Combined Grey Prediction and Neural Network Model for Oil and Gas Pipeline Wall Thinning

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Abstract. It is difficult to use a single model to effectively predict the complex factors influencing oil and gas pipeline wall thickening. This paper analyzed the grey prediction model and neural network model according to the characteristics of the Southwest Mountain pipeline and examined the combination of the grey GM (1, 1) model and BP neural network. After realizing the traditional GM (1, 1) prediction, the G-B-I and G-B-II prediction models were established, combining the grey GM (1, 1) and BP neural network. The principle of the G-B-I model involved using the characteristics of the BP neural network to regress the error of the GM (1, 1) model. Contrarily, the principle of the G-B-II model involved using the BP neural network to construct the mapping relation to obtain the revised prediction value. Examples were used to verified these two models, and the results showed that their errors were significantly reduced compared with the traditional GM (1, 1) method, while their prediction ability was superior.

1. Background and significance

With the rapid economic development in China, the demand for oil and gas resources has increased significantly, prompting the construction of oil and gas pipeline networks [1]. Since the mountainous areas of China account for about two-thirds of the total land area, the safe operation of mountainous pipelines in Southwest China plays a vital strategic role in public and national energy security. Wall thinning due to corrosion or other factors causes deformation and cracks in oil and gas pipelines since they cannot cope with the pressure. This may eventually cause accidents due to hazardous conditions, such as leakage, seriously threatening the safety of the environment and property. Therefore, appropriate maintenance measures for the pipeline can be implemented in advance by using a variety of oil and gas pipeline data, quantifying the corrosion rate, combining grey theory with the neural network, and establishing an effective wall thickness corrosion prediction model. Furthermore, it can be employed for the timely adjustment of the detection cycle to save costs and enhance the operational safety of oil and gas pipelines.

Extensive research exists involving the grey prediction model, representing a vital part of the grey system. The grey prediction model mainly includes the GM (1, 1) model, the grey Verhulst model, and the GM (1, n) model [2-3]. The basic idea is obtaining and transforming the random changes in the original information sequence into a new data sequence via the growth law. In other words, the law
governing the original data is obtained after modeling via the grey model [4]. The sample data is then fitted via the inverse calculation generated by consecutive subtraction to obtain the reduction and prediction values. The unique characteristics of the grey model have attracted significant research interest. Therefore, the grey prediction theory model has experienced substantial development, gradually expanding the initial prediction model into several others. These models are currently widely used in many fields, such as in agricultural and industrial applications, yielding excellent results while gradually gaining recognition and acceptance due to their valuable contribution.

The neural network presents a unique evaluation and learning ability during data analysis. However, the construction of an artificial neural network presents unavoidable limitations during the process of analyzing data and establishing a model [5-6]. First, although the trained neural network can process date, some elements reflecting the system characteristics within the sample are not satisfactory and may play a decisive role in the accuracy of the model. Second, the mapping rules established by the artificial neural network are denoted as a black box. In other words, its operational rules cannot be deduced artificially, preventing the grey model from describing the rule content [7]. Third, constructing a successful neural network that meets the accuracy expectations requires significant sample data for training. In conclusion, the limitations of this model cannot be improved. Therefore, a new model can be established by combining the grey prediction model and the BP neural network to enhance the accuracy of the prediction results.

2. Traditional prediction model

2.1. Prediction model based on grey theory

At the beginning of establishing the grey system theory, many famous scholars and experts have explored its application in different fields [8]. Grey system theory is designed to resolve the challenges of insufficient sample data and a lack of deterministic information, serving as a pioneering theory [9]. In other words, it can process the determined “poor information,” enhance the regularity of the data, and even clarify the development trend of the system while accurately predicting the changes.

The so-called grey prediction introduces grey system theory into the prediction process, processes the original sample data, and compares the existing data in a dynamic process. Here, the grey part of the system changes with time, allowing it to gradually become white with continuous accumulation and subtraction. Finally, the grey model of the differential equation is constructed, and the hidden distribution law of the system is fitted, predicted, and obtained, reasonably and accurately describing the future development of the system [10].

