JOURNAL LA SOCIALE

VOL. 06, ISSUE 02 (335-345), 2025
DOI:10.37899/journal-la-sociale.v6i2.1860

Value at Risk Analysis for Asset Acquisition Investment Needs Process Using Monte Carlo Method Based on Asset Return Level

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Article Info

Article history:
Received 16 December 2024
Received in revised form 22 January 2025
Accepted 10 February 2025

Keywords:
Value at Risk
Correlation
Forecasting
Mean Squared Error
Weighting

Abstract

This study aims to determine the Value at Risk (VaR) analysis process in measuring the maximum level of losses that can be accepted in the investment process to acquire assets that are already operating. An investment program must be able to measure the risks that will be faced in the future so that the VaR analysis. This study uses a quantitative approach through secondary data. The techniques used are data preprocessing scaling techniques, correlation between features and forecasting modeling through linear and non-linear regression mechanisms through repeated simulations (Monte Carlo). The research method for this VaR analysis uses several features from historical data with a probability level of 95%. From the results of the simulation of VaR, a prediction was obtained for the next 3 years, investors will not suffer losses, so that the profit obtained is $ 25 million from the estimated asset return value of 1.3% with a Mean Squared Error (MSE) value of 0.13. Based on the weighting results, it was also found that the asset value volatility parameter has the largest weight that affects the VaR value.

Introduction

The growth in the need for electricity consumption is increasing year by year because it is driven by the increasing standard of living of the community. In line with this, PLN as an electricity provider is required to provide the best quantity and quality to fulfill the electricity needs of the community and to obtain revenue from the sale of electricity to be able to enter the Global Fortune 500. There is a strategic program that has been planned by top management, one of which is to acquire captive power plants and IPPs, both those with an asset period that is already worth zero in bookkeeping but is still operating or those that still have asset value. To fulfill this strategy, a method is needed that can assess the level of return or maximum loss on the investment process in a particular year and has a small error result on the model or estimation method. In the business world, almost all investments contain uncertainty or risk, investors do not know for sure whether they are facing something else in the investment or getting high profit with high risk (Maronrong et al., 2022; Rachmawati, 2020). From this, a method is needed to be able to measure the impact of a risk on the results of the decision to invest at a certain level of possibility. Investors must understand the elements contained in the risk, namely the time period, scenario, scenario size and benchmark (Newell et al., 2023). For how long the risk will be managed can be determined by the investor, for the scenario element or single risk driver, the methods and tools used, one of the models and methods that can be used is Monte Carlo. The Monte Carlo method has the advantage of being able to show all the outputs of the decision scenario and see the impact of the risk of the research target (Qazi et

ISSN 2721-0960 (Print), ISSN 2721-0847 (online)

al., 2021; Züst et al., 2021). The scenario measurement elements are the forecasting of the business income of the Hydroelectric Power Plant (PLTA) assets, the forecasting of the total asset load (PLTA) and the forecasting of the asset value within the annual prediction period (Chabla-Auqui et al., 2023; Giachero, 2022). The benchmark element is the value of the predicted Return On Asset (ROA) value and the number of Monte Carlo simulations between 10,000 - 100,000 simulations. The main idea of using Monte Carlo as a model to calculate the prediction of each single risk driver which is an element of ROA itself is one of the cores of forming a portfolio. So when all the predicted values of the single risk driver have been calculated, it can be seen how much influence the changes in each single risk drive and the maximum or minimum value of ROA are influenced by the VaR concept. VaR simulation using the Monte Carlo concept forms a model using statistical methods (Saputra et al., 2023; Senova et al., 2023) and can use various types of regression. Therefore, it is expected that the VaR method with Monte Carlo can be used to determine the variety of distributions of the impact of investment to acquire an asset based on single risk driver prediction data for income, asset burden and asset value.

Income, Operating Expenses and Asset Value

According to Misbah et al. (2023) the parameter for income from hydroelectric power plants comes from the sale of energy from the generators produced from the rotation of the turbine against the amount of discharge. Susilowati & Hastiningrum (2005) stated that the amount of water discharge can be influenced by the reservoir operating system by regulating the amount of inflow and outflow, and to measure or find the optimum discharge pattern, historical data regression methods can be used.

