Journal of Infrastructure, Policy and Development 2025, 9(2), 10928.
https://doi.org/10.24294/jipd10928

Article

Optimization of the investment portfolio for oil and gas projects under conditions of risk and uncertainty

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CITATION

Marina K, Anastasiia S. (2025). Optimization of the investment portfolio for oil and gas projects under conditions of risk and uncertainty. Journal of Infrastructure, Policy and Development. 9(2): 10928. https://doi.org/10.24294/jipd10928

ARTICLE INFO

Received: 23 December 2024
Accepted: 5 February 2025
Available online: 13 February 2025

Abstract: The application of optimization algorithms is crucial for analyzing oil and gas company portfolio and supporting decision-making. The paper investigates the process of optimizing a portfolio of oil and gas projects under economic uncertainty. The literature review explores the advantages of applying various optimizers to models that consider the mean and semi-standard deviations of stochastic multi-year cash flows and revenues. The methods and results of three different optimization algorithms are discussed: ranking and cutting algorithms, linear (Simplex) and evolutionary (genetic) algorithms. Functions of several key performance indicators were used to test these algorithms. The results confirmed that multi-objective optimization algorithms that examine various key performance indicators are used for efficient optimization in oil and gas companies. This paper proposes a multi-criteria optimization model for investment portfolios of oil and gas projects. The model considers the specific features of these projects and is based on the Markowitz portfolio theory and methodological recommendations for project assessment. An example of its practical application to oil and gas projects is also provided.

Keywords: volatility; investment; risk management; portfolio analysis; oil projects; gas projects; high uncertainty affect

1. Introduction

According to the Energy Strategy of Russia until 2035, the main concerns regarding the Russian fuel and energy sector are the infrastructure deterioration and the technological shortfall relative to developed countries (Dvoynikov and Leusheva, 2022; Litvinenko et al., 2022), which necessitates integrating modern approaches to the extraction and use of natural resources, as well as increasing economic efficiency (Babyr, 2024; Litvinenko, 2020). The expert strategy for the mineral resource base development considers different perspectives for modernizing the economy of the oil and gas sector: Arctic fields (Dmitrieva and Solovyova, 2023; Stroykov et al., 2021), oil refining (Ulanov and Skorobogatko, 2022), and hydrocarbon transportation (Zemenkova et al., 2022).

Experts estimate that $130 billion should be invested annually in the fuel and energy sector until 2035, with 61–64% of this amount directed to the oil and gas sector. In the context of the global crisis, many Russian oil companies are facing limited investment. In this regard, the necessity of effective investment portfolio optimization is becoming especially relevant (Lebedev and Cherepovitsyn, 2024).

Successful implementation of the investment projects is a product of a company's effective management. However, in the process of projects implementing, there are also situations when their further implementation becomes ineffective. Based on the analysis of such situations, it was revealed that the main difficulties in projects implementing arise at the stages of composing a project portfolio and a plan-schedule for their implementation (Bratskikh et al., 2024). Consequently, to facilitate informed project selection under constrained investment conditions and to enhance the probability of project realization, it is imperative to establish a robust methodology for the management and optimization of investment projects.

Stochastic risk variation models are widely used and improved in optimizing stock market portfolios. These principles are also applied to enhance gas and oil asset portfolios, considering semistandard deviations. Risk assessment is conducted at the asset level and aggregated to produce a portfolio-wide risk metric (Alaali, 2020; Massel et al., 2024; Wood, 2016). However, there are alternative methods for selecting an oil and gas portfolio based on multicriteria decision models. For instance, the VIGOR method focuses on incorporating the industry's unique context; mean-variance stochastic models are used to select combinations of gas and oil assets (Baltuttis et al., 2020; Ikonnikova et al., 2022; Oosterom and Hall, 2022).

This paper presents an enhanced multi-objective optimization approach for the portfolio risk assessment, which utilizes three optimization tools: ranking and cutting, simplex/linear optimizer, and evolutionary/nonlinear optimizers. The development of the model is derived from a review of studies on the optimization of investment portfolios for oil and gas projects.

PJSC Gazprom Neft was chosen as an object of the study in determining the investment policy optimization method. The structure of PJSC Gazprom Neft includes subsidiaries engaged in various oil and gas activities: exploration and production, refining, marketing, etc. In 2020, oil production of PJSC Gazprom Neft decreased from 173.4 to 165.4 thousand tons per day due to the restrictions imposed by OPEC+. However, in the first three months of 2021, Gazprom Neft's revenue increased by 18.7% and reached 610.9 billion rubles (bln RUB), adjusted EBITDA increased by 95% (193.55 bln RUB), and profitability reached 31.68%. Net profit for the first quarter has amounted to 84.2 bln RUB. The current liquidity ratio is 1.01 (Cherepovitsyn and Tretyakov, 2023; Gazprom Neft's 2021 Net Profit Reaches an All-Time High, 2022).

By 2030, PJSC Gazprom Neft aims to achieve a 15% level of return on invested capital by 2030, by means of effective management of the project and asset portfolio. Yet, the company currently does not have any regulatory and methodological documents regulating the portfolio optimization procedure. The purpose of this work is to develop a universal multi-criteria model for optimizing the oil and gas project portfolio, as well as to examine in detail existing methodological approaches to its optimization.

2. Literature review

2.1. Optimization within the framework of the methodology for analyzing the portfolio of gas and oil assets

The three-stage system of strategic assessment and optimization of oil and gas asset portfolios will be examined in further detail. The advantage of this system over the goal integration system (VIGOR) is the use of both linear and nonlinear optimizers to achieve multi-objective optimization based on strategically defined goals and constraints in the second and third stages of the system (Gupta et al., 2022; Zhong and Bazilian, 2018). A schematic description and the sequence of the integrated three-stage system are shown in **Figure 1**.

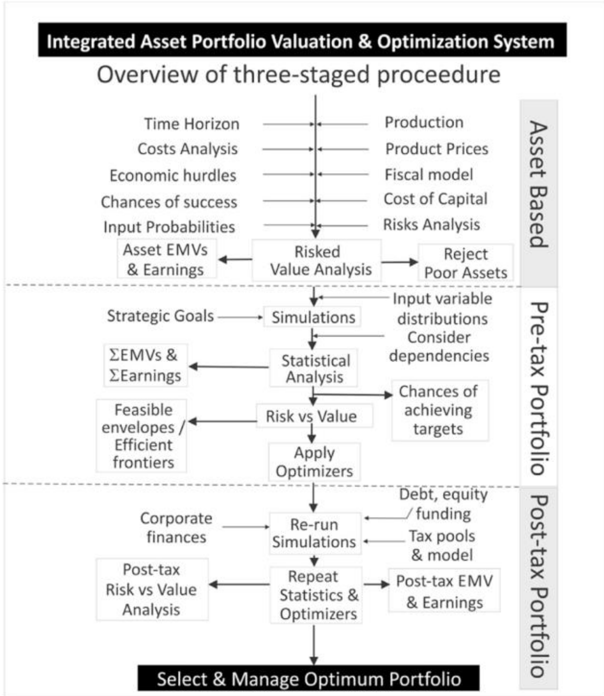

Figure 1. The description and sequence of the integrated three-stage system for the strategic assessment and optimization of oil and gas asset portfolios (Wood, 2016).

In the first stage, for a full analysis, assessment and optimization of the portfolio, it is necessary to use complex risk-based assessment models for each asset. The initial data for asset models are formed based on technical, commercial and financial information about each asset, without using the approximation, which ensures the greater accuracy (Ferriani and Veronese, 2022; Naeem et al., 2021).

In the second stage, transition from asset analysis to portfolio analysis is realized through strategic data. The objectives requiring optimization are determined by identifying key performance indicators and their priorities. The primary objective function, usually associated with the highest priority KPI, is formed to evaluate asset combinations and create additional objectives (Maitra et al., 2021).

Considering the values of corporate financial and tax positions, the new ones are formed in the third stage (Bigerna et al., 2022; Dai and Zhu, 2022; Milford et al., 2022):

1) Objectives: financial statement KPIs;
2) Constraints: debt/capitalization ratio; return on equity;
3) Opportunities: corporate borrowing;
4) Risks: failure to meet financial obligations.

