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A novel prediction method for favorable reservoir of oil field based on grey wolf optimizer and twin support vector machine

Kewen Li [a], Guangyue Zhou [a,*], Yaozhong Yang [b], Fulai Li [c], Zonghao Jiao [a]

[a] College of Computer Science and Technology, China University of Petroleum, Qingdao, Shandong, 266580, China
[b] Control Center of Informatization, Shengli Oilfield Company, SINOPEC, Dongying, Shandong, 257022, China
[c] School of Geosciences, China University of Petroleum, Qingdao, Shandong, 266580, China

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ABSTRACT

Most of the domestic oil fields are in the middle or late stage of exploration and development, and there are fewer and fewer oil fields that can be easily discovered. Proved reserves are dominated by concealed reservoirs, but concealed reservoirs are difficult to find. The prediction for favorable reservoir is a key in the process of exploration and development, but the traditional prediction methods of favorable reservoir rely on analysis of geological prospectors according to commonly used seismic attributes, which leads to low exploration efficiency. To improve effectiveness of the prediction for favorable reservoir, this paper introduces a multi-classification Twin Support Vector Machine (MTWSVM) method suitable for the case of insufficient reservoir label samples caused by fewer drilling data, which is used to identify favorable reservoirs. Since each sub-classifier of existing MTWSVM uses the same penalty parameters and kernel parameters, ignoring the differences between different classes, it cannot play the best role of each sub-classifier. We propose a multi-classification Twin Support Vector Machine based on hybrid parameters (HP-MTWSVM). This algorithm selects appropriate parameters for different sub-classifiers, maintaining the diversity of classifiers. Twin Support Vector Machine (TWSVM) is facing the problem that its parameters are difficult to be appointed. Additionally, HP-MTWSVM algorithm introduces a large number of parameters. This paper further proposes a hybrid parameter multi-classification Twin Support Vector Machine based on Grey Wolf Optimizer (GWO-HP-MTWSVM). This method uses GWO to optimize the parameters of HP-MTWSVM. Experiments show that the prediction accuracy of GWO-HP-MTWSVM is more than 64%, better than that of manual prediction in complex concealed reservoirs. The model can help geological exploration personnel quickly delineate favorable areas, provide basis for accurately drilling wells and avoid waste of resources caused by empty reservoirs.

1. Introduction

With the development of exploration technology, the number of oil and gas reservoirs in lithological formations is increasing. In both the high-mature exploration areas in the eastern and the low-level exploration areas in the central and western regions, the proportion of oil and gas reservoirs continue to expand, therefore, oil and gas reservoirs have huge exploration potential. The prediction of favorable reservoirs is the process of providing geological basis for well location deployment and development programs. Improving the accuracy of prediction can save a lot of human resources, material resources, and financial resources. Therefore, the prediction of favorable reservoirs is a crucial step in the exploration and development process.

The traditional prediction for favorable areas is generally to build a model which is based on geological information such as faults and landforms or small amount of seismic parameters. Many authors have conducted in-depth research in this field. Ye et al. (2015) combined stochastic simulation with seismic inversion, constrained by seismic data, and then predicted the distribution of reservoir by simulating reservoir's spatial distribution. Zhang et al. (2015) confirmed four-level hierarchical structure including basic data layer, plan layer, criterion layer and target layer by the analytic hierarchy process, and achieved the objective of predicting the reservoirs better and more completely. Li et al. (2018) proposed an impedance inversion based on small-incident angle stacking seismic data to predict thin reservoirs better. Liu et al. (2012) used pre-stack and post-stack techniques to predict reservoir in

* Corresponding author.
E-mail address: s17070770@s.upc.edu.cn (G. Zhou).

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terms of the relationship between the physical property and fluid property in carbonate reservoirs. The traditional prediction methods have low accuracy because of complex geological conditions, poor correlation of seismic attributes and poor matching relationship between wells data and seismic data. With the progress and development of geophysical technology, seismic reservoir prediction methods based on machine learning theory emerge as the times require. Wang et al. (2013) used the attribute optimization method based on cluster analysis to determine the optimal combination of attributes for reservoir prediction. Masoudi et al. (2012) used method of fuzzy classifier fusion to improve confidence of prediction and generalization ability of determining productive zones. Yin et al. (2012) introduced the kernel function into traditional fuzzy C-means method for reservoir prediction. Sebtosheikh et al. (Sebtosheikh and Salehi, 2015) used SVM method to lithology prediction from inverted seismic attributes data and petrophysical logs. Zhu et al. (2017) used multi-linear regression fusion technology to establish the regression equation between sandstone thickness and multi-seismic attributes. Song et al. (2018) applied strong tolerance random forest algorithm to seismic reservoir prediction. Yu et al. (2016) carried out neural network lithology inversion based on wave impedance to enhance the ability to identify thin reservoir. In addition to the mentioned above, there are many other machine learning methods that can also be applied to reservoir prediction (Lin et al., 2018a, 2018b). Support Vector Machine (SVM) is a novel few-shot learning method with solid theoretical basis, and can efficiently realize "transduction reasoning" from training samples to testing samples. SVM can greatly simplify the usual classification and regression problems, and is a common machine learning method for reservoir prediction. TWSVM proposed by Jayadeva is a novel machine-learning algorithm based on SVM (JayadevKhemchandani and Chandra, 2007). TWSVM transforms a large-scale classification problem into two small-scale classification problems. This algorithm improves the computational performance and generalization ability of SVM, and quickly becomes a research hotspot in the field of machine learning.

TWSVM provides new ideas and methods for prediction of favorable reservoir because of its wide application range, strong generalization ability and high computational efficiency. Taking Niuzhuang area of Dongying as the research object, through a large number of investigations and studies, it is found that the number of drilling wells in this area is small, and the favorable areas are not fully excavated. Reservoirs are distributed in three forms: favorable reservoir development area, reservoir development area and non-favorable reservoir development area. TWSVM was originally proposed for solving the binary-classification problem. If applying TWSVM to predicting for favorable reservoir, it is necessary to study the construction method of MTWSVM. Many authors have done a lot of research on the construction of MTWSVM. Xie et al. (2013) proposed one-versus-all Twin Support Vector Machine (OVA TWSVM). They extended TWSVM from binary classification to multi-classification by using one-versus-all method. Shao et al. (2015) indicated that the performance of one-versus-one Twin Support Vector Machine (OVO TWSVM) which extended TWSVM by one-versus-one strategy to solve multi-classification problems is better than that of OVA TWSVM. Ding et al. (2018) divided the machines into the following groups: multi-classification TWSVM based on "one-versus-one-versus-rest" strategy, multi-classification TWSVM based on binary tree, and multi-classification TWSVM based on "all-versus-one" strategy according to the structure of the sub-classifiers. Since each sub-classifier of existing MTWSVM uses the same penalty parameters and kernel parameters, ignoring the differences between different classes, it cannot play the best role of each sub-classifier. Combining reservoir distribution law, this paper designs the MTWSVM model suitable for reservoir prediction, gets the mapping relationship between seismic attributes and favorable reservoirs, and then assists geological exploration personnel to quickly delineate favorable areas.

2. Background

2.1. MTWSVM based "one-versus-one" strategy

To solve the low efficiency problem of SVM dealing with large-scale data, Jayadeva et al. proposed TWSVM based on SVM in 2007. TWSVM finds two hyperplanes, one for each class, and classifies samples according to which hyperplane a given sample is closest to. TWSVM determines hyperplanes by solving pair of quadratic programming problems, which not only owns the advantages of SVM, but also the time of training is 1/4 of that (Ding et al., 2014). Since TWSVM was originally proposed to solve the binary classification problem, the multi-classification problem can only be solved by combining additional combination strategies. "One-versus-one (OVO)" combination strategy was first proposed by Knerr for multi-classification SVM. Its principle is to construct binary SVMs between any two classes. If the samples belong to K categories, K(K-1)/2 binary SVMs are designed. This strategy generally judges which category a sample belongs to by "voting method". When deciding which category the given sample belongs to, the voting method judges by all binary classifiers of OVO TWSVM. If the classification function between category i and j classifies the given sample into category i, this binary classifier votes for category i. Otherwise, category j obtains the vote. Traversing all the binary classifier of OVO TWSVM, the given sample will be assigned to the category with the highest number of votes. The OVO TWSVM by combining "one-versus-one" strategy with binary classification TWSVM has better classification performance than OVO SVM. The basic principle of OVO TWSVM is as follows:

In n-dimensional space R^n, x represents n-dimensional sample, and samples belonging to category i and j are represented by matrices A_i and A_j, respectively. For linear separable cases, the binary TWSVM is constructed between samples from category i and j, and the following two hyperplanes are obtained:

$$x^T w_{ij} + b_{ij} = 0,\ x^T w_{ji} + b_{ji} = 0 \tag{1}$$

For non-linear separable cases, introducing the kernel function K, the two hyperplanes of TWSVM are as follows:

$$K\left(A_i, C^T\right) w_{ij} + b_{ij} = 0,\ K\left(A_j, C^T\right) w_{ji} + b_{ji} = 0 \tag{2}$$

where w_{ij} and w_{ji} are normal vectors of two hyperplanes, b_{ij} and b_{ji} are offsets. Where C is defined as $C = [A_i{}^T, A_j{}^T]^T$. We can obtain hyperplanes by solving the following pair of quadratic programming problems (3) and (4):

$$\min 1 \Big/ 2\left|\left|K\left(A_i, C^T\right) w_{ij} + e_{ij}^{(1)} b_{ij}\right|\right|^2 + 1 \Big/ 2 c_{ij} e_{ij}^{(2)T} \xi_{ij} \text{ s.t. } \left(K\left(A_j, C^T\right) w_{ij} + e_{ij}^{(2)} b_{ij}\right) + \xi_{ij} \geq e_{ij}^{(2)}, \xi_{ij} \geq 0 \tag{3}$$

$$\min 1 \Big/ 2\left|\left|K\left(A_j, C^T\right) w_{ji} + e_{ij}^{(2)} b_{ji}\right|\right|^2 + 1 \Big/ 2 c_{ij} e_{ij}^{(1)T} \xi_{ji} \text{ s.t. } \left(K\left(A_i, C^T\right) w_{ji} + e_{ij}^{(1)} b_{ji}\right) + \xi_{ji} \geq e_{ij}^{(1)}, \xi_{ji} \geq 0 \tag{4}$$

Where c_{ij} and c_{ji} are penalty parameters, $e_{ij}^{(1)}$ and $e_{ij}^{(2)}$ are column vectors composed of one, ξ_{ij} and ξ_{ji} are slack variables.

By solving the dual problem of (3), (4), the parameters of the hyperplanes are obtained, and the OVO TWSVM classifier is constructed. Finally, the new samples are classified by "voting method".

2.2. Grey wolf optimizer

GWO is an intelligent optimization algorithm proposed by Mirjalili et al. (2014) in 2014. Due to its simple principle, fewer parameters to be adjusted, simple implementation and strong global search ability, the method is becoming more and more popular. Many research have been carried out using GWO. Emary et al. (2015) used multi-objective GWO for feature selection, searching feature space to find the optimal feature subset. Elhariri et al. (2015) proposed GWO-SVM that optimized the parameters of SVM by GWO. Experiments showed that GWO-SVM has better classification performance than SVM. Heidari AA et al. (Heidari and Pahlavani, 2017) proposed that Levy flight and greedy selection strategy were combined with improved hunting stage to improve the efficiency of GWO. Zhu et al. (2015) proposed a novel method by hybridizing GWO with differential evolution. This method accelerates the convergence speed of GWO and has more advantages in optimization performance and detection method. Wei et al. (2017) controlled the position of grey wolf individual by fitness value, and realized the adaptive search of GWO algorithm. Therefore, it can speed up the convergence speed and avoid falling into local optimum.

GWO algorithm is inspired by the predatory behavior of grey wolves, and it optimizes search through hunting, searching for prey, encircling prey, and attacking prey. There is a strict hierarchy between them as shown in Fig. 1. α, β, δ and ω represent different grades of grey wolves, and the dominance rate decreases from top to bottom. In order to model the grey wolf's social system mathematically, α is regarded as the optimal solution, β and δ are regarded as the suboptimal solution and the third optimal solution, respectively. They lead other wolves toward the possible position of prey. ω is regarded as the rest of the solutions, which is updated according to the positions of α, β and δ. Three definitions of the algorithm are given below (Mirjalili et al., 2014).

Definition 1 Distance between Grey Wolf and Prey

$$\vec{D} = |\vec{C}\cdot\vec{X}_P(t) - \vec{X}(t)| \tag{5}$$

where t indicates the current iteration, $\vec{X}_P$ represents position vector of prey, $\vec{X}(t)$ represents current position vector of grey wolf.

$$\vec{C} = 2\cdot\vec{r_1} \tag{6}$$

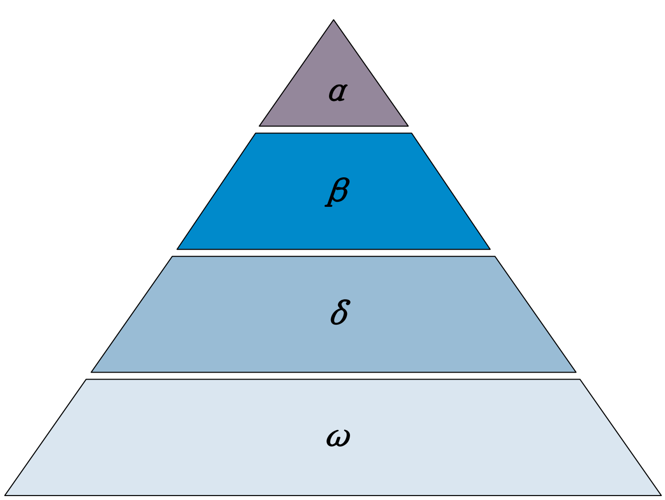


Fig. 1. Hierarchy of grey wolf.

where r_1 is random vector in [0, 1], $\vec{C}$ is coefficient vector. We can explore and exploit search space by randomly enhancing (C > 1) or weakening (C < 1) the distance between prey and grey wolf.

Definition 2 Update position of Grey Wolf

$$\vec{X}(t+1) = \vec{X}_P(t) - \vec{A}\cdot\vec{D} \tag{7}$$

$$\vec{A} = 2\vec{a}\cdot\vec{r}_2 - \vec{a} \tag{8}$$

where components of $\vec{a}$ are linearly decreased from 2 to 0, r_2 is random vector in [0,1]. As A decreases, half of the iterations are used for exploring ($|A|>1$), and the rest for exploiting ($|A|<1$).

Definition 3 Determine position of prey

In the abstract search space, the exact position of the prey (optimal solution) is not known. According to the hierarchy of grey wolves, hunting is usually guided by α, β and δ. Therefore, it is assumed that α (optimal candidate solution), β (suboptimal candidate solution), and δ (third optimal candidate solution) have a better acquaintance of the position of prey. It is known that grey wolvesα, β and δ are closest to prey. By preserving the obtained three optimal solutions during each iteration, the orientation of prey can be determined according to the positions of the three optimal solutions, and other grey wolf individuals are forced to update their positions according to the three optimal solutions. The mathematical descriptions of grey wolf individuals tracking prey orientation are as follows:

$$\vec{D}_\alpha = |\vec{C}_1\cdot\vec{X}_\alpha - \vec{X}|,\ \vec{D}_\beta = |\vec{C}_2\cdot\vec{X}_\beta - \vec{X}|,\ \vec{D}_\delta = |\vec{C}_3\cdot\vec{X}_\delta - \vec{X}| \tag{9}$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1\cdot\vec{D}_\alpha,\ \vec{X}_2 = \vec{X}_\beta - \vec{A}_2\cdot\vec{D}_\beta,\ \vec{X}_3 = \vec{X}_\delta - \vec{A}_3\cdot\vec{D}_\delta \tag{10}$$

$$\vec{X}(t+1) = 1/3(\vec{X}_1 + \vec{X}_2 + \vec{X}_3) \tag{11}$$

The distances between grey wolf individuals and α, β and δ are calculated in terms of formulas (9) and (10). Then the direction of grey wolf individuals moving towards prey are judged in terms of formula (11). Where $\vec{X}_\alpha$, $\vec{X}_\beta$, $\vec{X}_\delta$ represent the positions of α, β, δ respectively, $\vec{C}$, $\vec{C}_2$, $\vec{C}_3$ are random vectors and $\vec{X}$ is the position of the current solution.

