Research Article

Transformer health index prediction using feedforward neural network according to scoring and ranking method

Nur Ashida Salim[1]*, Jasronita Jasni[2], Hasmaini Mohamad[1] and Zuhaila Mat Yasin[1]

Faculty of Electrical Engineering, Universiti Teknologi MARA, Shah Alam, Selangor, Malaysia [1]
Advanced Lightning, Power & Energy Research, Faculty of Engineering, Universiti Putra Malaysia [2]

Abstract
This paper presents a transformer health index prediction applying feedforward neural network (FFNN) according to scoring and ranking method. Power transformer is an important asset of a power system where the function is to convert the level of electrical power and transfer it to the consumer. Outage in transmission line that is caused by the power transformer might lead to the interruption of power supply. Transformer asset management is vital to monitor the operation of transformers in the system to prevent failure. The technique in performing asset management of the transformer is health index (HI). Therefore, this paper presents the assessment of transformer HI by applying artificial neural network (ANN). The FFNN training algorithms proposed in this research to predict the transformer HI include Levenberg–Marquardt (LM), quasi-Newton backpropagation (QNBP), and scaled conjugate gradient (SCG). The HI values obtained from these FFNN techniques were compared to the scoring and ranking method to validate the proposed technique. The performance of the proposed ANN was assessed according to the correlation coefficient and mean square error (MSE). According to the findings obtained, the transformer HI can be successfully predicted by applying different training algorithm of ANN. LM, QNBP and SCG proposed in this research could identify whether the transformer condition is very good, good, fair or poor. The ANN proposed in this research also has been verified with the ranking and scoring method where it produces similar identification of the transformer health index. According to the HI, advance action could be initiated whether to perform upgrade, maintenance, replacement, monitoring, repair, and contingency control of the transformer.

Keywords
Feedforward neural network, Levenberg–marquardt, Quasi-newton backpropagation, Scaled conjugate gradient, Transformer health index.

1.Introduction

Power transformers have become one of the most vital assets in the energy transmission and power system. If any transformers fail to function properly, it will result in electrical supply interruptions and affect the reliability of the system. Power transformer is the most valuable and critical asset for utility companies and its condition needs to be monitored with proper assessments. Nearly 60% of the total investment is allocated for power transformers, and it becomes the highest value equipment in high-voltage substations [1]. Due to the lack of proper maintenance, many transformers fail to function and operate before they reach their rated lifetime.

Transformer life expectancy gradually decreases due to oxidation, humidity and temperature, acidity and pollution of oil insulation, seal, and deterioration of the gasket [2].

If the maintenance and assessment could not detect the presence of failure in the transformer, it may cause catastrophic failure which will affect the electric power system. As the demand on high system reliability increases, many electrical utilities have to concentrate more on the effectiveness of asset management. Performing an asset management would be the best way to overcome these problems because it could increase the reliability of the asset and reduce the main capital expenditure to either overhaul or change the assets. Asset management is known as the procedure of exploiting the return on

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*Author for correspondence

investment of equipment by providing the required level of performance and reducing cost over the life cycle of the system [3]. Health index (HI) is used to measure the findings of site and laboratory testing, field inspections, and functioning observations into a quantitative index and objective, providing the overall health of the assets. The asset HI is a powerful tool that can recognize investment requirements, prioritize investments, and organize assets into maintenance and capital programmes [4].

Generally, many techniques and assessment models have been used by researchers to perform the asset management. Pandey and Sonwane [5] presented about reliability centered maintenance (RCM) which includes many intermediate techniques such as failure mode and effect analysis (FMEA) and consequences of failure analysis (COFA). The research aims to attain cost effectiveness by monitoring maintenance routine and improving consistency. BlockSim Software was used for reliability analysis which can be a series, parallel model, or a combination of both transformers. Phadungthin and Haema in [6] used the scoring and weighting methods for transformer risk assessment. In scoring, the conditions are scored according to the planned limit. For example, the diagnostic tests for condition assessments are divided into five scorings which are 1 (very good), 2 (good), 3 (moderate), 4 (poor), and 5 (very poor). Weighting is referred as the items are weighted according to their importance. The scores and weight of each criterion are determined by specialists in the utilities. The findings for both assessments of the transformer are plotted in the risk model to achieve the proper bushing maintenance. A. Abu-Elanien et al. [7] suggested a method of finding a health condition transformer applying HI. Transformer HI was determined by a feedforward artificial neural network (FFANN) applying the actual measurement of the working transformer. In the study, FFANN was used to investigate the relationships between 11 data sets and the HI of each transformer with the support of the health indices given by the asset management health assessment (AMHA). Besides, W. Wattakapaiboon et al. presented a new improved technique of conventional HI table to evaluate the state of the transformer [8]. The scores gained from the conventional HI tables and new advanced HI tables were compared to measure the performance of the new HI tables. According to the findings, the difference (mean value of all case studies) between the advanced HI schedule and the conventional HI method was only 7%. Research paper [9] presents the

