Improvement of technical diagnostic methods of transformers

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Abstract

In this study technical diagnostic tests and economical lifetime assessment of transformers are investigated to evaluate the overall health condition of working transformers. Two artificial intelligence models including artificial neural network and adaptive neuro-fuzzy inference system models are presented to determine the health index for transformers. The technical and economical parameters are used as input parameters to develop the models. Technical parameters are extracted from oil characteristics and dissolved gas analysis of different transformers. Economical parameters are constructed with transformer capital investments, maintenance and operating costs. The models are developed using 226 experimental field datasets of transformers technical and economical parameters. The models are trained using 80% of the experimental datasets. The remaining 20% is used to evaluate the performance and applicability of the models. The results prove that the models can be used to determine the health condition of transformers with high accuracy.

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1 Introduction

Power transformer is one of the most critical assets in electricity networks. Comprehensive condition assessment of transformers should be developed to achieve sustainable reliability of power system. The overall condition of a transformer should be evaluated in a comprehensive method considering technical and economical parameters. It should be noted that most utilities operators are highly motivated to assess the overall condition of transformers because there is an increasing demand for improved economical and technical performance. To achieve the optimal balance among capital investments, asset maintenance costs, and operating performance, there is a need to provide economic and technical evaluation for engineering decisions and capital replacement plans [1-4].

Transformer condition assessment is an important issue that studied in the literature from different aspects. The frequency response analysis test as one of the sensitive tools for detecting electrical and mechanical faults inside transformers is presented in [5, 6]. Degradation of cellulosic insulation of transformer considering the formation of furan products in insulating oil and effects of oxygen and water content on transformer oil aging are studied in [7-9]. Investigation on furan compounds in transformer oil [7, 10], dissolved gas analysis (DGA) [9], transformer dielectric monitoring [11], and moisture content of oil and paper insulation [12-14] are presented in the literature. Methods for life assessment of transformers are investigated in [1, 4]. Condition assessment of power transformers, fault diagnosis of power transformers, and prediction of thermal ageing in transformer oil using artificial neural networks (ANN) are presented in [15].

Health Index (HI) is a procedure of combining complex condition information to give a single numerical value as a comparative indication of overall condition of transformer. It helps the operator to make the distinction between degradation which needs maintenance and diagnosis plans, and degradation that indicates approaching end of life. HI provides a methodology of employing existing engineering knowledge and experience to predict future performance, failure probabilities and replacement plans. Transformer HI evaluation using technical parameters are presented in [16-21], and the economical aspects of transformer operation are investigated in [22-26].

In this paper a quantitative approach is presented to calculate the HI of transformers, which combines the results of various chemical and electrical tests, and the information of operating and maintenance costs of transformers. It means that the proposed HI is calculated using the technical and economical parameters altogether.

ANN and adaptive neuro-fuzzy inference system (ANFIS) models are used to calculate transformer HI. The mature well-known ANFIS and ANN methods are used as modelling tools to calculate transformer HI with technical and economical parameters. ANN [**15**, **27**] and ANFIS [**28**, **29**] methods are used in the literature for fault diagnosis and aging of power transformers, but they have not been used for transformer HI calculation.

The models are applied on 226 experimental field datasets of transformers provided by Iran Transformer Research Institute (ITRI) and their performances are compared. The operating and loading conditions of transformers are different depending on the type of the industrial facilities they are utilised in, such as power plants, regional electricity companies, petrochemical and refinery plants, cement, steel and other industries.

Technical parameters obtained from transformer diagnostic tests include breakdown voltage (BDV), dissipation factor (DF at 90°C), *Acidity*, interfacial tension (IFT), *Water* (Water content in oil at 20°C), *%WaterPaper* (per cent Water in Paper insulation), *Furfural* (2-Furaldehyde content), and DGA factor (DGAF). Economical parameters obtained from transformer aging variables and cost functions are PE*%* [per cent of economical lifetime (EL)], and F_{AA} (aging acceleration factor). These 10 parameters are the inputs of ANN and ANFIS models, and the output parameter of the models is HI.