According to Achmad & Hidayat (2013), to calculate the ratio of total asset turnover or return on assets, there are detailed operating expense factors in the financial statements while the asset value itself is the total value of all fixed assets and non-fixed assets. Meanwhile, according to (Tinambunan et al., 2018) the asset value can be approached from the market data approach and the cost approach, for the cost approach using the parameters of all costs incurred until the asset is ready for operation then reduced by the amount of depreciation costs. Depreciation costs themselves are affected by inflation and the rupiah exchange rate.

Monte Carlo

In (Di Asih & Purbowati, 2009) said that the Monte Carlo simulation method assumes that the return is normally distributed which is simulated using appropriate parameters and does not assume that the portfolio return is linear to the return of its single asset. In certain cases, Monte Carlo simulation can use the assumption that the return on the portfolio is linear, this is based on research by (Alexander et al., 2006). Then it is also said that the parameters used can use parameters that are not normally distributed and have a correlation that is not too high according to (De Domenico et al., 2023)

Value At Risk

According to (Firdaus et al., 2023) VaR is defined as an estimate of the maximum potential loss in a certain period with a certain confidence level under normal market conditions. VaR can be used to estimate losses through several methods according to Ghulam & Joo (2023) divided into 3, Historical VaR, Monte Carlo VaR and Multivariate Model VaR. Using the VaR Multivariate Model based on Jorion (2007) is better than the two previous models because the structure of the single risk driver is more clearly described and provides insight into the correlation between the dependent and independent variables of the single risk driver at a certain scenario position, for example against volatility.

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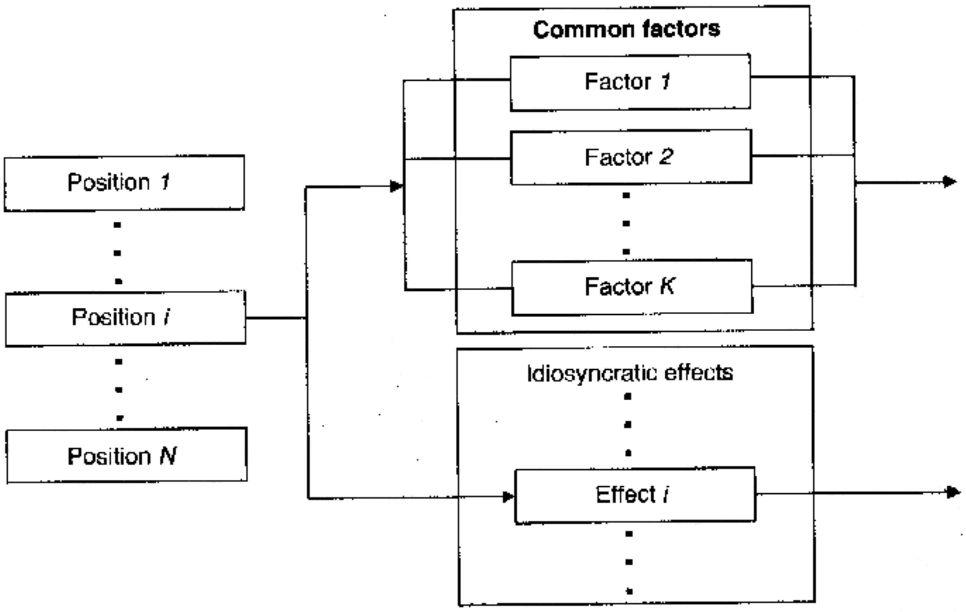

Figure 1. simplification of portfolio VaR

However, it should be noted in using VaR where there is a bias that can make forecasts inaccurate in determining numbers and cause errors in decision making. According to (Kaliappan et al., 2023) this can be overcome by looking at the MSE and Rsquared parameters. MSE itself is the level of model accuracy error in making predictions by regression while Rsquared is a method to determine how well the model explains data variability, so that the right machine learning model for VaR can be obtained.

Methods

This study adopts a quantitative method, namely first collecting secondary data on single risk drivers. The next process changes the data variables through scalarization and data transformation if needed. The next process performs statistical analysis of the distribution type, determines the best model and displays the MSE and Rsquared values. The next process performs simulations using python-based computing with a number of Monte Carlo iterations of 10,000 to 100,000.

