Machine Learning -Wavelet Protection Analysis for SVC Controlled Wide Area Network in Presence of Wind Energy Source

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Abstract- The power system network is one of the most extensively dispersed electrical engineering systems designed to transport the majority of electricity over distances of several kilometres from one end of the country to the other. New wind production units and balancing equipment are often added to an existing power system network as part of the integration of power projects. The network of an island power system is severely threatened in terms of security and protection due to the increased level of wind power generation penetration. To link the electrical system with smart environments based on Internet-of-Things technologies, quick detection methods are now required. In essence, wavelet (WT) analysis analyses transient signals at various frequencies and breaks down the waveform into successive precise and approximative coefficients, which are vital for determining the location and kind of fault. Machine learning has traditionally been used with great effectiveness in a variety of defect analysis fields. The implementation of mother wavelet-detailed coefficients for fault detection and localization and the use of machine learning for fault location on transmission lines This paper offers a detailed explanation of the suggested approach for the diagnosis of system defects using an IoT-wavelet-based mechanism that was created and put into use in the network of the SVC integrated power system and wind energy source with a machine learning approach.

Keywords Wind energy source, Internet-of-Things, Machine learning, Microgrid protection, wavelets
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1. Introduction

Transmission lines are used to move large amounts of power throughout the nation's most remote regions. Electricity lines that cross different geological zones are more susceptible to different forms of atmospheric disasters, which more commonly result in line faults. The damaged line must be removed as soon as feasible in order to avoid severe bulk power loss through the fault spot and to swiftly restore system stability [1]. Researchers have developed a number of approaches for creating enhanced power system protection algorithms that might be used to instantly fix defects when they occur [2]. This contributes to the safety of the associated operational staff and connected equipment, as well as the immediate reduction of unnecessary power waste. It is concluded that quicker estimation and problem detection offer great protection for the device while also limiting future harm. Unidirectional fault current flow has been used in traditional power system design and construction for radial distribution networks. However, the addition of DGs to the primary grid via microgrids causes a bidirectional change in the direction of fault current flow. A quick static switch connects the microgrid to the main power supply, protecting it from all fault types in both operating modes [3, 4]. The most frequently used in the wind power production business is the doubly fed induction generator (DFIG). Through a step-up transformer, the stator terminals of the DFIF are directly linked to the high-voltage DG bus. Two different types of converters make up the power electronics interface: a rotor-side converter and a grid-side converter. Through a shared DC link, both converters are cascaded together [5]. The grid-side converter checks the power factor and makes sure that it is close to unity, while the rotor-side converter fully manages generator operations, including controlling active and reactive power as well as harmonic injection. A static VAR compensator (SVC), which is also a member of the FACTS device family, is a shunt-connected CPD that may supply or absorb reactive power through the active control of passive components using power electronics, thereby adjusting the voltage profile of the system. SVCs' accuracy, usability, and dynamic performance enable these components to reduce steady-state and transient voltage problems [6]. Through reactive power control, SVCs can be used to increase transient stability limits, smooth out power fluctuations, and reduce power losses. Since it is difficult to build an effective protection system that must respond to both main grid and microgrid faults, microgrid protection poses the greatest obstacles. As a result, depending on the microgrid operation mode, system fault current magnitudes may differ dramatically between grid-connected and autonomous operation [7, 8].

In order to minimise cascading damage when faults occur, it is crucial to establish fault diagnosis processes for power system protection as it becomes more flexible and complicated. In recent years, a variety of machine-learning-based algorithms for identifying errors have been developed in response to the problems that vast amounts of data have raised [9]. In contrast to the outdated power system, the expansion of data of all types, the urgent demand for data storage, the growing penetration of distributed generations, and technological advancements are currently posing challenges to the modern power system. There is no doubt that the current power system needs more reliable and flexible protection and control. Because of their limitations in generalising conventional models, storing massive amounts of data, and the appropriateness and efficiency of real-time processing, standard techniques used in power systems are inherently insufficient to address the difficulties.

The assessment of IOT in the electrical power sector changed how things were conducted in the past. In order to reduce power consumption and costs, IOT expanded the use of wireless technologies to connect infrastructure and assets in the power industry [10]. SCADA, smart metering, building automation, the smart grid, and networked public lighting are a few examples of IOT applications. By gathering a significant amount of data with the aid of IOT for sensing real-time data to be transmitted, which qualifies for quick decision-making, it may increase system performance and make it more measurable and quantifiable [11, 12].

Fault categorization and forecasting of fault location are the two main duties that the protection system is capable of performing. primary significance in differentiating and locating the troublesome location. This quickly minimises unnecessary power loss and contributes to the protection of operational employees, connected equipment, or both. An algorithm for protecting a power system connected to a micro-grid is provided [13, 14] and is based on wavelet analysis of transient fault current data. When using the wavelet-detailed coefficients of the Bior-1.5 mother-wavelet, multi-resolution analysis (MRA) is used. Since modern digital relays are significantly faster and more precise than older prototypes, they can identify and isolate a defective line much earlier [15]. The parts that follow go through many efficient techniques for analysing the network problems of two area power systems using IoT-Wavelet and machine learning methods.

