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Grey Theory Based Neuro-Fuzzy Approach for State Assessment of Power Transformer Using Dissolved Gas Analysis

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Abstract: *Power transformers are key component because power system operation depends on it. The reliability of Power Transformer is essential and hence the monitoring of such equipment is necessary at substation level. The assessment techniques of transformer include various methods. Dissolved Gas Analysis (DGA) is a universally accepted and highly recommended technique for fault diagnosis of Power Transformer. There are several DGA methods for detection of faults to measure the concentration in particle per million in oil sample. Gas concentrations indicate fault type and accordingly health of Power Transformer can be judge. This paper introduces Grey Theory approach in which analysis is carried out based on partial information to help in standardizing DGA interpretation techniques and to identify transformer state assessment through it. Grey Theory is perfectly matched to the said problem as the DGA samples are less. The keystone of Grey Theory is to find target heart degree and from that making a decision. The key gases used for Grey analysis. Grey model built in soft computing tool Adaptive Neuro-Fuzzy Inference system (ANFIS). The results of soft computing tools compared with Grey Model output. The soft computing technique shows certain degree of success to validate benchmarking of Grey Model.*
Keywords: *Anfis, Dga, Grey Model, State Assessment*

I. Introduction

Power transformers are a vital link in a power system. Its running dependability has straight relation to the safe running of power system at substation level. Monitoring and diagnostic techniques are essential to decrease maintenance and improve reliability of the equipment. Currently there are several of chemical and electrical diagnostic techniques applied for power transformers [1]. The electrical windings in a power transformer consist of paper insulation immersed in insulating oil, hence transformer oil and paper insulation are essential sources to detect incipient faults, fast developing faults, insulation trending and generally reflects the health condition of the transformer. During faults and due to electrical and thermal stresses, oil and paper decomposition occur evolving gases hydrogen (H_2), methane (CH_4), acetylene (C_2H_2), ethylene (C_2H_4) and ethane (C_2H_6). DGA is widely used to detect incipient faults [2]-[3]. In the fault system of power transformer, it has uncertainty for the relation of conditionality between dissolved gases. It has not specific qualitative and quantitative classification which gases appear because of one certain fault. So the fault system of power transformer can be recognized as a typical grey system. The theory has particular function to deal with model recognition of small sample and poor information. It is one of the effective methods for Multi-objective decision-making [4]. Adaptive Neuro Fuzzy Inference System is the class of adaptive networks that are functionally equivalent to fuzzy inference systems. ANFIS is a multi-input and single output system. ANFIS represent Sugeno Fuzzy models. It uses a hybrid learning algorithm. A combination of least-squares and backpropagation gradient descent methods are used for training fuzzy inference system membership function parameters to model a given set of input-output data. A neuro fuzzy system is a combination of neural network and fuzzy systems in such a way that neural network or neural network algorithms are used to determine the parameters of the fuzzy system. This means that the main intention of neuro- fuzzy approach is to create or improve a fuzzy system automatically by means of neural network methods. An even more important aspect is that the system should always be interpretable in terms of fuzzy if-then rules, because it is based on a fuzzy system reflecting vague knowledge.

II. Grey Theory

Grey system theory or Grey target theory or Grey theory was presented by Prof. Julong Deng in 1980s. This theory is suitable for handling less data, incomplete information and devoid of experience. In this theory, a system is said to be a 'grey system' usually, if its information are wholly unknown; while 'whitening system' means that the information of a system are complete; If the information of a system are partly known and partly unknown, it means that the system has greyness, which is said to be 'grey system'. Recently, some researchers have applied grey relational analysis for multi-criteria vague decision making. But only grey relational analysis has been applied in multi criteria vague decision making. But in various practice, there is no given standard scheme for reference. Target Heart Degrees determined by grey system theory reflect the integrated sequence of interaction and impact of all factors. In the proposed model, the reference sequence can be constructed from those sequences to be analyzed [4]-[5].

