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Development of a Traveling Wave-based Protection Scheme for Power Systems with High Penetration of Renewable Energy Sources using a Hybrid Independent Component Analysis-Support Vector Machine Algorithm

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Abstract: The bulk integration of renewable energy sources into the power grid brings about fresh challenges in grid protection, notably in the modification of fault levels. Also, the intermittent nature of renewable energy source inputs makes it challenging for traditional protection methods like overcurrent and distance relays to reliably safeguard these systems. This study introduces an Independent Component Analysis-Support Vector Machine-based protection system tailored to tackle the protection issues arising from renewable energy integration. This method was developed and tested on a 50kV 180km transmission line that was highly penetrated with solar photovoltaics, simulated in MATLAB/Simulink. Simulations were conducted for different fault types, signal noise levels, and fault resistances. The simulation results were then compared with the results of other methods published in available literature. The accuracy of the Independent Component Analysis-Support Vector Machine algorithm in determining the location of faults for the different scenarios was above 99.7%. The fault classification accuracy ranged between 99% and 100% for different levels of signal to noise ratio. Although the method is not as accurate when applied to power systems with high penetration of renewable energy sources as opposed to when applied to conventional power systems, the simulation results are satisfactory since they are higher than 99% which is the accuracy threshold for fault location and classification.

Index Terms: RES, ICA, SVM, TWBFL.

I. Introduction

Due to government initiatives aimed at investing in clean energy, renewable energy sources (RES) are incorporated into the power grid at an increasing rate. The integration of RES, particularly solar and wind energy, is anticipated to grow steadily in the coming years. This integration brings about notable changes in power system operations [1]. Some of these changes have adverse effects, as the introduction of RES leads to a decrease in stability, a reduction in inertia, and an increase in predictability [2]. Additionally, since RES are primarily connected through inverters, their behavior during fault conditions differs from that of traditional energy sources [3]. In particular, integration of renewables can alter the fault levels and make it difficult for conventional protection schemes to operate reliably [4]. The intermittent nature of the infeed from renewables may also lead to nuisance tripping of over current relays under bulk penetration of renewables [5]. Consequently, the integration of RES in power systems poses new challenges for protection. Specifically, the intermittent nature of RES input and its impact on fault levels make it challenging for conventional protection schemes, to accurately determine the fault locations [1].

It is important to note that as the incorporation of RES, especially solar, in the power grid is currently low, the existing changes and power protection issues are seldom a significant concern, as current protection mechanism have the capability of ensuring the required reliability of the power system [6]. However, given the projected future integration, conventional protection methods may not suffice in providing the desired level of reliability [1]. Thus, the widespread integration of renewable energy sources undeniably raises substantial concerns regarding protection of such power systems. Specifically, there is an urgent need to adapt protection techniques that will meet the evolving requirements of highly RES integrated power systems, especially in the case of high integration of inverter-based photovoltaic RES. This calls for the development of new protection schemes that are highly dependable and accurate.

This article consists of seven sections. In section I, we offer the background of the topic and highlight the problem statement. Section II explores the protection strategies that have been proposed in previous studies, highlighting their strengths and weaknesses to identify a research gap. Section III introduces the problem formulation, mapping the method to the problem. Section IV presents the theoretical framework of the proposed method, detailing how it is applied to address the protection challenges in power systems with high penetration of RES. Section V presents a brief discussion of how the performance of the proposed method was evaluated. In section VI, we present and discuss the simulation results. Section VII is the conclusion, where we discuss the implications of the findings.

II. Protection Strategies

Numerous researchers have proposed protection strategies for power systems incorporating RES. Primarily, these strategies focus on fault identification and location mechanisms meant to complement traditional methods. Aftab et al. [3] categorize these strategies into two groups: those utilizing impedance computation and those employing traveling waves. While using impedance computation is advantageous due to its simplicity, low computational load, and cost-effectiveness [7], Lopes et al. [8] pointed out their limitations, particularly in cases of high line loading, sensitivity to frequency variations, and fault path resistance. On the other hand, techniques employing traveling waves for fault location offer the benefit of extremely rapid and accurate fault identification. However, Hasheminejad et al. [9] highlighted their higher cost due to the need for additional hardware like GPS and transducers for precise fault location. Nevertheless, the utilization of traveling wave-based techniques has increased due to their capability to provide precise and ultrafast fault detection, thus enhancing power system reliability [3]. These techniques leverage electromagnetic transients generated at fault points for swift and accurate fault detection, a crucial feature in power systems integrated with RES [10]. Furthermore, Ma et al. [11] asserted that traveling wave-based methods are exceptionally effective and precise in identifying the location of faults in transmission lines, irrespective of factors like the type of fault, level of resistance, distance, and inception angles. Given these merits, traveling wave-based strategies have lately been applied in safeguarding distribution networks.

The phenomenon of traveling wave propagation in electrical power lines is elucidated by Bewley [12]. Bewley [12] posits that disturbances in transmission lines give rise to traveling waves that propagate in all directions along the line. When these waves encounter abrupt changes in line parameters, a portion is reflected while the rest either refracts or continues to the transition point. Bewley [12] devised a lattice diagram to illustrate the propagation of traveling waves in transmission lines, depicted in Fig. 1.

