Classifications of disturbances using wavelet transform and support vector machine

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Abstract: This paper proposes a new method to detect and classify all kinds of faults, capacitor switching, and load switching in a power system network based on wavelet transform and support vector machines (SVMs). In this regard, a sample of a power system is simulated via MATLAB/Simulink, and by reading the voltage of the point of common coupling and using the wavelet transform, the differences of the outputs of the wavelet transform are investigated. The SVM approach is employed to distinguish the type of the transient (capacitor switching, fault, and/or load switching) in use for the high level outputs of the wavelet transform. Similar to neural networks, this method, which is based on learning, is considered as a proper tool for data classification. The results of simulations demonstrate that the combination of wavelet transform and SVM recognizes the type of the transient correctly and effectively as well as distinguishes capacitor switching and load switching events from all kinds of faults such as three-phase-to-earth fault, phase-to-phase fault, two-phase-to-earth fault, and single-phase-to-earth fault. In the end, the accuracy of the presented approach is evaluated and the simulation results are proposed for different attributes of transients in the power system network.

Key words: Disturbance detection, support vector machine, wavelet transform

1. Introduction

During operation of a power network various transient states may occur with different sources. The most important sources of voltage and current transients include capacitor switching, fault occurrence (e.g., three-phase fault, phase-to-phase fault, two-phase-to-ground fault, and single-phase-to-ground fault), and load switching. Fault occurrence may lead to voltage sag or load curtailment, which, in turn, results in damages to electrical and industrial facilities; therefore, rapid fault detection is a prominent issue that must be considered to increase system reliability and avoid load curtailment and damage to equipment. Moreover, the fault detection system must be able to precisely determine which type of fault has occurred (capacitor switching, load switching, or other transients) as the reaction of the system depends on the source of the transient. Otherwise, improper corrective attempts might be made (such as isolating or disconnecting the fault location) that do not match the corresponding fault and damage the network.

Various publications have focused on introducing wavelet transform and its application in the classification of power quality disturbances. A detailed comparative evaluation of using different wavelets in power quality

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identification was provided in [1]. In this paper, seven types of power quality disturbances were classified considering 11 decomposed levels as 11 features. However, the validity of this classification is reduced in practical cases under noisy conditions.

In [2], features were extracted from disturbed waveforms and several simulations were performed using thousands of data samples. As a result, among all introduced wavelets in the MATLAB Toolbox, the most appropriate ones were selected and compared. The application of wavelet transform in power systems including examining transient states [3], evaluating power quality [4], and modeling power systems in the wavelet domain [5] were investigated.

A combination of wavelet transform and artificial neural networks was utilized to classify seven types of power quality disturbances in [6]. Considering numerous features for classification of different types of disturbance signals requires a large volume of memory and significant computational time.

To classify high and low frequency power quality disturbances, a hybrid method was exploited consisting of an artificial neural network and the extracted features by wavelet transform [7,8]. Neural networks have considerable capabilities of extracting meaning from complex information sets and imprecise data. They could be used for pattern extraction and identifying confusing behaviors. Multilayer neural networks with different algorithms were utilized for disturbance classification in [9]; nevertheless, the classification precision was not acceptable. One of the main applications of disturbance classification can be distinguishing between fault occurrence, load switching, and capacitor switching (load and capacitor switching are frequently used in power networks). Though it facilitates correct and fast response to these events so that their consequences can be overcome, it was not investigated in the literature.

In this paper a novel method for detection and classification of disturbances (various types of faults, capacitor switching, and load switching) is proposed based on wavelet transform and support vector machines (SVMs). The SVM method is one of the learning schemes that are used in two manners: regression and classification. Since we aim to detect different types of transients (fault, load switching, and capacitor switching) the SVM method could be an appropriate tool.

The rest of this paper is organized as follows. Sections 2 and 3 introduce the wavelet transform and SVM method, respectively. Section 4 describes the proposed method. The simulated sample power system, implementation of wavelet transform, feature extraction, and generation of sample data are explained in this section. It also includes SVM design, simulation results, and a detailed explanation of the method. Finally, Section 5 concludes the paper.

2. Wavelet transform

Fourier transform uses sinusoidal waves that have infinite support in both directions. Similarly, in the discrete domain, Fourier basic vectors also have infinite support; therefore, this transform does not have compact support feature. In practical cases some transient signals are nonzero in a short time span and they are not similar to any Fourier basic functions. Fourier functions are not appropriate tools for analyzing signals that either include transient components or are concentrated in a specific time or space. Fourier transform is able to represent each imposed function (even a thin transient signal) in the form of sinusoid functions; nonetheless, the obtained coefficients cannot be considered as compact measures of signal information.