III. Key Gas Method

The standard of the Key Gas method is based on the quantity of fault gases released from the insulating oil when a fault occurs which in turn raise the temperature in the power transformer. The existence of the fault gases depends on the temperature or energy that will break the link or relation of the insulating oil chemical structure. This method uses the individual gas rather than the calculation of gas ratios for detecting fault. The significant and proportion of the gases are called key gases [6]. Transformer in-house faults are divided into thermal and electrical categories. Each fault category evolves particular characteristic gases. However, the analysis is not always straight forward as there may be more than one fault present at the same time. From the type and amount of gas, the fault nature can be determined. Various faults produce energy from low level to very high level sustained arcing. The low level energy is a partial discharge which produces H_2 and CH_4. The arcing is capable of generating all gases including C_2H_2. Except for CO and CO_2, all other gases are formed due to the decomposition of oil. CO and CO_2 in DGA represent a good source of paper monitoring. Presence of C_2H_2 in the oil is an indication of high energy arcing [6].

IV. Grey Model For Key Gas Method

In this section, Grey model is developed to estimate transformer Target Heart Degree based on DGA results. The 169 DGA samples of different Power Transformers are collected on which Grey Target Theory is applied. Out of 169, most of the samples are faulty. In this section 9 samples of Key gases are discussed to find Target Heart Degree. Input sequences to be analyzed are the 5-key gases in particle per million (ppm) as shown in Table1. The steps [4]-[5] for grey target algorithms can be described as follows:

i=1, 2,.., 9 (nine samples) and k=1, 2,3,4,5 (five gases)

Table 1 Key Gases Samples

Sample	**CH_4**	**C_2H_4**	**C_2H_6**	**C_2H_2**	**H_2**
1	372	1658	208	10	62
2	328	1462	205	10	55
3	128	1	23	0.01	2349
4	132	1	25	0.01	2460
5	2	3	1	0.01	2
6	116	265	28	204	88
7	169	26	56	0.01	2152
8	164	0.01	54	25	2291
9	153	22	46	0.01	2936

Step 1: Constructing Standard Pattern

Assume ω_i is the multi-polarity criteria sequence:

ω_i={ $\omega_i(1)$, $\omega_i(2)$,$\omega_i(3)$,$\omega_i(4)$,$\omega_i(5)$}

$\forall$ ω_i (k) ϵ =>k ϵ K={1,2,...,5}, i ϵ I={1,2,..,9}

K refers to the k^{th} criteria.

Define $\omega(k)$ as specification model sequence.

$\omega(k)$=($\omega_1(k)$, $\omega_2(k)$,..., $\omega_9(k)$)

$\forall$ ω_i (k) ϵ =>$\omega(k)$=> i ϵ I={1,2,..,9}

Suppose POL(max), POL(min), POL(mem) refer to the maximum polarity, the minimum polarity and the medium polarity, respectively, therefore

1) While POL $\omega_i(k)$ = POL(max), then $\omega_0(k)=\max_i \omega_i(k)$, $\omega_i(k) \in \omega(k)$

2) While POL $\omega_i(k)$ = POL(min), then $\omega_0(k)=\min_i \omega_i(k)$, $\omega_i(k) \in \omega(k)$

3) While POL $\omega_i(k)$ = POL(mem), then $\omega_0(k)=\text{avg}_i\ \omega_i(k)$, $\omega_i(k) \in \omega(k)$

And then the sequence ω_0={ $\omega_0(1)$, $\omega_0(2)$,..., $\omega_0(5)$}, is the standard pattern [4]-[5]. We construct sequence according to minimum polarity:

$$\omega_0= \{2, 0.01, 1, 0.01, 2\}$$

Step 2: Transforming Grey Target

Assume that T is a grey target transform [4]-[5], then

$$T\omega i(k) = \frac{\min\{\omega i(k), \omega 0(k)\}}{\max\{\omega i(k), \omega 0(k)\}} \qquad (1)$$

$T\omega_0$= x_0= (1, 1, 1, 1, 1)

