

Fault Detection in AC Power Systems using Discrete Wavelet Transform and Radial Basis Function Neural Network(RBFNN)

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Abstract— Accurate fault diagnosis and analysis are necessary for a continuous supply of electricity. Fault detection and location of fault in power transmission lines are important for protecting sensitive parts of the system. The stability of the power system can be disrupted by faults like short circuits or equipment breakdowns, thus prompt fault detection is crucial. Effective fault detection and response are essential for maintaining the security of power systems. It increases the power system's resistance to both natural and man-made disruptions, assuring the grid's dependable and secure functioning. Optimizing the cost of power system operations requires effective defect detection. Utility companies are better equipped to respond quickly to outages, minimizing downtime and associated costs. In this paper a SIMULINK model of the power system is developed using MATLAB software. Discrete wavelet transform (DWT) is employed to detect and distinguish among the fault types. Radial Basis Function Neural Network (RBFNN) method of detecting faults is also employed. The simulation results obtained is propitious and accurate for real time analysis.

Index Terms— Introduction and Literature survey, Motivation, Problem Domain, Problem Statement, Problem Representation using Simulink, Solution Methodologies, Extracting Model, Training System, Testing of System, Results, Conclusion, Future work References

I. INTRODUCTION & LITERATURE SURVEY

A fault is an abnormal connection (including an arc) of relatively low impedance, whether made accidentally or intentionally, between two points of different potential. Detection and classification of fault is essential, to prevent people and property from any potential damage, faults must be ascertained within one millisecond or less to protect power system from first peak of fault current. Many analogies have been carried out on fault detection. With the blooming of AI and machine learning, many algorithms have been developed in fault detection and classification. In [1] feed forward neural network has been used for fault detection but lacks in the aspects of computers able to handle large amounts of data and handle quicker calculations. [2] uses ChNN an improved AI studies for fault identification but proved efficient in digital relaying applications. Fourier transforms break down signals into oscillations that persist over the entire sequence, whereas wavelets provide a similar consequence with oscillations localized in space and time. A major disadvantage of Fourier transform is that frequencies persist over an entire signal. In [3] wavelet transform applied to power distribution system have provided good and enhanced results. RBFNN based method to find fault in the system is provided to overcome the limitations offered by the wavelet

transform method. Accuracy of ANN depends on input and output data. Larger the data higher will be the accuracy of the data. This means that there should be a large pool of input and output data for this system to increase its accuracy.

In this paper, all types of faults, that are, three line to ground fault, three line fault, line to ground fault, line to line fault, have been simulated in Simulink to determine their coefficients for the wavelet transform. The same data is tabulated and separated as training data, that is used to train the system and testing data, that can be used to test the system upon.

The future potential for fault detection in power systems using wavelet transform and RBFNN presents a number of intriguing possibilities. In terms of distributed generation (DG) and microgrids in particular. The further papers are referred as to study in depth about the DG and microgrids.

Paper [8]-[11] describe that due to their adaptable but sturdy architecture and a variety of control mechanisms, microgrids have emerged as attractive energy generation alternatives. The primary issues with microgrids relate to the bidirectional flow of power and the infusion of renewable energy at different locations of the microgrid. The material included in this paper includes a survey of the literature on microgrids, fault analysis, and power system protection measures II. MOTIVATION

The urgent need to improve AC power systems' fault detection capabilities served as the driving force behind this work. Power system malfunctions can have serious repercussions, such as equipment damage, power outages, and safety risks. To ensure the reliable operation of power systems, it is crucial to create precise and effective defect detection technologies. In general, the objective behind this paper is to provide a novel strategy that combines the wavelet transform and RBFNN in order to get over the constraints of conventional fault detection techniques in AC power systems. The goal is to improve fault detection accuracy, efficiency, and robustness, ultimately improving the reliability of the power system and reducing the impact of faults on electrical networks by utilising the advantages of these techniques.

