MODELLING NON PERFORMING LOANS (NPLs) IN ABC BANK SRI LANKA

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ABSTRACT

Despite the rapid growth in the banking sector in Sri Lanka, there is an increasing trend of NPLs in most of the Sri Lankan state banks including ABC bank. Therefore, the main purpose of this study is to develop a time series model to forecast the NPLs in ABC bank, while bridging the gap of developing novel model to forecast future NPLs. Based on the nature of the research objective it has been applied quantitative research methodology for the study. Secondary data on gross NPLs of ABC bank from fourth quarter of 2008 to fourth quarter of 2018 has been taken for the analysis and applied the technique of ARIMA as the main analytical tool. Moreover, MAPE and MAD have been used to check the accuracy of the fitted model. ARIMA (0,2,1) model was identified as the best fitted model to forecast the future NPLs in ABC bank after checking the accuracy through MAPE and MAD by using both training and validation datasets. According to the findings, the increasing trend of gross NPLs in ABC bank will continue in future and there will be nearly Rs. 64929.6 million of gross NPLs in this bank at the end of 2019. This is the only study which has been touched the area of forecasting NPLs in Sri Lankan context. Hence, it would provide insights to the rare literature, while enhancing the knowledge of financial forecasting. The study would be favorable to the management of ABC bank along with the Central Bank of Sri Lanka in order to mitigate the risk attached with NPLs.

Keywords: *ARIMA, MAD, MAPE, Non-Performing Loans, State Banks*

1 INTRODUCTION

The financial system of a country plays a major role in its economy. Maintaining financial system stability is one of two main objectives of the Central Bank of Sri Lanka (Central Bank of Sri Lanka, 2018).The banking sector is a major component of the whole financial system. In Sri Lanka, two licensed commercial banks and six licensed specialized banks continued to dominate the country's Banking sector accounting for almost 40 % of the total assets in the banking sector in 2017. The state banks accounted for 32 % of branches out of the total branch network in the banking sector in the country facilitating the government policy by ensuring better financial accessibility and inclusiveness (Ministry of Finance Sri Lanka, 2017).

The increasing trend in Gross Non Performing Loans (NPL) of Banking Financial Institutions in Sri Lanka is remaining for the last ten years. On the contrary, Central Bank of Sri Lanka (2018), has revealed further regulations need to be protected from an increase in NPL. Unexpected increases in NPL require banks to increase provision for loan losses, which tends to reduce a bank's profitability, thereby threatening its financial soundness (Greenidge & Grosvenor, 2010). However, recent practical examples show the banking sector is important in the stability of the whole financial system (Central Bank of Sri Lanka, 2017). Among these banking financial institutions, public or the state sector banks are the major players of the financial system, as well as the performance of public banks, were affected by a huge portion of NPL (Alamelu & Chandran, 2018). In fact, the problem of NPL is not limited only to one specific economy but prevails in the entire banking industry (Kumarasinghe 2017; Selvarajan & Vadivalagan, 2013).Therefore, having an earlier action for future problematic loans are significance in future industry performance as well.ABC bank has reported the highest average NPL out of state banks in Sri Lanka for the last six years thus, considered as the most problematic. The study was undertaken based on three main objectives. First, to develop a time series model to forecast NPL in ABC bank. Second, validating the developed model and third, to forecast the gross amount of NPL in ABC bank in future.

The significance of conducting this research will be helpful to recognize the level of NPL prior to arise them and to understand what will be the relevant loan loss provisions regarding NPL. An excellence projection of the future lets the managers and professionals invest only in the facilities, equipment, materials, and staffing required (Hyndman, 2009). Therefore, this will be supported to generate ideas on the level of NPL should be made and how much to develop the strategies. Further, helpful to policymakers in the banking industry as well as the top management and regulatory authorities of the bank to set up new policies for future developments. Forecasting is common and important in strategic decision making since it helps in clarifying decision makers on information about future events.Most of the researchers concentrated on multivariate modelling in the case of NPL since they are essentially driven by the factors external to its past (Greenidge & Grosvenor, 2010).However, this paper offers an opportunity to apply univariate forecasting to NPL for the first time. Earlier, Graham & Humphrey (1978) argued that using data only on past loans provides more accurate predictions than less parsimonious models. Generally, the behavior of NPL is not independent from its previous time period and might necessarily, attached with preceding NPL as well. On the other hand, ARIMA models are essentially "backward looking" and assume that past values of a time series plus previous error terms contain information for the purpose of forecasting (Meyler, Kenny, & Quinn, 1998). Here, NPL is forecasted based only on their past behaviour without concerning the external factors and the significance of conducting this research would address a new aspect of financial forecasting in Sri Lanka.

