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Estimation of Reserve Funds for E-Banking Transactions using Operational Value-at-Risks

Nurfadhlina Abdul Halim[1], Moch Panji Agung Saputra[2*]

[1]*Department of Mathematics, Faculty of Science and Technology, Universiti Sains Islam Malaysia, 71800 Nilai, Negeri Sembilan, Malaysia*

[2]*Master of Mathematics Study Program, Faculty of Mathematics and Natural Science Universitas Padjadjaran, Indonesia*

**Corresponding author email: moch16006@mail.unpad.ac.id*

Abstract

The "New Normal" state during the pandemic has made digital financial transactions important as an effort to reduce direct human interaction, to prevent the spread of the pandemic. The rate of financial transactions at banks has automatically increased, but in practice, several risks may occur about failed or incorrect digital transactions. Examples of digital transaction system risks are downtime and timeout services due to system failures, cyber-attacks, and system usage errors. These risks need attention from banking companies. One way to anticipate digital financial transaction failure happen is the readiness of a reserve fund that is used to cover the wrong amount of fund error in the bank's digital system. This research will discuss the estimation of operational reserve funds for digital banking financial transactions (e-banking) using the Operational Value-at-Risk (OpVaR) method, based on operational risk data for digital financial transactions to obtain the largest potential loss value from digital financial transaction activities at a bank. Based on calculations using the OpVaR method, it is known that the reserve fund required for the operational risk of digital financial transactions is IDR135,465,044,269.741. The results of this study show that the e-banking operational reserve fund is quite large due to the possibility of extreme losses. This provides a view to avoiding the worst risk of collapse due to an imbalance in the required reserve funds.

Keywords: E-banking, Operational risks, Operational Value-at-Risk (OpVaR), and Reserve funds,

1. Introduction

Banking activities during the pandemic have increasingly shifted to digital media because of the appeal to reduce direct interaction so that customers tend to choose online banking. In various areas affected by the pandemic, there has been a decline in traditional banking transactions and as a result, the increase in e-banking platforms is observed to be at a critical point in adapting to changes in New Normal activities (Haq and Awan, 2020). These external factors encourage innovation in the banking sector. Banks risk being left behind in responding to the current state of technology (Yanagawa, 2020). Banking companies need to ensure that they keep up and take significant steps to compete effectively with financial institutions at the forefront of technology as well as digital giants and FinTech companies. The introduction of next-generation technologies, such as application programming interfaces (API), artificial intelligence (AI), machine learning, and robotics, is demanded to be ready to bring the customer experience to a new level of convenience (Mishra, 2020).

The development of new digital information technology in banking has a positive effect on financial activities in banks (Carbó-Valverde, et al. 2020; Rahman, et al. 2018). The digital or electronic banking services include (Susanto, et al. 2016):

1. Account statements for customers;
2. Information on banking products (deposits, loans, securities);
3. Applications for opening deposits and obtaining loans and bank cards;
4. Internal transfers to bank accounts;
5. Transfer to an account at another bank;
6. Currency conversion.

The first two types of services can be done using only cellular communication, but for the other four services, usually, an internet connection is required. With various digital services for banking customers to make financial

transactions easier, the value of banking transactions will increase. However, data digitization activities and bank financial operations also create around 70% digital risk for banks. According to the analysis, 22% of banks worldwide have invested more than 25% of their annual budgets to digitize risk management (Institute of International Finance, 2017).

The risk of digital financial transaction activities in a bank can be generalized by several indicators such as (Aguayo, et al. 2020):

- Risk of defects and system failure;
- Risk of losing data integrity and unauthorized access to customer data;
- Risk of violation of technical systems in an information room;
- Risk of cyber-attack;
- Risk of misuse of the system,
- Annual risk of defects;
- Loss of annual data integrity and unauthorized access to customer data.

Banking companies need to pay attention to the existence of risks related to digital financial transactions. Besides taking advantage of these new opportunities, Banks must identify, measure, monitor, and control these risks with prudent principles. Banks have Real Time Gross Settlement (RTGS) systems and regulations that have consequences, namely digital financial transactions are required to minimize risk, and if there is a system failure in digital transactions, there is an obligation from the sending participant (bank) to issue orders to send new funds to the account. the intended recipient or customer the correct recipient without waiting for a refund. This makes it important to allocate reserve funds for operational risk (Alexander, 2019).