To address this issue, wavelet transform is employed. Wavelet transform analyzes signals in time-frequency space. Each transient component in a signal is mapped to a location in the time-frequency plane. This location depends on the dominant frequency of the component and its occurrence time. If important components

of a signal resemble one or more basic functions they could be denoted by large coefficients obtained from those basic functions. Thus, they can be easily found in a transform. Finally, if an undesired component (such as noise) is similar to one or more basic functions, it is easily detected and could be eliminated through minimizing (setting to zero) the corresponding coefficient.

In fact, the wavelet transform covers the limitations of the Fourier transform and extracts high and low frequency components of the main signal, which correspond to fast and slow variation of waveform, using scaling and transmission of wavelets. This transform examines the signal via windows with variable lengths. In this transform, information on high and low frequencies is available from small and big windows, respectively.

In wavelet transform a group of basic functions is derived via scaling and transforming a primary function $y(x)$, called the mother wavelet. This function has limited fluctuations while it is usually concentrated in a location. If x approaches infinity the value of this function rapidly reaches zero. Various mother wavelets have been defined so far, among which Daubechies functions are the most popular ones. They are a suitable choice for analyzing power system signals [10].

In addition to sound and image processing, wavelet transform might be applied for transient detection, power quality evaluation, and power system modeling in the wavelet domain. This transform extracts high and low frequency components of the main signal, which correspond to fast and slow variations of the waveform using scaling and transform of the mother wavelet. Hence, signals sampled in the frequency-time domain are divided into different levels leading to wavelet coefficients (detail coefficients and approximation coefficients). Consequently, it is possible to provide fast location in the time domain and divide the total energy of a signal in different frequency bands [10].

3. Support vector machine

SVM is a supervised learning method [11] that might be utilized for classification [12] and regression [13]. This method has recently demonstrated better performance compared to other older classification methods such as perceptron neural networks. The basis of the SVM is linear classification. During linear classification it tries to select a line that provides a larger margin. Finding the optimal line for data classification is done using quadrature programming methods, which are well-known schemes for solving constrained problems. In order for the machine to classify data in complex cases, data are transformed to higher dimensions [14] where the classification might be done. Figures 1 and 2 depict classification in SVM using a hypothetical line and transforming data to higher dimensions.
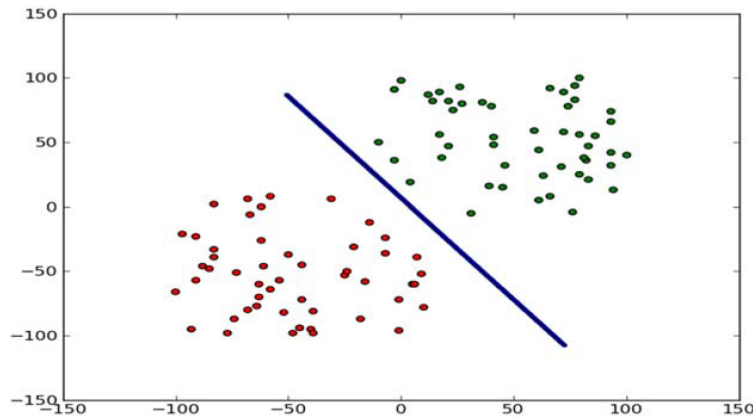

Figure 1. Classification scheme of SVM using a hypothetical line.
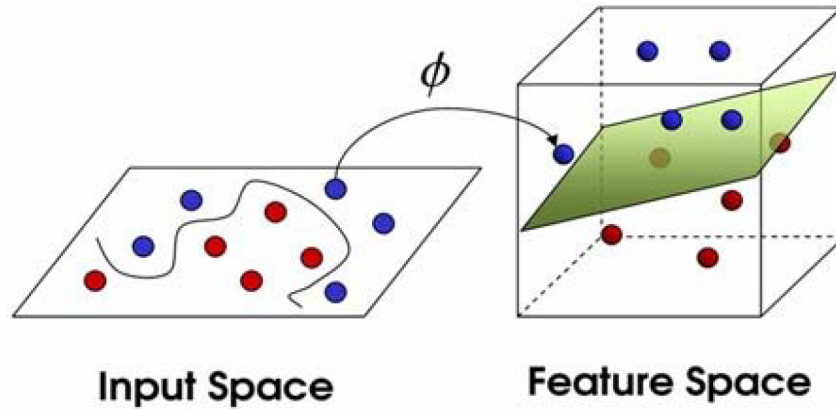
Figure 2. Classification scheme of SVM using hypothetical plane.

