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The Application of Visualization and Neural Network Techniques in A Power Transformer Condition Monitoring System

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Abstract. In this paper, visualization and neural network techniques are applied together to a power transformer condition monitoring system. Through visualizing the data from the chromatogram of oil-dissolved gases by 2-D and/or 3-D graphs, the potential failures of the power transformers become easy to be identified. Through employing some specific neural network techniques, the data from the chromatogram of oil-dissolved gases as well as those from the electrical inspections can be effectively analyzed. Experiments show that the described system works quite well in condition monitoring of power transformers.

1. Introduction

Effective and efficient condition monitoring is very important in guaranteeing the safe running of power transformers [7, 8]. With good condition monitoring, potential failures of the power transformers can be identified in their incipient phases of development so that the maintenance of the power transformers can be condition based in addition to periodically scheduled. Since the physical essence of the failures of the power transformers have not been clearly recognized at present, the monitors usually set up mappings between the failures and their appearances and then analyzes or predicts the potential failures with pattern recognition techniques. As an important pattern recognition technique, neural networks have been extensively applied in this area in past decades and have exhibited strong ability in modeling complex mappings between the failures and their appearances [1, 2]. However, in some cases the information on the condition of the power transformers can be visualized so that it is easy and intuitive for a human monitor to identify the potential failures, which can not only improve the accuracy of the analysis but also reduce the computational cost required by the analysis [14]. So, utilizing neural networks and visualization techniques together in a power transformer condition monitoring system seems an attracting alternative.

In this paper, visualization and neural network techniques are applied together to a power transformer condition monitoring system. In the system, the data from the chromatogram of oil-dissolved gases are visualized by 2-D or 3-D graphs. If a human monitor cannot identify potential failures from those graphs, the information on the condition of the power transformers is passed to a neural network module. The neural network module utilizes a specific paired neural network architecture, which enables it to deal with the data from the chromatogram of oil-dissolved gases as well as those from the electrical inspections. It employs some redundant input attributes to accelerate the training speed and reduce the number of hidden units in the networks. Moreover, the neural network module exploits fuzzy techniques to preprocess the primitive input data so that important features with relatively small values will not be blocked off by those with relatively big values. Experiments show that the described system attains good monitoring effect.

The rest of this paper is organized as follows. In Section 2, we briefly introduce the whole condition monitoring system. In Section 3, we describe the visualization techniques used in the system. In Section 4, we present the neural network techniques employed in the system. In Section 5, we report on some experimental results. Finally in Section 6, we conclude.

2. Sketch of the System

The data fed to the described system can be categorized into two types, i.e. the data from the electrical inspections and the data from the chromatogram of oil-dissolved gases. The former type of data include *ultrasonic measure* (abbr. UL), *abnormal sound* (abbr. AS), *direct current resistance* (abbr. DR), etc., some of which can be obtained when the power transformers are in running while some can be obtained only when the power supply are terminated. The latter type of data include the volume of H_2 in the oil-dissolved gas, the volume of CH_4 in the oil-dissolved gas, the volume of C_2H_6 in the oil-dissolved gas, etc., all of which can be obtained when the power transformers are in running.

When the system is working, the data from the chromatogram of oil-dissolved gases are visualized in 2-D or 3-D graphs at first, and a human monitor is asked to check the graphs. If he or she can identify some potential failures, the analysis process terminates. Otherwise the data from the chromatogram of oil-dissolved gases as well as those from the electrical inspections are fed to the neural network module which will return an analysis result. In summary, the analysis process of the system is depicted in Fig. 1.

3. Visualization

3.1 Visual Modelling

Visualization techniques enable the deep insight of the information by transforming the digital symbols to vivid images and/or graphs [9]. It could be used not only to enrich the interface between human and machine but also to help human recognize useful information more quickly and intuitively.

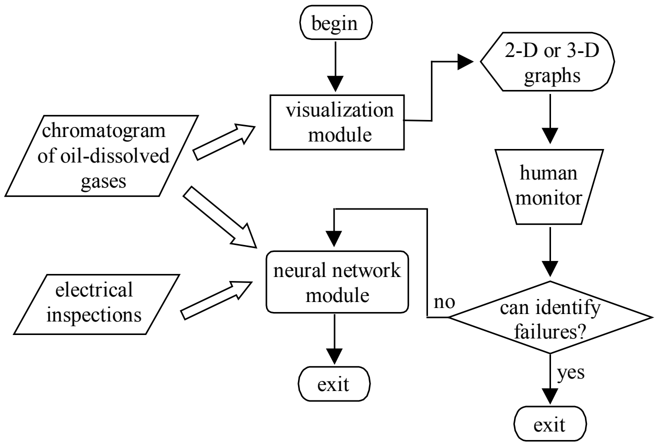

Fig. 1. The analysis process of the described system

At present treble-ratio-rule [10] is the most authoritative criterion in analyzing the data from the chromatogram of oil-dissolved gases in China. Treble-ratio-rule computes the ratios, including CH_4 / H_2, C_2H_2 / C_2H_4, and C_2H_4 / C_2H_6, of the volumes of H_2, CH_4, C_2H_6, C_2H_4, and C_2H_2 in the oil-dissolved gases, and then performs condition monitoring according to some empirical rules. In the described system, visualization techniques are introduced to depict those ratios, which endows data with spatial properties from multi-dimensional perspectives.

