JURNNAL MANAJEMEN DAN PERBANKAN (JUMPA)
Vol 11 Edisi 2 (Juni 2024, 1-11)

The Accuracy Forecasting of Cash Inflow and Cash Outflow Using Deterministic, Stochastic and Hybridization Models

Keakuratan Peramalan Uang Masuk (Inflow) dan Uang Keluar (Outflow) Menggunakan Model-Model Deterministic, Stochastic, dan Gabungan (Hybrid)

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DOI: 10.55963/jumpa.v11i2.628

Abstract - Time series forecasting is an essential feature in finance and banking activities. This study employs deterministic, stochastic, and hybridization models to forecast inflow and outflow of Bank Indonesia representative office in Aceh. Previous researches have shown that there were no standard models to forecast regular money requirement of Bank Indonesia. The proposed methodology in this research consists of two steps. The first step, classical models are used to analyze the linear part of inflow and outflow data. In the second step, a support vector regression model is applied to model the residuals obtained from the classical models. By using the given 210 observations, this research finds that the superiority of hybridization model is suitable to forecast inflow series and the simple individual classical model is appropriate to predict outflow series. In the context of net cash flow, the forecasted values approached the ideal feature of inflow and outflow series patterns.

Keywords: Deterministic, Forecasting, Hybridization, Inflow and Outflow, Stochastic.

Abstrak - Peramalan deret waktu merupakan suatu hal yang sangat penting dalam dunia perbankan dan keuangan. Dalam kajian ini menggunakan model deterministic, stochastics, dan model gabungan untuk memprediksi jumlah uang yang masuk dan jumlah uang keluar pada Bank Indonesia Kantor Perwakilan di Aceh. Pada penelitian sebelumnya menunjukkan bahwa tidak ada model yang standar untuk memprediksi jumlah kebutuhan uang pada Bank Indonesia. Metodologi yang diusulkan dalam penelitian ini terdiri dari dua langkah. Langkah pertama adalah, model-model klasik digunakan untuk memprediksi dan menganalisis bagian linier dari data. Pada langkah kedua, model support vector regression diterapkan untuk memodelkan residul yang diperoleh dari model–model klasik pada langkah pertama. Dengan menggunakan 210 observasi dari data yang tersedia, penelitian ini menunjukkan bahwa model gabuangan (hybrid) menunjukkan model yang terbaik untuk memprediksi jumlah uang masuk (inflow) dan model deterministic akurat untuk memprediksi jumlah uang keluar (outflow). Dalam kasus net cash flow, nilai-nilai ramalan ini memenuhi pola yang idial.

***Kata Kunci**: Deterministic, Hybridization, Inflow dan Outflow, Peramalan, Stochastic,.*

INTRODUCTION

There has been tremendous concern in developing forecasting models with high accuracy performance of time series data. It helps decision and policy makers to develop better future goals and objectives. One of the observed financial actions in time series data is cash inflow and outflow, where in the general statement of banking activities; it presents the deposit of money to bank and the withdrawal of money from bank. In Indonesia, cash inflow and outflow play a major role in supporting economic transaction in both national and regional level. The money circulation including cash inflow and outflow in commercial banks and community is regulated by Indonesian Central Bank (Bank Indonesia). As a central bank of Indonesia, Bank Indonesia has the objective to achieve and maintain the stability of Rupiah currency value[1].

[1] Source: Bank Indonesia (https://www.bi.go.id/en/fungsi-utama/moneter/Default.aspx)

The accuracy of money demand in each representative office of Bank Indonesia is beneficial for money requirement plan (MRP). Bank Indonesia designed such this MRP to control the inflow and outflow and other financial activities. Previous empirical researches about inflow and outflow at different regions in Indonesia have been studied with different time series models approach. Susanti, at al. (2018) for example, forecasted inflow and outflow of Bank Indonesia representative office in east java; Rachmawati et al. (2016) modeled inflow and outflow series of Bank Indonesia representative office in central java; at national level, Suhartono at al. 2019) applied time series model to forecast inflow and outflow of central Bank Indonesia. These findings indicate that the behavioural data patterns of inflow and outflow are vary in different representative office of Bank Indonesia. In addition, the empirical case studies of inflow and outflow of Bank Indonesia representative office in Aceh were rarely found in the literature.

In term of accuracy model, Bank Indonesia itself does not have a standard model to forecast money requirement regularly. Hence, this study contributes in enriching forecasting models of inflow and outflow series of Bank Indonesia, especially in representative office of Aceh province. Numerous time series forecasting models have been developed over the year, not only in financial issues but also in other multi-discipline knowledge ranging from natural sciences to social sciences. However, studies with reliable forecasting accuracy performance of inflow and outflow are rarely reported in majority literatures. This concern has motivated us to broadly study this area and boosted us to expansively contribute in the forecasting world. In this study we proposed deterministic, stochastic, and hybridization categories models to forecast inflow and outflow of Indonesian Central Bank, representative office in Aceh. The deterministic models comprises of holt and holt winter (HW), the stochastic models are represented by Subset ARIMA and support vector regression (SVR), and hybridization models, which is the combination of all deterministic and stochastic models. Generally, forecasting models refer to simple representation of data generating process of the real pattern. Deterministic and stochastic models are considered to be able to explain time series behavior properly. Besides, combination models are also powerful in improving the accuracy performance in many applications. The precedent of forecast accuracy is actually a challenging task and it avoid a conservative mindset among forecasters (Zhang, J. et al., 2015; and Papastamos, D., Matysiak, G. and Stevenson, S., 2016).

