Journal of Computer Networks, Architecture and High Performance Computing
Volume 7, Number 1, January 2025
https://doi.org/10.47709/cnahpc.v7i1.5534

Submitted : Feb 10, 2025
Accepted : Feb 18, 2025
Published : Feb 19, 2025

INFLATION RATE ESTIMATION USING HYBRID ARIMA-ADAPTIVE NEURO FUZZY INFERENCE SYSTEM METHOD

Nur Alvi Annisa[1, *)], Rina Filia Sari[2)]
[1,2]Department of Mathematics, Universitas Islam Negeri Sumatera Utara, Medan, Indonesia
[1)] nuralvi0703193095@uinsu.ac.id, [2)] rinafiliasari@uinsu.ac.id.

ABSTRACT

Inflation is an important issue that affects the economic stability of a country or region. Unstable inflation will have a negative impact on society, especially on commodity prices including food and energy. Inflation is classified as a time series and will usually recur over time, five years later, or ten years later. , the problem of inflation needs to be studied and analyzed using existing approaches in *time series*. This research focuses on the application of *Hybrid ARIMA-Adaptive Neuro Fuzzy Inference System* method for inflation estimation, which is expected to provide a more accurate picture of the price fluctuations of basic needs in North Sumatra. Overall, the results show that the ability of the *Hybrid ARIMA-Adaptive Neuro Fuzzy Inference System* method in estimating inflation values is quite good with the results tending to be stable and not experiencing many sharp fluctuations. The inflation value is in the range of around -2.69 to -2.73 throughout the predicted period. However, a continuous negative number indicates a price decline or economic pressure, so further analysis or development is needed to understand the cause. The estimation results may help to maintain stability or make desired changes in the future.

Keywords: Inflation, Forecasting, Hybrid ARIMA-Adaptive Neuro Fuzzy Inference System

INTRODUCTION

Price stability is one of the barometers of the stability of real economic growth, because controllable inflation guarantees an increase in people's purchasing power over time. In Indonesia, including in North Sumatra, the prices of basic necessities are very volatile. At certain times the prices of basic necessities rise and fall depending on *supply*. In addition, an increase in the price of basic necessities can be caused by an increase in domestic production costs, for example due to an increase in fuel prices.

In general, inflation is basically defined as the time when prices of goods, services, or factors of production generally increase. With inflation, the purchasing power of money will decrease over time. Observing various developments in the latest economic indicators, North Sumatra inflation in 2022 is predicted to be at risk of being above the national inflation target of 3% ± 1%. Responding to this, Bank Indonesia's policy mix is directed at maintaining inflation stability amidst continued economic recovery in various sectors.

Inflation is classified as a time series and will usually be repeated over time, five years later, or ten years later. , the problem of inflation needs to be studied and analyzed using approaches in *time series*. The development of the inflation rate in the future period needs to be done to anticipate the impact of high inflation. This needs to be considered considering its impact on the economy which can lead to instability, slow economic growth, unemployment that always increases. Inflation is not only influenced by the amount of goods and services (commodities) consumed by the people in the region concerned, but inflation is also influenced by the amount of money in circulation at a location in another region.

Both *current* and *expected* inflation rates have an important effect on economic agents' decisions to save, invest, produce and consume. Decisions based on the *expected* inflation rate may be misleading. The importance of estimation makes many organizations, both industrial and institutional, perform estimation techniques to set policies for desired changes in the future. This is also done by the central bank which targets the inflation rate in Indonesia based on the estimation of future inflation. One of the methods that can be used in inflation estimation is the combination of two methods, namely ARIMA and Adaptive Neuro Fuzzy Inference System or also called Hybrid ARIMA-ANFIS.

One of the frequently used forecasting methods is *Autoregressive Integrated Moving Average* (*ARIMA*). The weaknesses of this method are the assumption of stationarity and the difficulty in determining the order (p,d,q). But

* Corresponding author

Journal of Computer Networks, Architecture and High Performance Computing
Volume 7, Number 1, January 2025
https://doi.org/10.47709/cnahpc.v7i1.5534

Submitted : Feb 10, 2025
Accepted : Feb 18, 2025
Published : Feb 19, 2025

along with the development of science, there is one method part of the expert system, namely the *Adaptive Neuro Fuzzy Inference System* (*ANFIS*) which is a combination of *Artificial Neural Network* (*ANN*) and *Fuzzy Inference System* (*FIS*) (Jang *et al.*, 1997). The use of the *ANFIS* method does not require assumptions of independence, homoscedasticity, and normally distributed residuals that are often not found in data so that this method is considered suitable for estimating data that has extreme values.

Previous research shows that the combination of two methods, namely ARIMA-ANFIS, shows quite good results for forecasting or estimating inflation and other fields. For example, research conducted by Wardani (2023) shows that the use of the ARIMA-ANFIS method in forecasting the inflation rate in Central Java has the lowest RMSE value of 0.004656. Diarsih (2022) also conducted research using the hybrid ARIMA-ANFIS method in modeling shallot production, where the results of the study had smaller RMSE and AIC values.

