Application of WNN-GNN-SVM combined algorithm to time series analysis of SF6 decomposed gas signal detected by photoacoustic spectroscopy

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Abstract. This paper first analyzes the principle of the photoacoustic spectroscopy detection technology, gives the absorption wavelength and the absorption line intensity of typical SF6 decomposition gas, and establishes the original database of the photoacoustic spectroscopy combined with the existing experimental platform. Furthermore, the principle of WNN-GNN-SVM combined algorithm and its construction method model are proposed, and the combined algorithm is applied to fit and predict the time series curve of sulfur hexafluoride characteristic decomposition gas with 6 peaks. The results show that the photoacoustic spectrum detection technology can effectively obtain the time series of typical sulfur hexafluoride decomposition gas, such as SO2F2, H2S, COS and CS2, and the WNN-GNN-SVM combination algorithm proposed in this paper can effectively select key points of sulfur hexafluoride decomposition gas characteristic peak for the multi spline curve quantitative fitting, and reasonably predict its change trend. In this paper, the optical detection method for typical decomposition gas of sulfur hexafluoride is effectively proposed, and the fitting and prediction post-processing method of the original data is given based on the detection results. The research results of this paper have good engineering application and theoretical research value for the detection and evaluation of the operation state of sulfur hexafluoride gas insulated power equipment.

1. Introduction

Sulfur hexafluoride (SF6) gas, as an excellent insulation and arc extinguishing medium, is widely used in SF6 gas insulated circuit breaker, gas insulated switchgear, transformer, mutual inductor, power cable and other electrical equipment. The content of SF6 decomposition product can characterize the operation status of the high-voltage equipment[1-3]. The detection of decomposition product component is very important. Optical detection method is used to detect decomposition product. It has gradually become the mainstream detection method. When a certain intensity of light passes through a certain gas, some frequencies of light will be absorbed, resulting in the weakening of light intensity. It is the basic method to study the characteristics of gas by the absorption of light. The absorbed light energy will be converted into another kind of energy, namely molecular oscillation energy. In the absorption process, the molecular oscillation frequency is related to the characteristics of the molecule, and the radiation is absorbed only at the wavelength corresponding to these frequencies. When the light beam passes through, the intensity and the frequency of light absorption are also different. The absorption spectrum of the gas can be obtained by measuring the frequency and intensity of the absorbed light[4,5]. The frequency characteristics of the spectrum reflect the structural characteristics of the gas to be measured, which can be used to qualitatively determine the composition of the gas.
The intensity of the spectrum is related to the content of the gas to be measured, which can be used to quantitatively analyze the concentration of the gas. It can be seen that the gas group can be obtained by using the selective absorption properties of the molecules. Photoacoustic spectroscopy (PAS) is the spectrum technology based on photoacoustic effect. By modulating the monochromatic light source, excited light with acoustic modulation characteristics is generated and coupled to the photoacoustic cell. After absorbing the light energy, the specific gas molecules in the photoacoustic cell are stimulated to transition to the high-energy state of the vibration energy level, and then the energy is converted into translational energy through non-radiative transition, forming pressure wave in the photoacoustic cell[6,7]. The intensity of pressure wave is detected by microphone. According to the proportional relationship between the amplitude of photoacoustic signal and the incident light intensity, gas absorption coefficient and content, the content of photoexcited gas molecules in photoacoustic cell is determined.

Based on this, this paper first analyzes the principle of the photoacoustic spectroscopy detection technology, gives the absorption wavelength and the absorption line intensity of the typical SF6 decomposition gas, and establishes the original database of photoacoustic spectroscopy combined with the existing experimental platform. Furthermore, the principle of WNN-GNN-SVM combined algorithm and its construction method model are proposed, and the combined algorithm is applied to fit and predict the time series curve of sulfur hexafluoride characteristic decomposition gas with 6 peaks. The results show that the photoacoustic spectrum detection technology can effectively obtain the time series of typical sulfur hexafluoride decomposition gas, such as SO2F2, H2S, COS and CS2, and the WNN-GNN-SVM combination algorithm proposed in this paper can effectively select the key points of sulfur hexafluoride decomposition gas characteristic peak for multi-spline curve quantitative fitting, and reasonably predict its change trend. In this paper, the optical detection method for typical decomposition gas of sulfur hexafluoride is effectively proposed, and the fitting and prediction post-processing method of the original data is given based on the detection results. The research results of this paper have good engineering application and theoretical research value for the detection and evaluation of the operation state of sulfur hexafluoride gas insulated power equipment.

