Time-series Modeling for Consumer Price Index Forecasting using Comparison Analysis of AutoRegressive Integrated Moving Average and Artificial Neural Network

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Abstract: The Consumer Price Index (CPI) is an index number that measures the average price of goods consumed by households and is one factor that influences inflation in a country. The CPI forecast is calculated in monthly periods each year to anticipate the possibility of a spike in the inflation rate. Forecasting the CPI makes use of past values, commonly known as time-series data (TSD). One method to assist the forecasting process on TSD is the Autoregressive Integrated Moving Average (ARIMA). However, ARIMA is less accurate for nonlinear data problems. Another method that can also be used for forecasting with linear data problems is the Artificial Neural Network (ANN). This study compared the two forecasting methods between ARIMA and ANN by predicting the Indonesian CPI value from January - December 2018. The TSD used is in data on the Indonesian CPI value between January 2009 and December 2017. This study indicates that the ANN method is better than ARIMA because it produces a smaller MSE of 59.23. However, ARIMA is also good because the two methods' forecast results are in the range of the CPI value.

1 INTRODUCTION

In economic terms, inflation is a term that significantly affects the economy of a country, which is a process of increasing prices for both goods and services continuously during a specific period measured using a price index (Nopirin, 1987). One of the most frequently used price indexes to measure inflation is the Consumer Price Index (CPI). CPI compares prices in a month against the previous month, which is based on the base year for calculating the CPI. The effect on inflation is that the higher the resulting index value, the greater the possibility of inflation. In one condition, inflation can be considered beneficial, but it can also be regarded as detrimental. But in general, inflation can lead to economic instability, failure to carry out development, and lower levels of living and welfare.

Monthly CPI values may be predicted for the next several periods using statistical analysis. CPI forecasting can be made with one of the forecasting methods that use time-series data, including AutoRegressive Integrated Moving Average (ARIMA), AutoRegressive Fractionally Integrated Moving Average (ARFIMA), Winter, Autoregressive Conditional Heteroskedasticity (ARCH), and other algorithms (Wigati, Rais, & Utami, 2016). However, in general, economic data forecasting such as CPI, mostly uses the ARIMA method (Pimpi, 2013) (Deswina & Desmita, 2015), (Wigati, Rais, & Utami, 2015), (Mohamed, 2020). This is because the ARIMA method is sufficient for short-term forecasting, whereas if used for long-term forecasting, the resulting value will tend to be constant (Djawoto, 2010). In (Hiteshi Tandon, 2020) a model has been developed to forecast future COVID-19 cases in India using ARIMA based time-series analysis. ARIMA is also successful in predicting stock price which is a short term prediction (Adebiyi, Adewumi, & Ayo, 2014). According to (Janah, Sulandari, & Wiyono, 2014), the ARIMA model is a time series modeling for linear data, but in reality, not all phenomena that use time series have a linear relationship. Instead, some are nonlinear. Therefore, we also need a method that

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can solve nonlinear problems. One such approach is the Artificial Neural Network (ANN) (Fitriani, Ispriyanti, & Prahutama, 2015), which is a system utilized by modeling the workings of the human brain neural network to complete calculation forms (Susilokarti, Arif, Susanto, & Sutiarso, 2015). Similar approach was also proposed by (Domingos S. de O. Santos Júnior, 2019) which evaluated the use of hybrid systems of ARIMA combined with Multilayer Perceptron and Support Vector Machine, while (Ümit Çavuş Büyükşahin, 2019) used ARIMA-ANN hybrid method improved by Empirical Mode Decomposition.

This study compared two forecasting methods, ARIMA and ANN, to predict the Indonesian CPI with time-series data for January 2009 - August 2018 and assessed the accuracy of forecasting based on the MSE criteria and the calculation of the CPI value range.

2 MATERIALS AND METHOD

2.1 Dataset

Dataset used is a secondary data on the Indonesian Consumer Price Index (CPI), which is quantitative starting from January 2009 - December 2018 (120 data) and was officially published by the Central Statistics Agency (BPS) online on its website (www.bps.go.id). The proportion of training data is 108 data (taken from January 2009 - December 2017), while testing was 12 (from January 2018 - December 2018). Table 1 lists a part of the CPI as the dataset as an example. Before proceeding to each method, data needs to be normalized within the range 0 to 1 using MinMax normalization.

Table 1: Indonesian CPI 2009-2018.

