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COMPARISON OF ARIMA, ARFIMA AND ARTIFICIAL NEURAL NETWORK MODELS FOR INDONESIAN STOCKS MARKET

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Abstract. *Predicting the price of a stock can be modeled by various methods. Commonly used methods are linear regression, time series analysis, stochastic models, machine learning, artificial neural networks, and many other methods. The focus of this study will compare the so-called ARIMA (Autoregressive Integrated Moving Average), the enhanced version of ARFIMA (Autoregressive Fractionally Integrated Moving Average) and ANN (Artificial Neural Network) method to forecast weekly stock prices in Indonesia. This research will look at the ability of each method in forecasting stock prices and determine the best method, especially in Indonesia from January 2014 to July 2021. The ARFIMA method will also be compared to the ARIMA method or autoregressive integrated moving average, to find out if ARFIMA performance is better than the ARIMA method to describe time series data that has long-term memory. The findings in this study show that the ARIMA and ARFIMA methods have an advantage in describing the stock price in Indonesia when compared to the ANN method as seen from the Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and R-squared. In addition, the study also found that the ARFIMA method produces almost the same result as the ARIMA method.*

Keywords: Autoregressive Fractionally Integrated Moving Average (ARFIMA), Artificial Neural Network (ANN), ARIMA, Forecasting, Weekly stocks price

1. **Introduction.** Research about forecasting stocks price had been done with various methods. The most commonly used method is Autoregressive Integrated Moving Average (ARIMA). ARIMA has been used because of the efficiency towards forecasting time series dataset [1]. Time series method (ARIMA), stochastics method (Geometric Brownian Motion), and machine learning method (Artificial Neural Network or ANN) also have been used to predict and to be compared for S&P500 stocks price [2]. Their result shows that ARIMA and GBM produce similar prediction, so these two methods can substitute one another, even if prediction from ANN method is not as good as the other two methods. ARIMA model is known for its ability to predict datasets with Short-Term Memory (STM), instead of predicting datasets with Long-Term Memory (LTM). This is the main reason Granger and Joyeux introducing Autoregressive Fractionally Integrated Moving Average (ARFIMA) as advancement of ARIMA model [3], addressing the LTM. In ARIMA(p, d, q) model, d is always non-negative integer numbers, but in ARFIMA(p, d, q) model d is a real number which means it can be a fractional number. Sowell [4] developed ARFIMA further with exact maximum likelihood to estimate different parameters, this way ARFIMA method can handle LTM as well as STM. ARFIMA being used to predict interest rate of PUAB (Pasar Uang Antar Bank or money market between banks) [5],

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the result shows that ARFIMA model can predict interest rate of PUAB for the next three periods. Another research shows the same result that ARFIMA model is better to forecast time series data with long-term memory than non-ARFIMA model [6,7].

Another method for forecasting stocks prices is Artificial Neural Network (ANN). ANN is one of many machine learning methods which is commonly used in many areas, such as nuclear physics, automated car, software development, robot aided surgery, and finance [8]. ANN has the ability to find nonlinear correlation between input and output without needing a-priori assumption [9]. Research showed that both ARIMA and ANN can achieve good forecast of stock price [1]. In Devadoss and Ligori's research, ANN can predict good results with more inputs, and the forecast result can be improved to get higher accuracy [10]. Khashei and Bijari combined two methods between time series model and neural network that can produce a more accurate prediction than traditional ANN [11]. Vui et al. stated that to produce more accuracy in ANN prediction, we can use hybrid model and consider external factors [12]. When several types of neural network are being compared to predict S&P500 stock price, convolutional neural network can model the data better than other neural networks [8]. Past research has shown that ARIMA, ARFIMA, and ANN can be used to predict stocks price, but we know the results vary. Although in most of the cases ARIMA produces better result than ANN, a few studies also show that ANN produces better result than ARIMA [1,13]. ARFIMA is developed to improve prediction result of time series data based on ARIMA method. We want to see the performance of these methods to predict Indonesian market as the world's 10th largest economy in terms of purchasing power parity [14].