2. Power System Network with Iot Monitoring

Perception, network, and application layers together with other components comprise the three layers that secure transmission lines using Internet of Things (IoT) construction. In applications for power system protection, Figure 1 shows the essential architecture of the Internet of Things. The perception layer can utilise sensors, RFID, and cameras to keep an eye on the electrical equipment required for communication and transmit the information to the network layer for the safety of transmission lines [16]

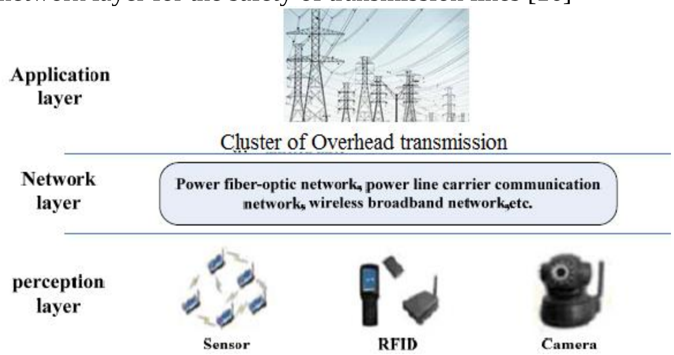


Fig. 1. The three-layer Architecture of Internet of Things in Applications for Power System Protection.

The network layer includes wireless networks for remote data collection and fiber-optic communication lines for long-distance data transmission. Additionally, electrical data must be transferred across power line carriers. Before converting the security measure into a real-time system, the application layer gets data from several sources. The Internet of Things (IoT) processes, integrates, and analyses data to produce intelligent control services and decision-making that strengthen the security system.

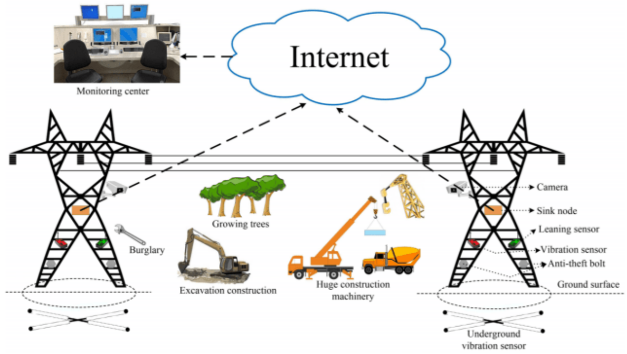


Fig. 2. IoT aided protection of transmission system.

This system has several sensors that can send early warnings to monitoring centres concerning conductor and tower mechanical and physical issues as well as dangers to high-voltage transmission towers. The sensors have vibration sensors that keep track of subsurface vibrations [17]. According to Figure 2, the mechanical and electrical protection of transmission towers against the dangers of natural disasters, crude construction, and expanding trees is a component of IoT-based protection.

