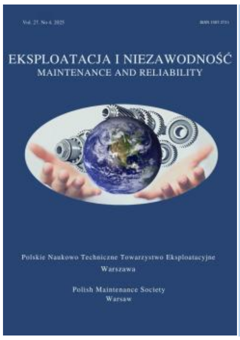

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Fault Detection in Power Transmission Lines: Comparison of Chirp-Z Algorithm and Machine Learning Based Prediction Models

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Highlights

- The Chirp-Z algorithm provided high-resolution spectral analysis of fault signals
- The integration of ML and signal processing ensured fast, reliable fault detection
- Transient events were seamlessly integrated with modal transformation and Chirp-Z
- Fault detection integrated with machine learning significantly reduced error rates
- The GBE model stood out with the lowest error rate and the highest accuracy.

Abstract

Fast and accurate detection of faults in power transmission lines is of great importance for the safety and continuity of power systems. This study develops a predictive model using chirp-z transform and machine learning algorithms to locate single-phase-ground faults. During the study, 39 different fault locations were modelled, current and voltage signals of these locations were analysed and frequency spectra were obtained. The fault signals were decomposed into their components using the modal transformation matrix and then spectral analysis was performed using the Chirp-Z algorithm. The resulting spectra were used as input data for the prediction algorithms. Gradient Boosting Ensemble, Support Vector Regression and Random Forests algorithms were used for fault prediction and the performance of the models was compared. The accuracy of the models was evaluated using various metrics. The results show that the Gradient Boosting Ensemble model has the lowest error rates and the highest accuracy, which is important for early fault detection, maintenance and repair processes.

Keywords
fault detection, power transmission lines, Chirp-Z algorithm, machine learning, fault location.

1. Introduction

The detection and location of faults on power transmission lines are critical to the reliability of power systems. Single-phase-ground faults are among the most common types of faults on transmission lines and significantly impact system instability and power quality. Traditional fault detection methods cannot fully meet the needs of modern power systems due to limitations such as insufficient measurement data, high error rates, and low sensitivity [1]. Therefore, it is necessary to develop more accurate, faster and more reliable fault detection methods. [2].

In recent years, techniques based on artificial intelligence and machine learning have been increasingly used for fault detection in power systems [3,4]. These techniques offer higher accuracy rates than traditional methods, thanks to their ability to analyse large amounts of data and their ability to learn automatically [5–7]. However, the use of appropriate signal processing techniques is of great importance for the accurate analysis of fault signals. In this context, the Chirp-Z algorithm stands out as an important alternative for the spectral analysis of transmission line signals due to its high resolution and flexibility [8,9].

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The performance of the Chirp-Z algorithm on narrowband signals provides higher resolution compared to Fourier transform based techniques. This method allows a more detailed analysis of low frequency components and enables more sensitive detection of weak fault signals [10]. In addition, the Chirp-Z algorithm can be easily adapted to different operating conditions by adjusting the parameters. This minimises uncertainties caused by varying load conditions or differences in line impedance and provides more reliable fault detection [11].

The integration of artificial intelligence-based methods with the Chirp-Z algorithm can make fault detection processes faster and more efficient. In particular, hybrid systems supported by deep learning models and optimisation algorithms can contribute to the development of both signal processing and decision mechanisms. These approaches can improve the safety of modern energy systems by helping to build fault detection and classification models with high accuracy rates.

In this study, the Chirp-Z algorithm and machine learning models are used to detect and locate single-phase-ground faults. The Chirp-Z algorithm offers a more flexible frequency resolution compared to other signal processing methods, enabling a more precise analysis of signal spectra. This allows for more accurate predictions in the fault localization process. Gradient Boosting Ensemble (GBE), Support Vector Regression (SVR), and Random Forests (RF) algorithms were used for fault prediction. Each of these algorithms has different data distributions and modelling approaches, providing various advantages in terms of fault detection and distance prediction. However, limitations include the focus on single-phase ground faults only and a fixed fault resistance scenario.

2. Literature Review

The effectiveness of the methods developed for fault detection in transmission lines has been widely discussed in the literature. These studies focus on enhancing the accuracy and speed of fault detection processes by employing various signal processing techniques, artificial intelligence-based algorithms, and hybrid approaches. Reviewing these studies not only helps identify the advantages and limitations of existing methods but also provides a crucial foundation for developing new approaches. Some significant studies in this area are discussed below.

