Comparison study of transfer function and artificial neural network for cash flow analysis at Bank Rakyat Indonesia

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ABSTRACT

The cash flow analysis is essential to examine the economic flows in the financial system. In this paper, the financial dataset at Bank Rakyat Indonesia was used, it recorded the sources of cash inflow and outflow during a particular period. The univariate time series model like the autoregressive and integrated moving average is the common approach to build the prediction based on the historical dataset. However, it is not suitable to estimate the multivariate dataset and to predict the extreme cases consisting of nonlinear pairs between independent-dependent variables. In this study, the comparison of using two types of models i.e., transfer function and artificial neural network (ANN) were investigated. The transfer function model includes the coefficient of moving average (MA) and autoregressive (AR), which allows the multivariate analysis. Furthermore, the artificial neural network allows the learning paradigm to achieve optimal prediction. The financial dataset was divided into training (70%) and testing (30%) for two types of models. According to the result, the artificial neural network model provided better prediction with achieved root mean square error (RMSE) of 0.264897 and 0.2951116 for training and testing respectively.

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1. INTRODUCTION

As the effect of global industrialization, mainly on the financial system, finance has been becoming a vital concern in the economic flows [1]. Finance includes budgeting, cash management, financial forecasting, credit, investment analysis, and also modern business analysis required to adopt technology that is suitable to the global environment [2]. Generally, finance can be classified into two categories i.e., public finance and private finance. Private finance includes firms, individual businesses, and corporate. Meanwhile, public finance concerns the disbursement and revenue related to the government such as state government, central government, and semi-government [3]. Several techniques are widely used to determine the operational and financial performance of the business activity such as comparative statement analysis (e.g., comparative income and position statement analysis), trend analysis, fund flow statement, common-size analysis, ratio analysis, and cash flow statement [4].

Cash flow analysis is essential because it can be used to determine the amount of money to run business operations and complete transactions. It records the sources of cash inflow and the use of cash outflow during a particular period such as cash assets, near-cash assets, current liabilities, and notes receivable [5]. Generally, the forecasting method in cash prediction uses time series techniques that create models by capturing patterns in historical data and extrapolating these patterns into the future [6]. There are several models of time series forecasting such as linear time series models, regression, and exponential smoothing [7]–[9]. However, those models have limitations, for example, in the linear time series model, the pair of independent and dependent variables are assumed linearly correlated, whereas many financial cases are non-linear [10]. Furthermore, in the regression model, it is broadly reported that this model requires the basic assumption i.e., normality in residual, no multicollinearity, and homoscedasticity [11], [12]. Afterward, exponential smoothing, this model also has a lagging effect and requires the updated actual cash flow regularly [13]. Another conventional model widely used for financial forecasting is the Box-Jenkins model known as autoregressive integrated moving average (ARIMA) [14], [15]. ARIMA essentially relies on the complete historical data to do forecasting, it is also relatively robust and efficient for short-run forecasting [16]. However, the ARIMA is not suitable to estimate the extreme cases consisting of a nonlinear relationship [17]. The transfer function includes the coefficient of moving average (MA) and autoregressive (AR) [18]. It is a time series approach that can explain the dynamic series case in the model prediction [19].

Recently, an artificial intelligence algorithm has also attracted many researchers and is extensively applied in forecasting models in many areas such as engineering, social, business, finance, stock problem, and weather prediction [20], [21]. To build a model using an artificial neural network (ANN) does not need to meet any basic assumption and can capture nonlinearity. In addition, ANN has the learning mechanism at the training process to minimize the error which becomes one of the main advantages of this algorithm to generalize result prediction based on the historical data and elaborate the latent part between input-output pair [22], [23].

In this paper, the comparison between machine learning ANN and classical parametric modeling (multi-input transfer function) was studied for cash flow analysis at Bank Rakyat Indonesia (BRI). Furthermore, the novelty of this study was also by the inclusion of four dummy variables i.e., i) day (1 to 30), ii) weekday (1 to 7), iii) holiday (0 or 1), and iv) month. The importance level of the independent variable and dummy variable examined using significance test were included here. In addition, the optimal model generated by the algorithm was also reported. This paper is organized as follows: the definition of cash flow analysis, model prediction using transfer function, and ANN are explained in section 2. Section 3 presents the analysis of the results. Finally, in section 4, we build our conclusion.