3. The proposed methodology

3.1. HP-MTWSVM

The performance of TWSVM is greatly affected by the parameters selection. Good parameters will directly improve the performance of classifiers. TWSVM mainly considers two parameters. One is the kernel parameter and the other is the error penalty parameter. For the kernel parameters, the kernel function used in this experiment is Gaussian kernel, so the kernel parameter is δ. The change of δ leads that the complexity of the feature space of TWSVM is changed. If the value of δ is large, the complexity of the feature space is low, and the linear separability is poor. If the value of δ tends to zero, the complexity of the feature space tends to infinite, and any data can be linearly separated, but it often results in over fitting (Chen et al., 2018). For the error penalty parameters, the larger the penalty parameters are, the smaller the tolerance of error is, the easier over fitting is. The smaller the penalty parameters, the larger the tolerance of error is, the easier under fitting is (Zhang et al., 2011). Therefore, it is very important that how to select the appropriate kernel parameters and penalty parameters for the classification effect and generalization performance of TWSVM.

In this paper, we extend binary TWSVM to MTWSVM according to "one-versus-one" strategy. However, each sub-classifier in MTWSVM uses the same penalty parameters and kernel parameters, ignoring the differences among different sub-classifiers. It is difficult to improve the performance of each sub-classifier at the same time with the same parameters, which limits the improvements of overall performance of

MTWSVM. Therefore, we propose the HP-MTWSVM method. This method selects appropriate parameters for different sub-classifiers, keeps the diversity of classifiers, and constructs the MTWSVM according to the "one-versus-one" strategy.

3.2. GWO-HP-MTWSVM

Although HP-MTWSVM improves the classification performance of TWSVM, it introduces many parameters. Due to the increase in the number of parameters, the complexity of the algorithm increases. TWSVM is confronted with the problem that parameters are difficult to determine. Therefore, it is necessary to solve the problem of parameter selection while using hybrid parameters to improve classification performance. Therefore, this paper further proposes the GWO-HP-MTWSVM method. The GWO algorithm has the advantages of simple structure, easy implementation and good global performance. By optimizing the parameters of HP-MTWSVM through GWO, it not only can find better parameters than traditional optimization methods, but also can improve classification accuracy of the algorithm to a certain extent.

For GWO algorithm, the position of the grey wolf individual represents the possible solution of the optimization problem. In the proposed GWO-HP-MTWSVM, classification accuracy is considered as the problem to be optimized, and the potential solutions are the penalty parameters c_{i1}, c_{i2} and kernel parameter δ_i of each binary classifier of MTWSVM. Assuming the number of sample categories is m, the number of binary TWSVM to be trained according to "one-versus-one" strategy is m (m-1)/2.

The GWO-HP-MTWSVM algorithm is described as follows:

Algorithm1
GWO-HP-MTWSVM

Input: seismic dataset
Output: the trained MTWSVM model.
For $i = 1$ *to* $m(m-1)/2$
1. Initialize the grey wolf population, generate n positions of individual wolf randomly, and initialize $a, A, C, X_\alpha, X_\beta, X_\delta$.
For $iter = 1$ to Max iterations % *iter* represents the number of iterations
(a) Assign the position vectors of grey wolves to the parameter pairs (c_{i1}, c_{i2}, δ_i) of i th binary TWSVM, and calculate fitness value of each individual. % accuracy of training set as fitness value
(b) Determine the current optimal, suboptimal, third optimal solutions X_α, X_β, X_δ by comparing the fitness value of grey wolf individual.
(c) Calculate the value of a, A, C.
(d) Update the current position of individual according to formula (11).
2. Assign the optimal solution to the parameters of i th binary TWSVM
Construct a MTWSVM by combining m(m-1)/2 trained binary TWSVMs

In order to provide the more intuitive description of the algorithm, we draw an algorithm flowchart of it. It is shown in Fig. 2.

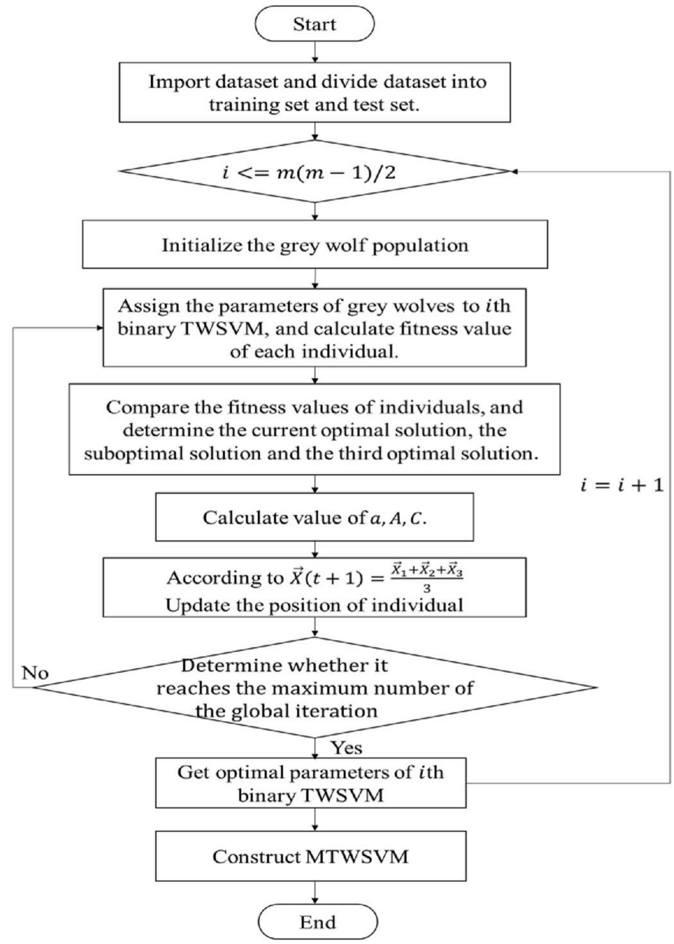


Fig. 2. The flow chart of GWO-HP-MTWSVM.

4. Experiment results and analysis

4.1. Evaluation measures

Confusion matrix is the common method to reflect performance of classification model. Taking a two-class model as an example, the confusion matrix of this model is calculated as shown in Table 1 (Wang et al., 2018).

Table 1
Confusion matrix.

		Predicted class	
		Positive	Negative
Actual class	Positive	TP	FN
	Negative	FP	TN

Where TP is the number of true positives, which represents cases that the positive class are correctly classified. Where FN is the number of false negatives, which represents cases that the positive class are classified as negative. Where TN is the number of true negatives, which represents cases that the negative class are correctly classified. Where FP is the number of false positives, which represents cases that negative class are classified as positive.

Based on the confusion matrix, the Accuracy, Precision, Recall and F1-Measure are defined as follows:

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \tag{12}$$

Accuracy represents the percentage of correctly predicted samples in the total samples.

$$Precision = \frac{TP}{TP + FP} \tag{13}$$

Precision represents the probability of actually positive samples in all predicted positive samples. The higher the precision, the better.

$$Recall = \frac{TP}{TP + FN} \tag{14}$$

Recall represents the probability of predicted positive samples in all actually positive samples. The higher the recall, the better.

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{15}$$

F1 value takes both precision and recall into account, so that both of them can achieve the highest at the same time. The higher the F1 value, the better.

4.2. Experiment results and analysis on seismic dataset

4.2.1. Data description

The actual data used in this paper is the 3D seismic data of Niuzhuang area. The fourth layer of the whole region is taken as the research object. The well and seismic information that includes seismic attributes, well data, lithology profile data, time-to-depth conversions and horizon data of the target horizon, which is extracted from data sources such as exploration databases and seismic data volumes. The above-mentioned data are all used as the data sources for prediction of favorable reservoirs. Though the values of seismic attributes are easy to be obtained, the types of reservoirs can only be obtained by drilling results. Traditional methods generally predict reservoirs according to conventional seismic attributes, because different combinations of seismic attributes can reflect the characteristics of different reservoirs. The implicit relationship between seismic attributes and reservoirs is explored by using machine learning methods, then the type of unknown reservoirs are determined based on known the values of seismic attributes. Because of the variety of seismic attributes, there are a lot of useless attributes which are not related to reservoir classification. The existence of these attributes will not only affect the accuracy of prediction, but also increase the time complexity of prediction. In this paper, variance analysis is used to calculate the variance between seismic attributes and reservoir types. The smaller the variance, the smaller the correlation between attributes and reservoir types. We set the threshold value to 0.1, remove the seismic attributes whose variance is lower than 0.1, and then adjust the remaining seismic attributes according to the experience of geological experts. Through the correlation analysis between seismic attributes and reservoir types and artificial selection, we selected 22 seismic attributes with the strongest correlation with reservoir characteristics including amplitude, frequency and so on in Table 2 as input variable $X_i = \{x_{i1}, x_{i2}, \cdots, x_{in}\}$, where n is the number of seismic attributes, and i is the number of seismic samples. In this paper, we obtain 6600 seismic samples as input, and divide the favorable areas into three classes according to the three different degrees of good, medium and poor. According to the statistics of development wells in this area by geological prospectors, it is stipulated that in the depth range corresponding to seismic attributes, the accumulative thickness of sandstone is more than 10 m, labeled as 2, the accumulative thickness of sandstone is more than 4 m and less than 10 m, labeled as 1, and the accumulative thickness of sandstone is less than 4 m, labeled as 0. Therefore, the class label is recorded as the output variable y, where $y = \{0,1,2\}$, and $\{0,1,2\}$ represent the non-favorable reservoir development area, reservoir development area and favorable reservoir development area respectively.

