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A novel protection scheme for synchronous generator stator windings based on SVM

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Abstract

This paper proposes a novel scheme for detecting and classifying faults in stator windings of a synchronous generator (SG). The proposed scheme employs a new method for fault detection and classification based on Support Vector Machine (SVM). Two SVM classifiers are proposed. SVM1 is used to identify the fault occurrence in the system and SVM2 is used to determine whether the fault, if any, is internal or external. In this method, the detection and classification of faults are not affected by the fault type and location, pre-fault power, fault resistance or fault inception time. The proposed method increases the ability of detecting the ground faults near the neutral terminal of the stator windings for generators with high impedance grounding neutral point. The proposed scheme is compared with ANN-based method and gives faster response and better reliability for fault classification.

Keywords: Support vector machine, Artificial neural networks, Synchronous generator, Differential protection, Fault detection, Fault classification

1 Introduction

Synchronous Generators are the majority source of commercial electrical energy. The failure of SGs cause severe damage to the machine, interruption of electrical supply, and ensuing economic loss. Therefore, it is essential to have a protection system that is able to detect and diagnose all credible faults and provide effective protection for the SG to increase their useful life and reliability. Internal faults present a real challenge for the protection of electrical machines; especially ground faults in case of high impedance grounding as they are not detectable by differential relays, the most commonly devices used for generator protection. Hence, a reliable and accurate diagnosis of internal faults is still a challenging problem in the area of fault diagnosis of electrical machines [1]. This fact has motivated many works over long period to develop various protection techniques [2–13] include digital, Artificial Intelligence (AI) and other machine learning techniques.

A digital computer technique for the protection of a generator against internal asymmetrical faults has been introduced in [2]. The technique relies on the detection of a second harmonic component in the field current at the onset of a fault in the armature windings. The discrimination against external faults is achieved by monitoring the direction of the negative sequence power flow at the machine terminals. In [3], a digital technique for detecting internal faults in the stator windings of synchronous machine, using positive- and negative-sequence models of the SG, has been introduced. The performance of that technique was evaluated using fault data generated by applying electromagnetic transient program (ETP). Authors in [4, 5] introduced a power-based protection algorithm to provide protection for non-utility generation units against islanding. Another power-based algorithm was introduced in [6] for detecting pole-slipping conditions using three phase power measurements taken at the generator's terminals.

AI techniques have been increasingly used for fault diagnosis of SGs. Among various AI techniques, Artificial Neural Network (ANN) method has become the most widely used tool for solving complex electric power system problems. Fault detection in SGs is one of the areas of intensive application of ANN because of their superior learning, generalization capabilities, and fault-tolerance capabilities [8–13]. Unfortunately, the diagnostic accuracy of ANN cannot be high enough due to the limitations of 'over-fitting' and slow convergence velocity.

Rapid development of the Support Vector Machine (SVM) [14] and its capability to successfully solve the

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problems with ANN [15] resulted in a wide use of this tool in many applications in recent years [16–23]. These applications include: fault detection in transformers during impulse test [16], prediction and control of fuel cell operating conditions [17], load forecasting process in a deregulated power system [18], fault detection [19, 20], modeling of nonlinear dynamic systems [21], power quality events recognition [22] and voltage disturbance classification [23].

In this paper a new scheme for protecting the stator windings of a SG using SVMs is introduced. A multi-layer SVM classifier is proposed to detect and classify the internal faults on stator windings of a SG using the instantaneous values of three phase currents on both sides of the SG stator windings. The algorithm is verified using simulation results to evaluate the performance of the proposed method in terms of accuracy and speed. A typical 100 MVA, 13.8 kV, 50 Hz synchronous generator is simulated using Matlab/Simulink software to generate the required test data. The test data obtained from simulation covers all possible states of the SG; namely normal state, internal fault state and external fault state at various conditions such as: fault type, fault location, fault resistance and fault inception angle.

The rest of the paper is organized as follows. Following this introduction, a brief description of the SVM is presented in Section 2, whereas in section 3 the proposed protection scheme is presented. The test system and results are presented in section 4.

2 Classifications with SVM

SVM is a machine learning based method that is applied to classify input data patterns into predefined classes. SVM is based on the idea of a hyper plane classifier, where data space is divided into classes separated by a hyper plane. The goal of SVM is to find a linear optimal separating hyper plane so that the margin of separation between the two classes is maximized [24–27]. Figure 1 illustrates the SVM classification principles where it shows the support vectors and the training data.

Assuming that the data space X consists of several input vectors, x_i :(i = 1, 2,.... N), where x_i are components belong to one of two different classes, and N is the number of samples. The class label of x_i is $y_i = \{1, -1\}$ which indicates the class to which xi belongs.

The principle of operation of SVMs classifier will be modified according to the type of the data samples. For linearly separable data the hyper-plane satisfies the following equality equation:

$$w^T x + b = \sum_{i=1}^{N} w_i x_i + b = 0 \tag{1}$$

where w is a normal vector on the hyper-plane, and b is a bias representing the distance from the origin.