2. RESEARCH METHOD

The financial statement of BRI from July 2019 to September 2020 was used in this study accessed through the Kaggle board [24]. Table 1 summarizes all the parameters linked to the money flows at BRI. According to Table 1, there are nine parameters included in the historical financial dataset at BRI. In this study, the parameters in Table 1 were divided into the dependent and independent variables. The dependent variables included four variables i.e., *cash_in_echannel*, *cash_out_echannel*, *cash_in_office*, *cash_out_office*. Furthermore, the independent variables were all parameters in Table 1 other than those dependent variables. In addition, besides independent and dependent variables, the dummy variables were also added in this study such as day, month, weekday, and holiday.

Table 1. Explanation of all parameters linked to the cash flow at BRI

No.	Parameter	Description
1.	cash_in_echannel	Total cash inflow to cash recycles machine (CRM) and automated teller machine (ATM)
2.	cash_out_echannel	Total cash outflow from CRM and ATM
3.	cash_in_office	Total cash inflow to BRI
4.	cash_out_office	Total cash outflow from BRI
5.	current account	Total current account
6.	deposits	Total deposits
7.	other_liabilities	Investment other than current accounts, savings, and deposits
8.	savings	Total savings
9.	ave_weekly_dpk	Average of dpk's weekly balance
10.	day	Day 1 to 30
11.	month	July 2019 to September 2020
12.	weekday	Weekday 1 to 7 (1 for Sunday; 2 for Monday; 3 for Tuesday; 4 for Wednesday; 5 for Thursday; 6 for Friday; 7 for Saturday)
13.	holiday	Holiday and Non-Holiday (0 for holidays (not operating); 1 for effective days (operating))

In this paper, two kinds of models were used to assess the financial statement forecasting at BRI i.e., transfer function and ANN. The transfer function model was built using statistical analysis software (SAS) and ANN used IBM SPSS software. To build the prediction model using the transfer function or ANN, the dataset was divided into training (70%) and testing (30%). The training dataset was from July 31, 2019 to May 18, 2020 and the testing dataset used the BRI's financial statement from May 19, 2020 to September 30, 2020. This proportion of split was adapted from the work by Ulyah *et al.* [25] who compared some ratios of training and testing data and concluded that the highest accuracy of ANN was obtained in the ratio of 70:30.

2.1. Transfer function

The transfer function is a time series model which explains the dynamic characteristics of the series process. Herein, the transfer function model was used to estimate four dependent variables and all linked parameters to the cash flow at BRI (including the dummy variable), which was summarized in Table 1. The general formula of the transfer function used in this study can be written in (1) [26], [27],

$$\hat{Y}_t = \sum_{j=1}^{k} \frac{\omega_j(B)}{\delta_j(B)} B^{bj} X_{jt} + \frac{\theta(B)}{\phi(B)} \alpha_t \quad (1)$$

where,
$\hat{Y}_t$: predicted dependent variable
X_t : independent variable
$\omega(B)$: coefficient of MA with order s, where $\omega(B) = 1 - \omega_1 B - \omega_2 B^2 - \cdots - \omega_s B^s$
$\delta(B)$: coefficient of AR with order r, where $\delta(B) = 1 - \delta_1 B - \delta_2 B^2 - \cdots - \delta_r B^r$
$\theta(B)$: coefficient of MA with order q, where $\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$
$\phi(B)$: coefficient of AR with order p, where $\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p$
α_t : residual at t
r, s, p, q, and b are constant.

2.2. Artificial neural network

The ANN was used to predict four dependent variables for cash flow analysis in BRI during the period from July 2019 to September 2020 with total data points of 425. The architecture of ANN used in this study consisted of four layers i.e., one input layer followed by two hidden layers and one output layer, as depicted in Figure 1. The input layer included several nodes from the independent variables and dummy variables. All nodes from the input layer were connected to the nodes at the subsequent layer. As shown in Figure 1, two hidden layers were applied in this architecture. Then, the output layer consisted of four predicted dependent variables i.e., *cash_in_echannel* $(\hat{Y}_1)$, *cash_out_echannel* $(\hat{Y}_2)$, *cash_in_office* $(\hat{Y}_3)$, and *cash_out_office* $(\hat{Y}_4)$.