From Table 2, it can be seen that the seismic attributes used in this paper cover Amplitude category, Magnitude category, Attenuation category, Frequency category and other categories. These attributes are commonly used categories in traditional favorable reservoir prediction methods, and the selected seismic attributes are uncorrelated with each other, thus avoiding the reduction of classification accuracy caused by attribute redundancy.

Table 2
Seismic attributes.

Type	Seismic attribute
Amplitude	RMS_Amplitude, Max_Amplitude, Min_Amplitude, Sum_Amplitude, Sum_Positive_Amplitude, Sum_Negative_Amplitude, Avg_Peak_Amplitude, Avg_Trough_Amplitude
Magnitude	Sum_Magnitude, Avg_Magnitude, Max_Magnitude, Energy_Half_Time
Attenuation	Bandwidth, Bandwidth_Rating_Bias, Bandwidth_Rating_Debias
Frequency	Instantaneous_Frequency, Dominant_Frequency
Others	Ratio, Seismic_Arc_Length, Zero_Crossing_Count, Window_Length, Instantaneous_Phase

4.2.2. Data processing

4.2.2.1. Generating training sample set. Firstly, we select the seismic traces that are the closest one to the coordinate of development wells, and extract the seismic attributes corresponding to the seismic trace as the input variable X.

Secondly, according to the horizon data, we take the range of time window $[t_1, t_2]$ of the seismic traces. According to the time-depth pair of the calibration data, the depth range $[d_1, d_2]$ corresponding to $[t_1, t_2]$ can be calculated.

Lastly, we count the cumulative thickness of the sandstone in the range of $[d_1, d_2]$, and calculate the class label y. Therefore, $[X, y]$ represents the training sample set.

4.2.2.2. Standardized processing. As input variable, the scales of seismic attributes are quite different. We need normalize these seismic attributes to regulate the value of them to a certain range. In this paper, Min-max normalization method is used to transform the values of seismic attributes into the range of [0, 1], so as to ensure that data are trained in the same dimension, and avoid affecting the accuracy of prediction. The formula of min-max method is as follows

$$x_{ij} = \frac{x_{ij} - min\{X_i\}}{max\{X_i\} - min\{X_i\}} (1 \le j \le n) \tag{16}$$

where n is the number of seismic attributes, and i is the number of seismic samples.

4.2.3. Analysis of HP-MTWSVM

In this paper, the normalized seismic attribute set is input to the classification model, and the Gauss kernel is set to the kernel function. The accuracy, precision, recall and F1 values of different classification models are obtained.

At present, the parameters of TWSVM are mainly determined by artificial experience or grid search. The proposed method in this paper is aim to determine the parameters for different sub classifiers that can give full play to their own advantages. The method of determining parameters based on artificial experience is not advisable. Therefore, comparative experiments were performed between proposed HP-MTWSVM optimized by grid search, referred to as Grid-HP-MTWSVM, with the other competitive methods, including OVO TWSVM (Shao et al., 2015), OVA TWSVM (Xie et al., 2013), as mentioned above both are commonly used to construct MTWSVMs, and OVO TWSVM optimized by grid search, referred to as Grid-MTWSVM. When the optimal parameters are not determined, OVO TWSVM and OVA TWSVM are trained by selecting commonly used parameters. Experimental results show that for seismic data sets, the penalty parameters of OVO TWSVM and OVA TWSVM are set to 1, and the kernel parameters are set to 2 are better than the default parameters, so we set the parameters of the comparative methods OVO TWSVM and OVA TWSVM as these two parameters. However, Grid-MTWSVM determines parameters through grid search rather than artificial experience. For grid search, the searching range of two penalty parameters is {0, 1, 2 … 9, 10} and that of kernel parameter is {0, 1, 2 … 9, 10}. The optimal combination of parameters is found by traversing the three-levels of grid search. During the experiments, we select parameters through nested cross validation (CV). Nested CV is divided into outer loop and inner loop. In the outer

Table 3
Comparison of classification performance among four methods on the seismic dataset.

Methods	Accuracy	Precision	Recall	F1
OVO TWSVM	0.547	0.315	0.547	0.401
OVA TWSVM	0.542	0.365	0.542	0.413
Grid-MTWSVM	0.583	0.445	0.583	0.458
Grid-HP-MTWSVM	**0.605**	**0.465**	**0.605**	**0.478**

loop, we divide the dataset into training set and test set. In the inner loop, we further divide the training set into training set and test set (also called validation set). Model parameters are selected by performing 10-folds CV in the inner loop, and 10-folds CV in the outer loop is used to evaluate the model. The 10-folds CV mentioned without special explanation below defaults to the outer loop. The average metric values across the 10-folds CV results of above methods are shown in Table 3. From Table 3, we can see that the classification performance of Grid-HP-MTWSVM algorithm is highest. The performance of Grid-MTWSVM is higher than that of both OVO TWSVM and OVA TWSVM, which proves that the selecting suitable parameters is important. Grid-HP-MTWSVM and Grid-MTWSVM optimize parameters using grid search, and the performance of Grid-HP-MTWSVM is better than that of Grid-MTWSVM, which proves the effectiveness of HP-MTWSVM.

In order to eliminate the impact of data division and guarantee valid results, the 10-folds CV were carried out to evaluate the classification performance. In the case of fewer favorable reservoir samples, we select the accuracy that can measure overall prediction performance and F1 value that can measure prediction performance of favorable reservoirs as the evaluation indexes. The detailed comparison results on seismic dataset in terms of the accuracy and F1 value are showed in Figs. 3 and 4. From Figs. 3 and 4, we can see the accuracy and F1 value of the HP-MTWSVM algorithm are better than the other three competitors in six runs of the 10-folds CV, and are comparable to the Grid-MTWSVM method in remaining four runs.

One of the critical challenges for favorable reservoir prediction is the reliability of the model, which indicates the model not only can achieve a high accuracy, but also can sustain the high accuracy stably. In order to test the reliability of HP-MTWSVM model, we recorded the average accuracy, F1 value and standard error across the 10-folds CV results of OVO TWSVM, OVA TWSVM, Grid-MTWSVM and Grid-HP-MTWSVM in Table 4. As we can be seen from Table 4, the standard errors of the four methods are about 3%, and the standard errors are relatively small. Compared with the other three methods, Grid-HP-MTWSVM has the highest accuracy and F1 value, which further illustrates that HP-MTWSVM maintains high performance while maintaining good stability.

4.2.4. Analysis of GWO-HP-MTWSVM

The above experiments prove that HP-MTWSVM algorithm is effective, but there are still some shortcomings of HP-MTWSVM. The number of parameters increases, which makes the algorithm more complex. This paper further improved the HP-MTWSVM algorithm and proposed GWO-HP-MTWSVM. GWO-HP-MTWSVM determines the optimal parameters using grey wolf optimizer algorithm. In order to prove the validity of GWO-HP-MTWSVM, this method is compared with Grid-HP-MTWSVM and HP-MTWSVM optimized by Particle Swarm Optimization (PSO-HP-MTWSVM). PSO is widely used in various optimization problems, and it is a classical algorithm in the optimization field. In recent years, PSO also has been widely applied to reservoir model calibration and well optimization (Hutahaean et al., 2014, 2017). In this paper, the conventional parameter optimization method grid search and the classical algorithm PSO in the field of heuristic optimization are used as comparison algorithms, which can further prove the effectiveness of GWO-HP-MTWSVM. Since Section 4.2.3 optimizes the parameters of HP-MTWSVM and MTWSVM by using grid search, the range of optional parameters is limited. From Section 4.2.3, it shows that compared with Grid-MTWSVM, the average accuracy of Grid-HP-MTWSVM is improved by 2%. In order to further verify the effectiveness of HP-MTWSVM, GWO-MTWSVM is also used as a comparative method for experiments. Table 5 lists performance comparisons values between Grid-HP-MTWSVM, PSO-HP-MTWSVM, GWO-MTWSVM and GWO-HP-MTWSVM by calculating the average of 10-folds CV.

