Research Article

Construction of a Coupled Mathematical Model of Oil and Gas Risk Relying on Distributed Computing

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With the rapid economic development in recent years, the development of oil and gas has become more and more rapid. Oil and gas are essential energy sources, but oil and gas risks hinder the development of the oil and gas industry. *Purpose.* This article mainly introduces the relevant theoretical knowledge of distributed computing and the coupled mathematical model of oil and gas risk and relies on the distributed calculation to analyze the oil and gas risk, thereby constructing the mathematical model of coupled oil and gas risk. The coupled mathematical model is based on the theories of rock mechanics, seepage mechanics, and heat transfer to study the interaction between fluid seepage and rock mass deformation under nonisothermal conditions in the reservoir and to establish the mathematical equations of the three fields (seepage field, temperature field and stress field) and their coupling action. *Methodology.* It mainly relies on distributed computing, analyzes oil and gas risks through distributed computing, builds a mathematical model for oil and gas risk coupling, and also inputs oil and gas risks into the network through neural network calculations to achieve the purpose of risk assessment. Finally, through the experiment and analysis of the questionnaire, the whole article is completed. *Research Findings.* The experiment in this article mentioned that the demand for oil and gas has been increasing in recent years, from 350 million tons in 2011 to 10.3 tons in 2016, an increase of 680 million tons, an increase of 48%, but the amount of oil and gas extracted is far below the demand for oil and gas. In 2011, the amount of oil and gas extracted was only 210 million tons, and in 2016, it was only 570 million tons, so the extraction of oil and gas needs to be accelerated. However, there are many risks in oil and gas exploitation. Therefore, how to build a mathematical model of oil and gas risk coupling based on distributed computing is the most important problem to be solved at present. *Research Implications.* Based on previous research results, this paper systematically studies the related issues of oil and gas exploration risk assessment. The thesis first summarizes the current research status of oil and gas exploration risk assessment. The risk of oil and gas exploration is a hot topic in the current research field of oil and gas exploration and development. Its research focuses on the adverse effects of the uncertainty of geology, technology, engineering, ecological environment, etc., on the entire exploration investment project, finds out their gaps and problems through comparison, and clarifies the direction of the next oil and gas exploration risk assessment. *Practical Implications.* This paper uses evidence theory to effectively realize the basic probability distribution of attributes while solving the difficult problems of most qualitative indicators in risk assessment. The two effective combinations provide new ideas for risk assessment and scientific decision-making.

1. Introduction

With the economic development in recent years, the oil and gas industry is also making continuous progress. Oil and gas exploration projects are also facing high risks and high investment. If it succeeds, it can bring relatively rich returns; but if it fails, it will bring no small losses. Therefore, for exploration projects, scientific risk assessment is needed to make better project decisions. Overseas oil and gas companies are located in different countries or regions. With the continuous innovation and development of Internet technology, relying on the Internet for risk management will bring great convenience and will surely become the trend of future development.

Oil and natural gas exploration is a very complex and large-scale system engineering, and exploration and development are accompanied by many uncertain factors. It has the characteristics of huge investment, long cycles, complex technical requirements, and high risk. Therefore, risk analysis needs to be placed in an important position. The risk assessment of oil and gas exploration is to evaluate the results of various risk events to determine the order of their severity. Distributed computing has a flexible architecture and a distributed management and control mechanism. Based on distributed computing, corresponding countermeasures can be proposed. Research on risk assessment issues is very important for oil and gas projects.

With the rapid development of the oil and gas industry in recent years, oil and gas risks have also followed. Xinhong discovered that submarine pipelines are the main mode of transportation for subsea oil and gas production. Due to the combined effect of internal and external factors, the probability of failure of submarine pipelines is increasing, which is likely to cause oil and gas leakage accidents. Effective risk analysis is essential to prevent and mitigate such potential accidents. He proposed a risk-based accident model and constructed an object-oriented Bayesian network with a smaller and clearer structure by modularizing the primary Bayesian network [1]. Savas E Y studies and analyzes whether the hedging activities of oil and gas companies have a significant impact on company performance. He built a panel regression model to estimate the company's value and the coefficient of derivative use. Savas E Y stipulates that the speculative use of derivatives is eliminated in the model, and the result provides key information about asymmetric information and signal effects. Since the derivative use coefficient is negative, it illustrates the importance of disclosure for financial health. If the company releases a high level of hedging activity, it may be a warning to investors to avoid investing in the company. He also sought the explanation behind the corporate hedging decision, which was one of the first studies with a wide range of areas and data [2]. Tian D mainly proposed a new method to establish a risk matrix to assess the safety risks of the oil and gas industry. The frequency and consequences of risks are two ideal criteria in the process of building a risk matrix. Therefore, a multistandard and multiexpert information integration model is constructed. The method of determining expert weights is introduced, combining objective weights and subjective weights to evaluate scores by experts [3]. Khalilzadeh M discovered that oil and gas projects incorporate a large amount of uncertainty due to their unique characteristics, complexity, and uncertain environment. His purpose is to identify and evaluate the main risks of such projects under uncertain conditions. Then, a hybrid fuzzy technique is used to determine the correlation between risk and its importance weight. The final result shows that the problem of underinvestment in oil and gas is mainly due to the failure to attract foreign investors and the lack of regional infrastructure [4]. Cheng C found that international oil and gas projects are characterized by high capital intensity, high risk, and diversified contracts. Therefore, in order to help decision-makers make more reasonable decisions under