SVM parameters are acquired by solving the following optimization problem.

$$Min \left\{ \frac{1}{2} \|w\|^2 + C \sum_{i=1}^{n} \zeta_i \right\} \tag{1}$$

$$St. \begin{cases} y_i \left(w^{'} \phi(x_i) + b \right) \geq 1 - \zeta_i \\ \zeta_i \geq 0, \, i = 1, \ldots, n \end{cases} \tag{2}$$

Here, ζ_i and C are the slack variable and regulation parameter, respectively; $w \in R^n$ and $b \in R$ are parameters related to a hyperplane; and $\phi(x)$ is a transfer function that transforms data from input space to high-dimension space [15]. By minimization of the first and second parts of Eq. (1), the complexity of the SVM and the error amount of data training are decreased, respectively. Minimization of the second part is equal to maximization of the distance between the hyperplane and the closest samples to borders on both sides. On the other hand, considering that $\phi(x)$ is a nonlinear transform, kernels are used for transferring data to a high-dimensional space. For this purpose, the earlier optimization problem is transformed to the following form, which is modeled by the Lagrange method of multipliers [16].

$$Min \, L(\lambda) = -\frac{1}{2} \sum_{i,j=1}^{L} \lambda_i \lambda_j y_i y_j K(x_i, x_j) + \sum_{i=1}^{L} \lambda_i \tag{3}$$

$$St. \sum_{i=1}^{L} y_i \lambda_i = 0, \, 0 \leq \lambda_i \leq \frac{C}{L}, \, i = 1, \ldots, L \tag{4}$$

Here, λ_i represents the Lagrange coefficients and $K(x_i x_j)$ represents a kernel function, which is calculated by $K(x_i, x_j) = \phi(x_i)^T \phi(x_j)$.

Basically, the SVM algorithm is a binary classifier. In the previous section the basic concepts of SVM theory for two-class classification were explicated. Multiclass pattern recognition might be implemented using several two-class SVMs. Generally, there are two approaches to this objective: a "one against all" strategy (for classifying each pair of classes and remaining classes) and a "one against one" strategy (for classifying each pair). The latter is suitable for cases where the former leads to a vague classification. For multiclass problems,

the main approach is reducing the multiclass problem to several binary problems, each of which could be solved using a binary classifier. Afterwards, the outputs of SVM binary classifiers are combined and the multiclass problem is solved.

4. Proposed method

The block diagram of fault detection and classification as well as distinguishing among faults, capacitor switching, and load switching are illustrated in Figure 3. As can be seen in the figure, first, point of common coupling (PCC) voltage is measured. Then the signal is transformed to the wavelet domain by wavelet transform. Finally, the fault is detected according to a disturbance feature extracted by SVM method. In the following, each block is explained for a sample network and the simulation results are presented.
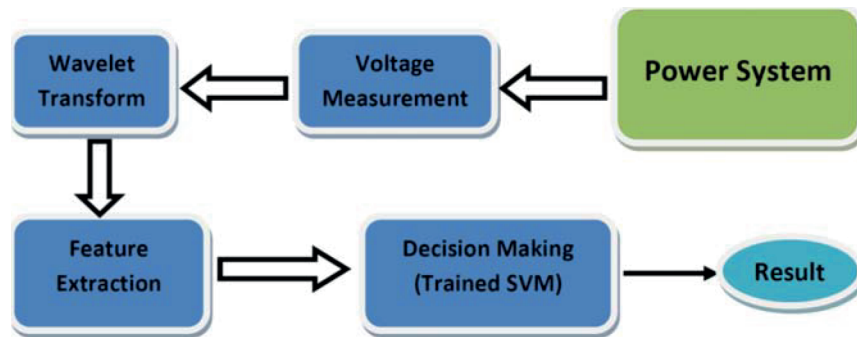

Figure 3. Block diagram of detection procedure.