capability of a Malaysian utility company, Tenaga Nasional Berhad (TNB) in handling condition assessments and life management programmes on power transformers through a diagnostic method and calculation of transformer HI. There are three main stages called as Tier 1, Tier 2, and Tier 3. The failure mode and critical analysis (FMECA) was selected for the condition-based maintenance. For condition assessment, transformer HI is used by the power system utility to inspect the condition of the transformer and decide whether to perform upgrade, maintenance, replacement, monitoring, repair, or contingency control [10]. F. Scatiggio et al. presented a new model of periodic test evidence (dissolved gas analysis [DGA], furans, acidity, inductance, frequency dielectric spectroscopy) that combines with the koranic properties of a substation [11]. The first parameter is static depending on the koranic level (frequency of light) on the location, the substation layout, and repetition of catastrophic events on the site. The next parameter depends entirely on the transformer and must be considered dynamic. The HI of the transformer is created from the combination of two parameters. Each transformer is divided according to the HI range according to the probability of failure and degrees of strength in terms of electrical, thermal, mechanical, and oil conditions.

According to the detailed review of the subject matter, the main objective of this paper is to model an artificial neural network (ANN) to evaluate the HI of a transformer. The ANN learns by examples which is self-learning, self-studying, and self-adaption; it can be trained with known data sets for acquiring knowledge and experience [12]. The feedforward neural network (FFNN) was applied in this research, and it comprises of input, output, and hidden layers. The ANN was inspired by the biological neural network in human brain that serves as an information processing model [13]. It has a significant skill to get the meaning from complex or inaccurate data. It is used to extract the trend or pattern which is difficult to be solved by humans and computers. This study proposed three types of ANN training algorithm which are Levenberg–Marquadt (LM), quasi-Newton backpropagation (QNBP), and scaled conjugate gradient (SCG) to predict the transformer HI. These three training algorithms are the novelty of this paper where none of the previous researchers have considered. The validation of the proposed model was done by comparing the proposed method with the scoring and ranking method.

2.Material and methods

This section explains the methodology of transformer health assessment proposed in this research. First, the proposed technique of ANN is described in detail. The three ANN training algorithms which are LM, QNBP, and SCG are explained in this section. The scoring and ranking method is also explained. The explanation and implementation of the proposed method is limit to data and parameters obtained for this case study where it might differ from other types of transformer.

2.1FFNN using LM training method

In this paper, FFNN applying LM training method was proposed to predict the HI of a transformer. The neural network comprises of several layers such as input, hidden, and output layers. The neural network will learn the relationship between the input and target to produce the predicted output. In ANN, the learning rate, momentum rate, and number of hidden layer help in accelerating the convergence of ANN model, speeding up the training process, and reducing the error between the targeted and predicted outputs [14]. The proposed FFNN structure with input, hidden, and output layers is shown in *Figure 1*. This

is the system configuration that will be used throught this paper.

Normally, the range of learning rate and momentum rate is between 0 to 1. The accuracy of the prediction was evaluated according to the mean square error (MSE) and mean absolute percentage error (MAPE), which can be obtained applying Equations (1) and (2), respectively:

$$MSE = \frac{1}{N} \sum \frac{|P_Q - P_P|}{P_Q} \tag{1}$$

where,
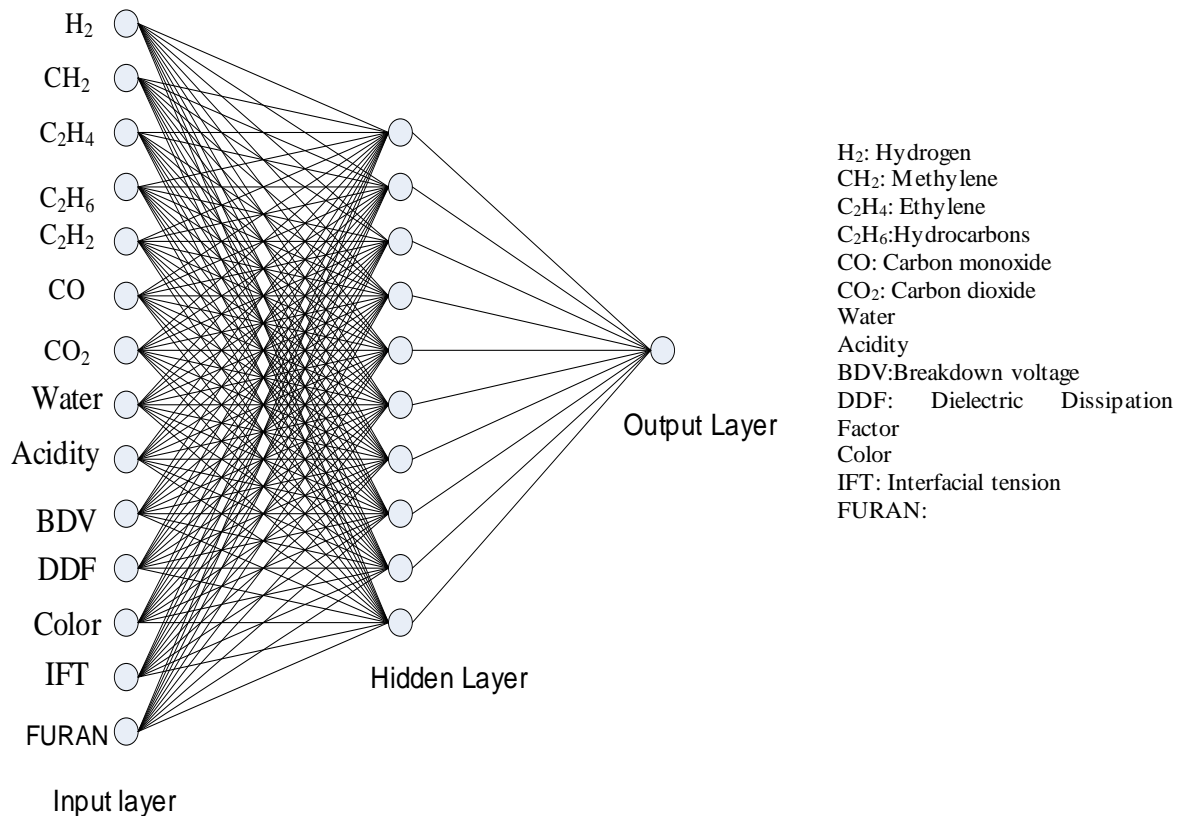N = total number of data
P_Q = target result
P_p = actual result

$$MAPE = \frac{1}{T} \sum_{i=1}^{T} \frac{|Hi.target - Hi.predict|}{Hi.target} \times 100\% \tag{2}$$

Where,
T = total number of data
$Hi.target$ = HI target result
$Hi.predict$ = HI predict result

H₂: Hydrogen
CH₂: Methylene
C₂H₄: Ethylene
C₂H₆:Hydrocarbons
CO: Carbon monoxide
CO₂: Carbon dioxide
Water
Acidity
BDV:Breakdown voltage
DDF: Dielectric Dissipation Factor
Color
IFT: Interfacial tension
FURAN:

Figure 1 Structure of proposed FFNN

The LM training algorithm is one of the algorithms used for fitting problems in ANN trainings. The algorithm has a faster convergence and fewer iterations than other training algorithms. It is also relatively stable. This algorithm is the most suitable for heuristic techniques and known as the most accurate in reducing errors [14]. This algorithm can minimize the error [15], therefore it can be obtained applying Equations (3) and (4):

$$x^* \in E^N \qquad (3)$$

Where,

$x^* =$ contained among the zeros of $\frac{1}{2}\nabla\emptyset(x) = J(x)^T F(x)$

$\nabla\emptyset(x) =$ gradient of $\emptyset$

$J(x) =$ Jacobian matrix of F

$$\emptyset(x) = \|F(x)\|_2^2 = \sum_{i-1}^{M}|fi(x)|^2 \qquad (4)$$

Where,

$F(x) =$ residual vector obtained from dataset by a nonlinear form

The ANN comprises of training and testing processes. In this study, the parameters include 70% training data and 30% testing data. The steps for the training process are described as follows:

a) The input and output parameters of the training are identified.
b) A trial and error method are implemented with the ratio of 70:30 training data.
c) The ANN configuration is designed.
d) The value of epochs, goal, learning rate, momentum rate, and hidden layer are set.
e) The training algorithm of LM backpropagation is set.
f) The ANN is executed, and the findings are analyzed and compared to the convergence result according to MSE and regression (R). If the results did not converge, the heuristic method is used, the value of training parameter is modified, and the ANN is retrained.
g) All the outputs are saved for testing process.

Next, the testing process as described below was conducted after the training process of ANN was done.

a) The testing input and output data are identified.
b) The saved network from the training process is loaded.
c) The testing simulation process is executed.
d) The convergence of the result is compared according to the MSE and R.
e) If the result still does not converge, the network is retrained and the training procedure from the previous step is repeated.
f) All results are saved.