uncertain circumstances, it is necessary to measure the risks of international oil and gas projects. To this end, he built a probability model based on the traditional economic evaluation model, introduced a valuable risk measurement tool in finance, and used it to measure royalties contracts, production sharing contracts, and services for an international oil and gas project contract. In addition, he also used the simulation results to compare the impact of different risk factors on the project's net present value. The results show that (1) Risk has a great influence on the project's net present value; therefore, if the risk is ignored, the decision may be wrong; (2) The simulation method is used to simulate the random distribution of risk factors in the probability model, so the probability is related to the project's net present value [5]. Trofimov V T found that onshore oil and gas production is often accompanied by accidents of varying severity and negative consequences. Operations in the surrounding seas and ocean regions of the world have seriously worsened the situation and pushed most of the emergencies related to hydrocarbon production to the regional and global levels. The application of new technology in the production of shale hydrocarbons has added a new problem, that is, the probability that a large amount of geological environment will be completely polluted by highly toxic chemicals. The discovery of a new and promising fossil energy natural gas hydrate makes it possible to outline only the possible related hazards and indicates that environmental risks may increase many times. In order to resist the threat of emergencies related to the growth of oil and gas production, it is recommended to establish a special control and rapid response agency nationwide. If necessary, such structures can be opened up for international cooperation [6]. Yu X found that onshore oil and gas pipeline maintenance process risk assessment research has attracted more and more academic attention. Due to uncertainty, it is difficult to accurately or robustly assess risk spread. Therefore, he considered that decision-makers prefer risk information informed by uncertainty rather than unreliable accurate risk values, and he provided new insights for dealing with the risk assessment of the onshore pipeline maintenance process under uncertainty. The risk assessment model is based on a quantitative risk assessment framework based on the analytic hierarchy process and expert knowledge. At the same time, in order to express and quantify the uncertainty, interval analysis is used to extend the entire model to an interval environment. Therefore, he established an interval quantitative risk assessment model for the onshore pipeline maintenance process. Studies have shown that interval analysis can effectively internalize, represent, quantify, and spread the uncertainty in the risk assessment model [7]. Epelle E I found that even under unfavorable technical and environmental conditions, the ever-increasing global energy demand has driven the oil industry to develop more innovative and advanced methods to improve oil recovery. The severity of many operational problems affecting the drilling and production of oil and gas wells has been exacerbated by the inconvenience of transportation, so the overall situation must be remedied. In addition, the pressure loss of the toroidal geometry, as well as the reduced penetration rate due to the accumulation of downhole drill
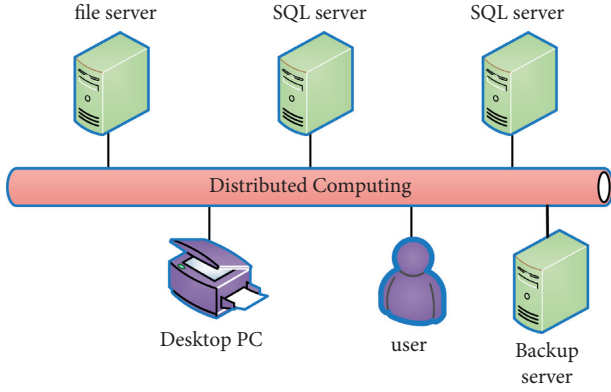
Figure 1: Distributed computing project diagram.

cuttings, constitutes an important part of the total energy to be provided. Therefore, if appropriate and economical drilling program design is required, the application of complex modeling techniques and the reliable clarification of phase distribution (solid, liquid and gas) and popular flow patterns become essential [8]. Through the experimental research of scholars, we can know that there are more and more risks in the oil and gas industry, and the traditional model can no longer satisfy the analysis of oil and gas risks. Therefore, how to rely on distributed computing to establish a mathematical model of oil and gas risk coupling so as to reduce oil and gas risks is what needs to be solved most.

The innovations of this paper are as follows: (1) The experiment based on distributed calculation has completed the construction of the oil and gas risk coupling mathematical model and found the oil and gas risk assessment method, which makes the development of the oil and gas industry more effective. (2) Using distributed parallel computing and risk assessment methods to solve risk factors. As a result, the risk of oil and gas is reduced, and the construction of the coupled mathematical model is more complete.

2. Distributed Calculation Method and Neural Network Method

2.1. Distributed Parallel Computing. Distributed computing is a computer science, and the main research object is distributed systems. A distributed system is a software and hardware system composed of several computers interconnected by a network. At present, the most common distributed computing project is the use of global volunteer computers for computing. Volunteer computers transmit idle computing power through the Internet to send data so that they are logically connected as a whole to carry out some scientific research projects that require large-scale calculations [9], as shown in Figure 1.

As shown in Figure 1, compared with other algorithms, distributed computing has the following advantages:

(1) Rare resources can be shared.

(2) Through distributed computing, the computing load can be balanced on multiple computers.

(3) The computing power of cheap computers can be integrated to reach or exceed the performance of some supercomputers in order to complete some projects that require high computing capacity and high performance [10]. Its disadvantage is that if one or more computers fail, or one or more network links fail, it will cause problems in the distributed system.

The distributed SNESIM (single normal equation) design ideas in this article are as follows.

Discretize the training image U, as in the following formula:

$$U = \begin{bmatrix} u_{1,1}, u_{1,2}, u_{1,n} \\ u_{2,1}, u_{2,2}, u_{2,n} \\ ... \\ u_{m,1}, u_{m,2}, u_{m,n} \end{bmatrix}. \tag{1}$$

Among them, $u_{m,n}$ represents the state value of each grid in the training image, and m n is the size of the training image.

The core of the distributed strategy is to use the principle of hierarchical parallelism. Each node in the cluster (except the main node) only has a part of the search tree set, and each part is independent of each other, and the number of events in each subset is also mutually exclusive. Independent, each record only represents a state and corresponding frequency [11]. The data management strategy of SparkRDD (Spark Resilient Distributed Datasets) is shown in Figure 2.

As shown in Figure 2, because the characteristics of RDD cannot ensure the order of data in RDD, it is necessary to make the data independent of each other to fully ensure its computational efficiency [12]. For the grid to be simulated, given a data event on the grid to be simulated, the label of the event can be used to judge whether the data event of the corresponding training image node matches. If it matches, the corresponding event in the global search tree is incremented by one count according to the value of the discrete variable of the point on the training image; conversely, edge probability is used instead of conditional probability, the probability of one event happening has nothing to do with other events. This is the marginal probability. Taking the variables x and y, in their joint distribution, in the joint probability, the events that are not needed in the final result are merged into the full probability of their events and disappear [13].