Data and Samples

The object of the data population is hydroelectric power data and for this study the data population taken is the population of historical reservoir and penstock data in m3/s, historical total hydroelectric power asset load value in $ million and historical total hydroelectric power asset value in $ million. The population is taken with an annual time span with the following details: a) Reservoir data is taken from daily data and combined into an annual average; b) Total annual asset load data is taken from audited asset financial reports; c) Total asset value data is taken from management reports and audited financial reports

Furthermore, using qualitative methods by involving asset managers and related divisions to conduct discussions.

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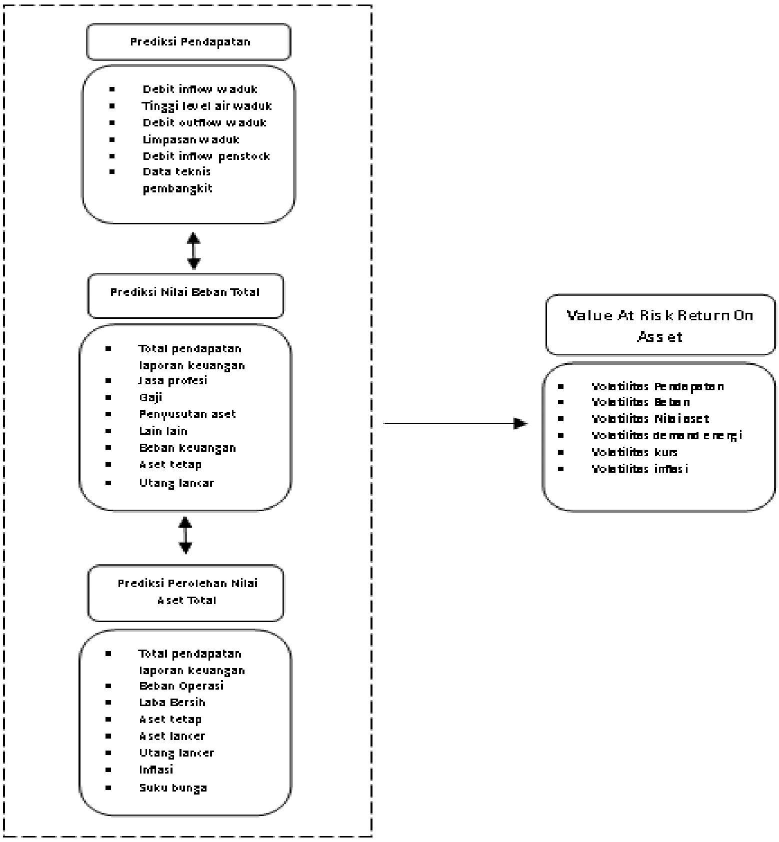

Figure 2. conceptual model

Scalarization

Perform the scalarization process on the data using the standard scaler and robust scaler if necessary. The equation for performing scalarization for the standard scaler is as follows:

$$x_{scaled} = \frac{x - \mu}{\sigma} \quad (1)$$

Where:

x is the original value

μ is the mean (average) of the feature

σ is the standard deviation of the feature deviation

Statistical Analysis of Distribution

Perform a process to see data patterns, correlations between features and create a description of the distribution of the data presented. Use Pearson's mathematical formula to see the degree of correlation between features

$$P_{x,y} = \frac{Cov\,(x,y)}{\sigma_x \sigma_y} \quad (2)$$

Where it is calculated using *the values of xke-n* and *yken* to find the average value of each feature

$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n} \quad (2)$$

$$\bar{y} = \frac{\sum_{i=1}^{n} y_i}{n} \quad (3)$$

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The average value of each feature is used as the basis for calculating the standard deviation of each feature

$$\sigma_x = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n}} \quad (4)$$

$$\sigma_y = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \bar{y})^2}{n}} \quad (5)$$

Then both the results x and y are recalculated to find the covariance value between the two features

$$Cov(X, Y) = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{n-1} \quad (6)$$

Then conduct a test on the type of distribution in order to determine the type of distribution using the shapiro test

$$W^* = \frac{W}{W'} \quad (7)$$

Where to find each W using the test statistical coefficient of each feature value

$$W = \frac{(\sum_{i=1}^{n} a_i X_{(i)})^2}{\sum_{i=1}^{n}(X_i - X)^2} \quad (8)$$

