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Reserve Fund Optimization Model for Digital Banking Transaction Risk with Extreme Value-at-Risk Constraints

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Abstract: The digitalization of bank data and financial operations creates a large risk of loss. Losses due to the risk of errors in the bank's digital system need to be mitigated through the readiness of reserve funds. The determination of reserve funds needs to be optimized so that there is no large excess of reserve funds. Then the rest of the reserve fund allocation can be used as an investment fund by the bank to obtain additional returns or profits. This study aims to optimize the reserve fund allocation for digital banking transactions. In this case, the decision variable is value reserved based on potential loss of each digital banking, and the objective function is defined as minimizing reserve fund allocation. Furthermore, some conditions that become limitation are rules of Basel II, Basel III, and Article 71 paragraph 1 of the Limited Liability Company Law. Since the objective function can be expressed as a linear function, in this paper, linear programming optimization approach is thus employed considering Extreme Value-at-Risk (EVaR) constraints. In the use of EVaR approach in the digital banking problem, it is found that the loss meets the criteria of extreme data based on the Generalized Pareto Distribution (GPD). The strength of reserve funds using linear programming optimization with EVaR constraints is the consideration of potential losses from digital banking risks that are minimized so that the allocation of company funds becomes optimum. While the determination of reserve funds with a standard approach only considers historical profit data, this can result in excessive reserve funds because they are not considered potential risks in the future period. For the numerical experiment, the following risk data are used in the modeling, i.e., the result of a sample simulation of digital banking losses due to the risk of system downtime, system timeout, external failure, and operational user failure. Therefore, the optimization model with EVaR constraints produces an optimal reserve fund value, so that the allocation of bank reserve funds becomes efficient. This provides a view for banking companies to avoid the worst risk, namely collapse due to unbalanced mandatory reserve funds.

Keywords: digital banking; reserve fund; optimization; EVaR**MSC:** 90C05

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1. Introduction

Digital banking services are one of the supporters of the transformation of the industrial revolution 4.0 in the banking sector. This creates changes in the behavior patterns of bank customers who prefer digital transactions over conventional methods [1]. The existence of various digital services for customers to make financial transactions easier results in the value of banking transactions increasing [2,3]. However, the digitalization of bank data and financial operations also creates around 70% of digital risks for banks. In addition, it is known that more than 25% of the annual budget of banking companies is

used for digitizing risk management. This commitment has been made by more than 22% of banks worldwide [4].

Defect systems, unauthorized access to customer data, cyber-attacks, and misuse of computer systems are some indicators of the risk of digital financial transaction activities in a bank [5]. The Financial Services Authority of Indonesia stated that there were losses worth IDR 246 billion caused by cyber-attacks in Indonesian banks during the period from the first semester of 2020 to the first semester of 2021. In addition, a case related to digital banking system risks was experienced by Bank Indonesia in January 2022. The cyber-attack caused a leak of 74 GB of Bank Indonesia data with 237 hacked devices [6,7].

The risks of digital financial transactions need to be considered by banking companies. Banking companies must be able to identify, measure, and control risks. Based on the applicable regulations, the bank has an obligation to implement the Real Time Gross Settlement (RTGS) system. The RTGS regulations require banking companies to cover losses in real time. This means that, in the event of a system failure in a digital transaction, the sender (bank) is obliged to issue a new remittance order to the correct recipient account without waiting for a refund. The reserve fund for operational risk is used to replace failed transactions. Hence, it is crucial to allocate it properly [8].

The current banking reserve fund allocation regulation in Indonesia refers to the Circular Letter of Financial Services Authority of Indonesia (also known as OJK in Indonesian) Number 6 of 2020. The regulation provides a reserve fund allocation model using the Basel II standard. Reserve funds with Basel II standards only take reference to the company's historical data in the form of gross and net profits, but there is no consideration of potential losses on the risk. Therefore, the model used in accordance with OJK regulations has shortcomings as it does not interpret the possibility of future losses [9]. Based on this, a new model approach is needed to provide a more appropriate allocation of reserve funds to secure future risks.

In relation to operational risk and the need for reserve fund allocation, an appropriate reserve fund calculation method is required. The approach method that is suitable for reserve fund calculation is optimization with Extreme Value-at-Risk (EVAR) constraints. This research uses the maximum loss estimation model for digital banking created by Saputra et al. (2022) [10] as a risk measure constraint on reserve fund optimization.

Schalkwyk and Witbooi (2017) [11] have considered the model for allocating bank reserves due to the risk of withdrawal of deposits. Some of the things considered in the model are net cash flow and cumulative costs. The research was conducted using optimal control with a stochastic approach. The result of this study is the allocation of reserve funds that minimizes deposit risk.

Discussion of Value-at-Risk (VaR) and its relevance in banking has been carried out in several previous studies. Esterhuysen et al. (2008) [12] conducted the management of operational VaR management in a financial institution. VaR is used to perform calculations related to the effect of capital values on the operational risk of banking companies. Several approaches have been used, namely the Advanced Measurement Approach (AMA) and Standardized Approach (SA). The results obtained are that the AMA approach provides better results than the SA approach.

Baran and Witzany (2011) [13] conducted research related to the comparison of Extreme Value Theory (EVT) and Standard Value-at-Risk (VaR), which provides an explanation of the largest risk expectation (claim) based on VaR, which is used to estimate the largest possible loss for the risk faced.

