An EMD Based Fault Type Identification Scheme in Transmission Line

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Abstract— **Fault classification in distance protection of transmission lines, with considering the wide variation in the fault operating conditions, has been very challenging task. In this paper, an approach is presented to classify the fault in transmission line based on Empirical Mode Decomposition (EMD) using instantaneous power for each phase of only one terminal. For decision making stage of proposed methodology, three famous algorithms (Artificial neural network, support vector machine and decision tree) are used and it is shown that support vector machine demonstrate a suitable approach for selecting the faulty phase/phases. The results denote that suggested scheme is independent of effects of variation of fault inception angle, fault location, fault resistance, fault type and noise in current and voltage signals and also the proposed method is able to classify all the faults on transmission line within half cycle after the inception of fault.**

Keywords-Fault Classification; EMD; ANN; SVM; DT

I. INTRODUCTION

Distance relaying of transmission lines requires fast and accurate detection, classification and location of faults to improve the stability and reliability of power system operation [1]. The objective of fault classification is to identify the type of fault and the faulted phase/phases, which is an important aspect of transmission line fault analysis. In a three phase transmission line, different types of faults are classified as: single line-to-ground fault (LG) , double line fault (LL), double line to-ground fault (LLG), three phase fault and three phase to ground fault. The occurrence of faults on transmission lines often results in severe problems. Therefore, fault detection and classification need to be done as accurately as possible leading to improved post-fault analysis, subsequently creating an easier task for inspection, maintenance, and repair of transmission line so that the line can be restored as soon as possible [2].

As transmission systems are of large physical dimensions, conventional faulty phase selection schemes are found to be inadequate in protecting transmission lines when fault occurs. Several fault classification methods are presented in last few years and it shows the importance of transmission line protection. In [3, 4] authors use wavelet transform as a tool for classifying the faults in a test system. Although it is simple and powerful approach for mentioned purpose but it has some drawbacks due to their complexity and high computational tasks. Short Time Fourier Transform (STFT) is another attitude for protection of transmission line [5] however it can’t operate well in noisy environments which are a common situation for power system. S-transform is also used for transmission line fault analysis [6] and it is suitable method for extracting the features from current and voltage signals but authors in [7] show that this technique has some shortcomings which is why it does not reliable. Empirical Mode Decomposition (EMD) is a prevailing and appropriate scheme for signal processing in power system [8] to be precise a novel approach for detection and classification of faults in transmission line [9]. Artificial Neural Networks (ANNs), Support Vector Machines (SVMs) and Decision Trees (DTs) are three popular and useful approaches which are widely used in power system protection [10-12]. Usage of instantaneous power in [13] proves that it is a trustful way besides of current and voltage signal which is commonly used in recent studies.

Considering the strengths and weaknesses of mentioned techniques, a novel fault type identification scheme based on EMD is proposed in this paper. In suggested method, first instantaneous powers of three phases are calculated then EMD is performed on half cycle window of post-fault power samples which the sampling frequency is 10 KHz. After that transient energy characteristics of Intrinsic Mode Functions (IMFs) which are derived from EMD feed to ANN, SVM and DT. Results for each mentioned decision making algorithms is evaluated for various fault scenarios (fault types, fault location, fault inception angle, fault resistance and noise in current and voltage signals). In the end a comparison is done and it is shown that SVM has the lowest error percentage in three mentioned algorithms for transmission line fault classification.

II. METHODOLOGY

A. Preliminaries

The proposed methodology involves four major stages: feature extraction, feature selection, decision making algorithms and classification. The block diagram of fault classification system is shown in figure 1. The method presented in this paper utilizes instantaneous power signal as input which is derived from instantaneous voltage and currents of the given power system measurements.

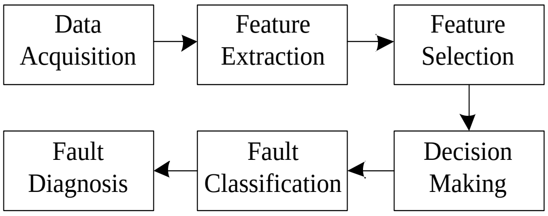

Figure 1- Block diagram of fault classification procedure

Once the voltage and current waveforms for various scenarios are obtained from one end of transmission line, instantaneous power for three phases are calculated as follows (the purpose of using instantaneous power is that it has both features of current and voltage signals):

$$P_A(t) = V_A(t) \times I_A(t)$$
$$P_B(t) = V_B(t) \times I_B(t)$$
$$P_C(t) = V_C(t) \times I_C(t) \qquad (1)$$