In order to conduct an accurate comparison, the same number of generations and the same population size were used for PSO-HP-MTWSVM, GWO-MTWSVM and GWO-HP-MTWSVM. They were set to 100 and 15, respectively. For Grid-HP-MTWSVM, the searching range of penalty parameters is {0, 1, 2 … 9, 10} and that of kernel parameter is {0, 1, 2 … 9, 10}. For the metaheuristic methods, the same searching range is [0, 10]. In the process of initialization, random values between [0, 10] are assigned to the position components of each intelligent individual. From Table 5, we can see that the classification performance of GWO-HP-MTWSVM are highest in terms of accuracy, precision, recall and F1 values, which shows that GWO algorithm has good global convergence. Therefore, the parameters optimized by GWO are better than those optimized by grid search and PSO, which proves that GWO-HP-MTWSVM further improves the classification performance of the algorithm.

In order to eliminate the impact of data division and guarantee valid results, the 10-folds CV were carried out to evaluate the classification performance. The detailed comparison results on seismic dataset in terms of the accuracy and F1 value are showed in Figs. 5 and 6. From Figs. 5 and 6, we can see the accuracy and F1 value of the GWO-HP-MTWSVM algorithm are better than the other three competitors in six runs of the 10-folds CV, and are comparable to the Grid-HP-MTWSVM in remaining four runs, which proves GWO-HP-MTWSVM is effective. Observing the two broken lines of GWO-HP-MTWSVM and GWO-MTWSVM in Fig. 5, we can see that the GWO-HP-MTWSVM algorithm is much higher than the GWO-MTWSVM in each run, and can also see from Fig. 5 that the average accuracy of GWO-HP-MTWSVM is 4% higher than that of GWO-MTWSVM. It can be seen that both average performance and each run performance GWO-HP-MTWSVM are superior to that of GWO-MTWSVM, which further proves that HP-MTWSVM is effective.

In order to test the model reliability of GWO-HP-MTWSVM, we recorded the average accuracy, F1 value and standard error (SD) across

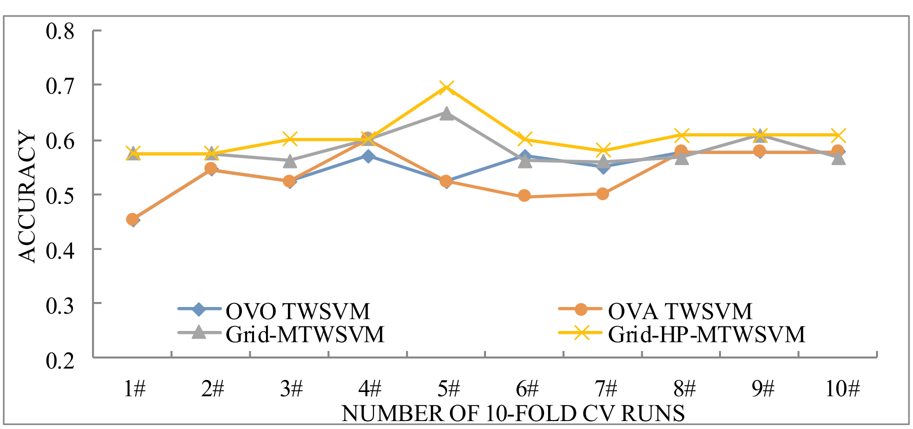


Fig. 3. The Accuracy obtained for each run by the four methods on the seismic dataset.

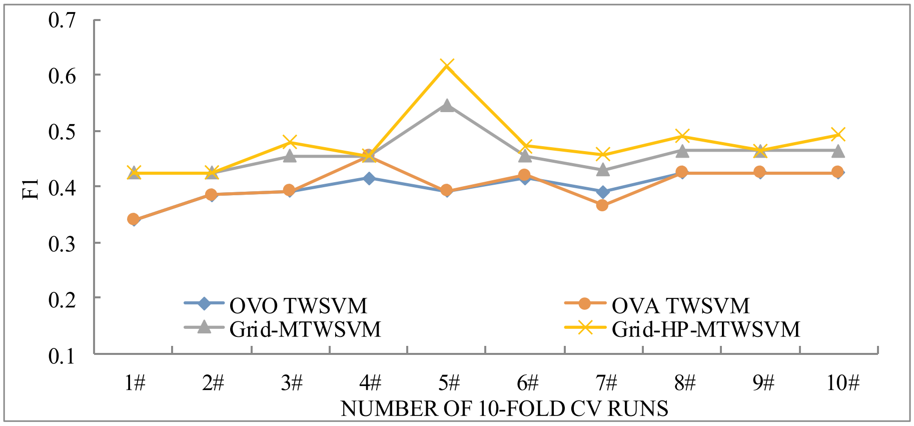


Fig. 4. The F1 obtained for each run by the four methods on the seismic dataset.

Table 4
Stability test results of four methods on the seismic dataset.

	OVO TWSVM	OVA TWSVM	Grid-MTWSVM	Grid-HP-MTWSVM
Accuracy (SD)	0.547 (0.0372)	0.542 (0.0401)	0.583 (0.0271)	0.605(0.0328)
F1(SD)	0.401 (0.0289)	0.413 (0.0319)	0.458 (0.0331)	0.478(0.0414)

Table 5
Comparison of classification performance among three methods on the seismic dataset.

Methods	Accuracy	Precision	Recall	F1
Grid-HP-MTWSVM	0.605	0.465	0.604	0.478
PSO-HP-MTWSVM	0.590	0.445	0.590	0.473
GWO-MTWSVM	0.595	0.455	0.595	0.468
GWO-HP-MTWSVM	**0.640**	**0.590**	**0.638**	**0.558**

the 10-folds CV results of Grid-HP-MTWSVM, PSO-HP-MTWSVM, GWO-TWSVM and GWO-HP-TWSVM in Table 6. As it can be seen from Table 6, though the standard error of Grid-HP-MTWSVM is the lowest, the accuracy and F1 value of Grid-HP-MTWSVM are much lower than GWO-HP-MTWSVM because it can only traverse the limited optional parameters set. In addition, with the expansion of parameter range, the time complexity of Grid-HP-MTWSVM to determine the optimal parameters increases exponentially. Therefore, intelligent algorithms such as GWO are used to optimize parameters. The optimization range of intelligent algorithm is infinite so that the optimal parameters can be found generally. Due to infinite optional parameters, optimal parameters may be different each run. In this case, the standard errors of GWO-MTWSVM, PSO-HP-MTWSVM and GWO-HP-MTWSVM methods are still very low, and the standard error of GWO-HP-MTWSVM is lower than that of PSO-HP-MTWSVM, which further proves that GWO-HP-MTWSVM is stable.

From the point of view of algorithm, the optimal parameters of different data sets are different. To further verify the difference between HP-MTWSVM optimized by Grid and HP-MTWSVM optimized by GWO, we only select experimental results of one run in the outer loop which arrive the highest accuracy for parameter analysis. The results of the parameter optimization are listed in Table 7. Sub-classifier 1, Sub-classifier 2 and Sub-classifier 3 represent three sub-classifiers of the favorable reservoir prediction model respectively, and c_{i1} , c_{i2} , δ_i represent two penalty parameters and kernel parameter of the *ith* sub-classifier respectively. Table 7 shows that the classification accuracy of GWO-HP-MTWSVM is 19% higher than that of PSO-HP-MTWSVM, which shows that GWO has better global convergence, is not easy to fall into local optimum, and can often find better parameters than PSO. The classification accuracy of GWO-HP-MTWSVM is 5% higher than that of Grid-HP-MTWSVM. According to the results of parameter optimization of these two methods, it can be seen that the grid search method can only optimize in a limited set of parameters, and the search time increases exponentially with the number of optional parameters, while GWO with good global optimization can optimize in an infinite set of parameters and find parameters that can not be found in grid search, further improves the performance of the algorithm.