Year / Month	2009	2010	2011	2012	2013
Jan	113.78	118.01	126.29	130.9	136.88
Feb	114.02	118.36	126.46	130.96	137.91
Mar	114.27	118.19	126.05	131.05	138.78
Apr	113.92	118.37	125.66	131.32	138.64
May	113.97	118.71	125.81	131.41	138.6
Jun	114.1	119.86	126.5	132.23	140.03

2.2 Research Method

The data used is the CPI for January - December 2018. To get the value of the three months, the time-series data, as sampled in Table 1, were processed in two stages: ARIMA and ANN. We perform forecasting with these two methods and also calculate their MSE values. We also checked to see whether the value is in the CPI value range or not.

2.3 ARIMA Method

ARIMA is a combined model of two models: AutoRegressive (AR), notated by p, and Moving Average (MA), notated by q. Thus, ARIMA's notation is ARIMA (p, d, q), where d is the differencing process level (Box, Jenkins, Reinsel, & Ljung, 2016).

The general form of the ARIMA model is in Equation 1:

$$Y_t = b_0 + b_1 Y_{t-1} + \cdots + b_p Y_{t-p} - a_1 e_{t-1} - \cdots - a_q e_{t-q} + e_t \quad (1)$$

where Y_t is data in time t $(t = 1,2,\ldots,n)$, b_0 is a constant, Y_{t-1}, Y_{t-p} is data in time $t-i$ $(i = 1,2,\ldots p)$, e_t is the error in time t, e_{t-1}, e_{t-q} is the error in time $t-j$ $(j = 1,2,\ldots,q)$, b_1, b_p is the i^{th} AR parameter, and a_1, a_q is the q^{th} MA parameter.

Because ARIMA requires that the data be stationary, it is necessary to test the stationarity, moving value to zero. In order to find out whether the data meets these requirements, we calculate the AutoCorrelation Function (ACF) and Partial AutoCorrelation Function (PACF) values from the raw data (120 data), and a correlogram is made to make it easier to see the resulting graphical shape directly. ACF is used to determine patterns related to time in a time series, whereas PACF is the set of a lag. Equation 2 and equation 3 are the formulas to calculate ACF, while equation 4 is the PACF formula.

$$r_k = \frac{\sum_{t=k+1}^{n}(x_t - \bar{x})(x_{t-k} - \bar{x})}{\sum_{t=1}^{n}(x_t - \bar{x})^2} \quad (2)$$

$$\bar{x} = \frac{\sum_{t=2}^{n} x_t}{n-1} \quad (3)$$

$$r_{kk} = \frac{r_k - \sum_{j=1}^{k-1} r_{k-1,j}\, r_{k-j}}{1 - \sum_{j=1}^{k-1} r_{k-1,j}\, r_j} \quad (4)$$

where r_k is the ACF value on lag k; x_t is the data value at time t; $\bar{x}$ is the average of all data, and r_{kk} is the PACF value on lag k.

From the ACF correlogram diagram, if the data formed forms a linear pattern, then the data is not stationary. However, if the pattern drops exponentially or waves close to zero, then the data is stationary. Suppose the graph has not yet produced a stationary form. In that case, the data must be carried out by a “differencing” process, which is subtracting the value from a period with the previous period’s value. The differencing process is defined in equation (5) for first order differencing and equation (6) for second order differencing.

$$X' = X_t - X_{t-1} \quad (5)$$

$$X'' = (X_t - X_{t-1}) - (X_{t-1} - X_{t-2}) \quad (6)$$

If the data has been through the differencing process, then the value of d will increase by how many times the data goes through the differencing process. Thus, the notation ARIMA (0,0,0) changes to ARIMA (0,1,0).

2.4 ANN Method

Artificial Neural Network (ANN) is a network modeled after human neural networks. ANN is often used in dynamic time sequence systems that are nonlinear on a large scale consisting of many processing elements connected in parallel. ANN consists of several connected units of input and output, and each connection has a weight that can change to get the desired forecasting result. There are three layers in ANN: the input layer, hidden layer, and output layer.

Two phases in ANN are the training and testing phase. The steps taken are to define the input pattern and its targets, initializes the initial weights with random numbers, specify the number of iterations and the desired error. This step is repeated as long as the iteration is not past the maximum epoch limit. For the training phase, there are 2 (two) sub-processes: feed-forward and backpropagation. Successfully trained model in the previous stage will be tested by providing input; then, the network will produce output as expected by applying the steps to the backpropagation algorithm above but only in the feed-forward section. Figure 1 is the general form of a traditional ANN, where $x_1, x_2, \ldots, x_n$ are nodes in the input layer, $y_1, y_2, \ldots, y_n$ are nodes in hidden layers, and z is the output layer.

