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Improved Monitoring and Diagnosis of Transformer Solid Insulation Using Pertinent Chemical Indicators

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Abstract: Transformers are generally considered to be the costliest assets in a power network. The lifetime of a transformer is mainly attributable to the condition of its solid insulation, which in turn is measured and described according to the degree of polymerization (DP) of the cellulose. Since the determination of the DP index is complex and time-consuming and requires the transformer to be taken out of service, utilities prefer indirect and non-invasive methods of determining the DP based on the byproduct of cellulose aging. This paper analyzes solid insulation degradation by measuring the furan concentration, recently introduced methanol, and dissolved gases like carbon oxides and hydrogen, in the insulating oil. A group of service-aged distribution transformers were selected for practical investigation based on oil samples and different kinds of tests. Based on the maintenance and planning strategy of the power utility and a weighted combination of measured chemical indicators, a neural network was also developed to categorize the state of the transformer in certain classes. The method proved to be able to improve the diagnostic capability of chemical indicators, thus providing power utilities with more reliable maintenance tools and avoiding catastrophic failure of transformers.

Keywords: transformer; condition assessment; degradation; furan; methanol; multi-layer perceptron (MLP)

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Citation: Behjat, V.; Emadifar, R.; Pourhossein, M.; Rao, U.M.; Fofana, I.; Najjar, R. Improved Monitoring and Diagnosis of Transformer Solid Insulation Using Pertinent Chemical Indicators. *Energies* **2021**, *14*, 3977. https://doi.org/10.3390/en14133977

Academic Editor: Ahmed Abu-Siada

Received: 13 May 2021
Accepted: 24 June 2021
Published: 2 July 2021

1. Introduction

Power and distribution transformers are considered to be one of the most important components of an electrical power system. Transformer failures not only cause blackouts and energy loss, but they also reduce system reliability and have a significant effect on power quality. Therefore, monitoring the condition of transformers during operation is necessary, and the issue is of great interest to engineers and researchers [1,2]. The lifetime of a transformer is generally assumed to be equivalent to the lifetime of its solid insulation. This is because many dielectric defects or failures in the insulating system lead to transformer collapse [3–6]. Figure 1 depicts two sets of distribution transformers that have been removed from the power system due to damage to their solid insulation.

During operation, the insulation system of oil and paper is exposed to a variety of electrical, thermal, and mechanical stresses that cause aging. The aging mechanism is a complex phenomenon that accelerates in the presence of oxygen, heat, and moisture [4,5]. The degree of polymerization is a reliable index to evaluate the mechanical strength and durability of the paper insulation. New insulating paper has an average DP of 1000–1200 [7]. As the paper ages, the DP decreases, and the color of the paper turns dark brown and loses tensile strength. A DP value of 200 means the end of its life [8].

DP measurement (according to IEC 60450 or ASTM D4243) has high accuracy and reliability for evaluating the quality of the paper. However, since sampling paper strips from the insulation system during operation is impossible because it requires the transformer to be taken out of service, this method is rarely used for evaluating solid insulation. For this reason, utilities would rather use indirect and non-invasive evaluative methods [8].

Figure 1. Deteriorated solid insulation of distribution transformers.

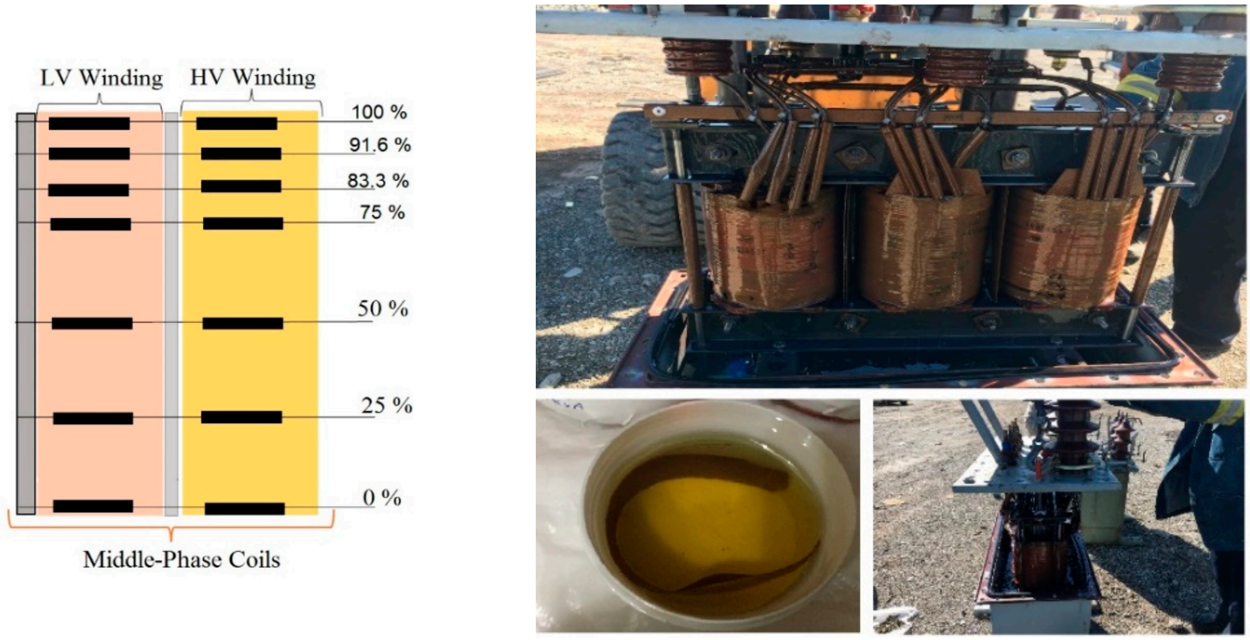
The byproducts of solid insulation degradation (e.g., furanic compounds, gases, acids, water, alcohols) remain dissolved in the transformer oil. The content and concentration of these byproducts can provide important information about the state of the paper [8–14]. The details of these diagnostic chemical tests are discussed in subsequent sections of this paper. Although these methods are effective in themselves, judging the transformer's overall status after a single test would be a challenge for a utility. It is accepted that dissolved methanol, furan and carbon oxides in the insulating oil are prominent markers of degradation. Using an artificial neural network (ANN) to combine them to access solid insulation degradation will assure a more reliable detection compared to individual tools.