All these training patterns are stored in the search tree structure, and the following data can be easily retrieved: W is the total number of categories. The ratio of N to K represents the ratio of training modes, and training mode (n_k/n) defines the value of the center position $P(t_1')$, as in the following formula:

$$\begin{aligned} P(t_1') &= W|D_n| \\ &= \frac{n_k}{n}, \ k = 0, 1, 2, \ldots, k - 1. \end{aligned} \tag{2}$$

K-type estimation with local data set $n(v)$ as the probability condition, as in the following formula:
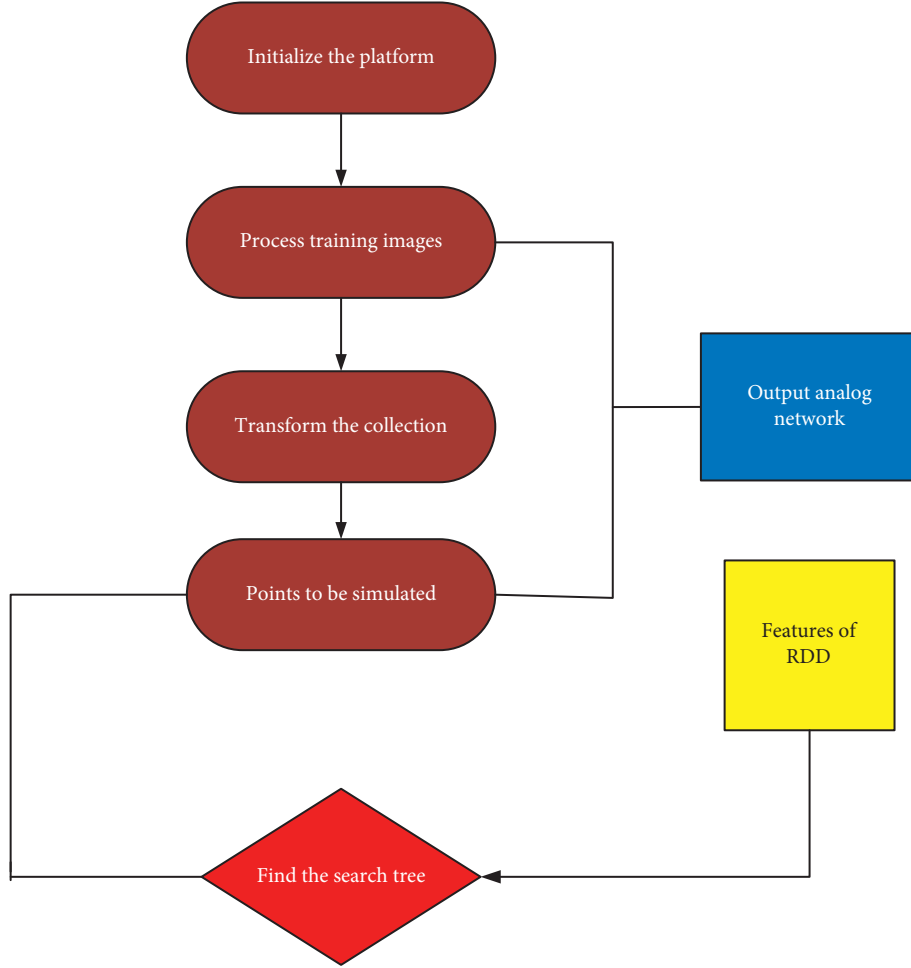
FIGURE 2: Data management strategy diagram of SparkRDD.

$$\text{prob}\{v \in k|n(v)\} \in [0,1]. \tag{3}$$

The indication of a class can be simulated in each simulation node V, where the indicator refers to the class or type indicator to which the continuous Z value belongs, as in the following formula:

$$\text{prob}\{Z(v) \leq Z_k|n(v)\} \in [0,1]. \tag{4}$$

Random function $Z(v)$ again uses the same geometry of "simulated" data $Z_{cs}^I(v)$. This process is as follows:

$$Z_{cs}^I(v) = Z_K^*(v) + \left[Z_{cs}^I(v) - Z_{Ks}^{*(i)}(v)\right]. \tag{5}$$

For the data value $Z_{cs}(v)$ at the data position v of each random function, ensure that it can satisfy the variance formula of $R(v)$, as shown in the following formula:

$$\text{Var}\{Z_{cs}(v)\} = \text{Var}\{Z_k^*\} + \text{Var}\{R(v)\}. \tag{6}$$

In general, any unsampled value $z(v)$ can be expressed as the sum of its estimated value $z(v)$ and its corresponding error $r(v)$, as in (6):

$$z(v) = z^*(v) + r(v). \tag{7}$$

Therefore, it can be seen that distributed computing is widely used in practice based on covariance simulation algorithms; covariance, as a quantity describing the degree of correlation between X and Y, has a certain effect under the same physical dimension, but the same two quantities adopt different dimensions to make their covariance show great differences in value. Its essence originates from two categories: the first type is a multivariate Gaussian random function model fixed on attributes; the second type is based on the interpretation of an indicator's expected value as a conditional probability [14].

