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Implementation of Auto ARIMA, PSO-LSTM, and PSO-GRU for Time Series Modeling of 3 Telecommunication Company Stock Prices on LQ45 Index

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Abstract

The Indonesia Stock Exchange (IDX) issues stock indices to make it easier for investors to choose company shares such as the LQ45 Index. This study focuses on forecasting the share prices of 3 telecommunications companies listed in the LQ45 Index, namely PT Telkom Indonesia Tbk with the stock code TLKM, PT Tower Bersama Infrastructure Tbk with the stock code TBIG and PT Sarana Menara Nusantara Tbk with the stock code TOWR in the future. The algorithms used for forecasting are Auto ARIMA, LSTM and GRU algorithms. In addition, the PSO method is used to find the optimal hyperparameters in the LSTM and GRU algorithms. The results of this study show that the GRU model has the best performance and produces the best model evaluation value compared to other models on TLKM and TBIG stock data, while on TOWR stock data the LSTM model is the best model. The GRU model on TLKM data results in an $\boldsymbol{R}^2$ value of 0,961, RMSE 122,291 on training data and MAPE 3,027% and an $\boldsymbol{R}^2$ value of 0,859, RMSE 114,703 and 2,109% on testing data. On TBIG data, the GRU model results in an $\boldsymbol{R}^2$ value of 0,984, RMSE 71,945 and MAPE 4,206% on training data and an $\boldsymbol{R}^2$ value of 0,967, RMSE 73,627 and 2,165% on testing data. The LSTM model on TOWR data results in an $\boldsymbol{R}^2$ value of 0,943, RMSE 43,824 and MAPE 4,274% on training data and an $\boldsymbol{R}^2$ value of 0,796, RMSE 42,597 and 3,117% on testing data.

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1. Introduction

The Indonesia Stock Exchange (IDX) is an official stock exchange in Indonesia that facilitates the buying and selling of shares of listed companies. The IDX classifies listed companies into several sectors including energy, raw materials, industry, primary consumer goods, non-primary consumer goods, health, finance, property & real estate, technology, infrastructure and transportation & logistics. There are quite a number of companies listed on the Indonesia Stock Exchange, so a stock index is issued to facilitate investors in choosing stocks including IDX 80, LQ45 Index, IDX 30, Kompas 100 Index etc. The LQ45 Index is an index that measures the share price performance of 45 stocks that have high liquidity and large market capitalization and are supported by good company fundamentals (Bursa Efek Indonesia, 2022). Telecommunications companies listed in the LQ45 Index include PT Telkom Indonesia Tbk, PT Tower Bersama Infrastructure Tbk and PT Sarana Menara Nusantara Tbk.

Time series forecasting methods are classified into parametric methods and non-parametric methods. One of the parametric methods is Autoregressive Integrated Moving Average (ARIMA). Non-parametric methods are based on Machine Learning with learning capabilities (Bousqaoui et al., 2021). Non-parametric methods such as Long Short Term Memory (LSTM). The Gated Recurrent Unit (GRU) algorithm is a modified result of the LSTM algorithm. The main difference between the GRU and LSTM algorithms is that GRU has two gates, namely reset gate and update gate, while LSTM has three gates, namely forget gate, input gate and output gate (Campesato, 2020).

Building effective LSTM and GRU models needs a suitable algorithm to obtain the optimal model architecture by determining the hyperparameters. Hyperparameters are parameters that cannot be estimated directly from learning data and must be set before training a Machine Learning model. Manual testing is the traditional way to obtain optimal hyperparameters. However, the hyperparameters obtained manually are not effective due to several factors such as large hyperparameters, complex models and time-consuming model evaluation. The process of automatically designing model architecture with optimal hyperparameter configuration is called Hyperparameter Optimization (HPO). One of the algorithms that can be used for HPO is Particle Swarm Optimization (PSO) (Yang & Shami, 2020).

In addition, a sliding window is used. The width of the sliding window will affect the prediction of the model. The window length is the amount of input data used. If too much input data is used, it will cause complex calculations and slow down the neural network training. Too little input data tends to include less data information so that it does not reflect the pattern of the data (Geng *et al*., 2023).

Previous research conducted by Yamak *et al*. (2019) in predicting Bitcoin prices using ARIMA, LSTM and GRU. The study produced an ARIMA model with a MAPE value of 2.67 and an RMSE value of 302.53, an LSTM model with a MAPE value of 6.8 and an RMSE value of 603.68 and a GRU model with a MAPE value of 3.97 and an RMSE value of 381.34.

