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Calculation of Value at Risk of Property Fire Losses in West Jakarta with the Extreme Value Theory Method

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Abstract

Property fires are an inevitable disaster, but their impact can be minimized through proper risk management. In urban areas such as West Jakarta, with high population density and economic activity, fires often cause losses. In the range of 2014 to 2023, the peak of the loss occurred in 2019 of IDR 103,354,500,000. Soto avoid unwanted things it is necessary to calculate the losses that may occur. The Extreme Value Theory (EVT) method is used in this study to analyze the risk of extreme losses. Using Peaks Over Threshold (POT), the estimated Value at Risk (VaR) shows a maximum loss of IDR 86,245,771,176 (95% confidence level) and IDR 255,535,153,859 (99% confidence level). These results help manage fire insurance risks to reduce future economic impacts.

Keywords: Fire, Extreme Value Theory, Value at Risk

1. Introduction

One of the disaster risks that can cause great economic losses to individuals or communities as a whole is property fires. One of the most detrimental fire incidents is fire incidents in urban/residential areas. In urban areas such as West Jakarta, which have a high rate of urbanization and high population density, a lot of economic activity, building density, and inadequate use of electrical installations increase the risk of fires. Electrical short circuits in many cases are caused by the use of non-standard electrical tools, as well as overloading outlets and electronic equipment (Rahmat et al., 2018).

Property fires in the West Jakarta area show significant potential for large losses. Based on data from the Central Statistics Agency (BPS) of West Jakarta, losses due to fires reached their peak in 2019 with a total loss of IDR 103,354,500,000. This figure is the highest in the period 2014 to 2023, reflecting the high economic impact of fire disasters in the region

Faced with the increasing risk of fires, a more comprehensive approach is essential to understand the characteristics of these risks and anticipate their impacts effectively. As Handayani et al. (2020) suggest, Extreme Value Theory (EVT) is a robust method specifically designed to analyze extreme values in data, making it highly effective for identifying potential maximum losses. This method has been widely applied in disaster risk analyses, including floods, earthquakes, and fires, as it provides precise estimates of significant losses that exceed ordinary expectations. In the context of property fires in West Jakarta, EVT offers a valuable framework for estimating the potential maximum damage that could occur, ensuring a better understanding of worst-case scenarios. This understanding is critical for developing informed and effective mitigation strategies.

The use of EVT in analyzing property fire risks is supported by findings from Suryana & Rahmawati (2019), who highlight its ability to identify the most severe risks. This capability enables stakeholders to formulate targeted policies and mitigation measures that address the most pressing vulnerabilities. Despite the proven utility of EVT in various fields, its application still presents challenges and opportunities for refinement. Several previous studies have explored these issues, identifying gaps in the methodology that could be addressed in future research. A detailed summary of these research gaps is presented in Table 1, highlighting areas where further investigation could enhance the reliability and application of EVT in disaster risk management.

Table 1: Research Gap

	2 40 10 21 11 0 5 0 1 1 0 1 p			
Author	Topic	EVT	Pareto Gene Distribution	Property Fires
Saputra et al. (2020)	Estimation of the maximum claim potential in the risk of house fire losses using the Extreme Value Theory method (EVT) in the city of Bandung	Yes	It	It
Pratiwi & Iswahyudi (2021)	Estimation of the risk level of gold investment using the Generalized Extreme Value and Generalized Pareto Distribution approaches	Yes	Yes	It
Hakam & Jaya (2024)	Estimating conditional Value at Risk in non-cyclical sector companies using the Extreme Value Theory Approach	Yes	Yes	It
Rahajeng & Sofro (2024)	Value at Risk Prediction on Gold Precious Metal Investment Using Extreme Value Theory (EVT)	Yes	It	It
This research	Calculation of Value at Risk of property fire losses in West Jakarta using the Extreme Value Theory method	Yes	Yes	Yes

2. Literature Review

2.1. Fire

Fire is one of the disasters that occurs very often, especially in densely populated urban areas. Fires are a disaster because they will destroy all property and can even cause a large number of casualties. According Sagala et al. (2013), fire is the existence of unwanted fire. Fire is a complex process in which fuel underheats up and is then triggered by fire and driven quickly because it reacts with oxygen (Yan et al., 2012). The fire occurred unexpectedly, it will not be extinguished if it is not extinguished. Fires can occur due to human, natural, self-ignition, and intentional factors.