The optimization, based on the systematic stochastic methodology of evaluation and characterization of gas and oil asset portfolios, allows to acknowledge the costs, risks and time in calculations (Anquetin et al., 2022; Tan et al., 2019). For enhancing the asset portfolio, it is in addition necessary to consider corporate goals, planning horizons and KPI limitations (Asl et al., 2021; Kimuli et al., 2022). Regarding gas and oil asset portfolios, KPIs are defined as a combination of financial indicators of costs and expenses, as well as non-financial indicators (Atmaca, 2022; Ranjbar et al., 2022):

1) Capital expenditure and cash flow before taxes;
2) Earnings before taxes, depreciation and amortization;
3) Discounted cash flow after taxes;
4) Expected cash value;
5) Debt/capitalization ratio;
6) Production volume and residual inventory levels.

2.2. Application ranking and cutting optimizers

The application of the simplex algorithm in optimization had begun in the 1940s, and became popular since the 1960s, with the development of computer technology. This method is effective for solving large-scale linear optimization problems, since it considers the values of income, costs and cash flows, which often change linearly (Jain et al., 2023; M et al., 2022; Sehatpour and Kazemi, 2018). The simplex algorithm enables to quickly find optimal solutions, focusing on a specific objective function from several metric dimensions. However, when the goals include risk minimization at the portfolio level, the simplex algorithm generally becomes less reliable (Valle et al., 2020; Vo et al., 2019; Živkov et al., 2022), since it does not consider many interactions and consequences (Chen et al., 2021; LaCosta and Milkov, 2022).

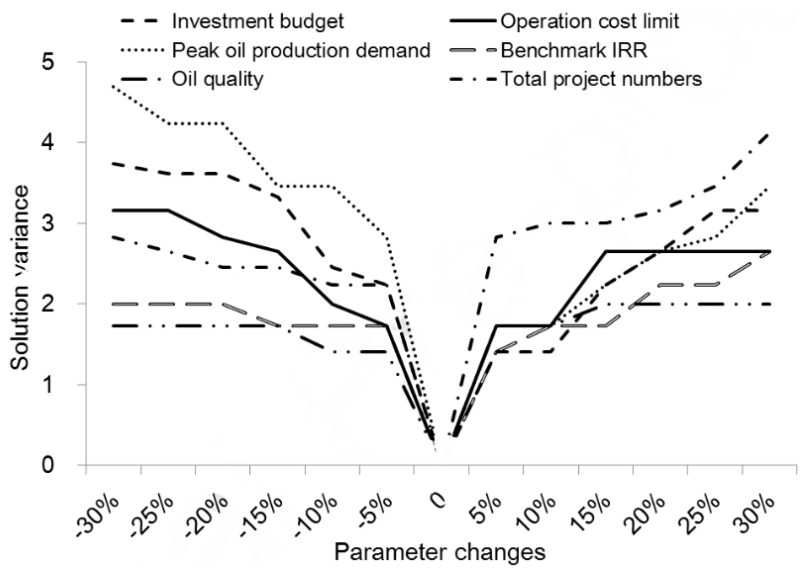

Figure 2. The risk probability for six indicators (investment budget, marginal operating cost, oil production peak, internal rate of return, oil quality, total number of projects) (Chen et al., 2021).

Simulated data sets consider such relationships and are used to complement the results of a linear optimizer. Until the 2000s, oil and gas asset portfolio optimization was performed using ranking and cutting algorithms and the simplex method. However, with the advent of nonlinear optimizers and evolutionary algorithms in the 1990s, methods for considering nonlinear relationships and multiple objectives had improved (Barroso et al., 2021; Ji et al., 2023; Nakagawa and Suimon, 2022). The algorithm goes through a series of steps, each of which brings it closer to the optimal solution. For the asset portfolio optimization purposes, the objective function is usually defined as maximization or minimization of a cost KPI (Faria et al., 2023; Konrad and Thum, 2023; Zabala Aguayo, 2022).

However, in scenarios with strict constraints, a feasible region of asset combinations may not exist. In such cases, the simplex algorithm cannot determine an optimal solution (Martins et al., 2023; Mensi et al., 2022).

The application of genetic algorithms for multi-attribute optimization has been widely used for more than fifteen years. The workflow of genetic algorithms simulates genetic evolution, involving the selection of high-performing solutions established by ranking. This algorithm is designed to thoroughly explore the feasible domain to identify solutions that optimize the fitness function. It integrates risk measures, such as semi-variance, into portfolio optimization and incorporates rebalancing mechanisms to address sudden market corrections. This method is also applicable to portfolio optimization of gas and oil assets in combination with other optimizers, for example, with asset risk indicators (**Table 1**) (Harjoto et al., 2021; Korotin et al., 2019; Ziakas and Getz, 2021). Some variations also use the Ftest score, which considers crossover and recombination (Afanasyev et al., 2021; Ciccone et al., 2022; Loban et al., 2021).

Table 1. The indicators of the risk of value decline.

Risk indicator	Description
SEM	The uncertainty around the mean (Iqbal et al., 2022; Ponomarenko et al., 2022).
Q	The number of iteration values that fell below the KPI target. A high value indicates a probability of not achieving the target (Kim, 2021; Luiz and Barnard, 2022).
MDR	A measure of average fall risk. The lower, the greater the risk of decline (Oikonomou et al., 2018).
SSD	Difference between KPI target value and actual values (Gargallo et al., 2022; Ghasseminejad and Jahan-Parvar, 2021).
Risk-adjusted mean	Portfolio risk value (Crozet et al., 2021; Samadi et al., 2021).
Mean/SSD	Portfolio value-to-risk ratio. High ratio - high cost of risk (Ellis et al., 2023; Fattahi and Nafisi-Moghadam, 2023; Vukovic et al., 2022).

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Financial and portfolio theory recognizes performance improvement of oil and gas company portfolios can be improved by means of combining assets with certain financial instruments, such as the use of temporal options or hedging strategies to insure against oil price fluctuations (Alnaqbi et al., 2022; Sharma et al., 2023; Wu et al., 2021).

If the portfolio is already optimal (selected on the efficient frontier), its value and risk can be further refined by incorporating additional projects or employing financial instruments. Frameworks such as the Capital Asset Pricing Model (CAPM) provide a methodological basis for evaluating the impact of such modifications on the portfolio's risk and expected returns (Ma et al., 2020; Nikolaichuk et al., 2023; Qamruzzaman et al., 2022).

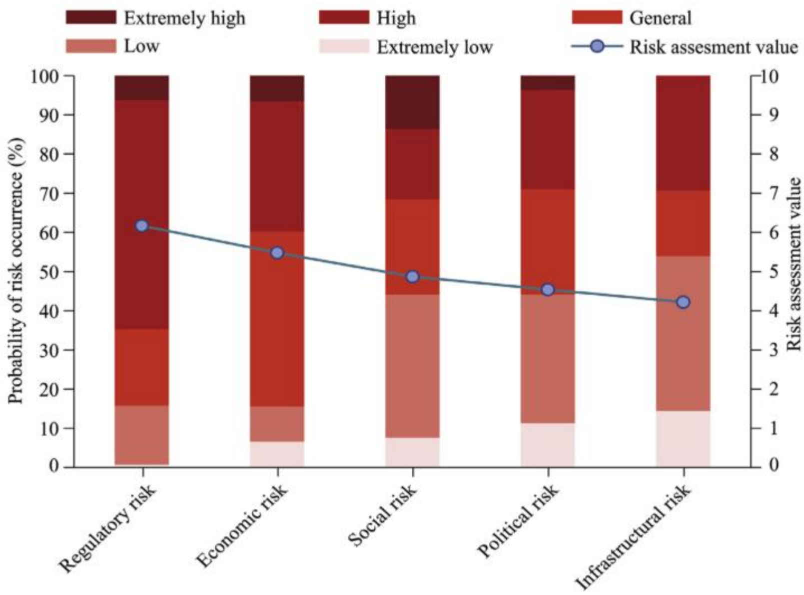

Figure 3. The probability of risk occurrence across five dimensions (regulatory, economic, social, political and infrastructural) for transnational oil investments (Ma et al., 2020).

