Received February 13, 2021, accepted February 16, 2021, date of publication February 18, 2021, date of current version February 26, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3060288

Enhancing Diagnostic Accuracy of Transformer Faults Using Teaching-Learning-Based Optimization

SHERIF S. M. GHONEIM[1], (Senior Member, IEEE), KARAR MAHMOUD[2,3], MATTI LEHTONEN[2], AND MOHAMED M. F. DARWISH[2,4]

[1]Department of Electrical Engineering, College of Engineering, Taif University, Taif 21944, Saudi Arabia
[2]Department of Electrical Engineering and Automation, School of Electrical Engineering, Aalto University, 00076 Espoo, Finland
[3]Department of Electrical Engineering, Faculty of Engineering, Aswan University, Aswan 81542, Egypt
[4]Department of Electrical Engineering, Faculty of Engineering at Shoubra, Benha University, Cairo 11629, Egypt

Corresponding author: Mohamed M. F. Darwish (mohamed.m.darwish@aalto.fi; mohamed.darwish@feng.bu.edu.eg)

This work was supported in part by the Department of Electrical Engineering and Automation, Aalto University, Espoo, Finland, and in part by the Taif University, Taif, Saudi Arabia, through the Taif University Researchers Supporting Project, under Grant TURSP-2020/34.

ABSTRACT The early detection of the transformer faults with high accuracy rates guarantees the continuous operation of the power system networks. Dissolved gas analysis (DGA) is a technique that is used to detect or diagnose the transformer faults based on the dissolved gases due to the electrical and thermal stresses influencing the insulating oil. Many attempts are accomplished to discover an appropriate technique to correctly diagnose the transformer fault types, such as the Duval Triangle method, Rogers' ratios method, and IEC standard 60599. In addition, several artificial intelligence, classification, and optimization techniques are merged with the previous methods to enhance their diagnostic accuracy. In this article, a novel approach is proposed to enhance the diagnostic accuracy of the transformer faults based on introducing new gas concentration percentages limits and gases' ratios that help to separate the conflict between the diverse transformer faults. To do so, an optimization model is established which simultaneously optimizes both gas concentration percentages and ratios so as to maximize the agreement of the diagnostic faults with respect to the actual ones achieving the high diagnostic accuracy of the transformer faults. Accordingly, an efficient teaching-learning based optimization (TLBO) is developed to accurately solve the optimization model considering training datasets (Egyptian chemical laboratory and literature). The proposed TLBO algorithm enhances diagnostic accuracy at a significant level, which is higher than some of the other DGA techniques that were presented in the literature. The robustness of the proposed optimization-based approach is confirmed against uncertainty in measurement where its accuracy is not affected by the uncertainty rates. To prove the efficacy of the proposed approach, it is compared with five existing approaches using an out-of-sample dataset where a superior agreement rate is reached for the different fault types.

INDEX TERMS Dissolved gas analysis, transformer faults, TLBO algorithm, insulating oil, uncertainty.

I. INTRODUCTION

Early discovery of faults in power transformers is a challenging task that can increase the lifetime of such important power system components while ensuring continuous operation. For this purpose, utilities follow strategies to avoids transformer outages due to undesired irregular operational situations, thereby increasing their revenue [1]. Typically, the expected faults in insulating structures of power transformers can result from diverse issues, most importantly mechanical, electrical, and thermal stresses [1], [2]. Such stresses can have negative impacts on the oil quality of power transformers, thus worsening their security and operation. Accordingly, the resulting combustible gases can involve hydrogen (H_2), methane (CH_4), ethane (C_2H_6), ethylene (C_2H_4), acetylene (C_2H_2), and carbon monoxide (CO) [3].

To diagnose and evaluate the diverse transformer fault types, the ratios of concentrated dissolved gases are employed as a common method in the dissolved gas analysis (DGA). The most various interpretation approaches for DGA that

The associate editor coordinating the review of this manuscript and approving it for publication was Shen Yin.

dependent on the gas concentration ratios are as follows: Roger's three and four ratios, IEC 60599 standard code, and Dorneneburg [1]. Further, different methods have been applied based on graphical approaches; such as Duval Triangle and Pentagon techniques [4], [5]. Depending on the previous approaches and graphical DGA techniques, they are easy to be implemented, but still have poor diagnostic accuracies for the transformer fault types [6], [7].

To guarantee high accuracy and efficient diagnostics of specified transformer fault types, various artificial intelligent techniques were implemented. The artificial neural network (ANN) is considered the most widely used method in the literature that has much training data adapting the network for DGA diagnosis [8]–[11]. The input data for ANN can be arranged and optimized for the dissolved gas percentages [8], gas concentration ratios [9]–[11], or others [11], [12]. Furthermore, the fuzzy logic system has been applied as a second example of artificial intelligent techniques in which multi If-Then rules have been executed to relate DGA with the actual fault diagnosis [13], [14]. The third one is a fuzzy logic system integrated with heuristic optimization approaches, such as the hybrid grey wolf optimizer (HGWO) adjusting DGA based on a diagnostic approach that is robust against measurement uncertainties [3]. Additionally, the particle swarm optimization with enhanced fuzzy logic system (PSO-FS) solver has been used to maximize the accuracy of IEC 60599 code methods as well as Rogers' four-ratio. Moreover, a support vector machine (SVM) has been introduced as a new machine learning technique used with a slight increase in the diagnostic efficacy [15]–[17]. Recently, HGWO combining the differential evaluation approach with the GWO and the supporting of the least-square SVM as a hybrid optimizer, which uses the powerful search ability to rapid the convergence speed and enhances the performance accuracy of the algorithm, resulting in better detection of transformer fault types [18]. Finally, other artificial intelligent approaches have been presented to improve the accuracy rate of transformer faults diagnostics like adaptive neural-fuzzy-inference framework [19], gene expression programming method [20], and Bayesian neural networks [21].

As demonstrated above, several studies are accomplished to develop efficient techniques to properly diagnose the various fault types of power transformers, most importantly the Duval Triangle method, IEC standard, and Rogers' ratios method, besides several artificial intelligence-based approaches. A novel approach to enhance the diagnostic accuracy of the transformer faults is proposed in this work by introducing new values for gas concentration percentages and ratios. Such introduced values can help to separate the conflict between the diverse transformer faults, thereby maximizing the accuracy rates. To accomplish this ambitious goal, an optimization-based model that simultaneously optimizes both gas concentration percentages and ratios, considering their operational limits, is proposed. The objective function is set to be a maximization for the agreement of the actual faults relating to the diagnostic faults by the proposed approach. In order to accurately solve the proposed optimization model, an efficient teaching-learning based optimization (TLBO) is developed, which can obtain the global optimal solution. Various practical datasets from the Egyptian chemical laboratory and literature (386 DGA data samples) are employed to construct the best-suited gas concentration percentages and ratios. The proposed TLBO based approach can enhance the accuracy rate of the diagnostic at a significant rate. The robustness of the proposed approach is also demonstrated against uncertainty in measurement where the accuracy of the proposed approach is not affected by the uncertainty rates. Further, the accuracy of the proposed approach is compared with five approaches from the literature by means of a practical out-of-sample dataset (a number of 89 samples). The proposed DGA algorithm has a higher agreement rate than the previous approaches for most fault types.

Most of the traditional DGA techniques have poor diagnostic accuracy and, in some cases, they fail to interpret the transformer faults. The researchers do their best to present a combination between the DGA techniques and artificial intelligence methods to enhance the diagnostic accuracy of the traditional DGA techniques or used the artificial intelligent methods individually with the gases concentrations to build new DGA techniques [22]–[24]. Recently several types of researchers attempt to enhance the artificial intelligent methods' performance by modifying the method parameters [25]–[28]. In the current work, one of the optimization techniques is TLBO which is the first time to apply it to solve the DGA analysis problem to enhance the diagnostic accuracy of transformer faults. The diagnostic accuracy of the novel TLBO based approach as illustrated in the obtained results is higher the most DGA techniques in the literature.

II. TLBO ALGORITHM AND IMPLEMENTATION TO DGA PROBLEM

In this work, we have employed a metaheuristic optimization method, called TLBO, that is widely used for accurately solving the nonlinear optimization models. Below, we describe the TLBO algorithm as well as its implementation to the DGA problem.