From the above experiments, it shows that the effect of sub-classifiers can be fully used by choosing the optimal parameters for each sub-classifier, and the performance of the whole classifier can be

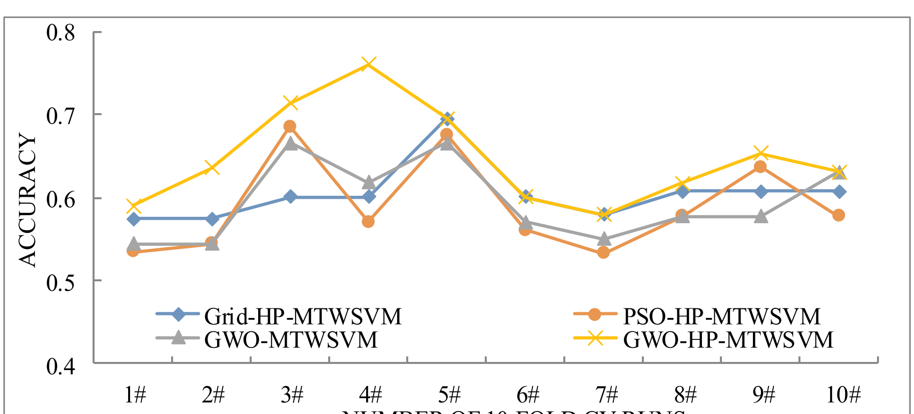


Fig. 5. The Accuracy obtained for each run by the three methods on the seismic dataset.

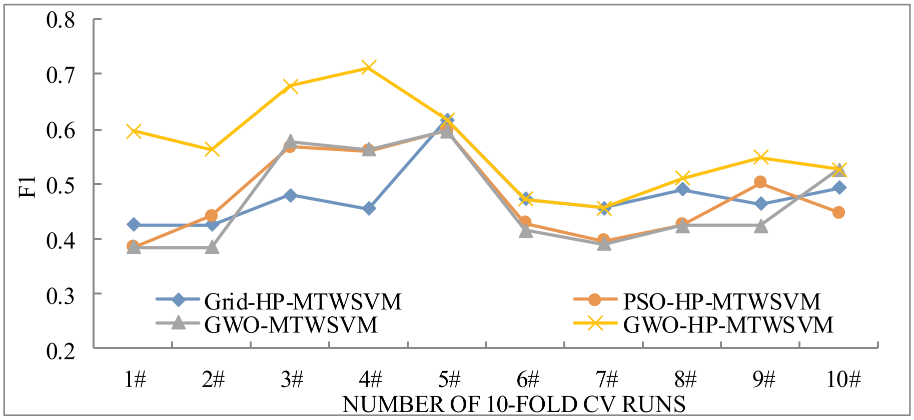


Fig. 6. The F1 obtained for each run by the three methods on the seismic dataset.

Table 6
Stability test results of four methods on the seismic dataset.

	Grid-HP-MTWSVM	PSO-HP-MTWSVM	GWO-MTWSVM	GWO-HP-MTWSVM
Accuracy (SD)	0.605(0.0328)	0.590(0.0566)	0.595 (0.0448)	0.640(0.0556)
F1(SD)	0.478(0.0414)	0.473(0.0806)	0.468 (0.0822)	0.558(0.0793)

effectively improved. At the same time, the GWO is simple and easy to converge, so it can quickly find the optimal solution. Compared with the traditional prediction method, the GWO-HP-MTWSVM method proposed in this paper has better prediction effect than the traditional method. The mapping model between seismic attributes and favorable reservoirs can be obtained through training, which can be quickly applied to other exploration areas.

5. Application of prediction model

5.1. Comparing with traditional methods

The traditional prediction of favorable reservoirs is generally based on the logging curve and one or two common seismic attributes. Synthetic records are created based on logging curves and seismic data, while the corresponding seismic profile depth of the target layer is found through tracing of horizons, then the attribute value of the corresponding depth is calculated. The category of the reservoir can be determined by observing the waveform of logging curve in this depth. Combining seismic attributes with logging interpretation, and selecting one or two seismic attributes which range of values are better consistent with the category of the reservoir. Finally, geological prospectors predict the distribution of reservoir according to these seismic attributes, and RMS_Amplitude and Instantaneous_Phase are the two seismic attributes they most commonly use. Figs. 7 and 8 are two-dimensional maps of the numerical distributions of the seismic attributes RMS_Amplitude and Instantaneous_Phase of the fourth layer in Niuzhuang area, respectively.

Taking the seismic data volume of the whole fourth layer in Niuzhuang area as input sample set, the categories labels of the input sample set are predicted by the trained GWO-HP-MTWSVM classification model, including 0, 1 and 2, which represent the non-favorable reservoir development area, reservoir development area and favorable reservoir development area respectively. Fig. 9 shows the prediction results of favorable reservoirs in Niuzhuang area using GWO-HP-MTWSVM model. In Figs. 7–9, the black dots indicate the locations of the wells, and the areas surrounded by black, red boxes and circles are as the indication areas. The areas surrounded by the black box and red box represent the areas around well X51 and well X28 respectively, and the areas surrounded by the black circle and red circle represent the areas around well X26 and well X24 respectively. From Figs. 7 and 8, the range of RMS_amplitude and instantaneous_frequency in the areas surrounded by black and red boxes are similar, and that of the areas surrounded by black and red circles are also. According to the traditional prediction method, it is possible to divide the areas surrounded by black

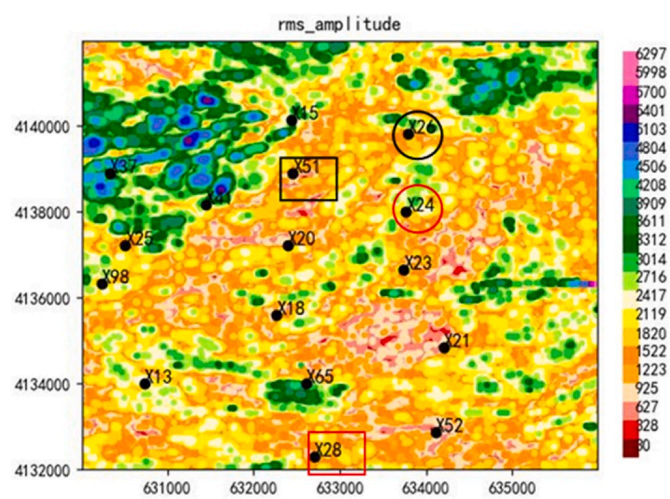


Fig. 7. Two-dimensional maps of the numerical distributions of RMS_Amplitude.

Table 7
Experimental results of parameter optimization.

	Sub classifier 1			Sub classifier 2			Sub classifier 2			Accuracy
	c_{11}	c_{12}	δ_1	c_{21}	c_{22}	δ_2	c_{31}	c_{32}	δ_3	
Grid-HP-MTWSVM	8	1	9	1	1	1	2	1	1	0.684
PSO-HP-MTWSVM	7.33	3.67	2.15	8.27	0.27	4.68	0.06	0.61	9.09	0.571
GWO-MTWSVM	0.50	0.24	1.76	0.50	0.24	1.76	0.50	0.24	1.76	0.619
GWO-HP-MTWSVM	0.43	0.81	5.93	0.34	0.93	3.40	0.57	0.18	6.12	0.761

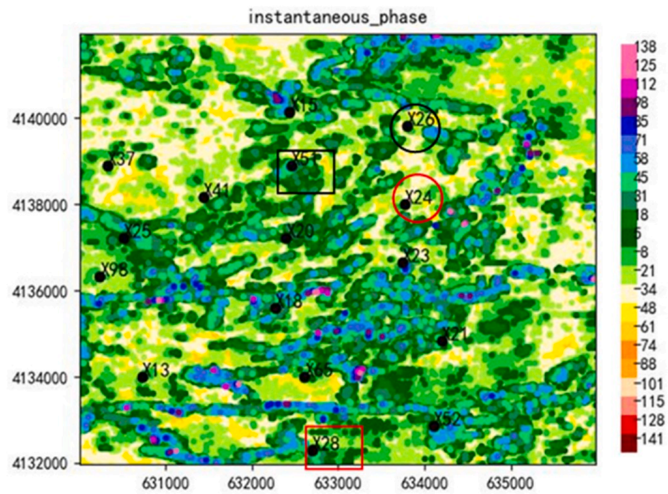


Fig. 8. Two-dimensional maps of the numerical distributions of Instantaneous_Phase.