The tangency frontier (the portfolio that lies on the efficient frontier and is tangent to the Capital Market Line) represents the highest ratio of the portfolio's return, less the risk-free rate, to its risk. In other words, this is the portfolio that offers the optimal risk-return trade-off, provided that the investor can borrow or lend funds at the risk-free rate. By borrowing funds at rates close to the risk-free rate, it is possible to form portfolios with borrowed funds whose risk-return ratios exceed the returns of portfolios located along the efficient frontier (Hailemariam et al., 2022; Hunt et al., 2022; Wachtmeister and Höök, 2020). These funds can be used to increase working shares in optimal assets by acquisition. This causes the portfolio shift to the upper right-hand side of the risk-return graph, forming a position with a higher value than the efficient frontier (Fu et al., 2022; Ilyas et al., 2021; Olmez Turan and Flamand, 2023).

An asset portfolio holder can reduce the leverage of its asset position by selling or leasing some of assets and investing the proceeds in low-risk financial instruments. Such actions will shift the portfolio toward the bottom line of the capital market (Appiah et al., 2021; Demirer et al., 2020; Wu and Wang, 2021). Therefore, portfolio optimization considers opportunities to further increase or decrease leverage through borrowing, lending, and hedging, which represents the third stage of post-tax portfolio optimization (Maghyereh and Abdoh, 2020; Wei et al., 2020).

2.3. Multi-objective optimization of gas and oil assets using programs

Multi-objective optimization of gas and oil projects is easily accomplished using spreadsheet models driven by Visual Basic for Application (VBA) macros (Alam et al., 2023; Monaldi et al., 2021; Yu et al., 2021). The Excel optimizer uses the simplex algorithm, generalized-reduced-gradient, and evolutionary optimization algorithms in its calculations, allowing asset portfolio optimization problems to be solved.

However, in practice, even for a small number of assets, the inclusion of KPIs, constraints, and multi-year planning horizons significantly complicates the implementation of calculations. This is primarily due to the lack of transparency in intermediate calculations and the absence of alternative solutions during the process (Morgunova and Shaton, 2022; Ramírez-Orellana et al., 2023; Sabet et al., 2018).

Compiling a table, which is based on statistical values obtained from simulation analysis, demonstrates some improvement. In such a case, the optimal solution of the simplex algorithm and the genetic optimizer can be linked. However, this task is difficult to implement in VBA (Berntsen et al., 2018; Huang et al., 2019; Rabello et al., 2019).

A multi-purpose analysis of the portfolio of gas and oil assets in the VBA program was studied (Ahmadi et al., 2019). Recommendations on the implementation of this method in portfolios of gas and oil assets will be presented. Initially, a multi-year cash flow model is necessary for asset calculations. In this case, the calculated output KPIs can be easily obtained by the modeling mechanism with subsequent deterministic analysis for each asset (Nejati and Bahmani, 2020).

Table 2. The components used in VBA calculations.

Component	**Description**
Imitation mechanism	Using VBA Macro to Simulate Monte Carlo for Each Asset Model (Tang et al., 2018)
Workbook and statistical analysis	Combining KPI values and conducting statistical analysis, obtaining basic and custom statistics on MDR and SSD (Dong et al., 2020)
Corporate financial model	Calculating after-tax income and corporate debt, deriving envelopes and efficient frontiers (Monaldi et al., 2021)
Optimization mechanism	Ranking, simplex linear and evolutionary algorithm, multi-objective optimization based on strategic goals and KPI constraints
Statistical analysis of optimal portfolios	Comparison with efficient frontiers, determination of chances of achieving target KPI indicators, assessment of leverage and deleverage of the asset portfolio

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It should be emphasized that large asset portfolios (more than 50 assets) necessitate the specialized software that is capable to effectively processes data sets (Chen et al., 2022; Cheng et al., 2018; Kimiagari et al., 2023). Alternatively, algorithms can be adapted into more adequate software packages for larger-scale applications (Harjoto et al., 2021; Milford et al., 2022).

3. Materials and methods

3.1. Proposed model of the company's asset portfolio structure change

There are several portfolio theories applicable to the formation of the oil and gas companies' portfolio: the Markowitz model, the Sharpe model, the "Defensive Portfolio" model. The investment portfolio was derived using Excel with Equations (1) and (2) (Gerasimova and Naumova, 2020; Zheng and Luo, 2009), and the asset model was calculated using the built-in function for creating covariance tables.

$$E = \frac{\sum_{i=1}^{n} Ln\left(\frac{V_t}{V_b}\right)}{n}, \tag{1}$$

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n}\left(Ln\left(\frac{V_t}{V_b}\right) - \frac{\sum_{i=1}^{n} Ln\left(\frac{V_t}{V_b}\right)}{n}\right)^2}{n-1}}, \tag{2}$$

where: E – expected return, σ – asset risk; V_t – asset value for the reporting period; V_b – asset value for the base period.

Within the methodological framework for calculations, the asset share limits were increased from 0 to 1%. This adjustment was necessary because the Markowitz theory, used for standard calculations, relies on a quantitative assessment of two parameters. It does not account for multiple definitions of risk or the profitability aspects of the oil and gas business, making it impossible to entirely eliminate asset share (Surovtsev et al., 2018).

Given the limitations, the "Solution Search" function was used, based on the general decreasing gradient method for smooth nonlinear problems, the simplex method for linear problems, and the evolutionary algorithm for non-smooth problems. The total return and risk of the portfolio were calculated using Equations (3) and (4).

$$T_y = E_{\text{м}1} \cdot W_{\text{м}1} + E_{\text{н}1} \cdot W_{\text{н}1} + E_{\text{н}2} \cdot \text{W}_{\text{н}2} + E_{\text{н}3} \cdot W_{\text{н}3}, \tag{3}$$

$$T_r = \left(\left(M_k \cdot W_{\text{м}1;\text{н}1;\text{н}2;\text{н}4}\right) \cdot W_{\text{м}1;\text{н}1;\text{н}2;\text{н}4}\right)^{0.5}, \tag{4}$$

where: W_i – asset share matrix, M_k – covariance matrix.

The portfolios were evaluated based on the maximum deviation of the difference between expected return and risk in the case of a positive result, and the minimum deviation in the case of a negative result.

3.2. Model for optimizing portfolio of oil and gas projects for production and exploration

For the portfolios of geological exploration and hydrocarbon production projects, the selection criteria are proposed: project priority, implementation schedule, indicators of performance and hydrocarbon production volume per unit of investment.

Three functions were used in the multi-criteria model: the net present value of the project portfolio (Equation (5)), the investment function (Equation (6)), and the liquid hydrocarbon production function (Equation (7)).

$$\sum_{j=1}^{m} NPV_j x_j \to max \,, \tag{5}$$

$$\sum_{j=1}^{m} K_j x_j \to min, \tag{6}$$

$$\sum_{j=1}^{m} P_j x_j \to max, \tag{7}$$

where: NPV_j – net present value of the project, RUB; x_j – a binary variable that takes the values 0 and 1; r – discount rate for the reporting period; t – reporting period; K_j – investments required for a project implementation, RUB; P_j – hydrocarbon production as a result of a project implementation, tons.

The following restrictions are also accounted for in the model: IRR > 15%; PI > 1; PP < 5 years, $M_j \leq N$, where: M_j – average minimum profitable flow rate of project wells, th. tons/day; N – minimum profitable flow rate according to the project document, th. tons/day.

The final market value was calculated according to the Equation (8).

$$EMV = NPV \cdot \mathrm{PoS} - E_t \cdot (1 - \mathrm{PoS}), \tag{8}$$

where: PoS – probability of economic success, E_t – cash inflow for the reporting period, RUB.

The assets should be then ranked from highest-performing assets to lowest-performing assets, and the best prospective properties were selected based on characteristics: PoS, NPV, IRR, EMV, until the available budget has been exhausted.

3.3. Proposed oil and gas projects portfolio optimization model under uncertainty conditions

The constraints within the investment portfolio optimization in oil and gas companies are the limited optimization of the portfolio by NPV or PI, and the failure to account for the benefits of delaying the project's start. To address these issues, the authors of this paper have developed a new approach that takes into account several criteria.

The first criterion is the uncertainty. Regarding the oil and gas projects, there may exist geological, technological, economic, political, social and environmental uncertainties. In particular context of drilling projects the main factors were considered to be geological uncertainty (lack of geological information about the reservoir), technological uncertainty (difficulty in predicting emergencies), economic uncertainty (unpredictable economic assumptions).

