Load Estimation for Transformers Based on Acoustic Features

Xin Zhao
China Electric Power Research Institute Co., Ltd,
Beijing, China
zhaoxin12021102@163.com

Junli Du
State Grid Henan Electric Power Company Power Science Research Institute,
Zhengzhou, China
dujunlizz@163.com

Shuai Han*
China Electric Power Research Institute Co., Ltd,
Beijing, China
*hanminghang@qq.com

Ning Yang
China Electric Power Research Institute Co., Ltd,
Beijing, China
ning_yang666@163.com

Yongfeng Zhao
State Grid Henan Electric Power Company Power Science Research Institute,
Zhengzhou, China
yongbubian109@163.com

Xin Wang*
Beijing Ensonictech. Co., Ltd.,
Beijing, China
*wangxin@ensonictech.com

2025 IEEE 5th International Conference on Power, Electronics and Computer Applications (ICPECA) | 979-8-3315-3369-4/25/$31.00 ©2025 IEEE | DOI: 10.1109/ICPECA63937.2025.10928810

***Abstract*—This paper introduces a novel approach for estimating the load of transformers by analyzing the radiated acoustic signals emitted by the transformers. The methodology involves the development of load-correlated acoustic features based on the principles governing the acoustic emissions of transformers. Through the collection and analysis of operational data from a traction substation, a predictive model correlating transformer acoustic signals to load is formulated using machine learning algorithms. The experimental findings demonstrate that this technique can accurately estimate transformer load utilizing solely the acoustic emissions from transformers, eliminating the need for electrical data after a brief period of data training. Consequently, this method holds promise as an innovative auxiliary tool for monitoring purposes.**

Keywords—Acoustic Features, Load Estimation, Acoustic Signal Analysis, Machine Learning

I. INTRODUCTION

Traction transformers are pivotal electrical components in traction substations, playing a critical role in voltage transformation, load regulation, and phase conversion. Their performance directly influences the operation and productivity of railway systems [1-2]. Unlike conventional transformers, traction transformers operate under highly dynamic load conditions characterized by sharp surges, rapid fluctuations, and pronounced intermittent variations between peaks and troughs [3-4]. These load uncertainties not only compromise the operational efficiency of the system but can also result in severe issues such as equipment overloading and insulation degradation, thereby impacting the safety and reliability of railway systems [5]. Consequently, effective monitoring of transformer load conditions is essential for maintaining system stability, optimizing energy usage, and enhancing overall economic efficiency [6-11].

In recent years, acoustic detection has emerged as a prominent auxiliary diagnostic technology in transformer monitoring, garnering significant attention in the research community. Compared to traditional approaches such as temperature monitoring, vibration analysis, and oil quality assessment [12 – 14], acoustic detection offers the distinct advantage of non-intrusive testing. Additionally, it features simplicity, flexibility in sensor selection, and reduced overall system complexity [15]. Reference [16] employed ultrasonic sensors to capture acoustic signals from transformers, enabling precise localization of partial discharges using a time difference of arrival (TDOA) approach combined with truncated singular value decomposition (TSVD) regularization. Reference [17] introduced a transformer fault diagnosis framework utilizing the Hilbert-Huang transform (HHT) and wavelet contour analysis, efficiently capturing operational state information from acoustic signals. Further advancements are demonstrated in Reference [18], which introduced a fault diagnosis method for power transformers utilizing gammatone frequency cepstral coefficients (GFCC) and convolutional neural networks (CNN). This approach achieved a recognition accuracy exceeding 95% in identifying faults across various operational states in 10 kV dry-type transformers. Reference [19] explored the application of mel frequency cepstral coefficients (MFCC) in diagnosing transformer faults by optimizing the MFCC components of acoustic signals in dry-type transformers. The study employed vector quantization algorithms to successfully identify core looseness within transformers. In Reference [20], an online state monitoring approach for power transformers was developed using Deep Q-Networks (DQN). By utilizing GFCC as input features and incorporating Q-learning strategies, the proposed DQN model achieved rapid convergence and high recognition accuracy in identifying transformer operational states.