2.2. Neural Network Algorithm Based on Distributed Computing.

A neural network is a kind of computing model which is composed of a large number of nodes (or neurons) connected to each other. Each node represents a specific output function, called the excitation function. Now, neural networks have made great progress. This is a learning algorithm that is often used in the fields of pattern recognition, signal processing, and data mining [15]. Neural network classification algorithms usually use multilayer neural networks [16]. An artificial neural network is imitating the information processing mechanism of the human brain.
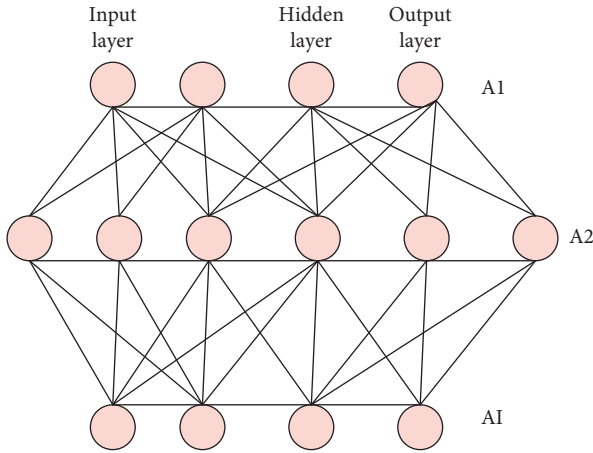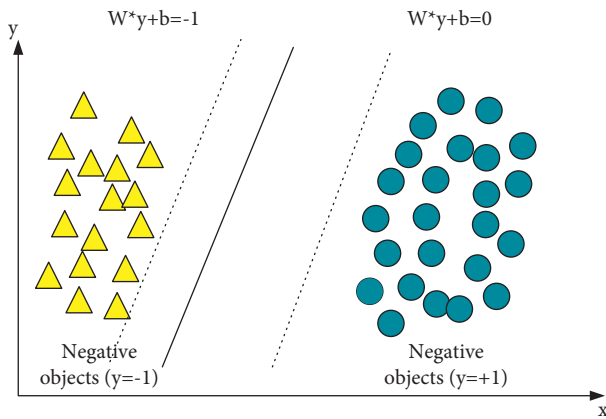
FIGURE 3: Multilayer feedforward neural network.

FIGURE 4: Example diagram of dimensionality separability.

FIGURE 5: "Geometric distance" from Y to the classification hyperplane.

Through the abstraction, simplification, and simulation of the brain mechanism, specific functions such as learning, memory, reasoning, and recognition are realized. That is, mathematical models are used to simulate the process of human brain thinking and information processing [17], as shown in Figure 3.

As shown in Figure 3, it consists of an input layer, several hidden layers, and an output layer. In the input mode, the input corresponds to the measured attributes of each training sample [18].

In the field of machine learning, the goal of classification is to gather objects with similar characteristics. A linear classifier makes classification decisions through linear combinations of features to achieve this goal. The data point is represented by n, and the category is represented by y. The learning goal of the linear classifier is to find the classification hyperplane in the n-dimensional data space [19]. The equation can be expressed by (7):

$$\omega^T y + b = 0. \tag{8}$$

In a 2-dimensional plane, there are star-shaped points and circular points. The solid line in the middle separates these two points. This solid line is a classification hyperplane,
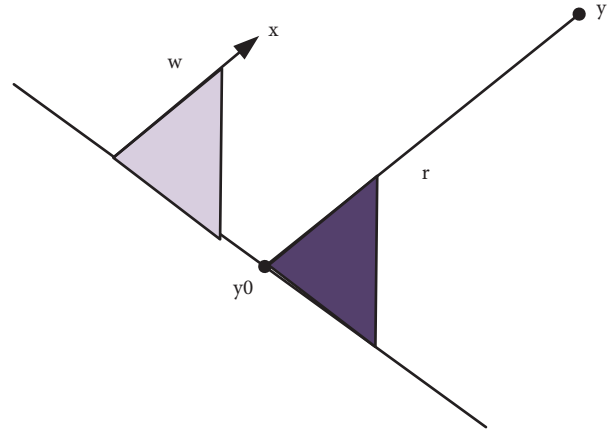
and the point on one side of the hyperplane is $x = -1$, the point $x = 1$ on the other side, as shown in Figure 4.

As shown in Figure 4, the hyperplane in the figure is close to the point of the hyperplane so that the distance can be extended [20]. Finding the maximum distance as follows:

$$f(y) = \omega^T y + b. \tag{9}$$

The distance from the "geometric interval" to the hyperplane is as follows:

$$\gamma = x \frac{\omega^T y + b}{\|\omega\|}$$
$$= x \frac{f(y)}{\|\omega\|}. \tag{10}$$

The "geometric distance" from Y to the classification hyperplane is shown in Figure 5.

As shown in Figure 5, the geometric distance γ is as follows:

$$\max \frac{1}{\|\omega\|},$$
$$\text{s.t}, x_i\left(\omega^T x_i + b\right) \geq 1, \, i = 1, 2, \ldots, n. \tag{11}$$

The above problem can be equivalently transformed into the following formula:

$$\max \frac{1}{2}\|\omega\|^2,$$
$$\text{s.t}, x_i\left(\omega^T x_i + b\right) \geq 1, \, i = 1, 2, \ldots, n. \tag{12}$$

By importing the Lagrangian multiplier and combining its constraints into the objective function, the following formula is obtained:

$$L(\omega, a, b) = \frac{1}{2}\|\omega\|^2 - \sum_i^n \alpha_i\left(\omega^T y + b\right). \tag{13}$$
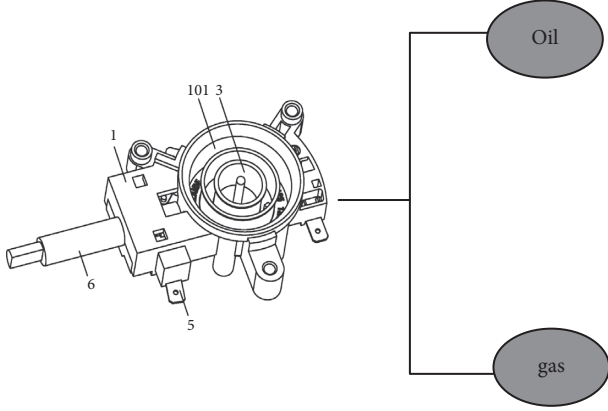
FIGURE 6: Oil and gas risk coupling model.

TABLE 1: Heavy oil classification table.

