Conference Paper

Can Lexicographic Goal Programming, Artificial Neural Networks, and Value-at-risk Methods be Effective in Analysis of 50 Highest Trade Frequency Issuers Optimum Portfolio

Andrian Anwar L Nata[1]*, Novi Riani[2], Allan Harris[3], Erike Anggraeni[4]

[1]Sekolah Tinggi Ilmu Ekonomi Syariah Alifa Lampung-Indonesia
[2]Universitas Islam Negeri Raden Intan Lampung - Indonesia

ORCID
Andrian Anwar L Nata: https://orcid.org/0009-0009-5056-7105
Novi Riani: https://orcid.org/0009-0009-5056-7105
Allan Harris: https://orcid.org/0009-0009-5056-7105
Erike Anggraeni: https://orcid.org/0000-0001-5309-415X

Corresponding Author: Andrian Anwar L Nata; email: andrian.aln@sties-alifa. ac.id

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Abstract.
This study aims to describe the optimal stock portfolio as a series of processes for selecting a stock portfolio that suits the needs and desires of investors. The variable used is the daily closing price of the stock exchanges listed on the Indonesia Stock Exchange for the period September 1, 2016 to September 1, 2022 for 50 stocks with the highest trading frequency in the first quarter of 2022 using the value at risk, lexicographic goal method, programming, neural networks, and artificial neural networks. It is known that the value-at-risk method in generating shortfalls is carried out using a valuable approach that exceeds the threshold where the assumption of a 5% tail minimum return is generalized with the Pareto distribution. The input of the neural network in producing the output obtained through the PACF and ACF plots is t1. Issuer price forecasts are obtained using the neural network method and the backpropagation algorithm for each issuer, an SSMS of Rp. 1808.3, ICBP of Rp. 12,717, ASII Rp. 6832.1, BBNI of Rp. 6234.6, INCO of Rp. 2781.8, CPIN of Rp. 12,763, TLKM worth 2630.1, SCMA Rp. 2885.5, and WSKT worth Rp. 1575.7. The issuers obtained have a small MAPE value, which is below 10%. Programming the lexicographical objectives resulted in the nine selected issuers having a minimum standard of risk with maximum returns. Of the nine stocks selected, CPIN, SSMS, BBNI, ICBP, TLKM, ASII, INCO, SCMA and WSKT.

Keywords: return, value at risk, lexicographic goal programming, backpropagation.

1. INTRODUCTION

Rational investors will invest their funds by choosing efficient stocks, which provide maximum returns with a certain risk, or certain returns with minimal risk (Cohen & Kudryavtsev, 2012). Rational investors are one of the keys to a more efficient stock market (Gerber et al., 2002). Rational investor before making an investment decision on share ownership, the investor certainly needs to make a choice on the company's shares in which the investor will invest. It could be said that investors need to form an optimal portfolio, in which the optimal portfolio will provide a high rate of return on their investment with a certain level of risk.

Where all business ventures is the main goal of profitability (Mahatma, 2013). Profitability is the ability of a company to generate profits during a certain period at a certain level of sales, assets and share capital. The profitability of a company can be assessed in various ways depending on profits and assets or capital that will be compared with one another (Ball et al., 2015). In the long term no business will survive without a profit. Profitability is the company's ability to generate profits with all the capital that works in it.

This optimal portfolio contains the best combination of return and risk from stocks, so as to generate maximum investment. Usually, the selected stocks are stocks that have an influence on the price of the Jakarta Composite Index (JCI). This index is influenced by stocks that have a large market capitalization and usually these stocks are in great demand by investors. Stocks in the financial sector are the most attractive stocks for young investors, followed by the infrastructure sector. The next industrial sector that has become the target of young investors is consumer goods stocks, both cyclicals (primary consumer goods) and non-cyclicals (non-primary consumer goods), and basic materials (Kenett et al., 2010).

Thus, issuers are an option as a very important stock portfolio. The selection of these issuers is certainly very influential on the income of investors.