The calculation of the economic effect of the oil and gas project is based on discounted free cash flow FCF and was calculated using the Equation (9).

$$NPV = \sum_{i=1}^{n} DCF_i, \tag{9}$$

where: n – number of years of investment project realization, $DCFi$ – discounted cash flow for the i-th year, calculated according to the Equation (10).

$$DCF_i = FCF_i \cdot (1 + \mathrm{r})^{-\mathrm{i}+0.5}, \tag{10}$$

where: r – discount rate, 0.5 – distribution coefficient, FCF – free cash flow calculated according to the Equation (11).

$$FCF = BP - IT - EI - CapEx + A, \tag{11}$$

where: BP – company's balance sheet profit, IT – income tax, EI - net income expense, $CapEx$ - capital expenditure, A - depreciation of fixed assets.

The balance sheet profit of the company and the income tax were calculated according to Equations (12) and (13).

$$BP = R - MET - T - OPEX, \tag{12}$$

$$IT = 1.2 \cdot BP, \tag{13}$$

where: R – revenue from hydrocarbon sales reduced by the amount of sales costs, T – other taxes, $OPEX$ – operational expenditure, MET – mineral extraction tax for extracted hydrocarbons, calculated according to the Equation (14).

$$MET = MET_o \cdot Q_o + MET_g \cdot Q_g, \tag{14}$$

where: Qo and Qg – oil and gas production accordingly, MET_g – gas extraction tax, MET_o – oil extraction tax calculated according to the Equation (15).

$$MET_o = MET_b \cdot К_o - P_м, \tag{15}$$

where: MET_b - base MET rate (919 RUB per ton of oil), Кo – coefficient depending on the Urals oil price and the dollar exchange rate, $P_м$ – coefficient based on complexity of oil extraction.

The revenues from hydrocarbon sales are comprised of revenues from oil sales and revenues from gas sales and are calculated according to the Equation (16). Since Urals oil price and dollar exchange rate are external economic parameters that are subject to fluctuations, therefore it is necessary to take into account their instability.

$$R = Q_o \cdot f_o(Do, Ur) + \ Q_g \cdot f_g(Do, Ur), \tag{16}$$

where: $f_o(Do, Ur)$ и $f_g(Do, Ur)$ - Netback on oil and gas, respectively (depends on Urals price and dollar exchange rate).

For each project, two key indicators of economic efficiency (NPV or PI) are selected, as well as indicators of the level of risk expressed as the sensitivity of the project to changes in macroeconomic parameters. In contrast to the traditional deterministic approach and statistical methods, NPV will be considered as a function of macroeconomic parameters using the Equation (17). The NPV calculation accounts for the predicted values of oil price and the dollar exchange rate scaled to a given level.

$$NPV_i = f'_i(Do, Ur) = f'_i(D \cdot Do_{base}, U \cdot Ur_{base}) = f_i(D, U), \tag{17}$$

where: $f'i$ – vector function, which type depends on the features of the i-th project, Do – vector of dollar values by forecast years, RUB/USD; Ur – vector of Urals oil price values, USD/barrel; D – level of dollar values by forecast years of, units; U – level of Urals oil price values, USD/barrel; Dobase и Urbase – basic vectors of economic macro-parameters; fi – the function, which type depends on the economic characteristics of the i-th project.

Additionally, the authors of this paper have introduced a parameter (Equation (18)), that reflect the sensitivity of the project to changes within the macroeconomic parameters. Its value is calculated by summing up the ratio of squares of partial derivatives of NPV indicator by values of independent variables to the initial value.

$$s_i = \sqrt{(\frac{\partial \mathrm{NPV}_i}{\partial D \cdot NPV_i{}^{00}})^2 + (\frac{\partial \mathrm{NPV}_i}{\partial U \cdot NPV_i{}^{00}})^2}, \tag{18}$$

where: PVi00 – NPV value of the i-th project at initial macroeconomic parameters.

To establish the correlation, an experimental calculation was carried out for an oil and gas project with changing macroeconomic parameters. The values of the NPV indicator corresponding to different combinations of oil price levels and dollar exchange rate were obtained by tabulating. The obtained values form a surface that is described by the Equation (19).

$$NPV_i = \alpha_i(U - \beta_i)(D - \gamma_i) + \delta_i, \quad (19)$$

where: U and D depend on the coefficients β and γ, δ reflects the NPV part, α_i is the coefficient of economic efficiency calculated by the Equation (20) at different values of NPV of the project at different levels of macro parameters.

$$\alpha = \frac{NPV^{11} + NPV^{00} - NPV^{01} - NPV^{10}}{(D^1 - D^0)(U^1 - U^0)}, \quad (20)$$

where: $U0$, $U1$, $D0$ and $D1$ – combinations of oil prices and dollar exchange rates, NPV^{11}, NPV^{00}, NPV^{01}, NPV^{10} – NPV values at combination of values.

Equations (21) and (22) are used to calculate the overall portfolio economic performance indicators.

$$\mathrm{N}PV_P = \sum_{i=1}^{n} NPV_i, \quad (21)$$

$$\alpha_P = \sum_{i=1}^{n} \alpha_i, \quad (22)$$

where: $NPVp$ – portfolio economic effect, αp – uncertainty of the economic effect of the portfolio.

The final optimization system considers maximizing the economic impact of the project and reducing the degree of uncertainty.

$$\begin{cases} max \sum_{i=1}^{n} NPV_i \\ min \sum_{i=1}^{n} \alpha_i \\ \sum_{i=1}^{n} C_{CAPEX_i} \leq L_{CAPEX} \end{cases}, \quad (23)$$

where: n – number of projects in the portfolio, $NPVi$ – economic effect of the i-th project, αi – uncertainty value of the economic effect of the i-th project, $CCAPEXi$ – capital expenditures for the implementation of the i-th project, $LCAPEX$ – capital expenditure limit.

Based on the obtained system, it was decided to use the NSGA-II genetic algorithm, which allows to find Pareto-optimal solutions by the category of actions (shifting projects into the future for a certain number of years and project exclusion).

Both categories of actions affect the portfolio return and risk. Postponing projects reduces return due to discounting but increases risk related to scheduling and resource availability (human resources: skilled personnel may become unavailable, increasing recruitment or training costs; equipment: shared machinery may be reallocated, leading to additional rental or procurement expenses; financial resources: budgets may need reallocation, affecting cash flow and financing costs; scheduling constraints: postponements disrupt investment plans, requiring revised phases and recalibration of portfolio optimization).

To mitigate risks, organizations can maintain resource buffers, enhance schedule flexibility, and monitor market conditions. This ensures better alignment with investment plans while managing the complexities of delays.

The company under investigation (PJSC Gazprom Neft) has established a five-year investment program, ensuring that any shifts in project implementation within this timeframe are safeguarded, as resources are allocated to all projects included in the program. Furthermore, PJSC Gazprom Neft has allocated additional contingency resources to address unforeseen circumstances, thereby preventing potential project stoppages.

The prohibition on halting all projects underscores the importance of NPV as a key decision-making metric, and the portfolio management process can be optimized by utilizing the PI with adjustment factors (e.g., the strategic significance of the project). The algorithm for optimizing the investment portfolio is illustrated in **Figure 4**.

