SVM and RVM Fault Model for Wind Energy Conversion Systm

Rekha S.N., P.Aruna Jeyanthy, D. Devaraj

Abstract: *The paper present the fault identification technique for wind Energy conversion system based on SVM (support vector machines) and RVM. A Relevance Vector Machine based fault detection technique and support vector machine fault detection technique with the Benchmark Model of the WECS is carried out with Multi class classification... The proposed implementation would carry out simulation which would consider multiple faults occurring simultaneously with a comparison study of both techniques can be achieved. The algorithm is carried out and the results are found to be satisfactory. The results in MATLAB shows that effective memory usage of each technique*.

Keywords: Relevance Vector Machine, Support vector machine, Wind Fault Benchmark Model, Wind Generation Fault Diagnosis.

I. INTRODUCTION

The innovation of wind power is progressively full grown as of late and wind turbine is additionally improvement towards huge power and too enormous power [1]. The length of the blade and the activity stature of wind turbine become longer and higher as per the expanding limit of wind turbine. Which indicates the blades are increasingly presented to harms during the operation and at the same time it is necessary to monitor the health of generators and converters. The regular strategies outwardly investigate blade's fault highlight, for example, lightning consuming and vibration splitting [2]. Long inspection cycles are the major defects of these methods.[3] The existing generator fault and converter fault are also very expensive.[4].

In wind energy conversion system, location and detection of faults have a significant role ,as the shortcomings in the framework would expand the maintenance cost and consequently increment absolute cost wind control. For wind fault identification a bench mark model is developed [5]. This developed model is based on a 4.8MW WECS to detect the fault in the system.

The fault recognition is completed with SVM and for the precision, preparing and tuning times the result is compared with the result obtained by ANN.[6] The comparison shows that the performance of SVM is better than ANN. Sound and vibration in the tower analysed by empirical mode decomposition technique is utilized to detect issue in wind generator bearing [7]. To detect the fault in individual wind turbine in nine turbine-based wind farms is really a challenge [5]. In [8] the identification of fault with noise is found by a state estimation membership approach.

In [9] a multi objective optimization model with H_∞ / H_- observer is developed to identify the fault in the sensor and actuator. In the area of application of fault detection the SVM is an efficient technique in machine learning [10],[11],[12] and with this techniques many fault detections are done [13].

In this paper, a comparison study for fault diagnosis method based on SVM and RVM are done for diagnosing different fault in wind energy conversion systems. By using SVM and RVM as fault classifiers, which only need a limited sample information and reaches a efficient diagnosis result [14],[15],[16].The present work actualizes the SVM and RVM on the benchmark model for finding multiple faults occurring simultaneously on the bench mark model developed by Odgaard et al [5].

II. BENCHMARK MODEL OF WECS WITH FAULTS

The present implementation is carried out by using the benchmark model developed in [5]. It includes all the parts model in WECS. The vector v_w denotes the input to the turbine which represents the different sequences of wind . The wind and pitch model combined with aerodynamic model is represents blade and pitch model. The wind turbine aerodynamics is modelled in terms of blades torque (1)

$$t_r(t) = \frac{r\rho R^3 C_q(/(t).b(t))v_w(t)^2}{2} \dots\dots\dots\dots\dots(1).$$

r represent the Air density , R represents the radius of rotor, C_q ,, $/$ is the coefficient of torque and tip speed ratio respectively, b is the pitch angle.

The torque equation of each blade is defined by (2)

$$t_w(t) = \sum_{1 \le i \le 3} \frac{r\rho R^3 C_q(/(t).b_i(t))v_w(t)^2}{6} \dots\dots\dots\dots\dots(2)$$

$$\frac{\beta(s)}{\beta_c(s)} = \frac{\omega_n^2}{s^2 + 2\varsigma\omega_n s + \omega_n^2} \dots\dots\dots\dots\dots\dots(3)$$

