International Journal on Science and Technology (IJSAT)

E-ISSN: 2229-7677 ● Website: www.ijsat.org ● Email: editor@ijsat.org

SVM Based Methodology for Classification of Internal Faults from Other Disturbances in Power Transformer

Patil Bhushan Prataprao[1], Dr. Shah Paresh Jaychand[2]

[1]R.C. Patel Institute of Technology,Shirpur, Maharashtra, India
[2]Shri Balaji Institute of Technology & Management, Betul, India

Abstract

This paper introduces a differential protection scheme for power transformers based on a Support Vector Machine (SVM) approach, designed to effectively classify internal faults while distinguishing them from other disturbances, such as magnetizing inrush currents and overexcitation conditions. The feature vector used for classification is extracted from the differential signal by computing the energy of the detail 2 coefficients obtained through wavelet transform analysis. This feature vector serves as input to the SVM classifier, ensuring accurate discrimination between fault conditions and non-fault disturbances. Comprehensive simulations are performed to evaluate the scheme under various scenarios, including internal transformer faults, diverse magnetizing inrush conditions, overexcitation states, and normal operating conditions with varying load levels. The power transformer is modeled and analysed using the MATLAB Simulink software environment.

Keywords: Power Transformer, Support Vector Machine (SVM), Wavelet Transform.

I. INTRODUCTION

The power transformer is a vital component of the electrical power system, and ensuring its reliable protection is essential. Currently, differential current-based relays are commonly used for transformer protection. These relays incorporate filters to suppress second harmonic components and, in certain cases, the fifth harmonic component, preventing false tripping caused by magnetizing inrush currents [2]. However, the harmonic content can be reduced by using high-quality magnetic materials in transformer core manufacturing [4]. Previous studies have explored artificial neural network (ANN)-based protection schemes to distinguish between magnetizing inrush and internal faults in power transformers [5]. Despite their potential, ANN-based approaches face challenges such as the requirement for extensive training data, slow training convergence, and vulnerability to overfitting [7].

Wavelet transform-based methods have also been proposed to separate internal faults from inrush currents [7]; however, such techniques typically fail to address overexcitation conditions. Alternative waveform identification techniques, such as principal component analysis (PCA) and mathematical morphology (MM), have been applied to transformer protection [8], [9]. Moreover, [10] introduced a scheme combining the S-transform with pattern classifiers, while [11] proposed a method using instantaneous frequency analysis of the average differential power signal to differentiate internal faults from inrush currents. Nevertheless, these approaches often overlook overexcitation conditions, leaving a gap in achieving comprehensive transformer protection.

The ANN-DWT (Artificial Neural Network-Discrete Wavelet Transform) method for identifying inrush currents and internal faults in transformers is detailed in [12]. This method employs the level 5 detail coefficient (d5) of the wavelet transform to extract critical features from the differential current signal. The data is collected for one cycle immediately following a disturbance during the transformer's online operation. The features extracted from the d5 coefficient enable the ANN to reliably classify internal faults and inrush conditions, demonstrating the potential of combining wavelet-based feature extraction with neural network classifiers to enhance fault discrimination accuracy in transformers.

This paper focuses on specific internal faults, such as turn-to-turn faults and primary-to-secondary winding faults, which have received limited attention in existing research. A Support Vector Machine (SVM)-based fault discrimination technique is employed in this study, effectively distinguishing internal faults, including turn-to-turn and primary-to-secondary faults, from other disturbances like magnetizing inrush currents and overexcitation conditions. By addressing these often-overlooked scenarios, the proposed approach provides accurate classification and robust transformer protection, offering a significant improvement over existing methods.

II. MODELING AND SIMULATION

Fig. 1 depicts the model of a three-phase, 50-Hz, 500-MVA, 500/230 kV power transformer used in this study. The transformer model is developed within the MATLAB Simulink environment. Differential currents from all three phases of the transformer are recorded to support detailed analysis. This simulation framework underscores the reliability and practical relevance of the proposed methodology in assessing advanced protection schemes for contemporary power systems. The generation of various simulation scenarios, including diverse internal fault conditions and other disturbances, is thoroughly discussed in the subsequent sections.

