International Journal of Technology 14(8) 1663-1674 (2023)
Received September 2023 / Revised November 2023 / Accepted December 2023

International Journal of Technology

http://ijtech.eng.ui.ac.id

Risk Modeling in the Oil and Gas Industry

Dmitriy Rodionov[1], Marcel Gataullin[2], Irina Smirnova[1], Evgenii Konnikov[1], Darya Kryzhko[1*], Alexey Shmatko[3]

[1]*Peter the Great St.Petersburg Polytechnic University, Russia, St.Petersburg, Polytechnicheskaya 29, 195251, Russian Federation*
[2]*Ufa State Petroleum Technological University, Ufa, Republic of Bashkortostan. Ufa. Kosmonavtov st., 1450064, Russian Federation*
[3] *Institute for Regional Economic Studies, Russian Academy of Sciences, St. Petersburg, Russian Federation*

Abstract. The oil and gas industry is a sector that is prone to risks that can have severe consequences for both the environment and the economy. In this study. the aim is to develop an effective mathematical tool for risk modeling in the oil and gas industry. The research proposes a simulation modeling approach that focuses on two key risk parameters - frequency and severity. By using differentiated distributions. the unique properties of risk in the oil and gas industry can be effectively described, and an algorithm can be developed for practical applications. The findings of this study have significant implications for the oil and gas industry, policymakers, and investors. By using an effective mathematical tool for risk modeling. they can identify and manage risks more effectively, reduce the likelihood of accidents and other events that can have severe consequences. and minimize the potential impact of these events. Overall, this research provides valuable insights into the development of an effective mathematical tool for risk modeling in the oil and gas industry. By using simulation modeling and differentiated distributions. this study proposes an algorithm that can be practically applied to manage risks effectively in this important sector.

Keywords: Environment; Investors; Oil and Gas Industry; Risk Modeling

1. Introduction

The oil and gas industry serves as the backbone of the GDP for many nations playing an integral role in numerous mass production chains. As one of the largest industries in terms of dollar value it not only contributes substantially to economic output but also generates hundreds of thousands of jobs worldwide (Piya *et al.*, 2020). A sudden breakdown in any of the three global sectors of the oil and gas industry (extraction, transfer, processing) has serious consequences directly disrupting the rhythm of the supply chain and creating the potential for an exponential increase in primary financial losses (Biezma *et al.*, 2020). In addition the oil and gas industry has an increased level of danger - the most fatal accidents in the history of oil and gas pipelines have resulted in the death of more than 4.000 people (Biezma *et al.*, 2020). Accordingly, there is a need to create mechanisms for managing oil and gas industry objects in terms of preventing the development of emergency situations which requires the formation of tools for predicting the predisposition of a particular object to the initiation of a breakdown-risk exposure (Yang, Haugen, and Paltrinieri, 2018).

*Corresponding author's email: darya.kryz@yandex.ru, Tel.: +7 (981) 0179230
doi: 10.14716/ijtech.v14i8.6852

Risks are a parameter category indicative of the internal environment of the oil and gas enterprise. Despite the production specificities of the oil and gas industry certain limitations apply to predictive mathematical models: it has a low-risk frequency (accidents happen at a low rate) and at the same time, a high level of financial losses (Olanipekun and Alola, 2020). Therefore, a comprehensive examination of the factors influencing the formation and dynamic activation of risks in the oil and gas industry should serve as the foundation for devising a mathematical mechanism to assess an object's risk exposure. This study is conceptually different from the previous ones in terms of the goal of developing a risk modeling toolkit that provides analytical capabilities in conditions of fundamental information constraints, which is typical for the oil and gas industry. It is precisely the development of a risk modeling toolkit with the corresponding properties that determine the scientific contribution of this research. It is necessary to clarify that the developed risk modeling toolkit is primarily specified in relation to the technical risks of the oil and gas industry, such as explosions and the release of hazardous substances.

2. Methodology

To Before selecting an instrument for modeling risk parameters it is necessary to determine its properties in the context of the oil and gas industry. The specifics of the frequency and severity of risk in the oil and gas industry can vary depending on many factors such as the field the technologies used on the field the climatic conditions, the economic and political stability of the region, etc. Analysis of the Rostekhnadzor (The Federal Service for Ecological, Technological and Atomic Supervision; Russian Federation) statistics (Gosnadzor, 2023) the total number of risk events in the industry (for Russia) in 2021 and 2022 is 36 with a total number of enterprises at 285. Thus, the frequency per enterprise is 3.16%. At the same time, the average severity is 149 342 767 rubles. Thus, it can be concluded that the oil and gas industry is low-frequency in terms of risk and significant in terms of the cost of damage (Olanipekun and Alola, 2020). This specificity produces the problem of insufficient statistical arrays for the training of statistical models with sufficient predictive accuracy. Thus, the most appropriate is the use of imitation modeling, which will allow us to model the current conditions of functioning of the industry's enterprises and thus estimate the most likely values of the considered risk parameters (Rodionov *et al.*, 2022). For these purposes Monte Carlo simulation can be used.

