Penerbit Akademia Baru

Journal of Advanced Research Design

Journal homepage: www.akademiabaru.com/ard.html
ISSN: 2289-7984

Transformer Health Index Sensitivity Analysis using Neuro-Fuzzy Modelling

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ARTICLE INFO

Article history:
Received 5 June 2017
Received in revised form 10 July 2017
Accepted 4 December 2017
Available online 16 March 2018

Keywords:
Asset management, condition monitoring, Health Index (HI), transformer tests, Particle Swarm Optimization (PSO), Self-Adaptive Neuro-Fuzzy Inference System (ANFIS)

ABSTRACT

In this paper a transformer Health Index (HI) sensitivity analysis study is presented. A HI prediction model is developed using a Self-Adaptive Neuro-Fuzzy Inference System (ANFIS). The ANFIS model is tuned using the Particle Swarm Optimizer (PSO). The utilized measurements are a combination of actual field measurements including Carbon Monoxide (CO), Acetylene (C_2H_2), Ethane (C_2H_6), Interfacial Tension (IFT) and Furans content (FFA) for 724 working transformers within a network of an industrial facility. Results show that the PSO based ANFIS model is capable of obtaining good and reliable results. The model response is tested and it is able to predict the HI numerically with high accuracy. Furthermore, it was found that the model yielded a good response in predicting HI change with respect to the change of transformer's measurement values.

1. Introduction

During the operational life, transformers are subjected to different failures due to internal and external causes. Faults diagnosis and condition assessment are a manner for adopting the maintenance strategy and enhancing the operating efficiency, while minimizing the risk of failure [1]. The modern trend in transformer condition assessment is by indexing the overall condition using Health Index (HI) tool. The health index can indicate transformer's proximity to end of life [2]. HI is a ranking tool that collects and combines a variety of data information that is related to long-term degradation of electrical equipment [3]. Probably no single test can be used for determining the overall condition of the transformer due to the complex nature of transformer insulation and the ways this insulation degrade and age in actual operation. The main requirements in determining the condition of transformer insulation in-service is a complete set of data [4].

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The reliable monitoring and condition assessment at minimum cost are some of the means to reduce the required data to assess the transformer condition. Researchers have studied the reduction in transformer tests on the HI accuracy; In [5], a study is presented to reduce transformer measurements needed for the SVM classification algorithm. Common factor analysis and minimum-Redundancy-Maximum-Relevance (mRMR) feature selection techniques are adopted to select a subset of the most significant oil characteristics. Results show an improvement in HI classification, but with a relatively high count of best-selected transformer tests. In [6], the author has presented a study in classifying HI into three groups with only CO, C_2H_2, C_2H_6, IFT and FFA measurements. The study is based on calculating HI in form of classes. The study of classes' variation and their effect on the selected measurements and the final accuracy are also investigated. The utilized HI classes have boundaries of (0-0.3) for good, (>0.3-0.7) for moderate and (>0.7-1) for bad transformers. Although this classification technique provides general insight about the transformer health condition it cannot be utilized for numerical calculation of transformer performance.

The main objective of this paper is to predict the HI in numerical form using the subset of most informative oil characteristics presented in [6]. The purpose of predicting HI in numerical form is to make the present transformer operating condition readily available for any future reliability and risk analysis. It is interesting to mention here that the numerical HI technique eliminates the need to determine both the number and the boundaries of these classes which are the main obstacles for using the HI classes based method.

Due to the complexity in determining the transformer overall health, fuzzy and Neuro-fuzzy methods are used in [2-4] and [7-10] for this purpose. Therefore, a Neuro-fuzzy interference system is adopted as a numerical predictor for HI. A supervised prediction model is developed using PSO [11-12] in combination with ANFIS. The developed model is fed with the most significant transformer measurements and predicts the corresponding HI within the best accuracy.

In our paper, actual field diagnostic tests for 724 working transformers within the distribution network of an industrial facility is utilized. The Proposed HI and the most significant measurements are calculated according to industry standards using 14 transformer measurements in a former study [6]; where the HI is graded from zero for a new transformer, to unity for a transformer at the end of its lifetime.

This paper is divided into five sections: Section II explains the data preprocessing steps. Section III analyzes the ANFIS model performance, Section IV applies the sensitivity analysis to the HI and Section V contains the conclusions.

2. Data Pre-Processing

ANFIS input data is presented by the five transformer measurements of CO, C_2H_2, C_2H_6, IFT and FFA. The output data is presented by the transformer HI calculated in [6]. The utilized database includes 724 transformer samples; these are divided into 3 unique databases by ratios of 60%, 20% and 20% for training, validation and testing of the ANFIS model respectively.