Operational risk management has also been stated to play an important role in decision-making for banking companies. In a study by Yao et al. (2013) [14], the measurement of operational risk was carried out using the Conditional Value-at-Risk (CVaR) model. Then, based on the extreme characteristics of operational risk, the EVT approach was used. Calculations were made using the loss data of a banking company. The results obtained were that VaR and CVaR calculations with extreme value theory provide a good measure of operational risk.

Tran and Tran (2023) [15] conducted research on the role of VaR in the risk estimation of banking companies during the global financial crisis. This study used the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) approach for VaR estimation. The results showed that VaR with GARCH can provide fairly good extreme loss estimation results. Then, Kyoud et al. (2023) [16] used CVaR to analyze extreme conditions in banking, especially in Morocco. This research aimed to evaluate the banking business's systemic risks due to the pandemic. The results of this study provided the view that pandemic conditions increase the risk of bad credit, thus affecting the stability of banking companies. Therefore, banks need to raise their operating capital, liquid assets, and reserves to maintain the company's financial stability.

Chikobvu and Ndlovu (2023) [17] have applied VaR with Generalized Extreme Value Distribution (GEVD) to measure the risk of two exchange rates. The exchange rates are South African Rand/US Dollar (ZAR/USD) and BitCoin/US Dollar (BTC/USD). The study aims to compare the risk of the two exchange rates. Based on the research, BTC/USD is more risky than ZAR/USD. The risk estimation results can help investors to determine their strategies in forex trading. Based on the previous literature, the research gaps of this study are summarized in Table 1.

Table 1. Research Gap or Content Analysis on Determination of Optimum Reserve Fund.

Authors	Variables	Method	Use of Value-at-Risk	Use of EVT Approach	Determination of Optimum Reserve Fund
Gilli and Kellezi, 2006 [18]	Market risk, and daily returns of some portfolios.	VaR, EVT, and expected shortfall.	-	Yes	-
Esterhuysen et al., 2008 [12]	Operational losses, net interest income, and gross income.	OpVaR, SA, and AMA.	Yes	-	-
Yao et al., 2013 [14]	Operational risks of commercial bank.	CVaR, EVT, and peak value method.	Yes	Yes	-
Schalkwyk and Witbooi, 2017 [11]	Cumulative cost, net cash flows, and deposit risk.	Portfolio, stochastic optimal control	Yes	-	-
Saputra et al., 2022 [10]	Digital Banking Transaction Operational Risk	Extreme Value-at-Risk	Yes	Yes	-
Tran and Tran, 2023 [15]	Risks of global financial crisis	Value-at-Risks, GARCH	Yes	-	-
Kyoud et al., 2023 [16]	Systemic risks of banking company	CVaR, Extreme approach	Yes	Yes	-
Chikobvu and Ndlovu, 2023 [17]	Exchange rates risks (ZAR/USD and BTC/USD)	VaR, GEVD	Yes	Yes	-
This Research	Digital Banking Transaction Risk	Extreme Value-at-Risk, Linear Programming Optimization	Yes	Yes	Yes

Based on these descriptions, the motivation and focus of this research is to determine the optimization of reserve funds for digital banking transaction risks with Extreme Value-at-Risk (EVaR) constraints. The development of this research is based on differences with other studies that have been conducted, namely the optimization method combined with the Extreme Value Theory (EVT) approach to determine the size of EVaR. The optimization of reserve funds with the EVaR measure as a constraint has not yet been done. This is an advantage of this research, as in determining the reserve fund for digital banking, the optimization method with EVaR constraints will be better than determining the reserve fund with normal assumptions. The reserve fund optimization results with EVaR are better since it also considers the extreme risks of digital banking.

The creation of a reserve fund optimization model has the aim of not only taking the largest value to secure risk but also the right optimum value so that there is no large excess of reserve funds. The remaining reserve fund allocation can be used as an investment fund by the bank to get additional return or profit. Furthermore, the results of the optimization of the reserve fund are expected to be useful for related parties, namely the bank organizing the digital banking system, in analyzing the number of losses from the risk of digital banking transactions. This is to avoid the worst risk of collapse due to the imbalance of the required reserve funds.

2. Literature Overview

2.1. Digital Banking Transaction Risk

Digital banking transactions are an online banking system that provides banking services via the internet. It refers to a system that allows bank customers to access their accounts as well as general information about bank products and services via personal computers or mobile devices [19]. Customers can conduct financial transactions on trusted websites and applications operated by a retail bank company. Internet banking services can include both wholesale and retail products for customers [20].

However, transactions using digital banking can pose several risks of transaction failure. The risk of loss can be caused by cyber-attacks, system defects, system timeouts, and system downtime on digital banking platforms [21]. Risks in digital banking transaction activities can be divided into system risk and operational risk. System risk is an error caused by defects in the system used. Then, operational risk is a threat caused by errors in operating a system, both internal and external. Based on this, potential losses from digital banking transaction services can be measured based on these system and operational risks [22], hence the need on mitigating risk to cover these potential losses. Risk mitigation can prevent banking companies from collapsing due to losses that occur [23].

2.2. Digital Banking Reserve Fund

A bank reserve fund is the minimum amount of cash that a banking company is required to hold based on central bank requirements. Banks could not lend the money; hence, they must keep it in safes to mitigate unexpected risks. Reserve funds are also used as an anticipation if there are transaction failures so that the replacement funds are needed for these transactions. Hence, financial institutions such as banks must prioritize establishing and maintaining reserve funds to ensure compliance with commitments and regulatory requirements [24,25].

