EAI Endorsed Transactions
on Energy Web

Research Article EAI.EU

Improving Fault Classification Accuracy Using Wavelet Transform And Random Forest With Statcom Integration

Shradha Umathe[1*], Prema Daigavane[1], Manoj Daigavane[2]

[1]Department of Electrical Engineering, GH Raisoni University Amravati, Amravati Maharashtra, India- 444701
[2]Department of Electrical Engineering, Government Polytechnic Sadar Nagpur, Nagpur Maharashtra, India- 440001

Abstract

INTRODUCTION: Fault detection in transmission lines is critical for keeping the grid stable and reliable. This research offers a new methodology, the Wavelet Transform-Enhanced Random Forest Fault Classification System with STATCOM Integration (WERFCS-SI), to solve the shortcomings of existing fault detection approaches.
OBJECTIVES: The integration of STATCOM-compensated transmission lines improves fault detection capabilities. The Wavelet Transform finds faults by analysing approximation and detail coefficients, allowing for multiresolution analysis and exact fault localisation.
METHODS: Feature selection approaches, such as information gain, are used to discover and keep relevant features, increasing classification accuracy.
RESULTS: Due to its ability to process complex, high-dimensional data and identify minute feature connections, Random Forest (RF) is utilised for classification tasks. The proposed approach improves RF model performance while maintaining precision.
CONCLUSION: The integrated technique simplifies fault categorisation, increasing accuracy and efficiency by detecting problems in the transmission line system.

Keywords: Transmission lines, fault detection, Wavelet Transform, Random Forest, STATCOM Integration

Received on 30 April 2024, accepted on 20 October 2024, published on 02 November 2024

doi: 10.4108/ew.5950

1. Introduction

A three-phase STATCOM (Static Synchronous Compensator) compensated gearbox line is an advanced solution in power systems engineering. As the demand for stable and dependable electrical power transmission grows, utilities and industries increasingly rely on modern technologies such as STATCOM to efficiently regulate voltage and reactive power across transmission lines [1]. A STATCOM device uses power electronics to dynamically adjust an electrical system's voltage and reactive power flow. In the context of a three-phase transmission line, the STATCOM regulates voltage levels, corrects power factor imbalances, and reduces voltage fluctuations, improving the power grid's overall stability and reliability [2]. A STATCOM is installed in a three-phase transmission line by integrating it at important spots, usually substations or key junction points. The STATCOM can inject or absorb reactive power as needed by monitoring and controlling system parameters in real time, effectively correcting for fluctuations in load demand or grid disturbances [3]. One of the primary benefits of using a STATCOM in three-phase transmission systems is its capacity to deliver fast and exact reactive power adjustment, which improves voltage stability, reduces losses, and increases overall network efficiency [4]. STATCOMs also provide operational flexibility, allowing seamless connection with existing infrastructure and compatibility with multiple control schemes to optimise performance under varying operating situations [5]. Wavelet transform is a powerful mathematical technique for analysing signals and images at different sizes, providing information about their

*Corresponding Email: shradhatul07@gmail.com

frequency and spatial features [6]. Unlike standard Fourier transform, which decomposes a signal into sine and cosine functions of fixed frequencies, wavelet transform uses small wavelets, or localised oscillations, to capture both frequency and position information simultaneously [7]. This makes it ideal for analysing signals with non-stationary or transitory properties. The wavelet transform's ability to accurately describe signals in terms of time and frequency is one of its main benefits [8]. This means it can reliably detect transitory elements in a signal while delivering detailed frequency content at various time points [9]. This makes it important in signal processing, data compression, and picture analysis, where knowing temporal and frequency dynamics is essential [10]. The DWT sequentially filters and downsamples the signal to extract information at various resolutions. In contrast, the CWT gives a continuous representation of the signal by convolving it with a scaled and translated version of the wavelet function [11]. The versatility of the wavelet transform has made it widely applicable in many fields, such as geophysics, biomedical engineering, signal processing, and image analysis [12]. Its capacity to capture both global and local aspects of signals and images makes it an essential tool for extracting meaningful information from complex data [13]. Furthermore, its computing efficiency and flexibility have made it a key component in modern data analysis methodologies, allowing researchers and practitioners to understand the underlying structure and dynamics of many events better [14]. The wavelet transform has become an effective flaw identification technique in many engineering applications because it can simultaneously evaluate signals in the time and frequency domains [15]. A signal is broken down into component wavelets via the wavelet transform; wavelets are small, frequency- and time-localized functions that resemble waves [16]. This decomposition technique extracts features at several scales, enabling the detection of abrupt shifts or abnormalities that indicate system failures [17]. Wavelet transformations can effectively identify minute variations linked to issues amongst background noise or normal functioning because they capture the high-frequency and low-frequency components of a signal with different resolutions [18]. The wavelet transform is often employed with sophisticated signal processing methods such as time-frequency analysis, feature extraction, and algorithmic pattern recognition in identifying defects applications [19]. These techniques allow for identifying specific fault signatures or patterns within complicated signals, which aids in detecting and diagnosing flaws before they worsen [20]. Furthermore, wavelet transform has advantages such as computing efficiency, scalability, and adaptation to different signal sources, making it ideal for real-time fault detection systems used in various industrial contexts. Its capacity to handle non-stationary signals and localise characteristics in both temporal and frequency domains makes it a top choice for identifying problems in dynamic systems where standard approaches may fail [21]. In conclusion, wavelet transforms play an important role in fault identification by providing a solid foundation for analysing signals with complicated dynamics and finding fault signatures among the noise and normal variations. It is a vital instrument for guaranteeing significant components' reliability, security, and effectiveness across various engineering disciplines due to its efficacy and versatility [22]. In ML and data analysis, feature selection is a crucial step that enhances computational efficiency, interpretability, and model performance. It comprises narrowing down the original set of variables or attributes needed to create a model predicting the most pertinent feature subset [23]. This method helps mitigate the effects of the "curse of dimensionality," suggesting that too many features can lead to overfitting, increased computational cost, and poor generalisation performance. The basic goal is to keep only the most important elements and delete redundant or useless ones. By lowering the dataset's dimensionality, feature selection enhances model interpretability by focusing on the most informative variables [24]. Methods for selecting features include filtering, wrapping, and embedding. The technique used is determined by the type of dataset, computational resources available, and analytic objectives. Feature selection can result in significant computational savings, particularly in high-dimensional data or resource-constrained contexts [25]. Feature selection speeds up machine learning models' training and inference phases by focusing computational resources on the most relevant features, making them more useful in real-world applications. In ML and data analysis pipelines, feature selection is a crucial pre-processing phase that facilitates the creation of prediction models that are more accurate, efficient, and comprehensible [26]. Random forests are a powerful ensemble learning technique utilised in various sectors, including finance and healthcare, to handle complicated datasets with high-dimensional feature spaces [27]. They excel in fault classification, a key activity in engineering and industrial applications that categorises instances based on specified quality properties [28]. Random forests can manage vast amounts of data with varying characteristics and imbalanced datasets, making them useful in real-world applications. Random forests reduce majority prejudice by aggregating predictions from many decision trees trained on bootstrapped samples. Their inherent feature selection capability helps them perform well in fault classification since each decision tree analyses only a subset of features at each split, leading to more diversified and less correlated trees. This decreases the risk of overfitting while improving generalisation performance [29]. However, because of the complexity and diversity of fault signals, effectively classifying faults within these systems remains a significant issue. High accuracy is frequently difficult for traditional fault classification techniques in the presence of noise and non-stationary signal characteristics. In fault classification applications, interpretability is critical, and random forests provide insights into feature importance, allowing engineers and domain experts to determine which features have the greatest impact on classification judgments.