The main contributions of the paper are: (i) Considering the technical and economical aspects of transformer characteristics (using 10 various technical and economical parameters) at the same time to calculate an overall HI for transformers. (ii) Considering DGAF parameter instead of total dissolved combustible gas, and proposing the inclusive PE*%* parameter to provide a comprehensive economical view. (iii) Investigating on a large experimental dataset collected from different power transformers.

2 Modelling

In this section ANN and ANFIS models are presented to calculate the transformer HI value. Dataset is divided randomly into training (80% of dataset) and testing (20% of dataset) subsets which the testing dataset is used to evaluate performance of the models. The models should be trained in order that predict the HI for unseen data (testing dataset) with possible least deviation (error) from experimental field HI values.

One of the strong points of this work is use of a large experimental dataset. In this paper a diverse dataset of 226 test records of power transformers with different voltage levels and power ranges in different weather and operating conditions are used. Diagnostic tests are conducted on power transformers located in different regions of vast country of Iran with different climates in terms of temperature, humidity and atmospheric pressure. Moreover, operating and loading conditions of transformers are different depending on the type of the industrial facilities they are utilised in. Therefore, the results of the models will be accurate by using such a diverse and large dataset. The model provides the best prediction of the HI and decisivelycan be referred as a reliable model trained by the diverse dataset. ANN and ANFIS methods are data driven tools and their parameters and weight matrices are adjusted using input/output data.

2.1 ANN model

ANN is an artificial intelligence method that its idea is inspired by biological structure of the human brain. Each kind of data with complicated relations can be modelled via ANN which can operate like a black box model that requires no detailed information about the investigated system [**15**, **30**].

ANN is an efficient model that assesses transformer health condition by learning the relationships between inputs (transformer technical and economical parameters) and output (HI) based on training data.

To apply the technique, a three-layer (one hidden layer) feed-forward neural network trained with the Levenberge–Marquardt (LM) back-propagation (BP) algorithm is employed. From a practical perspective, it has been

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shown through extensive experiments that single-hidden-layer neural networks are superior to networks with more than one hidden layer with the same level of complexity and also the latter are more susceptible to fall into poor local minima. In engineering applications, there is a clear tendency toward using neural networks with only one hidden layer [**30**].

2.2 ANFIS model

ANFIS is an adaptive network, consisting of a number of nodes connected through directional links, which uses neural network learning algorithms and fuzzy reasoning to map inputs into an output. The ANFIS is a strong tool for the prediction and simulation of complex non-linear systems. The hybrid neuro-fuzzy approach works by applying neural learning rules to identify and tune automatically the membership function parameters [**31**]. The ANFIS structure consists of five layers (fuzzy layer, product layer, normalised layer, defuzzify layer, and total output layer) is shown in Fig. **2**.

Schematic diagram of the ANFIS structure

In this work, the ANFIS model is developed on the basis of the subtractive clustering algorithm with eight inputs and one output. The subtractive clustering method partitions the data into groups called clusters, and generates a fuzzy inference system with the minimum number of rules required to distinguish the fuzzy qualities associated with each of the clusters. The advantage of the subtractive clustering algorithm is the fact that the number of clusters does not need to be specified in advance and the algorithm itself determines the number of clusters. In this method, the total number of fuzzy rules is only related to the number of clusters. Hence, it will be a correct choice to use this algorithm for solving the problems with the large number of input dimension.

ANFIS applies a hybrid learning algorithm which is a combination of least-squares and BP gradient descent methods, in order to train the network according to input–output data pairs. In the hybrid learning algorithm the gradient descent method is used to assign the premise parameters in layer 1, whereas the least-squares method is employed to identify consequent parameters in layer 4. The hybrid learning procedure is an efficient method to obtain the optimal premise parameters and consequent parameters in the learning process [**31**].

