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Autoregressive neural network (AR-NN) modeling to predict the inflation rate in West Java Province

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ABSTRACT

The Autoregressive (AR) model describes the situation where the data in the current observation of a time series depends on the previous observation data. AR models have linearity assumptions. However, in reality there is a non-linear tendency in the data so it needs to be combined with a Neural Network (NN) model. NN models can overcome nonlinear problems in data. The purpose of this research is to build an AR-NN model and apply it to the inflation rate data of West Java Province. The result of this study is an AR(2)-NN model generated by summing the AR(2) prediction results with the residual AR(2) prediction results using a NN model that has a network architecture (4-5-1). The results of data processing show that the AR(2)-NN model is able to increase the level of forecast accuracy from a reasonable forecast to an accurate forecast so that the AR(2)-NN model is better used in West Java Province inflation rate data. This is supported by the smaller MAPE values compared to the AR(2) model. The AR-NN model is expected to be a recommendation for predicting inflation rates in the future.

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INTRODUCTION

Rapid economic growth is one factor that causes inflation in the economy. Inflation is defined as an increase in prices in general and continuously (Simanungkalit, 2020). An increase in the price of goods and services can cause the cost of living to increase including basic necessities such as food and clothing. Low interest rates can also trigger inflation because with low interest rates people are reluctant to save their money and as a result there is a lot of money in circulation (Silvia, Wardi & Aimon, 2013). The highest inflation rate in West Java Province reached 9.15% in 2013, one of the causes being the increase in the price of fuel oil (BBM). This also causes public transport fares to increase. Meanwhile, the lowest inflation reached 1.69% in 2021. This was due to the Covid-19 pandemic which limited mobility and decreased domestic demand. In 2022, it increases again to reach 6.04% when Covid-19 ends.

The rate of inflation can be predicted by making forecasts, so that both the government and the public can prepare things that can handle the rate. Forecasting is important for planning and controlling operations in areas such as production management, inventory systems, quality control, financial planning, and investment analysis (Wei, 2006). One of the forecasts that can be used is the Autoregressive (AR) model. The AR model is a statistical model that describes the situation where the data in the current observation of the time series depends on the data in the previous observation (Wei, 2006). There is an assumption that must be met in AR models which is linearity, but in reality, that assumption is not always met where there is a non-linear trend. Likewise, the West Java Province inflation rate data has a non-linear component and cannot be overcome with the AR model. The non-linear component can be overcome with the Neural Network (NN) approach. Therefore, there is a necessary model that can overcome it, which is the Autoregressive Neural Network (AR-NN) with a back propagation algorithm that is often applied in forecasting. AR-NN models have the advantage of capturing nonlinear patterns that may not be captured by AR models.

AR model formation uses three stages in time series analysis namely (Box, Jenkins & Reinsel, 2008):

1. Identification of models that include data processing and stages in data modeling.
2. The parameter estimates for the estimation and test parameters are good in the model.
3. Diagnostic checks are carried out to see the weaknesses of the model and make improvements.

Neural Networks (NN) are mathematical or computing models based on biological neural networks (Singh & Chauhan, 2009). A Neural Network consists of several layers, each layer having at least one or more units/neurons. NN has the advantage that neural networks are able to solve nonlinear problems, have a relatively high tolerance for data containing noise and are able to capture very complex relationships between predictor and output variables, but Neural Networks also have weaknesses, namely overgeneralization, which is good for training data , but fails to work well for validation data (Yunita, 2018).

A previous study on ARIMA-NN modeling was done by Kamadewi & Achmad in 2020 by comparing ARIMA and ARIMA-NN forecasting models with Indonesian inflation data forecasts. The result of the study is that the ARIMA-NN model is a more accurate model than ARIMA(1,1,0) based on the MSE value (Kamadewi & Achmad, 2020).

Following the study by Pratiwi & Hadijati in 2021, this study models inflation in Indonesia using a hybrid ARIMA-NN. The result if this study is the ARIMA-NN model has a high prediction accuracy compared to ARIMA itself (Pratiwi & Hadijati, 2021).

