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Development of Power Transformer Health Index Assessment Using Feedforward Neural Network

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ABSTRACT

The role of a power transformer is to convert the electrical power level and send it to the consumer, making it an essential component of a power system. In addition, transformer asset management is essential for monitoring the functioning of transformers in the system to prevent failure and anticipating the health state of transformers, using a technique known as the health index (HI). However, the calculation and computation to determine the transformer HI based on a scoring and ranking technique is complex and required expert validation. Therefore, this paper presents a transformer HI prediction using a feedforward neural network (FFNN) to improve the existing complex scoring and ranking technique. Levenberg–Marquardt (LM), Bayesian Regularized (BR), and Scaled Conjugate Gradient (SCG) are the FFNN training techniques presented in this study to forecast the transformer HI. To validate the techniques, the HI values generated by different FFNN techniques were compared to the scoring and ranking system. Then, the performance of the proposed ANN was evaluated using the correlation coefficient and mean square error (MSE). As a result, the transformer HI was successfully predicted by employing three FFNN techniques, namely the LM, BR, and SCG techniques, which were able to determine whether the transformer's condition is very good, good, fair, or poor. In conclusion, the ANN suggested in this study has also been validated with the ranking and scoring approach, which provides high similarity score in comparison to the transformer health index.

1. Introduction

The previous multiple failure of more than 150 power transformer connected in a radial network at a petrochemical plant in Malaysia caused an interruption in the process and affected the 24-hour operation of the plant, forcing the plant operator to invest more than an additional RM 4 million to replace the transformers [1]. This situation has shown that a comprehensive and accurate assessment of the power transformer in operation is crucial for the operation of the plant, and that a failure of this strategic unit will result in a significant loss of revenue. In general, production

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efficiency is very important, with power interruptions being a serious problem that can lead to losses, as reported in [2-4].

Technically, a high number of installed power transformers requires the asset manager to optimise or balance capital investment with maintenance costs and ensure the performance or reliability of the power transformers. In addition, the maintenance strategy based on the calculation of the health index (HI), which combines complex data and information, is currently used to help the asset manager decide which units need maintenance and diagnostic plans or units that require immediate action. More specifically, the accuracy of HI requires many parameters that can be costly, and the rules for calculating HI are derived from heuristic experiences of experts and are often difficult to translate into mathematical formulas.

In addition, the latest technology that allows accurate on-site measurement has led to the collection of more data and information, which allows for a better assessment of the condition of transformers. Therefore, in this research, a machine learning technique (ML) using an artificial neural network (ANN) is used to develop the HI computational algorithm for assessing the health of the transformer and the associated risk to the maintenance decision-making process, while reducing the reliance on expert validation practised previously.

In general, the technique of machine learning (ML) with artificial neural networks (ANN) requires input data for the learning process, the development of the correlation and the prediction of the desired output. The input data is determined using data from previous diagnostic tests, historical operation and maintenance information, inspection data and risk information related to transformer failure. The failure mode of each transformer component and its detection method are determined using Failure Mode Equipment Analysis (FMEA) or Failure Mode Effect Causes Analysis (FMECA) [5]. In addition, the FMEA/FMECA also determines the permissible limit value for each diagnostic indicator, the interval for maintenance tests and appropriate maintenance measures.

ANN is used in this study to develop a multitude decision trees and form the transformer prediction class based on the similarity pattern [6]. The accuracy of the developed ML algorithm in assessing the state and risk of the transformer population is compared with the validation data, history of failed transformers and interpretation by human experts. ML with ANN technique can be performed in several ways, namely supervised learning, reinforcement learning and unsupervised learning. For this study, supervised learning was chosen. Supervised learning can be explained in layman's terms by giving an example of an input-output pair and the network tries to match that example [7].

The Health Index (HI) is a practical tool for combining the results of multiple operational observations, field inspections, site and laboratory tests into a single objective index that quantifies the overall condition of an operating power transformer. The conventional HI assigns a score to each condition indicator. Each score on the list is then assigned a weighting to indicate its relative importance. The overall health condition is later determined by multiplying the individual weights by their respective scores and dividing the result by the sum of all weights times the maximum score per individual parameter [8-10]. The accuracy of CHI depends on the weightage chosen by the experts and is very subjective. Poorly chosen weightage can overshadow the importance of other parameters and thus underestimate potential problems.

The decision-making process based on the HI calculation for transformer population is usually based on technical parameters [11-13]. Understanding the asset risk and increasing confidence in the actual condition of the transformer enables the asset manager to maximise the return on the transformer asset by ensuring high reliability, reduce life cycle costs and optimised overall performance [14-17].