3 Input parameters for the models

The technical and economical input parameters of the models used to calculate the output of the models (HI value), are BDV, DF, *Acidity*, IFT, *Water*, *%WaterPaper*, *Furfural*, DGAF, PE*%*, and F_{AA}. The experimental field HI values provided by transformer experts at ITRI are used as the output for the presented models.

3.1 Breakdown voltage

BDV is a measure of the ability of the insulating oil to withstand electric stress and has primary importance for the safe operation of electrical equipment. Dry and clean oil exhibits an inherently high breakdown voltage. Free water and solid particles, the latter particularly in combination with high levels of dissolved water, tend to migrate to regions of high electric stress and reduce breakdown voltage dramatically. A low value of breakdown voltage can indicate that one or more of these are present. However, a high breakdown voltage does not necessarily indicate the absence of all contaminants [**32**-**35**].

3.2 Dissipation factor at 90°C

DF is a measure for dielectric losses within the oil. This parameter is very sensitive to the presence of soluble polar contaminants, ageing products or colloids in the oil. Changes in the levels of the contaminants can be monitored by measurement of this parameter even when contamination is so slight as to be near the limit of chemical detection. High values of DF may deleteriously affect the dielectric losses and/or the insulation resistance of the electrical equipment. Useful additional information can be obtained by measuring DF at both ambient temperature and a higher temperature such as 90°C [32-35].

3.3 Acidity

The acidity (neutralisation value) of oil is a measure of the acidic constituents or contaminants in the oil. The acidity of used oil is due to the formation of acidic oxidation products. Acids and other oxidation products will, in conjunction with water and solid contaminants, affect the dielectric and other properties of the oil. Acids have an impact on the degradation of cellulosic materials and may also be responsible for the corrosion of metal parts in a transformer. The acidity increment rate of the oil in service is a good indicator of the ageing rate. The acidity level is used as a general guide for determining when the oil should be replaced or reclaimed [32-35].

3.4 Interfacial tension

The IFT between oil and water provides a means of detecting soluble polar contaminants and products of degradation. This characteristic changes fairly rapidly during the initial stages of ageing but levels off when deterioration is still moderate. With overloaded transformers, the deterioration of materials is rapid and IFT is a tool for detection of deterioration [32-35].

3.5 Water content in oil at 20°C (Water)

Depending on the amount of water, the temperature of the insulating system and the status of the oil, the water content of insulating oils influences the breakdown voltage of the oil, the solid insulation, and the ageing tendency of the liquid and solid insulation. There are two main sources of water increase in transformer insulation: ingress of moisture from the atmosphere; and degradation of insulation.

For the proper interpretation of moisture content and for trending purposes, the analytical result of water content in the oil given at a sample temperature needs to be corrected to that at a defined temperature. For practical reasons, the defined temperature is set at 20°C, since below 20°C the rate of diffusion of water is too slow to achieve equilibrium in operational equipment [32]. In this paper in order to make the parameters at different oil temperatures comparable, the corrected values (to 20°C) are used according to standard [32-35].

3.6 Per cent water in paper insulation

Monitoring water content in oil is part of a set of routine tests for transformer oil. However, wet oil does not always mean a wet paper insulation. As a transformer cools down due to load reduction or shut down, water tends to return to the paper, but this process is slow. Hence, there is a water buildup in the oil, giving the impression of a wet transformer. Such variations in oil water content hardly affect water content of paper. This is not surprising because more than 99% of the water is in the solid insulation. The water in the oil could be a true indicator of the water in paper, only if the paper and oil are in thermal equilibrium, which almost is never the case in operating transformers [32-35]. In this paper the *%WaterPaper* parameter is considered as an individual parameter to monitor the insulating paper condition, because the condition of transformer solid insulation is very important factor in determination of transformer health condition.

