International Journal of Applied Engineering Research.
ISSN 0973-4562 Volume 10, Number 10 (2015), pp. 26689-26697

http://www.ripublication.com

# Condition Monitoring of Synchronous Generators Using Sparse Coding

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**Abstract**

This paper presents an efficient approach for condition based maintenance (CBM) of three phase synchronous generators for diagnosing inter-turn faults using current signatures. Support vector machines (SVM) are one of the widely used algorithms for the purpose of decision making in CBM. To improve the performance of the classifier, either we can select the kernel according to the features or select the features according to the kernel or linearize the features into a higher dimensional space and use linear SVM. In this work, we experiment with the third approach for improving the performance of the system. Sparse coding is an effective feature mapping technique that can be used to linearize the features into a higher dimensional space. Sparse coding improves the performance from 58.19% to 91.14% for R phase fault and from 67.64% to 91.50% for Y phase fault and 73.02% to 94.79% for B phase faults respectively.

**AMS subject classification:**
**Keywords:** Condition based monitoring, Inter-turn faults, Electrical Generators, Support vector machines, Sparse coding.

## 1. Introduction

Electrical generators form an integral part in most of the industrial applications. It constitutes a key element in the generation of electrical energy and its applications range from power houses to highly complex aeronautical and space applications. But as time progresses, generators suffer deterioration which may lead to catastrophe in the entire system. This has caught the attention of many researchers to concentrate more on early detection of faults pertaining to generators to avoid any chaos at a later stage. There are several kinds of faults occurring in the generators [1], namely bearing faults, broken rotor bars, gear box failures, air gap irregularities, faults due to tearing of insulation materials in the armature winding etc. Among the different kinds of faults, the stator fault contributes for almost 30-40% of machine deterioration [2]. The stator faults refer mainly to inter-turn faults that are caused due to internal short circuit occurring between coil turns in the armature winding. The position where the fault occurs is equally important because it also contributes significantly to the damage of the system. Another important aspect of inter-turn short circuit faults is that it has negligible effects at the incipient stages but if kept unnoticed it will cause severe phase to phase and eventually phase to ground short circuit and ultimately damaging the machine [2]. This makes early diagnosis of inter-turn faults a subject of key importance.

The maintenance actions required for diagnosis of faults in any machine can be broadly classified as breakdown maintenance, preventive maintenance and condition based maintenance [3]. Breakdown maintenance is the most primitive kind of maintenance technique where maintenance is done only when a fault occurs. The main drawback of this technique is that it causes unscheduled shutdowns of the machine which is unaffordable. This problem was overcome by using a little more advanced technique called as periodic or preventive maintenance. Here the maintenance actions are scheduled periodically which produces zero down time. But the maintenance cost will be high since we need to do the maintenance even though fault may not be present. Condition based maintenance (CBM) is the most robust and cost effective maintenance technique where specific parameters which are measured are made indicators of an impending failure [3]. The CBM approach follows several sequential procedures. First step is the data acquisition stage, followed by data processing and finally maintenance decision making. Many researchers have used artificial intelligent systems like artificial neural networks, fuzzy inference systems etc. for fault classification. Hamid et al. [4] uses artificial neural network for classification of faults in electrical generators. Zacharias et al. [5] uses artificial neural network along with wavelet decomposition technique. Jianhua et al. [6] uses Support vector machine for gear box fault identification with vibration signals. Support vector machines are found to be more accurate and have excellent performance [7].

In this work, we diagnose the inter turn faults in the 3 kVA synchronous generator. We experimented with SVM kernels for the fault classification. From our experiments, it is found that non linear kernel performs better than linear kernel as the features are non-linear. Though non linear kernel performs better, the classification accuracy is not sufficient for effective CBM system. The performance of the classifier can be improved by selecting the features matching a particular kernel or choosing an appropriate kernel that fits the features or linearize the features to a higher dimensional space and match with linear kernel. In this work, we experiment with the third approach for improving the performance of the classifier.

