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Electric Power Systems Research 67 (2003) 53–58
ELECTRIC POWER SYSTEMS RESEARCH
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Novel grey model for the prediction of trend of dissolved gases in oil-filled power apparatus

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Received 17 October 2002; received in revised form 18 February 2003; accepted 19 February 2003

Abstract

The power transformer is a major apparatus in a power system; it is of great importance to detect incipient failures in power transformers as early as possible in order to minimize system outage. In this paper, the modified grey model was applied to predict the oil-dissolved gas trend of power transformers. Then, the future fault of power transformer can directly be identified by the trend analysis, so that we can switch them off safely and improve the reliability of power systems. To verify the proposed approach, 46 sets of power transformer records in Taiwan have been tested. It is shown that the proposed method is simple and efficient.

Keywords: Fault diagnosis; Dissolved gas analysis (DGA); Grey theory; Grey model

1. Introduction

Monitoring and maintenance of mineral-oil-filled power transformers are of critical importance in power systems. Failure of a power transformer may interrupt the power supply and result in loss of profits. Therefore, it is of great importance to detect incipient failures in power transformers as early as possible, so that we can switch them off safely and improve the reliability of power systems. If a long in-service transformer is subjected to electrical and thermal stresses, it may generate byproduct gases due to the incipient failures. Dissolved gas analysis (DGA) is a common practice for incipient fault diagnosis of power transformers [1–3]. The utility tests and periodically samples the insulation oil of transformers to obtain the constituent gases in the oil, which are formed due to breakdown of the constituent insulating materials inside. In the past, various fault diagnosis techniques have been proposed, including the conventional key gas method, gas ratio method [2–4], expert systems [5], neural networks (NN) [6], and fuzzy logic approaches [7,8]. Recently, the combinations of fuzzy logic and AI have given promising results in the fault analysis [9]. As study results indicate, corona, overheating and arcing are the three main causes for insulation degradation in a transformer [2–4]. The energy dissipation is the least in corona, medium in overheating, and highest in arcing. The fault related gases include hydrogen (H_2), methane (CH_4), acetylene (C_2H_2), ethylene (C_2H_4), ethane (C_2H_6), carbon monoxide (CO), and carbon dioxide (CO_2). Therefore, if we can relate the future gas content of transformers with the faults, then forecasting fault conditions for power transformers will be easily done. Future prediction of fault conditions is the most import information for maintenance engineering group to avoid system outages.

In the past, forecasting approaches have mostly used time series like least-squares regression or neural network models like back propagation based neural networks. Generally, these traditional forecasting models need a large amount of input data. However, the DGA of a power transformer is usually done only once in every year by power companies due to inspection cost consideration, so the historical database is very limited. The traditional forecasting methods are not appropriate for application in this field. The grey dynamic model

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0378-7796/03/$ - see front matter
doi:10.1016/S0378-7796(03)00047-6

(GM model) was originally created by Deng [10,11] in China. The GM model is particularly designed for handling situations in which only limited data are available for forecasting while system environment is not well-defined and fully understood. The GM model has been proved successful in many forecasting fields [11–13].

In this paper, the grey model was applied to predict the future faults of power transformers. Due to few historical dissolved gas records (only one test value for a year), a modified grey model (MGM) is proposed to predict the trend of dissolved gases. Then, future faults of power transformers can be directly identified by the fault diagnosis techniques, so that we can switch them out safely and improve the reliability of power systems. To verify the proposed approach, 46 sets of the Taiwan power transformer gas records have been tested. The tested results show that the proposed method is simple and efficient.

2. Grey forecasting model of oil-dissolved gas

Applications of grey forecasting techniques to predict oil-dissolved gas are described in this section. According to the transformer test report of the Taiwan Electric Research and Testing Center (TERTC), the historical data of oil-dissolved gas are available only one value for a year, so there is rarely limited data at the power companies. Therefore, the grey forecasting model used in this paper features just a small amount of historical data (4–6 points of data) required to set up the model and to achieve accurate forecasting.