3.7 2-Furaldehyde content (Furfural)

Furanic compounds are generated by the degradation of cellulosic materials used in the solid insulation systems of electrical equipment. Furanic compounds that are oil soluble to an appreciable degree will migrate into the insulating liquid. All of these compounds except 2-furaldehyde are not very stable under operating conditions found in transformers. These compounds apparently form and then further degrade to 2-furaldehyde over a time span of a few months. 2-furaldehyde is apparently stable for several years under the same conditions. The presence of high concentrations of furanic compounds is significant in that this may be an indication of cellulose degradation from aging or incipient fault conditions [**34**, **35**].

3.8 Dissolved gas analysis factor

In this paper the purpose of using DGA is to assess the overall health condition of the transformer, not to determine the types of faults inside the transformer. Therefore, the DGA parameters (seven dissolved gases) are combined to one inclusive DGAF [**18**] parameter. In some studies the effect of DGA parameters on transformer HI is considered using dissolved combustible gas parameter [**17**] which is the simple summation of DGA gases except CO and CO_2 and has two disadvantages. The first is that CO and CO_2 gases which have useful information about paper insulation degradation [**16**, **36**, **37**], are ignored. The second disadvantage is that the importance and weighting of different gases [**16**, **18**] is not considered.

3.9 Per cent of economical lifetime (PE%)

In this paper, the economical lifetime (EL) is calculated by life cycle cost (LCC) analysis performed in accordance to standard [**38**]. LCC analysis is an essential method of analysis in economic evaluation which structurally decides and equalises costs within overall life cycle. Life cycle costing is the process of economic analysis to assess the total cost of acquisition, ownership and disposal of a product. It can be applied to the whole life cycle of a product or to parts or combinations of different life cycle phases. The primary objective of life cycle costing is to provide input to decision making in any or all phases of a product's life cycle [**38**].

Annual equivalent cost analysis is used to model cost function in LCC analysis. In this study, the equivalent uniform annual cost (EUAC) method for a cash flow analysis during an operation period is employed [**22**, **39**, **40**].

While a transformer ages, the maintenance costs should be increased to maintain the optimal performance of transformer. Therefore, the operating and maintenance costs are considered in the economic lifetime evaluation by calculating the minimum EUAC of the transformer [**22**, **39**, **40**].

The EUAC is used to determine an EL with consideration of an interest rate on investment cost (IC) and operating cost (OC), both of which refer to the cash flow during a time period [22, 39, 40].

4 Results and discussion

The dataset includes 226 sets of technical and economical data of transformers provided by ITRI. This dataset divided randomly into training (80% of dataset) and testing (20% of dataset) subsets. Therefore, 181 sets of training data have been used for developing the models whereas the remaining 45 sets of testing data are used to evaluate and demonstrate the performance of the trained model in the HI prediction with the transformer parameters. The results of HI calculation with ANN and ANFIS models are illustrated in the following.

Performance of ANN is generally based on parameters of its architecture and setting. Appropriate designation of the initial amounts of weights and biases is very effective on the performance of the network. The BP LM training algorithm is a non-linear optimisation method which may not necessarily lead to a unique solution at each run. One of the most difficult tasks in studying ANN is finding an appropriate architecture. This task is performed via trial and error and the optimum number of neurons in hidden layer is identified. Increasing the number of the hidden layer neurons leads to improvement of the estimation ability of ANN, but when it exceeds an optimum number, the over-fitting problem may occur. It means that the network has memorised the training examples, but it has not learned to generalise for the new situations (unseen data). The way of identifying suitable architecture of ANN that is very time-consuming is the trial and error.

In this study ANN has 10 input neurons, one hidden layer containing *S* neurons and one output layer with one neuron. Therefore, the numbers of ANN modifiable parameters (weights and biases) are 12*S* + 1. Since the size of training dataset should be several times the number of modifiable parameters, the number of hidden neurons should not be high. Moreover, as a rule of thumb the number of hidden neurons should be between the size of the input layer and output layer [42]. Therefore, in this study it is not considered more than eight neurons in hidden layer. The optimal number of hidden neurons can be determined by finding the network through comparison among average calculated root mean squared error (RMSE).

