Optimizing Transformer Fault Detection: An Investigation into Current Signal Feature Extraction

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I. Introduction

Identifying faults is a crucial element in the realm of preventive maintenance and the condition monitoring of transformers. For fault detection of transformers many different conventional or advanced techniques such as short circuit impedance measurement, vibration and sound analysis, frequency response analysis (FRA), dissolved gas analysis and machine learning or deep learning have been used. Offline methods of fault detection are being experimented since faults can be detected at the earliest stages, the detection process does not disrupt power supply. By using feature extraction of the fault current waveform, the performance of the fault detection algorithm can be improved, and the accuracy of fault discrimination can be increased.

The purpose of this study is to evaluate the use of feature extraction of current in fault transformers using wavelet transform in order to enhance the effectiveness of the fault detection in transformers. A simulated PSCAD model derived using lumped parameter network in [1] is used for the generation of different types of faults and obtaining their fault current waveforms for feature extraction.

II. Literature Review

Numerous techniques have been employed for feature extraction in research studies related to power systems. As noted in [2], one frequently utilized signal processing method is the wavelet transform, which enables the extraction of both high and low-frequency components from signals. In this context, it has been applied to extract features from zero sequence currents. The selection of a specific wavelet depends on the nature of the application, and Daubechies wavelets are particularly prominent for detecting, localizing, and classifying disturbances, as highlighted in [3]. Additionally, the Daubechies family of wavelets, known for its versatility, is considered highly suitable for analyzing power system transients, as affirmed in [4].

Within the Daubechies family, there exists a wide range of wavelets, each with distinct characteristics. In [3], three Daubechies wavelets—Daub4, Daub12, and Daub20—are discussed. Daub4, due to its limited number of filter coefficients, stands out as a short wavelet, offering a higher level of temporal localization compared to other wavelets. It is noteworthy that this study follows suit by employing the Daub4 wavelet to extract features from the primary and secondary zero sequence currents, as well as the three-phase currents of transformers.

The transformer fault detection process has made use of a variety of machine learning models. Support vector machines (SVM), relevance vector machines (RVM), random forests (RF), decision trees (DT), and hierarchical ensemble extreme learning machines are the most often utilized methods. According to [5] SVM is inherently designed for binary classification. [6] states that RF offers non-linear classification and is a more potent classifier than SVM. According to the studied literature it is clear that Random Forest technique is a good fit for transformer fault detection.

III. Materials and Methods

The zero-sequence current is a crucial indicator of malfunctioning circumstances. Therefore, initially, the three-phase currents were transformed into zero-sequence currents through the application of Fortescue's transformation.

$$x_P = [x_a \ x_b \ x_c]^T$$

$$x_F = T_{P>F} \, . \, x_P$$

$$T_{P3>F3} = 1/3 \, . \, [[1 \ 1 \ 1] \ [1 \ a_3 \ {a_3}^2 \ ] \ [1 \ {a_3}^2 \ a_3]]$$

