The Forecasting Model for Time Series of Transformer DGA Data Based on WNN-GNN-SVM Combined Algorithm

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Abstract- **The power transformer is an important equipment in the power system. Its running state is directly related to the safe and stable operation of the power grid. The volume fraction of the dissolved gas in the oil of the transformer body and its variation law are closely related to the fault mode of the transformer, therefore, the dissolved gas analysis (DGA) technology in transformer oil is widely used. Actually, the relationship between the volume fraction of the dissolved gas in transformer oil and the time is a multi-dimensional time series. The sequences are arranged in the same time interval or in different time intervals, which contains the external environment of the power transformer, the operation conditions and the inherent relationship between the gas content in the transformer oil. Therefore, the operation status of the power transformer can be revealed by the prediction of the time series. Based on this, the fault type of the transformer can be determined. At present, many literatures have been applied to a single time series forecasting method, such as BP neural network and radial basis function neural network. The single prediction method can obtained certain accuracy by adjusting the weights and thresholds of the network. To further improve the prediction accuracy, a combined forecasting model should be proposed. The research result of this paper is to predict the DGA data of transformer, and has a certain guiding significance to determine the transformer fault types. The proposed method for time series prediction can also be used in other time series prediction of the electric power system.**

I. INTRODUCTION

The power transformer is an important equipment in power system, its running state is directly related to the safe and stable operation of the power grid. The volume fraction of dissolved gas in transformer oil and its variation are closely related to the fault mode of transformer. So the application of dissolved gas analysis technology in oil is widely used. The change of dissolved gas volume fraction in transformer oil with time is actually multidimensional time series. The sequence is arranged at the same intervals or different time intervals, including the internal relations and operation status of gas content in oil, thus to reveal the operation condition of power transformer by predicting the time series.

At present, most literatures use single time series forecasting methods, such as BP neural network and radial basis and radial basis function neural network. The single prediction method can be used to obtain certain accuracy by modifying the weights and thresholds of the network. The combination forecasting model is proposed to improve the prediction accuracy. Various single prediction models are combined according to certain rules. Using the advantage of a single prediction model to achieve the purpose of improving forecast accuracy.

On the other hand, the power transformer is one of the most important equipments in the power system. The transformer failure may cause the major power outage. To find the fault, the international electro-technical commission recommended the dissolved gas in oil analysis as the fault diagnosis method of the oil immersed transformer. At present, there are many effective methods to diagnose transformer faults by combining DGA data with BP neural network and support vector machine. However, there is little literature to predict the time series of DGA data. This paper attempts to combine wavelet neural network with support vector machine/grey neural network, and to optimize the above network by PSO-BP algorithm, by which the short term prediction of transformer DGA time series can be finished.

Based on this, principle of wavelet neural network/support vector machine/grey neural network is introduced, the topology optimization variables are selected. Particle swarm optimization algorithm is used to optimize the structural parameters of the three single prediction methods. The time series forecasting model based on PSO-BP algorithm is proposed. The calculation method of the optimal weight coefficient of the combined forecasting model was derived. The results of this paper are useful for the prediction of transformer DGA data. On basis of this, it has certain guiding significance for determination of transformer fault type.

II. THEORETICAL ANALYSIS OF SINGLE TIME SERIES FORECASTING METHOD

The time series of the volume fraction of the dissolved gas in oil has been obtained using the dissolved gas analysis technique. The sequence can reflect the relationship between the operation status of the transformer and the dissolved gas content in oil. Therefore, the operation status of the transformer can be revealed by the time series prediction. In this paper, the principle of wavelet neural network/support vector machine/gray neural network has been introduced. The structure parameters of the above three basic prediction methods have been optimized based on the particle swarm optimization (PSO) algorithm. Finally, a combination

978-1-5090-5736-8/17/$31.00 ©2017 IEEE

forecasting model based on BP neural network is proposed. The prediction results show that, the PSO algorithm can improve the prediction accuracy by optimizing the topological structure parameters of these support vector machine (SVM)/grey neural network (GNN)/wavelet neural network (WNN)single prediction model. The WNN-GNN-SVM has been combined with PSO-BP algorithm. The calculation method of the optimal weight coefficient of the combined forecasting model is derived. The PSO algorithm was applied to optimize the topological structure parameters of the combined forecasting model. The combination model has higher prediction accuracy than the single model. The research results show that the topological structure parameters of the WNN/GNN/SVM can be optimized including the network weights and neuron threshold b, the network initialization parameter a、b_{n-1}, the weight coefficient C and kernel function parameter g. The topology structure of WNN, GNN , SVM has been shown in Fig 1.

