Advances in Economics, Business and Management Research, volume 160
Proceedings of the International Conference on Business and Management Research (ICBMR 2020)

Operational Risk Loss Reserve Analysis of a Non-Financial Company:
A Case Study of PT. KLM

Aryo Candra Hilali[1,*] Adi Vithara Purba[1]

[1]*Department of Management, Faculty of Economics and Business, Universitas Indonesia*
[*]*Corresponding author. Email: aryohilali@gmail.com*

ABSTRACT
The purpose of this research is to analyze the operational risk of a car rental company and whether it can be applied within the company to measure the risks. This research is conducted by measuring the Operational Value at Risk (OpVaR) of PT KLM. The data used in this research is the operational losses of PT KLM for the past 26 months starting from January 2018 to February 2020. This research uses a loss distribution approach-aggregation method in measuring the operational risk. The results indicate that the value of OpVaR of PT KLM is valid after backtesting of the one-year period from January to December 2019 with the lowest OpVaR value of IDR91.053.721 and the highest OpVaR value of IDR104.550.879. This research is expected to provide additional understanding of operational problems and the amount of risk that might be faced by car rental companies, so that it can be used in planning as well as providing mitigation alternatives that can be applied to minimize potential operational losses.

Keywords: *Operational Ris,; Loss Reserve; OpVaR, Advanced Measurement Approach, Loss Distribution Approach, Car rental company.*

1. INTRODUCTION

Nowadays, various unexpected incidents of business activities are often faced by companies. An incident could have either a negative or a positive impact. COSO [1] defines incidents with positive impacts as opportunities, whereas incidents with negative impacts are called risks. ISO 31000 defines risk as the impact of uncertainty on business targets. Opportunities or risks could derive from the company's internal and external environment and could create uncertainty for the achievement of organizational goals. Usually, the management associates these opportunities and risks to formulate business strategies and plans.

One type of risk that a company may face in carrying out its business activities is operational risk [2]. Thus, an operational risk measurement is needed as a basis to manage and mitigate the risks. The Basel II Capital Accord stated that capital reserve is needed to mitigate operational risk which is currently only applicable to financial industry. There are no rules or regulations yet governing the implementation of operational risk management for the non-financial industry. Nevertheless, the fact is that companies in the non-financial industry are also exposed to operational risk.

PT KLM is a non-financial company, specifically a car rental company. One example of operational risk faced by PT KLM is the loss due to vehicle repair costs. These costs are mainly due to external factors and human error. For example, external factors include damage due to natural disasters while examples of human error are the negligence of the driver or car inspector before and after the car is being rented.

One way to measure operational risk is using a loss distribution approach (LDA) method, which is part of the advanced measurement approach (AMA) according to the Basel II Capital Accord. This method can be used by any company because it is an internal approach that is prepared by the respective company and not by the regulator [3].

There are several examples of non-financial companies that have tried to calculate their operational risk loss reserve using LDA, such as the retail store industry, manufacturing industry, and printing industry. The results varied from too low, too high, to invalid OpVaR values. However, to the best of the authors' knowledge there is no similar research has been conducted on car rental companies.

Therefore, this study is conducted in order to test whether the calculation of operational risk carried out by the company using the LDA method can be effectively used to mitigate operational risk and to protect companies, especially car rental companies, from unexpected operational losses. Besides this, PT KLM currently still has no policy regarding operational risk.

2. LITERATURE REVIEW

2.1 Definition of Operational Risk

According to The Basel Committee for Banking Supervision [4], operational risk is defined as a risk of loss that arises either directly or indirectly due to non-functioning or failure of internal processes, people and systems, and external events. Meanwhile Marshall [5] said that operational risk is a potential disruption in the company's operational processes. Disturbances that occur can originate from a mistake or error in all operational activities, lack of thoroughness or lack of control from the people involved, and system failure or disruption.

2.2 Operational Risk Management

Operational risk is an inseparable part of any business. In many businesses, most of the revenue is lost systematically due to ongoing processing errors and human errors [6]. Businesses also face greater operational risk incidents such as lawsuits, natural disasters, system failures and surveillance, as well as other external events.

Basically, risk management is an art to identify risks and decide how to control and respond to these risks with available resources [2]. The overall risk management process includes risk identification, risk measurement and risk mitigation. One example of the output of the operational risk management process in a company is a mitigation policy to transfer the risk to another party. There are few ways to transfer the risk to other parties such as insuring the asset and transferring some processes to the vendors. For car rental companies, insuring the asset (vehicles) is the most common method used to transfer the risk.

