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Cogent Engineering (2015), 2: 995786



Received: 28 March 2014
Accepted: 27 November 2014
Published: 09 January 2015

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Reviewing editor:
Duc Pham, University of Birmingham,
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Decision about criticality of power transformers using whitenization weight functions on DGA caution levels

Vikal R. Ingle^{1*} and V.T. Ingole²

Abstract: Power transformers are the most significant as well as the major asset of any power system network. The condition monitoring and assessment is the main concern in transformer management activities. As a first information source, dissolved gases-in-oil analysis (DGA) is universally accepted. The assessment of dissolved gases is characteristically observed analogous to grey system analysis. Grey system theory is supportive to the cases, when less information about the system is available. The cluster of grey incidences and whitenization weight functions classifies the factors of same type, in order to simplify a complex system. Three caution levels of key gases specified in IEEE standards are utilized in this study, to whiten the weight functions. The whitenization weight function with lower measure is selected for caution level-1. However, whitenization weight functions with middle measure are preferred for level-2 and level-3. Several key gas samples of the equal rating transformers are collected from gas analyzer section and utilized in condition assessment computations. The test samples are verified with variable and equal weight clustering criteria. The criticality judgment of transformer with variable weight clustering successfully identifies the crucial elements amongst samples.



ABOUT THE AUTHOR

Vikal R. Ingle was born on 1 January 1969. He received his BE (Electronics) and ME (Digital Electronics) degrees in 1996 and 2009, respectively. At present, he is an associate professor in Electronics engineering department of BDCE, Sevagram. He is a PhD researcher at PRMIT&R, Badnera. His major area of research includes electrical machines, Grey theory, and AI applications. He is a fellow of Institution of Engineers (India).

PUBLIC INTEREST STATEMENT

Power transformers are the most significant and the very expensive equipment of any electrical power supplying network. Reliable operation of this equipment is needed for uninterrupted power supply. Transformer outages can be catastrophic, and cause both direct and indirect costs to be incurred by industrial, commercial, and residential sectors. Direct costs include but are not limited to loss of production, idle facilities and labor, damaged or spoiled product, and damage to equipment. For commercial customers, the effects may include damage to electrical and electronic equipment, and in some cases, damage to goods. For residential customers, outages may cause food spoilage or damage to electrical equipment. In addition to direct costs, there are several types of indirect costs that may occur, such as accidental injuries, damage, legal costs, and increases in insurance rates. Therefore, vigilant management is the concern to extend their life, and to obtain the services for longer periods.

Subjects: Technology; Engineering & Technology; Electrical & Electronic Engineering; Fuzzy Systems

Keywords: DGA; key gas method; grey incidence analysis; whitenization weight functions; grey classes

1. Introduction

Power transformers play a key role in production and services, and in supplying the electricity to industrial and commercial sectors as well as to the domestic consumers. Maintaining the strength and reliability of the transformer has been a concern to avoid the power failure. There are several techniques for the maintenance, lifespan assessment, and condition evaluation of power system assets. Dealing with the problem of indicating and assessing the health of a transformer, several key measurements are available. The standards providing the guidance for use, analysis, and applications are included in ANSI/IEEE C57.104™ (2009) and IEC 60599 (1992). These standards are commonly known as the gas guides, which include the safety ranges of dissolved gases-in-oil. The dominating gases consist of 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). These seven gases are referred as key gases in the literature. The IEC and IEEE specified that three caution levels of key gases are useful in condition judgments (Scatiggio & Pompili, 2013). In condition-based ranking, transformer's DGA data are evaluated against the established industry standards (Field, Cramer, & Antosz, 2002). Since the transformer condition was judged through health index or with criticality index, several groups assign scores as well (Jahromi, Piercy, Cress, Service, & Fan, 2009). These indices are vital in evaluating the state ranking of transformers (Abu-Siada, Arshad, & Islam, 2010). Researchers also attempt the different condition factors for every subsystem of transformer in preparing the concluding rank (Field et al., 2002; Hydroelectric Research and Technical Services Group, 2003; Toronto Hydro-Electric System Limited, 2010). However, condition-monitoring devices of power transformer are disseminated in nature and hardly interpret the inclusive and precise results for judgments about transformer health. As an immediate indicator, dissolved gas analysis is a simple and secured technique of power transformer testing. Significant weights are recommended in gas guide to main tank oil DGA. Furthermore, to draw a quantitative conclusion about the transformer reliability on numerical DGA data, appropriate assessment methods are desired.