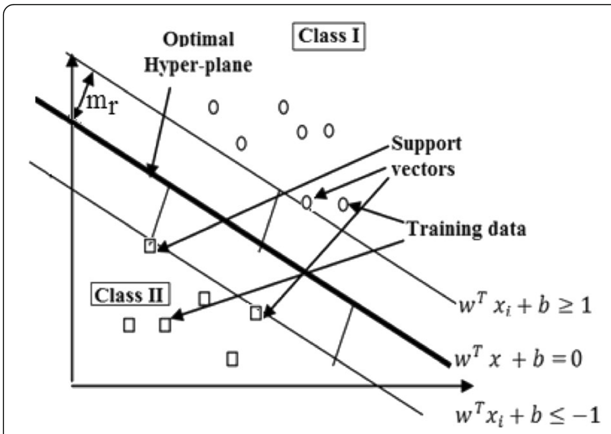

Fig. 1 SVM classification principles

The separating hyper-plane that creates the maximum distance between the plane and the nearest data is called the optimal separating hyper-plane as shown in Fig. 1. The maximum-margin classifier is the discriminate function that maximizes the geometric margin $1/||w||$, which is equivalent to minimizing $||w||^2$. This leads to the following constrained optimization problem [28, 29]:

Minimize: $m = \frac{1}{2}\|w\|^2$

Subject to:

$$y_i\left(w^T x_i + b\right) \geq 1 \ \text{ for } i = 1, 2, \ldots N \tag{2}$$

The constraints in this formulation ensure that the maximum margin classifier classifies each example correctly, which is possible since we have assumed that the data are linearly separable.

The objective of maximizing the margin i.e., minimizing $||w||^2$, will be augmented with a term $C\sum_{i=1}^{N}\zeta_i$ to penalize misclassification and margin errors, where ζ_i are slack variables that allows an example to be in the margin and is called a margin error ($\zeta_i \geq 1$). The optimization problem now becomes [28]:

Minimize:

$$\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N}\zeta_i \tag{3}$$

Subject to:

$$\begin{aligned} &y_i(w^T x_i + b) \geq 1 - \zeta_i \ \text{for} \ i = 1, 2, \ldots N \\ &\zeta_i \geq 0 \quad \text{for all} \ i \end{aligned} \tag{4}$$

With the help of Lagrange multipliers, the dual form of the above minimization problem is:

Minimize:

$$W(\alpha) = \sum_{i=1}^{N}\alpha_i - \frac{1}{2}\sum_{i,k=0}^{N}\alpha_i \alpha_k y_i y_k x_i^T x_k \tag{5}$$

Subject to:

$$\sum_{i=1}^{N} y_i \alpha_i = 0, \quad 0 \le \alpha_i \le C, \quad i = 1,\ 2,\ \dots..N \tag{6}$$

The number of variables of the dual problem is the number of training data. Let us denote the optimal solution of the dual problem with α* and w*. The training examples x_i is a support vector (SV). The number of SVs is considerably lower than the number of training samples making SVM computationally very efficient. The value of the optimal bias b* is found from the geometry,

$$b^* = -\frac{1}{2}\sum_{SVs} y_i \alpha_i^* \left(S_1^T x_i + S_2^T x_i\right) \tag{7}$$

where S_1 and S_2 are the arbitrary SVs for class-I and class-II, respectively.

Only the samples associated with the SVs are summed because the other elements of the optimal Lagrange multiplier α* are equal to zero. The final decision function is given by:

$$f(x) = \sum_{SVs} \alpha_i y_i x_i^T x + b^* \tag{8}$$

The unknown data sample x are then classified as:

$$x = \in \begin{cases} Class\text{–}I & \text{if} \quad f(x) \ge 0 \\ Class\text{–}II & \text{otherwise} \end{cases} \tag{9}$$

The nonlinear classification problems can be solved by applying Kernel functions. The classified data is mapped onto a high-dimensional feature space where the linear classification is possible. Kernel functions are defined as follows:

$$K(x_i, x_k) = \varphi(x_i).\varphi(x_k) \tag{10}$$

substituting by (10) into Kuhn-Tucker conditions (5) results in:

Maximize:

$$W(\alpha) = \sum_{i=1}^{N} \alpha_i - \frac{1}{2}\sum_{i,k=0}^{N} \alpha_i \alpha_k y_i y_k K(x_i, x_k) \tag{11}$$

Subject to:

$$\sum_{i=1}^{N} y_i \alpha_i = 0\ , \quad 0 \le \alpha_i \le C, \quad i = 1,\ 2,\ \dots..N \tag{12}$$

Different types of kernels can be used to train SVMs. The most commonly used kernel functions in power system applications are Linear, Polynomial and Gaussian radial basis functions (RBF) [22, 23, 26–33], they can be defined as:

Linear:

$$K(x_i, x_k) = x_i.x_k \tag{13}$$

Polynomial:

$$K(x_i, x_k) = \left(x_i^T.x_k + 1\right)^n, \quad n > 0 \tag{14}$$

Gaussian (***RBF***):

$$K(x_i, x_k) = \exp\left(\sigma \left\| x_i^T - x_k \right\|^2\right), \quad \sigma > 0 \tag{15}$$

where n is the degree of kernel inner product, $\sigma = -\frac{1}{2\gamma^2}$ and γ is the kernel width parameter.

3 SVM Methodology for Generator Protection

This section describes the generalization of SVMs classification technique to the protection of a SG stator windings. Firstly, the proposed scheme is introduced followed by the details of each of its parts. The heart of the proposed scheme composed of two SVM classifiers that receive instantaneous 3 phase current measurements and based on these current measurements the classifiers decide whether the SG is in normal or fault condition. The classifiers also determine whether the fault is internal or external. The main purpose of using SVM classifiers is to free the proposed protection scheme of the over fitting and slow convergence limitations experienced by other techniques, and hence to improve the diagnostic accuracy. The diagnostic accuracy of the proposed scheme, as all other machine learning based techniques, depends on its training in terms of how sufficient and representative the training data sets are.

3.1 Proposed protection algorithm

Figure 2 presents a combined functional block diagram and a flow chart of the proposed protection scheme. The proposed procedure for fault classification can be described in the following steps:

1- The three phase currents at both ends of the SG stator windings are sampled at a sampling frequency of 1 kHz.
2- An anti-aliasing filter eliminates the current samples corrupted by high frequency transients to ensure effective and accurate discrimination of internal faults.
3- A moving window current waveform of 4 samples width, less than a quarter of a cycle, is used as the input pattern to the SVM1 classifier. The output will be -1 in case of a fault occurrence (either internal or external), and will be +1 for normal state.
4- In case of a fault occurrence, SVM2 discriminates between internal and external faults.
5- The step length of moving window is taken as one sample, where the window is moved one sample ahead in each calculation step. The steps 1 to 4 are repeated unless a fault is detected and the SG is tripped.