2.2. The Economic Impact of Fire

The impact of fires can be divided into several categories, which include physical, economic, social, and environmental impacts (Renn et al., 1992). Here is an explanation of each of these categories:

- 1. Physical Impact, which is damage to buildings and assets, where fires can destroy building structures, furniture, and other valuables. In addition, fires also pose a serious health risk, which can result in injury or even death from smoke, burns, or poisoning.
- 2. Economic Impact, can cause significant financial losses. Fire recovery costs are often very high, including repair costs, lost inventory, and lost revenue due to business disruption
- 3. Social Impact, resulting in displacement and homelessness for residents, which has the potential to cause disruption to their social life.
- 4. Environmental Impact, will experience ecosystem damage, where fires can destroy natural habitats and affect local flora and fauna.
- 5. Long-Term Impacts, can lead to broader social and economic changes, including population shifts and declining property values.

Overall, fires have a broad and profound impact that affects various aspects of people's lives

2.3. Extreme Value Theory (EVT)

EVT is one of the statistical methods that discusses data deviations from the average value of an opportunity distribution (Echaust & Just, 2020). EVT studies stochastic behavior at a minimum or maximum. The goal of EVT is to estimate the probability of extreme events by studying the tail of distribution using extreme values. In EVT, the construction of extreme value movements is carried out through two approaches, namely Peaks Over Threshold (POT) and Block Maxima (BM). BM forms a block based on the highest value in a period while POT takes the value of the return data that passes the threshold value.

3. Materials and Methods

3.1. Materials

The data used in this study is secondary data, namely the number of losses due to fires that occurred in West Jakarta for the period 2014 to 2023. The data can be accessed on <u>jakbarkota.bps.go.id/id</u>.

Tuble 2. Illiste	rical data on the losses in West sustaita
YEAR	LOSS (IDR)
2014	IDR 99,963,400,000
2015	IDR 91,057,400,000
2016	IDR 54,408,325,000
2017	IDR 58,003,700,000
2018	IDR 57,339,300,000
2019	IDR 103,354,500,000
2020	IDR 73,364,450,000
2021	IDR 68,866,600,000
2022	IDR 76,901,635,000
2023	IDR 74,337,150,000

3.2. Methods

3.2.1. Data Collection

This study uses initial loss data, which consists of 10 sample data, as a starting point in data collection. The data was then developed into 1,000 data using the random number method to improve the accuracy of the analysis and allow for more robust modeling. EasyFit tools random numbers software is used to perform this action.

3.2.2. Peak Over Threshold (POT)

Peaks Over Threshold (POT) is one of the methods to identify extreme values using a reference value called threshold (u). Data above the threshold will be identified as extreme values. The extreme value obtained is then modeled the distribution. The POT method applies the Pickland Balkema-DeHann theorem which states that the higher the threshold, the distribution for data above the threshold generally follows the generalized pareto distribution. Extreme data collection with the POT method by sorting the largest data to the smallest. Next, set the threshold value on the data with the 10% percentage method, namely

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

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

where m is the amount of data above the threshold, n is a lot of observation data, and u is the location of the threshold data.

3.2.3. Generalized Pareto Distribution (GPD)

Generalized Pareto Distribution (GPD) is a distribution to model the distribution of data with extreme events obtained from the POT method. Suppose X is a random variable of daily losses with 2 GPD parameters, the GPD distribution function of X is as follows:

$$g_{\xi,\beta}(x) = \begin{cases} \frac{1}{\beta} \left(1 + \frac{\xi}{\beta} x \right)^{-1 - \frac{1}{\xi}}, & \xi \neq 0 \\ \frac{1}{\beta} \exp\left(-\frac{x}{\beta} \right), & \xi = 0 \end{cases}$$
 (3)

where, if $\xi > 0$ then $\beta > 0$ and .On the other hand, if $\xi < 0$ then $0 \le x \le -\frac{\beta}{\xi}$ with ξ : shape parameter and β : scale parameter.

3.2.4. GPD Distribution Conformity Test

Distribution conformity test is needed to determine the compatibility of the data pattern with the distribution of the analyzed data. In this study, the process of testing the suitability of GPD distribution to extreme data using Kolmogorov-Smirnov with the Goodness of Fit software tool rock. The concept of the test is to compare the theoretical distribution with the distribution of samples based on cumulative frequency.

