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Dynamic Evaluation of Drilling Leakage Risk Based On Fuzzy Theory and PSO-SVR Algorithm

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Abstract: In recent years, artificial intelligence has gradually penetrated into various fields, and has become a research hotspot. The modern industrial upgrades and transformation of the petroleum industry, makes it closer to the direction of intelligence. For the research of drilling risk evaluation, choosing the right evaluation model to achieve real-time risk dynamic evaluation which is important for risk judgement and response time. However, drilling system never considered as a complex system in the research of drilling risk assessment. When the sensor of the well site collects the relevant parameters, the remote monitoring system carries on the real-time data analysis, because of the instrument or transmission process, the drilling parameters appear fuzziness and randomness. To realize real time dynamic evaluation of drilling risk this paper proposed a fuzzy multilevel algorithm based on Particle swarm optimization (PSO) to optimize Support vector regression machine(SVR), and takes drilling leakage risk as an example. And two main objectives has been achieved. The first is to establish a fuzzy multi-level drilling leak risk evaluation system. The second is to use the PSO-SVR algorithm to study the risk evaluation results and realize the real-time dynamic risk evaluation. This paper first summarizes the characterization phenomena and laws of the occurrence of acquisition and loss parameters, and uses this as an indicator to establish a multi-level index system for risk assessment. Second, combined with fuzzy theory, a risk assessment model is established. And in final, the parameters C and g of the SVR model are optimized by using the SVR algorithm improved by PSO, which solves the problem that the parameters such as penalty factor c, kernel function k and sensitivity coefficient ε are difficult to select in the traditional *SVR* model, improves the accuracy of the model, and realizes more accurate real-time dynamic evaluation of risk. The algorithm proposed in this paper achieves two goals. Taking the XX oilfield as an engineering example, the results show that the accuracy of the PSO-SVR model can reach 99.99%, with high convergence degree, which is obviously higher than that of the multilayer perceptron neural network model.

Keywords: Leakage Risk; Artificial Intelligence; PSO-SVR; Fuzzy Multilevel; Dynamic Evaluation; Heuristic Algorithm

1. Introduction

1.1 Background

Drilling operation safety is a key technical issue in oil and gas exploration, and drilling engineering is full of challenges due to its professionalism, concealment and high investment characteristics [1，2]. As petroleum exploration continues to extend to deeper and more complex areas, the probability of drilling safety accidents due to increased uncertainty and complexity of geological conditions is increasing. In all drilling safety incidents, leakage is one of the biggest threats to drilling operations. The leakage may not only cause damage to drilling tools, large consumption of drilling fluids and plugging materials, unbalance of bottom holes pressure, but also the collapse of well walls and scrap of wellbores [3]. For instance, in 2010, serious blowouts occurred on the Deepwater Horizon drilling rig in the Gulf of Mexico [4，5]. The accident caused heavy casualties and serious oil spills and polluted the offshore environment. In order to avoid such catastrophic accidents, it is of great importance to predict and analyze the risks during drilling operations. In 2005, the tragedy happened at BP's Texas City Oil Refinery resulted in serious casualties and severe economic losses due to inaccurate technical judgment of the accident [6].In order to avoid such catastrophic accidents, it is especially important to extract the real-time monitoring data of the drilling based on data mining technology and analyze the risk early warning [7].In this process, the qualitative and quantitative analysis of the risk of loss is beneficial to the timely follow-up control of the risk [8]. It is important to ensure the possibility of accidents and to ensure continuous and safe operation of the drilling.

1.2 Research motivation

Alessandro et al. believe that a strong risk assessment procedure of offshore petroleum and natural gas operation is a major factor in assessing potential feedback between planned activities and the environment [9]. But it failed to consider that drilling engineering is a complex system and ignore the characteristics of the input sensor's parameters collected with ambiguity and uncertainty. If the risk of leakage occurs during the actual drilling process, the driller should be responsible for taking countermeasures to control risk. Therefore the response time of the drillers and correct judgment of the accident are crucial. Lagging, erroneous, and inaccurate judgments not only affect the safety of operations but also the loss of life and property. Therefore, the main purpose of this paper is to propose a real-time dynamic risk assessment, and use the PSO heuristic algorithm to optimize the SVR model. It can achieve an accurate and rapid assessment of the risk of drilling leakage, which can improve the response time of the on-site drillers and the judgment rate of risks, avoid false positives and missed judgments, and lead to continuous expansion of risks, and finally become serious accidents. This paper proposes a solution for the application of leakage risk assessment, which can effectively and accurately evaluate the risk in real-time. It can effectively and accurately evaluate the risk in real time. The proposed solution is based on fuzzy multi-level analysis method. The PSO heuristic algorithm is used to optimize the SVR model parameters c and g. It solves the shortcomings of traditional SVR for difficult parameter selection and realizes the mapping relationship between missing parameters and risk, and form a "black box" model. Finally, the established model has been applied to the XX oilfield and compared with the multilayer perceptron neural network model to verify the feasibility of the proposed scheme.

1.3 Main contributions

Three main contributions of the present paper are as follows:

(1) The influencing factors of the risk of leakage have summarized, and the fuzzy multi-level evaluation method can used to establish the evaluation model of the risk of loss and realize the safety evaluation of risk.

(2) This paper collects 50 sets of data from XX oilfield for machine training. The PSO-SVR machine learning algorithm has used to mine the mapping relationship between the missing risk data and the risk of drilling loss, and real-time dynamic security evaluation of risk is realized.

(3) Two different machine learning algorithms are used to study the model accuracy of dynamic security evaluation, and the analysis and comparison of the results of different methods has been completed, resulting the PSO-SVR machine learning algorithm proposed in this paper has been more convincing.

The section 2 defines the structure of this paper and the related work. The section 3 explains a fuzzy multi-level evaluation model for risk of leakage. The section 4 establishes the loss risk model of the PSO-SVR algorithm. The section 5 simulates the results. The section 6 summarizes the full text.

2. Related work

2.1 Introduction to risk assessment

Research data shows that there are many methods for risk assessment. Muhammad Zubair presents a computer based living probabilistic safety assessment (LPSA) method named as online risk monitor system (ORMS)，The essential features and functions of ORMS have been described[10]. J.Wang et al. proposed Fault-tree-based instantaneous risk computing core in nuclear power plant risk monitor [10], and many other risk assessment methods [11,12].

The drilling risk assessment mainly includes the following studies. Wu S, Zhang L et al. proposed a method based on risk dynamics, Dynamic Bayes theory (DBN) by taking into account the real-time information of changing model parameters for prediction and diagnosis of dynamic risk [13]. Abimbola et al. proposed a real-time predictive model which was on the basis of Bow-tie and real-time obstacle failure probabilities and switch obstacle failure probability for dynamic risk evaluation of drilling operations. And its method can be transferred to real-time risk monitoring equipment on the sites [14]. Zhang L et al. pointed out a dynamic Bayesian networks (DBNs) to analyze the situation of a managed accidental accident (MPD) safety accident and perform a dynamic quantitative risk evaluation. Probability parameters are added to study on effects of uncertain risk factors [15]. Siotani M et al. first used bow-tie models to draw safety challenges and operating pressure conditions of shaft bottom pressure drilling technology. Then the model was mapped to the Bayesian network to evaluate key factors of constant shaft bottom pressure and safety operating pressure conditions [16]. Meng X presented an integrated method of Dynamic Quantitative Risk Assessment (DQRA)—using the Decision Making Trial and Evaluation Laboratory (DEMATEL)-Bayesian Network (BN)—for evaluation of the system vulnerabilities and prediction of the occurrence probabilities of accidents induced by leakage[17], and other petroleum industry quantitative risk assessments [18~22].

2.2 Fuzzy –AHP (Analytic Hierarchy Process)

The following is the application of Fuzzy-AHP. R Mosadeghi et al used two quantitative techniques (analytic hierarchy process and fuzzy analytic hierarchy process) to compare urban spatial use comparison planning spatial multi-decision models [23]. HR Wang et al. proposed a risk assessment method that based on Fuzzy-AHP model, and established the LNG station risk assessment method [24]. K Bian proposed a method of Fuzzy-AHP to select optimal dry ports construction projects, which provides scientific reference on the reasonable distribution of dry ports, saves cost of logistics and ports construction, avoids reduplicate port construction [25]. JK Hamidi et al. discussed the use of a fuzzy analytical hierarchy process as an efficient means of decision making. It is applied to rock TBM risk assessment under adverse geological conditions [26].