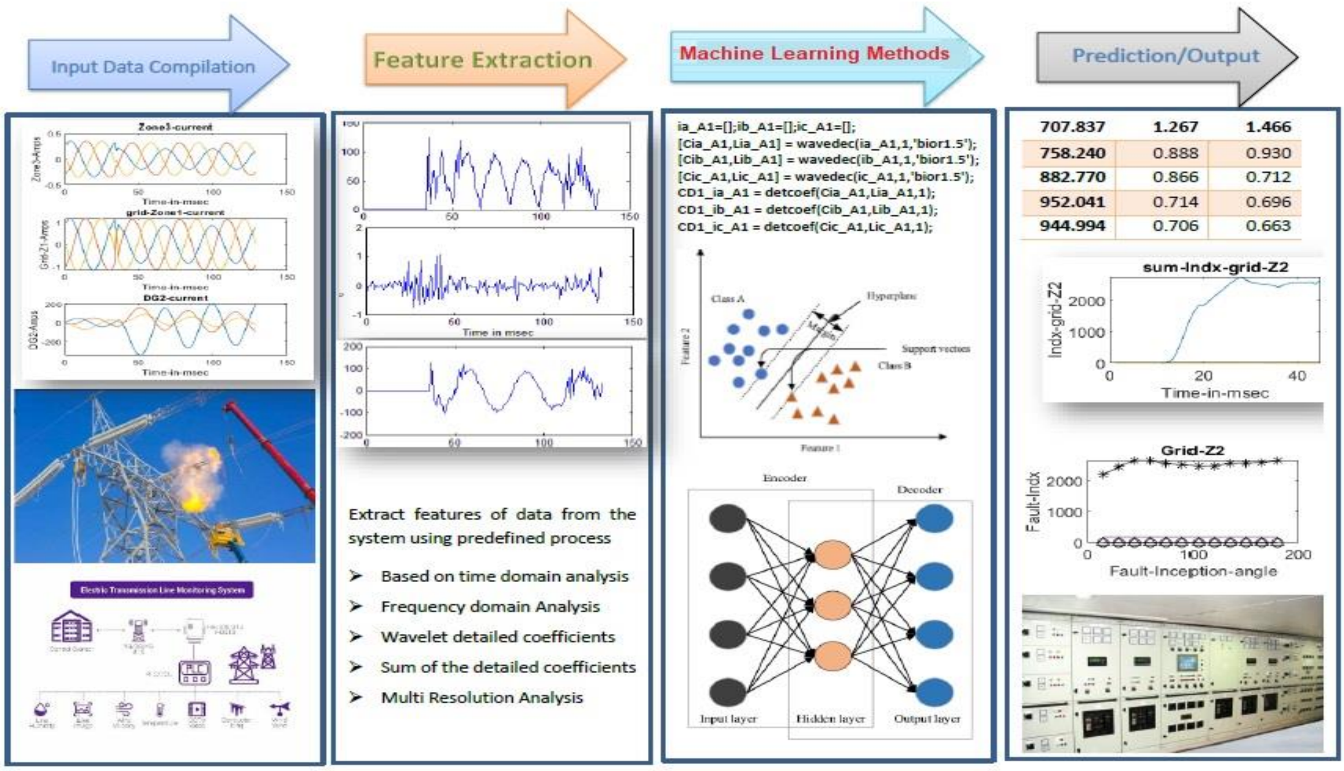


Fig. 3. Simplified machine learning framework for wide area power system Network.

3. Wavelet Analysis in Power System Protection

One of the research tools for transient fault investigation is the wavelet transform (WT). To classify and locate faults, it analyses various transitory signal types and decomposes the waveform into approximate and precise coefficients [18] using a simple mother wavelet. In [19], WT was used to break down fault signals into several frequency bands, and multiresolution analysis, or MRA, was then used for additional processing to create a real-time digital distance protection method for transmission lines. [20] presents a micro-grid-connected power system safety programme that analyses transient fault current signals using wavelet technology. The biorthogonal 1.5-wavelet detailed coefficients are utilised with multi-resolution analysis (MRA).

The discrete variant of the Wavelet Transform (WT), known as the Discrete Wavelet Transform (DWT) technique, is more and more in demand for digital relaying systems. Many WT-based contemporary and digital fault investigation techniques are DWT-based [21]. Iterative processes are used until the required level is attained. The choice of the mother wavelet, which is more appropriate for fault location in system operation, is a challenging task [22]. The threshold value for the detection of defective phases that was established after evaluating wavelet-detailed coefficients is greater than the values for healthy phases and less than those for faulty phases.

4. Machine Learning Framework for Fault Diagnostics

It is based on the fault characteristic, which was used to build a function connecting inputs and outputs from a large experimental input data set. The machine learning-based defect diagnostic procedure is broken down into four parts in Fig. 3: data collection, feature extraction, model learning, and diagnosis [23]. First, monitoring sensors scattered throughout the power system continuously collect data on vibration, noise emission, feeder status, and current.

In feature extraction, various frequently used aspects of data from multiple-source monitoring devices are retrieved, including time-domain, frequency-domain, and time-frequency-domain features. In order to choose sensitive characteristics indicating the condition of the power system from the collected data, it is important to keep in mind that the extracted features typically contain redundant information and may increase the computing burden. The machine-learning-based diagnosis models create a relationship between the sensitive characteristics that are chosen and the outputs that show the health states of the equipment, which is what is meant by the term "learning," based on the sensitive features that are gathered [24]. Last but not least, based on the anticipated results of the fault diagnosis, the relevant protection system will act to disconnect problematic components in order to protect the remaining network.

4.1 Machine Learning code Implementation

The MATLAB code for the analysis of faults in the proposed system as follows:

4.1.1 Input Data Initialisation

iaZ1 =[];ibZ1=[];icZ1=[];iaZ11 =[];ibZ11=[];icZ11=[];
open('swami_wind.slx');   : Open the simulation file
for km1=10:10:110
km2=130-km1   : Sectionalising the transmission line
for tt=0.015625:0.0009765:0.0234375: Sectionlising the time cycle Ts1=1/1920;
Ts=1/192000   : setting sampling frequency

```
sim('swami_wind_grk.slx');    :Simulation of test system
```

4.1.2 Wave-Decomposition Of Current Signal

```
[CiaZ1,LiaZ1]= wavedec(iaZ1,1,'bior 1.5');
[CibZ1,LibZ1] = wavedec(ibZ1,1,'bior 1.5');
[CicZ1,LicZ1]=wavedec(icZ1,1,'bior1.5');
[CiaZ11,LiaZ11]=wavedec(iaZ11,1,'bior1.5');
[CibZ11,LibZ11]=wavedec(ibZ11,1,'bior1.5');
[CicZ11,LicZ11]=wavedec(icZ11,1,'bior 1.5');
```