Sparse coding is an efficient feature mapping technique where the input vectors are represented as the linear combination of basis vectors or codebooks. Liu et al. [8] describes a sparse coding algorithm using vibration signals for bearing fault detection. Sparse coding reduces computational complexity from $O(n^2)$ to $O(n)$ [9], where $n$ is the training size. When compared with vector quantization, which is the traditional encoding technique, sparse coding is more optimum with a reduced quantization error because of an additional [10] sparsity regularization term, added to its constrained equation. In this work, we improve the performance of the fault diagnosis system using sparse coding with linear SVM as a back-end classifier.

The structure of the paper is as follows: section 2 gives the system description and section 3 describes about the experimental results and finally the conclusion in section 4.

## 2. System description

### 2.1. Experimental Setup

The experimental setup consists of a 3 kVA, three phase synchronous generator with construction modification to allow fault simulation. The construction modifications comprise of 54 electrical taps distributed all over the stator windings of the machine. Each phase of the generator consists of six coils, where in each coil, the taps are distributed at 30%, 60% and 82% of the length of the coil respectively. The taps can be interconnected manually to emulate an inter-turn fault. Therefore, each phase consists of 18 taps and the three phases totally constitute 54 external taps. The data acquisition step consists of collecting both the faulty and non-faulty data. The load conditions are varied from 0.5A, 1A, 1.5A, 2A, 2.5A, 3A and 3.5A. The data acquisition is done by inducing faults as well as without inducing faults under each load conditions. From each coil three sets of data are collected as shown in figure 3.This is repeated six times to get a total of 18 data sets from one coil. Thus from one phase a total of 108 data sets were collected. The raw data comprises of three phase currents as shown in Figure 1 and Figure 2. The data is sampled with a sampling frequency of 1kHz for 10 seconds resulting in 10,000 samples for each data set. The raw data is transformed to frequency domain using Fast Fourier Transform (FFT). Then we extracted frequency domain features that are listed in Table 1. For the three phase current, a total of $3 \times 13 = 39$ features were extracted.

### 2.2. Sparse coding

Sparse coding (SC) is an encoding technique, where in the features are coded using a set of basis vectors called as code books [9]. Consider a data set X consisting of entries with D dimensions which represents the number of features. That is, $X = [x_1, x_2, \ldots, x_M]^T \in R^{M \times D}$. In the traditional vector quantization (VQ) approach, it solves the following constrained equation based on $k$-means clustering problem,

$$\min_{v} \sum_{m=1}^{M} \min_{k=1,\ldots,K} ||x_m - v_k||^2 \tag{1}$$

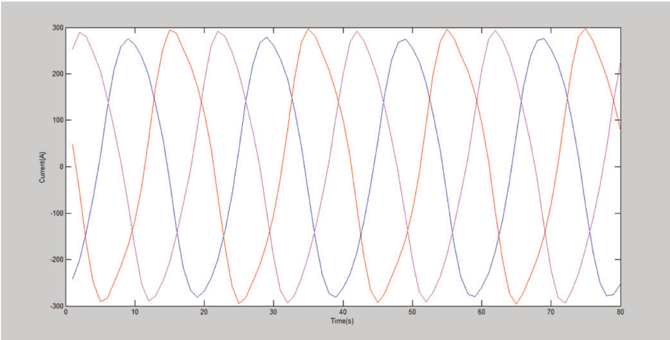


Figure 1: Current signature for the faulty condition (inter-turn fault) at R phase stator winding loaded at 1A.

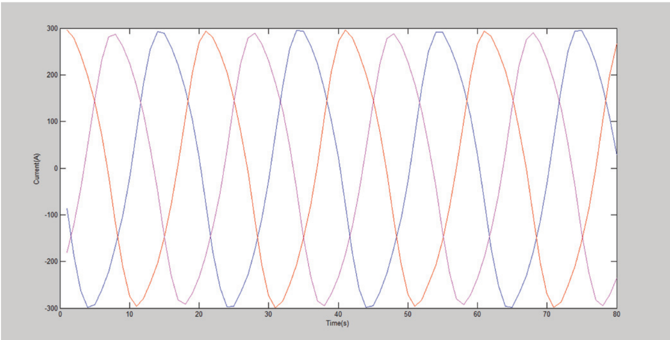


Figure 2: Current signature for the no fault condition loaded at 1A.