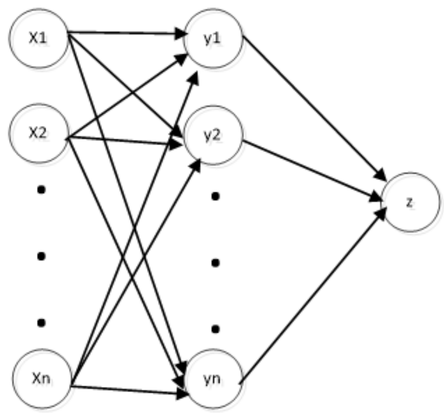


Figure 1: A traditional ANN architecture.

3 RESULTS AND DISCUSSIONS

All methods in this research are implemented in Python.

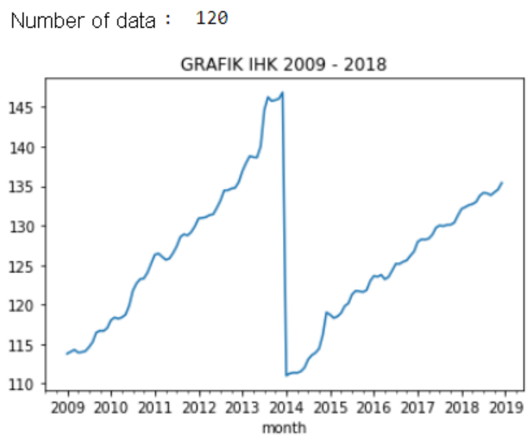
3.1 ARIMA Forecasting

3.1.1 Data Identification

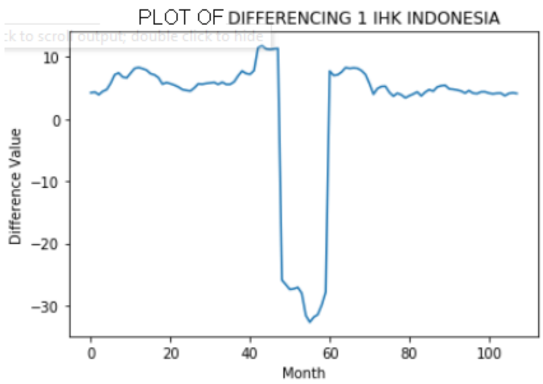
The data identification stage is carried out to identify whether the data to be used met the ARIMA method requirements' assumptions or not, which is stationary. If the resulting data is non-stationary, it is necessary to carry out the differencing stages first. Based on the plot in Figure 2(a), the time series data for the CPI value are still non-stationary, with a trend that tends to be linear starting in 2009. In 2014, the plot showed that the CPI value decreased drastically with a massive difference in values and returned to a linear pattern until 2018. Therefore, data must be processed with the differencing step to produce stationary data. Figure 2(b) plots the data after a differencing process of level one.

Because it has passed one differencing level, the ARIMA model (p, d, q) is now ARIMA (p, 1, q). Meanwhile, the p and q values can be determined through the correlation test between the time series by utilizing the ACF and PACF.

After getting the temporary model ARIMA (p, 1, q), the next step is to calculate the ACF and PACF from the data and then plot them. The data used to calculate ACF and PACF is stationary data, which come from the first level of differencing. Thus, the number of data calculated is 108 data, because the 12 initial data in the 2009 period did not have the results of differencing calculations.



(a)



(b)

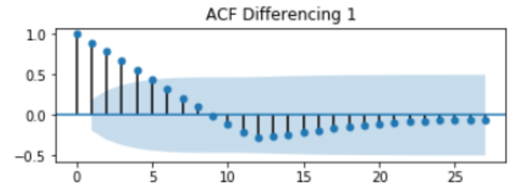
Figure 2: Plot of CPI Data (a) before and (b) after differencing step.

3.1.2 Model Parameter Estimation

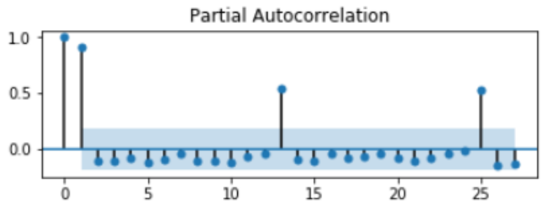
The data used to calculate ACF and PACF are stationary (from the first level of differencing). Thus, the number of data to be calculated is only 108 data because the 12 initial data in the 2009 period did not have the results of differencing calculations. In ACF and PACF, there is a lag term used to determine how many ACF and PACF values will be calculated. On this 108 CPI data, the number of lags is n / 4 = 108/4 = 27 lag. Because ACF and PACF are only used to support transient parameter estimates and determine p and q models, the calculations use Python's already available functions. The ACF and PACF calculations results are in Figure 3(a) and 3(b), respectively.