This research contributes the following:

- Introducing a novel method that combines Wavelet Transform (WT) and Random Forest (RF) for fault detection in compensated transmission lines with STATCOM integration, thereby enhancing accuracy and efficiency.

- Utilizing information gained for feature selection improves classification accuracy by focusing on relevant fault signal characteristics and enhancing fault detection performance.
- Overcoming limitations such as the assumption of feature independence and the complexity of travelling wave-based detection, the methodology that has been proposed provides a thorough approach to fault identification and classification, specifically for compensated transmission lines.

The organisation of this research is as follows: Section 1 provides a detailed introduction to the study. Section 2 represents a literature review based on fault classification phenomena. Section 3 indicates a thorough explanation of the proposed model. Section 4 provided an analysis of the experimental results, and finally, Section 5 concluded with the Conclusion section.

2. Literature Survey

Aker E. et al. [30] provided a method for defect identification and categorisation for shunt-compensated STATCOM transmission lines that makes use of Naive Bayes (NB) and Discrete Wavelet Transform (DWT) classifiers. The db4 Daubechies mother wavelet was utilised to process three-phase fault current waveforms and extract information such as energy levels and standard deviation (SD). These characteristics were then used to train classifiers for fault type classification, such as Multi-Layer Perceptron Neural Networks (MLP), Bayes, and NB. NB's limitation is its assumption of feature independence, which may not be accurate in real-world data, and its potential bias in handling imbalanced datasets.

Mishra.S et al. [31] examined how well four signal decomposition procedures performed to support Fault Location Methods (FLMs) in FACTS-compensated systems for fault localisation. The methods that were discussed were the S-transform (ST), the Empirical Mode Decomposition (EMD), the Intrinsic Time Decomposition (ITD), and the Estimation of Signal Parameters via the Rotational Invariance Technique (ESPRIT). A 500 kV system fitted with a 100 MVAr FACTS device was used to simulate and analyse several scenarios, including series, shunt, and series-shunt FACTS-compensated networks. Travelling wave-based fault detection excels in precise fault location but is costlier, sensitive to fault types and noise, and requires complex data analysis.

Duku Otuo-Acheampong et al. [32] presented a method for evaluating the dynamic security of transient stability utilising Thyristor Controlled Series Capacitor (TCSC) devices. This method relied on severity indices to analyse power system faults, employing time domain analysis simulations for enhanced readiness in anticipating system behaviour during disturbances. Due to its effective convergence, the Flower Pollination Algorithm (FPA) was utilised to discover the best location for TCSCs and the appropriate parameter settings. The suggested method was used to analyse the effects of three-phase short circuit faults, fault locations, and clearing techniques on the IEEE 14-bus system. The analysis revealed that TCSC implementation significantly improved voltage stability and increased stability margins during short circuit faults on transmission lines. The proposed method does not determine the location of the fault.

ANI HARISH et al. [33] utilised Phase Measurement Units (PMU) data to concentrate on fault recognition and categorisation in transmission lines for wide-area backup protection. Using weighting, a Weighted Extreme Learning Machine (WELM) method was applied, considering the varied data distribution among various fault classes. Wavelet transform-based ensemble feature extraction was used to get input features, and Particle Swarm Optimization (PSO) was employed to optimise the WELM classifier. WELM's limitation is its reduced interpretability compared to SVM due to the random weight initialisation and lack of a precise geometric interpretation of decision boundaries.

Zhang C et al. [34] study uses large-signal analysis to examine how a phase-locked loop (PLL) affects a Type-IV wind turbine's stability. A nonlinear reduced-order model is built to determine grid-synchronizing stability (GSS) resulting from grid faults, as demonstrated by the equal-area principle (EAP). To quantify the effect of system variables, including PLL bandwidth, on the GSS margin, critical clearing time (CCT) is calculated. This knowledge may be assessed via a Type-IV wind turbine system switching model in PSCAD/EMTDC and applied to PLL parameter design. The results could help determine PLL parameters for low-voltage ride-through (LVRT) wind turbine design.

Wang, X. et al. [35]; Smart cities and nations are quickly becoming a reality, with smart grids playing a critical role. However, privacy-preserving multisubset data aggregation is a challenge because present solutions frequently need a trusted third party (TTP), which can be difficult and increase threat exposure. This paper provides a fault-tolerant multisubset data aggregation system that calculates overall electricity usage value without TTP. The system analysis demonstrates that this technique prevents single data loss while also ensuring efficiency when new users join and existing users leave. The system's robustness is achieved at a minimal cost.