Parametric data of transformer incorporated with soft-computing techniques are another kind of decision-making, applied in condition assessment of transformer. The several soft-computing methods are proposed and implemented based on DGA data intended for fault detection, criticality judgment, fault classifications, and state ranking. ANN with expert system (Wang, Liu, & Griffin, 1998), neuro-fuzzy inference system (Sun, Au, & Choi, 2007), fuzzy logic (Abu-Siada et al., 2010; Nemeth, Laboncz, & Kiss, 2009), and genetic algorithm (Zheng, Zhao, & Wu, 2009) deduce the results effectively. However, these model-free methods necessitate massive data for precise analysis. Similarly, the existing parametric methods need large or reasonable samples with typical probability distributions. However, the conclusions drawn from quantitative analysis differ from that of qualitative results. In contrast, non-parametric test is competent in treating the distribution-free samples but applicable only to a continuous population distributions. Although in reality, the sample size may be prohibited from being large, either due to physical limitations or due to practical difficulties. Therefore, applying the statistical methods or model-free methods can hardly achieve useful solutions, when the system information becomes partially available. The solution to such problems with incomplete or non-deterministic information is always not unique. Whereas, the non-uniqueness is a basic law of the application of grey system theory and one can feel free to look at the problem with flexibility (Kuo, Yang, & Huang, 2008).

A system with partially known and partially unknown information is recognized as grey system. Grey system theory is useful in the condition, when less information about the system is available. It assists in determining the system's key factors and in identifying the factors' correlations. Grey numbers, grey relations, grey decision, grey predictions, and controls are the main subjects of grey

system theory (Yang, 2008). The grey incidence analysis of grey theory is applied to the cases of different sample sizes and distributions. Relatively small computations are required and the conclusions drawn from quantitative analysis differ from that of qualitative results. The grey clusterings based on matrices of grey incidences or whitenization weight functions on grey numbers are useful in classifying the observational objects into predefined classes (Deng, 2005; Liu & Lin, 2006). Deng presented a grey whitenization weight function clustering method, wherein the weight of each index was calculated with the critical value of whitenization function (Deng, 2002). Zhang investigated the greyiness of cluster result by establishing grey cluster on grey hazy set and combined the cluster result with cluster weight sequence (Zhang, 2002). Xiao et al. put forward grey optimal clustering, whitenization weight function constructed with the standard values of each class, and clustering performed with generalized weighted distance method (Xiao & Xiao, 1997). Liu et al. offered a grey fixed weight cluster decision analysis. The weight of each index has been determined by qualitative or quantitative analysis through Delphi method or analytic hierarchy process, and clustering carried out by whitenization function (Liu, Shen, Tan, & Guo, 2012). Liu and Xie proposed a grey cluster evaluation method based on triangle whitenization weight function; the method divides the values into a range of index “s” clusters so to fulfill the evaluation requirements. The calculation was conducted on grey fixed weight clustering (Liu & Xie, 2011). Qiu projected a grey correlation cluster analysis method (Qiu, 1995). Grey similarity matrices were calculated on the computation of grey correlation degree and clustering performed with maximal tree method or coding method.

The whitenization weight functions mainly classify the factors of same type in order to simplify the complex systems or phenomenon like DGA. This paper demonstrated the synthetic evaluation of DGA test samples, on both fixed and variable weight grey clustering decision. Three caution levels of key gases are utilized in whitening the three weight functions. The whitenization weight function with lower measure is selected for caution level-1. However, whitenization weight functions with middle measure are preferred for caution level-2 and level-3. While identifying the criticality of transformers, representative DGA samples are divided into three grey classes by means of grey clustering.

2. Grey clustering method

In classification of clustering method, grey clusters are divided into grey correlation cluster and grey whitenization weight function cluster. Among which, grey correlation cluster is mainly employed to incorporate the factors of same class for the simplification of a complex systems. However, grey whitenization weight function is majorly applied to inspect the presence of observational objectives in a predefined class. Grey clustering is also known as grey evaluation. The variable and fixed weight clustering is offered in whitenization weight functions. The fundamentals of both the methods are presented in next section, which covers a small part of grey incidence analysis but the conceptual framework is believed to be enough to realize the clustering methodology.

2.1. Grey clusters with variable weights

The grey clusterings based on matrices of grey incidences or whitenization weight functions of grey numbers are used in classifying the observational objects into predefined classes. In general, the whitenization weight function of the j -criterion and k -subclasses is determined by considering the objects of clustering or looking at all the same type of objects as a complete system. Assume that, there exist “ n ” objects to be clustered according to “ m ” cluster criteria into different grey classes. The clustering method based on the observational value of the i th objects, $i = 1, 2, \dots, n$ with j -criterion, where $j = 1, 2, \dots, m$. Then the i th objects are classified into k th grey class, where, $1 \leq k \leq s$. This process of computation is commonly known as grey clustering. Some of the imperative definitions are presented as follows:

Definition 1: All the s grey classes formed by the n objects, defined by their observational values at criterion j , are called the j -criterion with subclasses of k . The whitenization weight function on k -subclass of the j -criterion is denoted as $f_j^k(\cdot)$.

