Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 179 (2021) 480–487

Procedia Computer Science

www.elsevier.com/locate/procedia

5th International Conference on Computer Science and Computational Intelligence 2020

Forecasting Indonesia Exports using a Hybrid Model ARIMA-LSTM

Emmanuel Dave [a,*], Albert Leonardo[a], Marethia Jeanice[a], Novita Hanafiah[b]

[a]*Computer Science Department, School of Computer Science, Bina Nusantara University, Jakarta, Indonesia 11480*
[b]*Computer Science Department, BINUS Online Learning, Bina Nusantara University, Jakarta, Indonesia 11480*

Abstract

Export is an important factor that keeps the economy of a country going. Local export forecast guides government for a better policy making, local productivity measurement and international trade preparation. This research aims to provide governments with an accurate prediction of Indonesia's future exports by building an integrated machine learning model. This hybrid learning model is compared with individual learning models to obtain the most accurate model. The hybrid model integrates ARIMA and LSTM models based on their specialties, where LSTM was applied on the non-linear component of the data and ARIMA was applied on the linear component of the data. The hybrid (LSTM-ARIMA) model achieves the lowest error metrics among all the tested models. It succeeds to outperform the other standalones models, achieving a MAPE value of 7.38% and a RMSE of 1.66×10^{13}. Lastly, the entire dataset is used to train the final hybrid model to forecast Indonesia's exports one year ahead. This forecast can be used by government in guiding them in decision making to foster the future economy.

Keywords: forecast; exports; lstm; sarima; hybrid;

* Corresponding author. Tel.: +62-819-1119-0011;
E-mail address: emmanuel.dave02@gmail.com

1877-0509
10.1016/j.procs.2021.01.031

1. Introduction

For a developing country like Indonesia, one factor that keeps the economy growing is exports. All countries in the world are encouraging economic trade between countries. This will always involve the terms called exports and imports. Both are equally important, however forecasting exports can support government policy making, prepare human resources, act as a measurement of local productivity and prepare this country to compete internationally. Indonesia's economy experienced a sharp spike in the year 1998 after a recession. This is also reflected in the number of exports during that year, as it rose rapidly. In addition to that, the Export-Led Growth Hypothesis (ELGH) states that an increase in export is one of the main factors of economic growth.

A lot of methods are available for forecasting time series data. In this study, we are adopting the ARIMA model and Long Short-Term Memory (LSTM), as they are two of the most accurate and popular models in predicting time series. However, it is still unclear on which decomposition method is the most suitable for time series data. This research aims to experiment on the seasonal decomposition method commonly used for time series analysis. The outcome of this research can provide tools to support governments in leading this country in the international world and to contribute to the literature by adding an experience of our own with a hybrid model. It is expected that by constructing a hybrid model (LSTM and ARIMA), it can guide governments in taking future decisions to foster the economy.

2. Related Works

ARIMA has been widely used to make various predictions. Ghosh[5] used ARIMA to forecast cotton exports and resulted better prediction accuracy compared to Simple Exponential Smoothing (SES) and Holt Two Parameters Exponential Smoothing (HES). Fattah et al. [2] experimented with ARIMA for demand forecasting and they discovered that the ARIMA model requires large number of observations and estimations from ACF and PACF models to fit the model. After using the Box Jenkin's method with Autocorrelation and Partial Correlation, they found that the AIC is not the minimum value and non-linear residuals were found. [26, 6] Haviluddina and Jawahrib[7] compared the ARIMA model with a Radial Basis Function Neural Network (RBFNN) to predict tourists in Indonesia. The RBFNN is able to surpass ARIMA achieving 0.00098188 MSE. In addition to that, Adebiyi, Adewumi and Ayo[1] also compared the ARIMA model with the Artificial Neural Network (ANN) to forecast stock prices. Again, the ANN model had better prediction accuracy than the ARIMA model.