Where for W is a correction of W'

$$W' = \frac{(1 - C_1)^2}{\sum_{i=1}^{n}(X_i - X)^2} - \frac{(\sum_{i=1}^{n} a_i X_{(i)})^2}{\sum_{i=1}^{n}(X_i - X)^2} \quad (9)$$

Komputasi Value at Risk Monte Carlo Multivariate

It is assumed that the return of the asset is normally distributed, so the value of VaR will not experience significant errors. The mathematical formulation for the VaR value is that it should estimate the confidence level *of Zscore* in an annual time period.

$$VaR = Z * \sigma * V \quad (10)$$

With the value of σ is the average volatility of each of each feature measured using a certain range and V is the value of the initial investment in this case is the result of the acquisition prediction. Then for the VaR scenario, it is considered that the value of V is 49% of the remaining asset ownership owned by the IPP.

$$Return\ On\ Aset = \frac{Laba\ Bersih}{Total\ Nilai\ Aset} \quad (11)$$

Then repeat the iteration on monte carlo VaR for 1000 – 10000 simulation iterations.

Results and Discussion

Normality test

Based on the results of the normality test, it was found that:

Dependent *and* independent *variables* for random parameters of total discharge prediction are not normally distributed (<0.05)

The *dependent* and *independent variables* for the random parameters of total expense prediction, salary parameters and asset depreciation have an abnormal distribution (<0.05)

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The *dependent* and *independent variables* for the random parameters of asset value prediction, profit parameters, current debt and asset value have an abnormal distribution (<0.05) and the profit parameter has a very extreme P value of 0.00006

Based on the results of the normality test above, the distribution data is prioritized using a uniform distribution to minimize errors in determining the distribution in each variable that constitutes *the risk driver*.

MSE and Rsquared

Using the MSE and Rsquared parameters in each variable calculation that is the reference, the following results are obtained:

Single Risk Driver Debit

Table 1. MSE and Rsquare Discharge Prediction Parameters

Single Risk Driver Debit				
Model	**Cross Validation**		**Boostrap Prediction**	
	MSE	**Rsquared**	**MSE**	Rsquared
Linear Regression	3.1E-28	1.00000	0.000	1.00000
Ridge Regression	0.45589	0.99811	0.106	0.99956
Lasso Regression	3.05508	0.98735	0.665	0.99725
Elastic Net	3.19430	0.98678	0.6426	0.99734
Decision Tree	126.44435	0.47660	9.7199	0.95977
Random Forest	128.26116	0.46908	29.1237	0.87945
Gradient Boosting	116.29344	0.51862	9.4525	0.96087
Support Vector Machine (Linear)	0.08643	0.99964	0.0556	0.99977

Using *support vector machine regressor linear* is the best model option because the MSE is the least and the reduction in errors is significant by using 100 times of synthetic data simulations, in addition to having a probability of model overfitting of 36%.

Single Risk Driver Total Asset Load

Table 2. Comparison of Model Performance Metrics for Single Risk Asset Load Driver

Single Risk Asset Load Driver				
Model	**Cross Validation**		**Boostrap Prediction**	
	MSE	**Rsquared**	**MSE**	**Rsquared**
Linear Regression	0.33826	0.66174	0.0020	0.99802
Ridge Regression	0.06312	0.93688	0.0160	0.98396
Lasso Regression	0.98992	0.01008	0.8846	0.11537
Elastic Net	0.65093	0.34907	0.4988	0.50125
Decision Tree	0.41303	0.58697	0.0246	0.97536
Random Forest	0.29287	0.70713	0.0634	0.93664
Gradient Boosting	0.28861	0.71139	0.0297	0.97032
Support Vector Machine (Linear)	0.06308	0.93692	0.0168	0.98325

Better load prediction using *Elastic Net* is because by using 100 times of synthetic data simulations, the error value has decreased significantly, in addition to having a probability of model overfitting of 23%

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Single Risk Driver Asset Value

Table 3. Comparison of Model Performance Metrics for Single Risk Driver Asset Value

