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Comparison Of Radial Basis Function Neural Networks (RBFNN) And Autoregressive Moving Average (ARMA) Algorithms On Inflation Rate Prediction Models In Batam City

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ABSTRACT

The inflation rate in the city of Batam from January 2023 to April 2024 continues to fluctuate, so an accurate prediction model is needed so that inflation control can be carried out optimally. In this study, we conducted a comparative analysis between the Radial Basis Function Neural Network (RBFNN) method and the Autoregressive Moving Average (ARMA) model in predicting the inflation rate. The data used is historical data on the inflation rate of Batam City from January 2009 to April 2024. The results of the analysis show that the RBFN method with an MSE value of 0.239 is able to provide a more accurate prediction compared to the ARMA model (2.3) with an MSE value of 0.246 in predicting the inflation rate in Batam City. This is due to the RBFN's ability to capture complex and non-linear patterns contained in inflation data. In addition, the performance of RBFNN is also affected by the number of neurons and the basis function used. Thus, the results of this study show that the RBFN method can be an effective and efficient alternative in predicting the inflation rate in Batam City.

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INTRODUCTION

Batam City is one of the cities that has rapid economic growth in Indonesia. With the rapid economic development, the inflation rate in the city of Batam is also one of the focuses of attention. Inflation is a general and sustained increase in the prices of goods and services in an economic system (Hamdani et al., 2020; Sari & Nurjannah, 2023). The inflation rate is one of the important economic indicators in determining a country's monetary policy. High inflation rates can have a negative impact on a country's economy, which can result in a decrease in people's purchasing power and increase production costs for companies (Maghfiroh et al., 2021). Therefore, a predictive model is needed to predict the inflation rate because it is very important to help governments, companies, and communities in planning their economic activities. Accurate inflation rate prediction is needed in the city of Batam so that the government and economic actors can plan the right economic policies in the face of price fluctuations (Kasim et al., 2021; Permata Sari, 2022).

One method that can be used to predict inflation rates is the Radial Basis Function Neural Network (RBFNN). RBFNN is a type of artificial neural network that is able to recognize complex and non-linear patterns (Hong et al., 2020; Izonin et al., 2021; Rad et al., 2022). RBFNN can be used to predict trends and patterns in data (Deng et al., 2021; S, 2019; Zhou, 2020). This method has been used in various fields, including in the prediction of the inflation rate (Madhiarasan, 2020; Pazouki et al., 2022). Several previous studies have proven that the RBFNN method can be effectively used in predicting stationary time series data (Pazouki et al., 2022; Xin et al., 2021). Several studies have explained that the RBFNN model is effective and reliable in predicting time series data such as oil prices, consumer price indices and stock price movements (Hemageetha & Nasira, 2013; Izonin et al., 2021; Rifa'i, 2020). A study also shows that the use of the RBFNN method can help in predicting inflation rates well (S, 2019).

In addition to RBFNN, one of the methods that has been used to predict inflation rates is the Autoregressive Moving Average (ARMA). The ARMA method combines Moving Average (MA) and Autoregressive (AR) models to model and predict data based on historical relationships between those data points. MA focuses on the relationship between variables and the values of the impairment in the data at the previous time point, while AR focuses on the relationship between the variable and the values of the self at the previous time (time lag) (Dalimunthe et al., 2023; Maqsoom et al., 2024). Previous research on the ARMA method in predicting inflation rates has shown mixed results. Some studies have found that ARMA is effective in predicting inflation trends in the short term, while others have found that its performance depends on the current state of the economy and can become less accurate under certain conditions (Araujo & Gaglianone, 2023; Dalimunthe et al., 2023; Maqsoom et al., 2024). Some studies have also compared ARMA with other models, such as linear regression models or artificial neural network models, to assess its relative rate in predicting inflation rates. Although ARMA has become one of the main methods in the analysis and prediction of inflation rates, technological developments and methodology continue to give rise to new approaches that may be more effective in modeling and predicting complex phenomena such as inflation (Araujo & Gaglianone, 2023; Dong & Franses, 2023; Mahmudy et al., 2021).