Definition 2: Assuming that the whitening weight function $f_j^k(\cdot)$ for k -subclass of the j -criterion is shown in Figure 1 and the points $x_j^k(1)$, $x_j^k(2)$, $x_j^k(3)$ and $x_j^k(4)$ are called turning points of $f_j^k(\cdot)$.

Definition 3: Whitening weight functions:

- (a) If the whitening weight function $f_j^k(\cdot)$ above does not have first $x_j^k(1)$ and second $x_j^k(2)$ turning points then $f_j^k(\cdot)$ is called whitening weight function of lower measure as shown in Figure 2.
- (b) If the second $x_j^k(2)$ and third $x_j^k(3)$ turning points of whitening weight function $f_j^k(\cdot)$ coincide as shown in Figure 1 then the function $f_j^k(\cdot)$ is called a whitening weight function of middle measure, shown in Figure 3.
- (c) If the whitening weight function $f_j^k(\cdot)$ as shown in Figure 1 does not have third $x_j^k(3)$ and fourth $x_j^k(4)$ turning points then $f_j^k(\cdot)$ is called whitening weight function of upper measure, shown in Figure 4.

PROPOSITION 1: (a) The typical whitening weight function as shown in Figure 1 is expressed with:

$$f_j^k(x) = \begin{cases} 0, & x \notin [x_j^k(1), x_j^k(4)] \\ \frac{x-x_j^k(1)}{x_j^k(2)-x_j^k(1)}, & x \in [x_j^k(1), x_j^k(2)] \\ 1, & x \in [x_j^k(2), x_j^k(3)] \\ \frac{x_j^k(4)-x}{x_j^k(4)-x_j^k(3)}, & x \in [x_j^k(3), x_j^k(4)] \end{cases}$$

(b) The whitening weight function of lower measure as shown in Figure 2 is given as:

$$f_j^k(x) = \begin{cases} 0, & x \notin [0, x_j^k(4)] \\ 1, & x \in [0, x_j^k(3)] \\ \frac{x_j^k(4)-x}{x_j^k(4)-x_j^k(3)}, & x \in [x_j^k(3), x_j^k(4)] \end{cases}$$

Figure 1. A typical whitening function.

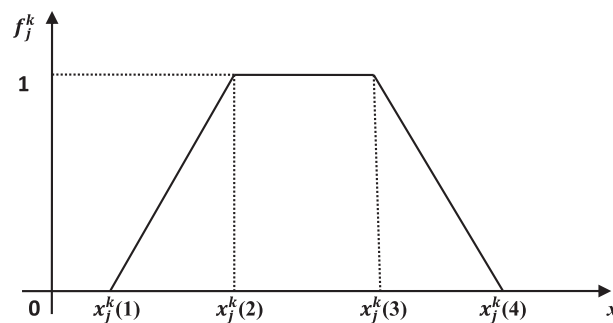
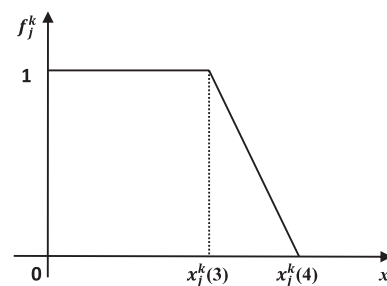


Figure 2. WW function of lower measures.



(c) The whitenization weight function of middle measure as shown in Figure 3 is given by:

$$f_j^k(x) = \begin{cases} 0, & x \notin [x_j^k(1), x_j^k(4)] \\ \frac{x-x_j^k(1)}{x_j^k(2)-x_j^k(1)}, & x \in [x_j^k(1), x_j^k(2)] \\ 1, & x = x_j^k(2) \\ \frac{x_j^k(4)-x}{x_j^k(4)-x_j^k(2)}, & x \in [x_j^k(2), x_j^k(4)] \end{cases}$$

(d) The whitenization weight function of upper measure as shown in Figure 4 is given as:

$$f_j^k(x) = \begin{cases} 0, & x < x_j^k(1) \\ \frac{x-x_j^k(1)}{x_j^k(2)-x_j^k(1)}, & x \in [x_j^k(1), x_j^k(2)] \\ 1, & x \geq x_j^k(2) \end{cases}$$

Definition 4: Critical value for k -subclass of the j -criterion is defined as:

The whitenization weights function in Figure 1

$$\lambda_j^k = \frac{1}{2} [x_j^k(2), x_j^k(3)]$$

The whitenization weights function in Figure 2

$$\lambda_j^k = x_j^k(3)$$

The whitenization weights function in Figures 1 and 4

$$\lambda_j^k = x_j^k(2)$$

Figure 3. WW function of middle measures.