III. PROBLEM DOMAIN

Fault Detection in an AC (Alternating Current) power systems is one of the main challenge and hence topic of this article. It belongs to the domain, applications of soft computing techniques in power systems. Equipment malfunctions, short circuits, deteriorating insulation, and other electrical anomalies are only a few of the faults in AC power systems. To avoid potential harm, ensure safety, and reduce downtime, it is crucial to detect and locate these issues properly and quickly.

IV. PROBLEM STATEMENT

The problem can be further defined as:

1. *Complex Operating circumstances:* Transient events, harmonics, and noise are just a few of the complex operating circumstances that affect how AC power systems function. The dynamic behaviour of the system and the overlapping characteristics of several fault kinds make it difficult to detect defects accurately.
2. *Multiple Fault Types:* The fault types that an AC power system may encounter include single-phase faults, three-phase faults, and transient faults. Effective fault management requires differentiating between these fault kinds and precisely locating the faulty part or area.
3. *Limited Fault Detection Accuracy:* Conventional fault detection techniques that rely on time-domain or frequency-domain analysis could be unable to accurately detect faults or extract fault-related characteristics. This restriction may lead to false alarms and decreased accuracy in fault detection, which will affect the dependability of power systems.

To overcome these limitations, the paper proposes the following methods:

A. Fault Detection Using Wavelet Transform

A wavelet is wave-like oscillation that is localized in time. The scale of a wavelet tells how much a wave is stretched or compressed. The location tells about its position in space. Wavelet transform is used for signal processing applications. The characteristics of a wavelet are used in modelling non-linear signals. Wavelet transforms are divided into two groups Discrete wavelet transform (DWT) and Continuous wavelet transform (CWT). Equation (1) expresses continuous wavelet transform.

$$W_f(a, b) = \langle f, \psi_{a,b} \rangle = |a|^{-\frac{1}{2}} \int_{-\infty}^{+\infty} f(t) \psi^*\left(\frac{t-b}{a}\right) dt \quad (1)$$

Equation (1) serves a continuous wavelet transform of a function $x(t)$, where $\psi(t)$ is function called mother wavelet and represents the complex conjugate operation. The scale factor a either dilates or contracts a signal.

B. Artificial Neural Network

The neural network, inspired from the biological neurons structure consists of finite number of layers with its components similar to neurons. However, the number of layers is desired to be small to reduce the problem solving time. The development of neural networks is to solve particular problems that are difficult to solve by human beings which can be achieved by “training” the neural networks, according to [4]. This training implies to adjusting the weights of certain key elements in a network by providing it with input values and target values. The approach of back propagation is useful for the detection and analysis of fault in any power system [5]. This algorithm minimizes the error between the actual output vector and the desired vector by the method of iteration. The network of neurons roughly looks like Fig.1 where there are three input, hidden and output layers. The output received from the output layer is compared with the desired result. If matches the desired result the output is give out however if not the output is sent back to the system for error reduction through weight adjustment.

$$y(x) = f(W_2 \cdot f(W_1 \cdot x + b_1) + b_2) \quad (2)$$

In (2) $y(x)$ represents the output of the ANN for the input x .

$f()$ denotes the activation function, which introduces nonlinearity to the network.

W_1 and W_2 are the weight matrices.

b_1 and b_2 represent the bias vectors.

x denotes the input vector.

V. PROBLEM REPRESENTATION THROUGH SIMULATION

For fault detection and analysis a simple power system model as shown in Fig. 2 is considered. It consists of :

- Three phase voltage source block functioning as generator with $V_{rms} = 250e3$ V, frequency = 60Hz, phase angle = 0 degrees, source resistance = 0.829 Ohms , source inductance = 16.583-3 Henry
- A three phase RLC series branch operating as transmission line with branch type RL Resistance=6 Ohms, Inductance=0.053052 Henry
- Three phase RLC load operating as load with configuration Y grounded, $V_{rms}=220e3$, frequency=60Hz, Active power=304.8e6 W, Reactive power(positive Ver)=228.6e6VAR
- Three phase V-I measurement block, Three phase Fault block
- Required number of scopes, current measurement, demux, to workspaces etc.