At present, the more common grey prediction model is the GM (n h) model group, in which G denotes grey and M denotes the model. Therefore, GM represents the grey model, n represents the order of the model, and h denotes the number of model variables. The most popular and widely used grey prediction model, GM (1, 1), in grey theory refers to a situation where n=1 and H=1. The specific calculation formula of the GM (1, 1) model is as follows:

There is a set of original data sequence x(0):

\[ x^{(0)} = [x^{(0)}(1), x^{(0)}(2), ..., x^{(0)}(n)] \] (1)

The sequence of x(0) is recorded after one accumulation as x(1):

\[ x^{(1)} = [x^{(1)}(1), x^{(1)}(2), ..., x^{(1)}(n)] \] (2)

Where

\[ x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i) \quad (k=1, 2, ..., n) \] (3)

The sequence Z (1) is obtained by generating the nearest neighbor mean:
\[ Z^{(1)} = \left[ z^{(1)}(2), z^{(1)}(3), \ldots, z^{(1)}(n) \right] \]  

Where

\[ z^{(1)}(k) = 0.5x^{(1)}(k) + 0.5x^{(1)}(k-1) \quad (k=2, 3, \ldots, n) \]  

The first order of the grey differential equation is established:

\[ \frac{dx^{(1)}}{dt} + ax^{(1)} = b \]  

Where \( a \) is the development coefficient, and \( b \) is the grey action quantity.

The least-square method is used to calculate the model parameters \( \hat{a} \):

\[ \begin{bmatrix} \hat{a} \\ \hat{b} \end{bmatrix} = (B^T B)^{-1} B^T Y_n \]  

Where

\[ B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix}, \quad Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix} \]  

The prediction formula is obtained if \( x^{(1)}(0) = x^{(0)}(1) \):

\[ \hat{x}^{(1)}(k + 1) = \left( x^{(0)}(1) - \frac{b}{a} \right) e^{-ak} + \frac{b}{a}, \quad k = 1, 2, \ldots, n \]  

A consecutive subtraction is performed to equation (9) to obtain the original data reduction value sequence:

\[ \hat{X}^{(0)} = \left[ \hat{x}^{(0)}(1), \hat{x}^{(0)}(2), \ldots, \hat{x}^{(0)}(k) \right] \]  

Where

\[ \hat{x}^{(0)}(k + 1) = \hat{x}^{(1)}(k + 1) - \hat{x}^{(1)}(k) \]  

When \( k \leq n \), \( \hat{x}^{(0)}(k) \) is the fitting value of the original data and \( k > n \), \( \hat{x}^{(0)}(k) \) is the prediction value of the original data. After the GM (1, 1) model is established, the sample data can be entered to obtain the prediction value of the pipeline wall thickness.

2.2. BP neural network model

An artificial neural network is a kind of physical system or computer simulation system that can simulate the structure and thinking mode of the human brain by connecting and establishing models of many simple neurons with the same structures [11]. It displays a strong nonlinear mapping ability that can map the nonlinear input and output relations in conditions where this information is completely unknown. By learning an extensive amount of experimental data, it can automatically extract the characteristics of the learning data [12], achieving excellent learning, association, memory, and recognition. The neural network exhibits more obvious characteristics, meaning that its learning is constantly developing. Under the influence of its system environment, it continuously enters sample data into the neural network, which has simple self-adaption and self-organization functions. This paper used the commonly used BP neural network model.
A BP neural network generally consists of the input layer, the hidden layer, and the output layer [13-14], and includes two processes, namely signal forward propagation and error backward propagation. When the input signal reaches the output layer, the error value between the actual output value and the target output value is determined via hidden layer calculation, after which the calculated error is returned to the input layer. Following calculation, learning, and training, the weights and thresholds of the data are corrected in the reducing direction of the system error until the error between the expected and the output values have decreased to the expected error range.

A three-layered neural network model (single hidden layer) can solve the nonlinear problem to a certain extent via training and learning. Therefore, a three-layered BP neural network model was constructed that adopted the 1-5-1 structure.

The signal forward propagation process is as follows:

\[ y_j = f(x_j) \]  
\[ x_j = \sum_{i=1}^{N} \omega_{ij} x_i + \theta_j \]  

\( x_j \) is the activation value of node j, \( f(x) \) is the activation function of the neurons, \( y_j \) is the output value of the j-th node, \( \omega_{ij} \) is the connection weight from the j-th node to the i-th node, \( \theta_j \) is the threshold value of the i-th node of the first layer, and \( N \) is the number of nodes.

During the error backward propagation phase, the weight of the output layer is modified using the gradient descent method, as follows:

\[ \Delta \omega_{ij} = -\eta \frac{\partial E}{\partial \omega_{ij}} \]  

Where \( E \) is the error function and \( \eta \) is the learning rate [15].

3. The combined GM-BP prediction model

The traditional methods for predicting the pipeline wall thickness typically involve single models that do not fully present the trend in the nonlinear data. Although the GM (1, 1) prediction model is simple, its ability to control errors and process nonlinear data is lacking. This paper attempted to combine the BP neural network model with the GM (1, 1) model to construct the combined GM-BP prediction model to more comprehensively reflect the changes in the wall thickness of oil and gas pipelines.