Single Risk Driver Asset Value				
Model	**Cross Validation**		**Boostrap Prediction**	
	MSE	**Rsquared**	**MSE**	**Rsquared**
Linear Regression	136.72591	(135.72591)	0.40387	0.59613
Ridge Regression	0.68357	0.31643	0.1518	0.84821
Lasso Regression	1.12110	(0.12110)	0.8968	0.10323
Elastic Net	0.85662	0.14338	0.5628	0.43718
Decision Tree	0.51143	0.48857	0.0429	0.95706
Random Forest	0.38607	0.61393	0.1006	0.89937
Gradient Boosting	0.48655	0.51345	0.0519	0.94813
Support Vector Machine (Poly)	0.42039	0.57961	0.0850	0.91502

Asset prediction is better using *Random Forest Regression* because by using 100 synthetic data simulations, the error value has decreased significantly, in addition to having a probability of model overfitting of 34%.

Nilai Uji Err Bhar

Table 4. Model Evaluation Results with Monte Carlo VaR Error Test

Uji Eror VaR Monte Carlo		
Best Models	**MSE Values**	**Rsquared Values**
Random Forest Regression	0.15	0.99

It was found that the modeling results had a significant MSE value of small and had a high Rsquared, so it can be said that the model can be used to perform regression and forecasting techniques.

Prediction and VaR Calculation Results

The following are the results of each prediction that has been made by Monte Carlo

	Debit Air Optimal	Batas Atas	Batas Bawah	Energy Output Rata Tahunan	Energy Output Maks	Energy Output Min
1	87.352018	88.848659	85.855377	1.274847e+08	1.285982e+08	1.263712e+08
2	87.977755	89.467615	86.487894	1.279503e+08	1.290587e+08	1.268418e+08
3	86.400494	87.892657	84.908331	1.267768e+08	1.278870e+08	1.256666e+08
4	87.244122	88.734296	85.753949	1.274044e+08	1.285131e+08	1.262958e+08
5	87.563415	89.061068	86.065762	1.276420e+08	1.287562e+08	1.265278e+08
6	88.007079	89.506384	86.507773	1.279721e+08	1.290876e+08	1.268566e+08
7	87.185169	88.690069	85.680269	1.273606e+08	1.284802e+08	1.262409e+08
8	86.484858	87.972523	84.997192	1.268396e+08	1.279464e+08	1.257327e+08
9	86.633505	88.122709	85.144301	1.269502e+08	1.280581e+08	1.258422e+08

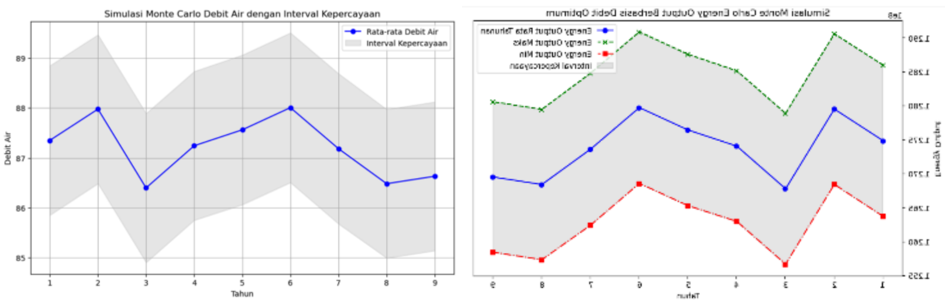

Figure 3. Estimated results of discharge and energy output

ISSN 2721-0960 (Print), ISSN 2721-0847 (online)

The results of the estimated discharge parameters were obtained that the optimum discharge value for 5 years ranged from 88 m3/s to 87 m3/s and the average energy produced was 1.27 GWh per year

	Prediksi Beban	Batas Bawah	Batas Atas
0	9.013076e+06	8.996866e+06	9.029285e+06
1	9.024822e+06	9.008641e+06	9.041003e+06
2	9.016237e+06	9.000033e+06	9.032441e+06
3	9.000903e+06	8.984876e+06	9.016930e+06
4	9.005293e+06	8.989218e+06	9.021367e+06
5	9.008775e+06	8.992815e+06	9.024735e+06
6	9.019059e+06	9.002940e+06	9.035178e+06
7	9.015551e+06	8.999540e+06	9.031562e+06
8	9.022052e+06	9.005918e+06	9.038187e+06