Xu *et a*l. (2022) conducted short-term flood forecasting research using rainfall observation data. The method used by PSO-LSTM is better than LSTM. The PSO-LSTM model has an NSE of 0.9912, RMSE of 9.2461 and bias of 0.5065, while LSTM has an NSE of 0.9761, RMSE of 10.4314 and bias of 0.6265.

This research focuses on forecasting the stock prices of companies telecommunications listed on the Indonesia Stock in the LQ45 Index in the future using the Auto ARIMA, LSTM and GRU algorithms. HPO used in training LSTM and GRU models is Particle Swarm Optimization (PSO). Evaluation of forecasting results using R Square Score, Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). The telecommunication companies are PT Telkom Indonesia Tbk with TLKM stock code, PT Tower Bersama Infrastructure Tbk with TBIG stock code and PT Sarana Menara Nusantara Tbk with TOWR stock code.

2. Method

The data used in this study is the stock price dataset of PT Telkom Indonesia Tbk (TLKM), PT Tower Bersama Infrastructure Tbk (TBIG) and PT Sarana Menara Nusantara Tbk (TOWR) from January 01, 2014 to December 31, 2023. The data is secondary data obtained from the website www.finance.yahoo.com. Stock price data consists of date data (date data), open data (stock opening price), high data (highest stock price), low data (lowest stock price), close data (stock closing price), adj close data (stock closing price adjusted for corporate actions such as dividends and stock splits) and volume data (transaction volume in number of shares). The data is selected first by taking date data and close data.

The next process is to create a consistent format for the date data, check for missing values and check for duplicate data. Checking for missing values or data completeness so that the missing data does not affect the overall data processing. To overcome the missing value in the missing data, the value is filled using the overall data mode. The next data preprocessing stage is the division of data into training data and testing data. In this study, the data is divided into 80% for training data and the remaining 20% for testing data. So that the training data used in the study amounted to 1.985 data and 497 data for testing data.

Furthermore, the ADF Test is carried out to determine stationary data and the value of d. Auto ARIMA using AR(0) to AR(5) and MA(0) to MA(5). ARIMA model results with the lowest AIC value.

LSTM and GRU models use window sizes 10, 15 and 20. Hidden layers used are 25 and 50. In addition, it uses epochs 10, batch size 32, uses a learning rate of 0,0001, dropout rate 0,2, activation tanh, optimizer Adam, loss function mean squared error and early stopping. The LSTM and GRU models also use PSO to find the optimal hyperparameters. PSO searches for window size values from 10 to 25, hidden layers from 25 to 50, epochs from 1 to 10 and batch size from 1 to 32.

3. Results and discussions

Data preprocessing shows that there is one missing TLKM and TOWR stock data. TLKM and TOWR stock data amounted to 2.481 data and TBIG stock data amounted to 2.482 data. To overcome the missing value in the missing data, the value is filled using the overall data mode. The plot of TLKM, TBIG and TOWR stock price data is shown in Figure 7.

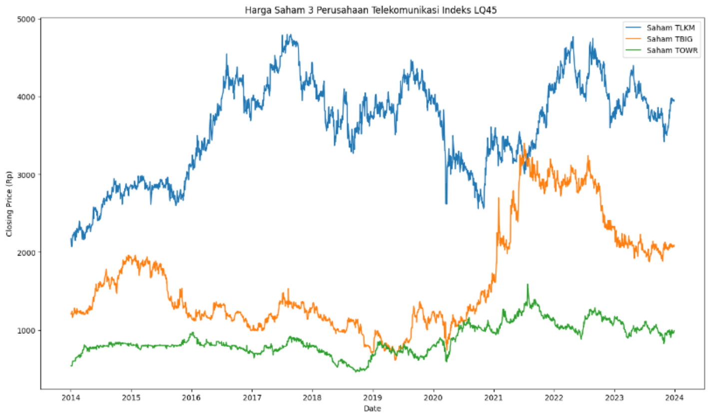

Figure 1 Plot data

Auto ARIMA model using data that is not normalized. Data normalization results are used for LSTM, PSO-LSTM, GRU and PSO-GRU models. The Auto ARIMA function will find the value of p and q with the minimum AIC. The results of Auto ARIMA and model evaluation of the three data are shown in Table `1.

