Prediction of Corrosion Rate in Submarine Multiphase Flow Pipeline Based on PSO-SVM Model

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Abstract. In view of the internal corrosion rate of submarine multiphase flow pipelines, this paper analyzes the related factors affecting the corrosion rate of this type of pipeline, and introduces PSO algorithm and SVM algorithm respectively. Based on the PSO-SVM combination model, the 44 groups of data was used to study the influencing factors and corrosion rate, meanwhile the 10 groups of data was used to predict. The predictions are compared with the GA-SVM model, the LS-SVM model and the CV-SVM model to verify the advancement and feasibility of the proposed method. The results show that the temperature has a relatively large influence on the corrosion rate of the multiphase flow pipeline in the seabed. The influence of pressure on the corrosion rate of the multiphase flow pipeline in the seabed is relatively small. The PSO-SVM combined model is used in the submarine multiphase flow pipeline. The error of corrosion rate prediction is only 1.848% on average, and the model training time is only 3.17s, both of which are smaller than other models. The research proves that the PSO-SVM combination model has strong advancement and feasibility for the prediction of the internal corrosion rate of submarine multiphase flow pipelines.

1. Introduction
With the continuous development of submarine oil, the construction of submarine pipelines has also continued to grow. According to the statistics of the Energy Bureau, by the end of 2017, the length of China's submarine pipelines has reached more than 8,000 kilometers, which has become the “lifeline” of offshore oil and gas transportation [1-2]. Once the submarine pipeline fails or ruptures, it will not only affect normal operations, but also cause serious damage to biodiversity and cause great economic losses. According to the relevant data, 40% of the total accidents caused by corrosion caused by the failure of the submarine pipeline were found. Therefore, through the prediction of corrosion in the multiphase flow pipeline under the seabed, the corrosion profile in the pipeline can be effectively detected, the pipeline failure event can be reduced, and reasonable advice and suggestions can be provided for the corrosion protection measures of the subsea pipeline.[3][4]

For the study of the prediction rate of internal corrosion, in 2015, Deng Zhian [5-6] and others established a new prediction model to study the corrosion rate of marine pipelines, but the limitation of this method is that it could be used only when the influencing factors are small. In 2015, Sun Zhe [7] established a BP neural network algorithm to predict the corrosion rate of a multiphase flow submarine pipe section in the South China Sea, and compiled a corrosion rate prediction program. However, the error of the program results was relatively large and the results were not satisfactory. In 2018, María Jesús and KAVEH A [7] analyzed the corrosion resistance of stainless steel sodium chloride solution under different conditions (chloride ion concentration, acidity and temperature)
based on support vector machine algorithm. Corrosion pitting model, the research results show that the support vector machine is only suitable for small sample problems with higher precision.

Faced with the increasing power of artificial intelligence under big data, this paper proposes a new prediction method based on PCA-PSO-SVM combination model, which uses some actual pipeline corrosion rate and related influencing factors data to train and predict the model. A part of the data is predicted, and the actual corrosion rate and prediction results are compared to verify the accuracy of the model. This study can provide a reliable theoretical basis for the calculation of corrosion failure of submarine multiphase flow pipelines, which is the risk of submarine pipeline integrity. Evaluation provides scientific guidance.

Analysis of Factors Affecting Internal Corrosion of Submarine Multiphase Flow Pipelines:

(1) Temperature: When the temperature is greater than 60 °C, the surface of the steel pipe tends to form a corrosive protective film, which hinders the reaction between the steel and the medium, so that the corrosion rate becomes slow. When the temperature is below 60 °C, the internal corrosion rate will be significantly accelerated due to the absence of a protective film. The degree of pitting and pitting will be more serious, and it will occur peak corrosion rate between 60-70 °C.

(2) The pH value: CO₂ forms a weak acid H₂CO₃ in water, which makes the pH of the solution decrease, and the reaction of the anode is aggravated after the occurrence of H⁺. The literature shows that when the pH is between 4 and 6, the reaction will occur violently and the internal corrosion phenomenon is serious.

(3) Fluid flow rate: The internal corrosion rate will increase due to the increase of body velocity, because the increase of fluid velocity will accelerate the corrosion process, and the tangential force will destroy the protective film formed on the surface of the steel, resulting in serious local corrosion.

(4) Pressure: Pressure also has a significant effect on corrosion. When the pressure is high, the pipeline is subjected to stress perpendicular to the corrosion surface, accompanied by chemical corrosion, the corrosion rate of the pipeline becomes large, and the pipeline life is shortened.

(5) CO₂ partial pressure: When the temperature is lower than 60 °C, the corrosion rate increases with the increase of CO₂ partial pressure. When the temperature is higher than 60 °C, the corrosion product film forms on the inner surface of the pipeline with the increase of CO₂ partial pressure, hindering the occurrence of corrosion reactions, and the corrosion rate is slow.

(6) Liquid holdup: When the liquid phase accounts for a large proportion in the multiphase flow system, the metal surface is easy to form a water film, and the acid gas dissolves in the liquid phase faster, providing an acidic medium to facilitate the occurrence of corrosion; When compared, the corrosion rate is significantly reduced.

