The MAED and SVM for Fault Diagnosis of Wind Turbine System

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Abstract-Fault diagnosis is the best discipline to control the operation and maintenance costs of the wind turbine system. However, the fault diagnosis of wind turbine finds difficulties with the variation of wind speed and electrical energy (generator torque).

In this work, the proposed fault diagnosis approach is based on the Feature set algorithm, manifold learning and the Support Vector Machine classifier. First, the construction of the feature set is very important step, with the high dimension after application the MAED (Manifold Adaptive Experimental Design) algorithm on the data set. Moreover, the NPE (Neighborhood Preserving Embedding) manifold learning algorithm is applied for directional reduction of feature set by the eigenvectors; it is easy to use as the input for the last step. Finally, the low dimensions of eigenvectors are exploited by the (SVM) Support Vector Machine classifier for recognition fault and making the maintenance decision.

This approach is implanted on the faults of the benchmark wind turbine and gives the best performance.

Keywords: Fault diagnosis, Wind turbine, Data-based diagnosis, MAED algorithm, NPE algorithm, SVM classifier**.**

1. Introduction

The wind turbine is the system for the power energy; it is renewable energy, that system contains different parts (blades, gearbox, tower…).

During its work, it has occurrence of several faults that influence the maintenance costs and the best performance of the wind turbine.

For these reasons, the faults diagnosis system is very important to supervise the parts of the system. An approach will be proposed to improve the rate of performance**.** So there are two main methods of fault diagnosis, the first is model-based diagnosis, that requires the best comprehension of physical model of the system, but the second is data-based diagnosis, that means the historical data are very important to use with the mathematical methods for the pattern recognition.

In literature there are a lot of propositions to solve these problems, as well as the author [1] proposingan algorithm based on the empirical mode decomposition and energy separation for the fault diagnosis of planetary gearbox. It detects and locates the wear and chipping faults for the gear of planetary gearbox,also the Adaptive Optimal Kernel (AOK) used for the time frequency analysis to indicate the frequency characteristic of non-stationary signals [2, 3], where the AOK extracts the impulses induced by gear faults under time-varying running conditions.

In [4], authors presented data mining approaches to monitor the blade pitch based on genetic algorithm; they give the best accuracy and were selected to perform prediction at different time stamps. In [5], the monitoring approach based on alarms of wind turbine SCADA (Supervisory Control And Data Acquisition) is proposed, it gives the alarm data requiring little storage capacity and provides the rich information of condition monitoring.

The auto-regressive model is applied by [6] for diagnosing the very complex high-power planetary gearbox of wind turbine, this model is very quick, technically simple, robust and intuitive. In [7], the authors proposed the calculated distance using as a fault indicator to diagnose shaft crack, it demonstrated the use of a full lifetime gear shaft.

Among the 126 articles found in Web of Science, the database of ISI Thomson, the most recent and related to this work are chosen for state of the art (Table1).

Table 1. State of the art of diagnosis of wind turbine system

Year	Authors	content	remarks
2016	Hu, Bingbing; Li, Bing [8]	Proposed an approach Multiscale noise tuning stochastic resonance (MSTSR) based on dual-tree complex wavelet transform (DTCWT) for diagnosis the gearbox bearing faults.	Extracts the fault features of weak fault signatures and gives the best performance.
2016	Chacon, Juan Luis Ferrando; Andicoberry, EstefaniaArtigao; Kappatos, Vassilios; et al.[9]	Presented an approach based on the Envelope analysis of acoustic emission signature of the gearbox wind turbine.	Improves the detection fault step of the gearbox wind turbine.
2016	Qiu, Yingning; Feng, Yanhui; Sun, Juan; et al.[10]	Presented an approach for diagnosis the gearbox and generator of wind turbine based on the thermophysics model	Is efficient to indicate the gearbox degradation
2016	Yang, Zhi-Xin; Wang, Xian-Bo; Zhong, Jian-Hua [11]	Proposed an approach based on the multiple extreme learning machines (ELM) for diagnosis the fault of wind turbine generator	Gives the best recognition accuracy in multiple faults.
2016	Mollasalehi, Ehsan; Sun, Qiao; Wood, David [12]	Proposed demodulation technique approach based on calculating the energy band by the wavelet packet for the diagnosis of the bearing generator	Gives the best result of the localization for the outer race bearing fault.