Table 1 Auto ARIMA result

		Data TLKM	Data TBIG	Data TOWR
Model		(2,1,0)	(0,1,2)	(0,1,1)
AIC		-10.377,451	-8.938,403	-9.739,791
R^2	Training	0,984	0,992	0,986
	Testing	-0,004	-2,595	-0,609
RMSE	Training	78,090	47,961	21,480
	Testing	300,909	775,509	118,600
MAPE	Training	1,301%	1,767%	1,365%
	Testing	6,230%	30,446%	9,988%

TLKM stock data is optimal for ARIMA(2,1,0) with $\varphi_1 = -0{,}0616$ and $\varphi_2 = -0{,}1350$, TBIG stock data is optimal for ARIMA(0,1,2) with $\theta_1 = -0{,}0889$ and $\theta_2 = -0{,}0315$ and TOWR stock data is optimal for ARIMA(1,1,0) with $\varphi_1 = -0{,}1888$ dan $\theta_1 = 0{,}0004$. In Table 2, the LSTM model with a combination of window size and hidden layers results in a model evaluation value.

Table 2 LSTM Model Results

	Window Size	Hidden Layers	Epochs	Batch Size		R^2	RMSE	MAPE
Data TLKM	10	25	10	32	Training	0,922	172,573	4,422%
					Testing	0,735	156,185	2,795%
	10	50	10	32	Training	0,941	149,854	3,806%
					Testing	0,797	136,601	2,532%
	15	25	10	32	Training	0,927	166,804	4,209%
					Testing	0,750	152,462	2,819%
	15	50	10	32	Training	0,956	129,538	3,095%
					Testing	0,824	128,006	2,376%
	20	25	10	32	Training	0,928	164,168	4,101%
					Testing	0,773	145,965	2,746%
	20	50	10	32	Training	0,960	122,496	2,844%
					Testing	0,844	121,058	2,285%
Data TBIG	10	25	10	32	Training	0,974	91,665	5,267%
					Testing	0,951	89,702	2,755%
	10	50	10	32	Training	0,971	95,222	5,451%

	Window Size	Hidden Layers	Epochs	Batch Size		R^2	RMSE	MAPE
					Testing	0,942	97,455	3,313%
	15	25	10	32	Training	0,979	80,419	4,290%
					Testing	0,964	76,405	2,489%
	15	50	10	32	Training	0,968	100,609	5,919%
					Testing	0,952	88,328	2,678%
	20	25	10	32	Training	0,969	98,442	5,928%
					Testing	0,960	80,364	2,568%
	20	50	10	32	Training	0,969	99,507	5,551%
					Testing	0,959	80,745	2,518%
Data TOWR	10	25	10	32	Training	0,868	66,840	6,155%
					Testing	0,228	82,393	6,650%
	10	50	10	32	Training	0,883	62,921	5,616%
					Testing	0,271	80,089	6,407%
	15	25	10	32	Training	0,891	60,632	5,691%
					Testing	0,460	69,013	5,306%
	15	50	10	32	Training	0,913	54,103	5,051%
					Testing	0,581	60,836	4,643%
	20	25	10	32	Training	0,879	63,809	6,285%
					Testing	0,477	68,262	5,205%
	20	50	10	32	Training	0,943	43,824	4,274%
					Testing	0,796	42,597	3,117%

From Table 2, it can be seen that the LSTM model with a combination of window size and hidden layers results different evaluation values. In TLKM stock data, the optimal LSTM model with window size 20 and hidden layers 50. The model results in an R^2 value of 0,960, RMSE 122,496 and MAPE 2,844% in training and R^2 0,844, RMSE 121,058 and MAPE 2,285%in testing.

On TBIG stock data, the optimal LSTM model with window size 15 and hidden layers 25, The model results in an R^2 value of 0,980, RMSE 80,419 and MAPE 4,290% on training and R^2 0,964, RMSE 76,405 and MAPE 2,489% on testing.

The optimal LSTM model on TOWR stock data with window size 20 and hidden layers 50, The model results an R^2 value of 0,980, RMSE 80,419 and MAPE 4,290% on training and R^2 0,796, RMSE 42,597 and MAPE 3,117% on testing.