In Table 1 the average and standard deviation of RMSE for testing dataset is presented for different number of hidden neurons for 100 trails.

Table 1. Comparison of average RMSE for different ANN configurations

No. of hidden neurons	Best	Worst	Average	Standard deviation
1	0.1704	0.3816	0.2311	0.0802
2	**0.1398**	**0.2076**	**0.1804**	**0.0211**
3	0.1726	0.2560	0.2112	0.0263
4	0.1622	0.3280	0.2321	0.0499
5	0.1569	0.3056	0.2324	0.0365
6	0.1634	0.2356	0.2033	0.0262
7	0.1861	0.3019	0.2200	0.0348
8	0.1748	0.3659	0.2436	0.0551

It can be concluded from Table 1 that optimal ANN configuration has two neurons in hidden layer, because it results minimum average and standard deviation of RMSE.

The weight and bias values of the optimal ANN configuration (with two hidden neurons) have been given in Table 2.

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Table 2. Weight and bias values of the optimal ANN configuration

Neuron	Hidden layer									
	Weights (w_{ij})									
	BDV	DF	*Acidity*	IFT	*Water*	*%WaterPaper*	*Furfural*	DGAF	PE%	F_{AA}
1	0.1514	−0.3776	−0.1479	−0.3690	0.2942	−0.0165	−0.0351	−0.0342	0.1259	−0.2501
2	0.4849	7.2802	−14.2057	−8.2666	−1.0531	12.9325	−2.1099	12.2466	15.5378	31.6857

In this paper the ANFIS model with subtractive clustering method and hybrid learning algorithm is developed. The premise and consequent parameters for the optimum ANFIS model are given in Tables 3 and 4.

Table 3. Premise parameters of the optimum ANFIS model

	BDV [σ_{i1},c_{i1}]	DF [σ_{i2},c_{i2}]	*Acidity* [σ_{i3},c_{i3}]	IFT [σ_{i4},c_{i4}]	*Water* [σ_{i5},c_{i5}]	*%WaterPaper* [σ_{i6},c_{i6}]	*Furfural* [σ_{i7},c_{i7}]	DGAF [σ_{i8},c_{i8}]	PE% [σ_{i9},c_{i9}]	F_{AA} [σ_{i10},c_{i10}]
rule 1	[8.96 75]	[0.173–0.0011]	[0.0517 0.0629]	[4.043 33.8]	[5.582 2.3]	[0.6889 1.908]	[0.4121 0.116]	[0.3125 0.993]	[124.1 63.16]	[0.0178–0.0056]
rule 2	[8.961 72.5]	[0.145 0.0147]	[0.0431 0.0564]	[4.056 32.8]	[5.582 5.9]	[0.6671 3.193]	[0.4413 0.184]	[0.3711 1.118]	[124.1 73.68]	[−0.0024 0.0103]

Table 4. Consequent parameters of the optimum ANFIS structure for predicting HI

	p_{i1}	p_{i2}	p_{i3}	p_{i4}	p_{i5}	p_{i6}	p_{i7}	p_{i8}	p_{i9}	p_{i10}
rule 1	0.006527	−0.3871	0.6645	0.01995	−0.03556	−0.1573	−0.5607	−1.347	0.00004034	0.4428
rule 2	0.01076	−2.698	−0.6902	0.01893	0.001488	−0.09745	−0.1325	−0.7119	−0.0001259	15.5

For example, Rule 1 is as follows:

Unlike the ANN model, the ANFIS model is robust that gives the same result in each run. The error criteria RMSE and R^2 of the HI evaluation for the presented ANN and ANFIS models with training, testing and total dataset are given in Table 5. First the models are constructed with training dataset and then HI values are evaluated with trained model, and the RMSE is calculated. The purpose of doing training with 80% of dataset and remaining 20% of dataset for testing is for verification of the performance of the models. It can be seen from Table 5 that the error values for test dataset are close to the errors for train dataset. It proves the performance and accuracy of the models confronted with unseen test dataset.