4.1.3 Sample Detailed-Coefficients Calculation Code

```
CD1-iaZ1 = detcoef(CiaZ1,LiaZ1,1);
CD1-ibZ1 = detcoef(CibZ1,LibZ1,1);
CD1-icZ1 = detcoef(CicZ1,LicZ1,1);
CD1-iaZ11 = detcoef(CiaZ11,LiaZ11,1);
CD1-ibZ11 = detcoef(CibZ11,LibZ11,1);
CD1-icZ11 = detcoef(CicZ11,LicZ11,1);
```

4.1.4: Calculation Of İmpact Analysis Of Faults

```
Zone1-iaZ = (CD1-iaZ1-CD1-iaZ11);
Zone1-ibZ = (CD1-ibZ1-CD1-ibZ11);
Zone1-icZ = (CD1-icZ1-CD1-icZ11);
```

4.1.5: Test Data Generation For SVM To Find The Location Of Fault

```
Zone1-iaZ = (CD1-iaZ1);
Zone1-ibZ = (CD1-ibZ1);
Zone1-icZ = (CD1-icZ1);
```

4.1.6: Preparation Of Fault İndex

```
Sum1-iaZ(i)=CD1-iaZ(i)+CD1-iaZ(i+1)+CD1-
iaZ(i+2)+CD1-iaZ(i+3)+CD1-iaZ(i+4)
 Sum1-ibZ(i)=CD1-ibZ(i)+CD1-ibZ(i+1)+CD1-
ibZ(i+2)+CD1-ibZ(i+3)+CD1-ibZ(i+4)
 Sum1-icZ(i)=CD1-icZ(i)+CD1-icZ(i+1)+CD1-
icZ(i+2)+CD1-icZ(i+3)+CD1-icZ(i+4)
```

4.1.7: Data Visualisation

```
plot (CD1-iaZ),xlabel('Time-msec'),ylabel('z1-Index-iaZ');
plot(CD1-ibZ),xlabel('Time-msec'),ylabel('z1-Index-ibZ');
plot (CD1-icZ),xlabel('Time-msec'),ylabel('z1-Index-icZ');
plot(x,Sum1-iaZ,x,Sum1-ibZ,x,Sum1-icZ,x,y,'--k'),
xlabel('T-msec'),ylabel('Flt-Index');
plot(x,Sum2-iaZ,x,Sum2-ibZ,x,Sum2-icZ,x,y,'--k'),
xlabel('T-msec'),ylabel('Flt-Index');
plot(x,Sum3-iaZ,x,Sum3-ibZ,x,Sum3-icZ,x,y,'--k'),
xlabel('T-msec'),ylabel('Flt-Index');
plot(x,Sum4-iaZ,x,Sum4-ibZ,x,Sum4-icZ,x,y,'--k'),
xlabel('T-msec'),ylabel('Flt-Index');
plot(x,Sum5-iaZ,x,Sum5-ibZ,x,Sum5-icZ,x,y,'--k'),
xlabel('T-msec'),ylabel('Flt-Index');
plot(x,Sum6-iaZ,x,Sum6-ibZ,x,Sum6-icZ,x,y,'--k'),
xlabel('T-msec'),ylabel('Flt-Index');
```

4.1.8 Data Extraction For İmplementing SVM

```
xlswrite('zone4\Pv-hvdc-Z4-AG',Indx-a1-11,'Zone1-a')
xlswrite('zone4\Pv-hvdc-Z4-AG',Indx-b1-11,'Zone1-b')
xlswrite('zone4\Pv-hvdc-Z4-AG',Indx-c1-11,'Zone1-c')
```

5. System Analysis and Methodologies

Two utility grids, two 100 MW wind turbines, a static variance controller (SVC) with a number of different distance zones, and a 230 kV transmission system make up the test system shown in figure 4. The system's 290 km total transmission line length is made up of six zones. There are 10 faults overall in each zone, changing in distance in increments of 10. The proposed scheme parameters are specified in Table 1.

