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Prediction of corrosion failure probability of buried oil and gas pipeline based on an RBF neural network

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Risk assessment is critical to ensure the safe operation of oil and gas pipeline systems. The core content of such risk assessment is to determine the failure probability of the pipelines quantitatively and accurately. Hence, this study combines the MATLAB neural network toolbox and adopts an Radial Basis Functions (RBF) neural network with a strong non-linear mapping relationship to build a corrosion failure probability prediction model for buried oil and gas gathering and transmission pipelines. Based on the hazard identification of pipeline corrosion failure, the model summarizes the causes of corrosion failure and determines the input and output vectors of the neural network based on the fault tree. According to the selected learning samples, through the design and training of network parameters, the RBF neural network that can predict the system failure probability is finally obtained. Taking the failure probability of 30 groups of high-pressure gathering and transmission pipelines of gas storage as an example, the capability of inputting the probability of the bottom event and outputting the probability of the top event is demonstrated through training data. Our results show that the calculated failure probability based on the fault tree analysis model is consistent with the predicted failure probability based on the RBF neural network model. Hence, the RBF neural network model is shown to be reliable in predicting the corrosion failure probability of buried pipelines.

KEYWORDS

buried oil and gas pipeline, RBF neural network, fault tree analysis, failure probability, risk assesment

1 Introduction

Oil and gas pipelines bring a convenient and efficient energy supply to economic development. Due to the vulnerability of pipeline materials and the particularity of transmission medium, long-term oil, and gas pipelines face the risk of corrosion failure (Amaechi et al., 2022; Li et al., 2022; Wu et al., 2022). In the corrosion failure risk assessment of oil and gas pipelines, the failure probability assessment of pipelines is the core content of a quantitative risk assessment of corrosion failure. The assessment of failure probability can provide a basis for making monitoring and maintenance plans for corroded pipelines, which is more practical. Therefore, it is necessary to study the evaluation method of corrosion failure probability of oil and gas pipelines.

Many scholars have studied the calculation method of corrosion failure probability of oil and gas pipelines. According to the principle of Bayesian network analysis, Hu et al. (2009) calculated the probability of pipeline corrosion failure by analyzing the probability and statistical relationship between the sub-node and the root node and using conditional independence. Luo and Jiang (2015) proposed an evaluation method for calculating the reliability of oil and gas pipelines based on the probabilistic artificial neural network of the Bayesian classification decision. Yu et al. (2016) combined the grey theory and Markov chain theory to predict the corrosion life of oil and gas pipelines through the constructed model. In order to predict the occurrence of pipeline corrosion failure and reasonably control pipeline corrosion, Liu et al. (2019) established the failure probability analysis model of the minimum cut-set basic event parallel system based on the failure fault tree. Based on the JC method and orthogonal transformation, Zhang et al. (2019) proposed a multi-mode failure probability calculation method for corroded pipelines considering relevant random variables using a multidimensional normal distribution function. To improve the prediction accuracy of pipeline corrosion rate, Li et al. (2021) built an unbiased grey model based on the traditional grey model. They introduced the Markov model to modify the prediction results.

According to the existing research, the mathematical models for estimating the corrosion failure probability of oil and gas pipelines mainly include the Markov model, common cause failure model, Bayesian network model, and artificial neural network model (Li et al., 2017; Taleb-Berrouane et al., 2021). However, these estimation methods have limitations. For example, the main problem of the Markov model is that it is based on exponential distribution and assumes that the failure probability of the bottom event remains unchanged. The distribution of conditional failure probability in the common cause failure model cannot be obtained. Still, it is assumed that it obeys a certain distribution, and the result deviates significantly from reality. The Bayesian network model can effectively combine prior knowledge and subjective probability. However, it requires a lot of data, and its analysis and calculation are more complex. In the case of complex problems, this contradiction will be more prominent. In addition, the traditional fault tree analysis method combines the importance method and the fuzzy evaluation method. Although it can calculate the more comprehensive failure probability, it cannot make a large number of probability predictions. At the same time, the comprehensive application of multiple models makes the fault tree software unable to play its expected role in the calculation, which also leads to a considerable amount of calculation. Thus, the neural network has irreplaceable advantages in predicting the failure probability of oil and gas pipelines.

