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Is the hybrid method more adequate for measuring operational risk?

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Abstract
Research aims: Risk management in financial institutions struggles with setting suitable capital charges for operational losses, resulting in large, disproportionate reserves that impact profits. This study, therefore, aims to develop a tailored operational risk measurement model for general takaful companies, addressing this challenge and optimizing capital allocation.
Design/Methodology/Approach: This study employed a hybrid approach, merging the loss distribution approach (LDA) with historical data and scenario analysis for insurance company loss events. Compiling data into distributions, it utilized Monte Carlo simulations to determine value at risk (VaR). The resulting VaR guided the calculation of operational risk capital charges for future periods.
Research findings: Measurement using the hybrid method could produce more adequate operational risk capital charges. These results confirm the acceptability of the VaR calculation and have been validated by the Kupic test.
Theoretical contribution/Originality: This research offers a more comprehensive alternative method of measuring operational risk by combining historical company data with expert opinions, making it more likely to be practiced in the industry.
Practitioner/Policy implication: The results of this study put forward an alternative, more suitable model for industry and regulators to measure operational risk management in general *takaful* companies.
Keywords: Operational Risk Modeling; Hybrid Method; Loss Distribution Approach; Scenario Analysis; General *Takaful*

Introduction

Operational risk exists in all types of organizations and business units of financial institutions (Cornwell et al., 2023; Darmawan, 2014). It can be called a significant risk in almost all industries (Neil et al., 2009; Corrigan & Luraschi, 2013). Operational risks can result in substantial financial losses, reputational damage, and losses to customers and employees, either directly or indirectly (Cornwell et al., 2023).

Operational risks are responsible for a significant portion of the major losses experienced in the financial sector (Neil et al., 2009; Berger et al., 2022). For instance, the $1.6 billion loss suffered by Barings in 1995 was a result of operational risk (Smithson, 2000). JP Morgan Chase's losses were over $5 billion from unauthorized trading; major banks lost tens of billions of dollars to Bernard Madoff's Ponzi scheme; Wells Fargo suffered several operational failure losses resulting in $1 billion in fines from the Consumer Financial Protection Bureau (CFPB) and Office of the Comptroller of the

Currency (OCC) for mortgage and insurance violations entirely due to failure to anticipate operational risks (Berger et al., 2022).

In the insurance industry, life and general insurance and reinsurance companies place operational risk as the dominant financial, market, and credit risks (Neil et al., 2009; Lima et al., 2020) . The same principle applies to Islamic insurance, commonly known as *takaful*. *Takaful* operations are characterized by the concept of risk-sharing, involving the segregation of funds between participants (*tabarru'*) and the company acting as the operator (Rahman & Mohamad, 2010; Mohd. Ma'sum Billah, 2019), which also face operational risks. Therefore, Islamic general insurance (general *takaful*) must also establish appropriate operational risk management and measurement aligned with Sharia law (Alokla & Daynes, 2017).

Operational risk also has a substantial adverse effect on a company's earnings and triggers a large-scale decline in revenue that could result in bankruptcy (Wei, 2003). Berger et al. (2022) stated that operational risks could be more systemic than imagined. In detail, Wei (2003) has shed light on why attention to operational risk continues to increase. First, it is due to the higher growth in operating losses. Second, increasingly sophisticated financial technology causes the emergence of deregulation. Third, increased regulatory attention is being paid to operational risk management. Especially in insurance companies, operational risks can substantially affect the company's risk situation (Gatzert & Kolb, 2012). This denotes that operational risk can become a more significant part of the total risk portfolio that is increasing in technology-based financial systems and become the dominant risk in some institutions (Wei, 2003; A. S. Chernobai et al., 2007).

As a result of the ever-increasing complexity of products, good monitoring processes and adequate quantification of operational risk losses are becoming increasingly necessary (Brandts, 2004; Gatzert & Kolb, 2012). For this reason, as the main risk guarantor, insurance companies need to adopt quality practices and measures in risk management (Akotey & Abor, 2013). In addition, the regulations in Solvency II are made to increase the need for effective operational risk management, development, and application of structured methodologies for its analysis. Thus, many researchers began to study classical modeling techniques, value at risk (VaR), and other methodologies for analyzing and quantifying operational risk for insurers (Torre-Enciso & Barros, 2013).

Additionally, financial institutions recognize the importance of managing and measuring operational risk. The potential for destructive operational risk has been demonstrated by the large number of operational losses (Angela et al., 2009). The regulatory framework in the banking sector (Basel II) and solvency projects in the insurance sector (Solvency II) recognize the importance of operational risk by requiring explicit treatment with the determination of specific capital requirements. They can be meaningfully exercised if the effectiveness of the organization's risk management and control processes is regularly assessed and included in the modeling (Neil et al., 2009).

Large selection of operational risk measurement methods, Basell II, offers three main measurement methods, consisting of (1) Basic Indicator Approach (BIA); (2) Standardized Approach (SA); and (3) Advance Measurement Approach (AMA) (Neil et al., 2009; Chapel et al., 2012). AMA is widely adopted as a guideline for measuring operational risk in many financial industries, including insurance. The AMA approach introduces the Loss Distribution Approach (LDA), Bootstrapping Approach, Bayesian Approach, and Extreme Value Theory (EVT) (Fuadi et al., 2020). According to Wang et al. (2017) and Leone et al. (2018), LDA is the most accurate and popular approach to measuring operational risk, well-defined, although it is very complex.

