Available online at http://scik.org
Commun. Math. Biol. Neurosci. 2023, 2023:43
https://doi.org/10.28919/cmbn/7932
ISSN: 2052-2541

A NARX-NN OPTIMIZATION ALGORITHM FOR FORECASTING INFLATION DURING A POTENTIAL RECESSION PERIOD USING LONGITUDINAL DATA

RESTU ARISANTI*, YAHMA NURHASANAH, SRI WINARNI

Department of Statistics, Padjadjaran University, Bandung, Indonesia

Abstract: The global economy is facing the potential of a recession in 2023, and inflation is one of the factors that could trigger it. This study focuses on forecasting inflation using longitudinal data and the NARX NN method, which combines Generalized Linear Mixed Model (GLMM) and Neural Network (NN) approaches. The accuracy of the NARX NN method's prediction results will be measured using evaluation values such as RMSE and MAE. The aim is to provide insight into the credibility of the potential recession in the next few years. The major findings from this study are as follows: 1) The best performing Feed Forward Neural Network (FFNN) model is FFNN (7-15-5), which was applied to all exogenous variables data and achieved RMSE values of $X_1 = 5.158$, $X_2 = 7.377$, $X_3 = 4.054$, $X_4 = 0.456$, $X_5 = 5.130$ and MAE values of $X_1 = 3.533$, $X_2 = 4.667$, $X_3 = 2.522$, $X_4 = 0.216$, $X_5 = 4.101$; 2) The NARX NN series parallel model was utilized to forecast the USD/IDR exchange rate and its relationship with the exogenous variables, resulting in the best model of NARX NN (9-5-1). This model was applied to all inflation rate data and produced RMSE of 3,375 and MAE of 2,552; 3) Based on the forecasting results for the next 5 years (2022-2026), inflation rate is expected to experience an upward trend, indicating the possibility of an economic recession.

Keywords: NARX-NN; inflation; recession; longitudinal data.

2020 AMS Subject Classification: 92B20.

*Corresponding author
E-mail address: r.arisanti@unpad.ac.id
Received February 28, 2023

1. INTRODUCTION

Recently, the global economy has been threatened by the possibility of a recession. Speculation about this potential recession has been persistent throughout 2022, and it is now widely believed to be inevitable in 2023 [1]. A recession refers to a situation where a country's economic activity slows down or deteriorates, which can last for years if a country's Gross Domestic Product (GDP) growth decreases for two consecutive quarters. GDP represents a country's economic activity over a period of time. If a country experiences a continuous decline in economic activity over two consecutive periods, it is considered to be in recession [2].

Several factors can trigger a recession in a country, one of which is inflation. The World Bank's comprehensive study suggests that as central banks raise interest rates in response to inflation, the world may be heading towards a global recession in 2023, as well as financial crises in emerging markets and developing economies that could cause lasting harm [3]. Inflation refers to a general and persistent increase in the prices of goods and services over time, which weakens people's purchasing power and leads to a decrease in the production of goods and services [4]. In this study, inflation forecasting will be the main focus, and several other economic indicator variables will also be used to reduce the error rate of the inflation forecasting results.

The type of data that will be used in this research is longitudinal data, which is obtained from repeated measures of multiple individuals (cross-sectional units) over time (time units) [5]. The GLMM (Generalized Linear Mixed Model) method is commonly used for longitudinal data analysis due to the correlation between observations in the same unit [6,7]. In addition, many studies have been conducted on the machine learning method as an alternative method to GLMM [8,9]. However, this study will use the NARX NN method, which is a combination of Generalized Linear Mixed Model (GLMM) and Neural Network (NN) approaches, to handle the complex temporal and cross-sectional structure of panel data. Evaluation values such as RMSE and MAE will be used to measure the accuracy of the NARX NN method's prediction results. It is expected that the results of this study will help to clarify whether the threat of a recession in the next few years is a credible concern.

2. PRELIMINARIES

2.1 Research Data

The dataset utilized is a longitudinal dataset obtained from the World Bank Dataset website [10]. It comprises a sample of 48 countries from 7 regions, and the following shows the allocation.

Table 1. Allocation of the Number of Countries for Each Region.

Regional	Number of Countries
East Asia	7
Europe	13
Latin	15
Middle East	3
North America	1
South Asia	2
Sub Saharan	7
Total	**48**

The data consists of a 24-year period, starting from 1998 to 2021. The dataset consists of 1 main variable and 5 exogenous variables. Table 2 describes the variables used in this study.

Table 2. Dependent and Independent Variables used

Variable Type	Variable Name	Variable Code	Explanation
Main Variable	Inflation, GDP deflator (annual %)	Y	Inflation as measured by the annual growth rate of the GDP implicit deflator shows the rate of price change in the economy as a whole. The GDP implicit deflator is the ratio of GDP in current local currency to GDP in constant local currency [11].