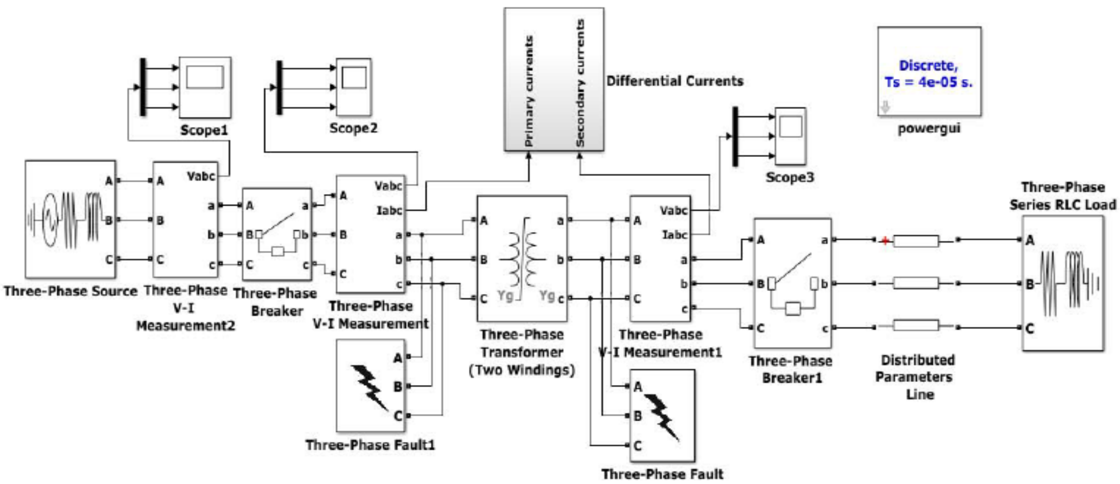

Fig.1. MATLAB /Simulink Model of the proposed system

A. Internal faults

Various types of internal faults, including line-to-ground (LG), line-to-line (LL), double-line-to-ground (LLG),LLLG, turn-to-turn, and primary-to-secondary winding faults, have been simulated using MATLAB Simulink.

1) Line-to-Ground (LG), Line-to-Line (LL), LLLG, and Double-Line-to-Ground (LLG) Faults: A comprehensive model has been developed in MATLAB Simulink to simulate these internal winding fault scenarios. Fault conditions such as LG, LL, and LLG are introduced at the transformer terminals under varying fault inception angles (FIA) of 0°, 70°, and 150°. Additionally, different source impedance values of 100%, 120%, and 80% are considered to replicate realistic and diverse fault conditions for in-depth analysis. The waveforms of differential currents for LG, LL, and LLG faults are presented in Fig. 2 to Fig. 4, highlighting the behavior of the transformer under these fault scenarios.