The determination of reserve funds is based on the possibility of loss due to the risks of digital banking transactions. Risk is basically divided into two categories: speculative and pure. Speculative risk has four types: market, credit, liquidity, and operational. The risk of operational risk is caused by faults and malfunctions in internal processes, human errors, system failures, and external events that affect bank operations [26]. Hence, this study uses system risks and operational risks that have the potential for losses due to failed purchase, payment, and transfer transactions from digital banking users.

Based on regulation of Basel II, the standardization in measuring operational risk losses is divided into several methods: 1. Basic Indicator Approach (BIA); 2. Standardized Approach (SA); and 3. Advance Measurement Approach (AMA) [10].

The AMA method uses an internal approach to measure risk. In-company assumptions, key performance indicators, statistical methods, and financial mathematics tools construct the internal approach. The internal approach is influenced by the characteristics of the company's internal data. Therefore, the quality of risk measurement results will depend on internal data collection. AMA methods can be categorized as follows: Loss Distribution Approach (LDA), Bootstrapping Approach, Bayesian, Internal Measurement Approach (IMA), and Extreme Value Theory [27].

Operational risk used in this study is a form of potential loss for the bank operating the digital banking system, namely the risk of failed purchase, payment, and transfer

transactions. The characteristics of these risks are extreme, namely the form of risk that in quantity does not often occur, but when it occurs, the impact is of great value. Therefore, based on the extreme nature of the three types of digital banking risk, it becomes the basis for risk measurement using the Extreme Value Theory approach.

3. Materials and Methods

3.1. Materials

The modeling is based on several materials in the form of BIA and SA regulations in Basel II and Basel III, the Limited Liability Company Law, and Financial Services Authority Regulation Number 6 of 2020. The optimization model completion in this study uses digital banking losses data due to downtime, timeout, user failure, and external failure. The object used as a loss data sample is a commercial bank in Indonesia.

The digital banking loss data used in this study is a sample of risks that occurred in the second quarter of 2020. The simulation of digital banking losses is based on the distribution of the sample data. The commercial bank sampled in this study is one of the banks in Indonesia which is categorized as a *BUKU 4*. According to the regulation of Central Bank of Indonesia, *BUKU 4* is a bank with at least IDR 30,000,000,000 in core capital.

3.2. Methods

The research methods for obtaining a digital banking reserve fund optimization model are linear programming, the percentage threshold method, generalized pareto distribution, and EVaR. In addition, the software used for computing is EasyFit Version 5.5 and R Version 4.1.2.

3.2.1. Threshold Selection

Threshold is the data value in order $n_u + 1$, where n_u is the number of extreme values. The method that can be used to determine the threshold and the number of extreme values is the percentage method. Rydman (2018) [28] recommends selecting the number of extreme values (n_u), which are data in the order of 15% of the total data. Therefore, the threshold value can be found by using the following equation:

$$u = n_u + 1 = (15\% \times n) + 1 \quad (1)$$

where n is the total observational data, n_u is the number of extreme values, and u is the threshold value.

3.2.2. Generalized Pareto Distribution (GPD)

According to Baran and Witzany (2011) [13] and Zhao et al. (2019) [29], data above the threshold value can be defined as the Generalized Pareto Distribution (GPD). Suppose there is a random variable x from extreme loss data, and the distribution function can be formed in the Generalized Pareto Distribution in Equation (2):

$$g_{\xi, \beta}(x) = \begin{cases} \frac{1}{\beta} \left(1 + \frac{\xi}{\beta} x\right)^{-1-\frac{1}{\xi}}, & \xi \neq 0 \\ \frac{1}{\beta} \exp\left(-\frac{x}{\beta}\right), & \xi = 0 \end{cases} \quad (2)$$

where if $\xi > 0$ then $\beta > 0$; $x \geq 0$, if $\xi < 0$ then $0 \leq x \leq \frac{\beta}{\xi}$, with ξ : shape parameter and β : scale parameter. GPD parameter estimation is performed using the fit distribution tool on Easyfit.

3.2.3. Extreme Value-at-Risk (EVaR)

According to Saputra et al. (2022) [10], a loss from risk can be measured and estimated using the EVaR method. EVaR is obtained by calculating the threshold value by adding extreme data limits with the following formula:

$$\text{EVaR} = u + \frac{\beta}{\xi} \left\{ \left[\frac{n}{n_u} (1 - p) \right]^{-\xi} - 1 \right\} \quad (3)$$

where u : Threshold, β : Scale parameter, ξ : Shape parameter, n : Number of observation data, n_u : Number of data above the threshold, p : Confidence level.

3.2.4. Linear Programming Optimization Modeling

Linear programming is a method used to obtain optimal results from a mathematical model arranged as a linear function. Linear programming can be called a solving technique in mathematical optimization. In other words, linear programming is a technique for solving optimization problems that have a linear objective function and a constraint function in the form of a linear equality or linear inequality. The linear program aims to determine the optimum value (maximum or minimum) obtained from a set of feasible solutions [30].