So far, the application of neural network models in oil and gas transportation safety evaluation has not been comprehensive. Although a neural network model can evaluate pipeline corrosion rates and risks, there is no mature research on pipeline failure probability prediction (Xiao et al., 2022; Yu et al., 2022). However, the RBF neural network can better capture the multidimensional non-linear correlation between the relevant parameters and the pipeline failure probability. Hence, this paper attempts to apply the RBF neural network model to predict the corrosion failure probability of oil and gas pipelines. An RBF neural network is adopted for prediction. Through network training and learning of the known samples, the optimal parameters are derived, based on which the corrosion failure probability of other samples is predicted.

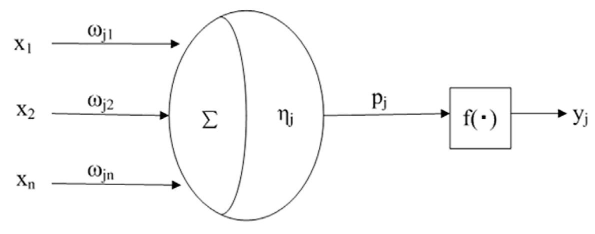

FIGURE 1
Element relation diagram of neural network.

The rest of the paper is organized as follows. The necessity of the RBF neural network is analyzed, and its MATLAB implementation is explained based on the introduction of the RBF neural network model in Section 2. After identifying the hazards of corrosion failure of oil and gas pipelines, the input and output vectors of the RBF neural network are designed, and appropriate network parameters are selected through training and learning samples in Section 3. In Section 4, based on the comparative analysis of fault tree analysis results and RBF neural network prediction results, the feasibility of using RBF neural network to predict the corrosion failure probability of buried oil and gas pipelines is verified. Finally, a summary of the results and further understanding are considered.

2 Neural network model and its implementation in MATLAB

2.1 Selection of neural network model

The artificial neural network is a theoretical mathematical model modeled on brain activity. It is a non-linear adaptive system composed of a large number of processing units (i.e., neurons) connected in a certain way. A typical feature of a neural network is that it can predict multivariable models without any correlation transformation or assumption of relevant input variables. It is based on actual observation data or other theoretical data used for training verification. The implicit non-linear relationship between input and output variables is extracted and approximated by a training neural network model (Xu et al., 2021; Zhang et al., 2021; Zhang et al., 2022). The elements of the neural network include neurons, weights, etc. The relationship between the elements is shown in Figure 1.

According to the relationship between the elements of the neural network, the neural model can be expressed as follows:

$$p_j = \sum_{i=1}^{n} \omega_{ji} x_i - \eta_j \tag{1}$$

$$y_j = f\left(p_j\right) \tag{2}$$

where p_j is the activation level of neurons. ω_{ji} is the weight. x_i is the input of neural network. η_j is the network system threshold. y_j is the output of neuron. $f(\cdot)$ is the activation function of neurons, which is usually a non-linear function.

At present, the BP network and RBF network are used in the prediction of pipeline failure probability. BP network model is a feedforward neural network that propagates the error back. It uses

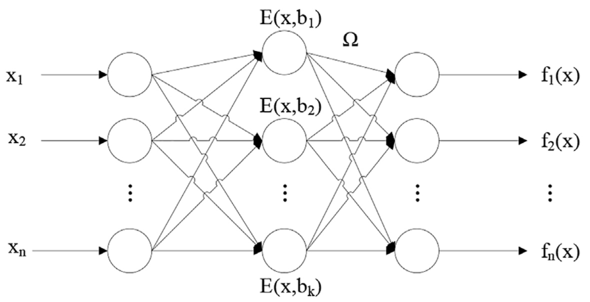

FIGURE 2
Topological structure diagram of RBF neural network.