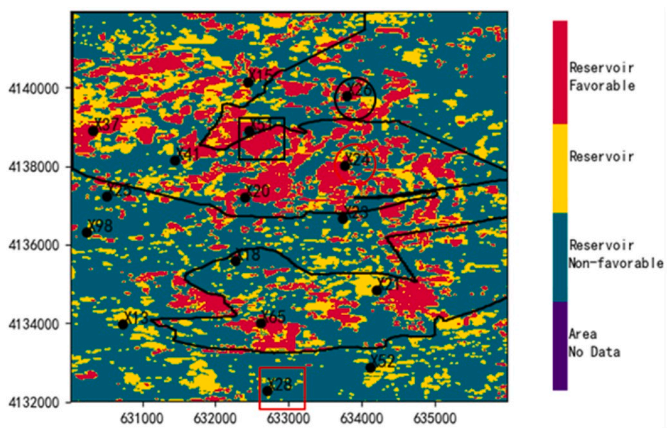


Fig. 9. Prediction results map of favorable reservoirs in Niuzhuang area.

and red boxes into the same type of reservoir, and the areas surrounded by black and red circles are also. As shown in Fig. 9, GWO-HP-MTWSVM prediction model divides the areas surrounded by black and red boxes into favorable and non-favorable reservoirs respectively, and divides the areas surrounded by black and red circles into same favorable reservoirs.

The actual exploration results are drawn in the form of black curves in Fig. 9. The area surrounded by the curves is the favorable reservoir and reservoir development areas delineated by geological prospectors. According to the actual exploration results, it is known that the areas surrounded by black box and red circle are favorable reservoir development areas, the areas surrounded by red box and black box are non-favorable reservoir development areas. From Figs. 7 and 8, it shows that the areas surrounded by black and red boxes are judged to same type of reservoirs by using the traditional prediction method, which is not consistent with the actual exploration results. From Fig. 9, it shows that the area surrounded by black box is judged to favorable reservoir, and the area surrounded by red box is judged to non-favorable reservoir, which is consistent with the actual exploration results. The areas surrounded by black and red circles are judged to same type of reservoirs by using the traditional prediction method and GWO-HP-MTWSVM method, and they are also judged to the favorable reservoirs by using GWO-HP-MTWSVM method, which indicates that the area surrounded by black circle is likely to be the potential favorable reservoir development area.

Comparing the prediction results of favorable reservoirs with the numerical distribution maps of attributes, it illustrates that one or two commonly used attributes cannot reflect the characteristics of the favorable reservoirs, and the determination of the favorable reservoirs is the result of the interaction of various attributes. The proposed GWO-HP-MTWSVM in this paper can effectively identify favorable reservoirs and solve the problem of multi-solution caused by seismic attributes.

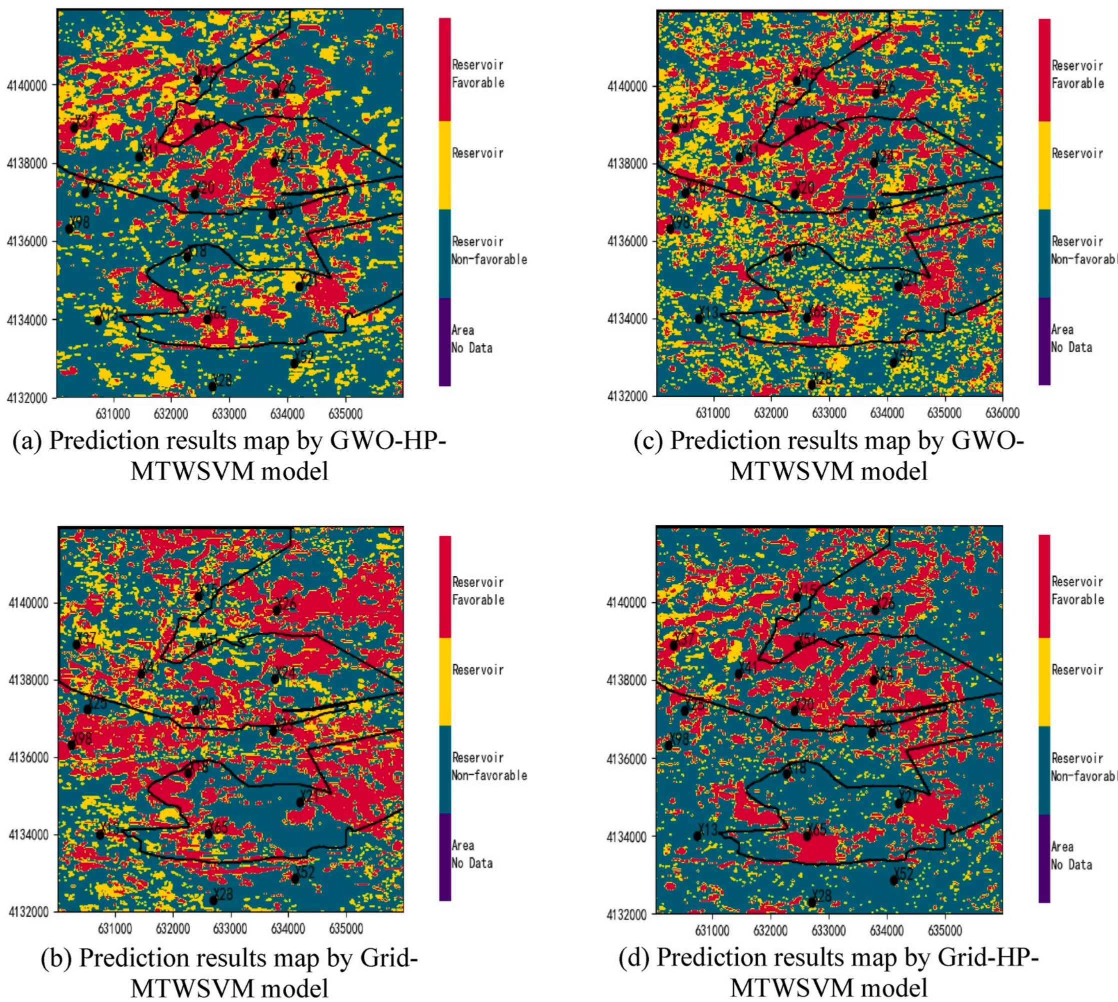
5.2. Comparing with machining learning methods

To further verify the effectiveness of GWO-HP-MTWSVM, the prediction results of GWO-HP-MTWSVM applied to the fourth layer seismic data volume in Niuzhuang area are compared with that of GWO-MTWSVM and Grid-HP-MTWSVM. Fig. 10 shows the overlap maps of the prediction results of GWO-HP-MTWSVM, Grid-MTWSVM, GWO-MTWSVM and Grid-HP-MTWSVM with the actual exploration results. Fig. 10(a) shows the range of favorable reservoir and reservoir development areas predicted by GWO-HP-MTWSVM is roughly consistent with the reservoir area surrounded by black curve. Fig. 10(b) shows the reservoir areas predicted by Grid-MTWSVM are extensive, but most of them are distributed outside the actual exploration areas, and the areas around well X28 are misjudged as reservoir areas. Fig. 10(c) shows the reservoirs predicted by GWO-MTWSVM are dispersed and it is difficult to determine the range of reservoir. The area where well X28 is located are also misjudged as reservoir areas. Fig. 10(d) shows Grid-HP-MTWSVM only predicts many favorable reservoir development areas, the number of reservoir development areas is small, which is not in line with the actual exploration situation. Part of areas where well X28 is located are also misjudged as favorable reservoir development zones. At the same time, geological exploration personnel also need to know the distribution of reservoirs. Compared with Grid-HP-MTWSVM, the GWO-HP-MTWSVM method can not only approximately show the distribution of favorable reservoirs, but also approximately show the distribution of reservoirs.

In order to further prove that GWO-HP-MTWSVM is better than Grid-HP-MTWSVM, we have analyzed the comparative results between the prediction results of well X52 using GWO-HP-MTWSVM and Grid-HP-MTWSVM methods and the actual exploration situation. According to the actual exploration results that delineated by geological prospectors, although well X52 is not in the delineated reservoir and favorable reservoir areas, we can know from situation of the previous exploration wells that well X52 has detected reservoirs, indicating that there are a small number of reservoirs around well X52. As we can see from Fig. 10 (a), a small number of reservoirs around well X52 can be predicted by using GWO-HP-MTWSVM. As we can see from Fig. 10 (d), almost no reservoirs around well X52 can be predicted by using Grid-HP-MTWSVM, which further illustrates the GWO-HP-MTWSVM is better. From Fig. 10, we can know that the GWO-HP-MTWSVM model proposed in this paper is not only superior to other algorithms in trained data sets, but also can be better applied to unexplored areas. The accuracy of traditional favorable reservoir prediction in complex concealed reservoirs zones such as Niuzhuang is generally 60%. The classification accuracy of the proposed method in this paper is not only better than the traditional prediction method, but also saves manpower and material resources. It can also provide favorable reference for geological prospectors to delineate favorable areas in complex concealed reservoirs zones.