2.3 Algorithm introduction

Support Vector Regression (SVR) is gaining popularity in regression and classification due to its excellent generalization performance. The SVR method has been successfully applied to several different applications, such as face recognition, object detection, handwriting recognition, text detection, speech recognition and prediction, etc. [27]. When SVR optimizes the mapping relationship of the "black box" model, the optimization formula implicitly matches the appropriate structure with some complexity to the available small size samples. Therefore, its generalization ability is strong, and the dimension independent of the problem is realized to control this type of structure, which makes it superior to the traditional machine learning technology. In regression applications, to extend to nonlinear regression, the SVR kernel function has been used to project the input space into the feature space, producing a linear or nearly linear regression hypersurface in the feature space. Therefore, the selection of the SVR penalty parameter c and the kernel function parameter g has an important influence on the SVR regression performance.

For all heuristic algorithms [28~30]，genetic algorithm has strong local search ability[31], but there are disadvantages such as non-standard coding and premature solvent convergence. Artificial bee colony algorithm and ant colony algorithm are characterized by slow convergence rate and local optimum [32~34]. The PSO algorithm is simpler compared with rules of the genetic algorithm [35]. Therefore, in this article, the Particle Swarm Optimization (PSO) method is used to optimize the SVR model. Through the machine learning to construct the mapping relationship between the missing impact factor and the missed risk, the dynamic evaluation of the risk of drilling loss is realized. In the subsequent chapters, the XX oilfield specific data was applied to study the results, and the validity and accuracy of the PSO-SVR model are verified.

3. Establishment of Risk Assessment Model for Leakage Based on Fuzzy Multi-Level Evaluation Method

3.1 Evaluation index parameter selection

Monitoring data often vary with the occurrence of the risk of leakage, therefore, it is of great significance to select appropriate monitoring parameters and carry out feature extraction and early warning analysis of monitoring parameters based on data mining technology in order to realize timely and accurate early warning of leakage risk [36].

- Standpipe pressure and casing pressure: Standpipe pressure is generated by mud entering the riser through a mud pump, it reflects the pressure loss of drilling fluid in drill string, bit water hole and annulus, which is approximately equal to circulating pump pressure; casing pressure can reflect the annulus condition in the wellbore, and if the risk occurs, the casing pressure may change accordingly.
- Flow of entrance and exit: Flow of entrance and exit can directly reflect the leakage, wellbore and other accidents. When leakage occurs, the drilling fluid in the wellbore flows into the formation and the mud return rate is obviously smaller than the entrance flow rate. The entrance flow rate affects the flow velocity of drilling fluid and ultimately the bottom hole pressure balance.
- Density of entrance and exit: The density of the drilling fluid can reflect the solid particle content of the drilling fluid, which may affect the hydrostatic column pressure of the drilling fluid and then the bottom hole pressure.
- Temperature of entrance and exit: During the normal drilling operation, when the bit meets the deep formation, the formation temperature and pressure are higher. Under this environment, the rheology and density of drilling fluid may be affected, and the bottom hole pressure system might be unbalanced.
- Rotational speed: While drilling, if the rotational speed is too fast, it may lead to the increase of annulus cuttings concentration and the increase of cycle equivalent density, which might affect the bottom holes pressure.

3.2 Leakage risk evaluation multilevel index system

Combined with affecting factors causing leakage and its phenomena, a multi-level indicator system for risk evaluation of well leakage is established, which is shown in Fig.1.

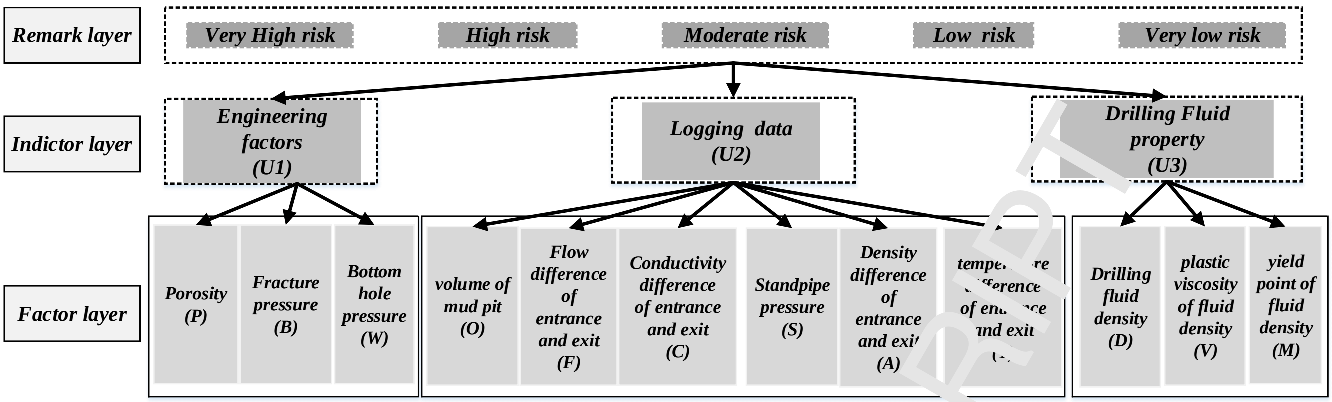


Fig.1. Leakage risk assessment multi-level indicator system diagram.

3.3 Determination of leakage risk fuzzy membership function

According to the relevant industry standards, expert experience and above-mentioned evaluation index system, historical sample data of the XX Oilfield XX well is applied to establish a membership function table for various factors of the XX well in the XX Oilfield. As shown in Table 1.

Table 1 Membership function

indicators		*quantization method*
Engineering factors (U1)	*porosity (P)*	$\varphi_1(x) = \begin{cases} 0.1\,; & 0.00 \le x < 0.05 \\ 0.3\,; & 0.05 \le x < 0.10 \\ 0.5\,; & 0.10 \le x < 0.15 \\ 0.7\,; & 0.15 \le x < 0.20 \\ 0.9\,; & 0.20 \le x < 0.25 \\ 1\,; & 0.25 \le x \end{cases}$
	Fracture pressure (B)	$\varphi_2(x) = \begin{cases} 0.7; & 16.00 \le x < 16.15 \\ 0.5\,; & 16.15 \le x < 16.30 \\ 0.3\,; & 16.30 \le x < 16.45 \\ 0.2\,; & 16.45 \le x < 16.50 \\ 0.1\,; & 16.50 \le x \end{cases}$
	Bottom hole pressure (W)	$\varphi_3(x) = \begin{cases} 0.3\,; & 28 \le x < 30 \\ 0.5\,; & 30 \le x < 32 \\ 0.8\,; & 32 \le x < 34 \\ 0.9\,; & 34 \le x \end{cases}$
Logging data (U2)	*volume of mud pit (O)*	$\varphi_7(x) = \begin{cases} 0.7\,; & x \le 80 \\ 0.5\,; & 80 \le x < 85 \\ 0.3\,; & 85 \le x < 90 \\ 0.1\,; & 90 \le x \end{cases}$
	Flow difference of entrance and exit (F)	$\varphi_8(x) \begin{cases} 0.9\,; & x < 0 \\ 0.3\,; & x = 0 \\ 0.1\,; & x > 0 \end{cases}$