4.1. Structure and components of sample power network

In Figure 4 a schematic of a sample power system is illustrated, which is simulated in the Simulink environment. On the left side, the system includes a three-phase voltage source, which is connected to the PCC via a three-phase transformer. On the right side, there are five capacitor banks together with a connectable load and a few fault blocks (simulating different conditions). It must be noted that measured voltages are transmitted to the MATLAB workspace for further processing where the wavelet transform and SVM detection technique are applied to data.
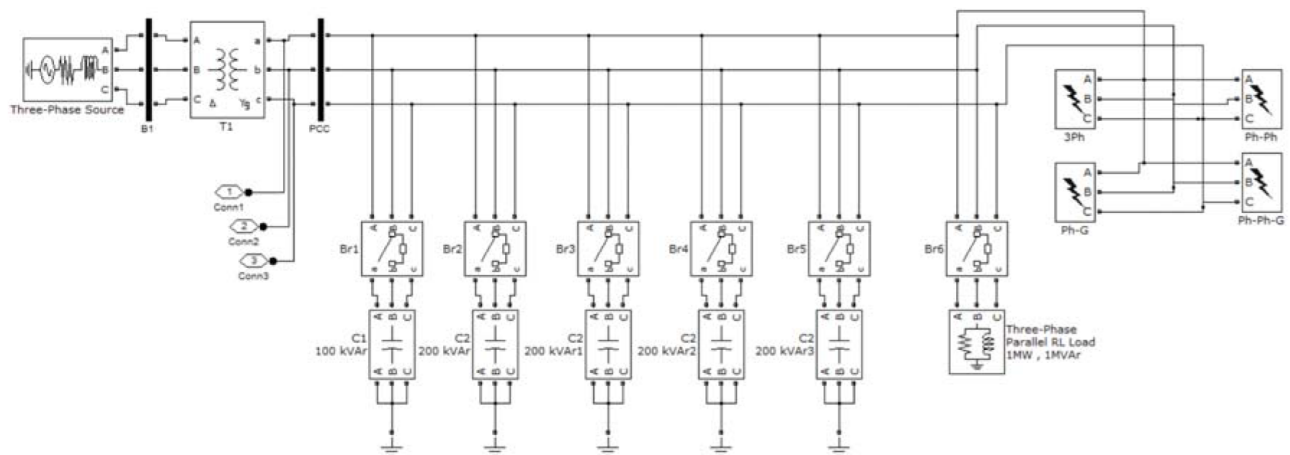

Figure 4. Schematic of sample power network.

4.2. Waveform transform implementation

Figure 5 shows the implementation of the wavelet transform via high-pass and low-pass filters.
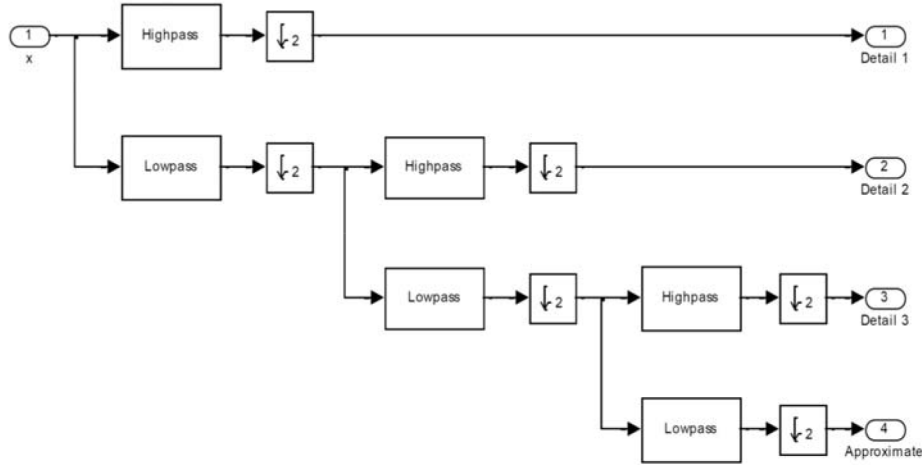

Figure 5. Filter bank representation of the wavelet transform dilation.

Considering $a_0(n)$ as sampled values of the $f(t)$ signal, each wavelet function consists of two sets of coefficients that divide $a_0(n)$ into two groups. One of these is the set of coefficients for the high-pass decomposing filter denoted by $g(n)$. The other one, denoted by $h(n)$, consists of the low-pass decomposing filter coefficients. Values derived by applying $g(n)$ filter coefficients to $a_0(n)$ are called signal details and represented by d (stands for detail). On the other hand, values obtained via applying $h(n)$ filter coefficients to $a_0(n)$ are called signal approximation and denoted by a (stands for approximation) [17].

When voltage values of each phase are measured at the PCC during simulation, their wavelet transform is calculated using the Daubechies mother wavelet in a time span of 20 ms (one cycle) up to tenth-order detail.

The wavelet transform could be considered as a 20-ms window, which moves along the simulation time, and its output is the wavelet transform of each phase. In this step the system is simulated several times and the output of the wavelet transform for each phase is examined so that distinct features of various details during fault occurrence, capacitor switching, and load switching can be identified.