In Figure 3(a), the ACF value in lag 1 is outside the blue line, which indicates that the series still influence or correlate. The ACF value is used to estimate the value of the MA or q parameter. Thus, based on the displayed graph, it can be estimated that the Indonesian CPI time series model used is a moving average model. Also, because the graph is disconnected at lag 1, the provisional model estimates show that the MA parameter is 1.

The ARIMA pattern (p, 1, q) now becomes ARIMA (p, 1,1). If the ACF value is used to indicate the MA parameter, the PACF value indicates the AR or p parameter. Based on Figure 3(b), because the blue line also breaks lag one, it can be estimated at this time, the time series model also contains an autoregressive pattern. The p parameter has now also changed its value to 1. Identification for the estimated parameter ARIMA (p, d, q) is now known; all the parameters are ARIMA (1,1,1). Furthermore, the ARIMA model (1,1,1) will be used to formulate forecasting the value of Indonesia's CPI.



(a)



(b)

Figure 3: ACF (a) and PACF (b) calculations.

3.1.3 ARIMA Forecasting Result

From the estimated ARIMA parameters (p, d, q), forecasting the CPI value in 2018 will use ARIMA (1,1,1). The coefficients for AR and MA are $1.309\,x\,e^{11}$ and $4.760\,x\,e^{-16}$, respectively. The overall results for the 12 months in 2018 using ARIMA (1,1,1) are in Figure 4. The Minimum Square Error (MSE) is also computed.

	REAL IHK	ARIMA-ANN	ERROR	SSE	TOTAL
	0	0	0	0	0
0	132.100006	123.78	8.32	69.22	69.22
1	132.320007	124.08	8.24	67.90	137.12
2	132.580002	124.06	8.52	72.59	209.71
3	132.710007	124.17	8.54	72.93	282.64
4	132.990005	124.67	8.32	69.22	351.86
5	133.770004	125.56	8.21	67.40	419.27
6	134.139999	125.84	8.30	68.89	488.16
7	134.070007	125.75	8.32	69.22	557.38
8	133.380005	125.92	7.46	55.65	613.03
9	134.199997	125.93	8.27	68.39	681.43
10	134.559998	126.19	8.37	70.06	751.48
11	135.389999	127.12	8.27	68.39	819.88

MSE : [68.3229844]

Figure 4: ARIMA Forecasting and its MSE.

The forecast value generated by ARIMA has a reasonably large error. However, the ARIMA forecast value can still be useful if the next stage's testing is in the CPI value range.

3.2 ANN Forecasting

The training and testing data to be used as input on ANN need to be normalized first to get values from

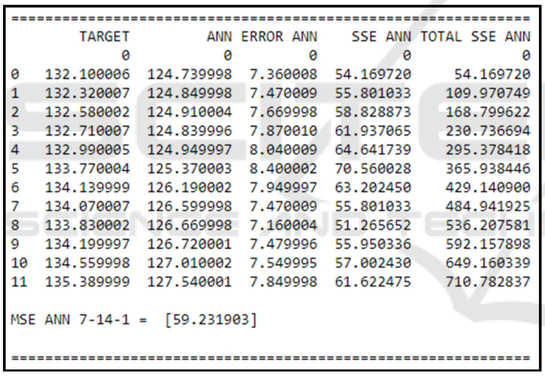
0 to 1. Normalized training and testing data have seven columns (including the last column as CLASS), so the initial ANN architecture is 7-x-1. The x value is determined by experimenting on different values such as 8, 9, 10, and 14, and the best value (which has the lowest MSE of 59.23) is 14. Therefore, the ANN architecture 7-14-1 is used in the forecasting phase. Table 1 lists the MSE comparison of four ANN architectures.

Table 2: MSE Comparison of four ANN architectures.

ANN Architecture	MSE Denormalized Output
7 – 8 -1	77.35
7 – 9 – 1	70.26
7 – 10 – 1	65.07
7 – 14 – 1	59.23

3.3 ANN Forecasting Result

The ANN 7-14-1 is used to forecast the CPI value in 2018, and the result is in Figure 5.