And the research that has been done by Anggraini, Wahyuningsih, & Siringoringo in 2023 by comparing the forecast performance of Sepinggan Yakin Mix crude oil prices between the ARIMA and ARIMA-NN models. This research produced the best model which is ARIMA(2,1,0)-NN based on MAPE value (Anggraini, Wahyuningsih & Siringoringo, 2023).

This research aims to build an AR-NN model and apply it to the inflation rate data of West Java Province. The AR-NN model is expected to improve the accuracy of the AR forecast and become a better model used to predict the inflation rate of West Java Province. In this research, the accuracy of the model is measured by Mean Absolute Percentage Error (MAPE).

AR-NN Modeling

The data used is secondary data on the inflation rate of West Java Province from January 2009 to December 2023 taken from the West Java Central Statistics Agency with pages https://jabar.bps.go.id/indicator/3/46/1/inflasi-bulanan-tujuh-kota-y-on-y-.html.

Model identification is the first stage of the AR model formation process based on the three Box-Jenkins stages. The model identification stage includes data plotting, stationary testing, and AR model identification.

Stationary data has three characteristics which are constant variance, constant mean, and constant covariance (Rusdi, 2011). Data is said to be stationary if the data is stationary in mean and variance. If the data is not stationary, the data should be made stationary by differentiation and Box-Cox transformation (Sorlury, Mongi & Nainggolan, 2022). The stationary test used in this research is the Augmented Dickey-Fuller (ADF) test. The ADF test is used to check the null hypothesis that the time series has a unit root or is not stationary to the mean (Enders, 2015). The criterion of the ADF test is that the data are stationary to the mean if the $p-value < \alpha = 0.05$. Then perform a Box-Cox transformation if the data is non-stationary to variance. The Box-Cox transformation is a level transformation on the response variable developed by Box and Cox, aimed at overcoming the problems of abnormality, heteroskedasticity, and asymmetry in the data (Wilujeng, 2018). Data are stationary to variance if $\lambda \geq 1$. The Box-Cox transformation is defined as the following equation (Wei, 2006)

$$W = \begin{cases} (Z_t^{\lambda} - 1)/\lambda, & \lambda \neq 0 \\ \ln Z_t\,, & \lambda = 0. \end{cases}$$

with Z_t is observation data at t-time, and λ is singular parameter. Box-Cox transformation is presented in Table 1.

Table 1. Box-Cox transformation

λ	Transformation
-1	$1/Z_t$
-0.5	$1/\sqrt{Z_t}$
0	$\ln Z_t$
0.5	$\sqrt{Z_t}$
1	Z_t

Identification of the order of the AR model can be done by looking at the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. ACF is the correlation function between observations at time-t with observations at $(t+k)$ −times. The model is called AR(p) if the ACF plot descends exponentially and the PACF plot is discontinuous at lag p (Wei, 2006).

The general form of the AR(p) model can be written as the following equation (Wei, 2006)

$$Z_t = \phi_1 Z_{t-1} + \phi_2 Z_{t-2} + \cdots + \phi_p Z_{t-p} + e_t$$

with Z_t is observation data at t-time, ϕ_p is AR parameter at p, p is AR order, and e_t is an *error* at t-time.

The method used for parameter estimation is Maximum Likelihood Estimation (MLE). The likelihood function for the AR model can be shown in the following equation (Wei, 2006)

$$L(e|\phi, \sigma_e^2) = (2\pi\sigma_e^2)^{-\frac{n}{2}} \exp\left[-\frac{1}{2\sigma_e^2}\sum_{t=1}^{n} e_t^2\right].$$

After the estimated value is obtained, the significance test for the parameter of the AR(p) model is conducted with the test criterion that the parameter is significant. if $p - value < \alpha = 0.05$.