3.2 SVM classifiers

As stated earlier and illustrated in Fig. 2, the proposed protection scheme employs two SVM classifiers to discriminate between the normal, internal fault and external fault states of the SG. SVM1 is trained to distinguish between normal and fault states. If the input pattern to

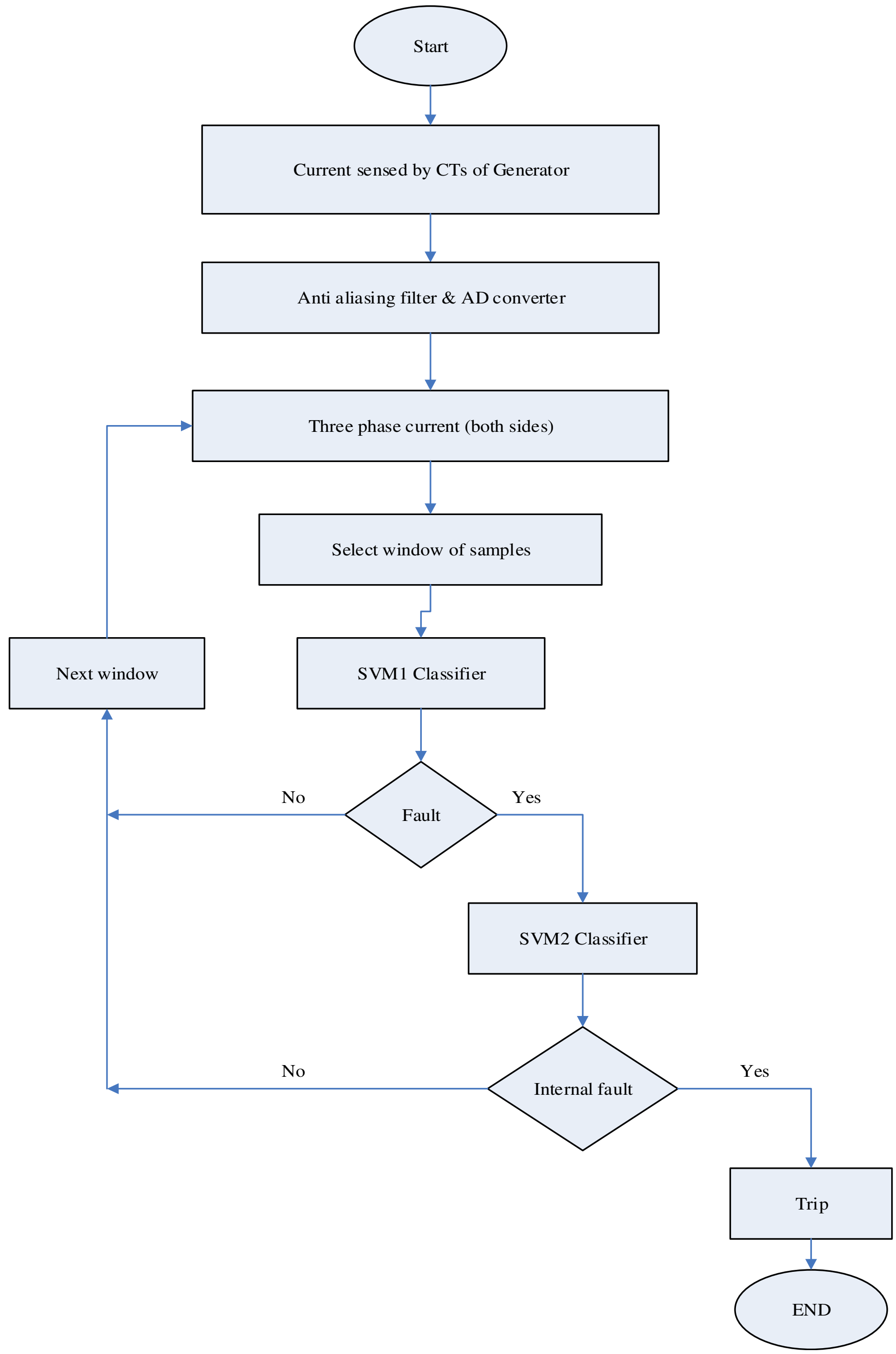

Fig. 2 Procedure for fault classification

SVM1 represents a normal state, its output is set to +1; otherwise it is set to - 1. On other hand, SVM2 is trained to discriminate between internal fault state and external fault state. Its output will be +1 for input patterns representing internal faults and -1 otherwise.

In the training process of SVMs, the three prescribed kernel functions are tried and tested. The two functions that give the desired performance are used for the test cases. These two functions are the polynomial kernel function and the kernel radial basis function (RBF). Selection of the optimum parameters for SVMs is done during the training process using training data. The SVM classifier with the best performance is obtained by testing different values of the kernel parameters. These parameters are varied in the following manner; kernel width parameter γ is varied in the range [0.1, 5] with a step of 0.05. The order of the polynomial kernel n is varied in the range [1, 10] with a step of 0.5. The penalty due to the error C is varied in range [1, 1000] with a step of 1. The values of the used kernel parameters are shown in Table 1. The performances of the two SVMs are assessed for each combination of these values by calculating the classification accuracy (CA) defined as:

$$CA\% = \frac{Correctly\ classified\ patterns}{Total\ \ patterns} \times 100 \quad (16)$$

From these results, the SVM classifier with the highest percentage classification accuracy is selected. The testing and generalization processes are then performed.