2. **Problem Statement and Preliminaries.** Previously, similar research had been done to predict S&P500 [2]. Therefore, in this study we will try to model the weekly Indonesian stocks price using ARFIMA and ANN. Then we compare the ability of three models (ARFIMA, ANN, and ARIMA) to forecast Indonesian stocks prices. Main purposes of this study are to model and to determine the best model to forecast or represent weekly Indonesian stocks price. At the end of this study, we will compare the finding during this study with other preceding studies. Weekly Indonesian stock prices that will be used are Indonesian stocks index LQ45 from January 2014 until July 2021. There are nine stocks that are always included in LQ45 in this period, but this study used five stocks, namely PT Astra Internasional Tbk (ASII), PT Bank Central Asia Tbk (BBCA), PT Indofood Sukses Makmur Tbk (INDF), PT Perusahaan Gas Negara Tbk (PGAS), and PT Telekomunikasi Indonesia Tbk (TLKM). The reason why we choose these stocks is that for each sector that represented in those nine stocks, these companies have the biggest market capitalization. Since there are five sectors in those nine stocks, we choose the highest market capitalization on each sector per June 2021. In percent towards the whole market, BBCA has 10.35% market cap, TLKM 4.39%, ASII has 2.81%, INDF 0.76%, and PGAS 0.34% [15]. We hope that by choosing these stocks would reflect the LQ45 and entire stock market performance.

3. Main Results.

3.1. Data.

This research used weekly Indonesian stocks price from 6 January 2014 to 26 July 2021 with a total of 395 data row. Data will be divided into two groups, which is training data from 6 January 2014 to 28 September 2020, and testing data from 5 October 2020 to 26 July 2021. The dataset consists of five variables, namely Open, High, Low, Close, and Volume. For the ARFIMA and ARIMA models, we only used the close price data, while for ANN model, we use every variable and another variable, which is Stock Return. Stock Return can be calculated using $\text{Return}_t = \ln \frac{C_t}{C_{t-1}}$, where C_t is the close price at time t.

3.2. **Time series model.** Time series data is a group of data collected from observation in a series of time. There are two common purposes of time series analysis, i.e., to understand and to model stochastic mechanics that increase the observed data series and to predict or to forecast future value of certain data according to historical data and/or other related factor(s) [16]. Before modeling a time series data, we should make sure the data satisfy stationarity assumption and statistical test for time series model assumption. Augmented Dickey-Fuller (ADF) test used to formally prove a time series data is stationary or not. If stationary assumption has not been satisfied, we can transform the dataset by differencing until null hypothesis of ADF test is rejected, which means the dataset is stationary. After that, we can continue to check the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) of the training data set to identify whether our data satisfies either pure autoregressive model or pure moving average model and to identify LTM process of the dataset [5]. If the ACF graph of a data has a hyperbolic decreasing tendency, then it can be said that the data has an LTM process; otherwise when ACF graph has an exponential decreasing tendency, the data has an STM process. We can check the LTM dependence with Hurst Exponent [17], and the Hurst Exponent value can be used when building the ARFIMA model.

Afterwards, we knew the data has LTM, and the next step is to identify the order of the model. We used Extended Autocorrelation Function (EACF) to identify the order of the combine model ARMA, because ACF and PACF can only be used to identify either pure AR or MA model [16]. We will get multiple possible orders for ARFIMA model, so we will consider all the possible models and will determine which model to use with Bayesian Information Criterion (BIC). We use BIC rather than Akaike Information Criterion (AIC) because the AIC provides overfitting and non-significant parameters [2].

In the process of building ARFIMA models, we will first build ARIMA model. To build ARIMA model we only need the stationary assumption to be fulfilled, and all the possible model order which we get from EACF. We choose ARFIMA and ARIMA models that have the most negative BIC for each stock. The next step after building model is testing model residual using statistical test. We used Kolmogorov-Smirnov for normality test and Ljung-Box Pierce for autocorrelation test. If the residual of chosen models is proven to be normally distributed and free of autocorrelation, we can proceed to predict the testing data and find error measurements.

First, we check the stationarity of data set, and the result before differencing shows that the data are not stationary, so we need to perform differencing on the dataset and the result after differencing the dataset and it shows data has become stationary. The next step is to identify the order of the model using EACF. We got several possible orders of the model, so we tried all possible orders to find the best model. We determine the best model using the BIC value of each model. The final chosen model for ARFIMA is presented in Table 1 and for ARIMA is presented in Table 2. The chosen model for ASII is ARFIMA$(1, -0.00934, 0)$ and ARIMA$(1, 0, 0)$, BBCA are ARFIMA$(0, -0.06314, 1)$ and ARIMA$(0, 0, 1)$, INDF are ARFIMA$(1, -0.00177, 0)$ and ARIMA$(1, 0, 0)$, PGAS are

Table 1. ARFIMA models

		BIC
ASII:	$(I + 0.12814T)(I - T)^{-0.00934}(Y_t - 0.00108) = e_t$	-2174.16
BBCA:	$(I - T)^{-0.06314}(Y_t - 0.00308) = (I - 0.13489T)e_t$	-2412.81
INDF:	$(I + 0.16539T)(I - T)^{-0.00177}(Y_t - 0.00017) = e_t$	-2258.23
PGAS:	$(I - T)^{-0.03917}(Y_t + 0.00448) = (I + 0.07527T)e_t$	-1923.7
TLKM:	$(I - T)^{0.02087}(Y_t - 0.00061) = (I - 0.23440T)e_t$	-2380.88