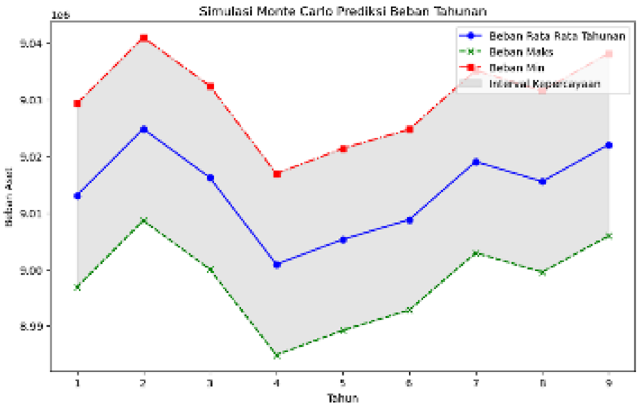

Figure 4. Total load prediction results

The results of the total load parameter estimate obtained that the total load value for 5 years ranges from $9.2 Million to $9.4 Million m3/s.

	prediksi nilai aset	lower_bound	upper_bound
0	165.204505	161.643110	167.437536
1	164.309993	150.614415	172.505234
2	161.163339	147.883150	169.777815
3	159.994154	153.924629	163.636656
4	155.871865	144.196617	162.509882
5	138.058736	114.607970	151.735938
6	117.930544	96.209398	140.804738
7	103.067627	82.231904	143.920676
8	84.426710	53.586171	133.831076

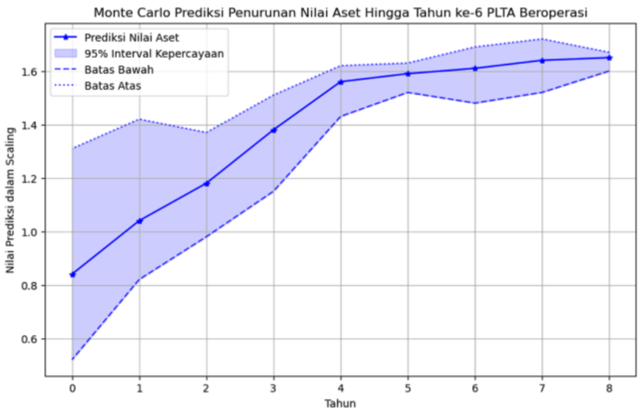

Figure 5. of the asset value prediction results

Table 5. Estimated ROA over a period of 5 years

Year	Total Revenue	Total Expenses	Net Profit	Total Asset Value	ROA
2024	11,353,280	9,013,076	1,861,040	165,210,144	1.13%
2025	11,361,730	9,024,822	2,128,631	164,309,330	1.30%
2026	11,345,140	9,016,237	2,011,746	161,163,339	1.25%
2027	11,363,620	9,000,903	2,135,525	159,994,154	1.33%
2028	11,342,150	9,005,293	1,915,902	155,871,865	1.23%

The results of the estimated total asset value parameter obtained that the total asset value in 2024 (index 8) ranges from $165.2 Million and decreases until 2029 (index 4) to $155.8 Million.

So based on formulation (11), an estimate of ROA for 5 consecutive years is obtained which will be used as a target in calculating VaR.

ISSN 2721-0960 (Print), ISSN 2721-0847 (online)