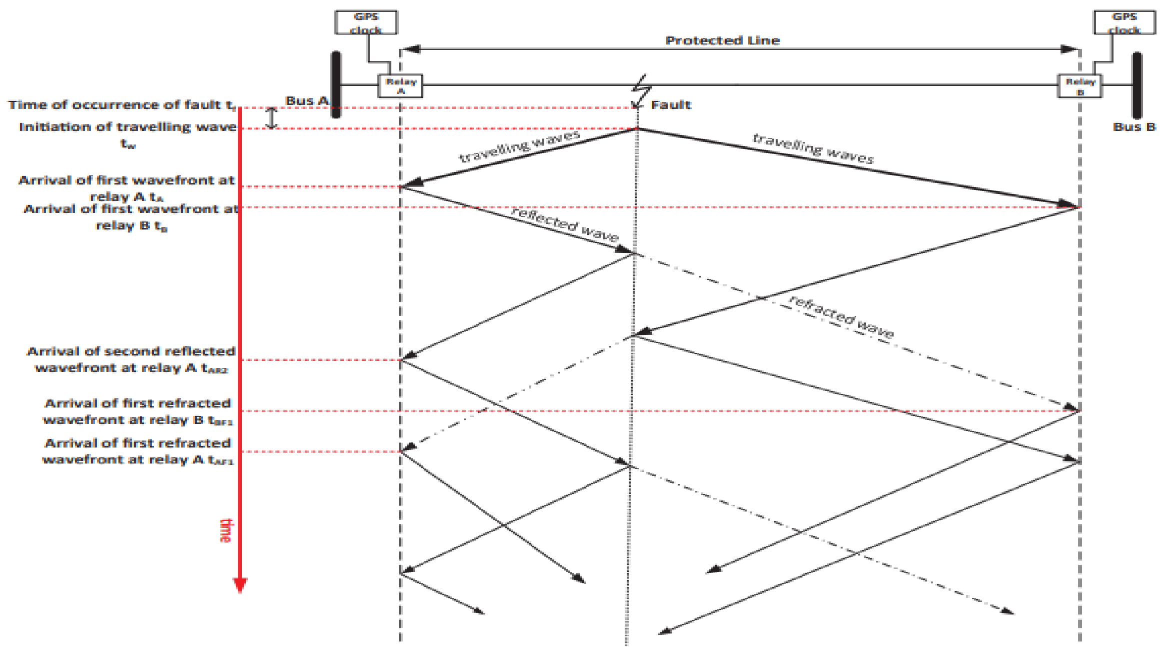

Figure 1: Bewley's Lattice Diagram [12]

The fault location is determined by calculating the time taken for the initial wavefront to reach one end compared to when the second wavefront reaches the other end, as depicted in the figure above. The formula for computing the fault from point A is given by;

$$x = \frac{(t_A - t_B)u}{2} + \frac{L}{2} \qquad (1)$$

In order to employ traveling wave-based fault location (TWBFL) techniques for fault detection, the traveling waves must first be extracted. This necessitates the utilization of mathematical tools and signal processing techniques to arrive at a reduced solution for locating the fault. Various methods for extracting information have been proposed in the literature. These include Wavelet Transform (WT), Teager Energy Operator (TEO), Principal Component Analysis (PCA), Mathematica Morphology Function (MMF), Park's Transformation, and Ensemble Empirical Mode Decomposition (EEMD). Combinations of these extraction techniques have also been suggested to develop more robust dynamic protection schemes. For example, Ekici et al. [13] employ a mixture of WT and Artificial Neural Networks (ANN), [14] utilizes support vector machine (SVM) and WT, and Almeida et al. [15] combined SVM and Independent Component Analysis (ICA). Among these approaches, the combination of ICA and SVM stands out for its remarkably high accuracy, with an error rate of less than 1% [3]. This elevated accuracy is a function of the fact that ICA is not affected by noise and can precisely extract information from a signal with multiple variables.

Several traveling wave-based protection schemes have also documented in existing literature for highly RES integrated power systems. Li et al. [16] proposed an MMF based algorithm for detecting and locating faults in microgrids that are integrated with numerous inverters. The MMF based method is effective in filtering noise and has a very low computation volume. The method also possesses good accuracy and can detect faults even in the presence of high fault impedances and weak TW amplitudes. The MMF based method can also be modified to provide fast and accurate fault detection in meshed networks. While the method has a low computational burden and is able to filter noise, it is not as highly accurate as the method involving a combination of ICA and SVM. Jia et al. [17] employed a line protection method that was based on TWBFL. With this method, the authors successfully isolated an SLG fault in a distribution system with distributed generation (DG) sources. The method was accurate in detecting the location of the fault and cleared the SLG fault with a high speed. However, the method had a very high computational burden. While the method was highly accurate and isolated the SLG fault quickly from both sides, its accuracy cannot match that of ICA-SVM, particularly if the protected system is noisy. Sahoo and Samantaray [18] proposed a protection approach utilizing Fast Discrete S-transform (FDST) to detect and locate points of fault occurrence in TCSC compensated lines connected to wind turbines. While the method demonstrated better performance than the Continuous Wavelet Transform (CWT) under various fault locations, resistances, types, sections and inception angles, it has a huge computational burden, is susceptible to noise and is not as accurate as the ICA-SVM method.