This study aims to measure dissolved methanol, furanic compounds, and carbon oxides to achieve a more reliable assessment of solid transformer insulation. The study had at its disposal several distribution transformers (aged 4–49 years) belonging to the Iran electric power distribution utility. To perform direct tests on the paper, some of the transformers were taken out of service for sample collection. For the rest of the transformers, indirect methods were adopted, and cellulose decomposition byproducts were considered for analysis. Based on an analysis of furans, methanol, and carbon oxides of the transformer fleet, four classes of transformers were identified. Furthermore, an artificial neural network model was designed to assign a comprehensive index of solid insulation degradation to each transformer. The accuracy of degradation assessment proved to be better with the neural network than by individual measurement.

The rest of the paper is organized as follows. Detailed measurements and analyses of the dissolved gases, furanic compounds, and methanol are presented in Section 2. The experimental and practical studies are discussed in Section 3. The design and performance of the intelligent neural network are presented in Section 4. Conclusions and future directions of research are given in Section 5.

2. Chemical Tests to Monitor the Status of Transformer Solid Insulation

The aging of insulation paper is associated with the breakdown of its chemical bonds and is measured according to its degree of polymerization (DP), the average number of cellulosic monomers in the paper's polymeric chain. As the paper ages, the mechanical properties of cellulose are affected more than its electrical properties are. The aging rate depends on temperature, humidity, oxygen content, type of oil, and type and thickness of paper. The coil temperature may be high during normal operation, which in turn may cause a breakdown in the cellulosic chain, thereby reducing the paper's mechanical strength [9]. To determine the DP value directly, paper samples should be taken from various locations along the transformer windings, because the degree of polarization varies across different sections of the transformer coil, and sent to a laboratory for analysis. To do this, the transformer must be overhauled and removed from the circuit. Given the cost associated with the analysis of each paper sample, and to limit the amount of paper samples to a reasonable size, various samples were taken at intervals between the bottom ends to the top end of the coils. The approach adopted in this study, according to the findings of [10], took samples at 0, 25, 50, 75, 83.3, 91.6, and 100% of the winding height, and the average DP value of these samples could be used to represents the coil's DP value. Figure 2 illustrates the sampling points of an overhauled distribution transformer.



(a) (b)

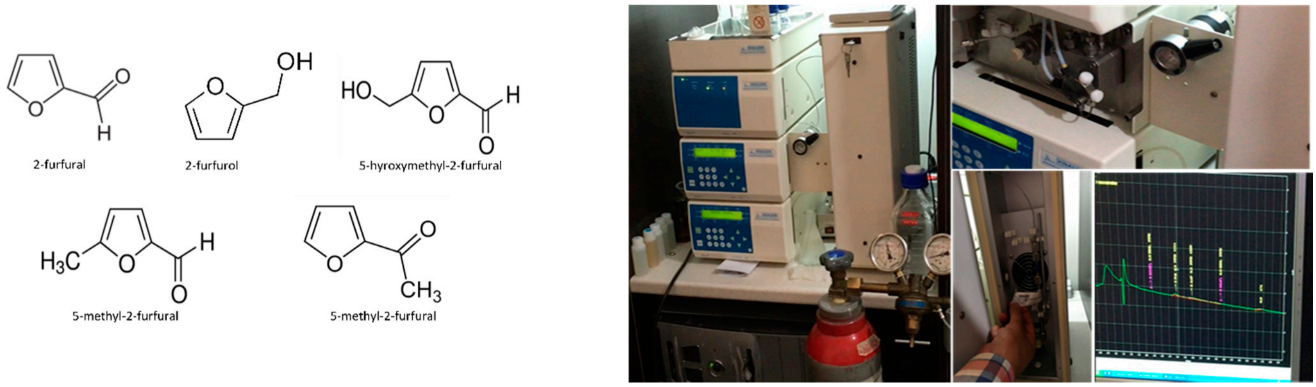
Figure 2. (**a**) Illustration of the sampling points on a coil; (**b**) View of overhauled transformer and samples of paper collected for testing the DP.