The problem statement of this research is the inflow and outflow data show the unpredictable behaviour of their patterns. Such this phenomenon is also considered as the problem in majority finance and banking data set. This research offers a spectacular method to overcome undetected pattern of these time series data by using hybrid method. More interestingly, the proposed hybrid model tends to capture a particular nuance of both linear and non linear nature of data pattern. Hence, this model is generally considered as one of an effective time series forecasting model. Actually, there are many other method can be implemented in financial issues, e.g. EGARCH model which was applied by Surya and Ikrima (2023) to analyze volatility spillover bitcoin, multivariate regression was used by Aang and Lufi (2022) to determine financial ratio. However, the methods involved in this research are limited to the three categories models (Deterministic, Stochastic, and Hybrid method).

LITERATURE REVIEW

In this research, we forecast the variables of inflow and outflow of Bank Indonesia in Aceh. The accuracy forecast of these variables is very essential. Bank Indonesia formulates the appropriate policies and decisions in controlling money circulation regularly. Therefore, the description of inflow and outflow in a certain location is highly required before decision and policies are made.

Many time series forecasting models have been intensively developed over the years. Classical models like random walk, autoregressive (AR), moving average (MA), holt and winter, and ARIMA are recognized statistically to predict the future observations of a time series on the basis of linear past values and white noise terms. These models impose the constraint of linearity data generating function. To anticipate this, non linear model like support vector regression model presents to enrich the forecasting accuracy in literatures.

Various empirical studies of the proposed models occur in many literatures for decades. For instance: Wu et al. and Yang (2016) used holt model to forecast pig price in China; Supriatna, A., Susanti and Hertini (2017) applied holt model for forecasting data population in West Java. As an extension of holt model, holt winter (HW) model recorded a remarkable forecasting accuracy under deterministic setting (Elmunim et al., 2016 and Dantas et al., 2017). In stochastic model, ARIMA is popular as a linear model and it has been widely used in time series forecasting. During the past few years, Calster et al. (2017) evolved evolutionary algorithm for ARIMA model in sales forecasting, whereas García et al. (2017) developed ARIMA model to forecast rare earth elements price. Due to complex system and high dimensional pattern of time series data, the non linear support vector regression (SVR) is famous and it has been extensively studied for many years. Guo et al. (2017) forecasted power demand using SVR, Tao et al. (2018) applied SVR model in predicting air conditioning load, and Nourali and Osanloo (2018) estimated mining capital cost using SVR model. They noticed that SVR model improved the forecast accuracy and it was a reliable model in stochastic framework. Another feature of time series modeling is the hybrid model. This model is appraised as a well known model in shrinking error in comparison to the individual models. The superiority of the hybridization model in the performance accuracy for various combination categories have been evinced by a number of authors at different time (Xuan et al. (2018); Büyüksahin and Ertekin (2019); Chen et al. (2018); Smyl (2020); and Abdolahi (2020)). In addition, the combination of linear and non linear models is considered able to increase the performance accuracy. The mathematical formulation of the proposed models is elaborated as follow:

A. Holt Model

Holt model is also known as double exponential smoothing with two parameters. This model involves the level of data series, trend, and smoothing parameters (Booranawong and Booranawong, 2018). The formula of Holt model is as follow:

$$L_t = \alpha y_t + (1-\alpha)(L_{t-1} + b_{t-1}) \quad (1)$$

$$b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1} \quad (2)$$

$$\hat{y}_{t+h|t} = L_t + hb_t \quad (3)$$

Where L_t is an estimate of the series level at time t, b_t is an estimate of the trend at time t, $\hat{y}_{t+h|t}$ is the h step ahead forecast, and α and β are the smoothing parameters with values between 0 and 1 for the level the level and the trend, respectively.

B. Holt Winter Model

As an extension of holt method, the holt winter (HW) model was designed to capture seasonality with three smoothing parameters. Holt Winter incorporated two variations to differ the behavior of seasonal component, namely multiplicative and additive method (Tratar and Strmcnik, 2016). In this study, multiplicative method is adopted to show the forecasting performance by using the following equation:

$$L_t = \alpha \frac{y_t}{S_{t-m}} + (1-\alpha)(L_{t-1} + b_{t-1}) \quad (4)$$

$$b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1} \quad (5)$$

$$S_t = \gamma \frac{y_t}{(L_{t-1} + b_{t-1})} + (1-\gamma)S_{t-m} \quad (6)$$

$$\hat{y}_{t+h|t} = (L_t + hb_t)S_{t-m+h_m} \quad (7)$$

Where m is the length of seasonality, L_t is a level equation, $b_t$is the trend equation, and S_t is seasonal equation. The smoothing parameters are $\alpha, \beta, \text{and} \gamma$which is restricted to between 0 and 1. The forecast equation is marked as $\hat{y}_{t+h|t}$with h is step ahead forecast.

