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Research Article

Estimation of Audible-Noise Level in Transformers Aging with Artificial Neural Networks

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Abstract

Transformers are vital components of the electrical grid. As they age, performance deteriorates and the risk of failure increases. Noise change is an indicator of aging and audible noise reflects the condition of transformer components. In this study, the noise level, temperature, load values and environmental conditions of eight transformers located in the Istanbul İkitelli Organized Industrial Zone were monitored at different time intervals for four months and a data record was created. When the obtained data were examined, it was determined that the noise levels varied depending on the environmental conditions. The collected data were transferred to the MATLAB environment and the input parameters and target variables were determined. Within the scope of the data analysis, feed forward artificial neural network and recurrent artificial neural network models were modeled using different training percentages. The aim of the study was to reach the most accurate estimation results. When the results were examined, it was observed that the recurrent artificial neural network model performed better and that the estimation accuracy increased when the training percentage was increased. In our study, it was observed that Recurrent Neural Networks had approximately 8 percent less error in terms of the average error with regard to Feed Forward Neural Networks.

Keywords: Neural networks, Feed forward, Transformer noise, Noise estimation.

Trafo Yaşlanmasında Duyulabilir Gürültü Seviyesinin Yapay Sinir Ağları ile Tahmini

Öz

Trafolar elektrik şebekesinin hayati bileşenleridir. Yaşlandıkça performansları düşer ve arıza riski artar. Gürültü değişimi yaşlanma göstergesidir ve duyulabilir gürültü, trafo bileşenlerinin durumunu yansıtır. Bu çalışmada, İstanbul İkitelli Organize Sanayi Bölgesi'nde bulunan sekiz adet trafonun gürültü seviyesi, sıcaklık, yük değerleri ve ortam koşulları, dört ay boyunca farklı zaman dilimlerinde izlenerek veri kaydı oluşturulmuştur. Elde edilen veriler incelendiğinde, gürültü seviyelerinin çevresel koşullara bağlı olarak değişkenlik gösterdiği tespit edilmiştir. Toplanan veriler MATLAB ortamına aktarılmış ve giriş parametreleri ile hedef değişkenler belirlenmiştir. Verilerin analizi kapsamında ileri beslemeli yapay sinir ağı ve tekrarlayan yapay sinir ağı modelleri, farklı eğitim yüzdeleriyle kullanılarak modellenmiştir. Çalışmanın amacı, en doğru tahmin sonuçlarına ulaşmaktır. Sonuçlar incelendiğinde, tekrarlayan yapay sinir ağı modelinin daha iyi performans gösterdiği ve eğitim yüzdesinin artırılması durumunda tahmin doğruluğunun yükseldiği gözlemlenmiştir. Çalışmamızda Tekrarlayan Sinir Ağlarının ortalama hata açısından yaklaşık %8 daha az hataya sahip olduğu gözlemlenmiştir.

Anahtar Kelimeler: Sinir ağları, İleri besleme, Transformatör gürültüsü, Gürültü kestrimi.

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1. Introduction

The rapidly increasing electrical energy consumption has necessitated the establishment of a greater number of substations near urban areas and has led to a rise in their rated power capacity. Consequently, the noise emitted by transformers has emerged as a significant concern for industrial and residential environments, compelling transformer manufacturers to invest in noise reduction techniques and research aimed at quieter operation. Transformer noise was first recognized as a problem in the early 20th century, prompting initial investigations into its sources. A review of the literature and various examinations has indicated that the primary sources of transformer noise are structural characteristics and operational conditions. These include factors such as the current drawn from the transformer, the frequency of operation, demand-side power variations, and environmental conditions—including ambient temperature, transformer spacing, and surrounding pressure (ambient conditions)[1].

One of the earliest studies on transformer noise measurement was conducted by Robert B. George in 1931. His work aimed to identify noise sources in transformers through surface vibration measurements on transformer components. With the growing concern over transformer noise, research efforts intensified in the second half of the 20th century and beyond. These studies not only focused on identifying the sources of noise but also explored active sound control strategies, improvements in core materials, and the implementation of Computer-Aided Design (CAD) and Computer-Aided Engineering (CAE) techniques for noise mitigation. Substantial progress has been made in transformer noise reduction through these approaches[2].

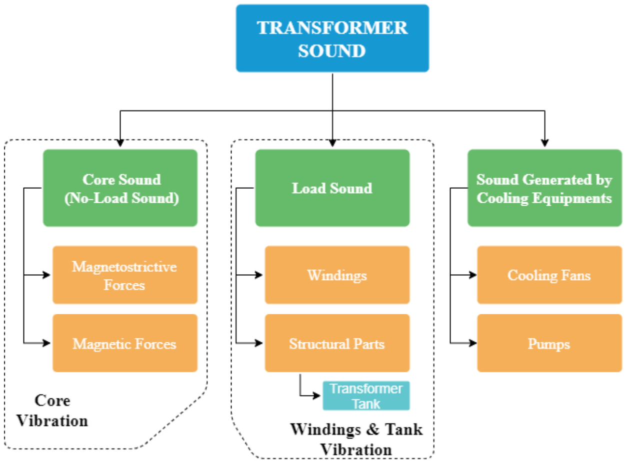

Figure 1. Transformer Noise Causes.

