Analysis and Development of Mathematical Models for Assessing Investment Risks in Financial Markets

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Abstract
In this paper we have analyzed existing approaches and mathematical models for forecasting investment risks. We have applied an existing methodology to actual financial markets using different investment strategies (for companies working in different areas and having different potential) and extra preliminary analysis as well as data mining methods. The study investigates how to analyze investors' interests, calculate their profits and possible losses based on the financial risks that exist in the market at the moment. For this reason, we proposed our own mathematical models based on the Value-at-Risk and Conditional VaR methodologies. For practical modeling, the stock market and the S&P 500 companies of different lines of business were chosen. The asset prices of companies in the industrial sector over the past 5 years were studied. The time series of share prices were constructed and processed in the form of profits for one day for each share, VaR, CVaR, Monte Carlo VaR models were developed.

Keywords
Investment risks, VaR, CVaR, financial market, time series analysis

1. Introduction

Information technologies for banks and business today are greatly wanted. The problem of ensuring their efficiency is extremely relevant in our rapidly changing world. The basic ground of suspicious business activity lies in adopted financial instruments and suitable business models. Financial instruments for increasing equity capital are one of the most common objects for researching and developing mathematical models. This is due to people's subconscious desire to multiply their savings by putting them on deposits, investing in precious metals, investing in real estate, cryptocurrency, or shares of the most famous companies. The choice and investment opportunities are significantly limited by the available material means, legislation, access, and opportunity to invest in the financial (stock) markets, and most importantly – the investor's readiness and tolerance for risk. The main goal of investing is to save funds from inflation and multiply them. Therefore, creating a high-quality investment portfolio is necessary, taking into account both the risks of the stock market and the human factor.

Modern financial processes are characterized by high dynamics, non-stationarity, nonlinearity, large and time-varying volatility, presence of deterministic and random components in data time series. Usually, financial processes function under the influence of a set of various natural random disturbances (noise components), which introduce significant uncertainties into data analysis. The two most important aspects that characterize risks are, firstly, the volatility, or changeability, of financial indicators, the probability or frequency of events, and, secondly, the sensitivity (exposure) of activity criteria to their consequences.

Qualitative methods of risk assessment are used to determine the type of risk and highlight those risks that require a quick response and are the most significant for financial systems. Most often the method of decision trees is used for qualitative assessment. It allows to determine the finite number of options for the development of events, establish the probability of their implementation and determine

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the qualitative and quantitative risk characteristics for each option. Also the method of scenario analysis is used. It considers the sensitivity of the net value criterion (NPV) to changes in key variables and the range of their probable values [1].

Quantitative methods of risk assessment make it possible to determine the probability of occurrence and consequences of the impact of risk on the company's activities. Among the main methods of quantitative risk assessment are probabilistic methods, game-theoretic methods, break-even point analysis, the simulation model of D. Hertz, an equivalent method, profitability estimation method, etc.

Risk assessment requires the use of appropriate mathematical apparatus, the development of application methods in accordance with the recognized international standards, and the implementation of appropriate software and technical tools to achieve the necessary speed and relevance of dynamic assessment of indicators.

2. Problem statement

The main idea of this article is to develop an approach allowing investors to use different risk metrics and deep analysis of portfolios to choose the optimal strategy with minimum risks and maximum earnings. For this reason, we need to calculate the mathematical metrics Expected Shortfall, VaR, CVaR with the confidence limits and to find the optimal period (duration) for investing.

3. Methods and technologies for risks assessment

Models that allow obtaining the loss distribution function in an explicit form can be used both for estimating average losses and for estimating maximum losses at a given level of significance. At the same time, simplified models or models based on expert evaluation do not allow obtaining quantitative estimates of these parameters and are used to solve a narrow class of problems

Let us recall the meaning of some basic risk assessment methods. Among the whole set of methods, we should single out the *method of adjusting the discount rate* which takes into account the risk. It is most often used in practice and involves the adjustment of some basic discount rate [1] (due to the introduction of a risk premium) that is considered risk-free or minimally acceptable.