2.2FFNN using QNBP training method

The QNBP training algorithm was used to complete the model. It has a high accuracy rate; thus, it has faster convergence speed [16]. The computation of iteration was obtained as in Equation (5) [17], where the Hessian matrix was used for the performance of the iteration. Since computing the iteration for FFNN is time consuming, the QNBP method was proposed as in Equation 5 [18]:

$$X_{k+1} = X_k - H_k^{-1}g_k \qquad (5)$$

Where,

X_k = iteration k

$H_k^{-1}g_k$ = Newton's training direction

The performance of the training process was determined according to the minimum error in MSE andMAPE that can be obtained by using Equations (1) and (2), respectively. ANN is a system that mimics the neural behavior in the human body. It contains perceptron or neuron units where its adjusted weight for predicting response is according to given input features. Creating the ANN system is comparable with the human learning process, where it should take more training before the testing process. According to the given input and desired output, the neuron or perceptron units learned by adjusting the interrelated neural weights. The learning process of FFNN determines the weight for connecting neurons with the inputs and outputs [19]. The procedure for the training applying QNBP is explained in the steps as follows:

a) The input and output parameters of the training are obtained.
b) The QNBP configuration is designed. The number of epochs, goals, momentum rate, learning rate, and number of hidden layers of the network related to the training algorithm are set.
c) Try and error method is used to get the best training parameter.
d) The results are analyzed from the FFNN-QNBP model. The result from the training and testing processes are compared according to the lowest MSE and the highest R applying Equations (1) and (2), respectively. If the results did not converge, the value of training parameter is modified and the FFNN-QNBP model is retrained.
e) The best network is saved. The HI value of FFNN-QNBP method is compared to that of the scoring and ranking method.

2.3FFNN using SCG training method

The SCG was combined with the line search strategy for fast speed convergence as proposed by Leonard and Kramer. Mostly, the training algorithms used

learning rate to update the weight and threshold. The SCG algorithm was updated automatically applying its own steps [20]. The search direction (Po) of the algorithm was started from the steepest descent direction (go), as shown in Equation (6).

$$Po = -g_o \qquad (6)$$

The weight and threshold value were obtained applying Equation (7):

$$X_{k+1} = X_k - \alpha_k + P_k \qquad (7)$$

Where,

P_o = search direction

g_o = steepest descent direction

X = weight and threshold value

α = decrease the gradient in the search direction

The procedure for the training applying the SCG is explained in the steps as follows:

a) The input and output parameters of the training are obtained.
b) The SCG configuration is designed. The number of epochs, goals, momentum rate, learning rate, and number of hidden layers of the network that related to the training algorithm are set.
c) The try and error method is used to obtain the best training parameter.
d) The results from the FFNN-SCG model are analyzed. The results between the training and testing process are compared according to the lowest MSE and the highest R applying Equations (1) and (2), respectively. If the results did not converge, the value of training parameter is modified and the FFNN-SCG model is retrained.
e) The best network is saved. The HI value of FFNN-SCG method is compared with that of the scoring and ranking method.

2.4 Scoring and ranking method

The scoring and ranking method is a conventional technique to calculate the final HI value of a power transformer [21]. The input parameter for this method comprises of the outcomes of functioning observation, field assessments, and site and laboratory testing [10]. Next, the results are transformed to a quantitative index which indicate the general state of the transformer. Due to data limitation, only three parameters were considered in this study: oil quality, dissolved gasses in oil, and furans. The DGA technique was used to identify incipient faults which may happen in transformers such as partial discharge, thermal error, and electrical damage. In this study, seven gases were considered which are hydrogen (H_2), methane (CH_4), ethane (C_2H_6), ethylene (C_2H_4), acetylene (C_2H_2), carbon monoxide (CO), and carbon dioxide (CO_2). The oil quality test results represent the quality of oil and the parameters such as dielectric strength (BDV), dielectric dissipation factor (DDF), acidity, moisture, color, and oil's interfacial tension (IFT) were included. First, the scoring and weighting factor was determined for each parameters according to the corresponding ranges in [22]. The oil quality factor (OQAF) and dissolved gas analysis factor (DGAF) can be determined by applying Equation (8).

$$DGAF\,/OQAF = \frac{\sum_{i=1}^{n}(S_i \times WF_i)}{\sum_{i=1}^{n} WF_i} \qquad (8)$$

Where S_i is the score of each parameter, WF_i is the proper weighting factor for each condition parameter, and n is the number of parameters in each factor. Next, the rating codes for DGAF, OQAF, and furans were determined according to the ranges in [23, 24] as shown in *Tables 1, 2,* and *3*, respectively. These tables indicate the standard rating codes of the three parameters mentioned.