Exogenous Variables	Real interest rate (%)	X1	Real interest rate is the lending interest rate adjusted for inflation as measured by the GDP deflator. The terms and conditions attached to lending rates differ by country, however, limiting their comparability [11].
	GDP per capita growth (annual %)	X2	Annual percentage growth rate of GDP per capita based on constant local currency. GDP per capita is gross domestic product divided by midyear population. GDP at purchaser's prices is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources [11].
	Final consumption expenditure (% of GDP)	X3	Final consumption expenditure (formerly total consumption) is the sum of household final consumption expenditure (private consumption) and general government final consumption expenditure (general government consumption). This estimate includes any statistical discrepancy in the use of resources relative to the supply of resources [11].
	Population growth (annual %)	X4	Annual population growth rate for year t is the exponential rate of growth of midyear population from year t-1 to t, expressed as a percentage . Population is based on the de facto definition of population, which counts all residents regardless of legal status or citizenship. [11]

Exports of goods and services (% of GDP)	X5	Exports of goods and services represent the value of all goods and other market services provided to the rest of the world. They include the value of merchandise, freight, insurance, transport, travel, royalties, license fees, and other services, such as communication, construction, financial, information, business, personal, and government services. They exclude compensation of employees and investment income (formerly called factor services) and transfer payments. [11]

2.2 NARX-NN

Artificial Neural Network (ANN), commonly referred to as Neural Network, is a type of information processing system that exhibits properties similar to biological neural networks [12]. Neural networks are effective in modeling nonlinear relationships. These systems are designed to repeatedly learn from patterns in data, enabling prediction without being influenced by the initial data pattern. One of the developments in Neural Network method is the Nonlinear Autoregressive Exogenous Neural Network (NARX NN), which is a nonlinear regression technique that uses Neural Network (NN) for time series data prediction with the inclusion of additional exogenous variables for more accurate forecasting [13].

The NARX network utilizes past values of the target time series and past values of other inputs to make predictions about future target series values. These networks can be classified as series-parallel or parallel architecture. In this study, we will use a series-parallel. The series-parallel architecture of the NARX network is depicted in Figure 1.

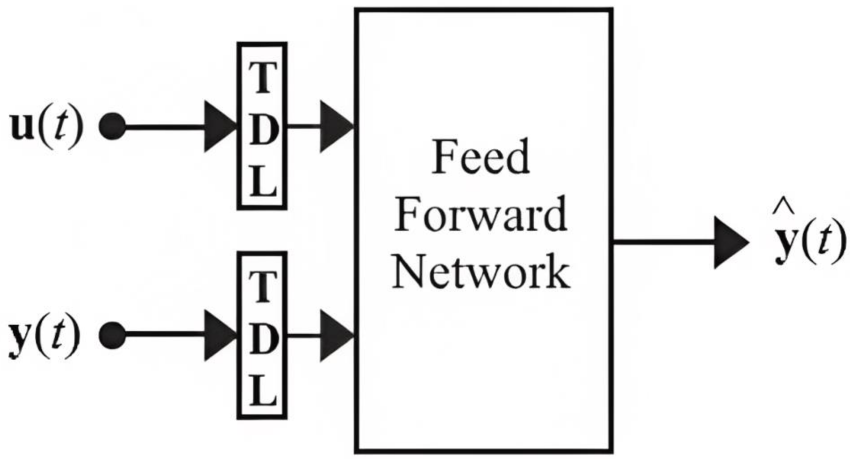


Figure 1. Series-parallel architecture of NARX network.

Source : https://www.researchgate.net/figure/Series-parallel-model-based-on-the-improved-NARX-forward-neural-network-open-loop-in_fig2_350445550 (accessed on 29 January 2023).

Figure 1 depicts the series-parallel architecture of the NARX network. The input values (u(t)) represent past exogenous values, while the output values (y(t)) represent past values of the actual series to be predicted. The predicted values (ŷ(t)) are indicated by ŷ(t).). In the series–parallel model, the future value of the time series ŷ(t) is derived from the current and/or past values of u(t) and the actual past values of the time series y(t) [14]. If the past values of the actual series are not recorded, they will not be available to the system and the network will use its past predicted values instead. However, in this study, we will use actual past values, which are more reliable than predictions [15].

The NARX model sets the current value of the dependent variable (Y) in relation to the past value or the current value of the independent variable (X) and the past value of the dependent variable (Y). The NARX model can be expressed as:

$$y_t = f(y_{t-1} + y_{t-2} + \ldots + x_t + x_{t-1} + x_{t-2} + \ldots) + \varepsilon_t \quad (1)$$

Here, y is the response variable and main observed variable, while x is the predictor variable and exogenous variable that explains the response variable. The past value of the response variable, along with information from the predictor variable, is used to predict the current value of the response variable. The model uncertainty of measurement noise is represented by a random variable $\boldsymbol{\varepsilon}$. The f function can be a nonlinear function, such as a neural network function or wavelet, among others [13].

In a series-parallel model, multiple parallel networks are connected in series, allowing the model to learn both temporal and cross-sectional dependencies in the data. For example, in a time series forecasting task, a series-parallel model could use a parallel network to learn the cross-sectional dependencies between different variables, and a series network to learn the temporal dependencies in the time series data.