Classification	First indicator	Second indicator	Second indicator
Classification	Viscosity	Density	Severe
Heavy oil	200–10000	900–1200	10–23
Heavy oil	300–20000	700–1100	11–22

2.3. The Establishment and Algorithm of the Coupling Model. The coupling model is a collection of unit bodies, and each unit body is composed of some basic information, such as nodes, material names, and node coordinates. The grid can be generated in the form of a command stream [21]. The coupled model grid is formed by corresponding materials and some parameters, such as initial conditions and boundary conditions. Macroscopically, it is also a collection of unit bodies. The entire model is mainly composed of information such as the direction of the connection between adjacent centers and the area of adjacent surfaces [22].

As shown in Figure 6, the steps to establish a calculation model are as follows: First, split the finite difference grid. Then, select the appropriate composition model and material parameters. Finally, the initial conditions and boundary conditions of the model are set [23].

Regarding the two-phase flow of oil and gas in unsaturated soils, first, assume that the existing pores are filled with gas and oil. The equation for the flow of gas and liquid is shown in (11):

$$\frac{\partial\left[\varphi W_\beta \rho_\beta\right]}{\partial t} + \text{div}\left(V_\beta \rho_\beta\right) = 0. \tag{14}$$

In the formula, β represents oil, φ represents porosity, W_β represents saturation of β, and β represents the density of β. Therefore, the fluid phase velocity is as follows:

$$u_\beta = -k \frac{k_{rb}\left(S_1\right)}{\mu_\beta}\left(\Delta\rho_\beta - \rho_\beta g\right). \tag{15}$$

The permeability is as follows:

$$Y_Y = Y\left(1 + \frac{K_b}{\rho}\right). \tag{16}$$

Putting the flow velocity expressed by formula (16) in the mass balance equation of formula (15) can obtain the following formula:

$$\frac{\partial\left(\varphi s_\beta \rho_\beta\right)}{\partial_u} = \text{div}\left(\rho_\beta k \frac{k_{r\beta}}{\mu_\beta}\right). \tag{17}$$

With abundant oil and gas resources, oil and gas exploitation has become a top priority. At present, the total oil and gas resources are estimated to be approximately 21 billion tons. Depending on the nature of the high viscosity oil mixture, steam injection is generally used in heat recovery. A few years ago, this technology was applied to the development of heavy oil storage layers and achieved amazing results [24].

Under oil layer conditions, crude oil with a viscosity of more than 50 mpas and a relative density of not less than 0.9 is called heavy oil. The classification of heavy oil is shown in Table 1.

As shown in Table 1, the heat resistance of the first heavy oil reached 200–10000, and the second reached 300–20000. It can be known that the heat resistance of heavy oil is very high, and the viscosity of crude oil will drop drastically when the temperature rises. The higher the viscosity of crude oil, the greater the decrease. The relationship between them is as follows:

$$\mu = \partial e^{|(b/t)|}. \tag{18}$$

In the case of hot oil recovery, the volume expansion of water, oil, and the storage layer can provide electricity to discharge the oil. The expression of the oil thermal expansion coefficient is (15):

$$C_O = \frac{\mathrm{d}u_0}{u_o t}$$
$$= -\frac{\mathrm{d}\rho_0}{\rho_0 d\mathrm{t}}. \tag{19}$$

Under certain temperature conditions, the components of oil and gas are decomposed to produce light components such as coke, gas phase, and oil. If there are light ingredients, the oil displacement effect will be greatly improved. When the formation is above the bubble point temperature, the heavy components in the oil exist in the form of liquid, and the light components separate the liquid from the gas. In the presence of steam, the amount of separation of light components will greatly increase. It can burn heavy oil to transfer heat, increase the temperature of the oil layer, and improve the oil replacement effect.

$$-V^0 = 1.21\left(H\right) - 0.19\left(0 + N\right) + 0.34\left(C\right) + 0.15\left(S\right). \tag{20}$$

Among them, H represents the content of hydrogen elements. O represents the content of the oxygen element. N stands for nitrogen content. C stands for carbon element content. S stands for sulfur content.

At present, in important topics such as energy development, radioactive waste treatment, and foundation engineering, the combination of temperature field,

Year	Consumption	Percentage increase (%)
2011	3.5	12.7
2012	5.4	13.5
2013	6.7	13.8
2014	7.6	14.1
2015	9.7	14.6
2016	10.3	15.1

permeability field, and deformation field plays an important role. In the research process, the uncoupled model developed into a coupled model. The uncoupled model ignores the analysis of the interaction between energy propagation, fluid penetration, and deformation of porous media. The oil-gas coupling model is mainly used to study the interaction between the seepage field and the deformation field. On the contrary, the coupled model can more accurately study the risk of oil and gas, but in this coupled model theory, the change of the temperature field is not considered. In terms of actual coupling issues, the temperature of heavy oil storage and geothermal utilization systems in the oil and gas industry will continue to change.

3. Experiment and Analysis of the Questionnaire Survey

3.1. Overview of Oil and Gas Risks. The decision-making process of oil and gas exploration projects is a dynamic process. From the establishment of the project to the final completion of the detailed evaluation, a process is required. The established risk assessment model should have the ability to adapt to environmental changes, that is, adaptability. The principle of adaptability requires that the evaluation index system be dynamic.

Looking at the last century, the country's oil and gas industry was basically self-sufficient, with no external dependence, so there was no strategic reserve. However, with the development of the national economy, the consumption of oil and gas has increased, and the contradiction between supply and demand has gradually deepened. The country began to import oil and gas, and its dependence on foreign oil and gas has further increased.

3.2. Investigation and Analysis of Oil and Gas Demand and Supply. This article uses questionnaire survey method to investigate the oil and gas consumption in recent years, as shown in Table 2.

As shown in Table 2, the consumption of oil and gas has increased in recent years, from 350 million tons in 2011 to 1.03 billion tons in 2016, an increase of 680 million tons, and the percentage increase is 15.1%. It can be seen that the demand for oil and gas continues to expand, and the demand for oil and gas continues to rise. However, with the development of the national economy, the consumption of oil and gas has increased, and the contradiction between supply and demand has gradually deepened. The country began to

import oil and gas, and its dependence on foreign oil and gas has further increased.

