

# Fault Detection of Induction Motor Using Optimized Support Vector Machine

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**Abstract—** This paper presents a methodology for identifying two critical faults in variable-speed induction motors controlled by field-oriented control (FOC). If these defects are not detected early, they may lead to unexpected shutdowns of industrial processes, resulting in significant financial losses. It is necessary to ensure the smooth operation of industrial machinery to develop a reliable diagnostic system for identifying inter-turn short circuits and broken bars under varied load conditions. The suggested method overcomes the drawbacks of conventional fault detection methods, particularly for non-stationary signals, by utilizing the discrete wavelet transform (DWT). This method's innovative feature is its combination of support vector machines (SVM) and DWT for efficient fault detection. The process involves analyzing the current signal using the DWT, which decomposes it into different frequency bands. The SVM classifier is then trained using the energy at each level of decomposition as a feature. The study was enhanced by testing different orthogonal wavelets energies, revealing that the Daubechies 44 (db44) is the most suitable mother wavelet for accurately detecting and classifying these motor faults. The results show that the proposed system achieves an effectiveness of 98.62% , across both ITSC and BRB faults under different load conditions, providing a robust solution for fault diagnosis in induction motors.

**Keywords—** SVM, Inter-turn short circuits, Broken bars Include, Classification, Diagnosis.

## I. INTRODUCTION

Induction motors represent the backbone of industrial applications, including manufacturing, energy, and transportation, accounting for approximately 75% of the electricity consumed. They are widely used, especially in variable-speed operation, due to their robustness, simplicity, and low cost. Despite their reliability, they are susceptible to electrical and mechanical faults. Inter-turn short circuits in stator [1-2]. and broken rotor bars [3-4] at various levels are significant faults affecting motor systems.

Detecting such faults early is crucial for preventing damage and ensuring reliable operation. Traditional fault detection methods include vibration analysis [4], thermal imaging, and current signature analysis[5]. More advanced approaches, such as neural networks[6], fuzzy logic[5], wavelet analysis[6], machine learning-based approaches, particularly SVM[8], have gained attention due to their ability to classify faults with high accuracy.

Support Vector Machine (SVM) is a powerful intelligent classifier based on statistical learning theory and has shown strong performance in solving complex analytical problems as well as automating monitoring tasks. Introduced by Boser, Guyon, and Vapnik in 1992[7], are a foundational supervised learning method for classification and regression.

However, SVM has a notable drawback, determining the optimal parameter values can be challenging. To address this challenge, genetic algorithms (GA)[9]and particle swarm optimization (PSO)[10] ,have been proposed as methods to search for the optimal parameter values, improving the classification accuracy of SVM.

The paper is organized as follows: Section 2 provides a brief overview of the dynamic model of the IM and the function of the vector-controlled drive. Section 3 presents the application of discrete wavelet analysis and calculates the energy level of decomposition. Section 4, the optimization of SVM with GA and PSO of the machine under different faults is discussed. Finally, both approaches are compared.

## II. FEATURE EXTRACTION USING DISCRETE WAVELET TRANSFORM (DWT)

A current signal  $I_{sa}(t)$  can be decomposed and reconstructed using two components: the approximation ( $aj$ ) and the detail ( $dj$ ). The approximation component behaves like a low-pass filter ( $LPF$ ), whereas the detail component acts as a high-pass filter ( $HPF$ ) [6][11], as illustrated in Fig. 1.

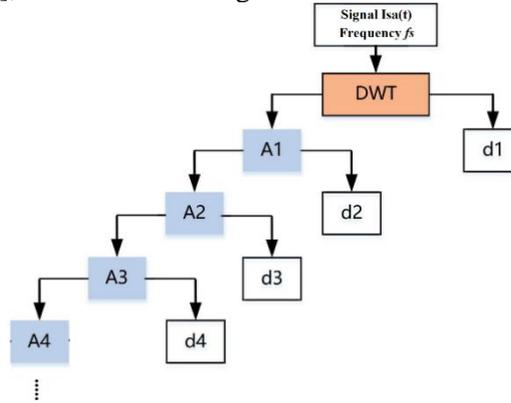


Fig. 1. DWT decomposition process

The decomposition of a signal using the discrete wavelet transform (DWT) is achieved through successive filtering operations with HPF and LPF in the time domain. The original signal  $I_{sa}(t)$  can be approximated through DWT reconstruction as:

$$I_{sa}(t) = d_1 + d_2 + \dots + d_n + a_n \quad (1)$$

#### A. Wavelet Energy

Wavelet coefficients describe the portion of the signal contained within each associated frequency band. The energy parameter  $E_j$  provides useful information about the stator current profile of the motor. Variations in these energy values can signal the existence and intensity of faults, making  $E_j$  an effective indicator for detecting short-circuit and broken bar anomalies.

According to [11], the energy at a given decomposition level is defined as:

$$E_j = \sum_{k=1}^N D_{j,k}^2(n) \quad (2)$$

Where  $j$  denotes the detail level,  $D_{j,k}$  is the detail coefficient at level  $j$ , and  $n$  represents the total number of samples.

The distribution of energy across the decomposition levels contains essential diagnostic information. Plotting these energy values facilitates the detection of faults in squirrel-cage induction motors and helps in assessing their severity. Before computing the wavelet energy, the appropriate number of decomposition levels should be determined using the method described in [11].

$$N = \text{int} \left[ \frac{\log\left(\frac{f_e}{f_s}\right)}{\log(2)} \right] + 2 \quad (3)$$

where  $N$  is the number of decomposition levels,  $f_e$  is the fundamental frequency of the signal,  $f_e = 22$  Hz;  $f_s$  is the sampling frequency,  $f_s = 10$  kHz;

### III. SUPPORT VECTOR MACHINE AND OPTIMIZATION

#### B. Support Vector Machines (SVMs)

SVM is a generalized linear model used for classification and regression, making decisions based on linear combinations of input features. In SVM classification, the model is trained using labeled data (training set) and evaluated using test data [12-13].

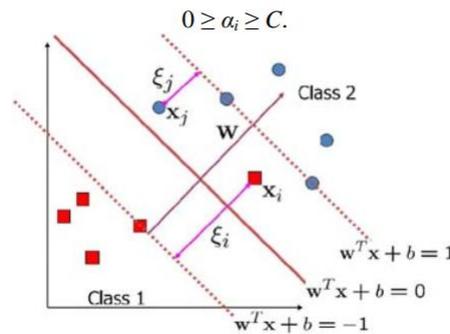


Fig. 2. Soft margin hyperplane

The core idea behind SVMs, originally designed for binary classification, is the use of hyperplanes to separate data from different classes. The data points closest to this optimal separating hyperplane are known as support vectors, and only these points influence the decision boundary. The SVM algorithm seeks to maximize the margin, which is the distance between the hyperplane and the nearest training samples, thereby achieving the best possible class separation [14].

The form of the equation defining the decision surface separating the classes is a hyperplane of the form:

$$x_i w + b = 0 \quad (4)$$

- $w$  is a weight vector
- $x$  is the input vector
- $b$  is bias

The two classes can be separated by a pair of parallel bounding planes. The first delimiter field limits the first class while the second delimiter field limits the second class, so that it is obtained [15-17]:

$$\begin{cases} x_i w + b \geq 0 & \text{for } d_i = +1 \\ x_i w + b \leq 0 & \text{for } d_i = -1 \end{cases} \quad (5)$$

The margin value between the two classes is  $m = \frac{2}{\|w\|}$ . The margin can be maximized using the optimization function, Lagrangian:

If data cannot be perfectly separated by linear separation, SVM is modified by adding variables  $\xi_i$  ( $\xi_i \geq 0, \forall i$ ;  $\xi_i = 0$  if  $x_i$  classified correctly) so that the best divider form search formula becomes:

$$\min \frac{1}{2} \|w\|^2 - C \sum_{i=1}^n \xi_i \quad (6)$$

$$s.t. y_i(w \cdot x_i + b) \geq 1 - \xi_i; \quad \xi_i \geq 0$$

The search for the best splitter field with the addition of  $\xi_i$  variable is called the soft margin hyperplane.  $C$  is the parameter that determines the magnitude of the penalty due to errors in the classification. Thus, the dual problem generated in a non-linear problem equals the dual problem generated by linear problem only the  $\alpha_i$  range between

$$0 \geq \alpha_i \geq C.$$

$$\min L = \frac{1}{2} w'w - \sum \lambda_k (y_k (w'x_k + b) + s_k - 1) + \alpha \sum s_k \quad (7)$$

In this study, the radial basis function (RBF) kernel is selected as the primary kernel for SVM modules developed fault diagnosis due to its strong ability to handle nonlinear relationships within the data. The RBF kernel is defined as:

$$K(x_i, x_j) = \exp\left(-\gamma \|x_i - x_j\|^2\right), \gamma > 0 \quad (8)$$

### C. Genetic Algorithm (GA)

GA is a metaheuristic optimization method inspired by the principles of natural selection and evolution. Applying GA to optimize SVM parameters including penalty factor  $C$  and radial basis kernel function parameter  $\gamma$  is

straightforward. Each individual in the population represents a pair of parameters  $C$  and  $\gamma$ , and the fitness of each individual is evaluated based on accuracy or classification error [15].

#### D. Particle Swarm Optimization (PSO):

PSO is another algorithm inspired by the movement of birds or fish in a swarm. PSO treats each candidate pair ( $C$ ,  $\gamma$ ) as a particle in a swarm that moves through the search space to find the parameter combination that maximizes classification accuracy. Through iterative updates, PSO efficiently explores the search space, avoids local minima, and converges toward an optimal or near-optimal set of SVM parameters [16].

### IV. SIMULATION RESULTS

In this paper, several cases are considered, including, healthy case, inter inter-turn fault case and a broken rotor bar case applied with different levels of severity. The prediction system starts with dataset preparation, which is then divided into training and testing sets. The training data is employed for the classification modelling process. The input dataset is generated through simulations conducted under a range of load conditions and fault severities, from no load up to full load with variable speed 100rad/s. The SVM was trained using samples corresponding to seven different load torques (1:1:7 N·m), which reflect various operating states. These include healthy conditions (7 samples), faults involving an even number of shorted turns (2:2:10 turns), as well as faults caused by single and double broken rotor bars (BRB).

The test dataset for the induction motor (IM) under various operating conditions, including the healthy state (7 samples), shorted-turn faults (1:2:9 turns), and faults caused by one or two broken rotor bars (BRB). All cases were evaluated under seven load torque levels: (0,5:1: 6,5 N·m).

Fig 3 shows a multi-level discrete wavelet decomposition of stator phase current signal  $i_{as}$  in different cases (healthy case, inter-turn short circuit 10%, Broken 1 rotor bar), typically used in signal processing and fault diagnosis. High amplitudes or characteristic oscillations in certain detail levels can indicate specific fault signatures, such as broken bars or short circuits.