Abdelsattar, M. et al. [36]: The need for more electricity has led to a focus on renewable energy sources, especially wind energy. Due to their ability to operate at different speeds and control power output, doubly fed induction generator (DFIG)--based wind farms are becoming increasingly common. Nonetheless, voltage stability is essential to a DFIG-based wind farm's capacity to function during grid delays and outages. To restore voltage levels in the Egyptian power system connected to the Al Zafarana-5th stage wind farm, this article uses a static synchronous compensator (STATCOM). According to simulation studies, STATCOM devices with fuzzy logic controllers reduce disturbances and grid fault effects, which makes them perfect for wind farms of the present and the future.

Vimalraj, M et al. [37]: This study looks at a fixed-speed wind farm under an imbalanced grid voltage fault with squirrel cage induction generators (SCIG) connected to the grid and indirect torque control (ITC) technique developed using STATCOM. A review of several control techniques and theoretical and simulation studies are included. Unbalanced dips in grid voltage cause more oscillations in torque generation. Simulation outcomes show that using a STATCOM for voltage correction improves voltage stability and reduces torque oscillations in a SCIG wind farm.

Mosaad, M. I et al. [38] study looks at how a static compensator (STATCOM) can help reduce Ferro resonance overvoltage in grid-connected wind energy conversion systems (WECSs). The controller, which includes proportional-integral (PI) controllers and employs a modified flow-pollination algorithm (MFPA), is introduced to regulate reactive power quickly. Two test examples demonstrate the controller's capacity to prevent Ferro resonance overvoltage. The findings indicate that Ferro resonance disturbance can arise in power transformers used in wind farms, even when the transformer terminals are coupled. The suggested STATCOM controller optimises the wind turbine's voltage and speed profile while protecting system components from Ferro resonance overvoltage.

3. Proposed Methodology

The WERFCS-SI is a fault detection system for transmission lines outfitted with Flexible Alternating Current Transmission System (FACTS) components. It detects faults using wavelet transforms, which allow for multiresolution analysis and exact fault localisation. This technique enhances accuracy by detecting minor changes produced by faults. STATCOM integration introduces dynamic compensation capabilities, which help to mitigate the consequences of transmission line faults and disturbances. Feature selection approaches like information gain improve classification accuracy by selecting and preserving the most informative properties. Random Forest (RF) is the major classifier, which handles complicated, multidimensional data and captures subtle feature associations. The ensemble learning approach distinguishes between different fault classes in compensated transmission lines, which improves overall detection accuracy. The WERFCS-SI technique provides a comprehensive solution for detecting faults in transmission lines, maximising performance while retaining precision and dependability.

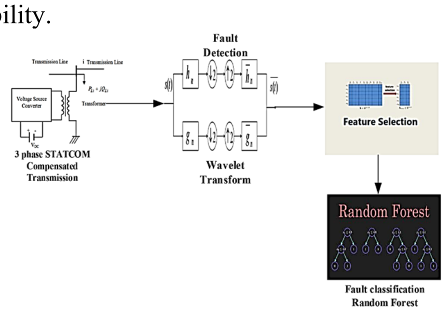

Figure 1: Workflow of WERFCS-SI technique

3.1. STATCOM Compensated Transmission Line

The STATCOM is the cornerstone of the FACTS (Flexible Alternating Current Transmission System) device family, having played a vital role for decades due to its economic and technological advantages. Its rapid response time, precision, and dependability make it a highly effective instrument for regulating voltage steady states and transients, outperforming traditional compensators. Figure 2 shows STATCOM's general architecture, which contains a Voltage Source Converter (VSC), a DC energy storage unit, and a coupling transformer interconnected in shunt with the AC system. Figure 3 depicts the STATCOM's characteristic curve, representing the voltage-current relationship. As a shunt-connected device, the STATCOM functions in two modes: capacitive and inductive. The phase angle difference between line and VSC voltage determines how these modes transition. This phase angle difference directs the STATCOM's transition from capacitive to inductive mode, allowing it to react flexibly to changing system conditions and requirements. The STATCOM setup is a system for controlling voltage levels in an alternating current power system. It comprises a semiconductor device called the Voltage Source Converter (VSC), which uses precise modulation techniques to generate regulated AC voltages and currents. The VSC can manage voltage levels by either injecting or absorbing reactive power into the system. A DC energy storage device, such as capacitors or batteries, guarantees the STATCOM's quick reaction and versatility.

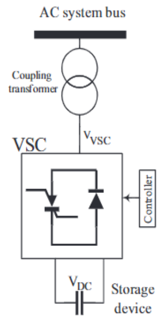

Figure 2: STATCOM Configuration

This storage unit ensures grid stability during transitory situations or changes in load demand. The coupling transformer connects the device to the alternating current power system, allowing for power transfer and providing electrical isolation. It also enables the STATCOM to function properly at various voltage levels and grid topologies. When these components are linked in shunt to the AC system, they form the STATCOM, which can dynamically change reactive power injections to regulate voltage levels. The STATCOM improves power system performance by increasing stability and dependability while reducing voltage fluctuations and transients. The equivalent circuit of the STATCOM thoroughly describes its internal components and linkages, allowing for examination and comprehension of its operation. It comprises a Voltage Source Converter (VSC), a semiconductor device that regulates output voltage, and a DC energy storage device, usually a capacitor or battery bank. The coupling transformer connects the STATCOM to the AC network, ensuring isolation and impedance matching between the two systems.

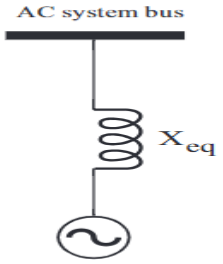

Figure 3: Equivalent Circuit of the STATCOM

The VSC is represented by an equivalent voltage source and internal impedance, whereas an analogous capacitance or battery model represents the DC energy storage device. The coupling transformer is defined by its equivalent impedance and turns ratio, which accounts for impedance transformation and voltage level adjustment between the STATCOM and the alternating current system. The V-I characteristic curve of a STATCOM is an essential tool for analysing and optimising its operation within the power system. It sheds light on the link between voltage and current, demonstrating the device's ability to adjust voltage and accept varied levels of reactive power exchange. The curve's slope reflects the device's dynamic response capabilities, with steeper slopes suggesting more excellent responsiveness to changes in current or voltage. The STATCOM may operate in both capacitive and inductive modes, delivering reactive power to maintain voltage stability and sustain loads while also absorbing reactive power from the system to regulate voltage and power factor. The device's operating limitations specify the highest and lowest voltage and current levels it can manage without exceeding its design constraints. Understanding these boundaries is critical for assuring safe and dependable functioning within the stated parameters. The V-I characteristic curve is essential for increasing power system stability, dependability, and efficiency.