C. Subset ARIMA Model

Autoregressive integrated moving average (ARIMA) model is very popular and widely used in time series forecasting. ARIMA model requires a stationarity condition to ensure the mean and covariant are constant over time. Consequently, differencing method *d* is applied to overcome non stationary series. A specific form of a general ARIMA model with irregular pattern is called subset ARIMA. This model includes parameters for only certain lags, hence it cannot be written in general form (Tarno et al., 2012). A general ARIMA (*p,d,q*) model and a particular example of subset ARIMA ([1,5],0,[1,9]) model with $d = 0$ can be mathematically formulated as in Eq. (8) and Eq. (9), respectively.

$$x_t = \sum_{1}^{p} \emptyset_i \, x_{t-i} + \varepsilon_t - \sum_{1}^{q} \theta_j \, \varepsilon_{t-j} \tag{8}$$

$$y_t = \emptyset_1 y_{t-1} + \emptyset_5 y_{t-5} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_9 \varepsilon_{t-9} \tag{9}$$

Where $x_t$and y_t are the actual values, $\emptyset_i(i = 1,2,\cdots,p)$ is the general autoregressive coefficients, $\theta_i(j = 1,2,\cdots,q)$ is the general Moving Average coefficients, $\emptyset_1$ and $\emptyset_5$ are Autoregressive coefficients at lag-1 and lag-5, θ_1 and θ_9 are Moving Average coefficients at lag-1 and lag-9, and ε_t is a white noise process.

D. Support Vector Regression Model

Support vector regression (SVR) is a learning algorithm that tolerates the errors through an accepted margin error and tuning rate. For *n* records of sample training data, $\{x_i, y_i\}, (i = 1,2,\cdots,n)$, then $x_i \in \mathbb{R}^d$ is recognized as the input vector with *n* dimension and $y_i \in \mathbb{R}$ is denoted as the corresponding output vector. Hence, the training data x_i is mapped into the high dimensional optimized hyperplane. This mapping represents the non linear relationship between input and output vector (Al-Musaylh et al., 2018). The SVR function can be mathematically formulated as follow:

$$f(X) = \omega \cdot \Phi(X) + b \tag{10}$$

Where the ω is the weighted vector, b is constant, and $\Phi(X)$ denotes the mapping function. From Eq. (10), ω and b are obtained by minimizing the following function:

$$\text{Minimize} \quad \frac{1}{2}\|w\|^2 + C\frac{1}{N}\sum_{i=1}^{N}(\xi_i, \xi_i^*) \tag{11}$$

$$\text{Subject to} \begin{cases} |y_i - (w, x_i + b)| \geq \varepsilon + \xi_i \\ \langle w, x_i \rangle + \mathrm{b} - y_i \leq \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \geq 0 \end{cases} \tag{12}$$

Where C is the parameters that trades off the error between training data and the hyperplane space, ε is the relaxation variable, $\xi_i$and $\xi_i^*$are non negative slack variable. A non linear regression function of SVR is obtained by applying the Lagrangian multipliers and optimizing conditions. Hence, it is written as

$$f(X) = \sum_{i=1}^{i=N}(\alpha_i - \alpha_i^*)K(x_i, x_j) + b \tag{13}$$

Where $\alpha_i \text{and} \alpha_i^*$ are Lagrangian multipliers, $K(x_i, x_j)$ is the non linear kernel function that maps the training data into a high dimensional space. The popular kernel function which is suit to address a non linear relationship problem is Gaussian Radial Basis function. This function is defined as:

$$K(x_i, x_j) = \exp\left(\frac{-\|x_i - x_j\|^2}{2\sigma^2}\right) \tag{14}$$

Where x_i is the input variable in the i^{th} dimension and x_j is the training sample in the j^{th} neuron of the pattern layer with the kernel width σ.

E. Hybridization Model

Combining time series models is aimed to capture the different aspects and characteristics of the data in a real circumstance. The most popular combination of time series forecasting model is Zhang hybrid model (Zhang, 2003). This model consists of linear and non linear component. In this study, we adopt this concept with a slightly different by avoiding the sequential structure of linear and non linear components. The proposed hybrid model is also called additive method consists of two stage, the first stage can be a linear model and the second stage can be a non linear model or vice versa. The composition of the proposed model consist of

$$y_t = f(A_t, B_t) = A_t + B_t \tag{15}$$

Where A_t denotes the first individual model and B_t denotes the second individual model. The residual from the first model A_t, (e.g. $\varepsilon_t = y_t - \hat{A}_t$), where $\hat{A}_t$ is the forecast values from the first individual model, is then remodeled by using the second individual model B_t. Let $\hat{B}_t$ is the forecast values of B_t, then the structure of hybridization model can be written as

$$\hat{y}_t = \hat{A}_t + \hat{B}_t \quad (16)$$

This hybrid model is considered able to capture the different behavioral pattern of the data.

RESEARCH METHOD

Dataset

The monthly datasets of inflow and outflow of Indonesian Central Bank (Bank Indonesia) representative office in Aceh are used in this study[2]. Inflow is the deposits from other commercial banks to Bank Indonesia, whereas outflow is withdrawal from Bank Indonesia to other commercial banks. These datasets, recorded in trillion IDR, are applied to demonstrate the effectiveness of the proposed three categories time series models–deterministic, stochastic, and hybrid models. The totals of 210 observations starting from the period of January 2003 to June 2020, these two datasets are plotted in Figure 1.