In this North Sumatra inflation estimation research, it is expected that the use of the Hybrid ARIMA-Adaptive Neuro Fuzzy Inference System method can provide a more accurate picture of fluctuations in the price of basic necessities in North Sumatra. In the context of this estimation, the data used is inflation data for a certain period. The results of this study are expected to provide a deeper picture and insight into the importance of maintaining inflation stability and helping related parties in setting policies for the desired changes.

Based on the background that has been discussed, this research aims to analyze and develop methods in estimating inflation in North Sumatra using the Hybrid ARIMA-Adaptive Neuro Fuzzy Inference System method by paying attention to several existing rules. From the results of this analysis, it is expected to be one of the evaluation references for the preparation of strategies to maintain inflation stability in North Sumatra for the following years.

LITERATURE RIVIEW

Definition of Inflation

According to Ebert and Griffin, inflation is a condition where the amount of goods in circulation is less than the amount of demand so that it will result in widespread price increases in the economic system as a whole. The types of goods that are classified for inflation calculation include the prices of food group goods, housing group goods, and clothing group goods. Inflation usually refers to consumer prices, but can also use other prices (wholesale prices, wages, prices, assets, etc.).

Inflation can occur from two directions, the first is domestic inflation which is inflation that arises due to a country's deficit, crop failure, or increased demand for certain goods. The second is foreign inflation, which is inflation that arises due to rising prices of goods that we import or due to a continuous surge in demand for exports from abroad.

Autoregressive Integrated Moving Average (ARIMA)

The ARIMA (p, d, q) model is the result of combining nonstationary processes that have been stationaryised with p and q expressing the order of the autoregressive and moving average and d is the order of the difference. The general form of the ARIMA (p,d,q) model can be defined as follows:

$$\boldsymbol{\phi_p(B)(1-B)^d Z_t = \Theta_q(B)a_t} \quad \textbf{(1)}$$

The subset ARIMA model is part of the generalised ARIMA model, so it cannot be expressed in general form. An example of a subset ARIMA model ([1,5],0,[1,12]) can be written as follows:

$$\boldsymbol{\left(1-\phi_1 B-\phi_5 B^5\right)Z_t = (1-\phi_1 B-\phi_{12}B^{12})a_t} \quad \textbf{(2)}$$

Thus the ARIMA subset model is an ARIMA model with some of its parameters equal to zero. In determining the ARIMA model, the Box-Jenkins method is used which consists of several stages, namely identification, parameter estimation, diagnostic checks, and forecasting.

Adaptive Neuro Fuzzy Inference System (ANFIS)

ANFIS is an architecture that is functionally the same as Sugeno's fuzzy rule base model and is a method in which rule tuning uses a learning algorithm on a set of data and also allows rules to adapt. If given two inputs consisting of $Z_{t,1}$ i.e. Z at time t-1 and $Z_{t,2}$ i.e. Z at time t-2 and an output $\hat{Z}_t$ then based on the assumptions in the first-order Sugeno rule base there are two rules as follows:

* Corresponding author

Journal of Computer Networks, Architecture and High Performance Computing
Volume 7, Number 1, January 2025
https://doi.org/10.47709/cnahpc.v7i1.5534

Submitted : Feb 10, 2025
Accepted : Feb 18, 2025
Published : Feb 19, 2025

Aturan 1 : $if\ Z_{t,1}\ is\ A_1\ and\ Z_{t,2}\ is\ B_1\ then\ \ Z_t^{(1)} = p_1 Z_{t,1} + q_1 Z_{t,2} + r_1$
Aturan 2 : $if\ Z_{t,1}\ is\ A_2\ and\ Z_{t,2}\ is\ B_2\ then\ \ Z_t^{(2)} = p_2 Z_{t,1} + q_2 Z_{t,2} + r_2$

$Z_{t,1}\ is\ A_1\ and\ Z_{t,2}\ is\ B_1; Z_{t,1}\ is\ A_2\ and\ Z_{t,2}\ is\ B_2$ are premises (nonlinear), while $Z_t^{(1)} = p_1 Z_{t,1} + q_1 Z_{t,2} + r_1$ dan $Z_t^{(2)} = p_2 Z_{t,1} + q_2 Z_{t,2} + r_2$ are consequents (linear). $p1, p2, q1, q2, r1, r2$ are the consequent parameters (linear) and $A1, B1, A2, B2$ are the premise parameters (nonlinear).

If the firing strength of each rule is w_1 and w_2 for $Z_t^{(1)}$ and $Z_t^{(2)}$ with output $\hat{Z}_t$, then it can be calculated as follows:

$$\hat{Z}_t = \frac{w_1 Z_t^{(1)} + w_2 Z_t^{(2)}}{w_1 + w_2} = \bar{w}_1 Z_t^{(1)} + \bar{w}_2 Z_t^{(2)} \quad (3)$$

Hybrid Learning Algorithm in ANFIS

Adaptive Neuro Fuzzy Inference System (ANFIS) applies a hybrid learning algorithm in its system to identify parameters. The hybrid learning algorithm will set the consequent parameters pi, qi, and ri forwardly identified using least square and will set the premise parameters backwardly using the gradient descent method.

Hybrid model is a combination method of one or more models in the function of a system. In general, the combination of time series models that have linear and non-linear structures.