As mentioned, since access to solid insulation is difficult once the transformer is commissioned and energized, the DP measurement is sometimes performed by taking paper samples from an old transformer and extrapolating the results over a similarly designed transformer fleet. However, this approach is not useful for providing an exact degradation level of the solid insulation. With all these observations, indirect methods like relating furan analysis to the DP to estimate the deterioration will be more meaningful.

2.1. Furan Analysis

It is widely accepted that furans arise from paper degradation but the actual mechanism of formation is not yet fully understood [4]. However, it is known that furans are produced from the pyrolysis of levoglucosan (LG) and hydrolytic degradation of cellulose [14]. LG, the precursor of the furanic compounds, is the byproduct of the thermal degradation of cellulosic paper at temperatures higher than 130 °C [14]. Scheirs et al. [14] found that LG leads to the production of all five types of furanic compounds: 2-furfural (2-FAL), 5-methyl-2-furfural (5-MEF), 5-hydroxymethyl-2-furfural (5-HMF), 2-acetylfuran (2-ACF), and 2-furfurylalcohol (2-FOL). The studies revealed through laboratory tests that 2-furfural (2-FAL), also referred to as 2-furaldehyde is a byproduct of cellulose aging that can remain stable for years. Its concentration is, therefore, widely used as an to predict the paper DP value.

High-performance liquid chromatography (HPLC) is normally used to measure furanic compounds based on the test procedure described in ASTM-D-5837 [15] and IEC 61198 [16]. However, no standard has yet been developed for interpreting the results, but 2-FAL was the stablest of the five furanic compounds. Figure 3a shows the furfural compounds produced by paper insulation deterioration, and Figure 3b shows the HPLC device used in this study when transformer oil was injected for furan measurement.



(**a**) (**b**)

Figure 3. (**a**) Furan components in transformer oil; (**b**) HPLC test set-up for furan measurement of oil samples in this study.

Laboratory studies showed that paper degradation with the generation of furan compounds occurs at temperatures above 100–120 °C [12]. Equations (1)–(5) resulted from the experiences of four research groups relating furan compound concentration to the degree of polymerization. In these equations, f represents 2-FAL concentration in ppm, and DP is the degree of polymerization [17–19].

$$DP = \frac{2.6 - \log[f]}{0.0049} \quad (1)$$

$$DP = \frac{1.51 - \log[f]}{0.0035} \quad (2)$$

$$DP = 325(\frac{19}{13} - \log[f]) \quad (3)$$

$$DP = \frac{1850}{[f] + 2.3} \quad (4)$$

$$DP = \frac{800}{0.1862 \times [f] + 1} \quad (5)$$

Equations (2) and (4) are suggested for 2-furfural concentration up to 5 ppm. However, studies show that these equations approximate the condition of the paper better early in the operation of a transformers [19]. It is worth noting that despite many studies on furan compounds, no single standard has yet been developed for all transformers, especially since research shows that in transformers that use thermally upgraded paper, have a very low concentration of furan compounds; therefore, their use as a valid and reliable criterion for assessing the state of paper insulation is still questionable.

2.2. Carbon Oxides

The other major byproduct of cellulose aging is carbon oxides, which also serve as an aging indicator. These gases are formed not only during aging but also formed from other activities such as partial discharges and overheating. During an electrical discharge, carbon monoxide and carbon dioxide are formed. These gasses can also be formed from materials other than those containing cellulose, such as oil under some conditions.

Dissolved gas analysis (DGA) is the globally accepted method for monitoring the dissolved carbon oxides and other soluble gases arising from cellulose deterioration in transformer oil. The first step in analyzing the oil sample is to extract soluble gases using the Toepler Pump, a traditional, low-cost gas extraction method [20–22]. Figure 4a shows the vacuum-soluble gas extraction system that is used in this study. Gases extracted from our samples were further separated and measured using different gas chromatography (GC) devices, as shown in Figure 4b. GC is able to measure the concentration of hydrogen, methane, ethane, ethylene, acetylene, carbon monoxide, carbon dioxide, oxygen, and nitrogen [8,23,24].

(**a**) (**b**)

Figure 4. (**a**) Extraction of oil-soluble gases by vacuum; (**b**) Gas chromatography test set-up.