4.3. Feature extraction

Due to the high frequency nature of transients in power systems (compared to its nominal frequency), transient identification requires examining high-order details of wavelet transform output. After several simulations and investigating wavelet output for each phase, it was concluded that the average amplitude of three-phase seventh-order detail is considerably higher in the case of capacitor switching. For instance, Figures 6 and 7 demonstrate the voltage waveform of phase A during capacitor switching and single-phase-to-ground fault, respectively. Both events occur at t = 34 ms.

Figure 8 presents seventh-order detail output (average of three phases) for capacitor switching and fault condition. Before event occurrence both outputs have the same value but after t = 34 ms, seventh-order detail output for capacitor switching increases, and during 20 ms (allowable detection time), seventh-order details of the two conditions have meaningful difference.
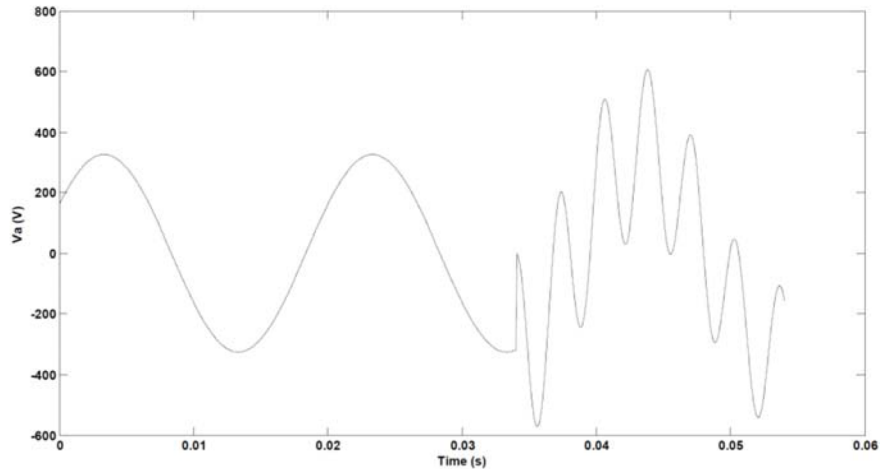
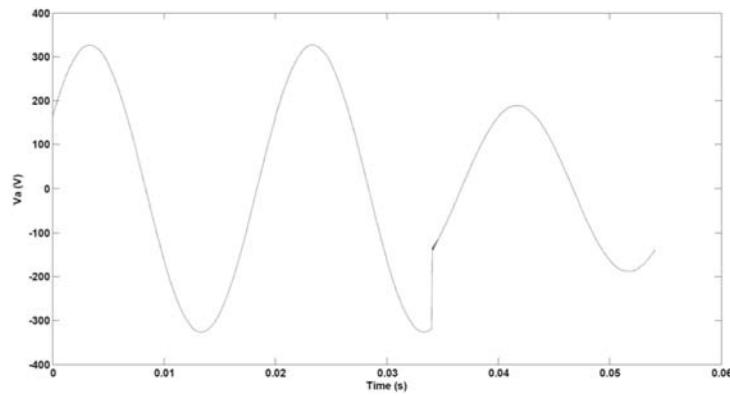**Figure 6.** Phase A voltage waveform during 200 kVAR capacitor bank switching.

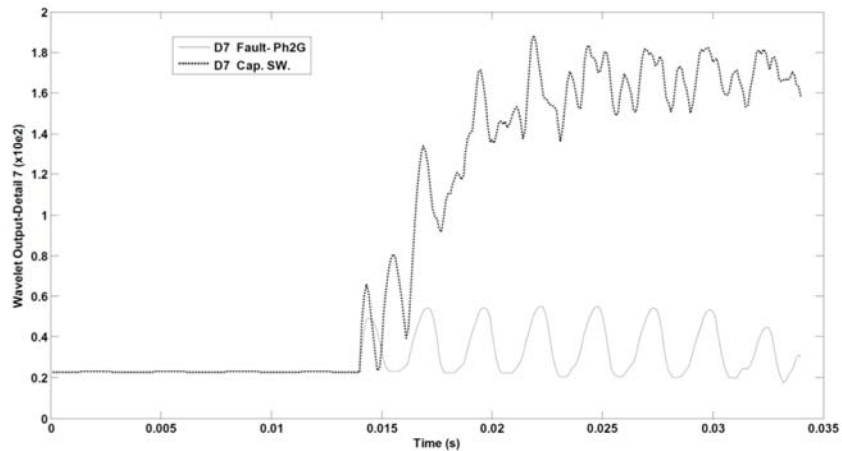**Figure 7.** Phase A voltage waveform during single-phase-to-ground fault.

Figure 8. Average of seventh-order detail output of wavelet transform for three phases during fault and capacitor switching.