Table 1 Transformer rating code for DGAF

Rating Code	Conditions	Description
A	Good	DGAF<1.2
B	Acceptable	1.2≤DGAF<1.5
C	Need Caution	1.5≤DGAF<2
D	Poor	2≤DGAF<3
E	Very Poor	DGAF≥3

Table 2 Transformer rating code for OQAF

Rating code	Conditions	Description
A	Good	OQAF<1.2
B	Acceptable	1.2≤OQAF<1.5
C	Need Caution	1.5≤OQAF<2
D	Poor	2≤OQAF<3
E	Very Poor	OQAF≥3

Table 3 Furfural test rating

Rating code	Furaldehyde [ppm]
A	0–0.1
B	0.1–0.25
C	0.25–0.5
D	0.5–1.0
E	more than 1.0

The rating codes (A, B, C, D, and E) for each parameter was converted to a factor between 4 and 0 [25]. Then, the final HI was obtained by applying Equation (9).

$$Final\ HI = \frac{\sum_{j=1}^{n}(K_j \times HIF_j j)}{\sum_{j=1}^{n} 4K_j} \times 100\% \qquad (9)$$

Where HIF_j is the rating code for each parameter and K_j is the weighting factor for the parameter. The condition of the transformer was determined by the value of final HI. The range is between 100% means very good condition to 0% means very poor condition. *Table 4* shows the HI and expected lifetime of the transformer [26].

Table 4 Transformer HI and expected lifetime

Final HI (%)	Condition	Expected lifetime	Requirement
86-100	Very Good	≥15 years	Regular Maintenance
71-85	Good	≥10 years	Regular Maintenance
51-70	Fair	from 3 to10 years	Increase Diagnostic Testing
31-50	Poor	≤3 years	Begin Arranging Procedure to Adjust or Reconstruct Considering Risk
0-30	Very Poor	close to the end of life	Instantly Assess Risk

2.5Overall research workflow

This research is divided into four major procedures. The main aim of these procedures is to obtain the transformer HI by applying ANN and scoring and ranking techniques. The findings of the transformer HI were compared to validate the proposed technique. The overall flowchart of this research is depicted in *Figure 2*.

3.Results & discussion

This section discusses the findings of transformer HI prediction applying FFNN with LM, QNBP, and SCG as training algorithms. The findings were analyzed according to the MSE, R, and MAPE. This section also explains the findings of transformer HI applying the scoring and ranking method.

3.1Results of transformer HI applying LM training algorithm

Table 5 shows the configuration of ANN with LM training algorithm. The number of hidden layers, momentum rate, and learning rate were set applying the heuristic method to find the best findings. The

data consist of 160 transformer data with 112 training data and 48 testing data. The epoch and goal were set to 800 and 1×10^{-15}, respectively. From the findings, the values of MSE training and MSE testing were 1.5207 and 8.4705, respectively. The values of MAPE were 0.000844% and less than 10% for accurate prediction. The value of R was 0.99717.

The findings of predicted transformer HI applying LM training algorithm were compared to the calculation of ranking and scoring method. *Table 6* shows the comparison of 20 transformers HI predicted applying the proposed method and the actual value obtained applying the scoring and ranking method. *Figure 3* shows the comparison for all 160-transformer data. According to the findings, there was a slight difference between the ANN and the scoring and ranking method. Therefore, the proposed model of ANN is acceptable and can be used to predict the transformer HI.
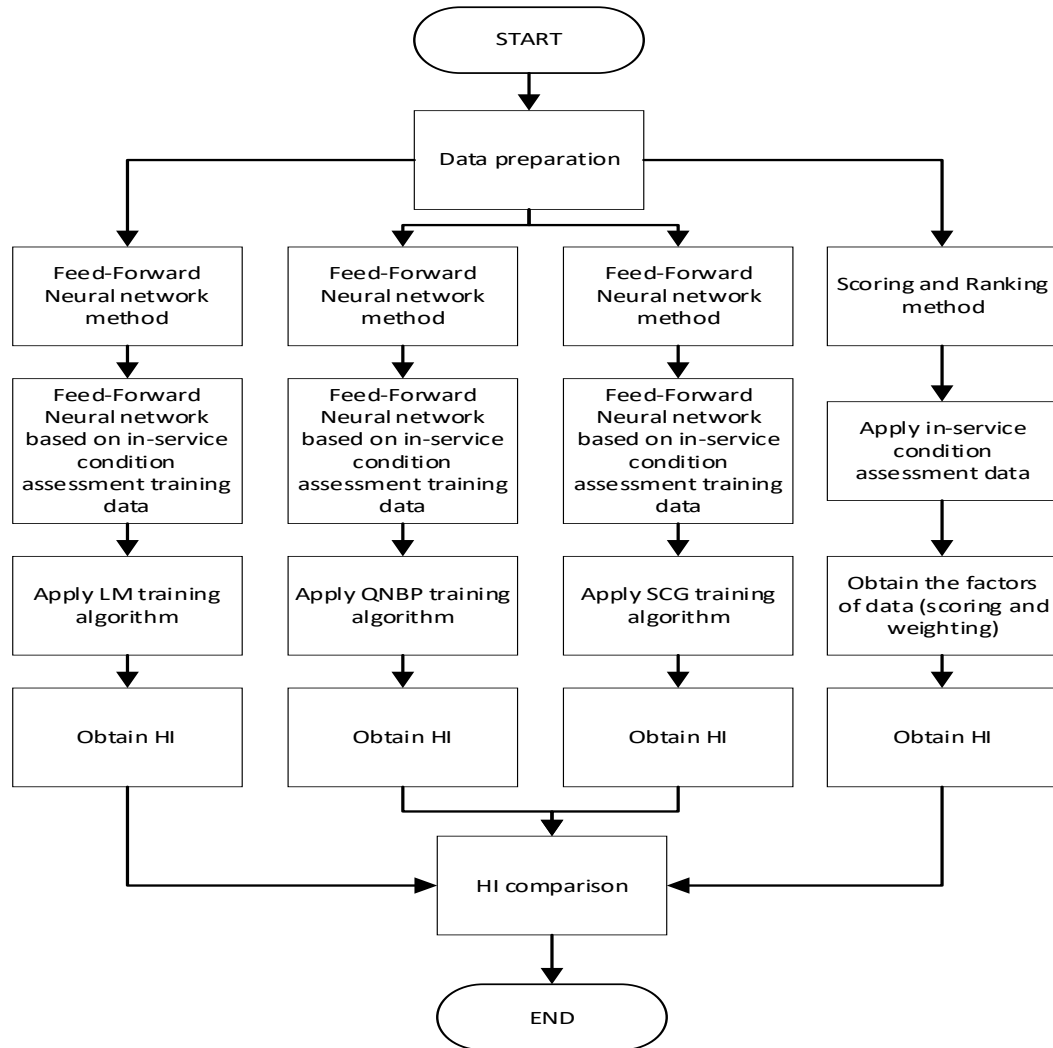
Figure 2 Overall flowchart of the research