Regarding CO_2 and CO as indicators for cellulose degradation, the IEC-60599 standard suggests a CO_2/CO ratio in the range of $3 < CO_2/CO < 10$ for normal paper aging. The ratio becomes significant when individual gases are above 5000/500 ppm [25]. A ratio below 3 or above 10 may indicate aging by different mechanisms. As carbon oxides can have other origins apart from cellulose degradation, IEC-60599 recommends that if the CO_2/CO ratio is lower or higher than the specified values, other tests such as furan concentration should be used to better interpret the results.

2.3. *Methanol*

Methanol (CH_3OH) was introduced as an indicator for aging transformer paper in 2007 [26]. Experiments showed that a large proportion of methanol was produced from the destruction of the 1,4-β-glucosidic bond that holds the monomers of cellulose together [26,27]. According to the literature [8,26–29], the amount of furan or 2-FAL concentration produced from cellulose destruction in the early stages of deterioration is very small or near zero, but the amount of methanol produced is significant and increases linearly. So, for the early periods of paper deterioration, methanol is a more reliable indicator than carbon oxides. Other advantages are that methanol is stable under transformer operating temperatures and the amount produced is independent of the type of insulating paper (Kraft and thermally upgraded) [8].

Methanol is the simplest alcohol that is liquid at room temperature. Different chromatographic methods have been used to detect alcohols and gases in insulating oils, such as Gas Chromatography–Mass Spectrometry (GC–MS), Flame Ionization Detection (FID), High-Performance Liquid Chromatography (HPLC), and Solid-Phase Micro-Extraction (SPME) [8,29]. In this work, the method presented in [8] was used to measure the methanol concentration in the oil. A system consisting of a 6890 N gas chromatograph equipped with a 5973 network mass spectrometer (MS), in the absence of a costly headspace autosampler, was used to measure the alcohols.

2.4. Hydrogen (H_2)

Hydrogen is one of the oldest indicators used to assess of transformers dating back nearly 100 years. At least 95% of online monitors measure hydrogen gas concentration in transformer monitoring [30].

In all the electrical and thermal faults that occur inside the transformer, hydrogen is produced in greater or lesser amounts in the oil [31]. This is because the energy required to break hydrogen bonds to form H_2 is much less than the energy required to break the carbon bonds in other degraded materials. Hydrogen gas is produced abundantly as a result of thermal errors, especially electrical discharges. Under the influence of an electrical discharge, certain hydrocarbon bonds may break and increase free radicals such as H, CH_3, CH_2, and CH. The recombination of these free radicals may produce gases such as hydrogen, methane, ethane, ethylene, and acetylene.

Low-energy discharge in the oil (without paper) by itself also leads to the production of hydrogen, methane, and ethane. However, in the paper–oil system, hydrogen production increases and reaches about 85% [32]. Hydrogen is also produced as a result of sparking fault conditions, and its concentration is directly and linearly related to the number of sparks [33].

A concentration of 100 ppm (0.01%) is a critical value for hydrogen gas. Values less than 100 ppm indicate a normal transformer operating conditions, but for values above 100 ppm, more tests should be performed on the oil to determine the source of the fault.

There are several different methods for measuring the concentration of H_2 in oil, including gas chromatography (GC), Photo-acoustic (PA) spectrometry, and Calorimetry spectroscopy [34]. In this work, GC was used according to the method described in Section 2.2.

Although hydrogen is the main gas in transformer fault detection, concerns have been raised about hydrogen gas-based analysis because of its low measurement accuracy at low concentrations in the oil, the possibility that it was produced by other materials inside the transformer, and stray gassing [30,32].

3. Experimental Investigation of the Transformer Fleet and Laboratory Testing

As previously discussed, dissolved-gas, methanol, and furan analyses are widely accepted as indirect measures to assess transformer insulation, but a single measurement would not be reliable enough to identify the condition of the transformer effectively, so most of the research in the literature was carried out in a laboratory.

In this paper, aged transformers with Buchholz relay faults were investigated and tested to develop a more comprehensive index of solid insulation degradation. For this purpose, 40 service-aged oil-filled distribution transformers belonging to Iran's electric power distribution utility were selected, and oil samples were taken for analysis. Based on the available technical documentation, the insulation paper used in these transformers was of normal kraft-type and the ages of the transformers ranged from 4 to 49 years.

Oil samples were taken according to the IEC 60567 standard for analysis of furan concentration and dissolved gases. Then, furan compounds, gases and methanol were measured according to [8,15,20]. In addition to age, the concentration of furan compounds, methanol, carbon monoxide, carbon dioxide, and hydrogen were studied.

It should be noted that despite the limitations mentioned in Section 2.4 regarding the use of hydrogen in the analysis and evaluation of insulation conditions, the concentration of this gas in this study was used to classify the insulation conditions of transformers. Because the research team believes that hydrogen is still one of the main products of partial discharge, arcing and sparking, the use of this index with the furan and methanol concentrations, can help accurately analyze the insulation status of the transformer.