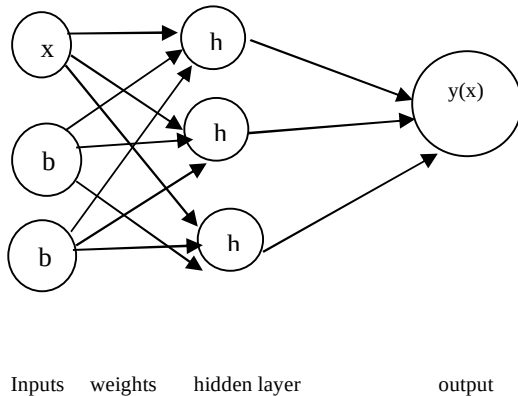


Figure 1. Schematic of ANN logic

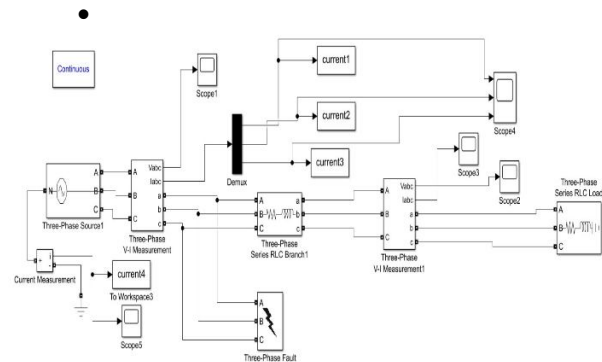


Figure 2. Simulation Circuit 1

Fault is applied to the three phase transmission line and abnormalities in the current values are observed. A sudden increase in the magnitude of current.

VI. SOLUTION METHODOLOGIES: WAVELET TRANSFORM METHODOLOGIES

When the model shown in Fig. 2 is simulated it gives measurements of phase A, B, C and ground currents.

Wavelet transform is then applied to these phase and ground currents. Wavelet function is applied on a signal.

$$[c,l] = \text{wavedec}(x,n,wname); \quad (3)$$

In (3) *wavedec* is a function that decomposes the signal, x being the signal, n is the wavelet layer (default $n=1$), $wname$ being the type of wavelet, c is the output wavelet decomposition vector, l is the number of coefficients by level (subscript indicating the particular phase).

$$D = \text{detcoef}(C, L, N); \quad (4)$$

Equation (4) gives the exact coefficient value. At the time of fault magnitude of the fault value will be very high in that particular phase and zero or a very small value in other phases. Under normal conditions fault value will be zero or very small in all the phases.

VII. RESULTS AND ANALYSIS

The data collected through wavelet transform is observed in this section. The simulation is carried out in MATLAB Simulink environment. System under consideration is monitored for various types of faults. The system consists of three phase source, three phase VI measurement, three phase RLC branch, three phase RLC load along with scopes, voltage measurements, current measurements and power GUI.

Once run with a specific input value given, following outputs as fault waveforms was obtained.

The Simulation time was observed to be 9.94 secs.

Here Fig. 4 represents a double line to ground fault where phases A and C are noted to be lines in blue and black with fluctuations whereas phase B is in red and is zero throughout.

Similarly Fig. 5 shows a single line to ground fault with phase A varying and phase B and C with values zero since grounded. Fig. 6 represents three phase fault. Where the phases A, B and C are all varying with colours red, blue and black.