Suhartono[20] and Kongcharoen[13] experimented with ARIMAX in handling linear models and Neural Network with the non-linear models. ARIMAX has better prediction accuracy compared to ARIMA. Kim and Kim[12] also experimented with a hybrid model to predict stock prices. They called it a feature fusion LSTM-CNN model where they took the stock prices charts as input for CNN and times series data to the LSTM model. Stoean C, Paja W, Stoean R, Sandita A[19] also experimented with LSTM and CNN to predict stock prices and discovered that by improving from 2 layers to 3 layers of CNN didn't show a significant improvement based on MSE success criterion, however it costed almost twice the running time. On the other hand, when experimenting with LSTM they found that the improvement in performance from 2 to 3 layers is quite significant. Helmini, Jihan, Jayasinghe and Perera[8] improved the LSTM model by adding known features of the future to predict sales of drugs in Germany. Namini, Tavakoli and Namin[18] used different financial time series from Yahoo finance to compare how BiLSTM, ARIMA and LSTM performs. They discovered that a deep-bidirectional LSTM (BiLSTM) has better prediction accuracy compared to LSTM, however it has a slower training process. Selvin, Vinayakumar, Gopalakrishnan, Menon, and Soman also experimented with LSTM, CNN, and RNN to predict stock prices. The result was that the stock market prediction works best with CNN where it relies on the given current window for prediction. This enables the model to identify changes and patterns in the window on the other hand, LSTM and RNN are able to predict long-term predictions due to their dependency on past data.

Suhartono et al.[21] used hybrid models consisting of Singular Spectrum Analysis (SSA)-Time Series Regression (TSR)-ARIMA for water demand forecasting. SSA was used to decompose data into trend, seasonal and oscillatory components. Next, TSR is applied to model the trend component and ARIMA was used to model seasonal and noise components. These models were combined to achieve a better overall forecast prediction with 9.37 MAPE on the testing dataset.

Temur, Akgun, and Temur[24] applied a hybrid model to predict housing sales in Turkey. ARIMA was used to focus on the linear component of the time series and LSTM with the non-linear component. They proved that the hybrid model (LSTM-ARIMA) gives higher accuracy. Zhou, Zhao, Wu, Cheng and Huang[27] divided the time series, where ARIMA was used for the linear component and a non-linear Autoregressive Neural Network (NARNN) to model the non-linear component that exists in the residuals from the ARIMA model. They predicted the number of new admission inpatients. The sum of the predicted value from ARIMA and NARNN will be the final outcome. Khandelwal, Andhikari and Verma[11] used Discrete Wavelet Transform (DWT) to separate linear and non-linear components of the time series. They applied the model to 4 different datasets, in order to have a fair comparison. ARIMA is applied to the linear component and ANN to the non-linear component. Sunil, Satyanarayana, Acharya and Jogi[22] also tested the hybrid model (ARIMA-ANN) to forecast pricing sales of Jasmine flower in Bangalore, India and compared it with ARIMA, SARIMA, MLP (Multilayer Perception Model), ELM (Extreme Learning Machine) and NNETAR (Neural Network Auto Regression Model). The hybrid (ANN-ARIMA) indeed outperforms all of the other models. Gosasang, Chandraprakaikul and Kiattisin[4] compared traditional and latest techniques (neural networks) by predicting the number of containers in port. They discovered the MLP has the best result, however it has a slow training process compared to linear regression. Gijka, Ferrja and Kamberi[3] forecasted precipitation and water inflow for Fierza HPP. They used ARIMA to deal with the trend and seasonality, then the ETS (Error, Trend, Seasonal) model was used to give weights to the error, seasonality and the trend. Artificial Neural Network (ANN) is then applied to model the nonlinear component. Finally, a Least Square Support Vector Machine (LSSVM) is applied to approximate weights to ARIMA, ETS and ANN for the final result. Hasin, Ghosh and Shareef[5] forecasted the demand of noodles in a supermarket in Dhaka, Bangladesh by using a single ANN model. The ANN model outperformed the Box Jenkin's method. Omar, Hani, Van, Duen-Ren[16] also experimented with Hybrid ARIMA-BPNN for search popularity of article titles. ARIMA is applied to the linear model and Back Propagation Neural Network handled the non-linear data of the residuals from the ARIMA models. Ji, Zou, He, Zhu[9] made their hybrid forecasting model by combining ARIMA with a deep neural network combination model, CNN and LSTM, to predict future prices of carbon. They found out this hybrid model gives the best prediction accuracy.