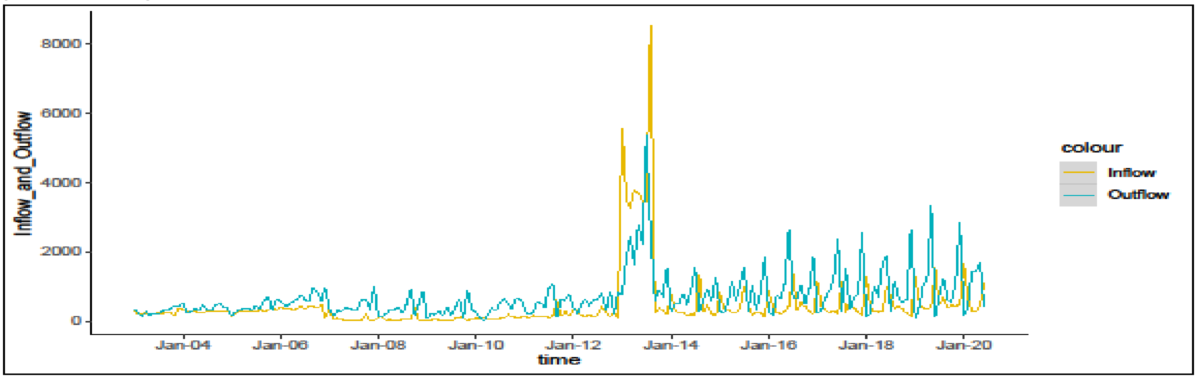


Figure 1. Actual Inflow and Outflow Series

Source: Minitab output of Inflow and Outflow actual data

Figure 1 plots the actual values of inflow and outflow (in trillion IDR) of Bank Indonesia representative office in the province of Aceh, started from January 2003 to June 2020. In general, the cash inflow and outflow oscillate fluctuatively over the given period. Although they sharply increased in 2013 due to the effect of Islamic great days as well as huge government projects payment, but starting in 2014 the patterns are fluctuated normally.

Methodology

There are three categories of time series models proposed in this study, deterministic, stochastic, and hybridization. Each data set is analyzed separately by applying these three model categories. In deterministic and stochastic categories, each individual model is built and the forecast values are computed, then the given model is evaluated separately. In hybrid model, the residual obtained from the first individual model is then remodeled by using the second individual model. This step is repeated for all possible combinations.

The procedure of data analysis in this research is performed by using several softwares. Deterministic models like holt and holt winter is analysed by using R software. The stochastic subset ARIMA and support vector regression are respectively modelled by using SAS and R softwares. At the end, the combination model is calculated manually with the support of MINITAB software graphical plotting.

The inflow and outflow series are divided into training data (204 of 210 observations) and testing data (6 of 210 observations). The training data is used to estimate any parameters of the forecasting models and the testing data is used to evaluate their performance accuracy. The training data is started from January 2003 to December 2019 and the rest of it, correspond to first quarter (Q1) and second quarter (Q2) of 2020, is used to assess the forecasting performance of the given models. For evaluating the forecasting accuracy performance, two forecast error measures are used, root mean

[2] Inflow and outflow dataset can be found at https://www.bi.go.id/en/statistik/sistem-pembayaran/indikator-pengedaran-uang/Contents/Default.aspx

square error (RMSE) and the Mean Absolute Percentage Error (MAPE). These two equations are quiet often used in the literatures (e.g.: Zhu et al., 2018 and Li et al., 2018), and they can be expressed as

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{y}_t - y_t)^2} \qquad (17)$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{\hat{y}_t - y_t}{y_t}\right| \times 100\% \qquad (18)$$

Where N is the length of forecast horizon, $\hat{y}_i$ is the forecasted value for time *t*, and y_t represents the actual data value at time *t*. To accomplish the comparative analysis, the following five time series models are introduced to demonstrate the performance accuracy of time series forecasting models. The accurate models are selected on the basis of the models with the lower error.

FINDINGS AND DISCUSSION

The Accuracy Performance of Inflow and Outflow

The measurement accuracy performances of RMSE and MAPE results indicate the possible models can be selected to forecast the future inflow and outflow values.

Table 1. Performance Accuracy of Inflow Series

Model Category	Time Series Model	RMSE	MAPE
Deterministic	Holt	549.67	49.59
	Holt winter (HW)	357.85	64.08
Stochastic	Subset arima	503.80	34.45
	SVR	514.60	52.04
Hybridization	Holt-HW	750.75	62.45
	Holt-subset_arima	711.64	58.39
	Holt-SVR	682.64	45.36
	HW-holt	672.33	43.87
	HW-subset_arima	465.84	39.84
	HW-SVR	528.75	52.12
	Subset_arima-holt	653.00	43.30
	Subset_arima-HW	668.58	46.29
	Subset_arima-SVR	619.58	46.04
	SVR-holt	672.33	43.87
	SVR-HW	356.05	63.00
	SVR-subset_arima	590.48	52.96

Source: Analysis result of inflow series

Table 1 reports the forecasting performance accuracy of inflow series. The RMSE is recorded in trillion IDR and the MAPE is recorded in percentage. These measurements applied to the three models developed (deterministic, stochastic, and hybridization). The lowest RMSE and MAPE value indicates the better performance accuracy.