Before visualization, the problem to be solved must be modelled. Nowadays, pipeline model [4] is one of the most prevailing visualization models. In the described system, the pipeline model is adapted according to the requirements of the condition monitoring of power transformers, which is shown in Fig. 2.

The functions of the components in Fig. 2 are as follows.

1) Simulation: to generate primitive data, i.e. the data from the chromatogram of oil-dissolved gases, for visualization.

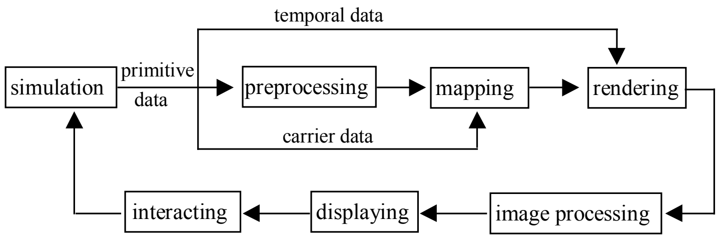

Fig. 2. Visualization model used in the described system

2) Preprocessing: to transform and filter the primitive data, which filters out noise, extracts interested data, and derives new data such as gradients and interpolations.

3) Mapping: to provide functions of modelling and classifying. Modelling means to extract geometrical elements such as points, lines, etc. from the filtered data. Classifying is to classify voxels with different values.

4) Rendering: to derive basic geometrical elemental information.

5) Image processing: to assemble basic functions of graphics transformation, e.g. scaling, rotating, etc.

6) Displaying: to display the images in a way that diverse perspectives and queries are available.

7) Interacting: to help the human monitor track the analysis process so that the simulation can be controlled and guided.

3.2 Implementation

In the described system, the data from treble-ratio-rule of the chromatogram of oil-dissolved gases are visualized in 2-D or 3-D graphs. In 2-D visualization, the fault space is depicted as an equilateral triangle where the axes are respective the percentage of the volumes of CH_4, C_2H_4, and C_2H_2 in the oil-dissolved gases. Thus, there are six states in the fault space as shown in Fig. 3. In 3-D visualization, the fault space is depicted as an open-cube where the axes are the ratios of the five characteristic gases, i.e. H_2, CH_4, C_2H_6, C_2H_4, and C_2H_2. Thus, there are also six states in the fault space as shown in Fig. 4.

In Fig. 3 and Fig. 4, PD denotes *partial discharge*, D1 denotes *low-energy discharge*, D2 denotes *high-temperature discharge*, T1 denotes *high-temperature overheat* with $t < 300°$ C, T2 denotes *high-temperature overheat* with $300°C \leq t < 700°$ C, T3 denotes *high-temperature overheat* with $700°C \leq t$.

From the 2-D and 3-D graphs, some potential failures are easy to be identified.

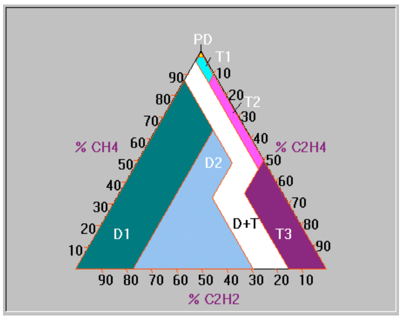

Fig. 3. 2-D visualization

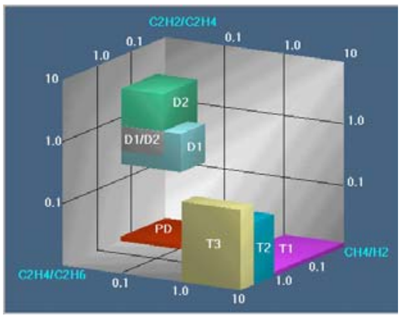

Fig. 4. 3-D visualization

Since different measurements of the data are used in those two graphs, the analysis results could verify each other so that the accuracy of analysis is improved.