By the *method of reliable equivalents*, the expected values of the payment quantities are set through the formation of reducing coefficients in order to bring the expected revenues to the number of payments adjusted, the receipt of which is practically not in doubt (guaranteed to be received) and the value of which can be reliably determined.

The *method of scenarios* allows you to combine the study of the sensitivity of the result indicator with the analysis of probabilistic estimates of its deviations, and to get a visual picture of various variants of events. This method is a certain development of the sensitivity analysis method, as it involves the simultaneous change of several factors.

The *methods of expert evaluations* are a set of methods and procedures for processing the results of a survey of an expert group (using their knowledge and experience), which are a single source of information. A significant advantage of the expert method is that it can be used in conditions of lack of information, but it is only necessary to ensure the exclusion of the mutual experts' influence and the agreement of their assessments.

The *method of assessing financial stability* (expenditure feasibility analysis) involves the identification of potential risk areas, attribution of the actual or projected state of the enterprise to one of the areas of financial stability, and respective areas of the risk. The method allows us to determine whether the enterprise's working capital supply (owned or borrowed resources) is sufficient for the formation of reserves and covering the costs associated with the implementation of the considered types of activities [1].

The *rating method* of evaluation provides for the possibility of selecting coefficients based on the specific purpose of the analysis. The system of rating evaluation consists of the following elements: a system of evaluation coefficients; coefficient weight scales (if necessary); scales for evaluating the values of the obtained indicators; formulas for calculating the final rating [2].

Advantages of the method: it involves the analysis of large data sets; the obtained result is immediately ranked according to a certain scale; the amount of necessary mathematical knowledge is within the limits of elementary financial calculations.

Disadvantages: the problem of choosing a standard for comparison, as it requires clarification for each type of risk.

The *regulatory method* is based on the usage of a system of financial ratios: liquidity, indebtedness, autonomy, maneuverability, coverage, etc. The advantage of the method is the fact that calculations are easy and quick. The system of standards is a kind of improvement of the rating method, which involves the formation of a predetermined evaluation scale with a minimum of ranking values [1]. The method allows you to establish the degree of risk with relative accuracy: the comparison with the standard is made in a scale of “low”, “normal”, and “high”, and therefore does not allow taking into account all the nuances of a specific situation. The disadvantages of the method are the low accuracy of the assessment, and the inability to take into account the specifics of a certain situation.

Fundamental method. The overall financial risk is calculated using the following fundamental indicators: volatility of the asset’s profitability, the small size of the company (P/BV), unbalanced growth (return on equity (ROE) is higher than the ratio of balanced growth), etc. Internal and external factors are significant such as the structure of costs per unit of revenue; periodicity of operational processes and trade policy in relations with debtors and creditors; the additional cost of capital investments; the financing structure, and these factors, thanks to analytical processing, undergo variability for each factor as a measure of the breakdown of the values of key landmarks (detailing by ROE). The description of risk characteristics can be illustrated by detailing the rate of ROE.

The basis of the financial risk assessment is the structural formalization of indicators based on factor analysis, namely, the calculation of the risk measure thanks to the definition of important factors that can be quantitatively measured or identified. The interpretation of the fundamental method is the method of risk assessment according to Sharpe [3], which is based on the amount of expected profit, which takes into account statistical data about its level during a certain time, trend, and the division of risk into systematic and unsystematic [4]. The value of the expected profit is determined based on the average industry rate of return and the trend of market development as a whole.

The *analog method* is used when the use of other methods is unacceptable for any reason. For this, a database of similar objects is used to identify common dependencies and transfer them to the object under study. Results are analyzed based on previous experience to identify potential risk factors, which is an advantage in the absence of a clear baseline for comparison. Disadvantages of the method: the factor of constant development is ignored, and the dynamism of the system and changes in the external environment are not taken into account.

The *“Risk Metrics”* technology was developed by the company “J.P. Morgan” [2] for assessing the risks of the securities market. The method aims to determine the degree of impact of risks on the event by calculating the “risk measure”, that is, the maximum possible potential change in the price of the portfolio, with a given probability for a given time period.