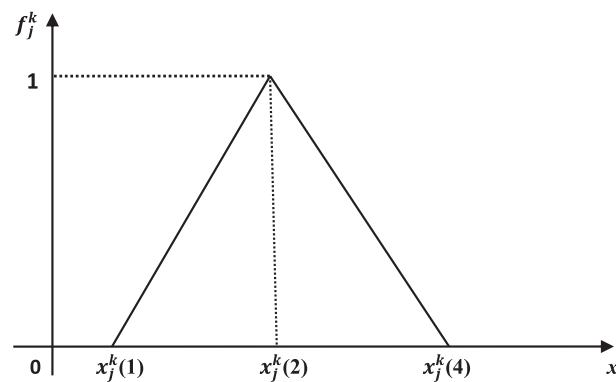
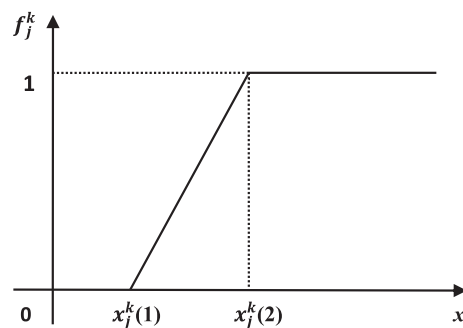


Figure 4. WW function of upper measures.



Definition 5: Assuming the critical value λ_j^k for k -subclass of the j -criterion, then the weight of the j -criterion with respect to k -subclass is:

$$\eta_j^k = \frac{\lambda_j^k}{\sum_{j=1}^m \lambda_j^k}$$

Definition 6: Assume that X_{ij} is the observation values of object “ i ” and criterion- j , the whitenization weight function $f_j^k(\cdot)$ of k -subclass of the j -criterion and the η_j^k weight of the j -criterion with respect to k -subclass. Then

$$\sigma_i^k = \sum_{j=1}^m f_j^k(X_{ij}) \times \eta_j^k$$

is said to be the cluster coefficient of variable weight for object “ i ” that belongs to the k th grey class.

Definition 7: (a) The following

$$\sigma_i = \{\sigma_i^1, \sigma_i^2, \dots, \sigma_i^s\}$$

is called the cluster coefficient vector of object “ i ”.

(b) The matrix of such vector represented as:

$$\Sigma = \left[\sigma_i^k \right]_{n \times s}$$

and is called the cluster coefficient matrix.

Definition 8: If

$$\sigma_i^{k*} = \max_{1 \leq k \leq s} \{\sigma_i^k\}$$

Then object i belong to the grey class k^* .

2.2. Fixed weights clustering

A fixed weight clustering equally weights all criteria under consideration and also applicable to the situations, where observational data or dimensions are different.

Definition 9: For any K_1 and $K_2 \in \{1, 2, \dots, s\}$ and if $\eta_j^{k1} = \eta_j^{k2}$ then η_j is applied instead of η_j^k . Therefore, fixed weight criteria coefficient is:

$$\sigma_i^k = \sum_{j=1}^m f_j^k(X_{ij}) \times \eta_j$$

where, $j = 1, 2, \dots, m$.

Definition 10: Assuming that x_{ij} ($i = 1, 2, \dots, n; j = 1, 2, \dots, m$) stands for the observational values of the object “ i ” with respect to criterion j , and $f_j^k(\cdot)$ is the whitenization weight function of the k th subclass of the j -criterion, then for any $j = 1, 2, \dots, m, \eta_j = \frac{1}{m}$ holds true and

$$\sigma_i^k = \sum_{j=1}^m f_j^k(X_{ij}) \times \eta_j = \frac{1}{m} \sum_{j=1}^m f_j^k(X_{ij}) \times \eta_j$$

is called the equal weight cluster coefficient for object “ i ” belongs to k th grey class.

3. Configuration of whitenization weight functions

Several dissolved gas analysis (IEC, IEEE, CIGRE, and MSZ National standard’s ratio codes and graphical techniques) schemes are developed on empirical assumptions and experts’ knowledge in the interpretations (IEC 60599, 1992; Scatiggio & Pompili, 2013). These standards provide the threshold limits for guidance, investigation, and analysis. The IEEE Std. C.57.104 specified key gas values of three evaluation levels (Table 1) are considered for three cluster criteria.

Applying the whitenization weight function $f_j^k(\cdot)$, synthetic clustering performed on three different caution levels, where $j = 1, 2, \dots, 7$; for the criteria $k = 1, 2, 3$. The whitenization weight function of lower measure is used to figure out the caution level-1. However, whitenization weight functions with middle measure are preferred for caution level-2 and caution level-3 in experimentation. The chosen whitenization weight functions are configured with the equations to apprehend the three caution levels and displayed separately in the following in Tables 2-4.