### 2. Principle of photoacoustic spectroscopy

The basic principle of the photon absorption is the theory of selective absorption of gas molecules. Different gases have different absorption of light frequency due to different molecular structures, that is, gas molecules can only absorb photons whose energy is just equal to the difference between the energy of its two energy levels, which is called the selective absorption characteristics of the gas molecules[8,9]. Due to the discontinuity of energy levels, the same kind of gas can selectively absorb light frequency, while different kinds of gas have different absorption due to different molecular structures. Table 1 shows the different absorption coefficients of several typical gases at different wavelengths in the near infrared band.

| Gas type | Absorption wavelength $\lambda$ / nm | Absorption line strength $S$ cm$^{-1}$/molec·cm$^{-2}$ |
|----------|-------------------------------------|----------------------------------|
| CO$_2$   | 1572.66                            | 1.778×10$^{-23}$                |
| CO       | 1665                               | 2.165×10$^{-23}$                |
| H$_2$S   | 1541                               | 3.219×10$^{-22}$                |
| HI       | 1554                               | 3.219×10$^{-22}$                |
| NH$_3$   | 1544                               | 3.219×10$^{-22}$                |
| CH$_4$   | 1665                               | 1.074×10$^{-21}$                |
| C$_2$H$_2$ | 1532.83                           | 1.074×10$^{-20}$                |

The detection principle of the photoacoustic spectroscopy is shown in Figure 1. The first focused, modulated and filtered infrared beam (0.6-25μm) enters the photoacoustic cell, which is filled with the
gas to be measured. When the gas molecules to be measured absorb the infrared photons of a specific wavelength, they will be excited, and some molecules in the excited state will quickly return to the ground state through the non-radiative relaxation process, and the absorbed photons will be excited. The energy is converted into the average kinetic energy of molecules, which makes the gas thermal expansion and the produces periodic weak acoustic signal. The intensity of the acoustic signal is corresponding to the composition and the content of the micro gas molecules measured in the photoacoustic cell. Therefore, the content of the gas can be obtained by detecting the acoustic signal with the microphone and converting it into the electrical signal.

![Figure 1 Principle diagram of photoacoustic spectroscopy](image1)

When the measured gas is excited by the light beam of intensity $I(r,t)$ and frequency $\omega$, the gas molecules absorb the light energy and form a heat source $H(r,t)$:

$$H(r,t) \approx \alpha I(r,t)$$

Where, $\alpha$ is the gas absorption coefficient, in cm$^{-1}$. For the specific gas $\alpha = \beta C$, $\beta$ is gas absorption cross section, which is related to the wavelength range of the light source, and $C$ is the gas volume fraction. Since the photo-acoustic signal is generated by the infrared light energy in the wavelength range allowed by the measured gas absorption filter, there can be multiple absorption spectral lines corresponding to the conversion of light energy for the continuous wide spectrum infrared light source:

$$\alpha = \sum \alpha_i, \quad i=1,2,3,\ldots$$

Among them, $\alpha_i$ is the corresponding filter passes through the $i$th absorption line of the measured gas in the wavelength range. The equation (2) shows that when the continuous light source is used, the measured gas has the larger absorption coefficient, which can enhance the light energy absorption and
effectively improve the detection sensitivity. If the cylindrical photoacoustic cell with the first order longitudinal resonance mode is used, the amplitude of photoacoustic signal can be expressed as:

$$M_j(\omega) = -\frac{i\omega}{\omega_0^2} \frac{\alpha(\gamma - 1)W_j}{V_c(1 - \frac{\omega^2}{\omega_0^2} - \frac{i\omega}{\omega_0^2}Q_{res})}$$  (3)