2 LITERATURE REVIEW

Meeker & Gray (1987) was given the first opportunity to assess bank asset quality in form of non-performing assets in the United States. Further, NPL has been identified in individual bank level as well as the aggregate level. Recently a study was done by Ozili (2019) to discuss the influence of financial development on aggregate NPL across the globe. To analyze the association between NPL and financial development, the researcher used two data sets. Regional graphical analysis and global empirical analysis of 2003 to 2014-time period was developed through cross country and regional data. The researcher has found that NPL are positively associated with financial development with the presence of financial intermediation and foreign banks. Therefore, believe that this had happened due to weak supervision of lending standards of banks and other non- banking financial institution.

Sri Lankan financial sector is not an exception on NPL. Similar as previously discussed, in Sri Lanka, furthermost studies have done with related to elements or the contributing factors of non-performing loans. Recently, Kumarasinghe (2017) has discussed on determinants of NPL in Sri Lanka by analysing secondary data. But the scope of this research has limited to explore the determinants of macroeconomic variables. The time series data were taken into the study over the period of 1998–2014. This comes under a correlational study which was an attempt to identify the relationship between the macro-economic determinants of NPL in Sri Lanka. Data that is taken to study was analysed using Ordinary Least Square (OLS) method of regression. Out of six determinants, GDP growth rate and Export growth rate were statistically significant. Previously, Ekanayake & Azeez (2015) have evaluated the determinants of NPL in the public commercial banks, large private commercial banks and small private commercial banks in Sri Lanka by looking at both bank-level data and macroeconomic indicators over the period of 1999–2012. Same as the previous research, this research also comes under correlational study which revealed that NPL tend to increase deterioration with bank efficiency. Among the macroeconomic variables, GDP growth rate, and Inflation has a negative correlation while Prime lending rate has a positive correlation. Additionally, bank-specific variables displayed that NPL vary negatively on credit growth and bank size and Loan to asset ratio vary positively on NPL. NPL is identified as a major threat to banking sector in Sri Lanka by

Kousthupamany (2015). Determinants of NPL in commercial banks in Batticalo district in Sri Lanka were identified by using qualitative methodology. Poor business knowledge and management skills of borrower's have to be identified as the main reason for NPLs. In addition to that, difficulties in obtaining proper data from customer as poor record maintenance by customer, Over/under financing for the project by the bank, lack of tight credit monitoring, willful defaulter, fund diversion by the customer for unprofitable source ascribe identified as the causes of NPLs in Batticalo district. Moreover, NPL has been discussed indirectly in various scenarios as profitability determinants in banking industry. In Sri Lanka, Weerasinghe & Perera (2013) has focused on the determinants of profitability of commercial banks in Sri Lanka using bank specific and macroeconomic determinants. Under the bank specific determinants, they focused on credit risk and it measured through NPL.