From literature, the most used approach for fault diagnosis of vibration wind turbine (gearbox, generator …) is based on three main steps [11], the first is the signal processing of vibration signal, the second is the directional reduction and the last is the recognition fault.

In proposed fault diagnosis approach, the structure and number of steps are the same, the first step is focused on another concept and it is based on the selection of system parameters and the extraction of the feature set.

The proposed approach of fault diagnosis wind turbine system is based on the historical data. First, vectors with high dimension should be constructed for each state, using the different parameters of wind turbine. After that, these vectorsare exploited to apply the reduction dimension methods, to make easy the exploitation of these vectors with low dimensions using the pattern recognition classifier to diagnosis the types of defaults.

In this work, a novel MAED algorithm is selected for the feature set with the high performance [13] applied on text categorization.

There are a lot of reduction dimension methods, these methods were divided into two types: the first type is classical methods, like the Multidimensional Scaling (MDS) [14], and the Independent Component Analysis (ICA) [15], but the second one is recent method and based on the manifold learning, like the Locally Linear Embedding (LLE) [16] and Locality Preserving Projection (LPP) [17], so the NPE algorithm is used for directional reduction in this work.

After the step of reduction of dimension, the vectors are used as input for pattern recognition.

There are a lot of learning machines for pattern recognition, as common the SVM using the statistical theory [18].

The SVM has high performance of classification; it uses the kernel function [19].

This work is organized as follows: in section 2, the MAED algorithm, the reduction dimension method and the SVM classifier are presented. Section 3 is reserved to describe the wind turbine benchmark model and its faults. The proposed approach of fault diagnosis is described in section 4. After that, the fault diagnosis model is applied to benchmark model and discussion of results in section 5, and finally a conclusion.

2. Theoretical Background

2.1. The Manifold Adaptive Experimental Design (MAED) Algorithm

In the first time, the feature set selects the sample data to present all the data, among these references [20, 21, 22] described the categorization of feature selection. The MAED algorithm is summarized as follows [13]:

2.1.1. Construct the manifold adaptive kernel

The G set of nearest neighbor is constructed for each x_i data point and find its k nearest neighbors, denoted $N(x_i)$, where an edge is put between its neighbors and data point x_i. The weight matrix on the graph is:

$$W_{ij} = \begin{cases} 1 & \text{if } x_i \in N(x_i) \text{ or } x_j \in N(x_j), \\ 0 & \text{otherwise .} \end{cases} \quad (1)$$

The Laplacian graph is calculate by $L = D - W$

So the diagonal matrix is D, where the columns are the entries (or row, since W is symmetric) and the sums of W, $D_{ii} = \sum_j W_{ji}$

Put the K the kernel of independent data, as the linear or Gaussian kernel, related with the kernel matrix K.

That is, $K_{ij} = K(x_i, x_j)$

The *i-th*column vector of K is denoted k_i, and the matrix of manifold adaptive kernel K_M is calculated as follows:

$$K_{M,ij} = K_M(x_i, x_j) = K_{ij} - \gamma {k_i}^T (I + LK)^{-1} L k_j \quad (2)$$

2.1.2. Solve manifold adaptive active learning optimization problem.

Put the u_i the *i-th* row (or column, since K_M is symmetric) vector of K_M. In the beginning $\alpha_{i,j} = 1$, and computing the iterative until convergence.

$$\beta_j = \sqrt{\frac{\sum_{i=1}^{n} {\alpha_{i,j}}^2}{\gamma}} \;, j = 1, \dots, n. \quad (3)$$

$$\alpha_i = (\mathrm{diag}(\beta)^{-1} + K_M)^{-1} u_i \;, i = 1, \dots, n. \quad (4)$$

2.1.3. Data selection

The data points are rankedin descending order according toβ_j $(j = 1, \dots \dots \dots, n)$, and the top K data points are selected.

2.2. The Neighborhood Preserving Embedding (NPE) algorithm

The NPE algorithm was developed by several authors [23], they used the moving window technique based on the dynamic multiway neighborhood preserving embedding to monitor the fed-batch process, and [24] presented the time neighborhood preserving embedding for fault detecting of dynamic process.

The orthogonal neighborhood preserving embedding and Shannon wavelet support vector machine are used for fault diagnosis of wind turbine transmission system by the author [25].

In this Section, a linear directional reduction algorithm is presented, called the NPE [26].