The *Stress Testing method* is a method of quantitative risk assessment, which consists in determining the size of the uncoordinated position that exposes the bank to risk, and determining the shock value of the change in an external factor - the exchange rate, interest rate, etc. The combination of these values determines the total amount of losses or income the bank will receive if the events unfold according to the set scenario.

The method of assessing financial risks based on probability calculations from the point of view of a financial manager is inconvenient because it only determines the probability distribution of losses and does not provide a specific assessment of financial risk.

4. Assessment of investment risk

Value-at-risk (VaR method) is a method of estimating financial risks based on the analysis of the statistical nature of the market. This is a universal method of assessing various types of risks (price, currency, credit, and liquidity risk). The VaR method has become a generally accepted method of risk assessment among participants in the Western financial system and regulatory bodies. In fact, the VaR technique is currently promoted as the standard for risk assessment [1,5,6]. Non-financial corporations can use VaR to assess cash flow risks and make hedging decisions (protecting capital against adverse price movements). One of the interpretations of VaR is the amount of uninsured risk assumed by the corporation. Investment analysts use VaR to evaluate various projects. Institutional investors, such as pension funds, use VaR to calculate market risks.

According to the Value at Risk (VaR) methodology, it is possible to calculate with a certain confidence level the upper limit of losses as a result of changes in risk factors in the confidence interval:

$$P(Loss_t(k) < VaR_t(k)) = (100-\alpha)\%,$$

where $Loss_t(k)$ are the actual losses at the moment of time t for the period of k days, $VaR_t(k)$ are the predicted losses at the moment of time t for the period of k days, α is the confidence level.

Conditional Value at Risk (CVaR) [1,7,8] defines the amount of risk or "tail thickness" for an investment portfolio, and is calculated as a weighted average of the "extreme" losses in the tail beyond the VaR threshold.

$CVaR = E(X \mid X > VaR)$, that is,

$$CVaR = \frac{1}{1-c}\int_{-1}^{VaR} xp(x)dx,$$

where $p(x)$ is the density of the loss distribution, c is the cut-off point on the distribution, set by the analyst as the VaR threshold, VaR is the agreed upper limit of VaR.

Then the expected loss or profit of the investor will be determined as the average value of VaR within a certain confidence interval (quantile).

Parametric VaR is calculated as follows [1]:

$$VaR = \alpha * \sigma * OP * \sqrt{\mathrm{N}},$$

where α is the confidence interval quantile; σ is the volatility (the rate of variability); OP is the value of open position; N is the forecasting period.

In the paper [5] the authors proposed CVaR-based method to learn robust options optimized for the expected loss using the extended gradient method proposed by Chow and Ghavamzadeh [6]. These options refer to a temporally extended sequence of actions [6]. Their method makes the expected loss lower than a given threshold in extremely unlikely events. The method makes it possible to reflect the model parameter distribution in learning options and thus prevents the learned options from overfitting an environment with an extremely rare worst-case parameter value[5].

Some interesting approaches to CVaR-based reinforcement learning [6,7,8] have been proposed, and they have been found to be applicable to learning flat policies.

In the paper [9] researchers measured investment risk using VaR and Expected shortfall. They compared the risk of investment on the cryptocurrencies market and S&P 500 index, and as a result, practically approved the hypothesis that the quantity of risk measured by 99% VaR is approximately the same as a 97.5% Expected shortfall and practice showed the same results for a two cryptocurrencies for BTC and ETH.

In investment companies and banks the VaR methodology is used to perform the following tasks [1]:

1. Internal monitoring of market risks: aggregate portfolio, asset class, issuer, counterparty, trader, portfolio manager, etc. From the point of view of monitoring, the accuracy of the VaR value assessment recedes into the background. The value of the relative and not the absolute value of VaR is important (the manager VaR or the portfolio VaR in comparison with the etalon portfolio VaR or the another manager's VaR or the same manager but in the previous time moments.

2. For external monitoring, VaR allows the creation of an idea of the market risk of the portfolio without disclosing information about the composition of the portfolio and to assess whether the accepted risk is permissible (acceptable).