There is also a study by the expert to compare the results with numerous types of ML such as Linear, Ridge, Lasso, Random Forest, Support Vector, Deep Neural Network (Regression). In [18], the performance is compared between the different types of ML where the input for each ML is from offline data and insulation of result. Sarajcev *et al.,* use a different type of technique, namely Bayesian method, which is different from scoring and ranking [19]. The calculation of this method is understandable and is classified as a "white box" model with high interpretability [20].

Most researchers focus only on the input data from insulation oil when developing HI. For example, the technique in [21-22] developed the calculation method for HI based on specific components using the results of oil insulation. In [21], 14 data from insulation oil were used as input data for ML using an artificial neural network (ANN).

ANN also have several types to perform iteration, such as Feed Forward Neural Network (FFNN) and Recurrent Neural Network (RNN). In [23], 11 input data only from insulation oil is used to calculate ANN technique using ANN FFNN method.

Himawan *et al.,* in [24] use data from insulation oil quality and dissolved gas analysis to calculate HI by identifying the error between the calculation between scoring and ranking method and ANN. On the other hand, in [25], the use of data from the oil with FFNN was applied to the ongoing process of training data with 3 types of ANN training algorithms, namely Levenberg-Marquardt (LM), Quasi-Newtown Backpropagation (QNBP) and Scaled Conjugate Gradient (SCG). All results are compared with the scoring and ranking of HI.

Gajana *et al,* [26] use data from online monitoring such as current, voltage, oil temperature and oil level as input to the system ANN, in order to work more cost-efficiently and not shut down the transformer. The transformer status is available on the display after evaluation by ANN in the OCMS system. However, the research conducted by Wang Jian *et al.,* in [27] is more advanced as the real-time data is collected from online sensors installed in the transformer. The real-time data from various sensors and devices such as vibration sensor, partial discharge sensor, insulation oil and grounding current of the iron core provide the input for the calculation of HI. However, this approach is very costly as a large number of sensors need to be installed for online monitoring.

2. Methodology

This section explains the methodology proposed in this study to assess the condition of transformers. First, the proposed technique of ANN is described in detail based on the three training algorithms of ANN, namely LM, BR and SCG. All these 3 methods are compared with the manual calculation. Moreover, the explanation and implementation of the proposed method is limited to data and parameters of 106 transformers from a petrochemical plant, including oil quality test, DGA test and electrical parameter test.

Table 1 shows the 18 variables used as input to ANN training and as a ranking and scoring system. The following list of variables

Table 1
List of variables and associated standard of evaluation

Type of Test	Variables	Standard for evaluation
Oil Quality	Moisture	IEC 60422
	Acidity	IEC 60422
	Breakdown voltage (BDV)	IEC 60422
	Dissipation factor	IEC 60422
	Color	ASTM (C scale)
	Interfacial tension	IEC 60422
	Inhibitor content	IEC 60422
	Sludge sediment	IEC 60422
	Dibenzyl Disulphide (DBDS)	IEC 60296: 2012
	Corrosive Sulphur	IEC 62535
	Furan	I.A.R Gray (Furan)
DGA Result	Key gasses	IEC 60599
	IEEE gases limit	IEEE C57.104
	Rate of increase	
	CIGRE ratio	CIGRE guidelines
	Duval triangle	IEC 60599
Offline Data Test (2 type of result)	Insulation resistance test	IEEE C57.152
	Tan delta	

2.1 FFNN using LM Training Method

In this part, an FFNN using the training method LM was proposed to predict the HI of a transformer. The ANN consists of several layers, namely the input layer, the hidden layer and the output layer. The neural network learns the relationship between the input and the target to produce the predicted output. In ANN, the learning rate, the momentum rate and the number of hidden layers help to speed up the convergence of the ANN model, speed up the training process and reduce the error between the target and the predicted output. Normally, the range of learning rate and momentum rate is between 0 and 1. The LM training algorithm is one of the training techniques in the development of algorithms used for fitting problems in ANN. The algorithm has high prediction accuracy, fast convergence speed and minimum training time. It also has a larger amount of data and a smaller error. This algorithm is best suited for heuristic techniques and is known to reduce errors most accurately.

The ANN consists of a training and a testing process. In this study, the input and output parameters comprise 70% training data and 30% test data. The steps for the training process are described as follows

i. The input and output parameters of the training are identified.
ii. A selection of training data for validation and testing in the ratio of 70:30.
iii. The set of neurons for the training data.
iv. The training algorithm of LM is determined and set.
v. The ANN is run and the results are analysed and compared with the convergence result after MSE and regression (R). If the results do not converge, ANN is re-trained.
vi. The algorithm or script has been saved to determine the health index of each transformer.
vii. The process is repeated for 10 neurons, 20 neurons and 30 neurons.