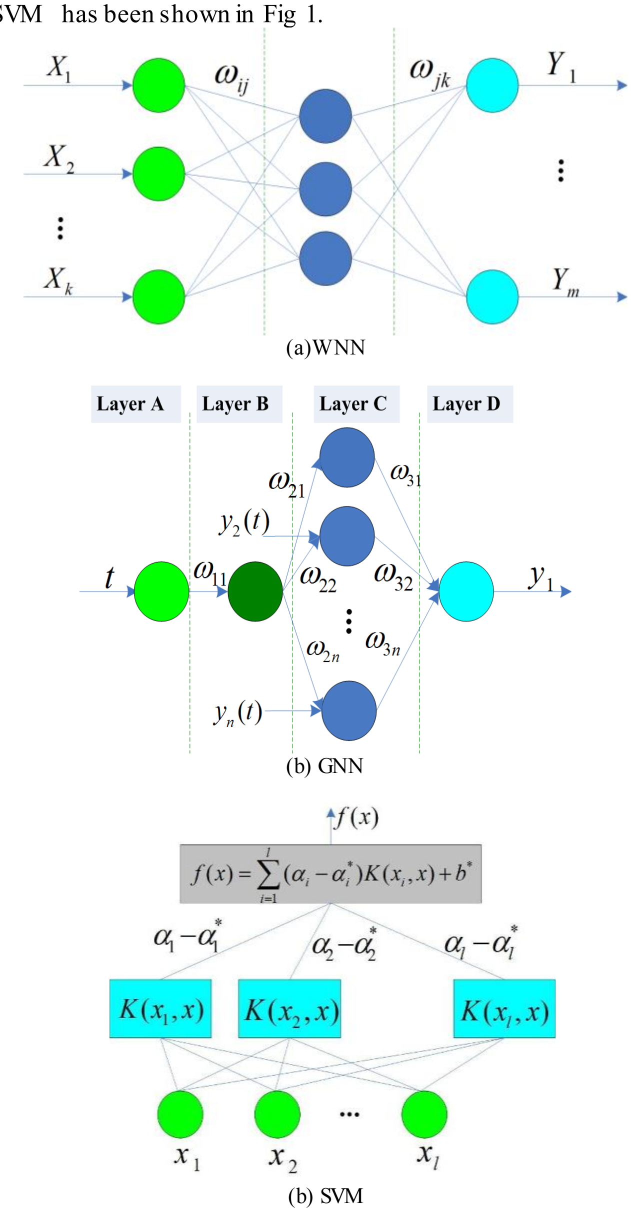

Fig. 1. The topology structure of WNN, GNN and SVM

The prediction of time series based on one method is one-sided and unstable. Hypothetical the historical time series $x_1, x_2, \ldots, x_n$, and the predicted values for the above historical time series is $x_{i1}, x_{i2}, \ldots, x_{in}$, i=1,2,3 using WNN/GNN/SVM. And the prediction error matrix E can be expressed as below:

$$E=[(e_{it})_{3\times n}][(e_{it})_{3\times n}]^{\mathrm{T}} \quad (1)$$

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

$$y^{'}(t)=\omega_1 y_1(t)+\omega_2 y_2(t)+\omega_3 y_3(t) \quad (2)$$

$\boldsymbol{W}=(w_1, w_2, w_3)$ is the weighted coefficients of the linear combination of forecasting model, and $w_1+w_2+w_3=1$.The sum of squared error of linear combination prediction is:

$$S=\sum_{t=1}^{n}(\sum_{i=1}^{m}\omega_i e_{it})^2=W^{\mathrm{T}}EW \quad (3)$$

In order to obtain the optimal weight coefficient $\boldsymbol{W}$, it can be converted to the two programming problem:

$$\begin{cases}\min S=W^{\mathrm{T}}EW \\ s.t. R^{\mathrm{T}}=1,\ R^{\mathrm{T}}=(111)\end{cases} \quad (4)$$