4. Neural Networks

4.1 Paired Neural Networks

In most condition monitoring systems that utilize neural network techniques, only the data from the chromatogram of oil-dissolved gases are processed while those from the electrical inspections are seldom used [5]. The reason lies in the diversity, the high cost, and the temporal relationships of the electrical inspections. On one hand, there is accurate symbolic criterion [10] in analyzing the data from the chromatogram of oil-dissolved gases so that dealing with only gas data does not well exert the power of neural techniques. On the other hand, the data from the electrical inspections is very useful in locating some potential failures that can not be identified by the analysis of gas data. Therefore building a neural network module that has the ability of dealing with the data from the chromatogram of oil-dissolved gases as well as those from the electrical inspections is of great value to condition monitoring of power transformers.

The temporal relationships of the electrical inspections lie in the orders of inspections, that is, whether an inspection *B* is required is determined by the result of an inspection *A*. For example, the *insulation resistance* need not be measured if other inspections show that the power transformer is well running. If it is measured preceding some other electrical inspections, unnecessary cost is paid because measuring the *insulation resistance* requires terminating the power supply. Such kind of orders of electrical inspections lead to the result that it is almost impossible to attain all the helpful data from the electrical inspections at the same time without unnecessary cost. However, neural networks claim that all the input data should be provided before the training begins. Thus the obstacle appears.

In order to get across the obstacle, the described system adopts a specific paired neural network architecture based on the fault set and the fault attribute set [6]. At first, features from some important online electrical inspections and those from the analysis of the chromatogram of oil-dissolved gases are selected to constitute the online fault attribute set. The failure types that could be identified from the online fault attribute set constitute the online fault set. An online monitoring neural network is built by regarding the online fault attribute set and the online fault set as the input and output attribute sets respectively. Then, features from some important offline electrical inspections, along with features from the selected online electrical inspections and those from the analysis of the chromatogram of oil-dissolved gases, are selected to constitute another fault attribute set, i.e. the offline fault attribute set. The failure types that could be identified from the offline fault attribute set constitute the offline fault set. An offline monitoring neural network is built by regarding the offline fault attribute set and the offline fault set as the input and output attribute sets respectively. Both the online and the offline neural networks are trained so that the former is applicable when the power transformers are in running while the latter is applicable when the power supply is terminated.

As for the online monitoring neural network, since obtaining the inputs does not require terminating the power supply, its inputs could be easily collected at the same time. But as for the offline monitoring neural network, obtaining the inputs may require terminating the power supply. However, the inputs of the offline monitoring neural network could be obtained at the same time when the power transformers are in periodic termination and examine.

Moreover, since the online fault set and the online fault attribute set are proper subsets of the offline fault set and the offline fault attribute set respectively, the online monitoring neural network is also applicable when the offline monitoring neural network is applicable. Therefore the accuracy of the analysis could be improved in simulating the consultation of multiple experts where the analysis result of one network is verified with that of the other network.

4.2 Redundant Input Attributes

In the described system, the percentage of the volumes of H_2, CH_4, C_2H_6, C_2H_4, and C_2H_2 in the oil-dissolved gases are included as inputs to the neural networks. In addition, since the volumes of *total hydrocarbon* (CH_4+C_2H_6+C_2H_4+C_2H_2, abbr. C1+ C2), CO, and CO_2 are helpful in locating some potential failures, they are also included as inputs to the neural networks.

Among the features from the electrical inspections, *ultrasonic measure* (abbr. UL), *abnormal sound* (abbr. AS), and *current from iron core to earth* (abbr. CE) are included as inputs to the online monitoring neural network; *direct current resistance* (abbr. DR) and *iron core insulation resistance* (abbr. IR), along with those used for the online monitoring neural network, are included as inputs to the offline monitoring neural network.

Note that *total hydrocarbon* is a redundant attribute because it does not provide any information that cannot be derived from the attributes CH_4, C_2H_6, C_2H_4, and C_2H_2. Therefore *total hydrocarbon* can be automatically learned by the neural networks through their implicitly constructive learning ability [3]. However, explicitly providing such a helpful redundant attribute as input could not only increase the learning ability of the neural networks but also reduce the number of hidden units required in achieving good generalization ability [3]. So, *total hydrocarbon* is included as mentioned above. Similarly, the ratios of CH_4 / H_2, C_2H_2 / C_2H_4, and C_2H_4 / C_2H_6 are also included as inputs to the neural networks.

4.3 Fuzzy Preprocessing

There are great differences in the value ranges of the input attributes. For example, the value of the attribute CO_2 is usually bigger than 1,000 while the value of the attribute CH_4 / H_2 is usually between 0 and 1. If the primitive attribute values are directly input to the neural networks, the features with relatively small values may be blocked off by those with relatively big values. The solution is to map the value ranges of different attributes to a same interval, e.g. [0, 1].

It is easy to transform all the primitive attribute values to the interval [0, 1] through dividing them by the length of their corresponding value ranges. However, such a linear mapping may drop some important characteristics of the original probabilistic distribution of the attributes. Instead, the described system employs fuzzy techniques.