Capital market consisting of the words market and capital, so the capital market can be defined as a meeting place for supply and demand for capital, both in the form of equity and long term (Mahatma, 2013). The capital market is an activity related to public offerings and securities trading, public companies related to the securities they issue, as well as institutions and professions related to securities (Beaver, 2002). The capital market is a market for various long-term financial instruments with maturities of more than one year, such as stocks, bonds (bonds), mutual funds, and various derivative instruments of securities or securities. The capital market is a means of funding for

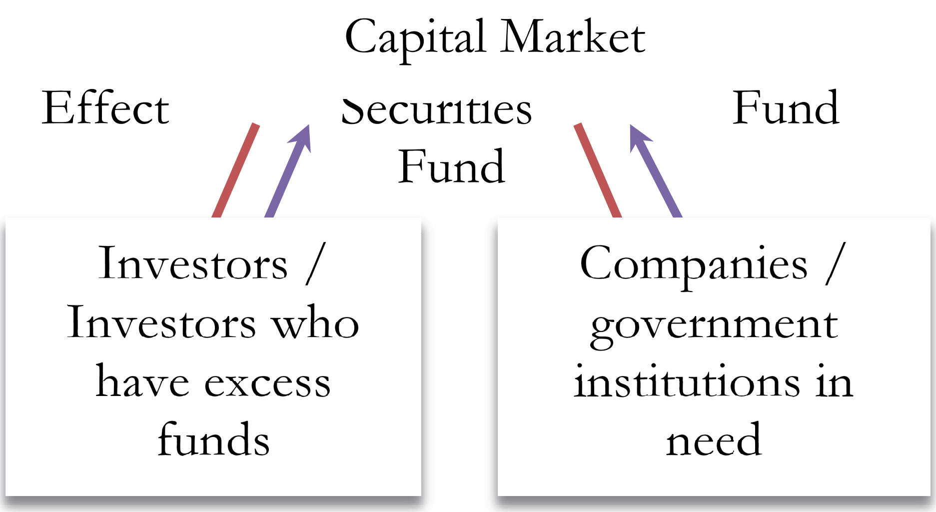

Figure 1

companies and the government, and a means of investing activities for owners of funds (investors) (Ocampo & Stiglitz, 2008). The capital market is not just a market where there are buying and selling transactions. The capital market has a large role for the economy of a country because the capital market performs two functions at once, namely the economic function and the financial function.

Analysis in the selection of portfolio or stock combinations, where stocks can be done with several approaches, namely the conventional approach consisting of a fundamental approach, namely an investment approach using economic information, such as historical financial statements or basic information about companies and a technical approach, namely an approach using historical data patterns. a stock for example the lowest, highest price and trading volume or a combination of fundamental and technical analysis approaches which are complementary approaches, to get optimal profit (Peylo, 2012).

Lexicographic goal programming or often called preemptive goal programming is a model of goal programming where the goals to be achieved have different levels of priority or importance. Lexicographic goal programming is sometimes called pre-emptive goal programming in some literature (Tamiz et al., 1995).

To find out the general model of lexicographic goal programming, suppose there are Q goals, each f (x), f_2(x), ... , f_Q (x), then the formula can be written as follows:

$\sum_{j=1}^{n} c1jxj$ = b_1 (objective function to -1)

$\sum_{j=1}^{n} c2jxj$ = b_2 (objective function to - 2) ..

$\sum_{j=1}^{n} cQjxj$ = b_Q (objective function to - Q)

1. The first priority (P_1) aims to optimally utilize the amount of funds available for investment with a maximum proportion of 1.

$$\sum_{j-1}^{j} Xj + d1 - d1 = 1$$

2. The second priority (P_2) has the objective of maximizing the expected return on ir's expected daily return.

$$\sum_{j-1}^{j} rj + d2 - d2 = R$$

3. The third priority has the objective of minimizing the risk of (P_3) , which is obtained from the value at risk.

$$\sum_{j-1}^{j} \beta jxj + d3 - d3 = \varnothing$$

The purpose of goal programming is to approach the planned targets as closely as possible in advance and if there is a deviation, the deviation must be as minimal as possible. Because it's impossible

To achieve all targets, it is necessary to define an overall objective function for goal programming that relates to the goal of achieving several targets.

Value at risk (VaR) is the maximum loss of a financial position in a certain timeframe.