Saleh et al. [19] used a scheme that utilizes traveling waves to detect, classify and locate SLG, LL and open circuit (OC) fault in utility-scale PV arrays. The method was reported to meet the speed threshold for the protection of DC microgrids. This protection scheme also had a very low computational burden. While the method is accurate, fast and scalable, it is prone to noise and its accuracy is not as high as the ICA-SVM method. On their part, Al Hassan et al. [20] utilized a model-based, communication-free approach for microgrids integrated with inverters. The protection scheme can detect faults irrespective of the mode of operation and level of fault current of the microgrid. This method is particularly effective in overcoming protection challenges such as blinding and nuisance tripping in distribution networks. Additionally, the method is very robust in cases of distributed loads and does not require communication as is the case for other methods such as overcurrent relays that require a communication system to operate well against distributed loads. While the method can detect faults for numerous fault and load impedances, it is susceptible to noise and is not highly accurate. Alasali et al. [21] developed a hybrid tripping characteristic-based protection scheme to be used for photovoltaic power systems. The protection scheme effectively reduced the operating time (35% reduction) of overcurrent relays and increased the sensitivity of the relay in different fault conditions. While the tripping time of the overcurrent relays was reduced, the fault location accuracy did not significantly improve. The protection scheme was also susceptible to noise and its fault detection speed was not as high as the ICA-SVM based protection scheme. While the methods developed by Aboshady et al. [22] and Kant et al. [23] provided acceptable accuracy, they were also susceptible to noise.

However, the reliability of the ICA-SVM method has not been tested for power systems with bulk penetration of RES. Considering that RES integrated power systems introduce new protection challenges, and that protection strategies that prove effective in conventional power systems may be ineffective in RES integrated power systems, the present study seeks to apply the combination of ICA and SVM on power systems with high penetration of RES, and evaluate its reliability in protecting such systems.

This paper presents a dynamic protection scheme based on traveling waves, employing an ICA-SVM algorithm to a highly RES integrated power system. This innovative approach is anticipated to enhance the accuracy of fault detection and localization in power systems integrated with RES to a degree surpassing that of conventional protection methods. To assess the sensitivity and stability of this proposed scheme, various testing scenarios were utilized, encompassing different fault types, levels of signal noise, and fault resistances. Evaluation of the performance of the proposed approach involved conducting extensive simulations using MATLAB/Simulink on a 50kV, 180km transmission line model. This model incorporated a total of two inverter-interfaced generators (IIG) representing the RES, and inverters were realized using a mode-adaptive droop-based d-q frame controller. Additionally, two dynamic motor loads were connected to two buses within the microgrid model. After full integration of the microgrid and protection scheme, the scheme was tested to detect LG and LLG faults.

III. The Ica-Svm Algorithm

A. Independent Component Analysis

This formulation analyses a traveling wave signal modelled by f(n) as follows:

$$\mathrm{f(n)}(0 < n < N) \qquad (2)$$

where N = length of the moving window which can be as short as two samples.

Considering matrix X of size $m \times n, m \leq n$ defined by;

$$\mathrm{X} = [\mathrm{x}_1, \mathrm{x}_2, \dots, \mathrm{x}_\mathrm{m}]^\mathrm{T}$$

Where x_i = mixture signals of size $1 \times n, i = 1,2, \dots, m$ that are observed when a fault occurs,

Matrix X can be modelled using a basic ICA model as:

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$X = AS = \sum_{i=1}^{m} a_i s_i$ (3)

Where a_i = i^{th} column of unknown matrix A of size m x m and, s_i = i^{th} row of source matrix S of size m x n.

It is worth noting that the vector s_i is seldom directly observed from the mixture signals x_i

The ICA model is used to find a demixing matrix, say B of size m x m defined by:

$Y = [y_i] = BX = [b_i X]$ (4)

Where y_i = i^{th} row of Y, i = 1, 2, …, m., and y_i = independent components (ICs) which are by definition statistically independent, as much as possible.

The ICs are an estimation of the rows of matrix S of size m x n defined by s_i.

In the ICA-SVM scheme, the ICA model generates the approximated ICs from the traveling wave signal f(n). These ICs are then used as inputs for the SVM for determining the location of a fault. In this thesis, the ICA (FastICA) algorithm was used because it is robust, fast and easy to use in practical applications.

B. Support Vector Machine

The SVM algorithm is defined, thus:

Consider a training set having input vectors and labels given as;

$\{(x_i, y_i)\}_{i=1}^{N}, x_i \in R^d, y_i \in \{-1,1\}$ (5)

Where; N = number of observations in the sample and d = the dimension of individual observations.

The target is represented by y_i. The above SVM algorithm then uses the ICs from the ICA model to accurately estimate the point of fault occurrence. For purposes of this project, I used the LibSVM algorithm because it is one of the efficient SVM algorithms in practical applications.

IV. Basic Principle of the Ica-Svm Protection Scheme

The traveling wave is treated as a composite signal x_i consisting of N observations, formed by a linear combination of s_{ji} with basis function a_m. This can be expressed as:

$x_i = a_1 s_{1i} + a_2 s_{2i} + \cdots + a_m s_{ji}$ (6)

Here; j = 1, … m, and s_{ji} represents a source vector. Notably, the source vector s_{ji} undergoes mixing with a defined mixer represented by a mixture matrix A. Equation 2 can be reformulated as:

$X = AS$ (7)

It is important to emphasize that the observer has no knowledge of the underlying linear system comprising S and A. The ICA model aims to estimate both A and S by observing X. The ICA computation used to estimate A and the independent components of S is shown in Fig. 2 below.