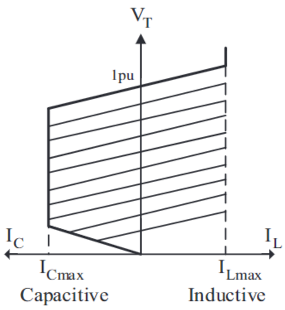

Figure 4: STATCOM $V - I$ Characteristic Curve

STATCOMs are critical components of modern power systems, regulating voltage and adjusting for reactive power imbalances shown in Figure 4. They improve stability and adjust grid voltage, particularly in systems with variable loads or renewable energy sources. They can also help to reduce power quality concerns, including voltage sags, swells, and flicker caused by unexpected load changes or industrial equipment connections. STATCOMs provide versatility in grid operation and control by functioning in capacitive and inductive modes, allowing for fine-tuning power factor and reactive power compensation. However, they have drawbacks, including high initial costs, sophisticated management and monitoring systems requirements, and dependency on power electronics components such as voltage source converters (VSCs), prone to failure or malfunction. As a result, a thorough analysis of these criteria is critical for determining the viability of STATCOMs for specific applications in power system architecture.

3.2. Wavelet Transform

The wavelet transform is an effective data analysis technique that overcomes the limitations of the Fourier transform. It has been extensively used in pattern identification, image, and signal processing. Mallat proposed the Mallat method in 1989, which is a rapid decomposition and reconstruction approach that uses an orthogonal wavelet. To accomplish rapid wavelet decomposition, this method filters the processed signal and downsamples the filtered output. The decomposition procedure is applied cascade-wise to multi-level wavelets, beginning with low-frequency components from the previous decomposition. The associated decomposition approach is the opposite of the quick wavelet reconstruction process. The discrete wavelet transform's primary action is explained by equation (1).

$$y[n] = (x * g)[n] = \sum_{k=-\infty}^{\infty} x[k]g[n-k] \quad (1)$$

To preserve the connection between inverse wavelet transform (IDWT) and wavelet transform (DWT), Equation (2) provides an orthogonal requirement.

$$|H(w)^2| + |G(w)^2| = 1 \quad (2)$$

The wavelet transform is a sophisticated signal processing method that can analyse signals at several scales, providing benefits such as multiresolution analysis, temporal and frequency localisation, signal adaptation, and compression and data reduction. Its multiresolution capability allows for a thorough investigation of signal properties, particularly identifying high and low-frequency components. The wavelet function can be modified to match the features of the signal, allowing for more efficient analysis of various data types. However, some things could be improved in the wavelet transform, including interpretation complexity, wavelet parameter selection, boundary effects, and processing cost. The multiresolution aspect of wavelet transforms can make interpretation difficult, especially for those inexperienced with wavelet theory. The performance of the wavelet transform is strongly reliant on the choice of wavelet parameters, which can be difficult and require domain-specific knowledge. Boundary effects can influence analysis results around signal boundaries, causing feature extraction and reconstruction mistakes. Signal padding and boundary wavelets are two techniques that can help to lessen these effects, but they may also increase complexity.

3.3 Feature Selection with Information Gain

Feature selection is an essential stage in ML and data analysis since it aims to pick the most relevant characteristics from a dataset to improve model performance and reduce computing complexity. Information Gain is a prominent feature selection strategy that uses the concept of entropy from information theory. Entropy evaluates the uncertainty or disorder in a set of data, whereas Information Gain determines how much the presence of a specific feature reduces uncertainty in predicting class labels. The dataset's entropy is computed both before and after splitting to calculate Information Gain based on a feature. Features with higher information gain are regarded as more informative for classification tasks since they help to reduce confusion regarding class labels. Information Gain is widely utilised in decision tree methods like C4.5 and C5.0, which split the dataset depending on the feature with the highest Information Gain at each step, yielding a tree structure with the most informative features closer to the root. However, Information Gain has limits, such as favouring characteristics with many unique values and underperforming for continuous or highly linked features. As a result, it is frequently used in conjunction with other feature selection methods or as part of a more prominent feature engineering approach.

The idea of entropy serves as the foundation for the formula used to determine Information Gain (IG) in feature selection. Entropy quantifies uncertainty or disorder in a collection of data. The Equation (3) determines entropy H(S) of a set S with n possible classes:

$$H(s) = -\sum_{i=1}^{n} p_i \, log_2(p_i) \tag{3}$$

Information Gain is calculated as the difference between the entropy of the dataset before and after splitting it based on a particular feature. We have dataset D with feature A and n possible classes. Equation (4) calculates the Information Gain IG (A) for feature A as follows:

$$IG(A) = H(D) - \sum_{v \in \, values(A)} \frac{|Dv|}{|D|} H(Dv) \tag{4}$$

- $H(D)$ is the entropy of dataset D before splitting
- Value (A) is the unique value of feature A
- Dv is the subset of D where feature A takes the value v
- $|D|$ is the total number of instances in dataset D
- $|Dv|$ is the number of instances in subset $|Dv|$

This formula calculates the difference between the original dataset's entropy and the weighted sum of the entropies of the subsets formed by partitioning the dataset based on feature values (A). Splitting on feature A reduces uncertainty in predicting class labels, resulting in a more considerable Information Gain (IG). In actual applications, this method is frequently performed recursively for each feature to select the feature with the greatest Information Gain at each phase of a decision tree construction algorithm. In actual applications, this method is frequently performed recursively for each feature to select the feature with the greatest Information Gain at each phase of a decision tree construction algorithm.