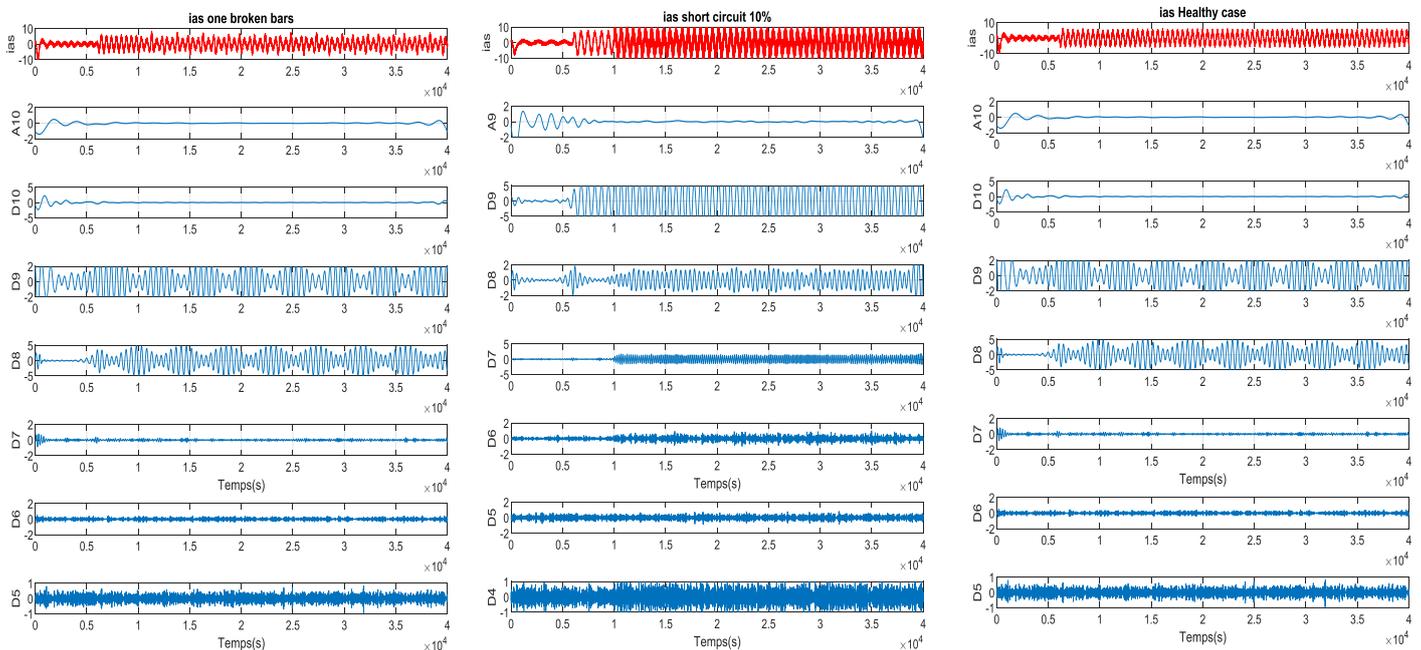


Fig. 3. Time-frequency decomposition with wavelet function DB44 of the stator phase current.

Fig. 4 displays the energy distribution across frequency bands for different motor conditions. Each fault type manifests a unique energy signature across the frequency bands. Healthy motors show low energy concentrated in

low-frequency bands, while faults, especially short circuits and broken bars, produce significant energy in higher frequency bands. These energies can serve as fingerprints to distinguish between healthy and faulty conditions.

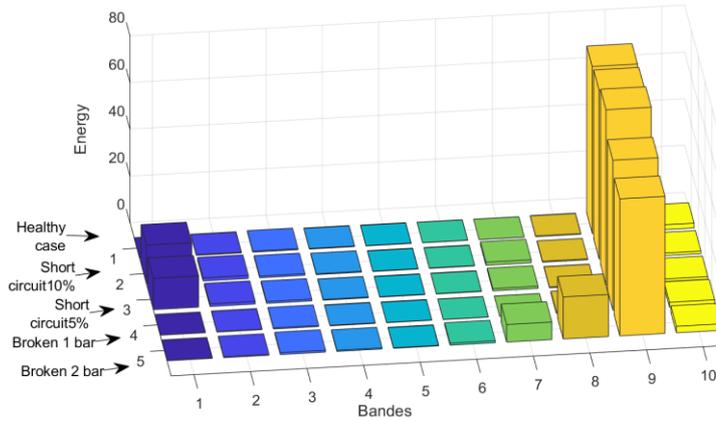


Fig. 4. Energy value by DWT DB44

The PSO and GA algorithms are used to optimize the penalty C and sigma parameters for the RBF kernel in the SVM model. After determining the optimal parameters, the SVM model is trained, and its performance is evaluated. This process is repeated until a satisfactory classification accuracy is achieved as illustrated in Figure. 5.