Under deterministic category of inflow series, holt winter (HW) model produced better forecast accuracy than does Holt model. The holt winter model reduced the error over holt model of 53.6% for RMSE, unfortunately, it has a poor MAPE value. For stochastic category, Subset ARIMA model managed to decrease the RMSE and MAPE over SVR model of 2.14% and 51%, respectively.

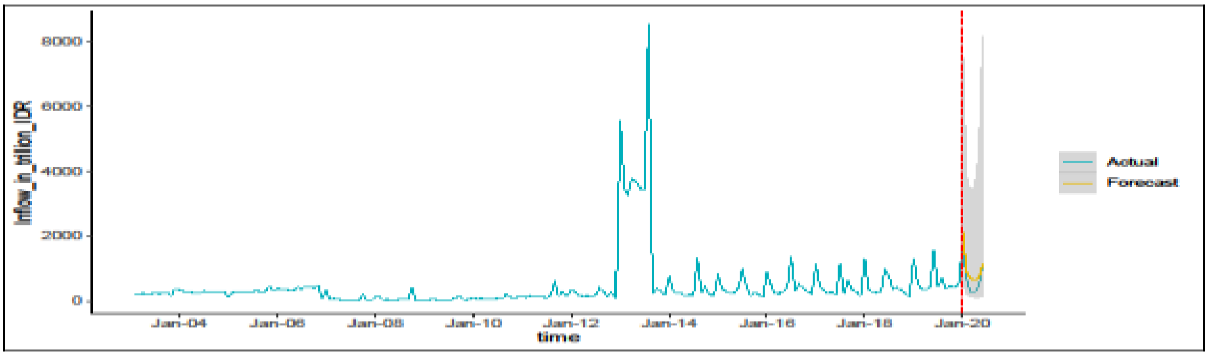


Figure 2. Actual and Forecasted Values of Inflow

Source: Minitab graphical plot of actual inflow vs its forecasted values

By applying the hybrid model, the lowest error is recorded by the combination of SVR-HW models. Although the MAPE of some other combination models are noticed small, the RMSE of these combinations are still high. Accordingly, the hybrid SVR-HW model was able to lift the performance accuracy in comparison to individual model of holt winter model in deterministic category and individual subset ARIMA model in stochastic category. In term of RMSE, this hybrid model was able to shrink error to 0.50% and 41.49% over individual holt winter and subset ARIMA models, respectively. On the basis of this evidence, the hybridization SVR-HW model is the parsimonious model of inflow series and will be used to forecast future values. The actual and the forecasted values of inflow series using this selected hybrid SVR-HW model is visualized in figure 2.

In similar fashion to inflow series, the measurement accuracy performances of RMSE and MAPE are recorded to analyze the performance of outflow series. The lowest RMSE and MAPE value indicates the better performance accuracy. Table 2 summarizes the forecasting performance accuracy of outflow series.

Table 2: Performance Accuracy of Outflow Series

Model Category	Time Series Model	RMSE	MAPE
Deterministic	Holt	719.66	180.65
	Holt winter (HW)	269.31	24.24
Stochastic	Subset arima	713.29	113.00
	SVR	597.84	64.79
Hybridization	Holt-HW	863.92	117.35
	Holt-subset_arima	735.43	134.84
	Holt-SVR	835.36	61.10
	HW-holt	633.10	96.53
	HW-subset_arima	920.71	103.28
	HW-SVR	699.27	82.98
	Subset_arima-holt	686.03	79.84
	Subset_arima-HW	883.13	44.54
	Subset_arima-SVR	586.22	99.18
	SVR-holt	635.65	96.29
	SVR-HW	817.04	122.58
	SVR-subset_arima	670.77	108.57

Source: Analysis Result of Outflow Series

Table 2 shows that the individual holt winter model of outflow series under deterministic category outperforms the individual holt model fantastically. This model diminished the error over holt model of 167.2% and 645.3% for RMSE and MAPE, respectively. In stochastic category, subset ARIMA model cut down 19.31% in RMSE and 74.41% in MAPE over SVR model. Under hybrid category, the smallest error of outflow series was recorded by hybridization model of subset ARIMA-SVR. When compared to the other individual models, the hybrid subset ARIMA-SVR model does not show better improvement of accuracy performance. However, the individual holt winter model of the outflow series is capable of improving the accurate forecast and it is selected as the model to forecast the future values. In term of RMSE, this individual Holt Winter model marked a noticeable improvement of the accuracy performance with 121.98% and 117.67% over individual SVR in stochastic category and Subset ARIMA-SVR in hybridization category, respectively. The plot of actual and forecasted values of outflow series is shown in figure 3.

In many literatures, the hybridization models, which is considered as a complex and sophisticated models, demonstrated a strong accuracy performance. In this study, the sequential structure of the hybrid model is nonlinear-linear structure. Although the sequent of linear-nonlinear structure of hybrid models developed in many literatures are also superior in improving accuracy performance, there is no universal agreement that claim the certain sequential hybrid structure should be applied in order to achieve high accuracy performance (Hajirahimi and Khashei, 2019). The selected hybrid SVR-HW model of inflow series has shown how the performance accuracy can be improved by applying combination model. Such this superiority of hybrid models have been recorded in the second finding of M4 Competition by Makridakis (Makridakis et al., 2020).