Since transformers are fundamental devices in electrical transmission and generation, they inherently produce noise[3]. The three primary sources of transformer noise are illustrated in Figure 1. The dominant source of noise generation in transformers stems from the mechanical deformation experienced by the transformer core and winding coils due to fluctuations in electromagnetic flux. The core material exhibits magneto-strictive properties, which contribute to noise generation. Mizokami's study on core vibration demonstrated that magnetostriction is amplified by vibrations, thereby increasing noise levels[4]. Furthermore, Zhu's findings indicate that filling the gaps between the layers with nanocrystalline soft magnetic composite materials reduces both magnetostriction and core vibrations[5]. Excessive gaps between the core's laminated sheets can lead to periodic magneto-repulsive forces, causing the sheets to collide and generate noise. Additionally, if the windings of the current-carrying coils are not adequately secured, they can vibrate and contribute to noise emissions[6]. Apart from these internal sources, auxiliary devices such as cooling fans and pumps in transformers also serve as potential noise contributors.

The estimation of audible noise levels in aging transformers has become a critical research area, primarily due to the impact of noise on both performance and safety. Recent advancements in artificial intelligence (AI), particularly artificial neural networks (ANNs), have provided innovative methods for accurately predicting and analyzing transformer noise levels over time. ANNs, known for their ability to model complex relationships within data, have been successfully applied to noise estimation in diverse fields, including electrical transformers. Zhang and Sun emphasize that ANNs can aid in diagnosing transformer faults, including abnormal noise emissions caused by aging components[7]. Similarly, research by Uddin et al. demonstrates that ANNs can efficiently denoise ultrasound signals, suggesting potential applications for noise suppression in transformers[8]. The study by Ledesma et al. further highlights that neural networks outperform traditional deterministic approaches, particularly in analyzing complex nonlinear systems[9].

Transformer operation generates various noise types, including electrical, mechanical, and environmental noise, all of which are influenced by aging components and external disturbances. He et al. discuss the challenges posed by noise interference in monitoring systems, particularly in aging transformers, where the accuracy and reliability of data are crucial for effective transformer condition assessment[10]. The application of ANNs allows for the development of models that can account for inherent noise, thereby enabling more precise transformer health monitoring and noise estimation.

Moreover, integrating advanced signal processing techniques with ANNs offers a promising solution to these challenges. Aghaeipoor et al. demonstrate that methods such as wavelet transforms can effectively isolate and filter noise from data before applying neural networks, enhancing prediction accuracy[11]. This comprehensive approach improves the reliability of noise estimations and facilitates the implementation of predictive maintenance strategies tailored to the operational history and aging patterns of transformers. Such strategies help mitigate risks associated with operational failures, ensuring the long-term efficiency of power systems.

In conclusion, the integration of artificial neural networks in transformer noise estimation represents a significant advancement in predictive maintenance and reliability assessment. By leveraging the capabilities of ANNs in conjunction with signal processing methods, it is possible to develop adaptive models that address the dynamic characteristics of transformer operations and aging behavior. These advancements ultimately contribute to enhanced transformer maintenance strategies, reduced noise emissions, and improved system reliability.

In Gunlemis' study [12], the noise emitted by transformers was analyzed using the artificial neural network method, with a particular focus on demand-side behavior and the impact of environmental parameters. The findings revealed that while ambient temperature did not directly influence transformer noise, changes in demand-side conditions led to a 15% increase in noise levels for oil-immersed transformers from 61 decibels to 71 decibels.

2. Material and Methods

2.1. Material

During the months of December, January, February and March, when the winter season is observed, the times when the most power is drawn depending on the consumption and the environmental temperature is as low as possible and the drawn load is as high as possible were selected and the changes in the fluctuation were tried to be revealed more clearly as much as possible in the measurements taken. Noise measurements of eight different transformers were made for a period of four months and data were collected on various days when the air temperature changed between -1°C and 14°C during the selected time period. The reason for choosing this time period is to eliminate other effects that may be observed after the extra heat generation of the transformer due to seasonal effects. Based on the obtained data, the noise levels of the transformers were analyzed in terms of environmental conditions based on the winter season.