Continue to introduce the operator $2\lambda(R^{\mathrm{T}}W-1)$, finding the derivatives of $\boldsymbol{W}$ and λ:

$$\frac{\mathrm{d}[W^{\mathrm{T}}EW-2\lambda(R^{\mathrm{T}}W-1)]}{\mathrm{d}W}=0\Rightarrow EW-\lambda R=0 \quad (5)$$

$$\Rightarrow W=\lambda E^{-1}R$$

$$\frac{\mathrm{d}[W^{\mathrm{T}}EW-2\lambda(R^{\mathrm{T}}W-1)]}{\mathrm{d}\lambda}=0\Rightarrow R^{\mathrm{T}}\lambda E^{-1}R=1\Rightarrow \quad (6)$$

$$\Rightarrow \lambda=(R^{\mathrm{T}}E^{-1}R)^{-1}$$

Therefore optimal weight coefficient is $\boldsymbol{W}=\boldsymbol{E}^{-1}\boldsymbol{R}/\boldsymbol{R}^{T}\boldsymbol{E}^{-1}\boldsymbol{R}$。

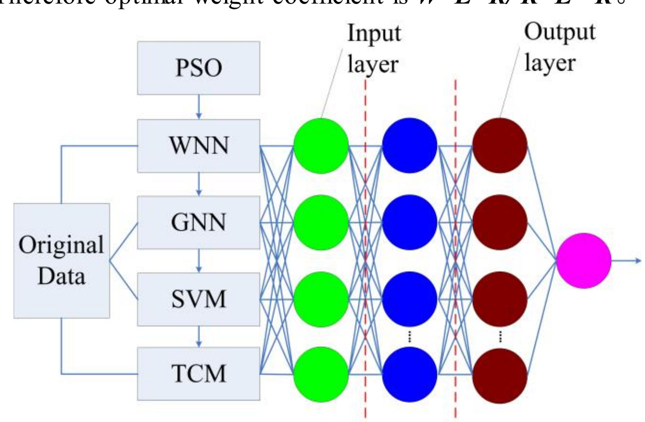

Fig.2. The combined forecasting model of time series based on PSO-BP algorithm

On the basis, the paper proposes a combination forecasting model of time series based on the BP neural network. The advantages of various prediction methods can be effectively utilized. The basic modeling idea of the combined model is:
(1) The wavelet neural network WNN, gray neural network GNN and support vector machine SVM are used to forecast the time series, the topology optimization variables are

optimized by PSO algorithm. （2）Based on the results of the three single models, combined with the calculation method of the optimal weight coefficient, the results of the combined forecasting model are obtained. （3）The predicted results are used as the input vector of BP neural network. Take the original historical time series as output vector of BP neural network. The combination model based on BP neural network is established and optimized by PSO algorithm. The topology is shown in Fig 2.

Transformer oil will decompose to produce characteristic gas under the condition of overheat or discharge fault, mainly includes hydrogen(H_2), carbon dioxide (CO_2), methane(CH_4), ethane(C_2H_6), ethylene(C_2H_4) ,acetylene(C_2H_2) six kinds of fault gases. The content and proportion of the above gas components have reference value for the judgment of fault types. The following is the analysis of the dissolved gas in the transformer oil. It was found that total hydrocarbon exceeded the value of attention, and the follow up tests were carried out. It was found that the gas content increases rapidly. To verify the validity and reliability of time series prediction, the combined forecasting method is verified by taking the content of one kind of gas (H_2) as an example.

III. CALCULATION AND ANALYSIS OF THE FIELD DATA

As for the wavelet neural network, grey neural network and support vector machine, output vector is content of hydrogen (H_2), the input vector is the content of the other 5 gases except the input vector. The expected goal of the prediction model is to enter the 5 gas contents, then output target is the content of hydrogen (H_2) at the corresponding time point. In this paper, the simulation platform is MATLAB(R2009b), the operating environment is Intel Core i5-3230, 4G memory, 500G hard disk. In order to meet the needs of wavelet neural network, grey neural network and support vector machine, it is realized by MATLAB own function mapminmax, and combined with apply and reverse commands.

1)SVM-PSO

The parameter optimization of SVM model is realized by the PSO algorithm. The PSO parameters are set as: $c1$=1.5， $c2$=1.7, the evolutionary algebra is 300, and the maximum number of particles is 20. The effect of the PSO algorithm optimizing SVM is shown in Fig 3.