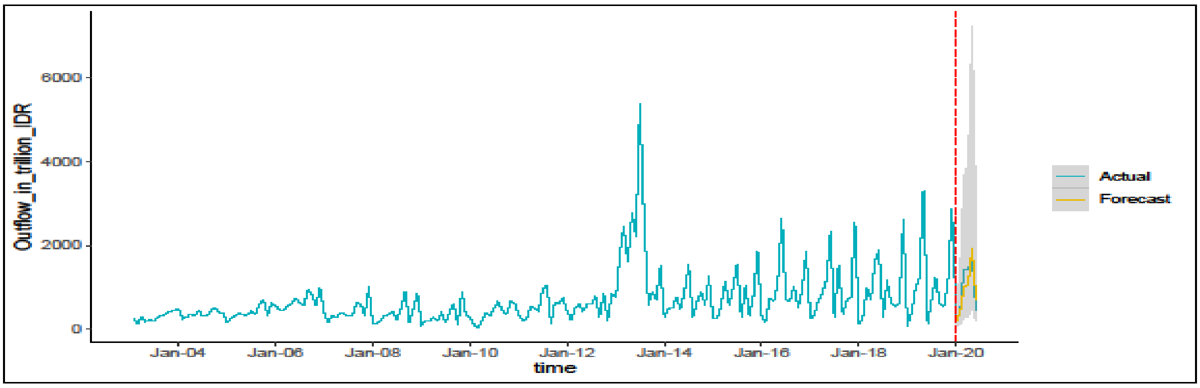


Figure 3. Actual and Forecasted Values of Outflow Series

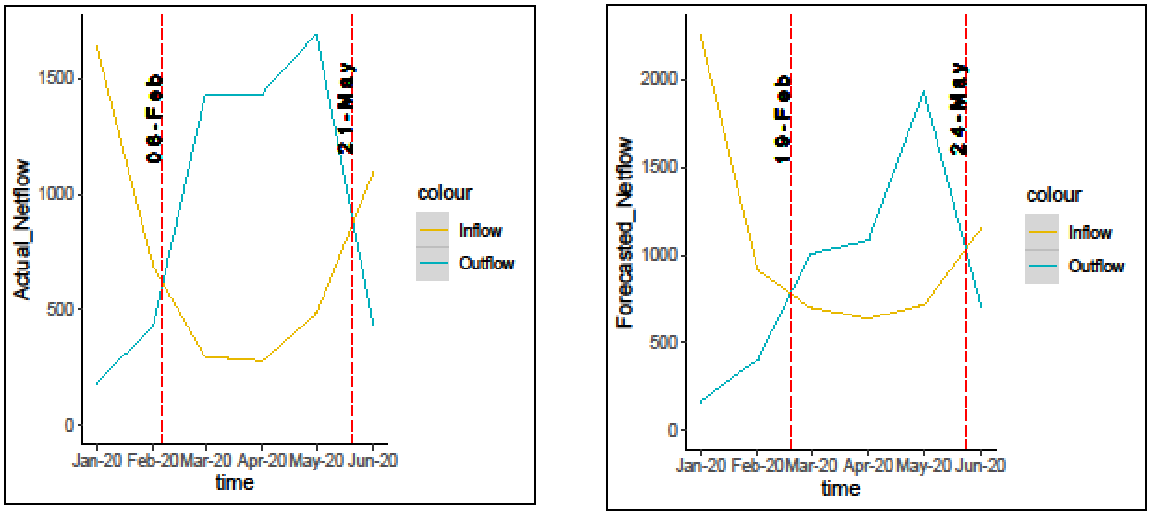
Source: Minitab graphical plot of actual outflow vs its forecasted values

Otherwise, the individual models in deterministic and stochastic categories are appraised as simple models. The selected holt winter model of outflow series has shown the improvement of accuracy performance. This empirical result directly supports the conclusion of M3 competition by Makridakis (Makridakis and Hibbon, 2000) which stated that statistically sophisticated or complex methods do not necessarily produce more accurate forecasts than simpler ones.

Net Cash Flow Analysis

Banking managerial will be assisted by having a well documented of cash flow during the specific period of time. As a regulator and a maintainer of payment system, Bank Indonesia continuously comply the needs of community cash requirement appropriately. Amid of the uncertainty of economic situation due to covid-19 outbreak, the sufficient cash available at Bank Indonesia representative office is very important. Bank Indonesia with net inflow will be able to gratuitously finance other commercial banks and community services in order to lift up the economic condition at provincial level.