Where, $\gamma$ is the specific heat capacity ratio of the gas; $W_j$ is the power of the light source; $\omega_0$ is the resonant frequency; and $l$, $V_{res}$ and $Q$ are the length, volume and quality factor of the photoacoustic cavity. After the photoacoustic signal passes through the microphone, it is converted into the voltage amplitude of:

$$U = C_{cell}W_j\beta C$$  (4)

Where, $C_{cell}$ is the constant of the photoacoustic cavity, which is determined by the geometric size, material, quality factor, microphone sensitivity and other factors of the photoacoustic cell. Generally, it can be obtained by using the standard gas with known volume fraction[10]. It can be seen that the size of the photoacoustic signal is related to the structure of the photoacoustic cell, the power of the light source, the volume fraction of the measured gas and the modulation frequency. Under the same experimental conditions, the photoacoustic signal intensity will change linearly with the change of the volume fraction of the measured gas. The volume fraction of the measured gas can be determined by detecting the photoacoustic signal intensity. In addition, because different gases have their own absorption spectrum characteristics, the volume fraction detection of the multi-component gases can be realized only by selecting the filter with the specific central wavelength. A typical photoacoustic spectrum gas detection system is shown in Figure 2.

3. Construction of WNN-GNN-SVM combination algorithm

3.1 BP neural network prediction optimized by genetic algorithm

The specific steps of BP neural network prediction algorithm optimized by genetic algorithm are as follows:

Step 1: set the group size as $P$. The initial population of $P$ individuals is randomly generated, and given a data selection range, because the determination of the initial population has a great influence on the global optimization of GA, the linear interpolation function is used to generate a real vector $W_1$, $W_2,...,W_S$ of individual $W_i$ in the population as a chromosome of genetic algorithm[11,12]. The length of the chromosome is as follows:

$$S = RS_1 + S_1S_2 + S_1 + S_2$$  (5)

Figure 3 The wavelet neural network topology
Where $R$ is the number of input layer nodes, $S_1$ is the number of hidden layer nodes, and $S_2$ is the number of the output layer nodes. The each individual $W_i = (w_1, w_2, ..., w_P)(i = 1, 2, ..., P)$ in determined population represents the initial value of a BP neural network, and the gene value $W_i$ in individual $w_j$ represents a connection weight or threshold value of the neural network. In order to get high-precision weight and shorten the length of chromosome string, floating-point coding method is used.

Step 2: determine the individual evaluation function. Given a BP neural network evolution parameter, the chromosome obtained in the first step is used to assign the weights and thresholds of BP neural network, and the training samples are input to train the neural network to achieve the set accuracy to obtain a network training output value. Then the fitness value $fitness_i$, and average fitness value $\overline{f}$ of individual $W_i$ in population $W$ are defined as:

$$fitness_i = \sum_{j=1}^{M} (\hat{y}_j - y_j)^2 (i = 1, 2, ..., P) \quad (6)$$

$$\overline{f} = \frac{\sum_{i=1}^{P} fitness_i}{P} \quad (7)$$

Where $\hat{y}_j$ is the training output value, $y_j$ is the expected value of training output, $M$ is the number of phase points in the reconstructed phase space, $P$ is the population size. Step 3:

Using roulette selection operator, that is to say, the selection strategy based on fitness proportion is used to select the chromosomes in each generation of the population:

$$p_i = \frac{f_i}{\sum_{i=1}^{P} f_i} (i = 1, 2, ..., P) \quad (8)$$

Where $f_i = 1/fitness_i$, $P$ is the population size. Step 4: because the individual uses real number coding, so the crossover operation method uses real number crossover method. The cross operation of the $k$-th gene $w_k$ and the $L$-th gene $w_l$ at the $j$ position is as follows:

$$w_{kj} = (1 - b) w_k + b w_l \quad (9)$$

Where $B$ is a random number of $[0, 1]$. Step 5: mutation operation: select the $j$-th gene of the $i$-th individual for mutation operation:

$$w_{yi} = \begin{cases} w_{yi} + (w_{yi} - w_{max}) f(g) r & \text{if } g \geq 0.5 \\ w_{yi} + (w_{min} - w_{yi}) f(g) r & \text{if } g < 0.5 \end{cases} \quad (10)$$