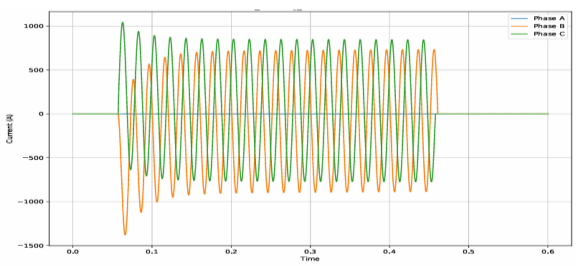

Fig.2 LG fault

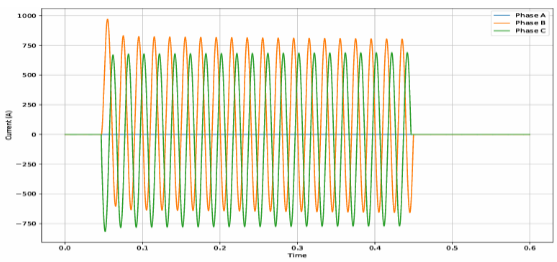

Fig.3 L-L fault

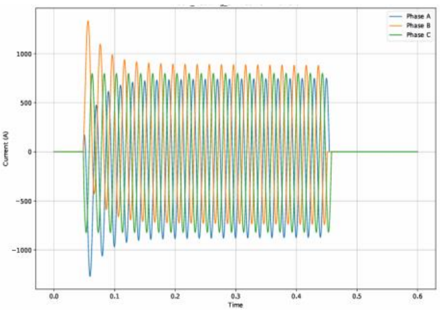

Fig. 4 LLLG fault

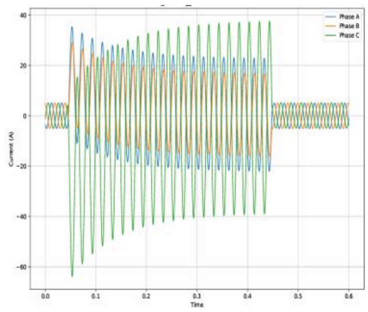

Fig.5 T-T fault

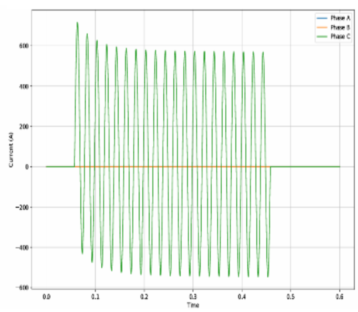

Fig.6 PR to SR fault

2) Turn-to-turn insulation breakdowns account for approximately 70%–80% of power transformer failures, primarily due to thermal, electrical, and mechanical stresses. If not detected promptly, these faults can escalate into severe ground faults or internal arcing within the transformer tank. While conventional relays can detect such faults, their delayed response may allow further fault progression. In this study, turn-to-turn faults are modeled in MATLAB Simulink using a transformer with tap changers. Differential current waveforms for these faults, with 2%, 4%, and 6% winding short-circuits on both the primary and secondary sides, are illustrated in Fig. 5.

3)Differential current waveforms for primary-to-secondary winding faults are illustrated in Fig. 6. Economically and structurally, the low-voltage (LV) winding is placed closer to the transformer core, while the high-voltage (HV) winding is positioned above it, separated by inter-winding insulation. Aging and prolonged exposure to electrical and thermal stresses gradually weaken the mechanical and dielectric properties of the windings, potentially leading to insulation failure or winding damage. These faults are modeled in MATLAB Simulink by short-circuiting the primary and secondary windings under varying fault inception angles and source impedance conditions to replicate real-world fault scenarios accurately.

B. Other System Disturbances

Various disturbances, including multiple types of inrush currents such as residual inrush, sympathetic inrush, and recovery inrush, along with overexcitation conditions, have been carefully considered for developing simulation cases.

1) Magnetizing inrush arises when a transformer is energized at a flux point misaligned with the instantaneous flux, producing a momentary sawtooth current. Residual flux from previous operations can amplify this inrush, influenced by its polarity and magnitude. Simulations, varying source impedance, switching angles, and loading conditions, were conducted to study this phenomenon, as shown in Fig. 7.

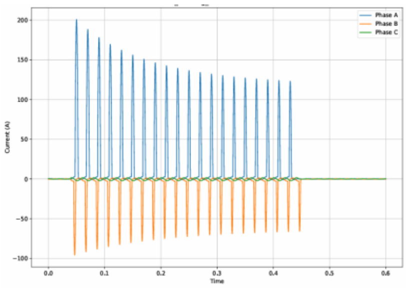
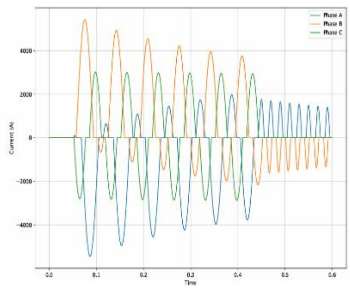
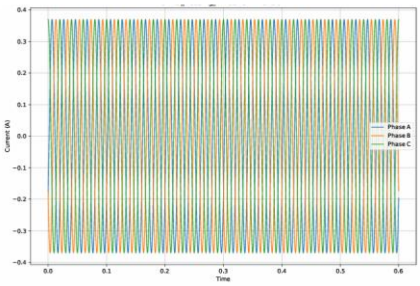

Fig.7 Magnetizing inrush current Fig.8 Overexcitation current Fig.9Normal current

This occurs when energizing a parallel transformer induces core saturation and a superimposed inrush current in an already operational transformer. Simulations with different loading conditions and source impedance angles provide valuable insights into this behaviour.

2)Figure 8 illustrates the waveform for the differential current under an overexcitation condition. To ensure the reliability of the differential protection scheme during such scenarios, the implementation of a dedicated transformer overexcitation protection circuit is essential. This analysis involves simulating overexcitation events by varying the transformer terminal voltage levels relative to its rated voltage and incorporating a ±5% deviation in the fundamental frequency of 50 Hz.