2.3 Performance Evaluation Model

To evaluate the suitability of the models to the actual data, error measures are required. In this study, the model's error is measured using Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). The formulas for calculating the error of the model are shown in Table 3.

Table 3. Metrics Equation

Metrics	**Equation**
RMSE	$\sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}}$
MAE	$\frac{1}{n}\sum_{i=1}^{n} \lvert y_i - \hat{y}_i \rvert$

2.4 Research Procedure

1) Data partitioning

In this study, the dataset is split into 15% for testing data and 85% for training data. The training data covers the years from 1998 to 2017, while the testing data covers the years from 2018 to 2021. The model formation process will be performed on the training dataset to optimize it for panel data analysis. The formed model will then be tested on the testing dataset to assess its effectiveness.

2) Normalization

The variable data is normalized using a standard scaler with the scale() function in R or using the following formula:

(2) $$y_i{}' = \frac{y_i - \underline{y}}{s}$$

y_i : original i_{th} data value

$y_i{}'$: i_{th} data value after standardization

$\underline{y}$: mean of original data value

s : standard deviation of original data value

3) Model fitting

The NARX NN and FFNN models are built using the Keras package in the R software. The activation function used in this study is tanh for the hidden layer and linear for the output layer, with the loss function mean squared error.

4) Model Evaluation

The evaluation process in this study involves assessing the RMSE and MAE values, as well as visualizing the predicted training and test sets compared to the actual data.

5) Forecasting exogenous variables

The forecasting of the exogenous variables is performed using the FFNN method, which best fits the characteristics of the variables. A denormalization is required to obtain the true forecast value from the forecast result in standardization form, using the following formula:

(3) $$y_i = [y_i{}' \times s] + \underline{y}$$

y_i : original i_{th} forecast result

$y_i{}'$: i_{th} forecast result in standardization form

$\underline{y}$: mean of original data value

s : standard deviation of original data value

6) Predicting the main variables

The NARX NN model with the smallest RMSE and MAE values is used to predict the main variable, which is the inflation rate. The forecast result must be denormalized to obtain the true forecast value, using the same denormalization formula mentioned in step 5.

3. MAIN RESULTS

3.1 Descriptive Statistics

The initial step involved conducting a descriptive statistical analysis of the main and exogenous variables to gain insights into the data. The findings of this analysis are presented in the following table.

Table 4. Descriptive Statistics for Main Variable and Exogenous Variables

Variables	Min	1st Quartile	Median	Mean	3rd Quartile	Max
Inflation (Y)	-22,091	2,401	5,073	7,280	8,634	316,793
Real interest Rate (X1)	-63,761	2,570	5,909	7,679	10,957	93,915
GDP per capita growth (X2)	-55,091	0,4319	2,3785	2,2773	4,4699	33,0305
Final consumption Expenditure (X3)	26,04	71,53	79,73	79,54	88,39	115,91
Population growth (X4)	-4,170	0,436	1,250	1,163	1,809	11,794
Exports of goods and services (X5)	4,549	22,079	34,060	42,399	49,376	228,994

Table 4 shows the minimum, 1st quartile, median, mean, 3rd quartile, and maximum values for the two variables. The results indicate the need for normalization prior to being input into the model, as the variables have different value ranges.

3.2 Linearity Test

The linearity of the model between the main variable (Y) and the exogenous variables (X1, X2, X3, X4, and X5) was tested. If the model of the data does not fulfill the linearity assumption, the NARX NN method is an appropriate time series data analysis technique that is used to overcome the nonlinearity relationship [16]. The linearity was tested using the Ramsey RESET test statistic as follows:

- Hypothesis

  H_0 : The model is linear, or there is no misspecification in the relationship between the main variable (Y) and the exogenous variables (X1, X2, X3, X4, and X5).

  H_1 : The model is nonlinear, or there is misspecification in the relationship between the main variable (Y) and the exogenous variables (X1, X2, X3, X4, and X5).

- Test Statistics: Ramsey RESET Test

$$\text{RESET} = \frac{[(\hat{e}'\hat{e}-\hat{u}'\hat{u})/p*]}{[(\hat{u}'\hat{u})/(n-k)]} \tag{4}$$

Table 5. Reset Test Result

RESET	p-value
1299	2.2e-16

- Test criteria

  Reject the null hypothesis (H_0) if the calculated p-value is less than the significance level (α), otherwise accept it.

- Conclusion

  The null hypothesis is rejected because the calculated p-value of 2.2e-16 is less than the significance level alpha of 0.05. It means that the model is nonlinear or there is a misspecification in the model.

3.3 NARX-NN Model

The dataset consists of 24 years of data, which were divided into two parts, training and testing. The training data covers the years 1998 to 2017, while the testing data covers the years 2018 to 2021. After splitting the data, the network architecture of the NARX-NN was formed to predict inflation as the response variable. In this study, the inputs for inflation prediction included past values of inflation, current real interest rates, GDP per capita growth, final consumption expenditure, population growth, exports of goods and services. Two lags of inflation were used as the data was annual, meaning that was influenced by and . The country and region names were also used as inputs as this study uses longitudinal data, resulting in a total of 9 input neurons. One hidden layer was used with the number of hidden neurons determined by trial and error, selecting the number of neurons that produced the lowest error value. One output neuron was used as there was only one output, the inflation rate.