Next, the testing process described below was carried out after the training process of ANN was completed.

i. The testing input and output data are identified.
ii. The saved algorithm script from the training process is loaded.
iii. The testing simulation process is executed.
iv. The convergence of the result is compared using to the MSE and R.
v. All results are saved.
vi. The result is analyzed and compared with the manual calculation.

2.2 FFNN using BR Training Method

The BR training algorithm was used to complete the model. It has high prediction accuracy, but has a slower convergence speed compared to LM. BR is lower than LM in terms of error.

The procedure for the training method using BR is explained in the following steps

i. The input and output parameters for training are identified.
ii. A selection of training data for validation and testing in the ratio of 70:30.
iii. The set of neurons for the training data
iv. The training algorithm of BR backpropagation is determined and set.
v. The ANN is run and the results are analysed and compared with the convergence result after MSE and regression (R). If the results do not converge, the ANN is re-trained.
vi. The algorithm or script has been saved to determine the health index of each transformer
vii. The process is repeated for 10 neurons, 20 neurons and 30 neurons

2.3 FFNN using SCG Training Method

Compared to the other 2 training methods, the SCG is less inaccurate in predictive accuracy and slow in convergence speed as well as training time. The SCG was combined with the line search strategy proposed by Leonard and Kramer for fast convergence.

The procedure for the training method using SGC is explained in the following steps

i. The input and output parameters of the training are identified.
ii. A selection of training data for validation and testing in the ratio of 70:30.
iii. The set of neurons for the training data
iv. The training algorithm of BR backpropagation is determined and set.
v. The ANN is run and the results are analysed and compared with the convergence result after MSE and regression (R). If the results do not converge, the ANN is re-trained.
vi. The algorithm or script has been saved to determine the health index of each transformer
vii. The process is repeated for 10 neurons, 20 neurons and 30 neurons

2.4 Scoring and Ranking Method

The scoring and ranking method or manual calculation method is a conventional technique for calculating the final HI value for power transformers. The input parameters for this method consist of laboratory analysis and on-site electrical testing. Then the results are converted into a quantitative index that indicates the general condition of the transformer. Due to the limited amount of data, only three parameters were considered in this study: Oil quality, dissolved gases in the oil and electrical test. The DGA technique was used to identify the presence of incipient faults, ageing of the insulation system and deterioration of the insulation system quality for power transformers.

In this study, seven types of gases were considered, namely hydrogen (H2), methane (CH4), ethane (C2H6), ethylene (C2H4), acetylene (C2H2), carbon monoxide (CO) and carbon dioxide (CO2). All gases were analysed using 5 assessment methods, namely the key gases, the IEE gas limit, the gas rise rate, the CIGRE ration and the Duval triangle. The results of the oil quality tests represent the quality of the oil and the variable parameters such as dielectric strength (BDV), dielectric loss factor (DDF), acidity, moisture, colour and interfacial tension of the oil (IFT), furan, corrosive sulphur and dibenzyl disulphide. First, the point value and weighting factor for each parameter were determined according to the corresponding ranges. The accuracy of the prediction was evaluated using the manual calculation according to the formula given.

$$HI_{each\_parameter} = \frac{\sum_{i=1}^{n} Si \times Wi}{\sum_{i=1}^{n} Wi} \tag{1}$$

Si = score obtain from the scoring rank
Wi = weightage for the each of elements
N = number of parameters

Table 1
Transformer variables weightage, Wi

Diagnostic Indicator, *Si*	Group	Weightage, *Wi*
Moisture	Group Oil Quality Result	7.5
Breakdown Voltage		0.6
Acidity		5.5
Interfacial Tension		5.5
Dissipation Factor		0.3
Color		0.4
DBDS		4
Corrosive Sulphur		4
Sludge Sediment		0.3
Inhibitor Content		0.4
Furan		0.4
IEEE Gas Limit	Group DGA Quality Result	0.3
Key Gasses		7.5
Rate of Gas Increase		0.2
CIGRE Ratio		0.1
Duval Triangle		0.2
Insulation Resistance	Group Offline Testing Result	1
Tan Delta		2

Table 2
Transformer weightage for each of group

Group Factor	Weightage of each Group, *Wi*	Percentage
Group of Oil Quality	4	40%
Group of DGA Quality	3	30%
Group of Offline Testing	3	30%

Table 3
Transformer HI based on ratio and percentage

Ranking	Ratio	Percentage
Normal	3.00 – 2.55	85% -100%
Moderate	2.54 - 2.13	71% - 84%
Attention	2.12 - 1.53	51% - 70%
Fail	1.52 - 0.93	31% – 50%

2.5 Overall Research Workflow

This research is divided into four main procedures. The main objective of these procedures is to obtain the transformer HI by running ANN and comparing it with scoring and ranking techniques. Then, the process continues with matching multiple neurons to obtain multiple results. The results of the transformer HI were compared to validate the proposed technique. The general flowchart of this research is shown in Figure 1.