Data samples are normalized by dividing them by their corresponding service limit identified by IEEE [13-14]. Table 1 shows the service limit for each test.

3. ANFIS Model Analysis

This section discusses the simulation and the results of the ANFIS prediction model. The MATLAB fuzzy toolbox is used to construct a Sugeno model. Command genfis3 with fuzzy clustering c-means (FCM) tool are used for the partitioning data process and creation of initial membership functions. The model is trained and adapted using the PSO. A software package developed by Yarpiz

[15] is adopted and utilized for building the proposed HI prediction model. Figure 1 shows the block diagram of the proposed ANFIS predictor model.

Table 1
Tests max service limits

Test no.	Test	Max limit	Unit
1	CO	1400	ppm
2	C_2H_2	35	ppm
3	C_2H_6	150	ppm
4	IFT	25	mN/m
5	FFA	7.33	ppm

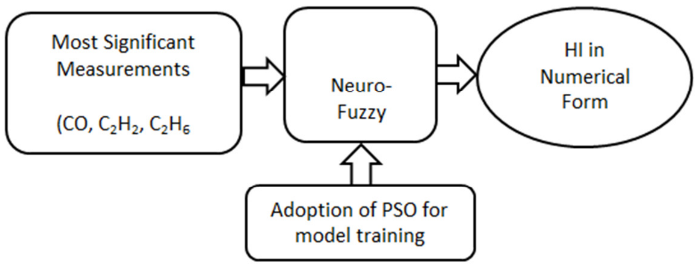

Fig. 1. Block diagram of the HI Neuro-Fuzzy predictor

Results show that the error mean is 0.000426, -0.00122 and -0.000752 for training, validation and testing respectively. Moreover, Predicted HI results show that only 5 samples have an absolute error over 0.1 and the majority of errors are close to the mean error. The prediction statistics are acceptable and can be practically utilized. Yet, the response of the model with respect to the practical measurement variation needs to be analyzed.

4. HI Sensitivity Analysis

A sensitivity analysis is used to assess the response of the model due to the change in the transformer measurements. In other words, it helps in identifying the effect of the changes in measurements on the values of the predicted HI.

Table 2 shows the test data for the discussed case studies. Case I is probably a new transformer that have a good health condition and case II is a transformer with a bad health condition.

Table 2
Sensitivity analysis case studies

Test	CO	C_2H_2	C_2H_6	IFT	FFA	HI
Case I	519.1	0	2.1	34	0.05	0.13
Case II	572.3	0	3.5	16	5.74	0.82

The model response is tested by selecting one measurement each time and change its values from zero to the service limit while keeping the remain measurements constants, i.e. in case I, fixing C_2H_2, C_2H_6, IFT and FFA values and changing CO values from zero to its service limit value in step of 10% and observing the change in HI values. By repeating this process for each measurement in both cases, Figures 2, 3, 4, 5 and 6 are generated. Table 3 shows the percent change of HI with the variation of each measurement from zero to the service limit for both cases.

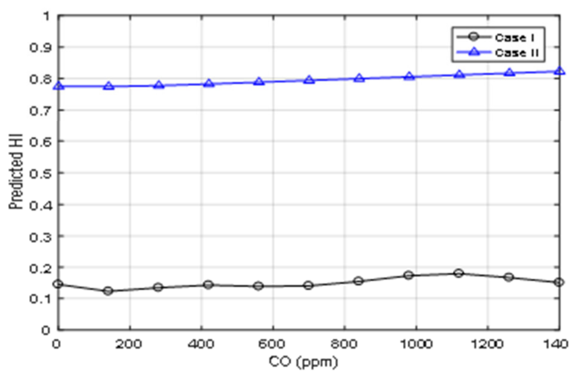

Fig. 2. Variation of HI with carbon monoxide

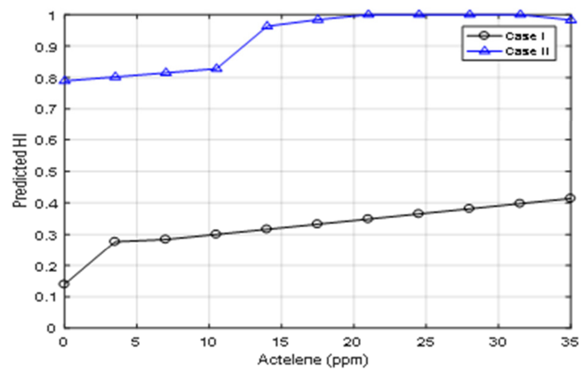

Fig. 3. Variation of HI with acetylene

Figure 2 shows the variation of HI with CO, a simple linear relationship between HI and CO can be developed. The variation of CO from zero to the service limit has low impact on the HI. From Table 3, HI is changed by 1% and 4% for the variation of CO from zero to the service limit of 1400ppm for both cases.