FLIR T-335 thermal camera was used to measure transformer temperature, while the Cem DT-8820 four-in-one measuring device was employed to record transformer noise. The FLIR T-335 thermal camera operates within a working temperature range of -15°C to +50°C and has the capability to measure object temperatures ranging from -20°C to +650°C with a thermal sensitivity of 0.05°C. The Cem DT-8820 device can measure ambient temperature, humidity, light, and sound, with a sound measurement range of Lo (Low) 35dB - 100dB / Hi (High) 65dB - 130dB and a sound sensitivity of ±3.5 dB at a 94 dB level.

Label values of 8 transformers located in Istanbul İkitelli Organized Industrial Zone are given below on Table 1. These transformers were measured at different times in December 2020 and March 2021.

2.2. Method

In 2001, A.S. Farag et al. developed an Artificial Neural Network (ANN) system aimed at diagnosing faults in distribution transformers[13]. The ANN models were trained using real-world operational data through the Back-Propagation Algorithm, enabling them to effectively identify and classify faults in distribution transformers. Farag and colleagues designed six separate ANN models, each corresponding to a specific diagnostic factor, to generate precise outputs. These factors were identified as the transformer's age, weather conditions, damaged bushings, casing damage, oil leakage, and faults in the windings[13].

The study by Farag et al. underscored that distribution transformers can fail during operation due to various factors, with lightning strikes and switching surges being among the most common causes. The identification of these failure mechanisms is crucial for understanding the vulnerabilities of distribution transformers and for devising effective diagnostic and preventive maintenance strategies. The most frequently observed failure causes were categorized as follows:

- Mechanical defects or chemical degradation of oil and insulation, as well as extreme conditions such as lightning strikes and switching surges,
- Short-circuit faults and insufficient protective measures,
- Manufacturing defects,
- Leaky gaskets, covers, and bushings,
- Severe overloading,
- Environmental factors,
- Accidents,
- Unknown causes.

The developed artificial neural network (ANN) system provides a comprehensive diagnostic framework for operational transformers, assisting in the early detection and prevention of potential failures under varying operating conditions. This approach significantly enhances the practical applicability of ANN models by offering precise fault predictions and maintenance recommendations, thereby reducing the likelihood of unexpected failures[13].

Table 1. Transformer label values.

	YEAR	**TOTAL WEIGHT (KG)**	**CAPACITY (kVA)**	**VECTOR DIAGRAM**	**IMPEDANCE (%Uk)**	**NO-LOAD LOSS (W)**	**LOAD LOSS (W)**	**FREQUENCY (HZ)**	**HICH VOLTAGE (V)**	**LOW VOLTAGE (V)**
Transformer-1	1997	3950	1600	DYN11	6,59	2590	16190	50	1- 30000	
									2- 31500	
									3- 33000	400/231
									4- 34500	
									5- 36000	
Transformer-2	1994	3805	1250	DYN11	6,12	2030	14383	50	1- 36000	
									2- 34500	
									3- 33000	400/231
									4- 31500	
									5- 30000	
Transformer-3	2017	4570	1600	DYN11	6,22	2014	13513	50	1- 28500	
									2- 30000	
									3- 31500	
									4- 33000	400/√3
									5- 34500	
									6- 36000	
Transformer-4	2017	3539	1600	DYN11	6	1799	13764	50	1- 28500	
									2- 30000	
									3- 31500	
									4- 33000	400/231
									5- 34500	
									6- 36000	
Transformer-5	1997	2721	1000	DYN11	5,88			50	1- 30000	
									2- 31500	
									3- 33000	400/231
									4- 34500	
									5- 36000	
	1997	2721	1000	DYN11	5,78			50	1- 30000	

Transformer-6									2- 31500	
									3- 33000	400/231
									4- 34500	
									5- 36000	
Transformer-7	1998	4421	1600	DYN11	6			50	1- 30000	
									2- 31500	
									3- 33000	400/231
									4- 34500	
									5- 36000	
Transformer-8	2017	4570	1600	DYN11	6,06	2058	13227	50	1- 28500	
									2- 30000	
									3- 31500	
									4- 33000	400/231
									5- 34500	
									6- 36000	

2.2.1.Artificial Neural Networks (ANN)

Artificial neural networks (ANNs) are recognized as a subfield of artificial intelligence, specifically within the domain of cybernetic artificial intelligence. These networks process information by training models designed to simulate the human brain, enabling self-learning and evaluation mechanisms to approximate the most accurate predictions based on the provided data (Figure 2).