The ARIMA model is used to solve linear cases, where the residuals of the linear model still contain non-linear relationship information. Mathematically, it can be written as follows:

$$e_t = Z_t - \hat{L}_t \quad (4)$$

Where $\hat{L}_t$ is the ARIMA forecast value at time t and Z_t is the initial data at time t. Then modeling the residuals of the ARIMA model using ANFIS, the non-linear relationship can be resolved. The ANFIS forecast results are then combined with the ARIMA method forecast results. Mathematically, the overall forecast results obtained are as follows:

$$\hat{Z}_t = \hat{L}_t + \hat{N}_t \quad (5)$$

Where $\hat{N}_t$ is the forecast from equation (2.8) and $\hat{Z}_t$ is the forecast result from the combination of ARIMA forecast values and ANFIS forecasts.

Performance Measurement Evaluation Index Estimation Results

The lower the error rate in the forecast data, the more feasible the forecast data is to use. To test the level of forecast error in this study, the Mean Absolute Percentage Error (MAPE) method was used with the formula:

$$\text{MAPE} = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{Z_t - \hat{Z}_t}{Z_t}\right| \text{ x } 100\% \quad (6)$$

Previous Research

Research conducted by Diarsih (2018) using the Hybrid ARIMA-ANFIS method in modeling shallot production in Central Java. The results show that the Hybrid ARIMA-ANFIS method has an RMSE value of 12033 and an AIC of 21.6634. In a study conducted by Wardani (2023) using the Hybrid ARIMA-ANFIS method to predict the inflation rate in Central Java. The results show that the Hybrid ARIMA-ANFIS method has an RMSE value of 0.004656. And in a study conducted by Tarno (2018) using the Hybrid ARIMA-ANFIS method to predict horticultural crop production data in Central Java. The results show that the Hybrid ARIMA-ANFIS method has a Root Mean Squared Error (RMSE) value of 39.99.

METHOD

The data in this study were obtained from the official website of the Central Bureau of Statistics of North Sumatra Province which can be accessed at sumut.bps.go.id. This research is included in the type of quantitative research. The variable in this study is the inflation rate (Z_t). In this study what is meant by inflation rate (Z_t) is the monthly inflation rate of North Sumatra. Furthermore, the data is divided into two parts, namely 48 data as *training* data and 12 data as *testing data.* The data is then analyzed using a combination of two methods, namely the Hybrid ARIMA-Adaptive Neuro Fuzzy Inference System method. The Hybrid ARIMA-Adaptive Neuro Fuzzy Inference System method is used because it does not require independent assumptions, and normally distributed residuals are often not found in the data so this method is considered suitable for forecasting extreme values.

* Corresponding author

Journal of Computer Networks, Architecture and High Performance Computing
Volume 7, Number 1, January 2025
https://doi.org/10.47709/cnahpc.v7i1.5534