2.1. Outline of grey system theory

Deng in China first derived the concept of the grey system theory [10,11], the grey theory describes random variables as a changeable interval number that varies with time factors and uses 'color' to represent the degree of uncertainty in a dynamic system. If a system whose information is completely clear is called as a white system. In opposition, if a system whose information is not clear at all is called as a black system. In other words, if a system whose information is partly clear or partly unclear is called as a grey system. The grey forecasting model is one of the applications of the grey theory. Instead of analyzing the characteristics of the grey systems directly, the grey model exploits the accumulated generating operation (AGO) technique to outline the system behaviors. The AGO practice may reduce the white noise embedded in the input data from statistics. If we set the original data series as a vector $x^{(0)} = \{x^{(0)}(1),\ x^{(0)}(2), \ldots,\ x^{(0)}(n)\}$, the h-AGO transformation is expressed as:

$$x^{(h)}(k) = \sum_{j=1}^{k} x^{(h-1)}(j) \tag{1}$$

Where the h is the number of the transformation, k is the data number. Using the transformation, the original random data series will be transformed into a new regular or smooth data series as shown in Fig. 1. In fact, functions derived from AGO transformation of original series are always well fitted to exponential functions, from which it is relatively easy to obtain a differential equation of the grey model. For generalization, the general form of the grey model, GM(n,m), is defined as a higher-order multivariable differential equation:

$$\frac{\mathrm{d}^n x_1^{(1)}}{\mathrm{d}k^n} + a_1 \frac{\mathrm{d}^{n-1} x_1^{(1)}}{\mathrm{d}k^{n-1}} + \cdots + a_n x_1^{(1)} = b_1 x_2^{(1)} + b_2 x_3^{(1)} + \cdots + b_{m-1} x_m^{(1)} \tag{2}$$

Where n is the order of the differential equation and m is the number of types of observed data. The GM(n,m) model is a differential equation with an adaptive property, and also it is a difference equation with a time-varying structural property. The boundary conditions of Eq. (2) are:

$$x_1^{(0)}(0) = x_1^{(1)}(1) \tag{3}$$

$$x_i^{(1)}(k) = \sum_{j=1}^{k} x_i^{(0)}(j) \tag{4}$$

According to the boundary conditions, the parameters of the GM(n,m) model are determined by the minimum least square estimation algorithm [10,11]. In the grey theory, the standard GM(1,1) model is the simplest form of the GM(n,m) model and it is also the most common model in forecasting as follows:

$$\frac{\mathrm{d}x^{(1)}}{\mathrm{d}t} + a x^{(1)} = b \tag{5}$$

The GM(1,1) model is used in this forecasting problem since a small amount of historical data is required to set up the model.

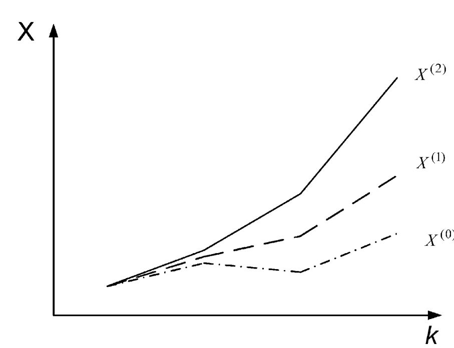

Fig. 1. Image of AGO transformation.

2.2. The proposed grey forecasting method of oil-dissolved gas

In this section, a modified GM(1,1) model will be proposed to predict oil-dissolved gas. Because the historical data of oil-dissolved gases are usually the larger changes, the standard GM(1,1) model does not give better forecasting results. Therefore, the proposed grey model uses the double AGO (2-AGO) transformation of original series to set up the forecasting model, which can contribute to the provision of a data set with lower white noise. Based on the GM(1,1) model, the modified grey model can be expressed as a first-order ordinary differential equation:

$$\frac{\mathrm{d}x^{(2)}}{\mathrm{d}t}+ax^{(2)}=b \tag{6}$$

Where $x^{(2)}$ is the 2-AGO transformation of original series that can be obtained by:

$$x^{(1)}(k)=\sum_{j=1}^{k}x^{(0)}(j) \tag{7}$$

$$x^{(2)}(k)=\sum_{j=1}^{k}x^{(1)}(j) \tag{8}$$

In the grey theory, Eq. (6) is called 'white descriptor' for modeling a white system. The b on the right-hand side of Eq. (6) corresponds to the sum of the factors affecting physical phenomena, and a is the state parameter. The parameters (a,b) can be found by the following grey-differential equation:

$$\frac{\mathrm{d}x^{(2)}}{\mathrm{d}t}+ag=b \tag{9}$$

$$g(k)=\frac{x^{(2)}(k)+x^{(2)}(k-1)}{2} \tag{10}$$

For simplification, if we set the sampled time of past measurement x as a unit, then the first term of Eq. (9) is a discrete system and it can be written as:

$$\frac{\mathrm{d}x^{(2)}}{\mathrm{d}t}=\frac{x^{(2)}(k)-x^{(2)}(k-1)}{1}=x^{(1)}(k) \tag{11}$$