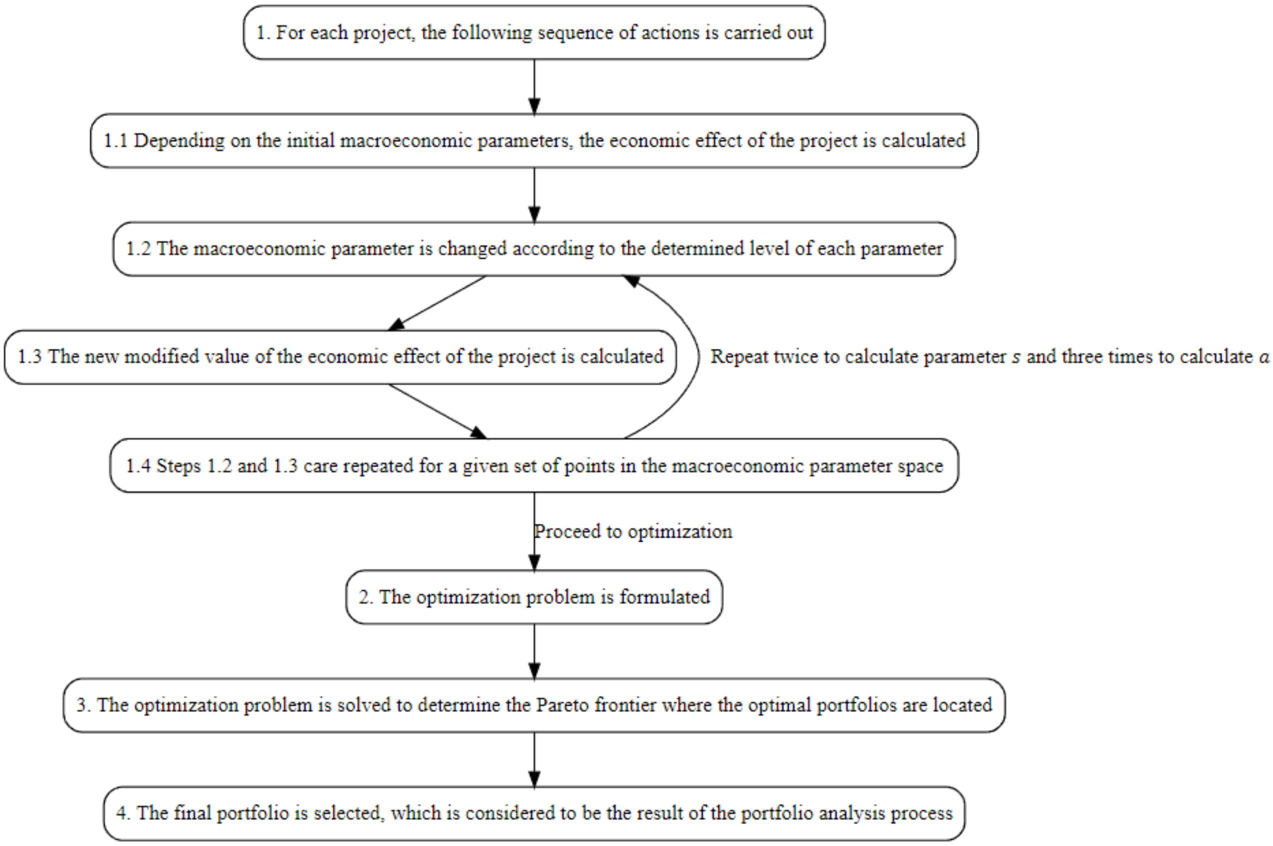

Figure 4. The algorithm of investment portfolio optimization.

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The computational procedure is executed as follows:

Data Acquisition and Preprocessing: The raw input data about projects is read and preprocessed to ensure it is in a suitable format for subsequent analysis.

Case Construction: Project-specific cases are generated from the preprocessed tabular data, with each case encapsulating the necessary information for a single project (the computation of the parameters previously referenced in the formulas in the section 2.2).

Macroeconomic Parameter Integration: Relevant economic macroparameters are loaded and processed to facilitate their incorporation into the financial-economic model (FEM).

Project Evaluation and Uncertainty Analysis: For each project, the following steps are performed:

1) Baseline NPV Calculation: The net present value (NPV_{00}) of the project is computed under the initial macroeconomic conditions using the FEM module.
2) Macroparameter Variation: The macroeconomic parameters are systematically varied according to predefined levels.
3) Adjusted NPV Computation: The project's economic effect (NPV) is recalculated under the modified macroparameters.
4) Uncertainty Quantification: The above-mentioned steps are repeated across a defined set of macroparameter points to derive the uncertainty parameters s (computed twice) and α (computed three times).

Optimization Input Preparation: The computed NPVs and uncertainty parameters serve as inputs for multi-criteria optimization.

Optimization Problem Definition: An optimization problem is formulated based on the derived data and predefined objectives (maximize NPV while minimizing α (risk)).

Pareto Frontier Identification: The optimization problem is solved, yielding the Pareto frontier, which represents the set of optimal project portfolios.

Final Portfolio Selection: A single optimal portfolio is selected from the Pareto frontier, concluding the portfolio analysis process.

Pareto-optimal solutions can be obtained through various methods. One of the simplest yet most time-consuming approaches involves manually constructing the parameter space by exhaustively enumerating possible values of the optimized parameters. These algorithms are computationally intensive and impractical for portfolio optimization tasks involving more than 15 projects. This limit is derived by setting a 15-minute threshold for a single portfolio optimization operation. Given the financial-economic model's processing speed of 50 recalculations per second, the maximum number of portfolio combinations that can be evaluated is 45,000. This estimate does not account for potential shifts in project start times. It is worth noting that linear optimization requires only seconds to execute; however, it provides just a single portfolio solution. Consequently, for large portfolios, the authors recommend employing genetic algorithms, specifically the NSGA-II algorithm, to efficiently identify optimal solutions and manage run time.

For the final selection of projects, an indicator similar to the Sharpe ratio (Equation (24)) was used, and the portfolio with the highest ratio value was selected.

$$S'_p = \frac{NPV_p}{\alpha_p}, \tag{24}$$

where: S'_p – a coefficient reflecting the amount of return per unit of uncertainty; NPV_p – portfolio economic effect, α_p – uncertainty of the economic effect of the portfolio.

Furthermore, the programming language NSGA-II algorithm from the pymoo Python program library was used to solve the problem.

The program code was divided into three main parts:

1) The main part processes the raw data and passes the results to the optimization module.
2) The financial and economic model calculates data based on various parameters, including oil and gas production, expenditures and macroeconomic indicators (oil price, dollar exchange rate, oil export duty, MET rate).

3) The intermediate layer interacts with the optimization library, generates computational cases and processes economic parameters for the model.

At the completion of the program, we obtain information about the generated portfolios: their performance and uncertainty, coefficients S', reflecting their risk and profitability and years of project entry into the portfolio.

The Python-based dynamic model handles rapid changes in macroeconomic parameters (e.g., oil prices, exchange rates) through real-time data integration and automated updates.

4. Results

Firstly, it was obtained the model of structure's change of the company's asset portfolio (section 3.1). The information about the financial indicators of PJSC Gazprom Neft is taken from the consolidated financial statements for the period from 2017 to 2022 on the company's official website (**Table 3**).

Table 3. Asset value of Gazprom Neft's portfolio for 2016–2021.

Assets, million RUB	Year					
	2016	**2017**	**2018**	**2019**	**2020**	**2021**
"Resource exploration and evaluation" (M1)	75,343	110,027	97,286	155,466	178,155	192,889
"Exploration and production (goodwill)" (H1)	28,926	36,899	33,793	48,191	50,317	58,217
"Land rights and other" (H2)	26,306	23,620	25,765	40,147	54,155	53,455
"Software" (H3)	13,919	16,668	18,581	14,282	15,293	23,130

Compiled by the author: Shabalina.

The M1, H1, H2, H3 assets in the portfolio account for 58.86%, 17.76%, 16.31% and 7.05% of the total value. From 2016 to 2021, the value of M1, H1, H2, H2 assets increased by 142.74%, 101.26%, 103.2% and by 66.18%, respectively. The return on assets calculated using Equations (1) and (2), is presented in **Table 4**. The covariance matrix of Gazprom Neft's asset portfolio is presented in **Table 5**.

Table 4. The return on Gazprom Neft assets, 2016–2021.

Year	Return on assets, %			
	M1	**H1**	**H2**	**H3**
2016	-	-	-	-
2017	37.87	24.34	−10.77	18.02
2018	−12.31	−8.79	8.69	10.86
2019	46.88	35.49	44.35	−26.31
2020	13.62	4.32	29.93	6.84
2021	7.95	14.58	−1.30	41.37
ri	18.80	13.99	14.18	10.16
σ	23.79	17.19	22.64	24.38

Compiled by the author: Shabalina.

Table 5. The covariance matrix of Gazprom Neft's asset portfolio, 2016–2021.

Share (w)		**M1**	**H1**	**H2**	**H3**
0.5963	M1	0.0453	0.0111	0.0016	−0.0135
0.1778	H1	0.0111	0.0237	−0.0047	−0.0160
0.1668	H2	0.0016	−0.0047	0.0410	−0.0249
0.0591	H3	−0.0135	−0.0160	−0.0249	0.0476
Share (w)		0.596336	0.5963	0.1778	0.1668

Compiled by the author: Shabalina.

The calculation of the asset portfolio (portfolio return and risk) was carried out using Equations (3) and (4) and is reflected in **Table 6**.

Table 6. Asset's portfolios for 2021.