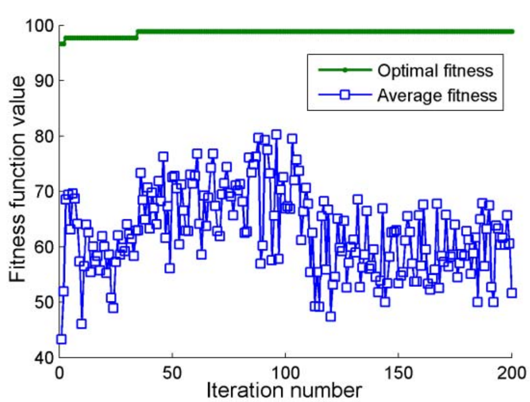

Fig.3. The effect of PSO algorithm optimizing SVM

Optimum parameters of C & g are 5.66 & 0.25. The support vector machine prediction results are shown in Fig 4.

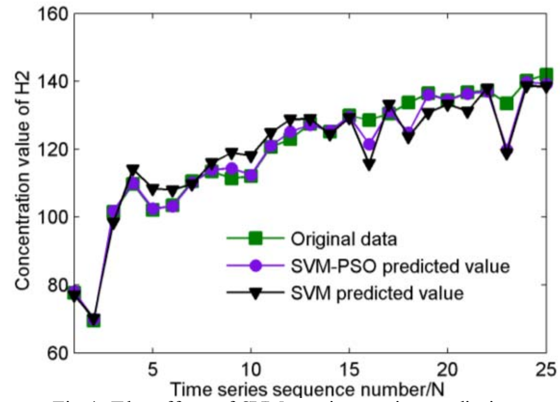

Fig.4. The effect of SVM on time series prediction

2)WNN-PSO

The number of input nodes of the wavelet neural network is set to 5, and the output node is set to 1, in which the hidden layer node number is set to 10. The parameter learning rate of WNN is set to 0.01. The number of learning iterations is set to 200. The initial value of weights between neurons is evaluated by randn function. The wavelet base function is Morlet basis function. The PSO algorithm is used to optimize the weights of the wavelet neural network and neuron threshold. The prediction error trend of H_2 using WNN is shown in Fig 5.

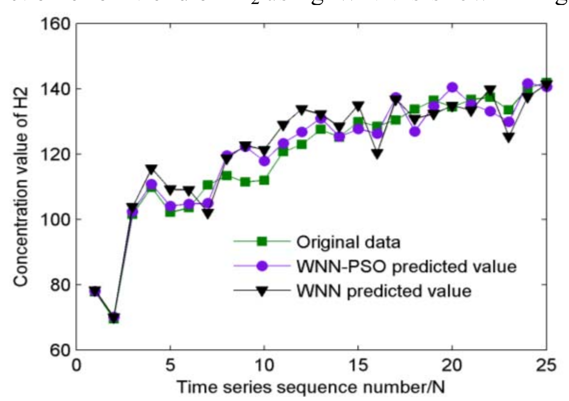

Fig.5. The effect of WNN on the time series prediction

Using PSO algorithm, the prediction results of time series are more close to the true value. The prediction accuracy of the first 15 sequence points is high, and then prediction sequences diverge gradually, and the accuracy is reduced.

3)GNN-PSO

The grey neural network needs to initialize the network parameters of a、b_{n-1}, random assignment by rand function, the optimal parameters of grey neural network include a、b_1、b_2、b_3、b_4、b_5、b_6. The GNN model is used to accumulate original gas concentration time series. The accumulated time series showed quasi-exponential variation, then the first order differential equation is used to fit it. The PSO algorithm optimizes the grey neural network prediction model and fitness function value decreases gradually with the number of iterations, which proves that PSO algorithm has good stability. The effect of GNN on the time series prediction is shown in Fig 6.

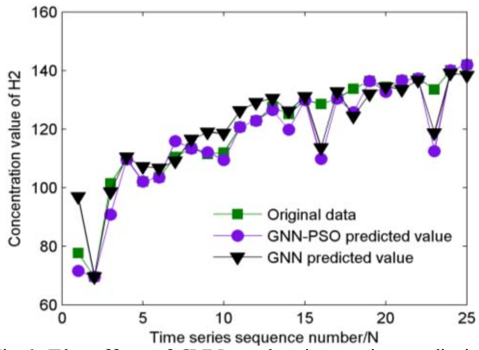

Fig.6. The effect of GNN on the time series prediction

The prediction accuracy is improved by using PSO, but the prediction accuracy of the first 10 time series is low, the time series jump in the prediction.