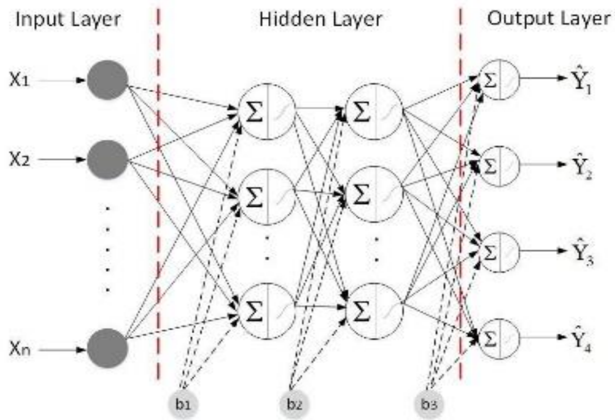


Figure 1. The architecture of the ANN model used in this study

In this study, the hidden layer and output layer used the tangential hyperbolic (tanh) as the activation function (Φ) determined in (2). The (3) to (5) are for the forward computation i.e., input layer to hidden layer $(\bar{h}_1)$, hidden layer to hidden layer $(\bar{h}_{p+1})$, and hidden layer to output layer $(\bar{o})$ respectively, where W is the weight matrix and $\bar{x}$ is the input vector. Furthermore, the backward computation from the output layer to the input layer is presented in (6), it is to update the weights through the learning process using the gradient of the loss function, where the loss function is symbolized as L, the connected weight from hidden unit h_{r-1} to h_r is $w_{(h_{r-1},h_r)}$, and the output is o [28].

$$\Phi(x) = \frac{e^{2x}-1}{e^{2x}+1}, \tag{2}$$

$$\bar{h}_1 = \Phi(W_1^T \bar{x}) \tag{3}$$

$$\bar{h}_{p+1} = \Phi\left(W_{P+1}^T \bar{h}_p\right) \forall_p \epsilon \{1 \dots k-1\} \tag{4}$$

$$\bar{o} = \Phi\left(W_{k+1}^T \bar{h}_k\right) \tag{5}$$

$$\frac{\partial L}{\partial w_{(h_{r-1},h_r)}} = \frac{\partial L}{\partial o} \cdot \left[\frac{\partial o}{\partial h_k} \prod_{1=r}^{k-1} \frac{\partial h_{1+k}}{\partial h_i}\right] \frac{\partial h_r}{\partial w_{(h_{r-1},h_r)}} \forall_p \epsilon \{1 \dots k\} \tag{6}$$

2.3. Model evaluation

In this study, the root mean square error (RMSE) calculated in (7) was used to evaluate the result from the two models i.e., transfer function and ANN. The predicted and observed dependent variable is denoted as $\hat{Y}$ and Y respectively. Then, the total number of observations is N. As explained before, the dataset was divided into training and testing processes with the total number of observations are 293 and 132 respectively.

$$RMSE = \sqrt{\sum_{i=1}^{N} \frac{(\hat{Y}_i - Y_i)^2}{N}} \tag{7}$$

3. RESULTS AND DISCUSSION

Table 2 summarizes the descriptive statistics from all variables linked to BRI's cash flow from July 31, 2019 to September 30, 2020. It consisted of the independent and dependent variables, the average, the maximum and minimum money flow, and the standard deviation. It was beneficial for the initial statistical analysis purposes.

Table 2. Descriptive statistics of all parameters linked to the financial statement at BRI

Variable	Parameter	Average (Rupiah)	Max (Rupiah)	Min (Rupiah)	Standard Deviation (Rupiah)
$Y_{1,t}$	cash_in_echannel	703.341.411,7647	3.744.400.000	0	342.185.918,984555
$Y_{2,t}$	cash_out_echannel	-699.203.294,1176	0	-2.670.100.000	373.507.578,335473
$Y_{3,t}$	cash_in_office	89.779.694.500,3	656.925.500.445	0	92.603.694.469,84
$Y_{4,t}$	cash_out_office	-62.862.353.977,7	0	-344.749.440.186	52.247.391.640,6855
$X_{1,t}$	current account	881.283.069.011,1	4.678.342.418.901,08	382.093.559.530,92	386.604.058.906,816
$X_{2,t}$	deposits	900.630.117.960,0	3.464.394.920.252	729.321.441.460	191.594.178.022,817
$X_{3,t}$	other_liabilities	13.765.019.988,40	47.590.591.383,56	10.080.295.595,6199	3.401.930.180,24512
$X_{4,t}$	savings	678.195.351.169,58	2.794.601.471.249,23	617.056.714.583,39	109.363.810.824,234
$X_{5,t}$	ave_weekly_dpk	309.217.338.523,2	451.620.877.687,121	254.411.463.022,328	37.614.262.501,333