This article then investigates the amount of oil and gas imports from 2011 to 2016, as shown in Table 3.

As shown in Table 3, the demand for oil and gas is much higher than the output of oil and gas, resulting in only oil and gas imports. The degree of dependence on foreign oil and gas has increased from 13.1% in 2011 to 30% in 2016. This means that beyond the current warning line, national oil and gas companies need to pay more attention to the country's energy security tasks, and "increasing income and reducing expenditure" has become a common understanding. Therefore, national oil and gas companies need to strengthen the "going out" strategy and strengthen open source work.

This paper investigates the trend of oil production in the two years from 2015 to 2016, as shown in Figure 7.

As shown in Figure 7, it can be seen that the lowest oil and gas output in 2015 was about 400 million tons, and the highest was 2 billion tons; in 2016, oil and gas production was at a minimum of about 1 billion tons and a maximum of 2.1 billion tons, and the overall increase. It can be seen that the output of oil and gas is increasing year by year. At present, the risk assessment of overseas exploration projects by oil and gas companies is in primitive qualitative and simple subjective phases. Therefore, it is necessary to study how to conduct risk assessment more scientifically and rationally to provide a basis for a better understanding of overseas oil and gas exploration risks, avoiding important risks in advance and project decision-making. In order to provide comprehensive and scientific decision-making for overseas exploration projects, it is necessary to use scientific methods. Taking risk assessment as the starting point, using scientific and mathematical methods to evaluate overseas exploration projects provides the accuracy of risk information, and reduce project risks.

This paper investigates the trend of oil and gas demand from 2015 to 2016, as shown in Figure 8.

As shown in Figure 8, it can be seen that the minimum demand for oil and gas in 2015 was 1 billion tons and the highest was 4.3 billion tons; the minimum demand for oil and gas in 2016 was 1.9 billion tons, and the highest was 4.3 billion tons, which is generally increasing. It can be seen that the demand for oil and gas is increasing year by year. And it is much higher than the output of oil and gas, which leads to the shortage of oil and gas.

3.3. Investigation and Analysis of Oil and Gas Risk Types. Although the existing methods that are suitable for carrying out oil and gas risk assessment can accurately assess the level of potential risks in the current oil and gas status, they are too professional. However, because overseas oil and gas pipeline companies are located in poor and backward countries and regions, the local employees recruited by overseas pipeline companies have limited education and lack professional technical support personnel. This leads to the fact that it is difficult for most of the employees on the enterprise site to participate in the actual risk assessment,

TABLE 3: Survey of oil and gas imports from 2011 to 2016.

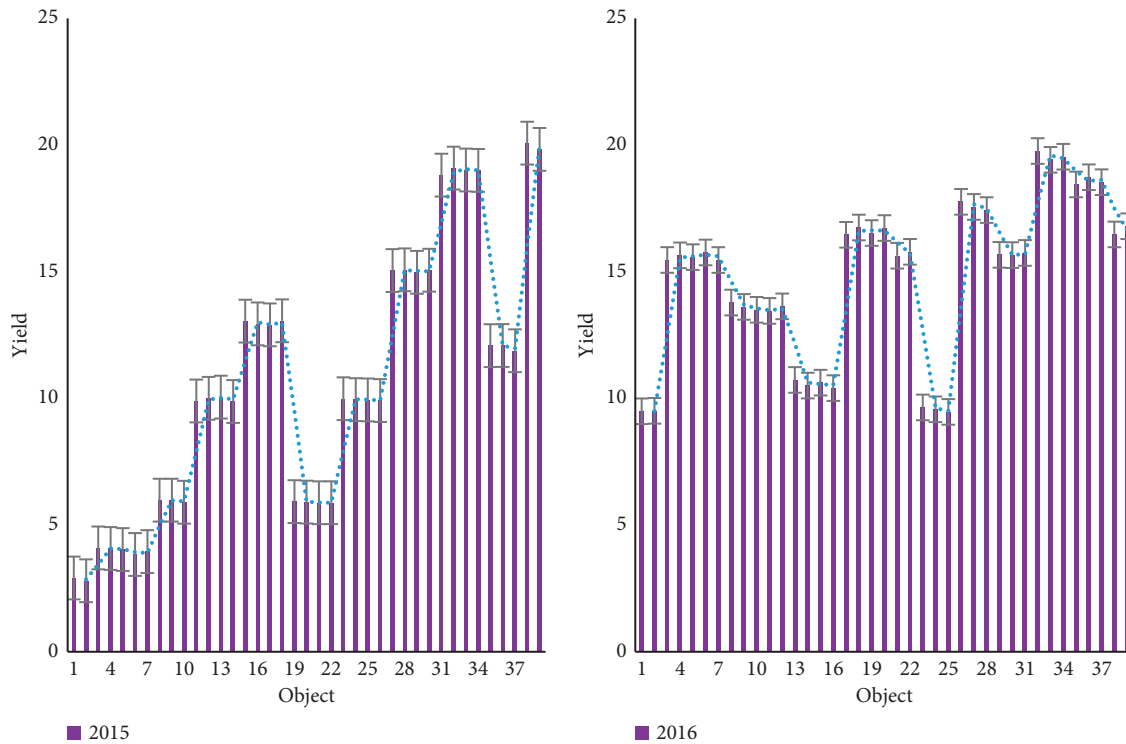| Year	Consumption	Import volume	Percentage increase (%)	External dependence (%)
2011	3.5	1.1	12.7	13.1
2012	5.4	1.4	13.5	13.6
2013	6.7	2.6	13.8	21.1
2014	7.6	5.4	14.1	23.3
2015	9.7	4.3	14.6	24.2
2016	10.3	6.3	15.1	30.0

FIGURE 7: Comparison chart of oil production trends from 2015 to 2016.

and most of them require professional and technical personnel to assist or execute.