Table 6. NARX-NN Network architecture

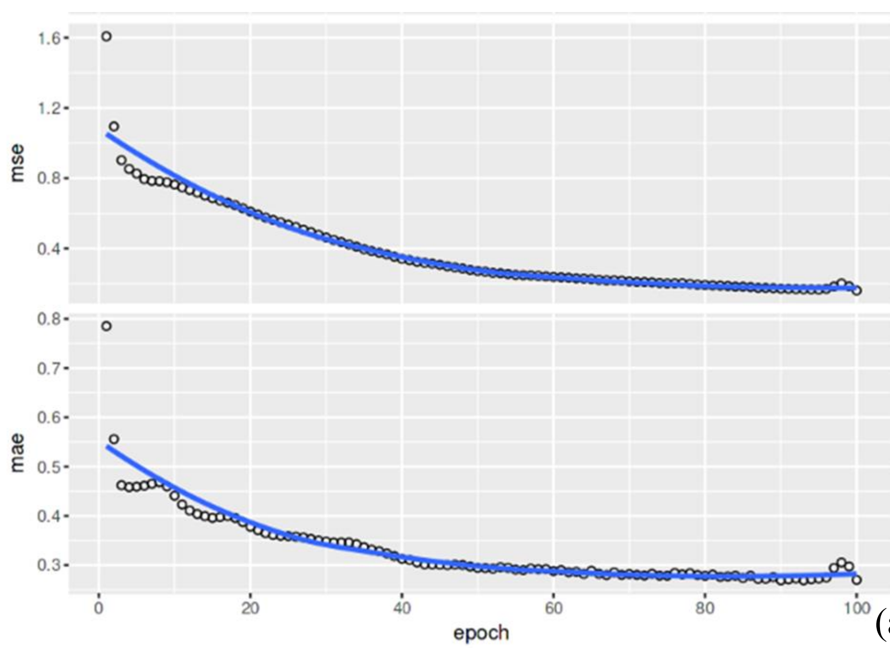
Input neurons	9 neurons, consisting of: Regional, Country Name, Lag 1 to 2 from inflation, and the current value of real interest rate, GDP per capita growth, final consumption expenditure, population growth, and exports of goods and services
Hidden layer	1 layer
Hidden neurons	1, 5, 10, 15 neurons (trial and error)
Output neurons	1 neuron

After establishing the network architecture, the next step is to conduct the training, testing, and evaluation of the model. Before beginning the training phase, the data was normalized using standard scaling. This study employs the tanh activation function in the hidden layer during the training process and a linear activation function in the output layer. The performance of the model is evaluated by computing the RMSE and MAE values for each network architecture with a specified number of hidden neurons, as shown by the results below.

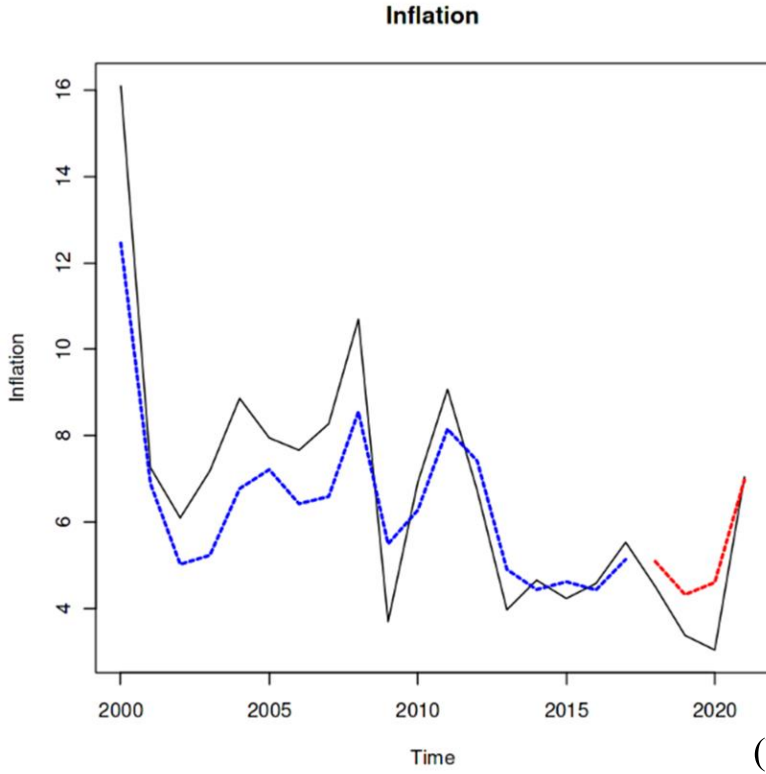
Table 7. NARX-NN Evaluation Metrics

Neuron	Train		Test	
	RMSE	**MAE**	**RMSE**	**MAE**
1	6,003	3,443	3,899	3,211
5	4,104	2,788	3,375	2,552
10	3,558	2,316	4,286	3,002
15	2,839	2,003	3,959	2,804

Table 7 shows that 5 neurons are utilized for the NARX NN model, as it has the smallest RMSE and MAE values for the test dataset. Figure 2 displays the training process of the NARX NN (9-5-1) model using 100 epochs. The graph demonstrates that as the number of epochs increases, the MAE and MSE values decrease.