In connection with operational risks and the need to allocate reserve funds, it is necessary to calculate these reserves. The approach method that can be used for the calculation of reserve funds is Operational Value-at-Risk (OpVaR). One of the studies that have carried out the calculation or modeling of bank reserve funds is the consideration of the bank reserve spread model to overcome the risk due to deposit withdrawals by Schalkwyk and Witbooi (2017) by formulating optimal stochastic control problems related to minimizing the risk of deposits and the reserve process, net cash flow from storage activity, and the cumulative costs of the bank's strategic sector.

Several other previous studies have also discussed the problem of calculating OpVaR and its banking relationship. Esterhuysen et al. (2008) perform OpVaR management in financial institutions through strong calculation techniques and the effect of this value on the capital owned by the bank for operational risk. Then illustrate the differences in regulatory capital when using the Advanced Measurement Approach (AMA) and the Standardized Approach (SA) by using examples of banking problems.

Yao et al. (2013) observe that operational risk management plays an important role in decision-making for banks. The Conditional Value-at-Risk (CVaR) model based on the peak value method from the extreme value theory is used to measure operational risk. Bank loss data used, used with empirical analysis. Tests are conducted using the VaR and CVaR calculation models at 95% and 99% confidence levels to assess expected and unexpected losses in operational risk.

Based on this description, the motivation and purpose of this study are to determine the estimated reserve fund for operational risk digital financial transactions (E-Money) using the Operational Value-at-Risk (OpVaR) method. It is hoped that the results of the reserve fund estimation will be useful for related parties, namely banks administering digital financial transaction systems, in analyzing the loss figures from the operational risks of digital payment systems. So that it can avoid the worst risk, namely a collapse due to an imbalance of the required reserve funds.

2. Literature Overview

2.1. E-Banking Transactions Risks

Digital financial transactions are an online banking system where banking services are offered via the internet. Digital financial transactions are related to a system that allows bank customers to access accounts and overall information about bank products and services through computers or personal gadgets (Ojeniyi, et al. 2019). Digital financial transactions allow customers to make financial transactions on trusted websites and applications run by retail or virtual banks, credit unions, or building organizations. Internet banking products and services may include wholesale products for corporate customers as well as retail products for consumers or customers (Sarma and Singh, 2010).

Digital financial transaction risk includes the risk that occurs for the failure of a system in digital financial transactions. Some of the risks that may occur, such as the threat of cyber-attacks, errors from system users, the possibility of defects from the internet system or application used, or downtime services due to system failure on the application side (Belás, et al. 2016).

The possible risk of digital financial transaction activities in banking can be observed in terms of operational risk. Operational risk is the risk threat caused by errors in the operation of a system, both internal and external factors. In this context, the provision of digital financial transaction services has potential losses arising from operational risks (Tănase and Şerbu, 2010).

2.2. Bank Reserve Funds

A bank reserve fund is the minimum amount of cash that financial institutions must keep to meet central bank requirements. The bank cannot lend the money but must keep it in a safe or somewhere and/or at the central bank, to meet large and unexpected withdrawal requests. As well as in anticipation of a transaction is not completed perfectly by the system so that it needs replacement funds for the transaction (Keister and McAndrews, 2009).

3. Materials and Methods

3.1. Materials

This research uses e-banking transaction risk data. The nominal risk loss data is obtained by simulating the risk data sample at one of the commercial banks in Indonesia. As for the initial sample data, it represents the risk of e-banking losses due to system defect. The sample data becomes material for digital banking risk simulation.

3.2. Methods

The methods used in this study are maximum entropy bootstrapping (MEBoot), the threshold percentage, the peak-over-threshold, and Operational Value-at-Risk (OpVaR). In addition, this study uses several software to process the data, namely R software, Excel, and EasyFit.

3.2.1. Maximum Entropy Bootstraping (MEBoot)

Bootstrapping was first introduced as a method to resample the data by Efron on 1982. Then, Vinod and Lacalle (2009) has developed bootstrapping based on maximum entropy principle and usually called MEBoot. MEBoot is essentially a method for derives strong estimation from standard error and confidence interval as estimation of proportion, mean, median, odds ratio, correlation coefficient or regression coefficient.

