New normal policy on the Rupiah exchange rate using Long Short-Term Memory

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Abstract. Since the world is facing health problems due to COVID-19, Indonesia was not success to surge the outbreak. In addition to the risk of health problems, this pandemic is also disrupting the global economy. The rupiah exchange rate also saw a devaluation during the COVID 19 outbreak. The Indonesian economy is expected to grow negatively in the third quarter of 2020 and predicted to continue until the end of the year. The measure from the government impacted the economic circumstances then along with the decline in new cases of the spread of COVID-19 the government was implementing a new normal, after the completion of large scale social restrictions weakened the economic development, with one of its goals to improve and try to save Indonesia's economy from a possible worse recession. This study attempts to use the forecasting method to find out whether the application of the new normal will strengthen the Rupiah exchange rate in the coming period. The methods that will be used is Long Short Term Memory as the best model to overcome long-term dependencies to obtain a predictive model that most closely approximates existing data patterns. The most suitable model is Long Short Term Memory with 50 epochs using five hidden neurons. Based on the results, it seems that the Rupiah exchange rate tends to weaken in the next five-day

1. Introduction

On January 30, 2020, the World Health Organization (WHO) declared the COVID-19 outbreak as a global emergency. Besides the threat of health problems, the COVID-19 outbreak has also disrupted the economy globally and triggered fears of an economic crisis and an upcoming recession [1]. The market participant feels worried because of the uncertainty situation, thereby this causes a chain effect on investment. Investors tend to sell off riskier assets and seek safer instruments, such as cash and U.S. treasury bonds. As an effect, it causes a decreased investment in risk assets of developing countries then the lack of capital inflows hit the market and weakened the currency of developing countries [2].

The strength of economic in a country showed by an instrument called an exchange rate [3]. It also shows how economic performance encompasses financial and investment transactions between countries. The Indonesian government absolutely tries to keep the Rupiah as Indonesian currency stable. The movement of a currency is influenced by many factors, both macroeconomic and non-economic factors.

In macroeconomic fundamentals, several factors related to exchange rate movements are differences in inflation between countries, interest rates between countries, Gross Domestic Income (GDP) between countries, gross domestic capital inflows, international capital flows, foreign exchange reserves, central bank reserves, and currency interventions.
countries, the balance of international payment, economic growth, capital outflows in the form of debt payments, and capital inflows in the form of investments and debt growth [4]. For non-economic factors, the instability of the socio-political situation could disrupt the overall economic stability. Non-economic factors will influence the market participant's expectations of opportunities and risks in the short term [5]. Therefore, market participants often take advantage of the situation happen that ultimately causes high fluctuations in the short-term.

In Indonesia, the exchange rate of Rupiah has experienced depreciation during the COVID-19 outbreak. This depreciation can be seen from the exchange rate of the Rupiah in Figure 1. The main concern is the exchange rate of Rupiah toward USD that has reached the lowest level at Rp. 16,471. This intention of depreciation can be settled by aggressive interventions from Bank Indonesia and an economic rescue package announced in the United States [2]. Moreover, pandemic also impacts the consumption pattern [6]. Thousands of people infected with this virus causing panic and fear throughout the community and led to the phenomenon of panic buying. The result of panic buying is the scarcity of goods and the imbalance in demand and supply then the price was rose and it will encourage an increase in inflation and disrupt economic stability.

Figure 1. The time-series plot of Rupiah exchange rate dataset from May 20, 2012, to September 24, 2020
From Figure 1, it can be seen that the Rupiah exchange rate against the US Dollar has weakened since the announcement of the first case of COVID-19 in Indonesia. However, after the government intervened in the form of large-scale regional restrictions (Bahasa: PSBB) on April 10, 2020, the Rupiah exchange rate has gradually strengthened to a narrow level before there was no case in Indonesia.

Based on the East and Pacific Asia Economic Development Report in October 2020, Indonesia’s success in eradicating the COVID-19 pandemic in Indonesia as one of the regions of East and Pacific Asia has not shown satisfactory results [7]. This indicates that the pandemic control system from the governments, such as implementing strict health protocols, is not working well. If this continues along with the rise in COVID-19 cases, the government will be forced to take measures that limit the undertaking of economy's abandon. Minister of Finacial said economic growth in Indonesia is expected to be negative in the third quarter and even into the fourth quarter [8]. Moreover, this would be exacerbated by a decline in household consumption and although it could increase, yet weak investment and unstable export performance could lead to negative economic growth. As a result, the government has cut its growth forecast this year to -1.7 to -0.6 per cent. Therefore, it can be concluded that Indonesia is going through a recession.