This paper investigates the consumption of oil and gas from 2013 to 2014 and 2018 to 2019, as shown in Figure 9.

As shown in Figure 9, the consumption of oil and gas is on the rise every year. Driven by the rapid social and economic growth in 2013, the annual apparent consumption of oil and gas was 550 million tons, an increase of 13.3% over 2014. From 2017 to 2018, oil and gas consumption increased rapidly, with the lowest growth rate of 6% and the highest rate of 20%.

Therefore, to a certain extent, the "going out" strategy of oil and gas companies is an important direction for the country to use foreign resources and realize the country's sustainable development, and it is the internal demand for the country's sustainable development. Therefore, for the country's sustainable development, the country urgently needs the "going out" strategy of energy resources, encouraging national oil and gas companies to go abroad and develop international markets. National oil and gas companies must formulate corresponding internationalization

strategies, make full use of foreign oil and gas resources, optimize the allocation of corporate resources, and strive to improve their competitive position in the world. Extracting more oil and gas is currently the most important thing to do. However, there are many risks in the exploitation of oil and gas.

This article takes oil and natural gas exploration risk assessment as an example and adopts a new exploration risk assessment model to conduct a more comprehensive risk assessment of the project. Exploration risk mainly refers to geological risk assessment. This article focuses on geological risk assessment, combining economic risk, reserve risk, financial risk, technical risk, management risk, and geological risk to evaluate projects in this field. The basic attributes of oil and gas exploration risk assessment projects that determine the attributes of the comprehensive index as shown in Table 4.

As shown in Table 4, it can be seen that there is a lot of uncertain information in the process of risk assessment. Due to high information asymmetry, no objective data, and different risk preferences, traditional assessment methods
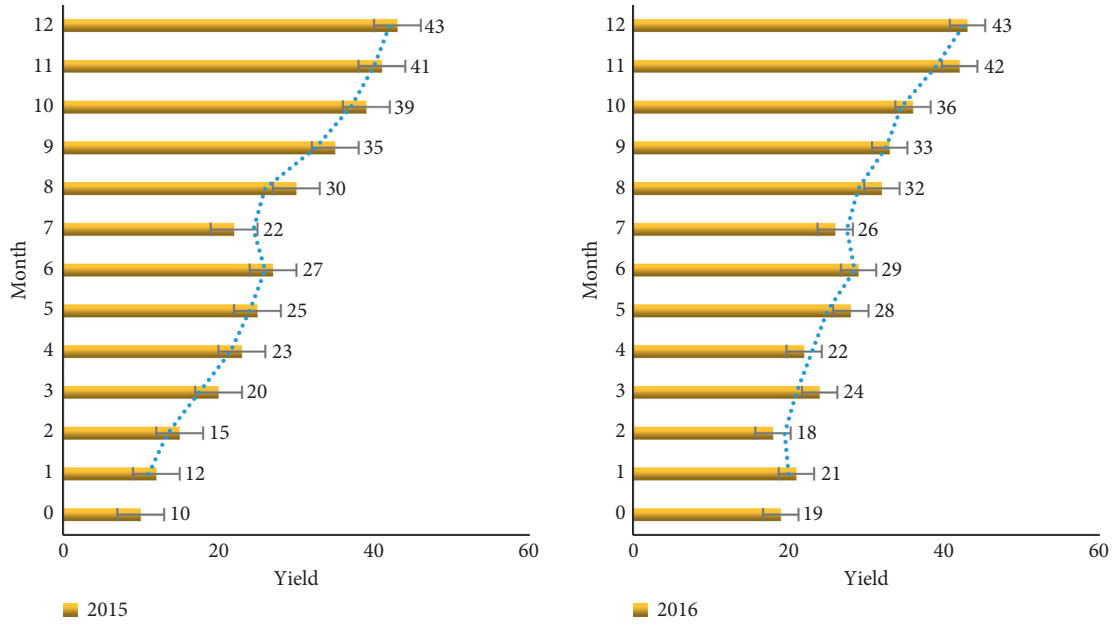
Figure 8: Comparison of trends in oil and gas demand for the two years from 2015 to 2016.
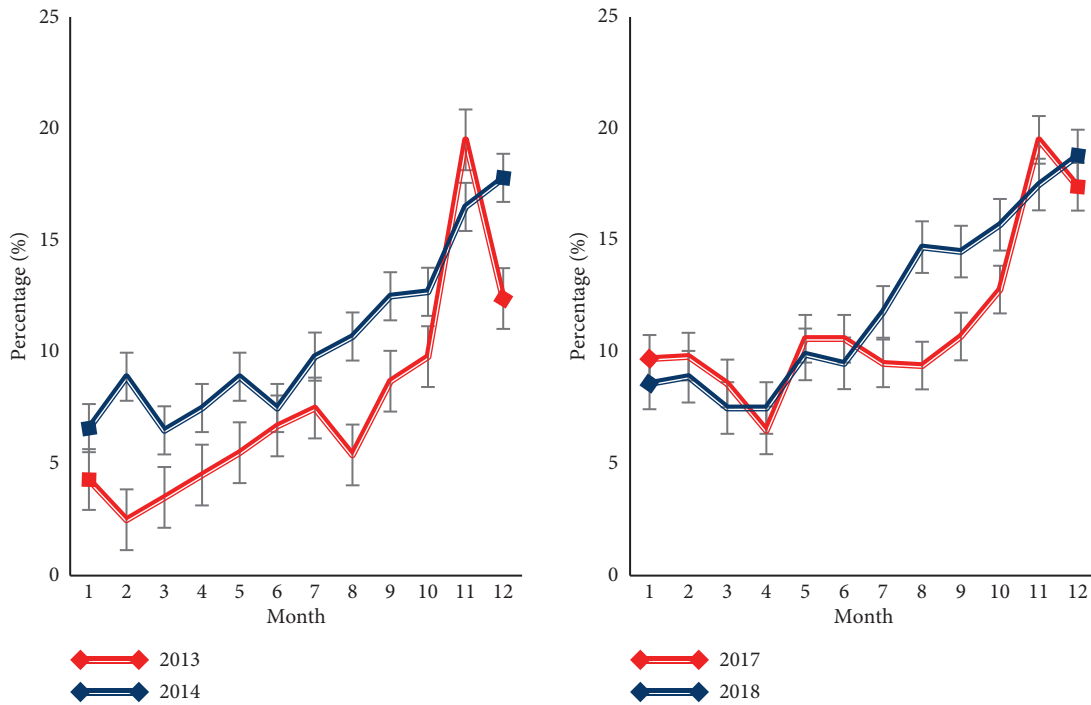

Figure 9: Consumption comparison chart between 2013-2014 and 2018-2019.