The future values (forecast horizon) in this study are predicted for the 1st quarter (Q1) and the 2nd quarter (Q2) of 2020. Figure 4a and figure 4b show the actual net cash flow and forecasted net cash flow of Q1 and Q2 of 2020. From these plotted graphs (figure 4), it can be obviously seen that there are two periods of net inflow from actual net cash flow, i.e., periods of January to February in Q1 and June in Q2. Similarly, the forecasted net cash flow shows the net inflow in the periods of January to February in Q1 and June in Q2. There are no significant different of pattern between actual net cash flow and forecasted net cash flow. However, when large amount of money were going out from Bank Indonesia, the large gap between inflow and outflow (net outflow) appeared in actual and forecasted net flow around March (Q1) to May (Q2) 2020.



a **b**

Figure 4. Actual and Forecasted Values of Net Flow

Source: Minitab graphical plot of actual and forecasted values of net flow

Bank Indonesia recorded the actual net inflow at representative office in Aceh during the periods of January and February in the first quarter 2020 is 1.641,95 trillion IDR and 692.75 trillion IDR, respectively. The actual net inflow in the period of June in the second quarter of 2020 was recorded as 1.095,11 trillion IDR. By applying the selected forecasting models, the forecasted net inflow is predicted as 2.252,27 trillion IDR and 915.44 trillion IDR in the periods of January and February of the first quarter 2020, respectively. In the period of June in the second quarter, the forecasted net inflow is predicted as 1.153,1 trillion IDR. It can be seen from figure 4a and 4b, the pattern of predicted values shows smaller gaps between inflow and outflow for both actual net cash flow and predicted net cash flow. It is an indication that the forecasting modes developed in this study approached the ideal feature of inflow and outflow pattern of Bank Indonesia representative office in Aceh.

Overall, according to the research results above, it is revealed that our proposed models do not guarantee to perform well in sophisticated model inclusively. Holt winter model which is supposed as classical method in time series modelling was able to beat sophisticated stochastic and hybrid models for outflow series. When compared to others previous research in different areas of Bank Indonesia, the most accurate models are vary due to the difference behavioural data patterns of inflow and outflow data set in each region. It is evident that the scientific findings of M3 and M4 competition by Makridakis (Makridakis et al. 2000, 2020) confirm that the accuracy models depend on how far the developed models able to capture the linear and non linear structure in data. The novelty of these accurate forecast findings is beneficial for prediction inflow and outflow of Bank Indonesia, representative office in Aceh.

SUMMARY

The research area in time series forecasting is intensively studied in multi discipline knowledge over the past few decades. The development of forecasting models is essential for future prediction, however, the accuracy of the developed models are more important than that of just a model building process. One of the more significant findings to emerge from this study is that the accuracy model of inflow and outflow of Bank Indonesia representative office in Aceh are vary on the basis of accuracy performance measurements. Holt winter (HW) model is superior to holt model under classical individual deterministic category for inflow and outflow series. Under individual stochastic category, subset ARIMA model is more accurate than that of SVR model for inflow series, but SVR model is better than subset ARIMA model for outflow series. The superiority of hybridization models in achieving the accuracy performance of inflow series in comparison to other individual models shows the impressive result.

In contrast, simple linear deterministic model is a parsimonious model to predict outflow series. In term of net cash flow balance, the actual net cash flow and the forecasted net cash flow do not show the major differences. However, the gaps between inflow and outflow (net outflow) produced by the forecasted values are smaller than that of the gaps produced by the actual values. This finding may suggest that the models developed in this study are appropriate to forecast the future inflow and outflow values. Finally, to enhance the further accuracy performance of time series forecasting models, the different spectrum of combination structure models can be considered in an extension of this study.

REFERENCE

Abdolahi, H. (2020). A novel hybrid model for forecasting crude oil price based on time series Decomposition. *Applied Energy*, V. 267, 115035.

Al-Musaylh, M., Deo, R., Adamowski, J., & and Li, Y. (2018). Short-term electricity demand forecasting with MARS, SVR and ARIMA models using aggregated demand data in Queensland, Australia. *Advanced Engineering Informatics* , V. 35, P. 1–16.

Booranawong, T., & and Booranawong, A. (2018). Double exponential smoothing and Holt-Winters methods with optimal initial values and weighting factors for forecasting lime, Thai chili and lemongrass prices in Thailand. *Engineering and Applied Science Research*, V. 45(1), P. 32-38.

Büyüksahin, Ü., & and Ertekin, S. (2019). Improving forecasting accuracy of time series data using a new ARIMA-ANN hybrid method and empirical mode decomposition. *Neurocomputing* , V. 361, P. 151–163.

Calster, T., Baesens, B., & and Lemahieu, W. (2017). ProfARIMA: a Profit-Driven Order Identifcation Algorithm for ARIMA Models in Sales Forecasting. *Applied Soft Computing*, S1568-4946-30089-3.

Chen, S., Jia, R., Liu, J., & and Zhang, H. (2018). A Hybrid Wind Power Forecasting Approach Based on Bayesian Model Averaging and Ensemble Learning. *Renewable Energy*, V. 145, P. 2426-2434.

Dantas, T., Oliveira, F., & and Repolho, H. (2017). Air Transportation Demand Forecast Through Bagging Holt Winters Methods. *Journal of Air Transport Management* , V. 59 , p. 116-123.

Elmunim, N., Abdullah, M., Hasbi, A., & and Bahari, S. (2016). Comparison of GPS TEC Variations with Holt-Winter Method and IRI-2012 over Langkawi, Malaysia. *Advances in Space Research*, V. 60, P. 276-285.

