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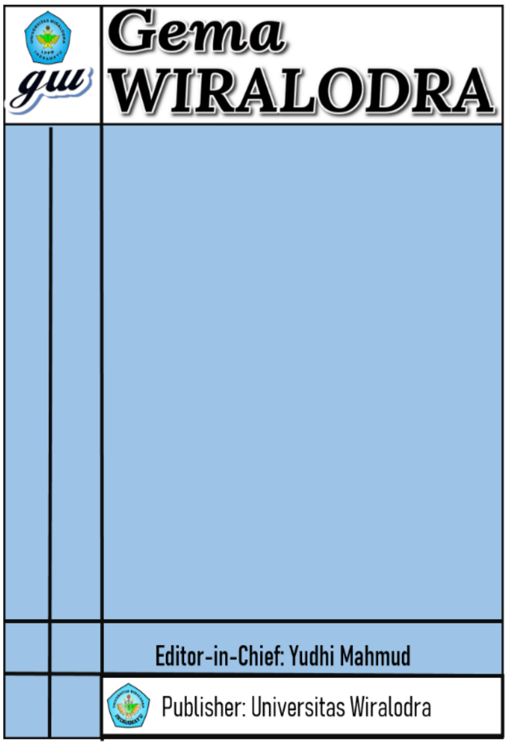

Capital reserve calculation analysis of operational risk in submarine cable service portfolio

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Original Article

Capital reserve calculation analysis of operational risk in submarine cable service portfolio

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Abstract
This study analyzes the amount of capital reserves required for the Submarine Cable Service PT AAA to mitigate the risk of delays in completing work without disrupting the company's cash flow. Data used in this paper is the operational loss of delay work in the Submarine Cable Service portfolio from 2016 to 2019. The method and analysis used in this paper are the Monte Carlo simulation to calculate Operation Risk Variance (OpVar) by analyzing the distribution of severity and frequency. The result of the study shows that delayed work is the risk that has the most influence on the company's cash flow. PT AAA needs Rp 2.16 billion per event as capital reserve PT AAA to mitigate the risk of work delays in the Submarine Cable Service portfolio. Risk mitigation needs to minimize the potential loss are choosing the right partner in the operational process, scheduling the cable repair process, and securing the amount of capital reserve that has been counted.
Keywords: Capital Reserves, Operational Risk, Monte Carlo, Submarine Cable, Mitigation

1. Introduction

PT AAA provides telecommunications infrastructure management services, especially in the Submarine Cable Service, an underwater cable service carried out by submarine cable vessels in charge of establishing communication links across the ocean, avoiding submarine cable irregularities with preventive maintenance, and repairing the damage with corrective maintenance. Submarine Cable Service is PT AAA's exceptional portfolio that other subsidiaries do not own. PT AAA's revenue contribution from Submarine Cable Service has increased significantly since 2016, starting from 14% and rising to 46% in 2019. Meanwhile, in 2020, there was a decline of 36% due to the COVID-19 pandemic. Besides being measured by revenue contribution, submarine cable service has enormous market potential. The potential for Submarine Service captive market project laying service in Indonesian waters reaches 29,130 km in 2021-2026. In 2022-2023, international projects are estimated to reach 32,000 km, namely the ECHO and Bifrost projects by Google and Facebook.

Operational risk is the potential losses resulting from events caused by inadequate or failed processes, people, equipment, and systems or from external events. One of the most critical challenges for the company's management is improving its results through operational risk identification and evaluation (Ruiz-Canela López, 2021). In his book Fundamentals of Risk Management, Hopkin describes the stages that build valuable risk management activities, each of which makes an important contribution. One is in response to significant risks, including decisions about appropriate actions regarding the following options: tolerate, treat, transfer, or Terminate (Hopkin, 2017). PT AAA is not optimal in managing the company's risk management, so problems often cause losses. Operational Risk events in Submarine Cable Service are the selection of inappropriate partners, delay of the work process that impacts customer penalties, and lack of team members' capability to manage projects. Therefore, the formulation of the problem of this research is knowing the potential risks that often occur in PT AAA Submarine Cable Service portfolio and calculating how much capital reserve PT AAA

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needs to cover the risk of delays in completing work on the Submarine Cable Service portfolio using operational risk variance (OpVar) calculations using the Monte Carlo simulation method.

