

Fault Classification in Transmission Line Using Support Vector Machine (SVM) and Wavelet Features

Mat Nizam Mahmud, Mohamad Nizam Ibrahim,
Muhammad Khusairi Osman and Zakaria Hussain
Faculty of Electrical Engineering, Universiti Teknologi MARA,
3500 Permatang Pauh, Pulau Pinang, Malaysia

Abstract: Welded joints are widely used in automotive industry in order to form a complete vehicle. The welded joints not only provide connections between components but are essential in controlling the dynamic characteristics of the vehicle. The dynamic characteristic of the vehicle is highly influenced on determining the level of car Noise, Vibration and Harshness (NVH) performance. Since, the characteristics of the welded joints plays a significant in the dynamic characteristics of vehicle structures, the accurate predictive models of the joints is vitally important. Hence, in this study, the feasibility of usage of connector elements such as ACM2, CWELD and CFAST on Door In White (DIW) structure is investigated. The study highlight on the influence and feasibility of each connector elements to produce correlated response with measured data. Correlation level between the predicted results and measured data were assessed through frequency deviation and MAC value.

Key words: DIW, welded joints, dynamic characteristic, frequency, data

INTRODUCTION

The fault that takes place in the power system may lead to the interruption of power supply to consumers. As a consequence, the performance of the electrical energy utility is considered to be unsatisfactory. To minimize such weak performance, an effective protection system is the most important matter since it helps in fast maintenance and restoration of the electrical power supply. The effective system improves the economy and system availability, reduces cost maintenance and shortens the repair duration.

Many researchers have proposed fault classification methods in power systems using Artificial Intelligent (AI) technique (He *et al.*, 2014; Megahed *et al.*, 2006; Dasgupta *et al.*, 2012; Chen *et al.*, 2011). The methods for the fault analysis based on the AI technique can be divided into two stages. The first stage is the feature extraction whereby significant important features are extracted using a signal processing tool from the input of the three phase voltage and/or current signals. The second stage is the classifier selection in which the extracted features are input to the selected classifiers in order to perform a variety of protection functions such as fault detection, classification, location and zone identification (Megahed *et al.*, 2006; Abdollahi and Seyedtabaai, 2010).

Traditionally, steady state components from the three phase signals had been used to extract the significant

features for the fault classification in power systems. However, the steady state component signals are inconsistent and they are easily affected by a number of surrounding elements such as noise, power angle, fault resistance, fault location and inception angle. Therefore, some researchers have used the fault-generated transient component where the component is immune to the transmission line inconsistency (Silva *et al.*, 2006; Jamehbozorg and Shahrtash, 2010; Reddy *et al.*, 2013).

A proper extracting tool for extracting fault transient signals is also important. This is necessary to provide an efficient signal processing tool where the significant features from fault transient signals can be extracted and input to the classifiers. Wavelet Transform (WT) is a well-known signal processing tool with a superior ability to localize the time-frequency that was selected in this study. A steady stream of literature has shown that WT is able to provide excellent results when applied in the power system protection to perform fault detection, classification, zone identification and location estimation (Yadav and Swetapadma, 2015; Jamil *et al.*, 2014; Livani and Evrenosoglu, 2014). Furthermore, Discrete Wavelet Transform (DWT) has been used in (Megahed *et al.*, 2006) to extract spectral energy feature for boundary protection in the transmission lines. The DWT consists of the Wavelet Multi Resolution Analysis (MRA) that has capability to extract from the selected time window sub-band of the fault transient signals (He *et al.*, 2014). In

(Chanda *et al.*, 2003; Gaouda *et al.*, 1999) MRA was used for fault detection and classification in power systems. In (He *et al.*, 2014) the MRA was used to extract the energy feature successfully. Therefore, WT is a good signal processing tool for fault classification in the transmission line.

The type of classifier used for fault classification is also important to achieve good performance result. The Support Vector Machine (SVM) is the classifier type most frequently used by researcher to perform the fault analysis in the power system. Some researchers have indicated that the SVM is a better classifier for fault classification in the power system (Dash *et al.*, 2007; Vyas *et al.*, 2014). To provide a comparative study, the Artificial Neural Network (ANN) has also been applied in this study. The Multi-layered Perceptron (MLP) Network classifier was chosen for the comparative study with the SVM classifier. Both classifiers were injected with the same features to determine which classifiers produce a better result.