Submitted : Feb 10, 2025
Accepted : Feb 18, 2025
Published : Feb 19, 2025

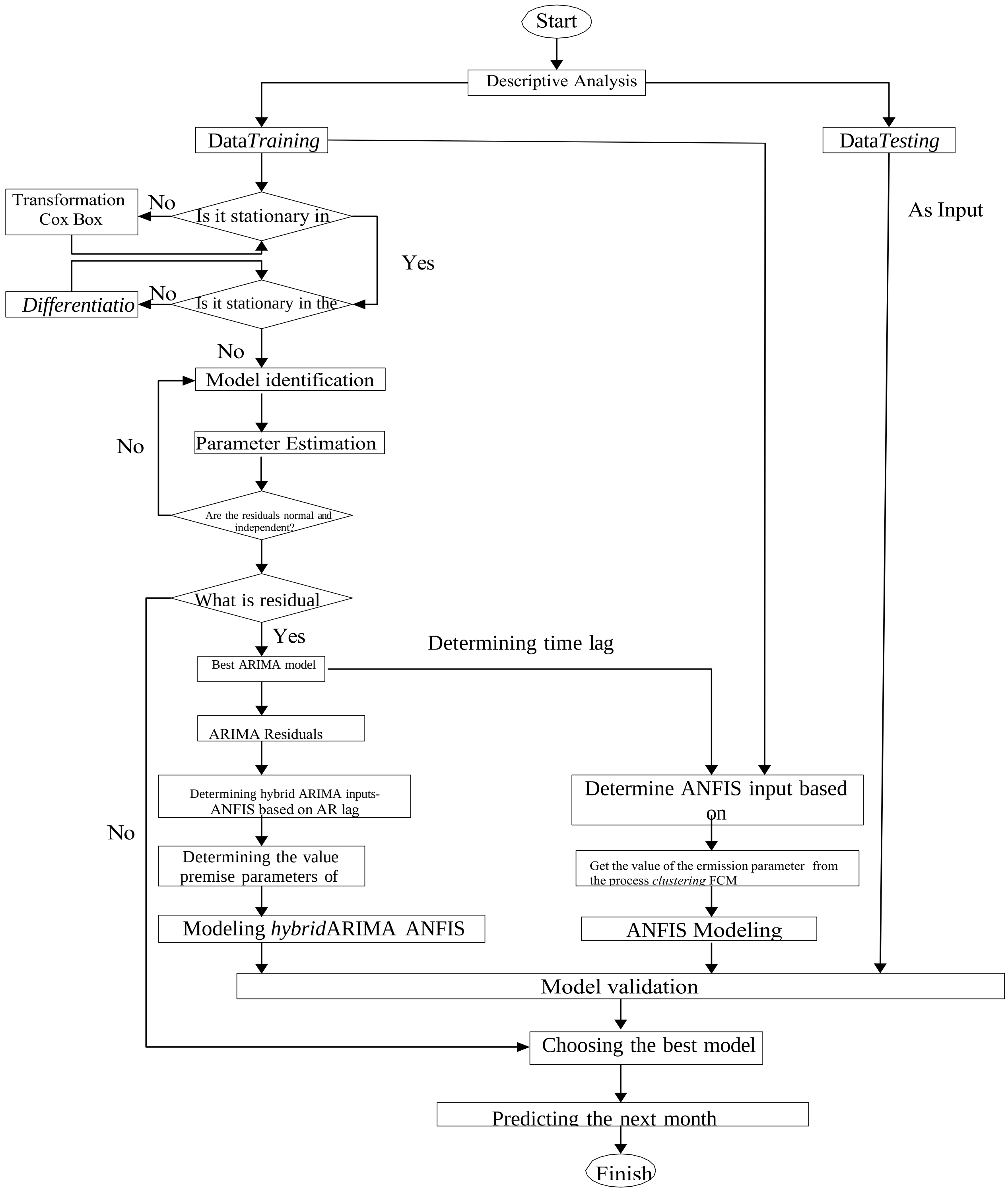

Figure 1. Flow Chart

* Corresponding author

Journal of Computer Networks, Architecture and High Performance Computing
Volume 7, Number 1, January 2025
https://doi.org/10.47709/cnahpc.v7i1.5534

Submitted : Feb 10, 2025
Accepted : Feb 18, 2025
Published : Feb 19, 2025

The steps of the process in this study, starting with the collection of secondary data, namely North Sumatra inflation rate data starting from January 2018 to December 2022 obtained from the *website of* the Central Bureau of Statistics of North Sumatra Province. The data obtained is then separated into two parts, namely training data and testing data. Training data is used to build and form forecasting patterns, while testing data is used to test the accuracy of the forecasting method that has been made.

Once the data has been grouped, the next process is to plot the time series data to understand the patterns in order to perform preliminary examination and processing of the inflation data. This includes removing outliers, filling in missing values, and transforming the data if necessary. Next, identify the ARIMA model to see which model fits the inflation data. Use graphical analysis, *autocorrelation plot (ACF)* and *partial autocorrelation plot (PACF).* This step involves selecting the optimal *p, d* and *q* values for the ARIMA model.

After obtaining the optimal values of *p,d* and *q*, estimate the ARIMA model using historical inflation data. This process involves determining the most suitable ARIMA model parameters using the model testing and evaluation method. Next, perform model diagnosis to see the accuracy in using the model.

Based on model diagnosis, the use of ARIMA shows that the residuals are not normally distributed. Therefore, it is necessary to create an Adaptive Neuro Fuzzy Inference System model. Using historical inflation data as input, the application of the ANFIS model consists of fuzzy rules and membership functions generated from the learning process. After that, training and evaluation of ANFIS. Train the ANFIS model using a suitable learning algorithm, such as backpropagation or genetic algorithm. The final process is to integrate ARIMA-ANFIS. Combine the prediction results from the ARIMA model and ANFIS model to get the final inflation rate estimation result.

By using the combination of these two methods, namely the Hybrid ARIMA-Adaptive Neuro Fuzzy Inference System method in this study is expected to provide the results of the estimation of future inflation rates and help related parties in strategizing to make changes in the future to maintain inflation stability in North Sumatra

RESULT

Data Collection

The data in this study were obtained from the official website of the Central Bureau of Statistics of North Sumatra Province which can be accessed at sumut.bps.go.id. This research is included in the type of quantitative research. The variable in this study is the inflation rate (Z_t). In this study what is meant by inflation rate (Z_t) is the monthly inflation rate of North Sumatra. Furthermore, the data is divided into two parts, namely 48 data as *training* data and 12 data as *testing* data by making a time series plot.

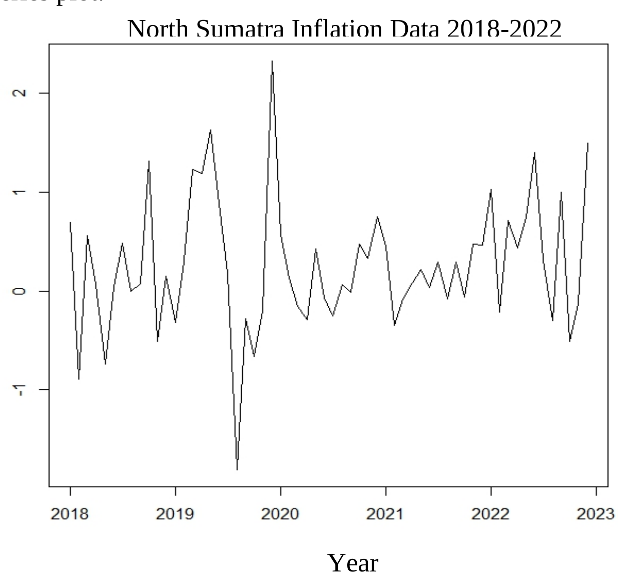

Figure 2. Plot of Inflation Data 2018-2022

* Corresponding author

Journal of Computer Networks, Architecture and High Performance Computing
Volume 7, Number 1, January 2025
https://doi.org/10.47709/cnahpc.v7i1.5534