It is noticeable that the length of the wavelet window is considered to be one cycle; therefore, the output of the transform seen in Figure 8 leads to waveforms of Figures 6 and 7 for 20 ms. In other words, if the event occurs at t = 34 ms, wavelet output changes at t = 14 ms. Investigating seventh-order details for fault

condition and load switching reveals that they are not significantly different (Figure 9), whereas their difference might be observed when ninth- and tenth-order details are considered. For this purpose, the sum of ninth- and tenth-order details of all three phases are utilized. Figure 10 depicts the difference between these transients.
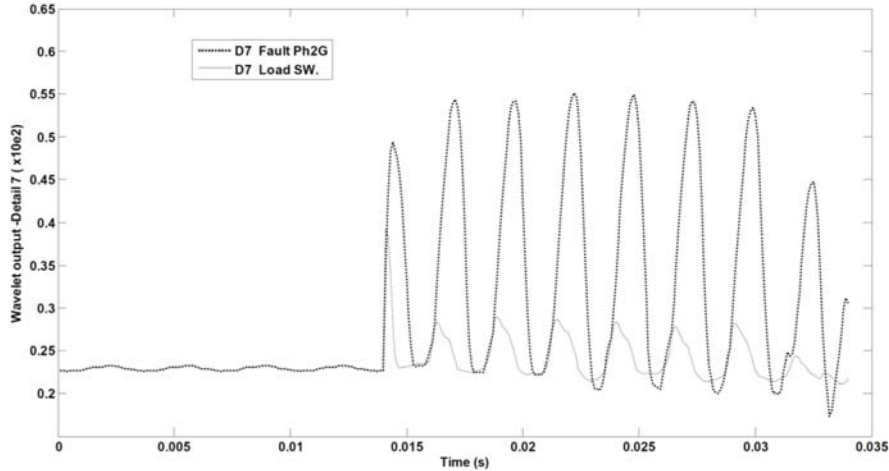

Figure 9. Average of seventh-order detail output of wavelet transform for three phases during fault and load switching.
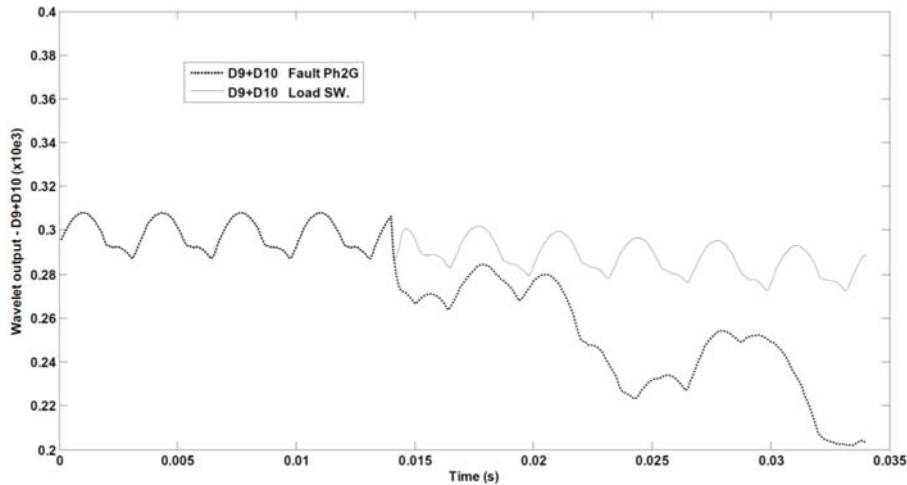

Figure 10. Average of sum of ninth- and tenth-order details output of wavelet transform for three phases during fault and load switching.

4.4. Generating sample data

Sample data for training the SVM are generated by changing the event time during one cycle and varying the type of event. Changing the event time from 0 to 20 ms with 200-μs steps generates 100 values for the voltage wavelet output in each phase. Furthermore, diverse data are generated by changing the type of event. The considered events include four types of error after the transformer (three-phase, single-phase-to-ground, phase-to-phase, and phase-to-phase-to-ground), seven types of capacitor switching (considering different combinations of connecting five capacitor banks to the system), and load switching. Moreover, data associated with fault events that occur before the transformer are considered.

4.5. SVM design

In this study two approaches are proposed for data classification and SVM design considering the number of inputs (seventh-order details and sum of ninth and tenth details) and output (identifying load switching, capacitor switching, and different types of faults).