3) Figure 9 presents the differential current waveform under normal operating conditions. Simulations were carried out for varying load levels, source impedance values, and switching instances to analyze the system's behavior comprehensively.

III. PROPOSED APPROACH

A. Feature Extraction Using Wavelet Transform

The wavelet transform is a versatile mathematical tool widely applied in signal analysis and fault detection, particularly in power systems, including transformer defect identification. This technique enables signals to be decomposed into multiple frequency components, facilitating the analysis of localized features in both time and frequency domains. A crucial aspect of the wavelet transform is the selection of the "mother wavelet," which serves as the foundation for signal decomposition. Commonly used mother wavelets include Haar, Daubechies, Coiflet, and Symmlet, each offering distinct properties that influence the accuracy and reliability of analysis.

The Daubechies wavelet, particularly the db4 variant, has proven effective in transformer fault detection due to its ability to identify localized irregularities and transient features in non-stationary signals. Its balanced time-frequency resolution makes it well-suited for analyzingfault currents in transformers. In this study, the db4 wavelet was employed to decompose fault current signals into approximation and detail coefficients. Special attention was given to the second-level detail coefficients (D2), which encapsulate high-frequency transient information critical for fault identification.

The energy of the D2 coefficients was calculated as the primary feature for diagnosing transformer defects. This approach achieved a fault detection good accuracy so the effectiveness of the db4 wavelet for diagnostic tasks in power systems. The second-level decomposition strikes a balance between computational efficiency and diagnostic precision, making it practical for real-time applications. However, higher decomposition levels, while offering additional insights, were excluded due to the associated increase in computational demands.

The studies could explore the trade-offs between computational complexity and diagnostic accuracy by incorporating advanced decomposition levels. Such efforts would aim to optimize the diagnostic process while maintaining feasibility for real-time fault detection in power systems.

B. SVM-based Scheme

Support Vector Machines (SVMs) have proven to be highly effective for classification tasks across diverse domains, particularly in distinguishing between fault conditions and normal operations. The primary goal of an SVM is to construct a predictive model capable of classifying data instances based on their features. In this study, SVMs are employed to classify transformer fault conditions using a Python-based implementation. The dataset is divided into training 80% and testing 20% subsets, and the Radial Basis Function (RBF) kernel is selected for its ability to handle non-linear decision boundaries and improve classification accuracy. The feature vectors used for SVM training are derived from the energy of wavelet coefficients obtained through a two-level wavelet decomposition process applied to three-phase differential current samples over one cycle. The wavelet decomposition extracts high-frequency features from the current signals, focusing on the second level, where the energy of the coefficients is computed to form the feature set. This approach ensures practical applicability by relying on current samples easily obtained from transformer models. During testing, the trained SVM classifier assigns binary labels to new data instances, outputting "1" for internal faults and "0" for normal conditions or disturbances. This binary classification effectively distinguishes fault conditions while minimizing false positives. The combination of wavelet-based feature extraction and the SVM classifier proves particularly advantageous for analyzing transient signals, as wavelets provide critical time-frequency information for fault detection. The classification performance is evaluated using the formula Accuracy (%) = (TP + TN) / Total Testing Dataset × 100. Here, TP and TN represent true positives and true negatives, respectively, while the total testing dataset refers to all instances used for evaluation. Results demonstrate that integrating wavelet features with SVM classification achieves high accuracy, underlining the robustness of the proposed method. The use of the RBF kernel further enhances the model's ability to generalize to unseen data, ensuring reliable fault detection and disturbance identification. This approach combines computational efficiency with precise fault discrimination capabilities, making it a valuable tool for fault detection in power systems under diverse operating conditions.