Various studies have given confidence that LDA is the most recommended method by actuaries, considering that, in general, the available operational loss data is minimal (Leone et al., 2018). Thus, by simply compiling data on a specific frequency and severity distribution, Monte Carlo simulations can be carried out to obtain projections of future loss values. In addition, LDA can describe the data distribution by historical data (internal company data) and can be combined with external company data so that, empirically, it is valid data or the magnitude of past losses experienced (Wang et al., 2017). Calculations with LDA are also considered more accurate since they are the company's data (bottom-up), not based on values regulated by regulators (top-down) (Habachi & Benbachir, 2020).

Nevertheless, LDA also has disadvantages. LDA is still deemed a complicated and complex method, so it is still challenging to apply in industry. In addition, because LDA is an actuarial model development, quantitative approaches alone are considered inadequate, as it is still possible to contain unexpected events that may not have been experienced in the past, such as catastrophic events (Habachi & Benbachir, 2020). For that, it needs to be combined with data in the form of intuition or the opinion of experts experienced in risk management (Mwangi, 2017). In this case, it can be developed with a scenario analysis method to compile pessimistic, moderate, and optimistic scenarios for a risk.

In operational risk modeling, the abundance of qualitative information, uncertainty, and low frequency of operational risk events are challenges (Pena et al., 2021). Therefore, some experts propose approaches that integrate techniques tailored to specific scenarios. Scenarios enrich data on operational risk events by performing simulations that have not yet occurred and are, therefore, not part of an organization's internal database but may occur in the future or have already occurred in other companies (Bonet B et al., 2021).

Bonet et al. (2021) propose scenarios with fuzzy methods to add risk scenarios as a valuable data source to the data used for operational risk measurement. Meanwhile, Pena et al. (2021) designed new models for modeling in organizations by bringing together their best features with the fuzzy convolutional deep-learning model. It is already machine learning-based and refers to Basel III. Various fuzzy models, ranging from developing operational risk management frameworks to estimating risk events using machine learning and artificial intelligence, using fuzzy logic, will be convulsed to obtain a more perfect model. Of course, this requires the availability of more data, as well as a more complicated process. Scenarios using expert opinions in predicting loss data are easier to obtain without reducing the data quality added.

Further, operational risk is one of the most challenging types of risk to measure, although it can be measured through proxy or internally developed models (Acharyya, 2012). In many cases, the proxy does not truly reflect the operational risk profile of the company. Internally developed risk-based models can reflect a company's risk profile (Smerald et al., 2016). However, the model needs to consider relevant data elements, such as internal events of operational risk, expert opinion on the scenario, and, where possible, the output of the risk and risk control self-assessment (Mwangi, 2017).

Drawing from both supporting and opposing perspectives, this study seeks to develop a hybrid approach for computing operational risk capital charges by integrating LDA and scenario analysis. Expert opinions supplement historical data, facilitating Monte Carlo simulations to derive OpVaR. This method ensures precise operational risk capital charge, contributing to insurance practices and regulatory oversight. Crafting alternative calculation models for the insurance sector enhances the accuracy of capital charges, providing a detailed depiction of a company's actual risk profile and advancing risk management in Islamic insurance entities.

Literature Review

Operational risk, according to POJK Number 44/POJK.05/2020, is a risk due to inadequacy and/or malfunction of internal processes, human error, system failure, and/or external events that affect the operations of Non-Bank Financial Services Institutions (LKJNB). Hence, operational risk has a broad and complex dimension, covering internal processes, company human resources, systems, and events originating from outside the company/external factors (Acharyya, 2012; A. S. Chernobai et al., 2007; Torre-Enciso & Barros, 2013). Failure of internal processes can result in the non-running of the control function and affect the company's operations (Arbi et al., 2011). In addition, failure to address operational risks related to human resources results in the occurrence of fraud (Brandts, 2004; Gatzert & Kolb, 2014), such as embezzlement, abuse of authority, bookkeeping errors due to carelessness, lack of employee competence, work accidents, and others (Wei, 2003).

System failure, which is an operational risk, is also faced by many insurance companies (Torre-Enciso & Barros, 2012; Oscar Akotey & Abor, 2013). When insurance companies are highly dependent on information technology, the opportunity for data damage, system errors in making programs, untested technology, and information system security are among several risks that can threaten the company's sustainability. Eling and Wirfs (2018) place cyber risk as a risk that must be taken into account with a high catalytic risk. A significant source of cyber risk is human behavior, which is very different from other risk categories, so some researchers separate this risk from operational risk (Eling & Wirfs, 2018).

Lastly, risks from external parties are operational risks originating from outside the company and the company's control; for example, natural disasters or security disturbances, such as riots, commotions, or even terrorism, although this rarely happens (Wei, 2003; Acharyya, 2012). The Aceh tsunami disaster (2004) is a clear example of how insurance company assets suffered tremendous destruction due to external risks.