It is also can be proven in Figure 1, at the beginning of the implementation of the new normal, the Rupiah exchange rate strengthened for several days as economic activity began to run as usual. However, a few days later, the Rupiah's exchange rate fluctuated trend to show an upward trend, in other words, its value was weakening. This is due to the fact that the number of additional new cases increases significantly every day, as well as economic activity is easily disrupted. In order to surge the number of new cases again, PSBB transition was being announced by the Governor of Jakarta province with the intention of continuing to pursue economic activities with various strict rules that must be obeyed. However, the trend of the exchange rate in this circumstance has not shown anything.

Bank Indonesia is the only institution responsible for maintaining the stability of the rupiah will keep on observing the dynamics of the global financial markets and the economy day by day as well as the COVID-19 epidemic and its economic impact of Indonesia. The risk of a global economic recession will peak in the second and third quarters of 2020, reflecting the peak of this outbreak. The recovery should begin in the final quarter of 2020. By 2021, global monetary development is expected to recover as a result of the various directives implemented around the world. In the meantime, the global financial panic that peaked in March 2020 began to subside in line with positive sentiment regarding the global political response. The risk of the global financial market has decreased, which is confirmed by a drop in the VIX volatility index from 85.4 on March 18, 2020, to 41.2 on April 14, 2020 [9].

The economy is expected to grow again in the fourth quarter of 2020. Total growth is estimated at around 2.3% before increments fundamentally in 2021 [9] but this has certainly not been possible. Notwithstanding the worldwide monetary reclamation, the financial recoupment by various directives implemented by Bank Indonesia, and other relevant authorities will also be driven by different rules.

From this situation, this study tries to follow the most appropriate forecasting method to predict further values of the Rupiah exchange rate. The goal of this research is the most useful method of predicting the Rupiah exchange rate, which can be used to capture different data patterns caused by the COVID-19 pandemic. The methods that will be involved in this study is Long Short Term Memory which has the smallest error measures according to the previous study [10] and its ability to overcome the long term dependencies in the dataset [11] because in this study will also consider previous patterns from a long time ago, not just during a pandemic.

2. Data and Method

2.1. Data
The data used in this research are historical data of daily exchange rate of the Rupiah counter to the U.S. Dollar from May 20, 2013, to September 24, 2020, for 2685 periods which was collected from Bank
Indonesia. The methods that will be involved in this research are Long Short Term Memory as an expansion of the neural network method for data with long-term dependencies.

2.2. Neural Network (NN)
McCulloch and Pits first introduced NN in 1990. NN is an information processing system that has systems as biological networks and claims have very high accuracy [12] with three layers. Some commonly used activation functions are sigmoid and tanh (hyperbolic tangent). Two types of NN structure are Feed Forward Neural Network (FFNN) and Recurrent Neural Network (RNN). FFNN is a network in which connections between neurons in a layer do not form cycles means that inputs only propagate forward from the input level to the output level. On the other hand, when a cycle is added to FFNN, the network is known as the Recurrent Neural Network (RNN).

Since the neuron layer has its own connections, RNN is considered a network with memory. RNN has unique properties that FFNN does not have. Its architecture has at least one feedback loop therefore it can store data that contains information and is recorded for further input. The optimization used in NN also offers a different accuracy. However, the RNN has weaknesses, the vanishing and exploding gradient problems during the training process due to a period of increased training data [13]. If there is a gap between the current data and the previous data, the RNN cannot connect the input, on the other word, this is known as long-term dependency. The development of RNN that can overcome the problem of gradient disappearance and burst is the Gated Recurrent Unit (GRU) [14] and Long Short Term Memory (LSTM) [15].

2.3. Long Short Term Memory
GRU and LSTM have the same function to find out whether there is a long-term dependency and overcome the problem of the vanishing and exploding gradient. LSTM has three gates, namely a forget gate that controls how much information needs to be removed, an input gate that controls how many cell states need to be stored, and an output gate that controls how many cell states are sent to the next one cell. While GRU operates with two gates, a reset gate that lies between the previous activation function and the next candidate to eliminate previous information, also an update gate that decides how often the candidate activation function is used to update the cell status. Each goal has weights and prejudices that are independent of each other.