Diagnostic tests are used to assess the quality of the model and confirm whether the model meets the necessary assumptions (Mawaddah, 2023). A so-called model is feasible if the residuals are not autocorrelated and normally distributed. This test uses the Ljung-Box test to automatically check for uncorrelated AR residuals, and uses a

Quantile-Quantile plot (Q-Q plot) to check whether the AR residuals approach a normal distribution. Residuals are not autocorrelated if $p - value > \alpha = 0.05$.

The assumption of normality on the Q-Q Plot is met if the points are spread very close to the diagonal line. Otherwise, the assumption of normality is not met if the points are spread far from the diagonal line (Gio & Irawan, 2016).

If both assumptions are met, then it can be concluded that the model can be used for forecasting. In the forecasting process, it will produce residuals that will be predicted by the NN method.

Data normalization in this research uses Min-Max normalization. Min-Max Normalization is a normalization method by performing a linear transformation of the original data so that it will produce a balanced comparison of values between the data before and after (Henderi, Wahyuningsih & Rahwanto, 2021). Min-Max normalization can be written as the following equation,

$$X_{new} = \frac{X - \min(X)}{\max(X) - min(X)}$$

with X_{new} is result value after normalize, X is original value, $min(X)$ minimum value on the data, and $max(X)$ is maximum value on the data.

This research uses the backpropagation algorithm that is often used for forecasting. Backpropagation is a systematic method on NN that uses a supervised algorithm that has many layers to change the weights connected to the neurons in the hidden layer (Astuti, Bekti, Keliat & Sebo, 2023). Errors are calculated based on the Mean Squared Error (MSE). The back propagation network architecture contains an input layer, a hidden layer and an output layer. The network architecture is chosen through a trial-and-error process.

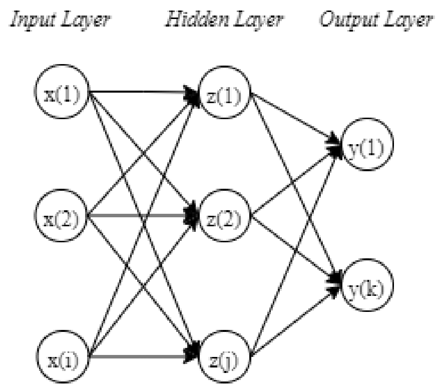

Figure 1. Backpropagation Network Architecture

Backpropagation training includes 3 phases (Fausett, 1994).

1. Feedforward phase, where the input pattern is computed forward from the input layer to the output layer using the specified activation function.
2. Backward propagation phase, where the difference between the network output and the desired target is the error. Errors that occur are propagated backward starting from the row corresponding to the unit in the output layer.
3. Weights change, modify the weights to reduce the error.

Activation functions are functions used in neural networks to activate and deactivate neurons that are useful to help neural networks learn complex patterns in data (Julpan, Nababan & Zarlis, 2015). The activation function for backpropagation must have the important characteristics of being continuous, differentiable, and non-monotonically decreasing (Fausett, 1994). The activation function used is a binary sigmoid function. The binary sigmoid activation function is often used because the value of the function lies between 0 and 1, and can vary easily. The binary sigmoid activation function can be written as the following equation:

$$f = \frac{1}{1 + e^{-x}}.$$

The AR-NN model is a combined AR and NN model used to solve linear and non-linear problems. A combined prediction that has linear and non-linear components can be written as the following equation (Zhang, 2003)

$$\hat{y}_t = \hat{L}_t + \hat{N}_t$$

with $\hat{y}_t$ is the AR-NN forecast results, $\hat{L}_t$ is the AR forecast results, and $\hat{N}_t$ is the residuals forecast results by NN.

Mean Squared Error (MSE) measures the mean of the squared error between the original value and the estimated value. MSE can be calculated with the following equation (Lawrence, Klimberg & Lawrence, 2009).

$$MSE = \frac{1}{n}\sum_{t=1}^{n}\left(Z_t - \hat{Z}_t\right)^2$$

with n is the numbers of observation, Z_t is observation at t-time, and $\hat{Z}_t$ is estimated data or forecast result at t-time.