A. DGA OPTIMIZATION MODEL

Here, the DGA optimization problem is formulated as a constrained mathematical optimization model. The fitness function and the constraints are formulated as follows:

$$Max\, f(x) = \frac{N_{Tr}}{N_{Tot}} \tag{1}$$

$$s.t.\; r_i^{min} \le r_i \le r_i^{max}, \quad i = 1, 2, \ldots, 7 \tag{2}$$

where the fitness function is calculated using the ratio of the number of true estimated transformer fault types by the proposed TLBO based approaches (N_{Tr}) and the overall number of samples (N_{Tot}). The gases' ratios are indicated in Equation (2) with their corresponding minimum r_i^{min} and maximum r_i^{max} limits, which is presented in [6], can be expanded as follows:

$$\begin{pmatrix} r_1 \\ r_2 \\ r_3 \\ r_4 \\ r_5 \\ r_6 \\ r_7 \end{pmatrix} = \begin{pmatrix} C_2H_2/H_2 \\ C_2H_2/CH_4 \\ C_2H_2/C_2H_6 \\ C_2H_4/H_2 \\ C_2H_4/CH_4 \\ (C_2H_4/H_2) + (C_2H_4/CH_4) \\ C_2H_4/C_2H_6 \end{pmatrix} \quad (3)$$

B. TLBO ALGORITHM

The TLBO solver has been inspired by a teaching system in nature. Specifically, it involves two items: a teacher as well as several learners [29]. Typically, the teacher of TLBO can share its information with the corresponding learners for improving the quality pattern of all learners. The teacher and the learner stages, respectively, are created to improve the performance of all learners. For the teacher stage, every learner benefits from the corresponding best individual, i.e. the teacher, during the iterations to improve its values. If we assume that the teaching outcome of a typical teacher can be also alerted by the mean capability of a given class. Under this condition, each learner x_i will update its position throughout the teacher stage by the following formula:

$$x_{new,i} = x_i + r_i(x_{teacher} - x_F x_{mean}) \quad (4)$$

in which r_i represents a random number from zero to one. T_F represents a teaching index to choose the mean value to be altered, which can be either one or two. Note that $x_{new,i}$ can replace x_i if the value of $x_{new,i}$ is better than the value of x_i.

Another note is that every learner tries to expand its experience with the help of communication with the available learners during the learning stage. In turn, a typical learner x_i arbitrarily picks a peer learner x_j firstly. Later, this learner decides on the route to transfer based on (5) and (6). Also, $x_{new,i}$ can swap x_i in the case that the $x_{new,i}$ value is better than the x_i value.

$$x_{new,i} = x_i + r_i\left(x_i - x_j\right) \quad if\ f\ (x_i) < f(x_j) \quad (5)$$
$$x_{new,i} = x_i + r_i\left(x_j - x_i\right) \quad if\ f\ \left(x_j\right) \le f(x_i) \quad (6)$$

Note that the proposed TLBO considers only the diagnostic of the transformer fault based on the concentrations of dissolved gases in the insulating oil of transformers, and so the degree of deformation has not been taken into account in our study.

C. TLBO IMPLEMENTATION

The following step-wise procedure can be implemented for applying TLBO [29] to the DGA problem:

Step 1: Construct the DGA optimization model and initialize its parameters that are defined in this step. Specifically, it is required to initialize the following: 1) population size (P_n), 2) number of generations (G_n), 3) boundaries of design variables (U_L, L_L), and 4) the number of design variables (D_n). Then, the optimization problem can be defined as: Minimize $f(X)$, Subject to $X_i \in x_i = 1, 2, \ldots, D_n$. Note that $f(X)$ formulated in (1) represents the objective function and X represents a vector for design variables where $L_{L,i} \le x_{,i} \le U_{L,i}$.

Step 2: In this step, the population is initialized according to the size of the population and the number of variables. This population is expressed as:

$$Population = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,D} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,D} \\ \vdots & \vdots & \ddots & \vdots \\ x_{P_n,1} & x_{P_n,2} & \cdots & x_{P_n,D} \end{bmatrix} \quad (7)$$

Step 3: This step represents the teacher phase in which, first, it is required to compute the mean of the population column-wise, which will deliver the mean for the particular subject (M_D) as follows:

$$M_D = [m_1, m_2, \ldots, m_D] \quad (8)$$

Note that the best-given solution will consider as a teacher during the corresponding iteration represented by:

$$x_{teacher} = x_{f(x)=\min} \quad (9)$$

Later, the teacher will tend to shift the mean value from M_D towards x_{teacher}. This will represent a new mean during the corresponding iteration:

$$M_{\text{new},D} = x_{\text{teacher},D} \quad (10)$$

The variance between the two calculated mean values (Dif_D) can be formulated as follow:

$$Dif_D = r(M_{new,D} - T_F M_D) \quad (11)$$

The value of the parameter T_F is designated as 1 or 2. The attained difference can be added to the existing solution for updating its calculated values by:

$$x_{new,D} = x_{old,D} + Dif_D \quad (12)$$

Admit x_{new} when it yields improved function value.

Step 4: Learners can increase their knowledge through the assistance of their shared interaction. The mathematical expression is clarified in the above subsection.

Step 5: Terminate if the maximum number of generations is attained; otherwise, go to Step 3.

As noticed, the above steps have not addressed the constraints of the DGA problem. In this article, we utilize the Deb's heuristic technique [30] to handle the constraints with the TLBO technique. In this technique, a tournament selection operator is utilized where two candidate solutions are nominated and a comparison is established between them. For the optimal selection, the next three rules can be applied:

- In the case that a particular solution is feasible while the other one is infeasible, thence the feasible one is adopted.

TABLE 1. Distribution of the training samples according to the fault types and the references.

Ref.	PD	D1	D2	T1	T2	T3	Total
[5]	9	24	48	0	0	18	99
[4]	2	0	0	3	0	0	5
[17]	0	2	1	1	3	1	8
[31]	27	42	55	70	18	28	240
[32]	1	0	5	2	0	1	9
[33]	3	0	4	4	3	5	19
[34]	1	1	2	1	0	1	6
Total	43	69	115	81	24	54	386

- In the case that the two solutions are feasible, thence the solution with the best objective function value is adopted rather than the other solution.
- In the case that the two solutions are classified as infeasible ones, thence the preferred solution is the one that has the smallest violation of the constraints.

These three rules are incorporated in the TLBO to handle the constraints. Specifically, they are involved in Step 3 and Step 4 which represent, respectively, the teacher and the learner phases. In place of adopting the solution x_{new}, when it gives better objective value in Step 3 and Step 4, Deb's heuristic technique described in [30] can be utilized to update x_{new} by the three abovementioned rules.

III. RESULTS AND DISCUSSION

The optimization method (i.e. TLBO) is used to enhance the diagnostic accuracy of the traditional DGA methods such as IEC code, Rogers ratio method, Duval triangle method, and the other recent DGA methods in the literature. The optimization method is used to identify the transformer faults by adjusting the dissolved gases concentration limits according to six transformer fault types. Specifically, they are categorized into partial discharge (PD), low energy discharge (D1), high energy discharge (D2), low thermal fault (T1), medium thermal fault (T2), and high thermal fault (T3). A number of 386 data samples are utilized with TLBO to construct the diagnostic model that achieving the highest diagnostic accuracy by reducing the diagnostic error between the estimated diagnostic fault and the actual fault. These data samples are collected from the central chemical laboratory of the Egyptian Electricity Holding Company, the Ministry of electricity and renewable energy in Egypt, and the literature. Table 1 illustrates the distribution of the data samples based on the fault types and their sources. The 386 data samples are categorized as 43 data samples for PD, 69 for D1, 115 for D2, 81 for T1, 24 for T2, and 54 for T3. The number of the data samples according to each reference is identified as in Table 1, i.e. samples are collected from the laboratory and literature. Specifically, there are 240 samples from [31], which were considered as field data. The distribution of the samples according to each fault according to Table 1, besides there are 99 samples from practical work that is published in detail in [5].

The experimental data collected through the online gas chromatography device to get the dissolved gas concentration in the oil by the chemists in the chemical laboratory. The distribution of the gas concentration percentages according to each fault type is illustrated in Fig. 1. It is seen that the percentage concentration of H_2 is very high and then it can be used as a key or indicator gas for PD fault (see Fig. 1a). For D1 fault, as shown in Fig. 1b, the C_2H_2 has a high percentage concentration with H_2, then the two gases are indicators for D1 fault, but the percentage concentration of H_2 decreases for D2 fault and the percentage concentration of C_2H_2 increases than in the case of D1, as illustrating in Fig. 1c. The C_2H_6 and CH_4 percentage concentrations are used as indicators for the T1 fault type (Fig. 1d). As in Fig. 1e, three gases are the indicators of T2 (CH_4, C_2H_6, and C_2H_4); therefore, the interfaces with T1 and T3 are obvious and may develop incorrect diagnostic of the transformer fault. The C_2H_4 is a key gas for T3, Fig. 1f, where C_2H_4 concentration is very high compared with the other gases' concentrations. Note that Fig. 1 illustrates the distribution of the gas concentration percentage of each sample. For example, Fig. 1a explains the gas concentration percentage for PD fault (Green symbol) where the concentration percentage of H_2 is higher than the other gases and some of the samples has also high values of C_2H_6 concentration (black symbol). The percentage of each gas is its concentration divided by the same of the five gases (H_2, CH_4, C_2H_6, C_2H_4, and C_2H_2). Fig. 1 was modified to explain the gas concentration percentage at each transformer fault type.

Applying the TLBO on 386 samples developed the percentage concentration limits for each gas based on the fault type to extract the appropriate percentage gases' concentrations and gases' ratios that achieve the highest diagnostic accuracy of transformer faults. To obtain the highest diagnostic accuracy, two scenarios are proposed, the first one (scenario 1) is only handling with the percentage gases' concentration limits, and the other scenario (scenario 2) is based on developing new gases' ratios in addition to the percentage gases' concentrations to separate between the interfaces faults to enhance the diagnostic accuracy of the first scenario.