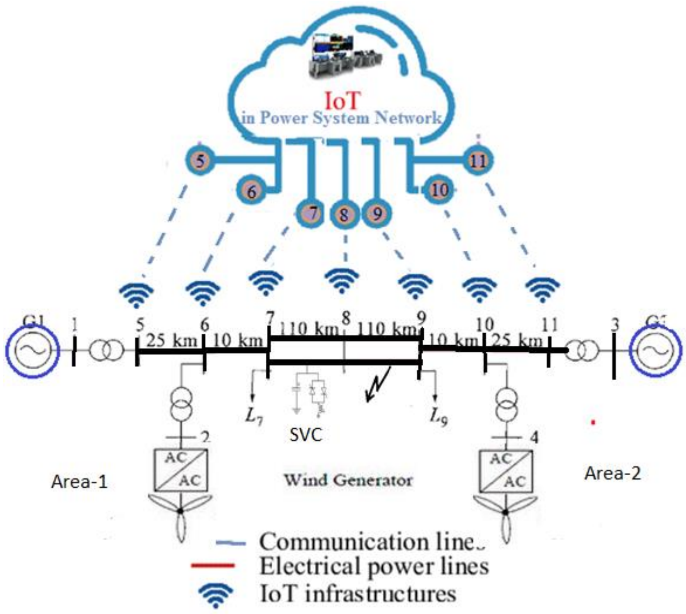


Fig. 4. Scheduled mechanism to test the two-area power network.

Table 1. Technical Parameters of Proposed System

1&3 Terminals	Utility Grid, 230KV
2&4 Terminals	Wind Energy source, 100 MW_P
Line parameters	R=0.01273 Ω/Km, R_0 = 0.3864Ω/Km L=0.9337e-3H/Km, L0=4.1264e-3H/Km C=12.74e-9 F/km, C0 = 7.751e-9 F/km
SVC	Rating: 300-Mvar, Coupling transformer: 230kV/16-kV,333-MVA TCR: One 109-Mvar, TSC: Three 94-Mvar

After choosing an appropriate wavelet, the zone current signal, which samples at a rate of 264 kHz from Z1 to Z6, is then used to evaluate the data during the failure.

6. Simulation Results

The two-area network simulation model with wind integrated energy sources was created using the MATLAB/Simulink software. The exploration of the system is studied at distinct faults that are generated and tested with interactive programming with synchronisation of the simulation model illustrated in Figure 5.

Every zone of the 10 different sorts of defects is considered when analysing the fault cases. The whole transmission line distance (from 0 km to 290 km) is divided into 6 zones, with zones 1 and 6 being 10 km and 25 km, respectively, and zones 2 and 4 being 110 km. The transmission line fault in Zones 3 and 4 varies the line length by increments of 10 km and the angle of fault initiation (from 0^0 to 180^0 in increments of 15^0). The transmission line's Zone-4 waveform displays higher values as compared to other indices, which indicates the LG fault in Zone-4 as shown in Figure 6.

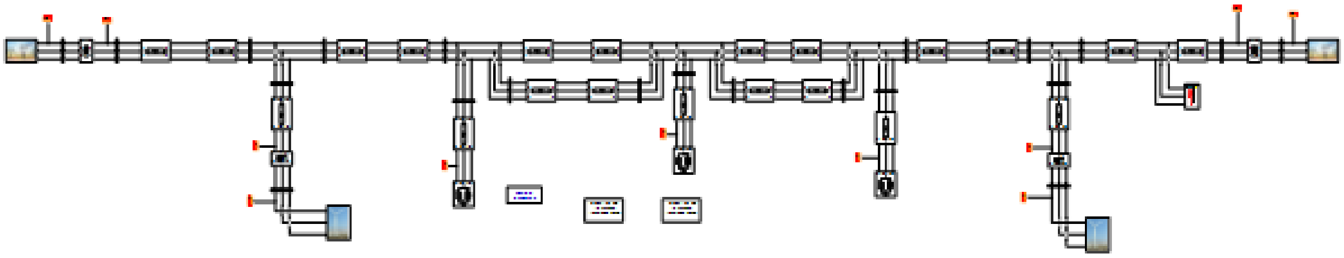


Fig.5. Simulation Diagram for SVC Compensated wide area network in presence of Wind Energy Source.