The NN training and testing process will produce two types of MSE, namely MSE training and MSE testing. A network is called good if it has the smallest MSE value in training and testing. But, if both are differences, then the selected network is the one with the smallest MSE test.

MAPE is a predictive evaluation method that considers the effect of actual values (Lawrence, Klimberg & Lawrence, 2009). The smaller the MAPE value, the more accurate the prediction model. MAPE can be written as the following equation,

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{Z_t - \hat{Z}_t}{Z_t}\right| \times 100\%$$

with n is the numbers of observation, Z_t is observation at t-time, and $\hat{Z}_t$ is estimated data or forecast result at t-time.

The evaluation characteristics of MAPE can be seen in Table 2 (Lawrence, Klimberg & Lawrence, 2009).

Table 2. MAPE Scale and Accuracy Level

MAPE Scale	Accuracy Level
$\leq 10\%$	Highly accurate
$10\% < MAPE \leq 20\%$	Good forecast
$20\% < MAPE \leq 50\%$	Reasonable forecast
$> 50\%$	Inaccurate forecast

RESULTS AND DISCUSSION

The research data divided into insample data and outsample data with a ratio of 80:20. The best and most accurate results are achieved when using 70-80% for training and 20-30% for testing (Gholamy, Kreinovich & Kosheleva, 2018). The insample data is the inflation rate of West Java Province from January 2009 - December 2020 with 144 data, and the outsample data is the inflation rate of West Java Province from January 2021 - December 2023 with 36 data.

The identification model stage includes data plots, stationary tests, and and AR model identification. The data plot for the inflation rate of West Java Province can be shown in Figure 2. It shows that there are fluctuations in the data where the data is not fixed or changing. This means that the data is not stationary, but the determination of stationarity based on data plots is still subjective.

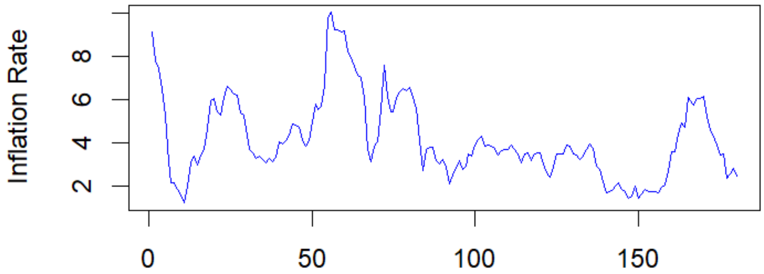

Figure 2. Plot Data of Inflation Rate in West Java Province

A statically stationary check can be performed with the Augmented Dickey-Fuller (ADF) test to see if the data are stationary to the means. Based on the ADF test obtained $p-value = 0.01 < \alpha = 0.05$, it can be concluded that the data has a stationary mean.

A Box-Cox transformation is performed if the data are non-stationary to variance. In the first calculation obtained $\lambda = 0.3985$. Therefore, it is necessary to transform using λ for all datasets, so it obtains $\lambda = 1.026264$ after transforming. Figure 3 shows that the transformed data is normally distributed, which is shown by the histogram graph that has a bell-like shape and the data is centered around the mean. The transformed data is then used to form an AR model.

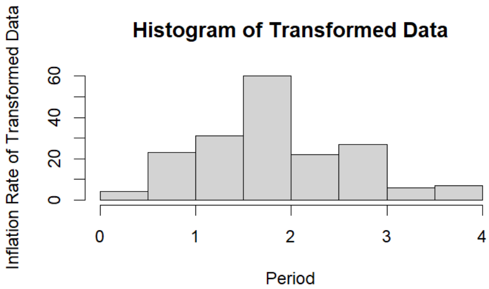

Figure 3. Histogram of Transformed Data

The next step is to determine the order of the model using ACF and PACF plots with a maximum lag of 10. The following figure shows that the ACF plot goes down exponentially, otherwise the PACF plot breaks off at lags 1 and 2. Based on the ACF and PACF plots, it generates a temporary model, which is AR (1) and AR(2).