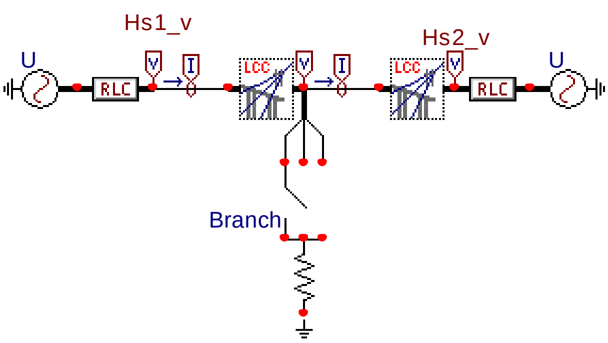
Rajesh et al. proposed a hybrid Truncated Singular Value Decomposition (TSVD) and Human Urbanisation Algorithm (HUA) based Recurrent Perceptron Neural Network (RPNN) model for prediction and classification of transmission line faults in power systems. The model was tested in MATLAB/Simulink environment by optimising the fault detection and classification and showed an accuracy of 99.77% at 20 dB noise level. The study presented an effective approach to provide fast and accurate fault analysis in power systems with low complexity [12]. Shadi et al. developed a model for real-time fault detection, classification and localisation using Phasor Measurement Unit (PMU) data and deep learning. The model, which includes Recurrent Neural Network (RNN) and Long Short Term Memory (LSTM) algorithms, was tested on IEEE 14, New England 39-bus and IEEE 118-bus systems and showed high accuracy rates. The study provided fast and reliable fault analysis with low computational cost [13]. Dashti et al. extensively investigated fault prediction and location methods in electricity distribution networks. The study evaluates different fault detection techniques in traditional and smart grids and considers factors such as distributed generation, AC/DC systems and automation standards. Unlike other studies in the literature, it also focuses on fault prediction. [14]. Chavez et al. developed a fault detection method based on phasor measurement unit (PMU) voltage drop for backup protection of transmission lines. The proposed method identifies the faulted line, fault type and distance using delta algorithm and least squares technique. The model categorises the network into specific sub-areas using PMU data and increases the accuracy rate. Tested with simulations on the IEEE 39 bus system, the method provided fast and reliable fault detection. The study provides an effective protection method with low computational cost for real-time applications [15]. Rezaee Ravesh et al. developed an artificial neural network and wavelet packet transform based method for fault detection in hybrid transmission lines. Support vector machines and particle swarm optimisation were used to determine the most appropriate features, and a three-layer neural network was used to detect the faulty section and half. The fault location was determined using the Bewley diagram, and tests on the IEEE 230 kV system showed high accuracy. The study provided fast and reliable fault detection in hybrid lines [16]. Azeroual et al. developed a multi-agent system-based method for fault detection and localisation in power distribution systems with distributed generation. The proposed approach is tested on the distribution network of the city of Kenitra (Morocco) and aims to provide fast fault detection and automatic power restoration through agent coordination. The method estimates the fault distance using an impedance-based fault location algorithm and provides high accuracy protection in the distribution system. The simulations show that the method provides fast and reliable fault detection [17]. Tavoosi et al. developed a hybrid method that combines impedance-based methods and deep learning for fault location in distribution networks. The proposed model determines the fault distance using impedance-based calculations and accurately locates the fault line using a deep neural network. According to the simulation results, the method achieved 99% accuracy and determined the fault location in less than 6 seconds. The study was developed to provide more accurate fault detection, especially in systems with more than one line [18]. Jin et al. developed a travelling wave-based method for fault detection in high-voltage AC cable transmission lines. The model calculates the travelling wave propagation speed more accurately by considering frequency-dependent electrical parameters. The fault location is determined using the arrival time and instantaneous frequency of the first wave front. Simulations in PSCAD/EMTDC software showed that the method provides high accuracy for different fault types, distances, ground resistances and noise levels. The study provides a more accurate and reliable approach to fault location compared to existing methods [19]. Shi et al. developed a one-dimensional convolutional neural network (1D-CNN) based method for fault location in distribution systems. The model automatically learns fault location using three-phase voltage and current data. The model, trained with fault data generated in the PSCAD environment, was tested with 5-fold cross-validation and showed high accuracy. The study provided fast and reliable fault detection in distribution networks [20]. Kalita et al. developed a non-iterative fault detection algorithm for transmission lines with non-synchronised terminals. The two-terminal impedance-based model works on transposed and non-transposed lines without requiring signal alignment. Tests with data from the Power Grid Corporation of India Limited (PGCIL) showed that the method provides high accuracy. The study presented a sensitive fault detection method that does not require time synchronisation [21]. Zhao et al. developed a method based on deep convolutional neural networks for fault detection and fire risk assessment in power distribution networks. The model classifies fault types using measurement data and identifies potential fire sources. Tested on various fault types and levels of system observability, the model achieved 85% accuracy in detecting fire sources, with some cases reaching close to 100% accuracy. The study presents an economical and effective approach to fault detection with limited measurement locations [22]. Jiang et al. developed a Block Quarter Bayesian Learning (BSBL) based method for fault detection in active distribution networks. The model estimates the fault current and identifies the faulty line using a limited number of synchronised measurement data. The Kron reduction model is applicable to both balanced and unbalanced networks and is able to ignore the effect of distributed generation units. Tests on the IEEE 123-node distribution system have shown that the method provides high accuracy and fast computation time [23]. Thomas et al. developed a convolutional neural network (CNN) and transformer-based model for fault detection in power systems. The model learns long-term dependencies in time-series data to determine fault type, phase and location. Tests on the IEEE 14 bus system have shown that it provides higher accuracy than traditional methods, especially for high impedance faults. The study presents an effective deep learning approach for fast and accurate fault detection in power distribution systems [24]. Akdag et al. developed a method based on transient frequency spectrum analysis (TFSA) for fault detection in transmission lines. The model determines the fault location by analysing the current and voltage spectra at the time of the fault. The accuracy is improved by evaluating the effects of welding inductance, series compensation, fault arc and current transformer. The study presents an effective fault location method that provides high accuracy with low sampling frequency and single-ended measurements [25]. Yu et al. developed a signal-to-image transform (SIG) and convolutional neural network (CNN) based method for fault detection in distribution systems. The model converts time series data into images, analyses them with CNN, and classifies and locates the fault zone. The method, which does not require synchronised devices and has a low memory footprint, can be easily integrated into hardware. Tests on the IEEE 10 kV distribution system have shown that the method provides high accuracy under different fault conditions [26]. Mirshekali et al. developed a time domain-based method for fault location under line parameter uncertainties in intelligent distribution networks. The model combines gradient descent and particle swarm optimization to identify the faulty section. Tests conducted on the IEEE 123-node test network and in the laboratory have demonstrated that the method provides high accuracy. This study presents a reliable fault detection method that is compatible with various operating conditions [27]. Khoa et al. compared impedance-based methods for fault detection in transmission lines. A 220 kV line was modelled in the MATLAB/Simulink environment and different short-circuit scenarios were tested. The results evaluated the accuracy rates of the methods as a function of fault resistance and location. The study analysed the effectiveness of impedance-based methods for fast and accurate fault detection [28]. Akmaz and Mamiş developed a method for fault detection in two-ended transmission lines using synchronised time information. The model determines the fault location by calculating the time difference of travelling waves using the Clarke transform and approximate derivative (AD) signal processing. Simulations show that the method achieves higher performance compared to the Discrete Wavelet Transform (DWT) with low sampling frequency and robustness to noise [29]. El Mrabet et al. proposed a Random Forest Regression (RFR) based method to determine fault location and duration in power systems. The model simultaneously detects fault location and duration using high-resolution phasor measurement units (PMUs). Simulation results show that RFR provides higher accuracy, low error rate and faster processing time compared to other state-of-the-art machine learning models [30]. Wang et al. developed a Traveling Wave (TW) based fault location method utilizing a Frequency Modification (FM) algorithm for overhead transmission lines (OTLs) with structural variations. The proposed method corrects frequency distortions caused by reflections, refractions, and distributed line resistance. Simulations performed on a 500 kV system demonstrated superior fault location accuracy compared to traditional traveling wave methods [31]. Rahman et al. presented an ensemble-learning approach including decision tree, random forest, XGBoost, CatBoost, LightGBM, and multilayer perceptron neural networks (MLPNN) for classifying transmission line faults under noisy and imbalanced data conditions. Results indicated XGBoost achieved the highest classification accuracy , proving robust against imbalanced and noisy scenarios. The study emphasizes the effectiveness of ensemble learning algorithms for reliable fault classification in transmission systems [31].

