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Power Transformer Load Noise Model based on Backpropagation Neural Network

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Abstract. The operation of power transformer in an electric system is the cause of noise in form of sound. At a certain level, this noise can be considered as pollution, interfering with the comfort and health of human hearing. The phenomenon shows the need to understand load noise that is generated during the design process of power transformer. However, a major related problem is the unavailability of an accurate load noise model capable of precise prediction during the design stage. Therefore, this research aimed to develop load noise model based on an artificial neural network for power transformer to predict the generated load noise value. The development process was carried out using a trained backpropagation neural network (BPNN) with the Levenberg-Marquardt algorithm. Before training for neural network, input parameters such as power, impedance, and winding geometry factors were selected and normalized. The linear regression method was used to assess the quality of neural network model training results. For performance comparison, the multiple linear regression (MLR) model and the Reiplinger method were also developed. The results showed that load noise model was developed based on BPNN with seven hidden layers and nine neurons for each layer. Model showed acceptable output variables, with mean absolute percentage error (MAPE), mean absolute error (MAE), root mean square error (RMSE), and correlation coefficient (R) of 0.007, 0.464, 0.708, and 0.998, respectively. Furthermore, the prediction of load noise achieved through BPNN showed significantly high accuracy compared to the existing standard formulas.

Keywords: Backpropagation; Load noise; Model; Neural network; Power transformer

1. Introduction

Power transformer is an essential component in the electric system, playing an important role in meeting the energy demands of customers (Aziz, Indarto, and Hudaya, 2021; Rozhentcova *et al.,* 2020; Indarto *et al.,* 2017). During operation, power transformer generate noise, which can be considered as pollution, potentially disturbing the comfort of surrounding community. This noise is classified into three types, namely no-load, load, and noise caused by the cooling system (Al-Abadi, 2019). Based on classification, no-load noise

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has an almost constant value during the operation of power transformer (Shilyashki *et al.*, 2016). In contrast, load noise varies significantly depending on the amount of electric current flowing and the winding parameter (Al-Abadi *et al.*, 2017; Rohilla and Palani Samy, 2015). Among these three types, load noise becomes the most dominant source, particularly as power transformer increases (Vasques, Miguel, and Campelo, 2013; Lukic *et al.*, 2012). Load noise is an important aspect that is considered during the design process after power losses, efficiency, dimension, and costs of power transformer. Designers usually use an empirical formula to predict the amount of load noise. However, this formula has not considered all aspects affecting load noise value, resulting in inaccuracies in the predicted values (Paghadar and Kantaria, 2016). Reiplinger has developed the formula for predicting load noise. The formula shows a significant difference in measured value, without considering other variables, such as physical form and electromagnetic force, which are sources of load noise (Girgis, Bernesjö, and Anger, 2009). Therefore, the empirical method must be modified to include other parameters affecting load noise (Lukic *et al.*, 2012). Previous research has included the effect of transformer impedance and the presence of tap winding in the formula to improve the method. Although the results show a better value compared to Reiplinger formula, there is a high standard deviation of 3.5 dB (Girgis, Bernesjö, and Anger, 2009). A new calculation method for load noise caused by windings has also been carried out by considering both radial and axial forces (Yoshida *et al.*, 2021; Witczak and Swiatkowski, 2017), influenced by load current flowing (Kim *et al.*, 2020). The results showed superior measurement accuracy, but the standard deviation is still 1.4 dB (Girgis, Bernesjö, and Anger, 2009). The main problem associated with load noise is the difficulty of accurately quantifying the value of noise generated by transformer. The incompatibility of load noise values against the standards or consumers' specifications poses a significant problem for power transformer manufacturers (Pramono *et al.*, 2021; Pramono, Wijaya, and Hadi, 2020). Several efforts that have been carried out to reduce load noise in power transformer require high costs and a longer time, causing losses to manufacturers. Therefore, knowledge about load noise at the design stage is essential to minimize losses and implement corrective measures (Zhu, Hao, and Lu, 2022).

Based on the background above, this research aimed to develop load noise model generated by power transformer based on design data using backpropagation neural network (BPNN). Generally, power transformer parameters have a very complex relationship with each other, leading to difficult application in conventional mathematical methods. To address this challenge, an artificial neural network (ANN) offers a promising solution by effectively modeling complex system without previous knowledge of mathematical relationships (Alas and Ali, 2019; Dhini *et al.*, 2015). In addition, ANN can generalize model to predict outcomes with new input data, which are suitable for handling high data volatility and non-constant variance. One learning method that has been proven effective with good accuracy and speed is backpropagation, providing additional advantages such as minimal parameter tuning requirements, flexibility, and independence from knowledge of network features (Dhini *et al.*, 2020). This load noise model will incorporate the main parameters, known as noise sources and others to provide accurate values. This research is organized as follows, the first part discusses the proposed method, consisting of selecting input parameters and developing load noise model. The second part presents the result, validation, and comparison. The last part contains conclusions and opportunities for improvement.