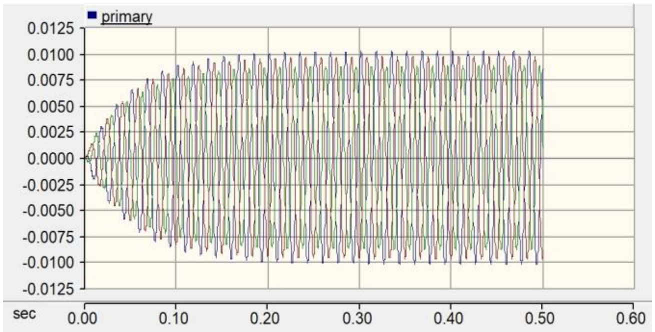

Fig. 1. Primary Current Waveform

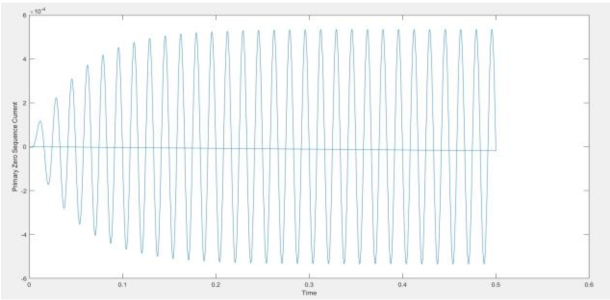

Fig. 2. Primary Zero Sequence Current Waveform

Subsequently, features were extracted from both the zero-sequence and three-phase currents on both the primary and secondary sides of the transformer with the aim of achieving better accuracy. As previously mentioned, this feature extraction process was accomplished using Daubechies 4 wavelet transformation with a level-2 decomposition.

In wavelet transformation, the process involves decomposing a given function, denoted as x(t), into a set of functions known as wavelets. Each wavelet is generated through a combination of scaling and translation operations applied to a fundamental function referred to as the mother wavelet.

During a level-2 decomposition, it is possible to extract three distinct coefficients, which are as follows: the level-2 approximation coefficient (cA2), the level-2 detail coefficient (cD2), and the level-1 detail coefficient (cD1).

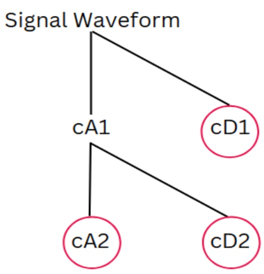

Fig. 3. Coefficients at each level of decomposition

From each of these coefficients, we have extracted a set of features, which includes the maximum coefficient, the minimum coefficient, and the wavelet energy entropy coefficient.

Following feature extraction, a machine learning model was created to use current waveform data to identify transformer fault states. The Random Forest approach, which offers highly accurate nonlinear classification, was applied.

IV. Results and Discussion

In this study, a total of 72 features have been successfully extracted from both primary and secondary side 3 phase and zero sequence currents.

The subsequent phase entails optimizing the number of features extracted according to the accuracy of the trained machine learning model.

V. Conclusion

Feature extraction was effectively performed from both fault currents and normal currents.

Based on insights garnered from the literature review and the obtained results, it is evident that optimizing the number of features extracted and the level of decomposition can lead to an improvement in model accuracy.

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References

[1] Jayarathna, P., Ediriweera, S., Samarasinghe, R., & Lucas, J. R. (2023). Modelling the lumped parameter network of a power transformer using sweep frequency response analysis. Australian Journal of Electrical and Electronics Engineering, 20(4), 309–321. https://doi.org/10.1080/1448837x.2023.2206602

[2] M. Dashtdar, M. Esmaeilbeig, M. Najafi, and M. E. N. Bushehri, "Fault Location in the Transmission Network Using Artificial Neural Network," Automatic Control and Computer Sciences, vol. 54, no. 1, pp. 39–51, Jan. 2020, doi: https://doi.org/10.3103/s0146411620010022.

[3] S. Dantas, B. Alencar, and F. A. C. Pires, "Daubechies wavelets in quality of electrical power," Nov. 2002, doi: https://doi.org/10.1109/ichqp.1998.759961.

[4] A. H. Osman and O. P. Malik, "Protection of Parallel Transmission Lines Using Wavelet Transform," *IEEE Transactions on Power Delivery*, vol. 19, no. 1, pp. 49–55, Jan. 2004, doi: https://doi.org/10.1109/tpwrd.2003.820419.

[5] O. Sobhana and Surya Kalavathi Munagala, "Application of Machine learning algorithms for Power transformer Internal faults identification," Mar. 2021, doi: https://doi.org/10.1109/icaccs51430.2021.9441719.

[6] [10] A. M. Shah and B. R. Bhalja, "Fault discrimination scheme for power transformer using random forest technique," IET Generation, Transmission & Distribution, vol. 10, no. 6, pp. 1431–1439, Apr. 2016, doi: https://doi.org/10.1049/iet-gtd.2015.0955.