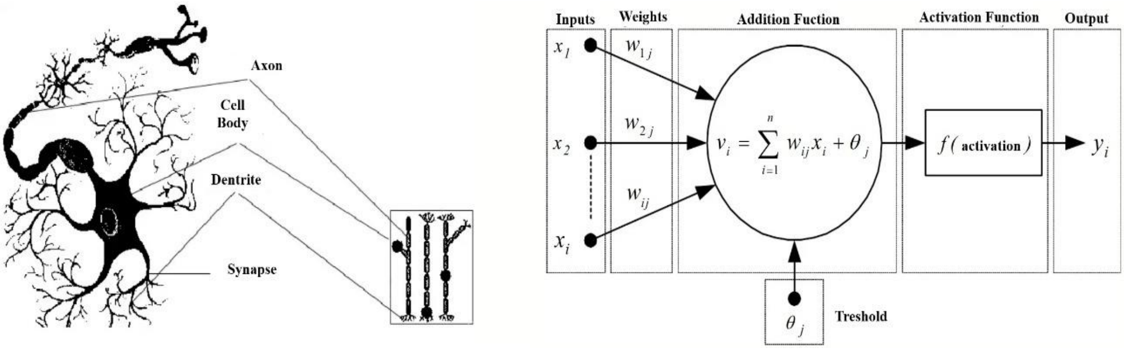

Figure 2. Biological Neuron and Artificial Neural Network [14].

Artificial neural networks comprise five primary components, which mimic the structure and decision-making processes of biological neurons, thereby earning the designation of artificial neurons. These components are systematically outlined in Table 2[14].

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Table 2. Comparison of Biological Neural Network and Artificial Neural Network.

Biological Neural Network	Artificial Neural Network
Nervous system	Neural Computing System
Nerve	Node (Neural, Process Element)
Synapse	Interneural Connection Weights
Dendrite	Addition Function
Cell Body	Activation Function
Axon	Nerve Output

The input data fed into the neural network undergoes evaluation through various activation functions. The optimal target values for the network's output are determined by experimenting with different activation functions to achieve the best predictive performance. Some of the most commonly utilized activation functions in artificial neural networks are listed as follows (Figure 3)

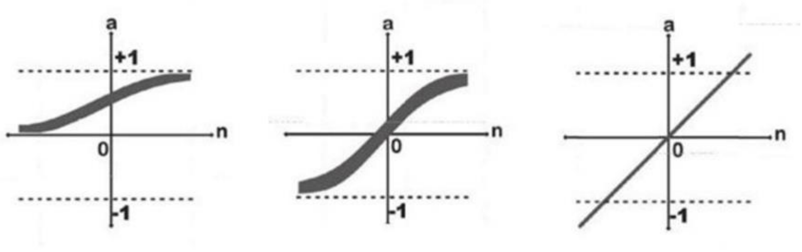


Figure 3. Sigmoid, Tanh, Linear Activation Functions.

The sigmoid activation function models both linear and nonlinear relationships, producing output values constrained within the range of [0,1] in (1):

$$\boldsymbol{F(Net) = \frac{1}{1 + e^{-Net}}} \quad (\mathbf{1})$$

The hyperbolic tangent (tanh) function maps input values to an output range of [-1,1], effectively enhancing network performance in cases where negative values contribute to model optimization in (2).

$$\boldsymbol{F(Net) = \frac{e^{Net} - e^{-Net}}{e^{Net} + e^{-Net}}} \; (\mathbf{2})$$

The linear activation function generates outputs that maintain a direct proportionality to the input values, making it particularly suitable for regression-based neural network models in (3).

$$\boldsymbol{F(Net) = Net} \; (\mathbf{3})$$

2.2.2. Single Layer Feed Forward Neural Networks (Single Layer FFNN)

In a single-layer feedforward neural network, input information is directly introduced to the network without any feedback mechanism. The key characteristic distinguishing this type of model is the absence of recurrent connections, making it a purely feedforward system. During training, weight values are iteratively adjusted to minimize error and achieve the desired output values. The training process continues until the network reaches the target outputs. This model is primarily employed for solving linear problems, as it lacks the capability to classify nonlinear data points or handle complex problems effectively[15].

In a single-layer neural network model, a threshold value—fixed at 1—is utilized to ensure that the elements following the input layer and preceding the output layer do not converge to zero, thereby maintaining effective network functionality[16] as depicted as in Figure 4.

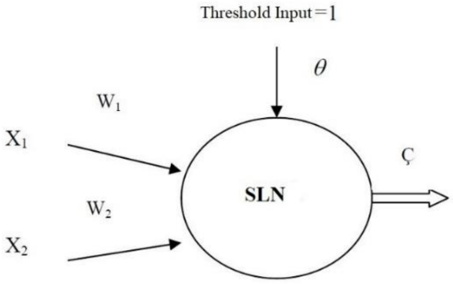


Figure 4. The Simplest Single-Layer Neural Network Model Consisting of Two Inputs and One Output[16].

2.2.3. Multi-Layer Feed Forward Networks (Multi-Layer FFNN)

The limitations of single-layer neural networks in addressing nonlinear problems have necessitated the development of multi-layer neural network models. Although research on artificial neural networks had temporarily stagnated due to these limitations, advancements in multi-layer models have revitalized the field. In a multi-layer neural network, data flows in a unidirectional manner from the input layer to the output layer. Each layer is dependent solely on the next layer; the output of neurons in one layer serves as input for neurons in the subsequent layer, but not for neurons within the same layer[15].