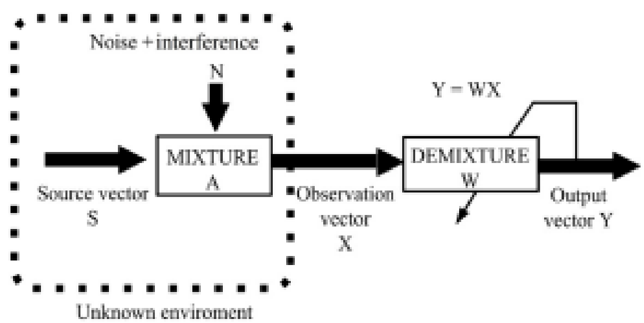

Figure 2: ICA Computation

In ICA computation, the source signal S undergoes mixing with A, where only vector X is provided. The main goal of ICA computation is to derive a demixing matrix W that allows the generation of an output Y.

In this context, W is assumed to consist of linear filters, given by:

$S = WX$ (8)

Assuming the demixing matrix is invertible, the ICA estimation is obtained from the equation:

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$X = W^{-1}S$ (9)

And the output matrix is defined as;

$Y = WX$ (10)

Matrix A from the ICA model represents the basis functions.

Following this, an SVM algorithm is employed to train and test the subspaces derived from the ICA basis function. The decision function for the SVM algorithm is:

$f(x) = \sum_{j=1}^{m} \alpha_j y_j K(x_i, x)$ (11)

where α_j = Lagrange multiplier and y_j = output vector using an ICA component j

Fig. 3 shows the operation of the proposed approach. The power system design used for simulation is shown in Fig. 4.

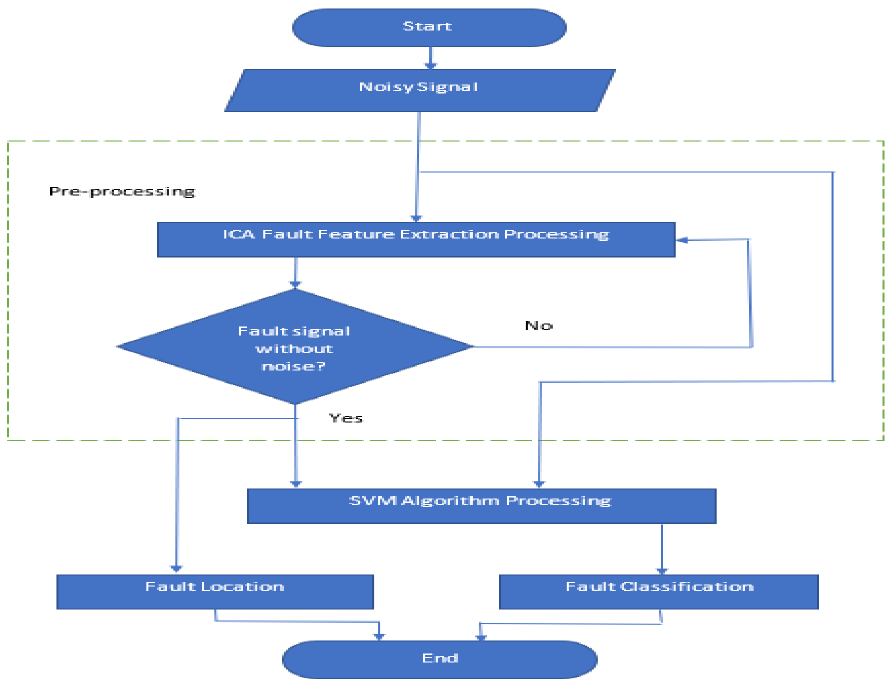
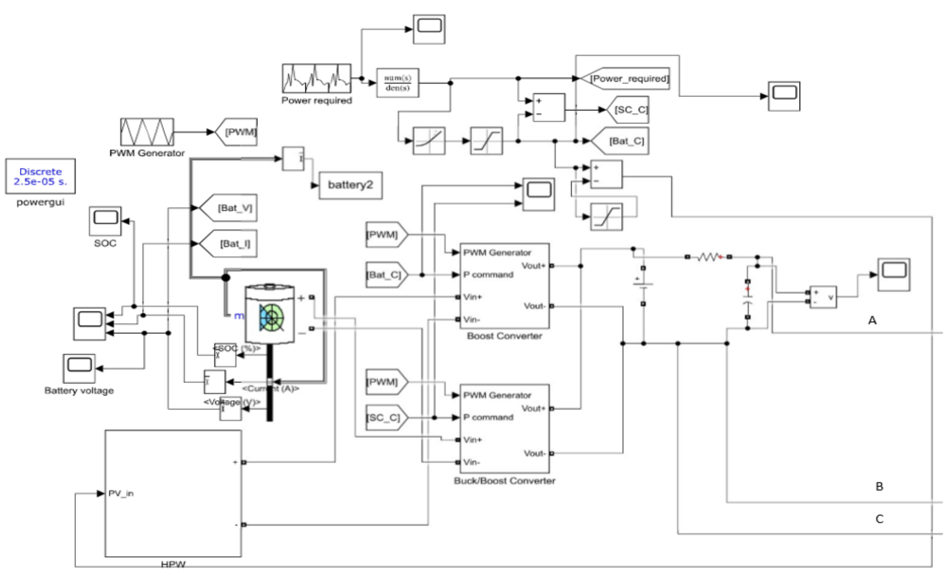