2. Materials and Methods

The first step in the proposed is the selection parameters that significantly affect load noise. Subsequently, the second step is to develop load noise model using MLR and BPNN methods, while the last step is testing of model.

2.1. Selection of The Input Parameters

This research developed model for predicting load noise by considering the main contributing parameters. During the selection of input parameters, there is a need to consider factors that closely influence the final model of load noise (Fagbola, Thakur, and Olugbara, 2019). The parameters used in the development process are the nominal power, impedance, and winding geometry factor (WGF). Specifically, nominal power is the product of the current's square and transformer's impedance. The square of current flowing directly correlates with the electromagnetic force in the winding (Jin and Pan, 2016; Negi, Singh, and Kr Shah, 2013). Therefore, the nominal power is a parameter that significantly affects the amount of load noise.

The impedance of power transformer for each phase is influenced by the number of turns, the axial height of the winding, the winding width, the duct channel width, the average length of the conductor, and frequency. Furthermore, the impedance parameters refer more to the physical geometric shape of the winding (Al-Abadi, 2019). Generally, the current flowing in the winding produces magnetic flux, causing vibrations that serve as primary sources of noise (Duan *et al.*, 2018; Al-Abadi *et al.*, 2017; Jingzhu *et al.*, 2016). In the event of a short circuit occurs, the calculation of axial and radial forces becomes essential. According to (Sathya and Savadamuthu, 2019), axial and radial forces of the winding are influenced by several parameters of height, diameter, the average diameter of the two windings, width, and the channel width. As described by (Yu *et al.*, 2022; Lukic *et al.*, 2012), load noise is affected by axial and radial forces, showing the importance of selecting appropriate impedance parameters. WGF mechanically influences load noise generated. This is attributed to WGF, serving as the ratio between the winding height, diameter r_{hd}, weight of LV, G_{LV} (kg), and HV, G_{HV} (kg) (Pramono *et al.*, 2023).

2.2. Selection of The Output Target

BPNN or MLR output in target data containing load noise data was measured in this research. The measurement of load noise was carried out on power transformer during short circuit testing. Although the current flowing was nominal, the input voltage was not more than 10% of nominal voltage. Therefore, noise generated by power transformer was predominantly load current. Input and output data, serving as targets, have a large variation in values. This variation can be overcome by changing data input such as power, impedance, and the weight of the winding in the form of logarithmic functions in dB, as shown in Table 1. Based on the analysis, load noise data are obtained from short circuit testing, while other parameters are collected from power transformer design data.

Table 1 Data of input parameters

Load Noise Measured (dB)	*Input Parameters*				*Load Noise Measured (dB)*	*Input Parameters*			
	$\log(S)$	$\log(Z)$	$\log(G_{LV} + G_{HV})$	r_{hd}		$\log(S)$	$\log(Z)$	$\log(G_{LV} + G_{HV})$	r_{hd}
51	0.6990	0.7709	3.2299	1.2516	72.5	1.6532	1.1239	3.9658	1.3050
63.8	0.8751	0.9800	3.3948	1.5986	75	1.7782	1.1931	3.9352	1.2589
56.5	1.0000	0.9956	3.5717	1.0508	67.5	1.8129	0.9956	4.0527	1.3833
63.5	1.2304	1.1875	3.6096	1.6166	81.8	1.8751	1.5315	4.2048	1.3204
69.5	1.4471	1.4150	4.0918	1.2407	74.9	1.9031	1.1303	3.9898	1.3531
67.5	1.4471	1.1271	3.8302	1.2777	78.4	1.9031	1.0828	4.1651	1.4260
69	1.5441	1.1303	3.7582	1.5166	78.5	1.9542	1.1541	4.2379	1.9788
77.8	1.6021	1.3979	4.0925	1.3316	77.3	2.1303	1.0997	4.1217	1.2293
73	1.6021	0.9085	3.8640	1.8836	80.8	2.1614	1.1206	4.1847	1.3142
61.7	1.6021	1.0719	3.9428	1.1801	90.8	2.3802	1.1458	4.5795	0.9997

2.3. Development of Load Noise Model

The development of load noise model was carried out using two methods, namely multiple linear regression (MLR) and BPNN.