In operational risk measurement, the first step is risk identification by compiling a loss event database (LED). Preparing operational loss data is vital because, without data, preparing operational risk measurement models becomes very difficult and cannot even be done (Muslich, 2007). In particular, the Operational Risk Consortium (ORIC) Ltd (2015) has elaborated more specifically on the operational risk taxonomy for insurance companies. Seven loss events fall into operational risk: (1) internal fraud; (2) external fraud; (3) employment practice and workplace safety; (4) client, products, and business practices; (5) damage to physical assets; (6) business disruption and system failures; and (7) execution, delivery, and process management (Acharyya, 2012; Torre-Enciso & Barros, 2012; Wei, 2003; Abdullah et al., 2011; Wyman & International, 2015; Angela et al., 2009).

Operational Risk Measurement Model

Measurement techniques or models that can determine the capital burden of operational risk are indeed needed in a healthy organizational risk management process (Chen et al., 2022). These models help companies reduce capital requirements, allowing excess money to be used elsewhere to acquire more profitable investments while maintaining exposure to risks that could affect future revenue-generating capabilities (Torre-Enciso & Barros, 2013).

Various studies have been conducted to develop quantitative operational risk models to help management make independent considerations (Orkut et al., 2013). Cruz et al. (1998), for example, presented a quantitative operational risk measurement model based on extreme value theory long before the rules of Solvency II and Basel II were applied. The model is very similar to the methodology value-at-risk-type used in the measurement of market and credit risk (Wang et al., 2017).

Following Cruz et al. (1998), the quantification of operational risk is growing. Smithson (2000), Kato (2012), and Gatzert and Kolb (2012) provide an overview of the techniques used in quantifying operational risk. Operational risk moves from a traditional to a fully integrated approach (G.L.Overton et al., 2004). Several techniques from probability and statistics prove useful in quantitative modeling environments (V. Chavez-Demoulin et al., 2006). Besides, Tripp et al. (2004) and Chernobai and Rachev (2007) offer actuarial techniques to measure operational risk. Using qualitative data, Acharyya (2012) tried to design an operational risk management optimization model from a perspective of risk-return trade-off.

By far, LDA is the most popular and widely used method in the financial industry. The LDA method utilizes data on the company's operational losses. The collected data is tabulated in the frequency distribution of events and the distribution of operational loss severity and then processed using actuarial models (Angela et al., 2009). Neil et al. (2009) further developed using Hybrid Dynamic Bayesian Networks (HDBNs) to model operational risk in the context of AMA. This approach focuses on causal modeling, including the interaction between failure and control modes.

LDA also provides a rigorous approach to modeling past loss distributions. It has become standard practice to model operational risk, where historical loss distributions are assumed to predict best future losses (Einemann et al., 2018). The roots of quantitative LDA come from actuarial techniques developed by the insurance industry over the years. However, caution is still needed due to the specificity of operational risks, especially reporting bias and lack of data (Frachot et al., 2003).

Although LDA has evolved for quite some time as an industry standard for operational risk models, it does not mean it does not have weaknesses. LDA's focus on historical loss data often ignores expert knowledge of more predictable types of operational risk (Mwangi, 2017). In addition, using LDA becomes very complex when many theories and models are used, such as the probabilistic approach, Bayesian approach, Markov chain approach, Monte Carlo, and copulation-to-model correlation (Habachi & Benbachir, 2020).

Einemann et al. (2018) then offer an alternative quantification technique called an exposure-based operational risk (EBOR) model that can be applied to many operational risks. In addition, Eckert et al. (2020) propose a mathematical model for the spillover effect caused by operational losses and calibrate them based on extensive empirical studies of spillover effects and factors affecting them in the banking and insurance industry.

Additionally, Mwangi (2017) researched general insurance companies creating simulation hybrid models for operational risks and compared them with the regulator's predetermined model. The result is that the hybrid model produces more careful operational risk capital estimation than the model used by the regulator. The modeling of operational risk, which relies on various distributions to assess frequency and severity, is contingent upon the specific nature of the operational risk being modeled and the accessibility of relevant loss data for each company (Sharma, 2020).

The use of the latest approach, Standardized Measurement Approach (SMA), although Basel III has proposed it, still raises pros and cons (Peters et al., 2016). The SMA method is considered to have instability, risk insensitivity, super-additivity, and an implicit relationship between the SMA capital model and systemic risk in the financial/banking sector (Shevchenko et al., 2016). It was found that SMA lacked risk responsiveness and interpretive capabilities and did not consider the primary sources of operational risk. Mignola et al. (2016) argue that SMA is not only backward in its ability to quantify risk, but perhaps more importantly, it fails to create any link between management actions and capital requirements.

Therefore, the AMA approach, especially LDA (quantitative), is still deemed relevant to be applied to insurance companies but needs improvement from a qualitative side by considering expert opinions. This approach can be done using a hybrid method that combines the LDA method (based on the model in Basel II) and scenario analysis by paying attention to experts' opinions.

Loss Distribution Approach (LDA)

LDA is a statistical method widely used in actuarial science to calculate the distribution of aggregate losses, so it is also called the actuarial model (Angela et al., 2009). LDA concerns measuring the risk of random loss resulting from a matrix whose elements correspond to a combination of lines of business and types of events within one year (Chavez-Demoulin et al., 2006). This model determines each loss event's frequency distribution and severity and identifies the most appropriate empirical data distribution. The operating risk capital expense is then estimated by calculating the value at risk and expected loss (Angela et al., 2009).