The formulation of an optimization model can be started by determining the variables, constraints, and objectives of the problem to be solved. The stages in forming an optimization model can be expressed in the following three steps:

- (a). **Determination of Decision Variables** In an optimization problem, it must first be stated what variables are to be determined as the result of optimization. For example, if there is a decision of n measurable variables, then $x_1, x_2, \dots, x_n$ can be formed as a decision variables. The value of the decision variable will be determined based on the optimization result.
- (b). **Determination of Objective Function** Optimization problems require an objective function as the optimum result in the form of maximization or minimization. The formulation of the objective function is based on the size of the cost coefficient of the decision variable corresponding to the problem to be solved (for example, as $c_1, c_2, \dots, c_n$). The objective function in linear programming can be written in standard form as follows:

$$\text{Maximize } \sum_{j=1}^n c_j x_j \quad (4)$$

- (c). **Determination of Constraint Function** Optimization problems must have limitations that affect the decision variables. The limitations of the decision variables need to be formed in a constraint function. The formulation of the constraint function is based on the technology coefficient (for example, as a_{ij} for $i = 1, 2, \dots, m$ and $j = 1, 2, \dots, n$) and right-hand-side constraints (for example as b_i for $i = 1, 2, \dots, m$). In addition, in optimization problems, there are non-negativity constraints which indicate that all decision variables must have values equal to or greater than zero. Therefore, the constraint function in linear programming can be written in standard form in Equations (5) and (6).

$$\sum_{j=1}^n a_{ij} x_j \leq b_i, i = 1, 2, \dots, m \quad (5)$$

$$x_j \geq 0, j = 1 \dots n \quad (6)$$

The optimization problem can be written using matrix terminology as follows:

$$\text{Maximize } \mathbf{c}^T \mathbf{x} \quad (7)$$

$$\begin{aligned} &\text{subject to } \mathbf{Ax} \leq \mathbf{b} \\ &\mathbf{x} \geq \mathbf{0} \end{aligned} \quad (8)$$

Regarding the existence of optimal solutions for linear programming, it can be stated that linear functions are convex functions. Therefore, when minimizing a linear function, any local optimum solution is the global optimum [31]. Then, related to solving optimization problems with computation in this case, the linear programming form has been guaranteed to be computationally tractable. It means that the result of the optimization model can be solved computationally at a certain time [32]. Therefore, the optimization problem in this study was carried out using the linear programming method.

4. Results

In this section, the reserve fund is formulated using EVaR. The optimization model is discussed.

4.1. Reserve Fund Using EVaR

Banking reserve funds for Digital banking risk are obtained by calculating the proportional profit from digital banking services. The profit proportion reserved is 15%, and this is based on Basel II rules. In addition, to secure the risk of digital banking, banking companies also need to measure potential losses from risks that may occur in the next period. Under the rules of Basel II or Basel III, there is no calculation of estimated losses on reserve funds. In the BIA and SA methods from Basel II-III, the indicator of reserve funds involved is only profit or gross and net income (less expenses). This method does not describe the possible risks that will occur. Therefore, it underlies the use of a measure of the potential loss risk added to the reserve fund.

$$\text{Reserve Fund} = \alpha \sum_{j \in J} P_j + \sum_{i \in I} x_i + \sum_{k \in K} y_k ; i \in I, j \in J, k \in K \quad (9)$$

P_j : Average profit for each digital banking service (historical 3 years before)

α : Weight coefficient for value reserved based on average profit is 15%

x_i : Value reserved based on potential loss of each digital banking system risks

y_k : Value reserved based on potential loss of each digital banking operational risks

I : Form of digital banking system risk; downtime services ($i = 1$) and timeout services ($i = 2$)

K : Form of digital banking operational risk; external risk failure ($k = 1$) and user failure ($k = 2$)

J : Type of digital banking service; internet banking ($j = 1$) and mobile banking ($j = 2$)

The formation of the reserve fund has a variety of results, because the value of potential losses is interpreted in many cases. Therefore, this reserve fund model is suitable for optimization. The optimization is meant to minimize the value of reserve funds. That would benefit the company, as the remaining capital allocation can be used to diversify other assets. One of the allocations is as an investment fund. Funds that are not reserved can be used to receive a return from investment results as additional income. Based on these reasons, the formation of a reserve fund optimization model requires constraints that limit the desired state. The descriptions of the constraints that must be met to achieve the minimum optimal reserve fund are as follows:

- (a). Ensuring that the value reserved based on potential digital banking system risk losses should not be less than the estimated digital banking losses ($EVaR_{System_i}$);

$$x_i \geq EVaR_{System_i} \quad (10)$$

- (b). Ensuring that the value reserved based on potential digital banking operational risk losses should not be less than the estimated digital banking losses ($EVaR_{Operational}$);

$$y_k \geq EVaR_{Operational_k} \quad (11)$$

- (c). Guaranteeing that the total value reserved based on potential digital banking loss must not exceed the average profit value of the digital banking itself;

$$\sum_{i \in I} x_i + \sum_{k \in K} y_k \leq \sum_{j \in J} P_j \quad (12)$$

- (d). Ensuring that the reserve based on the estimated loss of digital banking risk must not be less than the 20% (β) weight of the capital (M_j) for the implementation of digital banking. The weight coefficient β_j has been set at 20% based on Article 71 paragraph 1 of the Company Law.

$$\sum_{j \in J} P_j \alpha_j + \sum_{i \in I} x_i + \sum_{k \in K} y_k \geq \beta \sum_{j \in J} M_j \quad (13)$$

4.2. Reserve Fund Optimization Model Using Constraint of $EvaR$

Constraints to get the optimum value of reserve funds need to be overcome by optimization techniques. The optimization of reserve funds with the $EvaR$ risk measure is obtained by minimizing the objective function of Equation (9) and meeting the constraints (10) to (13). Therefore, the reserve fund optimization model with the $EvaR$ risk measure can be written in Equations (14)–(18) as follows.

