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Prediction of Farmer Exchange Rate in NTB Province Using Gated Recurrent Units (GRUs): A Time Series Model for Agricultural Development Planning

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Abstract: This research is important because the Farmer Exchange Rate (NTP) is a key indicator of farmer welfare and agricultural sector stability in West Nusa Tenggara (NTB) Province. Therefore, the purpose of this research is to build an NTP forecasting model using the Gated Recurrent Units (GRU) method to produce predictions for the next five years with a high level of accuracy. This research is an experiment to forecast NTP data for the period 2025 to 2029 based on actual data from 2015-2024. The data is taken from the Central Bureau of Statistics. The results showed that the GRU model was able to predict the NTP value with a good level of accuracy, indicated by the Mean Absolute Percentage Error (MAPE) value of 1.38%. The implication of the results of this study is that the GRU model can be used as a tool in policy planning in the agricultural sector, especially in anticipating fluctuations in farmer exchange rates that have an impact on the welfare of rural communities.

Keywords: Farmer Exchange Rate, Gated Recurrent Units, Time Series Forecasting.

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A. INTRODUCTION

The Farmer Exchange Rate (NTP) is the main indicator used to assess the level of farmer welfare, which describes the ratio between the price index received by farmers and the price index paid by farmers. NTP data has a time series nature because it is recorded periodically in certain time intervals, such as monthly or quarterly. A characteristic of time series data such as NTP is the inter-period dependency, where values in one period are influenced by values in the previous period. In addition, NTP is strongly influenced by seasonal factors, such as the planting season, harvest season, and changes in climatic conditions, which cause periodic fluctuations every year. Other external factors, such as the dynamics of agricultural input prices, government policies, and market changes, also contribute to the instability of the NTP pattern. Considering these characteristics, a forecasting approach that recognizes long-term patterns and seasonal variations in NTP data is needed to produce more accurate and reliable predictions.

In forecasting time series data such as the Farmer Exchange Rate (NTP), there are various approaches that can be used, both through traditional statistical methods and artificial intelligence-based techniques(Keumala et al., 2018). Some commonly applied statistical methods include Autoregressive Integrated Moving Average (ARIMA), Exponential Smoothing, and Seasonal Decomposition, which effectively capture seasonal patterns and trends in the data. Along with advances in computing technology, the use of machine learning and deep learning-based methods such as Support Vector Regression (SVR), Random Forest, and Artificial Neural Networks (ANN) is increasingly being developed, given their ability to cope with nonlinear and complex data (Suprajitno et al., 2022). Among deep learning methods, Recurrent Neural Networks (RNN) and its derivatives, namely Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU), are the main choices in processing time series data. GRU, as a variant of RNN, has the advantage of learning long-term dependencies with a simpler architecture than LSTM, resulting in a faster training process without sacrificing accuracy. Based on these considerations, this study chose GRU as the main method for building NTP forecasting models, with the aim of obtaining more accurate and efficient prediction results (Priambodo et al., 2023).

Various studies have shown that Gated Recurrent Units (GRU) can provide better performance than traditional models such as ARIMA in forecasting seasonal economic data, with higher accuracy and lower error rates (Meriani & Rahmatulloh et al., 2024). Studies comparing the performance of GRU and ARIMA reveal that although ARIMA records a Mean Absolute Percentage Error (MAPE) of 2.76% and GRU is slightly higher at 3.97%, GRU still shows competitive results in certain contexts. In terms of handling seasonal patterns, GRU proved to be superior, as evidenced in a study modeling short-term electricity loads in several European countries, where GRU was able to outperform other recurrent neural networks such as LSTM. The advantage of GRU lies in its ability to manage long-term dependencies with a simpler structure than LSTM, making it more efficient when used on certain data sets (Suranata et al., 2023). In addition, GRU's flexibility in adjusting to various seasonal patterns and trends is a plus, especially for dynamic economic data (Gede Agung, 2016). Nonetheless, ARIMA remains a competitive alternative, particularly on data with low complexity or in cases where traditional methods have proven effective. Therefore, the selection of forecasting methods should be tailored to the specific characteristics of the data being analyzed.