The aim of this study is to perform the Support Vector Machine (SVM) with wavelet mean and wavelet standard deviation features for fault classification in the transmission line. A typical 400, 50 Hz power transmission line was modeled using MATLAB/Simulink. The three-phase fault current signals are simulated for a variety of fault types. The main purpose of the applied scheme is to classify ten types of fault (A-g, B-g, C-g, AB, BC, CA, AB-g, BC-g, CA-g and ABC faults) and the performance of the applied scheme is evaluated based on the correct fault classification. The result of the applied scheme is also compared to the scheme based on the MLP Network classifier.

MATERIALS AND METHODS

System Model: The three-phase simulation circuit with two generator sources based on 400 kV, 50 Hz and 100 km transmission lines power system is shown in Fig. 1. The transmission line circuit consists of two generator sources (S1 and S2), two buses (Bus A and B) and one Circuit Breaker (CB). Meanwhile, CT and CVT represent the current transformer and capacitive voltage transformer, respectively.

The parameters for the transmission line considered in this study are as follows: $R_1 = 0.0154 \Omega \text{ km}^{-1}$, $L_1 = 0.89 \text{ mH km}^{-1}$, $C_1 = 13.065 \text{ nF km}^{-1}$ and $R_0 = 0.0461 \mu \text{ km}^{-1}$, $L_0 = 2.65 \text{ mH km}^{-1}$, $C_0 = 4.355 \text{ nF km}^{-1}$. Based on these parameter values, the training datasets were simulated at different numbers of fault locations, fault resistances and fault inception angles. The parameters and their varying values are tabulated in Table 1.

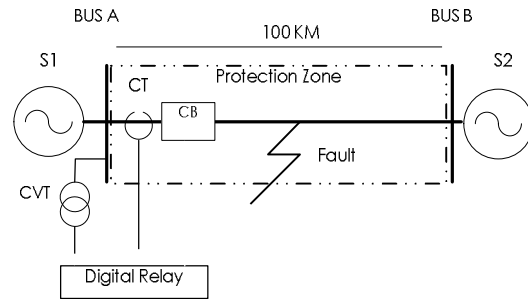


Fig. 1: Single line of transmission lines power system model

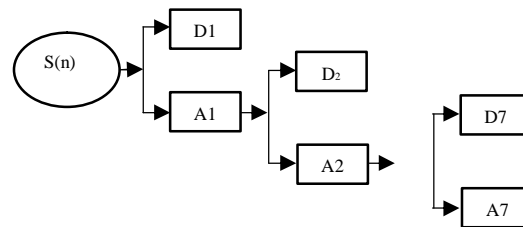


Fig. 2: Wavelet decomposition using MRA

Table 1: Training dataset parameters

Parameters	Variation values
Fault Locations L (km)	0, 20, 40, 60, 80, 100
Fault Resistance Rf (Ω)	0, 10, 20, 50, 80, 100, 150, 200, 400
Fault Inception Angle θ (°)	0, 30, 45, 60, 90

Features extraction: Features extraction is the very significant for any signal processing technique. This step is necessary because the input of the three phase signals contains a huge amount of features space that can be benefited. The suitable features extraction may result in an effective power protection scheme with better classifier performance. Figure 2 shows the time window with an A-g fault current signal. From the fault current waveform, one quarter cycle of the signal was captured to extract the important features. The one quarter cycle is equal to 5 ms duration of the waveform signal.

Wavelet Transform (WT): Wavelet Transform (WT) is a signal processing tool that is used widely by researcher to perform features extraction, especially in the power system fault transient signals analysis. Thus, WT was applied in this study to de-compose the three phase current signals from the transmission line simulation circuit into a series Approximate (A) and Detail (D) coefficients. The one quarter of the fault signal, S(n) is decomposing into different scales with high pass and low pass in pair. The approximation component (A) is a high scale, low frequency component while Detail component

(D) is the low-scale, high frequency one. Meanwhile, the MRA is a technique applied in WT to extract the sub-band (selected window) information from the fault transient signals. Then, the MRA can be used to extract sub-band information from the fault current transients. Figure 3 shows the MRA decomposition level applied in this study from level 1 (A1 and D1) to level 7 (A7 and D7). The composition level selected in this study is 7th level.