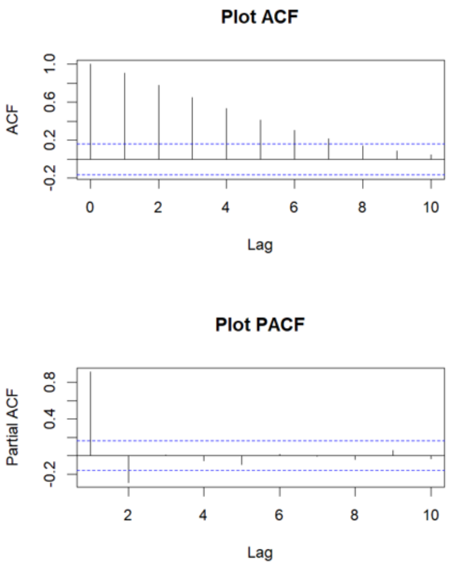

Figure 4. ACF and PACF Plot

After generating the temporary models that are AR(1) and AR(2), then parameter model estimation is carried out. Parameter estimation using the MLE method, then testing the significance of the model parameters. Based on the parameter significance test in the following Table, it was found that the AR(1) and AR(2) parameters are significant, which meets the test criteria when the $p-value < \alpha = 0.05$.

Table 3. Results of Estimation and Significance Testing of AR Parameters

Model	Parameter		Standard Error (SE)	$p-value$	Conclusion
AR(1)	$\hat{\phi}_1$	0.9937	0.0069	2.20×10^{-16}	Significant parameter
AR(2)	$\hat{\phi}_1$	1.3636	0.0775	2.20×10^{-16}	Significant parameter
	$\hat{\phi}_2$	−0.3727	0.0779	1.72×10^{-16}	Significant parameter

Diagnostic checks are conducted to find out whether the AR(1) and AR(2) models are feasible for forecasting. A model is feasible for forecasting when it meets the assumption of normally distributed and uncorrelated residuals. Checking the assumption of non-autocorrelation residuals can be done with the Ljung-Box test. The test results based on Table 4 obtained residual AR(1) generating a $p-value = 0.01808 < \alpha = 0.05$, so it can be concluded that the residuals are not automatically correlated. Therefore, the AR(1) model cannot be used for forecasting. Otherwise, the AR(2) residual generates a $p-value = 0.6446 > \alpha = 0.05$, so it can be concluded that the residuals are not automatically correlated. Therefore, the AR(2) model can be used to predict the inflation rate data of West Java Province.

Table 4. Ljung-Box Test

Model	$p-value$	Conclusion
AR(1)	0.01808	Residuals are autocorrelated
AR(2)	0.6446	Residuals are not autocorrelated

Checking that the AR(2) residuals are normally distributed can be done using a Q-Q plot. A Q-Q plot is used to visualize normally distributed data. The following figure shows that almost all the points in the Q-Q plot follow a straight line, so it can be concluded that the residuals are close to a normal distribution. Therefore, the model used for the forecasting process is the AR(2) model because it automatically satisfies the assumption that the residuals are normally distributed and uncorrelated.

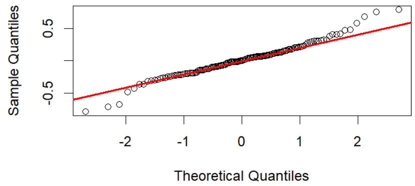

Figure 5. Q-Q Plot Residual AR(2)

Based on parameters significance test before in Table 4, it obtained AR(2) estimated model in the following equation:

$$\hat{Z}_t = 1{,}3636 Z_{t-1} - 0{,}3727 Z_{t-2}$$

After AR(2) is obtained through three stages of Box-Jenkins, then the prediction is carried out using the equation above for the out-of-sample data. The prediction results are then retransformed or returned to the original form using the inversion of the Box-Cox transformation below

$$Z_t = (W\lambda + 1)^{\frac{1}{\lambda}}$$

A comparison of AR(2) prediction results with actual data is presented in Figure 6.