To determine the maintenance and operation strategy of transformers according to their insulation conditions, they were divided into 4 classes. Based on studies and records of transformers that failed and in accordance with expert opinion of the utility, a classification algorithm was designed.

In this algorithm, critical ranges were extracted for each evaluation index (furan, hydrogen, carbon oxides, methanol, and age), and a number was assigned to each range. Table 1 shows the numbers assigned to the critical ranges of each index.

Table 1. Evaluation indicators, critical ranges, and assigned numbers.

Indicators	Range	A_i
Age (year)	0–10	1
	10–20	2
	>20	3
CO_2 (ppm)	0–1500	1
	>1500	2
CO (ppm)	0–500	1
	>500	2
CO_2/CO	3–10	1
	0–3 or >10	2
H_2 (ppm)	0–100	1
	>100	2
2-Fal (ppb)	0–100	1
	100–500	2
	500–1000	3
	>1000	4
CH_3OH (ppm)	0–0.2	1
	0.2–1	2
	1–2	3
	>2	4

To evaluate the condition, a parameter called **B** was defined, the value of which was obtained according to Equation (6):

$$\mathbf{B} = \sum_{i=age}^{i=\mathrm{CH_3OH}} \mathbf{A}_i \tag{6}$$

where $\mathbf{A}_i$ was obtained from Table 2 based on the range of measured indices and the age of the transformer.

Table 2. Classification of transformers based on insulation conditions and range of **B**.

Class	Description	Condition	Requirement
1	$7 \leq \mathbf{B} < 10$	Good	Normal Maintenance
2	$10 \leq \mathbf{B} < 13$	Fair	Increase Diagnostic Testing
3	$13 \leq \mathbf{B} < 16$	Poor	Start Planning Process to Replace or Rebuild Considering Risk
4	$16 \leq \mathbf{B} < 19$	Very Poor	Immediately Assess Risk

For each transformer, the value of **B** was calculated based on range of evaluation indicators and indicates the state of the solid insulation. For different values of **B**, the transformers were divided into four different classes, and for each the utility determined a specific maintenance strategy. According to Table 2, a maintenance and operating strategy can be defined for each transformer according to its class.

According to the abovementioned algorithm, the value of parameter **B** (age and concentrations of furan compounds, hydrogen, methanol and carbon oxides and the CO_2/CO ratio) was calculated for each transformer, which was then assigned to a class according to the condition of its insulation: good, fair, poor, or very poor (Table 2). Table 3 shows the classification ranges for all 40 transformers.

Table 3. Results of measurements and classification of the transformers.

Sample	Age (year)	CO_2 (ppm)	CO (ppm)	CO_2/ CO	H_2 (ppm)	2-Fal (ppb)	CH_3OH (ppm)	B	Class
S1	37	2569	187	13.7	12	42.3	2.203	14	3
S2	49	1983	189	10.4	11	6.3	0.884	12	2
S3	12	2998	197	15.2	10	98.6	0.976	11	2
S4	33	1760	379	4.6	3	715.1	12.34	15	3
S5	6	1283	157	8.1	10	9.1	0.735	8	1
S6	29	1903	192	9.9	1	92.7	0.138	10	2
S7	35	1734	83	20.8	3	5.8	1.123	13	3
S8	31	1666	159	10.4	1	15.8	0.455	12	2
S9	41	1504	192	7.8	1	13.6	0.867	11	2
S10	34	1720	152	11.3	1	587.0	3.458	16	4
S11	34	3461	219	15.8	16	55.1	0.542	12	2
S12	36	1867	194	9.6	3	192.7	4.658	14	3
S13	42	1351	183	7.3	1	186.9	3.370	13	3
S14	12	2460	155	15.8	18	64.0	0.534	11	2
S15	41	1669	126	13.2	1	185.6	1.183	14	3
S16	44	1979	117	16.9	6	177	20.20	15	3
S17	37	1808	227	7.9	4	47.5	1.675	12	2
S18	13	3644	167	21.8	9	90.0	0.873	11	2
S19	10	1319	120	10.9	0	75.0	0.124	9	1
S20	12	762	114	24.22	5	520	15.6	14	3
S21	15	1819	129	14.1	6	155.2	1.806	13	3
S22	14	3160	292	10.8	8	32.9	0.304	11	2
S23	14	2650	192	13.8	6	63.5	0.422	11	2
S24	14	3797	496	7.6	22	7.8	0.897	10	2
S25	4	2311	442	5.2	4	4.5	0.238	9	1
S26	25	3351	300	11.1	4	286.9	1.020	14	3
S27	13	1761	244	7.21	19	244	13.24	13	3
S28	15	2247	264	8.5	133	270.9	2.501	13	3
S29	14	2274	450	5.05	12	21.1	0.100	9	1
S30	6	2752	92	29.91	1	1391	20.16	15	3
S31	42	4778	1062	4.5	34	47.5	0.306	12	2
S32	42	7310	1128	6.5	64	120.5	1.090	14	3
S33	5	1261	139	9.0	4	23.6	0.603	8	1
S34	15	1752	235	11.71	5	222.2	10.108	14	3
S35	25	4778	457	10.4	0	519.1	1.846	15	3
S36	12	1296	255	5.08	2	305.3	13.83	12	2
S37	36	1335	110	12.1	5	24.4	0.768	11	2
S38	12	2131	220	9.7	2	450	16.6	13	3
S39	43	3144	400	7.8	9	1447	2.030	16	4
S40	23	1812	151	12	3	9.9	0.273	12	2

