasi Peramalan* [Method and Application on Forecasting]. Jakarta, Binarupa Aksara.

[10] Rahmani, Donya., 2014, A forecasting algorithm for *Singular Spectrum Analysis* based on bootstrap Linear Recurrent Formula coefficients. International Journal of Energy and Statistics, Vol. 2 (4), p 287–299.

[11] Wei, W. W. S., 2006, *Time series Analysis: Univariate and Multivariate Methods.* California: Pearson Education, Inc.

[12] Zhang, G.P., 2003, Time series Forecasting using a Hybrid ARIMA and Neural networks Model. Neurocomputing, 50, p 159.

[13] Zhang, Q., Wang, B.D.,He,B., Peng, Y., & Ren, M.L., 2011, Singular Spectrum Analysis and ARIMA Hybrid Model for Annual Runoff Forecasting. Water Resour Manage, 25, p 2683-2703.

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