A. DIAGNOSTIC ACCURACY OF TLBO SCENARIO 1

Identifying the fault type and computing the diagnostic accuracy of transformer faults can be accomplished via the flowchart in Fig. 2. This flowchart illustrates that the input data are the gases' percentages according to the summation of the main five gases (H_2, CH_4, C_2H_6, C_2H_4, and C_2H_2),

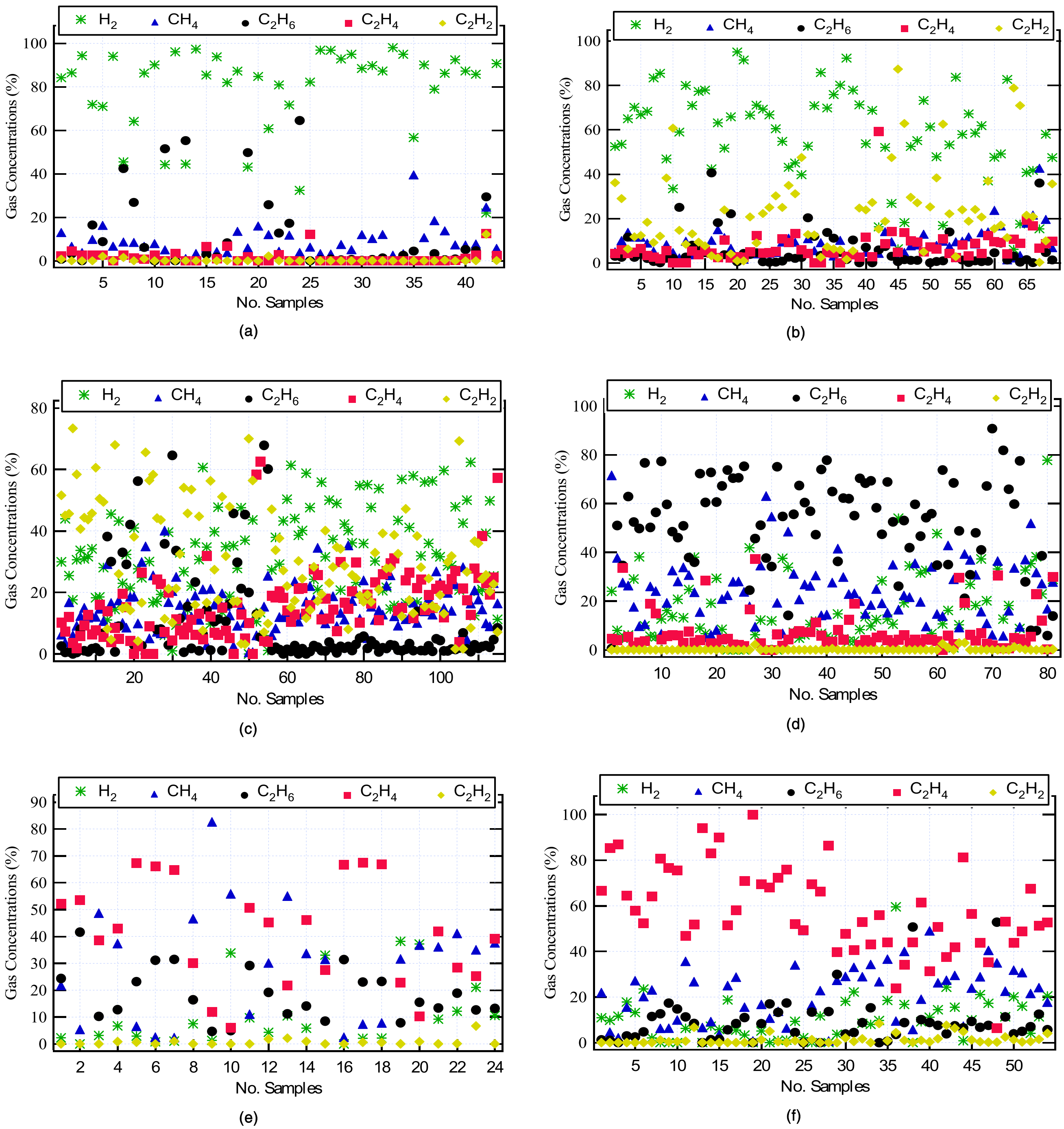

FIGURE 1. Distribution of the gases' concentration according to the transformer fault types. (a) PD fault, (b) D1 fault, (c) D2 fault, (d) T1 fault, (e) T2 fault, and (f) T3 fault.

then if the percentage gases' concentration confirms with the percentage gases' limits of a specified fault, then checking the same percentage gases' concentrations for the other faults, and by this way the transformer fault is identified. For example, if the percentage concentrations of the five main gases belong to PD percentage gases' concentration limits as in stage 1, these percentage concentrations of the gases are checked for the other faults (D1, D2, T1, T2, and T3), if the concentration is agreed with one of these faults, then the interface between two or more faults is considered, if not then the percentages' concentration of these gases refer to the PD fault type. If the estimated fault type is agreed with the actual fault, the diagnose is correct and takes number 1 and if not, the diagnose is incorrect and takes zero. When the computed percentage concentration of gases is out of the gases' concentration limits, then the model fails to identify the fault

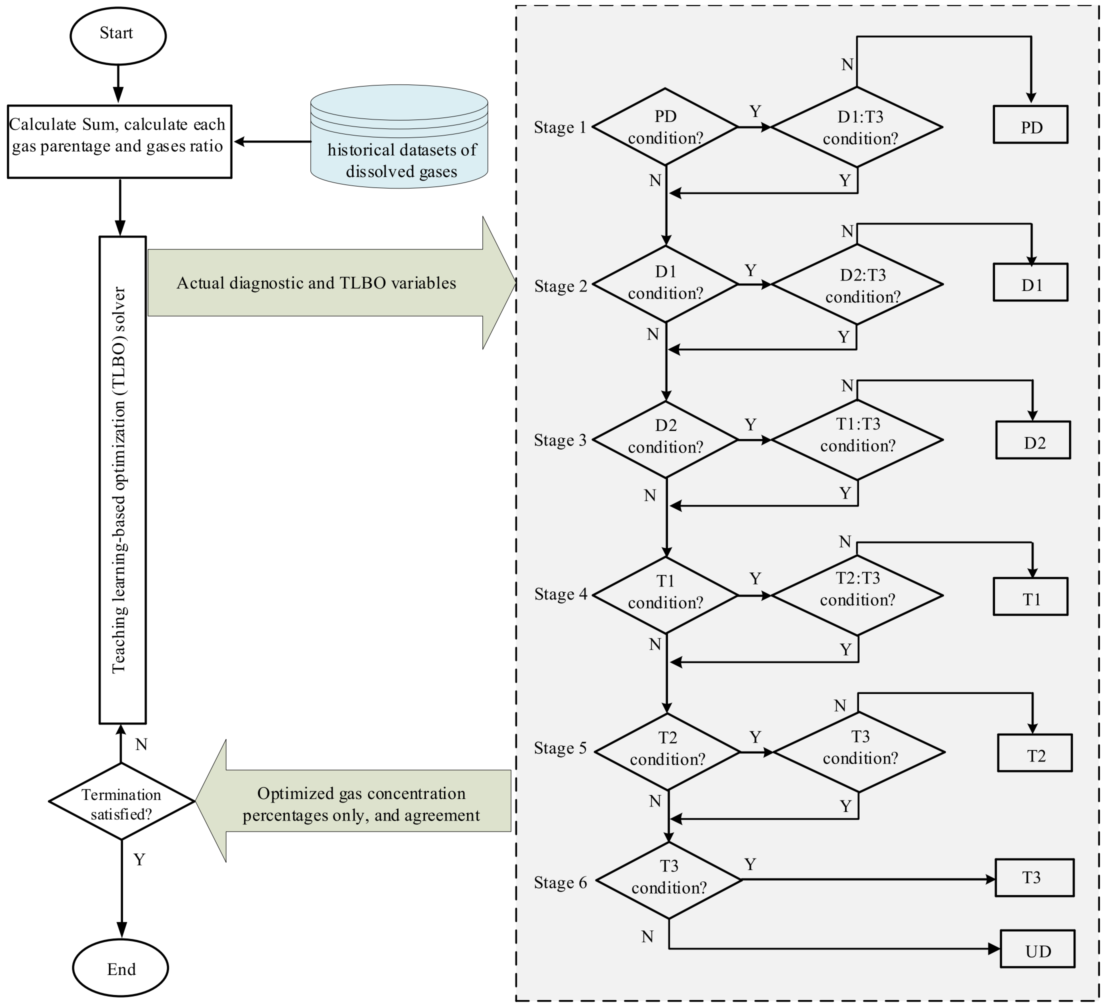

FIGURE 2. Flowchart of the new DGA approach (TLBO Scenario 1).

and the fault is identified as an undetermined fault (UD) and the diagnose is considered as zero. The diagnostic accuracy of the proposed method depends on the number of the correct diagnostic samples according to the total number of applied data samples.