$$\min. \quad \alpha \sum_{j \in J} P_j + \sum_{i \in I} x_i + \sum_{k \in K} y_k \quad (14)$$

subject to :

$$x_i \geq EVaR_{System_i}, \quad \forall i \in I \quad (15)$$

$$y_k \geq EVaR_{Operational_k}, \quad \forall k \in K \quad (16)$$

$$\sum_{i \in I} x_i + \sum_{k \in K} y_k \leq \sum_{j \in J} P_j \quad (17)$$

$$\sum_{j \in J} P_j \alpha_j + \sum_{i \in I} x_i + \sum_{k \in K} y_k \geq \beta \sum_{h \in H} M_j \quad (18)$$

P_j : Average Profit for each digital banking service (Historical 3 years before)

α : Weight coefficient for value reserved based on average profit is 15%

x_i : Value reserved based on potential loss of each digital banking system risk

y_k : Value reserved based on potential loss of each digital banking operational risks

M_j : Capital funds for service provision of each digital banking service

β : The coefficient of capital reserve of each digital banking services is 20%

$EVaR_{System}$: Estimation of potential digital banking system risk losses

$EVaR_{Operational}$: Estimation of potential digital banking operational risk losses

For the reserve fund optimization model in Equations (14)–(18), the decision variables of the reserve fund objective function are x_i and y_k . Each decision variable is a reserved value based on the potential loss of digital banking system and operational risks. The value P_j is certain based on historical data on average banking profits. Then, α is determined to use 15% based on the Basel II rules. Then, M_j value is certain based on capital data for the implementation of digital banking services. The coefficient of β has also been found to be 20% based on Article 71 paragraph 1 of the Limited Liability Company Law.

Constraints (15) and (16) aim to determine the value of digital banking risk losses. Constraints (15) and (16) require a measure of the estimated loss. Estimated losses use the size of $EVaR_{System}$ and $EVaR_{Operational}$. Based on the Basel II rules and the Law of Ltd. Company, the value of α and β can be directly written as 15% and 20%, respectively. Therefore, the reserve fund optimization model can be written in Equations (19)–(25).

$$\left(15\% \times \sum_{j \in J} P_j\right) + \min. \left(\sum_{i \in I} x_i + \sum_{k \in K} y_k\right) \quad (19)$$

subject to :

$$x_i \geq EVaR_{System_i}, \forall i \in I \quad (20)$$

$$y_k \geq EVaR_{Operational_k}, \forall k \in K \quad (21)$$

$$\sum_{i \in I} x_i + \sum_{k \in K} y_k \leq \sum_{j \in J} P_j \quad (22)$$

$$\left(15\% \times \sum_{j \in J} P_j\right) + \sum_{i \in I} x_i + \sum_{k \in K} y_k \geq 20\% \times \sum_{j \in J} M_j \quad (23)$$

$$x_i \geq 0, \forall i \in I \quad (24)$$

$$y_k \geq 0, \forall k \in K \quad (25)$$

Set:

I : Form of digital banking system risk; downtime services ($i = 1$) and timeout services ($i = 2$)

K : Form of digital banking operational risk; external risk failure ($k = 1$) and user failure ($k = 2$)

J : Type of digital banking service; internet banking ($j = 1$) and mobile banking ($j = 2$)

Parameter:

P_j : Average profit of the digital banking services- j

M_j : Capital funds for service provision of digital banking services- j

$EVaR_{System_i}$: Potential losses based on digital banking system risk- i

$EVaR_{Operational_k}$: Potential losses based on digital banking operational risk- k

Decision Variables:

x_i : Reserve value for digital banking losses from system risk- i

y_k : Reserve value for digital banking losses From operational risk- k

4.3. Computational Solution of Reserve Fund Optimization Model

4.3.1. Profit and Capital Data on the Implementation of E-Banking Services

The reserve fund Robust Optimization Model requires historical data of average profit in the past 3 years. The profit value is an indicator of reserve funds based on Basel II rules with a coefficient level of 15% as a reserve expense. The profit data used in this study are known from the annual report of “Bank XYZ” which can be seen in Table 2.

Table 2. Annual digital banking service profit data in million IDR.

Digital Banking Services	Profit of 2020	Profit of 2021	Profit of 2022
Internet Banking	2,467,284	4,360,382	5,059,046
Mobile Banking	2,800,607	2,552,457	2,616,315
Total of Profit per Year	5,267,891	6,912,839	7,711,361

Based on the profit data of digital banking services, the average profit value of each type of service, namely internet banking and mobile banking, can be taken. The average profit value data for each type of digital banking service can be seen in Table 3.

Table 3. Average profit in 2020–2022 for each type of digital banking service in million IDR.

Digital Banking Services	Average Profit
Internet Banking	3,962,237.33
Mobile Banking	2,656,459.67
Total of Average Profit	5,618,697

Recall the reserve fund optimization model with objective function (19) and constraint functions (22) and (23) that require the proportion value of total average profit with weight coefficient $\alpha = 15\%$.

Based on the data in Table 3, the average profit proportion values are as follows.

$$\begin{aligned}
 15\% \times \sum_{j \in J} P_j &= 15\% \times (P_1 + P_2) \\
 &= 15\% \times (3,962,237.33 + 2,656,459.67) \\
 &= 15\% \times (5,618,697) \\
 &= 842,804.55 \text{ million IDR}
 \end{aligned}$$

The value of the average proportion of digital banking profit expected is IDR 842,804,550,000. Furthermore, this value is used to determine the optimization of reserve funds.