Li, Ma and Yang[14] had a different take on hybrid models to predict monthly precipitation in two locations in China (Yan'an City and Huashan Mountain). They divided the time series using Variational Mode Decomposition (VMD) into several Intrinsic Mode Functions (IMF). Extreme Learning Machine (ELM) is then applied to each IMF. The predicted outcomes from each IMF are then accumulated to get the final prediction outcome.

Nanayakkara, Sajeeka and Vasana[15] experimented with Time Series and Neural Network to find out the Forecasting Exchange Rates. The model used in this case is ARCH Time series analysis and ANN was used as comparison. They found that Neural Networks always perform better compared to time series analysis.

Mustafa, Kamal, Bae, Sunghyun and Yun[10] had a different intake of a hybrid model in predicting the Baltic Dry Index (BDI). They assembled 3 RNN models (Deep RNN, LSTM and GRU). They called it the Deep Ensemble Recurrent Network (DERN). These state-of-the-art techniques have their own strengths and weaknesses. Therefore, the time series is applied to each of these models. The predicted outcomes were then inputted again to another learning process. The results of the ensemble outperformed all of the single models.

This research experiments on the widely used seasonal decomposition to validate whether it can be used as a tool to separate time series data into linear and non-linear data. The outcome of this research can contribute to the literature by offering a simpler model in decomposing time series data compared to the existing, complicated methods. In addition, it is observed from the literature that LSTM is best applied to non-linear data and ARIMA to the linear data. To test our decomposition method, the two most used time series models are implemented to the decomposed data.

3. Methodology

3.1 Data

Monthly Indonesian exports data was retrieved from the Federal Reserve Economic Data open-source website. The programme is coded using Python 3.6.10 and its open-source libraries. Exports from January 1998 to December 2019 were used. Validation set used the last 12 months. Data starting from 1998 is used because it is the start of the reformation era in Indonesia. Indonesia experienced a sharp rise in exports in that year. Data in its national currency over the years are represented in figure 1.

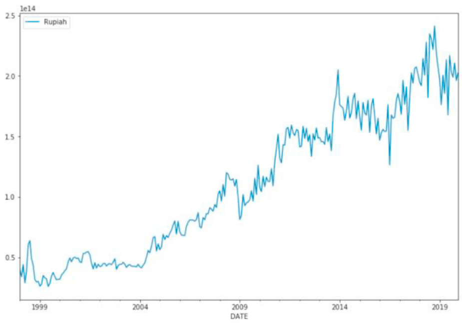

Figure 1. Indonesia exports in its national currency over the years

3.2 ARIMA

Several techniques are available to search for the best orders of ARIMA model. The Auto ARIMA method performs a grid search through all combinations of parameters at a given interval and selects a model with the minimum AIC (Akaike Information Criterion) value. Before applying Auto ARIMA to our model, a seasonal decomposition was conducted to test for seasonality behaviours in the dataset. After the decomposition, it is found that there are obvious seasonal patterns from the graph. Therefore, we set the seasonal parameter in Auto ARIMA to true, setting the seasonal cycle to 12 (12 months in a year).

3.3 LSTM

LSTM has a complex structure located in the hidden layer known as the memory block. It might contain more than 1 memory cell and each cell has a recurrent self connected linear unit called the Constant Error Carousel (CEC). It is responsible to solve the vanishing gradient problem. A memory cell is located beside the RNN cell, which allows memories from previous time frames to be collected and transferred into the next one. That is why LSTM is a well-known neural network due to its ability to cope with long term dependency. It is the optimal model for time series data. Since we have a long-range dataset from 1998, we are able to depend on LSTM to predict future exports.