The caution levels are used in tuning the preferred three whitenization weight functions. The critical values for k -subclass of the j -criterion with fixed weight clustering are given in Table 5. These critical values are used in computing the results of fixed weight clustering.

4. Identifying the criticality of transformers

This section presents execution of grey clustering on key gas data-set shown in Table 6. All seven key gases of every sample represent a characteristic of testing transformer. These key gas samples are the observational values represented as, x_{ij} ($i = 1, 2, \dots, 21; j = 1, 2, \dots, 7$) of different transformers. The object “ i ” with respect to criterion “ j ” is chosen for the specific key gas concentration. These 21 specimens are used to find the cluster coefficient vectors. The configured whitenization weight functions are employed for observation values with fixed weight criteria. In fixed or equal weight criteria, the considered key gases are treated with a weight of (1/7) for every elements and employed in computing the clustering coefficients.

Table 1. Key gas concentration in ppm (IEEE Std. C.57.104)

Key gases	Level-1	Level-2	Level-3
H ₂	100	700	1,800
CH ₄	120	400	1,000
CO	350	570	1,400
CO ₂	2,500	4,000	10,000
C ₂ H ₄	50	100	200
C ₂ H ₆	65	100	150
C ₂ H ₂	35	50	80

Table 2. Equations for lower measure WW function for caution level-1

Key gases	$f_j^1(x)$	$f_j^1(x)$	$f_j^1(x)$
H ₂ ($j = 1$)	0	1	$(x-200)/100$
	$x \leq 0$ and $x \geq 200$	$x \leq 0$ and $x \leq 100$	$100 \leq x \leq 200$
CH ₄ ($j = 2$)	0	1	$(200-x)/80$
	$x \leq 0$ and $x \geq 200$	$0 \leq x \leq 120$	$120 \leq x \leq 200$
CO ($j = 3$)	0	1	$(400-x)/50$
	$x \leq 0$ and $x \geq 400$	$0 \leq x \leq 350$	$350 \leq x \leq 400$
CO ₂ ($j = 4$)	0	1	$(3,000-x)/500$
	$x \leq 0$ and $x \geq 3,000$	$0 \leq x \leq 2,500$	$2,500 \leq x \leq 3,000$
C ₂ H ₄ ($j = 5$)	0	1	$(70-x)/20$
	$x \leq 0$ and $x \geq 70$	$0 \leq x \leq 50$	$50 \leq x \leq 70$
C ₂ H ₆ ($j = 6$)	0	1	$(70-x)/5$
	$x \leq 0$ and $x \geq 70$	$0 \leq x \leq 65$	$65 \leq x \leq 70$
C ₂ H ₂ ($j = 7$)	0	1	$(40-x)/5$
	$x \leq 0$ and $x \geq 40$	$0 \leq x \leq 35$	$35 \leq x \leq 40$

Table 3. Equations for middle measure WW function for caution level-2

Key gases	$f_j^2(x)$	$f_j^2(x)$	$f_j^2(x)$	$f_j^2(x)$
H_2 ($j = 1$)	0	$(x-100)/600$	1, when $x = 700$	$(1,300-x)/600$
	$x \leq 100$ and $x \geq 1,300$	$100 \leq x \leq 700$		$700 \leq x \leq 1,300$
CH_4 ($j = 2$)	0	$(x-120)/280$	1, when $x = 400$	$(680-x)/280$
	$x \leq 350$ and $x \geq 790$	$120 \leq x \leq 400$		$400 \leq x \leq 680$
CO ($j = 3$)	0	$(x-350)/220$	1, when $x = 570$	$(790-x)/220$
	$x \leq 120$ and $x \geq 680$	$350 \leq x \leq 570$		$570 \leq x \leq 790$
CO_2 ($j = 4$)	0	$(x-2,500)/1,500$	1, when $x = 4,000$	$(5,500-x)/1,500$
	$x \leq 2,500$ and $x \geq 5,500$	$2,500 \leq x \leq 4,000$		$4,000 \leq x \leq 5,500$
C_2H_4 ($j = 5$)	0	$(x-50)/50$	1, when $x = 100$	$(150-x)/50$
	$x \leq 50$ and $x \geq 150$	$50 \leq x \leq 100$		$100 \leq x \leq 150$
C_2H_6 ($j = 6$)	0	$(x-65)/35$	1, when $x = 100$	$(135-x)/35$
	$x \leq 65$ and $x \geq 135$	$65 \leq x \leq 100$		$100 \leq x \leq 135$
C_2H_2 ($j = 7$)	0	$(x-35)/15$	1, when $x = 50$	$(65-x)/15$
	$x \leq 35$ and $x \geq 65$	$35 \leq x \leq 50$		$50 \leq x \leq 65$