In practice, collecting adequate data from all lines of business is challenging. Therefore, financial institutions typically model the number of loss events separately in a given year and the number of losses from a single event according to the frequency distribution and severity distribution (Sharma, 2020). The standard LDA model expresses aggregate losses as the sum of individual losses, which is notated as follows Model 1.

$$L = \sum_{j=1}^{n} Lj \quad \text{...1)}$$

Where L is the aggregate loss; nj is the amount of loss per year (frequency of events); and Lj is the amount of loss (severity). Therefore, losses arise from two sources of randomness, i.e., frequency and severity, which must be modeled. Frequency and severity are assumed to be independent, and L_1,..., Ln is an independent random variable that follows the same distribution (Sharma, 2020).

In the LDA approach, the total operating loss is the sum (S) of the random variable (N) of individual operating losses (X1, X2, X3, ... XN) so that the number of operating losses can be expressed as follows Model 2.

$$S = X1, X2, \ldots XN = 0,1,2 \quad \text{...2)}$$

This LDA model assumes that the random variable operational loss X is independent and identically distributed. This assumption means that the frequency distribution of operational losses N (frequency) is independent of the losses' value or severity distribution (Xi).

$$G(x) = \begin{cases} \sum_{i=1}^{\infty} \mathrm{pi}\, F(x) & x > 0 \\ p(i) & x = 0 \end{cases} \quad \text{...3)}$$

Where F(x) is the cumulative probability of the i-th loss, which is x. Since the probability of distribution G(x) cannot be evaluated precisely, this probability can be evaluated with Monte Carlo simulations or algorithms recursive manager. The Monte Carlo simulation approach is more practical and widely employed (Muslich, 2007). Monte Carlo simulations are performed with frequency distribution model probability and loss severity simulated at least 10,000 times and calculated aggregate loss value at the desired confidence level, such as 95% or 99%.

Scenario Analysis

Scenario analysis is a method that allows us to fill in gaps by creating synthetic data that contains various scenarios (Sharma, 2020). In operational risk modeling, scenario analysis is a way to assume the magnitude of losses that will be incurred and the frequency of operational risk events that a financial institution may face. Scenarios enrich operational risk event data by simulating events that have not yet occurred but may occur in the future or have already occurred in other organizations (Bonet B. et al., 2021).

Sharma (2020) defines scenario analysis as a systematic process of obtaining expert opinions from business managers and risk management experts to assess the likelihood and impact of reasonable operational losses. One of the perceived benefits of scenario analysis is that it generates data that can be used to supplement historical data, especially at the distribution end (Pena et al., 2021; Bonet B. et al., 2021; Sharma, 2020). For example, it is possible to build optimistic, pessimistic, and disaster scenarios (catastrophes) for operational losses (Sharma, 2020). Once this scenario is created, it can be converted into three data points added to the historical data set (Pena et al., 2021).

Another procedure is to generate the scenario's loss distribution parameters, which can be combined with similar parameters derived from historical data. Compared to external data, the advantage of supplementing historical internal data with scenario data is that external data suffer from different types of bias (Sharma, 2020). On the other hand, scenarios are considered relevant and most accurate if there is no good quality internal data. Although scenario analysis still inherently contains subjective elements, if done well by utilizing the knowledge of experts, it will form a prospective view of risks related to state control and can identify risks that have not yet crystallized (Smerald et al., 2016; Mwangi, 2017).

Research Method

This research was conducted on a full-fledged Islamic general insurance (general *takaful*) company, Indonesia's largest and most comprehensive product. The utilized data encompassed internal secondary data or company claim data spanning three years, specifically from 2018 to 2020. This research employed a hybrid method in calculating operational risk capital charges. The hybrid method integrates LDA based on historical data from the company's past and scenario analysis constructed on expert opinions and future projection data (Neil et al., 2009; Einemann et al., 2018).

The procedural steps in the modeling process to generate combined scenarios were conducted as follows. Firstly, the relevant fundamental risk events were selected using operational risk categories defined in Basel II. Secondly, all potential causes of these risk events were considered (Mwangi, 2017). To conduct modeling for measuring potential operational losses, it is necessary first to understand the characteristics of the distribution of operational losses or claims. In addition, operational loss or claim data distribution was categorized into frequency and severity distributions. According to Mwangi (2017), one of the advantages of this method is that it can be incorporated into the internal model of insurance companies and adapted to all types of insurance businesses, including general, life, and reinsurance companies.

In an ideal scenario, the data employed to compute economic capital related to operational risk was derived from the seven risk loss events outlined by Basel II and ORIC. Nevertheless, due to restricted data access, claim data was utilized as a proxy. Moreover, claim data is frequently employed as a substitute for operational losses in insurance companies, including general takaful firms, as it adequately represents operational risk events or their associated impacts. The characteristics of claims data similar to operating loss events also make it a strong reason for researchers to use them to calculate potential operating losses of insurance companies (Muslich, 2007).

The claim data used was a settled claim, meaning that the amount of claim paid to participants/customers was reduced by *retakaful* and subrogation. The gathered claim data comprised various Classes of Business (CoB), such as motor vehicle, property, engineering, liability, marine hull, marine cargo, general accident, and miscellaneous. The operational loss or claim data 2018 - 2020 was further classified into frequency and severity distributions, as illustrated in Tables 1, 2, and 3.