Where: $W_{max}$ and $W_{min}$ are the upper and lower bounds of gene $w_{yi}$, $R$ is the random number of $[0, 1]$, $R_2$ is a random number, $G$ is the current iteration number, and $G_{max}$ is the maximum evolution algebra. Step 6: decompose the optimal individual of genetic algorithm into connection weights and thresholds of BP neural network, train the BP neural network prediction model with BP algorithm, and obtain the optimal solution of chaotic time series prediction.
3.2. Time series prediction based on Grey Neural Network

The grey model can predict the development of the behavior eigenvalues of the grey uncertain system. After accumulating the series, the series can be obtained. If the series presents the exponential growth law, the data can be predicted by the differential equation[13]. Assuming that the original time series is \( x(T) \), the sequence generated by one-time accumulation is \( y(T) \), and the prediction result is \( Z(T) \), the differential equation of the N-Parameter grey neural network model is as follows:

\[
\frac{dy_1}{dt} + ay_1 = b_1 y_2 + b_2 y_3 + ... + b_{n-1} y_n \quad (11)
\]

Where, the input parameters of the grey neural network are \( y_1, y_2, ..., y_n \) is the input of grey neural network, \( y_1 \) is the output of grey neural network, \( a_1, b_1, b_2, ..., b_{n-1} \) is the coefficient of the above differential equation. Let the general solution of the above formula be:

\[
y_1 = -\frac{k}{a} e^{-at} + \frac{u}{a} \quad (12)
\]

The above formula is mapped into BP neural network, which is a grey neural network with \( N \) input and 1 output. In the figure above, \( t \) is the input parameter serial number; \( y_1(t), y_2(t), ..., y_n(t) \) is the input parameter of the grey neural network; \( y_1 \) is the prediction value of the network; the grey neural network is divided into four layers A, B, C and D, and the network weights are as follows: \( \omega_{11} = a \), \( \omega_{21} = -y_1(0) \), \( \omega_{31} = (2b_{n-1}) / a \), \( \omega_{3n} = 1 + e^{-at} \).

3.3. Time series prediction based on support vector machine

The topological structure of support vector machine SVM is similar to that of BP neural network. The linear combination of the intermediate nodes of the vector machine constitutes the output, and each support vector corresponds to the intermediate node. The structure is shown in Figure 5. The basic idea of SVM used in regression fitting prediction is to find an optimal classification surface, and the goal is to minimize the error between training samples and the optimal classification surface. A linear regression function is established with the \( l \) training samples \( \{(x_i, y_i), i = 1, 2, ..., l\} \) and \( y_i \) as the corresponding output value:

\[
f(x) = w \Phi(x) + b \quad (13)
\]
In this paper, the variable $\xi_i, \xi_j$ is introduced, and the regression function for solving $W, b$ is as follows:

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

Where $K(x_i, x_j) = \Phi(x_i) \Phi(x_j)$ is the kernel function, and the Gaussian RBF kernel function can be selected:

$$K(x_i, x_j) = e^{-\frac{|x_i - x_j|^2}{2\sigma^2}} = e^{-\sigma^2|x_i - x_j|^2} \quad (15)$$

Therefore, the main parameters of SVM include weight coefficient $C$ and kernel function parameter $g$.