3.4 Random Forest

RF is an ML algorithm that utilises bagging and decision trees. Using dividing rules, techniques such as Decision Trees and Classification and Regression Trees (CART) make predictions. Nodes reflect the splitting rules, branches represent the decisions, and leaves represent the final predictions. For every new node, data is divided into two branches until a halt condition is satisfied, at which point a CART is created. To reduce variation in partitioned data, every ML node is given a feature, often referred to as a covariate, and a splitting threshold. Making a prediction involves going through nodes and branches and finally arriving at a single leaf. Compared to RF, CART is more straightforward, less biased, and easier to read. However, their prediction accuracy is reduced because they are not robust and overfitting training data. Created bagging (bootstrap aggregation) to overcome the limitations of CART. Using several weak learners, like CART, bagging is an ensemble ML technique that creates a single stronger learner. Bootstrapping, also known as sampling with replacement, generates an enormous amount of weak learners by repeatedly sampling the whole data set. The average of all weak learners' estimations is used to compute the forecast. By reducing prediction error variance, bagging improves the accuracy and stability of the model. As a weak learner, RF uses CART in conjunction with bagging and random feature selection. The problem with bagging is that dominating traits can be linked to bootstrapped samples. To address this issue, random feature selection is applied at each step of CART construction. The number of features and CARTs can be adjusted, with a recommended value of $\sqrt{m}$ for classification and $\frac{m}{3}$for regression, where m is the number of covariates. The forecasts of the full RF model can be calculated in Equation (5),

$$Z(S_0) = f(x_1(S_0), x_2(s_0), \dots x_m(s_0)) \tag{5}$$

Where xi (S_0) (i = 1... m) are covariates atS_0. RF can measure variable relevance, indicating how much each piece of information affects model correctness. RF can also evaluate accuracy using out-of-bag (OOB) error statistics. A straightforward RF modification called RFsp adds buffer distance maps as variables for each observation point. To create a buffer distance map, Euclidean distances are calculated between the centre of each forecast pixel and the centre of the observation pixel. In RFsp, the number of buffer distance maps matches the number of observations.

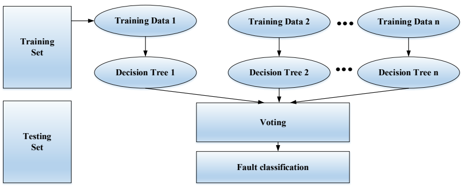

Figure 5: The structure of Random Forest for fault classification

Standard RF does not account for spatial autocorrelation between observations, except through indirect connection with variables. We included new covariates in the RF model to account for the impact of adjacent data on prediction values. The observations and the distances between the nearest and predicted locations are incorporated as covariates. Consequently, the RFSI structure is determined in Equation (6):

$$Z(S_0) = f(x_1(S_0), \ldots, x_m(S_0)Z(S_1), d_1Z(S_2)d_2Z(S_3)d_3, \ldots, Z(S_n), d_n) \quad (6)$$

Where si (i = 1... n) is the i-th nearest observation point from s0, di = |si - s0|. Figure 6 represents the flow diagram of the proposed model.

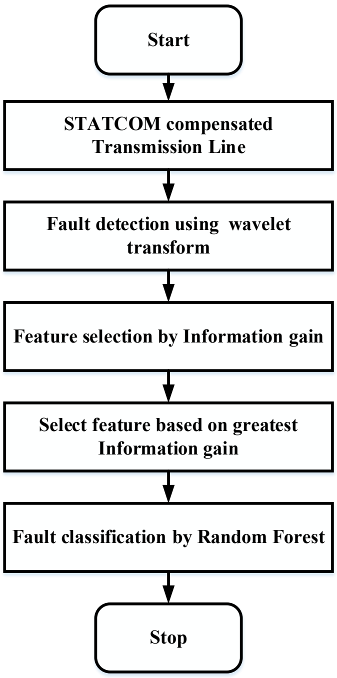

Figure 6: Flow diagram of the proposed model for the fault classification

The n-nearest places to the training location are determined, and their distances and observations are included as covariates and other environmental factors. The observations and distances to the n closest sites are used to forecast a location.

4. Results

The study uses a confusion matrix to assess the Random Forest algorithm's performance in classification tasks. The matrix helps to identify strengths and shortcomings, as well as areas for progress. A comparison is made between the algorithm's performance and alternative methods, including decision trees and support vector machines, using metrics like accuracy, precision, recall, and F1 score. Figure 7 shows the simulation model for the proposed work. The analysis emphasises the capacity to handle massive datasets with high dimensionality and complex variable interactions. However, the study reveals several drawbacks, such as computational complexity and overfitting susceptibility. The findings support the algorithm's effectiveness and add to machine learning approaches in categorisation problems.

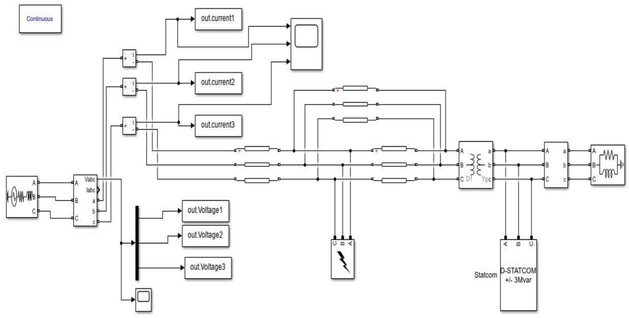

Figure 7: Simulink Diagram of the Proposed Model

4.1. Confusion matrix

In classification problems, the confusion matrix is a valuable tool for assessing the precision and effectiveness of predictive models. Predictions are separated into four groups: false positives, false negatives, true positives, and true negatives. Strong predictive capacity is implied by a substantial amount of true positives and true negatives; however, space for improvement is indicated by a rise in false positives or false negatives. The confusion matrix also computes performance measures like accuracy, precision, recall, and F1 score. Recall evaluates the model's capacity to recognise positive cases correctly; accuracy counts the overall correctness of the model's predictions; precision quantifies the percentage of true positive predictions between all positive predictions, and the F1 score offers a balanced performance assessment. "True Class" and "Predicted Class" assess how well an ML model performs in classification tasks. The "Predicated Class" is the model's predicted class or category, which assigns each instance to one of several predefined classes based on learned patterns and attributes. In binary classification, an email's predicted class is "spam". The "True Class" refers to the actual class or category decided by human annotation or ground truth. True class labels are often included in training data for supervised learning. Comparing each instance's true class to its anticipated class evaluates the model's correctness and efficacy, assisting academics and practitioners in understanding its generalizability to previously unknown data. Figure 8 shows the confusion matrix for the proposed technique.