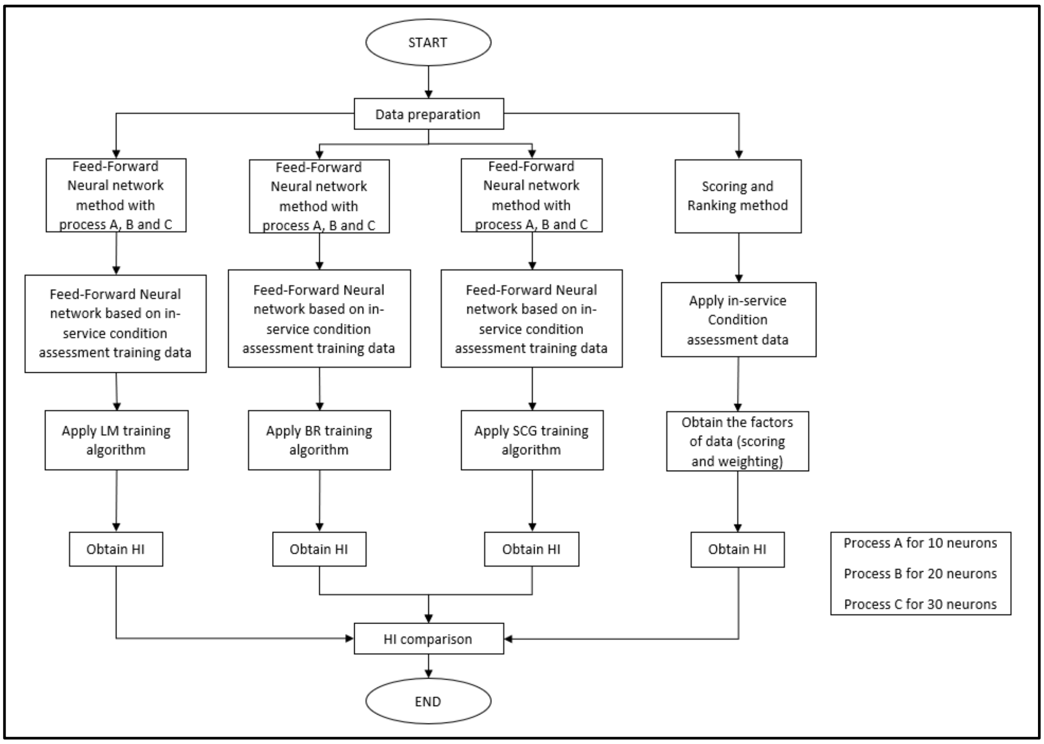

Fig. 1. Overall flowchart of the research

3. Results

In this section, all the results and findings on the prediction of transformers HI by applying FFNN with the training algorithms LM, BR and SCG were explained in detail. The results have been analysed using Mean Square Error (MSE) and Regression (R). In addition, the result of HI is compared with the training algorithm of FFNN.

3.1 Results of Transformer HI Applying LM Training Algorithm Compared With Scoring And Ranking

Table 5 shows the result of ANN using the FFNN LM training algorithm. It shows that the number of hidden layers, the number of neurons, the number of training data and the number of test data were determined by applying the empirical method to find the best results. The data consists of 106 transformer data with 75 training data and 31 test data. The epochs were 9, 13 and 10, for 10 neurons, 20 neurons and 30 neurons respectively. From the results, the values of MSE Training and MSE Testing for all 10, 20 and 30 neurons were 0.0392, 0.0192, 0.0167, 0.0398, 1.17 and 0.360 respectively. The value of R was 0.99991, 0.99988 and 0.99991 for 10, 20 and 30 for each of the selected neurons, respectively.

Table 4
Raining algorithm of ANN configuration applying FFNN-LM

Item	Model for 10NN	Model for 20NN	Model for 30NN
Number of Hidden Layer	1	1	1
Training Technique	Levenberg–Marquardt (LM)	Levenberg–Marquardt (LM)	Levenberg–Marquardt (LM)
Epoch	9	13	10
No. Of Training Data	75	75	75
No. Of Testing Data	31	31	31
MSE Training	0.03920	0.01920	0.01667
MSE Testing	0.03984	1.16585	0.35954
R	0.99991	0.99988	0.99991
Time (S)	0:00:00	0:00:00	0:00:00

The results of the FFNN LM training method were compared with the calculation of the ranking and the scoring method. Table 6 shows the comparison of 10 numbers of transformers HI prediction by using the FFNN LM training method with multiple neurons and the actual value obtained by the scoring and ranking method. Figure 2 shows the comparison for all 106 transformer data. The results show that there is a slight difference between ANN and the scoring-ranking method. Therefore, the proposed model of ANN is acceptable and can be used for predicting the transformer HI.