Eq. (11) can be rewritten as

$$x^{(1)}(k)=a\left[-\frac{1}{2}(x^{(2)}(k)+x^{(2)}(k-1))\right]+b \tag{12}$$

Substituting the sequential data $x^{(1)}$ and $x^{(2)}$ into Eq. (12), we get the following matrix relation and the optimal parameters $(\hat{a},\hat{b})$ can be obtained by the minimum least square estimation algorithm:

$$\begin{bmatrix}x^{(1)}(2)\\x^{(1)}(3)\\\vdots\\x^{(1)}(n)\end{bmatrix}=\begin{bmatrix}-g(2)&1\\-g(3)&1\\\vdots&\vdots\\-g(n)&1\end{bmatrix}[a\quad b] \tag{13}$$

$$Y'=BA \tag{14}$$

$$A=[\hat{a}\quad\hat{b}]^{\mathrm{T}}=(B^{\mathrm{T}}B)^{-1}B^{\mathrm{T}}Y' \tag{15}$$

Where

$$Y'=[x^{(1)}(2)\quad x^{(1)}(3)\quad\ldots\quad x^{(1)}(n)]^{\mathrm{T}}$$

$$B=\begin{bmatrix}-g(2)&-g(3)&\ldots&-g(n)\\1&1&\ldots&1\end{bmatrix}^{\mathrm{T}}$$

The solutions of Eq. (6) can be obtained by the optimal parameters $(\hat{a}\quad\hat{b})$. The gas forecasting equation of $x^{(2)}$ is expressed as follows:

$$\hat{x}^{(2)}(k+1)=\left(\hat{x}^{(2)}(1)-\frac{\hat{b}}{\hat{a}}\right)e^{-\hat{a}k}+\frac{\hat{b}}{\hat{a}} \quad \text{for } k=0,\ 1,\ 2,\ldots,\ n \tag{16}$$

Finally, the prediction result $\hat{x}$ of oil-dissolved gas at time $k+1$ can be obtained by the double inverse accumulated generating operation (2-IAGO) of Eq. (16).

$$\hat{x}^{(0)}(k+1)=\hat{x}^{(2)}(k+1)-2x^{(2)}(k)+x^{(2)}(k-1) \quad \text{for } k=0,\ 1,\ 2,\ldots,\ n \tag{17}$$

To evaluate forecast model performance, we may employ the absolute mean percentage error (AMPE) ε (%) as follows:

$$\varepsilon(\%)=\frac{1}{n}\sum_{k=1}^{n}\frac{|x^{(0)}(k)-\hat{x}^{(0)}(k)|}{|x^{(0)}(k)|}\times 100\% \tag{18}$$

If there are m sets of data, then the total absolute mean percentage error (TAMPE) $\bar{\varepsilon}$ (%) is defined as follows:

$$\bar{\varepsilon}(\%)=\frac{1}{m}\sum_{i=1}^{m}\varepsilon_i \tag{19}$$

The larger AMPE indicates that the lower accuracy of the forecasting model, which is usually an indication that the historical data contains too many or too large changes. Contrarily, The small AMPE means that the accuracy of the forecasting model is high.

3. The grey fault forecasting method of power transformer

In DGA, IEC codes have been used widely by the power utilities. For IEC std. 599, the codes of different gas ratios and fault classifications according to the gas ratio codes are shown in Tables 2 and 1, respectively. The IEC codes are useful for fault diagnosis in

Table 1
IEC gas ratio codes

Ranges of the gas ratio	Codes of different gas ratios		
	C_2H_2/C_2H_4	CH_4/H_2	C_2H_4/C_2H_6
<0.1	0	1	0
0.1–1	1	0	0
1–3	1	2	1
>3	2	2	2

Table 2
Fault types according to the gas ratio codes

Fault type no.	Fault type	C_2H_2/C_2H_4	CH_4/H_2	C_2H_4/C_2H_6
1	No fault	0	0	0
2	<150 °C thermal fault	0	0	1
3	150–300 °C thermal fault	0	2	0
4	300–700 °C thermal fault	0	2	1
5	>700 °C thermal fault	0	2	2
6	Low energy partial discharges	0	1	0
7	High energy partial discharges	1	1	0
8	Low energy discharges	1 or 2	0	1 or 2
9	High energy discharges	1	0	2

transformers. In this section, the grey fault forecasting method (GFFM) is proposed for power transformers, which is combination of the grey forecasting method and the IEC fault diagnosis. The GFFM is described as follows:

Step 1: Find the effective database for the transformer fault diagnosis. IEC method needs 5 gas data according to the gas ratio codes shown in Table 2.
Step 2: Setup the grey forecasting model of the required oil-dissolved gas by the proposed grey forecasting method.
Step 3: Use the proposed grey forecasting model to predict the gas data of the consecutive times.
Step 4: Calculate the gas ratio codes as Table 1, and to find the predicted fault shown in Table 2.
Step 5: Go back to step 2 for the next transformer when the diagnosis is completed, repeat the same for all.