In the first approach two SVMs are trained. As mentioned, seventh-order details of the wavelet for the fault event and capacitor switching are considerably different while these values for fault and load switching are almost the same. On the other hand, the sum of ninth- and tenth-order details could be used to distinguish between fault and load switching. Based on these facts, in the first SVM the input is D_7. One denotes capacitor switching, whereas zero is returned in the event of a fault or load switching. In the second SVM, the input is $D_9 + D_{10}$; 1 denotes load switching while zero represents a fault. These two SVMs are connected at the final stage.

In the second approach a three-class SVM is utilized instead of two SVMs. First, three two-class SVMs with D_7 and $D_9 + D_{10}$ as inputs are trained. Afterwards, they are related in such a way that they can demonstrate which type of event has occurred (fault, capacitor switching, or load switching). For this purpose, the sign of capacitor switching is assumed to be one while the others are zero. In the second SVM, load switching is denoted by one while the others are zero. Finally, in the third one, the sign of faults is one while the others are zero. Utilizing the values obtained from these three SVMs, one may conclude which of the above events has occurred.

4.6. Simulation results

In this subsection results of our program as well as waveforms are presented in different conditions. To gain a better understanding about the efficiency of our proposed method, various conditions such as simultaneous switching of several capacitor banks, capacitor switching, and fault occurrence are simulated. In Figure 11, the voltage diagram and the output associated with simultaneous switching of three capacitors are depicted. According to this figure, at t = 8 ms, three capacitor banks are connected to the system and change the voltage waveform. The type of transient is accurately identified. Additionally, Figures 12 and 13 respectively demonstrate the voltage diagram and output when load switching and a single-phase-to-ground fault occur at t = 8 ms; they are correctly detected, as well. Figure 14 illustrates a condition in which three different events occur simultaneously; two capacitors are switched, phase-to-phase fault on the right side of the transformer occurs, and load is switched. As can be seen, in this case the voltage waveform is complicated; however, the proposed method is able to detect the most suitable condition (fault occurrence).

4.7. Evaluating the precision of the proposed method

The proposed method is extremely precise. To prove the precision of our method, the MSE criterion is used to calculate the error. In this regard, a number of experimental data are randomly generated. Then they are checked using the trained SVM and the MSE is calculated. To obtain test data, the time of fault, capacitor, and load switching occurrence is considered to be between the times obtained from SVM training. The calculation is done similar to what was performed for the main data. Afterwards, the provided data are delivered to the trained SVM and the difference between the results and main data as well as the MSE are derived.

Moreover, the accuracy of the obtained results by the proposed method is compared to the neural networks method in this section. For this purpose, the accuracy of the neural networks method is evaluated by MSE criteria, similar to the proposed method. The Table displays the different methods' accuracy. According to this table, the acquired MSE by feedforward backpropagation neural network method is equal to 0.0047, which means that its accuracy is 99.53%.

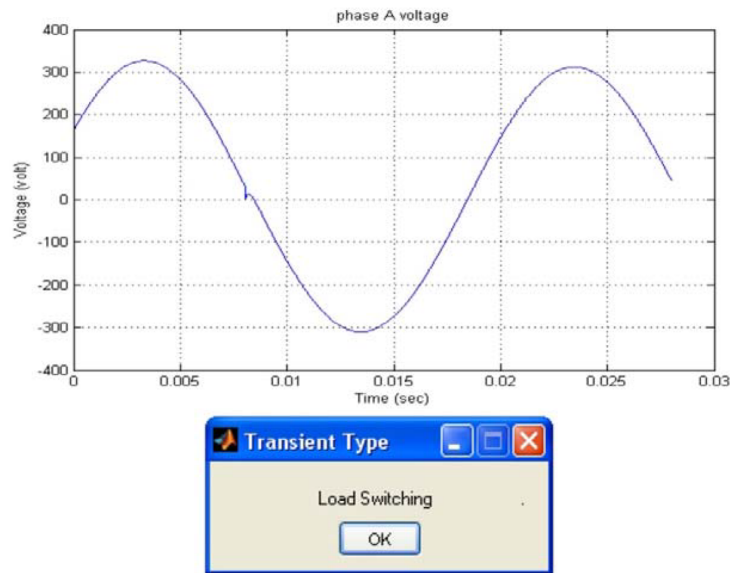**Figure 11.** Voltage diagram and the output associated with simultaneous switching of three capacitors.

Figure 12. Voltage diagram and output in case of load switching.

Table. Comparison between classification accuracy of the proposed approaches and neural network.

Proposed method				Neural network feedforward	
First approach		Second approach		backpropagation	
MSE	Accuracy	MSE	Accuracy	MSE	Accuracy
0.0041	99.59%	0.0031	99.69%	0.0047	99.53%

The MSE of the first approach (using two SVMs) is 0.0041. Thus, the accuracy is 99.59%. As there are two SVMs in this approach, two values are derived as MSEs, of which the larger is considered as error.