	TARGET	ANN	ERROR ANN	SSE ANN	TOTAL SSE ANN
	0	0	0	0	0
0	132.100006	124.739998	7.360008	54.169720	54.169720
1	132.320007	124.849998	7.470009	55.801033	109.970749
2	132.580002	124.910004	7.669998	58.828873	168.799622
3	132.710007	124.839996	7.870010	61.937065	230.736694
4	132.990005	124.949997	8.040009	64.641739	295.378418
5	133.770004	125.370003	8.400002	70.560028	365.938446
6	134.139999	126.190002	7.949997	63.202450	429.140900
7	134.070007	126.599998	7.470009	55.801033	484.941925
8	133.830002	126.669998	7.160004	51.265652	536.207581
9	134.199997	126.720001	7.479996	55.950336	592.157898
10	134.559998	127.010002	7.549995	57.002430	649.160339
11	135.389999	127.540001	7.849998	61.622475	710.782837

MSE ANN 7-14-1 = [59.231903]

Figure 5: ANN Forecasting and its MSE.

The forecast value generated by ANN has a lower error than ARIMA, which is 59.23.

3.4 CPI Range

The CPI range is calculated based on the price of goods in the current year used to predict (i.e., 2018) and the price of goods in the base year. Due to the large number of types of goods included in each category, this study only used a sample of 6 prices of most consumed goods from each category per year.

For the clothing category, the item prices used are men's t-shirts, women's t-shirts, men's underwear, women's panties, men's jeans, women's jeans, sarongs, and Muslim prayer gown (*mukena)*. For the food category, the prices of goods used are instant noodles, meatballs, fresh milk, cooking spices, chicken meat, and cigarettes. For the housing category, the prices of goods used are house contract rates, builders' rates, iron blocks, plywood, sand, and wall paint. As for the health category, the prices of goods used are general practitioner rates, hospital rates, drug prices, vitamins, men's haircuts and women's haircuts. From the calculation, the estimated CPI range for 2018 is between 100 - 176.

3.5 Comparison Analysis

Figure 6 compares ARIMA and ANN result in predicting the CPI value for the year 2018. The lower limit of the CPI range is marked with a straight blue line that stretches across the value 100 and the upper limit of the CPI range is marked with an orange straight line that stretches across the value 176. The actual CPI value data obtained from BPS as a reference for comparison is marked with blue circles for twelve data (representing each month), while the ARIMA forecast data is marked with a red circle. And the ANN forecast data is marked with a green circle. Both ARIMA and ANN results lie almost on the same line and are still in the blue-orange lines' accepted range, representing the min and max CPI range. Therefore, these two methods are sufficient enough to forecast the CPI data model.

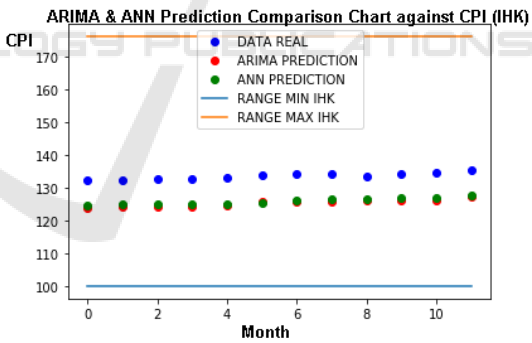


Figure 6: ARIMA and ANN Result Comparison

4 CONCLUSIONS

This research has resulted in several conclusions as follows. Firstly, both methods (ARIMA and ANN) can be used to predict the Indonesian CPI value from January 2018 - December 2018. The ARIMA model applied to this forecast is ARIMA (1,1,1) and produces CPI values of 123.77, 124.08, 124.05, 124.16, 124.66, 125.55, 125.83, 125.75 125.91, 125.93, 126.19, and 127.12. Meanwhile, ANN applies four forms of ANN architectures, which are ANN 7-8-1, 7-9-1, 7-10-1, and 7-14-1. However, the best form is 7-14-1 because it produced the smallest MSE value of 59.23, with the resulting CPI forecast values of 124.73, 124.84, 124.91, 124.83, 124.94, 125.37, 126.19, 126.59, 126.66, 126.72, 127.01, and 127.54.

Secondly, although both methods can be used for forecasting, ANN provides better forecasting results than ARIMA in forecasting research for the Indonesian CPI value, with a difference of 9.09 in MSE values, where ARIMA produced an MSE of 68.32 while ANN produced an MSE of 59.23. However, although the resulting MSE is quite large, all of the predicted values from these two methods are still in the CPI range between 100 and 176. So it can be said that the ARIMA and ANN forecast results are at a reasonable level and can still be calculated.

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