Figure 3 shows the variation of HI with C_2H_2, the variation in case I is linear except for the first 10%. In case II, to the variation is considered linear except for a step change from 30% to 40% of C_2H_2 values. A moderate impact on the HI is noticed when changing the value of C_2H_2 from zero to the service limit. From Table 3, HI is changed by 27% and 19% for the variation of C_2H_2 from zero to the service limit of 35ppm for both cases.

Table 2
Predicted HI values at zero and service limit for each test for cases I & II

Test		CO		HI Percent change	C_2H_2		HI Percent change %	C_2H_6		HI Percent change %	IFT		HI Percent change %	FFA		HI Percent change %
Value		0	1400		0	35		0	150		38	25		0	7.33	
HI value	Case I	0.14	0.15	1%	0.14	0.41	27%	0.14	0.23	9%	0.14	0.15	1%	0.13	0.79	66%
	Case II	0.78	0.82	4%	0.79	0.98	19%	0.79	0.91	12%	0.64	0.73	9%	0.28	0.91	63%

Figures 4 and 5 show the variation of HI with C_2H_6 and IFT measurements. HI is changed by 9% and 12% with C_2H_6, 1% and 9% with IFT in both cases respectively. It is noticed that the bad transformer in case II is highly affected by the change of both measurements over the good condition transformer in case I.

Figure 6 shows the variation of HI with FFA. HI is changed by 66% and 63% for the variation of FFA from zero to the service limit of 7.33ppm for both cases.

C_2H_2 and FFA measurements individually have the strongest relation with the transformers' health condition, any change of both will result in a large change of the HI value. Other measurements variation as CO, IFT and C_2H_6 individually has a low impact on the HI value. Practically, the change of CO will be accompanied with a change in FFA because both are results of paper insulation thermal degradation. This will tend to produce more affect the value of HI. Therefore, CO, IFT and C_2H_6 will also have an impact on the HI.