Monte Carlo simulation is a statistical method that is used for modeling random processes and making decisions based on probabilistic calculations (Hartoyo *et al.*, 2023; Tran, Robbe, and Lim, 2023; Clare, Piggott, and Cotter, 2022). It is based on the idea of generating random numbers that are then used to create a set of possible scenarios. Monte Carlo simulation has several drawbacks, the key of which is the sensitivity to the choice of the random number generator and the model parameters. Thus, the accuracy of the simulation results is determined by the quality of selecting the probability distribution parameters for the frequency and severity of the risk event. Thus, the algorithm requires aggregation of the historical array describing the frequency and severity of risk events in the oil and gas industry, determination of the parameters of frequency and severity of risk events distribution, generation of the set of component parameters, statistical generalization of the obtained results and calculation of the integral level of risk indicator. The described algorithm is presented in Figure 1.

There are a multitude of statistical distributions that can be used for risk parameter modeling. The choice of the distribution depends on the assumptions that can be made about the characteristics of the data. It is necessary to systematically consider a number of the most commonly used distributions for such tasks. There are several distributions that have unique advantages for the purposes of risk event severity modeling specific to the oil and gas industry:

1. The Gamma Distribution provides the possibility of fine-tuning the shape and scale, allowing the results of modeling to be adapted to the conditions of factual reality. Additionally, the Gamma Distribution is a “memoryless” distribution, which is extremely important for the oil and gas industry due to the low frequency of risk.

2. The Pareto Distribution provides the possibility of modeling “heavy tails”, which is also extremely important for the oil and gas industry due to the high weight of risk events caused by both technological specialties and the presence of post-event risks.

3. The Exponential Distribution, like the Gamma Distribution, is “memoryless”, which is extremely important for the oil and gas industry.

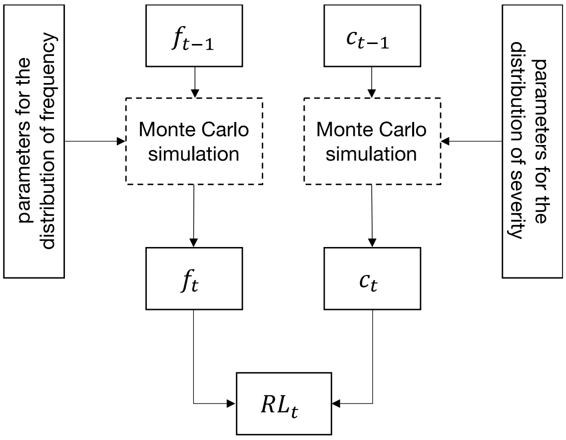

Figure 1 Algorithm for assessment of integral risk level indicator, based on Monte Carlo simulation

Modeling the severity of a risk event within the context of three distributions in combination with subsequent comparison of results will significantly increase the predictive accuracy of the modeling results.

The nature of risk frequency presents an ambiguous character. While aligning with the Central Limit Theorem suggests the relevance of utilizing the Normal Distribution, it is essential to consider potential chain reactions arising from the inherent risks in the oil and gas industry. This characteristic, often termed risk accumulation, underscores the need for a nuanced approach to modeling in this sector. The nature of risk accumulation implies an increased probability of consecutive risk events, as well as the reverse. Therefore, in the event of a risk occurrence within a simulation. the probability of subsequent risk events increases (Ting, Zakariah, and Yusri, 2022). The parameter that characterizes the strength of this dependence can be conditionally referred to as internal correlation. In this transformation, it is reasonable to move from a normal distribution to a multivariate normal distribution. The probability density function of the multivariate normal distribution has the following form:

$$f(y) = \frac{e^{-\frac{1}{2}(y-\mu)^T \Sigma^+ (y-\mu)}}{\sqrt{(2\pi)^k det * (\Sigma)}}$$

For risk modeling using the multivariate normal distribution, the parameters of the distribution need to be estimated: the vector of means and the covariance matrix. While the vector of means can be determined based on factual data, the covariance matrix requires a subjective-expert approach. The covariance matrix is a matrix containing the pairwise covariances between all the random variables. To construct the covariance matrix, one needs to assess the covariances between all the pairs of variables and then combine them into a matrix. The covariance matrix must be symmetric and positive definite. However, in this case, the simulation process takes on a one-dimensional character. Consequently, the covariance matrix is semantically defined by only one value, represented earlier by the coefficient of internal correlation ($corr_t$). This coefficient ranges from 0 to 1, signifying the degree of risk accumulation. A value of 0 indicates the absence of risk accumulation (implying a normal distribution), while a value of 1 denotes absolute risk accumulation. An example of the product of a risk frequency matrix built on the basis of a multivariate normal distribution and a risk severity matrix built on the basis of the gamma distribution for various values of the risk accumulation coefficient is shown in Figure 2.