3. To monitor the effectiveness of risk reduction operations.

4. Automatic analysis of possible management decisions. Transactions (deals) are monitored using VaR, there can only be an established rule for broker-dealers: "No transaction should lead to an increase in the value of VaR by more than X% of the initial capital".

With the help of the VaR methodology, it becomes possible to calculate risk assessments of various market segments and to identify the riskiest positions. VaR estimates can be used to diversify capital, set limits, and evaluate the company's performance. In some banks, the evaluation of traders' operations, as well as their remuneration, is as a return per unit of VaR calculated.

The VaR methodology by itself is not a method for financial risk management, as it does not eliminate financial losses. The VaR method cannot determine the optimal amount of risk that must be taken by the company (this is the task of the financial risk manager), but it allows you to estimate the amount of risk that has already been taken. The VaR method is part of a complex analysis of financial risks and should be used not instead of, but together with other risk assessment methods.

Shortfall-at-Risk (SAR-method) estimation of financial risks. Quite often, during risk assessment, the investor is not interested in the probability of receiving losses, but rather the expected size of the loss, because the probability of receiving a loss may be very small, but the size of the loss is so large that the consequences of an unfavorable result can be considered as catastrophic. Such a method of financial risk assessment is the SAR method [9].

Since the risk is caused by the uncertainty of the result, the smaller the variance of the possible values of the random variable, the greater its expected value, and, therefore, the risk decreases. This kind of reasoning led to the spread of the point of view that the mean square deviation of its profitability is a measure of the risk of an investment project considered. However, there are plenty of examples where increasing variance reduces the probability of losses. Under conditions, which signify a definite loss for the investor, he should choose strategies that lead to an increase in dispersion (risk).

Equivalent financial instrument method. The most understandable model for an investor to assess financial risk is the equivalent financial instrument method. So, if some financial strategy (financial instrument) fully insures against risk, then the total cost of current costs for strategy maintenance is the risk price that should be calculated. Moreover, if the instrument is traded on the market, then its market price determines the extent of the financial risk insured by this financial instrument.

The methods considered in this paper reflect an economic view of market analysis and are understandable for financiers. However, they do not make use of modern mathematical methods and information technologies for effective risk management. That's why in this paper we are focused on the application of the formalized mathematical models and developing informational technologies for simulating risk management for investors on different companies' shares on financial markets.

5. Modeling and simulation of the practical risk management task

First, we define and analyze the main risks for investors in financial markets over the last few years. These risks could cause both profits and losses due to their impact on other investors, industry and technological changes, and the political and economic situation in the world. While this cause was also really significant and still has some influence, that's why it was defined in our list of risks as "Covid-19 news". Firstly, a brainstorm was made and the expert's scores and opinions were included to define the most important risks for investors and to characterize and evaluate them by the probability and impact (losses). The results of the experts' rankings are shown in Table 1.

Various investment sectors from the S&P 500 portfolio from the most common areas such as industrial enterprises, IT companies, financial companies, and companies related to the healthcare industry were chosen (Figure 1).

Figure 1: Structure of S&P 500 portfolio

Table 1
The main risks of the investor in modern realities

N of the risk	Risks explanation	Impact	Risks' likelihood (probability)
R001	Key staff could leave in company	3	1
R002	Funding risk in company	1	1
R003	COVID 19 news	2	5
R004	Worker accidents in company	5	1
R005	Exchange rate changes	5	5
R006	Incomplete data in reports	4	1
R007	Data hacking	5	2
R008	Copyright issues with company	4	1
R009	Data loss from cloud	2	1
R010	CEO resigns	3	1
R011	CFO vanishes	3	1
R012	CTO elopes	4	1
R013	People uprising in the World	5	1
R014	Competition emerges on the market	5	5
R015	War	4	1
R016	News	3	5
R017	Crisis	5	1
R018	Shortage of sources in dependent industries	1	2
R019	Oil crisis	4	2
R020	Monitored policy	3	3
R021	Tweets	3	4
R022	Warming	1	4
R023	Inflation	4	4
R024	Change in sector	4	3
R025	Country	3	2
R026	Innovation	4	2

Figure 2 shows the industries with the highest ROI per day, so the sectors which are the most interesting for investing. As was expected, industrial enterprises and IT companies are the leaders.