This paper aims to give PT AAA suggestions on how much capital reserve they need to secure the potential loss of delayed works. It is also aimed as a reference for further research in the field of study related to operational risk and submarine cable. Functional risk analysis will be carried out quantitatively to calculate the capital reserves needed by PT AAA against the risk of delays in completing work on the Submarine Cable Service using operational risk variance (OpVar) calculations with the Monte Carlo simulation. By doing this research, it is hoped that the author will be able to provide suggestions to PT AAA regarding the amount of capital reserves needed so that if the risk of delays in completing work on the Submarine Cable Service occurs again, PT AAA already has capital reserves and without disturbing cash flow.

Research on operational risk variance calculations for banking aspects has been widely conducted. However, more needs to be done for non-banking elements, especially in the submarine cable sector. One of the studies regarding submarine cable is the Risk Management of the Sulawesi Maluku Papua Submarine Cable System Of 20-1000m Water Depth Using the Analytical Hierarchy Process (AHP) Method research (Mutalibov, 2021). Still, this research does not calculate Operational Risk Variance.

2. Method

Research Design

The research methodology of this paper describes the steps taken to calculate the capital reserve needed by PT AAA against delays in completing work on the Submarine Cable Service portfolio using operational risk variance (OpVar) calculations with the Monte Carlo simulation method. The method used in this paper is a quantitative method, which is the Monte Carlo simulation method, to obtain the results of calculating the capital reserves needed by PT AAA against the risk of delays in completing work on the Submarine Cable Service portfolio. Calculations using the Monte Carlo simulation method begin by calculating the frequency and severity of loss distribution, compiling a loss distribution model using R studio, and calculating the value of Operation Value at Risk (OpVar).

Data Sample

Data used in this study is operational loss data caused by delays in completing cable laying work, which causes penalties to occur to customers. The frequency of occurrence starts from 2016 to 2019, or for 48 months, and is obtained from reports of the Submarine Cable Service unit. The data is divided into four categories: first, delay between 14-30 days, 31-60 days, 61-90 days, and more than 91 days. These four categories of delay are presented in Table 1, followed by the number of losses that arise from each category The selection of the data is to meet the essential criteria for calculating the Loss Distribution Approach method, namely data of at least two years, and to describe conditions that are relevant to current conditions so that it is hoped that the research results can be applicable to current conditions as well.

Table 1
Category and Number of Losses (in Million Rp).

Delay Category	Number of Losses
14-30 days	Rp 659
31-60 days	Rp 842
61-90 days	Rp 1.024
>90 days	Rp 1.207

Source: PT AAA Financial Scheme Reports

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Data Processing

Data processing is carried out with the following steps:

Calculate the frequency of loss distribution and severity of loss distribution

Operational risk events that happened in the 2016 to 2019 period are shown in Table 2, and operational loss data of Submarine Cable Service in the 2016 to 2019 period are shown in Table 3.

Table 2

Operational risk events of Submarine Cable Service in 2016 to 2019

Year	14-30 days	31-60 days	61-90 days	>90 days	Total
2016	3				3
2017	1	2		1	4
2018	6	7	4		17
2019	2	8	1		11

Source: PT AAA Submarine Service Reports

Table 3

Operational loss of Submarine Cable Service in 2016 to 2019 (in million Rupiah)

Year	14-30 days	31-60 days	61-90 days	>90 days	Total
2016	1,977,779,499				1,977,779,499
2017	659,259,833	1,684,053,792		1,207,561,022	3,550,874,647
2018	3,955,558,998	5,894,188,273	4,099,175,837		13,948,923,108
2019	1,318,519,666	6,736,215,169	1,024,793,959		9,079,528,794

Source: PT AAA Submarine Service Reports

Determine the parameters of the risk distribution model using R Studio

The severity and frequency distribution parameters carried out in R studio aim to determine what type of distribution will be used in the Monte Carlo simulation. The results from R studio are for the frequency parameter using a Poisson distribution and the severity parameter using the Weibull distribution. This is shown by comparing the negative binomial, Poisson, and normal distribution parameters, where the Loglikelihood value of the Poisson distribution is the largest, and the AIC and BIC values are the smallest, as shown in Figure 1.