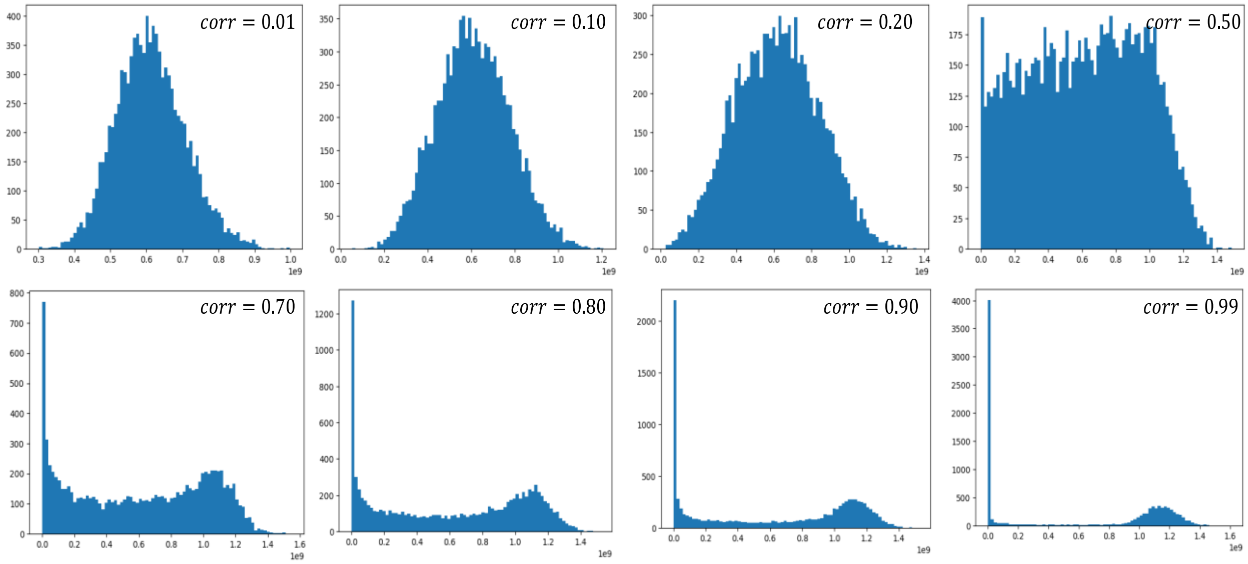

Figure 2 The variations of the risk frequency matrix constructed on the basis of the multivariate normal distribution and the risk severity matrix constructed on the basis of the Gamma distribution for different values of the risk accumulation coefficient.

In order for modeling purposes. the following parameters should become the input array:

1. The average retrospective value of the frequency of risk events (ft-1). This value can be determined on the basis of an existing statistical base and, if necessary, can be expertly corrected.

2. The average retrospective value of the severity of risk events (ct-1). The nature of this parameter is identical to the nature of the previous one.

3. The internal correlation coefficient ($corr_t$). It is determined by the expert and can be universalized at the industry level.

4. The shape parameter of the Gamma distribution (k). This parameter reflects the shift of the Gamma function. The scale parameter, in turn, is modeled on the basis of the severity of the risk event:

$$\theta = \frac{c_{t-1}}{k}$$

5. The shape parameter of the Pareto distribution (a) also reflects the shift in the function, like the shape parameter of the Gamma distribution. The minimum value that the random variable can accept is also determined by the severity of the risk event:

$$m = c_{t-1} * \frac{a-1}{a}$$

6. The number of risk events over the previous period (n) is determined based on actual data.

7. The maximum severity of a risk event (max-cit-1) is also determined based on actual data but may be subject to expert correction.

Hence, a critical aspect in the discussion revolves around establishing the modeling quality by accurately determining distribution parameters. This challenge is often addressed experimentally, comparing the target indicator derived from actual data with the modeled counterpart. Such an indicator could be the planned loss rate:

$$Uplan_t = \frac{c_{t-1} * f_{t-1} * n}{P_{t-1}}$$

Where:

P_{t-1} – the security fund for compensating for the consequences of the risk event (in rubles).