3.4 HYBRID (ARIMA-LSTM)

ARIMA and LSTM both have their own strengths and weaknesses. ARIMA has difficulties with non-linear time series. On the other hand, neural networks can work with linear and non-linear time series data. However, they require long training time and there are no clear steps in choosing the perfect combination of parameters. Based on these factors, a hybrid model is implemented so that these models can work with their own expertise. The model is expected to give more accurate predictions compared to the individual models. The hybrid model can make models work together to overcome each other's weaknesses.[11]

By using seasonal decomposition that is available in the statsmodels library, time series data can be separated into trend, seasonality and residuals. The ARIMA model is applied into the trend component, while the LSTM model is applied to both seasonal component and residual component. The final prediction outcome is obtained by using equation (1).

$$prediction[i] = TRENDprediction\ [i] + SEASONALpredction\ [i] + RESIDUALprediction\ [i] \quad (1)$$

4. Results and Discussions

4.1 ARIMA

Last 12 months of the entire dataset were selected as the validation set. Considering a seasonal component, Auto ARIMA was executed, setting seasonal as true with $m = 12$ (12 months in a year). The model SARIMAX (1, 1, 0) x (1, 0, 0, 12) was obtained from the grid search as it has the minimum AIC value. Prediction with the selected model was then compared to the real validation set. The comparison is shown in figure 2.

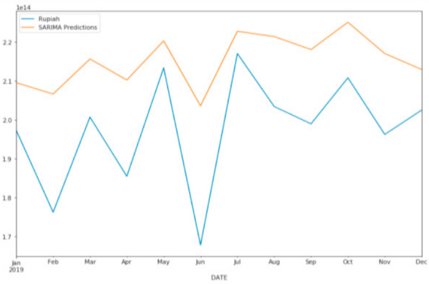

Figure 2. Comparison of prediction

After the graph is examined, the prediction is able to detect the trend of the real data. However, it does not overlap with any of the real data. In other words, there are no precise predictions. The model can still be deduced to have close predictions with a MAPE value of 9.38% and RMSE of 1.98×10^{13}. The RMSE value is still considered acceptable, considering that the mean of the validation set is far larger than the RMSE 1.97×10^{14}. The RMSE is 10% of the real dataset mean.

4.2 LSTM

Keras library was used to execute LSTM. Drawbacks of using LSTM is that it requires a lot of tuning to get the best set of parameters. The activation function used was the Rectified Linear Unit with 100 units. The model was trained with a different number of epochs and the model with the least error was selected as the final model.

The LSTM model reached a minimum error metrics at 1500 epochs with MAPE 8.56% and RMSE 1.90×10^{13}. Training was continued to check for a better model, however error metrics started to increase from there. A turnaround in error metrics signals overfitting. The 1500 epochs model was selected to predict future data. Predictions with 1500-epochs LSTM are shown in figure 3.

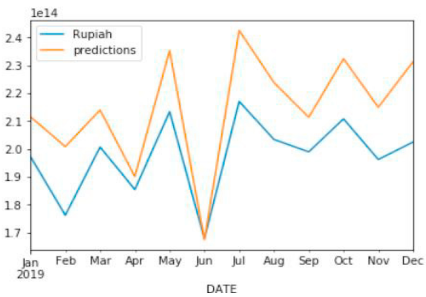

Figure 3. Prediction of the validation set using 1500 epochs on LSTM

By comparing the evaluation metrics of the LSTM and ARIMA, it can be deduced that LSTM performs better. LSTM is known to give better performance when it is trained using a lot of dataset. The neural network model took advantage of the large training set, therefore it gives better results compared to the ARIMA model.

4.3 Hybrid

To prepare the hybrid model, the time series was decomposed into trend, seasonality and residuals. It was achieved by using the seasonal decompose function available from the statsmodels library. Each of these components faced training of their own. Eventually, prediction results from all three components were accumulated for the final outcome.