Table 5 Raining algorithm of ANN configuration applying LM

Item	Model
Network Configuration	'Logsig', 'Purelin'
Learning Rate	0.2
Momentum Rate	0.5
Number of Hidden Layer	1
Training Technique	Levenberg–Marquadt (LM)
Training Goal	1×10^{-15}
Epoch	800
No. Of Training Data	112
No. Of Testing Data	48
MSE Training	1.5207
MSE Testing	8.4705
Mean Absolute Percentage Error (MAPE)	0.000844%
R	0.99717
Time (S)	0:00:00

Table 6 HI for ANN and scoring method

No. of transformer	Transformer health index (%)			
	Scoring method	Transformer condition	FFNN- LM method	Transformer condition
1	21.42857	Very Poor	20.65126	Very Poor
2	33.33333	Poor	33.34193	Poor
3	88.09524	Very Good	91.94967	Very Good
4	73.80952	Good	72.45868	Good
5	76.19048	Good	76.03481	Good
6	25.0000	Very Poor	25.01865	Very Poor
7	88.09524	Very Good	91.94967	Very Good
8	76.19048	Good	76.03481	Good
9	63.09524	Fair	64.16702	Fair
10	88.09524	Very Good	82.9665	Very Good
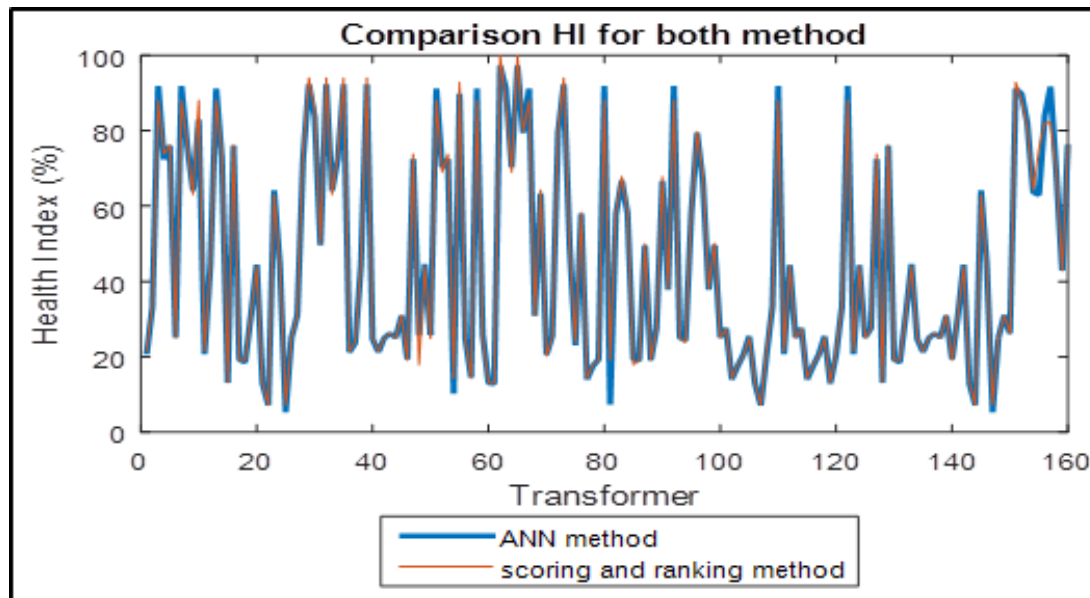
Figure 3 Comparison of transformer HI between the proposed ANN method and scoring and ranking method