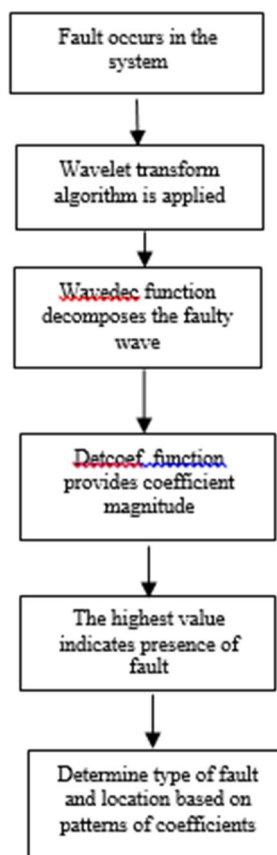


Fig.3 Flowchart of Wavelet transform algorithm

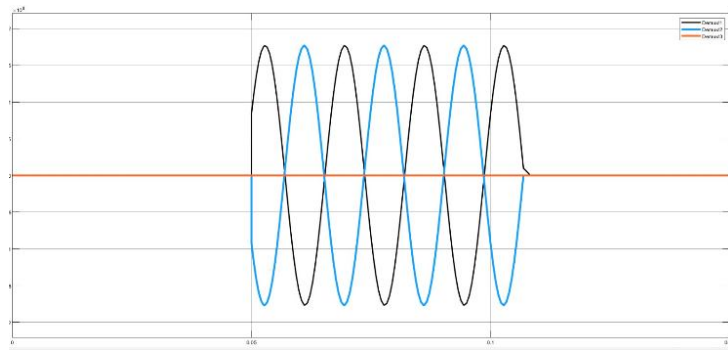


Figure.4 Double-line to ground fault (AC-G)

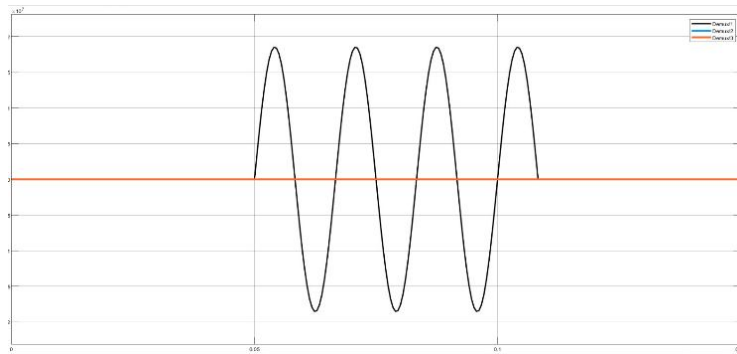


Figure. 5 Single-Line to ground fault(A-G)

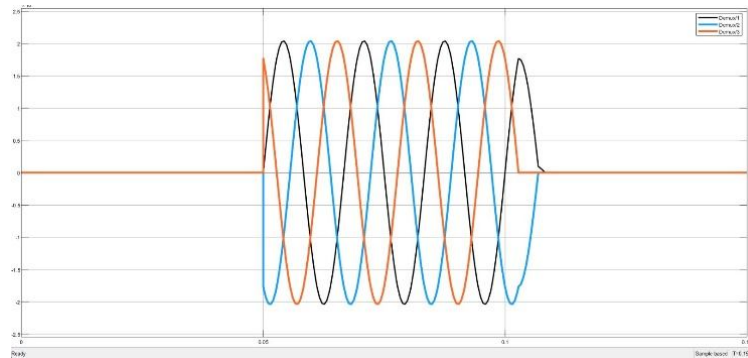


Figure.6 Three-phase fault

Maximum co-efficient value of all phases and ground currents: TABLE 1, provides the values obtained when different types of faults are applied namely

1. Three phase to ground fault G
2. three phase fault,
3. double line to ground fault like (AB-G),(AC-G),(BC-G). Line to line fault like (A-B),(A-C),(B-C).
4. Line to ground fault like (A-G),(B-G),(C-G)
5. system without fault.

The values underlined denotes non fault current which means that the current was not applied in that phase.

Clearly the values of the coefficients that are high in value indicates presence of faults.

On analysis of wavelet transforms method for fault detection for all faults, the following were observed

1. Wavelet transform based classification of faults in the power system depends upon the threshold value
2. Threshold value is not generalized and cannot be used for all types of power system and cannot be applied in unconventional topology such as in microgrids.
3. For each and every addition / removal of DG new power system, this threshold value needs to be determined again in order to successfully classify different types of faults

Hence to combat these limitations the approach of RBFNN is used in the upcoming part of the paper.