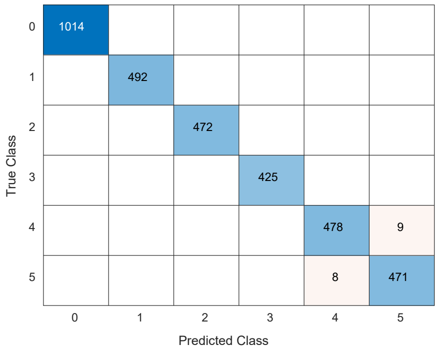

Figure 8: Confusion matrix

The confusion matrix is a method for classifying incidents into distinct groups. It has two classes: anticipated and true. True class values vary from 0 to 5, and anticipated class values range from 0 to 5. For the most part, the model's predictions are right, with 1014 occurrences categorised as true class 0 and 492 instances classified as true class 1. However, there is a significant difference in class 5, with only 471 cases accurately identified, a decrease of 9 from the expected number. This disparity necessitates more inquiry into the mechanisms causing misclassifications in this category. The confusion matrix offers essential information about the precision and misclassifications of the model, allowing researchers and practitioners to find areas for improvement and fine-tune the model's performance.

4.2. Comparison Results

The section compares Random Forest's performance against K-Nearest Neighbours (KNN), Decision Tree, and Naive Bayes classifiers. The accuracy%, precision%, and recall% metrics evaluate the model's ability to accurately categorise instances, detect true positives, and capture essential examples from the dataset. The relative strengths and limitations of each technique can be determined by comparing the findings to KNN, Decision Tree, and Naive Bayes classifiers. This aids in deciding Random Forest's viability for a specific task and its potential advantages over other approaches. The comparative analysis sheds light on Random Forest's usefulness in dealing with classification difficulties and its performance compared to other well-known classification algorithms.

4.2.1. Accuracy Comparison

The paper examines classification algorithms such as KNN, Decision Tree, and Naive Bayes and shows their accuracy rates. Decision Tree achieves 90% accuracy, but Naive Bayes obtains 79% due to conditional independence. Figure 9 shows the accuracy graph compared with the existing techniques.

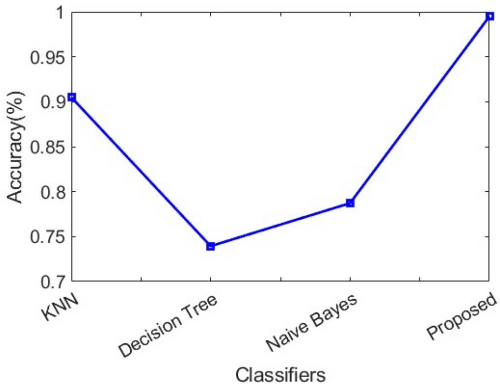

Figure 9: Accuracy Comparison

The suggested method surpasses these algorithms, obtaining 100% accuracy, which could be attributed to creative feature engineering or domain-specific expertise. However, receiving 100% accuracy is uncommon, raising worries about overfitting and data leaking. More research and validation on other datasets are required to grasp the method's potential and practical uses properly.

4.2.2. Precision Comparison:

The graphic compares classification algorithms such as KNN, Decision Tree, and Naive Bayes, and the proposed method outperforms all. Decision Tree has a precision of 89%, while Naive Bayes has a slightly lower precision (79%). Naive Bayes is widely used for classification applications, particularly with high-dimensional data. Figure 10 shows the precision graph compared with the existing techniques.

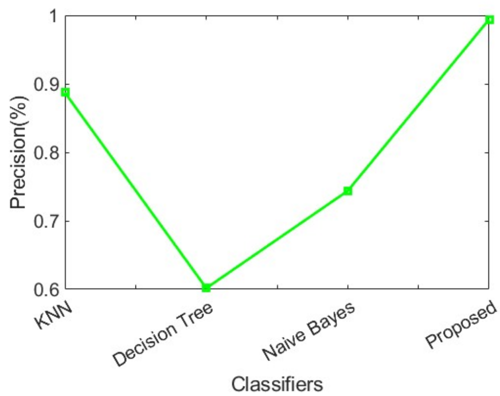

Figure 10: Precision Comparison

The proposed method yields a flawless precision rate of 100%, indicating its reliability in practice. However, reaching 100% precision raises concerns about overfitting and data leaking. More research and thorough validation of various datasets are required to properly comprehend the method's capabilities and possible consequences for practical applications. More research and thorough validation of varied datasets are necessary to understand their capabilities and possible ramifications properly.

4.2.3. Recall Comparison

Based on recall metrics, the graphic compares classification algorithms such as KNN, Decision Tree, and Naive Bayes. Decision Tree has a 90% recall rate, whereas Naive Bayes has a slightly lower recall of 79%. However, the suggested method outperforms them with a 100% recall rate, making it a promising medical diagnosis and fault detection contender. Figure 11 shows the recall graph compared with the existing techniques.

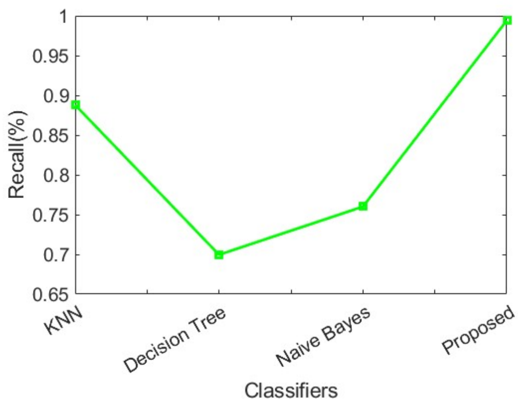

Figure 11: Recall Comparison

The suggested method's effectiveness is attributable to the rigorous validation of independent datasets, which provide generalizability and reliability in real-world circumstances. More research and validation on other datasets are required to grasp the method's capabilities and possible uses correctly.