the stored mapping relationship to output the data to be predicted without function. That is to say that the output value can be obtained without function operation. Before reaching the set error square sum, the weight value and threshold value can be adjusted by continuous backpropagation. Although the BP network is simple for calculation, it is easy to fall into a local minimum value, and its error cannot be reduced no matter how many iterations. Compared with many disadvantages of the BP network, the RBF (radial basis function) neural network shows its advantages. Its network topology can be changed according to specific problems. The network has adaptive and self-organizing capabilities and can also perform data fusion in a wide range in computing speed, thus reducing the network computing time (Peng et al., 2020). Therefore, this study intends to use RBF neural network to predict the corrosion failure probability of buried oil and gas pipelines.

2.2 RBF neural network

The RBF neural network is a supervised learning network. It has a simple structure, fast training speed, and can approximate non-linear functions with arbitrary accuracy. The most basic RBF neural network includes three layers: input layer, hidden layer, and output layer. After the samples are input into the network through the input layer, they reach the hidden layer. The hidden layer maps the input to a new space through an activation function, and then the system will linearly weigh the output of the hidden layer neurons to obtain the output value of the network (Wang et al., 2021; Yang and Fang, 2022). The topology of the RBF neural network is shown in Figure 2.

In Figure 2, $(x_1, x_2, \cdots, x_n)$ represents the input vector. $E(x, b_k)$ represents the activation function of the hidden layer. Ω represents the weight matrix between the hidden layer and the output layer. $f_n(x)$ represents the output value of output layer node n. The function of hidden layer is to map the vector from a low dimension to a high dimension. When the low dimension is linearly indivisible, it can be linearly separable when mapped to a high dimension.

2.3 Implementation of MATLAB

Since MATLAB provided a neural network toolbox, it has become the first choice for engineers to analyze and design neural networks (Zhu et al., 2021). The neural network toolbox is one of many toolboxes developed in the MATLAB environment. It is based on the artificial neural network theory. It uses Matlab programming language to form many activation functions of neural networks, such as S-type, linear, competitive layer, saturated linear, and other activation functions, so that the designer's calculation of the selected network output can be transformed into the call of activation functions. In addition, we can use MATLAB language to compile various subprograms for network weight training according to different typical procedures for modifying network weights and the training process of the network.

3 Corrosion failure probability prediction model for buried oil and gas pipelines

3.1 Hazard identification of corrosion failure of buried oil and gas pipelines

Based on fault tree analysis, this study analyzes the corrosion hazards of buried oil and gas pipelines. First, the top event of the fault tree should be defined. The top event is the starting point and main body of the fault tree analysis. The top event should be determined according to the characteristics of the analysis object. According to the risk degree of possible accidents in the fault tree, the hazardous event that has the most significant impact on the system should be taken as the top event of the fault tree. Then, the specific analysis should be carried out according to the principle of preparing a fault tree for one accident (Zhou et al., 2021; Chen et al., 2022; Irfan et al., 2022).

According to the above fault tree analysis principles, this study regards buried pipeline corrosion leakage as a top event. The direct cause of pipeline leakage is buried corrosion and internal corrosion, and any of these two causes will lead to pipeline failure. These two causes are taken as the second top events and analyzed similarly until the basic events representing various fault events are found (Ding et al., 2019; Huang et al., 2020). The specific list of basic events is shown in Table 1.

3.2 Establishment of RBF neural network prediction model

The corrosion failure probability of buried oil and gas pipelines is a non-linear function related to the basic event factors of the fault tree. The neural network model for predicting the failure probability of buried oil and gas pipelines established in this study is essentially a non-linear relationship mapping model between 77 input variables of failure influencing factors and one output variable of failure probability. The specific process is as follows.