Table 5
HI comparison of 10 transformer for ANN-LM with scoring and ranking method

No. of transformer	Transformer health index (%)						
	Scoring method (%)	Transformer condition	LM 10 Neuron (%)	LM 20 Neuron (%)	LM 30 Neuron (%)	Transformer condition	Within ±5% Tolerance
05-PTR2-001B	99	Normal	98.40333	98.62	99.1933	Normal	√
20-PTR3-001B	56	Attention	61.37	56.01	68.14	Attention	√
17-PTR3-002B	98.333333	Normal	98.1	98.7333	82.9766	Normal	√
14-PTR3-003B	62.333333	Attention	62.32333	62.27	62.3333	Attention	√
60-PTR3-004B	94	Normal	93.45	93.8466	94.5966	Normal	√
20-PTR3-001A	64.333333	Attention	65.24	66.3866	64.98	Attention	√
21-PTR4-002A	93	Normal	93.08	93.8033	93	Normal	√
24-PTR3-001A	75	Moderate	75.28333	76.6866	75	Moderate	√
13-PTR3-004	92.666666	Normal	92.66666	92.3833	91.02	Normal	√
14-PTR3-002A	84.333333	Moderate	85.29333	84.6	82.6066	Moderate	√

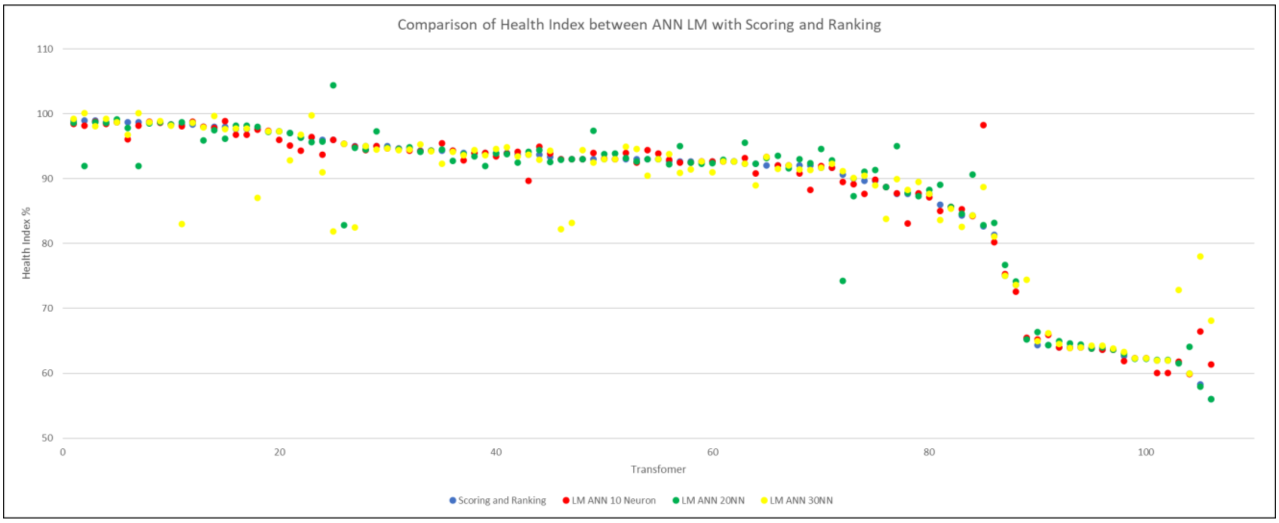

Fig. 2. Comparison of transformer HI between the proposed ANN method and scoring and ranking method

3.2 Results of Transformer HI Applying BR Training Algorithm Compared with Scoring and Ranking

Table 7 shows the result of ANN using the FFNN BR training algorithm. It shows that the number of hidden layers, the number of neurons, the number of training data and the number of test data were determined by applying the empirical method to find the best results. The data consists of 106 transformer data with 75 training data and 31 test data. The epochs were 773, 1000 and 867 for 10 neurons, 20 neurons and 30 neurons respectively. From the results, the values of MSE Training and MSE Testing for all 10, 20 and 30 neurons were 0.01955, 0.01647, 0.01752, 2.00789, 0.11123 and 1.42401 respectively. The value of R was 0.99992, 0.99999 and 0.99994 for 10, 20 and 30 for each of the selected neurons, respectively.