3. Material and Method

This section presents the ATP model, the modal-phase transformation matrix, the chirp-z signal processing algorithm and the structures of the single-phase fault estimation algorithms.

3.1. Single-phase-ground ATP model

Single-phase-ground faults are a common type of fault in power transmission lines and cause system imbalances. ATP (Alternative Transients Program), which is used to model this fault, allows the dynamic behaviour of the system to be studied by performing transient analysis. The modelling process involves determining the transmission line parameters and analysing the effects of the fault. In this study, the pole and line parameters are determined based on the methods presented in [33]. The ATP model is used to study current and voltage variations, phase imbalances and transient behaviour during the fault. The ATP model is used to study current and voltage variations, phase imbalances and transient behaviour during the fault. This modelling approach, supported by signal processing techniques, contributes to the development of fault detection algorithms. The ATP model for a single-phase-ground fault, including line modeling parameters and conductor geometric and electrical characteristics, is shown in Figure 1.



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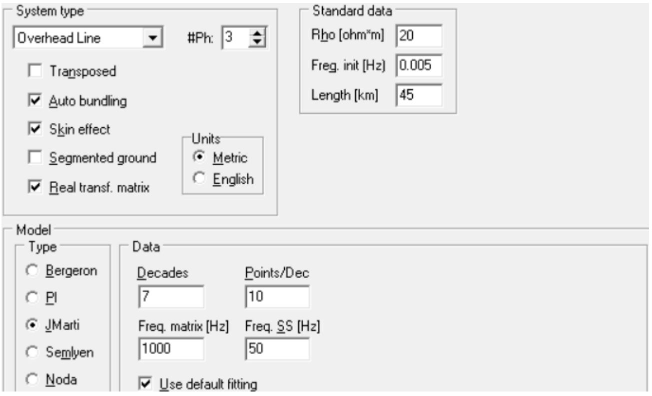

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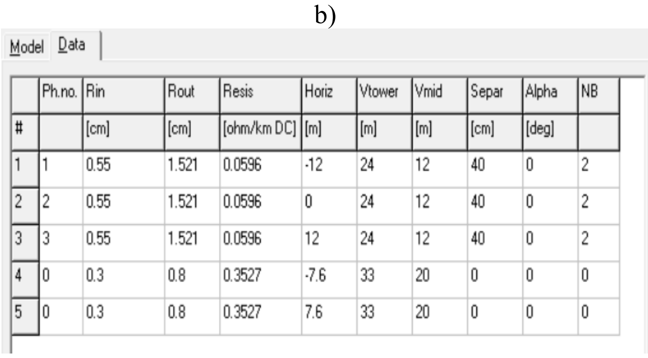


Model Data

	Ph.no.	Rin	Rout	Resis	Horiz	Vtower	Vmid	Separ	Alpha	NB
#		[cm]	[cm]	[ohm/km DC]	[m]	[m]	[m]	[cm]	[deg]	
1	1	0.55	1.521	0.0596	-12	24	12	40	0	2
2	2	0.55	1.521	0.0596	0	24	12	40	0	2
3	3	0.55	1.521	0.0596	12	24	12	40	0	2
4	0	0.3	0.8	0.3527	-7.6	33	20	0	0	0
5	0	0.3	0.8	0.3527	7.6	33	20	0	0	0

c)

Figure 1. Transmission line. a) Single-phase-ground fault, b) Line Modelling Parameters, c) Conductor Geometric and Electrical Parameters.

3.2. Modal Transformation matrix

In three-phase transmission lines, the travelling waves are interconnected, so to apply the travelling wave method, the phase field signals are first decomposed into their modal components using modal transformation matrices [34].

The steady state of a multi-conductor line at a discrete frequency can be described by the following equations;

$$-\frac{d^2V_{phase}}{dx^2} = zyV_{phase} \quad (1)$$

$$-\frac{d^2I_{phase}}{dx^2} = yzI_{phase} \quad (2)$$

Where *z* and *y* are the series impedance and parallel admittance matrix at each unit length, V_{phase} and I_{phase} are the vectors of the voltage and current phasors in the variable conductors.

$$V_{phase} = M_v V_{mod} \; and \; V_{mod} = {M_v}^{-1} V_{phase} \quad (3)$$

For three-phase transmission lines with crossover, a suitable transmission line matrix consisting of three column vectors proportional to the eigenvectors of *zy = yz* can be found in the form *M*. The above transformation matrix M is used in the application of modal transformation in this study.

$$M = \begin{bmatrix} 1 & 1 & 0 \\ 1 & 0 & 1 \\ 1 & -1 & -1 \end{bmatrix} \quad (4)$$

3.3. Chipr Z algorithm

The Chirp-Z algorithm is a signal processing algorithm that computes the Fourier transform of a signal in the Z-plane along a given axis. It provides a similar fast computational technique to the Fast Fourier Transform (FFT), but offers customisable flexibility over resolution and frequency bands instead of the fixed resolution of the FFT [35]. The main differences between the Chirp-Z algorithm and the FFT are in the flexibility of the analysis methods and the different application areas. The FFT is limited to a fixed frequency resolution and its transformation is performed on the unit circle. In contrast, the Chirp-Z algorithm is characterised by its ability to transform along any user-defined path in the Z-plane. In addition, the Chirp-Z algorithm provides the ability to adjust the frequency resolution, allowing for more precise and targeted analysis [36]. These features make the Chirp-Z algorithm a preferred choice, especially when the FFT is limited [35].