2.3 Operational Risk Measurement

The Basel Committee for Banking Supervision [4] explains that there are three methodologies in measuring operational risk to determine a company's capital adequacy i.e.:

- Basic Indicator Approach (BIA)
- Standardized Approach (SA)
- Advanced Measurement Approach (AMA)

2.3.1 Advanced Measurement Approach (AMA)

The AMA approach is a method of measuring operational risk by developing a model that is carried out internally by the company [3]. AMA emphasizes the analysis of operational losses as opposed to the analysis of gross income in the BIA and SA models. Therefore, companies must have a database of operational losses of at least two years to use the model in measuring operational risk [7]. There are three approaches in the AMA method that are often used, namely:

- Internal Measurement Approach (IMA)
- Loss Distribution Approach (LDA)
- Scoreboard/Scorecard

The effectiveness and consistency of an operational risk measurement is influenced by how operational losses are calculated and how sensitive the calculation is [8]. Risk measurement using the AMA method is said to be lower approximately 15% in gross income compared to the BIA or SA method.

Figure 1 compares the capital charge generated for operational loss reserves using various approaches. The AMA approach generates the lowest capital charge but has a higher complexity.

3. RESEARCH METHODOLOGY

3.1 Research Design

In general, the design of this study was carried out by conducting a literature review and identification of

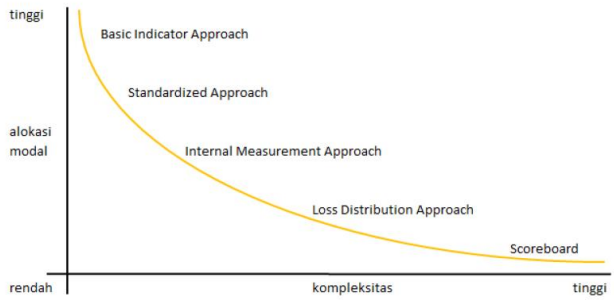

Figure 1 Methods in Operational Risk Measurement

operational risk types. Furthermore, the process of collecting data was carried out for analysis. The next step was to determine the distribution and estimate the corresponding parameters of the distribution for each severity and frequency of the loss data. The best suitable distribution was determined using the goodness of fit (GoF) test. Finally, the OpVaR was calculated using the LDA-Aggregation method. Backtesting was conducted to validate the OpVaR model.

3.2 Data

The data used is the company's operational loss data for the past 26 months, from January 2018 to February 2020. Hence, the study includes the most current data and has met the minimum 2-year requirements.

3.3 Research Method

3.3.1 Choosing Severity & Frequency Distributions Model

First of all, operational loss data will be grouped into severity data and frequency data. Both data are independent from each other. To determine the type of distribution of the severity and frequency data, the initial step is to calculate the descriptive statistics that represent the characteristics of the data. Distributions that can be used to describe the severity of losses include normal, beta, erlang, exponential, lognormal, pareto, and weibull [2]. Meanwhile, the popular types of distribution for loss frequency are poisson, binomial, and negative binomial distributions.

3.3.2 Goodness of Fit (GoF) Test

A goodness of fit (GoF) test was performed to test whether the distribution is a fit to the data.

- Graphical Test
  Graphical tests are performed to see whether the observed data follow the hypothesized distribution probability function. The closer the probability line of the `data to the reference line plots, the more fit the sample is. One type of graphical test among others is P-P Plot.

- Statistical Test
  One of the GoF statistical tests is the Kolmogorov-Smirnov (KS) test. The KS test is carried out by calculating the maximum difference between the hypothetical distribution function and the empirical distribution function. The difference is then compared to the critical value in the KS table. The maximum difference is calculated as Equation 1.

$$T = max\left[\left[F_n(x) - F(x)\right]\right] \quad (1)$$

Where $F_n(x)$ is the cumulative distribution function and $F(x)$ is the empirical distribution function

Another GoF statistical approach is the Anderson-Darling (AD) test. Unlike KS test, the calculation of critical value of AD test assumes a certain distribution. Thus, the AD test has the advantage of allowing a more sensitive test but has the drawback of having to calculate the critical value for each distribution.

For example, if X1, X2, ... Xn is the data that will be tested for normal distribution with a significance level α, then the AD test can be run using the following formula:

$$T = \frac{1}{n}\sum_{i=1}^{n}[2i-1]\left[\ln\left(F(Z_i)\right) + Ln\left(1 - F(Z_{n+1-i})\right)\right] \quad (2)$$

where Z_i is standardized data of operational loss

The null hypothesis and alternative hypotheses of the GoF tests are as follows:

H0: The distribution of operational losses follows the assumed distribution
H1: The distribution of operational losses does not follow the assumed distribution

If the test statistics are smaller than the critical value, then the data follows the distribution assumed, and vice versa.