Submitted : Feb 10, 2025
Accepted : Feb 18, 2025
Published : Feb 19, 2025

Figure 2 shows a plot of inflation rate data over a certain period in this study. From the visualization presented, it can be seen that in some years in the period there was a decline and increase in value that was too sharp so that it could disrupt the economy.

Descriptive statistical analysis is also needed in quantitative research to provide an overview of the variables used, such as minimum value, maximum value, average and standard deviation which can simplify a lot of data. As shown in Table 1 below.

Table 1. Descriptive Statistics 2018-2022

Descriptive Statistics						
	N	Minimum	Maximum	Mean	Std. Deviation	Variance
T2018	12	-.89	1.31	.1017	.62118	.386
T2019	12	-1.81	2.33	.3733	1.13489	1.288
T2020	12	-.29	.75	.1633	.34108	.116
T2021	12	-.35	.47	.1433	.26134	.068
T2022	12	-.51	1.50	.4983	.67712	.458
Valid N (listwise)	12					

***ARIMA* Model Formation**

1. *Stationarity* Test

Using *box-cox* analysis on *training* data.

$$y(\lambda) = \frac{y^{\lambda} - 1}{\lambda} \; untuk \; \lambda \neq 0$$
$$y(\lambda) = \ln(y) \; untuk \; \lambda = 0$$

Where:

- y is the original data,
- λ is the transformation parameter, which is usually sought by estimation to find a value that minimizes deviation or improves normality.

Before finding the value of λ we need to add a constant (ϵ\epsilonϵ) to ensure all values are positive before performing the Box-Cox transformation.

$$train_{ts_{pos}} = train_{ts} + \epsilon$$

Where:
$train_{ts_{pos}}$= data that has been transformed
$train_{ts}$= training data used to be transformed

$$\epsilon = |\min(train_{ts})| + 1$$
$$\epsilon = |-1{,}81| + 1$$
$$\epsilon = |1{,}81| + 1$$
$$\epsilon = 2{,}81$$

Here is a comparison of the original data with the transformed data.

Table 2. Comparison Results

MONTH	INFLATION(Original Data)	Transformation Data
JANUARY 2018	0,69	3,50
FEBRUARY 2018	-0,89	1,92
MARCH 2018	0,56	3,37
APRIL 2018	0,06	2,87
MAY 2018	-0,74	2,07
JUNE 2018	0,04	2,85
JULY 2018	0,48	3,29
AUGUST 2018	0,00	2,81

* Corresponding author

Journal of Computer Networks, Architecture and High Performance Computing
Volume 7, Number 1, January 2025
https://doi.org/10.47709/cnahpc.v7i1.5534

Submitted : Feb 10, 2025
Accepted : Feb 18, 2025
Published : Feb 19, 2025

SEPTEMBER 2018	0,07	2,88
OCTOBER 2018	1,31	4,12
NOVEMBER 2018	-0,51	2,30
DECEMBER 2018	0,15	2,96
JANUARY 2019	-0,32	2,49
FEBRUARY 2019	0,30	3,11
MARCH 2019	1,23	4,04
APRIL 2019	1,19	4,00
MAY 2019	1,63	4,44
JUNE 2019	0,88	3,69
JULY 2019	0,18	2,99
AUGUST 2019	-1,81	1,00
SEPTEMBER 2019	-0,28	2,53
OCTOBER 2019	-0,66	2,15
NOVEMBER 2019	-0,19	2,62
DECEMBER 2019	2,33	5,14
JANUARY 2020	0,57	3,38
FEBRUARY 2020	0,13	2,94
MARCH 2020	-0,16	2,65
APRIL 2020	-0,29	2,52
MAY 2020	0,43	3,24
JUNE 2020	-0,07	2,74
JULY 2020	-0,25	2,56
AUGUST 2020	0,06	2,87
SEPTEMBER 2020	-0,01	2,80
OCTOBER 2020	0,47	3,28
NOVEMBER 2020	0,33	3,14
DECEMBER 2020	0,75	3,56
JANUARY 2021	0,45	3,26
FEBRUARY 2021	-0,35	2,46
MARCH 2021	-0,08	2,73
APRIL 2021	0,08	2,89
MAY 2021	0,22	3,03
JUNE 2021	0,03	2,84
JULY 2021	0,29	3,10
AUGUST 2021	-0,08	2,73
SEPTEMBER 2021	0,29	3,10
OCTOBER 2021	-0,06	2,75
NOVEMBER 2021	0,47	3,28
DECEMBER 2021	0,46	3,27

2. Model Identification
Model identification is done by looking at the lag that has cut-off on the ACF and PACF plots. For each lag k, calculate the autocorrelation with the formula:

$$ACF(k) = \frac{\sum_{t=k+1}^{n}(yt-\bar{y})(yt-k-\bar{y})}{\sum_{t=1}^{n}(yt-\bar{y})^2}$$

where: yt is the value of inflation at time t
$\bar{y}$is the average of all time series.
N is the total number of observations.
Here are the ACF and PACF plots of the box-cox transformed data.