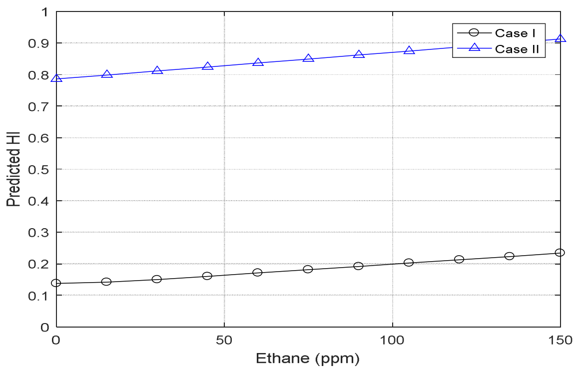

Fig. 4. Variation of HI with Ethane

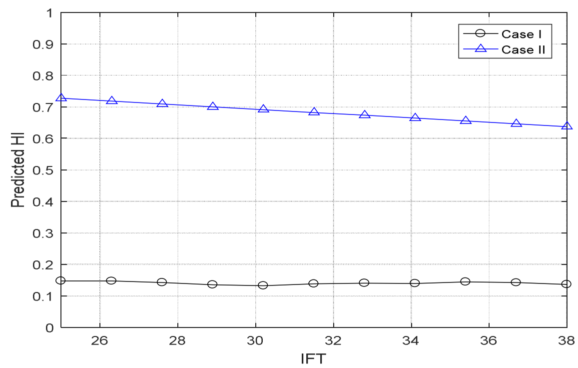

Fig. 5. Variation of HI with IFT

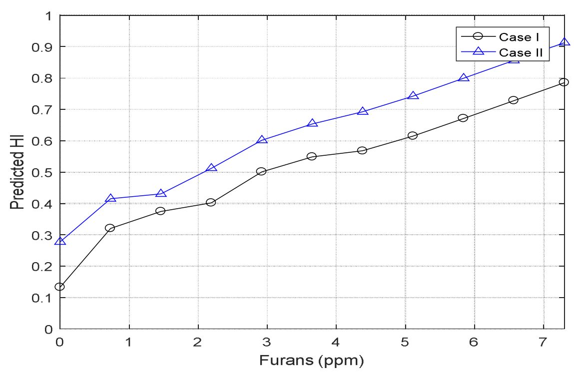

Fig. 6. Variation of HI with FFA

4. Conclusion

In this paper, A Self-Adaptive Neuro-Fuzzy Inference System is introduced for the purpose of predicting the transformer health index. The aim of this model is to predict the HI in a numerical form using the most significant measurements. This numerical HI form increases the reliability of identifying the transformer condition in order to take appropriate decisions with high confidence. Traditionally HI was defined within three subsets (good, moderate and bad). Results show that combined measurements of carbon monoxide, acetylene, ethylene, interfacial tension and furans content, are sufficient to identify transformer HI efficiently. ANFIS model response analysis demonstrates the effectiveness of the model to predict a reliable HI values with respect to the actual measurements variation. Sensitivity analysis results indicate that furans is the most important factor in transformer condition assessment followed by acetylene, ethylene, interfacial tension, and carbon monoxide respectively.

References

[1] Tang, W. H., K. Spurgeon, Q. H. Wu, and Z. J. Richardson. "An evidential reasoning approach to transformer condition assessments." *IEEE Transactions on Power Delivery* 19, no. 4 (2004): 1696-1703.

[2] Abu-Elanien, Ahmed EB, M. M. A. Salama, and M. Ibrahim. "Calculation of a health index for oil-immersed transformers rated under 69 kV using fuzzy logic." *IEEE Transactions on Power Delivery* 27, no. 4 (2012): 2029-2036.

[3] Ashkezari, Atefeh Dehghani, Hui Ma, Tapan K. Saha, and Chandima Ekanayake. "Application of fuzzy support vector machine for determining the health index of the insulation system of in-service power transformers." *IEEE Transactions on Dielectrics and Electrical Insulation* 20, no. 3 (2013): 965-973.

[4] Sharma, A. K., Anil Kori, and Nitin K. Vishwakarma. "Adaptive Neuro Fuzzy Model for Condition Assesment of Transformer."

[5] Ashkezari, Atefeh Dehghani, Hui Ma, Tapan K. Saha, and Yi Cui. "Investigation of feature selection techniques for improving efficiency of power transformer condition assessment." *IEEE Transactions on Dielectrics and Electrical Insulation* 21, no. 2 (2014): 836-844.

[6] Ibrahim, K., R. M. Sharkawy, H. K. Temraz, and M. M. A. Salama. "Selection criteria for oil transformer measurements to calculate the Health Index." *IEEE Transactions on Dielectrics and Electrical Insulation* 23, no. 6 (2016): 3397-3404.

[7] Krontiris, T., and G. Balzer. "Fuzzy and neuro-fuzzy models for condition assessment of power systems equipment." In *16th international symposium on High Voltage Engineering, paper F-4*. 2009.

[8] Kori, Anil Kumar, A. K. Sharma, and A. K. S. Bhadoriya. "Neuro Fuzzy System Based Condition Monitoring of Power Transformer." *International Journal of Computer Science* 9, no. 2 (2012): 495-499.

[9] Petersson, JO Persson KI Walldén L., and N. L. Fantana. "Condition based evaluation of net transformers-experience from a new ranking procedure." In *CIGRE Paris Conference Paper*, pp. 12-108. 2002.

[10] Arshad, Muhammad, Syed M. Islam, and A. Khaliq. "Fuzzy logic approach in power transformers management and decision making." *IEEE Transactions on Dielectrics and Electrical Insulation* 21, no. 5 (2014): 2343-2354.

[11] Eberhart, R. C., and J. Kennedy. "Particle swarm optimization, proceeding of IEEE International Conference on Neural Network." *Perth, Australia* (1995): 1942-1948.

[12] Panigrahi, Bijaya Ketan, Yuhui Shi, and Meng-Hiot Lim, eds. *Handbook of swarm intelligence: concepts, principles and applications*. Vol. 8. Springer Science & Business Media, 2011.

[13] IEEE Guide for Acceptance and Maintenance of Insulating Oil in Equipment, IEEE Standard C57. 106-2006 (Rev. IEEE Standard C57.106-2002), (2006): 1-36.

[14] IEEE Guide for the Interpretation of Gases Generated in Oil-Immersed Transformers, IEEE Std C57.104-2008 (Revision of IEEE Std C57.104-1991) ,(2009): 1-36.

[15] yarpiz,"http://yarpiz.com/319/ypfz104-evolutionary-anfis-training,"[Online].Available: http://yarpiz.com/319/ypfz104-evolutionary-anfis-training. [Accessed 25 12 2016].