Figure 3: Flowchart of the ICA-SVM Protection Scheme



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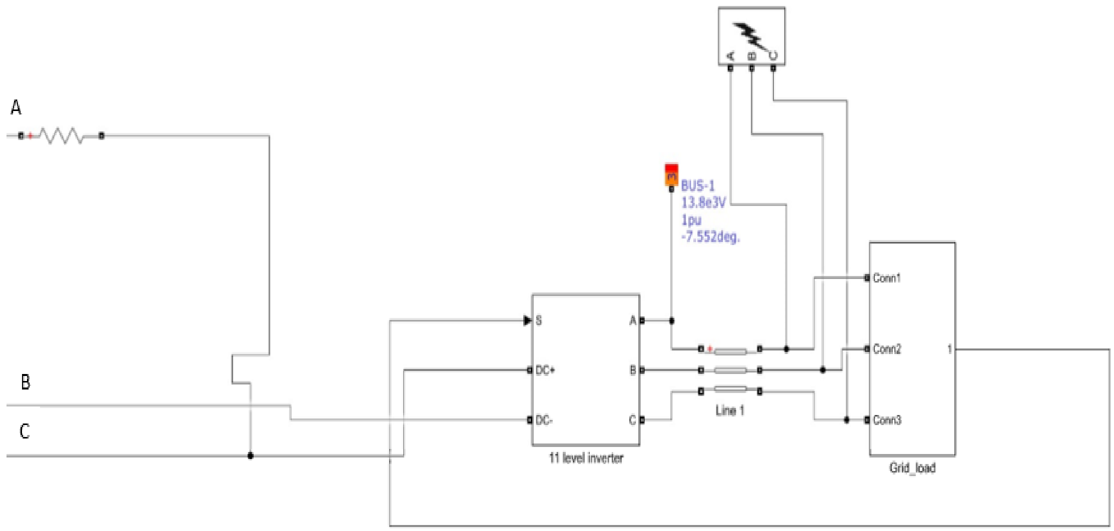

Figure 4: Power System Design

V. Performance Evaluation

As mentioned earlier, the simulations encompassed various testing scenarios, involving different types of faults, levels of signal noise, and variations in fault resistances. The ICA-SVM code was employed to analyze the voltage data obtained from these simulations, focusing on fault detection and classification. To assess the effectiveness of the developed ICA-SVM algorithm, the primary performance metric used was the relative error. This measure is defined as:

$$\text{Error}\ (\%) = \frac{|D_E - D_R|}{L_t} \times 100\% \qquad (12)$$

Where; D_E = estimated fault distance,

D_R = real fault distance, and

L_t = total length of the transmission line.

VI. Results and Discussion

The performance of the proposed algorithm was tested using a set containing two types of faults – LG and LLG applied on the 50kV, 180km line as shown in Fig. 5.

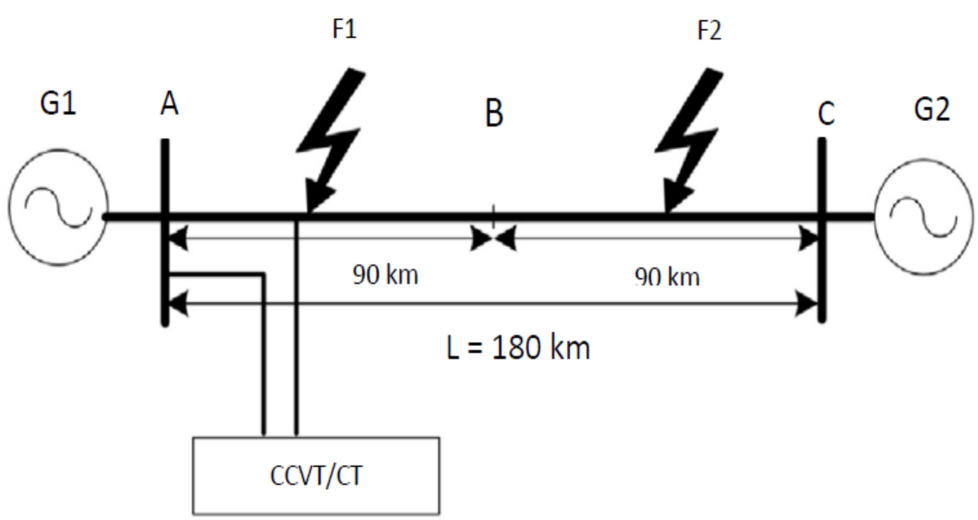

Figure 5: Transmission Line Model

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The line parameters included an inductance of 1.12mH/km and a capacitance of 8.205nF/km. The voltage data was sampled at a frequency of 200kHz. The SNR was between 30dB and 50dB. The actual parameters for the test scenarios are shown in Table 1.

Table 1: Test Scenarios

Type of Fault	LG and LLG
Real distance (km)	10, 135, 150
Resistance of fault (ohm)	20, 60, 85, 100
Angle of incidence (degrees)	0, 45, 90
SNR (dB)	30, 35, 40, 50
Inductance (mH/km)	1.12
Capacitance (nF/km)	8.205

A. Location of a Fault Simulated at 10km

Table 2 shows the results of locating a fault simulated at a distance of 10km for difference levels of SNR. For all noise levels, the relative error was 0.15%, representing an accuracy of 99.85%.

Table 2: Location of LG Fault for Fault Distance 10km using 50 ICA Base Functions

SNR (dB)	t_A	t_B	Distance (km)	Error(km)	Relative Error (%)
30	1.02	1.0203	9.735	0.265	0.1472
35	1.00	1.0003	9.735	0.265	0.1472
40	1.12	1.1203	9.735	0.265	0.1472
50	1.04	1.0403	9.735	0.265	0.1472

B. Location of a Fault Simulated at 150km

Table 3 shows the location of a fault simulated at a distance of 150km for different values of fault resistance. The relative error remained constant (0.26%) for all values of resistance, representing an accuracy of 99.74%.