The Chirp-Z algorithm allows the input signal *x[n]* to be evaluated along a specific path in the Z-plane:

$$X[k] = \sum_{n=0}^{N-1} x[n] \,.\, z_k^{-n} \quad (5)$$

In this equation, $X[k]$] is the *k-th* component of the transform and is calculated at a given point in the Z-plane. $x[n]$,is the *n-th* sample of the input signal, z_k is the *k-th* point on the transform path, and *N* is the total number of samples of the input signal. *n* is the index on the time axis and *k* is the index on the transform axis.

In frequency-based fault detection for transformers [37] and lines [38,39], it is found that the closer the fault location is to the measurement location, the higher frequency harmonics are generated. As the fault location moves away from the measurement location, the frequency value of the fault harmonics decreases and changes very little towards the end. For this reason, 3 different fault boundary ranges were determined and threshold limits were created for the Chip-Z algorithm and are given in Table 1. These frequency band threshold values provide more accurate frequency spectra on a narrower scale.

Table 1. Chirp-Z conversion frequency threshold ranges according to distance.

Fault distance (km)	Lower limit frequency (Hz)	Upper limit frequency (Hz)
0-10 km	10000	20000
10-20 km	5 000	10 000
20 ve üzeri	500	5 000

3.4. Prediction algorithms

3.4.1. Gradient Boosting Ensemble Model

Gradient Boosting is an ensemble learning method that aims to iteratively minimise prediction errors based on the gradient of a loss function [40]. In this method, each model is trained to correct the errors of the previous model and a robust prediction function is obtained at the end of the process. Gradient Boosting is highly effective in various application areas such as regression and classification problems [41].

Gradient Boosting method is expressed mathematically as follows:

$$F_m(x) = F_{m-1}(x) + \gamma h_m(x) \tag{6}$$

Where $F_m(x)$ is the prediction of the full model at the *m-th* iteration, $F_{m-1}(x)$ is the prediction of the model at the previous iteration, γ is the learning rate, a coefficient used to stabilise the predictions of the model, and $h_m(x)$ is the weak model trained based on the negative loss gradient.

This method corrects errors in an iterative manner, while at the same time increasing the generalisation ability of the model and reducing the risk of overfitting.

3.4.2. Support vector machines

Support Vector Regression (SVR) is a version of the Support Vector Machine (SVM) algorithm adapted for regression problems [42]. SVR aims to model the relationship between dependent and independent variables in a data set and generate a prediction function [43]. By only considering errors within a certain tolerance (epsilon), this method increases the generalisability of the model and reduces the risk of overfitting [44].

SVM is mathematically expressed as follows:

$$f(x) = w^t\,\theta(x) + b \tag{7}$$

Where: w is the weight vector, $\theta(x)$ is the function that transforms the input into the feature space (in particular, the kernel function for nonlinear SVR), and b is the bias term [45].

3.4.3. Random forests algorithm

Random Forests is an ensemble method of decision trees and is an algorithm that offers high accuracy in classification and regression problems. This method aims to construct a prediction function by modelling the relationship between dependent and independent variables. Random Forests reduce the risk of overfitting and increase the generalisation ability of the model by making use of several variations of decision trees [46].

RF is expressed mathematically as follows:

$$\hat{y} = \frac{1}{K}\sum_{k=1}^{K} h_k(x) \tag{8}$$

Here, $\hat{y}$ is the final algorithm result, K is the total number of decision trees in the forest, k is the prediction function of the *k-th* decision tree and x is the vector of input variables.

RF increase diversity in the training process by training decision trees on different data subsets and with randomly selected features. The final prediction is obtained by voting or averaging the results of these trees. This approach offers high accuracy while minimising the risk of overlearning

3.5. Models and obtaining comparisons

In this study, the flow chart of the model developed for the detection and prediction of single-phase-ground faults is shown in Figure 2. The process consists of three main stages: data acquisition, data processing and prediction and comparison. In the first stage, a single-phase-ground fault occurring on the power transmission line is modelled and voltage and current waveforms are collected to analyse the system response during the fault. The fault was modelled using circuit elements and the electrical changes during the fault were observed. In the second stage of the data processing process, fault scenarios were created at 39 different locations along the transmission line and the current-voltage signals from each location were obtained. The data was processed using the modal transformation matrix and the spectral components of the signals were analysed using the Chirp-Z transform. The frequency components obtained allowed the fault to be detected more accurately. In the third step, a machine learning based prediction and comparison process was performed. The data was split into 75% training and 25% testing, and the generalisation performance of the model was increased by applying a 10-fold cross-validation method. RF, GBE model and SVM algorithms were used to predict the distance and duration of defects. The accuracy and performance of the models were evaluated using error metrics such as Mean Squared Error (MSE), R^2, Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Explained Variance Score (EVS) and Mean Bias Error (MBE). As a result, it is observed that the developed model is able to analyse fault signals in more detail by spectral analysis with Chirp-Z transformation and provide high accuracy fault prediction with machine learning algorithms. This flow structure provides a holistic approach for fast, accurate and reliable fault detection in transmission lines.