3.2 Results of transformer HI applying QNBP training algorithm

Table 7 shows the configuration of the QNBP training algorithm. The training parameter was varied applying the heuristic method to obtain the best parameter. The total data of 160 transformer data were used and divided by the training-to-testing data ratio of 70:30. The learning rate, momentum rate, and hidden neuron were varied until a good value of MSE, R, and MAPE were obtained. The training goal and epochs were set to 0.001 and 5000, respectively. The time taken for the FFNN model according to QNBP method was 26 s. *Table 8* shows the

comparison of HI value between QNBP method and the scoring and ranking method for 10 transformers. The value of predicted HI was slightly different from the HI value of the scoring and ranking method.

Figure 4 shows the comparison of the HI value of 160 data between the FFNN method and the scoring and ranking method. The findings of the proposed model prediction were almost exactly similar to those of the scoring and ranking method. Thus, the model was validated, and it is accepted.
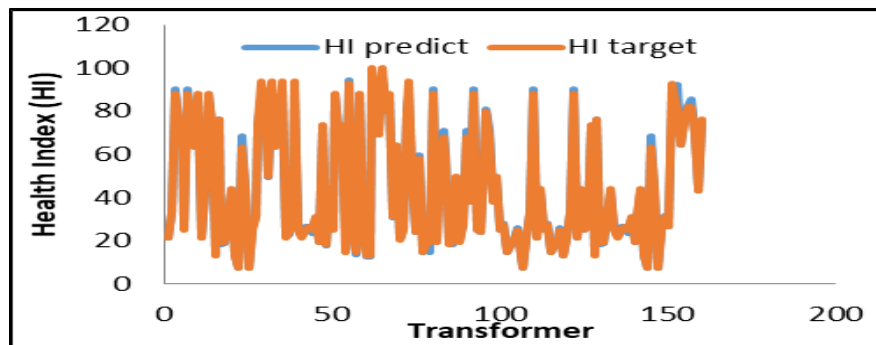
Table 7 Configuration of QNBP

Item	Model
Training Technique	Quasi-Newton Back Propagation (QNBP)
Network configuration	'logsig', 'purelin'
Learning Rate	0.2
Momentum Rate	0.5
Number of Hidden Layer	1
Number of Hidden neurons	10
Training Goal	0.001
Epoch	5000
No. of Training Data	112
No. of Testing Data	48
MSE training	0.00281
MSE Testing	0.00024
MAPE	0.00232%
R	0.99621
Time(s)	0:00:26

Table 8 Comparison Between FFNN-QNBP Model with Scoring and Ranking Method

No.of transformer	Transformer Health Index (%)			
	Scoring method	Transformer condition	FFNN- SCG method	Transformer condition
1	88.09524	Very Good	90.42863	Very Good
2	73.80952	Good	73.20018	Good
3	76.19048	Good	76.06048	Good
4	73.80952	Good	73.20018	Good
5	76.19048	Good	76.06048	Good
6	19.04762	Very Poor	18.77911	Very Poor
7	30.95238	Poor	30.35806	Poor
8	63.09524	Fair	30.35806	Fair
9	73.80952	Good	73.20018	Good
10	94.04762	Very Good	87.50267	Very Good

Figure 4 Comparison of HI value between proposed FFNN-QNBP with scoring and ranking method for overall transformer

3.3 Results of transformer HI applying SCG training algorithm

Table 9 shows the configuration of the FFNN proposed in this research. The learning rate, momentum rate, and number of hidden layers were set according to the value as in *Table 9*. The data comprises of total 160 data with 112 training data and 48 testing data. The goal and epoch were set to 1e-15 and 2000 iterations, respectively. From the study, the values of MAPE were 0.00274% and less than 10%, which indicate that the proposed model produced an accurate prediction. The values of MSE training and

testing were 0.3707 and 10.6723, respectively. The value of R was 0.99859.

The findings of transformer HI obtained applying the SCG are shown in *Table 10*. The findings show that

there was a slight difference between the two methods. Therefore, the FFNN method can be used to predict the transformer HI.