3.2.1 Design input and output vectors

In this study, 77 basic events determined by fault tree analysis are taken as neuron parameter vectors of the neural network input layer. According to the analysis, when hiring experts to evaluate the basic events of the fault tree, the experts give a linguistic description

TABLE 1 Basic event list of corrosion failure fault tree of buried oil and gas pipeline.

Number	Basic event	Number	Basic event	Number	Basic event
1	Pipeline stress concentration	27	Short protection distance	53	Untimely maintenance
2	Material itself defects	28	Cathode underprotection	54	Cold deformation
3	Unreasonable design standards	29	Cathode overprotection	55	Sulfide stress corrosion cracking
4	Unreasonable design parameters	30	Non-standard protection	56	CO_2 stress corrosion cracking
5	Design approval error	31	Failure of protective material	57	High airflow velocity
6	Mechanical damage	32	Coatings blistering	58	Assistance of airflow dust
7	Inadequate construction supervision	33	Anodic pit corrosion	59	SRB reduction yields H_2S
8	Welding non-standard	34	Vandalism	60	Anaerobic bacteria produce acetic acid
9	Unqualified welding materials	35	Improper handling of social relations	61	High relative humidity
10	Poor surface pretreatment	36	Poor surrounding economy	62	With condensate water
11	Incomplete fusion	37	Defects in laws and regulations	63	Scouring strengthens solution stirring
12	Lack of penetration	38	Poor enforcement of laws and regulations	64	Upper H_2S concentration higher than lower
13	Fissure	39	Individual lack of legal awareness	65	Erosion Elimination of Corrosion Products
14	Low soil resistivity	40	Insufficient patrols	66	Water vapor film on pipe surface
15	High water content	41	Alarm system failure	67	H_2S and CO_2 dissolved in water
16	High reduction potential	42	Patrolman poor sense of responsibility	68	H_2S solution on the pipe surface
17	Low PH	43	Low awareness of public property	69	Unqualified inner protective layer
18	Corrosion of sulfur compounds	44	Insufficient pipeline safety education	70	Internal protective layer falling off
19	Cl^- high content	45	Pipeline mark error	71	Long filling cycle of corrosion inhibitor
20	CO_3^{2-} high content	46	Shallow buried depth of pipeline	72	Less dosage of corrosion inhibitor
21	Iron bacterial corrosion	47	Unqualified anticorrosive coating	73	Corrosion inhibitor unqualified
22	High salinity	48	Coating stripping	74	Inappropriate inhibitor concentration
23	High temperature	49	Coating thinning	75	High flow rate damage inhibitor
24	Fe^{2+} destruction	50	Coating aging	76	Long-term undetected corrosion inhibitor
25	Direct stray current	51	Reduced adhesion	77	No corrosion inhibitor protection
26	Stray alternating current	52	Poor processing quality		

TABLE 2 Conversion between linguistic variables and numerical variables.

Linguistic variables	Little	Fairly little	Medium	Fairly big	Big
Numerical variables	0.1	0.3	0.5	0.7	0.9

Note: In RBF, neural network prediction, the input variable is the probability of the occurrence of the basic event, which must be a certain value. In the study, the possibility of the occurrence of the basic event is judged by the expert evaluation method, and then the fuzziness of the possibility of the occurrence of the basic event is solved by the transformation of linguistic variables into numerical variables. This can solve the uncertainty of input variables in neural network prediction.

of their probability of occurrence based on the attributes of the basic events. There are five natural language variables: little, fairly little, medium, fairly big, and big. Since the input variable must be a specific value between (0, 1) when conducting RBF neural network prediction training, this study will try to convert the language variable into a numerical variable (Landquist et al., 2016; Guo et al., 2019; Zhang et al., 2020), as shown in Table 2.

Through the corresponding transformation between language variables and numerical variables, it can be determined that the input layer neuron is a 77-dimension numerical vector, and the output layer neuron is a 1-dimension numerical vector.