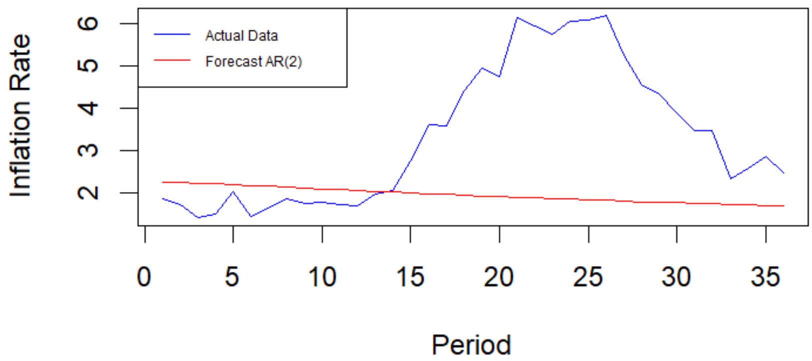

Figure 6. Comparison of AR(2) Retransformed Forecasting Results with Actual Data

Then generated model evaluation using Mean Absolute Percentage Error (MAPE), obtained MAPE value for AR(2) evaluation for outsample data is 42.12%, so it can be concluded that the forecasting ability of AR(2) model is reasonable. The final stage is to store the residual which is the difference between the actual data and the retransformed AR(2) predicted data. These residuals are then predicted using the NN (Neural Network) method.

The residuals generated from the AR(2) model were predicted using the NN method. The initial stage of AR(2)-NN model formation before forming the network architecture is as follows:

1. Normalize the residuals using Min-Max normalization to adjust the scale with the activation function used, which is a binary sigmoid activation function with a range of 0 to 1.
2. The normalized residual is divided into variable X_1, X_2, X_3, X_4 as input variable and Y as output and target variable.
3. The residuals is divided into training data and testing data with ratio of 80:20 (Gholamy et al, 2018) (Gholamy, Kreinovich & Kosheleva, 2018), which is 29 training data and 7 testing data.

Next enter the formation of the network architecture. The network formed is a multi-layer network consisting of one input layer, one or more hidden layers, and one output layer. Within each layer, there are several units or neurons. The construction of the network architecture used in the trial-and-error process is as follows:

1. In the input layer, the number of input units can affect the ability of the network in the training process. In this research, four input units were used.
2. In this research, a hidden layer was used. The use of one hidden layer is enough to model NN in general. The use of many hidden layers can also slow down the training process, The hidden units used are the result of a trial-and-error process. The number of units tested is 2 to 7 units.
3. In this research, one output unit has been used which is the result of AR(2) residual prediction.

Several other parameters have been determined before starting the training and testing process, namely learning rate, maximum duration and target MSE as follows.:

1. The learning rate is a parameter used to control the speed at which the algorithm updates the network weights with respect to decreasing error values (Dananjaya, Sutrisno & Fitriady, 2022). In this research, learning rate was chosen through trial-and-error process with tested learning rate is 0,01;0,05;0,07;0,1;0,5 dan 0,7.
2. One Epoch is when the entire data set is sent back and forth through the neural network just once (Sharma,

2017). The maximum epoch used is 100000, meaning the training process will stop after reaching 100000 iterations.

3. The MSE target used in this research is 0.05. There are two types of MSE produced, namely MSE training and MSE testing. A network is called good if it has the smallest MSE test.

After knowing the above parameters, the next step is a process of trial and error to determine the number of hidden units first. In this process, the learning rate used is 0.01. Each hidden unit in this trial-and-error generates the MSE presented in Table 5.

Table 5. MSE Training and Testing of Each Hidden Unit

Hidden Unit	MSE Training	MSE Testing
2	0.1043	0.0101
3	0.0805	0.0102
4	0.0809	0.0089
5	0.0651	0.0070
6	0.0611	0.0098
7	0.0636	0.3626

The smallest MSE test is owned by 5 hidden units which is 0.007, so it can be concluded that the optimal network architecture is 5 hidden units. This trace and error process is only performed up to 7 hidden units because the test MSE starts to increase significantly in those number units.