TABLE 2. ARIMA models

		BIC
ASII:	$Y_t = -0.0001 - 0.1367Y_{t-1} + e_t$	-1183.91
BBCA:	$Y_t = 0.0030 + e_t + 0.2018e_{t-1}$	-1422.16
INDF:	$Y_t = 0.00002 - 0.1670Y_{t-1} + e_t$	-1268
PGAS:	$Y_t = -0.0045 + e_t - 0.0354e_{t-1}$	-933.22
TLKM:	$Y_t = 0.0006 + e_t + 0.2098e_{t-1}$	-1390.59

ARFIMA$(0, -0.03917, 1)$ and ARIMA$(0, 0, 1)$, TLKM are ARFIMA$(0, 0.02087, 1)$ and ARIMA$(0, 0, 1)$. In this model Y_t is the Return of the stocks.

Residual of the chosen ARFIMA model will be tested with Kolmogorov-Smirnov and Ljung-Box Pierce. We want the residual to be normally distributed and free of autocorrelation before continuing to the next step. Kolmogorov-Smirnov and Box test will be done; thus, the ARFIMA model residual has been proven to be normally distributed and free of autocorrelation since all of the p-value $> \alpha$. By doing this, we can proceed to test the model using testing data. In this research, we will forecast 42 weeks trading. From the model, we will get 42 predictions of stocks return, and then we used the previous Close price and the predicted return to get the predicted Close price of the week. It can be written as $C_t = C_{t-1} \cdot e^{Y_t}$ where C_t is the predicted Close price, C_{t-1} is the previous Close price, and Y_t is the predicted Return we get from the built model. The ARFIMA results for each stock are shown in Figure 1 to Figure 5.

FIGURE 1. Real Close vs predicted Close (ASII)

3.3. **Artificial neural network.** ANN is one of popular machine learning techniques to model non-linear approximation, because of its ability to solve multiple functions with high accuracy [18]. There are three key components in ANN, namely input layer, hidden layer, and output layer. A simple neural network can be written as mathematical function $Y_t = W_0 + \sum_{j=1}^{q} W_j \cdot g\left(W_{0,j} + \sum_{i=1}^{p} W_{i,j} Y_{t-i}\right) + \epsilon_t$ [2] where W_0 represents initial weight for each node, $W_{i,j}$ and W_j for $i = 1, 2, \ldots, p$ and $j = 1, 2, \ldots, q$ are connections weight, p and q are the number of input and output layer, and ϵ_t is the error term. In ANN, each layer is connected by a sigmoid function as the activation function. Activation function

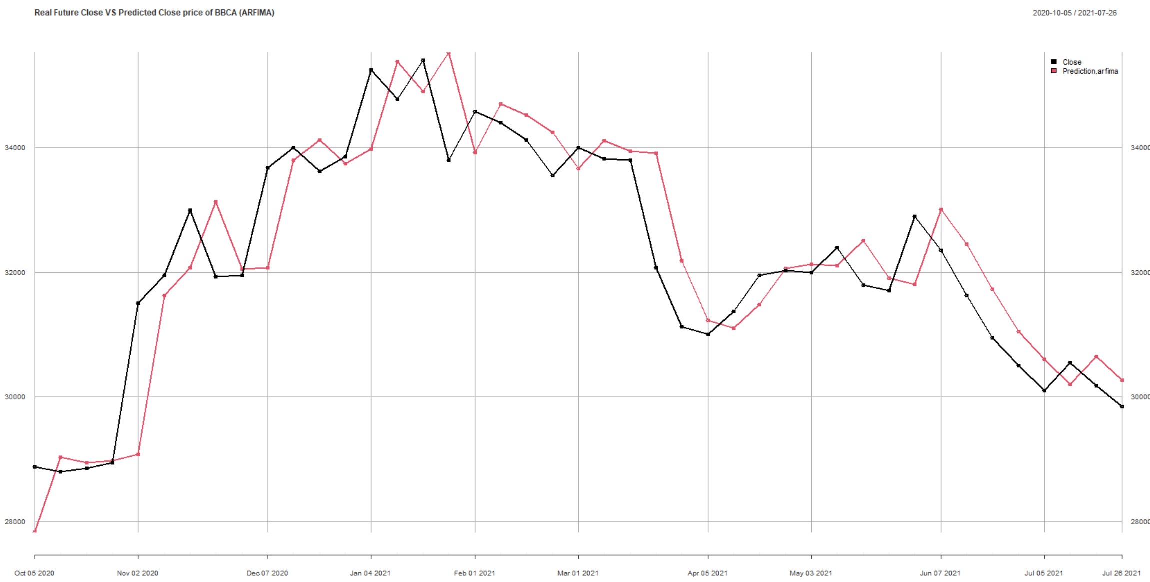

Figure 2. Real Close vs predicted Close (BBCA)