3.2.2 Select learning samples

The training verification samples proposed in this study are from the high-pressure buried gathering and transmission pipeline network of the Suqiao Gas Storage Complex in North China Oilfield. At present, there is no general method for selecting the number of training samples. Theoretically, fewer training samples may make a

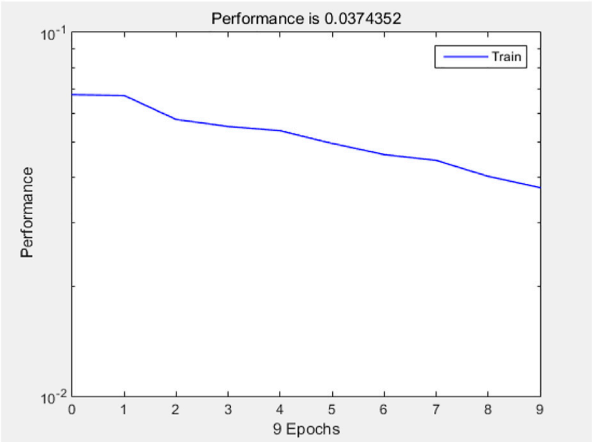

FIGURE 3
Training error curve of RBF neural network.

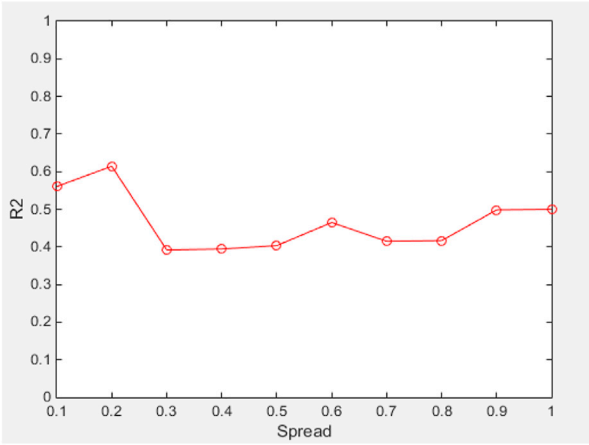

FIGURE 4
Influence of spread value on the performance of newrb radial basis function network.

neural network insufficient, leading to inadequate extrapolation ability of neural network prediction. Too many training samples will make the input variables of the neural network redundant, increasing the burden of neural network training. At the same time, the neural network will be overfitted due to excessive information surplus (Lin et al., 2018; Jiang et al., 2022; Xu et al., 2022). Based on this, this study extracts the first 25 pipeline segments from the 30 pipeline segments included in the gathering and transportation network as learning samples to train the network.

3.2.3 Design and training parameters

RBF neural network is a model widely used in system prediction and has mature technology. According to the design principle of the RBF neural network, the value of spread has a great impact on the network performance, which will be discussed in detail later.

Based on MATLAB programming operation, RBF neural network training curve is shown in Figure 3 (see the Supplementary Material for Matlab code). It can be observed that the global error of the network can reach below 0.05 after nine times of training. Therefore, the established RBF neural network can converge quickly.

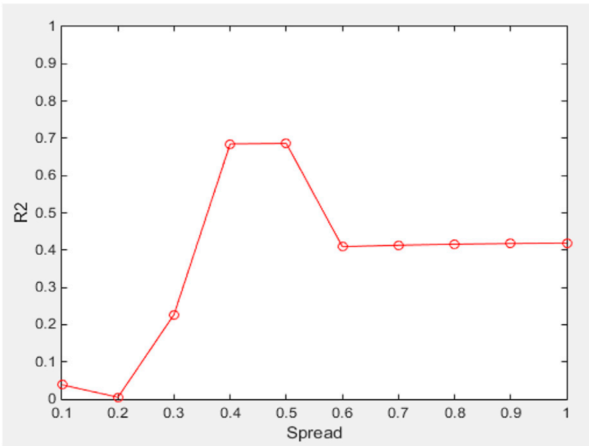

FIGURE 5
Influence of spread value on the performance of newrbe radial basis function network.