Portfolio for 2021	**Asset's portfolio**	**Assets portfolio with the aim of maximizing returns**	**Assets portfolio with the aim of risk minimization**
Construction conditions	$w_{м1} = 0.5963$ $w_{н1} = 0.1778$ $w_{н2} = 0.1668$ $w_{н3} = 0.0591$	$w_{м1} \geq 0.01$ $w_{н1} \geq 0.01$ $w_{н2} \geq 0.01$ $w_{м1} + w_{н1} + w_{н2} + w_{н3} = 1$ Total portfolio profitability ≥ 0.1664	$w_{м1} \geq 0.01$ $w_{н1} \geq 0.01$ $w_{н2} \geq 0.01$ $w_{м1} + w_{н1} + w_{н2} + w_{н3} = 1$ Total portfolio risk ≤0.1302
Result	Total portfolio profitability = 16.64% Total portfolio risk = 13.02%	Total portfolio profitability = 17.04 % Total portfolio risk = 14.76%	Total portfolio profitability = 16.51% Total portfolio risk = 12.76%

Compiled by the author: Shabalina.

The change in the structure of assets can be represented graphically.

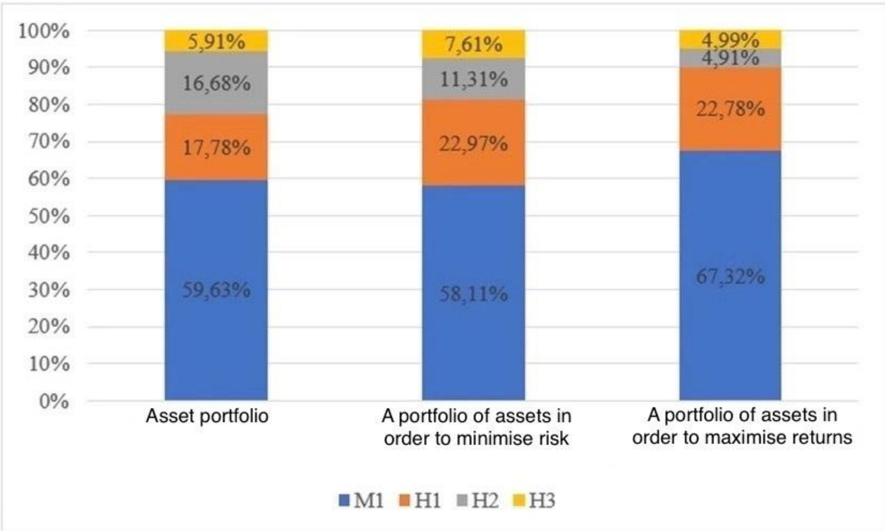

Figure 5. The change in the structure of Gazprom Neft's portfolio assets.
Compiled by the author: Shabalina.

The results of evaluating portfolios by the maximum deviation of the difference between expected return and risk in case of a positive result, and the minimum deviation in case of a negative result is presented in **Table 7**.

Table 7. Result of portfolios evaluation by maximum deviation.

Portfolio	Value of assets in 2021, million RUB	Expected return		Total risk		Expected profitability - risk, million RUB
		%	million RUB	%	million RUB	
Assets portfolio	327,691	16.64	54,527.78	13.02	42,665.37	11,862.41
Assets portfolio with the purpose of risk minimization	327,691	16.51	54,101.78	12.76	41,813.37	12,288.41
Assets portfolio with the aim of maximizing returns	327,691	17.04	55,838.55	14.76	48,367.19	7471.35

Compiled by the author: Shabalina.

To achieve this efficiency, it is required to increase the share of H1 and H3 assets, decrease the share of H2, and save the share of M1. The economic effect will be 426 million RUB, calculated as the difference between the values of current and selected asset portfolio.

Since the analysis indicated the necessity for the most significant increase in the asset H2 (“Exploration and Production (Goodwill)”), the subsequent step involved the optimization of specific projects within this asset at a single oilfield. Considering the uncertainty of macroeconomic parameters, an experimental calculation was carried out for an oil and gas project with changing macroeconomic factors (oil price and exchange rates).

The visualization of the dependence of oil and exchange rates allowed to assess the impact of macroeconomics parameters on the financial efficiency of the project and use it for further calculation of the surface (**Figure 6**) according to the Equation (19).

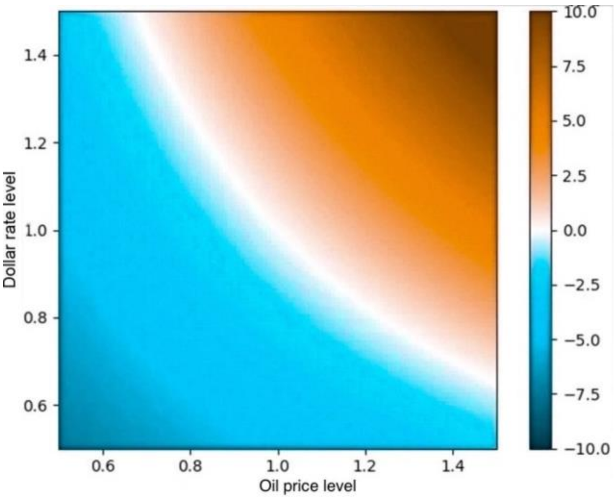

Figure 6. The relative change in NPV of an individual project with changes in the dollar exchange rate and oil price.

Compiled by the author: Shabalina.

The oil and gas portfolio under consideration consists of 33 projects, including sustainable, infrastructural, drilling and increasing production projects. The calculation of efficiency and uncertainty indicators is performed according to the same algorithm. The following will be considered for the project number 1.

Table 8. Input data for the project «Number 1».

Index	**Unit**	**Year**				
		1	**2**	**3**	**4**	**5**
Q_o	t	344.442	1274.438	1791.101	1377.768	861.105
Q_{apg}	th. m^3	126.588	443.058	746.865	519.0045	443.058
OPEX	th. RUB	2869.745	2816.478	2834.223	2853.06	2870.48
CAPEX	th. RUB	1293.579	0.126	0.126	0.126	0.126
A	th. RUB	129.36	129.3705	129.381	129.3915	129.4125
K_{DM}	-	0.6	0.6	0.6	0.6	0.6
Brent	USD/ barrel	57.7	56.3	55.7	50	50
Urals	USD/ barrel	56.2	54.8	54.2	48.5	48.5
USD exchange rate	RUB/ USD	71.8	72.6	73.6	73.6	73.6
EUR exchange rate	RUB/EUR	86.16	87.12	88.32	88.32	88.32
Netback (oil)	RUB/t	24,131.34	24,827.4	26,289.1	23,133.47	23,133.47
Netback (APG)	RUB/million m^3	2774.342	2814.588	2814.588	2814.588	2814.588
Netback (AG)	RUB/million m^3	2774.342	2814.588	2814.588	2814.588	2814.588
Netback (GC)	RUB/t	24,131.34	24,827.4	26,289.1	23,133.47	23,133.47
Discount rate	%	14	14	14	14	14

Compiled by the author: Kruk.

The revenue from hydrocarbon sales for the first year of the project is calculated according to the Equation (16).

$$R_1 = 344.44 \cdot 24{,}131.34 + 126.59 \cdot 2774.342 = 8.66305\ million\ RUB. \quad (25)$$

To obtain the cost indicator, the amount of mineral extraction tax paid must be computed. For this purpose, the mineral extraction tax rate for oil production is calculated using the Equation (15).

$$\text{К}o = (56.2 - 15) \cdot \frac{71.8}{261} = 11.33, \quad (26)$$

$$P_M = 559 \cdot 11.33 \cdot (1 - 0.6) - 428 - 456 - 4669 = -3\,026.32 \frac{RUB}{ton} of\ oil, \quad (27)$$

$$MET_o = 919 \cdot 11.33 - (-3013.97) = 13{,}438.59 \frac{RUB}{ton} of\ oil. \quad (28)$$

The MET rate for natural gas is zero. The total amount of mineral extraction tax paid by the Equation (14) is equal to

$$MET_1 = 13{,}438.59 \cdot 344.442 = 4{,}628{,}814.82\ RUB = 4628.81\ th.RUB. \quad (29)$$

The balance sheet profit of the enterprise is calculated according to the Equation (12).

$$BP_1 = 8663.05 - 4628.81 - 2869.75 - 129.36 = 1035.13\ th.RUB. \quad (30)$$

Income tax is calculated according to the Equation (13).

$$IT_1 = 1035.13 \cdot\ 20\% = 207.03\ th.RUB. \quad (31)$$

Free cash flow for the first year is found by the Equation (11).

$$FCF_1 = 1035.13 - 207.03 + 129.36 - 1293.579 = -336.11\ th.RUB. \quad (32)$$

DCF is calculated by the Equation (10).

$$DCF_1 = \frac{-336.11}{(1 + \frac{14}{100})^{0.5}} = \ -314.80\ th.RUB. \quad (33)$$

NPV is calculated by the Equation (9)

$$NPV\ = 33{,}639.6\ th.RUB. \quad (34)$$

The calculation was carried out for all projects within a fixed range of shifts in accordance with the company's five-year investment program. For each of the projects, it is necessary to compute the uncertainty factor. The calculation of the coefficient α will be considered using the example of the project "Number 1". Utilizing the automated NPV calculation for different values of microparameters, the values will be obtained (**Table 9**).