where, $V = [v_1, v_2, \ldots, v_k]^T$ are called the codebooks and they are the $K$ cluster centers. And the term $||.||$ denotes the $l^2$ norm or the Euclidean norm of the vectors. The constrained problem of VQ can be reformulated into a factorization problem by using certain membership indicators called $C = [c_1, c_2, \ldots, c_M]$ [9]

$$arg \min_{c} \sum_{i=1}^{M} ||x_i - Vc_i||^2$$

$$\text{subject to } ||c_i||_{l^0} = 1, ||c_i||_{l^1} = 1, c_i \succeq 0, \forall i \tag{2}$$

where $c_i$ is called as a code corresponding to the vector $x_i$. The constraint $l^0$ norm of $c_i$ = 1 means that the number of non-zero elements in C should be 1. $l^1$ norm indicates the summation of absolute values of each element in $c_i$. After the optimization is completed, there will be only one non-zero element in $c_i$ which indicates the cluster in which the vector $x_i$ should belong to.

During the training phase, the equation(2) has to be solved with respect to both V and C. While in coding phase, the same equation is solved with respect to C alone by applying the learned V into a new data set X. The constraint $l^0$ norm of $c_i$ to be one is very restrictive, and it gives rise to a coarse reconstruction of X. It may be relaxed by

Table 1: list of frequency domain features [11].

| | Frequency domain features |
|---|---|
| $F_1$ | $\frac{\sum_{k=1}^{K} s(k)}{K}$ |
| $F_2$ | $\frac{\sum_{k=1}^{K}(s(k)-F_1)^2}{K-1}$ |
| $F_3$ | $\frac{\sum_{k=1}^{K}(s(k)-F_1)^3}{K(\sqrt{F_2})^3}$ |
| $F_4$ | $\frac{\sum_{k=1}^{K}(s(k)-F_1)^4}{KF_2^2}$ |
| $F_5$ | $\frac{\sum_{k=1}^{K} f_k s(k)}{\sum_{k=1}^{K} s(k)}$ |
| $F_6$ | $\sqrt{\frac{\sum_{k=1}^{K}(f_k-F_5)^2 s(k)}{K}}$ |
| $F_7$ | $\sqrt{\frac{\sum_{k=1}^{K} f_k^2 s(k)}{\sum_{k=1}^{K} s(k)}}$ |
| $F_8$ | $\sqrt{\frac{\sum_{k=1}^{K} f_k^4 s(k)}{\sum_{k=1}^{K} f_k^2 s(k)}}$ |
| $F_9$ | $\frac{\sum_{k=1}^{K} f_k^2 s(k)}{\sqrt{\sum_{k=1}^{K} s(k) \sum_{k=1}^{K} f_k^4 s(k)}}$ |
| $F_{10}$ | $\frac{F_6}{F_5}$ |
| $F_{11}$ | $\frac{\sum_{k=1}^{K}(f_k-F_5)^3 s(k)}{KF_6^3}$ |
| $F_{12}$ | $\frac{\sum_{k=1}^{K}(f_k-F_5)^4 s(k)}{KF_6^4}$ |
| $F_{13}$ | $\frac{\sum_{k=1}^{K}(f_k-F_5)^{\frac{1}{2}} s(k)}{K\sqrt{F_6}}$ |

*where $s(k)$ represents the spectrum for the values of $K = 1, 2, 3, \ldots, K$, $K$ represents the number of spectrum lines and $f_k$ represents the frequency corresponding to $k^{th}$ spectrum line.

putting an $l^1$ norm regularization on $c_i$ which causes the $c_i$ to have a lesser number of non-zero elements in it. The incorporation of this new $l^1$ norm regularization term turns

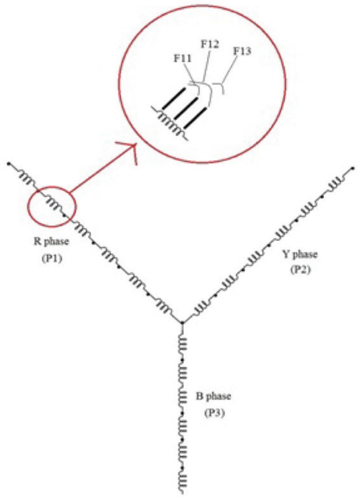


Figure 3: Schematic representation of a fault induced in a coil.

the VQ formulation into sparse coding (SC).

$$arg\ \min_{c} \sum_{i=1}^{M} ||x_i - Vc_i||^2 + \lambda||c_i||_{l^1} \tag{3}$$

The addition of the sparsity regularization term has many salient roles to play. It avoids trivial solutions and ensures a unique solution because usually the codebook V is an over complete basis. That is $K > D$. And also the quantization error during reconstruction is minimized in sparse coding when compared to VQ [9]. SC too has a training phase as well as a coding phase like VQ. In training phase, equation (3) is solved with respect to both V and C whereas in coding phase, equation (3) is optimized with respect to C only retaining V as the codebook.