3.3 Training and testing patterns for SVMs

Since the classification technique is based on a supervised learning mechanism, it needs to be trained for possible normal and faulty states of SG. In this paper, training and testing data sets are obtained through excessive simulations for different operating conditions.

In general, a large number of cases that covering all the credible conditions and representing the whole data space are required for training. In this work, a total training and testing set of 4600 patterns representing different cases of the generator states are generated via simulation of the SG. Each training or testing pattern consists of 24 elements; these elements represent 4 samples of each of the three phase currents at the two sides of the SG stator windings. Details of these training and testing patterns are presented in section 4.

3.4 Data preprocessing

Data preprocessing is implemented for the purpose of correcting errors that may present in the raw data. To improve generalization capability of SVM, the preprocessing of training data may include data smoothing, excluding odd values, and normalizing experimental data. Also, unequal interval data series are transformed into equal interval series by linear interpolation to train SVMs.

4 Results and Discussion

This section presents the test system and the details of the training and testing data sets as well as the results of applications of the proposed scheme.

Table 1 Values of the used kernel parameters

Parameter	Values
Kernel width parameter, γ	0.1:0.05: 5
Order of polynomial kernel, n	1:0.5: 10
Penalty due to the error, C	1: 1000

4.1 System under study

The data required for training and testing SVMs are obtained through Matlab/Simulink simulations. These training cases were selected so that the obtained training data should contain necessary information to generalize the problem. A suitable SG model is required to characterize the different operating and fault conditions. The fault conditions include fault type, location, and resistance and inception angle. In a previous work [34], the authors have developed a dynamic model to simulate generator states (internal fault, external fault, normal states). Three phase power system was simulated and the input/output pair patterns were generated. That developed model will be used in this paper to represent the SG.

The test power system consists of a three phase SG connected to an infinite bus through a transmission line. The measured devices are located at the two ends of the generator. A single line diagram of the modeled power system is shown in Fig. 3.

The training cases include: five generator loading conditions (50, 60, 70, 80 and 90% of rated MVA), three values of fault resistance (0 Ω, 10 Ω and 20 Ω), ten fault locations on stator windings (10, 20, 30, 40, 50, 60, 70, 80, 90, and 100% from the neutral point), four fault types (single line to ground (SLG), Double line to ground (DLG), line to line (LL), and three phase fault (3 ph)), seven fault incipient time instants (0.07, 0.072, 0.075, 0.078, 0.08, 0.085 and 0.088 s) and current transformer saturation condition.

The testing cases include: three generator' loading conditions (55, 65, 75% of the rated MVA), two values of fault resistance (5 Ω, 15 Ω), ten fault locations on stator windings (5, 15, 25, 35, 45, 55, 65, 75, 85, and 95% from the neutral point), four fault types (SLG, DLG, LL, and 3 ph) and current transformer saturation condition.

The total training and testing patterns are classified as:

- 1200 patterns represent the normal operation state. They are generated by applying three phase balanced operation at different loading conditions.

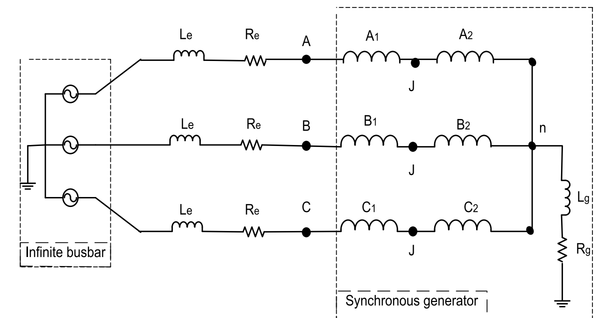

Fig. 3 Single line diagram of the modeled power system

- 800 patterns represent the external fault state. They are generated by applying different types of external faults at various locations along a transmission line.
- 2600 patterns represent the internal fault state. They are generated by applying different types of internal faults at different locations on the stator windings.

4.2 SVMs training and testing results

Many SVMs with different values of kernel parameters were trained and tested using Matlab toolbox. The classification accuracy of the SVMs is determined by applying (16) to all of the 3800 training patterns. Tables 2 and 3 show the SVMs with the highest classification accuracies for both the Polynomial kernel function; and the Gaussian kernel function respectively.

From the above results, it can be noticed that the highest training efficiency obtained with the polynomial kernel function is 99.8% for SVM1 and 99.67% for SVM2. The highest accuracy for SVM1 has been achieved with the value of $C = 883$, and $\gamma = 0.1$, whereas for SVM2: parameter values for the highest accuracy are $C = 725$, and $\gamma = 0.15$. These parameters are used for "learning" the two proposed SVMs. Once the training is completed, the trained SVMs are used for testing the new patterns. Table 4 illustrates the classification accuracy of the designed SVMs for testing data.

To help judging the validity and accuracy of the proposed system, the SVMs results have compared with those obtained using an ANN-based system [13]. In that study the ANN-based method was applied to detect and classify different types of SG faults. The same training and testing data described above have been used to train the ANN-based system. A comparison between the two methods is depicted in Tables 5 and 6. It can be noticed that the proposed SVMs-based technique is faster and more accurate (both for training and testing patterns) than ANN-based method.

Table 6 lists the time taken by both the ANN-based and the proposed methods to detect a fault. It is clear that proposed SVMs-based method takes shorter time to detect a fault for all of the tested fault types.