The ARIMA model was fitted to this component, due to its linear behavior. Auto Arima was executed to get the optimal combination of parameters, setting the seasonality as false. The ARIMA model (0, 1, 2) had the minimum AIC value and it was used to predict one year ahead. The result is shown in figure 4.

Just by purely analyzing the graph, the model did not perform quite well. However, the predictions give a MAPE value of 3.48%. The value represents a good performance from the ARIMA model as it is relatively small. The seasonality component is trained with different numbers of epochs of LSTM to obtain the optimal value.

The MAPE value reached a minimum at 4000 epochs with MAPE value of 0.026% and RMSE of 5.99 x 10^8. Errors started to increase from here. The 5000 epochs model's MAPE value was relatively high compared to the other MAPE value. This is an indicator that the model is learning too much. Figure 5 compares the prediction results using 4000 epochs with the actual seasonal component.

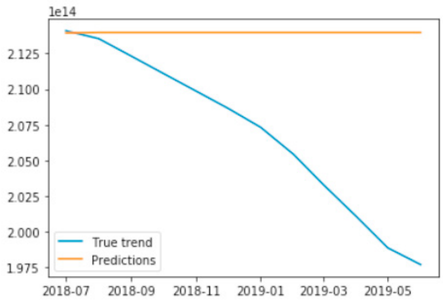

Figure 4. Prediction result using ARIMA model (0, 1, 2)

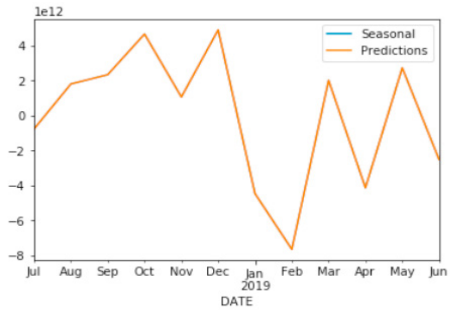

Figure 5. Prediction result using 4000 epochs

From figure 5, it is obvious that LSTM works best with non-linear data types. The MAPE value is under 1% and prediction outcomes are overlapping throughout the actual data. Similar steps were conducted to get the optimal LSTM model for the residual component.

The 2500-epochs model has the minimum errors with MAPE of 89.46% and RMSE of 1.42 x 10^{13}. Error metrics increased from 2500 epochs, signaling that the model started to overfit. Training was stopped and the 2500 epochs model was selected. Predictions from the 2500-epochs model is compared with the true value and is represented in figure 6.

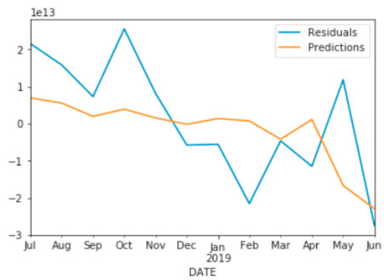

Figure 6. Comparison between predictions and true value

Predictions from all components were accumulated and the final prediction result is represented in figure 7.

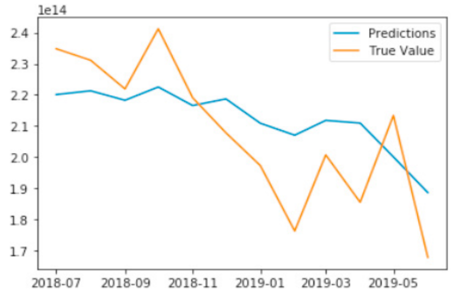

Figure 7. Result of final prediction

Table 1. Final prediction results

Model	MAE	MAPE	MSE	RMSE
SARIMAX(1, 1, 0) X (1, 0, 0, 12)	1.78×10^{13}	9.38	3.93×10^{26}	1.98×10^{13}
LSTM - 1500 epochs	1.72×10^{13}	8.56	3.63×10^{26}	1.90×10^{13}
HYBRID (ARIMA(0, 1, 2) - LSTM 4000 epochs – LSTM 2500 epochs)	**1.46×10^{13}**	**7.38**	**2.77×10^{26}**	**1.66×10^{13}**