### 3.4. Implementation of WNN-GNN-SVM combination algorithm

It is one-sided and unstable to predict time series based on only one method. The prediction values of WNN, GNN and SVM for above historical time series are $x_1, x_2, ..., x_n, x_1', x_2', ..., x_n'$, $i=1, 2, 3$, and the prediction error matrix $E$ is:

$$E = [(e_{it})_{3 \times n}]^T$$

Where $e_{it} = y(t) - y_i(t)$, which is the prediction error at $t$ time. The traditional combination forecasting model is as follows:

$$y(t) = \omega_1 y_1(t) + \omega_2 y_2(t) + \omega_3 y_3(t) \quad (17)$$

Where $W=(w_1, w_2, w_3)$ is the weighted coefficient of linear combination of prediction model, and $w_1 + w_2 + w_3 = 1$. The sum of square error of linear combination prediction is:

$$S = \sum_{i=1}^{n} \left( \sum_{i=1}^{m} \omega_i e_{it} \right)^2 = W^T E W \quad (18)$$

In order to obtain the optimal weight coefficient $W$ of the combination forecasting model, the above formula can be transformed into a quadratic programming problem:

$$\begin{cases}
\min S = W^T E W \\
\text{s.t.} R^T = 1, \quad R^T = (111) \quad (19)
\end{cases}$$

We continue to introduce the large range operator $2\lambda(R^T W - 1)$, and derive $W$ and $\lambda$ respectively:

$$\frac{d}{dW}[W^T E W - 2\lambda(R^T W - 1)] = 0 \Rightarrow E W - \lambda R = 0 \quad (20)$$

$$\Rightarrow W = \lambda E^{-1} R$$
Therefore, the optimal weight coefficient is obtained \( W = E^{-1} R / R^T E^{-1} R \). On this basis, a time series combination forecasting model based on BP neural network is proposed, which can effectively use the advantages of various forecasting methods and improve the accuracy and reliability of time series forecasting. The first mock exam of the combined model is: (1) the prediction of time series is carried out by using wavelet neural network WNN, grey neural network GNN and support vector machine SVM respectively, and the topology optimization variables are optimized by PSO algorithm. (2) based on the prediction results of the above three single models, the prediction model of weight coefficient combination model is obtained by combining the best weight coefficient calculation method. (3) The four groups of the grey prediction results are used as the input vector of BP neural network, and the original historical time series are used as the output vector of BP neural network. The combined model based on BP neural network is established and optimized by PSO algorithm. The topological structure is shown in Figure 6.

### 4. Establishment of original database for photo-acoustic spectroscopy

According to the above detection principle scheme of the photoacoustic spectroscopy, the defect simulation device platform is developed, as shown in Figure 7(a). Under the conditions of air gap discharge, the suspension discharge, the tip discharge and the suspended particle discharge, the micro decomposition gas content of SF6 in the device is analyzed by gas chromatography, as shown in Figure 7(b), and the original database for WNN-GNN-SVM combination algorithm is obtained.
software, the above single clustering algorithm and the combination clustering algorithm proposed in this paper are implemented respectively to verify the clustering accuracy of various algorithms. Considering the time cost of obtaining the original data, the amount of original data in this paper is generally taken as 150 groups, of which five defect states correspond to 30 groups of actual measurement data. In the process of program running, 20 groups of actual measurement data are selected as training samples from five defect states, and the remaining 10 groups of measurement data are selected as test sample data. The normalized local data are listed in Table 2.

Table 2. Local raw data after normalization

| HF       | SO2F2  | SOF2  | H2S    | CS2    | Output Code |
|----------|--------|-------|--------|--------|-------------|
| 0.1113   | 0.0463 | 0.0803| 0.0803 | 0.7929 | 0,0,0,0,1   |
| 0.4613   | 0.2148 | 0.6152| 0.1582 | 0.0116 | 0,0,0,0,1   |
| 0.6571   | 0.3109 | 0.0530| 0.1586 | 0.4772 | 0,0,0,1,0   |
| 0.0409   | 0.2286 | 0.1526| 0.6176 | 0.0010 | 0,0,0,1,0   |
| 0.1488   | 0.0786 | 0.0014| 0.1616 | 0.7583 | 0,0,1,0,0   |
| 0.4792   | 0.2960 | 0     | 0.2089 | 0.4950 | 0,0,1,0,0   |
| 0.3275   | 0.6581 | 0.1623| 0.1794 | 0      | 0,1,0,0,0   |
| 0.3356   | 0.5051 | 0.1389| 0.3536 | 0.0023 | 0,1,0,0,0   |
| 0.0419   | 0.2284 | 0.1509| 0.6197 | 0.0277 | 1,0,0,0,0   |
|          |        |       |        |        | 0,1,0,0,0   |