The source nodes in the network's input layer supply the activation model (input vector), which generates input signals for neurons in the second layer, also known as the hidden layer. The output signals from this hidden layer function as inputs to the subsequent layer, following this hierarchical structure throughout the network. Typically, neurons in each layer receive inputs exclusively from the preceding layer’s output signals. The final layer, known as the output layer, aggregates the signals from all previous layers, forming the network’s overall response to the input pattern supplied by the first layer[17].

In a network with a single hidden layer, the structure depicted in Figure 5 can be represented as a 10–4–2 network, where there are 10 input nodes, 4 hidden neurons, and 2 output neurons. This notation defines the architecture of the network by specifying the number of neurons in each layer[17].

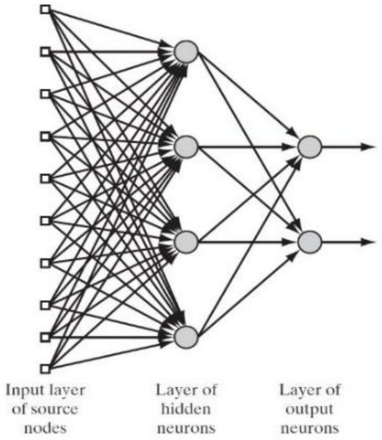


Figure 5. Multilayer Feed Forward Network Model[17].

2.3. Recurrent Neural Network (RNN)

In the 1980s, the recurrent neural network (RNN) was introduced as a model for time-series modeling within the field of artificial neural networks. Its architecture closely resembles that of a standard multi-layer perceptron, with the key distinction being its ability to establish connections between hidden units with a time delay. These connections enable the network to retain information from past inputs, allowing for more accurate estimations of output data. This functionality is achieved through a feedback loop within the network, enabling it to maintain relationships with previously stored data, ensuring the persistence of information over time[18].

In recurrent neural networks, as illustrated in Figure 6, neurons possess memory, and there is interlayer connectivity. In this network model, neuron inputs can be transmitted to neurons within the same layer or to preceding neurons. This repetition, known as data feedback, can be implemented using various methods, leading to the development of different network models. Through repeated learning cycles, the network can analyze and correct errors, preventing the recurrence of the same mistakes. By the end of the training process, the weight values between layers are adjusted. These weights can be modified between the input and hidden layers, between hidden layers, and finally, between the hidden and output layers[15].

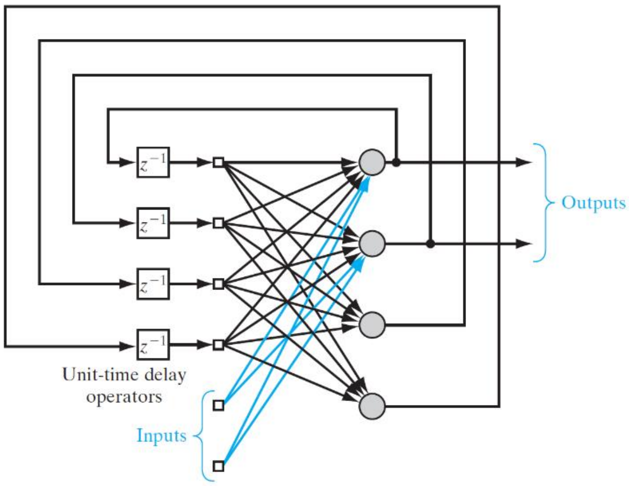


Figure 6. Recurrent Neural Network Model[17].

In a study conducted by P. Abhigna et al., RNNs were applied to the prediction of significant wave heights in meteorology and marine engineering applications. The results demonstrated that the recurrent model provided superior estimation accuracy with a lower error rate compared to the feedforward model[19].

3. Results

In this section, data collected between December 2020 and April 2021, including input and target values for the analysis of transformer noise, were imported into the simulation environment for the artificial neural network model of eight transformer centers located in the İkitelli Organized Industrial Zone in Istanbul. The dataset includes parameters such as load, air temperature, transformer temperature measured using a thermal camera, and transformer temperature recorded from transformer counters. The simulation studies were conducted using Matlab using the network structures in Figure 7.

Subsequently, the data were partitioned into training and test datasets with ratios of 75% and 60%, respectively. A three-layer network structure was selected for the hidden layer, with neuron compositions of 10, 40, and 40, respectively. The impact of the training percentage on performance improvement was analyzed. The field data were tested using two different network models: a feedforward model and a recurrent model.

(a) (b)

Figure 7. (a) Feed-forward network and (b) Recurrent ANN Models.