Table 6
Raining algorithm of ANN configuration applying FFNN-BR

Item	Model for 10NN	Model for 20NN	Model for 30NN
Number of Hidden Layer	1	1	1
Training Technique	Bayesian regularized (BR)	Bayesian regularized (BR)	Bayesian regularized (BR)
Epoch	773	1000	867
No. Of Training Data	75	75	75
No. Of Testing Data	31	31	31
MSE Training	0.01955	0.01647	0.01752
MSE Testing	2.00789	0.11123	1.42401
R	0.99992	0.99999	0.99994
Time (S)	0:00:06	0:00:22	0:00:42

The results of the FFNN BR training method were compared with the calculation of the ranking and the scoring method. Table 8 shows the comparison of 10 numbers of transformers HI prediction by using the FFNN BR training method with multiple neurons and the actual value obtained by the scoring and ranking method. Figure 3 shows the comparison for all 106 transformer data. The results show that there is a slight difference between ANN and the scoring and ranking method, which is about ±5% tolerance. Therefore, the proposed model of ANN is acceptable and can be used for predicting the transformer HI.

Table 7
HI comparison of 10 transformer for ANN-BR with scoring and ranking method

No. of transformer	Transformer health index (%) Scoring method (%)	Transformer condition	BR 10 Neuron (%)	BR 20 Neuron (%)	BR 30 Neuron (%)	Transformer condition	Within ±5% Tolerance
05-PTR2-001B	99	Normal	98.26333	98.326	98.3066	Normal	√
20-PTR3-001B	56	Attention	57.97333	57.61	57.68	Attention	√
17-PTR3-002B	98.33333	Normal	98.29	98.256	98.1266	Normal	√
14-PTR3-003B	62.33333	Attention	62.71	62.643	62.39	Attention	√
60-PTR3-004B	94	Normal	94.42	94.693	94.6533	Normal	√
20-PTR3-001A	64.33333	Attention	65.28333	65.136	64.9933	Attention	√
21-PTR4-002A	93	Normal	92.6	92.763	92.1466	Normal	√
24-PTR3-001A	75	Moderate	74.81333	75.126	75.2466	Moderate	√
13-PTR3-004	92.66666	Normal	91.99666	92.213	92.2533	Normal	√
14-PTR3-002A	84.33333	Moderate	82.78666	83.27	83.4833	Moderate	√

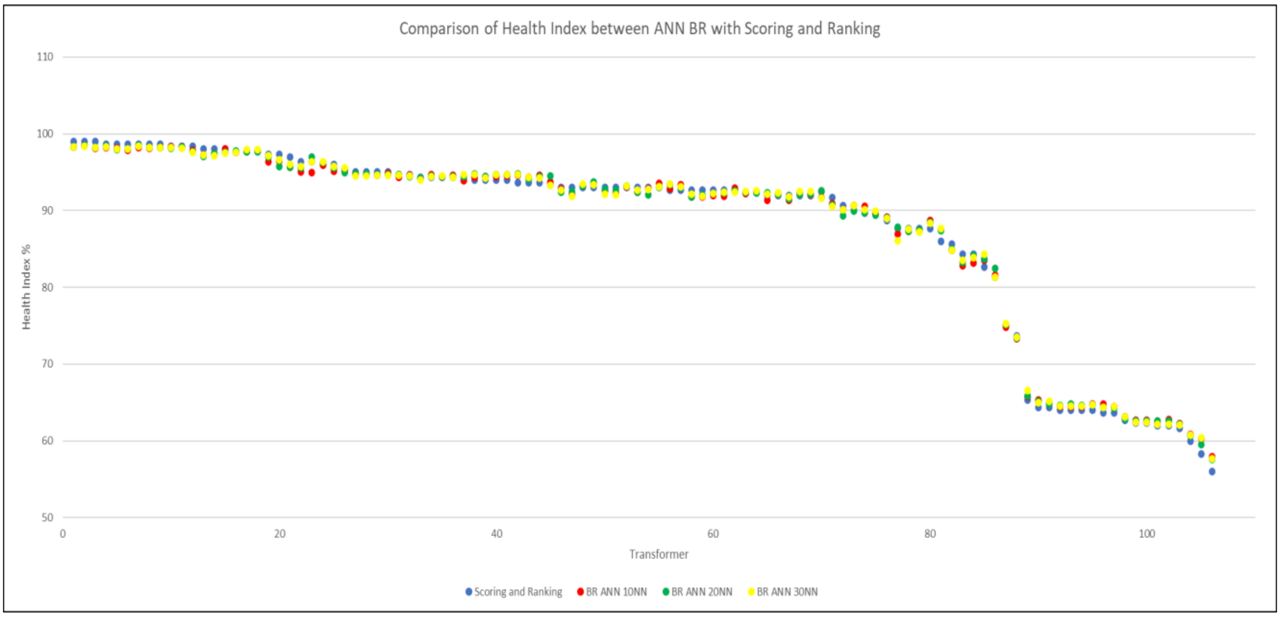

Fig. 2. Comparison of HI value between proposed FFNN-BR with scoring and ranking method for overall