Which in equation1 $P_A(t)$, $P_B(t)$ and $P_C(t)$ are instantaneous power of phase A, phase B and phase C in order. For detecting grounded faults from ungrounded ones, a feature is defined by usage of ground current and ground voltage that is described in following equation:

$$I_0(t) = \frac{1}{3}\left[I_A(t) + I_B(t) + I_C(t)\right]$$
$$V_0(t) = \frac{1}{3}\left[V_A(t) + V_B(t) + V_C(t)\right] \qquad (2)$$

After distinguishing ground current (I_0) and voltage (V_0), feature for detecting grounded faults is defined as below that called ground instantaneous power (P_0):

$$P_0(t) = V_0(t) \times I_0(t) \qquad (3)$$

In this paper, it is assumed that fault is detected and procedure of classifying the faults begins after that. For this purpose, $P_A(t)$, $P_B(t)$, $P_C(t)$ and $P_0(t)$ are acquired for half cycle after inception of fault. After that EMD is executed on them for feature extraction stage and signals are decomposed into mono component signals called Intrinsic Mode Functions (IMFs). For feature selection step transient energy characteristics of IMFs for different fault types is calculated and in decision making phase, ANN, SVM and DT are trained with energy characteristics of IMFs and results of them for classifying faults are compared with each other. In the normal operating condition of a power system, single phase instantaneous power is the sum of a dc and a sinusoidal component. If the frequency of the power system is *f*, the frequency of this sinusoidal component becomes *2f*. Hence, by applying half-cycle, the recommended algorithm operates. In the following each step of proposed faulty phase selection scheme will be explained. Block diagram of proposed method is shown in figure 2.

B. Empirical Mode Decomposition

Empirical Mode Decomposition (EMD) method is based on simple assumption that any data consists of different simple intrinsic mode oscillations. EMD uses sifting process for converting nonlinear and non-stationary signals into mono component and symmetric components. It breaks down given signal into its component Intrinsic Mode Functions (IMFs) [8].

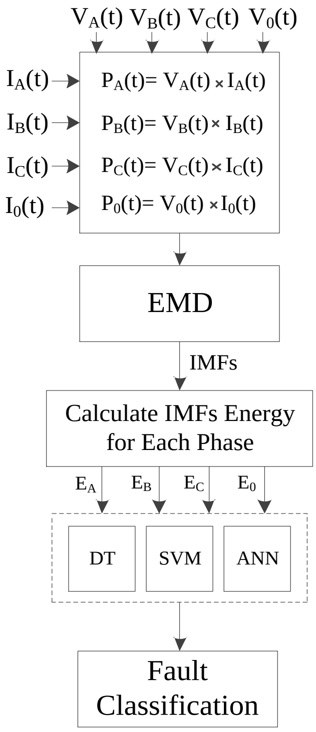

Figure 2- Proposed method

An IMF is defined as an oscillating wave which:

1. Has only one extreme between zero crossings, and
2. has a mean value of zero.

Sifting is implemented iteratively for extracting IMFs from parent signal using following algorithm:

1. Let m_1 be the mean of upper and lower envelopes of given signal X(t), which are determined from a cubic-spline interpolation of local maxima and minima. The first component, h_1 is calculated as shown in (4).

$$h_1 = X(t) - m_1 \qquad (4)$$

2. In next step, h_1 is considered as the parent signal, and m_{11} is the mean of h_1's upper and lower envelopes and h_{11} is calculated:

$$h_{11} = h_1 - m_{11} \qquad (5)$$

3. Above procedure is repeated *n* times, until h_{1n} satisfies the conditions of an IMF. Then it is designated first IMF, $I_1 = h_{1n}$, It is then separated from rest of the data using (6).

$$R_1 = X(t) - I_1 \tag{6}$$

4. Now R_1 is considered as main signal and steps 1–3 are repeated for obtaining second IMF.

5. The number of IMFs that can be extracted depends on the signal. The stopping condition is that the R_n becomes monotonic.

If n orthogonal IMFs are obtained in this iterative manner, the original signal may be reconstructed as,

$$s(t) = \sum_n c_i(t) + r(t) \tag{7}$$

In this algorithm as shown in figure 3, EMD is used to decompose a complex signal into various time-scale or frequency components, the energy concept is used to weigh the importance of each frequency component.