Table 4: Comprehensive index attribute oil and gas exploration risk evaluation table.

Plan	1 (%)	2	3	4 (%)	5 (%)	6 (%)	7 (%)
Reserve risk	16	10%	21%	12	9	12	5
Economic risk	23	26%	21%	19	18	11	16
Financial risk	23	16%	27%	31	32	29	25
Technology risk	6	8%	3%	10	5	9	7
Manage risk	2	4%	7%	5	2	3	5

are no longer suitable for today's complex oil and gas risk assessment. Therefore, when conducting risk assessment, we must adhere to the principle of combining subjectivity and objectiveness. The understanding of any complex system includes subjective and objective knowledge and comprehensively integrates subjective and objective knowledge. In the construction of the model, it not only uses the subjective knowledge of experts and scholars on risk issues to establish a subjective model but also integrates the characteristics of
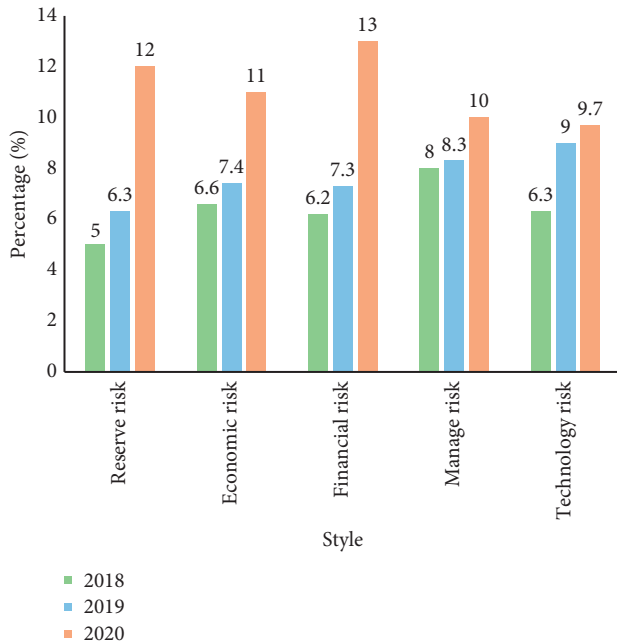
Figure 10: Diagram of the proportion of each risk from 2018 to 2020.

the thing itself to find a reasonable objective evaluation model, which is conducive to better evaluation of the research problem.

This paper investigates the proportion of each risk from 2018 to 2020, as shown in Figure 10.

As shown in Figure 10, the proportion of technological risks in each year from 2018 to 2020 is the highest, reaching 12% in 2018, so technological risks are the most important problem to be solved. This requires professionals to improve their professional knowledge and exercise their technical capabilities so as to achieve the purpose of reducing technical risks. Through professional knowledge and technical training for professionals, technical risks can also be reduced. Therefore, based on the analysis and summary of traditional risk assessment methods, the risk assessment model is applied to oil and natural gas exploration risk assessment and use powerful functions to reduce attributes, effectively solve the subjective problems of other optimization models, and use evidence theory to effectively realize the basic probability of attributes, and solve the difficult problems of most qualitative indicators in risk assessment. These two effective combinations will enrich and complete the model theory system of risk assessment and provide new ideas for risk assessment and scientific decision-making.

4. Discussion

This article explains the basic principles of distributed computing algorithms and introduces distributed computing algorithms in detail. At the same time, it also introduces the theoretical basis of neural networks and provides some commonly used methods. This paper draws lessons from the deficiencies and theoretically proves the convergence of the algorithm.

This article analyzed the research progress of oil and gas risks and coupled mathematical models, expounded the related concepts of oil and gas risks and coupled mathematical models, studied the related theories of oil and gas risk based on distributed computing and coupled mathematical models, explored methods based on distributed computing algorithms, and through the analysis of the questionnaire survey to discuss the importance of distributed computing algorithms to the construction of oil and gas risks and coupled mathematical models, and finally took the integration of distributed computing into the construction of coupled mathematical models as an example to explore the correlation between the two.

This article also makes reasonable use of distributed computing algorithms. With the increasing application scope of distributed computing algorithms and their importance gradually becoming more prominent, many scholars have begun to match certain specific fusion theories with real-life application scenarios and propose feasible algorithms. According to the algorithm, the analysis of oil and gas risks based on distributed computing is an essential part of constructing a mathematical model of oil and gas risk coupling.

5. Conclusions

This article mainly starts from distributed computing and oil and gas risk, discusses the relationship between the two, and how to integrate distributed computing into the construction of a mathematical model for oil and gas risk coupling. Based on distributed computing, we can know the importance of distributed computing in the construction of the oil and gas risk coupling mathematical model. Distributed computing is indispensable for the construction of an oil and gas risk coupling mathematical model. Do not blindly imitate and copy, based on distributed computing in the construction of oil and gas risk coupling mathematical model application research has always been a problem studied by many scholars. There is no good solution yet. Therefore, the author may still have many problems and shortcomings in the construction of the mathematical model of oil and gas risk coupling based on distributed computing in this article. However, the author has tried his best, and the author will continue to make progress through continuous learning.

Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding this work.

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