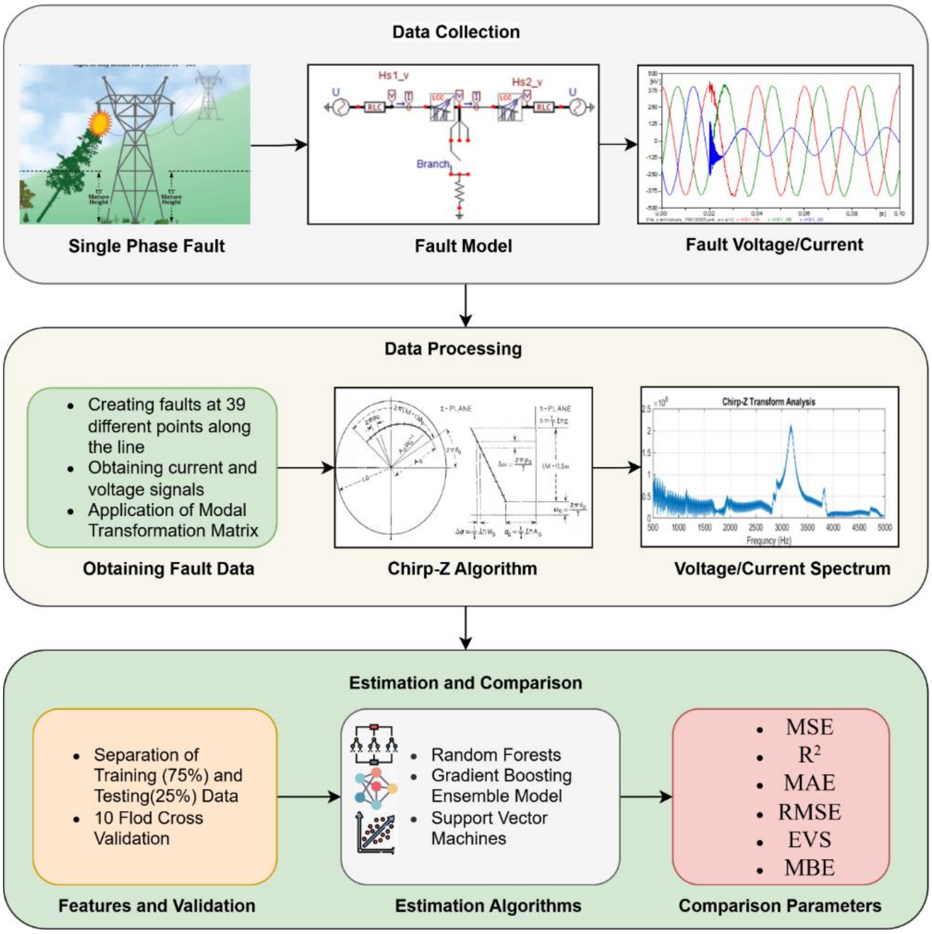


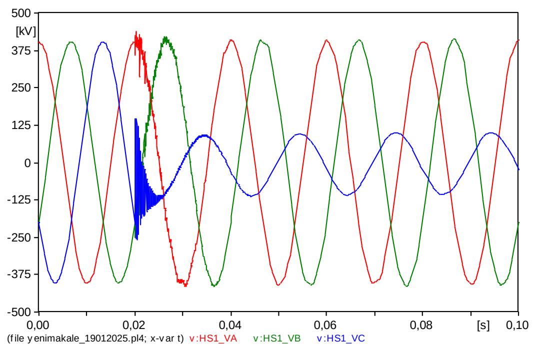
Figure 2. Flowchart of the models used.

4. Experimental Results

The analysis of power transmission lines begins with accurate calculation and modelling of the line parameters. These analyses are critical to understanding the energy losses, voltage drops and transient behaviour of the lines. The single-phase ground fault occurring in the line model, starting from the 5th km of the line to the 155th km, fault data were collected at a total of 39 points. Fault data were collected at 1 km intervals between 5 and 11 km, 2 km intervals between 11 and 19 km and 5 km intervals between 20 and 155 km. In addition, an intermediate data set was collected at 21 km. The line parameters and their role in power line analysis are explained in detail below. The analysis parameters required to perform the analyses are listed in Table 2.

Table 2. Analysis parameters.

Parameter	Value
Line Input Impedance	L=10 mH
Fault Earth Resistance	R=1Ω
Total Line Length	L=160 km
Voltage Sources (U1 and U2)	U=400 kV
Switching Time for Faults,	t=0.02 s
Total Analysis Time	t=0.1 s



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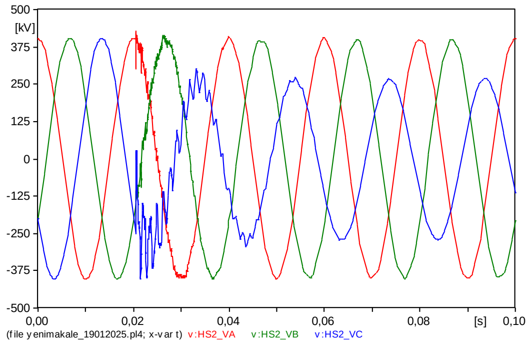


b)

Figure 3. Breakdown voltages of the line at km 21 a) beginning of the line, b) end of the line.

The line head (Source 1) and line end (Source 2) voltage information of the single-phase-ground fault in phase C occurring during 0.02 seconds of the fault on the transmission line are shown in Figure 3. During the single-phase-ground fault that occurred at km 21 of the line, a significant unbalance in phase voltages and transient were observed for approximately 0.02 seconds. At the beginning of the line (a), the effect of the fault on the phases was more pronounced, while at the end of the line (b), these effects were different depending on the physical characteristics of the line. These graphs clearly show the transient dynamic response of the system during the fault and the instability of the voltages.

The variation of currents during the single-phase-ground fault (C phase) occurring at km 21 of the transmission line is shown in Figure 4. At the time of the fault, a sudden increase in current is observed in the faulted C phase, while the other phases exhibit milder amplitude changes. This reflects the transient regime effect caused by the fault and the subsequent transition to equilibrium. The graph clearly illustrates the current behaviour during the fault.