	Conductivity difference of entrance and exit (C)	$\varphi_9(x)=\begin{cases}0.1\,;\ x<0.2\\0.3\,;\ 0.20\le x<0.4\\0.5\,;\ 0.40\le x<0.6\\0.7\,;\ 0.60\le x<0.8\\0.9\,;\ 0.8\le x<1.0\end{cases}$
	Standpipe pressure (S)	$\varphi_{10}(x)=\begin{cases}0.9\,;\ 10\le x<12\\0.7\,;\ 12\le x<14\\0.5\,;\ 14\le x<16\\0.3\,;\ 16\le x<18\\0.1\,;\ 18\le x<20\end{cases}$
	Density difference of entrance and exit (A)	$\varphi_{11}(x)=\begin{cases}0.3\,;\ -0.05\le x<0.00\\0.5\,;\ 0.00\le x<0.05\\0.7\,;\ 0.05\le x<0.10\end{cases}$
	temperature difference of entrance and exit (T)	$\varphi_{12}(x)=\begin{cases}0.3\,;0.0\le x<2.0\\0.5\,;2.0\le x<4.0\\0.7\,;\ 4.0\le x<6.0\end{cases}$
Drilling Fluid property (U3)	***Drilling fluid density (D)***	$\varphi_4(x)=\begin{cases}0.3\,;\ 1\le x<1.1\\0.5\,;\ 1.1\le x<1.2\\0.7\,;\ 1.2\le x<1.3\\0.9\ ;\ 1.3\le x\end{cases}$
	plastic viscosity of fluid density (V)	$\varphi_5(x)=\begin{cases}0.1\,;\ 10\le x<12\\0.2;\ 12\le x<14\\0.3\,;\ 14\le x<16\\0.5\ ;\ 16\le x\end{cases}$
	yield point of fluid density (Y)	$\varphi_6(x)=\begin{cases}0.1\,;\ 0\le x<5\\0.2\,;5\le x<10\\0.3\,;\ 10\le x<15\\0.5\ ;\ 15\le x\end{cases}$

3.4 Comprehensive factor evaluation set for leakage and establishment of weight matrix

According to the hierarchical structure of multilevel index system for risk evaluation of well leakage, judgment matrix can be constructed. Degree of importance is assigned according to the 1-9 scale method. According to expert opinion, a V-U judgement matrix is set up. As shown in Table 2.

Table 2 Judgement matrix

V	U1	U2	U3
U1	1	3	5
U2	1/3	1	3
U3	1/5	1/3	1

In order to attain the relative weights of each factor under each indicator level of leakage risk, in this paper, the author uses the root-finding method to solve the nth root of the product of each row of the judgment matrix:

$$\overrightarrow{\omega_i} = \sqrt[n]{\prod_{j=1}^{n} \alpha_{ij}}\,(i = 1,2,3,\cdots,n) \tag{1}$$

$\overline{\omega_i}$ is normalized to acquire:

$$\omega_i = \overrightarrow{\omega_i} / \sum_{i=1}^{n} \omega_i \tag{2}$$

That is, $\overrightarrow{\omega} = (\omega_1, \omega_2, \omega_3, \cdots, \omega_{n-1}, \omega_n)^T$ is the approximate value of eigenvector of judgement matrix A

Find the largest eigenvalue corresponding to eigenvector:

$$\lambda_{max} = \frac{1}{n} \sum_i \left(\frac{(A\overrightarrow{\omega})_i}{\omega_i} \right) \tag{3}$$

The random consistency indicator can be obtained by referring to Table 3.

Table 3 RI Table of Random Consistency Indicators

Matrix order	1	2	3	4	5	6	7	8
RI	0	0	0.52	0.89	1.12	1.26	1.36	1.41
Matrix order	9	10	11	12	13	14	15	···
RI	1.46	1.49	1.52	1.54	1.56	1.58	1.59	···

Table 4 Fuzzy evaluation table

<table>
<tr><th>Symbol</th><th>Symbol</th><th>Weight</th><th>λ_{max}</th><th>CR = CI/RI</th><th>Consistency check</th><th>Symbol</th><th>Weight</th><th>λ_{max}</th><th>CR = CI/RI</th><th>Consistency check</th></tr>
<tr><td rowspan="12">V</td><td rowspan="3">U1</td><td rowspan="3">0.6370</td><td rowspan="12">3.039</td><td rowspan="12">0.033</td><td rowspan="12">0.033<0.1 (Yes)</td><td>W</td><td>0.735</td><td rowspan="3">3.065</td><td rowspan="3">0.0559</td><td rowspan="3">0.056<0.1 (Yes)</td></tr>
<tr><td>B</td><td>0.188</td></tr>
<tr><td>P</td><td>0.081</td></tr>
<tr><td rowspan="6">U2</td><td rowspan="6">0.1047</td><td>O</td><td>0.211</td><td rowspan="6">6.547</td><td rowspan="6">0.0868</td><td rowspan="6">0.087<0.1 (Yes)</td></tr>
<tr><td>F</td><td>0.516</td></tr>
<tr><td>C</td><td>0.045</td></tr>
<tr><td>S</td><td>0.127</td></tr>
<tr><td>A</td><td>0.075</td></tr>
<tr><td>T</td><td>0.027</td></tr>
<tr><td rowspan="3">U3</td><td rowspan="3">0.2583</td><td>D</td><td>0.582</td><td rowspan="3">3.004</td><td rowspan="3">0.0032</td><td rowspan="3">0.003<0.1 (Yes)</td></tr>
<tr><td>V</td><td>0.309</td></tr>
<tr><td>M</td><td>0.109</td></tr>
</table>

Relative weights of risk factors comment layer in the leakage risk factor layer is calculated. This paper applies layer-by-layer calculation to perform hierarchical total order, and consistency check for the total order results.

Assume that the weight of n elements of $k-1$ layer relative to the comment layer is listed as follows:

$$\omega^{(k-1)} = (\omega_1^{(k-1)}, \omega_2^{(k-1)}, L, \omega_n^{(k-1)})^T \tag{4}$$

The relative weight vector of n elements of k layer to each element of k − 1layer is as follows:

$$p^{(k)} = (p_1^k, p_2^k, L, p_n^k)^T \tag{5}$$

A composite weight expression formula can be attained:

$$\overrightarrow{\omega^{(k)}} = \overrightarrow{p^{(k)}}\overrightarrow{p^{(k-1)}} \cdots \overrightarrow{\omega^{(2)}} \tag{6}$$

3.5 Leakage risk evaluation model based on fuzzy multi-level evaluation method [37,38].

A leakage risk evaluation model is established according to risk factors of leakage. The membership function of each index is $\Phi_i(x)$, the lowest level index corresponds to the highest level weight $\omega_i(x)$, so the system's risk evaluation model is:

$$\mathrm{P} = \sum_{i=1}^{12} \varphi_i(x)\,\omega_i(x) \tag{7}$$

In light of formula above, the final value of risk evaluation of well leakage can be obtained. Based on the calculated value, expected probability value for occurrence of leakage can be determined.

4. Dynamic evaluation of leakage risk based on PSO-SVR algorithm

As shown in Fig.2, this paper proposes a loss risk model based on PSO-SVR algorithm. Firstly, the fuzzy-AHP method is used to obtain the historical data of drilling risk assessment. Then the PSO optimized SVR algorithm is trained through the risk evaluation historical data to obtain the optimal missing risk data mining model. Finally, the optimal model and real-time logging data are used to realize the real-time dynamic evaluation of leakage risk.

4.1 Introduction to SVR model

Support Vector Machines (SVM) is a kind of algorithm in machine learning. It is based on statistical learning theory and statistical learning theory VC. Support vector machines include two sides: one is Support Vector Classification (SVC), which is mainly used to solve classification problems; the other is SVR (Support Vector Regression), which is mainly used for prediction. In this paper, SVR is used to intelligently predict the risk of leakage. The idea is to find an optimal classification surface so as to minimize the error of the missed training sample set from the optimal classification surface. Set the given sample data as follow:

$$\mathrm{T} = \{(x_1, y_1), \ldots, (x_n, \mathrm{n})\}, \mathrm{i} = 1,2, \ldots, \mathrm{n}, \ldots.$$

$x_i \in X = R^n$— input vector, $y_i \in Y = R$— output vector.

Finding a function $f(x)$ on R^n, using $f(x)$ to infer the value of the output y corresponding to any x, is a regression problem.

Assume that the linear regression function for $f(x)$ established in the high-dimensional feature space is shown in (8):

$$f(x) = w * \Phi(x) + b \tag{8}$$

where $\Phi(x)$ denotes a nonlinear mapping function.