2.3.1. MLR Method

MLR is a statistical method that simulates the relationship between two or more independent variables and a dependent variable through a relationship in the form of a linear equation (Rinanto and Kuo, 2021). The form of MLR equation used in this research is showed by Equation (1). The output variable, y, is a function of input variable $x_1, x_2 \ldots x_k$, and a random error $\hat{\varepsilon}$ added to develop a probabilistic model rather than deterministic. Subsequently, the coefficient $\beta_0, \beta_1 \ldots \beta_k$, usually unknown, are estimated, where y_j is a dependent variable, β_0 is an intercept for regression equations, β_i is the coefficients of independent variable x_i and $\varepsilon_{i,j}$ is an error between the measurement and the prediction result. Equation (1) can be written as Equation (2).

$$y_j = \beta_0 + \sum_{i=1}^{n} \beta_i x_i + \varepsilon_{i,j} \tag{1}$$

$$Y = XB + E \tag{2}$$

where Y is the matrix of dependent variables, X is the input matrix, and E is the error matrix. To obtain the coefficient value of each independent variable, the error value is made minimum with the least square method. Equations (2) and (3) are used to obtain the coefficient of independent variable. Finally, MLR equation can be written as Equation (4), where $\hat{Y}$ is the MLR model's output and X^T is the matrix transpose of X.

$$min \sum_{i=1}^{n} \varepsilon_i^2 = min\, \varepsilon^T \varepsilon = min \sum_{i=1}^{n} (Y - XB)^T (Y - XB) \rightarrow 0 \tag{2}$$

$$B = (X^T X)^{-1} X^T Y \tag{3}$$

$$\hat{Y} = XB = X(X^T X)^{-1} X^T Y \tag{4}$$

Optimum MLR was determined based on statistical performance criteria. These criteria included the coefficient of multiple determinations (R^2), adjusted coefficient of multiple determination ($\mathrm{R}^2_{\mathrm{adj}}$), and prediction coefficient of multiple determination ($\mathrm{R}^2_{\mathrm{pred}}$).

2.3.2. Artificial Neural Network (ANN) Method

The structure of ANN consists of input, hidden layer, and output. Among ANN architectures, network with MLP structures are very commonly used to model system (Sholahudina and Han, 2015). ANN architectures consist of three or more layers, namely the input, hidden, and output, with each neuron interconnected with a set weight. The determination of neurons in each layer lacks standard rules and varies based on the specific problem to be solved (Najemalden, Ibrahim, and Ahmed, 2020; Dhini *et al.*, 2015). Currently, there is no mathematical method capable of determining the exact number of hidden layers and neuron elements. According to (Haykin, 2008), it was suggested to start training on an ANN using a small number of hidden and increased neurons to obtain a satisfactory mean square error (MSE) value. Although no definite mathematical equation for the number of hidden layers and neurons, the theory by Kolmogorov as expressed in Eq. (5) has been proven effective (Wang *et al.*, 2021).

$$n_h = n_i + 1 \tag{5}$$

n_h and n_i is the number of neurons in the hidden and input layers.

ANN uses a supervised training method because the input and target have been known. Therefore, knowledge and appropriate input selection are needed during modeling with ANN (Munakata, 2007). Training ANN is a mathematical exercise that optimizes all weight and threshold values using fractions of the available data. Neural network provide empirical model of a complex system capable of unraveling the underlying relationships and completely understanding the system (Dhini *et al.*, 2015). In this research, the relationship between the input signal and the output is expressed by Equation (6).

$$y_i = \sum_{j=1}^{n} w_{ij} x_j + b_i \tag{6}$$

where w_{ij} is the weight of the relationship, b_i is the bias value.

ANN with hidden layer and adequate units has the capability to theoretically method a non-linear relationship model. The mathematical relationship between input X and output Y can be established by adjusting the weight of the matrix W as well as bias vector B in the hidden and output layers to minimize the MSE during the training process. This adjustment of network parameter values occurs iteratively during the training or learning phase. After training, network is tested with a signal $x_i^{(p)}$, transmitted forward from input to output. The output result $y_i^{(p)}$ is compared with the target $t_i^{(p)}$ to obtain the error, followed by evaluation of model performance using the determination coefficient (R), and the value of MSE. When the error obtained does not meet the required criteria, network parameters are recalculated. The correction of parameters is carried out in the backward direction and network trained are called backpropagation network. During the training process, the transmission of a single signal from the start to backpropagation of the error is called the epoch. The iteration process continues until one of the stopping criteria is met through many epochs or errors. Although various learning methods have been developed, this research uses Levenberg-Marquardt optimization.