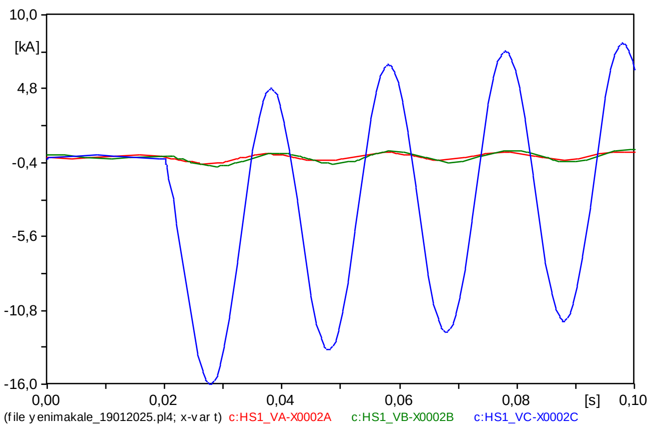


Figure 4. Fault current at 21 km of the line.

When the current value of the faulted C phase of Figure 5 is removed from the figure, the change in the currents of the A and B phases is shown in Figure 4. The transient effects in the fault phase increase due to mutual coupling.

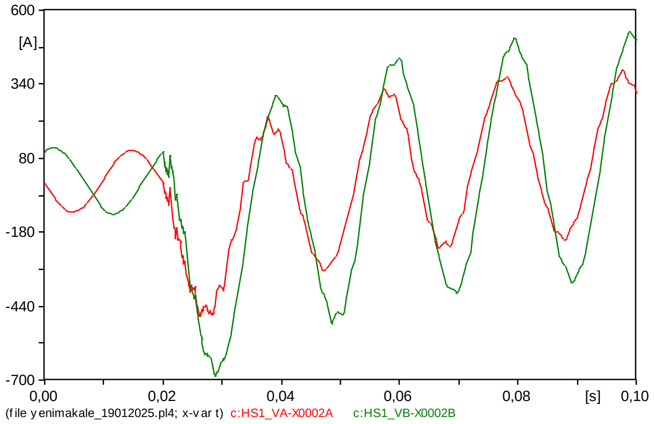
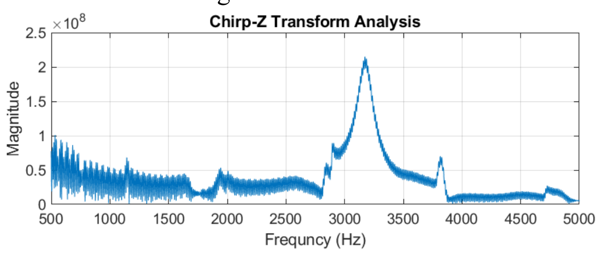


Figure 5. Variation of currents in other phases other than the fault phase.

The frequency spectra of the fault signals processed with the Chirp-Z algorithm show significant differences at different distances (25 km, 70 km, 120 km) and these differences are shown in detail in Figure 6. At 25 km, a dense peak and high amplitude values around 3000 Hz are observed and the frequency spectrum shows a very dense structure. At 70 km the dominant peak around 1000 Hz appears with lower amplitude values and the intensity of the frequency components decreases. At 120 km, the amplitude values decrease significantly and the spectrum becomes more sparse. This analysis shows that as the distance increases, the energy of the fault signals decreases and the effect of the frequency components diminishes. This shows that the Chirp-Z algorithm is an effective way of understanding the behaviour of fault signals at different distances.



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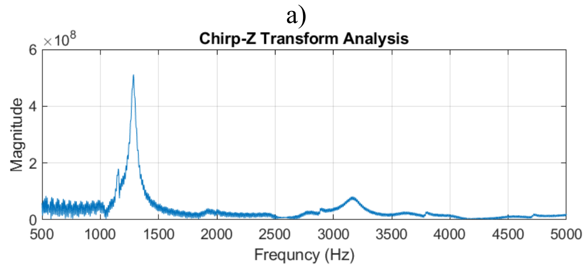

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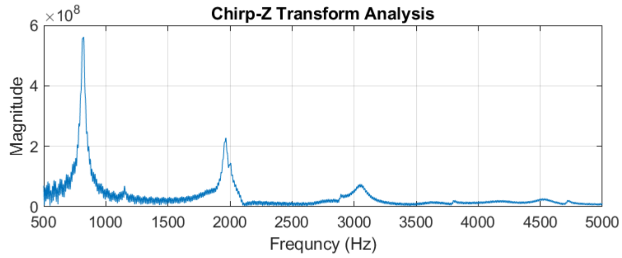
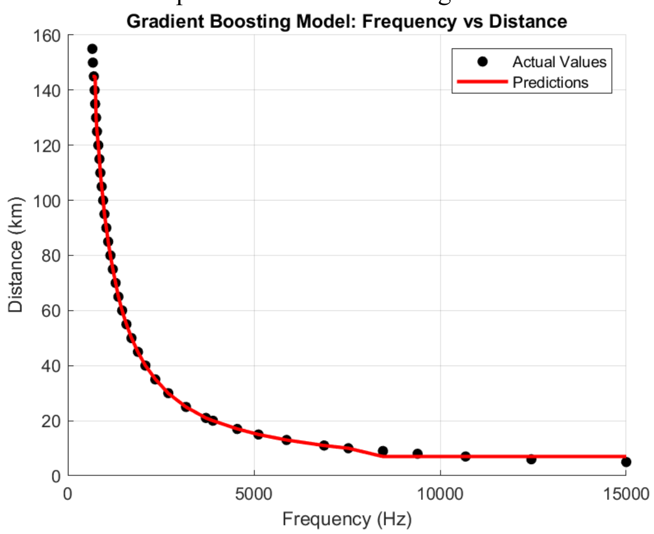


c)

Figure 6. Frequency spectrum of faults processed with Chip-Z algorithm. a)25th km, b)70th km, c)120th km.