As a security fund, the value of the net profit of the enterprise can be used and adjusted by a coefficient of growth. The quality of the modeling will in turn be determined by the closeness of the modeled value to the planned one. For selecting the optimal distribution parameters for modeling. statistical methods such as histograms and distribution graphs can be employed to identify the distribution that best fits the data. The most appropriate technique for this is the use of a cyclical algorithm, which examines combinations of distribution parameters and determines the effective magnitude of those leading to the desired modeled loss. The resulting object of analysis is the shape of the distribution itself. The shape of the probability distribution can tell a lot about the risks associated with a given event or phenomenon. For example, if the distribution is skewed to the right, it could indicate that risk is elevated and that unaccounted-for factors may increase the likelihood of an unfavorable outcome. If the distribution is symmetrical. it could indicate a uniform distribution of risks. Thus, the internal environmental state of the oil and gas enterprises can be determined by the collective of tested risk distribution characteristics and indicators describing loss, based on the solution of the following simulation problem (see equations 1-3):

$$U_t = \frac{\frac{1}{n}\sum_{j=0}^{n-1}\left(\left[a_{i.j}\right]_{n\times Nsim} * \left[\beta_{i.j}\right]_{n\times Nsim}\right)}{P_{t-1}} \tag{1}$$

$$a_{i.j} = \frac{e^{-\frac{1}{2}(f_{t-1}-\mu)^T\Sigma^+(f_{t-1}-\mu)}}{\sqrt{(2\pi)^k det * \left[corr_{t_{i.j}}\right]_{n\times Nsim}}} \tag{2}$$

$$corr_{t_{i.j}} = \begin{cases} 1.\ i = j \\ corr_t.\ i \neq j \end{cases} \tag{3}$$

The equation for the severity of a risk event for the Gamma distribution (see equation 4)

$$\beta_{i.j} = c_{t-1}{}^{k-1}\frac{e^{\frac{-y}{\frac{c_{t-1}}{k}}}}{\frac{c_{t-1}}{k}^k G(k)} \tag{4}$$

The equation for the severity of a risk event for the Pareto distribution (see equation 5)

$$\beta_{i.j} = \frac{a * \left(c_{t-1} * \frac{a-1}{a}\right)^a}{c_{t-1}{}^{a+1}} \tag{5}$$

The equation for the severity of a risk event for the Exponential distribution (see equation 6)

$$\beta_{i.j} = \lambda e^{-\lambda c_{t-1}} \tag{6}$$

Defining the shape parameter is determined by the following objective setting (see equation 7):

$$max\left|U^t - U^t_{plan}\right|. x \in [x.y] \tag{7}$$

The range of the Gamma distribution shape parameter – [0.1. 9.0]

The range of the Pareto distribution shape parameter – [1.0. 10.0]

However, the distribution itself cannot provide complete information about the risk, so it should be considered in conjunction with a set of indicative parameters, such as the probability quantiles and probability of exceeding the planned loss values (see equation 8):

$$PClaim_{t_x} = \frac{\left|i \in \left[a_{i.j}\right]_{n\times Nsim} * \left[\beta_{i.j}\right]_{n\times Nsim}: i > P_{t-1} * Uplan_t * (1+x)\right|}{Nsim} \tag{8}$$

Where:

$PClaim^t_x$ – the probability of exceeding the planned loss by X percent (%);

X – the level of exceeding the planned loss (ratio);

$Nsim$ – the number of Monte Carlo simulations.

The developed toolkit requires automation and verification for use in petroleum and gas industry enterprises. Step by step, the developed methodology can be described by the following algorithm: 1. Identification of risk portfolio categories. 2. Assessment of parameters of frequency and severity of categorically specified risk events based on past experience. 3. Monte Carlo generation of arrays describing the distribution of frequency and severity of risk events using the gamma distribution, Pareto distribution, exponential distribution, and multivariate normal distribution. 4. Evaluation of the distribution properties using the formed set of indicators.

3. Results and discussion

The system of modeling tools for indicators of the internal environment state of oil and gas industry enterprises developed implies using an array of empirical data which can be obtained both based on an analysis of specific enterprise activities as well as from official aggregate statistical sources. In the Russian Federation, control and accounting of risks of oil and gas industry enterprises is a function of the Federal Service for Ecological. Technological and Atomic Supervision (Rostekhnadzor), particularly of the department responsible for oversight of oil-and-gas extraction and chemical production objects.

According to the information provided on the department website (Gosnadzor, 2023), risk events are divided into four key groups: 1. Release of hazardous substances (36%); 2. Uncontrolled explosion (14%); 3. Destruction of structures (28%); 4. Destruction of equipment (22%).

As can be seen, the distribution of shares is quite uniform, indicating a systemic quality of control and supervision. The highest share is held by releases of hazardous substances, which is primarily due to the fact that this type of situational risk is a consequence of the realization of local resource risks (micro-level risks). The smallest share is held by uncontrolled explosions, which again indicates the systemic quality of control and supervision, leading to the possibility of preventing such risk events. A significant variance of shares is observed in the cost aspect (cost of damage or severity of risk events).