Table 4. Equations for middle measure WW function for caution level-3

Key gases	$f_j^3(x)$	$f_j^3(x)$	$f_j^3(x)$	$f_j^3(x)$
H_2 ($j = 1$)	0	$(x-700)/1,100$	1, when $x = 1,800$	$(2,900-x)/1,100$
	$x \leq 700$ and $x \geq 2,900$	$700 \leq x \leq 1,800$		$1,800 \leq x \leq 2,900$
CH_4 ($j = 2$)	0	$(x-400)/600$	1, when $x = 1,000$	$(1,600-x)/600$
	$x \leq 400$ and $x \geq 1,600$	$400 \leq x \leq 1,000$		$1,000 \leq x \leq 1,600$
CO ($j = 3$)	0	$(x-570)/830$	1, when $x = 1,400$	$(2,230-x)/830$
	$x \leq 570$ and $x \geq 2,230$	$570 \leq x \leq 1,400$		$1,400 \leq x \leq 2,230$
CO_2 ($j = 4$)	0	$(x-4,000)/6,000$	1, when $x = 10,000$	$(16,000-x)/6,000$
	$x \leq 4,000$ and $x \geq 16,000$	$4,000 \leq x \leq 10,000$		$10,000 \leq x \leq 16,000$
C_2H_4 ($j = 5$)	0	$(x-100)/100$	1, when $x = 200$	$(300-x)/100$
	$x \leq 100$ and $x \geq 300$	$100 \leq x \leq 200$		$200 \leq x \leq 300$
C_2H_6 ($j = 6$)	0	$(x-100)/50$	1, when $x = 150$	$(200-x)/50$
	$x \leq 100$ and $x \geq 200$	$100 \leq x \leq 150$		$150 \leq x \leq 200$
C_2H_2 ($j = 7$)	0	$(x-50)/30$	1, when $x = 80$	$(200-x)/50$
	$x \leq 50$ and $x \geq 110$	$50 \leq x \leq 80$		$80 \leq x \leq 110$

Table 5. Critical values of three whitenization weight functions

λ_j^K	H_2 ($j = 1$)	CH_4 ($j = 2$)	CO ($j = 3$)	CO_2 ($j = 4$)	C_2H_4 ($j = 5$)	C_2H_6 ($j = 6$)	C_2H_2 ($j = 7$)
$K = 1$	100	120	350	2,500	50	65	35
$K = 2$	700	400	570	4,000	100	100	50
$K = 3$	1,800	1,000	1,400	10,000	200	150	80

The cluster coefficient vectors of fixed weight clustering for all the observational objects are shown in Table 7. The result shows the classification of all observational objects which are divided into three desired grey classes.

Table 6. Dissolved gas-in-oil samples of testing transformers

Specimen	H ₂	CH ₄	CO	CO ₂	C ₂ H ₄	C ₂ H ₆	C ₂ H ₂
Tx ₁	53	49	748	6,021	2,824	514	31
Tx ₂	12	325	12	787	1	3	108
Tx ₃	1	2	34	322	1	1	1
Tx ₄	1	19	140	1,879	1	57	1
Tx ₅	19	303	432	3,114	1	157	1
Tx ₆	1	46	219	9,909	6	16	1
Tx ₇	1	2	34	327	1	1	1
Tx ₈	1	19	159	3,303	47	60	1
Tx ₉	12	8,778	317	2,959	11,900	4,834	19
Tx ₁₀	1	73	124	66,261	1	88	1
Tx ₁₁	66	87	211	1,902	77	53	24
Tx ₁₂	111	102	377	2,496	34	62	36
Tx ₁₃	103	114	327	2,734	66	32	17
Tx ₁₄	92	103	351	2,496	37	41	22
Tx ₁₅	57	64	218	2,210	41	63	33
Tx ₁₆	109	76	507	2,910	48	22	13
Tx ₁₇	29	123	344	2,506	12	5	1
Tx ₁₈	77	98	259	2,496	38	52	26
Tx ₁₉	18	76	153	2,107	31	27	5
Tx ₂₀	89	113	302	1,992	59	63	29
Tx ₂₁	22	106	514	13,327	36	72	28