In addition to the proportion of average profit, there is also the proportion of capital as an indicator of reserve funds. Based on the rules of the [33] Law of Ltd. Company Article 71 paragraph (1), the proportion of capital reserved is at least 20%. The capital data of digital banking service providers used in this study is known from the annual report of Bank “XYZ” in 2022 which can be seen in Table 4.

Table 4. Implementation capital for each type of digital banking service in million IDR.

Digital Banking Services	Capital
Internet Banking	4,437,864.10
Mobile Banking	3,569,658.65
Total of Capital	8,007,522.75

The value of the organizing capital is used in the constraint function (23) in the reserve fund optimization model. Based on the data in Table 4, the proportion of capital that needs to be reserved is obtained as follows:

$$\begin{aligned}
 20\% \times \sum_{j \in J} M_j &= 20\% \times (M_1 + M_2) \\
 &= 20\% \times (4,437,864.10 + 3,569,658.65) \\
 &= 20\% \times (8,007,522.75) \\
 &= 1,601,504.55 \text{ million IDR}
 \end{aligned}$$

The value of the proportion of capital for organizing digital banking services as the minimum limit of reserve funds is IDR 1,601,504,550,000. Furthermore, the value of the average proportion of digital banking profits and the proportion of digital banking capital is implemented in the reserve fund optimization model. The average proportion of profit is used in the objective function (19), constraint function (22), and constraint function (23), while the value of the proportion of organizing capital is used as a constraint function (23).

4.3.2. Data Simulation for Digital Banking Risk

The digital banking system risks used in this research analysis are downtime and timeout risks. While the operational risk of digital banking is based on external failure and user failure, digital banking risk of loss data is generated with GPD distributed random data in accordance with the application of EVT. The generation of risk of loss data is assisted by Easyfit Version 5.5 software.

Furthermore, to estimate losses using EVaR with the application of EVT, a threshold limit is required as a threshold value for extreme data. The threshold value is taken using the percentage method, which is approximately around the 15% percentile. The 15% percentile range is taken from data that have been sorted starting from the largest.

Then, if all extreme data are accepted as GPD distributed, the GPD parameters are estimated with the help of Easyfit software. Hence, the results of goodness of fit and GPD parameter estimation can be seen in Figures 1 and 2 and Table 5.