Table 3: Location of LG Fault for Fault Distance 150km using 50 ICA Base Functions

Resistance of fault in ohm	t_A	t_B	Distance in km	Error in km	Relative Error %
20	1.030	1.029	150.47	0.47	0.261
60	1.025	1.0246	150.47	0.47	0.261
85	1.133	1.1326	150.47	0.47	0.261
100	1.042	1.0416	150.47	0.47	0.261

C. Location of a Fault Simulated at 135km

Table 4 shows the location of a fault simulated at 135km for different values of fault resistance. A relative error of 0.13% was obtained, representing an accuracy of 99.87%.

Table 4: Location of LG Fault for Fault Distance 135km using 50 ICA Basic Function

Resistance of fault in ohm	t_A	t_B	Distance in km	Error in km	Relative Error %
20	1.023	1.0227	135.23	0.23	0.128
60	1.067	1.0667	135.23	0.23	0.128
85	1.210	1.2097	135.23	0.23	0.128
100	1.102	1.1017	135.23	0.23	0.128

D. Fault Classification using SVM

Fig. 6 is a graphical representation of fault classification using LibSVM for an LG fault simulated at 1 second, 2 seconds, and 3 seconds. In this sample test, the SVM algorithm was able to accurately classify the simulated LG faults, as indicated by the red dot in all the three instances.

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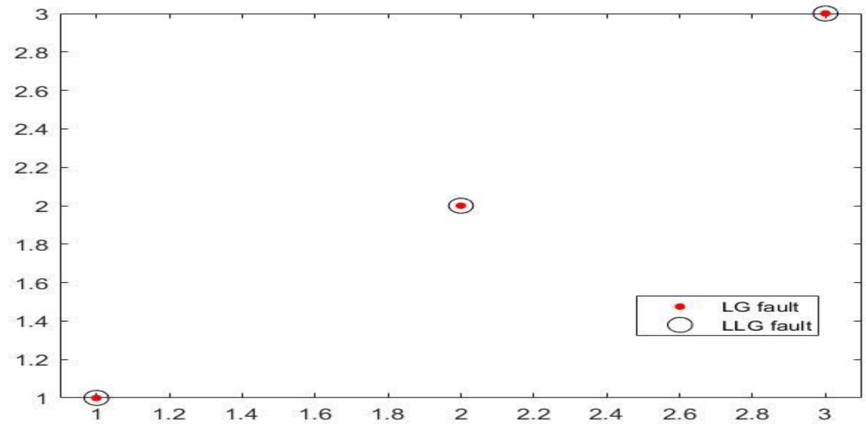

Figure 6: SVM Fault Classification

A detailed summary of the test results is shown in Table 5. Columns C and I represent correct and incorrect classification, respectively. In Table 5, when SNR is 30 dB, the classification rate is 100% when dealing with 150 cases regarding a LG fault. The best classification results are achieved with SNR = 45 dB for an accuracy of 100% considering both fault types.

Table 5: Test Results Regarding Classification of Fault using SVM

SNR (dB)	LG c	LG i	LLG c	LLG i	Total c	Total i	CR%
30	135	0	131	2	266	2	99
35	135	0	133	1	268	1	99.2
45	135	0	135	0	270	0	100

From Table 5, it is apparent that the accuracy of the proposed method in classifying faults is influenced by SNR. For the considered scenarios, fault classification accuracy is highest when SNR is 45dB.

E. Performance of the ICA-SVM Algorithm Under Transient Disturbances

To test the stability and performance of the ICA-SVM Algorithm under worst case scenarios, non-fault transient disturbances were introduced. In particular, a motor-starting event was simulated. Motor-starting was chosen because it is a common non-fault disturbance in microgrids. At a current of 0.01kA, the ICA-SVM based protection scheme did not produce any detectable response to the transients, as shown in Fig. 7. Therefore, the ICA-SVM based protection scheme has good stability in response to non-fault transient disturbances.

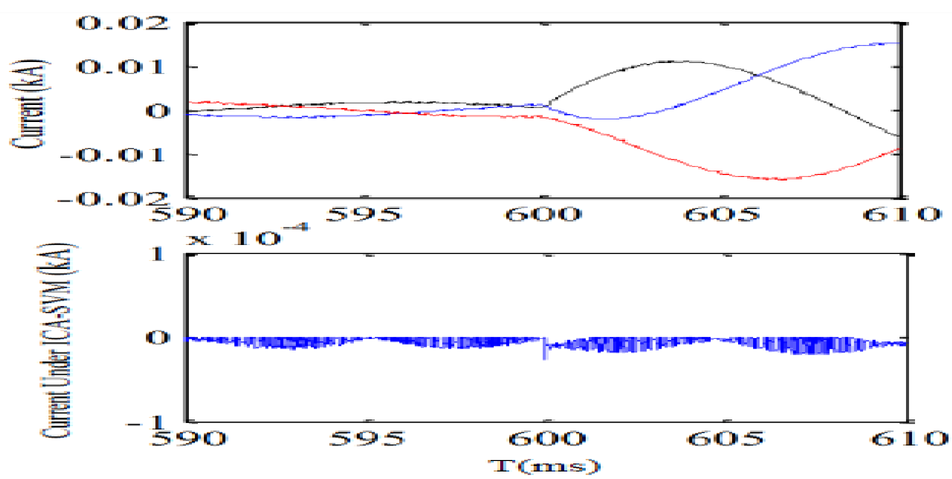

Figure 7: Stability During a Motor Starting Event

F. Sensitivity of the ICA-SVM Based Scheme at Difference Noise Levels

Fig. 8 shows the sensitivity of the protection scheme under different noise levels from 40dB to 10dB. It is clear that the ICA-SVM algorithm can successfully process a noisy signal with clear time location and wavefront polarity even at a SNR of 10dB.