In previous studies, no one discussed the comparison of the accuracy level of the model using the RBFNN and ARMA methods on stationare data. This study discusses the comparison of the accuracy level of RBFNN and ARMA in predicting the inflation rate in Batam City to get accurate prediction results so that the government and related parties can control the inflation rate so that the welfare of the Batam City Community can be improved. To see the best method between FBFNN and ARMA, use Mean Square Error (MSE) and Root Mean Square Error (RMSE).

METHOD

The steps taken in this study are:

Data Collection

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The data used in this study is data on the inflation rate of Batam City in January 2009 up to for April 2024 which amounted to 184 observations. The data used is secondary data obtained from the Central Statistics Agency (BPS) of Batam City. The data used consisted of training data and testing data. Training data was used as many as 147 data and testing data as many as 37 data. The data can be seen in website Data Inflasi BPS Kota Batam Tahun 2009-2024.

Perform Autoregressive Moving Average (ARMA) Analysis

The ARMA model consists of an Autoregressive (AR) model and a Moving Average (MA) model. The AR (p) model is an observation at time t expressed as a linear function of p at the previous time plus a random residual a_t that is white noise that is independent and normally distributed with a mean of zero and a constant variation. The general form of an autoregressive model with order p (AR(P)) is: (Dalimunthe et al., 2023)

$$X_t = \mu' + \varnothing_1 X_{t-1} + \varnothing_1 X_{t-2} + \cdots + \varnothing_p X_{t-p} + e_t \quad (1)$$

X_t is the inflation data at the t time period, X_{t-p} is the inflation at the t-p time period, μ' is the constant value, $\varnothing_p$ is the autoregressive parameter at the p period dan $\boldsymbol{e_t}$ is the error value at the t time period. The Moving Average (MA) model is used to explain a phenomena that an observation at time t is expressed as a linear combination of a number of random errors, while the value of X_t at MA shows a combination of past linear errors (lag) (Maqsoom et al., 2024). The general form of the Moving Average model with the order q (MA (q)) is expressed as follows: (Dalimunthe et al., 2023)

$$X_t = \mu' + e_t - \theta_1 e_t{-}1 - \theta_2 e_{t-2} - \cdots - \theta_q e_{t-q} \quad (2)$$

Autoregressive (AR) models can be effectively combined with moving average (MA) models to form a very common and useful class of models in periodic time series models commonly called patterns or autoregressive moving average (ARMA) models. The general model for pure AR(1) and pure MA(1) process mixtures, as follows: (Dalimunthe et al., 2023)

$$X_t = \mu\,' + \varnothing_1 X_{t-1} + e_t - \theta_1 e_{t-1} \quad (3)$$

The steps of the ARMA model are as follows:

a. Plot data to see if the data is stationare or not in mean or variance
b. Specify the Auto Correlation Function (ACF) to determine the MA order and the Partial Auto Correlation Function (PACF) to define the AR order
c. Define a tentative model
d. ARMA model estimation
e. Choos the best ARMA model to use for prediction

Perform Radial Basis Function Neural Networks (RBFN) Analysis

The Radial Basis Function Neural Network is a neural network model that transforms inputs non-linearly using Gaussian activation functions on the hidden layer before being linearly processed on the output layer. The Radial Basis Function Neural Network (RBFNN) contains three layers, namely the input layer, the hidden layer and the output layer (Ambarwati, 2023). The input layer conveys the coordinates of the input vector to each unit in the hidden layer. Each unit in the hidden layer then generates an activation based on the RBFNN relationship. In addition, each unit on the output layer will compute a linear combination of activation functions from the hidden unit.