* Corresponding author

Journal of Computer Networks, Architecture and High Performance Computing
Volume 7, Number 1, January 2025
https://doi.org/10.47709/cnahpc.v7i1.5534

Submitted : Feb 10, 2025
Accepted : Feb 18, 2025
Published : Feb 19, 2025

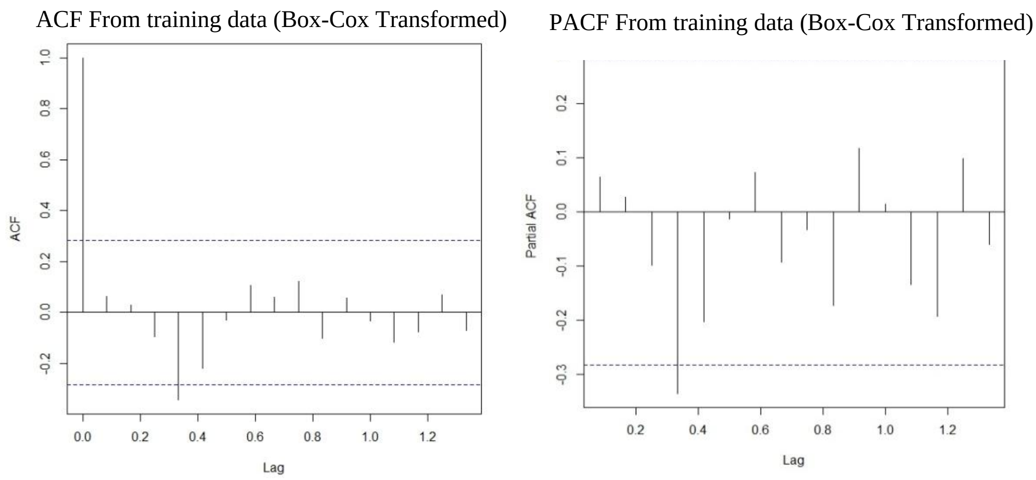

Figure 4. ACF and PACF plots of box-cox transformed data

Determine p and q

Value of p: Based on the PACF, select the lag where the partial autocorrelation starts to approach zero. From the results, p may be around 2, 3, or 4.

Value of q: Based on the ACF, choose the lag where the autocorrelation starts to approach zero. From the results, q may be around 3, 4, or 5.

3. Model Parameter Estimation

Here we use 3 ARIMA models, namely :

ARIMA model (2,0,3)

ARIMA Model (3,0,4)

ARIMA Model (4,0,5)

Table 3. Parameter Estimation Calculation Results

No.	ARIMA(p,d,q)	Coef. Parameter Estimation		Standard Error	AIC	RMSE	Description
1.	(2,0,3)	$\emptyset_1$	1.1300	0.2144	-67.98	0.0997	significant
		$\emptyset_2$	-0.5065	0.1920			
		θ_1	-1.3355	0.2162			
		θ_2	0.7974	0.3379			
		θ_3	-0.4618	0.2393			
2.	(3,0,4)	$\emptyset_1$	0.6606	0.6114	-66.5	0.0971	significant
		$\emptyset_2$	-0.2830	0.7286			
		$\emptyset_3$	0.0076	0.4474			
		θ_1	-0.7973	0.5971			
		θ_2	0.3348	0.8219			
		θ_3	-0.1476	0.6022			
		θ_4	-0.3899	0.3351			
		$\emptyset_1$	0.1052	1.2404			
		$\emptyset_2$	0.1957	0.4689			
		$\emptyset_3$	-0.2905	0.3735			
		$\emptyset_4$	0.0803	0.3547			in part

* Corresponding author

Journal of Computer Networks, Architecture and High Performance Computing
Volume 7, Number 1, January 2025
https://doi.org/10.47709/cnahpc.v7i1.5534

Submitted : Feb 10, 2025
Accepted : Feb 18, 2025
Published : Feb 19, 2025

3.	(4,0,5)	θ_1	-0.2346	1.2335	-62.81	0.0968	great significant
		θ_2	-0.2257	0.6082			
		θ_3	0.2001	0.3442			
		θ_4	-0.5734	0.2553			
		θ_5	-0.1665	0.6203			

In Table 2, it can be seen that the RMSE and MAE are lower in the ARIMA 3 model, which indicates that this model has a better performance in predicting the training data.
Furthermore, the diagnosis of the three models is to see whether the model is sufficiently feasible to use or not.