2.4. Prediction Performance Criteria

The determination of the best model was carried out by testing with the same data and selecting the optimal criteria. The best model was identified based on the smallest root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and the largest determination coefficient (R). Subsequently, Equations (7) to (10) were used to measure model's performance.

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_{act} - Y_{pre}}{Y_{act}}\right| \tag{7}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|Y_{act} - Y_{pre}\right| \tag{8}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}\left(Y_{act} - Y_{pre}\right)^2}{n}} \tag{9}$$

$$\mathrm{R} = \frac{\sum_{i=1}^{n}(Y_{act} - \bar{Y}_{act})(Y_{pre} - \bar{Y}_{pre})}{\sqrt{\sum_{i=1}^{n}(Y_{act} - \bar{Y}_{act})^2 (Y_{pre} - \bar{Y}_{pre})^2}} \tag{10}$$

3. Results and Discussion

3.1. MLR Model

Based on Table 2, with $\log(S)$, $\log(Z)$, $\log\,(G_{LV}+G_{HV})$, and r_{hd} as independent parameters and load noise as dependent, the initial step is to select the best model among the independent parameters.

Table 2 shows the possibility of MLR model with various parameter combinations. Since R^2 is significantly influenced by the number of parameters, there is a need to use other criteria for determining the best model. In this research, R^2_{adj} was used to combine the number of parameters affecting dependency. Specifically, R^2_{pred} value provides information on how well model can predict with new data, indicating that higher R^2_{pred} shows a better model for predicting load noise.

Table 2 Possibility of MLR model with various parameters

Pars	R^2	R^2_{adj}	R^2_{pred}	*Mallows Cp*	S	$log(S)$	$log(Z)$	$log\ (G_{LV} + G_{HV})$	r_{hd}
1	80.4	79.3	76.0	5.0	4.2643			x	
1	79.9	78.8	74.8	5.5	4.3154	x			
2	84.0	82.2	77.7	3.1	3.9589	x	x		
2	82.8	80.8	77.0	4.5	4.1107	x		x	
3	85.4	82.6	75.3	3.7	3.9063	x	x		x
3	84.5	81.5	75.6	4.7	4.0269	x	x	x	
4	86.0	82.3	71.7	5.0	3.9457	x	x	x	x

The results showed that model with two parameters, namely log (S) and log (Z) produced the best results, as indicated by R^2 = 84 %, R^2_{adj} = 82.2 %, and R^2_{pred} = 77.7 %. Based on Equations (1) to (4), load noise model was obtained in the form of MLR equation, as expressed in Equation (11) :

$$Y = 29.25 + 17.66\,log(S) + 11.92\,log(Z) \tag{11}$$

The comparison between MLR method and the measurement results is shown in Figure 2(a), presenting the maximum and minimum deviations of 7.41 dB and -8.62 dB, respectively, with a MAPE, MAE, RMSE, and R in a row 0.039, 2.727, 3.649 and 0.917.

3.2. BPNN Model

According to (Wang *et al.,* 2021), the number of neurons in each hidden layer can be determined by Equation (5). Since there are four input parameters, number of neurons in each hidden layer is nine. However, there are no exact rules or equations to determine the appropriate number of hidden layers for load noise model. Therefore, number of hidden layers in load noise model is carried out by trial and error, from the smallest number until the best results are achieved (Sadighi, Mohaddecy, and Abbasi, 2018).

In this research, the appropriate number of hidden layers is selected based on the MSE and R values of each test performed. According to the search results in Table 3, several hidden layers did not always give the best results. Therefore, seven hidden layers were selected with MSE and R values of 0.271 and 0.998, respectively. Figure 1 shows the BPNN structure that has the best results with seven hidden layers, each consisting of nine neurons.