A comparison between Gated Recurrent Units (GRU) and Long Short-Term Memory (LSTM) models in the context of time series data, such as inflation data, shows that GRU often offers faster training times with similar, if not better, levels of accuracy (Siboro & Martha, 2024). This is due to the simpler architecture of GRU, with a lower number of parameters and network complexity compared to LSTM, thus requiring less computational resources. Studies on various domains, such as stock price forecasting and text analysis, consistently show the superiority of GRU in terms of efficiency and effectiveness. For example, in a study using Yelp review data, GRU was 29.29% faster in the training process than LSTM (Yang et al., 2020), while another study showed that the more compact GRU architecture also reduced training time and computational costs (Elsayed et al., 2019). In stock price forecasting, GRU managed to record lower Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) values than LSTM, such as in the prediction of PT Mayora Indah Tbk's stock price. Similar findings are also confirmed in other studies that show the superiority of GRU in terms of stock price prediction accuracy. GRU's ability to effectively handle both long- and short-term dependencies makes it highly suitable for time series applications such as stock price prediction and inflation data analysis. In addition, the GRU-Fully Convolutional Network (GRU-FCN) hybrid model was shown to outperform the LSTM-FCN model in univariate time series classification, emphasizing the flexibility and reliability of GRU (Elsayed et al., 2019). Although the more complex memory structure of LSTM remains beneficial in conditions with highly complicated long-term dependencies, GRU is considered superior in many practical applications, especially for large-scale data or model applications that require fast response times.

The purpose of this research is to develop a forecasting model of Farmer Exchange Rate (NTP) in West Nusa Tenggara (NTB) Province by utilizing the Gated Recurrent Units (GRU) method. With the application of this method, it is expected to be able to obtain NTP predictions for the next five years with an optimal level of accuracy. This research also aims to evaluate and compare the performance of the GRU model and actual data, to assess its ability to recognize patterns and fluctuations in NTP that are influenced by seasonal and dynamic factors (Mulyawati & Kartikasari, 2024). As a scientific contribution, this research will produce a simple mathematical model based on the prediction results obtained, which can later be used as a reference in further analysis and support decision making in the agricultural sector in NTB Province.

B. METHOD

This research applies a quantitative-experimental approach that aims to build a predictive model based on numerical data processing and mathematical calculations. The quantitative approach is used because the research focuses on analyzing numerical data systematically to produce a forecasting model that can be measured objectively, while the experimental approach is used to test the effectiveness of the Gated Recurrent Units (GRU) method in modeling the Farmer Exchange Rate (NTP) pattern in West Nusa Tenggara (NTB) Province. The data used is secondary data obtained from the official publication of the Central Bureau of Statistics (BPS), so that the validity and reliability of the data is guaranteed. The data covers the last ten-year period in annual and quarterly form, providing a long enough time series to identify seasonal patterns, trends, and fluctuations in NTP data. With this data base, this research is expected to produce an accurate and applicable forecasting model as a basis for supporting policy making in the agricultural sector in NTB.

This research procedure was carried out systematically to ensure the accuracy of the results obtained. The initial stage began with the collection of Farmer Exchange Rate (NTP) data sourced from the official publication of the Central Bureau of Statistics (BPS), accompanied by verification of data completeness to ensure there were no data gaps, inconsistencies, or anomalies that could affect the validity of the analysis. Once the data was collected, tabulation and pre-processing were performed, where the data was arranged in a structured format and normalized so that all values were on a uniform scale, thus supporting the efficiency of the model training process and improving the stability of learning. The next stage was algorithm construction and computational scripting, which was performed using MATLAB software. At this stage, the GRU network architecture is determined, including the selection of the number of neurons in the hidden layer, the number of epochs for training, the selection of activation functions, and optimization algorithms, so as to obtain a model configuration that is effective in processing NTP time series data. The general formula of GRUs is as follows.

Update Gate (z_t)

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t] + b_z) \quad (1)$$

Reset Gate (r_t)

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t] + b_r) \quad (2)$$

Candidate Hidden State (h_t)

$$\tilde{h}_t = tanh(W_h \cdot [r_t * h_{t-1}, x_t] + b_h) \quad (3)$$

Hidden State (h_t)

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t \quad (4)$$

Description:

- ht = current hidden state
- h_{t-1} = previous hidden state
- x_t = input at time t
- z_t = update gate
- r_t = reset gate
- $\tilde{h}_t$ = new hidden state candidate
- W_z, W_r, W_h = matriks bobot
- b_z, b_r, b_h = bias
- σ = sigmoid activation function
- tanh = tanh activation function
- $*$ = elementwise multiplication operation

Once the model construction is complete, predictions are made for future periods, and the forecasting results are evaluated using two main parameters, namely Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE). MSE is used to measure the average square of the difference between the actual value and the predicted value, while MAPE is used to measure the average absolute percentage error. A low MAPE value indicates a high level of prediction accuracy. Based on this evaluation, the direction of the development of the Farmer Exchange Rate (NTP) in NTB Province is interpreted, and relevant conclusions are drawn to support the preparation of data-based agricultural sector developmentpolicies.