Table 4. Model Diagnosis

Assumption	**ARIMA(2,0,3)**	**ARIMA(3,0,4)**	**ARIMA(4,0,5)**
Normality	0,001521 < 0,05	0,00069 < 0,05	0,00062 < 0,05
Autocorrelation	0,7322 > 0,05	0,9749 > 0,05	0,979 > 0,05
Heterocedacity	0,7237 > 0,05	0,7255 > 0,05	0,7255 > 0,05

1. Normality: All three ARIMA models show that the residuals are not normally distributed. This can be a problem as the assumption of normality of residuals is important in ARIMA models.
2. Autocorrelation: There is no significant autocorrelation in the residuals for all three models. This is a good result as it indicates that the ARIMA model has captured most of the patterns in the data.
3. Heteroscedasticity: There is no significant heteroscedasticity in the residuals for all three models. This is also a good result as it indicates that the variability of the residuals is constant.

Given that the residuals of the ARIMA model are not normal, a hybrid ARIMA-ANFIS approach may still be suitable, especially since:

- ANFIS can handle non-linear components and potential non-normality in the residual data.
- The results of the autocorrelation and heteroscedasticity tests show that the residuals have no significant autocorrelation or heteroscedasticity patterns, which means that the remaining residual errors can be more effectively handled by ANFIS.

Hybrid ARIMA-ANFIS Model Formation

Since the ARIMA model is not feasible enough to be used to predict the inflation rate, it will be overcome by performing hybrid ARIMA - ANFIS modeling which is selected from the best ARIMA residuals that has the smallest AIC value. Model 1 (ARIMA(2,0,3)) has a low AIC (-67.98), which makes it the best candidate based on AIC criteria.

$$y_t = c + \emptyset_1 y_{t-1} + \emptyset_1 y_{t-2} + \theta_1 \epsilon_{t-1} + \theta_1 \epsilon_{t-2} + \theta_1 \epsilon_{t-3} + \epsilon_t$$

$$\hat{y}_t = 0{,}6438 + 1{,}1300 y_{t-1} - 0{,}5065 y_{t-2} - 1{,}3355 \epsilon_{t-1} + 0{,}7974 \epsilon_{t-2} - 0{,}4618 \epsilon_{t-3} + \epsilon_t$$

Furthermore, it is used to form a membership function. Mathematically, the membership function for each input is written as follows.

$$\mu_{A1} = \exp\left(-\frac{(z_{t-2} - 5{,}000)^2}{0{,}001^2}\right)$$

$$\mu_{A1} = \exp\left(-\frac{(z_{t-2} - 5{,}000)^2}{0{,}3497427^2}\right)$$

$$\mu_{B1} = \exp\left(-\frac{(z_{t-1} - 5{,}000)^2}{0{,}001^2}\right)$$

$$\mu_{B1} = \exp\left(-\frac{(z_{t-1} - 5{,}000)^2}{0{,}9710372^2}\right)$$

Fuzzy logic operations

Because the clusters used are 2, there are 2 rules formed. The 2 rules formed are as follows:

$f_1 = -0{,}07700673 z_{t-2} + 0{,}8558345 z_{t-1} + 0{,}14917224$

* Corresponding author

Journal of Computer Networks, Architecture and High Performance Computing
Volume 7, Number 1, January 2025
https://doi.org/10.47709/cnahpc.v7i1.5534

Submitted : Feb 10, 2025
Accepted : Feb 18, 2025
Published : Feb 19, 2025

$f_2 = 0{,}03955453 z_{t-2} + 0{,}1128910 z_{t-1} + 0{,}8187601$

Table 5. Input data results for ANFIS with 2 rules generated

Rule 1	Rules.
0,031031	-0,00448
0,032669	0,031031
-0,05091	0,032669
-0,00765	-0,05091
0,041031	-0,00765
0,046373	0,041031
0,004918	0,046373
0,030123	0,004918
0,011097	0,030123
0,054402	0,011097
0,026341	0,054402
0,072624	0,026341

The overall Hybrid ARIMA-ANFIS model formed is as follows

$$\hat{R}_t = \frac{w_1}{w_1 + w_2}(-0{,}07700673 z_{t-2} + 0{,}8558345 z_{t-1} + 0{,}14917224) + \frac{w_2}{w_1 + w_2}(0{,}03955453 z_{t-2} + 0{,}1128910 z_{t-1} + 0{,}8187601)$$

By

$$w_1 = \exp\left(-\frac{(z_{t-2} - 5{,}000)^2}{0{,}001^2}\right) . \exp\left(-\frac{(z_{t-1} - 5{,}000)^2}{0{,}001^2}\right)$$

$$w_2 = \exp\left(-\frac{(z_{t-2} - 5{,}000)^2}{0{,}3497427^2}\right) . \exp\left(-\frac{(z_{t-1} - 5{,}000)^2}{0{,}9710372^2}\right)$$

Table 6. Pred Arima and Pred Anfis

Pred Arima	Pred Anfis	Epsilon
0,6037123	-0,526557	3
0,6101139	-0,526557	3
0,5857884	-0,526557	3
0,5953215	-0,526557	3
0,6184147	-0,526557	3
0,6396828	-0,526557	3
0,6520206	-0,526557	3
0,6551914	-0,526557	3
0,6525257	-0,526557	3
0,6479074	-0,526557	3
0,6440387	-0,526557	3
0,6420058	-0,526557	3

* Corresponding author

Journal of Computer Networks, Architecture and High Performance Computing
Volume 7, Number 1, January 2025
https://doi.org/10.47709/cnahpc.v7i1.5534

Submitted : Feb 10, 2025
Accepted : Feb 18, 2025
Published : Feb 19, 2025

DISCUSSION

Prediction Results Using the Hybrid ARIMA-ANFIS Method

Predicting the inflation rate in Indonesia in 2024 using the Hybrid ARIMA-ANFIS model . The results of predicting the inflation rate in North Sumatra in 2024.