To reach a conclusion, the step taken is to compare statistical values D_{1-a} with critical values D_{1-a} at a predetermined level of significance. If it is $D_{count} > D_{1-a}$ then H_0 rejected

3.2.5. GPD Parameter Estimation

According to Sari and Sutikno (2013), one of the methods for estimating GPD parameters is Maximum Likelihood Estimation (MLE). The parameters obtained by the MLE method are as follows:

Shape Parameters:

$$\widehat{\xi} = \frac{n^2 s - \sum_{i=1}^{n} z_i}{\sum_{i=1}^{n} x_i - n \sum_{i=1}^{n} z_i}$$
(4)

with ξ : shape parameters, n: many extreme data, s: standard deviation of extreme data, and x_i : ith extreme datax_i

Scale Parameters:

$$\hat{\beta} = \frac{1}{n} \sum_{i=1}^{n} x_i \tag{5}$$

with β : scale parameter, n: number of extreme data, and x_i : ith extreme datax_i

3.2.6. Value at Risk (VaR)

Value at Risk (VaR) is the maximum loss that will be obtained at a certain level of confidence. VaR is defined as the percentile to of the random variable distribution function. VaR is a risk calculation method for normally distributed data.

$$VaR_{GPD} = u + \frac{\beta}{\xi} \left\{ \left[\frac{n}{N_u} (1 - p) \right]^{-\xi} - 1 \right\}$$
(6)

with : u Threshold, β : Scale parameters, ξ : Shape parameters, n: Lots of observational data, N_u : A lot of data above the threshold; and p: Confidence level

4. Results and Discussion

4.1 Threshold of Loss Data

The initial loss data consisting of 10 data was developed into 1,000 data with random numbers using EasyFit software. Historical data is taken at a threshold of 10% so that extreme data is obtained above the threshold value. The results are presented in Table 3.

Table 3: Threshold from the loss data

Lots of	Data Ex	treme Data	Threshold (IDR)
100	00	100 I	DR 103,301,518,583

Table 3 shows the number of loss data to 1000 data. The threshold value is then taken, namely data above 101 which is extreme data

4.2 Kolmogorov-Smirnov Test Extreme Data on GPD

Conformance tests on extreme data assuming GPD are carried out with the help of Easyfit software. The results of the conformity test are shown in Figure 1.

Gen. Pareto [#24]					
Kolmogorov-Si	Kolmogorov-Smirnov				
Sample Size Statistic P-Value Rank	100 0,06254 0,80569 1				
α	0,2	0,1	0,05	0,02	0,01
Critical Value	0,10563	0,12067	0,13403	0,14987	0,16081
Reject?	No	No	No	No	No

Figure 1: Kolmogorov-Smirnov test

Based on the Kolmogorov-Smirnov test, the data show a normal distribution, this is in accordance with the assumption that extreme data will correspond to the GPD distribution.

4.3 GPD Parameter Estimation

Here is a descriptive statistic of extreme data which will then be calculated shape parameters and scale parameters.

Table 4: Extreme data descriptive statistics

Descriptive Statistics		
Count	100	
Mean	IDR 110,841,924,822	
Minimum	IDR 103,441,693,305	
Maximum	IDR 125,224,126,255	
Sum	IDR 11,084,192,482,227	
Standard Deviation	4955527435	
Sample Variance	2.45573E+19	
Curtosis	-0.778470952	
Skewness	0.419933528	

Based on Table 4, n=100; s=4955527435; and $=11084192482227 \sum_{i=1}^{n} x_i$. Furthermore, the shape parameters and scale parameters are searched by equations (4) and (5) with the help of Microsoft Excel software so that the following results are obtained:

 Table 5: Estimation of GPD Parameters

Characteristic	Value
Scale Parameters (β)	1.10842E+11
Shape Parameter (ξ)	-0.035058647

The results of the GPD parameter show that the distribution function is valued, then $\xi < 0$ the x that satisfies the distribution is $0 \le x \le -\frac{\beta}{\xi}$ This means that the largest data (maximum) does not cross the upper limit value, so the GPD parameters are in accordance with the extreme data used in the GPD.

4.4 VaR Calculation

After obtaining two GPD parameters, then the Value at Risk (VaR) calculation was carried out as an estimate of property fire losses. This calculation uses the value u=10342000000, $\beta=110841924822$, $\xi=-0.03505864655$; n=1000; and $N_u=100$. The calculation results using equation (6) with the help of Microsoft Excel software are as follows:

Table 6: VaR Calculation

p	EVar	
0.95	IDR 86,245,771,176	
0.99	IDR 255,535,153,859	

The result of VaR with a confidence level of 95% is IDR 86,245,771,176 and with a confidence level of 99% is IDR 255,535,153,859 which shows that the percentage of confidence level is likely to lose does not exceed this value. The higher the confidence level (p), the greater the VaR because it covers extreme scenarios. This calculation estimation can help insurance companies in risk management and setting fire insurance premiums.

5. Conclussion

Taking into account extreme events, the analysis provided an overview of the losses that may be caused by property fires in West Jakarta. The results show that the risk of loss reaches Rp 86,245,771,176 at a 95% confidence level, and increases to Rp 255,535,153,859 at a 99% confidence level. This shows how important anticipation is in case of significant losses at higher levels of confidence. Insurance companies can use these results to create better risk management strategies and determine premiums proportionally.

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