The destruction of structures stands out as the most significant in terms of the severity of risk event implementation. This aligns with formal-economic logic, as the destruction of a structure entails not only the efforts involved in its restoration but also encompasses the restoration of technical infrastructure, affected assets, and the processes of dismantling and disposal (Ryan and Bristow, 2023). In this rating, the second is the release of hazardous substances. This fact is determined by the previously stated thesis regarding the significance of post-event risks, to which environmental risks are primarily applicable, which are in turn modeled by the emission of hazardous substances. An uncontrolled explosion, in turn, is the least significant in terms of the severity of the risk event, which indicates a high level of technical safety that minimizes chain reactions (Pishchalkina, Pishchalkin. and Suloeva, 2022).

The consolidated reports presented by Rostechnadzor allowed to compile a consolidated risk-statistics table (Table 1).

Before analyzing the corresponding statistical array, it is necessary to note a number of technical aspects:

When aggregating, only data detailed in terms of cost and risk subject (enterprises) were taken into account. In this regard, the list of risk events participating in the analysis is less than actual (36 risk events instead of 51 risk events).

Table 1 Consolidated Risk-Statistics of Oil and Gas Industry 2021–2022

N	Type of accident	Number of accidents	The average cost of damage	Damage limit	Frequency	Average profit of the previous period
1	Release of hazardous substances	13	126,219,152	1,210,000,000	4.56%	16,413,470,244
2	Uncontrolled explosion	5	49,029,453	131,011,761	1.75%	21,832,052,400
3	Destruction of structures	10	316,559,663	1,239,000,000	3.51%	672,989,600
4	Destruction of equipment	8	105,562,799	445,800,000	2.81%	22,954,384,625

The average profit of the previous period was obtained in accordance with the accounting data.

The frequency of a risk event was obtained per 1 enterprise. According to the data of the Ministry of Energy of the Russian Federation as of January 1, 2021, oil and gas condensate production on the territory of the Russian Federation was carried out by 285 organizations with the right to use subsoil.

The data aspects limit the objectivity of the conclusions that can be formulated based on the analysis. However, this restriction is insignificant in the context of comprehensive risk distribution analysis implied by the formed instrumentarium.

The formation of the instrumentarium was performed using the high-level programming language Python and a complex set of tools libraries, namely the Scipy library, that enables the generation of arrays of random numbers in accordance with assigned distributions. Before the risk modeling process is implemented, it is necessary to determine the level of internal correlation (corrt) (Paltrinieri, Louise, and Genserik, 2019). As noted earlier, this parameter is expert-driven in terms of definition. For the purpose of the current research, its value was determined based on the graph logic. According to this logic, the implementation of separate risk events on the technological level may lead to the implementation of subsequent ones, which in turn can be described as a chain reaction. The distribution of the internal correlation indicator in accordance with key risk groups is provided in Figure 3.

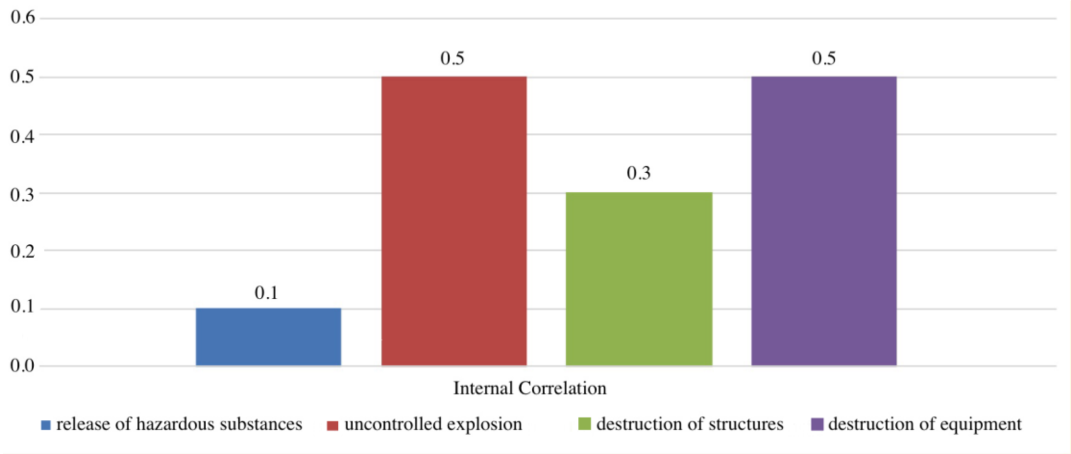

Figure 3 Distribution of Internal Correlation Indicators According to Key Risk Groups

The internal correlation indicator largely determines the distribution of frequency of highly weighty risk events. This specificity was reflected in the Gamma and Pareto distributions (Figure 4).