Table 3 GRU model result

	Window Size	Hidden Layers	Epochs	Batch Size		R^2	RMSE	MAPE
Data TLKM	10	25	10	32	Training	0,945	145,017	3,612%
					Testing	0,766	146,849	2,822%
	10	50	10	32	Training	0,953	134,836	3,358%
					Testing	0,791	138,79	2,593%
	15	25	10	32	Training	0,951	136,434	3,377%
					Testing	0,846	119,658	2,232%
	15	50	10	32	Training	0,961	122,291	3,027%
					Testing	0,859	114,703	2,109%
	20	25	10	32	Training	0,959	123,496	2,821%
					Testing	0,811	133,343	2,462%
	20	50	10	32	Training	0,954	131,303	3,203%
					Testing	0,843	121,581	2,263%
Data TBIG	10	25	10	32	Training	0,969	98,351	5,368%
					Testing	0,867	147,826	5,051%
	10	50	10	32	Training	0,984	71,945	4,206%
					Testing	0,967	73,627	2,165%
	15	25	10	32	Training	0,928	150,924	8,943%
					Testing	0,677	229,391	8,054%
	15	50	10	32	Training	0,982	76,082	4,183%
					Testing	0,959	81,919	2,624%
	20	25	10	32	Training	0,967	102,065	5,722%
					Testing	0,869	146,275	4,802%
	20	50	10	32	Training	0,977	86,399	4,612%
					Testing	0,952	88,502	2,989%
	10	25	10	32	Training	0,900	58,044	5,348%

	Window Size	Hidden Layers	Epochs	Batch Size		R^2	RMSE	MAPE
					Testing	0,429	70,902	5,704%
	10	50	10	32	Training	0,861	68,537	6,356%
					Testing	0,160	85,950	7,053%
	15	25	10	32	Training	0,884	62,516	5,986%
Data TOWR					Testing	0,389	73,376	5,871%
	15	50	10	32	Training	0,837	74,069	6,955%
					Testing	0,067	90,756	7,355%
	20	25	10	32	Training	0,863	67,988	6,134%
					Testing	0,152	86,932	7,115%
	20	50	10	32	Training	0,859	68,932	6,288%
					Testing	0,146	87,216	7,114%

Based on Table 3, the combination of window size and hidden layers in the GRU model results in different evaluation values. On TLKM stock data, the GRU model is optimal with window size 15 and hidden layers 50. The model results an R^2 value of 0,961, RMSE 122,291 and MAPE 3,027% on training and R^2 0,859, RMSE 114,703 and MAPE 2,109% on testing.

On TBIG stock data, the optimal GRU model with window size 10 and hidden layers 50. The model results in an R^2 value of 0,984, RMSE 71,945 and MAPE 4,206% on training and R^2 0,967, RMSE 73,627 and MAPE 2,165% on testing.

The GRU model is optimal on TOWR stock data with window size 10 and hidden layers 25. The model results in an R^2 value of 0,900, RMSE 58,044 and MAPE 5,348% on training and $R^2$0,429, RMSE 70,902 and MAPE 5,704% on testing.

Table 4 PSO-LSTM model results

	Window Size	Hidden Layers	Epochs	Batch Size		R^2	RMSE	MAPE
	18	44	9	1	Training	0,956	129,043	2,784%
					Testing	0,794	138,821	2,609%
Data TLKM	19	35	7	1	Training	0,952	136,095	2,774%
					Testing	0,719	162,381	2,948%
	10	25	5	1	Training	0,957	127,933	2,942%
					Testing	0,804	134,319	2,435%
	11	25	6	1	Training	0,983	73,932	3,671%
					Testing	0,967	73,969	2,304%
Data TBIG	16	27	8	13	Training	0,979	82,075	4,003%
					Testing	0,966	74,769	2,322%
	10	49	8	2	Training	0,977	85,503	3,584%
					Testing	0,925	111,035	3,368%
	15	49	10	28	Training	0,913	54,121	4,987%
					Testing	0,572	61,452	4,689%
Data TOWR	16	35	3	25	Training	0,905	56,658	5,201%
					Testing	0,507	66,016	5,084%
	8	50	4	32	Training	0,922	51,23	4,683%
					Testing	0,614	58,476	4,468%

Based on Table 4, it can be seen that the PSO-LSTM model results optimal hyperparameter values and different evaluation values. The hyperparameters are window size, hidden layers, epochs and batch size. In TLKM stock data, the PSO-LSTM model is optimal with window size 10, hidden layers 25, epochs 5 and batch size 1. The model results in an R^2 value of 0,957, RMSE 127,933 and MAPE 2,941% on training and R^2 0,804, RMSE 134,319 and MAPE 2,435% on testing.