Table 7. Coefficient matrix of grey cluster with fixed weights

σ_i^k	K = 1	K = 2	K = 3	σ_i^k	K = 1	K = 2	K = 3
i = 1	0.4285	0.0272	0.0787	i = 12	0.8786	0.0296	0
i = 2	0.7143	0.1045	0.0095	i = 13	0.8146	0.0687	0
i = 3	1	0	0	i = 14	0.9971	0.0006	0
i = 4	1	0	0	i = 15	1	0	0
i = 5	0.4285	0.205	0.1228	i = 16	0.7271	0.1431	0
i = 6	0.8571	0	0.1406	i = 17	0.9929	0.0021	0
i = 7	1	0	0	i = 18	1	0	0
i = 8	0.8571	0.0764	0	i = 19	1	0	0
i = 9	0.4402	0.0437	0	i = 20	0.9357	0.0257	0
i = 10	0.7142	0.0938	0	i = 21	0.5714	0.135	0.0636
i = 11	0.8571	0.077	0				

In reference to fixed or equal weight criteria, maximum values are obtain as

$$\begin{aligned} \max_{1 \leq k \leq 3} \{\sigma_1^1\} &= 0.4285; & \max_{1 \leq k \leq 3} \{\sigma_2^1\} &= 0.7143; & \max_{1 \leq k \leq 3} \{\sigma_3^1\} &= 1 \\ \max_{1 \leq k \leq 3} \{\sigma_4^1\} &= 1; & \max_{1 \leq k \leq 3} \{\sigma_5^1\} &= 0.4285; & \max_{1 \leq k \leq 3} \{\sigma_6^1\} &= 0.8571 \\ \max_{1 \leq k \leq 3} \{\sigma_7^1\} &= 1; & \max_{1 \leq k \leq 3} \{\sigma_8^1\} &= 0.8571; & \max_{1 \leq k \leq 3} \{\sigma_9^1\} &= 0.4402 \end{aligned}$$

$$\begin{aligned} \max_{1 \leq k \leq 3} \{\sigma_{10}^1\} &= 0.7142; & \max_{1 \leq k \leq 3} \{\sigma_{11}^1\} &= 0.8571; & \max_{1 \leq k \leq 3} \{\sigma_{12}^1\} &= 0.8786 \\ \max_{1 \leq k \leq 3} \{\sigma_{13}^1\} &= 0.8146; & \max_{1 \leq k \leq 3} \{\sigma_{14}^1\} &= 0.9971; & \max_{1 \leq k \leq 3} \{\sigma_{15}^1\} &= 1 \\ \max_{1 \leq k \leq 3} \{\sigma_{16}^1\} &= 0.7271; & \max_{1 \leq k \leq 3} \{\sigma_{17}^1\} &= 0.9929; & \max_{1 \leq k \leq 3} \{\sigma_{18}^1\} &= 1 \\ \max_{1 \leq k \leq 3} \{\sigma_{19}^1\} &= 1; & \max_{1 \leq k \leq 3} \{\sigma_{20}^1\} &= 0.9357; & \max_{1 \leq k \leq 3} \{\sigma_{21}^1\} &= 0.5714 \end{aligned}$$

Among the three grey classes, only one class (DGA level-1) has shown the effective response in classification. Observing the classification system as a whole, sample no. 1, 5, 9, and 21 are found in a critical level of maintenance. The judgment about criticality biased with one caution level i.e. level-1; reason is that the coefficients of other levels are contributed extremely imperceptibly in the classification. Therefore, it is evidently unreasonable to consider the effective weights of all gases equally. Hence, it is obvious that all the specifications have different weights on every caution levels, such as in case of variable weight clustering.

The critical values for variable weights clustering for three caution levels are obtained and displayed in Table 8. The ratio of specified safety concentration of a gas to the total concentration of all gases presented in a particular level is assigned for critical values. The observation values of object, whitenization weight function, and weights for variable clustering resulted into the cluster coefficient matrix as shown in Table 9.

The variable weight criteria of grey subclass with highest magnitude led to following results:

$$\begin{aligned} \max_{1 \leq k \leq 3} \{\sigma_1^3\} &= 0.2507; & \max_{1 \leq k \leq 3} \{\sigma_2^1\} &= 0.9518; & \max_{1 \leq k \leq 3} \{\sigma_3^1\} &= 1 \\ \max_{1 \leq k \leq 3} \{\sigma_4^1\} &= 1; & \max_{1 \leq k \leq 3} \{\sigma_5^2\} &= 0.3565; & \max_{1 \leq k \leq 3} \{\sigma_6^3\} &= 0.6731 \end{aligned}$$

Table 8. Critical values for variable weight clustering

η_j^K	H ₂ (j = 1)	CH ₄ (j = 2)	CO (j = 3)	CO ₂ (j = 4)	C ₂ H ₄ (j = 5)	C ₂ H ₆ (j = 6)	C ₂ H ₂ (j = 7)
K = 1	0.0310	0.0372	0.1086	0.7763	0.0155	0.0201	0.0108
K = 2	0.1182	0.0675	0.0962	0.6756	0.0168	0.0168	0.0084
K = 3	0.1230	0.0683	0.0956	0.6835	0.0136	0.0102	0.0054