3.3.3 Loss Distribution Approach (LDA) – Aggregate Loss Distribution

The OpVaR calculation was performed using a Monte Carlo simulation. Monte Carlo simulation generates an aggregated loss distribution, i.e. the aggregation of the severity and frequency distribution. Monte Carlo simulation generates the probability distribution of possible experimental results using random numbers. The aggregated loss cumulative probability can be stated as follows:

$$f(x) = \Pr(\sum U_t) \quad (3)$$

where U_t is individual operational losses

3.3.4 Backtesting

In backtesting, a frequent OpVaR violation implies that the estimated OpVaR is too small. On the other hand, an exceptionally low number of OpVaR violations indicates that the estimated OpVaR is too conservative or too high.

This test is carried out by comparing the OpVaR to the actual loss. A violation occurs when the actual loss is higher than the OpVaR. The ratio of the number of violations to the number of observations is called the failure rate. The failure rate is used in calculating the

Table 1. Descriptive statistics of severity loss data

Statistics	Parameter
N	316
Maximum	60.327.800
Minimum	5.011.096
Mean	16.939.780
Median	14.146.922
Standard Deviation	9.756.091
Skewness	1,42349
Kurtosis	2,19187

value of the log likelihood ratio (LR). Then the LR value will be compared with a critical value that follows a chi-squared distribution ($\chi\chi^2$). The LR value is calculated with the following formula:

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

The null hypothesis and the alternative hypothesis for backtesting are as follow:

H0: The OpVaR model is valid
H1: The OpVaR model is not valid

4. RESULTS

4.1 The Analysis of Severity & Frequency Data

One of the first steps in determining and estimating parameters for severity distribution is to create descriptive statistics that represent the characteristics of operational loss data.

Based on the Table 1, the distributions that are assumed suitable to describe the severity of the data are *lognormal* and *weibull* because both distributions have characteristics in accordance with the results of the descriptive statistics above. Furthermore, based on the results of parameter estimation using the R application, *lognormal* or *weibull* are also the distribution assumed

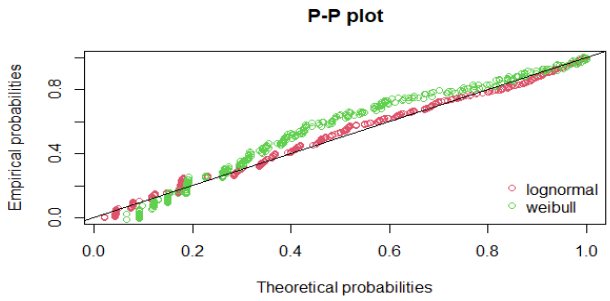

Figure 2 P-P Plot of Severity Distribution

to be suitable for severity loss data.

De Fontnouvelle, et al. [9] suggests that *poisson* distribution is the most common distribution for operational loss frequency data because of its simple characteristics and best fits the operational loss data in general. The distribution that can be fitted to the operational loss frequency data using the R application is the *Poisson* distribution. The frequency data has a *mean* (λ) of 2.45.

4.2 Goodness of Fit (GoF) Test

4.2.1 GoF Test - Severity Distribution

The GoF test based on P-P plot shows that the observed operational loss severity data has a pattern that is closer to the lognormal distribution than to the weibull distribution. The statistical test for GoF test will be carried out using Kolmogorov-Smirnov (KS) and Anderson-Darling (AD) approaches. This test is carried out to find the value of t-statistics which will be compared with the critical value of the KS table or the results of the calculation of the critical value of each particular distribution. The results can be seen on the table 2 and 3.

Table 2. Kolmogorov-Smirnov GoF Test of Severity Distribution

T Statistic	0,067		
α	0,1	0,05	0,01
Critical Value	0,069	0,077	0,092
Hypothesis	H0 : Severity loss data follows Lognormal distribution		
	H1 : Severity loss data does not follow Lognormal distribution		
Reject H0?	No	No	No

Table 3. Anderson-Darling GoF Test of Severity Distribution

T Statistic	1,206		
α	0,1	0,05	0,01
Critical Value	1,933	2,492	3,857
Hypothesis	H0 : Severity loss data follows Lognormal distribution		
	H1 : Severity loss data does not follow Lognormal distribution		
Reject H0?	No	No	No