3.1. Transfer function model

The financial statement from BRI was divided into training and testing datasets. The training dataset was used to build the transfer function model by including all the independent, dummy, and dependent variables. Table 3 shows the significance of all parameters required to generate the transfer function model. As shown in Table 3, every predicted dependent variable was affected by certain parameters, and not all the parameters were significant which was indicated by the P-value. The transfer model for predicted *cash_in_echannel* $(\hat{Y}_1)$, *cash_out_echannel* $(\hat{Y}_2)$, *cash_in_office* $(\hat{Y}_3)$, and *cash_out_office* $(\hat{Y}_4)$ were generated in (8) to (11) respectively. The transfer model for predicted *cash_in_echannel* $(\hat{Y}_1)$ was strongly affected by the independent variable of the current account shown in (8). Then, the transfer model for predicted *cash_out_echannel* $(\hat{Y}_2)$ was affected by two dependent variables i.e., deposits and *other_liabilities*, shown in (9). Furthermore, the transfer model for predicted *cash_in_office* $(\hat{Y}_3)$ was affected by the independent variable of the current account shown in (10). Finally, the transfer model for predicted *cash_out_office* $(\hat{Y}_4)$ was affected by the independent variable of savings shown in (11).

Table 3. Significant test results from all parameters to build the transfer function model

Transfer function model	Parameter	Estimate	P-Value	Conclusion
cash_in_echannel	μ	-950675112	0.1442	Not Significant
(b=0, r = 0, s = 2) ARIMA	ϕ_7	0.63924	<.0001	Significant
([1,7],[7])	θ_1	0.11465	0.0071	Significant
	θ_7	0.79782	<.0001	Significant
	ω_{10}	-0.0000353	0.9832	Not Significant
	ω_{11}	-0.0035181	0.0955	Significant
	ω_{12}	0.0009918	0.5505	Not Significant
cash_out_echannel	μ	1.04982E11	<.0001	Significant
	ϕ_1	0.09118	0.0217	Significant
MITF (b=1, r = 2, s = 2)	ϕ_7	0.80304	<.0001	Significant
(b=8, r = 0, s = 1) ARIMA	θ_1	0.0046551	0.7215	Not Significant
([1,7],[1,7])	θ_7	0.99534	<.0001	Significant
	ω_{20}	0.03218	0.0372	Significant
	ω_{21}	0.0062744	0.7890	Not Significant
	ω_{22}	-0.01060	0.6044	Not Significant
	δ_{21}	0.10445	0.7088	Not Significant
	δ_{22}	-0.81547	0.0010	Significant
	ω_{30}	-3.03614	0.0199	Significant
	ω_{31}	0.34128	0.7955	Not Significant
cash_in_office	μ	-637872059	<.0001	Significant
(b=8, r = 2, s = 2) ARIMA	ϕ_1	-0.13807	<.0001	Significant
([1,7],[7])	ϕ_7	0.84133	<.0001	Significant
	θ_7	0.99201	<.0001	Significant
	ω_{20}	0.00004724	0.4538	Not Significant
	ω_{21}	0.00002243	0.8309	Not Significant
	ω_{22}	0.00005089	0.4642	Not Significant
	δ_{21}	-1.76013	<.0001	Significant
	δ_{22}	-0.91038	<.0001	Significant
cash_out_office	μ	-7.1855E10	<.0001	Significant
(b=8, r = 2, s = 0) ARIMA	ϕ_1	0.76147	<.0001	Significant
([7],[7])	θ_7	0.99518	<.0001	Significant
	ω_{40}	0.01119	0.1952	Not Significant
	δ_{41}	0.24590	<.0001	Significant
	δ_{42}	-1.00000	<.0001	Significant