García, M., Krzemień, A., del Campo, M., Miranda, C., & and Lasheras, F. (2017). Rare Earth Elements Price Forecasting by Means of Transgenic Time Series Developed with ARIMA Models. *Resources Policy*, V. 59, P. 95-102.

Guo, Q., Feng, Y., Sun, X., & and Zhang, L. (2017). Power Demand Forecasting and Application Based on SVR. *Procedia Computer Science*, V. 122, p. 169-275.

Hajirahimi, Z., & and Khashei, M. (2019). Hybrid Structures in Time Series Modeling and Forecasting: A Review. *Engineering Applications of Artificial Intelligence*, V.86, P. 83–106.

Li, Y., Che, J., & and Yang, Y. (2018). Subsampled Support Vector Regression Ensemble for Short Term Electric Load Forecasting, Energy. *PII: S0360-5442(18)31705-5*.

Liequan, L., Zubing, F., Junwei, Y., & and Dongmei, P. (2018). Xuan, Z., Xuehui, ZForecasting Performance Comparison of Two Hybrid Machine Learning Models for Cooling Load of a Large-Scale Commercial Building. *Journal of Building Engineering, PII: S2352-7102(18)30710-1*.

Makridakis, S., & and Hibbon, M. (2000). The M3-Competition: Results, Conclusions and Implications. *International Journal of Forecasting 16 (2000)* , 451–476.

Makridakis, S., Spiliotis, E., & and Assimakopoulos, V. (2020). The M4 Competition: 100,000 Time Series and 61 Forecasting Methods. *International Journal of Forecasting, V.36*(Issue 1, Jan–March 2020), P.54-74.

Nourali, H., & and Osanloo, M. (2018). Mining Capital Cost Estimation Using Support Vector Regression (SVR). *Resources Policy*, V. 62, P. 527-540.

Papastamos, D., Matysiak, G., & and Stevenson, S. (2016). Assessing the Accuracy and Dispersion of Real Estate Investment Forecasts. *International Review of Financial Analysis*, V. 42, P. 141-152.

Rachmawati, N., Setiawan, S., & Suhartono, a. (2016). Peramalan Inflow Dan Outflow Uang Kartal Bank Indonesia Di Wilayah Jawa Tengah Dengan Menggunakan Metode Arima, Time Series Regression, dan Arimax. *Jurnal Sain and Seni, ITS, eISSN:2337-3520*.

Smyl, S. (2020). A Hybrid Method of Exponential Smoothing and Recurrent Neural Networks for Time Series Forecasting . *International Journal of Forecasting*, V. 36, P. 75–85.

Supriatna, A., Susanti, D., & and Hertini, E. (2017). Application of Holt Exponential Smoothing and ARIMA Method for Data Population in West Java. *IOP Conf. Series: Materials Science and Engineering, 166, 012034*.

Surya, D., & and Ikrima, S. (2023). Analisis Volatily Spillover Bitcoin Terhadap Ethereum, Tether, dan Emas Dunia Menggunakan Metode EGARCH. *Jurnal Manajemen dan Perbankan (JUMPA), 10*(2), 47-60.

Susanti, A., Suhartono, Setyadi, H., Taruk, M., Haviluddin, & Widagdo, P. (2018). Forecasting Inflow and Outflow of Money Currency in East Java Using a Hybrid Exponential Smoothing and Calendar Variation Model. *Journal of Physics: Conf. Series 979 (2018) 012096*.

Syahdina, A., & I, L. (2022). Determination of Financial Ratios on Financial Performance Manufacturing Companies. *Jurnal Riset Akuntansi dan Auditing, 9*(3), 57-68.

Tao, Y., Yan, H., Gao, H., Sun, Y., & and Li, G. (2018). Application of SVR Optimized by Modified Simulated Annealing (MSA-SVR) Air Conditioning Load Prediction Model. *Journal of Industrial Information Integration, S2452-414X(18)30001-3*.

Tarno, Suhartono, Subanar, & and Rosadi, D. (2021). New Procedure for Determining Order of Subset Autoregressive Integrated Moving Average (ARIMA) Based on Over-fitting Concept. *IEEE*, P. 1-5, doi: 10.1109/ICSSBE.2012.6396643.

Tratar, L., & and Strmcnik, E. (2016). The Comparison of Holte Winters Method and Multiple Regression Method: A Case Study. *Energy*, V. 109, p. 266-276.

Wu, L., Liu, S., & and Yang, Y. (2016). Grey Double Exponential Smoothing Model and Its Application on Pig Price Forecasting in China. *Applied Soft Computing*, V. 39, p. 117–123.

Zhang, G. (2003). Time Series Forecasting Using a Hybrid ARIMA and Neural Network Model. *Neurocomputing*, V. 50, p. 159 – 175.

Zhang, J., Florita, A., Hodge, B., and Lu, S., Hamann, H., Banunarayanan, V., et al. (2015). A Suite of Metrics for Assessing the Performance of Solar Power Forecasting. *Solar Energy*, V. 111, p. 157–175.

Zhu, S., Lian, X., Wei, L., Che, J., Shen, X., Yang, L., et al. (2018). PM2.5 Forecasting Using SVR with PSOGSA Algorithm Based on CEEMD, GRNN and GCA Considering Meteorological Factors. *Atmospheric Environment, PII: S1352-2310(18) 30229-2*.