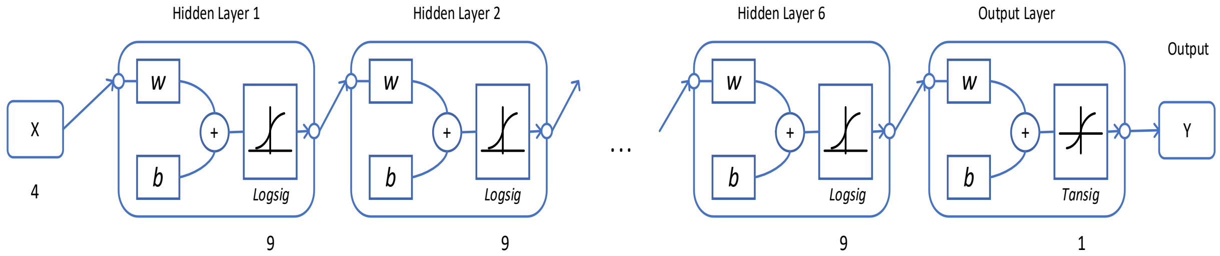
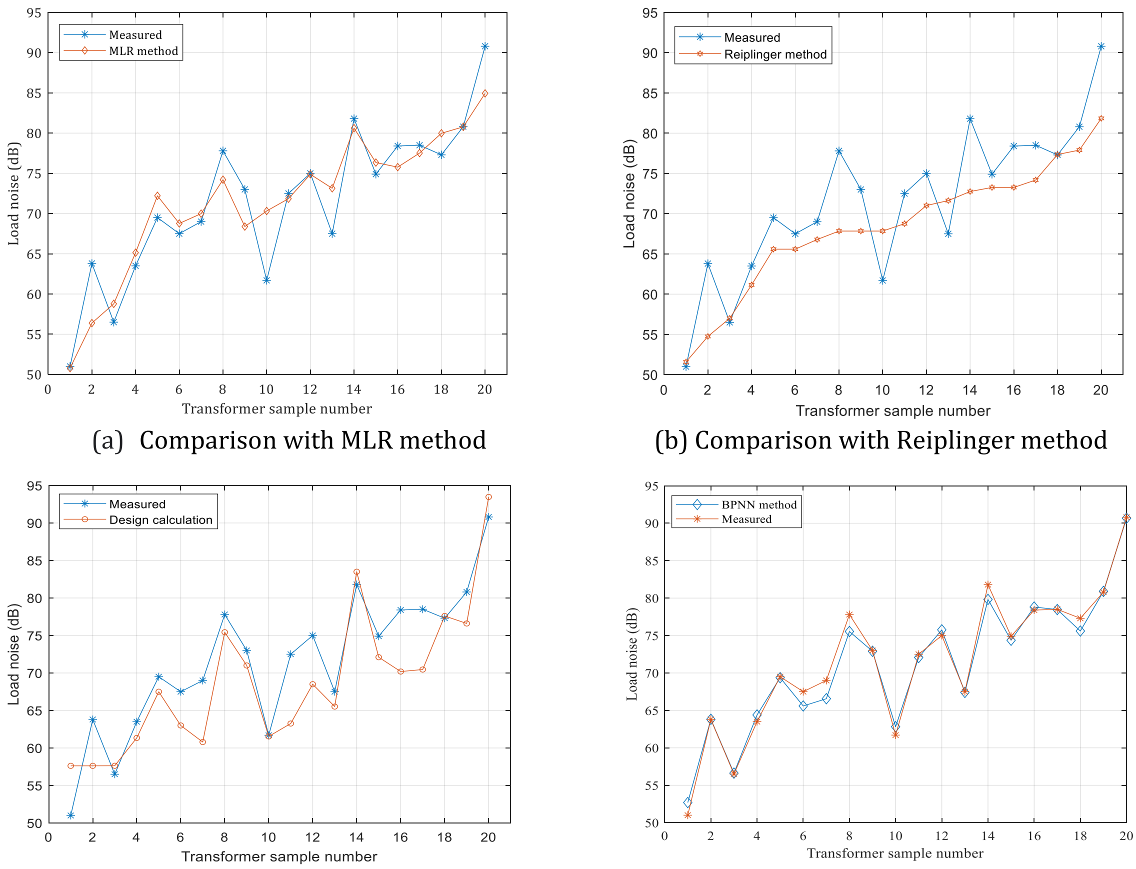


Figure 1 The structure of BPNN for load noise model

Table 3 Comparison of trained network for load noise model

No. of hidden layer	Hidden transfer function	MSE	R
4×9×9×1	Logsig, Logsig	65.38	0.589
4×9×9×9×1	Logsig, Logsig, Logsig	46.17	0.748
4×9×9×9×9×1	Logsig, Logsig, Logsig, Logsig	48.32	0.790
4×9×9×9×9×9×1	Logsig, Logsig, Logsig, Logsig, Tansig	0.877	0.996
4×9×9×9×9×9×9×1	Logsig, Logsig, Logsig, Logsig, Logsig, Logsig	70.83	0.479
4×9×9×9×9×9×9×9×1	**Logsig, Logsig, Logsig, Logsig, Logsig, Logsig, Tansig**	**0.271**	**0.998**

The bold values are selected as model with the optimum structure.