When discussing ARIMA model in unvariate time series forecasting, it was popular in the cases of financial and econometric time series. Not similarly with NPL, nonetheless in other financial time series equally, inflation (Abdulrahman, Ahmed, & Abdellah, 2018; Jesmy, 2013; Franses, 2018), exchange rates (Ngan, 2016; Olanrewaju, Olakunle, & Emmanuel, 2014), neutrality of money (Ekomie, 2018) and Treasury bill rates (Seneviratna & Shuhua (2013). NPL is not a new area of researching. However, concern on forecasting perspective, there are no researches which are coming under the modeling of NPL in Sri Lankan context. However, empirical studies show some works done related to NPL and, Staehr & Uuskula (2017) contributed to the literature on financial stability by forecasting models for NPL. They have estimated panel data models for forecasting the ratio of NPL in the European Union countries using macro-economic and macro-financial variables. Quarterly data from the fourth quarter of 1997 to the first quarter of 2017 is used for the analysis. The forecast horizon is baseline models in eight quarters consisting of the samples of Western, Central, and Eastern European Union countries. Estimations showed that the ratio of NPL presented considerable persistence indicated that the current ratio is important for forecasting. Apart from that, Azar & Nasr (2015) have conducted a study with the purpose of exploring whether the solvency of small and medium entities (SME hereafter) in Lebanon can be predicted merely by their financial ratios through three different approaches. The data for the study was extracted through financial statements of 222 SMEs in Lebanon for 2011 and 2012. In the analysis the Altman Z-scores were calculated, Independent sample t-test was performed, and models were developed by using binary logistic regression. Conversely, the Altman models and developed logistic regression models reached high accuracy levels in predicting the healthy state of solvent companies; they failed to achieve high accuracy results in the prediction of the bankrupt state of financially unhealthy companies. Finally, it can be concluded that models using only quantitative data (financial ratios) cannot predict which SMEs would be subject to NPL in Lebanon. Moreover, Greenidge & Grosvenor (2010) focused on formulating a multivariate model on the aggregate level as well as each individual bank level by combining macroeconomic and bank-specific variables to forecast the NPL ratio in Barbados. They have acquired quarterly data of six banks in Barbados spanning the period 1996-2008. From the data, it has been developed Autoregressive Distributive Lag (ARDL) models for forecasting NPL ratios. Diagnostic tests indicated that models were satisfactory. Addition to that, findings of the study revealed that GDP growth rate significantly and negatively impacts on NPL ratio of all banks. Finally, they have identified that their model is more accurate only for long prediction periods. The study also supported to the connection that commercial banks should pay attention to the performance of the real economy when providing loans so as to reduce the degree of NPL. In Sri Lanka, a previous publication is not available under modeling of NPL. Moreover, In Sri Lanka NPLs are forecasted at the industry level by Central Bank of Sri Lanka to comply with the industry requirements. Hence, NPL for whole banking industry is forecasted. However, this research would momentary bridge the gap of not having proper statistical forecasting model to forecast the future NPL of this particular bank.

3 METHODOLOGY

Secondary data on forty- one NPLs has obtained through the publications of Colombo Stock Exchange for the analysis. Using quantitative research methodology, time series data over the period of quarter four of 2008 to quarter four of 2018 used as the training dataset and NPL of quarter one of 2019 used as the validation data. This research focused organizational level and Box-Jenkins Auto Regressive Integrated Moving Average (ARIMA) methodology was applied in modelling NPL.

4 DATA ANALYSIS & RESULTS

The plot of the gross NPL of ABC bank in Sri Lanka from Q4 of 2008 to Q4 of 2018 are shown in Figure 1.

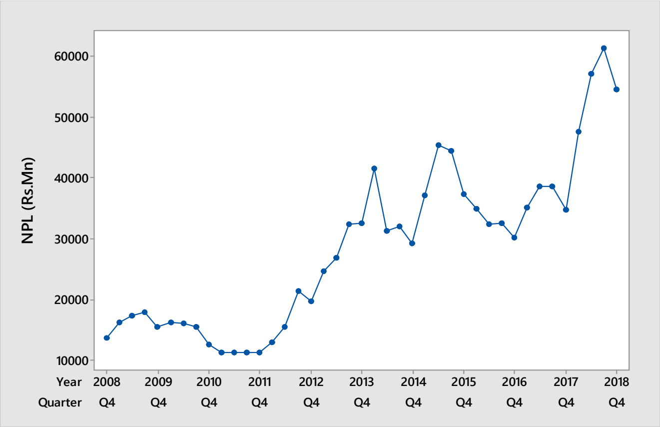

Figure 1: Time series Plot of Gross NPL

Source: ABC Bank from Q4 of 2008 to Q4 of 2018

As per the Figure 1, it can be seen that the gross NPL is fluctuated over the period of Q4 of 2008 to Q4 of 2018 without any seasonal or cyclical pattern, despite the upward trend. However, correlogram dies down very slowly and up to two lags are statistically significant indicated that the data may be non-stationary. Furthermore, the Augmented Dickey Fuller (ADF) test indicated the unit root process as follows.