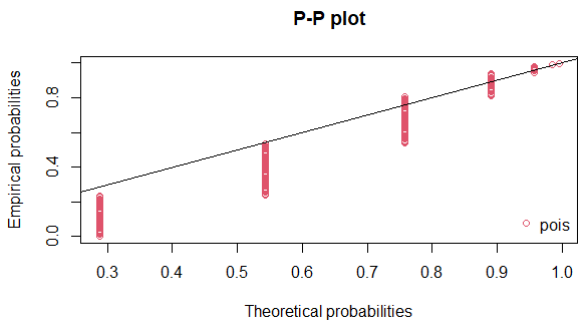

Figure 3 P-P Plot of Frequency Distribution

4.2.2 GoF Test – Frequency Distribution

The result of the graphical GoF test of the frequency data is shown in Figure 3. The frequency data has a plot similar to the P-P plot reference line of a *poisson* distribution. While the results of the statistical GoF test of frequency distribution can be seen on the Table 4 and 5.

4.3 Measurement of estimated Operational Value at Risk (OpVaR)

The LDA-aggregation approach was carried out by aggregating the two distributions, namely the frequency and severity distribution into one total loss distribution called aggregate loss distribution. A Monte Carlo (MC) simulation is used to produce the aggregated loss distribution.

The result of the MC simulation is the estimated OpVaR within a certain level of confidence and the estimated maximum frequency for periods starting from January 2018 to February 2020. The OpVaR illustrates the maximum potential loss that might occur in a company for a certain period of time with a certain degree of confidence. While the estimated maximum frequency implies the maximum events of operational losses that can occur in the next period (e.g. 1 day).

The estimated maximum event resulting from the MC simulation is 10 events, while the estimated OpVaR at 95% confidence level is IDR 100,214,018. The Table 6 shows the result of the estimated OpVaR.

4.4 Backtesting

The backtesting is carried out by calculating the log likelihood ratio (LR). The LR will be compared with the critical value of chi square. If the LR value is smaller than the critical value, then the model is declared valid, thus in H0 is not rejected, and vice versa. The backtesting period in this research is 1 year.

Based on the results in the figure 4, at a 95% confidence level, there are 2 violations i.e. when the actual loss exceeds the estimated OpVaR. With a number of testing periods of 56 days, this test produces an LR of 0.1155. While the critical value (following a chi-square distribution), at 95% confidence level is 3.84. Hence, the LR is smaller than the critical value which indicates H0 is not rejected. In other words, the daily OpVaR model with the LDA-aggregation method is valid.

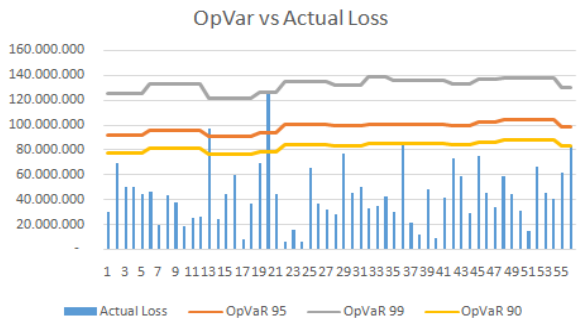

Figure 4 Comparison of the Daily OpVar Model with Actual Loss

Table 4. Kolmogorov-Smirnov GoF Test of Frequency Distribution

T Statistic	0,301		
α	0,1	0,05	0,01
Critical Value	0,431	0,481	0,576
Hypothesis	H0 : Frequency loss data follows *Poisson* distribution		
	H1 : Frequency loss data does not follow *Poisson* distribution		
Reject?	No	No	No

Table 5. Anderson-Darling GoF Test of Frequency Distribution

T Statistic	0,235		
α	0,1	0,05	0,01
Critical Value	1,933	2,492	3,857
Hypothesis	H0 : Frequency loss data follows *Poisson* distribution		
	H1 : Frequency loss data does not follow *Poisson* distribution		
Reject?	No	No	No

Table 6. Estimated calculation results for OpVaR

Percentile	Estimated OpVaR
99%	134,102,718
95%	100,214,018
90%	83,760,463

5. DISCUSSION

PT KLM currently has no policy regarding the operational loss discussed in this paper. There are no provisions, insurance, nor any other policy. Thus, to mitigate this operational risk, PT KLM may choose to do the following alternatives:

5.1 Reducing Risk

PT KLM may choose to build a one-year reserve according to the estimated OpVaR amounting to IDR36,578,116,570 and do regular monitoring to make adjustments if necessary. This reserve can be performed in two ways: the first is reserved in the equity section of the statement of financial position, namely in unappropriated retained earnings, and the second is by making provisions with the allowance system for reserve losses due to vehicle repairs.