Extensive research has explored the use of acoustics for transformer condition monitoring, yet its application for monitoring transformer load states has received little attention. To bridge this gap, we introduce a novel approach to estimate transformer load conditions using acoustic signals. Experimental validation was conducted on transformers under actual operating conditions. Load-related acoustic features for transformers is advanced, on the basis of the ratio of the energy between winding vibration frequency components and harmonic components in the acoustic signals. Additionally, we develop a predictive model that correlates these acoustic features with transformer load and introduce several evaluation metrics to assess its performance. The experimental results demonstrate a strong correlation between the proposed features and transformer load.

II. Transformer Sound Generation Mechanism and Load Acoustic Features

The acoustic emissions from a transformer primarily arise from two sources: core vibrations and winding vibrations [21]. Core vibrations are a result of magnetostriction, in which the magnetostrictive force is roughly proportional to the square of the applied voltage. Consequently, the core vibrates at twice the excitation frequency (typically 50 Hz or 60 Hz). Moreover, the leakage flux within the magnetic field introduces nonlinearities, leading to pronounced higher harmonic components. In contrast, the interaction between the current and the magnetic field in the windings produces electromagnetic forces — with both radial and axial components—that scale with the square of the current. Thus, the winding also vibrates at double the excitation frequency; however, when the windings are well-clamped and tightly wound, the higher harmonic contributions remain minimal so that the dominant component is at twice the excitation frequency [22].

Since transformer load conditions are generally inferred from variations in load current, the acoustic signals generated by winding vibrations are intrinsically linked to the load. Based on this relationship, we propose using the ratio of the energy in the primary winding vibration frequency components to that in the harmonic components as a load acoustic feature. The extraction method for this features is delineated in Fig. 1.

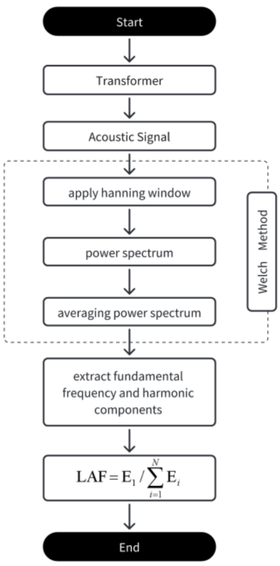

Fig. 1. Flowchart of features parameter extraction method

Under conditions where both current and voltage remain constant, the acoustic signal generated by a transformer can be considered steady-state. Therefore, applying the Welch method effectively mitigates the impact of transient disturbances from the surrounding environment. Typically, the power spectrum is calculated and averaged over frames within a 1-second duration of the acoustic signal. After extracting the fundamental frequency of the acoustic signal (i.e., the winding vibration frequency) and its harmonic components, the energy ratio between these components is computed. The load acoustic features (denoted by LAF) can be expressed as:

$$\mathrm{LAF} = \mathrm{E}_1 / \sum_{i=1}^{N} \mathrm{E}_i \tag{1}$$

In this context, E_i represents the fundamental frequency energy of winding vibration, and E_i denotes the energy of the i -th harmonic of the fundamental frequency. This form can further reduce the noise impact caused by non-transformer vibrations. It is important to note that the denominator in the above expression includes both the fundamental frequency and harmonic components, which confines the LAF within the [0,1] range, making it more universally applicable.

III. Load Estimation Method for Transformers Based on Load Acoustic Features

A. Data Collection

To investigate the relationship between the proposed load acoustic features and the load of transformers, this study conducted comprehensive data collection of both acoustic and load current data at a traction substation. As illustrated in Fig. 2, high-sensitivity acoustic sensors were strategically placed around the transformer to capture the acoustic signals generated during its operation at a sampling rate of 16 kHz. The acoustic feature data were extracted using the method detailed in Section 2. Simultaneously, a professional current measurement device was employed to record the real-time current of the transformer. The load data were then calculated using the method outlined in Reference [23]. To ensure data consistency and accuracy, both the load acoustic feature data and the load data were resampled and time-synchronized. This process guaranteed that each second of collected data included corresponding load acoustic feature samples and load samples, thereby providing robust data support for subsequent analyses and the development of load estimation methods.