Table 9. NPV values at different levels of microparameters.

NPV value, th.RUB		**USD exchange rate level**	
		1.0	**1.3**
Urals oil price level	1.0	33,639.59	38,344.11
	1.3	38,119.20	44,167.62

Compiled by the author: Shabalina.

Afterward, the following value will be acquired through the coefficient α according to the Equation (20).

$$\alpha = \frac{44{,}167.62 + 33{,}639.59 - 38{,}344.11 - 38{,}119.20}{33{,}639.59 \cdot (1.3 - 1) \cdot (1.3 - 1)} = 0.44. \quad (35)$$

The obtained value is calculated for the project "Number 1" without shifting the implementation period. The project is more sensitive to changes in the dollar exchange rate than to changes in the oil price. All possible shifting periods of the project implementation start and the values corresponding to them are shown in **Tables 10** and **11**.

Table 10. NPV values for the projects under consideration for different years of the project implementation.

Project №	**Shift in the year of the start of the project**				
	−2	**−1**	**+0**	**+1**	**+2**
1	42,847.31	38,145.64	33,639.59	29,173.04	25,288.73
2	1,155,145	1,744,720	2,255,074	1,759,967	1,674,799
3	247,148.7	209,018.5	175,023.6	151,134.2	127,957.1

4	311,080.9	273,154	217,729	186,472.3	161,161.2
5	185,539	129,402.5	76,040.22	31,297.64	−5360.24
6	512,785.2	490,023.1	515,884.2	388,611.3	260,605
7	2,396,873	2,137,646	1,987,346	1,469,667	1,140,258
8	141,484.8	97,218.64	80,648.99	66,189.06	50,911.69
9	436,747.9	363,932.6	287,254.2	210,796.9	139,838.3
10	2,741,487	2,561,221	2,350,914	1,966,630	1,706,510
11	424,713.1	367,822.3	316,604	269,351.8	230,160.6
12	608,675.4	529,089.4	445,151.4	288,416.8	180,152.4
13	10,852.25	10,201.64	10,477.64	5914.64	4637.525
14	53,235.16	49,195.57	40,445.64	35,037.28	30,365.09
15	103,991.9	86,892.51	75,463.55	65,357.25	56,196.42
16	69,939.29	60,726.94	52,519.93	45,130.43	39,557
17	31,697.18	26,907.08	22,690.44	19,870.7	17,405.25
18	113,451.3	99,511.77	87,287.25	76,565.09	67,162.36
19	68,266.09	57,541.52	54,652.36	41,795.71	35,446.59
20	46,765.25	44,869.71	38,124.15	33,295.55	28,739.28
21	(6043.54)	19,623.12	48,893.87	27,799.91	6767.408
22	14,488.46	12,802.65	11,281.63	9826.425	8555.789
23	28,500.94	38,111.56	51,760.26	46,174.02	41,378.61
24	(2762.79)	2,502.497	9869.538	8964.249	8197.466
25	15,921.37	18,855.52	24,208.72	21,445.14	19,049.32
26	(11,664.6)	(2151.61)	10,969.94	9980.66	9193.58
27	39,964.76	47,508.22	57,926.47	51,329.72	45,716.21
28	(543.995)	4695.359	12,920.71	11,516.43	10,329.44
29	38,386.41	40,851.25	46,534.77	41,180.03	36,535.11
30	48,619.56	105,151.1	30,539.69	15,565.37	14,352.82
31	28,725.57	50,761.76	92,980.87	19,622.53	17,617.1
32	1,171,391	1,085,173	994,654.6	903,819.9	821,249.8
33	3777.648	3820.446	3865.67	3904.866	3939.243

Compiled by the author: Shabalina.

Table 11. Values of the coefficient α for the projects under consideration for different years of the project implementation.

Project №	Shift in the year of the start of the project				
	−2	**−1**	**+0**	**+1**	**+2**
1	0.45	0.47	0.44	0.44	0.43
2	30.01	18.87	13.83	15.49	14.59
3	7.38	7.55	7.74	7.73	7.84
4	7.19	7.54	7.98	8.04	8.02
5	7.93	10.06	15.11	32.16	165.63
6	6.41	5.65	4.62	5.27	6.72
7	3.42	3.65	3.68	4.22	4.76

8	16.98	20.85	21.66	22.66	25.26
9	2.57	2.78	3.02	3.57	4.66
10	1.95	2.01	2.10	2.20	2.29
11	2.86	2.89	2.93	3.00	3.07
12	3.70	4.03	4.53	6.11	8.74
13	34.20	34.69	30.45	45.61	50.13
14	4.36	4.37	4.47	4.44	4.40
15	3.85	3.89	3.86	3.83	3.82
16	4.10	4.07	4.03	4.03	4.03
17	8.30	8.37	8.54	8.55	8.57
18	5.77	5.77	5.77	5.77	5.77
19	8.96	10.07	9.68	10.66	10.81
20	4,48	4,21	4.18	4.12	4.09
21	166,90	45,09	15.88	24.49	88.25
22	0.16	0.17	0.16	0.16	0.15
23	46.71	30.64	19.80	19.46	19.05
24	193.82	187.70	41.74	40.32	38.67
25	30.29	22.43	15.32	15.18	14.99
26	65.73	312.58	53.78	51.85	49.38
27	27.38	20.21	14.53	14.39	14.17
28	886.23	90.07	28.71	28.26	27.63
29	18.83	15.51	11.95	11.85	11.71
30	51.51	20.52	60.18	103.02	98.01
31	74.98	36.59	17.21	69.30	67.71
32	0.48	0.35	0.29	0.27	0.31
33	1.28	1.13	0.99	1,04	0.94

Compiled by the author: Shabalina.

Oil and gas companies operate under constrained financial capacities, therefore, capital investment constraints are incorporated into the model. The acquired indicators allow to compose portfolios with different levels of profitability and risk. The result of the optimization is the Pareto frontier, on which the optimal project portfolios are located on. As profitability rises, risk also increases; however, there is specific range within which a marginal increase in NPV corresponds to a significant rise in uncertainty.

These portfolios dominate others with lower returns and the same level of risk, and no portfolios exist that offer higher returns for the same level of risk (**Figure 7**). The S' ratios for each of the portfolios were also examined (**Figure 8**).

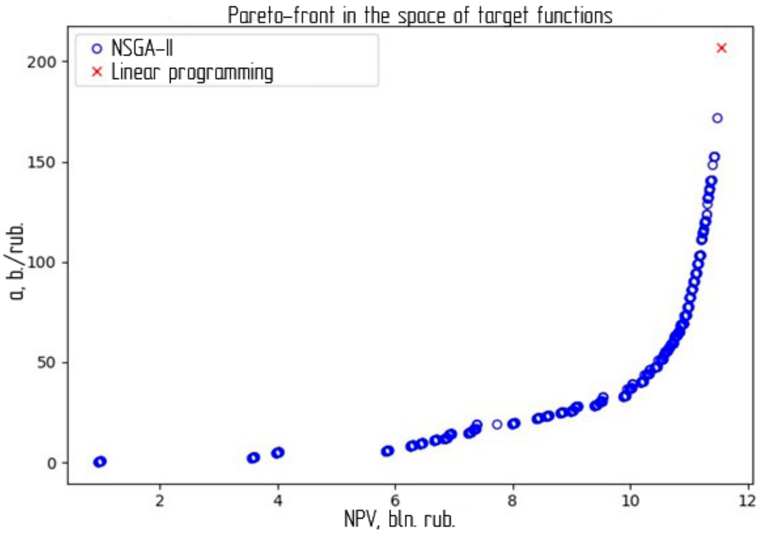

Figure 7. The distribution of received portfolios.