On TBIG stock data, the PSO-LSTM model is optimal with window size 11, hidden layers 25, epochs 6 and batch size 1. The model results in an R^2 value of 0,983, RMSE 73,932 and MAPE 3,671% on training and R^2 0,967, RMSE 73,969 and MAPE 2,304% on testing.

The optimal PSO-LSTM model on TOWR stock data with window size 18, hidden layers 50, epochs 4 and batch size 32. The model results in an R^2 value of 0,922, RMSE 51,230 and MAPE 4,683% on training and R^2 0,614, RMSE 58,476 and MAPE 4,468% on testing.

Table 5 PSO-GRU model results

	Window Size	Hidden Layers	Epochs	Batch Size		R^2	RMSE	MAPE
	10	25	10	32	Training	0,935	157,641	3,476%

	Window Size	Hidden Layers	Epochs	Batch Size		R^2	RMSE	MAPE
					Testing	0,553	202,947	4,192%
Data TLKM	10	50	10	32	Training	0,949	137,913	3,192%
					Testing	0,767	147,959	2,810%
	20	50	10	32	Training	0,921	172,699	4,405%
					Testing	0,682	172,407	3,332%
Data TBIG	10	25	10	32	Training	0,981	77,648	3,919%
					Testing	0,967	72,919	2,182%
	20	25	10	32	Training	0,978	83,313	3,603%
					Testing	0,917	116,361	4,041%
	20	50	10	32	Training	0,975	88,969	4,076%
					Testing	0,918	115,471	4,062%
Data TOWR	10	25	10	32	Training	0,897	58,904	5,296%
					Testing	0,411	72,294	5,694%
	20	25	10	32	Training	0,88	63,666	5,846%
					Testing	0,285	79,308	6,430%
	20	50	10	32	Training	0,889	61,049	5,208%
					Testing	0,173	85,544	6,971%

From Table 5, it can be seen that the PSO-GRU model results optimal hyperparameter values and different evaluation values. The hyperparameters are window size, hidden layers, epochs and batch size. In TLKM stock data, the PSO-GRU model is optimal with window size 20, hidden layers 35, epochs 8 and batch size 6. The model results in an R^2 value of 0,949, RMSE 137,913 and MAPE 3,192% in training and R^2 0,767, RMSE 147,959 and MAPE 2,810% in testing.

On TBIG stock data, the PSO-GRU model is optimal with window size 18, hidden layers 28, epochs 10 and batch size 7. The model results in an R^2 value of 0,981, RMSE 77,648 and MAPE 3,919% on training and R^2 0,967, RMSE 72,919 and MAPE 2,182% on testing.

The PSO-GRU model is optimal on TOWR stock data with window size 18, hidden layers 37, epochs 2 and batch size 1. The model results in an R^2 value of 0,897, RMSE 58,904 and MAPE 5,296% in training and R^2 0, 411, RMSE 72,294 and MAPE 5,694% in testing.

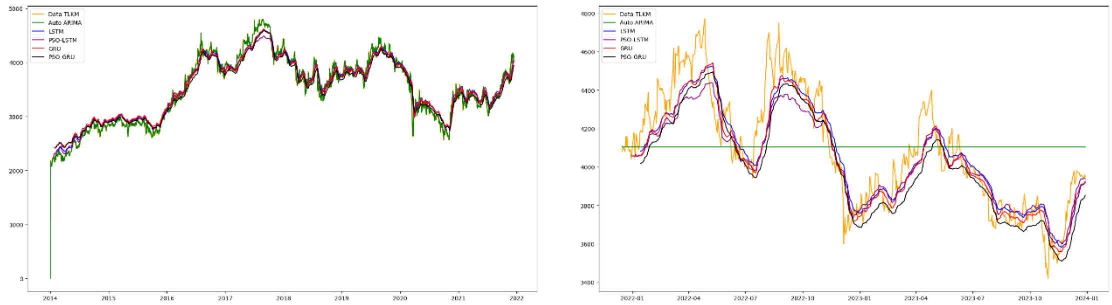

Figure 8 Training results and prediction plot on TLKM stock data

Table 6 Model evaluation on TLKM stock data

		R^2	RMSE	MAPE
Auto ARIMA	Training	0,984	78,090	1,301%
	Testing	-0,004	300,909	6,230%
LSTM	Training	0,960	122,496	2,844%
	Testing	0,844	121,058	2,285%
GRU	Training	0,961	122,291	3,027%
	Testing	0,859	114,703	2,109%
PSO-LSTM	Training	0,957	127,933	2,942%
	Testing	0,804	134,319	2,435%
PSO-GRU	Training	0,949	137,913	3,192%
	Testing	0,767	147,959	2,810%