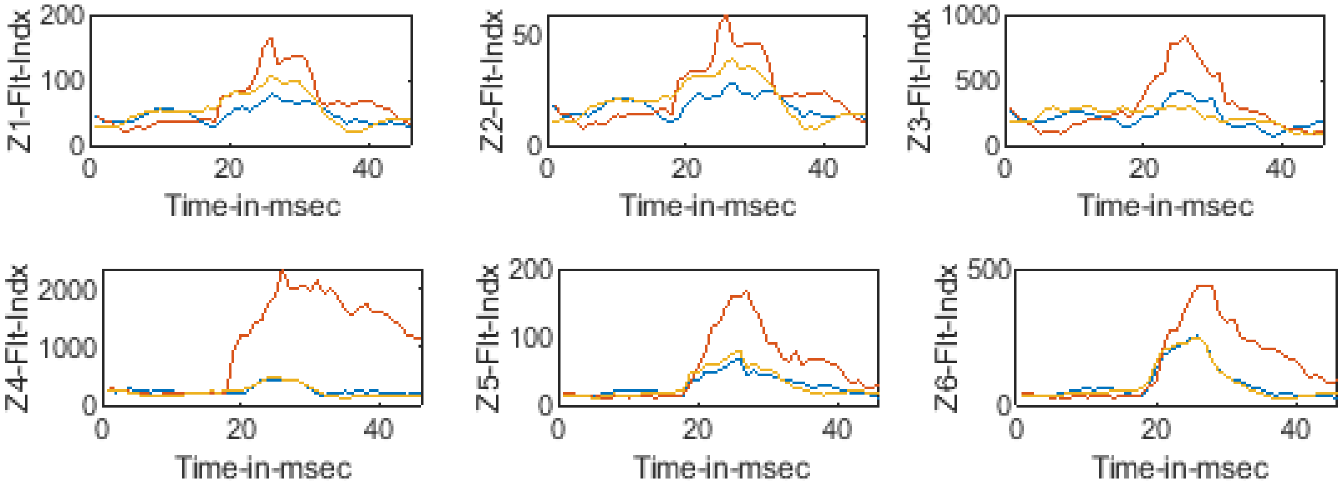
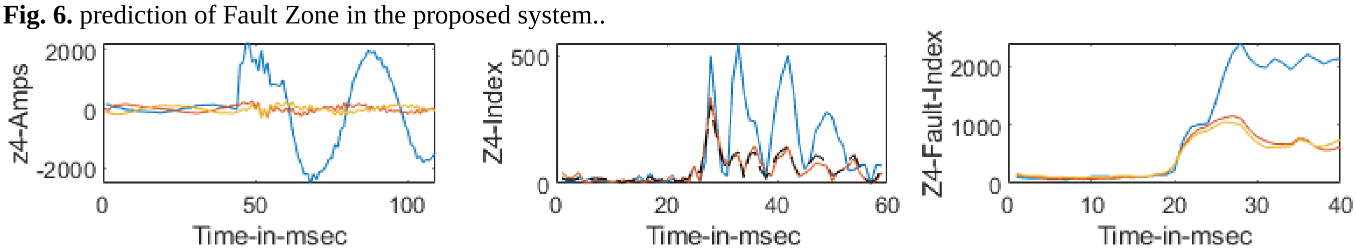
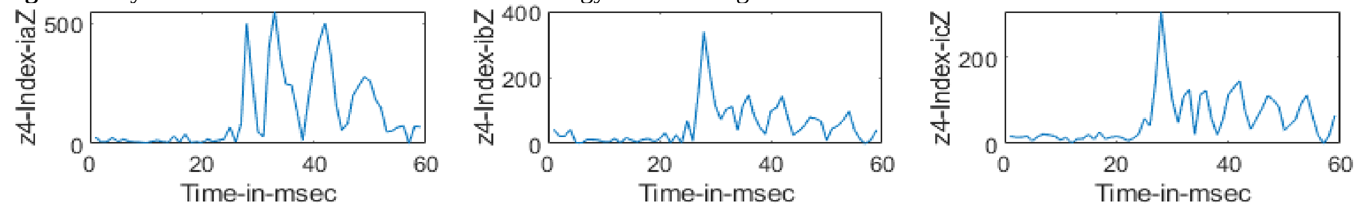


Fig. 6. prediction of Fault Zone in the proposed system..

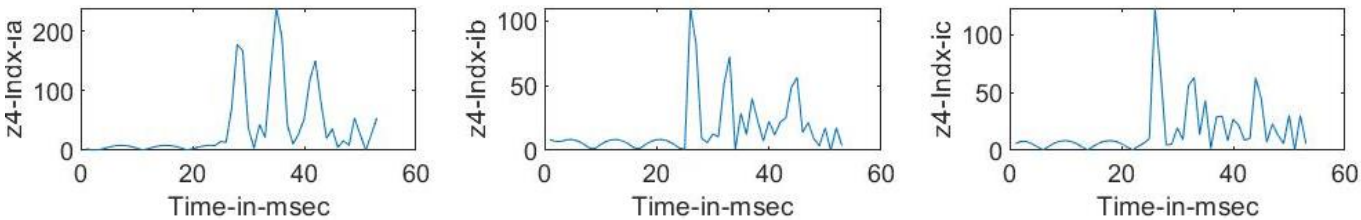


(a) Current (b) wavelet coefficients (c) Fault Index

Fig. 7. Analysis of SLG Fault at zone-4 on Wind Energy Source Integrated Grid network.



(a) Wind Source



(b) Wind-SVC Integration

Fig.8. Calibrated impact analysis of SVC for prposed network using Indices of zone-4 current signals .

Based on the prediction of an SLG fault at zone-1 using the current waveform,Wavelet coefficients and fault index in the Wind and SVC integrated network, the issue is identified as a ground fault on phase-A.Fault indices for three-phase current signal comparison with healthy phase current signals are derived. Figures 7 illustrate how wavelet-detailed coefficients and time quantum analysis of single line-to-ground faults can be utilised to understand how faults affect certain phases. Phase A has a much larger fault index than the other phases, as can be seen. As a result, locating the problematic stage is easy.