Defining ε linear insensitive loss function:

$$L(f(x), y, \varepsilon) = \begin{cases} 0, & |y - f(x)| \leq \varepsilon \\ |y - f(x) - \varepsilon|, & |y - f(x)| > \varepsilon \end{cases} \quad (9)$$

The slack variables ξ_i and ξ_i^* are introduced, and the problem of finding w, b is expressed mathematically:

$$\begin{cases} \min \frac{1}{2}||w||^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) \\ s.t \begin{cases} y_i - w * \Phi(x_i) - b \leq \varepsilon + \xi_i \\ -y_i + w * \Phi(x_i) + b \leq \varepsilon + \xi_i^* \\ \xi_i \geq 0, \quad \xi_i^*, 0 \end{cases} \end{cases} \quad i = 1,2,\ldots,n \quad (10)$$

If the penalty factor is larger, it is proved that the training error is large and the sample penalty of ε is larger; if ε is smaller, the error of the regression function is smaller.

Introduce Lagrange function, convert to dual form, as follows:

$$\begin{cases} \max[-\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}(\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*)K(x_i, x_j) - \sum_{i=1}^{n}(\alpha_i + \alpha_i^*)\varepsilon + \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)y_i] \\ s.t \begin{cases} \sum_{i=1}^{n}(\alpha_i - \alpha_i^*) = 0 \\ 0 \leq \alpha_i \leq C \\ 0 \leq \alpha_i^* \leq C \end{cases} \end{cases} \quad (11)$$

$K(x_i, x_j) = \Phi(x_i)\Phi(x_j)$— Kernel function.

Assume that the optimal solution of (12) is $\alpha = [\alpha_1, \alpha_2, \ldots \alpha_n]$,$[\alpha_1^*, \alpha_2^*, \ldots, \alpha_n^*]$, and then:

$$w^* = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*) * \Phi(x) \quad (12)$$

$$b^* = \frac{1}{N}\left\{\sum_{0<\alpha_i<C}\left[y_i - \sum(\alpha_i - \alpha_i^*)K(x_i, x_j) - \varepsilon\right] + [y_i - \sum(\alpha_i - \alpha_i^*)K(x_i, x_j) + \varepsilon]\right. \quad (13)$$

The regression function is as follows:

$$f(x) = w^*\Phi(x) + b^* = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)\Phi(x_i) + b = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)K(x_i, x_j) + b \quad (14)$$

SVR structure is as shown below Fig.2.

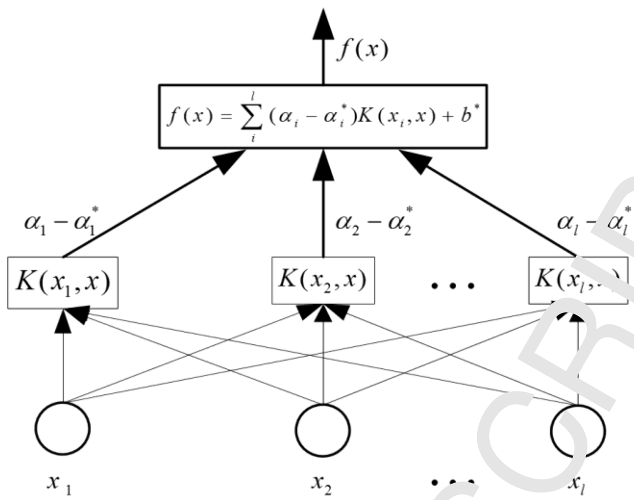


Fig.2. SVR structure.

4.2 Data processing

This paper selects the parameters that can best reflect the leakage during the drilling as input for SVR. Output item y is leakage value. As shown in Table 5.

Table 5 Input and output item establishment

Input parameter	Logging data	Unit
X1	Inlet and outlet flow difference	L/s
X2	Inlet and outlet density difference	kg/m^3
X3	Standpipe pressure	MPa
X4	Mud pool volume	m3
X5	Inlet and outlet temperature difference	$^{\circ}C$
X6	Inlet and outlet conductivity difference	S/m
X7	Drilling fluid density	kg/m^3
X8	Drilling fluid Plastic viscosity	MPa. s
X9	Drilling fluid dynamic shear force	Pa
X10	Downhole pressure	MPa
X11	Pore pressure	MPa
X12	Porosity	MPa

In the risk prediction process for drilling loss, since each input item has a different physical meaning and different dimensions, if the data is directly processed with the original data, the data error may be greatly increased during calculation. Therefore, it is necessary to perform data preprocessing on the collected data. Through a certain scale transformation, the input amount of the network is changed within the range of [0,1] or [-1,1] so that each input parameter has the same state. In order to make the prediction model have faster training speed, better performance, and accurate analysis results, this paper uses a linear normalization method to process the leakage risk data, making the data between [0,1]. The method is as follows:

$$\overline{x_i} = \frac{x_i - x_{min}}{x_{max} - x_{min}} \quad (15)$$

x_i — Initial sample data, $\overline{x_i}$ — Normalized data, x_{min} — the minimum value of the initial sample data, x_{max} — the maximum value of the initial sample data.

4.3 Design of Data Mining Model for PSO-SVR Missing Risk

Particle swarm optimization (PSO) is a nature-inspired optimization algorithm. Because PSO has few parameters [39], and only for particle position and speed the operation is simple, and easy to carry out mathematical analysis and draw out other advantages. It has been widely used in most modern scientific and engineering optimization problems to help and solve the problem of rapid convergence and global solutions. PSO is inspired by common social behaviors present on different groups of animals such as birds' flock. At present, the commonly used PSO algorithm is with inertia weights. We can look the iterative formula of velocity from the perspective of sociology. The first part shows the influence of the current velocity of the particle, indicating the inertia of the particle to the current motion state. The parameter ω shows the inertia weight. The second part depends on the distance between the current position of the particle and its optimal position as the "cognitive" part, indicating that the particle's motion is derived from the particle's own memory. The third part depends on the distance between the current position of the particle and the optimal position of the group, which is the "social" part, indicating the influence between the particle groups. So the parameter c2 is called the social learning factor. During each iteration, the particle group's velocity formula has updated to:

$$v_{ij}(t+1) = \omega v_{ij}(t) + c_1 r_{1j}(t)\left(p_{ij} - x_{ij}(t)\right) + c_2 r_{2j}(t)\left(p_{gi} - x_{ij}(t)\right) \quad (16)$$

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \quad (17)$$

Where t is the current iteration of the algorithm; $x_{ij}(t)$ is the current position of P_{ij};$v_{ij}(t+1)$ is velocity vector that applied to P_{ij} at time t;c_1 and c_2 are random values that represent the exploration and diversity component of the algorithm, c_1 is a cognitive learning factor, c_2 is a social learning factor. They usually follow a uniform distribution within the range [0, 1]; $P_{ij}(t)$is the local best of particle;$P_{gi}(t)$ is the global best of particle.

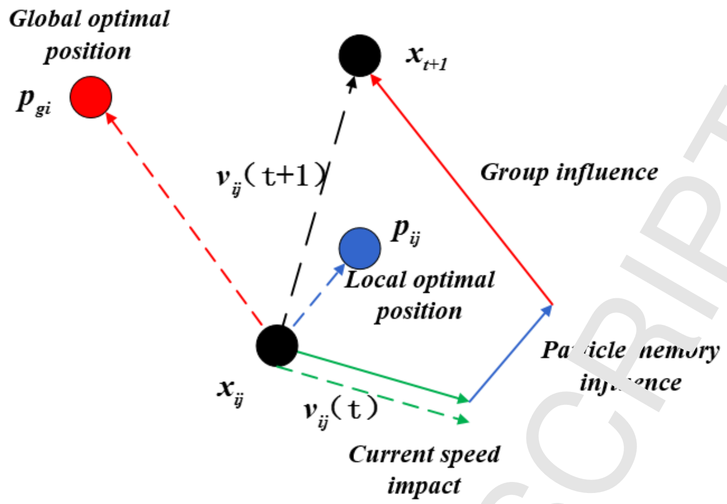


Fig.3. Particle update process.