In any WT, there is one unique analyzing function called mother wavelet that is assigned to perform decomposition task. Many types of the mother wavelet were proposed in literature including Symmlet (sym), Harr and Daubechies (db). The mother wavelet's function is for low frequency components (Approximation, A), then the time interval will last a long time, otherwise for the high frequency components (Detail, D), the time interval will be a short one. The suitable selection of the mother wavelet is also important. The mother wavelet which closely matches with the input signal characteristics may result in a better classification performance. The mother wavelet applied in this study is Daubechies 4 (db4). Many researchers also indicate that db4 mother wavelet is very effective and capable of providing enough information for classifiers (Dasgupta *et al.*, 2012; Silva *et al.*, 2006; Reddy *et al.*, 2013).

Wavelet feature: In this study, two features were extracted as input to SVM and MLP network classifiers. The features were extracted in term of mathematical statistic value. The features extracted are wavelet mean (μ) and wavelet standard deviation (σ). Then, both features were fed to the selected classifiers. In this study, all the Details (D) sample value were squared to obtain the absolute value. The formula to calculate the features are as follows.

Wavelet mean: The Wavelet Mean (μ_{A-C}) of the current signals is extracted based on the one quarter of the post fault current cycle. The μ_i was obtained from the value of the reconstructed detail from level 4 (D4) to level 7 (D7) of the current signal. The equation for extracting wavelet mean is given as follows:

$$\mu_i = \frac{1}{250} \sum_{h=4}^7 \sum_{j=1}^{250} (D_{ih}(j))^2 \tag{1}$$

Where:

- i = The current phases A-C, respectively
- h = The MRA decomposition level from level 4 (D4) to level 7 (D7)

The composition level used for the wavelet mean is from level four to level seven. The j is the sample index with time window 5 ms (250 sampling point) at 50 kHz sampling rate setting. Then, the normalized mean, μ_k is determined by using:

$$\mu_k = \frac{\mu_i}{\max(\mu_A, \mu_B, \mu_C)} \tag{2}$$

where, max () is the maximum value of μ_{A-C} . Besides, k stands for the normalized value with lower cases a-c that represent the upper case for current phases A-C, respectively. Then, all the data sets of normalized μ_k , μ_a , μ_b and μ_c values will be input to both classifiers for fault type classification.

Wavelet standard deviation: The wavelet standard deviation σ_{A-C} of the three-phase current is also extracted based on the one quarter of the post fault current cycle. The σ_i obtained was also from the value of the detail component from level 4 (D4) to level 7 (D7). The formula for calculating the wavelet standard deviation is given as follows:

$$\sigma_i = \left[\frac{1}{250-1} \sum_{h=4}^7 \sum_{j=1}^{250} ((D_{ih}(j)) - \mu_i(D_{ih}(j)))^2 \right]^{1/2} \tag{3}$$

The value of σ_i is also normalized to σ_k based on Eq. 2 before input the classifiers to perform fault type classification.

Classifiers

Support Vector Machines (SVM): Support Vector Machines (SVM) is a binary classifier based on the statistical learning theory. This classifier is a result of the development of the Artificial Neural Network (ANN) and the combination of the kernel theory, optimization and generalization theories. The SVM classifier is independent from the number of features input which makes it a better classifier. During calculations, the input dataset was mapped into a high-dimensional dot product space named a feature space using the kernel approach. Then, an optimal hyperplane is defined by applying the optimization theory and respecting the insight in maximizing the generalization capability of the SVM (Vyas *et al.*, 2014). The function of the hyperplane is to separate a datasets into two classes ($\{+1, -1\}$). Then, the llinear hyperplane is defined by a bias term/support vector b and weight vector W as:

$$W^T + b = \begin{cases} \geq 1, & \text{class +1} \\ \leq -1, & \text{class -1} \end{cases} \tag{4}$$