4.2.4. Specificity Comparison:

The graph compares the specificity value with methods such as KNN, Decision Tree, and Naive Bayes. Decision Tree has a 95% to 98% specificity, but Naive Bayes has a specificity of 96%. However, the proposed technique exceeds both with a 100% specificity rate, making it highly reliable in detecting negative situations. Figure 12 shows the specificity graph compared with the existing methods.

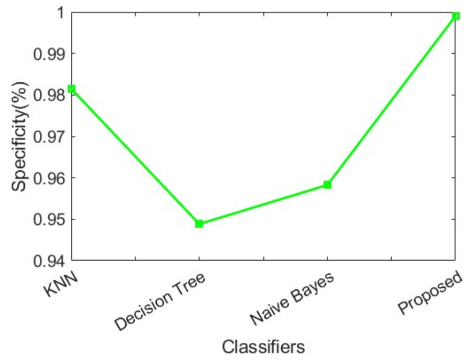

Figure 12: Specificity Comparison

4.2.5 F1 Score Comparison:

The figure compares classification methods such as KNN, Decision Tree, and Naive Bayes to a suggested method based on the F1 Score metric. The F1 Score accurately assesses a classifier's performance by contrasting precision and recall. Decision Tree has an F1 Score of 0.9 to 0.6, indicating improved performance. Naive Bayes has an F1 Score of 0.78, although it may struggle with complicated feature interactions. Figure 13 shows the F1 score graph compared with the existing techniques.

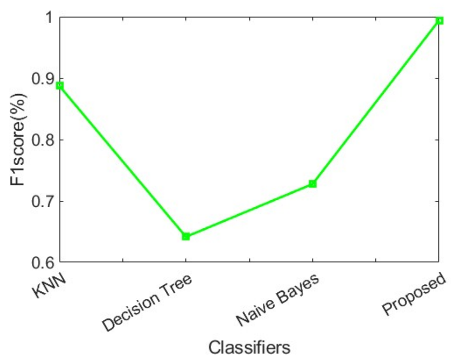

Figure 13: F1 Score Comparison

The proposed method outperforms Decision Tree and Naive Bayes, with a perfect F1 Score of 100%.

5. Conclusion

In conclusion, the proposed Wavelet Transform-Enhanced Random Forest Fault Classification System with STATCOM Integration (WERFCS-SI) effectively addresses the shortcomings of current fault detection systems in compensated transmission lines. Integrating STATCOM and using Wavelet Transform for fault detection results in precise fault localisation and multiresolution analysis, which improves fault detection capabilities. Furthermore, feature selection strategies like information gain increase classification accuracy by discovering and preserving significant features. The Random Forest classifier improves classification accuracy by handling complex data and capturing subtle feature interactions. As a result, implementing the proposed model provided significant results in several metrics, such as accuracy, precision, recall, specificity and F1 score. All the metrics used in this proposed model, such as 100%, attained the same result. By enhancing signal feature extraction and robust decision-making, the integration of wavelet transform and random forest with STATCOM improves the accuracy of fault classification in power systems. This results in more dependable and efficient fault detection and system stability. Overall, the integrated technique simplifies fault classification, resulting in more accurate and efficient problem detection throughout the transmission line system. Further research and validation on various datasets are required to explore the suggested method's potential and applicability properly.

Acronyms	Abbreviation
RF	Random Forest
STATCOM	Static Synchronous Compensator
NB	Naive Bayes
DWT	Discrete Wavelet Transform
SD	Standard Deviation
FLMs	Fault Location Methods
EMD	Empirical Mode Decomposition
ITD	Intrinsic Time Decomposition
MLP	Multi-Layer Perceptron
TCSC	Thyristor Controlled Series Capacitor
FPA	Flower Pollination Algorithm
PMU	Phase Measurement Units
WELM	Weighted Extreme Learning Machine
PSO	Particle Swarm Optimization
CCT	Critical Clearing Time
GSS	Grid-Synchronizing Stability
EAP	Equal-Area Principle
TTP	Trusted Third Party
SCIG	Squirrel Cage Induction Generators
ITC	Indirect Torque Control
WECSs	Wind Energy Conversion Systems
PI	Proportional-Integral
MFPA	Modified Flow-Pollination Algorithm
WT	Wavelet Transform
VSC	Voltage Source Converter
CART	Classification And Regression Trees
KNN	K-Nearest Neighbours