The MSE of the second approach (three-class SVM) is 0.0031, indicating 99.69% accuracy. In this approach the SVM has two inputs so it utilizes both of them for training, which, in turn, decreases the error.
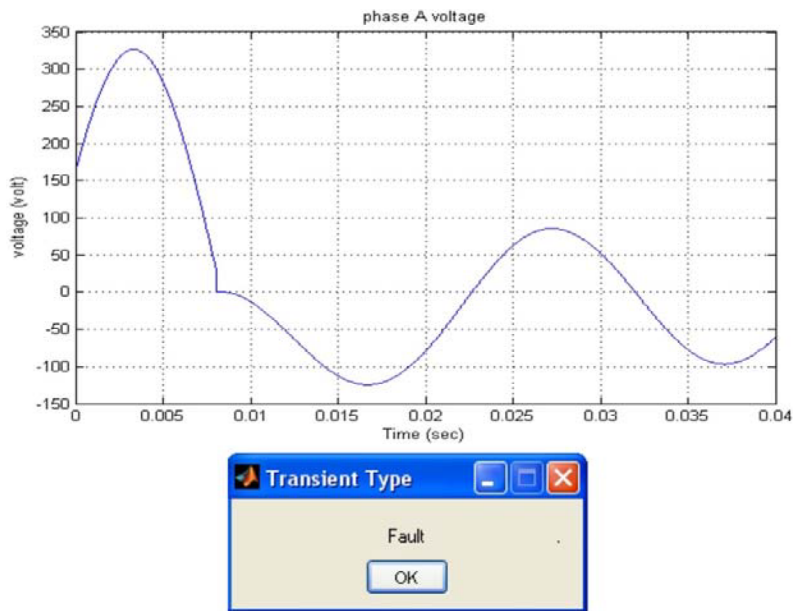
Figure 13. Voltage diagram and output in case of single-phase fault on the right hand side of the transformer.
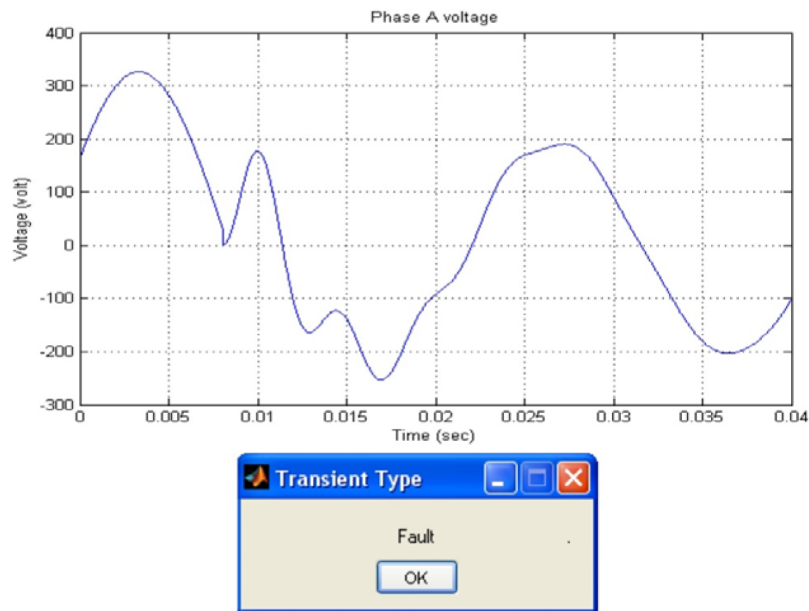

Figure 14. The voltage diagram and output when two capacitors are switched, phase-to-phase fault on the right side of the transformer occurs, and load is switched.

5. Conclusion

There are several methods to distinguish the transient phenomenon of capacitive switching from faults in systems, of which one of the most important methods is utilization of the wavelet transform. Using the wavelet transform, a sampling signal from intended quantity is broken to different frequency scales, and the possibility of finding common properties between switching phenomena and faults is provided according to the contribution of each of these scales.

In this paper, a new method for recognizing and classifying types of faults, transients due to capacitive switching, and loads is presented based on wavelet transform. Afterwards, a multiclass SVM method is presented with two approaches for the sake of classifying different phenomena, and the accuracy of the results is compared to the neural network method. It was demonstrated that the SVM is able to distinguish between faults, capacitor switching, and load switching with high accuracy. The results were explicated in detail and revealed that the SVM provides valid results. According to the results, the proposed method can be used as a classifier of different types of events to distinguish between faults and other transients of the system.

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