Figure 2. Network Structure of RNN, LSTM, and GRU. (Source: [16])

Figure 2 shows the structural differences from RNN, LSTM, and GRU. GRU uses fewer training parameters, so less memory is used and the training process is faster than LSTM. However, LSTM can achieve greater accuracy than GRU when using long sequence data, thereby LSTM will be used in this study.

LSTM section in Figure 2 is a flow of information ranging from forget gate to output gate. Information that passes through the forget gate ($f_t$) (Eq. 1) then the input gate ($i_t$) (Eq. 2). Input gate has the same input and output as the forget gate due to its activation function. The output of the input gate is multiplied by element-wise multiplication with the output intermediate cell state ($\tilde{C}_t$) (Eq. 3) and cell state at time $t-1$ which has been multiplied with forget gate is updated with this output gate by element-wise addition to getting a new cell state ($c_t$) (Eq. 4). The last gate is the output gate ($O_t$) (Eq. 5). The
new cell state that was previously obtained exits as input at time $t+1$ and through the \texttanh activation function to do an element-wise multiplication operation with the output gate, so that the output for the hidden state is obtained at time $t$ ($h_t$) (Eq. 6).

$$f_t = \sigma(W_f, [h_{t-1}, x_t]) + b_f$$  \hspace{1cm} (1)$$
$$i_t = \sigma(W_i, [h_{t-1}, x_t]) + b_i$$  \hspace{1cm} (2)$$
$$\tilde{c}_t = \tanh(W_c, [h_{t-1} + x_t]) + b_c$$  \hspace{1cm} (3)$$
$$c_t = (i_t \cdot \tilde{c}_t + f_t \cdot c_{t-1})$$  \hspace{1cm} (4)$$
$$o_t = \sigma(W_o, [h_{t-1}, x_t]) + b_o$$  \hspace{1cm} (5)$$
$$h_t = o_t \cdot \tanh(c_t)$$  \hspace{1cm} (6)$$

3. Result and Discussion

The selection of the appropriate forecast time steps is the first step in the financial forecast. From a monetary perspective, the projected time steps must be long enough to avoid over-negotiation that leads to excessive transaction costs. From a predictive point of view, the forecasted time steps must be quite short due to the persistence of a limited financial time series. For daily data, a five-day forecast horizon is a proper [17]. Since the exact value of the daily price is repeatedly as meaningful to the trade as its relevant size and the component with high frequency in tax data is frequently harder to model.

In the previous study [16], we have included four different methods, then the LSTM model was being used since this model has the smallest error measures. Before the analysis, the model identification is carried out to determine the properties of the data sets. Model identification begins by looking at the Autocorrelation function (ACF) and Partial autocorrelation function (PACF) diagrams to determine if there is a long-term dependency on data sets.

![Figure 3. The plot of ACF and PACF of the Rupiah exchange rate dataset](image)

Figure 3 shows that the first lag in the PACF diagram is interrupted. However, the ACF chart shows dies down, which means that the data sets have a long-term dependency. Due to this phenomenon, the LSTM model is used as the neural network method. The data sets are divided into training and test data with a ratio of 80:20. 80% of the records are used to train models (2146 data), and another 20% is used to test the best model from the training process (535 data).

In the first attempt, 1 neuron in the hidden layer, 10 batch sizes, 50 maximum epochs, and the optimizer the so-called Adam optimizer are used as parameter initialization. With this parameter initialization, the training process is carried out, thereby, the loss function of the testing data of this model was stopped after 16 epochs, it means that the optimal model is reached before 50 epochs. Furthermore, we try to use a different number of the hidden layer, which are 1, 5, and 10 neurons in hidden layers. All of the trial and error show a similar pattern on the testing data.
Figure 4. The plot of loss function using MSE in different hidden neuron

From the illustration above in Figure 4, we can see that the model was stopped in 16, 15, 17 epochs for 1, 5, and 10 neurons in hidden layers, in other words, before the maximum epoch was reached. This means that this model has reached a local minimum. The local minimum is the smallest loss function of the model. Also, shows that the local minimum began to increase slowly after 4 epochs. From the third model above, we compare the evaluation of the metrics as shown in Table 1.