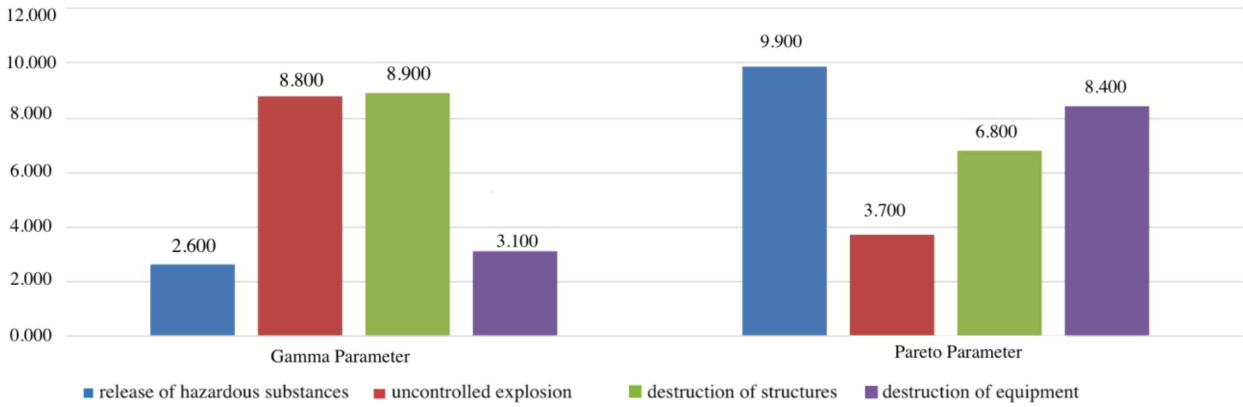

Figure 4 Gamma and Pareto Distribution Parameters

Based on the presented graph. it can be inferred that the most skewed distributions are associated with uncontrolled explosions and the destruction of structures, suggesting a relatively low probability of organizing these risk groups. On the contrary, the Pareto distribution displays an extremely opposite specificity, which is largely determined by the weightiness of the risks implied by the release of hazardous substances. Consequently, the risks of uncontrolled explosion and destruction of structures are most controllable, whereas the risks of release of hazardous substances are least controllable. This statement correlates with the previously made empirical conclusions. The consolidated results of the modeling of condition indicators within the oil and gas industry. according to the major risk groups, are presented in Table 2.

As can be seen, the planned loss for the destruction of structures group is several times higher than for other groups of risk. This fact is also related to the already described specificity. However, it differs from the specificity demonstrated by the modeled parameters of distributions. Therefore, despite the effectiveness of control, the implementation of risk events of the destruction of structures group brings losses that are incomparable to the profit of the enterprise. Consequently, measures to control resource risks should be directed primarily towards the prevention of such types of risk events. The described specificity is confirmed by the distribution of modeled losses. The quality of imitation modeling is principally demonstrated by the minimal deviation of modeled values of losses compared to the planned ones.

The maximum deviation is observed when using an exponential distribution, which confirms the hypothesis about the significance of parameter tuning for the form of the distribution. Much more detailed conclusions can be drawn from the analysis of the loss quantiles. The destruction of structures group remains the most significant in terms of potential damage. In 95% of cases, the damage from its implementation will be more than 90% of the profit, and in 99% of cases - more than 170% of the profit. The other risk groups are insignificant in comparison with it. However, it is worth noting the quantiles of the release of hazardous substances group, according to which the limit of damage can be about 4%. This specificity indicates that the destruction of structures is most likely a consequence of a systemic problem,which is realized primarily in enterprises with a low level of financial security. Thus, the risk specificity of financially stable enterprises is concentrated within the framework of the release of hazardous substances risk management.

According to the provided results, it can be concluded that the probabilities of exceeding the planned loss are extremely comparable, which in turn indicates a significant shift in the shape of the distributions. The most significant values of these indicators are reached for the release of hazardous substances group. Moreover, the variance of these parameters in terms of distributions is much higher, specifically in the case of the release of hazardous substances risks. This fact indicates a high variance of the risk nature and, consequently, a need for additional research on this risk group. At the same time, the uncontrolled explosion risks are much more stable and more predictable.

Table 2 Consolidated Results of the Modeling of Condition Indicators within the Oil and Gas Industry according to the Major Risk Groups

N	Index	Release of hazardous substances	Uncontrolled explosion	Destruction of structures	Destruction of equipment
1	The planned loss indicator	0.456%	0.020%	16.504%	0.103%
2	Modeled loss Gamma	0.456%	0.020%	16.497%	0.103%
3	Modeled loss Pareto	0.457%	0.019%	16.508%	0.103%
4	Modeled loss Exponential	0.457%	0.018%	16.214%	0.101%
5	95^{th} quantile of Gamma loss	2.032%	0.183%	93.894%	0.748%
6	95^{th} quantile of Pareto loss	1.655%	0.182%	91.563%	0.671%
7	95^{th} quantile of Exponential loss	2.328%	0.084%	108.815%	0.746%
8	99^{th} quantile of Gamma loss	3.241%	0.446%	173.027%	1.734%
9	99^{th} quantile of Pareto loss	2.707%	0.438%	171.751%	1.613%
10	99^{th} quantile of Exponential loss	4.038%	0.561%	208.727%	1.942%
11	The probability of exceeding the planned values for Gamma	0.000%	0.000%	4.391%	0.000%
12	The probability of exceeding the planned values for Pareto	0.000%	0.000%	3.732%	0.000%
13	The probability of exceeding the planned values for Exponential	0.000%	0.000%	5.665%	0.000%
14	The probability of exceeding the planned values by 5% for Gamma	32.401%	6.649%	23.282%	13.512%
15	The probability of exceeding the planned values by 5% for Pareto	41.366%	6.649%	23.405%	13.802%
16	The probability of exceeding the planned values by 5% for Exponential	27.014%	6.193%	18.243%	11.850%
17	The probability of exceeding the planned values by 10% for Gamma	31.713%	6.649%	23.245%	13.475%
18	The probability of exceeding the planned values by 10% for Pareto	41.366%	6.649%	23.405%	13.802%