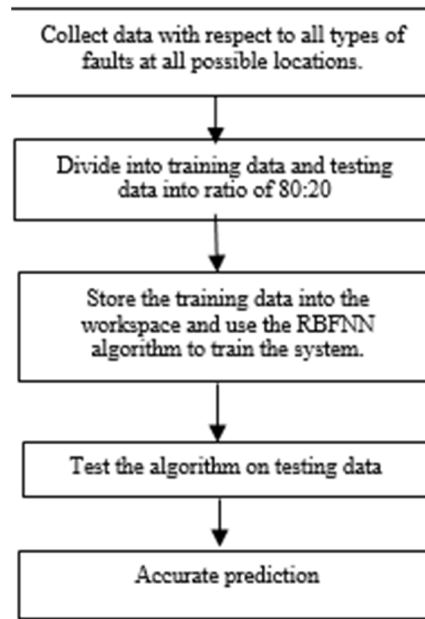


Figure.7 Flowchart of RBFNN algorithm

TABLE. I MAXIMUM CO EFFICIENT VALUE OF ALL PHASE AND GROUND CURRENTS WITH DIFFERENT FAULTS

Types of Fault	Max. coefficient of phase A Current	Max. coefficient of phase B Current	Max. coefficient of phase C Current	Max. coefficient of phase Ground Current
3 phase to G Fault	1.6097e+07	4.0725e+07	1.6097e+07	7.18424e+05
3 phase Fault	1.6097e+07	4.0725e+07	1.6097e+07	<u>0.0081</u>
(AB-G)	1.0796e+07	2.1332e+07	<u>103.9784</u>	7.757e+05
(AC-G)	1.9807e+07	<u>103.9784</u>	8.6730e+06	1.9393e+06
(BC-G)	<u>103.9784</u>	4.0725e+07	8.1478e+06	9.7619e+05
(A-B)	1.0796e+07	2.0363e+07	<u>103.9784</u>	<u>0.0087</u>
(A-C)	2.0363e+07	<u>103.9784</u>	8.6153e+06	<u>0.0204</u>
(B-C)	<u>103.9784</u>	4.0725e+07	7.2573e+06	<u>0.0100</u>
(A-G)	1.3523e+06	<u>103.9784</u>	<u>103.9784</u>	1.6087e+06
(B-G)	<u>103.9784</u>	3.702e+06	134.3960	1.1253e+06
(C-G)	<u>103.9784</u>	<u>103.9784</u>	1.4099e+06	3.7023e+06
System without fault	<u>103.9784</u>	<u>103.9784</u>	<u>103.9784</u>	<u>7.137e-10</u>

X TRAINING SYSTEM

All the training data input values ie, the maximum coefficient values from Table.II, are stored in the workspace under the name 'input'. Similarly all the output values of the faults have been stored in the workspace under the name 'output'. Similarly the workspace is used to create another variable 'testing' to fill in with the details of the

testing data. Once this is done a simple code is used to train the system. This program can be used for all kinds of power systems.

A. Code

```
I=Input'; // Input data stored in variable I
T=Output'; //Output data stored in variable T
goal=0.0; //represents the error goal that is set to zero
spread=1; // The spread constant is set to 1
net=newrb(I,T,goal,spread); // The last line is the initialising of the radial basis function neural network based
on the input and output of the system.
With 100 neurons it has provided highest successful training with error equal to 1.9747e-31.
```

XI. TESTING OF SYSTEM

For testing of the data, the following code is used.

A. Code

```
P=Testingdata'
Y=sim(net,P)
O=Y'
```

Here the first line represents the testing data ie, the maximum coefficient values from Table.III, stored in the workspace. The second line is used to simulate the RBFNN system to test the following testing data.

TABLE .II INPUT AND OUTPUT TRAINING DATA FOR RBFNN

S. No.	Type of Fault	Max. coefficient of Phase A Current	Max. coefficient of Phase B Current	Max. coefficient of Phase C Current	Max. coefficient of Ground Current	Output Value for Phase A	Output Value for Phase B	Output Value for Phase C	Output Value for Ground Current
1	ABC-G Fault	1.6097e+07	4.0725e+07	1.6097e+07	7.1824e+05	1	1	1	1
2	ABC Fault	1.6097e+07	4.0725e+07	1.6097e+07	0.0081	1	1	1	0
3	AB-G Fault	1.0796e+07	2.1332e+07	103.9772	7.7574e+05	1	1	0	1
4	AC-G Fault	1.9807e+07	103.9772	8.6730e+06	1.9393e+06	1	0	1	1
5	BC-G Fault	103.9784	4.0725e+07	8.1478e+06	9.7619e+05	0	1	1	1
6	A-B Fault	1.0794e+07	2.0363e+07	103.9772	0.0087	1	1	0	0
.	.	.	.	.	.	.	.	.	.
108	No fault	103.9784	103.9772	103.9772	7.1737e-10	0	0	0	0