The parameters used in RBFNN are the center value, the base function spread on the hidden layer and the weight value on the output layer. To produce a good functional approximation, the spread value must be larger. Large spread values mean that there are many neurons needed to adjust to changing functions quickly (Hemageetha & Nasira, 2013). The output of the RBFNN model can be formulated as follows: (Du & Swamy, 2014).

$$F(x) = \sum_{k=1}^{m} w_{ki}\theta(\|x - a_k\|) \quad (4)$$

w_{ki} is the connected weight, a_k is the RBFNN center, θ is the Gaussian function, and m is the number of units to be calculated. The RBFNN algorithm is as follows: (Hong et al., 2020; Rad et al., 2022)

1. Network training with the following stages:
   a. Initialization of RBFNN parameters c_i, α_i, w_{i1}, b, error limits and iteration maximums
   b. Entering normalized training data
   c. Calculate the Gaussian activation function on a hidden layer using the equation:
   $$Z_i(x) = \exp\left(\left(-Z_{in_i}\right)\right) \text{ with } Z_{in_i} = \alpha_i \sum_{i=1}^{I} \left|\left|x_i - c_i\right|\right|^2 \quad (5)$$
   d. Calculate the output signal of the gaussian activation on the output layer.
   $$Y = \frac{1}{1+e^{-Y_{in}}} \text{ with } Y_{in} = \sum_{i=1}^{I} w_{i1}Z_i + b \quad (6)$$
   e. Calculate network errors with equations:
   $$\delta = (t - Y)Y' \quad (7)$$
   f. Calculating error connections with equations:
   $$(\Delta w_{i1}) = \alpha\delta Z \quad (8)$$
   $$(\Delta b) = \alpha\delta \quad (9)$$
   Δw_{i1} is a weight error and Δb is bias.
   g. Updated the weights and biases on the hidden layer to the output layer based on the error correction of the weights and bias.
   $$\Delta w_{i1new} = w_{i1} + \Delta w_{i1} \quad (10)$$
   $$b_{new} = b + \Delta b \quad (11)$$

h. Repeat steps c to g until the network produces the maximum iteration or maximum error specified by the equation:

$$\delta = (t - Y)Y' \quad (12)$$

2. Validate the model with the following stages:
   a. Initialization of RBFNN parameters c_i, α_i, w_{i1}, b, error limits, and maximum iterations of training results
   b. Calculating the Gaussian activation function with equation 5.
   c. Calculate the output signal of Gaussian activation at the output layer with equation 6.

The RBFNN model estimation steps are:

a. Data normalization with equations:

$$x_i = \frac{x_i - \min(x)}{\max(x) - \min(x)} \quad (13)$$

b. Centroid initialization (cluster center)
c. Calculating the Radial Base Function (RBF)

$$RBF(x, c) = e^{-\frac{\|x-c\|^2}{2\sigma^2}} \quad (14)$$

d. Calculates the R matrix based on the RBF value and the Y matrix based on the output value.
e. Output layer weight training (W) with equations:

$$W = (R^T R)^{-1} R^T Y \quad (15)$$

f. Ensuring that the weight calculation is in accordance with the output using the equation:

$$RBF(x_{baru}, C_i) = e^{-2\sigma^2} \|x_{baru} - C_i\|^2 \quad (16)$$

g. Sum the results of the RBF calculation with the equation:

$$RBF(x_i, C_i)W_i \quad (17)$$

h. Evaluate model performance by checking weights using test data.

RESULTS AND DISCUSSION

ARMA Model

In this study, to analyze the ARMA Model, Minitab Version 18 software was used. To analyze the RBFNN model, SPSS Version 25 and Microsoft Excel software were used. The formation of the ARMA model begins with testing the stationare of the data, which can be done by looking at the data plot. Data stationare testing is carried out to find out which model to be used. If the data is stationare, then the AR, MA or ARMA model is used, but if the data is not stationare, the ARIMA model can be used.

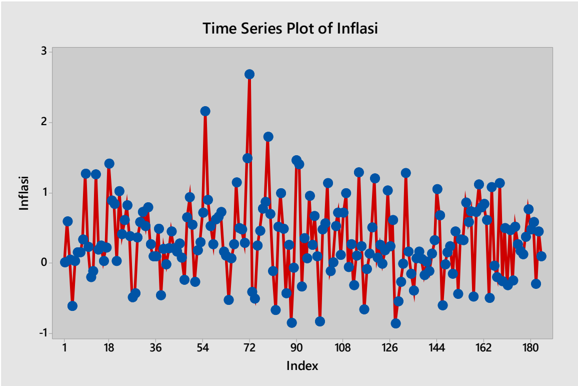

Figure 3.1. Inflation Data Plot

In Figure 3.1, it can be seen that inflation data in Batam City in the period from January 2009 to April 2024 fluctuated, so an accurate model is needed to predict the inflation rate in the next period. From Figure 3.1, it can also be seen that the data pattern does not experience a trend pattern, but leads to a stationer pattern, but to determine whether the data is stationer or not, it is necessary to form ACF and PACF plots. In addition to confirming whether the data is stationer or not, ACF and PACF plots are also needed to determine the order of the AR and MA models.