5. WNN-GNN-SVM combined algorithm for time series analysis of SF6 decomposition gas signal parameters

The time series of the SF6 decomposition gas signal is analyzed by WNN-GNN-SVM combined algorithm. There are six obvious peaks in the data, among which the peaks correspond to four typical sulfur hexafluoride characteristic decomposition gases: SO2F2, H2S, cos and CS2 which is shown in Figure 8. In the time range of 0 ~ 20min, it can be regarded as historical time series data, which has strong nonlinear and multi peak characteristics. The number of historical time data is 24021, and the amount of data is large. For WNN-GNN-SVM combination algorithm, because the output value of single multiplication neuron model is between [0,1], its input value is transformed into the value of [0.1,0.9] interval according to the following formula:

$$y_k = 0.8 \times \frac{y_{ok} - \min(y_{ok})}{\max(y_{ok}) - \min(y_{ok})} + 0.1$$ (22)

Where: $y_{ok}$ is the original actual data; $y_k$ is the value of [0.1,0.9] interval after processing; $\max(y_{ok})$ and $\min(y_{ok})$ are the maximum and minimum values of the original time series data respectively[14]. After the prediction process is completed, the data is converted to the original value range of the time series by the following formula:

$$y_{ok} = \min(y_{ok}) + (y_k - 0.1) \times [\max(y_{ok}) - \min(y_{ok})] / 0.8$$ (23)

The peak figure of SO2F2/H2S/COS is shown in Figure 9. Figure 9 shows that the peaks of each characteristic decomposition gas are smooth and significant. The peak value of SO2F2 gas appears earlier than that of H2S gas, and there is a platform area near cos for a long time. This paper takes cos as an example to illustrate the fitting effect of WNN-GNN-SVM combined algorithm, intercepts cos feature peak data points, and the peak contour can be seen from the data points. The randomly selected data points are relatively dense in the platform area, while the data points near the peak are relatively sparse, as shown in Figure 10. On the discrete data points shown in Figure 11 the traditional cubic spline interpolation method is used for peak fitting. It can be seen that the fitting effect is better in the peak area, but there is a large deviation in the platform area. Therefore, the effect of traditional interpolation fitting method is not ideal. On this basis, the WNN-GNN-SVM combined algorithm is
further used for peak region fitting, and the effect is shown in Figure 12. It can be seen that the algorithm has the good fitting effect in the peak region and platform region, which proves the effectiveness of the WNN-GNN-SVM combined algorithm in the time series processing of the sulfur hexafluoride decomposition gas.

![Figure 8 Time series of various decomposed gases](image1)

![Figure 9 SO2F2/H2S/COS time series](image2)

![Figure 10 CS2 time series and COS discrete data points](image3)
6. Conclusion

The results show that the photoacoustic spectrum detection technology can effectively obtain the time series of typical sulfur hexafluoride decomposition gas, such as SO2F2, H2S, COS and CS2, and the WNN-GNN-SVM combination algorithm proposed in this paper can effectively select the key points of sulfur hexafluoride decomposition gas characteristic peak for multi spline curve quantitative fitting, and reasonably predict its change trend. In this paper, the optical detection method for typical decomposition gas of sulfur hexafluoride is effectively proposed, and the fitting and prediction post-processing method of the original data is given based on the detection results. The research results of this paper have good engineering application and theoretical research value for the detection and evaluation of the operation state of sulfur hexafluoride gas insulated power equipment.

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