Table 5. RMSE of ANN and ANFIS models

	Error criteria	RMSE	R^2
ANN	train dataset	0.1657	0.9525
	test dataset	0.1804	0.9422
	total dataset	0.1688	0.9503
ANFIS	train dataset	0.1648	0.9529

Error criteria	RMSE	R^2
test dataset	0.1552	0.9592
total dataset	0.1629	0.9536

The low values of the RMSE and the R^2 values close to unity in Table 5 show the accuracy of the presented models to calculate the transformer HI. It can be seen from Table 5 that ANFIS method produces superior results for train, test and total dataset. This better performance can be explained by the fact that ANFIS combines the learning capabilities of neural network and reasoning capabilities of fuzzy logic. Hence it has an extended prediction capability compared with ANN and fuzzy logic.

To map the HI quantitative values into five qualitative condition categories [18, 43] to determine the overall health condition of each transformer, the HI values are normalised onto scale of 0 (completely degraded transformer) to 1 (perfect condition). Table 6 provides categories of HI values and correlates them to the failure probability and overall health condition of transformers. HI values are grouped into condition categories from 'very good' to 'very poor'.

Table 6. Transformer health condition based on the normalised HI value [18, 43]

HI	Condition	Probability of failure	Overall health condition
0.85–1	very good	low (0%)	satisfactory condition of transformer for continuous operation
0.7–0.85	good	low but slightly increasing (less than 1.6%)	normal operation together with specific monitoring
0.5–0.7	fair	rapidly increasing but lower than probability at mean age (between 1.6% and 6.9%)	increase diagnostic testing with strict overall monitoring
0.3–0.5	poor	higher than probability at mean age and increasing (between 6.9% and 14.2%)	restricted operation, increased interval sampling, and detailed diagnostics
0–0.3	very poor	very high, more than double the probability at mean age (more than 14.2%)	critical and immediate planning for emergency major refurbishment or replacement

The comparison of experimental normalised HI values provided by ITRI and those predicted by presented ANN and ANFIS models for 181 transformers of training datasets and 45 testing datasets are shown in Fig. 3. The horizontal dashed lines of Fig. 3 (which separate the HI ranges of Table 6) help to identify the health condition for each transformer of dataset (from 'very good' to 'very poor').

5 Conclusion

In this paper, two artificial intelligence models ANN and ANFIS are developed to determine a HI for transformers. The input parameters of the models are technical and economical parameters including oil characteristics and DGA related parameters and also maintenance and OCs and aging related parameters. The output parameter of the models is HI value. The proposed HI approach improves the quality of condition assessment of the transformer by combining results from various chemical and electrical tests, onsite inspections, and economical information regarding the transformer's maintenance and OCs.

An experimental field dataset with technical test records and economical information for 226 transformers with different voltage levels and power ranges in different weather and operating conditions is provided by ITRI. The case study demonstrates the applicability of the developed intelligent models in determining the HI of the transformers. At first each model is trained with 181 datasets and then the performance of the model is tested on other 45 sets. The results show that ANFIS model provides more accurate and robust results comparing with the ANN model. By the way, the two models can give satisfactory results, but the ANFIS model is somehow superior.

The condition of predicted HI and experimental HI for ANFIS and ANN are exactly the same for 80% of total 226 datasets. Nevertheless, the results for the remaining 20% of dataset are not away from the diagonal grids (matched points) and they are located at the border of two adjacent conditions ranges.

The developed transformer condition assessment strategies result in financial benefits with increased reliability, maximise the transformers availability, and allow the transformers to be in service beyond the expected design age.

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