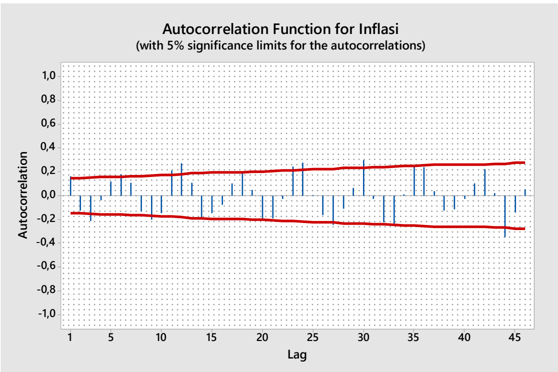

Figure 3.2. ACF Plot of Inflation Data

Based on the ACF plot, it can be seen that the first three lags are out of the confidence interval so it can be said that the data is stationary based on the ACF plot. The MA order based on the ACF plot is three.

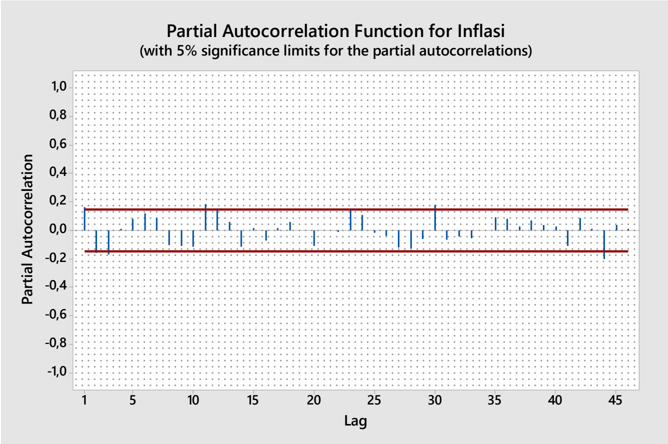

Figure 3.3. PACF Plot of Inflation Data

The PACF plot shows that the first three lags are also out of the confidence interval so it can be said that the data is stationare based on the PACF plot. The AR order based on the PACF plot is three. After obtaining the AR and MA orders, nine tentative models were formed as follows:

Table 3.1. Tentative Model

Num	AR Order	MA Order	Tentative Model
1	3	1	ARMA (3,1)
2	3	2	ARMA (3,2)
3	3	3	ARMA (3,3)
4	2	1	ARMA (2,1)
5	2	2	ARMA (2,2)
6	2	3	ARMA (2,3)
7	1	1	ARMA (1,1)
8	1	2	ARMA (1,2)
9	1	3	ARMA (1,3)

Parameter estimation is carried out for each tentative model. Next, a model goodness-of-fit test was carried out to obtain the best model which will be used as a prediction model for the inflation rate in Batam City. Based on the results of parameter estimation and hypothesis testing as well as model goodness-of-fit testing using MSE, the best ARMA model was obtained, namely ARMA (2.3). The results of the ARMA model parameter estimation (2,3) are as follows:

Table. 3.2. ARMA(2,3) Model Parameter Estimation Results

Type	Coef	SE Coef	T-Value	P-Value
AR 1	0,9882	0,0162	61,06	0,000
AR 2	-0,9974	0,0188	-53,10	0,000
MA 1	0,8941	0,0380	23,55	0,000
MA 2	-0,8505	0,0553	-15,37	0,000

Type	Coef	SE Coef	T-Value	P-Value
MA 3	-0,1197	0,0317	-3,78	0,000
Constant	0,3333	0,0392	8,50	0,000
MSE	0,246501			

In this model, all parameters are significant and this model has the smallest MSE value, namely 0.246. This value is relatively small and the model is said to be good so it can be used as an option for an inflation prediction model in Batam City.