Fig. 2. Acoustic Signal Collection

B. Load Estimation Method Based on Regression Models

This study employs four machine learning regression models—linear regression, ridge regression, decision tree regression, neural network regression [24]—to map load acoustic features to the actual load. These models cover a wide spectrum of algorithmic approaches, ranging from simple linear methods and their regularized variants to non-parametric tree-based techniques and deep learning architectures. To rigorously train and evaluate these models while avoiding data leakage, the study uses a time-series splitting strategy. As shown in Fig. 3, the continuously recorded acoustic signal data are partitioned chronologically into training and testing sets. The training sets is used to learn the temporal variation patterns in transformer load, while the testing set—comprising later time periods—assesses the model's ability to predict future load conditions. This approach reflects a best practice in time series analysis, ensuring that the model is exposed only to past data during training and is then validated on unseen, future data.

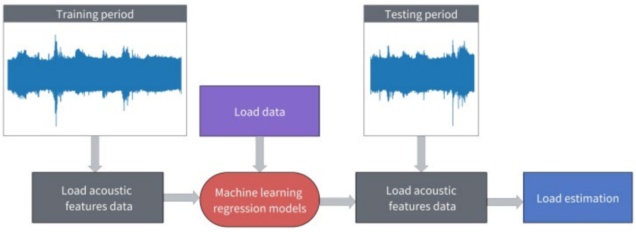

Fig. 3. Load Estimation Based on Regression Models

C. Evaluation Metrics

To comprehensively evaluate the performance of the constructed models, this study employs several evaluation metrics [25], which are described as follows:

- mean squared error (MSE)

MSE quantifies the average squared difference between the predicted values and the actual values, MSE places a greater penalty on larger discrepancies, offering a clear numerical measure of model accuracy.

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{2}$$

- root mean squared error (RMSE)

RMSE brings the error metric back to the same units as the target variable, which makes it more interpretable.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{3}$$

- coefficient of determination (R^2)

The R^2 measures the proportion of variance explained by the model relative to the total variance. Its value ranges from [0, 1]. An R^2 close to 1 indicates a high explanatory power of the model.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \overline{y})^2} \tag{4}$$

where $\overline{y}$ is the mean of all actual sample values.

- mean absolute error (MAE)

MAE quantifies the average magnitude of the errors between predicted values and actual values, without considering their direction.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{5}$$

- maximum error (Max Error)

Max Error is the largest difference between predicted and actual values across all samples, used to identify the maximum potential deviation in the model's predictions.

$$\text{Max Error} = \max_{i=1}^{n} |y_i - \hat{y}_i| \tag{6}$$

These evaluation metrics gauge the degree of discrepancy between the predicted and actual values from different perspectives, providing a scientific basis for model selection. By considering the results of these evaluation metrics comprehensively, suitable regression models can be identified.

IV. Experimental Results

In this section, we trained and tested the regression models for load estimation using the acoustic feature data and load data collected in Section 3.1. The models, introduced in Section 3.2, were evaluated using the performance metrics outlined in Section 3.3 to quantitatively assess their effectiveness and reliability. The primary objective was to validate the proposed method, which leverages load-related acoustic features for traction transformer load estimation. Additionally, the load estimation results from each model during the test period were visualized, further demonstrating the practical application value of the proposed method.

As shown in Table I, the performance evaluation results indicate that both linear regression and ridge regression models exhibit exceptional performance across all evaluation metrics. Notably, the ridge regression model demonstrates superior predictive accuracy and robustness, with an MSE of 0.0063, RMSE of 0.0794, MAE of 0.063, and MAX Error of 0.2402, along with an R^2 score of 0.9216. These results highlight the high predictive accuracy and strong explanatory power of the ridge regression model. In contrast, while the decision tree regression and neural network regression models also provide reasonable fits to the data, they exhibit lower precision in terms of prediction accuracy, particularly in the maximum error metric. The neural network regression model, in particular, performs notably poorer in this aspect, indicating a higher potential for significant deviations in predictions under certain conditions.

TABLE I. Model performance

Regression Models	MSE	RMSE	R^2	MAE	MAX Error
Linear	0.0065	0.0806	0.9193	0.0635	0.2314
Ridge	0.0063	0.0794	0.9216	0.063	0.2402
Decision Tree	0.0129	0.1138	0.8393	0.0856	0.401
Neural Network	0.0104	0.1021	0.8707	0.0833	0.2586

Figs. 4 and 5 illustrate the comparison between the predicted results of various models and the actual load values during the test period. As depicted in these figures, the predicted loads from the linear regression and ridge regression models exhibit a close alignment with the actual load trends, accurately capturing even rapid load dynamics. In contrast, while the decision tree regression model generally follows the overall trend, it displays more pronounced fluctuations. The neural network model, on the other hand, shows a decrease in predictive performance under low load conditions. These findings underscore the strong correlation between the proposed acoustic load features and the actual transformer load. They also demonstrate that machine learning regression models can effectively estimate transformer load through radiated acoustic signals, eliminating the need for electrical data. This novel approach offers a promising auxiliary method for transformer load monitoring, enhancing the comprehensiveness and accuracy of condition assessment.