MEBoot conducted in this paper was used R software (MEBoot package) to make it easier for manage the data. Command function that used is meboot (x, reps, trim=list (trim=0.10,), reachbnd=TRUE, expand.sd=FALSE, force.clt=TRUE, scl.adjustment=TRUE).

3.2.2. Threshold

The threshold is a lower limit value from the tail of the distribution that fit extreme value distribution. Determination of the threshold value is sought the optimal balance to obtain model errors and parameter errors to a minimum. One of the methods to determine the threshold is the percentage method. Determination of the threshold with the percentage method is more practical and easier to implement.

This paper used percentage method for determination of the threshold. Based on research extensive simulation, Chavez-Demoulin (1999) recommend to choose the threshold such that the data above the threshold value is approximately 10% of the total data. The data above the threshold value called extreme data.

Lots of extreme data is obtained used this equations:

$$m = 10\% \times n \tag{1}$$

where m is lots of extreme data and n is lots of data total observed. Then threshold value u is obtained used this equation

$$u = m + 1 \tag{2}$$

3.2.3. Peaks Over Threshold (POT)

The peaks over threshold (POT) method identifies extreme values by set the threshold values and ignoring the time of occurrence. Extreme values are data that are above threshold value. Later this extreme value will be the distribution model. The POT method applies the Pickland Dalkema-DeHaan theorem which states that the higher threshold then the distribution for data above the threshold will follow the Generalized Pareto Distribution (GPD) (Hubbert, 2012). Assumption of data above the threshold that follows the GPD is obtained by looking at the tail od the distribution away from the trust line. Heavy tail detected by making QQPlot against data above the threshold.

Formula of parameter estimation is obtained by the Maximum Likelihood Estimation (MLE) method as follows.

- Shape parameter

$$\hat{\xi} = \frac{n^2 s - \sum_{i=1}^{n} x_i}{\sum_{i=1}^{n} x_i - n \sum_{i=1}^{n} x_i} \tag{3}$$

where ξ: shape parameter, n: lots of extreme data, s: standard deviation of extreme data, and x_i: extreme data on index-i.

- Scale parameter

$$\hat{\beta} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{4}$$

where β: scale parameter, n: lots of extreme data, and x_i: extreme data on index-i.

3.2.4. Operational Value-at-Risk (OpVaR)

Operational Value-at-Risk (OpVaR) is a method for measuring losses arising from operational risk with a certain level of confidence (Esterhuysen, et al. 2008). OpVaR can be searched based on the threshold value for extreme risk data and the estimated value of extreme data distribution parameters so that the OpVaR value can be found using the formula (Hubbert, 2012).

$$OpVaR = u + \frac{\beta}{\xi}\left\{\left[\frac{n}{m}(1-p)\right]^{-\xi} - 1\right\} \tag{5}$$

where u: Threshold, β: Scale parameter, ξ: Shape parameter, n: Lots of observed data, m: Lots of data above threshold, and p: confidence level

4. Results and Discussion

4.1. MEBoot Process of Digital Banking Losses Data

Data values of digital banking losses processed by MEBoot used software. Then get threshold value with 10% percentage and lots of extreme data above the threshold. The summary results of the processed data are given in the following table.

Table 1. The summary results of the MEBoot processed

Risk Type	Resample	Lots of Data	Lots of Extreme Data	*Threshold* (IDR.)
E-banking Defect	10	1230	123	IDR 64,806,050,343

The results of the MEBoot processed in Table 1 showed lots of data is 1230. The results are taken because fit to the assumption of heavy-tail data distribution. Heavy-tail data distribution is seen from the QQPlot results against the MEBoot data. The QQPlot result is used for estimate the heavy-tail of distribution data to indicate the extreme data fit to Generalized Pareto Distribution (GPD). The QQPlot processed by *software R* : *QQPlot Package*. The following QQPlot result from MEBoot data can be seen in Figure 1.