(a) Comparison with MLR method (b) Comparison with Reiplinger method

(c) Comparison with design calculation (d) Comparison with BPNN method

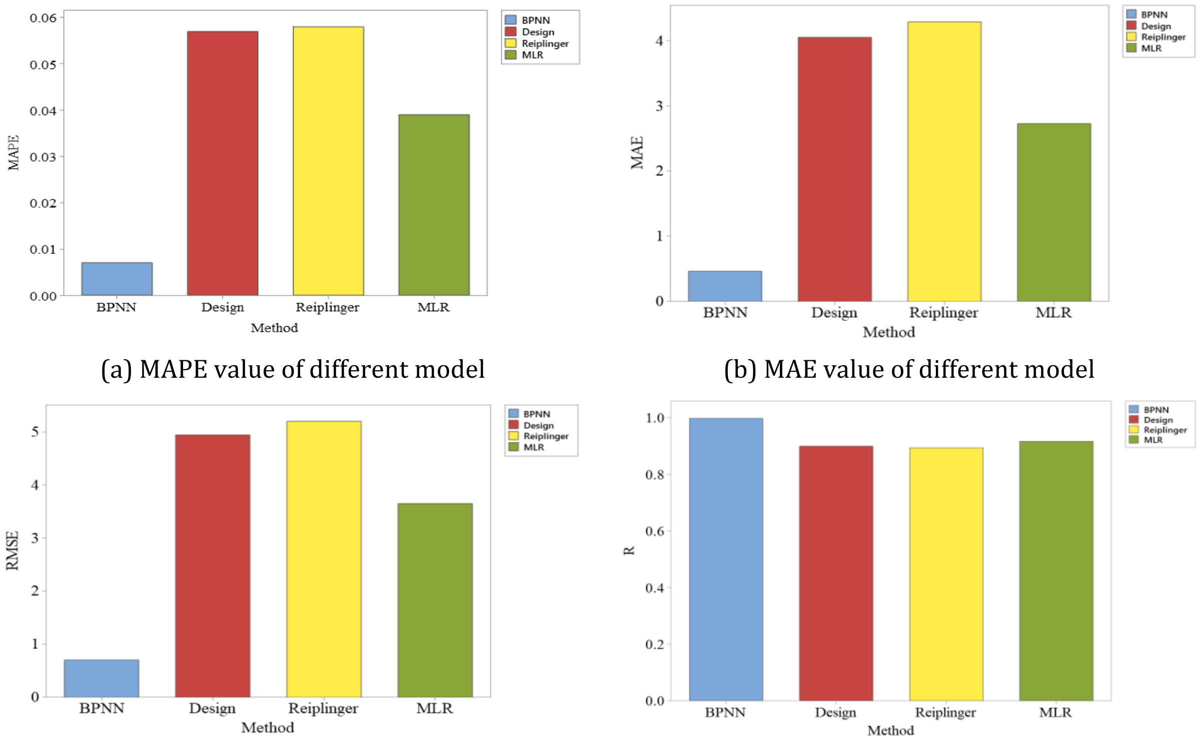
Figure 2 Comparison of load noise between measurement and the other method

The accuracy of model was evaluated by comparing the measurement results, the Reiplinger method, and load noise calculated at the design stage of the industry. Figure 2(b) shows that the Reiplinger method has a large deviation compared to the measurement results. Based on the results, the maximum and minimum deviations were 9.96 dB and -

6.14 dB, with MAPE, MAE, RMSE, and R in row 0.058, 4.285, 5.199, and 0.894, respectively. Meanwhile, Figure 2(c) shows the results of calculations carried out at the industrial design stage, which obtained the maximum and minimum deviation values of 9.24 dB and -6.62 dB, with a MAPE, MAE, RMSE, and R in a row 0.057, 4.049, 4.942, and 0.900, respectively.

Load noise model developed by BPNN method has the smallest deviation from the measurement results compared to others. The maximum and minimum deviations are 1.25 dB and -1.69 dB, with a MAPE, MAE, RMSE, and R in a row 0.007, 0.464, 0.708, and 0.998, respectively. These performance criteria showed that the development of load noise model with BPNN provided better accuracy. The comparison results in Figure 2(d) showed that BPNN could be developed for predicting load noise at the early design stage of power transformer.

Figure 3 shows a comparison of each performance criterion, where BPNN model produces the best results. Specifically, Figure 3(a) shows that the MAPE for BPNN model has the lowest value of 0.7% compared to others. The low MAE, as presented in Figure 3(b), shows that BPNN model can forecast load noise compared to others. The low RMSE, shown in Figure 3(c), indicates that the variation in predicted value is close to BPNN observational value. The R-value presented in Figure 3(d) shows the strong correlation between independent and dependent variables. Statistically, Table 4 shows a summary of the three models tested, with BPNN producing the best results compared to others.