3.3 Parameter selection of RBF neural network

The RBF neural network model mainly includes two parameters: the radial basis function and the value of the spread. In the study, the relative error E_i and the determination coefficient R^2 are selected as the evaluation indicators for parameter selection (Gao et al., 2019; Yang et al., 2022). They are calculated as follows:

$$E_i = \frac{|y_i^1 - y_i|}{y_i} \tag{3}$$

$$R^2 = \frac{\left(n\sum_{i=1}^{n} y_i^1 y_i - \sum_{i=1}^{n} y_i^1 \sum_{i=1}^{n} y_i\right)^2}{\left[n\sum_{i=1}^{n}\left(y_i^1\right)^2 - \left(\sum_{i=1}^{n} y_i^1\right)^2\right]\left[n\sum_{i=1}^{n}\left(y_i\right)^2 - \left(\sum_{i=1}^{n} y_i\right)^2\right]} \tag{4}$$

where y_i^1 represents the predicted value of indicator i. y_i represents the actual value of indicator i. n is the number of indicators.

In Eq. 4, the performance of the neural network model is inversely proportional to the value of the relative error E_i. The value of the determination coefficient R^2 is between [0, 1]. When its value is close to 1, the RBF neural network model has the best performance.

The general creation functions of RBF networks include newrb and newrbe. Combined with the calculation of the evaluation index, the influence of the value of spread on the performance of the RBF network mainly includes the following two cases.

3.3.1 Newrb radial basis function network creation function and spread value

When newrb is selected as the RBF network creation function, the network is trained according to the spread value, and the corresponding deermination coefficient R^2 is calculated. The result is shown in Figure 4 (see the supplementary material for Matlab code).

TABLE 3 Corrosion failure probability of buried gathering and transmission pipeline.

Pipe number	Start station	End station	Pipe length (km)	Failure probability (fault tree result)	Failure probability (RBF prediction result)
1	19,633	19,647	1.455	0.005733	0.0057
2	19,647	19,648	0.103	0.005718	0.0057
3	19,648	19,649	0.104	0.006774	0.0068
4	19,649	19,653	0.416	0.006756	0.0068
5	19,653	19,658	0.519	0.005221	0.0052
6	19,659	19,660	0.104	0.006142	0.0061
7	19,662	19,668	0.623	0.005531	0.0055
8	19,668	19,669	0.104	0.005929	0.0059
9	19,670	19,674	0.416	0.007342	0.0073
10	19,678	19,679	0.104	0.005586	0.0056
11	19,681	19,687	0.624	0.006528	0.0065
12	19,691	19,692	0.249	0.007027	0.0070
13	19,693	19,700	1.743	0.007726	0.0077
14	19,700	19,706	1.493	0.006505	0.0065
15	19,700	19,722	5.477	0.005942	0.0059
16	19,707	19,715	2.132	0.007294	0.0073
17	19,723	19,727	0.995	0.006113	0.0061
18	19,727	19,734	1.743	0.006037	0.0060
19	19,734	19,736	0.498	0.007112	0.0071
20	19,736	19,741	1.245	0.006117	0.0061
21	19,752	19,755	0.747	0.006505	0.0065
22	19,754	19,758	0.996	0.006276	0.0063
23	19,757	19,768	2.739	0.007211	0.0072
24	19,769	19,771	0.498	0.007185	0.0072
25	19,773	19,783	2.489	0.006816	0.0068
26	19,784	19,785	0.249	0.005653	0.0057
27	19,787	19,790	0.747	0.006117	0.0060
28	19,791	19,792	0.249	0.005583	0.0057
29	19,794	19,797	0.747	0.006604	0.0066
30	19,796	19,805	2.24	0.006173	0.0062

Note: the start station and end station are the starting and ending labels of segmented pipes. They are the marks determined when laying pipes. Pipe length represents the length of each segmented pipeline. The fifth column of data is the pipeline segment failure probability calculated based on the fault tree analysis method. Their values are obtained by the authors. Its first 25 groups of data are used for simulation analysis. The sixth column of data is the prediction data obtained based on RBF., They are calculated by neural network simulation.