Based on Figure 8, it is known that the training results formed can follow the actual data pattern. From Table 6 it can be seen that the GRU model on TLKM stock data shows the highest R^2 value as well as the lowest RMSE and MAPE values compared to the Auto ARIMA, LSTM, PSO-LSTM and PSO-GRU models. The GRU model results an R^2 value of

0,961, RMSE 122,291 and MAPE 3,027% on training data. On testing data, the GRU model results an R^2 value of 0,859, RMSE 114,703 and 2,109%. The R^2 value is close to 1 and the MAPE value is below 10%, indicating that the prediction has a very good level of accuracy. The RMSE values show that the model generated from this prediction has a small error rate.

On TLKM stock data, the LSTM and GRU models with a combination of window size and hidden layers show better results than the optimal hyperparameter search with Particle Swarm Optimization on the LSTM and GRU models. The LSTM model results an R^2value of 0,844, RMSE 121,058 and MAPE 2,285% while PSO-LSTM results an R^2 value of 0,804, RMSE 134,319 and MAPE 2,435%. While the GRU model results an R^2 value of 0,859, RMSE 114,703 and MAPE 2,109% while PSO-GRU results an R^2 value of 0,767, RMSE 147,959 and MAPE 2,810%. The GRU model has the most optimal model evaluation results compared to other machine learning models on TLKM stock data. Plot of prediction results on TLKM data as in Figure 8.

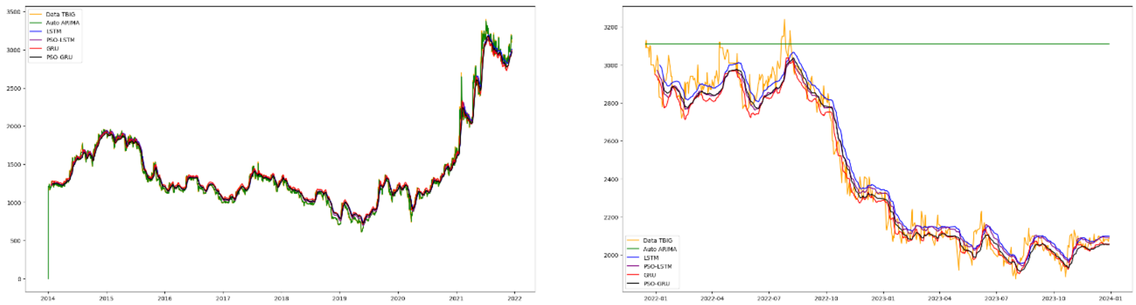

Figure 9 Training results and prediction plot on TBIG stock data

Table 7 Model evaluation on TBIG stock data

		R^2	RMSE	MAPE
Auto ARIMA	Training	0,992	47,961	1,767%
	Testing	-2,595	775,509	30,446%
LSTM	Training	0,979	80,419	4,290%
	Testing	0,964	76,405	2,489%
GRU	Training	0,984	71,945	4,206%
	Testing	0,967	73,627	2,165%
PSO-LSTM	Training	0,983	73,932	3,671%
	Testing	0,967	73,969	2,304%
PSO-GRU	Training	0,981	77,648	3,919%
	Testing	0,967	72,919	2,182%

Based on Figure 9, it is known that the training results formed can follow the actual data pattern. From Table 7 it can be seen that the GRU model on TBIG stock data shows the highest R^2 value as well as the lowest RMSE and MAPE values compared to the Auto ARIMA, LSTM, PSO-LSTM and PSO-GRU models. The GRU model results an R^2 value of 0,984, RMSE 71,945 and MAPE 4,206% on training data. On testing data, the GRU model results an R^2 value of 0,967, RMSE 73,627 and 2,165%. The R^2 value is close to 1 and the MAPE value is below 10%, indicating that the prediction has a very good level of accuracy. The RMSE values show that the model generated from this prediction has a small error rate.