3.1. The G-B-I model

The traditional GM model uses the fitting value directly for the next step in the analysis and prediction process and does not correct the error, eventually creating a significant difference between the actual value and the prediction value. In the G-B-I model, the BP neural network model was used for the error regression in the GM (1, 1) model. Therefore, the GM (1, 1) model was used to process the original sample data, while the error of the traditional model was calculated according to the processing results. The obtained error was used as the input layer information of the BP neural network, and the regression training was performed. After convergence, the error of the prediction value of the traditional model was obtained. The final prediction value was the sum of the error after training and the prediction value.

First, a set of original data was determined:

\[ x^{(0)} = [x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)] \]  

The GM (1, 1) model was used to process the fitting value series:

\[ \hat{x}^{(0)} = [\hat{x}^{(0)}(1), \hat{x}^{(0)}(2), \ldots, \hat{x}^{(0)}(k)] \]
The error sequence $\varepsilon^{(0)}$ was defined as the sequence formed by the difference between the fitting value and the actual value, and $\hat{x}^{(0)}(1) = x^{(0)}(1)$:

$$\varepsilon^{(0)} = (\varepsilon^{(0)}(2), \varepsilon^{(0)}(3), \ldots, \varepsilon^{(0)}(n))$$

$$\varepsilon^{(0)}(m) = \hat{x}^{(0)}(m) - x^{(0)}(m), m = 2, 3, \ldots, n \quad (17)$$

When $k = n + R > n$, the prediction value of the traditional GM method was obtained:

$$\hat{x}^{(0)}(n + 1), \hat{x}^{(0)}(n + 2), \ldots, \hat{x}^{(0)}(n + R) \quad (18)$$

$R$ represented the prediction order.

$\varepsilon^{(0)}$ was entered into the trained BP network, after which the approximation processing was conducted to obtain the prediction error series $\hat{\varepsilon}^{(0)}$:

$$\hat{\varepsilon}^{(0)} = (\hat{\varepsilon}^{(0)}(n + 1), \hat{\varepsilon}^{(0)}(n + 2), \ldots, \hat{\varepsilon}^{(0)}(n + m)) \quad (19)$$

The prediction value of the G-B-I model was obtained:

$$\hat{x}^{(0)}(i) = \hat{x}^{(0)}(i) + \hat{\varepsilon}^{(0)}(i), i = n + 1, n + 2, \ldots, n + m \quad (20)$$

### 3.2. The G-B-II model

When constructing the GM (1, 1) model, the final results of the GM (1, 1) can vary during its construction due to differences in the original data. The G-B-II model aimed to build GM (1, 1) model groups via specific data, obtain the reduction value using these model groups, import these reduction values into the BP neural network as the input layer, substitute the prediction values obtained by each model group into the trained network, and use the constructed mapping relationship to obtain the modified prediction values.

For example, the amount of data used in the construction of the GM (1, 1) model was $K$. For the determined original data,

$$x^{(0)} = [x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)]$$

The first $T$ data ($k \leq T \leq n$), that is, the GM model constructed is defined as $T$ data GM (1, 1) model. The $n$ data of the $T$ data GM (1, 1) model was followed by the prediction value. The analysis of several examples showed that the construction of the GM (1, 1) model required at least five data groups, that is, the minimum value of $K$ was 5. As the part of the data GM (1, 1) model group is the analysis of a part of the data, each model group was a reflection and simulation of the system in a sense, while the reduction and prediction values obtained with these model groups denoted approximate values.

The specific steps were as follows:

1. The GM model group was established using part of the data to obtain the fitting and the prediction values.

2. The fitting value was entered into the neural network as sample data for training, while the actual value was introduced to establish tutor learning. The trained neural network established the non-mapping relationship between the GM and the original data.

3. Finally, all the prediction values of the model group were imported into the neural network as samples, while the output layer obtained from this non-mapping relationship represented the final prediction value.
4. Wall thickness prediction analysis of the oil and gas pipeline

To verify the accuracy of the G-B model for predicting the pipeline wall thickness, the oil and gas pipeline wall thickness detection data of a particular company was used as the sample data while covering a period from the second quarter of 2016 to the first quarter of 2018. There was one detection for each quarter, with eight points of data in each group and 60 valid data groups in total. Since there were only eight data points in each group, the BP neural network training was of little significance. Accordingly, the prediction results of the BP neural network were not analyzed. Only the prediction results of the GM (1, 1) grey prediction model, the G-B-I model, and the G-B-II model were assessed.