4) The WNN-GNN-SVM Combined Algorithm

Based on the prediction model of SVM-PSO, WNN-PSO and GNN-PSO prediction model, the prediction error matrix e is obtained:

$$e=\begin{array}{c}\begin{bmatrix} -0.3455 & 0.0623 & -0.13 \\ -0.3516 & -0.0162 & -0.5797 \\ 0.286 & 0.0388 & 4.232 \\ -0.3401 & 0.2845 & 17.8122 \\ 0.5317 & -0.1621 & -0.279 \\ \vdots & \vdots & \vdots \\ 1.3348 & 2.3964 & 0.3981 \\ 2.7231 & 1.081 & 5.5733 \\ -0.7817 & -2.6155 & -0.4696 \\ 1.1381 & 1.2739 & 1.6961 \\ -0.1083 & -1.2474 & -1.4231 \end{bmatrix} \\ \begin{array}{ccc}\text{SVM-PSO} & \text{WNN-PSO} & \text{GNN-PSO}\end{array}\end{array} \qquad (7)$$

Then the corresponding prediction error matrix E:

$$E=[(e_{it})_{3\times n}][(e_{it})_{3\times n}]^{\mathrm{T}}=\begin{bmatrix} 20.1516 & 17.4262 & 26.9140 \\ 17.4262 & 30.2886 & 33.6307 \\ 26.9140 & 33.6307 & 474.8338 \end{bmatrix} \qquad (8)$$

Take the prediction error matrix E into $\boldsymbol{W}=\boldsymbol{E}^{-1}\boldsymbol{R}/\boldsymbol{R}^{T}\boldsymbol{E}^{-1}\boldsymbol{R}$, the optimal weight coefficient of combined forecasting is obtained:

$$W=[0.8328 \quad 0.1865 \quad -0.0193]^{\mathrm{T}} \qquad (9)$$

Therefore, the traditional combination forecasting model:

$$y^{'}(t)=W_{1,1}y_1(t)+W_{2,1}y_2(t)+W_{3,1}y_3(t) \qquad (10)$$

$y_i(t)(i=1,2,3)$ are the prediction time series of SVM-PSO、WNN-PSO、GNN-PSO respectively. And the optimization of BP neural network weights by PSO is shown in Tab 1. The effect of the BP neural network combined forecasting model is shown in Fig 7.

Tab.1 The optimization of BP neural network weights ω by PSO

2.3220	-0.6108	1.0440	-0.0175	-0.8907	-1.2598
0.9255	-3.3102	0.4337	-0.2059	-1.6009	0.6321
-0.4898	-2.7658	-4.2717	-0.1132	1.6165	2.8540
-1.2088	-0.6603	1.7137	-3.0722	-1.3807	-4.1899
0.1113	-0.9902	-1.3416	2.0716	-0.7136	-1.3454

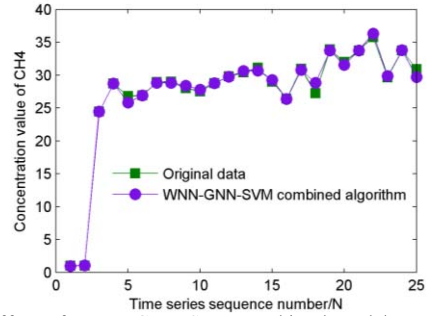

Fig.7 The effect of WNN-GNN-SVM combined model on the time series prediction

Fig 7 shows that the predicted value of WNN-GNN-SVM combined model is in good agreement with the real value of time series, which has strong nonlinear fitting ability and predictive performance.

IV. CONCLUSIONS

1)In the GNN/WNN/SVM, the topology parameters can be optimized respectively for the network weights and threshold of neurons, the network initialization parameters a、b_{n-1}, and the kernel function parameter g.

2)The PSO algorithm can improve the prediction accuracy, the combination of WNN-GNN-SVM and PSO-BP algorithm has higher prediction accuracy.

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