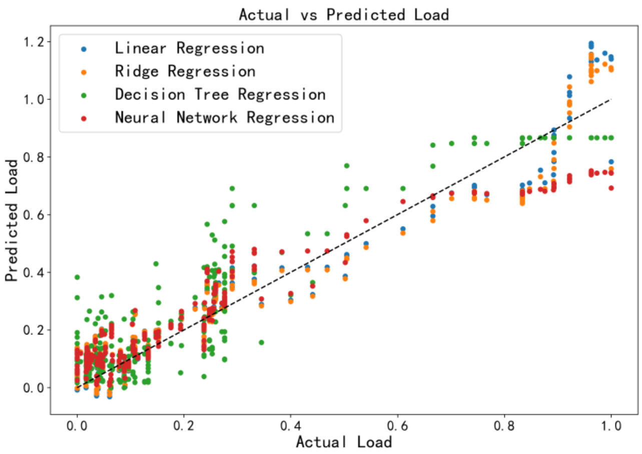

Fig. 4. Model Prediction Scatter Plot

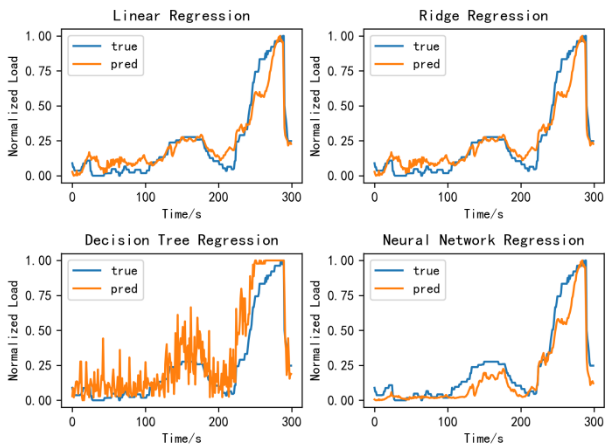

Fig. 5. Model Prediction Curve Plot

V. CONCLUSIONS

This paper introduces a novel method for estimating transformer load using acoustic features that closely reflect load conditions. By examining the sound-generation mechanisms in transformers, the study derives energy ratios between the winding vibration frequency components and their corresponding harmonic components from the radiated acoustic signals. These energy ratio features are then combined with machine learning techniques to develop predictive load models. Experimental results indicate that the ridge regression model achieves exceptional predictive accuracy and robustness, thereby confirming the efficacy of the proposed acoustic features for load estimation. Moreover, the research underscores the promising potential of acoustic signals in transformer condition monitoring. Future work will focus on refining acoustic feature extraction methods, exploring more advanced machine learning models, and extending the approach to monitor additional power system equipment. These developments are expected to enhance the scope and precision of condition monitoring systems, ultimately contributing to greater reliability and efficiency in power systems.

ACKNOWLEDGMENTS

This work was financially supported by State Grid Corporation of China science and technology Foundation (5500-202224139A-1-1-ZN): Research on non invasive measurement technology and critical structural state evaluation application of ultra-high voltage transformer (converter) reactor.

REFERENCES

[1] Xiong, Yumin, et al. The Electric Power Saving Schemes of High Speed Electrified Railway. Energy Procedia, 16 (2012): 1940-1947.

[2] Z. Y. He, and H. B. Cheng. Research on health management and early warning system for traction power supply system of high-speed railway. Power System Technology, 36.10, (2012): 259-264.

[3] Li, Ruoqiong, et al. Review on Capacity Optimization of Traction Transformer for High-Speed Railway. Energy Engineering, 119.6, (2022): 2533-2548.

[4] He Z, Zheng Z, Hu H. Power quality in high-speed railway systems. International Journal of Rail Transportation, 2016, 4(2): 71-97.