Table 1: Unit Root Test

Augmented Dickey- Fuller (ADF) Test		
Section	Statistic	P Value
Original Values	-0.436709	0.8927
First Difference	-5.516968	0.0000
Second Difference	-6.793787	0.0000

Source: ABC bank from Q4 of 2008 to Q4 of 2018

As per the Table 1, output P value (0.89) of original values of gross NPL, noted that null hypothesis of unit root can be rejected at 95 per cent confidence level. In line with Box- Jenkins methodology, first difference series were derived. While ADF test indicated stationary of series, Auto Correlation Function (ACF) and Partial Auto Correlation Function (PACF) are significantly deviated from stationary. Both theoretical ACF, PACF and ADF test of unit root confirmed the stationary of second differenced series graphically as well as mathematically. Thus, second difference of gross NPL has obtained for further analysis. Using that second order differencing, several models were developed and followings were identified as the significant parameters for Auto Regressive (AR) and Moving Average (MA) terms.

Table 2: Parsimonious Model Development

Model	Variable	Coefficient	P Value
ARIMA (1,2,0)	C	-166.6	0.863
	AR (1)	-0.4593	0.005
ARIMA (0,2,1)	C	64.78	0.427
	MA (1)	0.9700	0.000
ARIMA (1,2,2)	C	119.23	0.218
	AR (1)	-1.0026	0.000
	MA (1)	-0.0031	0.986
	MA (2)	0.9082	0.000

Source: ABC bank from Q4 of 2008 to Q4 of 2018

According to Table 2, ARIMA (1,2,0) should keep the MA term as well as ARIMA (0,2,1) should keep MA term and ARIMA (1,2,2) model should keep both AR and MA terms in their models. Further, Box- Pierce Chi- square statistic was used to confirm the models to be selected and it indicated that above three models were significant at different lags. Consequently, model adequacy of above models should be identified for selecting the best model for forecasting.

Table 3: Model Adequacy of Parsimonious Models

Model	Akaike Information Criterion (AIC)	Schwartz Bayesian Criterion (SBC)
ARIMA (1,2,0)	20.29	20.38
ARIMA (0,2,1)	19.43	19.51
ARIMA (1,2,2)	19.83	19.96

Source: Secondary Data, ABC bank from Q4 of 2008 to Q4 of 2018

Corresponding to Table 3, ARIMA (0,2,1) model has the lowest Akaike Information Criterion (19.43) and the lowest Schwartz Bayesian Criterion (19.51) among those three models, ARIMA (0,2,1) model was identified as the best fitted ARIMA model for NPL data modeling.

Table 4: Normality of Residuals

Residuals of ARIMA (0,2,1)	Anderson Darling Test		Jarque- Bera Test	
	Statistic	P Value	Statistic	P Value
	0.37	0.41	0.91	0.63

Source: ABC bank from Q4 of 2008 to Q4 of 2018

As per the Table 4, the output P values of Anderson Darling Test (0.41) and Jarque-Bera Test (0.63) confirmed that the residuals are normally distributed since their output P values are greater than the critical P value (0.05) at 95 per cent confidence level.

Table 5: Accuracy of Fitted Models

ARIMA (0,2,1)	Mean Absolute Percentage Error (MAPE)	Mean Absolute Deviation (MAD)
Training Dataset	12.15%	3678.08
Validation Dataset	17.22%	11893.17

Source: ABC bank from Q4 of 2008 to Q1 of 2019

In line with the Table 5, MAD of training data set (3678.08) is less than the validation data set (11893.17). MAPE of training data set is 12.15 percent while the validation data set having 17.22 per cent. According to Gnanapragasam & Cooray (2015), MAPE is less than 10 per cent, the model can be considered as an excellent model and if it is less than 15 per cent, the model is a better one and MAPE is less than 20 per cent, the model can be accepted. Since the MAPE of training dataset is less than 15 per cent, ARIMA (0,2,1) is considered as a better model for forecasting NPL of ABC bank.