$$Y_{1,t} = (-0.0000353 - 0.0035181B - 0.0035181B^2)X_{1,t} + \frac{(1-0.11465B-0.79782B^7)\alpha_t}{(1-0.63924B^7)} \tag{8}$$

$$Y_{2,t} = \left(\frac{0.03218-0.00627B+0.0106B^2}{1-0.10445B+0.81547\delta_2 B^2}\right)X_{2,t-1} + (-3.0361 - 0.34128B)X_{3,t-8} + \frac{(1-0.00466B-0.99534B^7)\alpha_t}{(1-0.09118B-0.80304B^7)} \tag{9}$$

$$Y_{3,t} = \left(\frac{0.00004724-0.00002243B-0.00005089\omega_{22}B^2}{1+1.76013B+0.91038B^2}\right)X_{2,t-8} + \frac{(1-0.99201B^7)\alpha_t}{(1+0.13807B-0.84133B^7)} \tag{10}$$

$$Y_{4,t} = \left(\frac{0.01119}{1-0.24590B+1.00000B^2}\right)X_{4,t-8} + \frac{(1-0.99518B^7)\alpha_t}{(1-0.76147B^7)} \tag{11}$$

3.2. Artificial neural network (ANN) model

In the same way as the transfer function model, herein, the dataset used to build the artificial neural network (ANN) model was divided into two categories i.e., training dataset and testing dataset. Figure 2 depicts the importance or significance of the independent variables used to build the ANN model. As shown in Figure 2, the importance of the independent and dummy variables in order was saving, deposits, *other_liabilities*, weekday, holiday, *current_account*, *ave_weekly_dpk*, day, and month. Furthermore, the summary result of the ANN model is presented in Table 4. The sum of squares error (SSE) was used to evaluate the ANN model, based on Table 4, the SSE for training and testing were 20,560 and 11,496 respectively.

3.3. Comparison of transfer function and artificial neural network model

The RMSE was used to evaluate the transfer function and ANN model. Table 5 summarizes the RMSE from the two types of models. The training dataset was from July 31, 2019 to May 18, 2020 with 293 of the number of observations. The testing dataset was from May 19, 2020 to September 30, 2020 with a total number of observations of 132.