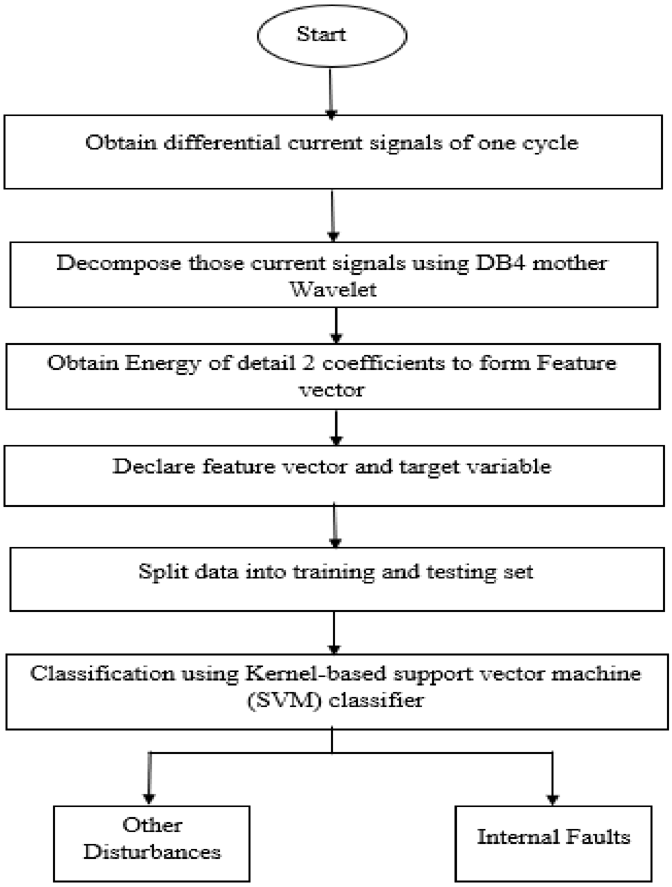

Fig.8. Block diagram of the proposed scheme

Figure 8 depicts the block diagram of the proposed framework, showcasing the synergy between Support Vector Machines (SVMs) and wavelet-based feature extraction for fault detection. The method utilizes energy-based feature vectors derived from the wavelet decomposition of three-phase differential current samples to effectively distinguish internal faults from external disturbances. By combining wavelet analysis with SVM classification, the framework captures transient signal features in the time-frequency domain, ensuring accurate fault detection. This integration demonstrates the practical applicability of SVMs for power system monitoring and highlights advancements in fault detection methodologies for improved operational reliability.

IV.RESULTS AND DISCUSSION

In this article to evaluate the performance of the classifier 80% of the dataset was allocated for training, while the remaining 20% was used for testing. A confusion matrix provides a comprehensive summary of classification results, offering critical insights into a model's performance by detailing both correct and incorrect predictions. This tool is invaluable for assessing classification accuracy and evaluating the ability of a predictive model to distinguish between classes. In this study, class 0 represents external disturbances, while class 1 represents internal faults. The dataset consists of 523 cases, with 418 instances used for training and 105 for testing.

Table 1 Confusion matrix for the SVM classifier

Test data						
Type	Total		TP	FP	% Accuracy	Overall accuracy
Other Disturbances	56	TP	50	6	89.28	93.33
Internal Faults	49	FN	1	48	97.95	

SVM classifier employed in this research was configured with the following fine-tuned hyperparameters: `'C': 1000`, `'gamma': 0.01`, and `'kernel': 'rbf'`. These parameters were optimized using the GridSearchCV algorithm with a support vector classifier estimator to ensure superior performance. The resulting confusion matrix highlighted 50 true positives (TP), 48 true negatives (TN), and 7 misclassified cases. The model achieved an exceptional training accuracy of 99.52%, indicating its effectiveness in learning from the training data. Furthermore, the test accuracy was measured at 93.33%, reflecting the model's strong generalization ability to unseen cases. The radial basis function (RBF) kernel, validated as the most effective kernel, played a pivotal role in achieving these high-performance metrics, solidifying the SVM classifier as a dependable solution for fault classification tasks.

These findings emphasize the significance of selecting appropriate hyperparameters and employing rigorous evaluation strategies to optimize classification performance. The confusion matrix not only provides a detailed breakdown of results but also serves as a diagnostic tool for identifying areas where the model may require refinement. By integrating machine learning techniques with robust validation processes, this study underscores the effectiveness of SVM-based approaches in distinguishing between external disturbances and internal faults in power transformer systems.

The proposed scheme effectively distinguishes between internal faults and external disturbances with high sensitivity, ensuring prompt detection and protective action to mitigate potential damage. Simultaneously, it maintains stability during external disturbances, preventing false tripping and minimizing unnecessary transformer outages. Moreover, the scheme demonstrates advanced functionality by accurately detecting challenging internal fault types, such as primary-to-secondary winding faults and turn-to-turn faults, even in the presence of external disturbances. These results highlight the innovation and reliability of the proposed approach, surpassing the capabilities of traditional transformer protection methods.