### 2.3. Support Vector Machines

Support vector machines is an efficient machine learning algorithm developed by Vapnik in the year (1996) [6]. The main objective of SVM is to find out an optimal hyper plane that separates the classes of data and also to maximize the margin between the separating hyper plane and the data. Given, a data set of vectors $X = \{x_i, y_i\}$, where $x_i$ is the data set with D dimensions, where D represents the number of features extracted which fully describes the data. And $y_i$ represents the class label corresponding to each $x_i$. Then the decision function which defines the class of a new data is given by,

$$f(x) = sgn\left(\sum_{i=1}^{N_{sv}} y_i \alpha_i K(x_i, x) + b\right) \tag{4}$$

Where $\alpha_i$ is the Lagrangian coefficient, $y_i$ is the class label for $x_i$, $x_i$ is the support vector, $b$ is a bias value and $K(x_i, x)$ is the kernel function used.

## 3. Experimental Results

The data set comprises of a total of 39 features, which is further divided into training and testing data set by choosing at random. There is no data overlapping between training and testing data set. The experiment is made into a two class problem by taking only one phase fault at a time with non faulty case. That is, R phase fault is considered with non faulty, similarly Y phase fault with non faulty and B phase fault with non faulty.

For the baseline system, we experimented with SVM kernels such as linear, radial basis function (RBF), Sigmoid, polynomial kernel. From our experiments, it is observed that, RBF kernel performs better than other kernel used. Table(2) lists the baseline system performance for identifying the inter turn faults of the synchronous generator. To improve the performance of the baseline system, we experimented with sparse coding to linearize the non linear features into the higher dimensional space, and then classify using linear SVM.

First, we found out the basis vectors or codebooks for the training data set. Then the training and test data sets are represented as a linear combination of basis vectors. We then used the sparse coded data sets for the fault classification. Experiments were conducted with different codebook sizes such as 256, 512, 1024, and 2048. Table 3 lists the performance of the sparse coding for the different codebook sizes for diagnosing the inter-turn faults of the generator. From our experiments, it is observed that 1024 codebook size gives the maximum classification performance for diagnosing the faults. Sparse coding has improved the baseline performance from 58.19% to 91.14% for R phase fault and from 67.64% to 91.50% for Y phase fault and 73.02% to 94.79% for B phase fault respectively.

## 4. Conclusion

In this paper, sparse coding was used to linearize the non linear features into the higher dimensional space to improve the performance of the fault diagnosis system. The performance of the baseline system was improved significantly, and reduced the computation complexity with the use of sparse coding from $O(n^2)$ to $O(n)$. We improved the baseline system performance by 32.95% for the R phase fault, and 23.86% and 21.77% for the Y Phase and B phase faults respectively.

Table 2: System performance using SVM with different kernels.

| **Phase** | **Linear kernel** | **RBF kernel** | **Sigmoid kernel** | **Polynomial kernel** |
|---|---|---|---|---|
| R phase | 58.19% | 76.05% | 65.33% | 55.54% |
| Y phase | 67.64% | 82.07% | 67.94% | 55.54% |
| B phase | 73.02% | 82.11% | 72.86% | 55.54% |

Table 3: System performance for sparse coding using different code book sizes.

| **Code book sizes** | **256** | **512** | **1024** | **2048** |
|---|---|---|---|---|
| R phase | 90.39% | 90.74% | 91.14% | 90.26% |
| Y phase | 90.95% | 91.22% | 91.50% | 91.22% |
| B phase | 93.83% | 94.43% | 94.79% | 94.36% |

## Acknowledgment

Authors would like to thank Ms. Aparna S Raghunath and Ms. Sandra Prasad for their help during this course of work.

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