3.3.2 Newrbe strict radial basis function and spread value

When newrbe is selected as the RBF network creation function, the network is trained according to the spread value, and the corresponding determination coefficient R^2 is calculated. The result is shown in Figure 5 (see the supplementary material for Matlab code).

It can be seen from Figures 4, 5 that different spread values have different effects on RBF neural network performance. For the newrb function, when the spread is 0.2, the network performance is the best, and the corresponding test set determination coefficient is 0.6145. For the newrbe function, when the spread value is 0.5, the network performance is the best, and the corresponding test set determination coefficient is 0.6864. Generally, the value of the spread is proportional to the smoothness of the function. According to the principle of network parameter selection, newrbe is selected as the radial basis function in this study, and the spread value is 0.5.

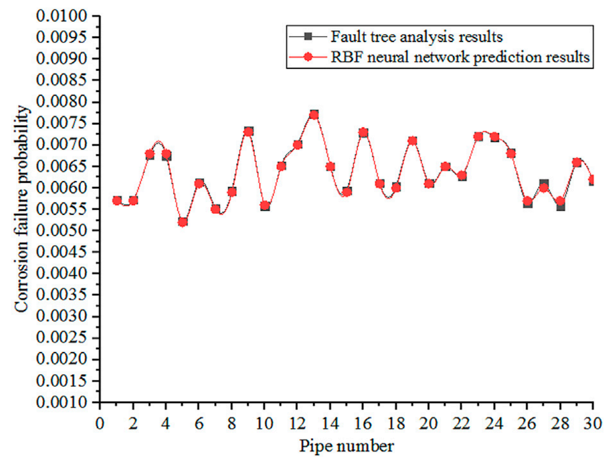

FIGURE 6
Comparison diagram of corrosion failure probability results of buried gathering and transmission pipeline.

4 Comparative analysis of prediction results

The corrosion failure probability of buried gathering pipelines is calculated based on the trained RBF neural network, and the specific results are shown in Table 3.

According to the data in Table 3, the comparison results are shown in Figure 6.

It can be seen that the failure probability calculated based on the fault tree analysis model is consistent with the failure probability predicted based on the RBF neural network model. It is feasible to use the RBF neural network to predict the corrosion failure probability of buried oil and gas pipelines. Therefore, managers can directly calculate the failure probability prediction data from the network by combining the actual original data and using the trained RBF neural network model. Because the neural network has a strong non-linear mapping relationship, the RBF neural network model improves the accuracy of pipeline corrosion failure probability prediction when the input and output relationships are completely unknown. At the same time, the RBF neural network model avoids the huge amount of calculation. It can save a lot of time and improve calculation efficiency, providing an evaluation method for the safety and reliability of the oil and gas transportation system.

5 Conclusion

In this study, an RBF neural network is introduced to predict the corrosion failure probability of buried oil and gas pipelines. A prediction model based on Matlab neural network toolbox is established. The prediction model is applied to calculate the corrosion failure probability of the high-pressure gathering and transmission pipeline network of the gas storage. Our results are consistent with the failure probability results obtained based on the fault tree model. Hence, the effectiveness of the RBF neural network prediction model is verified.

In this study, when using neural networks to solve practical problems, it is found that the radial basis function and the spread value of the RBF neural network prediction model will significantly affect the prediction accuracy. Through repeated trial and analysis, when the radial basis function is newrbe and the spread value is 0.5, the network performance of the RBF prediction model is optimal.

The accuracy of the prediction results of the RBF neural network model constructed in this paper is related to various factors. The selection of model layers, number of neurons, transfer function and training error values, and even the choice of training samples will significantly affect the accuracy of the prediction results. Therefore, for future research, it is necessary to conduct a more in-depth study on the selection of model-related parameters.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/feart.2023.1148407/full#supplementary-material

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