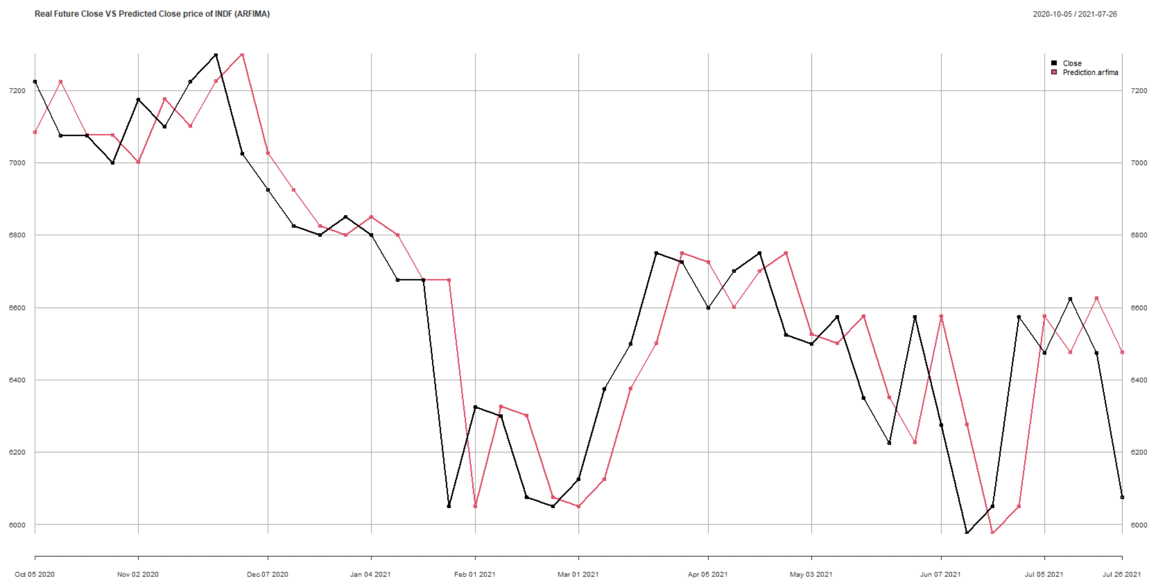

Figure 3. Real Close vs predicted Close (INDF)

is used to transform input signal, so it can be used in the next layer, and so until it produces the desired output. There are a lot of activation functions available, two of the most common functions are logistic function $\left(sig(x) = \frac{1}{1+e^{-x}}\right)$ and hyperbolic function $\left(\tanh(x) = \frac{1-e^{-2x}}{1+e^{-2x}}\right)$ [11].

From the two activation functions, hyperbolic function is the most used function because of its ability to converge faster and to be easily optimized [2]. For this reason, hyperbolic function is used as the activation function. We use six inputs in this research, i.e., Open, High, Low, Close, Volume, and Return, along with one output, i.e., Future Close (FClose). These inputs that will be used to build the model should be normalized first. We normalized the data using $X_t = \frac{x_t - x_{\min}}{x_{\max} - x_{\min}}$, with X_t the normalized data at time

FIGURE 4. Real Close vs predicted Close (PGAS)