To find the fault, it takes extra time quantum to compare the current signal to the fault index. It is clear that from 40ms to under 20ms, the time needed for fault identification has decreased. By getting the fault indices of three phase current signals and comparing them to other phase indices, the fault less than half cycle is identified.

Table 2. Fault analysis at various distances in Zone-4 of Area-2 of test system with the integration of SVC with Wind energy source.

	Wind Energy Source Integrated Network						**SVC-Wind Energy Source Integrated Network**				
	Zone4_index_IA						**Zone4_index_IA**				
Distance in Km	FIA	**0**	**30**	**60**	**90**	**120**	**0**	**30**	**60**	**90**	**120**
	10	1240.4	1571.9	1482.1	1273.1	1234.5	1403.8	1754.7	1521.6	1242.2	1344.2
	20	1350.7	1661.2	1390.7	1182.4	1177.7	1379.6	1704.8	1413.5	1155.1	1257.2
	30	1292.5	1568.6	1370.8	1170.0	1172.9	1287.7	1596.3	1373.1	1118.7	1213.3
	40	1352.6	1540.8	1328.7	1184.7	1198.7	1331.8	1586.7	1377.4	1173.6	1222.5
	50	1197.0	1478.6	1394.0	1204.3	1198.7	1175.3	1522.6	1405.4	1170.0	1211.0
	60	1220.7	1436.2	1324.9	1186.8	1174.4	1230.3	1529.5	1372.9	1172.8	1234.2
	70	1419.5	1534.3	1330.0	1114.7	1096.6	1388.8	1574.2	1304.5	1082.9	1111.4
	80	1458.3	1608.1	1451.3	1194.3	1194.3	1469.6	1681.7	1451.1	1161.4	1173.3
	90	1272.6	1818.0	1555.3	1253.9	1013.9	1331.2	1810.6	1518.2	1219.8	1232.1
	100	1593.2	1798.4	1528.0	1169.7	917.8	1554.1	1822.5	1538.3	1158.0	1158.9
	Zone4_index_IB						**Zone4_index_IB**				
Distance in KM	FIA	**0**	**30**	**60**	**90**	**120**	**0**	**30**	**60**	**90**	**120**
	10	254.85	142.10	138.18	171.77	158.45	244.92	258.80	172.40	173.43	210.37
	20	161.49	151.37	150.70	149.90	174.26	245.00	215.27	197.84	187.59	210.33
	30	186.83	141.86	136.23	163.10	171.68	294.31	240.62	153.66	163.24	137.28
	40	168.59	136.78	224.33	203.77	194.88	171.22	129.11	141.58	150.02	111.39
	50	219.13	208.74	167.25	117.57	79.91	260.45	227.68	168.17	167.96	114.07
	60	234.64	222.76	178.04	133.53	107.19	372.08	306.77	260.54	194.17	139.25
	70	165.55	119.34	164.45	203.86	211.20	173.20	144.02	168.57	186.84	127.46
	80	278.93	179.17	211.49	236.58	213.75	249.92	193.67	230.05	231.44	140.01
	90	124.96	88.15	185.06	206.45	221.25	155.76	127.48	172.74	153.67	128.63
	100	237.05	190.73	105.57	153.17	216.36	211.96	160.93	105.66	189.10	198.00
	Zone4_index_IC						**Zone4_index_IC**				
Distance in KM	FIA	0	30	60	90	120	0	30	60	90	120
	10	251.99	219.77	194.59	138.43	153.24	265.34	201.66	168.34	177.48	185.39
	20	205.47	144.34	110.91	150.38	140.90	286.45	160.62	162.58	151.86	125.15
	30	188.93	164.77	182.11	176.70	180.97	379.59	217.55	183.17	168.53	134.83
	40	215.87	168.81	149.56	168.21	177.76	382.59	300.11	220.97	196.59	171.99
	50	210.88	146.57	102.67	103.93	118.42	250.32	178.76	180.96	160.67	179.62
	60	271.85	194.65	122.35	93.81	109.43	215.01	230.45	202.01	197.62	119.17
	70	339.86	217.47	202.12	222.02	158.75	312.36	208.83	186.52	158.10	137.46
	80	203.88	96.52	134.68	129.90	108.55	251.85	232.99	184.46	186.22	182.25
	90	339.15	242.79	155.79	149.16	140.61	245.41	205.97	122.81	192.65	196.73
	100	161.57	226.98	244.82	198.66	168.25	184.79	253.10	235.63	196.14	206.28

The impact of SVC integration has been calibrated with the help of the fault index, which represents the variation of fault at different distances as represented by Figures 7 and 8. The fault index If the number of faulty phases varies according to the type of fault, however, its value remains greater than Threshold T_{h1}. The fault index for healthy phases remains below the threshold value. The flaw becomes more obvious over a shorter period, according to the sum of the precise coefficients for the Zone-4 current signal. At the moment of the fault, different distances are shown in figure 9, and the impact analysis of SVC is calibrated as shown in figure 10.