(a) MAPE value of different model

(b) MAE value of different model

(c) RMSE value of different model

(d) R value of different model

Figure 3 Statistical performance comparison of each model

Table 4 Summary of comparisons of all models

Performance criteria	BPNN method	Design calc.	Reiplinger method	MLR method
MAPE	0.007	0.057	0.058	0,039
MAE	0.464	4.049	4.285	2.727
RMSE	0.708	4.942	5.199	3.649
R	0.998	0.900	0.894	0.917

4. Conclusions

In conclusion, this research successfully developed load noise model using BPNN. Based on the results, the optimal structure of BPNN for power transformer load noise model with power, impedance, and WGF as inputs was found to be 4-9-9-9-9-9-9-9-1, with MAPE, MAE, RMSE, and R values of 0.007, 0.464, 0.708 and 0.998, respectively. This model should potential to predict load noise for power transformer without using detailed design data. The prediction of load noise with BPNN produced high accuracy compared to the existing standard formulas. Therefore, load noise model obtained in this research could be implemented for further investigation to design a low-load noise power transformer.

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References

Al-Abadi, A., Gamil, A., Schatzl, F., Vander, B., Groot, E.D., Declercq, J., 2017. Investigating The Effect of Winding Design and Clamping Pressure on Load-Noise Generation of Power Transformer. *In:* CIGRE Study Committee A2 Colloqium, pp. 1-10

Al-Abadi, A., 2019. Developing an Accurate Load Noise Formula for Power Transformers. *In:* 2019 6th International Advanced Research Workshop on Transformers (ARWtr), January, pp. 19–24

Alas, M., Ali, S.I.A., 2019. Prediction of the High-Temperature Performance of a Geopolymer Modified Asphalt Binder using Artificial Neural Networks. *International Journal of Technology*, Volume 10(2), pp. 417–427

Aziz, M., Indarto, A., Hudaya, C., 2021. Study of Material Characteristics of Core and Winding to Minimize Losses on Power Transformer. *IOP Conference Series: Earth and Environmental Science*, Volume 673(1), p. 012008

Dhini, A., Faqih, A., Kusumoputro, B., Surjandari, I., Kusiak, A., 2020. Data-driven Fault Diagnosis of Power Transformers using Dissolved Gas Analysis (DGA). *International Journal of Technology*, Volume 11(2), pp. 388–399

Dhini, A., Surjandari, I., Riefqi, M., Puspasari, M.A., 2015. Forecasting Analysis of Consumer Goods Demand using Neural Networks and ARIMA. *International Journal of Technology*, Volume 6(5), pp. 872–880

Duan, X., Zhao, T., Liu, J., Zhang, L., Zou, L., 2018. Analysis of Winding Vibration Characteristics of Power Transformers Based on the Finite-Element Method. *Energies*, *11*(9), p. 2404

Fagbola, T.M., Thakur, C.S., Olugbara, O., 2019. News Article Classification using Kolmogorov Complexity Distance Measure and Artificial Neural Network. International Journal of Technology, Volume 10(4), pp. 710–720

Girgis, R.S., Bernesjö, M., Anger, J., 2009. Comprehensive Analysis of Load Noise of Power Transformers. *In:* 2009 IEEE Power and Energy Society General Meeting, PES '09, pp. 1–7

Haykin, S., 2008. *Neural Networks and Learning Machines*. 3rd ed. Pearson Prentice Hall

Indarto, A., Garniwa, I., Setiabudy, R., Hudaya, C., 2017. Total cost of ownership analysis of 60 MVA 150/120 kV Power Transformer. *In:* 2017 15th International Conference on Quality in Research (QiR) 2017, pp. 291–295

Jin, M., Pan, J., 2016. Vibration Characteristics of a Disk-Type Winding Simulated by Coupled