Table 1: Metrics evaluation of the LSTM model with different maximum epochs

| Model | Number of neurons | RMSE | MAE | MAPE |
|-------|-------------------|------|-----|------|
|       | Train  | Test  | Train | Test  | Train  | Test  |
| A     | 1      | 610.290 | 545.037 | 533.625 | 311.588 | 8.845% | 2.762% |
| B     | 5      | 195.687 | 347.221 | 135.888 | 183.631 | 9.469% | 3.152% |
| C     | 10     | 210.754 | 400.511 | 180.721 | 218.712 | 9.733% | 3.011% |

As mentioned in Table 1, the value of metric evaluation of the testing data decreases with 5 neurons and rise again with 10 neurons. Figure 4 displayed the plot of the actual and prediction values for testing data of model A, B, and C. Therefore, a model with 5 neurons and 50 epochs will be used to forecast the future values of the Rupiah exchange rate in 5 days since this model has the smallest values of RMSE and MAE in testing data. In addition, all models have good accuracy since they obtain MAPE value of under 10% [18].
Figure 5 shows that the LSTM model can predict following the pattern of the actual values in long-term data, however, this model cannot follow the extreme value of the data. Moreover, it still can catch on the varying data even the intervention, the COVID-19 pandemic, was happening, additionally, the model with 5 hidden neurons predicts better than others. A good data prior to the COVID-19 case spreading until public health measures are likely to be in the same range, similar to Figure 5 (b). Hence it can be said that the prediction of the Rupiah exchange rate based on this model will weaken, although it is believed that there are no worldwide cases of COVID-19, while the prediction results are not the lowest point of the rupiah than the pandemic occurred.

The forecast will be conducted for the next five-day using a model with 5 hidden neurons, 15 epochs, and Adam optimizer. Additionally, Table 2 shows that the Rupiah exchange rate, which is based on forecast results from the LSTM model, will further strengthen in line with government measures to improve the economic situation.

Table 2: Forecasting results of the LSTM model for the further five-day exchange rate of Rupiah

| Date          | Forecasting results | Actual data | Error  |
|---------------|---------------------|-------------|--------|
| Sep 25, 2020  | Rp 13,685           | Rp 14,951   | 8.467% |
| Sep 26, 2020  | Rp 13,883           | Rp 14,951   | 7.143% |
| Sep 27, 2020  | Rp 14,034           | Rp 14,951   | 6.133% |
| Sep 28, 2020  | Rp 14,140           | Rp 14,959   | 5.475% |
| Sep 29, 2020  | Rp 14,209           | Rp 14,920   | 4.765% |

4. Conclusion

The time series methods of the neural network are examined in the previous study and LSTM obtained the smallest error measures, thus, LSTM model was used in this study. In the first trial, the LSTM model reached a local minimum before reach 50 epochs during the training process, it stopped at 16 epochs. After trying a different number of hidden neurons, conversely, the model with the minimum RMSE and MAE value is a model with a maximum of 50 epochs, 5 neurons, and using Adam optimizer.

In general, we can conclude that the LSTM model has good ability for predicting an exchange rate of Rupiah although it cannot hold the cumbersome changeable on data patterns. The best model supposed to be a very good model because the MAPE is under 5% for the testing data. Before the analysis has been carried out, we determined that there is a long-term dependency on this data set.
Therefore, the previous data may contain information that current data cannot provide. Since mid-2013, the Rupiah exchange rate has varied over time but shows an upward trend due to COVID-19 cases spreading around the world. In these circumstances, the government has announced interventions, so the trend shows a downward trend.

Although there were no COVID-19 events based on the model formed, it was predicted that the rupiah would decline in value against the US dollar. The COVID-19 case made the depreciation of the rupiah currency far greater than predicted. The declining growth of COVID-19 cases in Indonesia, accompanied by the Indonesian government’s policy on large-scale social restrictions (Bahasa: PSBB), appears to have managed to increase the value of the rupiah against the US dollar. Further investigation is needed to find out whether the movement of the Rupiah exchange rate is actually affected by the COVID-19 case or just a mere cycle.

Acknowledgments
Authors want to thank the Department of Statistics, Universitas Padjadjaran for fully supported and reviewers for the positive feedback.

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