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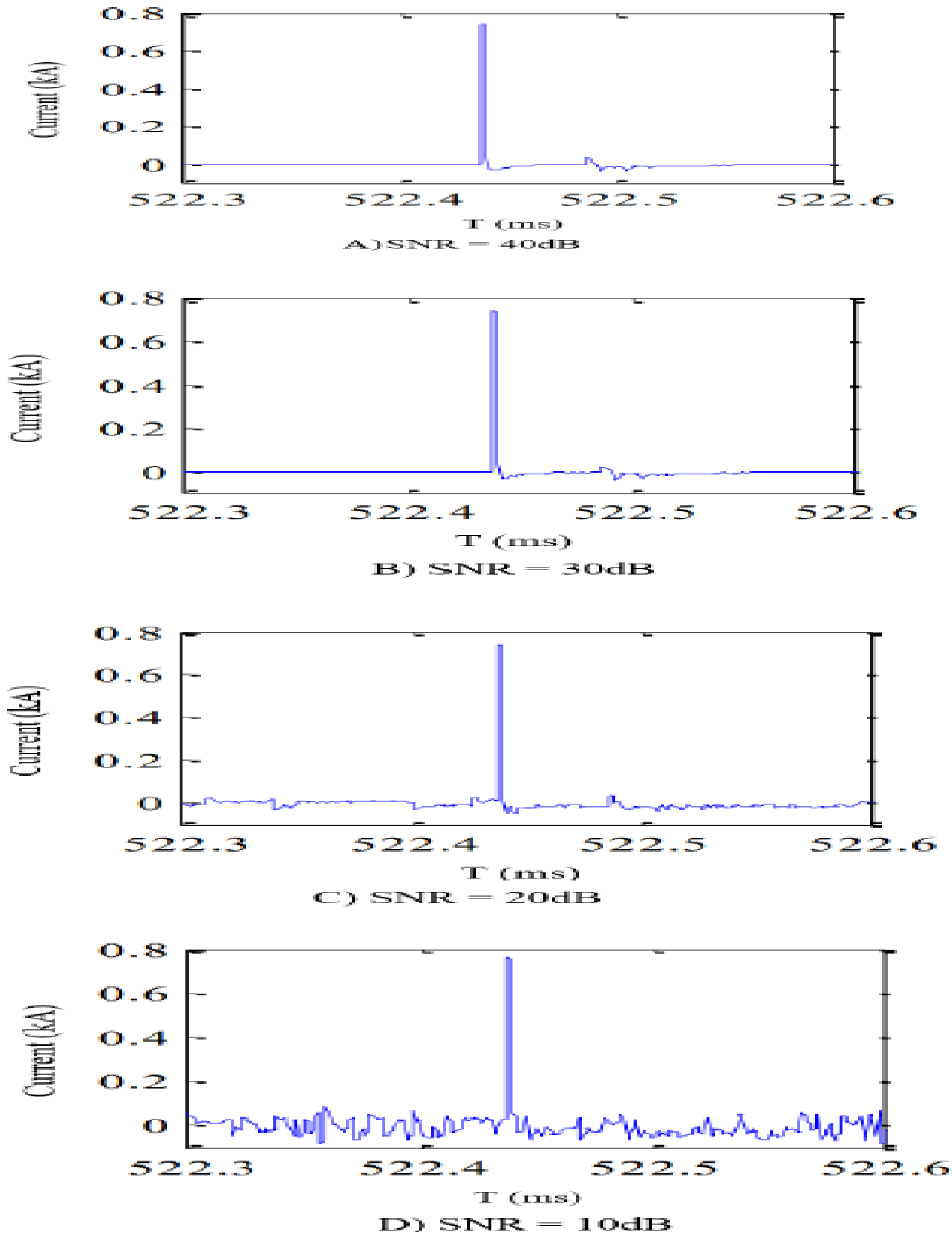

Figure 8: Sensitivity of the Scheme under Noise

From the above results, it is apparent that the accuracy of the ICA-SVM algorithm in determining the location of faults for the different scenarios is above 99.7%. Similarly, the fault classification accuracy is above 99% for different levels of SNR. It is important to note that, in this thesis, the ICA-SVM algorithm was tested on a microgrid model in which the RES supplied more than 40% of the total power. As such, the model met the criteria for bulk RES integration. Additionally, FastICA is used for fault classification. This ICA algorithm has been reported in literature to be among the most robust and fastest ICA algorithms, which can easily be utilized for practical implementations [15]. On another hand, the thesis uses LibSVM which is among the most efficient SVM algorithms for practical implementation [24]. These reasons affirm the validity of the obtained results. However, to effectively evaluate the performance of the ICA-SVM method, a detailed comparison with the results of other methods is necessary. A comparison of the present results against those of previous studies is shown in Table 6. From Table 6, it is apparent that the ICA-SVM algorithm developed in this thesis yielded a higher accuracy in fault location than a combination of SVM and Wavelet proposed in Ekici [24], a combination of ANN and Wavelet suggested by Ekici et al. [13], and the combination of Fuzzy Logic, S, and Wavelet proposed by Samantary [25]. The accuracy of the present algorithm is, however, less than the combination of ICA and SVM suggested by Almeida et al. [15]. It is worth noting that [15] applied their algorithm on a conventional transmission line. Therefore, the slight reduction in accuracy reported in the present results could be as a result of the dynamic nature of RES infeed in the highly RES integrated microgrid model used in the current study. Table 6: Performance Comparison