Concentric Rings. *Applied Acoustics*, Volume 101, pp. 104-114
Jingzhu, H., Dichen, L., Oingfen, L., Yang, Y., Shanshan, L., 2016 Electromagnetic Vibration Noise Analysis of Transformer Windings and Core. *IET Electric Power Applications*, Volume 10(4), pp. 251-257
Kim, D.K., Ryu, J.Y., Kim, D.M., Kim, D.J., Lim, M.S., 2020. Load Noise Prediction of High-Voltage Transformers by Equation Applying 3-D EMCN. *IEEE Access*, Volume 8, pp. 130669–130677
Lukic, L., Djapic, M., Lukic, D., Petrovic, A., 2012. Aspects of Design of Power Transformers for Noise Reduction. *In:* International Conference Noise and Vibration, pp. 255–262
Munakata, T., 2007. *Fundamentals of the New Artificial Intelligence*. Lodon: Springer
Najemalden, A.M., Ibrahim, S.W., Ahmed, M.D., 2020. Prediction of Collapse Potential for Gypseous Sandy Soil Using ANN Technique. *Journal of Engineering Science and Technology*, Volume 15(2), pp. 1236–1253
Negi, R., Singh, P., Shah, G.K., 2013. Causes of Noise Generation and Its Mitigation in Transformer. *International Journal of Research in Electrical and Instrumentation Engineering*, Volume 2(5), pp. 1732-1736
Paghadar, H., Kantaria, R.A., 2016. Accurate Estimation and mitigation of Audible Sound using Novel Technique of Flux Density Reduction at Design Stage in Transformer. *International Journal of Electrical and Electronics Engineering*, Volume 3(10), pp. 12–15
Pramono, W.B., Hadi, S.P., Wijaya, F.D., Nugroho, H.A., Wibirama, S., 2020. Study of Power Transformer Noise Prediction. *In:* 2020 7th International Conference on Information Technology, Computer, and Electrical Engineering (ICITACEE), pp. 213–218
Pramono, W.B., Wijaya, F.D., Hadi, S.P., 2021. Prediction Formula Development of Power Transformer No-Load Noise. *Journal of Physics: Conference Series*, Volume 1858(1), p. 012014
Pramono, W.B., Wijaya, F.D., Hadi, S.P., Indarto, A., Wahyudi, M.S., 2023. Application of a PCA-MLR Load Noise Prediction Model for The Power Transformer. *In:* 2023 7th International Conference on Electrical, Telecommunication and Computer Engineering (ELTICOM), pp. 188-193
Rinanto, N., Kuo, C.H., 2021. PCA-ANN Contactless Multimodality Sensors for Body Temperature Estimation. *IEEE Transactions on Instrumentation and Measurement*, Volume 70, pp. 1–16
Rohilla, V., Samy, C.P., 2015. A Study of Transformer Noise and Reduction Techniques of Transformer Noise. *Journal of Basic and Applied Engineering Research*, Volume 2(22), pp. 1911-1915
Rozhentcova, N., Galyautdinova, A., Khayaliev, R., Udaratin, A.V., Ilyashenko, S., 2020. Automated Diagnostic System for Power Transformers using a QR Code. *International Journal of Technology*, Volume 11(8), pp. 1519–1527
Sadighi, S., Mohaddecy, S.R.S., Abbasi, A., 2018. Modeling and Optimizing a Vacuum Gas Oil Hydrocracking Plant using an Artificial Neural Network. *International Journal of Technology,* Volume 9(1), pp. 99–109
Sathya, A., Savadamuthu, U., 2019. Electromagnetic Force and Deformation in Transformer Winding. *International Journal of Applied Engineering Research*, Volume 14(3), pp. 790–796
Shilyashki, G., Pfutzner, H., Hamberger, P., Aigner, M., Kenov, A., Matkovic, I., 2016. Spatial Distributions of Magnetostriction, Displacements and Noise Generation of Model Transformer Cores. *International Journal of Mechanical Sciences*, Volume 118, pp. 188-194

Sholahudin, S., Han, H., 2015. Heating Load Predictions using The Static Neural Networks Method. *International Journal of Technology*, Volume 6(6), pp. 946953

Vasques, C.M.A., Miguel, H., Campelo, R., 2013. Quiet Transformers : Design Issues. *Advanced Research Workshop on Transformers*, pp. 1–17

Wang, Z., Wei, W., Langari, R., Zhang, Q., Yan, Q., 2021. A Prediction Model Based on Artificial Neural Network for the Temperature Performance of a Hydrodynamic Retarder in Constant-Torque Braking Process. *IEEE Access*, Volume *9*, pp. 24872–24883.

Witczak, P., Swiatkowski, M., 2017. Modelling Axial Vibration in Windings of Power Transformers. *Journal Open Physics*, Volume 15(1), pp. 862-866

Yoshida, K., Hoshino, T., Murase, S., Murakami, H., Miyashita, T., 2021. Analysis of Load Noise Components in Small Core-Form Transformers. *IEEE Transactions on Power Delivery*, Volume 36(5), pp. 2694–2704

Yu, X.C., Zou, D.P., Fan, M.Z., Dong, X., Du, F., 2022. Vibration and Noise Suppression Method of Transformer. *Journal of Physics: Conference Series*, 2158 012030

Zhu, L., Hao, J., Lu, L., 2022. Research on Influence of Damping on the Vibration Noise of Transformer. *IEEE Access*, Volume 10, pp. 92128–92136