Tabel 7. Prediction Results with Hybrid ARIMA-ANFIS Method

No	Prediction Results
1.	-2.732845
2.	-2.726443
3.	-2.750769
4.	-2.741235
5.	-2.718142
6.	-2.696874
7.	-2.684536
8.	-2.681366
9.	-2.684031
10.	-2.688650
11.	-2.692518
12.	-2.694551

From Figure 5 shown in this study, it can be seen that the inflation value tends to be stable although there is a slight monthly variation but the changes between months are not too significant.

CONCLUSION

Based on the inflation prediction results, it can be concluded that inflation is expected to remain stable throughout the analyzed period, with values that tend to be in the range between -2.69 to -2.73. Although there is a slight variation between months, the change in inflation value is not significant, indicating that fluctuations in the prices of goods and services are relatively under control. This indicates a stable economy, where there are no major spikes in inflation. However, persistent negative numbers indicate falling prices or economic pressures that need to be analyzed further to understand the cause. Overall, inflation is not expected to experience drastic changes, reflecting price stability in the short term.

REFERENCES

Bishop, M. (2010). *Economics: A Complete Guide from A to Z.* Yogyakarta: Yogyakarta: READ.

Diarsih, I. H., Tarno, & Rusgiyono, A. (2018). Modeling Red Onion Production in Central Java Using *Hybrid Autoregressive Integrated Moving Average-Adaptive Neuro Fuzzy Inference System*. *Gaussian Journal*.

Fahmi, I. (2010). *Introduction to Political Economy.* Bandung: Alfabeta Publisher.

Faulina, R., and Suhartono. 2013. *Hybrid ARIMA-ANFIS for Rainfall Prediction in Indonesia.* International Journal of Science and Research (IJSR) Vol. 2, Issue 2: Pp159-162.

Hilwatunnadriyah. (2016). The Effect of Inflation on the Movement of Sharia Shares in the JII in 2012-2014. FEBI May 17.

Jang, J. S. R., Sun, C. T., & Mizutani, E. (1997). *Neuro Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence.* London: Prantice- Hall, Inc.

J. D. Cryer & K.-S. Chan. (2008). Time Series Analysis: With Applications in R, 2nd ed. USA: Springer Science.

Kurniawan, P., & Sri Budhi, M. (2019). *Introduction to Micro and Macro Economics Revised Edition.* Yogyakarta: Andi Offset.

Kusumadewi, S., & Hartati, S. (2006). *Neuro Fuzzy: Integration of Fuzzy Systems & Neural Networks*. Yogyakarta: Graha Ilmu.

Rahardja, P., & Manurung, M. (2008). *Macroeconomic theory: an introduction.* jakarta: Jakarta: Publishing House of the Faculty of Economics, University of Indonesia.

Soejoeti, Z. (1987). *Subject Matter of Time Series Analysis.* Jakarta: Karunika.

Suparmono, *Introduction to Macroeconomics*, (Yogyakarta: AMP YKPN Publishing and Printing Unit (UPP),), 128.

* Corresponding author

Journal of Computer Networks, Architecture and High Performance Computing
Volume 7, Number 1, January 2025
https://doi.org/10.47709/cnahpc.v7i1.5534

Submitted : Feb 10, 2025
Accepted : Feb 18, 2025
Published : Feb 19, 2025

Tarno. (2013). *Combination of ARIMA Subset Modeling Procedure and Outlier Detection for Time Series Data Prediction.* ISBN: 978-602-14387-0-1. Proceedings of the National Seminar on Statistics UNDIP Semarang.

Tarno, Rusgiyono, A., Warsito, B., Sudarno, & Ispriyanti, D. (2018). *HYBRID ARIMA-ANFIS* MODELING FOR HORTIKULTURA PLANT PRODUCTION DATA IN CENTRAL JAVA. *statistics media*.

Tarno, Subanar, Rosadi, D., & Suhartono. (2013). *Analysis of Financial Time Series Data Using Adaptive Neuro Fuzzy Inference System (ANFIS).* IJCSI, 10(1),491-496.

Wardani, R. P., & Winarno, B. (2023). Forecasting model of inflation rate in Central Java using hybrid ARIMA-ANFIS method. *PRISMA, Proceedings of the National Seminar on Mathematics*.

W. W. S. Wei. (2006). Time Series Analysis: Univariate and Multivariate Methods, 2nd ed. USA: Pearson Education.

Zhang, G. P. (2003). *Time Series Forecasting Using a Hybrid ARIMA and Neural Network Model.* Neurocomputing, 50: pp. 159-175.

https://sumut.bps.go.id/subject/3/inflasi.html

* Corresponding author