N	Index	Release of hazardous substances	Uncontrolled explosion	Destruction of structures	Destruction of equipment
19	The probability of exceeding the planned values by 10% for Exponential	26.478%	6.172%	18.033%	11.766%
20	The probability of exceeding the planned values by 50% for Gamma	26.274%	6.649%	22.558%	13.094%
21	The probability of exceeding the planned values by 50% for Pareto	41.366%	6.649%	23.405%	13.802%
22	The probability of exceeding the planned values by 50% for Exponential	22.471%	6.009%	16.408%	11.111%

To conclude it is necessary to analyze the overall form of the distribution of state indicators of oil and gas industry enterprises (Figure 5).

The given distributions demonstrate a low-frequency specificity of risk when it comes to the oil and gas industry. However, there are so-called 'long tails' that indicate that the realization of certain risks can lead to significant losses for the enterprise.

Therefore, it can be concluded that the primary factors for control, in terms of ensuring the sustainability of development. for an oil and gas enterprise are risks of hazardous substance release and destruction of structures. The former are universally significant, while the latter require a systematic analysis of preconditions that will identify minimal fluctuations in their probability of realization.

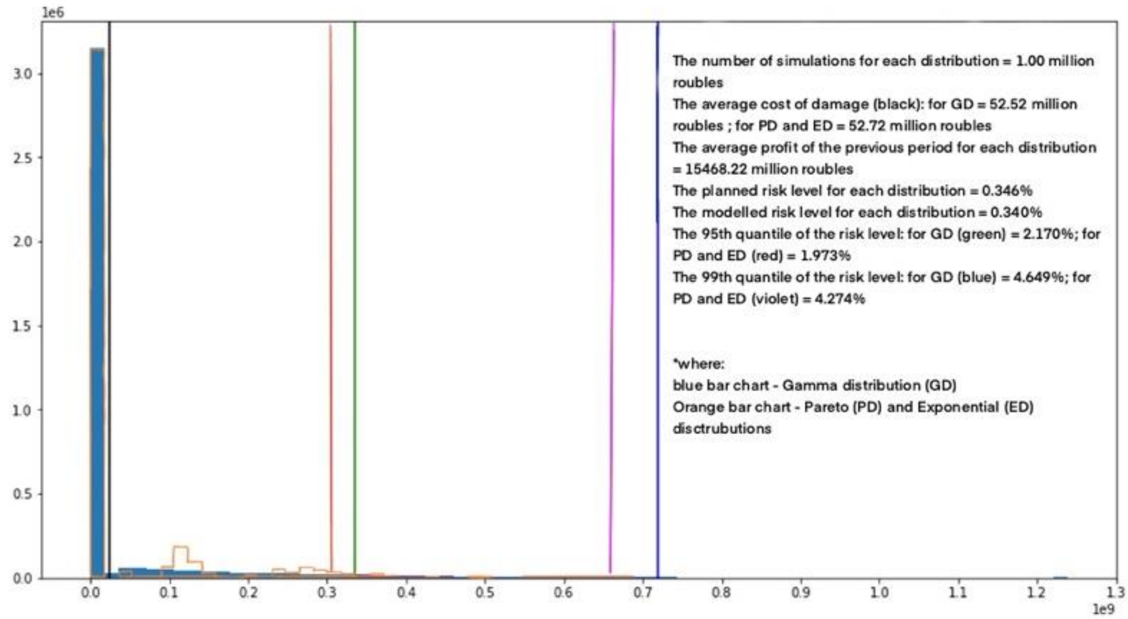

Figure 5 Gamma Pareto and Exponential distributions of state indicators of oil and gas industry enterprises