(a)



(b)

Figure 2. training metrics: MSE and MAE (a); comparison of predicted value in train and test dataset with the actual value for in (b).

Figure 2 (b) depicts the actual dataset in black, the predicted value for the training dataset in blue, and the predicted value for the test dataset in red. Since longitudinal data is utilized, the forecasting values are averaged for each year. The visualization above shows that the NARX-NN model is effective in forecasting both the training and test datasets.

3.4 FFNN Model for Exogenous Variables (X1, X2, X3, X4, X5)

The Feed Forward Neural Network will be employed for predicting the exogenous variables. The input for this prediction will be the past values of the exogenous variables. Since the data interval is annual, the previous values of the exogenous variables will be taken into account using 2 lags (i.e. is influenced by and). Since this study utilizes longitudinal data, the variables for the regional and country names will also be incorporated. Hence, the number of input neurons used is 7. A single hidden layer is utilized, and the number of hidden neurons is determined through trial and error, with the best number being the one that results in the lowest error value. The number of output neurons used is 5, as there are five exogenous variables to be predicted.

Table 8. FFNN Network architecture

Input neurons	7 neurons, consisting of: Regional, Country Name, Lag 1 to 2 from real interest rate, GDP per capita growth, final consumption expenditure, population growth, and exports of goods and services
Hidden layer	1 layer
Hidden neurons	1, 5, 10, 15 neurons (trial and error)
Output neurons	5 neurons, consisting of: the current value of real interest rate, GDP per capita growth, final consumption expenditure, population growth, and exports of goods and services

Following the formation of the network architecture, the next step is to undergo the process of training, testing, and evaluating the model. Prior to the training stage, the inflation data is normalized using standard scaling. This study employs the tanh activation function in the hidden layer during the training process and the linear activation function in the output layer. The model's evaluation is performed by calculating the RMSE and MAE values for each network architecture with specific hidden neurons, with the results as follows.

Table 9. FFNN Evaluation Metrics

Neuron	Variables	Train		Test	
		RMSE	MAE	RMSE	MAE
1	X1	9,834	6,320	7,787	5,624
	X2	4,053	2,732	7,260	4,488

	X3	8,522	6,562	8,376	6,436
	X4	1,167	0,832	1,029	0,762
	X5	21,819	15,185	20,015	13,897
5	X1	6,679	4,163	5,033	3,388
	X2	3,735	2,455	7,440	4,682
	X3	4,541	3,212	5,289	3,686
	X4	0,489	0,262	0,494	0,260
	X5	7,458	5,147	6,793	4,916
10	X1	6,500	4,144	5,275	3,626
	X2	3,452	2,305	7,489	4,676
	X3	3,712	2,617	4,141	2,788
	X4	0,455	0,229	0,515	0,278
	X5	6,936	5,122	6,748	5,214
15	X1	5,936	3,882	5,158	3,533
	X2	3,264	2,182	7,377	4,667
	X3	3,366	2,360	4,054	2,522
	X4	0,408	0,192	0,456	0,216
	X5	5,491	3,796	5,130	4,101

According to Table 9, the neuron used for the FFNN model will be 15 neurons because it has the smallest RMSE and MAE value for the test dataset. By using 100 epochs, Figure 1 shows a graph of the training process for FFNN (7-15-5). As we can see in the graph below, the larger the epoch, the lower the MAE and MSE values.