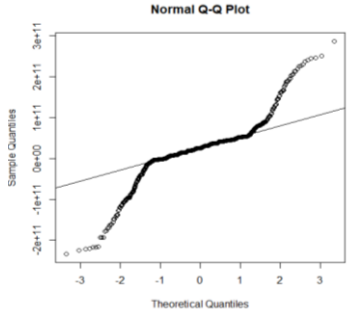

Figure 1. QQPlot Result from MEBoot Data

Figure showed the result that match the desired assumption that heavy-tail of data or away from near the normal line. The assumption results had an interpretation that extreme data will be accorded to the GPD distribution.

4.2. Goodness of Fit of Extreme Data to GPD

The extreme data value that assumed fit to the GPD distribution have to conducted Kolmogorov-Smirnov test used software *Easyfit*. The results of Kolmogorov-Smirnov test are given in the following Table 2.

Table 2. The Results of Kolmogorov-Smirnov Test

Sample Size	123		
Statistic	0.11357		
P-Value	0.07737		
Rank	7		
α	0.05	0.02	0.01
Critical Value	0.12245	0.13687	0.14688
Reject?	No	No	No

The Results of Kolmogorov-Smirnov Test in Table 2 can be concluded that extreme data values are fit to the *GPD* distribution because there are no reject on the test. Then GPD parameter can determined from the extreme data values.

4.3. GPD Parameter Approximation

The calculation of GPD parameter approximate require deviation standard (s), lots of extreme data (n), and sum of extreme data values $(\sum_{i=1}^{n} x_i)$ that taken from descriptive statistics extreme data.

Table 3. Descriptive Statistics Extreme Data

Data	123
Mean	118715100522.2
Standard Deviation	54110542295.94
Sample Variance	2.9279507875607(10^{21})
Kurtosis	0.263336436495423
Skewness	1.16545766227375
Minimum	65183178591.0188
Maximum	286932960062.233
Sum	14601957364231

Based on Table 3 obtained $n = 123$, $s = 54110542295.94$, and $\sum_{i=1}^{n} x_i = 14601957364231$. Then, obtained the results of shape parameter and scale parameter approximation used formula (3) and formula (4) on the following calculation.

$$\hat{\xi} = \frac{123^2\ (54110542295.94) - 14601957364231}{14601957364231 - 123\ (14601957364231)} = -0.4513410383432$$

$$\hat{\beta} = \frac{14601957364231}{123} = 118715100522.2$$

The results of the two GPD parameters showed the distribution function with $\xi < 0$ then x that bounded of $0 \leq x \leq -\frac{\beta}{\xi}$. upper limit value of x is $-\frac{\beta}{\xi} = -\frac{118715100522.2}{-0.4513410383432}$ = 263027490161.291. That upper limit value of x fit to the maximum values of extreme data in Table 3 because the maximum values of extreme data not pass through from upper limit value. After calculation of the two GPD parameters obtained and appropriate with extreme data value, then estimation of expected claim can be calculated with OpVaR.

4.4. Estimation of Bank Reserve Funds

After calculation of the two GPD parameters, then conducted the calculation of Operational Value-at-Risk (OpVar) as estimation of bank reserve funds for digital banking risks. The calculation of OpVaR require $u = 64806050343$, $\beta = 118715100522.2$, $\xi = -0.4513410383432$, $n = 1230$, and $m = 123$. The value of OpVaR obtained with 95% confidence level. The result of OpVaR used formula (5) on the following calculation.

$$OpVaR = 64806050343 + \frac{118715100522.2}{-0.4513410383432}\left\{\left[\frac{1230}{123}\ (1 - 0.95)\right]^{0.451341038} - 1\right\} = 135465044269.741$$

The result of OpVaR method is IDR135,465,044,269.741. The interpretation of OpVaR value with 95% confidence level is trusted of the value is 95% that required of bank reserve funds for digitabl banking risks in the amount of IDR135,465,044,269.741. The results of this research study show that the E-Banking operational reserve fund is quite large due to the possibility of extreme losses. This provides a view to avoiding the worst risk of collapse due to an imbalance in the required reserve funds.

5. Conclussion

Based on the results of Operational Value-at-Risk (OpVaR) calculation as an estimation of reserve funds of E-Banking Operational risks, the OpVaR is IDR135,465,044,269.741 with 95% confidence level. The results of this research study show that the E-Banking operational reserve fund is quite large due to the possibility of extreme losses. This provides a view to avoiding the worst risk of collapse due to an imbalance in the required reserve funds.

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