Some *attention values* are obtained from senior human monitors, which is shown in Table 1.

Table 1. Some *attention values* (abbr. *a.v.*) provided by senior human monitors. The metric of gases, CE, and IR are respectively *ppm*, *mA*, and *mΩ*.

attr.	H_2	CH_4	C_2H_6	C_2H_4	C_2H_2	CO	CO_2	C1+C2	CE	IR
a.v.	100	50	100	100	3	300	5,000	150	20	1,500

Based on those *attention values*, the membership grades of the primitive attribute values against their corresponding *attention values* are computed according to a membership function, and then the membership grades are regarded as the inputs to the neural networks instead of those primitive values. The membership function used here is *Sigmoid* function shown in Eq.(1), where x denotes the primitive value while x_a denotes its corresponding *attention value*.

$$x' = \left(1 + e^{-x/x_a}\right)^{-1} \quad (1)$$

Moreover, the values of binary attributes are mapped to 0.1 and 0.9, and the values of ternary attributes are mapped to 0.1, 0.5, and 0.9. Those mappings could speed up the converging of the neural networks [13].

5. Experiments

The described system is tested on a data set comprising 704 cases, among which 528 cases are used as the training set while the rest 176 cases are used as the test set. The data set is provided by the Institute of Electric Science of Shandong Province, P.R.China. All the cases are collected from real-world power transformers used in Shandong Province.

The neural networks are trained with SuperSAB algorithm [12], which is one of the fastest variations of Backpropagation. Tollenaere [12] reported that it is 10 – 100 times faster than standard BP [11]. The parameters of SuperSAB are set to the values recommended by Wasserman [13], i.e. the weight-increasing factor η_{up} is set to 1.05, the weight-reducing factor η_{down} is set to 0.2, and the upper ground of the maximum step of the *k*-th weight η_{ij}^k is set to 10.

In the experiments, the visualization results are checked by a junior human monitor. If he cannot identify any potential failures, the case is passed to the neural network module for further analysis. Experimental results show that the test set accuracy of the described system is 91.5%, which is better than the level of junior human monitors (usually 80.1%) and is very close to the level of senior human monitors (usually 93.2%).

For comparison, the treble-ratio-rule is also tested with the same test set. The results show that the monitoring effect of the described system is far better than that of the treble-ratio-rule. Some test cases and their corresponding results are shown in Table 2, where "*" denotes that treble-ratio-rule has not identified any potential failures. The abbreviations used in Table 2 are shown in Table 3.

Table 2. Some test cases and their corresponding results

H_2	CH_4	C_2H_6	C_2H_4	C_2H_2	CO	CO_2	UL	AS	CE	TRR result	our result	real result
29	23	40	12	4.7	140	790	1	0	1.3	*	OSP	OSP
40	15.7	1.8	35.5	6.59	446	809	1	0	1.0	HTD	OSP	OSP
69	12.9	7.2	5.6	12.4	377	554	2	1	0.9	*	OSE	OSE
44	7.3	1.6	2.2	3.1	558	1134	2	1	1.2	*	OSE	OSE
140	8.1	8.3	15	23	680	2020	0	0	0.6	*	OSE	ID
54	7	7.4	8.6	5.4	88	297	0	0	1.3	LED	ID	ID
350	1001	298	1001	7.9	131	1401	0	0	100.3	HTO	ICO	ICO
90	149	32.4	486	19.2	315	10305	0	0	501.2	HTO	ICO	ICO
747	2065	1029	4589	6.4	664	1430	0	0	0.1	HTO	TWO	TWO
428	1660	533	4094	11.4	637	4759	0	0	0.3	HTO	TWO	TWO

Table 3. Abbreviations used in Table 2

full description	abbr.
treble-ration-rule	TRR
high-temperature discharge	HTD
low-energy discharge	LED
internal discharge	ID
high-temperature overheat	HTO
iron core overheat	ICO
tap switch overheat	TWO
oil static electricity	OSE
oil submerged pump fault	OSP

6. Conclusion

In this paper, visualization and neural network techniques are applied together to a power transformer condition monitoring system where a visualization module is used to identify relatively simple potential failures while a neural network module is used to identify relatively complex potential failures. Differing from some previous condition monitoring systems, the described system has the ability of dealing with the data from the chromatogram of oil-dissolved gases along with those from the electrical inspections. Experiments show that the monitoring effect of the described system is close to that of senior human monitors.

The described system has been used by the Institute of Electric Science of Shandong Province, P.R.China, for over a year, and has received much appreciation for its good monitoring effect. We believe that the success of the described system shows that the techniques from diverse domains of computer science, such as neural networks from computational intelligence and visualization from graphics, could greatly profit practical engineering tasks when they are adequately combined.

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