To construct the energy function at various frequencies to better represent the input signals, the concept of energy is utilized. The energy of one IMF component in the data window can be expressed as:

$$E_i = \sum_{k=1}^{N} \left| i(t) \right|^2 \tag{8}$$

After introducing EMD, we compare it with classical time-frequency analysis methods, such as STFT and wavelets as follows.

(1) Although STFT can overcome the disadvantages of FFT-based methods in processing non-stationary signals, it produces constant resolution for all frequencies because it adopts the same window for the whole signal. This implies that if we want to obtain a good frequency resolution using wide windows, which is desired for the analysis of low-frequency components, we would not be able to obtain good time resolution (narrow window), which is desired for the analysis of high-frequency components. Therefore, STFT is suitable for the analysis of quasi-stationary signals instead of real non-stationary signals.

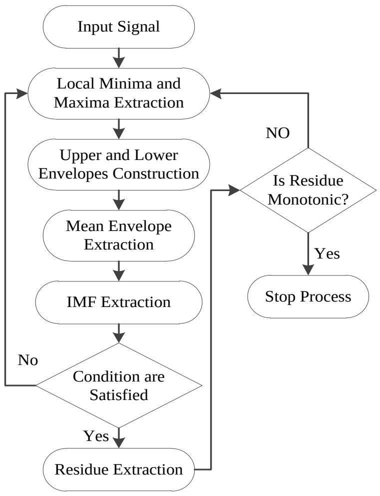

Figure 3- EMD algorithm

(2) Comparing with STFT, wavelets can be utilized to analyze multi-scale signals through dilation and translation, and extract time-frequency characteristics of the signals effectively. Therefore, wavelets are more suitable than STFT for analyzing non-stationary signals. Wavelets being non-adaptive, however, have its own disadvantage that their analysis results depend on the choice of the wavelet base function. This may lead to a subjective and a priori assumption on the characteristics of the signal. As a result, only the signal characteristics that correlate well with the shape of the wavelet base function have a chance to produce high value coefficients. Any other characteristics will be masked or completely ignored.

(3) Different from wavelets, EMD is a self-adaptive signal processing method. It is based on the local characteristic time scales of a signal and could decompose the signal into a set of IMFs. The IMFs represent the natural oscillatory mode embedded in the signal and work as the basis functions, which are determined by the signal itself, rather than predetermined kernels. Of course, EMD has weaknesses as well. For example, EMD produces end effects; the IMFs are not strictly orthogonal each other; mode mixing sometimes occurs between IMFs. In conclusion, each time-frequency analysis method suffers various problems. It is hard to say that one can always exceed others for any case.

C. *Artificial Neural Networks*

Artificial neural networks are computational paradigms based on mathematical models that unlike traditional computing have a structure and operation that resembles that of the mammal brain. Artificial Neural Networks (ANNs) or neural networks for short are also called connectionist systems, parallel distributed systems or adaptive systems, because they are composed by a series of interconnected processing elements that operate in parallel. Neural networks lack centralized control in the classical sense, since all the interconnected processing elements change or “adapt” simultaneously with the flow of information and adaptive rules. The application of artificial neural networks to discriminate the fault has given a lot of attention recently. Neural networks are typically organized in layers. Layers are made up of a number of interconnected 'nodes' which contain an 'activation function'. Patterns are presented to the network via the 'input layer', which communicates to one or more 'hidden layers' where the actual processing is done via a system of weighted 'connections' [10]. The hidden layers then link to an 'output layer' where the answer is output as shown in figure 4.

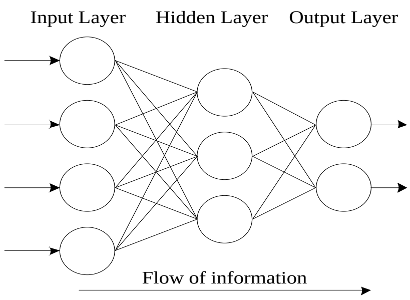

Figure 4- ANN structure

D. *Support Vector Machine*

In machine learning, support vector machines (SVMs) are supervised learning models with associated learning algorithms that analyze data and recognize patterns, used for classification and regression analysis. Given a set of training examples, each marked for belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples into one category or the other, making it a non-probabilistic binary linear classifier. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. As shown in figure 5 new examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on [11]. The SVM technique has been implemented in a MATLAB environment using the Lib-SVM toolbox.