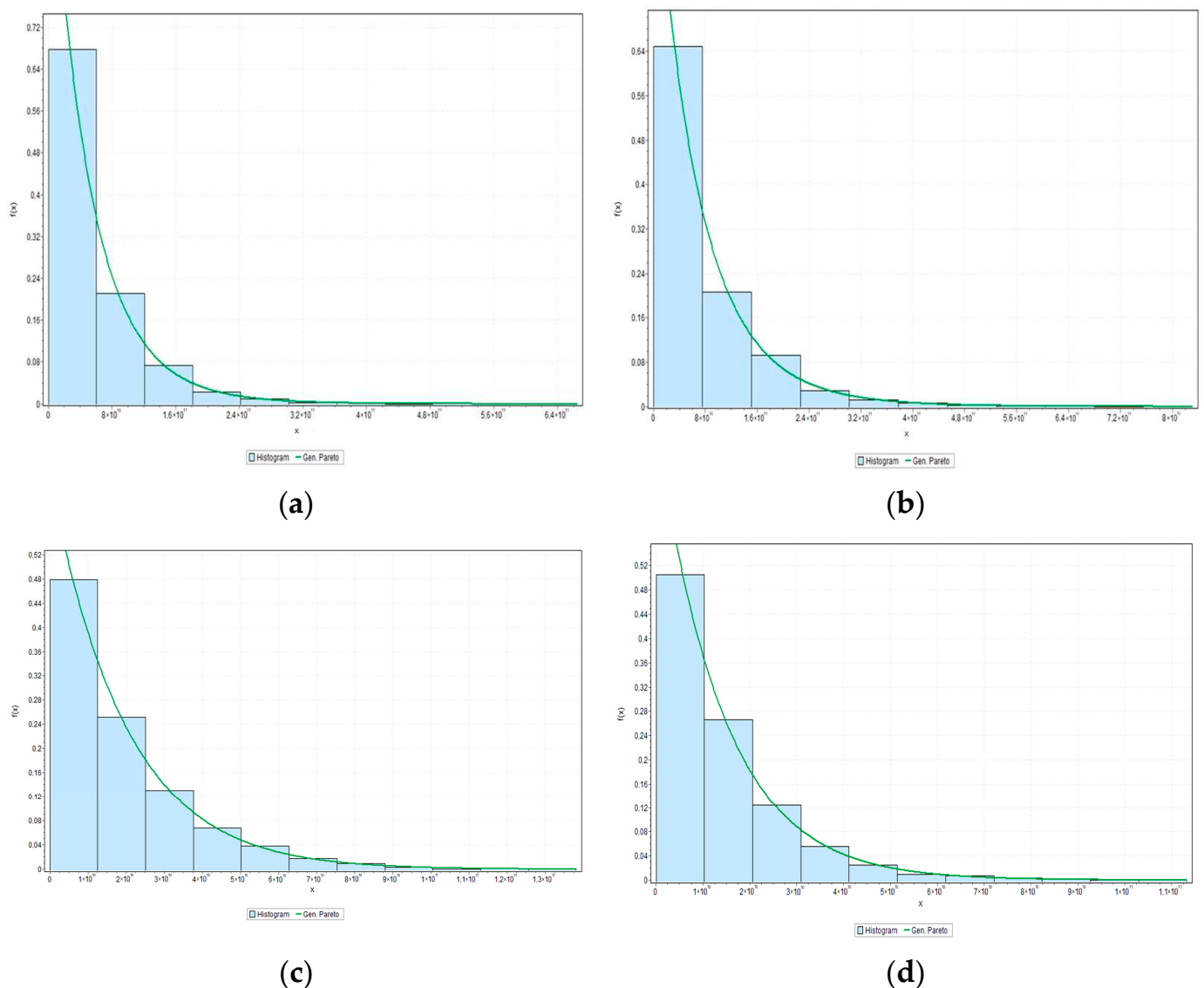


Figure 1. Results of Histogram Plot Results as an Indication of Heavy-tailed Distribution of GPD on Digital Banking Risk Extremes Data; (a) timeout system, (b) downtime system, (c) external failure, and (d) user failure.

Gen. Pareto [#1]						
Kolmogorov-Smirnov						
Sample Size	300					
Statistic	0.02727					
P-Value	0.9746					
Rank	1					
α	0.2	0.1	0.05	0.02	0.01	
Critical Value	0.06195	0.07061	0.0784	0.08764	0.09405	
Reject?	No	No	No	No	No	

(a)

Gen. Pareto [#1]						
Kolmogorov-Smirnov						
Sample Size	2000					
Statistic	0.01123					
P-Value	0.95995					
Rank	1					
α	0.2	0.1	0.05	0.02	0.01	
Critical Value	0.02399	0.02735	0.03037	0.03394	0.03643	
Reject?	No	No	No	No	No	

(b)

Gen. Pareto [#1]						
Kolmogorov-Smirnov						
Sample Size	300					
Statistic	0.02996					
P-Value	0.94311					
Rank	1					
α	0.2	0.1	0.05	0.02	0.01	
Critical Value	0.06195	0.07061	0.0784	0.08764	0.09405	
Reject?	No	No	No	No	No	

(c)

Gen. Pareto [#1]						
Kolmogorov-Smirnov						
Sample Size	2000					
Statistic	0.00914					
P-Value	0.99569					
Rank	1					
α	0.2	0.1	0.05	0.02	0.01	
Critical Value	0.02399	0.02735	0.03037	0.03394	0.03643	
Reject?	No	No	No	No	No	

(d)

Figure 2. Results of GPD Goodness of Fit using Kolmogorov–Smirnov test on Digital Banking Risk Extremes Data; (a) timeout system, (b) downtime system, (c) external failure, and (d) user failure.

Table 5. Results of GPD Parameter Estimation.

Digital Banking Risk	Risk Type	Lots of Data after Simulation	Lots of Data above Threshold (Extreme Data)	Threshold	Parameter Estimated Value	
		n	N_μ	u	$\hat{\beta}$	$\hat{\xi}$
System Risks	Timeout System	2000	300	102,240,679,399	56,769,000,000	0.05963
	Downtime System	2000	300	146,258,625,357	73,777,000,000	0.09501
Operational Risks	External Failure	2000	300	35,954,062,029	18,913,000,000	−0.09309
	User Failure	2000	300	20,768,602,154	7,546,800,000	−0.14352

The simulation results of digital banking risk loss data have been carried out with extreme data results that are in accordance with the GPD with each estimated parameter. Furthermore, EVaR analysis is carried out with the threshold size and estimated parameters in Table 5. Threshold selection determined with a level of 15% has been able to separate outlier points as extreme data that are above most other data, i.e., there are 300 data above the threshold as extreme data. One form of EVaR calculation for timeout risk at 15% threshold with 99% confidence level is as follows:

$$EVaR_{System_1} = u + \frac{\beta}{\xi} \left\{ \left[\frac{n}{N_\mu} (1 - p) \right]^{-\xi} - 1 \right\}$$

$$EVaR_{System_1} = 102,240,679,399 + \frac{56,769,000,000}{0.05963} \left\{ \left[\frac{2000}{300} (1 - 0.99) \right]^{-0.05963} - 1 \right\}$$

$$EVaR_{System_1} = 102,240,679,399 + 952,020,794,901.895 \left\{ \left[\frac{2000}{300} (0.01) \right]^{-0.05963} - 1 \right\}$$

$$EVaR_{System_1} = 102,240,679,399 + 952,020,794,901.895\{1.1752501675 - 1\}$$

$$EVaR_{System_1} = 102,240,679,399 + 952,020,794,901.895\{0.1752501675\}$$

$$EVaR_{System_1} = 102,240,679,399 + 166,841,803,822.36$$

$$EVaR_{System_1} = 269,082,483,221.22$$

The result of EVaR calculation for timeout risk at 15% threshold with 99% confidence level is IDR 269,082,483,221.22. This value has the interpretation that the timeout risk is 99% trusted to have a potential loss of IDR 269,082,483,221.22 within the next one-year period. The level of potential risk is the basis for estimating the losses that the company needs to reserve. Therefore, with the same EVaR calculation process, the results of the size of the potential loss for digital banking risk are shown in Table 6.

Table 6. EVaR results of each digital banking risk.