The comprehensive steps for calculating OpVaR can be observed in Figure 1. The next step was to identify the data distribution once the data were gathered. After selecting multiple distribution options for both frequency and severity data, statistical tests (Goodness of Fit – GoF) were conducted through Easyfit 5.6 software to validate the chosen distribution against empirical data. The statistical tests included Chi-Square, Anderson-Darling, and Kolmogorov-Smirnov (K-S). Subsequently, the distributions were ranked to determine the most suitable choice.

Following the statistical examination of the complete distribution, the LDA- LDA-aggregation model was subsequently applied in conjunction with scenario analysis. The available claims data was then integrated with expert opinions, including those from the head of the engineering and underwriting division and the claims manager.

Table 1 Frequency and severity of general *takaful* claims 2018

Class of Business	2018																							
	Jan		Feb		Mar		Apr		May		Jun		Jul		Aug		Sep		Oct		Nov		Dec	
	Freq	Sev	Freq	Sev	Freq	Sev	Freq	Sev	Freq	Sev	Freq	Sev	Freq	Sev	Freq	Sev	Freq	Sev	Freq	Sev	Freq	Sev	Freq	Sev
Engineering																			1	6,310	2	4,613	2	13,085
General Accident					1	36,000											1	196	5	4,150	6	3,826	4	715
Liability																								
Marine Cargo																								
Marine Hull																								
Miscellaneous	1	40,932	1	78,458					1	9,053					1	8,938							2	160,079
Motor Vehicle	19	177,480	21	80,641	13	93,608	19	97,544	8	114,200	5	20,369	7	53,531	17	102,629	11	62,180	23	122,739	26	192,542	28	241,252
Property					3	13,901									1	39			1	93	2	67,216	1	

Table 2 Frequency and severity of general *takaful* claims 2019

Class of Business	2018																							
	Jan		Feb		Mar		Apr		May		Jun		Jul		Aug		Sep		Oct		Nov		Dec	
	Freq	Sev	Freq	Sev	Freq	Sev	Freq	Sev	Freq	Sev	Freq	Sev	Freq	Sev	Freq	Sev	Freq	Sev	Freq	Sev	Freq	Sev	Freq	Sev
Engineering	1	26,240							2	19,381	6	15,135			4	15,769			1	33,320				
General Accident	3	3,202	4	2,592	5	5,025	7	6,220	5	6,830	2	497	7	2,938	6	5,733	19	25,000	35	94,457				
Liability																			1	750	71	226,364	248	302,097
Marine Cargo																	2	108,003			1	5,402		
Marine Hull																							2	189,075
Miscellaneous	1	40,554			1	6,830															1	180,401		
Motor Vehicle	31	184,338	24	171,018	37	422,364	26	159,193	52	670,073	21	142,508	44	356,368	56	357,607	39	286,000	58	472,785	42	277,433	40	259,380
Property			1	25,728	6	239,613	2	11,658	1	34,816	6	139,588	2	219,709			2	68,794	1	316	1	12,760	1	19,310

Table 3 Frequency and severity of general *takaful* claims 2020

Class of Business	2018																							
	Jan		Feb		Mar		Apr		May		Jun		Jul		Aug		Sep		Oct		Nov		Dec	
	Freq	Sev	Freq	Sev	Freq	Sev	Freq	Sev	Freq	Sev	Freq	Sev	Freq	Sev	Freq	Sev	Freq	Sev	Freq	Sev	Freq	Sev	Freq	Sev
Engineering					577		1	824	1	2,031	1	0							2	11,115	1	14,742	2	16,404
General Accident	201	245,464	1,126	550,246		529,520	515	152,054	352	79,056	193	34,156	277	111,585	583	193,013	354	61,385	204	45,762	242	106,088	469	107,772
Liability			1	950									3	774	2	4,020								
Marine Cargo													2	165,364			1	87,022	2	307,733	6	505,651	6	494,080
Marine Hull																					2	607,633	1	11,864
Miscellaneous			1	2,610	96						1	640												
Motor Vehicle	48	304,113	109	583,461	3	295,018	81	419,252	83	428,017	41	308,422	89	749,774	61	311,269	30	104,671	34	373,227	53	456,335	89	519,400
Property	1	21,037	1	19,780	676	22,751	1	7,848	1	132,857	3	146,657			1	1,216	2	37,107	3	1,144,226	3	36,785	7	732,531

They were asked to choose various scenarios, including optimistic, moderate, and pessimistic ones. With the existing empirical data, in the case of motor vehicle COB, for the optimistic scenario, experts were asked for their opinions on the smallest possible values of frequency and severity that could occur in a month based on experience and considering various events that might occur, assuming that risk management is functioning very well. Similarly, experts determined the frequency and severity of the most significant possible events for the pessimistic scenario, considering catastrophic events, such as tsunamis, pandemics, and others, not present in the empirical data. Besides, Monte Carlo simulations were employed to process data about claims and expert opinions for each CoB, deriving an OpVaR value at a specific confidence level.