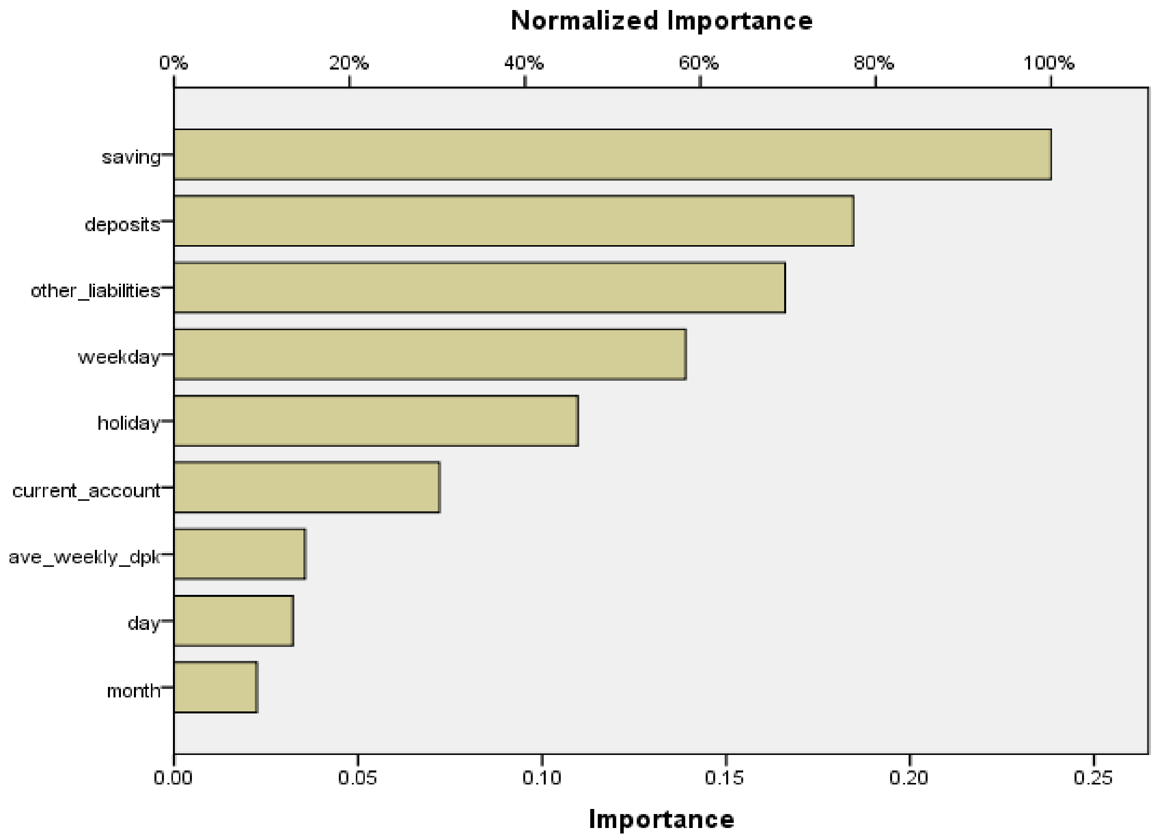


Figure 2. The importance of the independent variables used to build the ANN model

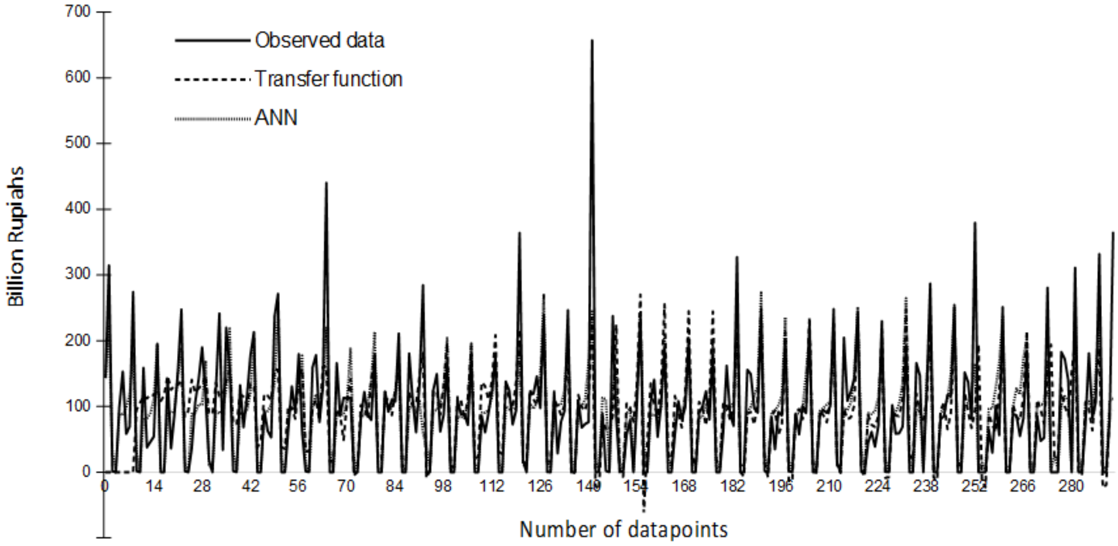
Table 4. Model summary result

Parameter		Training	Testing
Relative error for scale dependents	cash_in_echannel	0.721	1.054
	cash_out_echannel	0.480	0.806
	cash_in_office	0.378	0.435
	cash_out_office	0.303	0.444
Average overall relative error		0.426	0.588
Stopping rule used		1 consecutive step(s) with no decrease in error	-
Training time		12 seconds	-
Sum of Squares Error		**20.560**	**11.496**