F (x |ξ, σ) = $\{1 - \left(1 - \frac{\xi x}{\sigma}\right) \; 1 - expexp\,(-\frac{x}{\sigma}) \;\; - \frac{1}{k} \; \frac{jika\ \xi \neq 0}{jika\ \xi = 0}$

The value at risk or shortfall value that shows the minimum risk is as follows:

VaR_t (α) = $\mu + \frac{\sigma}{\xi} \left((\frac{n}{n_\mu} - \alpha \right) - -\xi \; - 1\,)$

Broadly speaking, the steps of the training algorithm on the backpropagation method are to perform the feedforward stage, where the input signal x_1, x_2, ... $x_n$will enter the hidden layer and be received by a hidden unit called z_1,...,$z_p$through a propagation and activation function to then be processed and produce output.

In this study, the input signal used is the closing stock price for a certain period of time. The input determination is carried out using the ACF and PACF values which represent the correlation in the t-th observation. Error measurement is done using MSE, RMSE and MAPE values.

The optimum stock portfolio is a series of stock portfolio selection processes that are in accordance with the needs and intentions of investors. The development of modern financial technology, modern portfolio theory intends to allocate assets by maximizing the expected return per unit of risk.

Hermuningsih said shares are one of the securities traded in the capital market that are ownership (Hermuningsih, 2012). In previous research, investors who have a rational mind will invest their money in an optimal portfolio consisting of 15 stocks that will become stock candidates. The optimal portfolio is formed by stocks that have the highest return and the highest risk (high return, high risk) (Abrami & Marsoem, 2021). Previous research also explained that the issuer's price assessment was obtained using a neural network and backpropagation algorithm which was used as a reference for issuer prices (Aliffia Permata Sakarosa, 2022). Then previous research explained that investing, will not be separated from the fluctuations in stock prices which have an influence on the magnitude of risk and return (yield) (I Made Dwi Rendra Graha, 2016).

From each of these studies it can be reduced, that research (Hermuningsih, 2012) mentions stocks as one of the valuable elements in the capital market. Then (Abrami & Marsoem, 2021) states that stocks can be formed through an optimal portfolio. Meanwhile (I Made Dwi Rendra Graha, 2016) mentions that investment can affect risk and return. Thus this study explains lexicographic goal programming, artificial neural networks, and value-at-risk methods to be effective in Analysis of 50 highest trade frequency issuers Optimum portfolio.

2. METHODS

The variable used is the daily closing price of stock exchanges listed on the Indonesia Stock Exchange in the period September 1, 2016 to September 1, 2022 on 50 stocks with the highest trading frequency for the first quarter of 2022. Daily closing price data obtained from http://finance. yahoo.com, while the 50 stocks with the highest trading frequency were obtained from the Indonesia Stock Exchange report in the first quarter.

Table 1

X_1	$r_{1,t}, r_{1,t-1}, \dots, r_{1,t-m}$
X_2	$R_{2,t}, r_{2,t-1}, \dots, r_{2,t--m}$
X_i	$R_{i,t}, r_{i,t-1}, \dots, r_{i,t-m}$

The steps in this study use steps, namely determining the literature review on the research subject and the method used, conducting descriptive statistical analysis to determine the initial analysis of the data pattern, conducting data pre-processing, the details of data pre-processing are that the data must be in the same time dimension. the same and zero return of less than 30%, determine the risk that may occur to each issuer of shares in a certain period with the value at risk method, perform variable reduction with certain constraints, namely maximum profit, minimal risk and the proportion of funds owned by investors, using the method optimizing lexicographic goal programming, forecasting stock prices in certain future periods using the neural network method, artificial neural network then predicting the price one day ahead.

Table 2

Emiten	Proporsi Dana	Return	Risk
X_1	X_1	r_1X_1	$\square_1X_1$
X_2	X_2	r_2X_2	$\square_2X_2$
X_i	X_i	r_iX_i	$\square_iX_i$
Batas	*1*	*R*	*ø*

Table 3

Emiten	Proporsi Dana	Return
X_1	$X_{1,t-1}$	$X_{1,t}$
X_2	$X_{2,t-1}$	$X_{2,t}$
X_n	$X_{n,t-1}$	$X_{50,t}$

The input and output data structure is x which is the nth daily closing price data with t being an observation at a certain time. Input is the daily closing price of shares at $X_{n,t-1}$ to $X_{n,t-20}$.

3. RESULTS AND DISCUSSION

3.1. RESULT

The most active stock is indicated as the most frequently traded stock. Thus, the list of 50 issuers with the highest trading frequency is a representation of the public's perspective on stocks that are favorites in trading or short-term stock trading.