Figure 7 compares the prediction performance of different algorithms between defect frequency and distance. The black dots show the actual values and the red lines show the predicted values. GBE is the most successful algorithm in terms of accurately predicting the fault distance with almost perfect agreement at low and high frequencies. The overlap of the predicted values with the actual values proves that the accuracy of GBE is quite high and provides an effective method for fault detection. The RF algorithm performed close to the actual values at low frequencies, but deviations were observed at high frequencies. This shows that RF has a more limited accuracy compared to GBE and SVR. SVR stood out with high accuracy at both low and high frequencies, and in its optimised form it provided high agreement between actual and predicted values. GBE and SVR were found to be the most successful algorithms for accurate fault distance, while RF showed a more limited performance compared to the other two algorithms.



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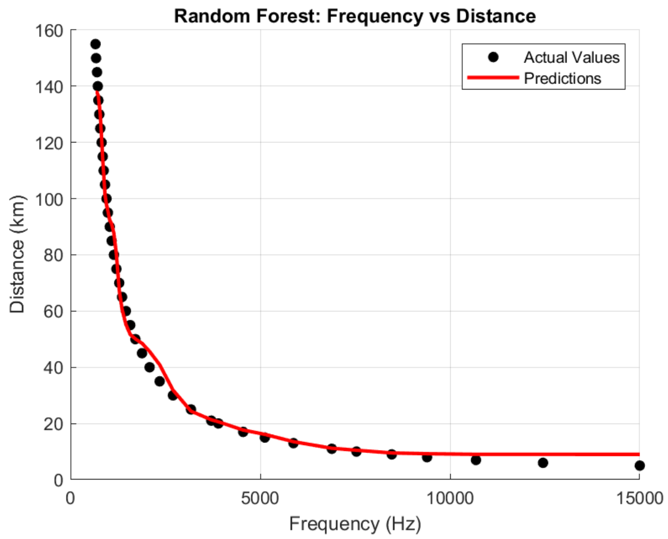
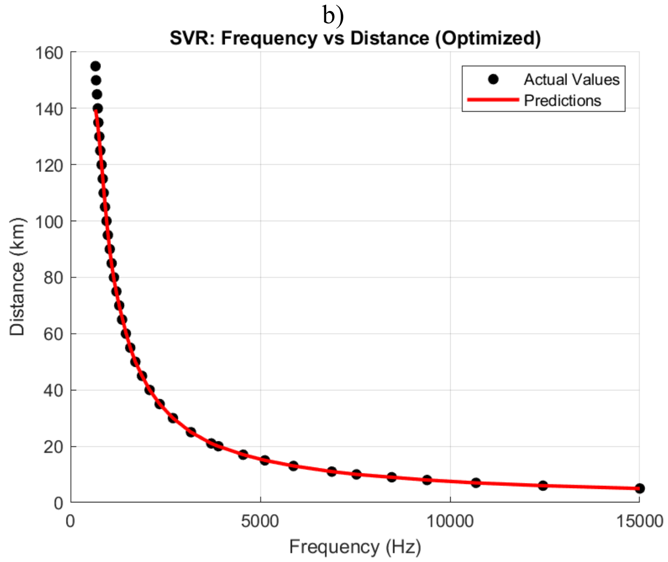


b)



c)

Figure 7. Representation of actual and predicted values of the prediction algorithms. a)25th km, b)70th km, c)120th km.

Mean Squared Error (MSE), R-Squared (R^2), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE) and Explained Variance Score (EVS).

Table 3 shows the results of various error metrics and statistical measures used to evaluate the performance of the different algorithms GBE, RF and SVR. These metrics provide critical data to compare the prediction accuracy and error rates of each algorithm.

GBE stands out as the most successful model as it has the lowest error rates and performs well in terms of R^2 and EVS values. In particular, the MSE (0.0682), MAE (0.1542) and RMSE (0.2582) values show that the model works with low error rates. In addition, the R^2 and EVS values of 0.9972 indicate that the model explains the data very well and has a high prediction accuracy. The MAPE value (0.2927) is at a very low level in terms of proportional error, proving that GBE is a powerful model on the dataset. Although RF has an acceptable performance, it lags behind GBE in terms of prediction accuracy and error rates. In particular, the MSE (0.2071) and RMSE (0.4522) values show that RF produces more prediction errors. Although the R^2 (0.9901) and EVS (0.9961) values are high, the MAE (0.3072) and MAPE (0.8172) values show that the model is more limited in terms of accuracy compared to GBE.

Table 3. Metric data performance.

Algorithms	MSE	R^2	MAE	RMSE	MAPE (%)	EVS	MBE
GBE	0.0682	0.9972	0.1542	0.2582	0.2927	0.9972	-0.0002
RF	0.2071	0.9901	0.3072	0.4522	0.8172	0.9961	0.2100
SVR	0.2231	0.9924	0.3324	0.4720	0.1983	0.9959	-1.1000

SVR shows the best performance in terms of proportional error with a MAPE value of (0.1983). This shows that SVR is a low percentage error model. However, it lags behind GBE in terms of metrics such as MSE (0.2231), MAE (0.3324) and RMSE (0.4720). Furthermore, although the R^2 (0.9924) and EVS (0.9959) values explain the data quite well, the negative MBE (-1.1000) value indicates that there is some systematic deficiency in the predictions.

The GBE model stands out as the most successful model, with a balanced performance across all metrics. It is the most appropriate model on the dataset analysed, especially with its low error rates and high data explanatory capacity. SVR can be recommended for situations where it is important to minimise proportional errors, while RF may be an acceptable option for more general applications. GBE efficiently integrates multiple spectral features from the Chirp-Z transform, enabling higher predictive accuracy. These specific conditions are clearly demonstrated in the experimental results, where GBE showed consistently lower error rates and higher predictive accuracy, particularly at longer fault distances and varying fault frequencies. These results demonstrate the complexity of the data set and the critical importance of the correct model selection on the analysis results.

Table 4. Fault distance prediction and fault rates.