$T\omega_1 = x_1 = (0.00538, 0.00001, 0.00481, 0.001, 0.03226)$
$T\omega_2 = x_2 = (0.0061, 0.00001, 0.00488, 0.001, 0.03636)$
$T\omega_3 = x_3 = (0.01562, 0.01, 0.043478, 1, 0.00085142)$
$T\omega_4 = x_4 = (0.01515, 0.01, 0.04, 1, 0.00081)$
$T\omega_5 = x_5 = (1, 0.00333, 1, 1, 1)$
$T\omega_6 = x_6 = (0.0172, 0.00004, 0.03571, 0.00005, 0.02273)$
$T\omega_7 = x_7 = (0.01183, 0.00038, 0.01786, 1, 0.00093)$
$T\omega_8 = x_8 = (0.0122, 1, 0.01852, 0.0004, 0.00087)$
$T\omega_9 = x_9 = (0.01307, 0.00045, 0.02174, 1, 0.00068)$

Step 3: Calculating Different Information Space

Different information space [4]-[5] is calculated by using formula,

$$\Delta_{oi}(k) = | x_0(k) - x_i(k) | = | 1 - x_i(k) | \quad (2)$$

$x_0(k) \in x_0 \Rightarrow x_0 = T\omega_0,$ i=1,2,..,9 and k=1,2,3,4,5; where $\Delta_{0i}(k)$ shows the grey relational different information between evaluated sequence $x_0(k)$ and $x_i(k)$

$\Delta_{01} = (0.9946, 0.9999, 0.9951, 0.999, 0.96774)$
$\Delta_{02} = (0.9939, 0.9999, 0.9951, 0.999, 0.9636)$
$\Delta_{03} = (0.9843, 0.99, 0.95652, 0, 0.9991)$
$\Delta_{04} = (0.9848, 0.99, 0.96, 0, 0.9991)$
$\Delta_{05} = (0, 0.9966, 0, 0, 0)$
$\Delta_{06} = (0.9827, 0.9999, 0.9642, 0.9999, 0.9772)$
$\Delta_{07} = (0.9881, 0.9996, 0.9821, 0, 0.999)$
$\Delta_{08} = (0.9878, 0, 0.9814, 0.9996, 0.9991)$
$\Delta_{09} = (0.9869, 0.9995, 0.9782, 0, 0.9993)$
$\Delta_{0i}(\max) = \max_i \max_k \Delta 0i(k) = 0.9999$
$\Delta_{0i}(\min) = \min_i \min_k \Delta 0i(k) = 0$

Step 4: Calculating Coefficient of Target Heart

The coefficient of target heart [4]-[5] is calculated by using formula,

$$\gamma\big(x0(k), xi(k)\big) = \frac{\min\limits_i \max\limits_k \Delta oi(k) + \rho \max\limits_i \max\limits_k \Delta oi(k)}{\Delta oi(k) + \rho \max\limits_i \max\limits_k \Delta oi(k)} \quad (3)$$

Where ρ is the resolving coefficient, $\rho \in [0, 1]$. Assume ρ=0.5. Grey target coefficients obtained for sample '1' are:

$\gamma(x_0(1),x_1(1))=0.3345$, $\gamma(x_0(2),x_1(2))=0.3333$, $\gamma(x_0(3),x_1(3))=0.3344$, $\gamma(x_0(4),x_1(4))=0.3335$, $\gamma(x_0(5),x_1(5))=0.3406$

Similarly for remaining samples grey target coefficients can be obtained.

Step 5: Calculating Target Heart Degree

Target Heart Degree [4]-[5] is calculated by using formula,

$$\gamma(x_0,x_i) = \frac{1}{n}\sum_{k=1}^{n} \gamma\big(x0(k), xi(k)\big) \quad (4)$$

By substituting the coefficients calculated from equation (3) in equation (4); Target Heart Degree obtained for sample '1' is

$$\gamma(x_0,x_1) = \frac{1}{5}\sum_{k=1}^{5} \gamma\big(x0(k), x1(k)\big) = 0.3353$$

Similarly for other samples the target Heart Degree can be obtained as per above steps. Table 2 shows the input key gases for Grey model and their corresponding calculated target heart degree. More is the Target Heart Degree better is the condition of transformer.