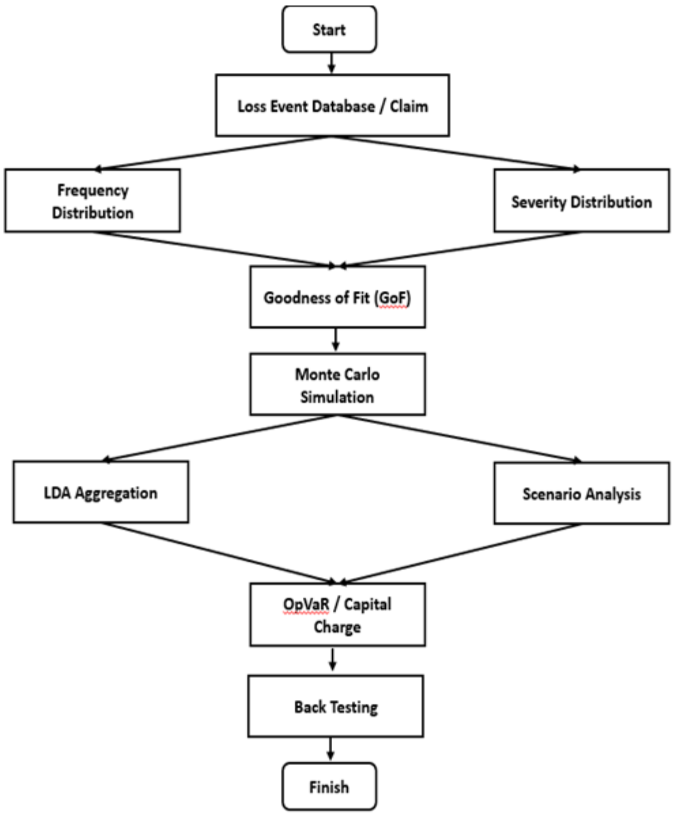

Figure 1 Research Process

The calculation of operational risk capital charges was obtained from Monte Carlo simulation results for all CoBs 10,000 times. The probability value of severity from each running number row was summed, the sum results were sorted from the largest to smallest severity value, and the 99% confidence level (percentile) percentage was done in the same order. The total severity in the row sequence corresponding to the 99% percentile was used to estimate OpVaR. Furthermore, the OpVaR value of each COB was added together so that the total OpVaR value was obtained. The total value of OpVaR was employed as the value of capital charges. The combination of frequency distribution and severity was done with Microsoft Excel software.

According to Navarrete (2006), OpVaR is a combination of expected and unexpected losses. Expected loss (EL) is a loss expected to occur or is normal as part of the day-to-day business of low severity (Neil et al., 2005). An example is losses due to unintentional miscalculation of foreign exchange transactions. Meanwhile, an unexpected loss (UL) is an extraordinary loss that rarely occurs and has a high severity level. The examples include major fraud activities (Neil et al., 2005). In risk management, unexpected loss is often referred to as tail risk. Tail risk is a loss that occurs with low probability but has a significant impact. In this regard, Navarrete (2006) argues that the capital that must be reserved for operational risk is as much as unexpected loss, i.e., the difference between OpVaR and expected loss.

To ensure whether the model used was valid, a model validity test was carried out (backtesting). This study used the proportional of failures (Kupic Test) method. According to Muslich (2007), the test step of this model includes determining the magnitude of OpVaR over time according to the projection period and then determining the actual amount of operating loss in the same period as the projection period. Furthermore, the binary indicator was determined, provided that if the OpVaR is greater than the actual operational loss, the value of the binary indicator is 0 (zero). Conversely, if it is smaller, the value of the binary indicator is 1. The binary indicator values were added together, becoming the sum of the failure rates. Then, the confidence level at 1-α = 99.9%, and the magnitude of the expected failure rate at α was determined.

The final step was to calculate the loglikelihood ratio (LR) by counting the number of errors (failure rate) that occurred compared to the sum of data using the formula in Model 4.

$$LR = -2\ln\left[(1-\alpha)^{T-V}\alpha^{V}\right] + 2\ln\left[\left(1-\frac{V}{T}\right)^{T-V}\left(\frac{V}{T}\right)^{V}\right] \text{.............................4)}$$

Where LR is loglikelihood ratio); α is probability of error below zero hypothesis; V is number of estimation errors; and T is number of observational data.

If the number of failure rates is smaller than the expected failure rate, operational risk models are valid for use in projections or by comparing LR values against chi-square critical values with freedom one at the expected significance level. If the LR value is smaller than the critical value of the chi-square, the risk calculation model is valid, and vice versa.

Result and Discussion

General *takaful* companies have various products that can be classified into several business classes (CoB). Different products have different characteristics. Motor vehicle insurance tends to have a high frequency of claims throughout the month (Figure 2), with relatively high severity (Figure 3). As for CoB property, the frequency of claims is low, but the severity can exceed the CoB of motor vehicles.

Based on the history of claim data in Figure 3, it can be seen that the claim with the highest severity occurred in the CoB general accident. This happened at the end of 2020. Personal accident plus products with a guarantee of death due to COVID-19 made this product sought after by many people. With many policies plus a pandemic atmosphere, the value of claims has soared dramatically at this CoB.