Because of the fault diagnosis method is the adoption of gas ratio codes, and the values of fault codes lying in the range. Therefore, the proposed GFFM can achieve accurate forecasting and shows good tolerance of forecasting errors.

4. Case studies and discussion

To demonstrate the effectiveness of the proposed method, 46 groups of field-test samples from power transformers in Taiwan collected for more than 10 years were tested. The DGA data include the 69, 161 and 345 kV power transformers supported by the TERTC. The gas record for each transformer is actually a compilation of several data. Each data set contains levels for 10 different gases at 4 or 5 different times. The total amounts of test data are 1840 values. In the database of the TERTC, all gas concentrations are expressed by ppm in volume concentration, e.g. 100 ppm is equal to 0.01 ml (gas)/100 ml (oil). The test results of the proposed method are shown as follows.

4.1. Forecasting results of the grey model

To evaluate the performance of the proposed grey forecasting method, the forecasting accuracy with different forecasting models is shown in Table 3, in which the standard GM(1,1) means the general grey GM(1,1) model, and the modified GM(1,1) model is the proposed grey forecasting model. The TCG means the total amount of combustible gas. From the test results, the model accuracy of the proposed method is always higher than the standard GM(1,1) model. According to Table 3, the forecasting models for both C_2H_2 and O_2 gas have high AMPE, since the C_2H_2 gas accounts for few data in the TERTC and the air easily contaminates the sampled oil of power transformer. The forecasting model of the gas CO has the lowest AMPE only about 1.2%. The TAMPE of the proposed grey forecasting model is only about 2.5%, which can also to say the accuracy of the forecasting model is about 97.5%.

4.2. Forecasting curves of the grey model

To compare forecasting curves of the oil-dissolved gas with different models, the partial forecasting results of transformer no. 23 in the Taiwan power system are

Table 3
The comparison of the forecasting accuracy using standard GM(1,1) and modified GM(1,1) models.

Gas types		O_2	N_2	CO_2	CO	H_2
ε (%)	GM	18.7%	13.2%	12.4%	6.3%	12%
	MGM	3.4%	2.3%	2.4%	1.2%	2.2%
Gas types		CH_2	C_2H_6	C_2H_4	C_2H_2	TCG
ε (%)	GM	9%	17.7%	18.5%	21%	7.3%
	MGM	1.6%	3.2%	3.4%	4.2%	1.4%
$\bar{\varepsilon}$ (%)	GM	13.6%				
	MGM	2.5%				

GM: standard GM(1,1) model. MGM: modified GM(1,1) model.

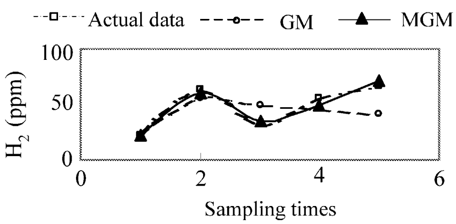

Fig. 2. Forecasting curves of hydrogen gas.

shown in Figs. 2–7. The sampled times were in the period between 1983 and 1995. The number of data is only 4 sets of data to set up the grey forecasting models. Most of the traditional forecasting methods, however, need a completed database to build the essential mathematical models. But many power companies in the developing countries may not have sufficient budget and management task force available to maintain a long-term and large-scale sampling data. Therefore, the grey forecasting method is much more suitable as a practical solution in this field. It is very clear that both GM models can predict the future data of oil-dissolved gas by the limited data; it is most useful for fault trend analysis. The forecasting curves of the proposed MGM are always better than the general grey model (GM), and the proposed method agrees well with the actual data. In other words, the functions derived from the 2-AGO transformation of original series are always well fitted to exponential functions, from which it is relatively easy to obtain a better grey model. But if we excessively use AGO transformation over 2-AGO in the modeling process, the test results prove that the forecasting model does not give better results in some tested cases.