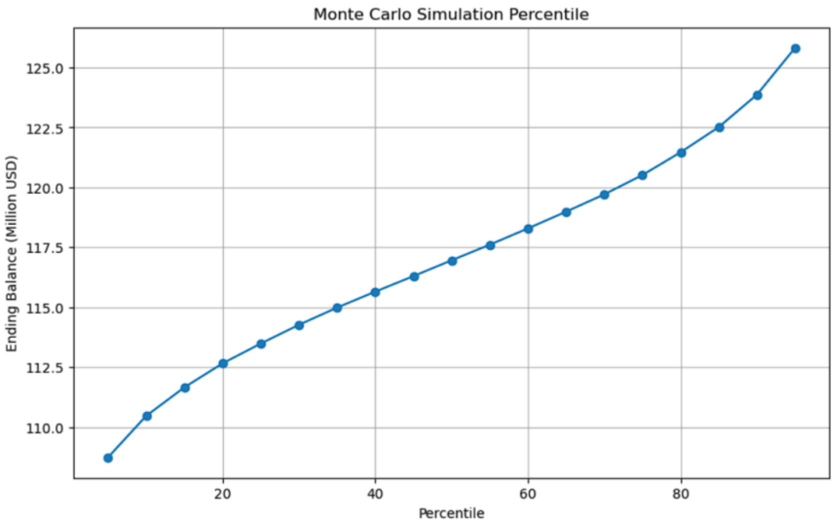

Figure 6. distribution of percentile values of 5 – 95%

It is predicted that the VaR value using the volatility of asset value, the volatility of the estimated value of income, the volatility of the estimated value of expenses, the volatility of exchange rates, the volatility of inflation and the volatility of *demand* will affect the prediction value. The result of the prediction value for the end of the 5th year is that *the cash balance* position is $125 million with the level of possibility of maximum profit that PLN will get if it acquires this asset of a maximum of $44 million and a minimum of $27 million with a confidence level of 95% if the asset operates optimally and the maximum value of losses that can occur or suffer PLN is a maximum of $25 million and a minimum of $3 million.

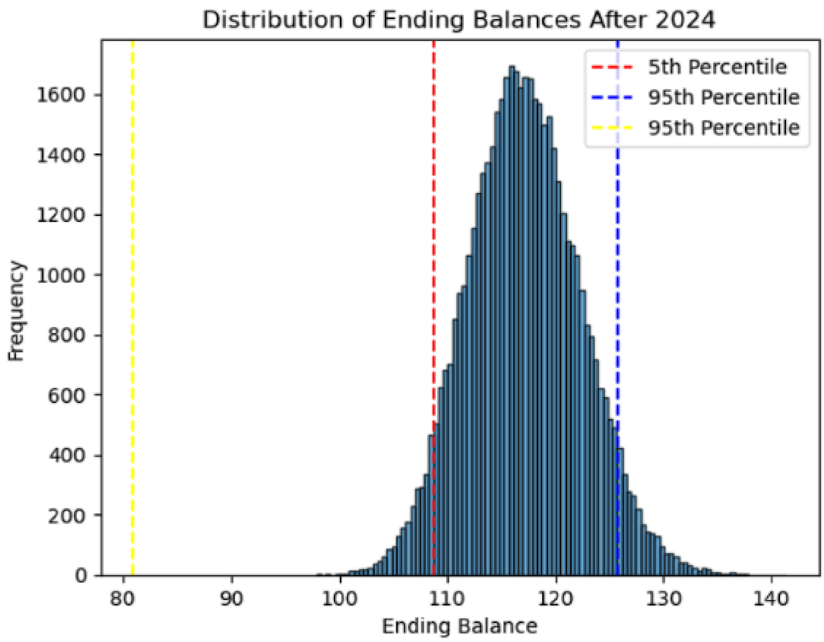

Figure 7. Distribution of asset cash balances prediction results in the next 5 years

The effect of volatility value on the calculation *of ending cash balances* can be seen by looking at the comparison between each volatility value and the total volatility over a period of 5 years.

Based on the results of the calculation, it was found that the volatility of asset values had a significant influence on *the ending cash balances*, which was 44%, while the volatility of external factors that had a big influence was the volatility of changes in electricity demand with an influence of 19%.

ISSN 2721-0960 (Print), ISSN 2721-0847 (online)

Conclusion

The model for predicting each single risk driver value using monte carlo with specific modeling is accurate because it has a small MSE value of 0.15 and an Rsquared that is close to 1. As for the estimated value of VaR, the resulting MSE is 0.25 with an Rsquared close to 1. But it needs to be noted Thus it is said that the modeling is accurate. To get a value with these small errors, it is done by running a program with certain parameters and models so that it is recommended for further research before running the Monte Carlo program, it is necessary to search for the best parameters and best models first on the data that will be carried out by the regression or forecast model so that the model is more accurate and does not take a long time.

Then in the VaR value, if the ROA with a target varies within a period of 5 years, it is estimated that the investment has a risk of a maximum loss of $25 Million and a minimum of $3 Million with a confidence level in the maximum and minimum values of 95%. This value is greatly influenced by volatility, so for future research it is recommended to improve the accuracy in performing VaR calculations with monte carlo, researchers have sufficient data and long history and add other types of volatility to macro risks.

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ISSN 2721-0960 (Print), ISSN 2721-0847 (online)