As acquisition of measurement data for predicting leakage risk has features of complexity and diversity, application for a single feature extraction method to analyze the risk of drilling leakage is not very timely and accurate. Therefore, it is necessary to find a suitable method to evaluate leakage risk effectively and dynamically. At present, there have been many methods for dynamic evaluation of drilling risk, such as the neural network method [40]. However, this method has the disadvantages such as being vulnerable to local optimization, poor model generalization. The expert system [41] combines various characterization phenomena and rules of risk caused by drilling accidents with expert knowledge and experience. Once there might be a risk involved in the process of safe drilling, the system may find out types and causes of risks, in accordance with the experts problem solving thinking. However, the method is strongly subjective. The method [42] for fault tree analysis requires statistical analysis for much drilling history data to determine the probability of all basic time, which ensures the accuracy of results of risk analysis. The analysis method is greatly affected by probability statistics. Considering that the SVR model can well solve problems of small sample learning and nonlinear, high-latitude pattern recognition of drilling acquisition data, the author uses SVR model to learn risk data.

However, this model meets some difficulty when selecting parameters of penalty function, kernel function, and sensitivity coefficient. And the biggest advantage of PSO is that it does not need to make adjustments to the parameters, it has a faster convergence speed, and the operation is simple. Therefore, this paper combines PSO and SVR to complement each other to form a dynamic evaluation model of PSO-SVR.

Finally, optimized SVR model is used for risk data in the drilling process, and a corresponding dynamic evaluation model of leakage risk is acquired. PSO algorithm parameter update process is shown in Fig.4. The dynamic risk assessment process based on PSO optimized SVR is shown in Fig.5 below.

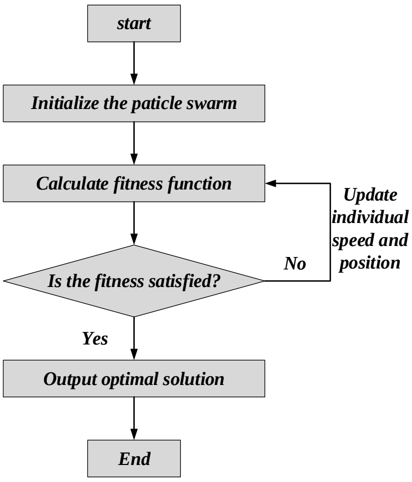


Fig.4. PSO algorithm parameter update process.

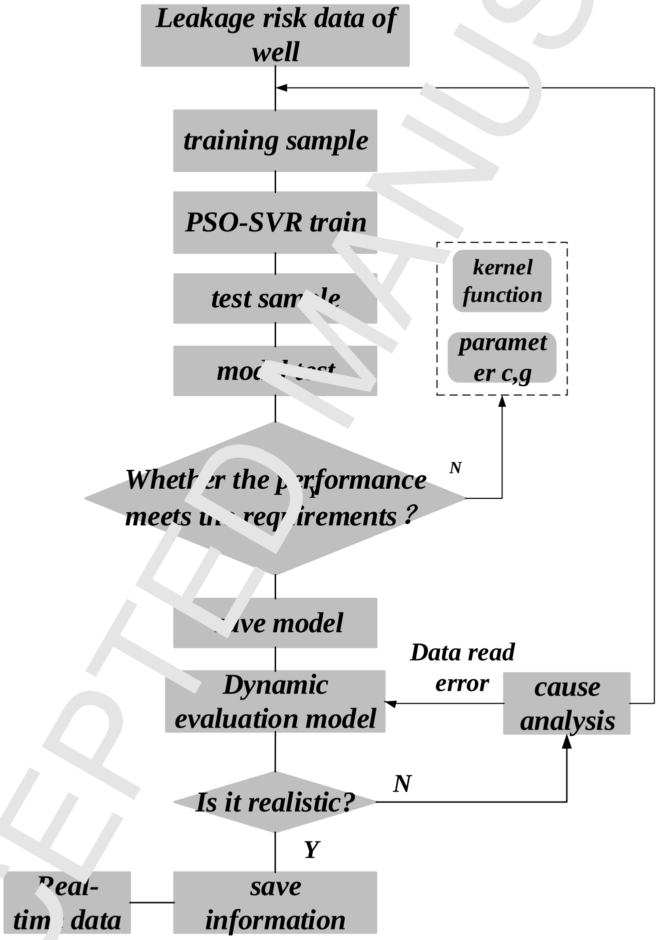


Fig.5.Dynamic Risk Assessment Process Based on PSO Optimized SVR.

First, the PSO-SVR is trained by using the sample factors selected from the data of the neighbouring wells in the same block. Optimal parameters c and g are achieved by making use of optimization seeking characteristics of the PSO. The achieved effect has been served as model preservation based on the fact whether the generated model achieves expected effect. It means to realize the mapping relationship between risk factors and risk values. Second, the input constiting real-time data is fed into the preservation model to realize the dynamic evaluation of leakage risk in the block drilling.

5. Analysis of case results

5.1 leakage risk probability result analysis

In this paper, the data of XX oilfield is used, and the fuzzy multi-level leakage risk assessment model established in Section 3 is used to obtain the fuzzy evaluation result of leakage risk. The results are shown in Table 6 below. The risk value of the evaluation result is taken as the abscissa, and the depth of the corresponding part is taken as the ordinate to obtain the result shown in fig.5.

Table 6 Sample Leakage of Wells Risk Values

Well depth (m)	P	B	W	O	S	A	…	D	M	V	Risk value
2501	0.5	0.5	0.5	0.3	0.1	0.5		0.5	0.2	0.3	0.486
2502	0.5	0.5	0.5	0.3	0.1	0.5		0.5	0.2	0.3	0.454
2503	0.5	0.5	0.5	0.5	0.1	0.5	…	0.5	0.2	0.3	0.459
2504	0.5	0.5	0.3	0.5	0.1	0.5	…	0.5	0.2	0.3	0.365
2505	0.5	0.5	0.5	0.5	0.1	0.5		0.5	0.2	0.3	0.459
					.						
2546	0.7	0.3	0.8	0.3	0.5	0.3		0.5	0.2	0.3	0.584
2547	0.7	0.3	0.8	0.3	0.7	0.5		0.5	0.2	0.3	0.621
2548	0.7	0.3	0.5	0.3	0.5	0.5	…	0.5	0.2	0.3	0.435
2549	0.7	0.3	0.5	0.3	0.7	0.5	…	0.5	0.2	0.3	0.4813
2550	0.7	0.3	0.5	0.3	0.7	0.5		0.5	0.2	0.3	0.448

The original input data in Fig.6 is derived from the fuzzy risk assessment results of the XX oilfield. The XX oilfield reservoir consists of a series of sandstones, siltstones and shale with gaps of limestone, coal and varying amounts of iron ore. Fig.6 shows the cross plot of the fuzzy evaluation values of well depth and leakage risk. The data shows a rough trend between the well depth and the fuzzy evaluation value of the risk of leakage; however, it can be seen from the distribution map that the discretization of the risk value is significant, indicating a high degree of heterogeneity in the reservoir.

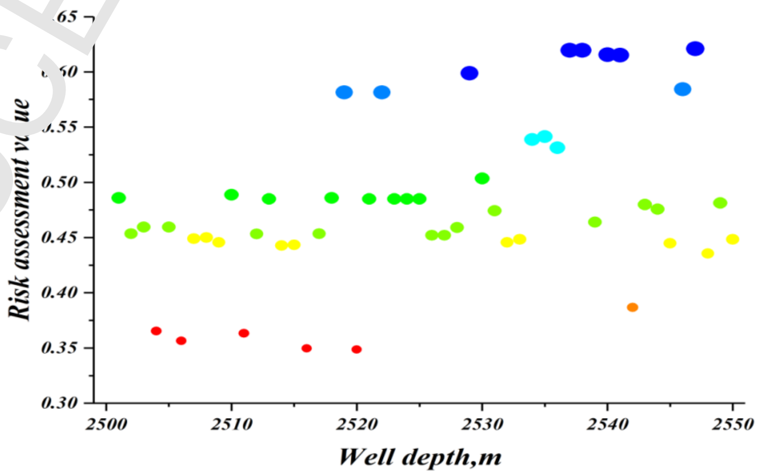
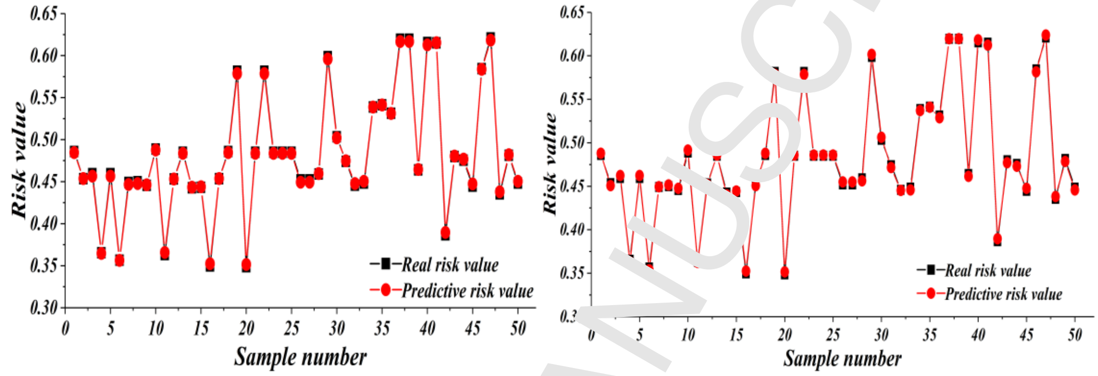


Fig.6. Cross plot of well depth versus risk assessment value.