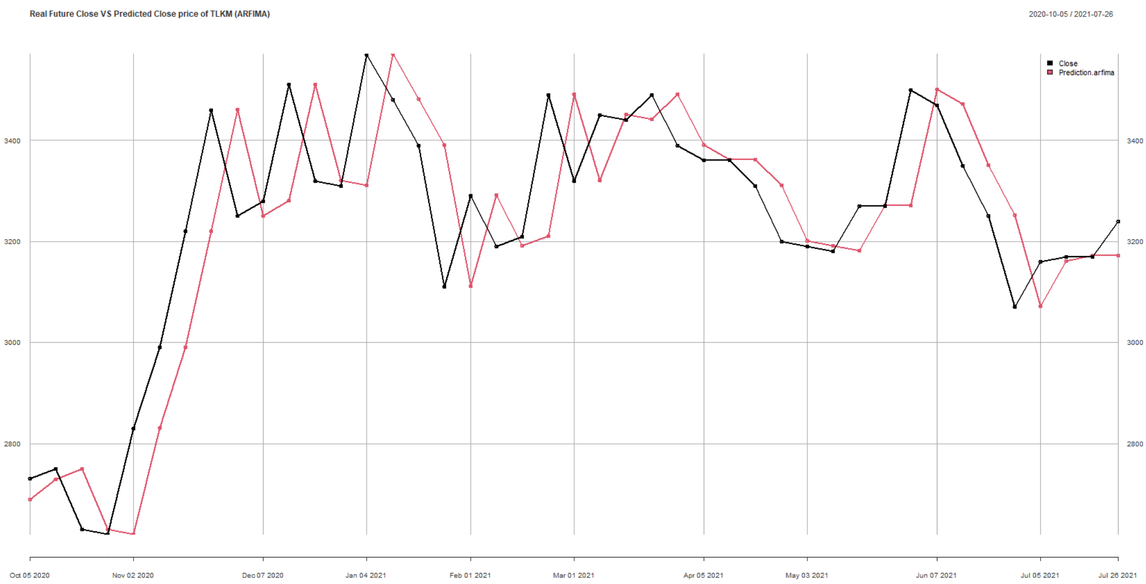

FIGURE 5. Real Close vs predicted Close (TLKM)

t, x_t the data at time t, $x_{\min}$ and $x_{\max}$ the minimum and maximum value of data set x [10], and this normalization made $X_t \in [0, 1]$.

Finding the best model for each stock will be conducted through simulations, which is to find the optimal number of hidden nodes. Since there are two hidden layers, we will find the optimal number of nodes in each hidden layer. The maximum number of nodes in each layer is 13, which we obtain from the $2p + 1$ [10], where p is the number of input layers. For each possible combination of hidden layers, we simulate for 100 times, to make sure we get the best model overall in the long run. In total, we simulated for 16,900 times for each stock to get the best possible model. We choose the best model according to the R-squared value for the model and test it with the testing data to find each error measurement.

After 100 simulations for each possible hidden layer, we present five possible models for each stock in Tables 3-7. We pick the best possible model which has the least error and the biggest R-squared. The chosen ANN model for ASII is ANN(6-(12-10)-1) which means ANN tree of ASII has two hidden layers with 12 nodes in the first hidden layer and 10 nodes in the second hidden layer, as for BBCA is ANN(6-(12-11)-1), INDF is ANN(6-(12-10)-1), PGAS is ANN(6-(12-9)-1), and TLKM is ANN(6-(13-12)-1).

Table 3. ANN possible result ASII

H1	H2	Error	R^2
12	10	0.18590	0.92483
11	7	0.18614	0.92473
12	11	0.18647	0.92460
13	9	0.18664	0.92453
12	13	0.18664	0.92453

Table 4. ANN possible result BBCA

H1	H2	Error	R^2
12	11	0.07439	0.98941
13	12	0.07457	0.98939
11	13	0.07459	0.98939
13	13	0.07474	0.98936
13	11	0.07496	0.98933

Table 5. ANN possible result INDF

H1	H2	Error	R^2
12	10	0.15551	0.90054
13	10	0.15624	0.90007
11	13	0.15630	0.90004
13	13	0.15641	0.89997
12	12	0.15654	0.89988

Table 6. ANN possible result PGAS

H1	H2	Error	R^2
12	9	0.11393	0.98780
11	13	0.11434	0.98776
11	6	0.11439	0.98775
13	11	0.11448	0.98774
12	10	0.11467	0.98772

We also check the residual of chosen model with Kolmogorov-Smirnov test for normality and Ljung-Box Pierce test for autocorrelation. The results of K-S test and Box Pierce test show that the residual of the chosen model is normally distributed and free of autocorrelation since all of the p-value $> \alpha$, so we will proceed to the next step, which is to test the model to predict test data. The results of the predicted FClose of ANN are in normalized numbers, so we will inverse the operation of the normalized step; therefore, we will get the value of predicted FClose. We present the comparison between real FClose and predicted FClose of each stock in Figures 6-10.

Table 7. ANN possible result TLKM

H1	H2	Error	R^2
13	12	0.10605	0.96789
13	11	0.10648	0.96777
11	13	0.10654	0.96775
11	11	0.10656	0.96774
12	12	0.10659	0.96773