Tables 2 display fault initiation angles for particular phase currents and Zone 4 wavelet-based fault indices at varying distances. Because all the Phase-A current fault indices are greater than the values of the other phase currents, the fault is Phase-A to ground.The proposed machine learning algorithm has been tested for 2160 fault simulations using MATLAB, and the threshold values Th1 have been fixed based on 2160 simulations involving variations in location, fault incidence angle, and fault impedance for various types of faults.

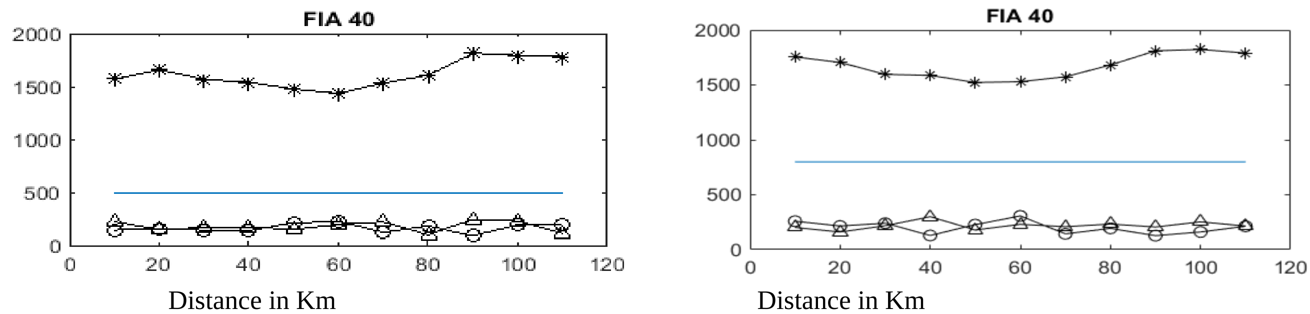


Fig. 9. Svc impact on fault at various distances using SVM learning analysis

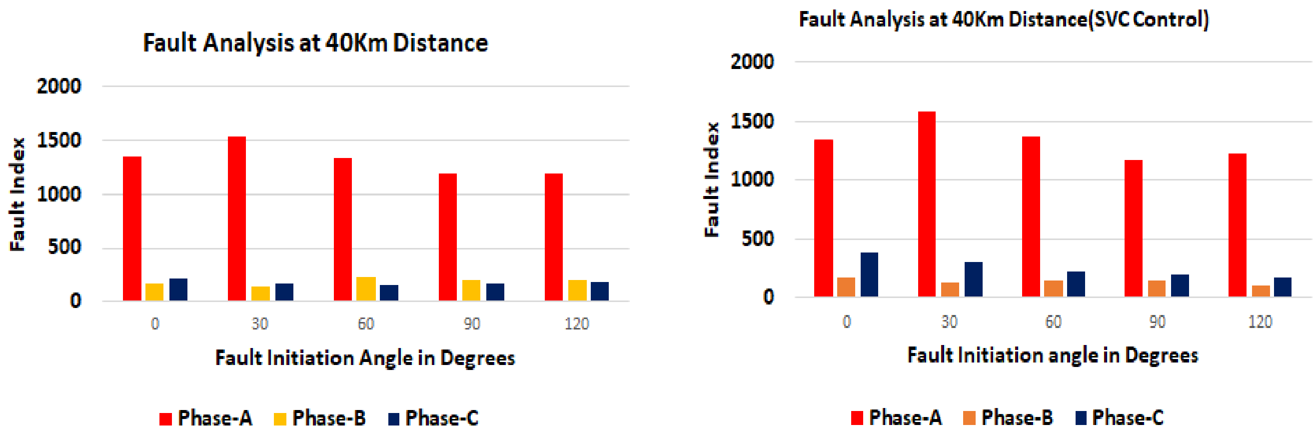


Fig. 10. SVC impact on fault at various Fault Initiation angles using SVM learning analysis.

6. Conclusions

This study advises monitoring the transmission system with the use of the Internet of Things (IoT) and its applications in order to establish powerful protective systems. IoT may successfully address practical mechanical and physical problems while fostering the development of fresh security measures. WT is one of the research strategies used to assess flaws in transient signals at various frequencies by dissecting the waveform into the ensuing exact and approximative coefficients. These coefficients offer crucial details regarding the type of defect and where it is in the current system in terms of time and frequency. New difficulties are being presented to traditional power system protection strategies by newer generation sources and loads. The solution to these problems is determined to be an adaptive and intelligent protection approach based on sophisticated measurement techniques and intelligent fault detection, such as machine learning. The recommended method has been tested using the IOT application for the detection and discrimination of faults under various fault types at various fault inception angles using Bios 1.5 mother wavelets with detailed coefficients through the MRA Technique.

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