Then, to evaluate the algorithm and classification method, five transformers were randomly selected from the fleet, and evaluation indices were measured according to [8,15,20]. Samples of insulation paper from selected transformers were taken according to [10] and Figure 2. Then the DP of the paper samples was measured directly according to IEC 60450 standard. The value of parameter **B** was calculated, and the class of the transformers was determined. Table 4 illustrates the results.

For sample 5, the 2-FAL content (587 ppb) and the methanol content (3.458 ppm) were unusual, and the ratio of carbon oxides according to IEC 60599 was unreliable. High amounts of both furan and methanol and the DP value showed accelerated paper aging.

Sample 4 had almost the same conditions as Sample 5 for concentrations of methanol, hydrogen, and carbon oxides, but its furan compound concentration was lower. Its DP value also indicated that the solid insulation of this transformer was in the early stages of degradation.

Table 4. Details of dissolved gases, furan concentrations, methanol in oil samples, DP of the paper samples, value of parameter **B,** and the class of each transformer.

Sample	Age (year)	CO_2 (ppm)	CO (ppm)	CO_2/CO	H_2 (ppm)	2-Fal (ppb)	CH_3OH (ppm)	DP	B	Class
1	41	1669	126	13.2	1	185.6	1.183	800	14	3
2	49	1983	189	10.4	11	6.3	0.884	800	12	2
3	4	2311	442	5.2	4	4.5	0.238	800	9	1
4	42	1351	183	7.3	1	186.9	3.370	740	13	3
5	34	1720	152	11.3	1	587.0	3.458	338	16	4

For Sample 2, the amount of furan and methanol are acceptable, the ratio of carbon oxides according to IEC 60599 was unreliable, and the DP value was good. The values showed normal aging without any electrical and thermal stress even though this transformer was old. In Sample 1, the amount of furan and methanol indicated that this transformer is probably in the early stages of insulation degradation but it was in better condition than sample 4. The ratio of carbon oxides was unreliable, and the DP value is good. Sample 3, showed that this transformer was aging normally and was in better condition than the others.

Based on the measurements of these 5 transformers, an improved method and algorithm for classifying transformers should place more importance on the furan and methanol indices. Therefore, furan and methanol concentrations are recommended as complementary diagnostic tools. For this purpose, the artificial neural network was used to improve the proposed method and algorithm and increase the classification accuracy in this paper.

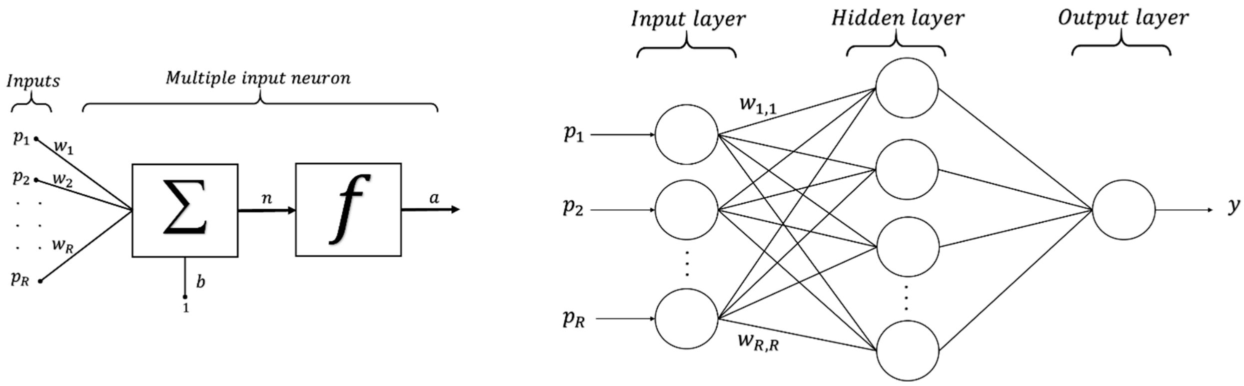
4. Intelligent Neural and Simulation Results

4.1. Description of Artificial Neural Networks

Artificial Neural Networks (ANNs) are outstanding tools for creating generalizable models in many disciplines. In this study, a multilayer perceptron (MLP), one of the most popular neural networks, was used to model and generalize the classification results for the whole transformer fleet of the power utility. The basic principle of an MLP is that applying a supervised training method to a few data samples with known outputs and then producing a nonlinear function model makes it possible to predict output data from new input data.