3.3 Results of Transformer HI Applying SGC Training Algorithm Compared with Scoring and Ranking

Table 9 shows the result of ANN using the FFNN SCG training algorithm. It shows that the number of hidden layers, the number of neurons, the number of training data and the number of test data were determined by applying the empirical method to find the best results. The data consists of 106 transformer data with 75 training data and 31 test data. The epochs were 83, 27 and 317, for 10 neurons, 20 neurons and 30 neurons respectively. From the results, the values of MSE Training and MSE Testing for all 10, 20 and 30 neurons were 0.15123, 1.78341, 0.03030, 1.25485, 3.39140 and 7.32181 respectively. The value of R was 0.99973, 0.99893 and 0.99896 for 10, 20 and 30 for each of the selected neurons, respectively.

Table 8
Raining algorithm of ANN configuration applying FFNN-SGC

Item	Model for 10NN	Model for 20NN	Model for 30NN
Number of Hidden Layer	1	1	1
Training Technique	Scaled Conjugate Gradient (SCG)	Scaled Conjugate Gradient (SCG)	Scaled Conjugate Gradient (SCG)
Epoch	83	27	317
No. Of Training Data	75	75	75
No. Of Testing Data	31	31	31
MSE Training	0.15123	1.78341	0.03030
MSE Testing	1.25485	3.39140	7.32181
R	0.99973	0.99893	0.99896
Time (S)	0:00:00	0:00:00	0:00:00

The results of the FFNN SCG training method were compared with the calculation of the ranking and the scoring method. Table 10 shows the comparison of 10 numbers of transformers HI prediction by using the FFNN SCG training method with multiple neurons and the actual value obtained by the scoring and ranking method. Figure 4 shows the comparison for all 106 transformer data. The results show that there is a slight difference between the ANN and the scoring and ranking method, about ±5% tolerance. Therefore, the proposed model of ANN is acceptable and can be used for predicting the transformer HI.

Table 9
HI comparison of 10 transformer for ANN-SGC with scoring and ranking method

No. of transformer	Transformer health index (%)						
	Scoring method (%)	Transformer condition	SGC 10 Neuron (%)	SGC 20 Neuron (%)	SGC 30 Neuron (%)	Transformer condition	Within ±5% Tolerance
05-PTR2-001B	99	Normal	90.31333	123.85	158.34	-	×
20-PTR3-001B	56	Attention	111.19	32.123	45.3166	-	×
17-PTR3-002B	98.33333	Normal	84.87	47.666	75.1733	-	×
14-PTR3-003B	62.33333	Attention	24.81666	35.436	91.45	-	×
60-PTR3-004B	94	Normal	82.71333	72.073	76.4533	-	×
20-PTR3-001A	64.33333	Attention	115.9633	24.756	50.4533	-	×
21-PTR4-002A	93	Normal	82.70666	96.39	148.913	-	×
24-PTR3-001A	75	Moderate	67.05333	82.82	156.613	-	×
13-PTR3-004	92.66666	Normal	66.00333	80.963	-11.5366	-	×
14-PTR3-002A	84.33333	Moderate	42.69	30.896	94.6866	-	×