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Proposed Method	Author	Error (%)	Accuracy (%)	Stability Unde Transient Disturbances	Noise Tolerance
SVM and Wavelet	Ekici [24]	1	99	Stable	Susceptible to noise
ANN and Wavelet	Ekici et al. [13]	2.05	97.95	Low stability	Susceptible to noise
Fuzzy Logic, S, and Wavelet	Samantary [25]	2	98	Low stability	Susceptible to noise
ICA and SVM (applied to conventional power system)	Almeida et al. [15]	0.1	99.9	Stable	Not Susceptible to noise
ICA and SVM (Applied to power system with high penetration of RES)	Present Study	<0.3	99.7	Stable	Not susceptible to noise

VII. Conclusion

The findings of this paper demonstrate that a combination of SVM and ICA offers excellent results when used to classify and determine the location of faults in power systems with high penetration of RES since the errors in fault location are less than 0.3%, and the classification accuracy is above 99% for all fault types. It is also apparent that the present technique has superior performance than conventional methods, such as a combination of ANNs and wavelets.

The proposed method also shows high stability in the presence of non-fault disturbances such as motor-starting. Precisely, when a threshold of 0.01kA is applied the method showed visible response to the transient disturbance, thereby demonstrating good stability under this condition. The method can also successfully process noisy signals with SNRs of even 10dB and accurately locate faults with clear time location and wavefront polarity. Thus, the method has high peak detection, which increases its reliability in detecting and locating faults. This ensures the safety of the grid whenever a fault occurs.

These findings are of significant importance to the protection literature, especially considering the high speed with which the ICA-SVM algorithm is able to accurately identify faults. The high speed is attributed to the fact that ICA analyses the first arrived wavefront of the voltage wave to locate faults, thereby significantly reducing the computation time required. The ability of the ICA algorithm to accurately identify and analyse the frequency spectrum of the first arrived wavefront not only reduces the computation time but also improves the reliability of the whole protection scheme. It has also been demonstrated that the ICA-SVM is not susceptible to noise. These findings position the ICA-SVM algorithm as an effective method of addressing the protection challenges associated with bulk integration of RES in electrical power systems.

The findings of this paper have demonstrated that the ICA-SVM algorithm can overcome the unpredictable behaviour of RES under fault conditions, and identify and locate faults with high accuracy. However, the analysis presented in this thesis considered only three scenarios – different fault types, signal noise levels, and fault resistances. Future research can be conducted on other scenarios such as considering different system topologies and sampling frequencies. In particular, the present study only used a sample frequency of 200kHz. Thus, analyzing the performance of the ICA-SVM algorithms on traveling waves of higher frequencies, especially in short lines with multiple feeders in distribution networks will be of great value in advancing the knowledge in this area.

This study also considered only two types of faults – line to ground and double-line to ground. Future studies can also test the method using other types of faults such as line to line fault. Special fault conditions simultaneous multi-located faults and switch on fault can also be considered. The impact of fault inception angles can also be considered in future studies. Developing a hardware laboratory prototype is also another important focus of future work, to allow the method to be tested in practical settings.

Because the integration of RES in power systems is projected to increase in future, it is recommended that power system protection schemes should incorporate a combination of ICA and SVM algorithms for accurate detection, location, and classification of faults. By including the ICA-SVM algorithm, faults in highly RES integrated power systems will be detected with high accuracy, thereby improving the reliability of the electrical grid. It is worth noting that this method can be adopted for both transmission and distribution systems. However, in developing the ICA-SVM algorithms, it is important to select the most robust and efficient approaches such as FastICA and LibSVM. In fact, the FastICA algorithm was used in this thesis because of its capabilities and features. Among ICA algorithms, FastICA is the easiest yet the most robust and fastest approach suitable for

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practical implementation. On its part, LibSVM has the highest efficiency among the available SVM approaches. It is also easy to implement, and hence suitable for practical applications.

Considering the current trends of increased RES integration in electrical grids, this thesis proposed an ICA-SVM algorithm-based protection scheme using TW theory for improving the accuracy of fault detection, location, and classification. Conventional protection schemes are not capable of protecting highly RES integrated power systems with the desired accuracy. In this thesis, it has been demonstrated that a combination of ICA and SVM solves this problem by providing highly accurate fault location and classification at an accuracy level of more than 99%. The present study has contributed to power system protection literature by demonstrating that a combination of ICA and SVM yields highly accurate fault location and classification with high reliability in power systems with high penetration of RES, even in the presence of noise.

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Data Availability

Question	Response
Data Availability Sharing research data helps other researchers evaluate your findings, build on your work and to increase trust in your article. We encourage all our authors to make as much of their data publicly available as reasonably possible. Please note that your response to the following questions regarding the public data availability and the reasons for potentially not making data available will be available alongside your article upon publication. Has data associated with your study been deposited into a publicly available repository?	No
Please select why. Please note that this statement will be available alongside your article upon publication. as follow-up to "**Data Availability** Sharing research data helps other researchers evaluate your findings, build on your work and to increase trust in your article. We encourage all our authors to make as much of their data publicly available as reasonably possible. Please note that your response to the following questions regarding the public data availability and the reasons for potentially not making data available will be available alongside your article upon publication. Has data associated with your study been deposited into a publicly available repository? "	Data included in article/supp. material/referenced in article

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