According to the graphical representation and the error metrics, it can be concluded that the hybrid model with ARIMA (0, 1, 2), 4000-epochs LSTM and 2500-epochs LSTM performs better compared to the individual models. It is supported by the lowest MAPE value with 7.38% and RMSE of 1.66×10^{13}. The individual model has a slightly difference in their RMSE value. Meanwhile, RMSE drops significantly by approximately 2.4×10^{12}. From table 1, it is clear that the hybrid model ouperforms the individual models.

Export predictions using the hybrid model for Indonesia starting from July 2019 to June 2020 is represented in figure 8.

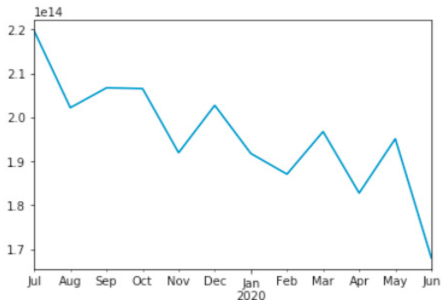

Figure 8. Predictions result using the hybrid model

5. Conclusions

Two of the most well-known time series prediction algorithms are merged to form the optimal model. The ARIMA model and LSTM model combined is able to give the lowest MAPE and RMSE value compared to the individual models. This is demonstrated by using monthly historical exports of Indonesia starting from 1998 and applying individual models and hybrid model for comparison of their prediction accuracy one year ahead. The LSTM model achieves 8.56% of MAPE and 1.90×10^{13} RMSE. The standalone ARIMA model achieves 9.38% of MAPE and 1.98×10^{13} RMSE. On the other hand, the hybrid model obtains a MAPE value of 7.38% and RMSE of

1.66×10^{13}, which is drastically less than the the individual models. This is inline to what is discussed in the literature where most hybrid models give out better accuracy compared to standalone models.

This research proves that the seasonal decomposition method successfully separates the time series data into linear and non-linear components. It adds another accurate decomposition method to the literature for others to implement. When ARIMA and LSTM models are added to the right component, it improves the accuracy of the entire model significantly. The result of the hybrid model can facilitate lawmakers in decision making, as it provides accurate predictions of Indonesa's exports a year ahead.