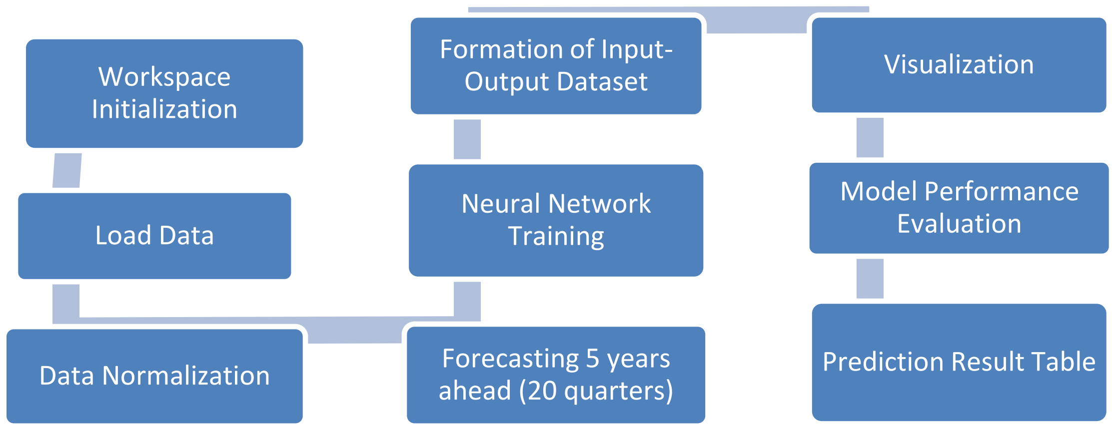

Figure 1. NTP Forecasting Algorithm Using Artificial Neural Network (JST)

Figure 1 shows that the Farmer Exchange Rate (NTP) forecasting process in this study begins with workspace initialization, namely cleaning all variables, command windows, and open graphs, followed by loading data from Excel files and normalizing data using the Min-Max method to be on a uniform scale for neural network training. Next, an input-output dataset with a shifted window approach is formed, where the previous four quarters are used to predict the next quarter, then a feedforward type artificial neural network (ANN) with one hidden layer is trained using the Levenberg-Marquardt algorithm. After the training is complete, the model is used to iteratively forecast NTP for the next five years (20 quarters), and the results are visualized in a graph with the actual data. Evaluation of model performance is done using the Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE) values on the training data, and the forecasting results are presented in tabular form. As a complement, a second-order polynomial fitting is performed on the prediction results to obtain an explicit mathematical model that represents the trend pattern of the forecasted data.

C. RESULTS AND DISCUSSION

1. Data Description

Table 1. Data To Be Predicted

Year	Farmer Exchange Rate Data
2015	106,22
2016	106,56
2017	107,48
2018	110,91
2019	115,27
2020	109,22
2021	106,88
2022	107,98
2023	122,81
2024	123,31

Table 1 shows annual data on Farmer Exchange Rate (NTP) from 2015 to 2024, showing fluctuations that reflect the dynamics of economic conditions in the agricultural sector. In 2015, the NTP was recorded at 106.22 and experienced a slight increase to 106.56 in 2016, then continued to increase until it reached 115.27 in 2019. However, there was a significant decline in 2020 to 109.22, which may reflect the impact of economic disruption due to the COVID-19 pandemic. NTP decreased again in 2021 to 106.88, but began to recover gradually in the following years, namely 107.98 in 2022, and jumped sharply to 122.81 in 2023. This upward trend continued in 2024 with an NTP value of 123.31. This pattern shows that despite economic pressures in some periods, the agricultural sector has shown the ability to recover and grow, especially in the last two years.

2. Forecasting and Decision Making Result Data

Table 2. Prediction Result Data Table

Quarterly	NTP Prediction
11.0000	112.4188
12.0000	91.6334
13.0000	127.0098
14.0000	121.2276
15.0000	122.3368
16.0000	108.4840
17.0000	112.7425
18.0000	125.5125
19.0000	135.7548
20.0000	114.5242
21.0000	110.5471
22.0000	140.4357
23.0000	126.4565
24.0000	108.3029
25.0000	127.1294
26.0000	116.0851
27.0000	117.4061
28.0000	106.6104
29.0000	110.3493
30.0000	122.6742

Based on Table 2, the forecast results for the next 20 quarters, the farmer exchange rate (NTP) shows a pattern that tends to fluctuate but remains in a relatively stable range. The prediction begins in the 11th quarter with a value of 112.42, then experiences a significant decline in the 12th quarter to 91.63. After that, the NTP is projected to increase sharply to reach 127.01 in the 13th quarter and remain in the high range for the next few quarters. The peak forecast value occurs in the 22nd quarter with an estimate of 140.44, indicating the potential for strengthening the farmer exchange rate in that period. On the other hand, the lowest value was recorded in the 12th quarter, reflecting the potential for seasonal or external instability.