IV. CONCLUSION

The proposed SVM-based differential protection scheme effectively differentiates internal faults from external disturbances in power transformers by combining wavelet transform techniques with Support Vector Machines (SVMs). Utilizing the Daubechies (db4) wavelet, the approach achieves accurate fault detection with 93.33% accuracy by extracting critical features such as the energy of second-level detail coefficients. The Radial Basis Function (RBF) kernel enhances the SVM classifier's ability to generalize, ensuring reliable classification of internal faults and disturbances. While the method balances computational efficiency and diagnostic accuracy, it highlights the potential for improved performance by exploring higher wavelet decomposition levels. This study demonstrates the value of integrating advanced signal processing with machine learning, laying the groundwork for future optimization of wavelet parameters and SVM configurations to develop more robust diagnostic solutions for power systems

REFERENCES

[1] A. M. Shah and Bhavesh R. Bhalja, "Discrimination Between Internal Faults and Other Disturbances in Transformer Using the Support Vector Machine-Based Protection Scheme", IEEE Transactions on Power Delivery, vol., 28, no. 3, July 2013

[2]P. M. Anderson, Power System Protection. New York: IEEE, 1999.

[3]Y. G. Paithankar, S. R. Bhide, Fundamentals of Power System Protection, Prentice-Hall of India Pvt. Ltd. New Delhi, 2003.

[4]M.-C. Shin, C.-W. Park, and J.-H. Kim, "Fuzzy logic-based relaying for large power transformer protection," IEEE Trans. Power Del., vol. 18, no. 3, pp. 718–724, Jul. 2003.

[5]M. R. Zaman and M. A. Rahman, "Experimental testing of the artificial neural network based protection of power transformers," IEEE Trans. Power Del., vol. 13, no. 2, pp. 510–517, Apr. 1998.

[6]M. Tripathy, R. P. Maheshwari, and H. K. Verma, "Power transformer differential protection based on optimal probabilistic neural network," IEEE Trans. Power Del., vol. 25, no. 1, pp. 102–112, Jan. 2010.

[7]J. Faiz and S. Lotfi-Fard, "A novel wavelet-based algorithm for discrimination of internal faults from magnetizing inrush currents in power transformers," IEEE Trans. Power Del., vol. 21, no. 4, pp. 1989–1996, Oct. 2006.

[8]E. Vázquez, I. I. Mijares, O. L. Chacón, and A. Conde, "Transformer differential protection using principal component analysis," IEEE Trans. Power Del., vol. 23, no. 1, pp. 67–73, Jan. 2008.

[9] Z. Lu, W. H. Tang, T. Y. Ji, and Q. H. Wu, "A morphological scheme for inrush identification in transformer protection," IEEE Trans. Power Del., vol. 24, no. 2, pp. 560–568, Apr. 2009.

[10]S. R. Samantaray, B. K. Panigrahi, P. K. Dash, and G. Panda, "Power transformer protection using S-transform with complex window and pattern recognition approach," Inst. Eng. Technol. Gen., Transm. Distrib.,vol. 1, no. 2, pp. 278–286, 2007.

[11]A. Hooshyar, S. Afsharnia, M. Sanaye-Pasand, and B. M. Ebrahimi, "A new algorithm to identify magnetizing inrush conditions based on instantaneous frequency of differential power signal," IEEE Trans. Power Del., vol. 25, no. 4, pp. 2223–2233, Oct. 2010

[12]Banerjee, M., Khosla, A. Utilization of Artificial Neural Network for the Protection of Power Transformer. In: Singh Tomar, G., Chaudhari, N.S., Barbosa, J.L.V., Aghwariya, M.K. (eds)

International Conference on Intelligent Computing and Smart Communication 2019. Algorithms for Intelligent Systems. Springer, Singapore.2020.

[13] B. Ravikumar, D. Thukaram, and H. P. Khincha, “Application of support vectormachines for fault diagnosis in power transmission system,” Inst. Eng. Technol. Gen., Transm. Distrib., vol. 2, no. 1, pp. 119–130, Jan. 2008.

[14] A. H. Osman and O. P.Malik, “Protection of parallel transmission lines using wavelet transform,” IEEE Trans. Power Del., vol. 19, no. 1, pp. 49–55, Jan. 2004.