4. Conclusions

This research has developed a tool that aggregates the utility of three distributions (Gamma, Pareto, and Exponential) to describe the probability of an event with global consequences occurring in a low-frequency (in terms of frequency of occurrence of such events) environment, whose retrospective statistical base does not allow for the application of simplified mathematical description methods. The tool was tested on data on the predisposition of enterprises in the oil and gas sector to risks - which made it possible to obtain an effective description of the probability of a breakdown of the studied system using data containing information about only 36 cases. It should be noted that within this study, the analysis was conducted solely based on data from the entire oil and gas industry in Russia. However, at the practical level, the use of this toolkit is most relevant at the specific enterprise level. This assumption is due to the low frequency of risk events, which allows for the aggregation of objective and sufficient data solely for the industry as a whole. In the future, there is a plan to gather more localized risk statistics within one of the most significant oil and gas industry enterprises and to test the proposed toolkit in relation to it. The developed model enables the effective management of risks in the oil and gas industry. mitigating the occurrence of emergency situations and minimizing the consequences of accidents. This unique mathematical tool has been crafted for adaptability to a broad spectrum of practical applications along with an associated algorithm for its seamless adaptation. The practical results of this study are presented as a universal risk modeling tool specified to meet the needs of enterprises in the oil and gas sector. The applicability of these results is determined by the conclusions resulting from the testing, which were reflected in decisions regarding changes in the development strategy of a number of oil and gas enterprises. The limitations of this study undoubtedly stem from the specifics of the statistical information based solely on data from the Russian Federation. In future research, it is advisable to expand the information base for analysis beyond the Russian Federation and to specify the developed toolkit to the needs of other industries and types of risks.

Acknowledgments

The materials were prepared as part of the implementation of the project of institutional changes of the strategic academic leadership program “Priority 2030” of the Russian Federation (agreement 075-15-2023-380 dated 02.20.2023).

References

Biezma, M.V., Andrés. M.A., Agudo. D., Briz. E., 2020. Most Fatal Oil & Gas Pipeline Accidents through History: A Lessons Learned Approach. *Engineering Failure Analysis,* Volume 110, p. 104446

Clare, M.C., Piggott, M.D., Cotter, C.J., 2022. Assessing Erosion and Flood Risk in the Coastal Zone through the Application of Multilevel Monte Carlo Methods. *Coastal Engineering.* Volume 174, p. 104118

Gosnadzor, 2023. Official site of the Gosnadzor. Available online at https://www.gosnadzor.ru/, Accessed on February 10, 2023

Hartoyo, F., Irianti, G.P., Fatriansyah, J.F., Ovelia, H., Mas’ Ud, I.A, Digita, F.R., Anis. M., 2023. Weibull Distribution Optimization for Piping Risk Calculation Due to Uniform Corrosion Using Monte Carlo Method. *Materials Today: Proceedings*, Volume 80, pp. 1650–1655

Olanipekun, I.O., Alola, A.A., 2020. Crude Oil Production in the Persian Gulf amidst Geopolitical Risk. Cost of Damage and Resources Rents: Is There Asymmetric Inference? *Resources Policy*, Volume 69, p. 101873

Paltrinieri, N., Louise, C., Genserik R., 2019. Learning About Risk: Machine Learning for Risk Assessment. *Safety Science,* Volume 118, pp. 475–486

Pishchalkina, I., Pishchalkin, D., Suloeva, S., 2022. Research of the Efficiency of Mining and Metallurgical Enterprises Based on the Environmental. Social. and Governance Risk Rating in the Context of Digital Transformation. *International Journal of Technology.* Volume 13(7). pp. 1442–1451

Piya, S., Shamsuzzoha, A., Khadem, M., Al-Hinai, N., 2020. Identification of Critical Factors and Their Interrelationships to Design Agile Supply Chain: Special Focus to Oil and Gas Industries. *Global Journal of Flexible Systems Management*, Volume 21, pp. 263–281

Rodionov, D., Kryzhko, D., Tenishev, T., Uimanov, V., Abdulmanova, A., Kvikviniia, A., Aksenov, P., Solovyov, M., Kolomenskii, F., Konnikov, E., 2022. Methodology for Assessing the Digital Image of an Enterprise with Its Industry Specifics. *Algorithms* Volume 15(6), p. 177

Ryan, B., Bristow., D.N., 2023. Climate Change and Hygrothermal Performance of Building Envelopes: A Review on Risk Assessment. *International Journal of Technology,* Volume 14(7), pp. 1461–1475

Ting, C., Zakariah, H., Yusri, Y.Z.M., 2022. Probabilistic Risk Assessment of COVID-19 Patients at COVID-19 Assessment Centre. *International Journal of Technology,* Volume 13(6). pp. 1193–1201

Tran, A., Robbe, P., Lim, H., 2023. Multi-Fidelity Microstructure-Induced Uncertainty Quantification by Advanced Monte Carlo Methods. *Materialia*, Volume 27, p. 101705

Yang, Haugen, S., Paltrinieri, N., 2018. Clarifying the Concept of Operational Risk Assessment in the Oil and Gas Industry. *Safety science*, Volume 108, pp. 259–268