Table 2 SVMs for the Polynomial kernel function during the training process

	SVM	kernel width parameter γ	Penalty due to the error C	Accuracy of SVM%
1	SVM1	0.55	231	98.601
	SVM2	0.40	437	96.455
2	SVM1	0.50	404	95.745
	SVM2	0.35	578	88.461
3	SVM1	0.3	77	99.117
	SVM2	0.8	85	98.096
4	SVM1	0.1	883	99.80
	SVM2	0.15	725	99.67

Table 3 SVMs for the Gaussian kernel function during the training process

	SVM	Order of polynomial kernel n	Penalty due to the error C	Accuracy of SVM%
1	SVM1	1.5	265	95.143
	SVM2	1	104	96.257
2	SVM1	2	513	95.328
	SVM2	6	682	81.250
3	SVM1	3	610	92.341
	SVM2	2	595	96.861
4	SVM1	8.5	490	94.654
	SVM2	9	463	86.095

4.3 Case studies

This section presents the details of four test cases to illustrate the ability and accuracy of the proposed method to detect and diagnose a fault.

4.3.1 Case I: External fault

An external SLG fault is simulated at the middle of the transmission line. The pre-fault power flow from generator to infinite bus is P =1p.u. at p.f of 0.85 lag. Figure 4-a shows the three-phase currents at the two ends of the stator windings for a fault incident at t =0.077 s. It can be noticed that currents at both ends of the stator windings are identical as the fault is external. Figure 4-b shows the classification label generated by SVM1 and SVM2. It can be seen that the output of SVM1 is +1 indicating no fault condition until t =0.077 s, time of fault occurrence, then it changes to -1 indicating a fault condition. The output of the SVM2 become +1 at t =0.077 s detecting the external fault.

4.3.2 Case II: SLG fault at 55% of stator windings

This is a case of an internal SLG fault occurred at 55% of stator windings away from the neutral point at $t = 0.077$ s. The fault resistance is 5 Ω, the pre-fault power flow from the generator to infinite bus is $P = 1$ p.u. at p.f 0.85 lag. Figure 5-a shows the waveform of the three-phase currents. It can be observed that the currents of phase (a) at both ends of the stator windings are now different ia1 and ia2. The current ia2 has a larger value due to short circuit occurrence (this is the sum of the ground fault current and the load current).

Table 4 Classification accuracy of the designed SVMs

SVM	No. of testing patterns	Correct patterns	Incorrect patterns	Classification accuracy %
SVM1	800	758	42	94.75
SVM2	600	553	47	92.17

Table 5 Comparison between accuracy and training time for ANN and SVMs methods

Method	Accuracy for training patterns %	Accuracy for testing patterns %	Training time (s)
SVM1	99.80	94.75	<1
SVM2	99.67	92.17	<1
ANN [13]	93.7	89.1	10

Figure 5-b illustrates the response of the SVM1 and SVM2 as a function of the time (sec). The output of SVM1 is almost the same as in case I, that is +1 indicating no fault until $t = 0.077$ s and then -1 indicating fault incidence at $t = 0.077$ and afterwards. The output of the SVM2 become -1 at $t = 0.077$ s indicating that fault detected by SVM1 is an internal fault. The response of SVMs in this case and in the previous case proved the ability of the proposed technique to discriminate between healthy and faulty conditions and also between internal and external faults.

4.3.3 Case III: Three phase to ground fault at 75% of stator windings

A three phase to ground fault is simulated at 75% of stator windings away from the neutral point. The fault resistance is 15 Ω. The inception fault time is $t = 0.075$ s. The pre-fault power flow from generator to the infinite bus is $P = 0.9$ p.u. at power factor of 0.75 lag. Figure 6-a shows the input current waveforms of the SVM fault classifier and Fig. 6-b illustrates the response of the SVM1 and SVM2 as a function of the time (sec). It can be noticed that despite the big difference in fault currents, the SVMs have given the right classification of the fault condition as in case II.

4.3.4 Case IV: SLG fault at 5% of stator winding

In this case a single line to ground fault is placed at 5% of stator windings away from the neutral point. The fault resistance is 15 Ω. The inception fault time is $t = 0.073$ s. The pre-fault power flow from generator to infinite bus is $P = 1$ p.u. at power factor of 0.8 lag.

Figure 7-a shows the input current waveforms of the SVM fault classifier and Fig. 7-b illustrates the response of the SVM1 and SVM2 as a function of the time (sec). It can be noticed that the SVMs have correctly classified the fault incident as an internal fault.

From the above case studies, it can be observed that the proposed method succeeded to detect and classify the internal faults in the stator windings whatever the changes

Table 6 Comparison between fault detection time for ANN and SVMs methods

Type of fault	Time to detect the fault (ms)	
	ANN [13]	SVM
Single line to ground	10.9	6.4
Phase to phase	12.8	8.5
Double line to ground	10.6	6.8
Three phase	8.3	5.4

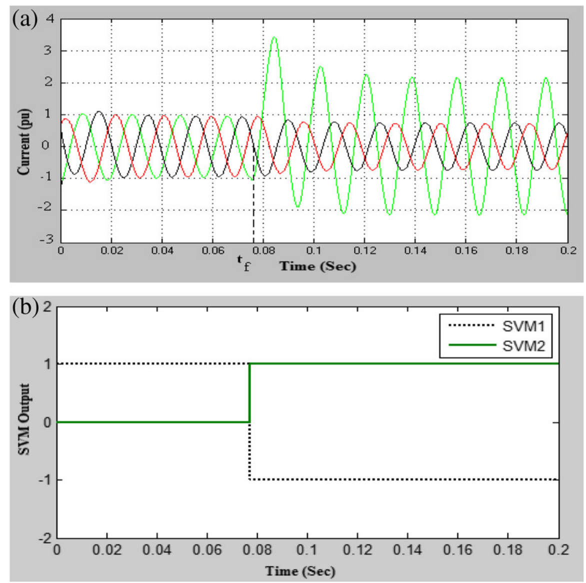

Fig. 4 Response of SVM1 and SVM2 to an external fault. **a** The waveform of the three- phase currents. **b** SVM outputs