The role of the TLBO is to adjust the limits of the gases' concentration to reduce the errors between the actual and estimated transformer fault types. The procedures of the flowchart are: 1) the summation of the five gases is carried out via the historical datasets of the collected data, 2) the gases percentages referred to the summation are developed, 3) the TLBO initiates the gases' percentages limits, 4) diagnose the transformer fault type based on the initially suggested limits, 5) the errors between the diagnosed faults and actual faults are computed and if the diagnostic accuracy is not reasonable, 6) the TLBO modifies the gases' concentration limits with new limits, and 7) repeats the diagnostic process to reduce the lowest errors between the actual and diagnosed faults. When the errors between the diagnosed and actual faults after some cycles are fixed then the program terminates with the best gases' concentrations limits and then the model is confirmed.

Figure 3 illustrates the percentage of gases' concentration limits developed by the TLBO algorithm at different iterations that shows the computed variables for scenarios 1. Specifically, the computed gas concentration percentages represented by 35 lines are shown in Fig. 3. The computed variables have initially fluctuated, and then after many iterations, all lines in scenario 1 is being fixed, implying the successful convergence of the proposed TLBO algorithm to diagnose transformer fault types.

Table 2 shows the limits of the gas concentration of scenario 1, which satisfies the best diagnostic accuracy by reducing the diagnostic error for each sample to increase the number of correct diagnostic samples. The diagnostic accuracy in scenario 1 is based on the gas limit concentration that gives the correct diagnostic transformer fault type. To apply the limits of the percentage concentration of the gases in Table 2, the next example can be considered which explains the flowchart in Fig. 2. If the concentration of gases

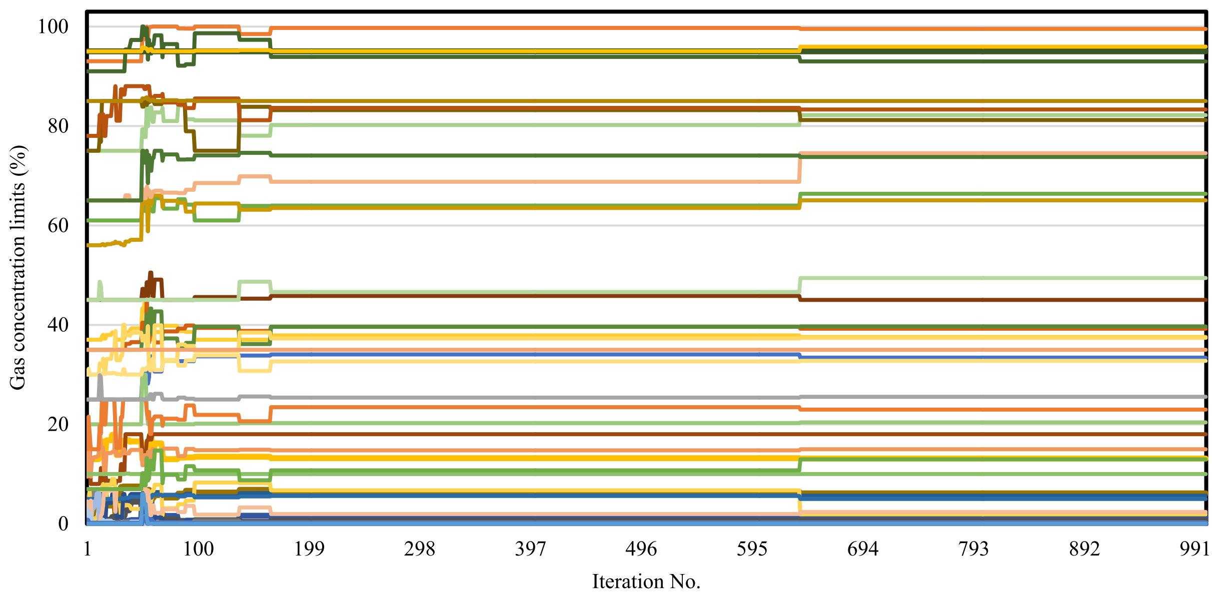

FIGURE 3. The computed Gas concentration limits (35 lines) by the TLBO algorithm for all iterations (Scenario 1).

TABLE 2. Optimized Gas concentration limits by the TLBO algorithm (Scenario 1).

Fault type	H_2%	CH_4%	C_2H_6%	C_2H_4%	C_2H_2%
PD	33.4–99.5	≤13.1	≤66.4	≤18.0	≤6.1
D1	5.7–93.0	≤15.0	≤37.6	≤10.0	1.2–39.2
D2	≤65.0	≤39.7	≤74.5	≤37.4	≤82.2
T1	≤45.0	0.7–81.2	≤95.0	≤35.0	≤1.9
T2	≤20.4	0.33–83.3	≤85.0	5.0–73.7	≤2.4
T3	≤32.8	≤49.4	≤23.0	25.5–96.0	≤13.0

TABLE 3. Confusion matrix for TLBO Scenario 1 (Gas percentage limit only).

	PD	D1	D2	T1	T2	T3	UD	Overall samples
PD	37(86.05%)	0	1(2.325%)	1(2.325%)	0	0	4(9.3%)	43
D1	0	48(69.57%)	17(24.64%)	1(1.44%)	0	0	3(4.35)	69
D2	0	1(0.87%)	110(95.65%)	0	0	1(0.87%)	3(2.61%)	115
T1	2(2.47%)	0	1(1.235%)	77(95.06%)	0	0	1(1.235)	81
T2	0	0	1(4.16%)	7(29.17%)	16(66.67%)	0	0	24
T3	0	0	2(3.7%)	3(5.56%)	3(5.56%)	45(83.33%)	1(1.85%)	54
Overall accuracy				333(86.27%)				386

in ppm of one sample is 32930 for H_2, 2397 for CH_4, 157 for C_2H_6, 1 for C_2H_4, and 0.001 ppm for C_2H_2, then the sum of these gases is 35486 ppm, therefore, the percentage concentration of each gas is 92.799, 6.754, 0.4424, 0.00282, and 0 for H_2, CH_4, C_2H_6, C_2H_4, and C_2H_2, respectively. Hence, these percentage concentrations of the gases are investigated with each fault limits as in Table 2, which satisfy only the percentage gas limits of PD fault after checking the same percentage concentrations with the other faults, then the estimated fault is PD and compares this result with the actual fault if the estimated fault is agreed with the actual fault, the diagnostic is 1 and if not, the diagnostic is zero.

Table 3 illustrates the confusion matrix of TLBO scenario 1, which was constructed based on the optimal gas percentage limits to enhance the diagnostic accuracy of transformer faults. From Table 3 it is obvious that the gray shaded cells in each row refer to the corrected diagnose of each fault where the corrected number of samples in case of PD fault is 37 sample which acts 86.05% for 43 overall PD samples. In turn, the incorrect samples are 6 samples which are categorized into 1 sample for D2, 1 sample for T1, and 4 samples for

TABLE 4. Comparison between the proposed TLBO scenario 1 and the DGA method in literature.

Fault type	Sample	New approach DGA [6]	Modified new approach DGA (%) [6]	IEC [35]	Duval [5]	Rogers [2]	TLBO Scenario 1
PD	43	56.97	95.34	37.21	48.83	23.26	86.05
D1	69	60.14	76.81	36.23	72.46	1.45	69.57
D2	115	88.69	85.215	44.34	59.13	56.52	95.65
T1	81	73.23	91.35	60.49	48.14	90.12	95.06
T2	24	64.58	62.5	66.67	29.16	12.50	66.67
T3	54	75	85.18	68.52	92.59	38.89	83.33
Overall	386	71.5	84.71	50.26	60.88	44.82	86.27

TABLE 5. Optimized gas concentration limits by the TLBO algorithm (Scenario 2).

Fault type	H_2%	CH_4%	C_2H_6%	C_2H_4%	C_2H_2%
PD	39.7–98.4	≤20.1	≤65.6	≤13.5	≤15.7
D1	11.4–97.2	≤13.6	≤43.4	≤13.8	≤40.3
D2	≤63	≤38.6	≤77.2	≤38.9	≤89.5
T1	≤42.4	≤71.8	≤92.2	≤39.1	≤3
T2	≤25.9	≤79.1	10.2–75.4	21.9–74.2	≤11.2
T3	≤39.6	≤60.8	≤19.5	29.5–100	≤12.4

TABLE 6. Optimized the gases' ratios by the TLBO algorithm (Scenario 2).

Fault type	PD	D1	D2	T1	T2	T3
Ratios	$r_2 \leq 0.2$, $r_4 \leq 1.0$	$r_1 \leq 1.2$, $r_3 \geq 1.5$, $r_4 \leq 1.7$	$r_2 \geq 1.1$, $r_3 \geq 0.9$, $r_4 \leq 1.2$	$r_6 \leq 4.1$, $r_7 \leq 1.1$	$r_7 \leq 3.7$	None

UD. The confusion matrix also described the overall accuracy of the TLBO scenario 1 where the correct diagnose samples are 333 out of 386 samples with an accuracy of 86.27%.