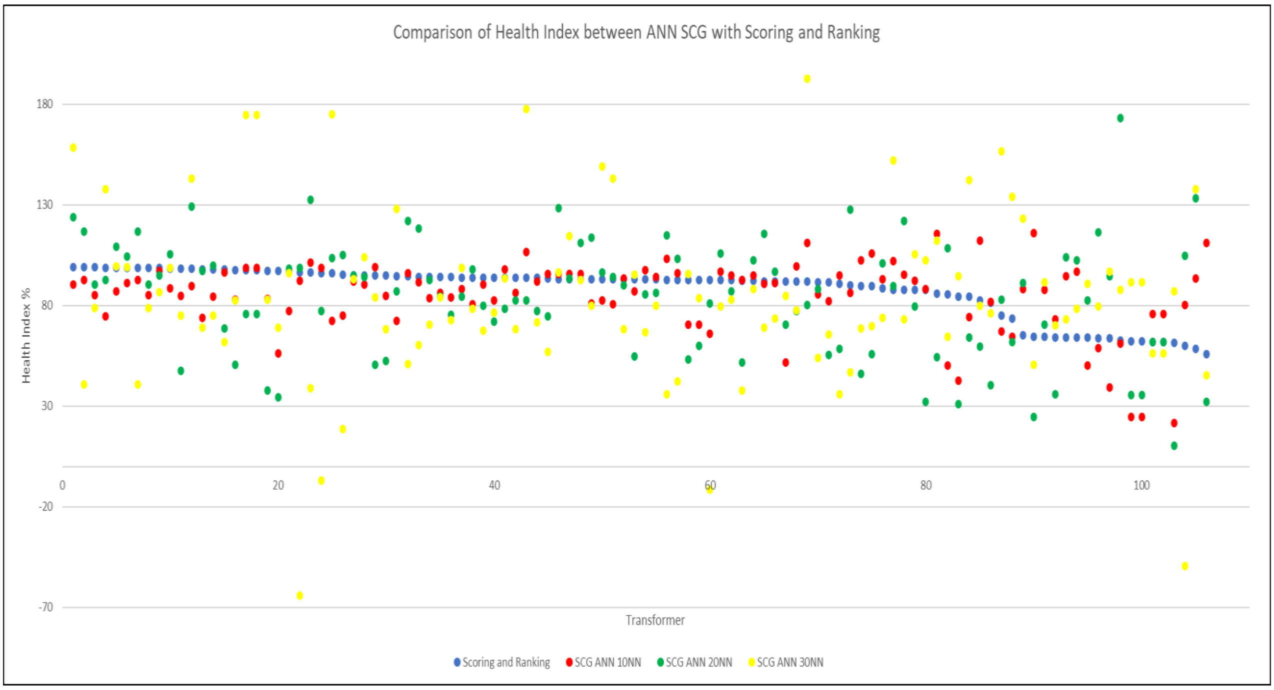

Fig. 3. Comparison of HI value between proposed FFNN-SCG with scoring and ranking method for overall

The comparison of the HI value with the score and ranking of 10 neurons for all methods (LM, BR and SCG) is shown in Figure 5. The best performance of FFNN-ANN was obtained with LM and BR, while the best neurons are 10 neurons instead of 20 or 30 neurons.

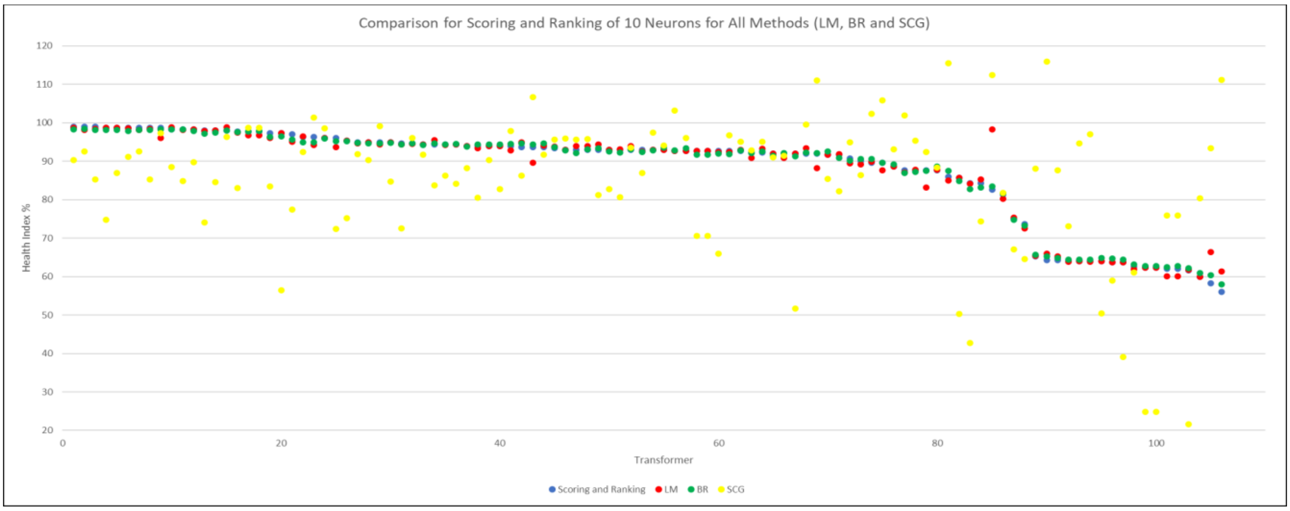

Fig. 4. Comparison of HI value with scoring and ranking of 10 neurons for all method (LM, BR and SCG)

4. Conclusions

In this paper, ANN was presented using FFNN to compute the transformer HI and reduce the error by creating multiple models of the training method by applying LM, BR and SCG with different numbers of neurons. As for the AI used, it would be a good influence to create a model that can predict the transformer HI. From the study, all the training models were successful considering the MSE and R score of the prediction. The best performance of FFNN-ANN is LM and BR, while the best neurons are 10 neurons instead of 20 or 30 neurons. Apart from this, HI can help speed up the owner's decision making when it comes to maintenance, replacement, monitoring, repair and control of the transformer during emergencies.

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