The MLP used in this study consisted of neurons with multiple inputs, the structure of which is shown in Figure 5a. Each of inputs: $\mathbf{p}_1, \mathbf{p}_2, \mathbf{p}_3, \ldots, \mathbf{p_R}$ is multiplied by weights ($\mathbf{w}_1, \mathbf{w}_2, \ldots, \mathbf{w_R}$) and added together. Finally, a constant value b is added to form n, which can be described as

$$\mathbf{n} = \mathbf{w}_1\mathbf{p}_1 + \mathbf{w}_2\mathbf{p}_2 + \ldots + \mathbf{w_R}\mathbf{p_R} + \mathbf{b} \quad (7)$$



(**a**) (**b**)

Figure 5. (**a**) A multiple input neuron; (**b**) Schematic diagram of the Multilayer Perceptron (MLP) neural network.

The above equation can be written in matrix form as

$$\mathbf{n} = \mathbf{W}\mathbf{p} + \mathbf{b} \tag{8}$$

The output of a multiple-input neuron can be written as

$$a = \mathrm{f}(\mathbf{W}\mathbf{p} + \mathbf{b}) \tag{9}$$

These multiple-input neurons stack together to produce multiple layers that operate in parallel. Finally, these layers are cascaded together to form a fully connected MLP network as depicted in Figure 5b, which was the structure used in this study.

This structure consisted of three layers: input, hidden, and output. Each layer consisted of several neurons: Vector $\mathbf{p}$ represented the network input; vector $\mathbf{w}$ the weight of the inputs; and vector $\mathbf{y}$ the output of the network output. Essentially, the input data were fed into the MLP through the input layer, and these data were passed to the hidden neurons via hidden weight connections. The hidden neurons performed some calculations and passed the computed output to the output layer through the output weight connections. Further computations were carried out at the output neurons, and results were presented.

4.2. Practice and Simulations

To increase the accuracy and efficiency of the proposed method for classifying transformers by insulation condition, a three-layer MLP neural network with 7 neurons for the input layer (for 7 evaluation indices) and one output neuron was designed. According to Table 4, the values of age, CO_2, CO, CO_2/CO, H_2, 2-Fal, and CH_3OH were considered as neural network inputs, and the transformer classification was the output. For th input layers, the Tansig function was used, and the Purelin function was use for the output layer. The Levenberg–Marquardt algorithm was used for training and estimating weights. Mean squared error (MSE) was selected as a training performance evaluation as described by the following equation

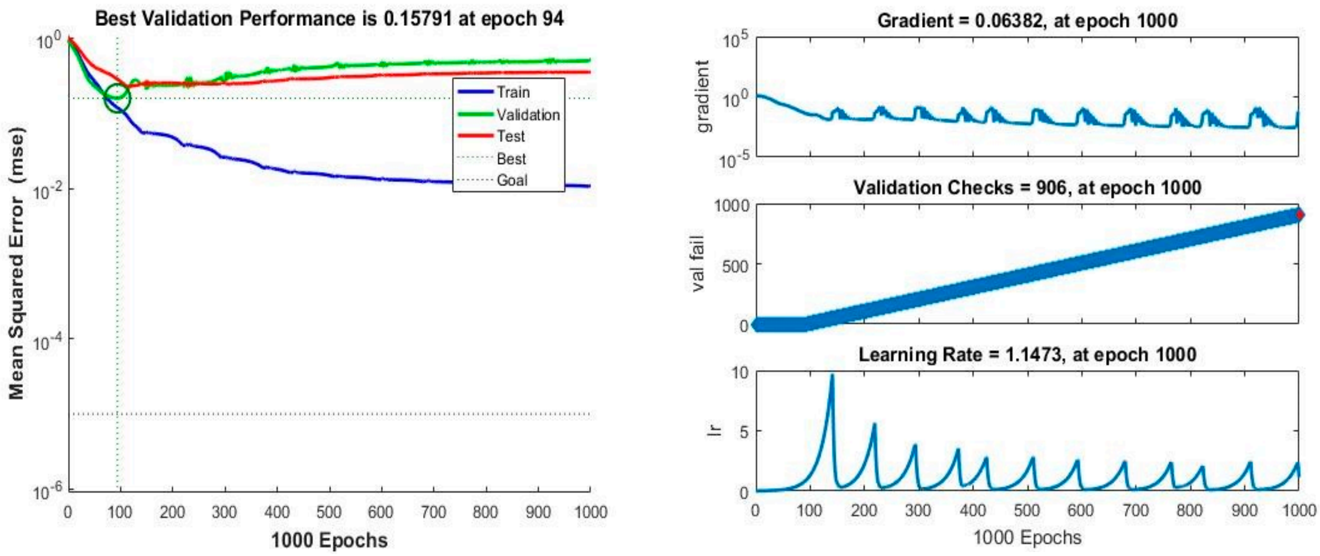
$$\mathrm{MSE} = \frac{1}{\mathbf{n}} \sum_{\mathbf{i}=1}^{\mathbf{n}} \left(\mathbf{y_i} - \hat{\mathbf{y}}_\mathbf{i} \right)^2 \tag{10}$$