Figure 6. Real FClose vs predicted FClose ASII

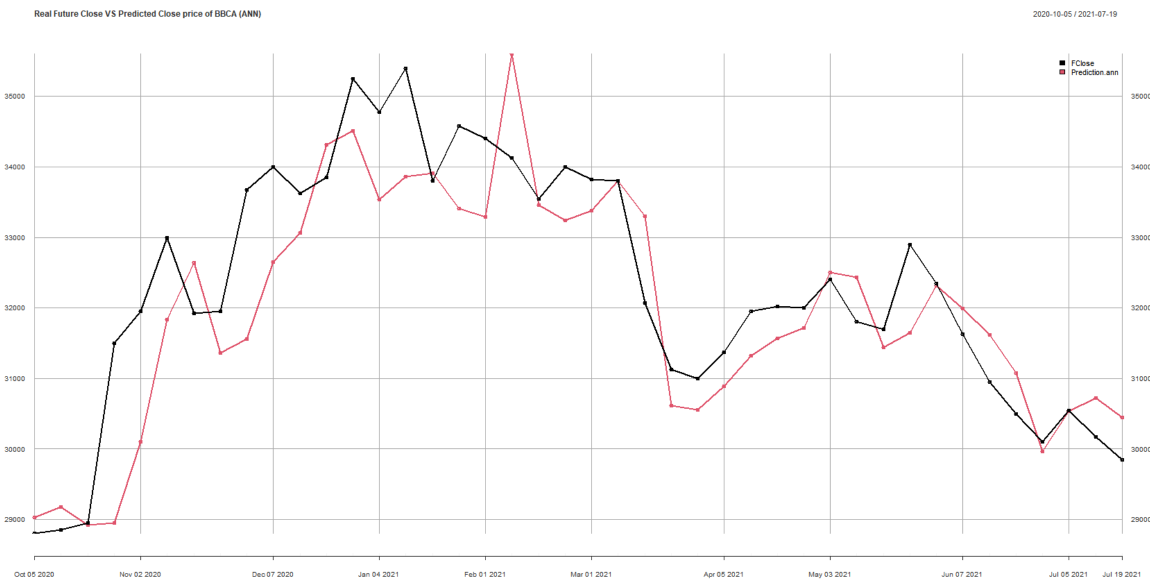

Figure 7. Real FClose vs predicted FClose BBCA

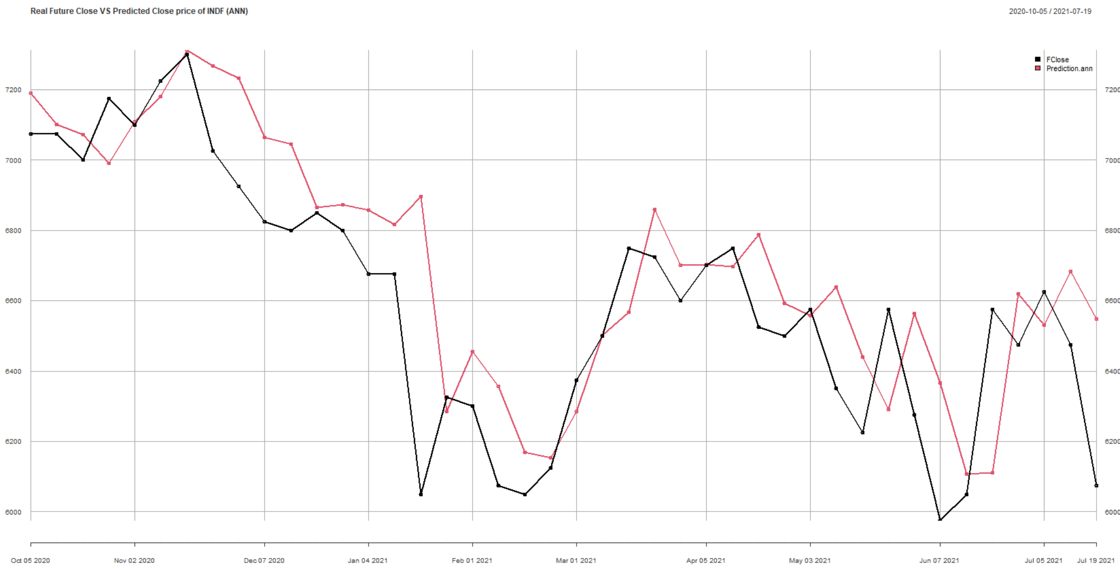

FIGURE 8. Real FClose vs predicted FClose INDF

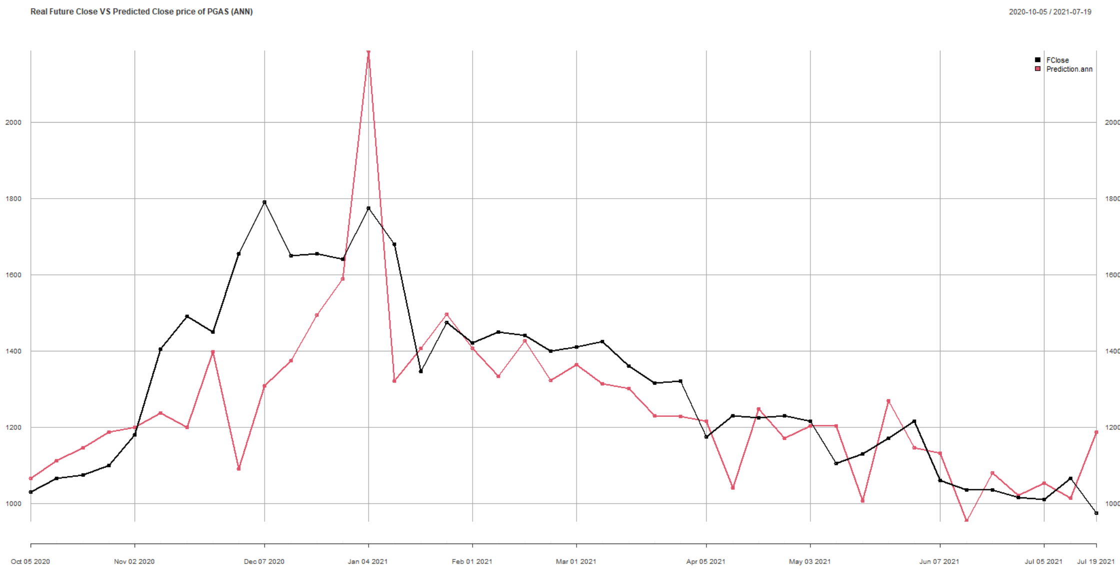

FIGURE 9. Real FClose vs predicted FClose PGAS

3.4. **Prediction result comparison.** Different methods will give different results and to know which model is better, we need an equal comparison measurement. There are a lot of measurements available, and in this research we used Mean Absolute Percentage Error $\left(\text{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{y_i - \widehat{y}_i}{y_i}\right|\right)$, Root Mean Square Error $\left(\text{RMSE} = \sqrt{\frac{\sum(y_i - \widehat{y}_i)^2}{N}}\right)$, and R^2 $\left(\text{R}^2 = 1 - \frac{\sum(y_t - \widehat{y}_t)^2}{\sum(y_t - \overline{y}_t)^2}\right)$ as comparison with N as number of observation data, y_t as real close price, $\overline{y_i}$ as mean of the real close price, and $\widehat{y}_i$ as the predicted close price. Table 8, Table 9, and Table 10 show the comparison of MAPE, RMSE, and R^2 among each stock training model and testing result, respectively.

From MAPE value, all methods are as good as the others when we compare the models of training data. On the other hand, MAPE shows that ARFIMA method is better to forecast testing data than ANN method, because we get less error prediction using ARFIMA

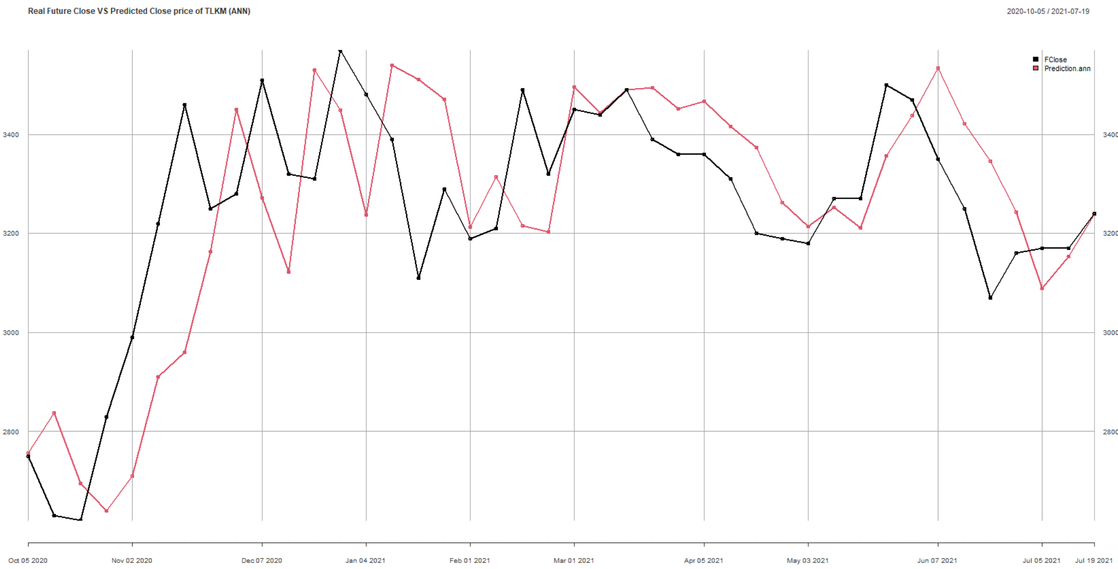

FIGURE 10. Real FClose vs predicted FClose TLKM

TABLE 8. MAPE comparison of each stock

	ASII	BBCA	INDF	PGAS	TLKM
MAPE Training ARIMA	0.0297	0.0209*	0.0272	0.0435*	0.0244
MAPE Testing ARIMA	0.0312**	0.0191**	0.0242**	0.0509	0.0328**
MAPE Training ARFIMA	0.0296*	0.0212	0.0272	0.0435*	0.0244
MAPE Testing ARFIMA	0.0312**	0.0191**	0.0242**	0.0506**	0.0328**
MAPE Training ANN	0.0299	0.0230	0.0259*	0.0457	0.0221*
MAPE Testing ANN	0.0465	0.0217	0.0267	0.0846	0.0434