The TBLO scenario 1 diagnostic accuracy is evaluated based on the 386 samples that are shown in Table 1. Table 4 illustrates the diagnostic accuracy of scenario 1 and compares its diagnostic accuracy with the accuracy of the other method in the literature. The results in Table 4 explain that the TLBO scenario 1 accuracy is higher than the other DGA in literature, especially the modified new approach DGA in [6]. The accuracy difference between the traditional DGA techniques (Duval triangle, IEC, Rogers) with TLBO scenario 1 is high as in Table 4 where the diagnostic accuracies of Duval triangle method, IEC code 60599, Rogers 4 ratios, TLBO scenario 1 are 60.88, 50.26, 44.72, and 86.27, respectively. The closest diagnostic accuracy is for the modified new approach DGA, which is 84.71. It is obvious from Table 4, although the diagnostic accuracies of PD, D1, T3 are decreased in TLBO scenario 1 than that in the modified new approach DGA, but the diagnostic accuracies improved for D2, T1, T2.

Due to the interfaces between the transformer faults, the diagnostic accuracy of TLBO scenario 1 is 86.27%, which is higher than the other DGA techniques in the literature as shown in Table 4. Therefore, a new attempt is provided to decipher the interfaces between converging faults such as discharge faults (PD, D1, and D2) and thermal faults (T1, T2, and T3) by assuming new gas ratios, which is considered one of the most objectives of this study to enhance the accuracy of diagnosis. In [6], the limits of the gases' ratios were presented, but the diagnostic accuracy of the investigated samples did not exceed 85%, then, the TLBO is applied to improve the gases' ratio limits to increase the diagnostic accuracy of the transformer fault. The optimized gas concentration limits and gases' ratios are presented in Tables 5 and 6, respectively.

B. DIAGNOSTIC ACCURACY OF TLBO SCENARIO 2

In the TLBO scenario 2, several gases' ratios in addition to the gas concentration percentages are developed to separate the interfaces occurring between fault types, such as the interfaces between PD, D1, and D2 for the discharge faults and between T1, T2, and T3 for thermal faults. The TLBO is applied on the 386 data samples as percentage concentration of the gases and the gases' ratios. The gases' ratios are indicated in Equation (3).

The limits of the percentage gases' concentrations and the gases' ratios are explained in Tables 5 and 6, respectively. The percentages of gases' concentrations in Table 5 are different than those in Table 4 because the TLBO scenario 2 considered several additional inputs such as the gases' ratios. The

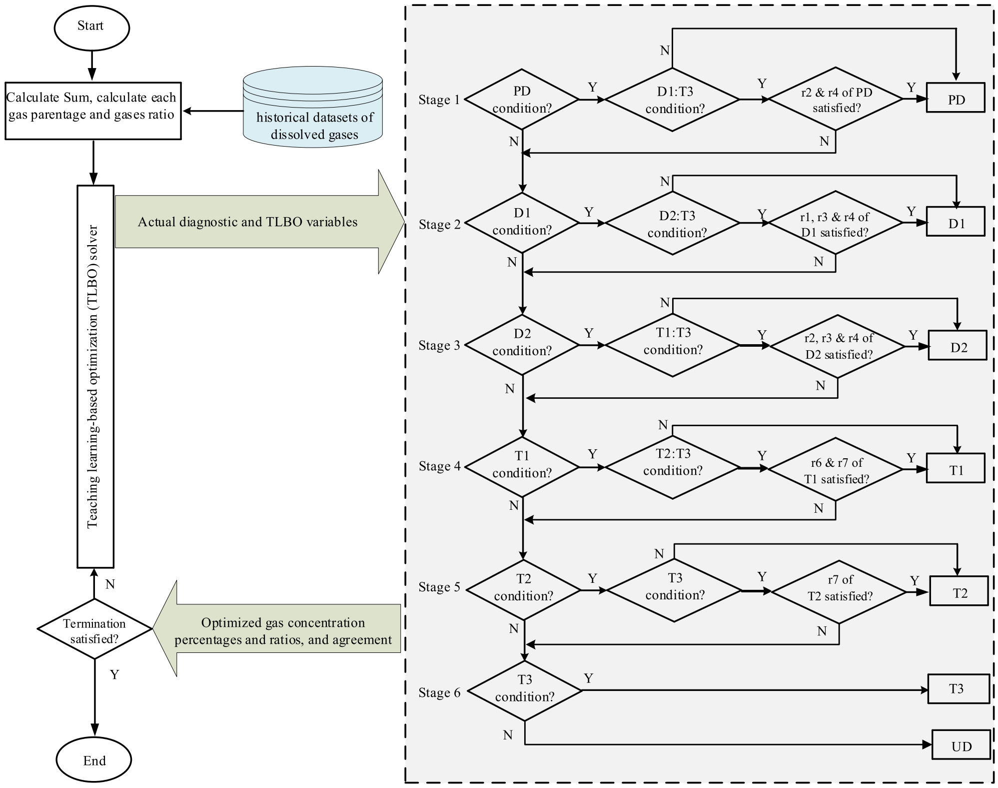

FIGURE 4. Flow chart of the second version of the proposed DGA approach (TLBO Scenario 2).

procedures to compute the diagnostic accuracy of the TLBO scenario 2 are carried out based on the stages in the flowchart in Fig. 4. The difference between the flowchart in Fig. 2 and Fig. 4 is the ability to separate between the interfaces' faults or correct the incorrect diagnosis of fault type by considering the gases' ratios in Equation (3). For example, if the concentrations of the five gases 105, 23, 13, 4, and 3 ppm for H_2, CH_4, C_2H_6, C_2H_4, and C_2H_2, respectively, then the percentages of the gases' concentrations according to the sum of five gases are 70.945, 15.54, 8.783, 2.7, and 2.02. Applying the gases' limits in Table 5 on the previous examples leads to the fault type is PD, which is compatible with the actual fault type, but when applying the gases' limits in Table 2 on the previous sample the fault type is an undetermined fault (UD), which is incorrect.

As in the flowchart of TLBO scenario 2 in Fig. 4, the fault order is PD, D1, D2, T1, T2, and T3. This order doesn't cause any problem because the gases' percentages of any sample are checked for all fault types and then the order is not important. For example, if the concentrations of the five gases 105, 23, 13, 4, and 3 ppm for H_2, CH_4, C_2H_6, C_2H_4, and C_2H_2, respectively, then the percentages of the gases' concentrations according to the sum of five gases are 70.945, 15.54, 8.783, 2.7, and 2.02, respectively. Applying the gases' limits in Table 5 on the previous examples leads to the PD fault type because the gases' percentages satisfy the gas percentages' limits of the PD, then the gases' percentages are checked for the gases' percentage limits of D1, which cannot satisfy the gases' limit of D1 (the gases' percentage of CH_4 is 15.54 in the applied sample and the gases' limit of CH_4 for D1 must be less than 13.6). After that, the gases' percentages of a sample are checked for D2, and it is obvious that the gases' percentage doesn't satisfy the gases' percentage limit of D2 (the gases' percentage of H_2 is 70.945 and the gas percentage limit of H_2 for D2 fault must be less than 63). When the gases' percentages of the applied sample are checked with the other faults T1, T2, and T3, the gases' percentage of H_2 for these faults differs from the gas percentage of H_2 of the applied sample. Therefore, the gases' percentage of the applied sample satisfies only PD. It is obvious that the order of the faults in the flowchart is not important because the applied sample is checked for all possible faults. On the other hand, if the applied gases' percentage of the sample satisfies two fault types, then the role of gas ratio appears for separating between these interface faults.

Table 7 illustrates the confusion matrix of TLBO scenario 2, which was constructed based on the optimal gas percentage and ratio limits to enhance the diagnostic accuracy of transformer faults. Based on the optimal gas percentage and ratio limits in Tables 5 and 6, it is obvious that the number of correct diagnosis samples is increased for all fault types except D2 where the number of correct PD diagnose increases from 37 for TLBO scenario 1 to 40 for TLBO scenario 2. Therefore, the results in Table 7 demonstrate the

TABLE 7. Confusion matrix for TLBO Scenario 2 (Gas percentage and ratio limits).

	PD	D1	D2	T1	T2	T3	UD	Overall samples
PD	40(93.023%)	0	1(2.325%)	1(2.325%)	0	0	1(2.32%)	43
D1	1(1.45%)	53(76.81%)	13(8.841%)	1(1.45%)	0	0	1(1.45)	69
D2	0	5(4.35%)	106(92.173%)	0	0	1(0.87%)	3(2.61%)	115
T1	3(3.7%)	0	0	78(96.296%)	0	0	0	81
T2	0	0	0	6(25.0%)	17(70.83%)	0	1(4.167%)	24
T3	0	0	1(1.851%)	1(1.851%)	3(5.556%)	49(90.74%)	0	54
Overall accuracy				343(88.86%)				386

TABLE 8. Comparison between TLBO scenario 2 and the other DGA techniques in literature for constructing data (386 data samples).