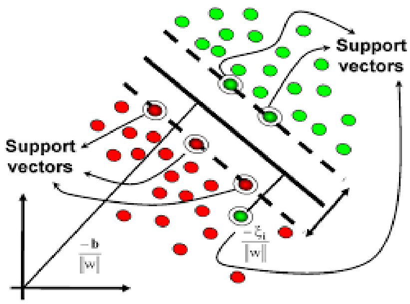

Figure 5- Example of SVM

E. *Decision Tree*

One of the attractive approaches in decision making methods is the decision tree (DT). The DT method provides a white box model for the classifier, that is, it has the advantage of revealing the entire process of decision making by interpreting the rules and constructing an appropriate framework to quantify the values of outcomes and the possibilities of achieving them. The DT, irrespective of the procedure used for creating the tree, has two stages: training and testing. In the first stage, after exact simulation of the entire system under different conditions, the input features, with known relevant output classes, are fed to the decision-tree algorithm. In the tree-building process, different criteria are used for evaluating the effect of input features in determining the output classes [12]. A typical DT is shown in figure 6.

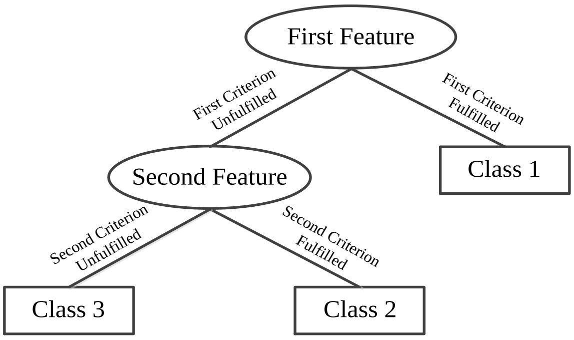

Figure 6- Typical DT

III. System under Study

The proposed algorithm is applied to a power system shown in figure 7. The system parameters are as follows:

- Generators: rated line to line voltage is 20kV, three-phase short-circuit power is 1000MVA, frequency is 50Hz, X/R ratio is 10. The voltage phase angle of generator 1 and 2 are 0 and -10 degree, respectively.
- Transformers: rated power is 600MVA; voltage ratio is 20/230kV with delta-star-grounded connection, with 0.002+j0.1 pu impedance.
- Lines: All of line impedances are 0.02+j0.15Ω/km with negligible capacitance. Line 1-2, 2-3, 3-4, 4-1, and 5-2 are 50, 35, 60, 20, and 25 kilometer, respectively.
- Loads: rated line to line voltage is 20kV, frequency is 50Hz. The active and reactive power of load 1 is 500MW and 100MVAr, respectively. The active and reactive power of load 2 is 100MW and 50MVAr, respectively.

The simulation time step is set to 100μs which makes 200 samples per cycle in a 50Hz system (sampling frequency is 10 KHz).

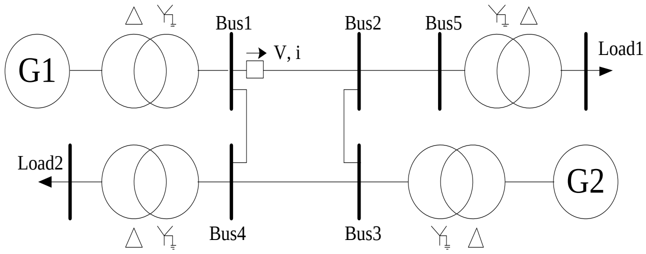

Figure 7- Test system

IV. Simulation and Result

In order to evaluate the performance of proposed method, the fault is applied to line 1-2 and more than 1000 scenarios in different conditions are simulated. The case studies include: different fault types, different fault locations, different fault inception angles and different fault resistance. Signals that are used to identify the type of fault are the measured three phase currents and voltages at the relay point of line 1-2. For each case study, energy characteristics of IMFs are calculated. In following sections E_A, E_B and E_C represents mentioned index for each phase instantaneous power (in order phase A, B and C) and E_0 signified ground instantaneous power energy of IMFs. After calculating E_A, E_B, E_C and E_0 for each case study, performance of ANN, SVM and DT will be deliberated.

A. *Case 1: Various fault types*

A fault is applied at the middle of line 1-2. This fault starts at 0.206s. In this test case, it is assumed that the fault and also the ground have a very small resistance. For each type of fault, energy of IMFs is calculated in table I. It is obvious that energy of IMFs for faulty phase is bigger than healthy phase, and also E_0 is a significant value for grounded faults and it is a negligible amount for ungrounded ones.