Compiled by the author: Shabalina.

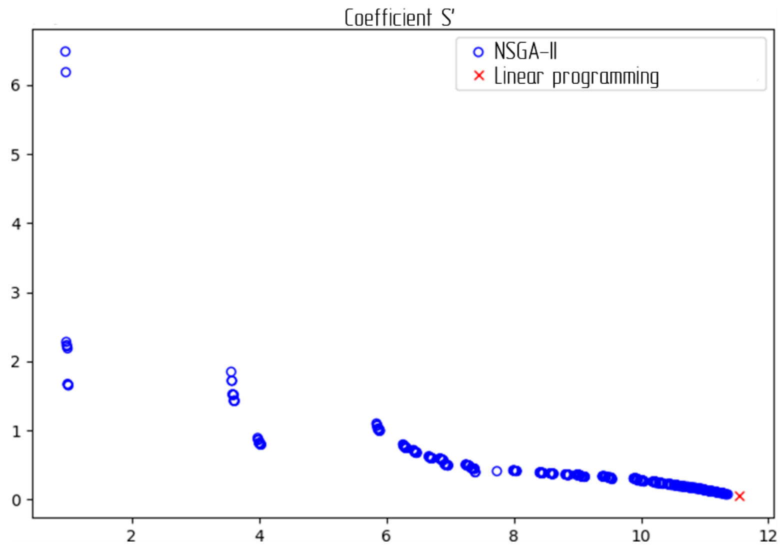

Figure 8. Coefficients S' of portfolios in the space of target functions.

Compiled by the author: Shabalina.

The portfolio was selected, reflecting its approximate position in the region of the inflection point on the Pareto frontier. The comparison of portfolios obtained by the two methods is presented in **Table 12**.

Table 12. The comparison of optimal portfolios obtained by different methods.

Indicator	**Portfolio NSGA-II**	**Portfolio LP**
NPV of the portfolio, bln RUB	10.901	12.122
Parameter α_p	41.96	209.14

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With NPV decreasing by a factor of 1.11, the portfolio risk decreases by a factor of 5, improving the stability of portfolio profitability. This confirms that the goal of investment optimization - strategic allocation of resources to maximize returns while minimizing risk has been achieved. It is also determined which projects should be implemented first to comply financial restrictions and achieve a better NPV/risk ratio. The comparison of portfolio structures, acquired using the genetic algorithm and the LP method, is presented in **Table 13**.

Table 13. Optimal portfolios obtained by different methods.

Project	LP method		GA Method		Project	LP method		GA Method	
	Shift, years	Entry	Shift, years	Entry		Shift, years	Entry	Shift, years	Entry
1	−2	1	−1	1	18	−2	1	−2	1
2	0	1	0	1	19	−2	1	0	0
3	−2	1	0	0	20	−2	1	−2	1
4	−2	1	−1	1	21	0	1	0	0
5	−2	1	−1	1	22	−2	1	−1	1
6	0	1	0	1	23	0	0	0	0
7	−2	1	0	0	24	0	0	0	0
8	−2	1	0	0	25	0	0	0	0
9	−2	1	0	0	26	0	0	0	0
10	−2	1	−1	1	27	−2	1	−1	1
11	−2	1	−2	1	28	0	0	1	0
12	−2	1	−2	0	29	−2	1	0	0
13	−2	1	0	0	30	0	0	0	0
14	−2	1	−2	1	31	0	0	0	0
15	−2	1	−2	1	32	−2	1	−2	1
16	−2	1	−2	1	33	−2	1	−2	1
17	−2	1	0	0					

Compiled by the author: Shabalina.

Moreover, the optimality of solutions on the Pareto frontier is confirmed by the fact that the project portfolio obtained through linear programming also lies on this frontier. If the Pareto frontier is conceptually extended beyond the points derived from the NSGA-II method, the portfolio optimized via linear programming would also reside on this line.

The portfolio derived from linear programming represents an extreme point on the Pareto frontier, characterizing a portfolio with the highest possible return and its corresponding risk. Its placement on the frontier is mathematically justified by the absence of other portfolios with the same or higher NPV value.

An additional advantage over the portfolio obtained through linear programming is the fact that when employing the method of multi-factor optimization using Genetic Algorithms, a set of optimal projects is obtained rather than a single portfolio. This set can serve as a foundation for managerial decision-making under various combinations of forecasted and actual values of economic macro-parameters. For instance, in the event of a general decrease in the volatility of currency and hydrocarbon markets, the decision-maker may reconsider the acceptable level of portfolio uncertainty and select a different optimal portfolio.

According to the regulations of the company under consideration, portfolio adjustments are conducted on a semi-annual basis. The process begins with a comprehensive data refresh, where macroeconomic indicators such as oil prices and exchange rates are updated in real-time or on a weekly basis, while project-specific data is reviewed semi-annually. Following this, the updated data is collected and validated to ensure accuracy. The financial-economic model (FEM) is then recalibrated to reflect the latest inputs. Using optimization frameworks like pymoo, the portfolio is reassessed to identify optimal configurations. Finally, scenario analysis is conducted to evaluate potential outcomes, and the resulting recommendations are presented to stakeholders for informed decision-making. Semi-annual re-optimization, integrated into corporate governance, ensures portfolios remain responsive to market changes and aligned with strategic goals.

5. Discussion and conclusions

The paper has developed a universal multi-criteria model for optimizing oil and gas projects under uncertainty conditions, which aims to help PJSC Gazprom Neft achieve a high level of return on invested capital through the effective project portfolio management.

The risk metrics used in this model are specifically designed for the oil and gas industry, addressing its unique challenges such as commodity price and exchange rate volatility, reserve uncertainty, and operational risks. Derived from historical data, stochastic modeling, and industry benchmarks, these metrics provide a comprehensive and adaptable framework for assessing and managing risks in oil and gas investments. Their integration into the FEM and optimization framework ensures that decision-making is informed, robust, and aligned with industry realities.

The validity of theoretical assumptions is confirmed, the NPV formula is verified for all projects, and the uncertainty indicators are compared. Using the developed algorithm, a family of Pareto-optimal portfolios was obtained, from which the optimal one was selected according to the research criteria.

The proposed methodology for portfolio analysis of oil and gas projects can be further modified and enhanced. For instance, additional factors beyond the exchange rate and oil prices could be incorporated into the analysis. By accounting for a broader range of dynamic external factors, such as geopolitical risks, regulatory changes, or technological advancements, the resilience and robustness of oil and gas projects can be further improved. This expanded approach would enable a more comprehensive assessment of risks and opportunities, ultimately supporting more informed decision-making and sustainable project performance.

Approaches, techniques, tools for optimization of investment portfolio of oil and gas projects of third-party authors were considered. The analysis has revealed that there is no unified approach to investment portfolio optimization. Additionally, it highlighted the limitations of existing portfolio optimization systems.

It was revealed that genetic algorithms are found efficient for high-performance solutions in asset combination calculations, as they compute complex weighted functions with multiple KPIs to obtain a set of high-performance solutions from nonlinear asset and constraint datasets.

These recommendations were used to develop a multi-criteria optimization model. The parameters of the portfolio obtained, using the genetic algorithm have demonstrated divergence from those obtained through the linear programming method, with a difference in portfolio return by a factor of 1.11 and a difference in the degree of uncertainty by a factor of 4.98.

The analysis has shown that the portfolio optimized by the proposed methodology practically does not differ in profitability from the traditional portfolio but has much lower risks of not achieving the required profitability. To maintain these advantages, the information for the model should be regularly updated depending on the political situation and macroeconomic parameters. Therefore, the developed approach is recommended for application in oil and gas companies to optimize the investment portfolio, enhance economic efficiency and maintaining the company's prosperity.

Author contributions: Conceptualization, KM; methodology, SA; program calculations, SA; validation, SA; literature analysis, KM; literature search, SA; writing, preparation of the original text, SA; reviewing and editing of the text, KM; visualization of graphs, SA. All authors have read and agreed to the published version of the manuscript.

Funding: The research was supported by the state assignment of the Ministry of Science and Higher Education of the Russian Federation FSRW-2023-0002, performed at St. Petersburg Mining University.

Conflict of interest: The authors declare no conflict of interest.

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