The transaction shows that 62.74% is carried out for the activities of shares traded which are on the list of 50 shares with the highest frequency of buying and selling. This means that although many issuers are listed on the Indonesian stock exchange, more than half of the market concentration is only on these 50 issuers. The trading value is up to 71.65% and the trading volume reaches 47.49% of all buying and selling activities that occur in one quarter.

The number of issuers in each business classification is included in the list of the 50 issuers with the highest trading frequency. There are 11 (eleven) stocks in the property industry which are included in the list of 50 most active stocks which explains that people make a property business sector a favorite as an investment destination. On the other hand, there are only 2 (two) issuers from the category of industrial types,

Table 4

	Frequency	Trending Value	Trending Volume
Total All Trades	14.330,70	408,5	402.539,50
Total 50 Most Active Stocks	8.990,70	292,8	191.154,20
Percentage of 50 Most Active Stocks Against Overall Trading	62,74%	71,65%	47,49%

indicating that the public's lack of interest to companies with a variety of industry business classifications.

The pattern has shown that based on the classification of business categories, the category of agriculture is stocks where the trading frequency gets the highest value. On the other hand, stocks from the service and trading categories with stocks from the property category, which have the most members in the list of 50 most active stocks, 10 and 11 shares respectively, actually have the lowest buying and selling frequency.

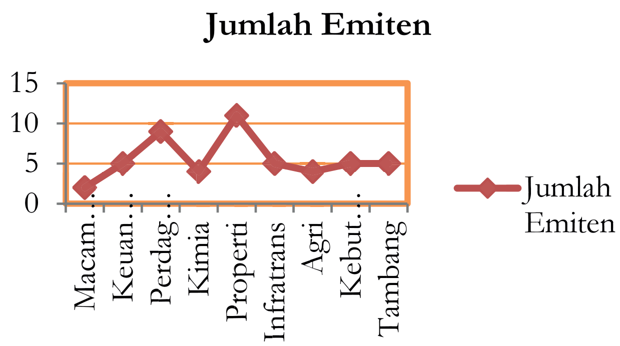

Figure 2

The application of value at risk using peaks over threshold (POT) which follows the generalized Pareto distribution is carried out in this study. However, not all of the issuers listed on the list of the 50 most active shares are used. By calculating the number of zero returns which is a representation of the issuer's stagnation. Then it was found that there were only 47 issuers that could be used as research subjects. Three of the issuers that cannot be used are LPKR, SIAP and CPRO, because these issuers have very high zero returns, namely 60.7%, 60.23% and 91.5%, respectively. The risk measurement is first done by setting the lower extreme quantile in defining the extreme values contained in the sample of 5% of the total return value.

Then the parameter estimation of extreme values is carried out using the maximum likelihood method. Furthermore, these parameters are used to determine the value at risk as follows:

The plot data shows the frequency and shortfall values for 47 issuers that have a random distribution and no shortfall pattern or trading frequency is found. However, there are some interesting data due to the pattern, namely LPPF which has the highest trading frequency value turns out to have a shortfall that is not too small or large, and does not have a pattern in its business group. On the other hand, BUMI is the issuer with the highest shortfall value of 5.9607, twice the minimum shortfall value which has a low trading frequency. This additionally proves that there is no pattern found between trading frequency and shortfall.

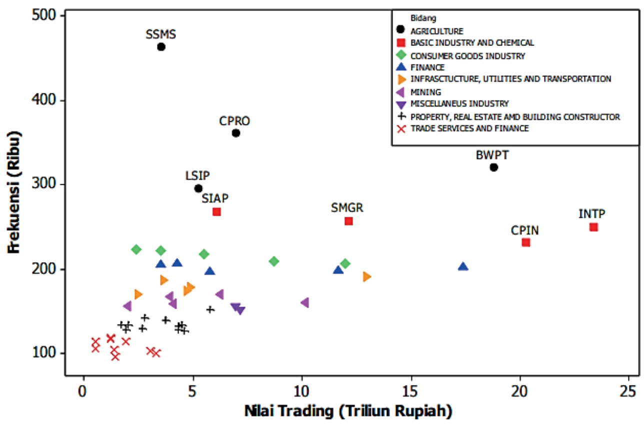

Figure 3

The lexicographic goal programming method is a development method of the goal programming method with additional priorities.