The activation functions utilized in the study were tansig, logsig, and purelin. The network was trained using the newelm and newff functions, and the resulting outputs were stored in Excel files. These procedures were applied to Elman recurrent neural networks (RNNs) and feedforward backpropagation networks for the eight transformers from which field measurements were obtained. The estimation results and average error values and comparison are presented in the following charts and tables (Table 3 and 4).

Table 3. MSE Results Obtained as a Result of Modeling.

Training Rates	**NN**	**Tr 1**	**Tr 2**	**Tr 3**	**Tr 4**	**Tr 5**	**Tr 6**	**Tr 7**	**Tr 8**
60	Feed Forward	39,793	34,652	15,608	64,632	22,874	21,081	19,959	16,648
	Recurrent	31,858	25,975	20,213	6,616	22,379	22,379	17,812	25,712
75	Feed Forward	25,865	23,824	14,197	14,507	14,514	9,498	11,756	14,546
	Recurrent	23,807	11,627	13,182	79,073	6,090	2,581	4,168	14,884

When trained with 60% of the data, the RNN model significantly outperforms FFNN. The error rate is lower, meaning the predictions are closer to the true values, as seen in Figure 8.

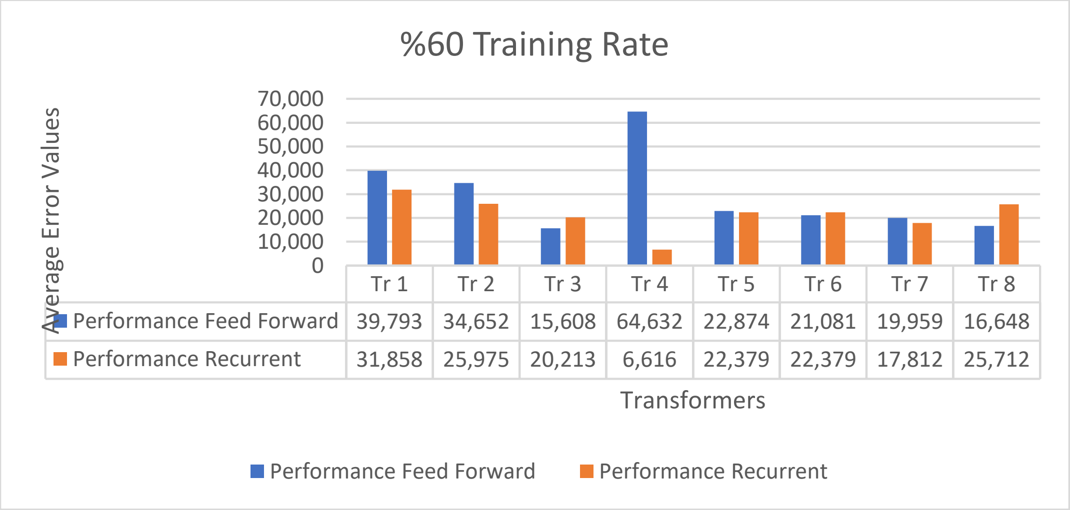


Figure 8. Recurrent and Feed Forward Network 60% Training Rate Comparison.

With a higher training rate of 75%, the performance of both models improves. However, the RNN still achieves significantly lower error rates, reinforcing its advantage over the FFNN in Figure.9.

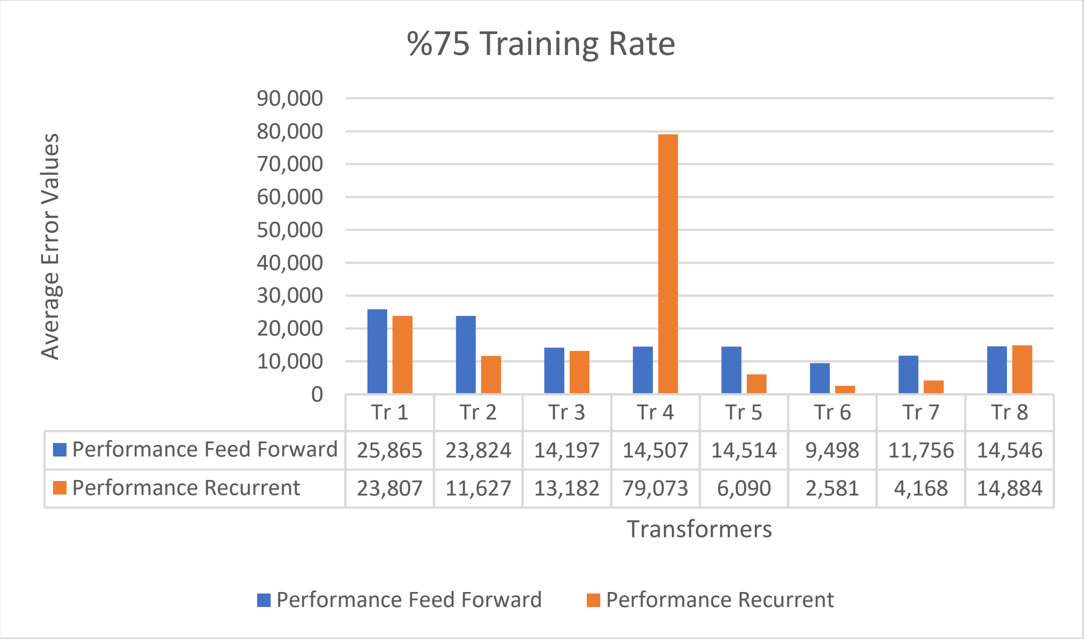


Figure 9. Recurrent and Feed Forward Network 75% Training Rate Comparison.