Table 2 Output of Grey Model for Key Gas Method

Sample	CH_4	C_2H_4	C_2H_6	C_2H_2	H_2	Target Heart Degree
1	372	1658	208	10	62	0.3353
2	328	1462	205	10	55	0.3355
3	128	1	23	0.01	2349	0.4698
4	132	1	25	0.01	2460	0.4696
5	2	3	1	0.01	2	0.8668
6	116	265	28	204	88	0.3367
7	169	26	56	0.01	2152	0.4680

8	164	0.01	54	25	2291	0.4681
9	153	22	46	0.01	2936	0.4682

The Grey model output for sample ‘1’ and sample ‘2’ is 0.3353 and 0.3355 respectively on the scale from 0 to 1 which is very low which indicates faulty condition of transformer. The excess quantity of ethylene and ethane indicates presence of Thermal Fault. The presence of ethylene may be due to overheating or improper cooling of transformer. The excess quantity of methane indicates Partial Discharge fault also.

The Grey model output for sample ‘3’ and sample ‘4’ is 0.4698 and 0.4696 respectively on the scale from 0 to 1 which is medium low which indicates middle fault condition of transformer. The excess quantity of hydrogen indicates presence of Corona Effect due to degradation of solid insulation.

The Grey model output for sample ‘5’ is 0.8668 which is high; it indicates the normal condition for transformer. The DGA results indicate concentration of dissolved gases in oil is well within normal limits.

The Grey model output for sample ‘6’ is 0.3367 which is low which indicates faulty condition of transformer. The excess quantity of ethylene and acetylene indicates presence of Thermal Fault and Arcing respectively.

The Grey model output for sample ‘7’, ‘8’,’ ‘9’ is medium low indicating medium fault condition. The DGA result shows excess quantity of hydrogen which denotes presence of Corona Effect.

Similarly Grey Target Theory applied on 169 DGA samples of oil and their Target Heart Degree calculated by using Grey algorithm steps. Figure 1 shows the graph of variation of Target Heart Degree obtained for 169 DGA samples of data. In all total 169 DGA samples maximum samples are faulty cases. Target heart degree calculated for these faulty samples are low in range of 0.3 to 0.5 which agrees the Power Transformer has fault for such cases.

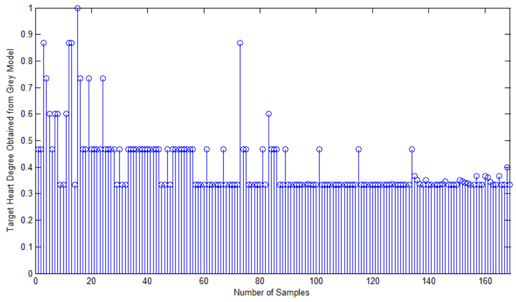

figure 1 Graph of Target Heart Degree

V. Neuro-Fuzzy Model

In this section, Neuro-Fuzzy system is developed to model a given set of input-output data of Grey Model. The model is developed in accordance to fuzzy inference system. Input variables to the model are the 5-key gases. The output of the model is the Target Heart Degree (0 to 1) of the transformer which gives health status of transformer. The grey model is implemented in Adaptive Neuro Fuzzy Inference System (ANFIS) tool available in Matlab. The ANFIS has been trained and tested for 169 different transformer DGA data. The results obtained are also comparable. Training data is the 5-key gases and single output Target Heart Degree obtained from Grey Model. The ANFIS generates the Fuzzy Inference System (FIS) model. The fuzzy inference system can be of two type’s mamdani and the Sugeno type. Here the fuzzy inference system used is of the Sugeno type. It obtains its output from judging all the written fuzzy rules by finding the membership function. The nonlinear DGA data insist to select Gaussian membership function. The ANFIS itself creates set of fuzzy logic rules is in the form of (IF-AND-THEN) statements from the inference of the Target heart Degree for input key gases. Here total 243 rules are created by ANFIS for five input variables and single output. The FIS model is built in graphical user interface tool ‘simulink’ provided by Matlab. Fig. 2 shows the FIS structure for the Grey model built in Fuzzy. Fig. 3 shows the rule base for Grey Model. The simulink Grey Theory based fuzzy model is shown in Fig. 4. The output of model is Target Heart Degree.