	Samples	TLBO scenario 2	Mod. new approach DGA [6]	Duval [5]	Rogers [2]	IEC [35]	Probability [36]	CSUS [11]	IEC Refined [7]	Rogers Refined [7]
PD	43	93.023	95.34	48.84	23.26	37.21	90.70	88.37	55.81	27.91
D1	69	76.811	76.81	72.46	1.45	36.23	68.12	62.32	31.88	11.59
D2	115	92.173	85.215	59.13	56.52	44.35	93.91	89.57	77.39	69.57
T1	81	96.2963	91.35	48.15	90.12	60.49	85.19	91.36	67.90	91.36
T2	24	70.833	62.5	29.17	12.50	66.67	91.67	66.67	70.83	37.50
T3	54	90.74	85.18	92.59	38.89	68.52	85.19	87.04	88.89	94.44
Total	386	88.86	84.71	60.88	44.82	50.26	85.75	83.16	66.06	60.62

importance of the gas ratio limits for enhancing the diagnostic accuracy of the transformer faults. The confusion matrix also described the overall accuracy of the TLBO scenario 2 where the correct diagnose samples are 343 out of 386 samples with an accuracy of 88.86%.

The limits of percentage gases and the gases' ratios are applied on the 386 data samples and the diagnostic accuracy results are shown in Table 8. Further, the diagnostic accuracy of the TLBO scenario 1 is enhancing by applying TLBO scenario 2 where the diagnostic accuracy for 386 data samples increases from 86.27 % for TLBO scenario 1 to 88.86 % for TLBO scenario 2. Moreover, the diagnostic accuracy of TLBO scenario 2 is higher than the diagnostic accuracies of several DGA methods in literature as in Table 8 where the highest diagnostic accuracy after TLBO scenario 2 is that for conditional probability (85.75), which is addressed in [36], [37]. Based on the comparison results between the proposed DGA techniques using TLBO scenario 2 and the other DGA techniques in literature, which were illustrated in Table 4, the diagnostic accuracy of the TLBO scenario 2 was higher than all DGA techniques except the modified new approach DGA. The modified new approach DGA gives a diagnostic accuracy of 83.51% for testing samples which is higher than the diagnostic accuracy of TLBO scenario 2, which gave 82.02% but the diagnostic accuracy of TLBO scenario 2 is higher than a modified new approach DGA in case of training sample (88.86 % for TLBO scenario 2 and 84.71 % for a modified new approach DGA). Therefore, the diagnostic accuracy of TLBO scenario 2 has a significant level.

Figure 5 shows the computed variables for scenarios 2 where the computed gas concentration percentages are represented by 35 lines as well as the gas ratios represented by 11 lines (in total 46 lines). The successful converge of the proposed TLBO scenario 2 to diagnose the transformer faults when all lines are being fixed after their fluctuations occur in the beginning. Regarding the computed objective function (agreement), Fig. 6 shows its convergence curve by the TLBO algorithm (Scenarios 1 and 2). Interestingly, both curves of the two scenarios are converged to optimal solutions. It is important to note that the calculated optimal agreement value of scenario 2 is better than that of scenario 1. For example, the calculated optimal agreement value of scenario 2 is 343 which is much higher than scenario 1 (333).

The diagnostic accuracy of TLBO scenario 2 is tested with additional 89 data samples that are collected from literature to investigate its robustness. The distribution of the 89 data samples according to the fault types and the sources is explained in Table 9. The distribution of the data samples according to fault types is 8 samples for PD, 13 for D1, 19 for D2, 13 for T1, 7 for T2, and 29 data samples for T3. The 89 data samples are new samples, which are different than the 386 data samples that are used to construct the TLBO scenario 2 models.

The diagnostic accuracy of TLBO scenario 2 is compared with the other DGA methods in literature as in Table 10. All DGA methods in literature gave diagnostic accuracies less than the TLBO scenario 2 except the modified new approach DGA in [6] where a slight difference is observed between the

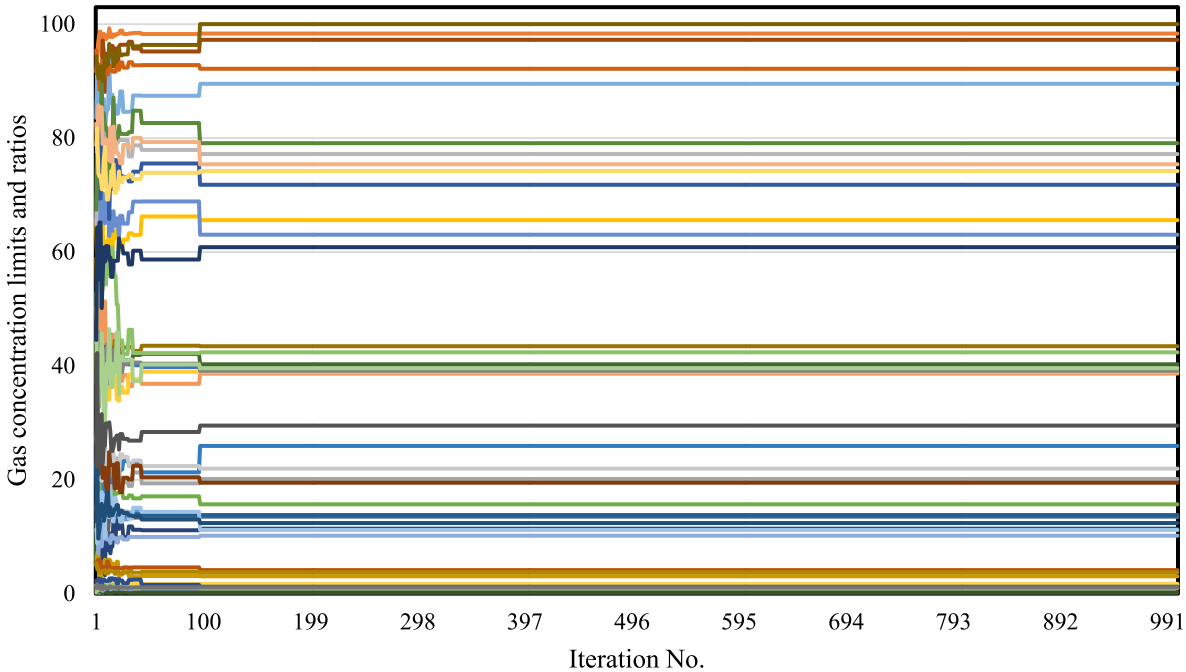

FIGURE 5. The computed Gas concentration percentages and the gases ratios (46 lines) by the TLBO algorithm for all iterations (Scenario 2).

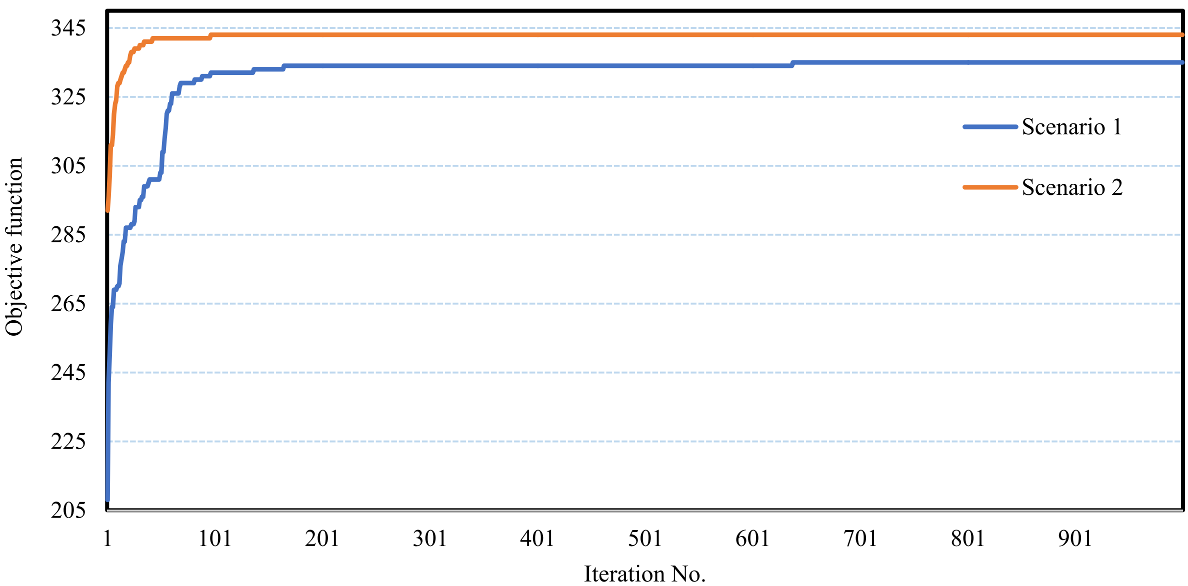

FIGURE 6. Convergence curve of the objective function by the TLBO algorithm (Scenarios 1 and 2).

accuracy of TBLO scenario 2 and the modified new approach DGA and this difference is 1.13%.

Some of the numerical examples to represent the mathematical modeling of the proposed algorithm is illustrated. Table 11 explains 6 data samples expressing the six transformer faults. For sample 1, the gases' percentage for actual PD fault is computed as (92.19, 6.76, 0.91, 0.14, and 0 % for H_2%, CH_4%, C_2H_6%, C_2H_4%, and C_2H_2%, respectively), the number is rounded to the nearest two decimal number. The gases' percentage was compared with the proposed TLBO scenario 2 gases' percentage limits in Table 5 and it is observed that the computed gases' percentage was fitted with the gases' percentage limits of PD and D1. Therefore, the proposed gases' ratios in (3) were investigated to separate between PD and D1 faults, the controlling ratios between PD and D1 are r_2, r_3, and r_4. When computing the r_2 and r_4, the results indicated that they also satisfy the two faults PD and D1, but r_3 for D1 must be greater than

TABLE 9. Distribution of the testing samples according to the fault types and the references.