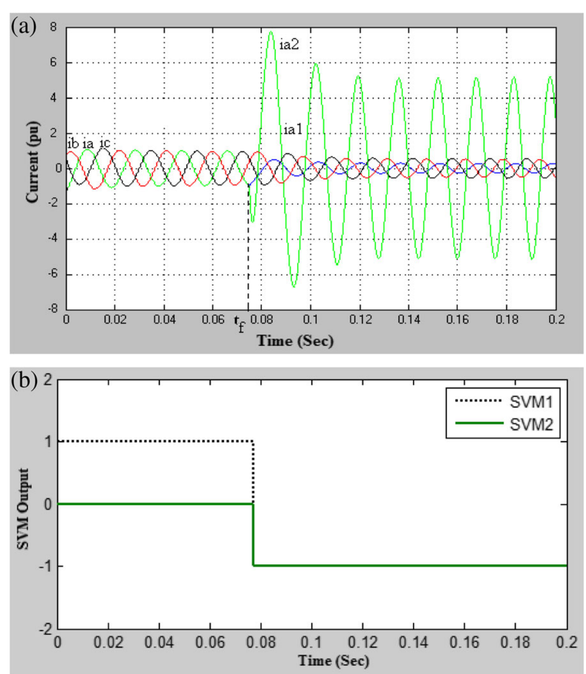

Fig. 5 Response of SVM1 and SVM2 to an internal SLG fault at 55% of stator winding. **a** The waveform of the three-phase currents. **b** SVM outputs

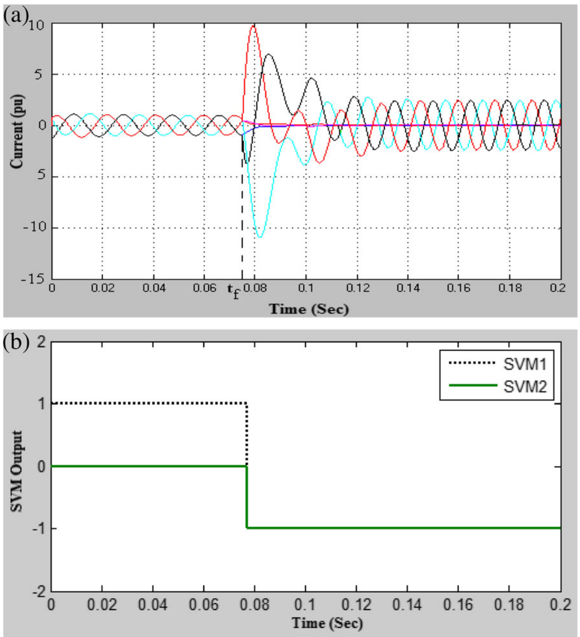

Fig. 6 Response of SVM1 and SVM2 to a three phase to ground fault at 75% of stator windings. **a** The wave form of the three phase currents. **b** SVM outputs

in the prescribed conditions i.e. the fault location, resistance, inception angle or the pre-fault loading conditions.

Extensive simulation results show that the SVM based fault classifier gave excellent predictive ability in all simulation tests. The results show also the stability of the SVM

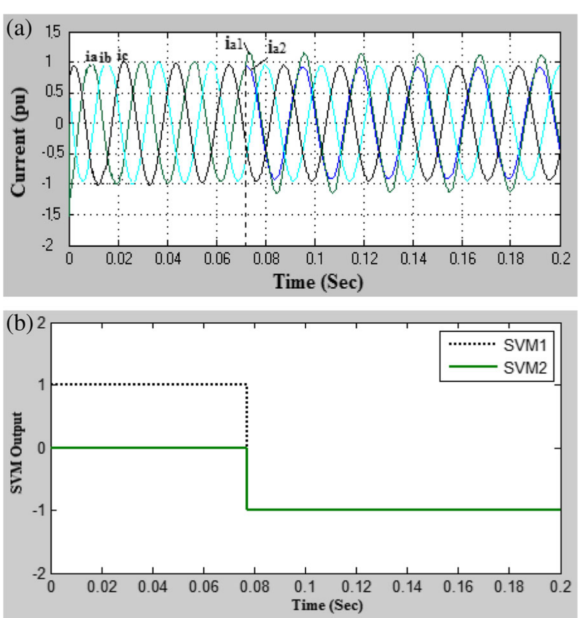

Fig. 7 Response of SVM1 and SVM2 to an internal SLG fault at 5% of stator windings. **a** The wave form of the three phase currents. **b** SVM outputs

outputs under normal steady state conditions and rapid convergence of the output variables to the expected values under fault conditions. This clearly confirms the effectiveness of the proposed SVM based fault detector.

4.4 Verification of synchronous generator internal fault model

The internal fault simulation was verified experimentally (A detailed description of this experimental work is explained in the Additional file 1). A three phase synchronous machine was physically modeled in electric machine lab. at Mansoura university, faculty of engineering. Figure 11 (in Appendix) shows some photos of the tested system. The overall schematic diagram of the experimental system setup is shown in Fig. 8.