Table 1. Part of the sample data

| Number | Original wall thickness (mm) | Data1 (mm) | Data2 (mm) | Data3 (mm) | Data4 (mm) | Data5 (mm) | Data6 (mm) | Data7 (mm) | Data8 (mm) | Remarks regarding the pipeline section |
|--------|-----------------------------|------------|------------|------------|------------|------------|------------|------------|------------|--------------------------------------|
| 1      | 4.6                         | 0.62       | 0.65       | 0.69       | 0.74       | 0.80       | 0.84       | 0.86       | 0.87       | 1707                                  |
| 2      | 16.5                        | 1.35       | 1.42       | 1.46       | 1.49       | 1.52       | 1.53       | 1.55       | 1.57       | 1766                                  |
| 3      | 10                          | 1.05       | 1.13       | 1.15       | 1.17       | 1.21       | 1.24       | 1.25       | 1.27       | 1767                                  |
| 4      | 10                          | 1.46       | 1.48       | 1.52       | 1.5       | 1.59       | 1.62       | 1.66       | 1768                                  |
| 5      | 10.9                        | 0.83       | 0.84       | 0.87       | 0.93       | 0.93       | 0.96       | 1.04       | 1.1        | 1769                                  |
| 6      | 10                          | 1.34       | 1.37       | 1.41       | 1.51       | 1.51       | 1.55       | 1.56       | 1.58       | 1770                                  |
| 7      | 10                          | 0.57       | 0.60       | 0.63       | 0.76       | 0.76       | 0.88       | 0.94       | 0.97       | 1771                                  |
| 8      | 20                          | 1.58       | 1.72       | 1.76       | 1.87       | 1.87       | 1.91       | 1.93       | 1.94       | 1772                                  |
| 9      | 17                          | 1.86       | 1.89       | 1.91       | 1.96       | 1.96       | 1.97       | 1.98       | 2.02       | 1773                                  |

4.1. Prediction results of the GM (1, 1) model

The data in No. 1 was selected to establish the GM (1, 1) model after first establishing the original sequence:

\[ x^{(0)} = (0.62, 0.65, 0.69, 0.74, 0.80, 0.84, 0.86, 0.87) \]

According to the formula in the first section, the MATLAB software was used to obtain the parameter vector to be estimated \( \hat{a} \), establishing the GM (1,1) model to acquire the fitting value of the data. Finally, the established model was used to predict data 7 and data 8, after which the difference was compared.

\[ \hat{a} = \begin{pmatrix} -0.097 \\ 0.4919 \end{pmatrix} \]

A total of 60 data groups were incorporated into the GM model to obtain the comparison results between the prediction and actual values of the pipeline wall thickness, as shown in Figure 2.
Combining the error values of all the data showed that the average error of the GM (1, 1) model was 9.37%, in which the average error of prediction value 1 was 7.92% and that of prediction value 2 was 10.82%. The average error was substantial, with the individual error even reaching 17%. The average error of prediction value 2 was significantly higher than prediction value 1.

Table 2. Prediction results of various GM (1, 1) models

| Number | Wall thickness of a straight pipeline section (mm) | Actual value 1 (mm) | Prediction value 1 (mm) | Absolute value of error | Actual value 2 (mm) | Prediction value 2 (mm) | Absolute value of error | Remarks regarding pipeline section |
|--------|-----------------------------------|------------------|---------------------|---------------------|------------------|---------------------|---------------------|----------------------------------|
| 1      | 4.6                               | 0.86             | 0.92                | 6.90                | 0.87             | 0.95                | 9.20                | 1707                             |
| 2      | 16.5                              | 1.52             | 1.59                | 4.61                | 1.53             | 1.62                | 5.88                | 1766                             |
| 3      | 10                                | 1.52             | 1.32                | 5.60                | 1.27             | 1.38                | 8.66                | 1767                             |
| 4      | 10                                | 1.62             | 1.68                | 3.70                | 1.66             | 1.74                | 4.82                | 1768                             |
| 5      | 10.9                              | 1.04             | 1.13                | 8.65                | 1.1              | 1.21                | 10.00               | 1769                             |
| 6      | 10                                | 1.56             | 1.63                | 4.49                | 1.58             | 1.67                | 5.70                | 1770                             |
| 7      | 10                                | 0.94             | 1.02                | 8.51                | 0.97             | 1.13                | 16.49               | 1771                             |
| 8      | 20                                | 1.93             | 2.1                 | 8.81                | 1.94             | 2.19                | 12.89               | 1772                             |
| 9      | 17                                | 1.98             | 2.07                | 4.55                | 1.98             | 2.11                | 6.57                | 1773                             |