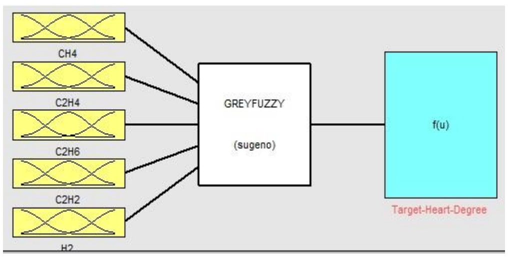

figure 2 FIS Structure

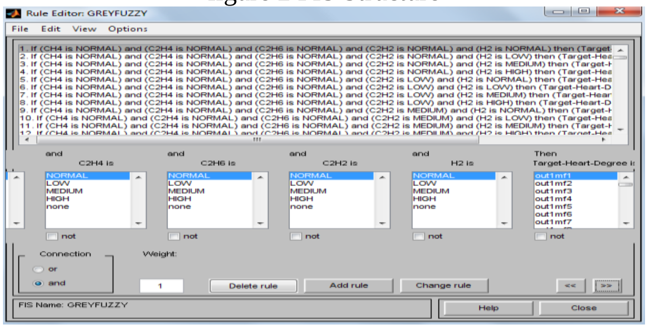

figure 3 Fuzzy Rule base

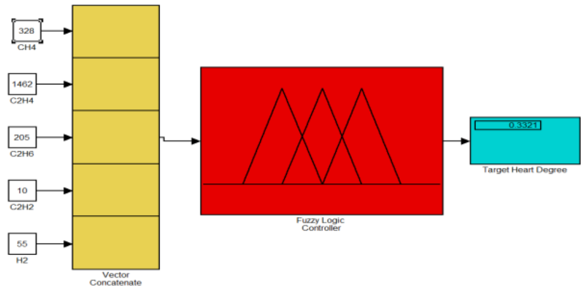

figure 4 Grey Theory Based Fuzzy Model

VI. Neuro-Fuzzy Model Results

Table 3 shows the comparison of output obtained from Grey model and Neuro-Fuzzy Model for nine DGA samples of data. The target Heart Degree obtained from neuro-fuzzy model or ANFIS model is nearly same as target Heart Degree obtained from grey Model. The ANFIS requires a training data that should represent all kind of data. If data of one certain kind is less then ANFIS is not able to make strong rule base for the matching output. In this case out of 169 samples there were very few normal samples and remaining most of the samples were faulty. Therefore only for normal samples the error is more while for faulty cases error is less. Therefore out of the nine samples of Table 1 the error for sample '5' is more as it is normal and for remaining samples error is less. Fig. 5 shows the graph of comparison between outputs obtained from Grey model and output obtained from ANFIS model for 169 DGA samples of data.

Table 3 Output Comparison

Sample	**Target Heart Degree from Grey Model**	**Target Heart Degree from Neuro-Fuzzy Model**
1	0.3353	0.3310
2	0.3355	0.3321
3	0.4698	0.4239
4	0.4696	0.4294
5	0.8668	0.4581
6	0.3367	0.3835
7	0.4680	0.4336
8	0.4681	0.4494
9	0.4682	0.4739

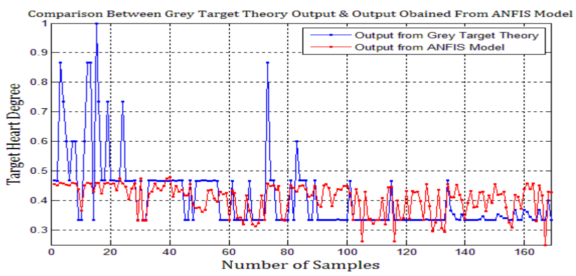

figure 5 Graphical Output Comparison

VII. Conclusion

This paper introduces soft computing approach to identify the transformer health based on DGA of transformer oil. Grey analysis provides an additional tool for the state assessment of Power Transformer. The Grey Theory applied on 169 samples of DGA data. The target heart degree calculated from grey analysis shows that for faulty cases target heart degree is less and for normal cases target heart degree are more. In all cases, the target heart degree calculated from Grey model agrees with the traditional DGA interpretation technique and can efficiently provide the transformer grade based on DGA data. Grey Model implemented in neuro-fuzzy system. The results of adaptive neuro-fuzzy system compared with Grey Model output. Target heart degree obtained from neuro-fuzzy model is close to the target heart degree calculated from Grey Model for faulty cases. The neuro-fuzzy model shows if training input data represent all types of samples for matching output then certain degree of success is there to validate benchmarking of Grey Model.

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