References

1. Ayala-Chauvin M, Kavrakov BS, Buele J, Varela-Aldás J. Static reactive power compensator design, based on a three-phase voltage converter. Energies. 2021;14(8):2198.
2. Sadiq R, Wang Z, Chung CY, Zhou C, Wang C. A review of STATCOM control for stability enhancement of power systems with wind/PV penetration: Existing research and future scope. Int Trans Electr Energy Syst. 2021;31(11)
3. Chorghade A, Deodhar VAK. FACTS devices for reactive power compensation and power flow control–recent trends. In: 2020 International Conference on Industry 4.0 Technology (I4Tech). IEEE; 2020. p. 217-221.
4. Olaoye AB. Enhancement of Voltage Stability on Nigerian Electricity Transmission Network Using Static Synchronous Compensator [Doctoral dissertation]. Kwara State University (Nigeria); 2023.
5. Xu S, Wang S, Zuo G, Davidson C, de Oliveira MM, Memisevic R, et al. Application examples of STATCOM. Flexible AC Transmiss Syst: FACTS. 2020:511-584.
6. Sadiq R, Wang Z, Chung CY, Zhou C, Wang C. A review of STATCOM control for stability enhancement of power systems with wind/PV penetration: Existing research and future scope. Int Trans Electr Energy Syst. 2021;31(11)
7. Ismail B, Wahab NIA, Othman ML, Radzi MAM, Vijyakumar KN, Naain MNM. A comprehensive review of optimal location and sizing of reactive power compensation using hybrid-based approaches for power loss reduction, voltage stability improvement, voltage profile enhancement, and load ability enhancement. IEEE Access. 2020;8:222733-222765.
8. Abbasi M, Abbasi E, Li L, Aguilera RP, Lu D, Wang F. Review the microgrid concept, structures, components, communication systems, and control methods. Energies. 2023;16(1):484.
9. Prasad L, Iyengar SS. Wavelet analysis with applications to image processing. CRC Press; 2020.
10. Guo T, Zhang T, Lim E, Lopez-Benitez M, Ma F, Yu L. A review of wavelet analysis and its applications: Challenges and opportunities. IEEE Access. 2022;10:58869-58903.
11. Zhuang C, Liao P. An improved empirical wavelet transform for noisy and non-stationary signal processing. IEEE Access. 2020;8:24484-24494.
12. Manhertz G, Bereczky A. STFT spectrogram-based hybrid evaluation method for rotating machine transient vibration analysis. Mech Syst Signal Process. 2021;154:107583.
13. Akan A, Cura OK. Time-frequency signal processing: Today and future. Digit Signal Process. 2021;119:103216.
14. Priyadarshini MS, Bajaj M, Prokop L, Berhanu M. Perception of power quality disturbances using Fourier, Short-Time Fourier, continuous and discrete wavelet transforms. Sci Rep. 2024;14(1):3443.
15. Akujuobi CM. Wavelets and wavelet transform systems and their applications. Springer Int Publ; 2022.
16. Kumar B, Dikshit O, Gupta A, Singh MK. Feature extraction for hyperspectral image classification: A review. Int J Remote Sens. 2020;41(16):6248-6287.
17. Ahmad AYB, Gongada TN, Shrivastava G, Gabbi RS, Islam S, Nagaraju K. E-commerce trend analysis and management for Industry 5.0 using user data analysis. Int J Intell Syst Appl Eng. 2023;11(11s):135-150.
18. Jalayer M, Orsenigo C, Vercellis C. Fault detection and diagnosis for rotating machinery: A model based on convolutional LSTM, Fast Fourier and continuous wavelet transforms. Comput Ind. 2021;125:103378.

19. Mourad T. Wavelets and wavelet transforms. In: ECG Denoising Based on Total Variation Denoising and Wavelets. Springer Int Publ; 2023. p. 1-18.
20. Zhao J, Feng X, Wang J, Lian Y, Ouyang M, Burke AF. Battery fault diagnosis and failure prognosis for electric vehicles using spatiotemporal transformer networks. Appl Energy. 2023;352:121949.
21. Lucas F, Costa P, Batalha R, Leite D, Škrjanc I. Fault detection in smart grids with time-varying distributed generation using wavelet energy and evolving neural networks. Evolving Syst. 2020;11(2):165-180.
22. Guo MF, Yao M, Gao JH, Liu WL, Lin S. An incremental high impedance fault detection method under non-stationary environments in distribution networks. Int J Electr Power Energy Syst. 2024;156:109705.
23. Gangsar P, Tiwari R. Signal-based condition monitoring techniques for fault detection and diagnosis of induction motors: A state-of-the-art review. Mech Syst Signal Process. 2020;144:106908.
24. Ranasinghe K, Sabatini R, Gardi A, Bijjahalli S, Kapoor R, Fahey T, et al. Advances in Integrated System Health Management for mission-essential and safety-critical aerospace applications. Prog Aerosp Sci. 2022;128:100758.
25. Dhal P, Azad C. A comprehensive survey on feature selection in the various fields of machine learning. Appl Intell. 2022;52(4):4543-4581.
26. Chen RC, Dewi C, Huang SW, Caraka RE. Selecting critical features for data classification based on machine learning methods. J Big Data. 2020;7(1):52.
27. Bhattacharyya S, Majumder S, Debnath P, Chanda M. Arrhythmic heartbeat classification using an ensemble of random forest and support vector machine algorithm. IEEE Trans Artif Intell. 2021;2(3):260-268.
28. Ahmed Q, Raza SA, Al-Anazi DM. Reliability-based fault analysis models with industrial applications: A systematic literature review. Qual Reliab Eng Int. 2021;37(4):1307-1333.
29. Azam Z, Islam MM, Huda MN. Comparative analysis of intrusion detection systems and machine learning-based model analysis through decision tree. IEEE Access.
30. Aker E, Othman ML, Veerasamy V, Aris IB, Wahab NIA, Hizam H. Fault detection and classification of shunt compensated transmission line using discrete wavelet transform and naive Bayes classifier. Energies. 2020;13(1):243.
31. Mishra S, Gupta S, Yadav A, Abdelaziz AY. Traveling wave-based fault localization in FACTS-compensated transmission line via signal decomposition techniques. Energies. 2023;16(4):1871.
32. Rashed GI, Otuo-Acheampong D, Mensah AA, Haider H. Fault Analysis of Power System Transient Stability with Thyristor-Controlled Series Capacitor Controller Model Using Flower Pollination Algorithm for Its Parameters. Electrica. 2023;23(3).
33. Harish A, Prince A, Jayan MV. Fault detection and classification for wide area backup protection of power transmission lines using a weighted extreme learning machine. IEEE Access. 2022;10:82407-82417.
34. Zhang C, Cai X, Rygg A, Molinas M. Modeling and analysis of grid-synchronizing stability of a Type-IV wind turbine under grid faults. Int J Electr Power Energy Syst. 2020;117:105544.
35. Wang X, Liu Y, Choo KKR. Fault-tolerant multisubset aggregation scheme for smart grid. IEEE Trans Ind Inf. 2020;17(6):4065-4072.
36. Abdelsattar M, Arafa Hafez W, Elbaset A, Kamel S, Kasem Alaboudy H, Khan B, Zaki Diab A. Voltage stability improvement of an Egyptian power grid-based wind energy system using STATCOM. Wind Energy. 2022;25(6):1077-1120.
37. Vimalraj M, Kumar MCS, Kumar MRV, Kumar MUN. ITC-STATCOM for Voltage Stability Enhancement Under Unbalanced Fault. Int J All Res Educ Sci Methods. 2021;9(3):1248-1253.
38. Mosaad MI, Sabiha NA. Ferroresonance overvoltage mitigation using STATCOM for grid-connected wind energy conversion systems. J Mod Power Syst Clean Energy. 2021;10(2):407-415.