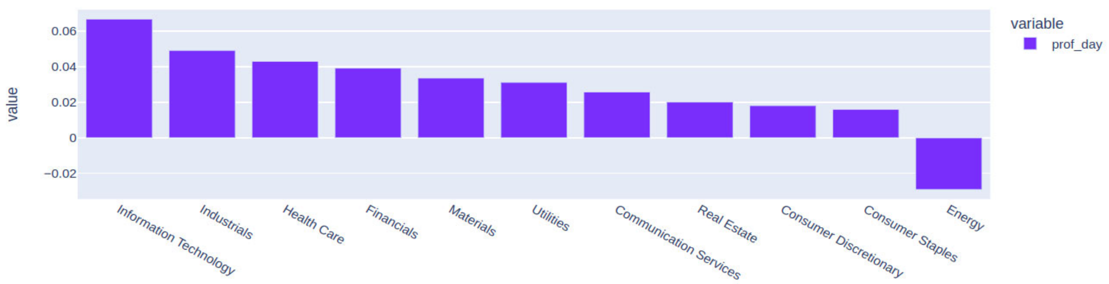

Figure 2: Industries with the highest ROI per day

Figure 3 shows the companies' tickers with the highest average revenue. The leaders are Carrier Global (CARA) for the health industry and Nvidia (NVDA) for IT.

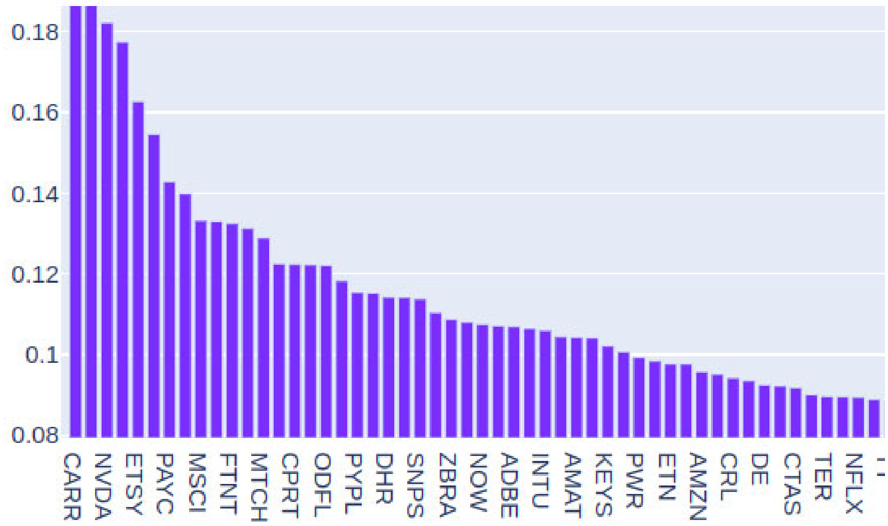

Figure 3: Companies with the highest average revenue

5.1. Data preprocessing

The initial dataset has been formed as follows: date, columns with the company's price per share, so it has been around 500 different time series for the companies for the same dates (Figure 4).