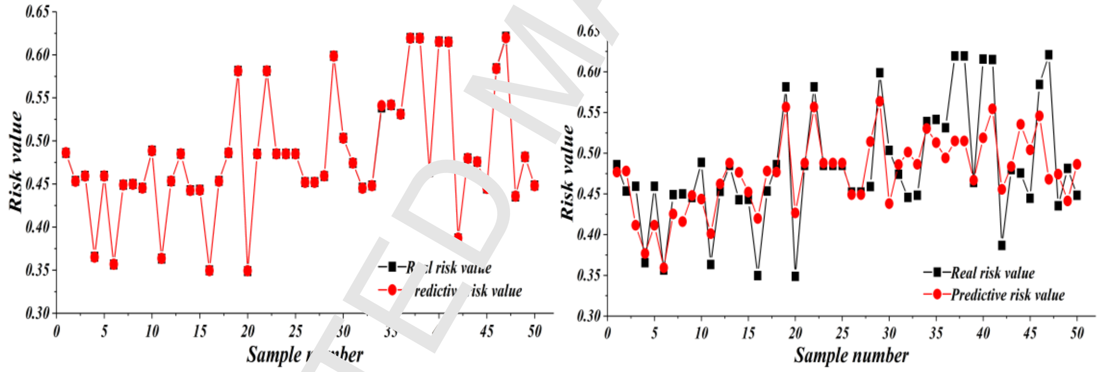
5.2 Analysis of PSO-SVR Dynamic Simulation Results

Since the selection of the kernel function of the SVR model may have an impact on the risk prediction results, this paper firstly analyzes the kernel function of the SVR model for optimal drilling risk dynamic regression prediction.

In order to analyze the results, the SVR (SVR-Linear) based on linear function, the SVR (SVR-Polynomial) based on polynomial, the SVR (RBR-RBF) based on Gaussian and the SVR (SVR-Sigmoid) model based on S-type have been drawn first. The simulation results are compared with the graph, and the results are shown in Fig. 7.



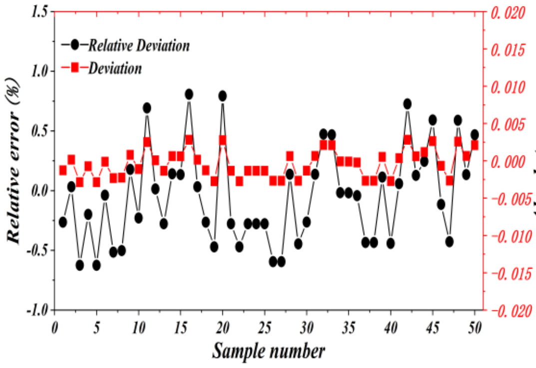
(a) Linear kernel function (b) Polynomial kernel function

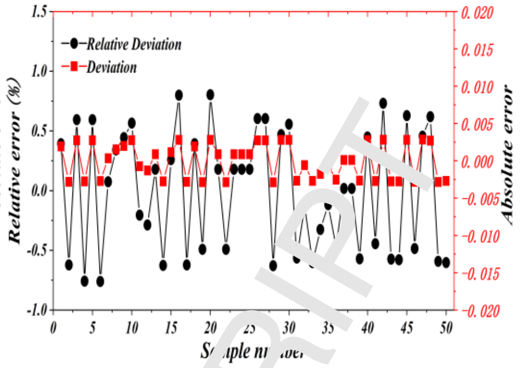


(c) RBF kernel function (d) Sigmoid kernel function

Fig.7. Comparative analysis of prediction results of different kernel functions.

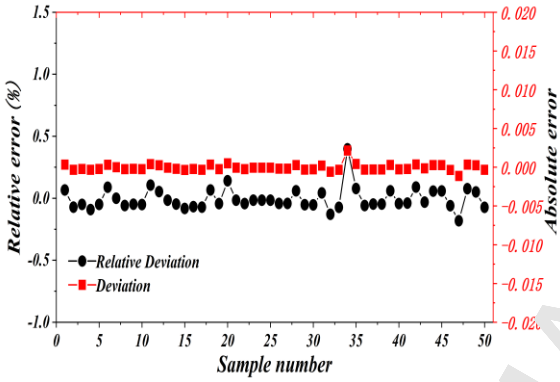
According to Fig.7, it can be known that when the sigmoid kernel function is selected, the effect is the worst, and the predicted value is larger than the actual value. When the polynomial kernel function and the linear kernel function are selected, the effect is better, and it can be seen that the predicted value and the actual value are closer. However, the effect of choosing the RBF kernel function is the best, the predicted value and the actual value are basically the same, and the prediction result is the most stable. The comparison of error results for different kernel functions is shown in Fig.8 below.

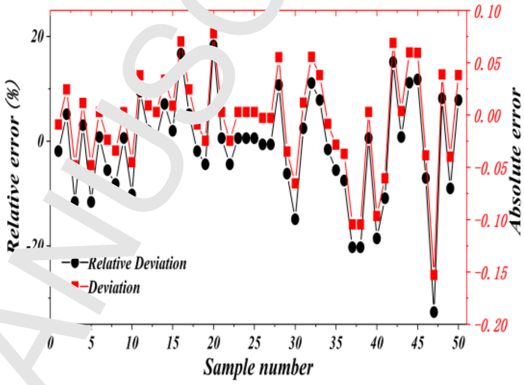




(a) Linear kernel function prediction error

(b) Polynomial kernel function prediction error





(c) RBF kernel function prediction error

(d) sigmoid kernel function prediction error

Fig.8. Comparison of error prediction results of different kernel functions.

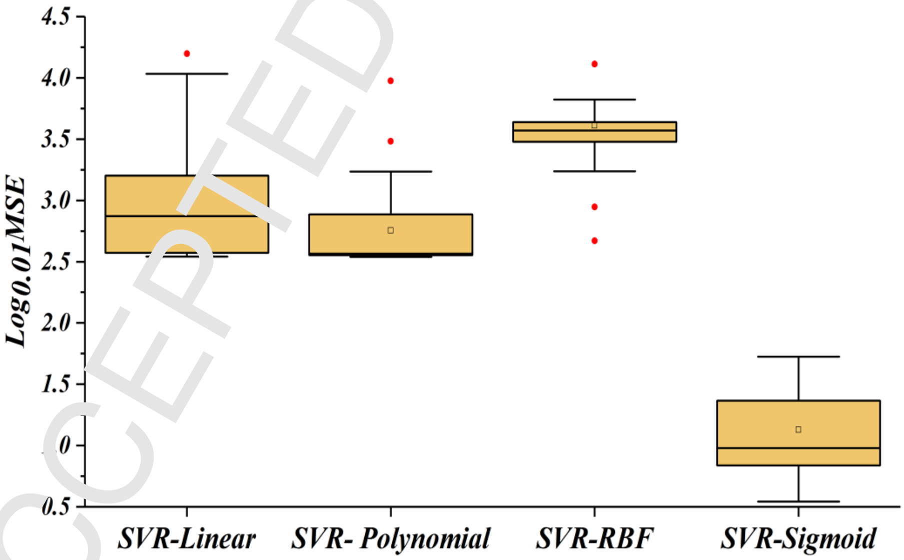


Fig.9. Different kernel function error analysis diagram.