References

1. Adebiyi AA, Adewumi AO, Ayo CK. Comparison of ARIMA and Artificial Neural Networks Models for Stock Price Prediction. Journal of Applied Mathematics. 2014;2014:1–7.
2. Fattah J, Ezzine L, Aman Z, Moussami HE, Lachhab A. Forecasting of demand using ARIMA model. International Journal of Engineering Business Management. 2018;10:184797901880867.
3. Gjika E, Ferrja A, Kamberi A. A Study on the Efficiency of Hybrid Models in Forecasting Precipitations and Water Inflow Albania Case Study. Advances in Science, Technology and Engineering Systems Journal. 2019;4(1):302–10.
4. Gosasang V, Chandraprakaikul W, Kiattisin S. A Comparison of Traditional and Neural Networks Forecasting Techniques for Container Throughput at Bangkok Port. The Asian Journal of Shipping and Logistics. 2011;27(3):463–82.
5. Hasin MAA, Ghosh S, Shareef MA. An ANN Approach to Demand Forecasting in Retail Trade in Bangladesh. International Journal of Trade, Economics and Finance. 2011;:154–160.
6. Hatta HHM, Daud FM, Mohamad N. An Application of Time Series ARIMA Forecasting Model for Predicting the Ringgit Malaysia-Dollar Exchange Rate. Journal of Data Analysis. 2018;1(1):42–8.
7. 7..Haviluddina , Jawahir, A. Comparing of ARIMA and RBFNN for short-term forecasting. Comparing of ARIMA and RBFNN for Short-Term Forecasting.2015;1:1-8
8. Helmini S, Jihan N, Jayasinghe M, Perera S. Sales forecasting using multivariate long short term memory network models. 2019Aug;
9. Ji L, Zou Y, He K, Zhu B. Carbon futures price forecasting based with ARIMA-CNN-LSTM model. Procedia Computer Science. 2019;162:33–8.
10. Kamal IM, Bae H, Sunghyun S, Yun H. DERN: Deep Ensemble Learning Model for Short- and Long-Term Prediction of Baltic Dry Index. Applied Sciences. 2020;10(4):1504.
11. Khandelwal I, Adhikari R, Verma G. Time Series Forecasting Using Hybrid ARIMA and ANN Models Based on DWT Decomposition. Procedia Computer Science. 2015;48:173–9.
12. Kim T, Kim HY. Forecasting stock prices with a feature fusion LSTM-CNN model using different representations of the same data. Plos One. 2019;14(2).
13. Kongcharoen C, Kruangpradit T. Autoregressive Integrated Moving Average with Explanatory Variable (ARIMAX) Model for Thailand Export. 2013
14. Li G, Ma X, Yang H. A Hybrid Model for Monthly Precipitation Time Series Forecasting Based on Variational Mode Decomposition with Extreme Learning Machine. Information. 2018;9(7):177.
15. Nanayakkara, N V Chandrasekara,D M Jayasundara, D. Forecasting Exchange Rates using Time Series and Neural Network Approaches. European International Journal of Science and Technology. 2014;3:1-2
16. Omar H, Hoang VH, Liu D-R. A Hybrid Neural Network Model for Sales Forecasting Based on ARIMA and Search Popularity of Article Titles. Computational Intelligence and Neuroscience. 2016;2016:1–9.
17. Selvin S, Vinayakumar R, Gopalakrishnan EA, Menon VK, Soman KP. Stock price prediction using LSTM, RNN and CNN-sliding window model. 2017 International Conference on Advances in Computing, Communications and Informatics (ICACCI). 2017
18. Siami Namini, Sima & Tavakoli, Neda & Siami Namin, Akbar. (2019). A Comparative Analysis of Forecasting Financial Time Series Using ARIMA, LSTM, and BiLSTM.
19. Stoean C, Paja W, Stoean R, Sandita A. Deep architectures for long-term stock price prediction with a heuristic-based strategy for trading simulations. Plos One. 2019Oct;14(10).
20. Suhartono, Rahayu S, Prastyo D, Wijayanti D, Juliyanto. Hybrid model for forecasting time series with trend, seasonal and salendar variation patterns. Journal of Physics: Conference Series. 2017;890:012160.
21. Suhartono S, Isnawati S, Salehah NA, Prastyo DD, Kuswanto H, Lee MH. Hybrid SSA-TSR-ARIMA for water demand forecasting. International Journal of Advances in Intelligent Informatics. 2018Nov;4(3):238.
22. Sunil,Satyanarayana,Acharya S, Jogi AK. Application Of Hybrid Model For Forecasting Prices Of Jasmine Flower In Bangalore, India. 2019Nov11;
23. Tatinati S, Veluvolu KC. A Hybrid Approach for Short-Term Forecasting of Wind Speed. The Scientific World Journal. 2013;2013:1–8.
24. Temür AS, Akgün M, Temür G. Predicting Housing Sales In Turkey Using Arima, Lstm And Hybrid Models. Journal of Business Economics and Management. 2019Dec;20(5):920–38.
25. Wali VB. Forecasting of Area and Production of Cotton in India: An Application of ARIMA Model. International Journal of Pure & Applied Bioscience. 2017;5(5):341–7.
26. Wang T. Forecast of Economic Growth by Time Series and Scenario Planning Method—A Case Study of Shenzhen. Modern Economy. 2016;07(02):212–22.
27. Zhou L, Zhao P, Wu D, Cheng C, Huang H. Time series model for forecasting the number of new admission inpatients. BMC Medical Informatics and Decision Making. 2018;18(1).