This Figure (fig.10) presents the FFNN's prediction results at both 60% and 75% training rates. While increasing the training rate helps reduce errors, the FFNN still struggles with making highly accurate predictions.

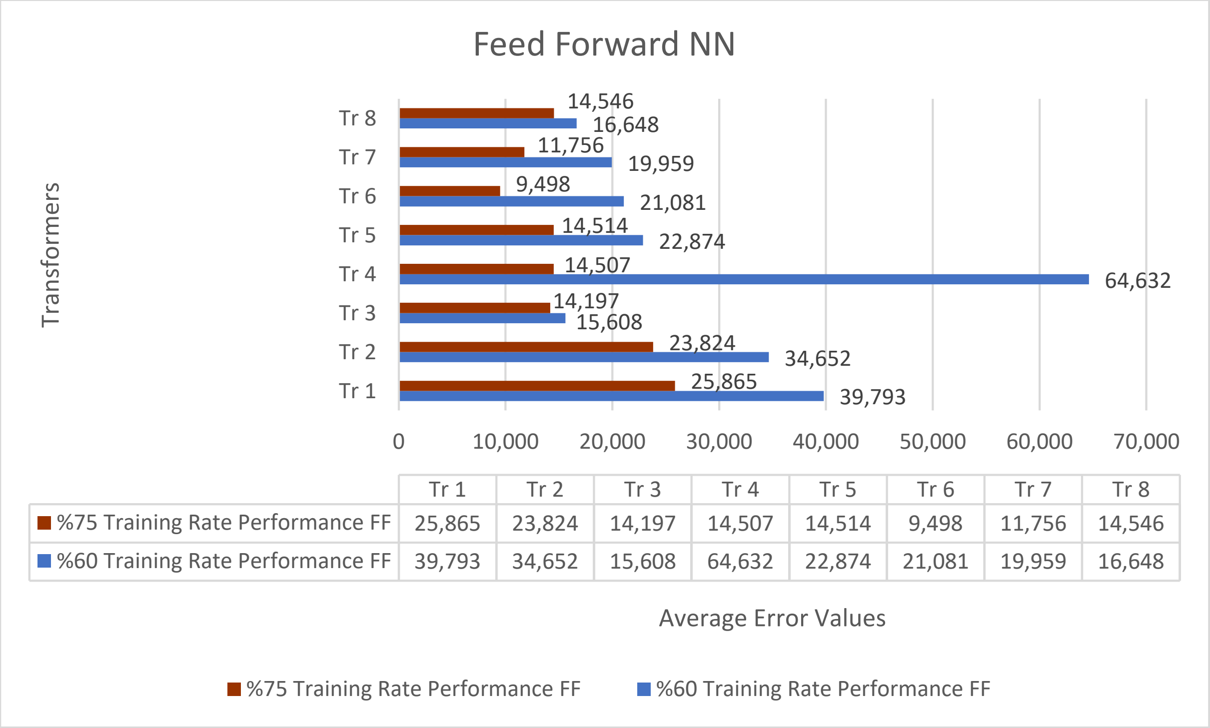
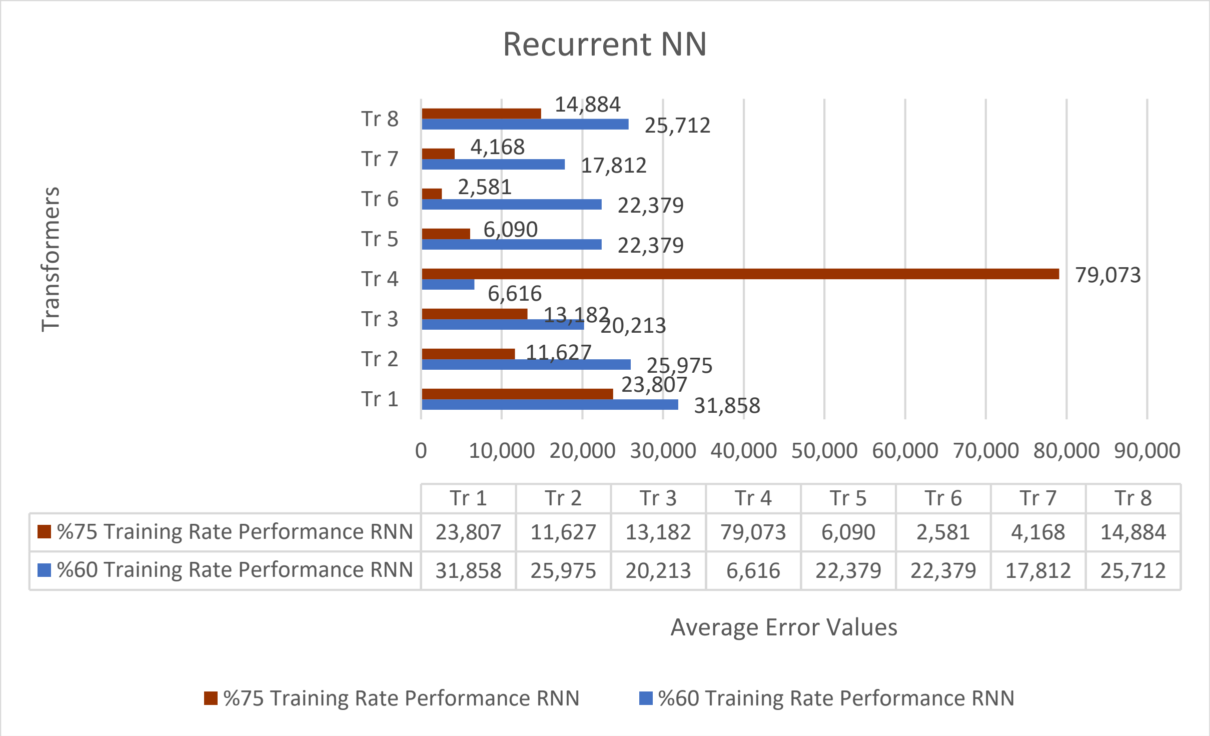