The current signals from the power system were obtained through a current transformer. The data acquisition board received the analog signals through an Analog Input Card. The analog filtered signal was then transferred to personal computer, and was converted to a digital one by internal Analog to Digital (A/D) converters. Details of these components are presented in the following items.

i. Universal laboratory machine
The B.K.B. universal laboratory machine set consists of a two-pole uniform air gap universal machine coupled to a dc dynamometer. The nominal rating of the universal machine is 2 kVA as a three phase 50 Hz, 3000 r.p.m. The dynamometer is rated at 3 kW, 220 V, 2000/3000 r.p.m. The parameters of the machine are shown in Appendix (Table 7). All of the winding connections are brought out to the large terminal panel. The stator connections are also terminated at a 24-way socket.

ii. Current Transformer
The current signals are obtained by 100/5 A current transformer. The CT secondaries are connected to shunt resistances to obtain an equivalent voltage signals. The low-level output voltage signals out from transformers are filtered and then are passed as an input to the data acquisition card.

iii. Analog filter
A 2^{nd}-order Butter worth band-pass filter is used to attenuate the dc component and high frequency components. The filter is centered at the nominal system frequency and its pass-band is chosen to be 80 Hz. An array of six filter circuits simultaneously filters the current signals before being fed to the data acquisition system. The filter unit circuit is preceded by an amplifier circuit.

iv. Data acquisition board
The objective of the DAQ is to convert the analog signals into a digital one so that it can be used by the computer. A 1 kHz sampling rate implies 1 ms time

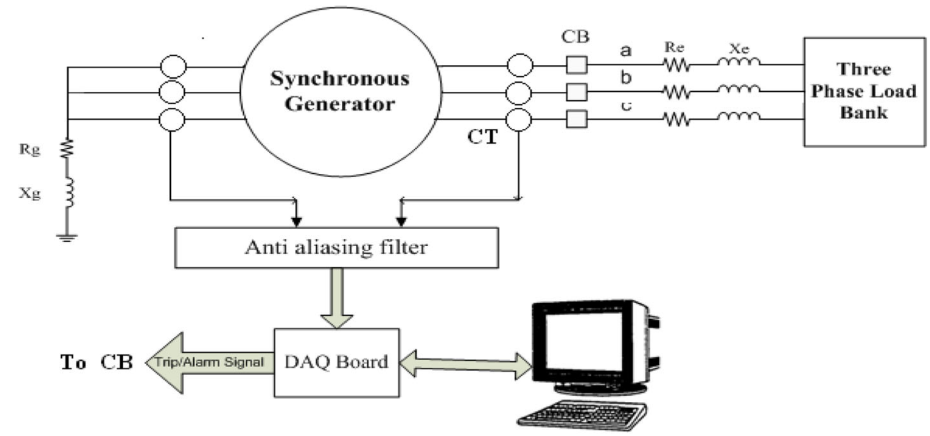

Fig. 8 Schematic diagram of lab work system

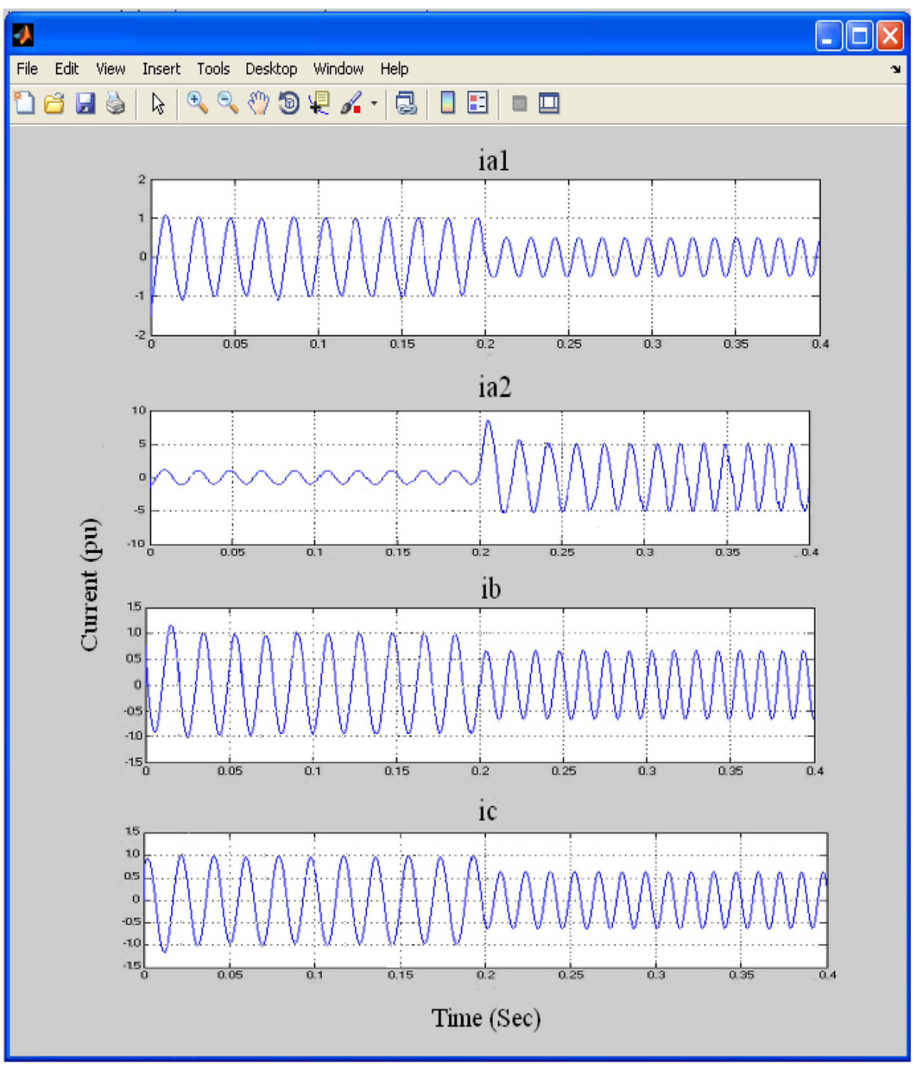

Fig. 9 Stator currents for an internal single phase to ground fault at 50% of phase A winding

interval between samples which is needed for an appropriate software and hardware setup to accomplish protecting relay task within this time interval. To acquire voltage and current signals, a national instruments NI USB-6008 multifunction I/O device is connected to the computer.

Numerous internal fault types such as single phase to ground fault, phase to phase fault, double phase to ground fault, and three phase fault at different locations, inception time and pre-fault loading were applied using the prescribed laboratory system.