TABLE 9. RMSE comparison of each stock

	ASII	BBCA	INDF	PGAS	TLKM
RMSE Training ARIMA	281.5043	688.4271	262.9316	146.9492*	113.5199
RMSE Testing ARIMA	226.5082	816.5435	206.8408	96.4436	137.9849**
RMSE Training ARFIMA	281.6029	687.9008	262.9165	147.3303	113.4913
RMSE Testing ARFIMA	226.4037**	813.0844**	206.8380**	96.2267**	138.1054
RMSE Training ANN	274.7522*	608.9230*	247.7739*	147.7326	103.4592*
RMSE Testing ANN	334.8125	922.1670	235.8203	175.0493	178.5697

TABLE 10. R^2 comparison of each stock

	ASII	BBCA	INDF	PGAS	TLKM
R^2 Training ARIMA	0.9319	0.9905	0.9020	0.9892	0.9699
R^2 Testing ARIMA	0.7787	0.7876	0.6759	0.8253	0.6429**
R^2 Training ARFIMA	0.9318	0.9906	0.9021	0.9891	0.9699
R^2 Testing ARFIMA	0.7789**	0.7894**	0.6760**	0.8261**	0.6423
R^2 Training ANN	0.9358*	0.9926*	0.9128*	0.9896*	0.9750*
R^2 Testing ANN	0.4971	0.7111	0.5587	0.4112	0.3397

method. We can also see from MAPE value that ARFIMA and ARIMA produce almost the same results when predicting testing data, the only difference is that ARFIMA is better at predicting testing data of PGAS.

From RMSE value, ANN is better than ARFIMA to build models from training data, except when building model for PGAS. So, from RMSE value we know that ANN is the best method that can be used to build a training data model. When we use the model to predict testing data, we can see from RMSE value that generally ARFIMA is better than both ANN and ARIMA except for TLKM, ARIMA is better than ARFIMA.

From R^2 value, again ANN is much better than ARFIMA to build forecasting model from training data. We can take note that ARFIMA is almost the same as ARIMA when building forecasting model. So, from R^2 value we know that ANN is still the best method that can be used to build a training data model. If we look performance of the model to predict testing data, we know that ARFIMA is much better than ANN and ARIMA, except in TLKM where ARIMA has the highest R^2 value than ANN and ARFIMA.

Summarizing from these three error measurement values in Tables 8-10, we try to indicate the best performance for each stock using * and **; * for the best method for training and ** for the best methods for testing. Based on these and the explanation above, we conclude that ANN can build better model than ARFIMA or ARIMA, but when we use the model to predict testing data, ARFIMA and ARIMA are better than ANN. We also note that performance of ARFIMA is only slightly better than ARIMA. We expect ARFIMA can produce better result compared to ARIMA because we know the LTM factor in stocks data.

We conclude that ARFIMA and ARIMA are better at predicting weekly Indonesian stocks price than ANN. As we already know that ARIMA is better at predicting stock price, that also found in [2]. Moreover, ARFIMA is good at predicting stock prices and real world data [5-7], also ARFIMA prediction result is almost the same as ARIMA [3]. However, our finding is different, which stated that the prediction of ANN is as good as ARIMA [1]. We also believe that ANN can be improved further to produce better prediction result, as stated by Devadoss and Ligori [10]. It should be noted while ANN method produces good model, overfitting might happen which causes the prediction result to differ far from the actual value. There are many ways to prevent this overfitting, such as implementing early stopping criteria when building the model [19], using ANN hybrid method [11,12], or applying more complex neural network method [8,20].

4. Conclusions.

This research shows that ARFIMA and ARIMA can yield better prediction than ANN, especially in predicting weekly stock prices in Indonesia. In fact, ARFIMA and ARIMA yield almost the same results, so we conclude that ARFIMA is not necessarily better at predicting data with LTM than ARIMA. There are still many improvements that can be implemented in the future research, such as using a better estimation fraction order, i.e., Geweke Porter-Hudak, Gaussian Semiparametric, Wavelet Ordinary Least Square, etc. [21]. For the next research, researcher can adjust the data training and testing splitting, also the research period accordingly.

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