The second alternative is reviewing policies and standard procedures related to operational losses, especially the reparation of rental vehicle units due to events that are not included in the clause with the insurance company.

This can be done by focusing more on the detailed procedure such as standardizing spare parts according to quality that has been determined to maintain the life of vehicle parts; improving training programs for mechanics and standardizing mechanical competencies related to vehicle maintenance; automating the process, especially in the inspection *car in/car out* procedure as a control if there is an accident/damage after the car is rented; increasing cooperation with car maintenance vendors/workshops as partners in vehicle maintenance; improving the internal control system, and testing them through conducting internal audits.

5.2 Transferring Risk

PT KLM can choose to insure each vehicle with scenarios/coverage in accordance with the risk profile in each branch or region. For example, insurance with coverage of flood damage in a city prone to flooding, or insurance with coverage of earthquake/mountain eruption for areas near mountains. On top of that, the company can enact an agreement with the customer to handle and cover the loss or damage to the vehicles due to external factors that have not been covered by the existing insurance clause

6. CONCLUSION

The conclusions of the study that can be drawn as follows:

The daily operational Value at Risk (OpVaR) at PT KLM using Loss Distribution Approach - Aggregate Loss Distribution from January to December 2019 is between IDR91,053,721 and IDR 104,550,879. While the OpVaR for the full data period of 26 months starting from January 2018 to February 2020 at a confidence level of 99%, 95%, and 90% are IDR 134,102,718, IDR100,214,018 and IDR83,760,463 respectively. The OpVaR is obtained from using the historical operational loss data, i.e. the repair costs of vehicle units that are damaged but not insured due to floods, storms, and landslides.

Based on the backtesting results, the daily OpVaR model is valid at a 90%; 95%; and 99% confidence level for having an LR smaller than the chi-squared critical value. Hence, the daily OpVaR model is a suitable method for estimating the maximum losses that can occur in the company based on historical loss data. This can have implications for the determination of reserves or even more accurate operational risk mitigation strategies.

After obtaining the OpVaR, PT KLM can choose several strategies in implementing operational risk management as operational risk mitigation. There are 2 main strategies, i.e. by reducing risk and by transferring risk. To reduce risk, the company can set a capital reserve based on the estimated OpVaR. The company may also review policies and standard procedures related to operational losses. Meanwhile to transfer risk, PT KLM can insure its assets. PT KLM could make a calculation in advance of the insurance applications to be compared with the reserve value resulting from the OpVaR calculation and with the actual loss from operational activity without insurance or provision.

Currently, PT KLM has recorded its operational loss of about IDR41,495,896 on average per day, with the highest loss in a single day amounted to IDR127,017,800. While the daily OpVaR is IDR100,214,018. PT KLM should calculate the forecasted cost of insurance application and then choose the best mitigation alternatives according to the calculation of the cost for each alternative and according to the management's risk appetite.

REFERENCES

[1] COSO, "Enterprise Risk Management-Integrated Framework," *Committee of Sponsoring Organizations of the Treadway Commission*, 2004.

[2] N. D. C. Lewis, *Operational Risk with Excel and VBA: Applied Statistical Methods for Risk*

Management. New York: John Wiley & Sons, 2004.

[3] M. Muslich, *Manajemen Risiko Operasional: Teori & Praktik*. Jakarta: PT Bumi Aksara, 2007.

[4] Basel Committee for Banking Supervision, "The New Basel II Capital Accord," *Consultative Document: Operational Risk; Supporting Document to the New Basel Capital Accord*, 2001.

[5] C. L. Marshall, *Measuring and managing operational risks in financial institutions: tools, techniques, and other resources*. New York: John Wiley, 2001.

[6] J. Lam, *Enterprise Risk Management: From Incentives to Controls*. New Jersey: John Wiley & Sons, 2014.

[7] M. G. Cruz, *Modeling, Measuring and Hedging Operational Risk*. New York: John Wiley & Sons, 2002.

[8] A. A. Jobst, "It's All In The Data–Consistent Operational Risk Measurement and Regulation," *Journal of Financial Regulation and Compliance*, 2007.

[9] P. De Fontnouvelle, E. Rosengren, and J. Jordan, "Implications of Alternative Operational Risk Modeling Techniques," in *The Risks of Financial Institutions*: University of Chicago Press, 2007, pp. 475-512.