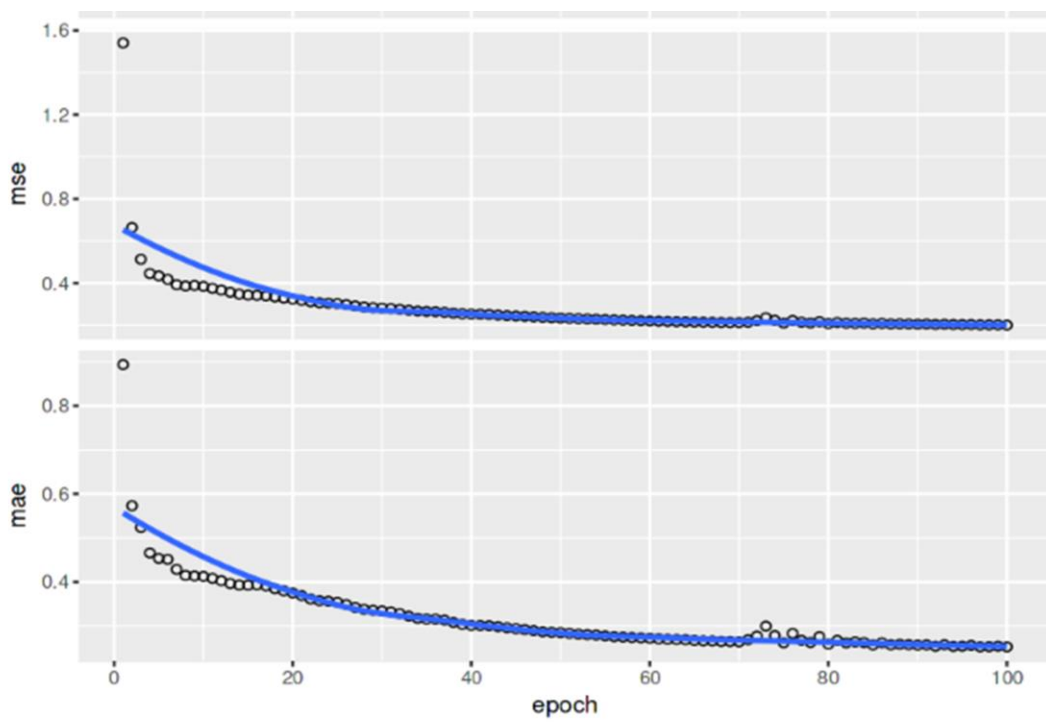


Figure 3. training metrics for FFNN: MSE and MAE

In Figure 4, the black line represents the actual dataset, the blue line represents the predicted value for the train dataset, and the red line represents the predicted value for the test dataset. For each year, the forecasting values are averaged because we use longitudinal data. As we can see from the visualization above, the FFNN model is quite good in forecasting the train and test dataset.

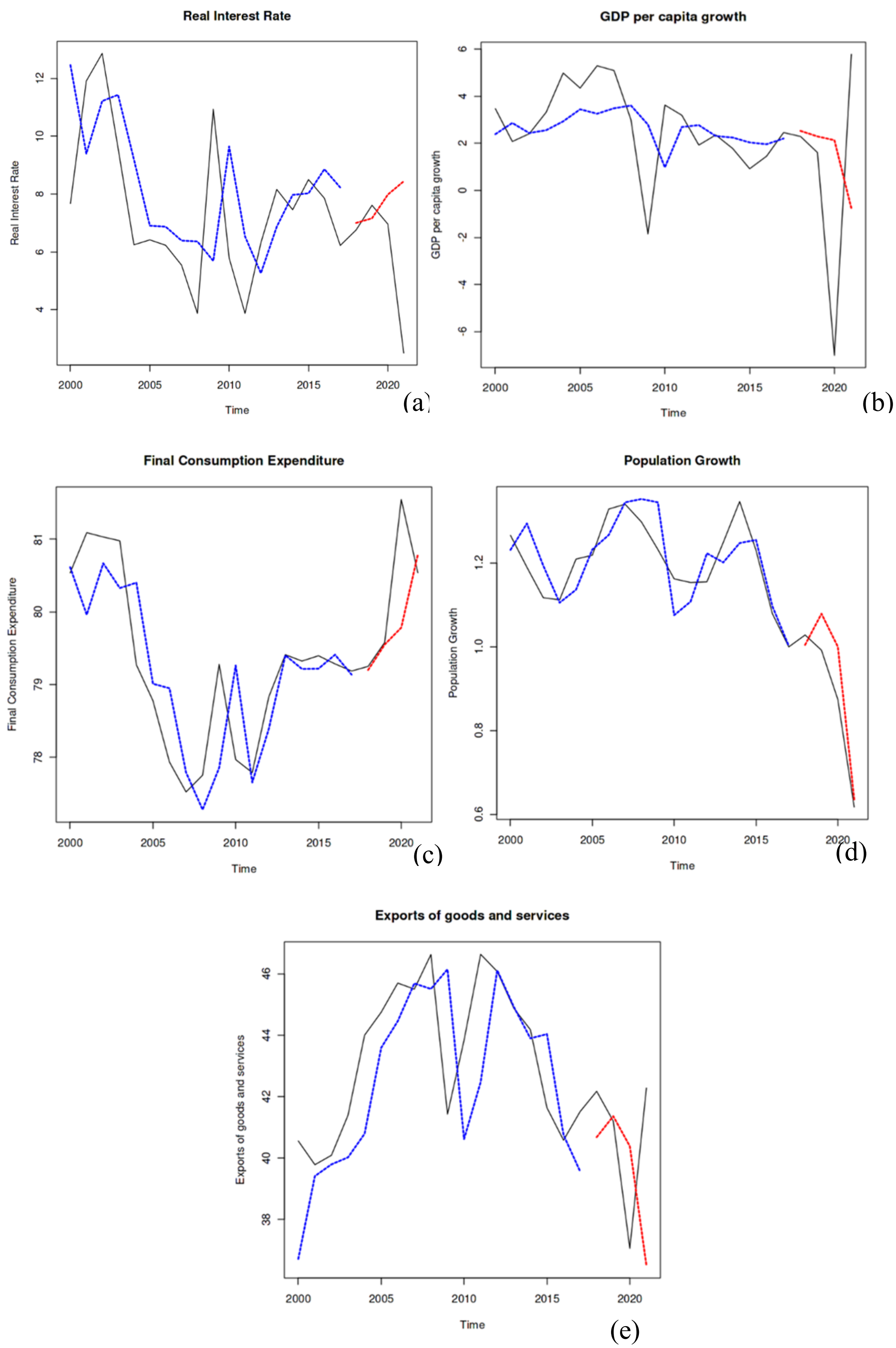


Figure 4. Comparison of predicted value in train and test dataset with the actual value for exogenous variables.