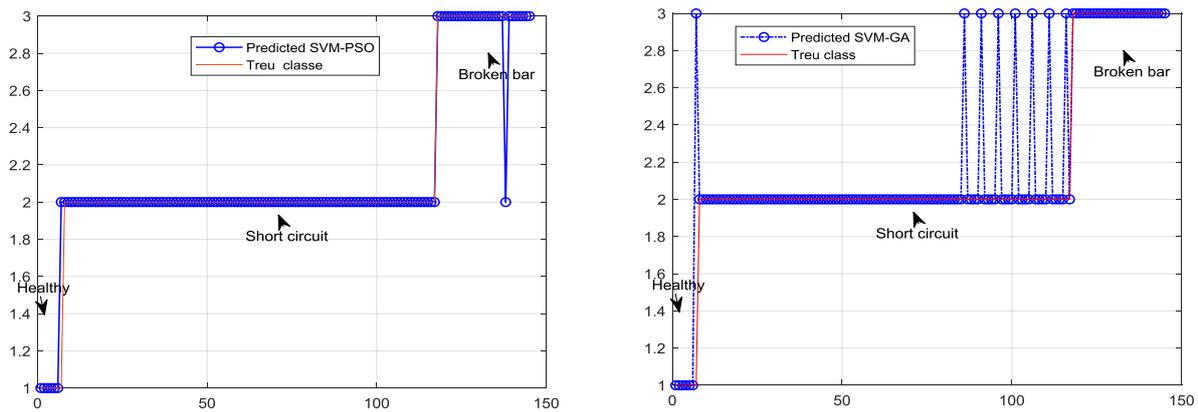


Fig. 5. SVM Test data a) SVM-PSO, b) SVM-GA with DWT DB44

TABLE 1. PERFORMANCE COMPARISON.

Wavelet Functions		C	sigma	accuracy
DB44	SVM-GA	12.8815	10.6804	94.48 %
	SVM-PSO	16.4330	12.1742	98.62%
Coif5	SVM-GA	26.0154	14.9316	90.92 %
	SVM-PSO	14.9316	9.7700	90.15 %
Bior6.8	SVM-GA	10.7597	9.8023	92.05%
	SVM-PSO	10.5521	9.6223	90.34%
Sym5	SVM-GA	36.3271	6.2700	89.39%
	SVM-PSO	16.4670	6.3868	90.92 %

Table 1 compares the performance of different wavelet functions combined with SVM classifiers optimized using Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). Among the four wavelets tested (DB44, Coif5,

Bior6.8, and Sym5). The wavelet function DB44 achieved the highest classification accuracy, particularly when optimized with PSO, reaching 98.62%, indicating that this wavelet is most effective for feature extraction in this dataset. In general, PSO tended to produce better SVM hyperparameters than GA, resulting in higher accuracy, though the difference varied depending on the wavelet. The values of C and sigma illustrate how the optimization algorithms adjust the SVM's flexibility and regularization, with PSO often selecting parameter combinations that balance model complexity and generalization more effectively than GA. Overall, the results suggest that careful selection of both the wavelet function and the SVM optimization method is crucial for maximizing accuracy.

## V. CONCLUSIONS

This paper proposes a fault diagnosis method for variable speed induction motor fault that combines the discrete wavelet transform (DWT) and the Support vector machine (SVM). The proposed fault diagnosis method for induction motors uses (DWT) to analyze current signals, and extracts energy features that serve as inputs to the SVM classifier, applied under various load conditions and fault types (ITSC and BRB). the proposed approach successfully detects and locates faults. The study demonstrates that combining SVM with Particle Swarm Optimization (PSO) significantly improves classification accuracy, achieving a good result of 98.62%. It can also be concluded that PSO effectively identifies optimal SVM parameters, outperforming SVM-based GA optimization approaches. Among the tested wavelets, the wavelet function DB44 generates the best results, confirming that optimized SVM-PSO with DWT provides an efficient and reliable tool for automatic fault detection. Future work could extend this method for real-time monitoring.

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