6. Conclusions

The main work of this paper is to predict the favorable reservoirs in Niuzhuang area of Dongying, assist geological exploration personnel quickly delineate favorable areas and avoid waste of resources caused by empty wells. In this paper, TWSVM suitable for prediction of small sample is introduced. Aiming at the drawbacks of existing methods for constructing MTWSVM, we design the GWO-HP-MTWSVM model for



(a) Prediction results map by GWO-HP-MTWSVM model

(c) Prediction results map by GWO-MTWSVM model

(b) Prediction results map by Grid-MTWSVM model

(d) Prediction results map by Grid-HP-MTWSVM model

Fig. 10. Prediction results map of favorable reservoirs in Niuzhuang area.

prediction. The seismic attribute values of each type reservoir are within a certain range, but the value ranges of different reservoirs are cross. Even if in high-dimensional space, it is difficult to find a hyperplane to completely separate samples of different reservoirs. The proposed GWO-HP-MTWSVM method optimizes the combination strategy of binary classification TWSVM so that can separate the samples corresponding to different reservoirs to each other as much as possible, so as to achieve the overall optimization. The model can give full play to the role of each sub-classifier and find the optimal parameters quickly. From experimental results of section 4.2.4, the prediction accuracy of GWO-HP-MTWSVM is 64% which is not very high. The reason is that the number of labeled reservoir samples is few and the reservoirs are mostly complex and concealed in Niuzhuang area. It is difficult to greatly improve the performance of machine learning methods under the condition of few and complex samples, but compared with the traditional prediction methods, conventional machine learning methods and deep learning methods, the GWO-HP-MTWSVM method greatly improves the efficiency of predicting favorable reservoirs, and is recognized by professionals.

Our proposed GWO-HP-MTWSVM model also has some limitations in practical application. If the number of labeled reservoir samples in real field is very small - only a few hundred samples, the prediction accuracy of model will be affected. In addition, the determination of the favorable reservoirs is not only related to the seismic attributes. In the future work, we will predict the favorable reservoirs by considering the geological structure characteristics, logging interpretation results, oil test conclusions, and so on. At the same time, we will continue to improve the algorithm to further improve the accuracy of predicting the favorable reservoirs by machine learning.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.petrol.2020.106952.

References

Chen, J., Xiong, H., Zheng, H., 2018. Parameters optimization for SVM based on Particle Swarm algorithm. Comput. Sci. 45 (6), 197–203.
Ding, S., Yu, J., Qi, B., Huang, H., 2014. An overview on twin support vector machines. Artif. Intell. Rev. 42 (2), 245–252.
Ding, S., Zhang, J., Zhang, X., 2018. Survey on multi class twin support vector machines. J. Software 29 (1), 89–108.
Elhariri, E., El-Bendary, N., Hassanien, A.E., Abraham, A., 2015. Grey Wolf Optimization for One-Against-One Multi-Class Support Vector Machines. Kyushu Univ, Fukuoka, pp. 7–12.
Emary, E., Yamany, W., Hassanien, A.E., Snasel, V., 2015. Multi-objective gray-wolf optimization for attribute reduction. Procedia Comput. Sci. 65, 623–632.

Heidari, A.A., Pahlavani, P., 2017. An efficient modified grey wolf optimizer with Levey flight for optimization tasks. Appl. Soft Comput. 60, 115–134.
Hutahaean, J.J., Demyanov, V., Arnold, D., Vazquez, O., 2014. Optimization of Well Placement to Minimize the Risk of Scale Deposition in Field Development. SPE Abu Dhabi International Petroleum Exhibition and Conference.
Hutahaean, J., Demyanov, V., Christie, M.A., 2017. On optimal selection of objective grouping for multiobjective history matching. SPE J. 22 (4), 1296–1312.
Jayadev, Khemchandani, R., Chandra, S., 2007. Twin support vector machines for pattern classification. IEEE Trans. Pattern Anal. Mach. Intell. 29 (5), 905.
Li, M., Liu, Z., Liu, M., Ma, Y., Shao, W., 2018. Impedance inversion based on small-angle stacking seismic data. Oil Geophys. Prospect. 53 (6), 1291–1297.
Lin, N., Zhang, D., Zhang, K., Wang, S., Fu, C., Zhang, J., Zhang, C., 2018a. Predicting distribution of hydrocarbon reservoirs with seismic data based on learning of the small-sample convolution neural network. Chin. J. Geophys. 61 (10), 4110–4125.
Lin, N., Fu, C., Zhang, D., Jin, X., Zhang, K., Wen, B., Wei, Q., Zhang, C., 2018b. Supervised learning and unsupervised learning for hydrocarbon prediction using multiwave seismic data. Geophys. Prospect. Pet. 57 (4), 601–610.
Liu, X., Wang, Y., Gong, X., Qin, L., Huang, W., 2012. The application of seismic reservoir prediction technology in carbonate of AMH region. J. Oil Gas Technol. (J. Jianghan Petroleum Inst.) 34 (8), 73–77.
Masoudi, P., Tokhmechi, B., Jafari, M.A., Moshiri, B., 2012. Application of fuzzy classifier fusion in determining productive zones in oil wells. Energy Explor. Exploit. 30 (3), 403–415.
Mirjalili, S., Mirjalili, S.M., Lewis, A., 2014. Grey wolf optimizer. Adv. Eng. Software 69 (3), 46–61.
Sebtosheikh, M.A., Salehi, A., 2015. Lithology prediction by support vector classifiers using inverted seismic Attributes data and petrophysical Logs as a new approach and Investigation of training data set size effect on its performance in a heterogeneous carbonate reservoir. J. Petrol. Sci. Eng. 134, 143–149.
Shao, Y., Chen, W., Wang, Z., Li, C., Deng, N., 2015. Weighted linear loss twin support vector machine for large-scale classification. Knowl. Base Syst. 73, 276–288.
Song, J., Yang, L., Gao, Q., Liu, J., 2018. Strong tolerance random forest algorithm in seismic reservoir prediction. Oil Geophys. Prospect. 53 (5), 954–960.
Wang, X., Lu, S., Xiao, D., 2013. Optimization of seismic attributes and reservoir prediction based on cluster Analysis—by taking Ao 9 working area in aobaota oilfield for example. J. Oil Gas Technol. (J. Jianghan Petroleum Inst.) 35 (3), 61–66.
Wang, H., Zheng, B., Yoon, S.W., Ko, H.S., 2018. A support vector machine-based ensemble algorithm for breast cancer diagnosis. Eur. J. Oper. Res. 267 (2), 687–699.
Wei, Z., Zhao, H., Han, B., Sun, C., Li, M., 2017. Grey wolf optimization algorithm with self-adaptive searching strategy. Comput. Sci. 44 (3), 259–263.
Xie, J., Hone, K., Xie, W., Gao, X., Shi, Y., Liu, X., 2013. Extending twin support vector machine classifier for multi-category classification problems. Intell. Data Anal. 17 (4), 649–664.
Ye, Y., Wang, Y., Zhou, H., Ye, T., 2015. Application of geostatistical inversion to reservoir prediction in Shifang gas field. Comput. Tech. Geophys. Geochem. Explor. 37 (2), 236–241.
Yin, X., Ye, D., Zhang, G., 2012. Application of kernel fuzzy C-means method to reservoir prediction. J. China Univ. Pet. (Ed. Nat. Sci.) 36 (1), 53–59.
Yu, W., Feng, L., Du, Y., Yang, Y., Zhou, M., Dong, Z., 2016. Reservoir prediction technology based on joint inversion of logging-constrained and neural network. Prog. Geophys. 31 (5), 2232–2238.
Zhang, P., Ni, S., Wang, Y., 2011. A method for parameter selection of support vector machine updated model. Electron. Optic. Contr. 18 (9), 87–90.
Zhang, J., Huang, G., Li, J., Yang, Y., Du, Y., 2015. Seismic favorable reservoir prediction based on analytic hierarchy process. Special Oil Gas Reservoirs 22 (5), 23–27.
Zhu, A., Xu, C., Li, Z., Wu, J., Liu, Z., 2015. Hybridizing grey wolf optimization with differential evolution for global optimization and test scheduling for 3D stacked SoC. J. Syst. Eng. Electron. 26 (2), 317–328.
Zhu, K., Wang, Y., Yi, Q., Wang, X., Li, M., Zhao, Z., Peng, L., 2017. Application of multi-seismic attribute information fusion in sandstone reservoir prediction in nantun formation in the eastern Wu slope in hailaer basin. Comput. Tech. Geophys. Geochem. Explor. 39 (1), 109–115.