Overall, despite the up and down dynamics, the medium-term trend that has formed shows the potential for promising recovery and growth in the agricultural sector.

3. NTP Data Description

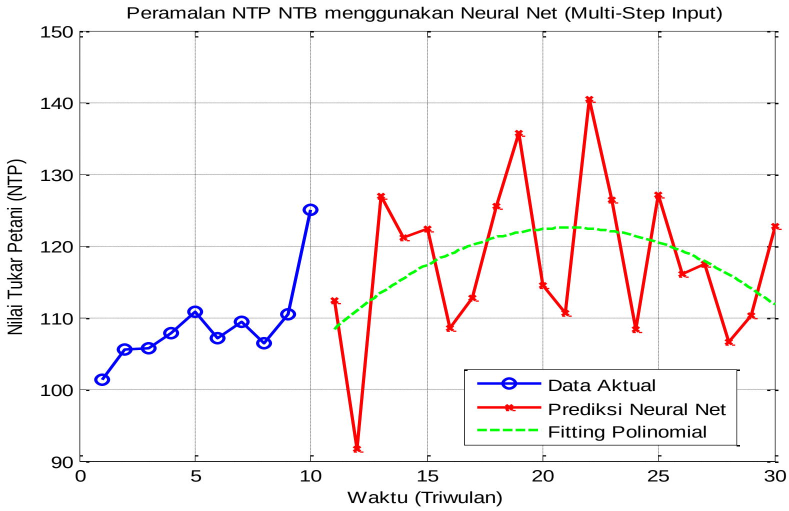

Figure 2. Actual Data and Predicted Data Approach

Figure 2 shows Based on the NTB NTP forecast graph using Neural Net (Multi-Step Input), it can be seen that the actual data shows a relatively stable trend at the beginning, then fluctuates in the following quarter. The prediction results using the neural network model show high and less stable fluctuations, making it less reliable for direct short-term decision making. Meanwhile, the polynomial fitting line shows a long-term trend that tends to increase more smoothly, making it more representative for use in macro policy planning. Therefore, long-term policies should be focused on efforts to maintain and encourage an increase in NTP, for example through improving market access, supply chain efficiency, and support for agricultural inputs. On the other hand, for short-term policies, the results of neural net predictions can be used as alternative simulations by considering the potential for seasonal fluctuations. It is necessary to improve the accuracy of the neural net model through parameter optimization, expanding training data, or using other prediction methods such as ARIMA or LSTM to produce more accurate and reliable forecasts.

Table 3. Table of MSE and MAPE Values of Prediction Results

MSE	MAPE
7.1093	1.38%

Based on the results of the performance evaluation of the prediction model using artificial neural networks, the Mean Squared Error (MSE) value was obtained at 7.1093 and the Mean Absolute Percentage Error (MAPE) was 1.38%. The relatively small MSE value indicates that the squared difference between the actual value and the predicted result tends to be low, indicating a good level of accuracy in modeling historical Farmer Exchange Rate (NTP) data. Meanwhile, the MAPE value which is below 2% indicates that the relative error in the prediction is very small in percentage terms, which further confirms the model's ability to produce estimates that are close to actual data. Overall, these two indicators indicate that the neural network model used has quite good performance and can be relied on for NTP forecasting purposes in the coming period.

D. CONCLUSIONS AND SUGGESTIONS

This study successfully built a forecasting model for the Farmer's Exchange Rate (NTP) of West Nusa Tenggara (NTB) Province using the Gated Recurrent Units (GRU) method. The developed model is able to produce NTP predictions for the next five years with a high level of accuracy, as indicated by the low Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE) values. Analysis of the NTP data trend for 2015–2024 shows a fluctuating pattern, with an average value of 114.94, a minimum value of 91.63, and a maximum value of 140.44. The formulated polynomial mathematical model describes an increase pattern up to a certain point before decreasing. Overall, the GRU method has proven effective in capturing the seasonal and dynamic characteristics of NTP data, so that it can be used as a basis for medium-term forecasting of the agricultural sector.

For further research, it is suggested that the GRU model be developed by adding parameter optimization techniques such as grid search or Bayesian optimization to improve prediction accuracy. In addition, the integration of the GRU model with other external data such as climate factors, commodity prices, and government policies can enrich the model and improve forecast accuracy. In practical applications, the results of this NTP prediction should be used as one of the considerations in formulating regional agricultural development strategies, especially in efforts to improve farmer welfare in NTB Province.

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