Table I. Energy of IMFs for various fault types

	E_A	E_B	E_C	E_0
A-G	15.4×10^5	8.1×10^3	7.5×10^3	4.6×10^3
B-G	6.3×10^3	14.7×10^5	5.7×10^3	4.1×10^3
C-G	6.7×10^3	7.1×10^3	12.7×10^5	3.9×10^3
A-B	11.3×10^5	12.8×10^5	8.1×10^3	0.98
A-C	8.7×10^5	8.1×10^3	9.7×10^5	2.09
B-C	5.2×10^3	10.1×10^5	10.3×10^5	1.15
A-B-G	12.5×10^5	11.9×10^5	7.2×10^3	3.7×10^3
A-C-G	10.7×10^5	6.5×10^3	10.9×10^5	5.5×10^3
B-C-G	9.2×10^3	11.1×10^5	13.5×10^5	5.9×10^3
A-B-C	14.2×10^5	13.8×10^5	12.9×10^5	3.42

B. *Case 2: Various fault resistances*

In this case, effect of fault resistance (R_f) between 10 Ω to 100 Ω is studied for the test system. To verify this behavior, consider the previous test case but this time the fault resistance is not negligible. Table II shows the results of IMF's energy for this case study for 10 Ω and 100 Ω fault resistances.

Table II. Energy of IMFs for various fault resistances

	R_f	E_A	E_B	E_C	E_0
A-G	10 Ω	11.2×10^5	6.8×10^3	7.3×10^3	3.8×10^3
	50 Ω	10.7×10^5	5.2×10^3	6.9×10^3	3.5×10^3
	100 Ω	10.1×10^5	5.9×10^3	7.1×10^3	3.1×10^3
A-B	10 Ω	9.6×10^5	8.8×10^5	6.7×10^3	0.78
	50 Ω	8.9×10^5	8.2×10^5	6.1×10^3	1.52
	100 Ω	8.2×10^5	7.7×10^5	5.5×10^3	1.44
A-B-G	10 Ω	10.2×10^5	10.5×10^5	5.9×10^3	4.1×10^3
	50 Ω	9.4×10^5	9.8×10^5	5.7×10^3	3.2×10^3
	100 Ω	8.7×10^5	9.2×10^5	5.4×10^3	2.9×10^3
A-B-C	10 Ω	13.4×10^5	14.2×10^5	13.1×10^5	1.08
	50 Ω	12.7×10^5	13.5×10^5	12.3×10^5	0.98
	100 Ω	12.1×10^5	12.8×10^5	11.7×10^5	1.27

C. *Case 3: Various fault inception angle*

Moment of fault inception as known fault inception angle (t_f) in transmission line protection methods is considered in this case. For brevity only one type of each fault category is shown in table 3. As it is obvious from Table III, effect of t_f is a considerable topic in energy of IMFs.

Table III. Energy of IMFs for various fault inception angle

	t_f	E_A	E_B	E_C	E_0
A-G	0^0	10.8×10^5	6.5×10^3	6.5×10^3	2.9×10^3
	45^0	11.8×10^5	7.2×10^3	6.9×10^3	2.5×10^3
	90^0	12.6×10^5	7.9×10^3	7.8×10^3	1.9×10^3
A-B	0^0	9.6×10^5	8.8×10^5	5.8×10^3	1.1
	45^0	9.9×10^5	9.2×10^5	6.9×10^3	1.45
	90^0	10.7×10^5	9.7×10^5	8.1×10^3	2.13
A-B-G	0^0	10.2×10^5	10.5×10^5	6.2×10^3	2.9×10^3
	45^0	10.9×10^5	11.8×10^5	6.8×10^3	2.2×10^3
	90^0	11.7×10^5	12.2×10^5	7.7×10^3	1.8×10^3
A-B-C	0^0	13.4×10^5	14.2×10^5	13.1×10^5	1.77
	45^0	13.7×10^5	14.5×10^5	14.3×10^5	1.15
	90^0	14.1×10^5	14.8×10^5	14.7×10^5	0.87

D. *Case 4: Various fault locations*

One of the other problems that should be considered for a fault identification technique is the location of the fault (d) in the transmission lines. This test case studies this subject by the proposed algorithm. The system is analyzed with a fault applied at 30%, 60% and 90% of the transmission line. The fault resistance of 50Ω is considered and results of three types of faults for brevity are shown in Table IV.