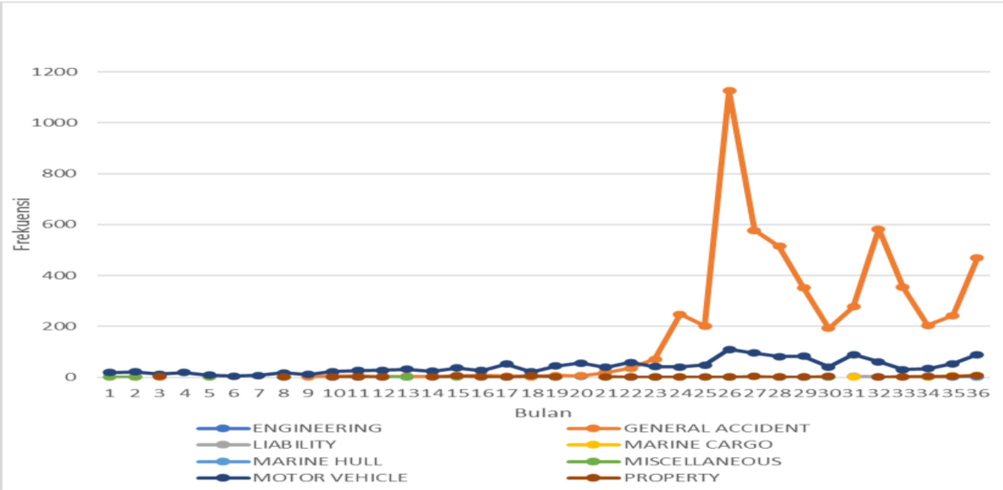

Figure 2 Frequency of Monthly Claim Data 2018-2020

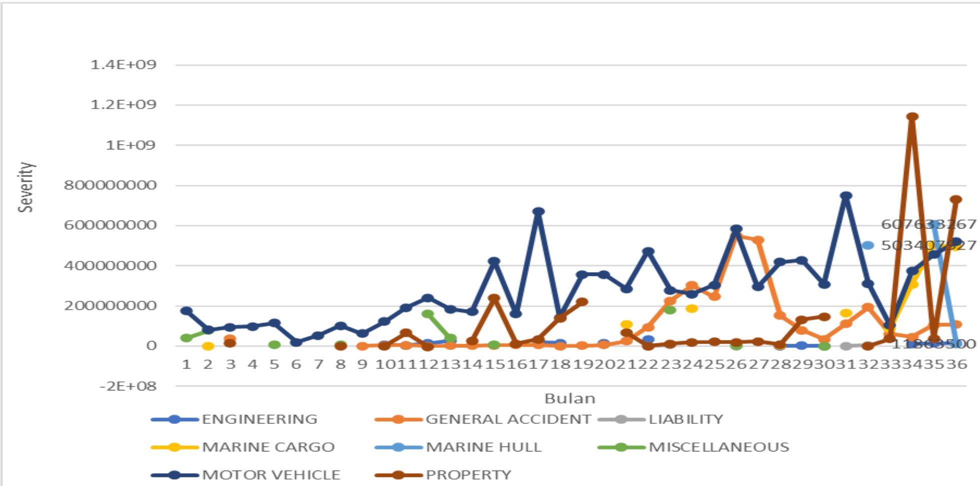

Figure 3 Severity of Monthly Claim Data 2018-2020

The GoF test results revealed that the frequency distribution predominantly followed a Poisson distribution, except for the CoB motor vehicle data, which exhibited a negative binomial distribution. This indicates that the data was discrete and displayed a consistent pattern. In summary, it can be concluded that most of the frequency distribution generally adheres to the Poisson.

Table 4 indicates that the severity distribution varied across different categories. CoB engineering followed a normal distribution, while general accident, marine cargo, and miscellaneous exhibited a lognormal distribution. Besides, liability, motor vehicle, and property followed Weibull and Gen Pareto distributions, respectively. This specific data distribution is essential for conducting Monte Carlo simulations. Notably, the lognormal distribution stood out as the predominant pattern in severity distribution and would be employed in Monte Carlo simulations.

Table 4 Frequency and severity distribution per COB

No	Class of Business (CoB)	Distribution	
		Frequency	Severity
1	Engineering	Poisson	Normal
2	General Accident	Poisson	Lognormal
3	Liability	Poisson	Weibull
4	Marine Cargo	Poisson	Lognormal
5	Motor Vehicle	Negative Binomial	Weibull
6	Property	Poisson	Gen Pareto
7	Miscellaneous/Marine Hull	Poisson	Lognormal

Calculating OpVaR Using Monte Carlo Simulations

Table 5 demonstrates the OpVaR calculation results from each CoB with a confidence level of 99%. With the aggregation model through a simulation process of 10,000 times, the total value severity loss of each simulation could be known. Next, the order of the total values of severities was sorted. The OpVaR value was obtained based on the percentile desired level of confidence. In this study, the level of confidence chosen was 99% (percentile 99%), and then, based on Table 5, an OpVaR value of IDR 1,172,491,160.95 was obtained. Operational value at risk can also be called the maximum potential loss value in one period that can occur on all CoB insurance claims with a confidence level of 99%.