Table 9. Variable weights clustering coefficient matrix of grey subclass

σ_i^k	K = 1	K = 2	K = 3	σ_i^k	K = 1	K = 2	K = 3
i = 1	0.0791	0.0183	0.2507	i = 12	0.9203	0.0145	0
i = 2	0.9518	0.0494	0.0003	i = 13	0.6232	0.1114	0
i = 3	1	0	0	i = 14	0.9978	0.0004	0
i = 4	1	0	0	i = 15	1	0	0
i = 5	0.0574	0.3565	0.0088	i = 16	0.2518	0.2555	0
i = 6	0.2236	0	0.6731	i = 17	0.9892	0.0034	0
i = 7	1	0	0	i = 18	1	0	0
i = 8	0.2236	0.3617	0	i = 19	1	0	0
i = 9	0.2142	0.2067	0	i = 20	0.9930	0.0030	0
i = 10	0.2114	0.0111	0	i = 21	0.0947	0.0751	0.3045
i = 11	0.9844	0.0091	0				

$$\begin{aligned} \max_{1 \leq k \leq 3} \{\sigma_7^1\} &= 1; & \max_{1 \leq k \leq 3} \{\sigma_8^2\} &= 0.3617; & \max_{1 \leq k \leq 3} \{\sigma_9^1\} &= 0.2142 \\ \max_{1 \leq k \leq 3} \{\sigma_{10}^1\} &= 0.2114; & \max_{1 \leq k \leq 3} \{\sigma_{11}^1\} &= 0.9844; & \max_{1 \leq k \leq 3} \{\sigma_{12}^1\} &= 0.9203 \\ \max_{1 \leq k \leq 3} \{\sigma_{13}^1\} &= 0.6232; & \max_{1 \leq k \leq 3} \{\sigma_{14}^1\} &= 0.9978; & \max_{1 \leq k \leq 3} \{\sigma_{15}^1\} &= 1 \\ \max_{1 \leq k \leq 3} \{\sigma_{16}^2\} &= 0.2555; & \max_{1 \leq k \leq 3} \{\sigma_{17}^1\} &= 0.9892; & \max_{1 \leq k \leq 3} \{\sigma_{18}^1\} &= 0.9203 \\ \max_{1 \leq k \leq 3} \{\sigma_{19}^1\} &= 1; & \max_{1 \leq k \leq 3} \{\sigma_{20}^1\} &= 0.9930; & \max_{1 \leq k \leq 3} \{\sigma_{21}^3\} &= 0.3045 \end{aligned}$$

It follows that the DGA sample no. 2, 3, 4, 7, 9, 10, 11, 12, 13, 14, 15, 17, 18, 19, and 20 are classified in grey level-1. If the magnitudes of cluster coefficients are considered as score of the transformers, and then sample no. 3, 4, 7, 15, 18, and 19 are referred as absolutely healthy transformers. Whereas sample no. 2, 11, 12, 14, 17, and 20 are observed to be in the normal condition, except for sample no. 9, 10, and 13. Therefore, these three samples are observed as the critical elements in grey class-1. The sample no. 5, 8, and 16 are measured in criticality level-2 cluster. Sample no. 1, 6, and 21 are found in grey class-3 which implies that these samples are the most critical elements among the considered test samples and need immediate attention. The effect of variable weight clustering shows the criticality judgments on different levels and useful in setting the priorities about maintenance. The variable weight clustering is effective to the cases, when whitenization weight functions are selected based on experience.

5. Conclusions

Information from the analysis of gasses dissolved in insulating oil of transformer is a primary source of state assessment. The simple and reliable process, similar to variable weight grey clustering, facilitates the categorization of objects, which identify the criticality of transformers at three caution levels. The results of grey clustering certainly helped in setting the priorities about preventive maintenance and recommended the straight action for critical cases. The results obtained in this experimentation are limited to dissolved gas in oil samples and the three caution levels refer to IEEE standard. However, the variable weight clustering method will be effectively implemented, if additional monitoring parameters and their specified safety values are used for comprehensive analysis.

Funding

The authors received no direct funding for this research.

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Citation information

Cite this article as: Decision about criticality of power transformers using whitenization weight functions on DGA caution levels, V.R. Ingle & V. Ingole, *Cogent Engineering* (2015), 2: 995786.

Cover image

Source: DGA samples are collected from gas analyzer sections of Maharashtra State Electricity Board, Nagpur (M.S.), India and B.R. Industrial services (Transformers oil testing laboratory), New Panvel, Raigad (M.S.), India.

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