RBFNN Model

In forming the RBFNN model, the first step is to determine the input layer and hidden layer. In determining the input layer, significant lags in the PACF plot are used as input data components. In this way, three input layer variables are obtained, namely lag 1, lag 2 and lag 3, so that the network built has three input layers, namely y_{t-1}, y_{t-2} and y_{t-3} with a target of y_t. The amount of data used was 184 data, with a data composition division of 147 training data and 37 testing data. After determining the input, data normalization is carried out first before the data is input to the network, so that it becomes data that is in the range 0 to 1. The results of estimated the RBFNN model parameters are obtained as follows:

Table 3.3. RBFNN Model Parameter Estimation

Predictor		Hidden Layer[a]			Output Layer
		H (1)	H (2)	H (3)	y
Input Layer	y_{t-1}	0.443	0.700	-0.022	
	y_{t-2}	0.024	0.708	0.188	
	y_{t-3}	-0.055	0.338	0.493	
Hidden Unit Width		0.484	0.534	0.619	
Hidden Layer	(Intercept)				0.300
	H (1)				0.490
	H (2)				0.152
	H (3)				-0.312

After obtaining the parameters from the input layer and hidden layer, the model is then tested using testing data to obtain the best network simulation results. A comparison graph between actual values and predicted values using RBFNN can be seen in Figure 3.4.

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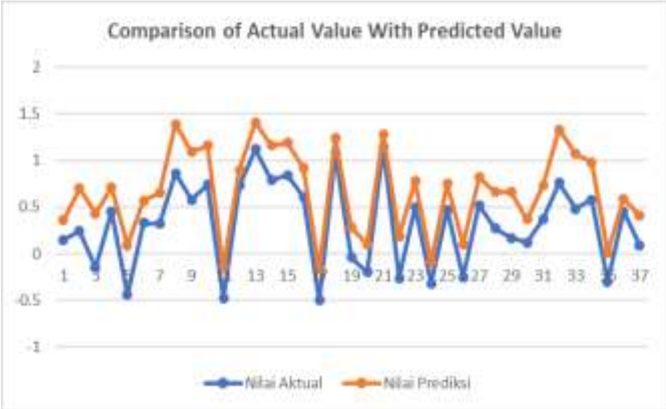

Figure 3.4. Graph of Actual Value and Predicted Value

Figure 3.4 shows that the actual values and predicted values have almost the same pattern. This shows that the RBFNN model can predict the inflation level in Batam City well. However, to obtain a more accurate prediction value, the goodness of the ARMA model and the RBFNN model was tested by looking at the comparison of MSE and RMSE values.

Table 3.4. Comparison of ARMA Model and RBFNN model

Model	MSE	RMSE
ARMA (2,3)	0.246	0.496
RBFNN	0.239	0.489

Based on the MSE and RMSE results, it was found that the best model for predicting inflation in Batam City for the period was the RBFN model with three input layers and three hidden layers. The results of this study are supported by previous research that the RBFNN model is more accurate as a prediction model than several models such as ARIMA, simple linear regression, SARIMA which has been applied to several cases such as rainfall prediction, rupiah exchange rate prediction against dollar, rainfall prediction, and crude palm oil price prediction (Alida & Mustikasari, 2020; Borman et al., 2022; Rachmadani, 2019; Rifa'i, 2020). So from the results of this study, it was obtained that the RBFNN model is more effective in predicting inflation in Batam City in order to produce accurate prediction values so as to produce the right decisions in tackling inflation in Batam City.

CONCLUSION

Based on the analysis results, it was found that the MSE value of the RBFNN model was 0.239 and the MSE value of the ARMA model was 0.246. From this value it can be seen that the MSE of the RBFNN model is smaller than the ARMA model (2.3) so that the best prediction model for predicting the inflation rate in Batam City is the RBFNN model. With the RMSE criteria, it was also obtained that the RMSE value of the RBFNN model was smaller than the RMSE of the ARMA model, so the FBFNN model was selected. However, further research needs to be carried out to improve the prediction results and take into account other factors that can influence the inflation rate in Batam City.

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