4.3. Fault forecasting results

To test the performances of the proposed GFFM, the fault codes of transformer no. 8920008 against the sampling times are plotted in Figs. 8 and 9. Because of the fault diagnosis method is the adoption gas ratio codes, and the values of fault code have a range. Therefore, the proposed method can be used to achieve accurate forecasting. The graph clearly shows that the forecasted fault codes by the proposed method agree well with the actual fault codes. On the other hand, the fault code of next future time is also supplied by the proposed method. In contrast, if we use the standard GM(1,1) model with IEC codes to forecast faults, the test results show that the standard GM(1,1) model does not give better results in some tested cases due to the large error. This forecasted information is important for any decision regarding the transformer refurbishment or

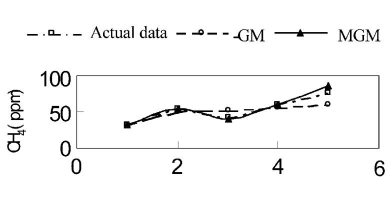

Fig. 3. Forecasting curves of methane gas.

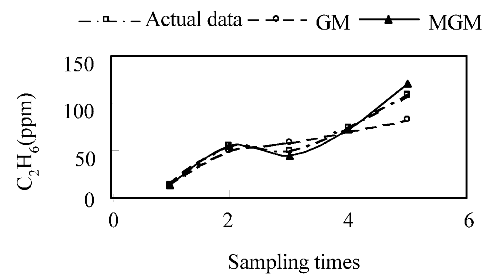

Fig. 4. Forecasting curves of ethane gas.

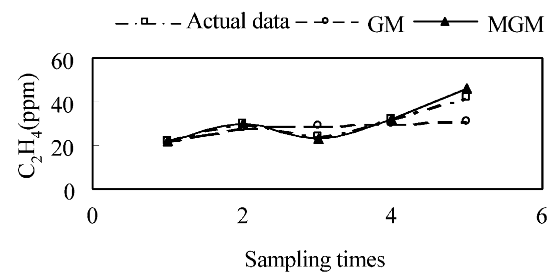

Fig. 5. Forecasting curves of ethylene gas.

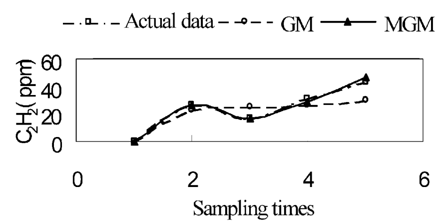

Fig. 6. Forecasting curves of acetylene gas.

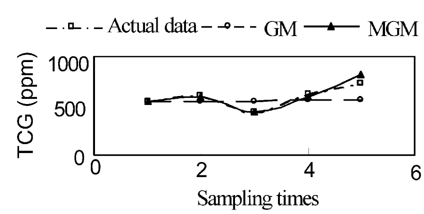

Fig. 7. Forecasting curves of TCG.

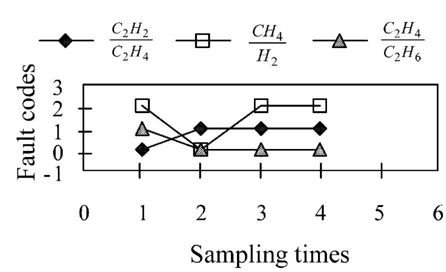

Fig. 8. Actual fault codes with different sampling times.

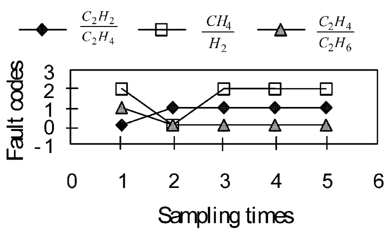

Fig. 9. Forecasting fault codes of the proposed method.

replacement, so the maintenance schedule can be optimized and a longer service life of power transformer could be achieved in the current economic climate.

5. Conclusion

In this paper, a novel forecasting technique based on the grey model has been proposed for power transformer incipient fault diagnosis. Due to the lack of sampling data, the grey model is very useful to set up the accurate forecasting model, since it can work with very little data. According to the field test results, it is shown that the proposed method can, not only provide the high accuracy model of the transformer oil-dissolved gas; it can also combine with other fault diagnosis method to detect useful information for future fault analysis. In addition, the calculation of the proposed method is fast and very simple and can be easily implemented by PC software.

Acknowledgements

The authors are greatly indebted to the engineers of the Taiwan Power Company for their providing the valuable field test data. We also gratefully acknowledge the financial support of the National Science Council, Taiwan, ROC, (Project No. 91-2213-E-167-014).

Appendix A: Nomenclature

$x^{(0)}$ original data series
$x^{(h)}$ h-order AGO transformation of original data series
h number of the AGO transformation
k data number
a state parameter
b parameter of the grey model

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