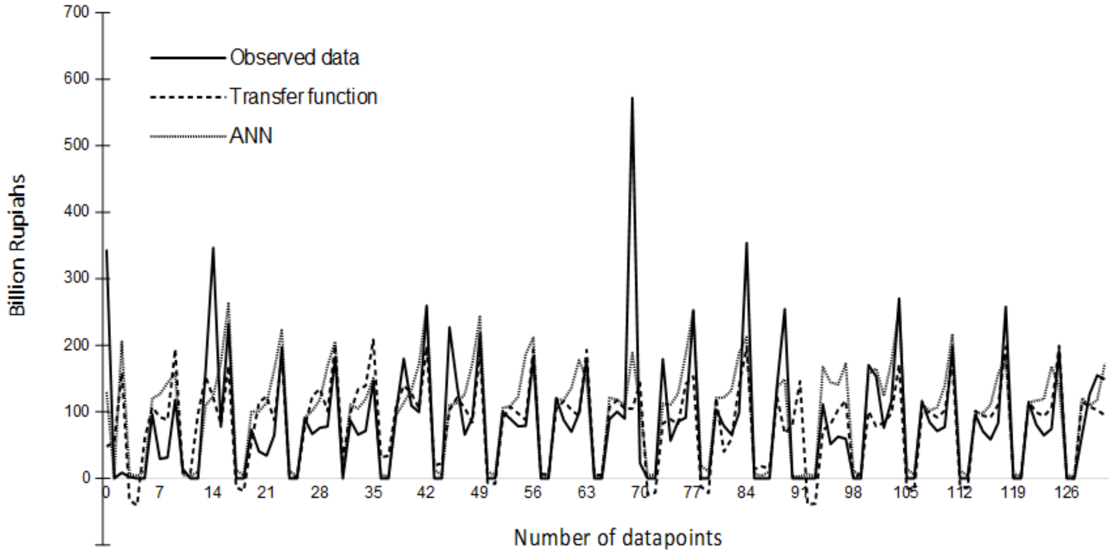
Table 5. The comparison between transfer function and ANN model

Model	RMSE	
	Training	Testing
Transfer Function	284,205,145.209827	319,686,051.63671
ANN	0.264897	0.2951116

The RMSE in Table 5 is the cumulative RMSE between the observed data $(i.e., Y_1, Y_2, Y_3, Y_4)$ and the predicted value $(i.e., \hat{Y}_1, \hat{Y}_2, \hat{Y}_3, \hat{Y}_4)$. According to Table 5, the numerical results of RMSE at the training and the testing were dropped significantly using the ANN model. Furthermore, Figure 3 demonstrates the comparison of the ANN model and transfer model to estimate the observed data of *cash_in_office* (Y_3) where Figure 3(a) describes the training stage and Figure 3(b) depicts the testing stage. According to Figures 3(a) and 3(b), overall, the ANN model estimated the observational data curve more accurately than the transfer function model. These results reveal that the ANN model has more favorable prediction capability than the transfer function does, it is mainly due to the ANN model including the learning process to adjust the weight to obtain the optimal prediction.



(a)



(b)

Figure 3. The comparison of two types of models to estimate the observed data of *cash_in_office*; (a) training process and (b) testing process

4. CONCLUSION

This paper successfully demonstrated the comparison study using the two types of models i.e., ANN and transfer function for cash flow analysis at Bank Rakyat Indonesia (BRI) from July 31, 2019 to September 30, 2020. In this study, besides including the independent variables and dependent variables provided by BRI, the dummy variables were also added to build the model. There was a total of 425 observational datasets which were divided into two stages i.e., training dataset and testing dataset with a total number of observations of 293 and 132 respectively. To build the transfer function model, all the significances of parameters were checked using P-value to obtain the optimal estimation. The transfer function model for predicted *cash_out_echannel* was strongly affected by independent variables of deposits and *other_liabilities*. Then, the transfer function model for predicted *cash_in_echannel* and *cash_in_office* was strongly affected by the independent variable of the current account. Furthermore, the transfer model for predicted *cash_out_office* was affected by independent variables of savings. The second model was ANN, herein, the importance of the independent and dummy variables was examined. The obtained high significance level in order was saving, deposits, *other_liabilities*, weekday, holiday, *current_account*, *ave_weekly_dpk*, day, and month, respectively. The RMSE achieved by the ANN model was 0.264897 and 0.2951116 for training and testing respectively. The comparison models between the transfer function and ANN were also analyzed. Based on the result, the achieved RMSE value for ANN dropped significantly. These findings indicate that the ANN has better prediction than the transfer function does. In the future study, we are concerned about using the ANN model by including several parameters to improve the current prediction model such as by adjusting the number of hidden layers, units, neurons, and the activation function.

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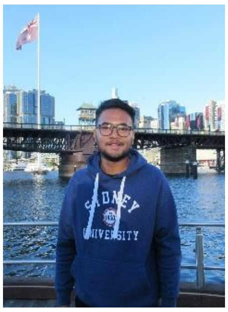

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