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Damping factor V, natural frequency W_n defines the second order transfer function of the hydraulic pitch system as shown in equation (3). The same transfer function is adopted for all three blades, If undisturbed the pitch system would remain the same. While any abnormal condition occurs in the pitch system a drop in hydraulic power would be evident along with the air pressure increase. The drop in power is affected by the parameters as defined as ω_{n2} and ς_2, air pressure parameters is ω_{n3} and ς_3. The sensed pitch value correction is calculated by finding the difference of the reference sensor value to the mean of the sensor values thus obtained. It is depicted as in (4).

$$\beta_{r,f,i}[n] = \beta_{r,i}[n] - \frac{\Delta\beta_{i,m1}[n] + \Delta\beta_{i,m2}[n]}{2} \dots\dots\dots\dots. (4)$$

Drive train model is that which would transfer the torque generated from the rotor to the generator. The drive train model as defined in (5) and (6) and represents the model of the gear box that ensures the variation of the speed from lower to higher speed.

$$J_r\omega_r(t) = \tau_r(t) - K_{dt}\theta_\Delta(t) - (B_{dt} + B_r)\omega_r(t) + \frac{B_{dt}}{N_g}\omega_g(t) \dots\dots\dots\dots\dots..(5)$$

$$J_g\dot{\omega}_g(t) = \frac{\eta_{dt}K_{dt}}{N_g}\theta_\Delta(t) + \frac{\eta_{dt}B_{dt}}{N_g}w_r(t) - \left(\frac{\eta_{dtB_{dt}}}{N_g^2} + B_g\right)\omega_g(t) - \tau_g(t) \dots\dots\dots\dots\dots (6)$$

$$\theta_\Delta(t) = \omega_r(t) - \frac{1}{N_g}\omega_g(t)$$

The low speed shaft moment of inertia is represented by J_r and the drive train torsion stiffness is represented K_{dt}, drive train torsion damping coefficient is represented B_{dt}, high speed shaft viscous friction is B_g. Gear ratio is N_g, high speed shaft moment of inertia is J_g, the drive train efficiency is η_{dt}. Drive train torsion angle is $\theta_\Delta(t)$. η_{dt} would be denoted as η_{dt2} when fault occurs in drive train.. The representation of electrical model is as defined in (7).

$$\frac{\tau_g(s)}{\tau_{g,r}(s)} = \frac{\alpha_{gc}}{s + \alpha_{gc}} \dots\dots\dots\dots (7)$$

Where α_{gc} represents the control parameters of the electrical model. The generator power is characterized by the following equation (8)

$$P_g(t) = \eta_g\omega_g(t)\tau_g(t) \dots\dots\dots.. (8)$$

The efficiency of the generator defined as η_g. While wind speed is more than the nominal speed a power optimization is considered. If there is less power generated then controller starts effect. Equation (9) is denoting the variation of power.

$$P_g[n] \geq P_r[n] \vee \omega_g[n] \geq \omega_{nom} \text{ ----------(9)}$$

Where ω_{nom} is the normal speed of generator .

$$\omega_g[n] \leq \omega_{nom} - \omega_\Delta$$

The offset value ω_Δ which makes to avoid the frequents changes between mode2 and mode 1. For the implementation purpose fault condition and variation of mode along with the parameters of the model is taken from [5].

III. IMPLEMENTATION OF FAULT DETECTION BASED ON SVM

The technique SVM depends on basic structural risk and statistical hypothesis, which can well take care of the issues of small samples, high measurements and non-linearity, yet uses restricted sample data and is another strategy. The SVM is predominantly contemplate linearly separable problems in pattern recognition. Suppose there is a hyperplane H: w.x +b =0, which can correctly separate the samples. At the same time there are two hyperplanes, both parallel to H, suppose H1 and H2:

$$w\cdot x + b = 1$$

$$w\cdot x + b = -1$$

Fig 1 shows the optimal hyper plane which SVM needs to get through training. Two different samples in the figure are circles and squares. Each circle and squares speaks to a sample direct relating toward space. The algorithm is scanned for hyper plane H and its course vertical to typical normal vector. H1 and H2 both parallel to H and cross the sample points hyperplane that is closest H. classified distance is the distance between them. The closest examples to H's plane simply fall on H1 and H2. The help vectors are the examples which fall on H1 and H2. The typical vector of hyper plane is w and the segmentation threshold is defined by b. All the preparation samples are situated outside of H1 and H2 and the accompanying imperatives are fulfilled.
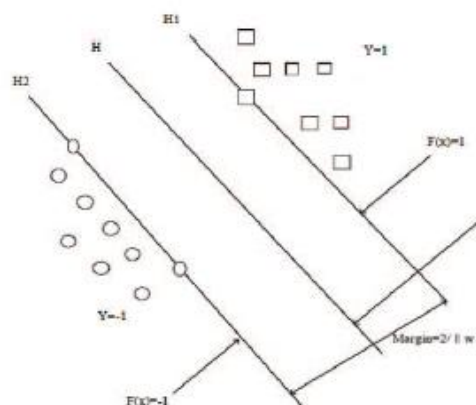

Figure 1. Optimal hyperplane of SVM

$$w\cdot x_i + b \geq 1 (y_i = 1)$$

$$w\cdot x_i + b \leq -1 \ y_i (= -1)$$

As appeared by figure 2 , five stages are required for issue identification is subjected to SVM . The signal received from the machinery operation is extracted and analysed to take

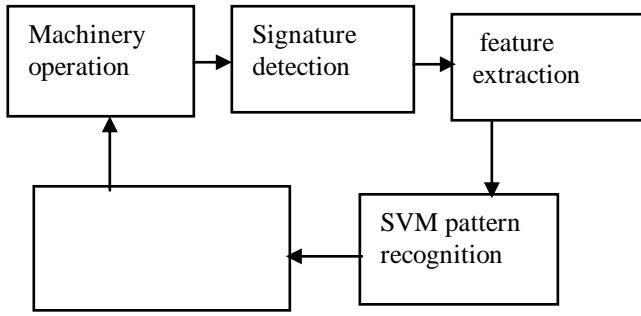the decision depends on SVM pattern recognition.

Machinery operation → Signature detection → feature extraction → SVM pattern recognition → [ ] → Machinery operation

Fig,2 SVM pattern recognition

Data acquisition → Data normalization → Fault diagnosis based on SVM → Whether fault or not → normal / Type of fault
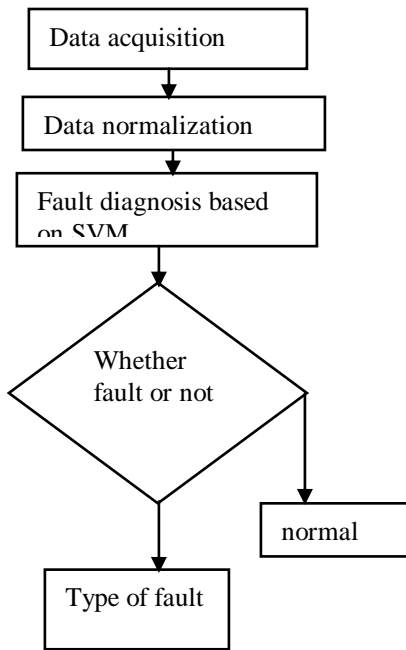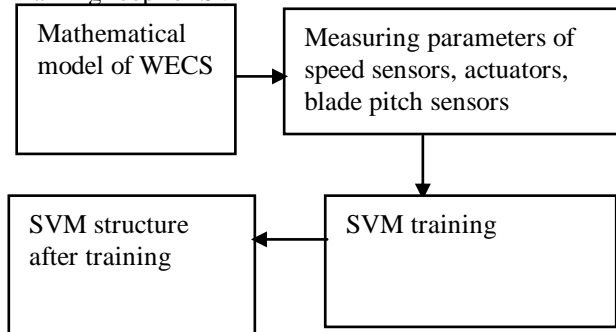
Fig.3 SVM based Implementation of Fault Detection