Figure 1

Comparison Parameter of Frequency Distribution

```
Fitting of the distribution ' nbinom ' by maximum likelihood
Parameters :
         estimate Std. Error
size 2.335832e+04        NaN
mu   7.082867e-01  0.1214718
Loglikelihood:  -53.75466   AIC:  111.5093   BIC:  115.2517
Correlation matrix:
     size  mu
size    1 NaN
mu    NaN   1

Fitting of the distribution ' pois ' by maximum likelihood
Parameters :
        estimate Std. Error
lambda 0.7083333  0.1214779
Loglikelihood:  -53.75466   AIC:  109.5093   BIC:  111.3805

Fitting of the distribution ' norm ' by maximum likelihood
Parameters :
      estimate Std. Error
mean 0.7083333 0.12132920
sd   0.8405934 0.08579216
Loglikelihood:  -59.77398   AIC:  123.548   BIC:  127.2904
Correlation matrix:
             mean           sd
mean 1.000000e+00 1.849027e-11
sd   1.849027e-11 1.000000e+00
```

Likewise, the results of comparing the parameters for the exponential, lognormal, Weibull, and gamma distributions were used to get the severity parameter. The results shown are the

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parameters using the Weibull distribution because they have the smallest AIC and BIC values compared to the other three, as shown in Figure 2.

Figure 2

Comparison Parameter of Severity Distribution

```
> summary(lnorm.f)
Fitting of the distribution ' lnorm ' by matching moments
Parameters :
          estimate
meanlog 19.7333623
sdlog    0.9457823
Loglikelihood:  -8700.95   AIC:  17405.9   BIC:  17409.64

> summary(weib.f)
Fitting of the distribution ' weibull ' by maximum likelihood
Parameters :
          estimate   Std. Error
shape   0.07226562 6.858967e-03
scale 555.15136719 3.759401e+02
Loglikelihood:  -562.7903   AIC:  1129.581   BIC:  1133.323
Correlation matrix:
         shape     scale
shape 1.0000000 0.3599232
scale 0.3599232 1.0000000

> summary(gamma.f)
Fitting of the distribution ' gamma ' by matching moments
Parameters :
          estimate
shape 6.915044e-01
rate  1.189777e-09
Loglikelihood:  -840.6016   AIC:  1685.203   BIC:  1688.946
```

3. Results and Discussion

Stage 1: Identification of frequency and severity parameters using R-studio

The severity and frequency distribution parameters in R studio aim to determine what type of distribution will be used in the Monte Carlo simulation. The results obtained from R studio are for the frequency parameter using a Poisson distribution.

Table 4

Fitting of the distribution 'pois' by maximum likelihood

Parameters:

	Estimate	Std. Error
Lambda	0.7083333	0.1214779
Loglikelihood	-53.75466	AIC: 109.5093
		BIC: 111.3805

As a result, above, it is known that the lambda of the Poisson distribution is 0.70833. Lambda shows the probability of data success with the expected number of events in a period. Because lambda means the occurrence per interval, this means the likelihood of a risk event occurring frequently. The severity parameter using the Weibull distribution shows the shape parameter is 0.07226562, and the scale parameter is 555.15136719. The Weibull distribution is widely used in reliability and life data analysis due to its versatility. Depending on the values of the parameters, the Weibull distribution can be used to model various life behaviors. An essential aspect of the Weibull distribution is how the values of the shape parameter, β, and the scale parameter, η, affect such distribution characteristics as the shape of the pdf curve, the reliability, and the failure rate.

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Table 5
Fitting of the distribution 'Weibull' by maximum likelihood

Parameters:			
	Estimate	Std. Error	
Shape	0.07226562	6.858967e-03	
Scale	555.15136719	6.858967e-03	
Loglikelihood	-562.7903	AIC: 1129.581	BIC: 1133.323
Correlation matrix:			
	Shape	Scale	
Shape	1.0000000	0.3599232	
Scale	0.3599232	1.0000000	

Stage 2: Monte Carlo method in 5000 times simulation using Excel

After getting the parameters, 5000 Monte Carlo simulations were carried out using Excel. Monte Carlo is a quantitative simulation technique used to assess risk by calculating the probability of the outcome due to uncertainty involving random variables based on distribution characteristics input/analyzed data. This technique is very appropriate to apply (applicable solid) in the risk evaluation process and can be applied in the analysis process risk (Carlo et al., 2020).