Through the above analysis, it can be found that temperature, pH, flow rate, pressure, CO₂ partial pressure and liquid holdup are main factors influencing internal corrosion of submarine pipelines, and the influence of pressure is negligible.

2. Model Establishment

2.1. Basic Principles of Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is an optimization algorithm that seeks optimal values through iterative methods through mutual cooperation and information sharing among groups. It is the most common optimization algorithm model [15-16]. The PSO algorithm assumes that each optimization problem is a particle in the search space, which is mainly characterized by three variables: speed, position and fitness. Suppose the search space is N-dimensional, there are M particles in the group, and the i-th particle represents an N-dimensional vector. In the search process, each particle continuously tracks two optimal solutions (one is its own optimal solution Pbest, and the other is the global optimal solution Gbestg) to update:

\[ V_{i}^{t+1} = \omega V_{i}^{t} + c_1 r_1 \left( P_{\text{best}_{i}} - X_{i}^{t} \right) + c_2 r_2 \left( P_{\text{best}_{g}} - X_{i}^{t} \right) \ldots \ldots \]  \hspace{1cm} (1)

\[ X_{i}^{t+1} = X_{i}^{t} + V_{i}^{t+1} \ldots \ldots \]  \hspace{1cm} (2)
In the above formula, $V_i^t$, $X_i^t$ is the current velocity and position of i particles respectively; $c1, c2$ acceleration factor, $\omega$ is the weighting factor; $g$ is the most particle position index; $r1, r2$ is between $[0, 1]$ Random number.

2.2. Basic Principles of Support Vector Machine (SVM)

Support Vector Machine (SVM) has obvious advantages for solving small sample, nonlinear and high-dimensional pattern recognition. It is a classification algorithm with good performance and can be applied to artificial intelligence and machine learning. An algorithm with strong generalization ability can adapt to the problem of small sample and high dimension in the process of application[12]. The basic prediction function formula of the SVM algorithm is as follows:

$$f(x) = \sum_{i \in SV} (a_i - a_i^*) K(x_i, x_j) + b$$

(3)

In the above formula, $a_i$ and $a_i^*$ represent the Lagrangian multiplier; $b$ represent the offset; $SV_i$ is the data set representing the prediction process; and the $K(x_i, x_j)$ is the kernel function representing the SVM prediction. $a_i$ and $a_i^*$ can be obtained by the following formula:

$$\begin{align}
\max \sum_{i=1}^{n} y_i (a_i - a_i^*) - \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} (a_i - a_i^*)(a_j - a_j^*) K(x_i, x_j) \\
\text{s.t.} \sum_{i=1}^{n} (a_i - a_i^*) = 0, 0 \leq a_i^* \leq C
\end{align}$$

(4)

In the above formula, $C$ is a penalty parameter is indicated; $\varepsilon$ indicating an insensitive loss parameter of the prediction process. At the same time, the kernel function of SVM regression takes Sigmoid function as shown below.

$$K(x_i, x_j) = \tanh(\gamma x_i x_j + f_{\text{bias}})$$

(5)

2.3. PSO-SVM Model Construction

In the PSO-SVM prediction model, the input factors are temperature, pH, flow rate, CO2 partial pressure, liquid holdup rate and partial internal corrosion rate data as PSO-SVM predictive input data, and the remaining internal corrosion rate is performed. prediction. The flow chart for predicting the internal corrosion rate of the submarine pipeline by the PSO-SVM model is as shown in Fig.1.
3. Instance Verification and Analysis

3.1. Data Sources

Through the internal detection of four submarine pipelines in a certain sea area of China [7], and the internal corrosion rate of 54 locations of four pipelines were calculated, the temperature, pH value and flow rate of the 54 locations were calculated by real-time simulation equipment. The five data of CO2 partial pressure and liquid holdup rate were simulated, and the corrosion rate and influencing factors data at these locations were obtained. Some of the data are shown in Table 1 below. The data of the 54 location points are divided into sets, which are a learning data set and a prediction data set, wherein the learning data set contains data of 44 position points for model training, and the prediction data set contains data of 10 position points for model prediction and model error checking [8].

| Number | Temperature (°C) | Liquid holdup | CO2 partial pressure (kPa) | Flow rate (m/s) | pH value | Corrosion rate (mm/y) |
|--------|------------------|---------------|---------------------------|----------------|----------|----------------------|
| 1      | 61.49            | 0.57          | 252.08                    | 0.68           | 4.87     | 2.6                  |
| 2      | 60.28            | 0.62          | 252.1                     | 0.86           | 4.87     | 2.67                 |
| 3      | 59.08            | 0.92          | 252.07                    | 0.69           | 4.87     | 2.79                 |
| 4      | 57.32            | 0.92          | 251.81                    | 0.53           | 4.88     | 2.54                 |
| 5      | 56.19            | 0.92          | 251.62                    | 0.53           | 4.88     | 2.98                 |
| 6      | 55.09            | 0.92          | 251.44                    | 0.53           | 4.88     | 3.05                 |
| 7      | 54.02            | 0.92          | 251.26                    | 0.53           | 4.88     | 3.11                 |
| 8      | 52.99            | 0.93          | 251.08                    | 0.53           | 4.89     | 3.11                 |
| 9      | 51.98            | 0.93          | 250.87                    | 0.53           | 4.89     | 3.05                 |
| 10     | 50.52            | 0.93          | 250.55                    | 0.52           | 4.89     | 2.67                 |