3.5 Exogenous Variables Forecasting

After obtaining the best model for the exogenous variables using the FFNN (7-15-5) method, the exogenous variables will be forecasted for the next 5 years. The longitudinal data used in this study requires that the forecast values for each year be averaged.

Table 10. Exogenous Variables Forecasting Value for the Next 5 Years

Time	X1	X2	X3	X4	X5
2022	-2,239	1,861	64,812	1,031	99,972
2023	-1,522	0,163	66,399	1,165	106,178
2024	4,789	-0,828	67,592	1,244	113,101
2025	5,891	-1,153	68,336	1,328	117,746
2026	5777	-0,799	68,750	1,466	122,554

In Table 10, the variables X1, X2, X3, X4, and X5 are respectively designated as the real interest rate, GDP per capita growth, final consumption expenditure, population growth, and exports of goods and services. With the 5-year forecasting results for these variables, we can then use them to make predictions for the main variable of inflation.

3.6 Inflation Prediction

After determining the optimal NARX NN model, which is NARX NN (9-5-1), and obtaining the forecasted values for the exogenous variables, the main variable of interest, inflation, will be forecasted for the next five years. As this study utilizes longitudinal data, the forecasting values for each year will be calculated as the average of the obtained results.

Table 11. Inflation Prediction Value for the Next 5 Years

Time	Y
2022	4,689
2023	17,814
2024	15,122
2025	17,486
2026	13,385

Here is the visualization of the prediction value for inflation.

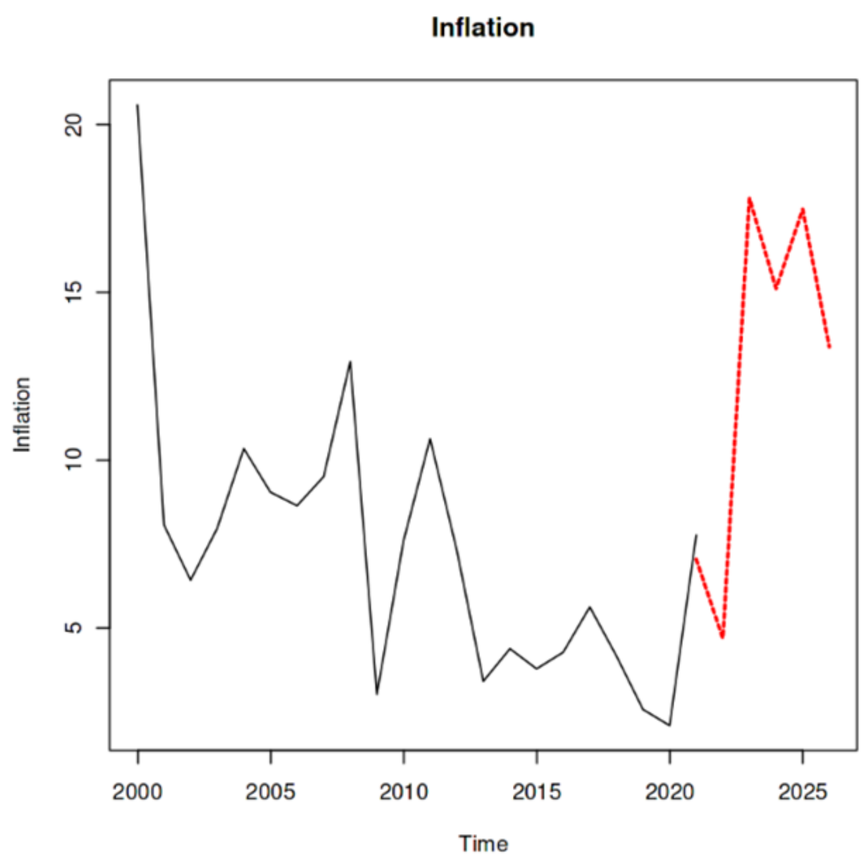


Figure 6. Inflation Prediction Value for the Next 5 Years

According to Figure 6, there will be a decrease in inflation average in 2021, followed by an increase to 17,814 in 2023. However, a slight decrease is expected in 2024, followed by another increase in 2025, although not as high as 2023. Finally, there will be another decrease in 2026. This suggests that the high inflation average in 2023 may cause a recession for many countries.

3. CONCLUSION

Analyzing longitudinal data is challenging as it requires consideration of multiple factors. The NARX NN approach, in this scenario, enables the analysis of the longitudinal data by incorporating regional and country variables. This integration captures the random effect from both and enhances the learning of the model with the combination of both temporal and cross-sectional dependencies present in the data. The resulting model is better suited for forecasting future trends and patterns in the data.