Digital Banking Risk	Risk Type	EVaR
System Risks	Timeout System	IDR 269,082,483,221.22
	Downtime System	IDR 374,106,598,772.46
Operational Risks	External Failure	IDR 81,225,609,878
	User Failure	IDR 37,702,356,747

4.3.3. Solution of Reserve Fund Optimization

Based on Tables 3 and 4, each parameter has been obtained, namely M_j and P_j . Meanwhile, in Table 6, the EVaR value for each digital banking risk has been obtained. Therefore, the complete reserve fund optimization model can be formed in Equations (26)–(34).

$$842,804,550,000 + \min. \left(\sum_{i \in I} x_i + \sum_{k \in K} y_k \right) \quad (26)$$

subject to :

$$x_1 \geq 269,082,483,221.22 \quad (27)$$

$$x_2 \geq 374,106,598,772.46 \quad (28)$$

$$y_1 \geq 81,225,609,878 \quad (29)$$

$$y_2 \geq 37,702,356,747 \quad (30)$$

$$\sum_{i \in I} x_i + \sum_{k \in K} y_k \leq 5,618,697,000,000 \quad (31)$$

$$842,804,550,000 + \sum_{i \in I} x_i + \sum_{k \in K} y_k \geq 1,601,504,550,000 \quad (32)$$

$$x_i \geq 0, \forall i \in I \quad (33)$$

$$y_k \geq 0, \forall k \in K \quad (34)$$

The optimization problem in Equations (26)–(34) is solved by linear programming on R Version 4.1.2 Software. The optimum solution results for the reserve fund optimization model with EVaR constraints can be seen in Table 7.

Table 7. Optimum Reserve Fund Results for Digital Banking Risks.

Digital Banking Risk	Risk Type	Potential Loss	Reserves
System Risks	Timeout System	IDR 269,082,483,200	IDR 643,189,082,000
	Downtime System	IDR 374,106,598,800	
Operational Risks	External Failure	IDR 81,225,609,878	IDR 118,927,966,625
	User Failure	IDR 37,702,356,747	
Average Proportion of Profit Reserved			IDR 842,804,550,000
Total of Optimum Reserve Fund for E-Banking Risk			IDR 1,604,921,598,625

Based on the settlement results for reserve fund optimization with EVaR constraints in Table 7, the value of system risk reserves is greater than the operational risk. This is in accordance with the simulation data obtained from digital banking losses, where system risk is much greater than the operational risk. However, the system and operational risk provisioning results have considered the maximum potential loss value based on EVaR. In this case, the provisioning value is greater than the potential loss result. This highlights the role of the EVaR parameter on digital banking risk losses. The optimum total reserve fund for digital banking risk is IDR 1,604,921,598,625.

The result of the reserve fund is optimal, which can be shown by several validations that meet the regulatory criteria, especially in Indonesia: (1) the provision of reserves (based on the Limited Liability Company Law), which must meet at least 20% of the operating capital or at least IDR 1,601,504,550,000; (2) the total value of the reserve fund does not exceed the company's profit, thus meeting the requirements of a company with positive profits; (3) therefore, the total value of the optimized reserve fund provides optimum minimization and meets all the constraints required to overcome the maximum potential loss. In this case, the reserve fund should be more than the maximum potential loss as measured by EVaR.

5. Conclusions

Based on the results and discussion of this research, the following conclusions can be drawn: The reserve fund optimization model that has been obtained has a linear programming form. The mathematical properties of the reserve fund optimization model have additivity properties and coefficient certainty properties. The additivity property assumes that there is no form of cross-multiplication between the corresponding variables. The additivity property applies to both the objective and constraint functions. Hence, there will be no cross-multiplication in the model. The property of certainty indicates that all model parameters are constant. The certainty property means that the coefficients of the objective function and the constraint function are exact values. Then, the simulation of loss data from digital banking risk produces data that follow the Generalized Pareto Distribution. In this case, the loss data can be continued to determine the maximum loss estimate using Extreme Value-at-Risk (EVaR). This is based on the extreme characteristics of digital banking transaction risk loss data. The results of the reserve fund optimization model comply with Basel II, Basel III, and Article 71 paragraph (1) of the Limited Liability Company Law regarding the minimum limit of reserve fund allocation. The result of the optimum reserve fund meets the reserve requirement (Law of Ltd. Company), which is at least 20% of capital. In addition, the total value of the reserve fund does not exceed the company's profit, thus fulfilling the requirements of a company with positive profits. Therefore, the total value of the optimized reserve fund provides optimum minimization and satisfies all the constraints required to overcome the maximum potential loss. The optimization model

in this study provides better optimum results when compared to the standard method of financial regulatory rules in Indonesia, because it considers the maximum potential loss in the future period (EVaR), while the determination of reserve funds with a standard method only considers historical profit data. The results of this reserve fund optimization are expected to be useful as theoretical recommendations for banks that operate digital banking systems in analyzing losses from digital banking transaction risks. This can be a practical recommendation to avoid the worst risk of a banking company, which is a collapse due to an imbalance in the required reserve funds.

In addition, this study has limitations. Hence, more in-depth exploration is needed in the future. The first limitation of this study is its focus on the case of banking regulation in Indonesia. Future research should be able to assess and validate the findings of this study in other countries to increase the generalization of the results. Second, this study used Linear Programming Optimization and EVaR methods to measure the potential losses from digital banking risks. Thus, future research can consider a combination of methods with Genetic Algorithms to predict potential risk losses in the future period; research conducted by [34] Abraham et al. (2022) can be used as a reference. Third, this study used four types of digital banking risks. Therefore, future research should employ other types of digital banking risks and increase the sample data of these risk losses. In addition, related to solving optimization problems with hyperparameter form, it is expensive to calculate computationally; then, a Bayesian optimization approach can be used for future work.

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