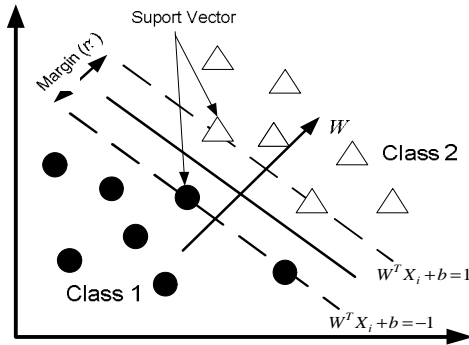


Fig. 3: Data classification by support vector machine

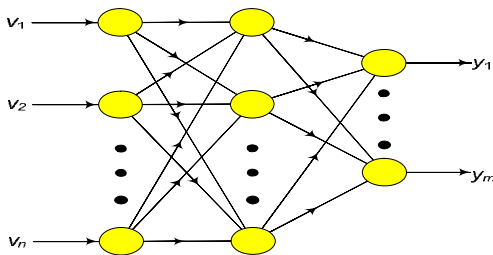


Fig. 4: MLP network

Figure 3 shows the hyperplane separated between two dataset classes. Then, the separation margin (m) between the dataset classes is given as follows:

$$m = \frac{2}{\|w\|} \tag{5}$$

In order to maximize the margin (m), should be minimized. Then, margin (m) can be calculated by solving the quadratic optimization problem as follows:

$$\min \frac{1}{2} \|w\|^2 \tag{6}$$

Subject to:

$$y_i (W^T x_i + b) \geq 1 \tag{7}$$

where, y_i ($\{-1 \text{ or } +1\}$) is the corresponding label for each x_i . There are many kernels used in the SVM including the polynomial kernel, linear kernel and Radial Basis Function (RBF) (Gryllias and Antoniadis, 2012; Ekici, 2012; Gayathri and Kumarappan, 2010). In this study, the RBF kernel was used to evaluate the performance of the SVM in classifying fault types in the transmission line. In RBF, there are two parameters that should be optimized to obtain highest accuracy which are regularization Constant

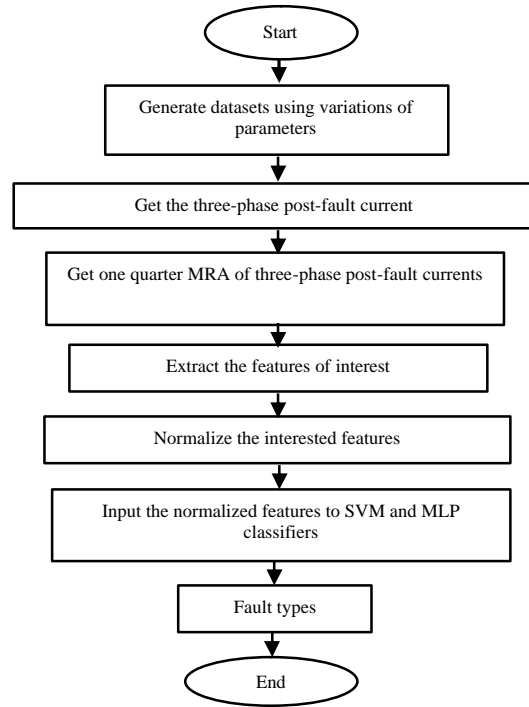


Fig. 5: Flowchart of fault classification scheme

(C_{svm}) and Gaussian function (σ_{svm}). The parameters C_{svm} and σ_{svm} varied from 1-200 and from 1-20, respectively.

Multilayered Perceptron (MLP) network: The MLP network was also introduced in this study. The aim is to facilitate the comparative study between the common classifier used in the fault analysis in the power system. Multilayered Perceptron (MLP) network is the common ANN classifier utilized to perform classification problems in any fields of study. The structure of one hidden layer feed-forward is illustrated in Fig. 5. The Levenberg-Marquardt Backpropogation (trainlm) is applied as the training algorithm for the network. In order to optimize the MLP network accuracy, the number of the hidden nodes for the MLP network varied from 1-50.