4.2. Prediction results of the G-B-I model

The error sequence $\varepsilon^{(6)}$ was obtained according to the G-B-I modeling method in the second section. The error sequence was used as the input layer of the BP neural network, while the purelin function was selected for activation in both the hidden and output layers. The final prediction value was obtained from the prediction error, and some results are shown in Figure 3.
Figure 3. A comparison between the G-B-I and the GM (1, 1) prediction results

Figure 3 shows that the accuracy of the prediction value obtained by the G-B-I model improved significantly compared with the fitting value acquired via the GM (1, 1) model. Some of the values were the same as the actual values, indicating the excellent fitting and prediction accuracy of the G-B-I model. The model was applied to all sample data for prediction, exhibiting an average prediction value error of 4.22%. Furthermore, the average error of prediction value 1 was 3.84%, while that of prediction value 2 was 4.6%. Compared with the 9.37% displayed by the GM (1, 1) model, the improved combined forecasting model exhibited excellent applicability.
4.3. Prediction results of the G-B-II model

GM (1, 1) models were established for the 5 data, 6 data, and 7 data groups, respectively. These model groups were then used to obtain the reduction values, which were imported into the BP neural network as the input layer, while the actual values were used as tutors for learning and training. The original prediction values obtained via the model groups were substituted into the trained network, while the constructed mapping relationship was used to obtain the modified prediction values.

The transfer functions used in the BP neural network were tansig for the hidden layer and purelin for the output layer. The final prediction value was obtained upon network convergence and completion of the training. The fitting and prediction results of several data groups were randomly selected, and the fitting conditions of several GM (1, 1) groups (5 data, 6 data, and 7 data) and the G-B-II model were compared to intuitively judge the advantages and disadvantages of the method. The specific results are shown in Figure 4.

![Figure 4. A comparison chart of the G-B-II prediction results](image-url)
Figure 4 shows that employing the G-B-II model for prediction displayed distinct advantages compared to the GM (1, 1) model. Furthermore, the sequence provided by the GM (1, 1) model based on partial data was more divergent over time and expanded in a trumpet shape. Therefore, the lower the amount of sample data, the lower the prediction accuracy and degree of fitting, which is characteristic of the GM (1, 1) and challenging to modify. The error of the G-B-II model substantially more effective than the GM (1, 1) model in fitting the first 7 data or regarding the prediction accuracy of the 8 data, indicating a distinct optimization effect.

Considering the 60 groups of data collectively, the combined prediction of the second model showed an average error in the prediction value of 4.49%, compared to the actual value, while the average error of the fitted value was 3.57%.

4.4. A comparison of the prediction results of the three models
The average error between the prediction value and the actual value of each model and between the fitting value and the actual value are listed in Table 3 to analyze and compare the differences between the combination forecast and the traditional GM (1, 1) model more intuitively.

|                           | Prediction value 1 error | Prediction value 2 error | Average error |
|---------------------------|--------------------------|--------------------------|---------------|
| GM(1,1)                   | 7.92                     | 10.82                    | 9.73          |
| G-B-I                     | 3.84                     | 4.6                      | 4.22          |
| G-B-II                    |                          | 4.49                     | 4.49          |

The data test indicated that the prediction accuracy of the two combined forecasting models was superior to the traditional GM (1, 1) model, while their average relative errors were considerably smaller. The G-B-I model was simpler and could predict two data. However, due to sample data limitations, the G-B-II model could only use one group of data for prediction, while establishing a mapping relationship was more complex. However, after comparison, the fitting effect of the G-B-II model was better. Furthermore, the nonlinear mapping may display higher medium- and long-term prediction accuracy. Consequently, although the two methods present distinct individual advantages and disadvantages, they were superior to the single GM (1, 1) model.

5. Conclusion
Since many influencing factors are involved in the wall thickness changes of oil and gas pipelines, their relationship is complex, and they undergo substantial modifications in different conditions. Considering that it is challenging to comprehensively and accurately predict the wall thickness changes in oil and gas pipelines using the single prediction model, two alternative models are created by combining the GM (1, 1) grey prediction method with a neural network algorithm. In addition, engineering practice is considered while performing the calculations and analysis to improve the accuracy when predicting wall thickness changes in oil and gas pipelines. The wall thickness prediction model established in this paper displays significant potential for practical application. Moreover, the short-term and medium-term wall thickness reduction is predicted based on the existing pipeline wall thickness data. According to the reduction level, a pipeline section can be selected for targeted maintenance or evaluation, ultimately decreasing the operational cost for oil and gas enterprises.

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