Ref.	PD	D1	D2	T1	T2	T3	Total
[4]	1	0	0	0	1	0	2
[5]	4	3	4	1	0	0	12
[31]	0	0	2	0	0	0	2
[38]	1	4	2	0	2	8	17
[39]	0	2	2	0	0	0	4
[40]	1	0	4	4	0	2	11
[41]	0	0	0	0	1	2	3
[42]	0	0	0	0	0	2	2
[43]	1	0	0	4	2	14	21
[44]	0	1	4	2	1	0	8
[45]	0	3	1	2	0	1	7
Total	8	13	19	13	7	29	89

TABLE 10. Comparison between the TLBO scenario 2 DGA and the other DGA methods in literature for testing data.

	Samples	TLBO scenario 2	Mod. new approach DGA [6]	Duval [5]	Rogers [2]	IEC [35]	Probability [36]	CSUS [11]	IEC Refined [7]	Rogers Refined [7]
PD	8	100	100.00	75	75	75	87.50	75	87.5	75
D1	13	61.53	69.23	61.54	0.00	38.46	53.85	38.46	30.77	7.69
D2	19	84.22	84.21	89.47	63.16	47.37	89.47	68.42	73.68	73.68
T1	13	92.30	92.31	69.23	76.92	61.54	61.54	92.31	69.23	76.92
T2	7	42.85	42.86	57.14	14.29	57.14	57.14	14.29	57.14	28.57
T3	29	89.65	89.66	93.10	55.17	86.21	93.10	62.07	89.66	93.10
Total	89	82.02	83.15	79.78	50.56	64.04	78.65	61.80	71.91	67.42

TABLE 11. Six DGA samples with the six transformer faults.

Sample	H_2	CH_4	C_2H_6	C_2H_4	C_2H_2	Actual	H_2%	CH_4%	C_2H_6%	C_2H_4%	C_2H_2 %	TLBO (Scenario 2)	TLBO Diagnose
1	2031	149	20	3	0.001	PD	92.19	6.76	0.91	0.14	0.00	PD	Correct
2	56	61	75	32	31	D1	21.96	23.92	29.41	12.55	12.16	D2	Not correct
3	57	24	2	27	30	D2	40.71	17.14	1.43	19.29	21.43	D2	Correct
4	12	18	4	4	0.001	T1	31.58	47.37	10.53	10.53	0.00	T1	Correct
5	19	47	27	62	0.001	T2	12.26	30.32	17.42	40.00	0.00	T2	Correct
6	56	286	96	28	7	T3	11.84	60.47	20.30	5.92	1.48	T3	Correct

1.5 but for this sample, it is $5.49*10^{-5}$, therefore, D1 is excluded and then the predicted fault is PD. Sample No. 2 is investigated, when the gas percentage as the previous order is 21.96, 23.92, 29.41, 12.55, and 12.16%, then compared these gases percentage with the proposed TLBO scenario 2 gases' percentage in Table 5. The gas percentage of sample 2 did not fit with PD and D1 faults, then the other gases limits are checked, and the gases' percentages were fit only with D2. Then the diagnostic fault is D2 which is not compatible with the actual fault D1 and then the TLBO fails to diagnose the fault correctly. For sample 3 and based on the gases' percentage limits in Table 5, the computed gases' percentage of sample 3 was fit only with D2 and it did not interface with another fault and then the checking of gases' ratio limits was not required. The gases' percentage of sample 4 as in Table 11 were 31.58, 47.37, 10.53, 10.53, and 0 %, checking the TLBO scenario 2 gases' percentage limits in Table 5 to identify the fault type. After checking the process, the gas percentage of sample 4 expressed the T1 fault only, then the TLBO scenario 2 diagnose is correct. For the gases' percentage of sample 5, the gases' percentage limit proposed by TLBO scenario 2 referred that their interfaces between T2 and T3 faults and then the gases' ratio limits must be checked. The controlling gas ratio that refers to T2 is r_7 (C_2H_4/C_2H_6) where it must be lower than 3.7. the computed r_7 based on the sample 5 data is 2.25, then the diagnostic fault is T2 and then TLBO scenario 2 detects the fault correctly. Sample no. 6 is investigated, the gases' percentage of this sample fitted only with T3 for TLBO scenario 2 and then TLBO diagnosis is correct where the actual fault is T3.

TABLE 12. The effect of uncertainty noise on the diagnostic accuracy of TLBO scenario 2.

	Accuracy without uncertainty	Accuracy with 5% uncertainty of H_2	Accuracy with 20% uncertainty of H_2
PD	(40/43), (93.02329%)	(40/43), (93.02329%)	(39/43), (90.6976%)
D1	(53/69), (76.81159%)	(52/69), (75.3623%)	(52/69), (75.3623%)
D2	(106/115), (92.17391%)	(105/115), (91.3043%)	(98/115), (85.21739%)
T1	(78/81), (96.2963%)	(78/81), (96.2963%)	(76/81), (93.82716%)
T2	(17/24), (70.8333%)	(17/24), (70.8333%)	(16/24), (66.6667%)
T3	(49/54), (90.74074%)	(49/54), (90.74074%)	(48/54), (88.888%)
Overall	(343/386), (88.8601%)	(341/386), (88.3419%)	(329/386), (85.23316%)

The uncertainty in the measurement approach is applied to the data samples to investigate the robustness of the TLBO scenario 2 DGA algorithm by changing the data for 5 %, 10 %, 15% 20%, and 25%. The data of the samples are varied using equation (13) as in [37],

$$N_l = [100 - m + (2m \times R_l)] / 100 \tag{13}$$

where N_l refers to the vector of noise, l indicates the number of testing samples (89 testing samples), m is the percentage uncertainty level (5%, 10%, 15%, 20%, and 25%), and R_l ranges from 0 to 1. After developing the N_l vector, it multiplies in the gas concentration of each gas $[H_{2new}] = [N_l]\,[H_2\%]$ and the new sum of the gases is developed based on the new percentage of gas concentration. When the TLBO scenario 2 DGA is applied, the same diagnostic accuracies with the uncertainty noises are developed and when the results are investigated, a surprising observation is concluded. The observation is when the uncertainty noise is applied of the gases' vectors the sum of the gases varies with the same uncertainty noise and then when the new gases' concentrations are divided by the sum, the same gases' percentages without uncertainty noise are obtained and then the uncertainty in case of using the gases' percentage is not effective. For example, when the gases' concentrations are 117, 17, 1, 3, 1 ppm for H_2, CH_4, C_2H_6, C_2H_4, and C_2H_2, respectively, then the percentage gases' concentrations according to the sum of the gases are 84.17, 12.23, 0.719, 2.15, and 0.719 %. When the random N_l is 1.048842 and is multiplied in the gases' concentrations, the new gases concentrations are 122.7145, 17.8303, 1.048842, 3.1465, and 1.048842 ppm for H_2, CH_4, C_2H_6, C_2H_4, and C_2H_2, respectively, and the sum of the new gases' concentrations are 145.7889 ppm and then the new percentages of the gases' according to the new sum are 84.17, 12.23, 0.719, 2.15, and 0.719 %, which are the same percentage gases' concentrations without uncertainty, therefore, the uncertainty noise doesn't influence on the percentage of the gases and then the diagnostic accuracies using uncertainty noises are not varied rather than that without uncertainty noises.

On the other hand, if the noise interfaces influence on single gas as H_2 with uncertainty noise of 5 % and 20 %, Table 12 illustrates the accuracy of the TLBO scenario 2 with considering 5 % and 20 % uncertainty noise. The uncertainty results in Table 12 indicated that at 5 % uncertainty of H_2, the overall accuracy of the 88.34% with an error (0.584 %) of the accuracy without uncertainty. Furthermore, when the H_2 concentration is varied with 20 % uncertainty noise, the accuracy will be 85.233 % with an error of 4.08 %. Therefore, the uncertainty noise that affects the gas concentration has an insignificant effect on the accuracy of the TLBO scenario 2.

The paper has presented a new application of teaching-learning based optimization for detecting the transformer faults based on the concentrations of the dissolved gases. The interfaces of some faults such as PD, D1, and D2 and also the interfaces between T1, T2, and T3 may reduce the diagnostic accuracy of the proposed method. Some proposed methods increase the diagnostic accuracy by emerging some of the interface faults such as D1, and D2 and also T1, T2, and T3. The proposed work using TLBO did not emerge the different faults and if the estimated fault is not fit with the actual fault then the diagnostic accuracy is zero for this sample.