TABLE. III INPUT AND OUTPUT TESTING DATA FOR RBFNN

S. No.	Type of Fault	Max. coefficient of Phase A Current	Max. coefficient of Phase B Current	Max. coefficient of Phase C Current	Max. coefficient of Ground Current	Output Value for Phase A	Output Value for Phase B	Output Value for Phase C	Output Value for Ground Current
1	ABC-G Fault	1.6097e+07	4.0725e+07	1.6097e+07	1.5785e+05	1	1	1	1
2	ABC Fault	1.6097e+07	4.0725e+07	1.6097e+07	0.0081	1	1	1	0
3	AB-G Fault	7.8178e+06	2.0564e+07	103.9772	1.6470e+05	1	1	0	1
4	AC-G Fault	2.0187e+07	103.9772	8.6774e+06	4.0322e+05	1	0	1	1
5	BC-G Fault	103.9784	4.0725e+07	7.8189e+06	1.9944e+05	0	1	1	1
6	A-B Fault	1.0794e+07	2.0363e+07	103.9772	0.0087	1	1	0	0
.	.	.	.	.	.	.	.	.	.
30	837.4944	676.1980	130.0680	130.0680	0.0314	1	1	0	0

XII. RESULTS

On running the program, we get the outputs as shown in Fig.9. On comparing the output received and the output desired from the output section in Table.III, we can conclude that the RBFNN form of detecting the fault is working.

XIII. CONCLUSION

In conclusion, fault detection is essential to guaranteeing the accuracy, cost-effectiveness, stability, and security of power systems. It enables proactive fault management, lowering the negative effects of faults on system stability, reducing security threats, decreasing downtime and related costs, and giving useful data for system study and improvement.

On comparison wavelet transform is more suitable for detecting transient faults in AC systems due to its ability to capture fast changes in signals. On the other hand RBFNN is more suitable for detecting steady state faults that may have longer duration. However this step is more data driven as collection of data plays a major role in training the system.

FUTURE WORK

With regard to distributed generation (DG) and microgrids in particular, the future potential for fault detection in power systems utilising wavelet transform and RBFNN offers a number of fascinating possibilities. Due to their resilience, dependability, and integration of DG sources, microgrids—localized, independent power systems—are becoming more and more common. Wavelet transform and RBFNN applications for fault detection in microgrids can offer precise and effective fault detection in these intricate systems. The development of fault detection methods specifically adapted to the special features of microgrids, such as numerous interconnected DG sources, bidirectional power flow, and islanding scenarios, can be the focus of future study.

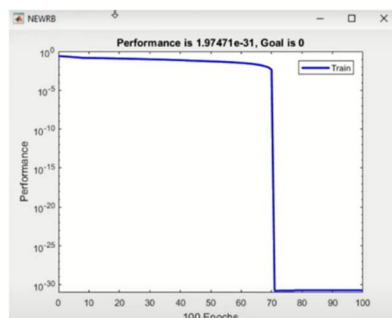


Figure.8 graph obtained on training the system

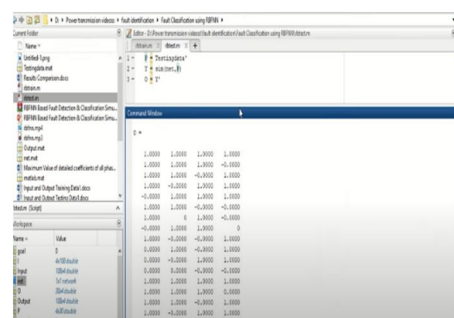


Figure.9 Outputs obtained on testing the system

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