In order to predict the inflation rate (Y) utilizing the NARX NN approach, it is crucial to first predict the exogenous variables (X1, X2, X3, X4, and X5). By utilizing the Feed Forward Neural Network (FFNN), the best performing model was FFNN (7-15-5). This optimal FFNN model was applied to all exogenous variable data, resulting in RMSE values of (X1 = 5.158, X2 = 7.377, X3 = 4.054, X4 = 0.456, X5 = 5.130) and MAE values of (X1 = 3.533, X2 = 4.667, X3 = 2.522, X4 = 0.216, X5 = 4.101) during the testing phase. By using this model, the next five years of exogenous variable data was forecasted and utilized as input variables in the prediction of the inflation rate.

In the effort to forecast the inflation rate and its correlation with the exogenous variables, the NARX NN series parallel model was utilized and the best model was identified as NARX NN (9-5-1). The testing of the NARX NN model with inflation rate data resulted in RMSE of 3,375 and MAE of 2,552. The results of the five-year forecast (2022-2026) indicate that the inflation rate is expected to experience an upward trend, pointing towards the possibility of an upcoming economic recession.

ACKNOWLEDGEMENT

The authors would like to express our gratitude to Padjadjaran University for providing us with the necessary resources and facilities for completing this study.

CONFLICT OF INTERESTS

The authors declare that there is no conflict of interests.

REFERENCES

[1] A. Jackson, How to prepare for a recession, TIME. 10 December 2022. Available online: https://time.com/6240221/a-recession-is-widely-expected-heres-how-to-prepare/. (accessed on 29 January 2023).

[2] BFI Finance, Recession is: definition, causes, impact, and how to deal with it, 21 October 2022. Available online: https://www.bfi.co.id/en/blog/resesi-adalah-pengertian-penyebab-dampak-dan-cara-menghadapinya. (accessed on 29 January 2023).

[3] World Bank, Risk of global recession in 2023 rises amid simultaneous rate hikes, World Bank. Available online: https://www.worldbank.org/en/news/press-release/2022/09/15/risk-of-global-recession-in-2023-rises-amid-simultaneous-rate-hikes. (accessed on 29 January 2023).

[4] Bank Indonesia, Definisi inflasi, bank Indonesia, Available online : https://www.bi.go.id/id/fungsi-utama/moneter/inflasi/default.aspx. (accessed on 29 January 2023).

[5] A.A.R. Fernandes, N.W.S. Wardhani, Analisis data longitudinal pada studi kasus pasien penderita decubitus wound, Research Report DPP-SPP, 2008.

[6] A. Adiatma, A. Sauddin, A. Hikmawati, Panel data regression analysis with GLMM approach (Case study: HDI in South Sulawesi Province), 1 (2021), 123-131.

[7] L.P.W. Adnyani, K.A. Notodiputro, B. Sartono, Method generalized linear model and generalized linear mixed model for panel data Human Development Index (HDI) in Indonesia, AIP Conf. Proc. 2662 (2022), 020003. https://doi.org/10.1063/5.0111780.

[8] M. Fokkema, J. Edbrooke-Childs, M. Wolpert, Generalized linear mixed-model (GLMM) trees: A flexible decision-tree method for multilevel and longitudinal data, Psychother. Res. 31 (2020), 329-341. https://doi.org/10.1080/10503307.2020.1785037.

[9] C. Ngufor, H. Van Houten, B.S. Caffo, et al. Mixed effect machine learning: A framework for predicting longitudinal change in hemoglobin A1c, J. Biomed. Inform. 89 (2019) 56-67. https://doi.org/10.1016/j.jbi.2018.09.001.

[10] World Bank, World development indicators. Available online: https://databank.worldbank.org/source/world-development-indicators. (Accessed on 29 January 2023).

[11] World Bank, Metadata glossary. Available online: https://databank.worldbank.org/metadataglossary/all/series. (Accessed on 29 January 2023).

[12] R. Arisanti, M.D. Puspita, Non-linear autoregressive neural network with exogenous variable in forecasting USD/IDR exchange rate, Commun. Math. Biol. Neurosci. 2022 (2022), 5. https://doi.org/10.28919/cmbn/6931.

[13] G. Zhang, B.E. Patuwo, M.Y. Hu, Forecasting with artificial neural networks:: The state of the art, Int. J. Forecast. 14 (1998), 35-62. https://doi.org/10.1016/s0169-2070(97)00044-7.

[14] R.S. Pontoh, T. Toharudin, B.N. Ruchjana, et al. Bandung rainfall forecast and its relationship with Niño 3.4 using nonlinear autoregressive exogenous neural network, Atmosphere. 13 (2022), 302. https://doi.org/10.3390/atmos13020302.

[15] R. Hossain, Forecasting of inflation in Bangladesh using ARIMA and ANN models, Thesis, Bangladesh University of Engineering and Technology, 2013.

[16] E. Diaconescu, The use of NARX neural networks to predict chaotic time series, WSEAS Trans. Computer Res. 3 (2008), 182-191.