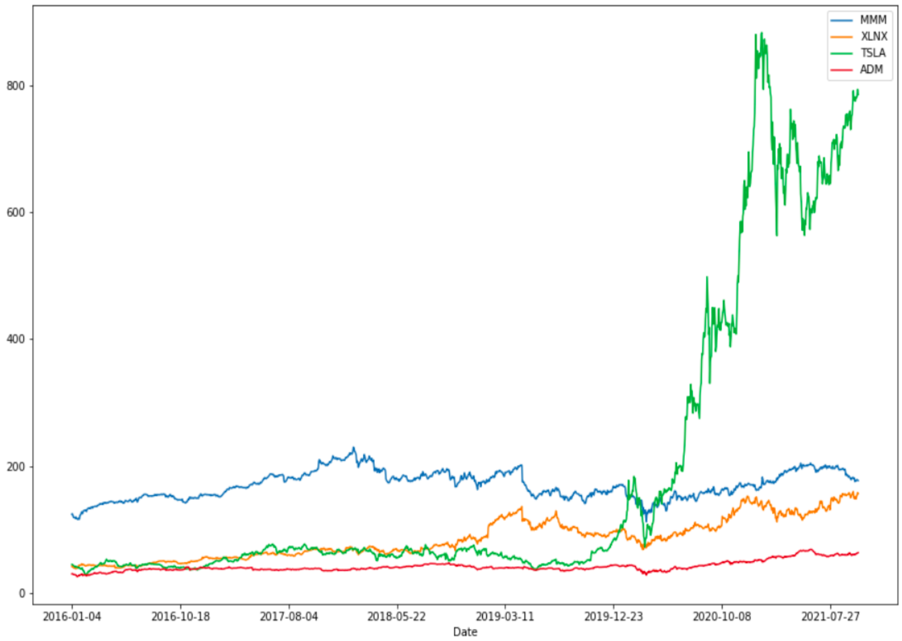

Figure 4: View of input data

In the data preparation phase, the time series were using a moving average over 5 days interpolated and smoothed. After these operations, the time series got rid of random noise. The final stage of data preparation was the transformation of the time series of share prices into the form of a one-day profit for the codeshare.

Table 2

The whole dataset was for investing used and expected losses were calculated

cash_type	time investment	time_model			
		1	7	30	90
Conditional VaR 95th CI	1	60.282	159.491	330.178	571.886
Conditional VaR 95th CI	3	128.740	340.613	705.135	1221.330
Conditional VaR 95th CI	7	**144.185**	381.478	789.735	1367.861
Conditional VaR 95th CI	30	95.059	251.502	520.658	901.806
Expected Porfolio Return	1	2.690	18.829	80.695	242.085
Expected Porfolio Return	3	9.540	66.778	286.190	858.570
Expected Porfolio Return	7	13.893	97.252	416.796	1250.389
Expected Porfolio Return	30	85.752	**600.263**	**2572.557**	**7717.670**
Value at Risk 95th CI	1	46.196	122.223	253.026	438.254
Value at Risk 95th CI	3	113.066	299.145	619.290	1072.641
Value at Risk 95th CI	7	133.977	354.471	733.824	1271.021
Value at Risk 95th CI	30	76.978	203.664	421.624	730.274

The four different types of experiments were conducted for different time series sizes on the entire size of training data from April 1, 2016, to October 2021. Experiments evaluated the different investment time intervals (1 day, 3, 7, and 30 days) and, accordingly, with a different time parameter for evaluating and planning the investor's income for a window of 1, 7, 30, and 90 days. Next, the most interesting companies for investment were selected and portfolios of so-called "blue chips" were formed. Var, CVar and Expected Portfolio Return models were built for 180 and 365 days built and the possible losses were calculated. (Tables 2-4). The average daily return was calculated using VAR and CVAR models with a confidence interval of 0.95. The investment portfolio was simulated for 100 days using the Monte Carlo VAR model with an initial investment of $10,000, and the entire investment period was built. In each table the maximum values are highlighted in bold, and the minimum values for each column are highlighted by colour.

Table 3

Only the last 180 days dataset for investing were used

cash_type	time investment	time_model			
		1	7	30	90
Conditional VaR 95th CI	1	61.013	161.426	334.184	578.823
Conditional VaR 95th CI	3	125.640	332.413	688.161	1191.930
Conditional VaR 95th CI	7	**177.222**	**468.886**	970.687	**1681.280**
Conditional VaR 95th CI	30	113.972	301.540	624.248	1081.229
Expected Porfolio Return	1	2.731	19.119	81.937	245.810
Expected Porfolio Return	3	7.353	51.470	220.585	661.756
Expected Porfolio Return	7	18.740	131.180	562.201	1686.602
Expected Porfolio Return	30	57.439	402.076	**1723.181**	5169.543
Value at Risk 95th CI	1	44.271	117.130	242.483	419.992
Value at Risk 95th CI	3	117.749	311.535	644.940	1117.068
Value at Risk 95th CI	7	167.327	442.707	916.490	1587.407
Value at Risk 95th CI	30	89.442	236.640	489.892	848.518