For example, simulation and laboratory results for internal single phase to ground faults at 50% of phase A winding are shown in Figs. 9 and 10 respectively. The currents on terminal sides of phase B and C are equal to their counter parts on neutral side, so it is sufficient to show only the currents of one side of each healthy phase. Figure 10 shows the laboratory fault currents for the same case. From the two figures it can be concluded that the current waveforms of the simulated and laboratory are very close in shape and magnitude. There is a small difference in the curves of simulated cases with respect to the experimental ones. These differences are due to the operating environment of physical system, which is not ideal due to the existence of noise, CT errors and CT saturation.

5 Conclusion

This paper proposed a novel scheme based on SVMs for detecting and classifying faults in stator windings of a synchronous generator. Two SVM classifiers have been proposed. SVM1 was used to identify the fault occurrence in the system and SVM2 was used to determine whether the fault, if any, was internal or external. In the proposed scheme, fault detection and identification was performed in less than a quarter cycle of the 3-phases current at the two ends of stator windings. The detection and classification of

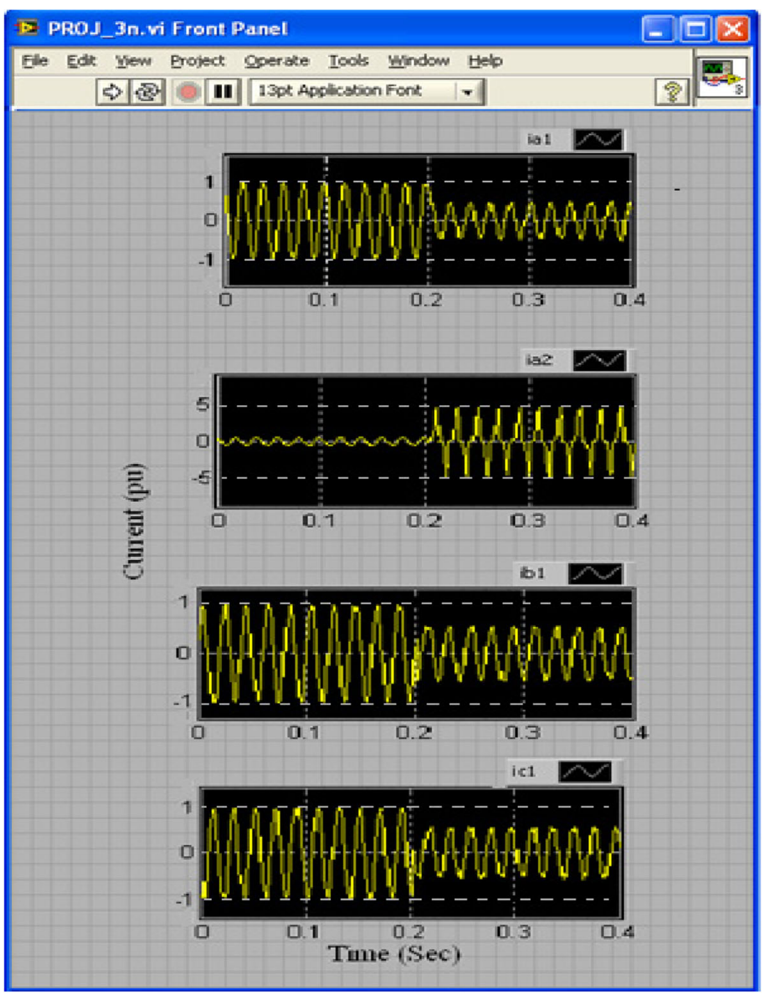

Fig. 10 Recorded stator currents for an internal single phase to ground fault at 50% of phase A winding

faults were not affected by the fault type and location, pre-fault power, fault resistance or fault inception time.

Comparing the proposed SVMs with the ANN-based method prove that the proposed SVM-based method is faster and more accurate. Applying the proposed method to several case studies has shown that the SVM based fault classifier has consistently accurate detection and discrimination in almost all operating conditions and for the expected ranges of different parameters.

The proposed SVMs classification technique has been proven to be highly reliable and very fast in detecting and classifying faults with an accuracy of 99.7% average for all the test cases. This makes the SVM a good candidate to compete with, or even replace, conventional methods. The SVM is proven to be able to generalize the situation from the provided patterns and accurately indicate the presence or absence of a fault. Its fast response compared to other techniques makes it more advantageous for on-line fault detection. In a future work the authors will develop a prototype using Digital signal processing (DSP) to test the ability of applying the proposed system in real life.

6 Appendix

Fig. 11 Photos of the tested system

Table 7 Principal data of the machine

Parameter	Value
Stator resistance/coil (R_s)	0.03
Rotor resistance/coil (R_f)	0.0057
Total moment of inertia of rotors plus coupling	$6.2{\times}10^{-2}$ kg.m^2
Self-inductance of stator winding (L_s)	2
Self-inductance of field winding (L_f)	1.37
Self-inductance of d-axis damper winding (L_D)	1.344
Self-inductance of q-axis damper winding (LQ)	1.357
Mutual inductance between stator and field windings (L_{sf})	1.34
Mutual inductance between stator and d-axis damper windings (L_{sD})	1.264
Mutual inductance between stator and q-axis damper windings (L_{sQ})	1.264
Mutual inductance between field and d-axis damper windings (L_{fD})	1.325

7 Additional file

Additional file 1: Verification of Synchronous Generator Model. (PDF 3520 kb)

Authors' contributions
The first author suggested the paper topic, planed the structure of the paper and reviewed it. The second author developed the computer program, implemented it and analyzed the results. He prepared the required figures and table and wrote the paper in its preliminary form. Both authors read and approved the final manuscript.

Competing interests
The authors declare that they have no competing interests.

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