A second process of trial-and-error is conducted to determine the optimal learning rate. This process uses a network architecture with 5 hidden units. Each learning rate tested in this trial-and-error process results in the MSE presented in Table 6.

Table 6. MSE Training and Testing of Each Learning Rate

Learning Rate	MSE Training	MSE Testing
0.01	0.06507	0.00704
0.05	0.06506	0.00704
0.07	0.06505	0.00704
0.1	0.06504	0.00704
0.5	0.01967	0.00703
0.7	0.01967	0.00702

The optimal learning rate produced is 0.7. That is evidenced by the smallest MSE test in addition to other learning rates. Therefore, the network architecture used for prediction is (4-5-1) with a learning rate of 0.7.

After the training and testing process, residual prediction is done using the optimal network architecture which is 4 input units in one input layer, 5 hidden units in one hidden layer, and 1 output unit in one output layer or can be written as (4). -5-1). The residual prediction result denormalized or returned to the original scale using the inverse Min-Max normalization which can be written in the following equation,

$$X = (X_{baru}(\max(X) - \min(X)) + \min\,(X)$$

The AR(2)-NN forecast is the sum of the AR(2) forecast and the residual AR(2) forecast by the NN method. The diagram below shows a comparison between the prediction results of AR(2) and AR(2)-NN with real data.

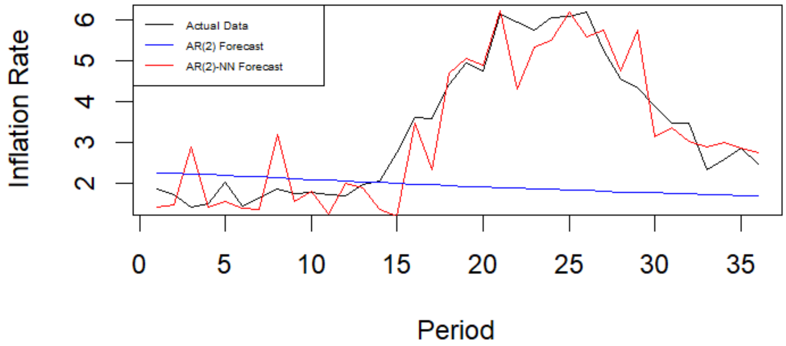

Figure 6. Comparison of AR(2) and AR(2)-NN Forecasting Results with Actual Data

Predictions using the AR(2)-NN model appear to be more accurate than the prediction results using the AR(2) model. This can be proven by evaluating the AR(2)-NN model using the MAPE presented in Table 7.

Table 7. AR(2) and AR(2)-NN Model Evaluation

Model	MAPE	Accuracy Level
AR(2)	42.12%	Reasonable forecast
AR(2)-NN	18.26%	Good forecast

Based on the analysis that has been done, it was found that forecasting using the AR(2) model on West Java Province inflation rate data produced a MAPE of 42.12% and forecasting using the AR(2)-NN model produced a MAPE. by 18.26%. Therefore, it can be concluded that the AR(2)-NN model can increase the accuracy of AR(2) prediction by 23.86%, so the AR(2)-NN model can be one of the good methods used to predict the data inflation rate for West Java Province .

Previous research used differentiation for stationary processes, but this study used a box-cox transformation. This proves that the box-cox transformation is also good for stationary processes.

CONCLUSIONS AND SUGGESTIONS

Based on the analysis carried out, it is concluded that the application of the AR(2)-NN model produces a smaller MAPE than the AR(2) model and increases the level of accuracy from a fair forecast to an accurate forecast. It shows that the AR(2)-NN model is better used in predicting West Java Province Inflation rate data.

Future research is recommended to use other AR model orders by testing each model order and trying more hidden units and learning rates through a trial and error process in NN training to choose a more optimal network architecture and learning rate by considering the evaluation. It is also recommended to use more and complex data so that the choice of NN network architecture is not limited.

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