The simulation results were obtained with a 95% confidence level; the OpVar results obtained are Rp 2,16 billion per event as capital reserve PT AAA to mitigate the risk of work delays in the submarine cable service portfolio, as shown in Table 4. This means that the capital reserve needed by PT AAA in mitigating the operational risk of work delays at the 95% percentile is Rp 2.16 billion per event, which means that there is only a 5% chance/probability that the loss due to operational risk is more than Rp 2.16 billion per event. In other words, if you have reserved Rp 2,16 Billion per event for operational risk, then there is only a 5% chance that the operating reserve will not be enough to meet operational risks that will occur.

Table 6
Monte Carlo 5000 Simulations Result

Confidence Level	Aggregate (Billions Rp's)	Number of Simulation
0.02%	2,168,842,626	1
0.04%	2,163,978,979	2
0.06%	2,165,207,534	3
0.08%	2,160,053,691	4
0.10%	2,167,527,493	5
0.12%	2,166,961,527	6
0.14%	2,168,376,020	7
0.16%	2,163,593,300	8
.	.	.
.	.	.
.	.	.
95%	2,163,975,476	4,750
.	.	.
.	.	.
.	.	.
100%	2,166,344,268	5000

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Stage 3: Backtesting

Statistical Analysis with the Kupiec test was used for backtesting in this research. The Likelihood Ratio (LR) value is compared with the chi-square critical value with a degree of freedom of one for each OpVar confidence level. The crucial value in the 99% confidence level is 6.63. The model is valid if the Likelihood Ratio (LR) value is smaller than the critical value (Muslich, 2007).

Figure 3
Likelihood Ratio

No.	Month	OpVar	Actual Loss	Difference	Binary Indicator
1	Jan-20	2,164,614,651	842,026,896	1,322,587,755	0
2	Feb-20	2,164,614,651	842,026,896	1,322,587,755	0
3	Mar-20	2,164,614,651	-	2,164,614,651	0
4	Apr-20	2,164,614,651	-	2,164,614,651	0
5	May-20	2,164,614,651	-	2,164,614,651	0
6	Jun-20	2,164,614,651	842,026,896	1,322,587,755	0
7	Jul-20	2,164,614,651	-	2,164,614,651	0
8	Aug-20	2,164,614,651	842,026,896	1,322,587,755	0
9	Sep-20	2,164,614,651	-	2,164,614,651	0
10	Oct-20	2,164,614,651	842,026,896	1,322,587,755	0
11	Nov-20	2,164,614,651	1,024,793,959	1,139,820,692	0
12	Dec-20	2,164,614,651	659,259,833	1,505,354,818	0
13	Jan-21	2,164,614,651	-	2,164,614,651	0
14	Feb-21	2,164,614,651	-	2,164,614,651	0
15	Mar-21	2,164,614,651	-	2,164,614,651	0
16	Apr-21	2,164,614,651	-	2,164,614,651	0
17	May-21	2,164,614,651	-	2,164,614,651	0
18	Jun-21	2,164,614,651	659,259,833	1,505,354,818	0
19	Jul-21	2,164,614,651	-	2,164,614,651	0
20	Aug-21	2,164,614,651	-	2,164,614,651	0
21	Sep-21	2,164,614,651	-	2,164,614,651	0
22	Oct-21	2,164,614,651	1,501,286,729	663,327,922	0
23	Nov-21	2,164,614,651	-	2,164,614,651	0
24	Dec-21	2,164,614,651	-	2,164,614,651	0
			V		0
			T		24
			p*	CL 99%	5.00%
			LR		**0**
			CV	CL 99%	**6.63**

Based on the data in Figure 2, it is known that there is no negative difference between the operational risk variance value that has been calculated and the actual loss in 2020 - 2021, so all binary indicators produce a value of 0. Therefore, it is known that the Loglikehood Ratio value from the data is 0 and above. Lower than the Critical Value 99% value of 6.63, hypothesis H_0, which states that the model is valid, can be accepted.

4. Conclusion

The study results indicate that delayed work is the risk that has the most influence on the company's cash flow, so it needs to be mitigated by knowing the amount of capital reserve needed. Six events caused the work delays: incomplete documents and a lengthy permit process required spare parts not to be available, unavailability of ships, weather not ideal for sailing, Analysis (survey results do not match conditions in the field), and damaged equipment. After the calculation using the Monte Carlo Simulation, it was obtained that PT AAA needed a reserve fund of Rp 2.16 billion per event to secure the cash flow when the delayed work in Submarine Cable Service happened, and the company must pay the penalty to the customer without disrupting the company's cash flow.

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