The constraints used in determining the optimum portfolio using lexicographic goal programming are represented in a limit function, namely a function of the limits on the proportion of funds, risk minimization and return maximization. The lexicographic goal programming method is implemented in each business classification, in which 9 issuers have been obtained from each business group.

The assessment of the average shortfall in which the selected issuer is 3.6106, while the median value is 3.7226, shows that in the list of selected issuers there are no issuers with outlier shortfalls. This is evidenced by the maximum value of 4.1414 and the minimum value of 2.6125. The value of the standard deviation is also not too large, which is 2.73, this all indicates that there is an outlier pattern in the list of selected issuers. There is a difference where the mean and median daily returns on the selected

Table 5

No	Emiten	Shape	Scale	Shortfall
1	SSMS	-0,2742	3,4004	2,6125
2	INDF	-0,0269	1,8656	2,8001
3	BBTN	0,1447	1,6678	3,6703
4	BBNI	0,1507	1,3939	3,2479
5	TRAM	0,8598	2,7837	3,6873
6	EXCL	0,1239	1,5129	3,7921
7	ICBP	-0,3697	1,8576	3,3507
8	ITMG	0,0934	1,4712	3,8862
9	PTBA	-0,0522	1,9547	3,6164
10	SRIL	0,1461	1,3111	3,3663
11	APLN	0,0069	1,7756	3,3793
12	BWPT	0,4543	1,5273	4,0112
13	SMGR	0,0455	1,4850	3,3637
14	WIKA	0,1913	1,7391	3,7319
15	BSDE	0,1453	1,5621	4,2758
16	ASRI	0,1109	2,0519	4,2824
17	PWON	0,2705	1,5977	3,7505
18	WSKT	-0,0322	2,6340	4,1414
19	SCMA	0,2577	1,5624	3,7322
20	MNCN	-0,0230	1,7439	4,3090
21	LPPF	0,2157	1,5500	3,7105
22	MPPA	0,4903	1,4662	3,7954
23	UNTR	0,0163	1,5514	3,7743
24	KLBF	0,2265	1,5413	3,7149
25	ADRO	0,0234	1,8259	4,1165
26	INTP	0,1416	1,5961	3,4007
27	BMRI	0,1793	1,1840	3,4359
28	INCO	0,2487	1,2636	4,0955
29	KIJA	0,2167	1,9091	3,8470
30	AKRA	-0,1065	2,0242	3,5532
31	ADHI	-0,0229	2,3846	4,0882
32	TLKM	0,2042	1,5787	3,7071
33	CPIN	0,3375	1,5593	3,8855
34	ASII	0,2410	1,5317	3,7226
35	BUMI	0,0390	3,2669	5,9607
36	INVS	0,2970	1,8679	3,7906
37	GGRM	0,0577	1,3444	3,0844
38	BMTR	-0,0054	1,8969	3,8941
39	BHIT	0,0486	2,6354	4,0759
40	MYRX	0,2685	1,5709	3,6079
41	UNVR	0,1857	1,2035	3,2092
42	BBRI	0,2401	1,5340	3,7219
43	PTPP	0,1884	2,0139	4,2322
44	PGAS	0,1603	1,2911	3,3443
45	SMRA	0,3261	1,5481	3,8598
46	LSIP	0,2700	1,5848	3,7496
47	BBCA	-0,0361	1,4339	2,7746

Table 6

No	Emiten	*Daily Return*	*Shortfall*
1	TLKM	0,0337	3,7071
2	SCMA	0,2004	3,7322
3	ASII	0,0262	3,7226
4	SSMS	0,2681	2,6125
5	ICBP	0,0961	3,3507
6	WSKT	0,2188	4,1414
7	CPIN	0,1189	3,8855
8	INCO	-0,0456	4,0955
9	BBNI	0,0782	3,2479

Table 7

Emiten	**Daily Return**	**Shortfall**
Minimum	-0,0456	2,6125
Mean	0,1105	3,6106
Maximum	0,2681	4,1414
Median	0,0961	3,7226
Standar Deviasi	0,1021	0,4775

issuers are greater than the overall data. All of this shows that selected issuers will generate higher profits

However, the minimum and maximum values indicate that the range of data on the selected issuers is narrower with a lower standard deviation value indicating that the risk is lower in the portfolios of the selected issuers.