In order to compare the pros and cons of the model, the paper further quantitatively compares and analyzes the box plot of the mean square error of the model as shown in Fig.9. A box diagram is an exploratory data analysis tool that provides a statistical summary of the underlying prediction error distribution. The top and bottom of the box represent the 25% and 75% percentiles of the mean square error, respectively. The black line in each box is the median of the mean square error. The whisker extends 1.5 times from each end of the box to the quartile range (the range of upper and lower quartile values extending above and below each box, including 50% distribution). Fig 8 also provides information about the data, which exceeds the end of the whisker (outliers) and is marked with a red circle symbol. Fig.7 uses 50 test data (sampled from the full data set) to present a summary of the prediction errors obtained from each regression model. The results show that the SVR-RBF model has the smallest interquartile range IRQ with a value of 0.000000058, indicating that there are very many predicted values in a very small error range. It in turn means an error distribution with a thinner peak, a higher kurtosis.

The results of the specific performance indicators are shown in Table 7 below. The kernel function is selected as a linear kernel function, a D-order polynomial kernel function, an RBF kernel function, and a sigmoid kernel function.

Table 7 Indicator Performance Results

Kernel function type/Indicator		*linear function*	*polynomial function*	*RBF function*	*sigmoid function*
Optimization index	*Bestc*	*0.7071068*	*0.0625000*	*8.0000000*	*4.0000000*
	Bestg	*0.0625000*	*5.6568542*	*0.0625000*	*0.0625000*
	Bestmse	*0.0047839*	*0.0118913*	*0.0003576*	*0.0339880*
Forecast error indicator	*MSE*	*0.0000450*	*0.0007200*	*0.0000027*	*0.0314500*
	Correlation coefficient R^2	*99.96%*	*99.89%*	*100.00%*	*55.86%*
Convergence time(s)		*2.02911*	*1.963788*	*2.032369*	*2.156163*

Combined with the above analysis, it can be concluded that for the intelligent dynamic evaluation model of drilling leakage risk in this paper, when the sigmoid kernel function is selected, the result of mean square error is the largest, reaching 0.0314500, with the lowest correlation between the input parameters of the prediction results and the risk evaluation value, the correlation coefficient R^2 is 55.86%. This model represents the lowest correlation between the input parameters and the risk evaluation value. On the contrary, when RBF kernel function is chosen, the result of mean square error is the smallest, which is 0.0003576, and the correlation between data is the highest, indicating that the hyperplane obtained by the kernel function can well map the high dimensional nonlinear risk data in the complex system of drilling engineering.

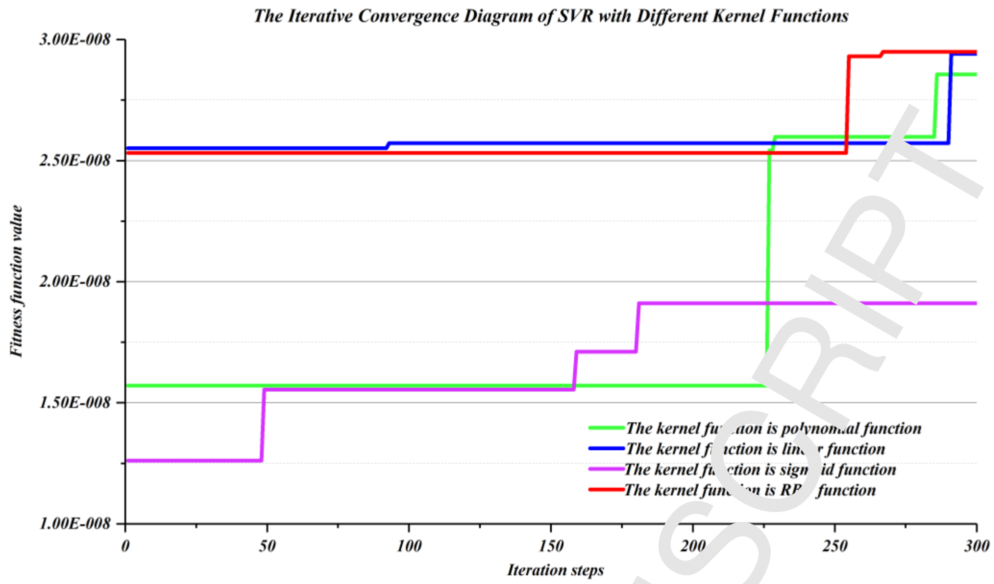


Fig.10. Fitness curve.

Fig.10 shows a comparative diagram of the evolution process of fitness values when PSO is used to optimize the SVM model when different kernel functions are selected. In the Fig.10, the red curve is the evolution process of the fitness of the RBF kernel function, the purple curve is the evolution process of the fitness value of the sigmoid kernel function, the blue curve is the evolution process of the fitness value of the linear kernel function, and the green curve is the evolution process of fitness of polynomial kernel function. From Fig.10, it can be inferred that the optimal kernel function in the dynamic evaluation model of leakage risk based on PSO optimization SVR algorithm is the RBF kernel function, which corresponds to the fastest convergence speed and higher accuracy of the model. The PSO optimization SVR algorithm proposed in this paper for the dynamic evaluation model of leakage risk considers the optimization of different kernel functions, a the same time, as a swarm optimization algorithm, each particle represents a possible solution in the process of particle swarm optimization (PSO). The optimal position of each particle in the population in the iterative process is the optimal solution found by the particle itself, that is, the individual extremum, the optimal position experienced by the whole population, and the global optimal solution. The iterative process of the optimization of PSO algorithm in this paper is shown in Fig 11. The particle converges to the optimal position and the fitness of the objective function increases gradually. As shown in Fig.11 below, the best parameters obtained from the optimization of the RBF kernel function in the SVR model are obtained by using the PSO algorithm.