Table 5 Operational value at risk (OpVaR)

Class of Business	OpVaR
Engineering	1,068,567.44
General Accident	2,413,189.63
Liability	71,771.57
Marine cargo	2,686,622.89
Motor vehicle	29,252,207.34
Property	451,398.33
Miscellaneous	1,340,876.07
VaR Sorted	1,172,491,160.95

With the known OpVaR, the value of unexpected loss could then be determined, as presented in Table 6 as follows:

Table 6 Unexpected loss calculation

OpVar CL 99% (IDR) (a)	Expected Loss (IDR) (b)	Unexpected Loss (IDR) (a-b)
1,172,491,160.95	529,921,126.62	642,570,034.33

Expected loss (EL) is the average loss calculated to occur in a certain period. EL is also one of the risk measures insurance companies use to calculate the premiums to be paid by policyholders. According to Navarrete (2006), the unexpected loss is generated from the reduction between VaR loss distribution and expected loss. According to the table above, the value of unexpected loss that must be anticipated due to claims was IDR 642,570,034.33.

Model Validity Test (Backtesting)

The backtesting results validated the quality and performance of the developed simulation model by comparing simulation outcomes with historical data. This study used data on actual loss per month in 2018-2020. The graph comparing the value of OpVAR with the actual data depicts that the violation was in addition to the two points. In addition, the value of OpVaR was constantly above the actual value of losses, as illustrated in Figure 4.

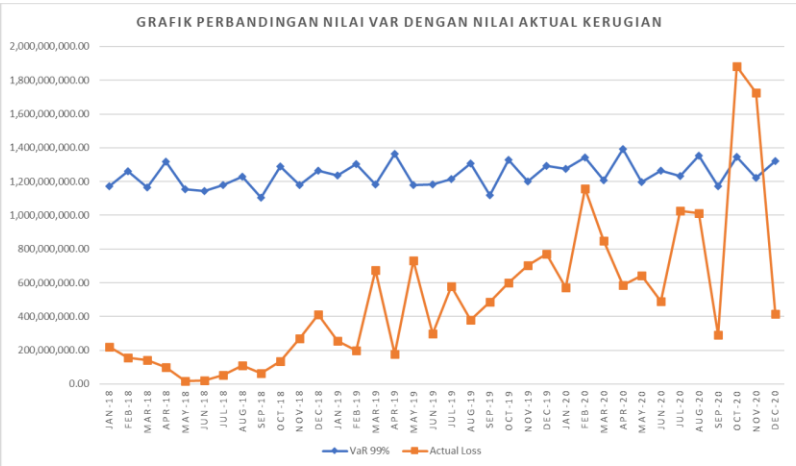

Figure 4 Comparison Graph of VaR with Actual Value of Loss

Using the Kupic Test formula, a loglikelihood ratio value of 3.656 was obtained with a confidence level of 99% and a test period of 12 months of observation period. This result was smaller than the chi-square value of 6.635. Therefore, the LDA-aggregation model used in the above OpVaR calculation was acceptable.

Based on backtesting results on the OpVaR estimation results by the hybrid method or a combination of LDA-aggregate and scenario analysis, it can be concluded that all CoBs studied obtained LR values smaller than the chi-square table with free degrees 1 and alpha 1%, which was 3.656. As such, Ho was accepted, meaning that the risk calculation model could be said to be fit or valid. Overall, hybrid methods (LDA-aggregate and scenario analysis) can be summed up as alternative methods to measure the operational risk of general *takaful*.

Discussion

The development of quantitative operational risk models has evolved, with contributions from various scholars, such as Cruz et al. (1998), Torre-Enciso and Barros (2013), Smithson (2000), Tripp et al. (2004), A. S. Chernobai et al. (2007), Kato (2012), Gatzert and Kolb (2012), Eling and Wirfs (2018), and Xie (2023). There is a consensus among these researchers that the loss distribution approach (LDA) is the most commonly utilized model. LDA is recognized for its ability to depict the distribution of internal historical data and integrate external data. However, its application complexity and challenges in the industry pose notable hurdles (Habachi & Benbachir, 2020).

Additional challenges encompass abundant qualitative information, uncertainty, and the low frequency of events (Bonet Peña et al., 2021), along with the potential existence of data experienced by other companies or extraordinary events that may not be captured in the company's historical data. These challenges prompt scholars to propose innovative solutions, such as combining LDA with scenario methods, to enhance the risk event data. It underscores the importance of exercising caution when considering the reliability of scenario data, particularly when incorporating expert opinions.

Further, research combining LDA with scenario-based methods has demonstrated capital charge outcomes that closely align with actual conditions within companies (Mwangi, 2017). Similarly, studies conducted by Bonet B. et al. (2021) and Pena et al. (2021) offer a combination of fuzzy scenarios. Hence, this research combines LDA with scenario analysis and terms it a hybrid method. The study's findings indicate that the hybrid method model produces adequate capital reserves.

Conclusion

In general, the operational risk measurement model with a hybrid method is adequate in calculating operational risk capital charge in general *takaful*. It is because the amount of capital charges obtained is close to the actual amount, not too large or too small. Testing model validity (backtesting) with a loglikelihood ratio also revealed that this model is valid. In addition, the proposed model follows the guidelines published by Basel, although the regulator in Indonesia (OJK) has not regulated the measurement model in detail. Better and more credible results are expected to be obtained with a hybrid measurement model.

The limitation of this study is the limited availability of operational risk event data, including Islamic insurance. This forced the researchers to continue using claim data as proxy operational loss data. Therefore, the next researcher needs to use the real value of operational losses. In addition, OJK is also recommended to ask the industry to develop an adequate general *takaful* information and data system to support better insurance development, specifically sharia insurance in the future.

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