Table 8

No	Emiten	MAPE	Ramalan	RMSE	*Node*
1	ASII	1,37	6832,1	139,53	10
2	ICBP	5,03	12.717	788,42	30
3	SCMA	1,76	2885,5	80,96	30
4	WSKT	8,3	1575,7	162,3	10
5	SSMS	4,95	1808,3	98,38	10
6	CPIN	7,63	12.763	1201,7	20
7	INCO	1,43	2781,8	60,3	10
8	BBNI	6,98	6234,6	593,6	20
9	TLKM	1,37	2630,1	53,67	20

Forecasting generated by the artificial neural network method shows the pattern recognition stage which is then forecasted using the backpropagation algorithm. The input determination is carried out using the ACF and PACF values, showing that the issuer's price at time t only affects the issuer's price at t 1, this is shown from the PACF which is cut off only in the first lag.

Some of the provisions used as a trining stop are the MSE training criteria worth 0 and the maximum number of epohs is 1000 and the number of nodes used to find out the pattern data for each issuer ranges from 10 to 50 in one hidden layer. Presenting the data nodes used on the network, MSE, MAPE and RMSE testing along with a one-step forward forecast, shows that all issuers are training as much as the maximum epoh value is 1000. Even though it has converged to an MSE training value, it turns out that the MSE testing made is not too low.

This is because the value of research subjects is very high, ranging from hundreds to thousands. Even though the RMSE result is very high, the value is smaller than the actual value of the data, so that it is used for the model generated from the ANN method in its application.

There are three things to consider in investing, namely the risk, the expected return, and the availability of the amount of money to be invested. Apart from these three things, in order to diversify investments or form not to be concentrated in one share, restrictions on the proportion of each share are imposed.

4. DISCUSSION

The value at risk method in generating shortfalls is carried out with a value approach that exceeds the threshold where the assumption of 5% tail minimum return is generalized Pareto distribution. The input of the neural network in producing the output t is obtained through the PACF and ACF plots is t–1.

It was found that the issuer's price forecast was generated by the neural network method and using the backpropagation algorithm on each issuer, the SSMS was Rp. 1808.3, ICBP was Rp. 12,717, ASII Rp. 6832.1, BBNI of Rp. 6234.6, INCO of Rp. 2781.8, CPIN of Rp. 12,763, TLKM worth 2630,1, SCMA of Rp. 2885.5, and WSKT worth Rp. 1575.7. The issuer obtained has a small MAPE value, which is below 10%.

According to research (Saepudin et al., 2017), The Expected Shortfall results from the calculation using 99% confidence level that may be experienced is at 0.039415 show that the risk exceed the VaR it is at 0.034245. For 95% confidence level that may be experienced is at 0.030608 show that the risk exceed the VaR it is at 0.024471. For 90% confidence level that may be experienced is at 0.026110 show that the risk exceed the VaR it is at 0.019172. Show that the greater the level of confidence that is used the greater the risk will be borne by the investor. Research (Dimas et al., 2018). The results showed the VaR value of GGRM and HMSP stock with the historical method is 3.28 and 2.54%. While the value of VaR shares GGRM and HMSP with Monte Carlo method is 3.52% and 3.14%. Monte Carlo simulation gives greater result than Historical Simulation, because Monte Carlo simulation do iteration repeatedly by involving random number generation and many synthesize the data so that sample data becomes more which makes the calculation is bigger. Research (Rohmah & Suharsono, 2017) risk level calculation is carried out using two EVT approaches, namely Block Maxima (BM) and Peaks Over Threshold (POT). The results show that the risk level generated by the BM method is greater than the risk level from POT. However, the backtesting results state that the POT method is more accurate than the BM method.

5. CONCLUSION

Lexicographic goal programming resulted in 9 selected issuers having a minimum standard of risk with a maximum return. Of the nine stocks selected, CPIN, SSMS, BBNI, ICBP, TLKM, ASII, INCO, SCMA, and WSKT.

The use of only one software by creating a dashboard can improve the method used in this study instead of having to use three software.

Previous studies have emphasized more on analyzing optimal portfolios with a single index model. However, in this study the emphasis is on using lexicographic goal programming methods, artificial neural networks and value at risk because they are proven to be more effective and more optimal.

From each business classification grouped in this study, the lexicographic goal programming method is used where the method is used for all issuer subjects but still uses additional priorities and limits.

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