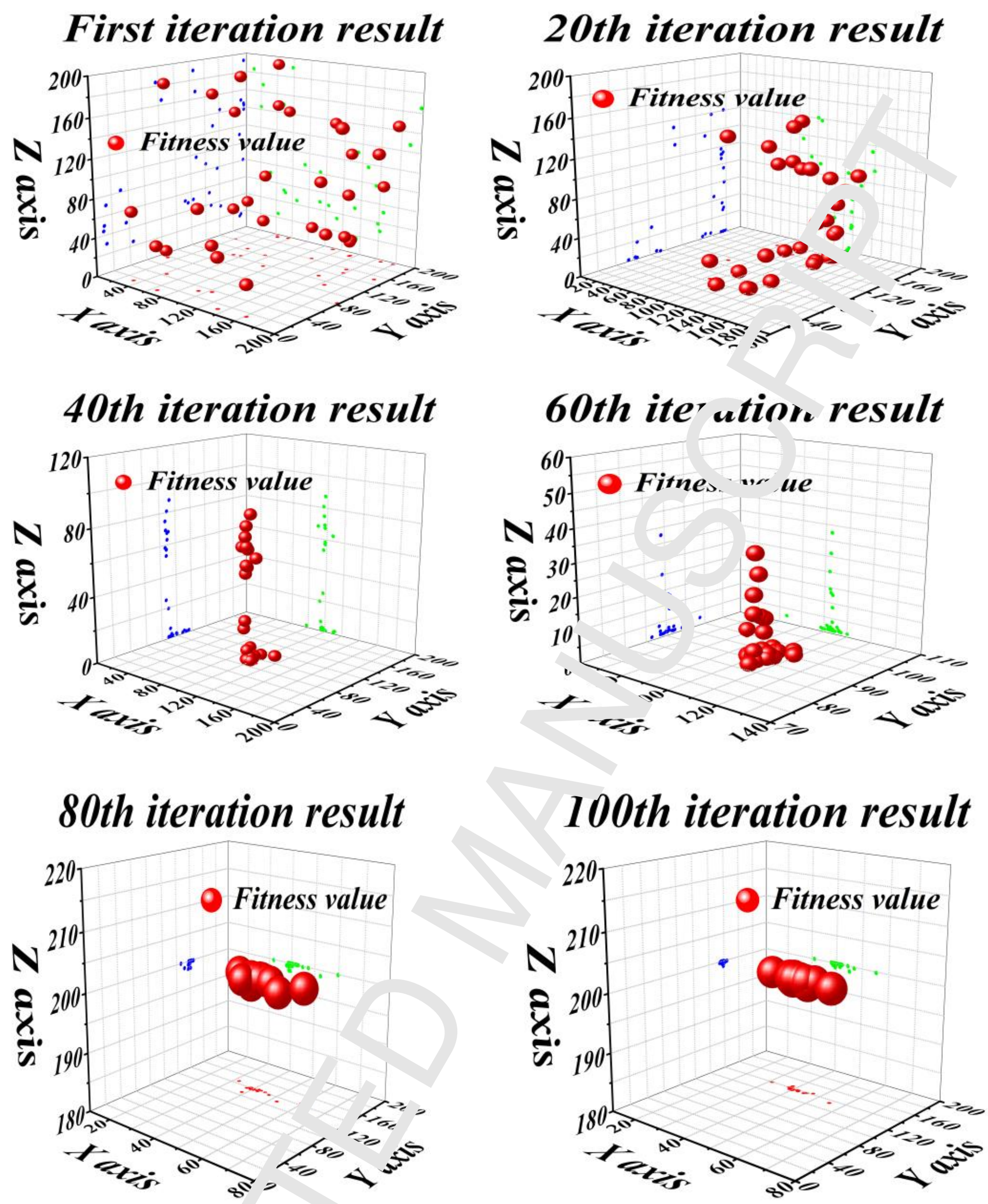


Fig.11. PSO optimization SVR algorithm particle position iterative update process.

In Fig.11 all the particles in the PSO algorithm are optimized, and finally all the particles tend to solve the coordinates in the space of x=39.409, y=138.744 and z=200. The size of the particle in the graph represents the appropriate value of the objective function, and the fitness of the objective function reaches the optimum value. The optimized parameters of the SVR are arec=8 and g=0. 0625, so the error reaches the minimum of 0.0004.

In order to show that the proposed model is more accurate than the Multilayer perceptron neural network, 50 groups of sample data are selected in this paper, where 40 groups of data are selected as training set and 10 groups of data as test set. The following Multilayer perceptron neural network prediction results are analyzed as follows:

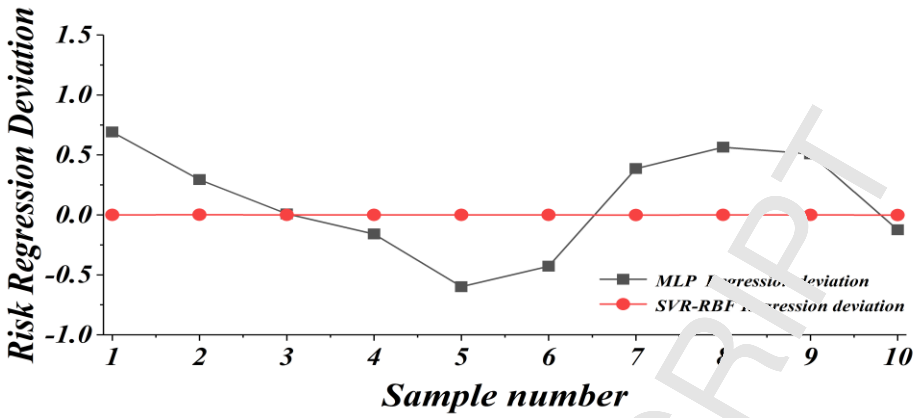


Fig.12. Comparison of PSO-optimized SVR-RBF and multi-layer perceptron neural network regression deviation.

In view of the comparative analysis of the above results, it is found that the average absolute error of MLP neural network is 0.054315, and the stability of prediction results is inferior, while the accuracy of PSO-SVR prediction model is significantly higher than that of MLP neural network. When the RBF kernel function is selected, the parameters of the SVR model can be optimized by PSO, and the performance of the SVR model can be optimized, and the generalization ability is better, and good results can also be obtained for the dynamic evaluation of drilling risk in small samples.

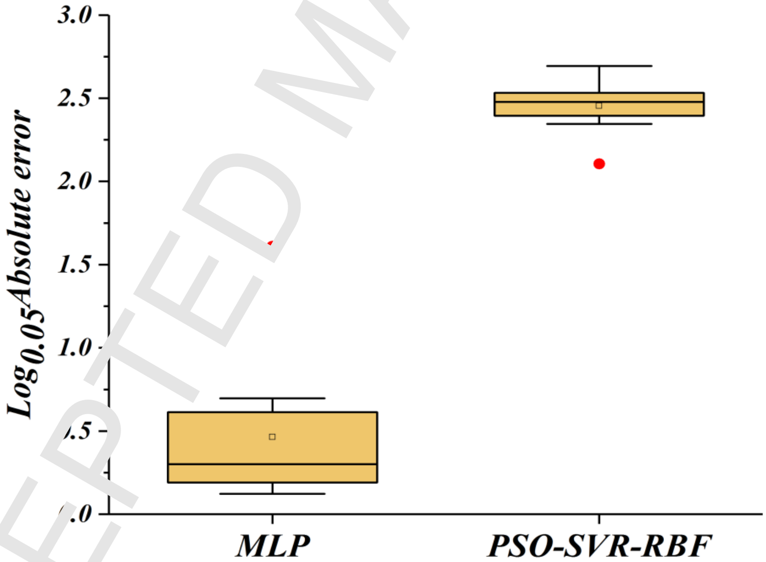


Fig.13. PSO optimization SVR-RBF and multilayer perceptron neural network error comparison analysis box diagram.

The average absolute error of the multilayer perceptron neural network is 0.0543 through the comparison and analysis of the above results, and the stability of the prediction results is poor. An interesting result is that the SVR-RBF model is equally stable to the risk prediction value, through the PSO optimization of SVR-RBF and multi-layer perceptron neural network error analysis box diagram. This powerful characteristic of SVR may be attributed to the potential SRM induction theory. On the other hand, the multilayer perceptron neural network MLP is highly sensitive to samples, which can explain that the classical model using the ERM principle converges to real risk only under asymptotic conditions where the sample size is large enough. However, the regression accuracy of the PSO-SVR-RBF model is significantly higher than that of the multilayer perceptron neural network. When the RBF kernel function is selected, the parameters of the SVR model can be optimized by PSO to optimize its performance and generalization ability. For the small-scale drilling risk dynamic evaluation problem, good results can also be obtained.

6. Conclusion

In the process of drilling risk control, the risk assessment is usually based on drilling parameters. However, drilling engineering is a complex nonlinear system, drilling parameters often exist fuzzy, randomness and other uncertain characteristics. Aiming at the uncertainty of drilling parameters that is not considered in the traditional drilling risk rating process, resulting in inaccurate judgments on risks and large errors, this paper first analyzes the factors influencing the risk of drilling leakage, and summarizes the evaluation index system of leakage risk, then establishes the model of leakage risk evaluation by fuzzy multilevel evaluation method, finally, proposes a fuzzy dynamic evaluation model of leakage risk based on PSO-SVR algorithm to explore the mapping relationship between drilling monitoring data and leakage risk. As the performance of the traditional SVR model is greatly affected by the penalty function and kernel function of the model, in order to analyze the leakage risk accurately and quickly, this paper optimizes the parameters of c and g in the SVR model by using the optimization characteristics of PSO, and selects the optimal kernel function as RBF to train the model. Through the field data validation and the comparative analysis of the results of the two models, it can be seen that the dynamic evaluation data mining model of leakage risk established in this paper is more effective and accurate, which can realize accurate dynamic evaluation of leakage risk and provide reasonable scientific basis for drilling risk control in this block.

7. Acknowledgements:

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5. Yanjun Lu

He is mainly engaged in the theory and technology of oil and gas production and transformation, and is interested in artificial intelligence. He is studying for a doctorate at Moscow State University.

Thank you very much for taking the time to read this article. Here are the highlights of the article:

1. The paper proposes a risk assessment method that considers the ambiguity of drilling parameters.
2. This paper proposes a real-time dynamic evaluation model of drilling risk based on PSO-SVR algorithm.
3. This paper compares the PSO-SVR algorithm in the real-time dynamic evaluation model of drilling risk with the BP neural network algorithm.