Algorithm	Fault Frequency (Hz)	Fault distances (km)	Predicted fault distences (km)	Error (%)
GBE	7535	10	10.0023	0.0230
	3175	25	24.9762	0.0952
	1710	50	50.1061	0.2122
	1210	75	75.0069	0.0092
	950	100	100.0004	0.0004
	785	125	124.9981	0.0015
	675	150	144.9878	3.3415
RF	7535	10	10.1939	1.9390
	3175	25	25.7214	2.8856
	1710	50	50.1249	0.2498
	1210	75	78.7949	5.0599
	950	100	97.9391	2.0609
	785	125	127.9434	2.3547
	675	150	144.5936	3.6043
SVR	7535	10	9.9240	0.7600
	3175	25	24.9852	0.0592
	1710	50	49.9984	0.0032
	1210	75	75.0022	0.0029
	950	100	103.7247	3.7247
	785	125	124.9865	0.0108
	675	150	144.9594	3.3604

Table 4 compares the fault prediction performance of different algorithms. The predicted fault distances and error rates of the GBE, RF and SVR algorithms are analysed. GBE showed the best prediction performance compared to the other algorithms with low error rates; for example, at a distance of 75 km, the error rate is very low, 0.0092%. The SVR algorithm performed close to GBE, especially at distances of 125 km (0.0108%) and 75 km (0.0029%), but was slightly behind at 150 km, where the error rate increased by 3.3604%. The RF algorithm showed lower performance with higher error rates compared to the other algorithms, especially at short distances (10 km, 1.9390%) and long distances (150 km, 3.6043%). GBE showed the best performance with low error rates and high accuracy, while SVR provided successful and consistent results, especially at long distances. RF performed relatively poorly with higher error rates compared to the other algorithms.

Table 5. Comparison of metric data with the literature.

Study	Algorithm	R^2 Score	MAE	MSE
Algorithms in the study	GBE	0.9972	0.0682	0.1542
	RF	0.9901	0.2071	0.3072
	SVR	0.9924	0.2231	0.3324
[47]	LTSM	-	0.183	0.072
[43]	SVR	0.7613	0.388	-
[48]	GPR	0.99	2.80	0.92
[49]	DT	0.8395	-	-

GPR: Gaussian Process Regression, **LTSM**: Long Short-Term Memory

When evaluating the metrics presented in Table 5, the proposed model shows a significant superiority in terms of performance compared to other studies in the literature. The SVR model used in [43] lags behind the proposed model due to its low R^2 score and high error rates.

Although the LSTM model used in [47] shows a remarkable performance with low MAE and MSE values, it is difficult to make a precise comparison in terms of overall accuracy since the R^2 score is not specified.

Although the GPR model used in [48] has a high R^2 value, the MAE and MSE values are significantly higher than the proposed model, which reduces the reliability of the prediction performance. The DT model used in the study in [49] shows a weaker performance than the proposed model with a low R^2 value. It is found that the prediction models used in this study provide a more reliable and effective prediction method compared to other approaches in the literature, especially with low error rates and high accuracy levels.

Table 6. Comparison of fault points and faults rates with the literature.

Study	Algorithm used	Error (%)	Algorithms in the study	Error (%)
50.km [50]	DT	0.80	GBE	0.21
10.km [51]	ANN	0.50	GBE	0.02
25. km [38]	ANN	0.92	SVR	0.05
75.km [52]	SVR	0.15	SVR	0.00

DT: Decision Trees, ANN: Artificial Neural Networks.

An analysis of Table 6 shows that the models used in this study have lower error rates compared to other methods in the literature. DT is used in [50]', ANN is used in [51] and [38] and SVR algorithm is used in [47] and these studies have higher error rates compared to the GBE and SVR algorithms used in the proposed model. In particular, although the SVR algorithm was used in [52], the fact that the error rate is reduced to zero in the SVR model in this study shows that the model uses this algorithm more effectively. In general, it is concluded that the proposed model provides a more reliable and effective approach to error detection than the methods used in the compared studies.

Tables 4 and 5 are now explained with greater detail, clearly highlighting the superior predictive performance of the proposed GBE model in comparison with other algorithms and previous studies from the literature. The advantages of the Chirp-Z algorithm in terms of high-resolution spectral analysis, flexible frequency range adaptability, and improved fault detection sensitivity are explicitly discussed.

5. Conclusion

In this study, a comprehensive analysis is carried out using the Chirp-Z algorithm and machine learning based prediction models for the detection of single-phase-ground faults in power transmission lines. The high-resolution spectral analysis capability of the Chirp-Z algorithm provides a significant advantage in the fault detection process and improves the accuracy of the prediction models. Among the prediction algorithms tested in the study, the GBE model stood out as the most successful method, offering the lowest error rates and the highest accuracy levels. The SVR algorithm showed strong prediction performance, especially at long distances, while the RF algorithm produced acceptable results at shorter distances, but error rates increased at longer distances.

The results show that the use of machine learning and advanced signal processing techniques is critical in power line fault detection. The high accuracy rates of the GBE and SVR algorithms prove that these methods can provide faster and more reliable fault detection in power transmission systems. The Chirp-Z algorithm provides flexible and highly accurate spectral analysis, allowing more detailed analysis of fault harmonics and more accurate predictions.

This study presents a framework that will contribute to faster and more accurate fault detection in power transmission lines. Investigating how the developed methods can be integrated into practical applications and examining their adaptation to different system conditions will be an important direction for future studies. In particular, the integration of factors such as different fault types, variable load conditions and line impedance into the model can enable the method to have a wider range of application in real systems. In future work, it is suggested to more thoroughly investigate the applicability of the Chirp-Z algorithm in various fields, such as not only single phase-ground fault, but also transformer winding faults, motor winding faults, and vibration-based fault detection. Given its ability to provide fast and reliable results, the study of these additional applications could significantly expand the utility and effectiveness of the Chirp-Z algorithm. The results obtained provide an important scientific contribution to increasing safety, optimising maintenance processes and improving fault management processes in energy systems.

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