C. SEVERITY OF TRANSFORMER FAULT TYPES

According to IEEE C57.104 [2], the severity of the fault can be determined based on the total amount of dissolved combustion gases (TDCG), which is the sum of the main combustible gases such as H_2, CH_4, C_2H_6, C_2H_4, C_2H_2, and CO, and its rate of change. It explains the maintenance strategy, the periodic tests, and the recommended action that must be considered based on the TDCG and its rate of change.

Several datasets were collected concerning the history of DGA results of one transformer in the Egyptian power networks. The proposed TLBO algorithm and other DGA techniques to identify both the transformer fault type and severity of this fault based on the total amount of TDCG. In addition, the recommended action based on TDCG is provided. Table 13 illustrates the collected data, and Table 14 demonstrates the results of the TLBO and other DGA techniques for the transformer oil samples during its operation. Table 14 shows the fault severity as a condition of the fault type where "1" refers to the TDCG ranges from 0-720 ppm and indicates the low fault type, further "2" refers to the range of TDCG more than 720 to 1920 ppm and indicates the

TABLE 13. Collected oil samples of the tested transformer and concentration of the combustible gases and the corresponding TDCG.

Sample No.	Date of sample	H_2	CH_4	C_2H_6	C_2H_4	C_2H_2	CO	TDCG	Actual
1	7/5/2006	33	4	20	21	1E-03	154	232	T1
2	5/11/2006	37	3	29	21	1E-03	180	270	T1
3	4/11/2007	1176	3426	1178	2931	1E-03	534	9245	T3
4	10/12/2007	66	11	50	61	1E-03	554	742	T1
5	4/5/2008	34	11	1	21	1E-03	121	188	T2
6	16/11/2008	38	4	1	41	1E-03	341	425	T3
7	10/5/2009	31	5	2	62	1E-03	420	520	T3
8	8/11/2009	22	8	4	55	1E-03	337	426	T3
9	9/5/2010	7	12	6	107	1E-03	565	697	T3
10	1/11/2010	31	25	3	81	1E-03	462	602	T3
11	2/5/2011	6	6	22	4	1E-03	149	187	T1

TABLE 14. Fault types of TLBO and other DGA techniques, the severity level condition of transformer, and the recommended action.

Sample No.	TLBO	Mod. new approach DGA [6]	Duval [5]	Rogers' [2]	IEC [35]	Probability [36]	CSUS [11]	IEC Refined [7]	Rogers' Refined [7]	Condition	Action
1	T1	T1	T3	UD	T1	T3	T1	D1	T3	1	Transformer in normal operation state
2	T1	T1	T3	UD	PD	T3	T1	PD	T3	1	Transformer in normal operation state
3	T1	T1	T2	T2	T2	T2	UD	T2	T2	4	Transformer must be out of service
4	T1	T1	T3	UD	T1	T2	T1	D1	T3	2	Exercise extreme caution
5	D2	D2	T3	UD	UD	T3	T1	T3	T3	1	Transformer in normal operation state
6	UD	UD	T3	UD	UD	T3	T1	D2	T3	1	Transformer in normal operation state
7	T3	T3	T3	UD	UD	T3	T3	D2	T3	1	Transformer in normal operation state
8	T3	T3	T3	UD	UD	T3	T3	T3	T3	1	Transformer in normal operation state
9	T3	T3	T3	T3	T3	T3	T3	T3	T3	1	Transformer in normal operation state
10	T3	T3	T3	UD	UD	T3	T3	T3	T3	1	Transformer in normal operation state
11	T1	T1	T2	T1	No fault	T1	T1	T1	T1	1	Transformer in normal operation state

moderate fault type, the condition "3" refers to the high fault type and the TDCG ranges more than 1920 to 4630 ppm. The last condition is "4" where the TDCG is more than 4630 ppm and it indicates an extreme fault so that the transformer must be urgently removed from the network. The fault types of TLBO and other DGA techniques of the collected oil sample for the tested transformer are also presented whereas most diagnostic fault types were matched with the actual faults. As shown in Table 13, the concentration of the combustible gases, for sample number 3, increased and exceeded the normal rate of all gases. Then, the TDCG was excessive and the fault type will be classified as high thermal faults. Subsequently, the oil temperature exceeds 700 °C, that is corresponding to condition "4" referring that the transformer must be out of service. The time that the TLBO was taken to identify the transformer fault type and severity in the case of the testing process for 89 data samples was 89.3 ms per sample. While the training time of transformer fault datasets equals 5.43 min.

IV. CONCLUSION

In this article, the TLBO has been used to enhance the diagnostic accuracy of the transformer faults by adjusting the percentage gases' concentration limits and the gases' ratios through the proposed two scenarios. The TLBO scenario 2 has enhanced the diagnostic accuracy with a reasonable limit where it gave a diagnostic accuracy of 88.86 % for training samples and 82.02% for the testing samples. These diagnostic accuracies are higher than that of the traditional and recent DGA methods where the maximum diagnostic accuracy of the other DGA methods is for the probability DGA method (85.75%, for training), which is reduced to 78.65% for the testing samples. The modified new approach DGA gave a higher accuracy than the TLBO scenario 2 for the testing data (83.15%) but it only gave 84.71% for the training samples. The uncertainty noises with 5, 10, 15, 20, 25% are applied to the data samples to investigate the robustness of the TLBO scenario 2 and the application of the uncertainty noise was not effective when the percentage gases according to its sum has been used for DGA diagnoses. The proposed approach is a helpful tool that could have a significant effect variation on transformer health by providing an accurate early diagnostic or prediction of expected transformer fault types.

ACKNOWLEDGMENT

The authors would like to acknowledge the financial support received from Taif University Researchers Supporting Project Number (TURSP-2020/34), Taif University, Taif, Saudi Arabia.

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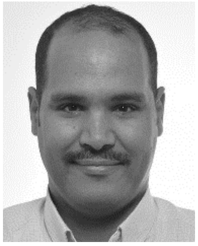
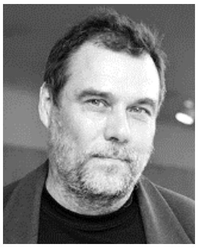
SHERIF S. M. GHONEIM (Senior Member, IEEE) received the B.Sc. and M.Sc. degrees from the Faculty of Engineering at Shoubra, Zagazig University, Egypt, in 1994 and 2000, respectively, and the Ph.D. degree in electrical power and machines from the Faculty of Engineering, Cairo University, in 2008. Since 1996, he has been teaching at the Faculty of Industrial Education, Suez Canal University, Egypt. From the end of 2005 to the end of 2007, he was a Guest Researcher with the Institute of Energy Transport and Storage (ETS), University of Duisburg–Essen, Germany. He joined Taif University as an Associate Professor with the Electrical Engineering Department, Faculty of Engineering. His research interests include grounding systems, dissolved gas analysis, breakdown in SF_6 gas, and AI technique applications.



KARAR MAHMOUD received the B.Sc. and M.Sc. degrees in electrical engineering from Aswan University, Aswan, Egypt, in 2008 and 2012, respectively, and the Ph.D. degree from the Electric Power and Energy System Laboratory (EPESL), Graduate School of Engineering, Hiroshima University, Hiroshima, Japan, in 2016. Since 2010, he has been with Aswan University, where he is currently an Assistant Professor with the Department of Electrical Engineering. He is currently a Postdoctoral Researcher with the School of Electrical Engineering, Aalto University, Finland. He has authored or coauthored more than 60 publications in top-ranked journals, including IEEE journals, international conferences, and book chapters. His research interests include power systems, renewable energy resources, smart grids, distributed generation, optimization, applied machine learning, industry 4.0, and high voltage.



MATTI LEHTONEN received the master's and Licentiate degrees in electrical engineering from the Helsinki University of Technology, Finland, in 1984 and 1989, respectively, and the D.Tech. degree from the Tampere University of Technology, Finland, in 1992. He was with VTT Energy, Espoo, Finland, from 1987 to 2003. Since 1999, he has been a Full Professor and the Head of the Power Systems and High Voltage Engineering Group, Aalto University, Espoo, Finland. His research interests include power system planning and assets management, power system protection, including earth fault problems, harmonic related issues, high-voltage systems, power cable insulation, and polymer nanocomposites. He is also an Associate Editor of *Electric Power Systems Research* and *IET Generation, Transmission and Distribution*.

MOHAMED M. F. DARWISH was born in Cairo, Egypt, in May 1989. He received the B.Sc., M.Sc., and Ph.D. degrees in electrical power engineering from the Faculty of Engineering at Shoubra, Benha University, Cairo, in May 2011, June 2014, and January 2018, respectively. From 2016 to 2017, he was with Aalto University, Finland, as a Ph.D. Candidate Student with the Electrical Engineering and Automation Department, with the Prof. M. Lehtonen's group. He is currently working as an Assistant Professor with the Department of Electrical Engineering, Faculty of Engineering at Shoubra, Benha University. He is also a Postdoctoral Researcher with the School of Electrical Engineering, Aalto University. His research interests include HV polymer nanocomposites, nano-fluids, partial discharge detection, dissolved gas analysis, pipeline induced voltages, electromagnetic fields, renewables, optimization, applied machine learning, industry 4.0, and superconducting materials. He received the Best Ph.D. Thesis prize that serves industrial life and society all over the Benha University staff for the academic year 2018/2019.