On TBIG stock data, the search for optimal hyperparameters with Particle Swarm Optimization in the LSTM model shows better results than the LSTM model with a combination of window size and hidden layers. However, the GRU model shows better results with a combination of window size and hidden layers than the optimal hyperparameter search with Particle Swarm Optimization. The LSTM model results an R^2 value of 0,964, RMSE 76,405 and MAPE 2,489% while PSO-LSTM results an R^2 value of 0,967, RMSE 73,969 and MAPE 2,304%. While the GRU model results an R^2 value of 0,967, RMSE 73,627 and MAPE 2,165% while PSO-GRU results an R^2 value of 0,967, RMSE 72,919 and MAPE 2,182%. The GRU model has the most optimal model evaluation results compared to other machine learning models on TBIG stock data. Plot of prediction results on TBIG data as in Figure 9.

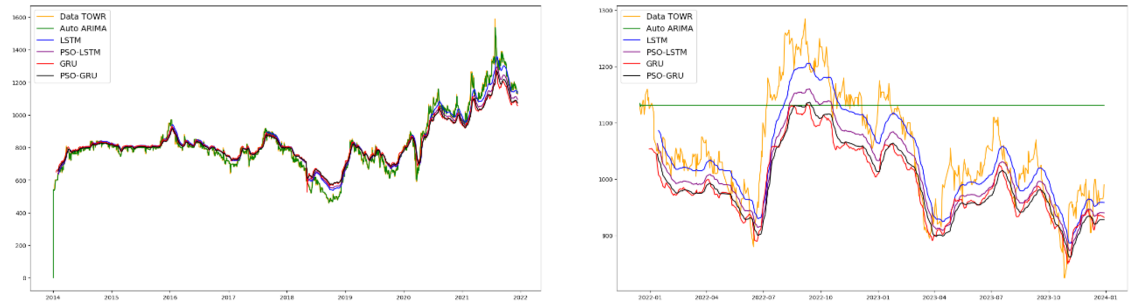

Figure 10 Training results and prediction plot on TOWR stock data

Table 8 Model evaluation on TOWR stock data

		R^2	RMSE	MAPE
Auto ARIMA	Training	0,986	21,480	1,365%
	Testing	-0,609	118,600	9,988%
LSTM	Training	0,943	43,824	4,274%
	Testing	0,796	42,597	3,117%
GRU	Training	0,900	58,044	5,348%
	Testing	0,429	70,902	5,704%
PSO-LSTM	Training	0,922	51,230	4,683%
	Testing	0,614	58,476	4,468%
PSO-GRU	Training	0,897	58,904	5,296%
	Testing	0,411	72,294	5,694%

Based on Figure 10, it is known that the training results formed can follow the actual data pattern. From Table 8 it can be seen that the LSTM model on TOWR stock data shows the highest R^2 value as well as the lowest RMSE and MAPE values compared to the Auto ARIMA, PSO-LSTM, GRU and PSO-GRU models. The LSTM model results an R^2 value of 0,943, RMSE 43,824 and MAPE 4,274% on training data. On testing data, the LSTM model results an R^2 value of 0,796, RMSE 42,597 and 3,117%. The R^2 value is close to 1 and the MAPE value is below 10%, indicating that the prediction has a very good level of accuracy. The RMSE values show that the model generated from this prediction has a small error rate.

On TOWR stock data, the LSTM and GRU models with a combination of window size and hidden layers show better results than the optimal hyperparameter search with Particle Swarm Optimization on the LSTM and GRU models. The LSTM model results an R^2 value of 0,796, RMSE 42,597 and MAPE 3,117% while PSO-LSTM results an R^2 value of 0,614, RMSE 58,476 and MAPE 4,468%. While the GRU model results an R^2 value of 0,429, RMSE 70,902 and MAPE 5,704% while PSO-GRU results an R^2 value of 0,411, RMSE 72,294 and MAPE 5,694%. The LSTM model has the most optimal model evaluation results compared to other machine learning models on TOWR stock data. The plot of prediction results on TOWR data is as shown in Figure 10.

4. Conclusion

Based on the comparison results on TLKM and TBIG stock data, it is obtained that the GRU model has the best performance and results the best model evaluation value compared to the Auto ARIMA, LSTM, PSO-LSTM and PSO-GRU methods. While in TOWR stock data, the LSTM model has the best performance and results the best model evaluation value compared to the Auto ARIMA, PSO-LSTM, GRU and PSO-GRU methods.

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