Table 9 Configuration of SCG propagation

Item	Model
Network Configuration	'logsig' 'purelin'
Learning rate	0.2
Momentum Rate	0.5
Number of Hidden Layer	1
Training Technique	Scale Conjugate Gradient (SCG)
Training goal	1e-15
Epoch	2000
No. of Training Data	112
No. of Testing Data	48
MSE Training	0.3707
MSE Testing	10.6723
MAPE	0.00274%
R	0.99859
Time(s)	00:00:01

Table 10 HI Comparison Between FFNN-SCG Model with scoring and ranking method

No. of transformer	Transformer health index (%)			
	Scoring method	Transformer condition	Ffnn- SCG method	Transformer condition
1	21.428	Very Poor	21.538	Very Poor
2	33.333	Poor	32.995	Poor
3	88.095	Very Good	88.323	Very Good
4	73.809	Good	73.686	Good
5	76.190	Good	76.529	Good
6	25	Very Poor	24.728	Very Poor
7	88.095	Very Good	88.323	Very Good
8	63.817	Fair	63.095	Fair
9	63.095	Fair	63.817	Fair
10	88.095	Very Good	82.442	Very Good

4.Conclusion

This paper has presented the use of FFNN to predict the transformer HI and minimize the error by creating the best ANN model applying LM, QNBP, and SCG as the training algorithms. Since artificial intelligence is widely used around the world, it would be a great contribution to create a model that can predict the transformer HI. The findings show that all training algorithms were well implemented according to the MSE, R, and MAPE performance evaluation of the prediction. According to the transformer HI obtained,

301

preliminary actions can be taken by the power system utility whether to upgrade, perform maintenance, replacement, monitoring, repair, and contingency control of the transformer. This technique could assist the power system operation so that the lifespan of the transformer can be increased in any transmission condition. The proposed method of predicting the transformer health index could be further improved by developing an algorithm for accurate weighting factor in order to obtain the more reliable prediction in the future.

Nur Ashida Salim et al.

Conflicts of interest
The authors have no conflicts of interest to declare.

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Nur Ashida Salim received her PhD in Electrical Engineering from Universiti Teknologi MARA in 2015, Master in Engineering (Power System & Electrical Energy) from Universiti Malaya in 2006 and Bachelor in Electrical Engineering (Hons.) from Universiti Teknologi MARA in 2003. She is currently an Associate Professor at the Centre for Electrical Power Engineering Studies, Faculty of Electrical Engineering, Universiti Teknologi MARA. Her research includes Power System Reliability, Power System Planning, Power System Stability, Power System Asset Management and other related areas. To date, she has published more than 40 journal articles and many proceeding papers.
Email: nurashida606@uitm.edu.my

Jasronita Jasni received the B.Eng. degree in electrical engineering from Universiti Teknologi Malaysia, Johor, Malaysia, in 1998, the M.Eng. degree in electrical engineering from Universiti Teknologi Malaysia, Johor, Malaysia in 2001 and the Ph.D. degreee in electrical power engineering from Universiti Putra Malaysia, Selangor, Malaysia in 2010. From 1998-1999, she was a system engineer and later in 1999-2001, she worked as a tutor in Department of Electrical and Electronics Engineering, Faculty of Engineering, Universiti Putra Malaysia. Then, in 2001, she started working as a lecturer in the same department at Universiti Putra Malaysia. Currently, she is an associate professor at Department of Electrical and Electronics Engineering, Faculty of Engineering, Universiti Putra Malaysia. Her research interest includes Power System, Renewable Energy and Lightning Protection. She has been actively involved in Advanced Lightning, Power and Energy Research Centre (ALPER) as one of their key researchers.
Email: nurashida606@uitm.edu.my

Hasmaini Mohamad received the B.Eng., M.Eng., and Ph.D. degrees from the University of Malaya, in 1999, 2004, and 2013, respectively. She started her career as a lecturer in Universiti Teknologi MARA in 2003 where currently she is an Associate Professor at the Centre for Electrical Power Engineering Studies, Faculty of Electrical Engineering. Apart from that, she has published more than 50 journal papers including high impact ISI journals and 20 conference papers. Her major research interest includes Islanding Operation of Distributed Generation, Hydro Generation, Load Sharing Technique, and Load Shedding Scheme.
Email: jas@upm.edu.my

Zuhaila Mat Yasin graduated from Universiti Sains Malaysia with honours degree in Electrical and Electronics Engineering in 1998. She obtained her MSc degree in 2008 and PhD degree in 2015 from Universiti Teknologi MARA. She is currently a senior lecturer at Universiti Teknologi MARA. Her research interest includes Power System Operation, Optimization, Distributed Generation, Artificial Intelligence and Smart Grid System
Email: hasmaini@uitm.edu.my