5 DISCUSSION OF THE FINDINGS

Initially, time series plot of NPL is demonstrated to show the pattern of NPL. ACF and PACF have been used to show the graphical presentation of stationarity of NPL series. Further, ADF test was calculated to confirm the stationarity of time series mathematically. Second difference series of gross NPL were found to be stationary. As Cooray (2008) and Gujarati & Porter (2009) typically, the financial time series are not stationary in their original state. Kumarasinghe (2017) and Weerasinghe & Perera (2013) confirmed that original NPL series were not satisfy the stationarity under Augmented Dickey Fuller unit root test hence the differentiation was done. Most of the researchers had determined the stationarity without considering the theoretical aspects of ACF and PACF. However, Gnanapragasam & Cooray (2015) has argued the importance of considering the theoretical patterns of ACF and PACF when determining the stationarity of a time series. ARIMA (p,d,q) model was assigned and the model selection criteria (AIC and SBC) confirmed that ARIMA (0,2,1) model was the most appropriate model for forecasting NPL in ABC bank. Gjika & Puka (2018) also suggested AIC or SBC for selecting the best model. It was recommended that minimizing of AIC and SBC gives best model prediction. Then the diagnostic of error terms was done by testing normality of error terms. In line with the normality, both Anderson Darling and Jarque-Bera tests confirmed the errors were normally distributed. Similarly, the histogram of residuals also satisfies the normality. Gijka & Puka (2018) emphasized that forecasts are reliable when histogram of residuals are normally distributed. Then accuracy of fitted models were calculated by using MAPE, and MAD. MAD of validation dataset having a higher value (11893) compared to training dataset (3678) occurred since validation dataset complied with only single value. Further MAPE confirmed that ARIMA (0,2,1) model is a better model for NPL forecasting. Then, time series equation was formulated and finally, forecasted NPL is calculated for the four quarters of year 2019.

6 CONCLUSION & CONTRIBUTIONS

The study attempts to develop an Auto Regressive Integrated Moving Average Model (ARIMA) to forecast the gross NPL of ABC bank. ARIMA (0,2,1) model gave better forecast values for NPL in ABC bank during Q4 of 2008 to Q4 of 2018. The forecasted gross NPL for four quarters of 2019 are 5.7146, 5.5968, 6.227, and 6.4929 billion rupees respectively. Until a further model is developed, ARIMA (0,2,1) model can be used to forecast NPL in ABC bank.

Managers and the officers who are working on loans and recoveries of loans can be able to get new insights and to mitigate the credit risk regarding NPL by referring the suggested model hence it directly caused to the profitability of the bank. The forecasted NPL for the year 2019 would be very useful to decision makers in the top management and to take necessary steps in ABC bank. Further bankers should closely monitor their customer profiles to get aware on repayment ability. Then, the repaying capacity should be re assured. Technology can be implemented to link the customer profiles to identify the unusual expenditure patterns and emphasize to repay before it takes ninety days. Along with above, policy makers in the banking industry can be able to implement strategies to reduce the level of gross NPL. In additionally, the authorized parties and the institutions such as Central Bank of Sri Lanka should take their attention to the increasing trend of gross NPL before it makes enormous impacts. However, unavailability of publicity accessible data regarding NPL prevents a comprehensive study. In Sri Lanka NPL is not heavily investigated. Hence, maintaining a separate statistical database in banks and other financial institutions would improve the area of researching.

Total Gross NPL can be divided in to several categories according to their loan portfolio. Here, total gross NPL of ABC bank has been taken to this study without considering the composition of NPL. Hence, future scholars are suggested to study and develop models by considering the composition of the loan portfolio. In this study, the researcher has examined only the movement of NPL according to the time. However, there are factors suggested in the literature which determines the NPL. Furthermore, it is suggested by the researcher to find the capability of multivariate time series techniques and neural network models by integrating the macro economic factors such as GDP growth, inflation, prime lending rate as well as the industry specific factors as bank size, bank risk taking behavior, and loan to asset ratio. Hence, a better method forecasting should be developed to estimate NPL in ABC bank as well as the other banks.

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