Figure 10. 75% And 60% Training Rate Results of Feed Forward NN.

Here, on Figure 11 the RNN's prediction results at different training rates. As expected, higher training percentages lead to better accuracy, and overall, the RNN consistently outperforms the FFNN.



	Tr 1	Tr 2	Tr 3	Tr 4	Tr 5	Tr 6	Tr 7	Tr 8
🟥 %75 Training Rate Performance RNN	23,807	11,627	13,182	79,073	6,090	2,581	4,168	14,884
🟦 %60 Training Rate Performance RNN	31,858	25,975	20,213	6,616	22,379	22,379	17,812	25,712

Figure 11. 75% And 60% Training Rate Results of Recurent NN.

Within the simulation studies, it is observed in Figures 8 and 9 that the performance results in the Recurrent model, for which the prediction results are given in the previous section, generally approach zero compared to the feed-forward model and the prediction values are better. It is shown in Figures 10 and 11 that in the prediction results of the iterative model and feed-forward model with 75% and 60% training rates, the results with 75% training rate are closer to the target.

Lastly, The RNN consistently outperforms the FFNN, regardless of the training rate. More training data leads to better estimations in both models, but the FFNN never quite matches the accuracy of the RNN. The last but not the least, RNN is the better model for predicting transformer noise.

Table 4. Comparison of RNN and FFNN Models.

Model	60% Training Rate	75% Training Rate	Overall Performance
Feed-Forward Neural Network (FFNN)	Struggles with accuracy, higher error rate	Improves with more training but still not optimal	Works for simpler problems but lacks reliability in complex scenarios
Recurrent Neural Network (RNN)	More accurate predictions, lower error rate	Even better performance with more training	Clearly the better choice for transformer noise prediction

4. Conclusion

In this study, field measurements were conducted on eight transformers under varying load conditions, air temperatures, and time periods over a four-month period from December 2020 to March 2021. The results indicate that noise levels fluctuated between 15-20% depending on whether the transformers were loaded or unloaded during these periods. Additionally, it was observed that cooling fans, which operate based on transformer noise levels, significantly contribute to noise emissions. Their impact is particularly influenced by the location of the transformer center, leading to an overall increase in noise levels.

Several recommendations have been proposed to mitigate transformer noise in transformer centers. These include tightening the connections of loose transformers, utilizing flexible busbars instead of rigid connections at transformer connection points, securing transformers on their respective rails, selecting high-quality core sheet transformers, and avoiding the operation of unnecessary cooling equipment. Implementing these measures can effectively reduce noise levels and improve overall transformer performance.

Ethics in Publishing

There are no ethical issues regarding the publication of this study.

Author Contributions

Yasin Günlemiş: Concept, Methodology, Theoretical Background, Writing.

Ertuğrul Adıgüzel: Methodology, Theoretical Background, Writing.

Aysel Ersoy: Methodology, Edit, Supervision.

Tarık Veli Mumcu: Methodology, Edit, Supervision.

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