[5] D. Feng, Z. He and Q. Wang, A reliability assessment method for traction transformer of high-speed railway considering the load characteristics, 2015 IEEE Conference on Prognostics and Health Management (PHM), 2015, pp. 1-7

[6] Hsi P H, Chen S L. Electric load estimation techniques for high-speed railway (HSR) traction power systems. IEEE transactions on vehicular technology, 2001, 50(5): 1260-1266.

[7] Liu H, Li Q, Gao F. Traction power system model and simulation for estimation and forecast of traction load. 2010 Asia-Pacific Power and Energy Engineering Conference. IEEE, 2010: 1-4.

[8] Zhou L, Wang L, Zhang X, et al. An estimation method for real-time thermal capacity of traction transformers under unbalanced loads. IEEE Transactions on Industrial Electronics, 2020, 68(11): 11438-11446.

[9] Che Y, Wang X, Lv X, et al. Impact analysis of traction loads on power grid based on probabilistic three - phases load flow. The Journal of Engineering, 2019, 2019(16): 2306-2311.

[10] Che Y, Wang X, Lv X, et al. Study on probability distribution of electrified railway traction loads based on kernel density estimator via diffusion. International Journal of Electrical Power & Energy Systems, 2019, 106: 383-391.

[11] Wang K, Hu H, Huang Y, et al. Study on Overvoltage Issues in the Traction Network of Electrified Railways Caused by the Reactive Power: Phenomenon, Analysis, and Solution. IEEE Transactions on Transportation Electrification, 2023.

[12] Zhang L, Zhao H, Li Y, et al. Study on Multi-parameter On-line Monitoring System for Transformer Bushing.2020 Asia Energy and Electrical Engineering Symposium (AEEES). IEEE, 2020: 54-58.

[13] Gui Y, Li J, Shuai M, et al. Multi-parameter sensing scheme based on monitoring of distribution trasformers.IET Conference Proceedings CP880. Stevenage, UK: The Institution of Engineering and Technology, 2024, 2024(6): 1090-1094.

[14] Gouda O E, El-Hoshy S H, EL-Tamaly H H. Condition assessment of power transformers based on dissolved gas analysis. IET Generation, Transmission & Distribution, 2019, 13(12): 2299-2310.

[15] Zhao J, Qi J, Gui Y, et al. Research on State Detection of Power Equipment Based on Acoustic Imaging Technology.2023 5th International Conference on Electrical Engineering and Control Technologies (CEECT). IEEE, 2023: 431-437.

[16] Ning, Shuguang, et al. A method for the localization of partial discharge sources in transformers using TDOA and truncated singular value decomposition. IEEE Sensors Journal, 21.5, (2020): 6741-6751.

[17] S. Zhao, L. Pan and B. Li, The Study of Transformer Fault Acoustic Signal Processing Based on HHT and Wavelet Contour, 2009 WRI Global Congress on Intelligent Systems, 2009, pp. 262-266.

[18] X. J. Dang, F. H. Wang and W. J. Ma, Fault Diagnosis of Power Transformer by Acoustic Signals with Deep Learning, 2020 IEEE

International Conference on High Voltage Engineering and Application (ICHVE), 2020, pp. 1-4.

[19] B. Yan, F. H. Wang, S. Chen, Noise recognition of power transformers based on improved MFCC and VQ, in 2016 IEEE PES T&D Conference &Exposition, pp.1-4, May 2016.

[20] Li, G. W., et al. Deep Q-network for the Condition Monitoring of Power Transformer with Acoustic Signals. 2022 IEEE International Conference on High Voltage Engineering and Applications (ICHVE). IEEE, 2022.

[21] GARCIA B, BURGOS J, ALONSO Á.Transformer tank vibration modeling as a method of detecting winding deformations—Part I: Theoretical foundation. IEEE Transactions on Power Delivery, 2006, 21(1): 157-163.

[22] International Electrotechnical Commission. Power transformers-Part 10: Determination of sound levels. International Standard, IEC 60076-10 Edition 1.0, 2001.

[23] Yu L , Yong-Hui D .The Selection of Traction Transformers Used in Electrified Railway[J]. Jiangsu Electrical Engineering, 2011.

[24] Pardoe I. Applied regression modeling. John Wiley & Sons, 2020.

[25] Tatachar A V. Comparative assessment of regression models based on model evaluation metrics. International Journal of Innovative Technology and Exploring Engineering, 2021, 8(9): 853-860.