Summary: The complete flowchart of the proposed scheme is represented by Fig. 5. First of all, the fault datasets were generated using a variation of parameters. Then, the signals from the three phase post-fault current were decomposed after the MRA processing. Two types of features were extracted which are wavelet mean (μ) and wavelet standard deviation (σ). After that, the features have been normalized in the range of [0, 1]. Finally, the classifiers were tested in three different testing

Table 2: Accuracy testing results

Classifiers	Accuracy testing			Average (%)
	No noise (ideal) (%)	30dB noise (%)	20dB noise (%)	
SVM	98.44	94.37	91.35	94.72
MLP network	98.41	96.07	88.78	94.42

datasets. The first was the ideal (no noise), the second was the system with the influence of 30 dB noise and the third was the system with the influence of 20 dB noise. The performance of classifiers was evaluated based on the percentage that has correctly classified the fault type in the transmission line.

RESULTS AND DISCUSSION

All the datasets were generated based on a Three-phase post-fault transient current signals in transmission line. The three-phase post-fault transient current signals were simulated with a wide variation of the fault resistance, inception angle, fault types and fault locations. The training dataset parameters had covered all possibility conditions of fault that might have occurred in the transmission lines. However, for testing dataset, the parameters varied randomly, as well as the fact that they were difficult and different from the training parameters setting.

In addition, testing datasets were also injected with different level of noises. The classifiers were tested under three conditions of noise levels. Firstly, the classifiers were tested with Ideal (no noise) dataset, secondly they were tested with 30 dB noise dataset (He *et al.*, 2014) and thirdly, they were tested with 20 dB noise dataset. The parameters for the SVM and MLP network had remained the same when performing all conditions of testing dataset’s fault classification. The accuracy (in percentages) of the classifiers performance was tabulated in Table 2.

Table 2 shows the results for accuracy testing for SVM and MLP networks with three system testing conditions. For no noise (Ideal), testing dataset SVM classifier achieved the highest accuracy with 98.44% and this is slightly higher than the MLP network classifier. The SVM classifier was 0.03% which was higher than the MLP network with 98.41% in accuracy. Then, for 30 dB noise testing dataset, the MLP network achieved 96.07% which was higher than SVM 1.70%. The accuracy achieved for the SVM was only 94.37%. Meanwhile, for 20 dB noise testing dataset, the SVM achieved 91.35% which was higher 2.57% than the MLP network which only achieved 88.78%.

However, the overall performance for each classifier was determined by averaging the accuracy from the three

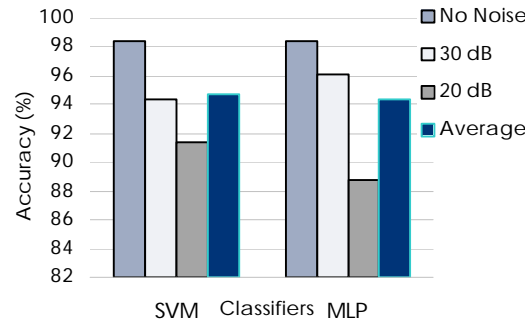


Fig. 6: Graph of classifiers performance

types of the testing datasets. The SVM classifier had shown the highest average accuracy with 94.72% which was 0.30% higher than the MLP network classifier. The average accuracy for the MLP network was only 94.42%. The performance of the SVM and MLP Network for three different testing datasets are clearly illustrated in Fig. 6. Figure 6, it clearly indicates that the presence of the noise in the system results in the decreased performance accuracy for both the classifiers. In case of the signal distortion with significant noise (20dB), the classifier performance accuracy was shown to be <92%. In real application, the influence of the noise in the power system should be well considered. Both classifiers show poor performance against the distortion signals. Both classifiers need other special features to overcome the poor performance against the influence of noise. However, from the graph, the average accuracy shows that the SVM was a better classifier as compared to the MLP network even though the MLP network produces a slightly better performance for the 30 dB noise dataset.

CONCLUSION

This study proposes the fault classification scheme in the transmission line using the Support Vector Machine (SVM) and wavelet features. Wavelet Transform (WT) was applied to extract wavelet mean and wavelet standard deviation as input features to the SVM. The MLP network which is the common neural network classifier was also applied in this study to compare the performance of the SVM classifier. Both the classifiers were tested in three different datasets including no noise (ideal), 30 noise and 20 dB noise datasets. The result shows that the SVM classifier achieved the highest average accuracy with 94.72%. The result has been able to prove that the SVM classifier was better than the MLP network classifier

for fault classification in the transmission line by applying the wavelet mean and wavelet standard deviation features.

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