Table IV. Energy of IMFs for various fault locations

	d	E_A	E_B	E_C	E_0
A-G	30%	13.5×10^5	5.6×10^3	4.3×10^3	3.3×10^3
	60%	12.7×10^5	5.1×10^3	4.1×10^3	3.1×10^3
	90%	11.3×10^5	4.3×10^3	3.6×10^3	2.7×10^3
A-B	30%	9.6×10^5	9.2×10^5	5.1×10^3	1.55
	60%	8.9×10^5	8.7×10^5	4.5×10^3	1.92
	90%	8.2×10^5	8.1×10^5	3.7×10^3	2.77
A-B-G	30%	10.2×10^5	11.2×10^5	8.6×10^3	4.5×10^3
	60%	9.4×10^5	10.5×10^5	7.9×10^3	4.8×10^3
	90%	8.7×10^5	9.9×10^5	7.2×10^3	4.9×10^3
A-B-C	30%	13.4×10^5	13.2×10^5	14.1×10^5	1.44
	60%	12.7×10^5	12.5×10^5	13.5×10^5	0.49
	90%	12.1×10^5	11.9×10^5	13.1×10^5	2.76

E. *Case 5: Noise in voltage and current signals*

Current and voltage waveforms measured from real power systems usually contain noise. Therefore, noise is added to the measured signals in order to simulate noise conditions occurred in real power systems. Three different noisy situations with 20, 30 and 40 dB Signal to Noise Ratio (SNR) values for instantaneous powers are apprehended. Any SNR value of a signal is calculated as in equation 9:

$$SNR = 10\log\left(\frac{P_s}{P_n}\right)(dB) \tag{9}$$

where P_n is the power of the noise and P_s is the power (variance) of the signal. A peak noise magnitude of nearly 3.5% of the voltage signal is equivalent to a typical SNR value of 30 dB [14]. In Table V results of energy for IMFs in noisy condition is shown.

Table V. Energy of IMFs for various noise SNRs

	noise	E_A	E_B	E_C	E_0
A-G	20dB	14.7×10^5	10.1×10^3	9.7×10^3	8.9×10^3
	30dB	15.6×10^5	10.7×10^3	10.3×10^3	9.9×10^3
	40dB	15.9×10^5	11.8×10^3	11.6×10^3	10.7×10^3
A-B	20dB	12.5×10^5	15.6×10^5	8.8×10^3	12.5
	30dB	13.7×10^5	15.9×10^5	9.5×10^3	23.6
	40dB	14.3×10^5	16.5×10^5	10.3×10^3	54.8
A-B-G	20dB	11.8×10^5	15.5×10^5	9.8×10^3	11.7×10^3
	30dB	12.6×10^5	16.8×10^5	10.6×10^3	12.9×10^3
	40dB	13.1×10^5	17.2×10^5	11.5×10^3	14.1×10^3
A-B-C	20dB	15.4×10^5	17.2×10^5	16.5×10^5	52.9
	30dB	15.8×10^5	18.5×10^5	17.1×10^5	68.7
	40dB	16.6×10^5	18.8×10^5	17.9×10^5	74.1

After knowing the energy of IMFs, a decision making technique should be implemented to identify type of fault. In this paper for each method, a well-known strategy that used by other authors in recent papers is considered. For ANN, the Radial Basis Function (RBF) network with Levenberg-Marquardt back-propagation training algorithm [10] is selected. For SVM, One Versus One (OVO) multiclass method [11] is utilized and for DT, Random Forest (RF) algorithm [12] is used for classification, where a user-defined number of trees are created.

Table VI. Comparison between decision making algorithms

	ANN%	SVM%	DT%
R_f	95%	99%	96%
t_f	91%	100%	92%
d	90%	99%	93%
noise	80%	98%	87%
General	89%	99%	91.2%

As it shown in Table VI, SVM is the best decision making algorithm among those three which can be used for fault type identification in transmission lines.

Using ANNs for classification has several disadvantages. As the first disadvantage, the error function is multimodal, which includes many local minima. Thus, the learning process of this classifier can face problems. The SVM evolved from theory to implementation and results, whereas ANN follows heuristic path from applications to experiments. Also, SVMs are less prone to over fitting problems and give sparse solution when compared to ANN and DT which they do not depend on input space dimensionality.

V. CONCLUSION

In this paper, a novel application of EMD for fault classification in transmission line is suggested. The proposed method uses only half cycle of instantaneous power for each phase and it only requires data from one side of protected line. Energy of IMFs are fed to three popular decision making networks and after a comparison between them, SVM was the appropriate choice for identification of faulty phase/phases. The influence of different parameters of the transmission line and the characteristics of the proposed procedure are investigated and represented, where the generalization capability and robustness of the proposed scheme are proven.

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