Fig.3 represent the general flow chart of SVM based fault diagnosis to be followed to detect different fault in WECS. In this paper mathematical model of wind energy conversion system is used to create various fault model

Training loop for SVM

Mathematical model of WECS → Measuring parameters of speed sensors, actuators, blade pitch sensors → SVM training → SVM structure after training

Testing loop

Mathematical model of WECS → Measuring parameters of speed sensors, actuators, blade pitch sensors → SVM fault structure → Fault Detection
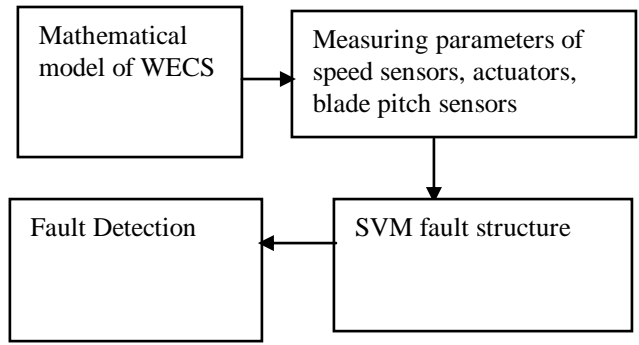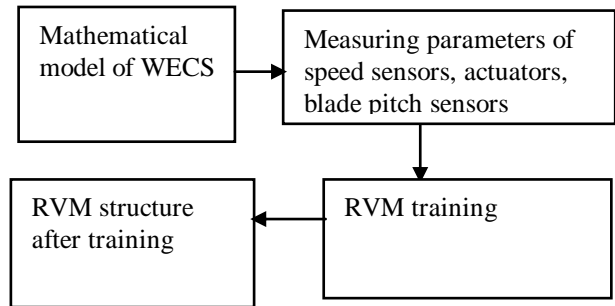
Fig 4 training and testing block of SVM

4. IMPLEMENTATION OF FAULT DETECTION BASED ON RVM

Assortment of fault stipulations are set up on the RVM and a multi classification structure is made so as to check the fault issue stipulations that are seen in [5].

The numerous RVM structures are created as talked about in [15]. The defective issue situations are mentioned in the Table 1 are presented for preparing and testing RVM:

Training loop of RVM

Mathematical model of WECS → Measuring parameters of speed sensors, actuators, blade pitch sensors → RVM training → RVM structure after training

Testing loop of RVM

Mathematical model of WECS → Measuring parameters of speed sensors, actuators, blade pitch sensors → RVM fault structure → Fault Detection
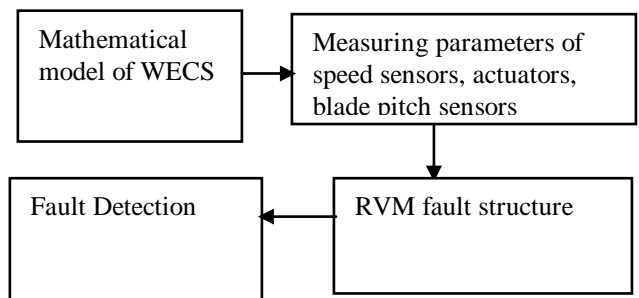
Fig.5 Training and testing block of RVM

The various conditions for faults are trained on the RVM and SVM. The above-mentioned structures are created and studied in detail about the performance of each structure

The various fault scenarios are stated in the Table 1 is for preparing both the RVM, SVM for identifying fault.

Fault No.	Fault Type	Fault Site	Symbols
1a	Fixed Value	Blade Positions Sensor Faults	$\Delta\beta_{1,m1}, \Delta\beta_{i1m2}$ $\Delta\beta_{2,m1}, \Delta\beta$
1b	Gain Factor		$\Delta\beta_{3,m1}, \Delta\beta_{3,m2}$
2a	Fixed Value	Rotor Speed Sensor Fault	$\Delta\omega_{r,m1}, \Delta\omega_{r,m2}$
2b	Gain Factor		
3a	Fixed Value	Generator Speed Sensor Fault	$\Delta\omega_{g,m1}, \Delta\omega_{g,m2}$
3b	Gain Factor		
4a	Offset	converter system Actuator Fault	$\Delta\tau_g$
5a	Abrupt Changed Dynamics	Actuator Fault Pitch Systems	$\Delta\beta_1, \Delta\beta_2, \Delta\beta_3$
5b	Slow Changed Dynamics		