Table 4
Using only "blue chips" for investing on the whole period for investing

cash_type	time investment	time_model			
		1	7	30	90
Conditional VaR 95th CI	1	117.211	310.111	641.991	1111.961
Conditional VaR 95th CI	3	282.734	748.043	1548.597	2682.249
Conditional VaR 95th CI	7	575.654	1523.036	3152.984	5461.129
Conditional VaR 95th CI	30	844.138	2233.380	4623.536	8008.199
Expected Porfolio Return	1	7.077	49.536	212.298	636.895
Expected Porfolio Return	3	22.328	156.299	669.853	2009.560
Expected Porfolio Return	7	54.197	379.382	1625.923	4877.769
Expected Porfolio Return	30	264.803	1853.625	7944.106	23832.317
Value at Risk 95th CI	1	63.957	169.215	350.308	606.751
Value at Risk 95th CI	3	150.236	397.486	822.875	1425.262
Value at Risk 95th CI	7	295.887	782.843	1620.638	2807.028
Value at Risk 95th CI	30	494.466	1308.235	2708.303	4690.920

As a result of modeling and forecasting, it was found that the most effective way of investing was to invest in "blue chips" over the entire time interval.

The number of investment portfolio simulations was set as 1000 times. The average results of the simulation turned out to be $10,352.53, that is, we have an average profit of 352.53$, which is 0.0353% of the initial investment. With a variance of $273.69, which is 0.0274% of the initial investment.

The Monte Carlo simulation was done on the different stock shares and it was confirmed that due to choosing different companies and strategies, we can receive higher incomes from our investments but also with a more probability of risks due to the risk of falling share prices and the higher volatility (Figure 5).

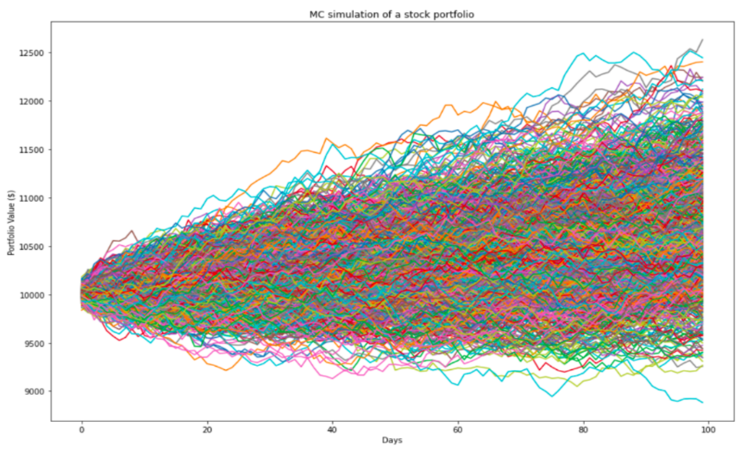

Figure 5: The Monte Carlo simulation on the different stock shares

6. Conclusions

The conducted research showed the possibility of creating new information technologies for building and combining various models based on VaR, CVar, Monte Carlo Var with methods of intelligent data analysis for developing an investment strategy and assessing possible profits and losses depending not only on the volatility of financial series but also on the risk tolerance of the investor himself [6-12].

Investing in blue-chip stocks was found to be more effective than investing in randomly chosen assets from the S&P 500. However, blue-chip investments come with higher risk, and the decision to invest or not should depend on the investor's risk tolerance.

Assuming an investor invests in the S&P 500 index with a random allocation of assets based on their mean return and correlation over the last 5 years, they would earn a return of 0.035% on their initial investment, with an expected standard deviation of 0.0378%. These calculations were made based on a 100-day investment period.

We proposed how to combine both the data mining methods with economical metrics for forecasting the income or losses on financial markets depending on the existing financial risks.

This approach can be applied in the development of mobile agents for work on financial markets, which, based on the initially set conditions and taking into account the investor's attitude to risk, will choose a strategy and behavior on the market and financial instruments (shares) that correspond to the expected volatility and income for the investor portfolio. Future research should assess the sustainability of the current approach across a wide range of investments and different instruments for investing.

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