3.2. PSO Optimization

In addition to the PSO algorithm, there are three common SVM algorithm parameter optimization algorithms, namely GA algorithm (Genetic Algorithm), LS algorithm (the Least Square Method.
Algorithm) and CV algorithm (Cross-Validation Algorithm), which use these four kinds of optimization respectively. The algorithm optimizes the parameters in the SVM algorithm. The optimization results are shown in Table 2 below. From the perspective of the optimization results, the superiority of the PSO-SVM model cannot be verified. Therefore, the PSO-SVM model and GA-SVM model, LS-SVM model and CV-SVM model error comparison.

| Model                        | C     | ε     | Optimal kernel function |
|------------------------------|-------|-------|-------------------------|
| Particle Swarm Optimization (PSO) | 28.7513 | 1.5364 | Sigmoidal Function |
| Genetic Algorithm(GA)        | 42.5123 | 0.9426 | Sigmoidal Function |
| Least Squares Algorithm(LS)  | 21.4289 | 1.8942 | Sigmoidal Function |
| Cross-Validation Algorithm(CV) | 36.8436 | 0.8579 | Sigmoidal Function |

3.3. Analysis of Prediction Results

According to the optimization results of PSO algorithm parameters, the SVM model is established in Matlab software, and the model is trained with data of 44 locations, and the corrosion rate of the remaining 10 locations is predicted. The average absolute error of the prediction results of the four models and the time required for the model training are shown in Figure 2 and Table 3.

![Figure 2. Comparison of prediction errors of four models](image)

### Table 2. Parameters C and kernel function types

| Model                        | C     | ε     | Optimal kernel function |
|------------------------------|-------|-------|-------------------------|
| Particle Swarm Optimization (PSO) | 28.7513 | 1.5364 | Sigmoidal Function |
| Genetic Algorithm(GA)        | 42.5123 | 0.9426 | Sigmoidal Function |
| Least Squares Algorithm(LS)  | 21.4289 | 1.8942 | Sigmoidal Function |
| Cross-Validation Algorithm(CV) | 36.8436 | 0.8579 | Sigmoidal Function |

| Model                        | PSO-SVM | GA-SVM | LS-SVM | CV-SVM |
|------------------------------|---------|--------|--------|--------|
| Average absolute error       | 1.848%  | 7.757% | 10.784% | 12.188% |
| Training time(s)             | 3.17    | 5.84   | 6.73   | 12.68  |

By analyzing the prediction results and prediction errors, it can be found that the prediction trend of the PSO-SVM model is consistent with the actual corrosion rate trend. At the same time, the prediction error of the 10 locations does not exceed 5%, and at the same time, compared with the other three models. Compared with this model, the average absolute error of the combined model is only 1.848%, which is much lower than other models. In terms of model training time, the model proposed in this study only needs 3.17s, which is also smaller than the learning time of other models. Therefore, in the prediction of corrosion rate in multi-phase pipelines on the seabed, the PSO-SVM model proposed in this study has strong advancement and feasibility.

4. Conclusion

In this paper, firstly the influencing factors of corrosion rate in submarine multiphase flow pipeline are analyzed. The PSO algorithm and SVM algorithm are introduced theoretically, and the PSO-SVM which can be used for the prediction of corrosion rate in submarine multiphase flow pipeline is proposed. Combined model. The paper shows that:
(1) The corrosion in the multiphase flow pipeline of the seabed is affected by six factors such as temperature, pH value, flow rate, pressure, CO\textsubscript{2} partial pressure and liquid holdup. However, among these six factors, the temperature has a relatively large influence on the pressure. The impact is relatively small. In order to simplify the model and improve the training time of the model, the influence of pressure on the corrosion of the multiphase flow pipeline in the seabed can be neglected.

(2) Simultaneously use the four models of PSO, GA, LS and CV to optimize the parameters $C$ and $\varepsilon$ of SVM algorithm. Under the premise of determining the sum of parameters $C$ and $\varepsilon$, the number of hidden layer nodes and the type of kernel function are based on the minimum average absolute error. Finally, the SVM algorithm is used for prediction. The results show that the error of the prediction result is no more than 5%. At the same time, the average absolute error is only 1.848%. In terms of model training time, the model proposed in this study only needs 3.17s, both of which are smaller than other models. Therefore, In the prediction of corrosion rate in multi-phase pipelines on the seabed, the PSO-SVM combination model is very theoretical and scientific.

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