Table-1 different fault condition

The vector that mirrors the abnormal situation of blade positions is as given in the accompanying equation for training structure.

$$x = \begin{bmatrix} \left|b_{k,m1}(t_j) - b_{k,m2}(t_j)\right| \\ \left|b_{k,m1}(t_j) - b_{k,m1}(t_{j-1})\right| \\ \left|b_{k,m2}(t_j) - b_{k,m2}(t_{j-1})\right| \end{bmatrix}$$

where k=1,2,3 which is the meaning blade number and i=1,2 signifies the mode where in the WECS is working. The t_j and t_{j-1} are the time moment at j and j-1 individually. The absolute estimation $\left|b_{k,m1}(t_j) - b_{k,m2}(t_j)\right|$ would change somewhere in the range of .001 and 2, however, so as to separate the abnormal and the ordinary situation the worth is predefined as 5000.

The fault conditions are characterized in table $\omega_{g,mi}, \omega_{g,mi}$ utilized for preparing RVM. The matrix for preparing is given by the accompanying,

$$x = \begin{bmatrix} \left|W_{p,m1}(t_j) - W_{p,m2}(t_j)\right| \\ \left|W_{p,m1}(t_j) - W_{p,m1}(t_j)\right| \\ \left|W_{p,m2}(t_j) - W_{p,m2}(t_j)\right| \end{bmatrix}, p = g,r$$

While measuring the Gaussian variance is extended to 15 to get the accuracy of measuring. For faults 4a and 6 the vector is as defined in the following

$$x = \begin{bmatrix} \left|W_{p,m1}(t_j) - W_{p,m2}(t_j)\right| \\ \left\|t_g^d(t_j) - t_g^m(t_j)\right\| \\ l_2 X \left|W_g^d(t_j) - (W_{g,m1}(t_j) - W_{g,m2}(t_j))/2\right| \end{bmatrix}$$

where t_g^d is the desired generator torque given by the controller($\frac{P_r}{t_g^d}$ where P_r is the power which is desired to be produced). The factor $l_2 = 10^{-6} X J_{wind}^6$ is the 3rd component of x in order to utilize the wind speed and for normalization.

5. OUTCOMES OF THE IMPLEMENTATIONS

The execution of the work completed, and the outcomes are shown in the accompanying exchange. The 3rd fault situation as talked about in [5] is connected for the usage. By giving the diverse wind speed, which is arbitrarily produced, the variety of speed the torque waveform created as Fig.5.
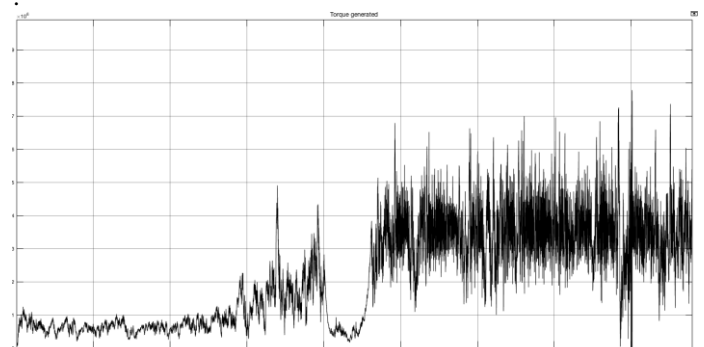