where $\mathbf{n}$ is the total number of inputs; $\mathbf{i}$ is the index of summation; $\mathbf{y_i}$ is the desired (target) output from the output layer; and $\hat{\mathbf{y}}_\mathbf{i}$ is the actual output.

Seventy percent of the available data, corresponding to the measurement results of the 40 transformers, was randomly selected and used to train the neural network to determine the values of the input weights. Of the available data corresponding to 4 transformers, 10 percent was applied to the neural network for validation purposes. The remaining 20 percent, corresponding to another 8 transformers, was used as test data. To reduce network error, the data were normalized, and the training was repeated for 1000 epochs. Figure 6a shows the progress of the network error in terms of training and data.

According to Figure 6a, epochs greater than 94 reduced the training error, but at the same time caused incorrect estimates of coefficients and weights of input data; consequently, they increased validation and test performance. According to the results, the best validation performance was obtained at the 94th iteration, in which the validation performance was equal to 0.15791, and the training data and test data errors were close to zero. Figure 6b shows the training state.

Table 5 shows the performance results of the network in analyzing the measurement results of the sampled oils. Each sample, based on its corresponding oil analysis result, fell into one of the four categories, described in Table 5 (class column). The columns representing the learning and training results are associated with the samples used for training and testing the network. With 10 testing samples and 32 training samples, the network showed an accuracy of 75%. Given the limited number of samples for training and testing the network, the results seemed to have appropriate accuracy. However, by increasing the number of samples, this error will be very close to zero.



(**a**) (**b**)

Figure 6. (**a**) Network Learning Error; (**b**) Progress of the training state.

Table 5. Performance results of the network in analyzing the measurement results of the sampled oils.

Sample	Class	Learning Results	Test Results	True/False
S1	3	3	-	T
S2	2	3	-	F
S3	2	2	-	T
S4	3	3	-	T
S5	1	2	-	F
S6	2	2	-	T
S7	3	3	-	T
S8	2	2	-	T
S9	2	2	-	T
S10	4	4	-	T
S11	2	1	-	F
S12	3	3	-	T
S13	3	3	-	T
S14	2	2	-	T
S15	3	3	-	T
S16	3	3	-	T
S17	2	2	-	T
S18	2	1	-	F
S19	1	1	-	T
S20	3	4	-	F
S21	3	3	-	T
S22	2	3	-	F
S23	2	2	-	T
S24	2	2	-	T
S25	1	1	-	T
S26	3	3	-	T
S27	3	2	-	F
S28	3	3	-	T
S29	1	1	-	T
S30	3	3	-	T
S31	2	2	-	T
S32	3	3	-	T
S33	1	-	1	T
S34	3	-	4	F

Table 5. *Cont.*

Sample	Class	Learning Results	Test Results	True/False
S35	3	-	3	T
S36	2	-	2	T
S37	2	-	2	T
S38	3	-	3	T
S39	4	-	3	F
S40	2	-	2	T

5. Conclusions

In this study, an improved model for assessing the solid insulation of transformers was developed based on a weighted combination of chemical indicators. A service-aged transformer fleet from an Iranian electric utility was considered as case study. Methanol, carbon oxides, 2-FAL, and hydrogen were four high-potential chemical indicators used to detect solid insulation degradation to categorize transformers into four groups. The classification was tailor-made to the specific maintenance and planning strategies of the utility. A neural network model was developed to provide it with a reliable assessment tool for assessing the condition of transformers by the degradation of their solid insulation. The results proved that the assessment model helped the utility improve the diagnostic value of the chemical indicators and avoid catastrophic failure from aged transformers. However, by extending the transformer fleet and adding more samples to the database, more accurate and reliable results are expected. This study could be helpful for researchers and utility engineers to monitor solid insulation degradation and improve risk assessment.

Author Contributions: Conceptualization, V.B., R.E., M.P.; investigation, V.B., R.E., M.P., R.N.; software; R.E., M.P.; validation; V.B., R.E., M.P., R.N.; writing—original draft preparation, R.E., M.P.; writing— review and editing, V.B., U.M.R., I.F. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Not applicable.

Acknowledgments: The authors would like to acknowledge the Iran Electric Power Distribution Company for supplying this research data.

Conflicts of Interest: The authors declare no conflict of interest.

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