Figure 5. Wind turbine Torque Waveform

The time taken for simulation is 4400 secs. The faults are applied at different places like the below with respect to RVM and SVM.
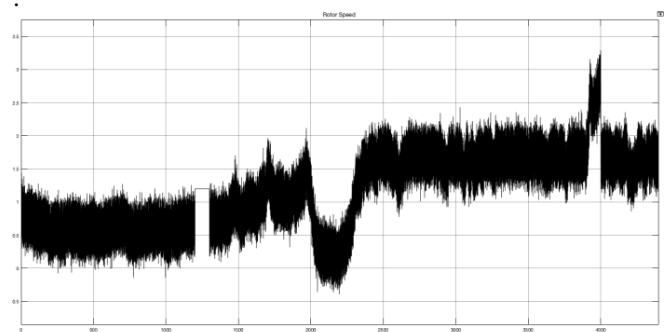

Figure 6. Speed in Wind measured by sensor 1 kept constant between 1200-1300s

The fault detection is obtained by the trained fault model developed by RVM with the above faults
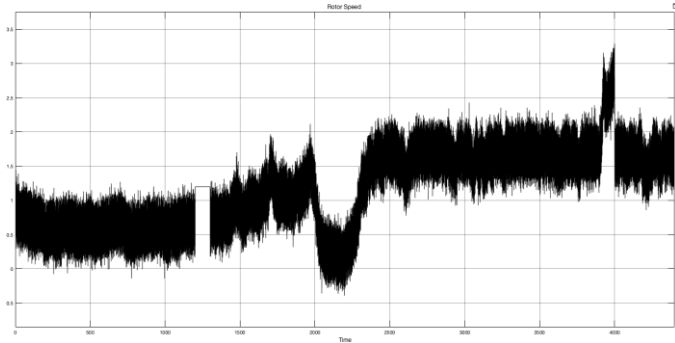
Figure 7 . Speed in Wind measured by sensor 2 kept constant between 1200-1300s

1 in the detection graph shows fault detection and zero in the detection graph when there is no fault.
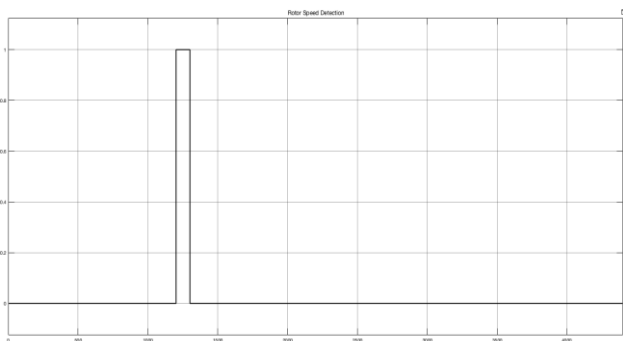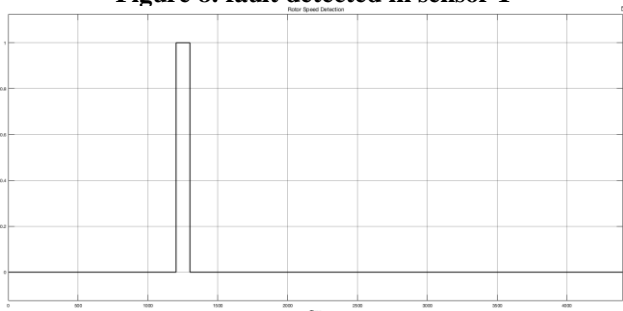

Figure 8. fault detected in sensor 1

Figure 9. fault detected in sensor 2

Figure 8, 9 displays the rotor speed fault identified in sensor 1 and sensor 2 in 1200-1300s simultaneously. The result obtained by SVM also same. Representation of graph for both SVM and RVM are same the major difference is in the training period the learning of RVM is better compare to SVM.

All the faults that were trained and were detected in the similar way.

IV. CONCLUSIONS

The RVM and SVM implementation were carried out with the benchmark model developed as mentioned [5]. The RVM and SVM function were trained and final structures created for various fault model and the results were found to be satisfactory. The major contribution of this work is to identify the fault with both RVM and SVM. The performance of RVM is better compared to SVM in learning period. Since the RVM is considering the probability of occurrence of fault the kernel function is fewer compared to SVM . Rapid prototype hardware in loop simulation can be done as a future work

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370

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