2.2.1. The linear directional reduction problem

The problem of directional reduction is to find a transformation matrix A, which transforms a set of points $x_1, x_2, \dots, x_m \in \mathbb{R}^n$to a set of points $y_1, y_2, \dots, y_m \in \mathbb{R}^d$ $(d < n)$, saving the same number of data *m*, such as y_i"represents"x_i, and $y_i = A^T x_i$.

In the special case, this method is applicable where $x_1, x_2, \dots, x_m \in M$ and $M$is a nonlinear manifold embedded in $\mathbb{R}^n$.

2.2.2. The algorithm NPE

The procedure of the NPE is formally as follows:

Constructing an adjacency graph: Put G a graph with m nodes, where each data point x_i corresponds to the$i$-th node.

- *Knearest neighbors (KNN):* Put an edge a directly from node $i$to j, if $x_j$is among the Knearest neighbors of x_i.
- *$\in$ −neighborhood:* if $\|X_i - X_j\|^2 < \in$, Put an edge between nodes *i*and *j*.

The complexity of computational is a major concern, which can switch to$\in$ neighborhood. The edge from $i$to j is denoted$i \sim j$.

Computing the weights: the weights are computed on the edges, the weight matrix is denoted W, this matrix has W_{ij} of the edge weight from node i to node j, and equal zero if inexistence of edge. The minimizing of following objective function can give the weights on the edges.

$$\min \sum_i \left\| x_i - \sum_j W_{ij} x_j \right\|^2 \quad (5)$$

with constraints$\sum_j W_{ij} = 1, j = 1,2, \dots, m$

Computing the Projections: The linear projections are computed to solve the problem of generalized eigenvector:

$$XMX^T \boldsymbol{a} = \gamma XX^T \boldsymbol{a} \quad (6)$$

Where

$X = (x_1, \dots, x_m)$, $M = (I - W)^T (I - W)$, and $I = \mathrm{diag}(1, \dots, 1)$

The solutions of equation (1) is the column vectors $a_0, a_1, \dots, a_{l-1}$, this order is according to their eigenvalues, $\gamma_0 < \gamma_1 \cdots < \gamma_{l-1}$. Thus, the embedding is as follows:

$$x_i \rightarrow y_i = A^T x_i, \; A = (a_0, a_1, \dots, \quad a_{l-1}) \quad (7)$$

Where A is a matrix of $n \times d$ dimension, and y_i is a *d*-dimensional vector

2.3. The Support Vector Machine classifier (SVM)

The SVM classifier was developed by several authors, [27] presented an approach based on multi-class fuzzy support vector machine (FSVM) classifier for fault diagnosis of wind turbine, it has better performance of recognition accuracy when applied on the both experimental and test rig. [25] proposed a new approach based on manifold learning and Shannon wavelet support vector machine for fault diagnosis of wind turbine transmission system, this approach improves the recognition accuracy (more than 92%) of fault diagnosis of the gearbox bearings. [28] proposed a novel hybrid algorithm for fault diagnosis of rotary kiln based on a binary ant colony (BACO) and the SVM, this algorithm gives the optimal SVM parameters and the best classification accuracy.

The approach is an effective fault diagnosis method for WT, which has a better performance and can achieve higher diagnosis accuracy.

The SVM classifier created the hyperplanes and is used as the decision boundary, with the maximal margin between these hyperplanes.

Figure 1 presented two samples of data, where H is optimal hyperplane and for each sample 1, 2, is correspondingH1 , H2 hyperplanes respectively.

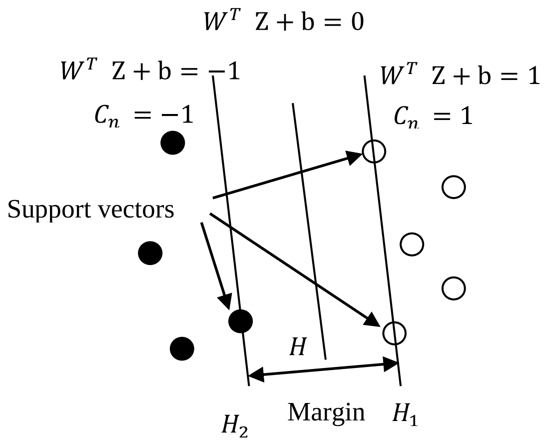


Fig. 1. Conceptual schema of the linear support vector machine.

Mathematically, there are the training samples Z_n, $n = 1,2,\dots,N_s$, and a label of each sample is $C_n \in \{1,-1\}$, thus the linear classifier is $g(Z) = W^T Z + b$.

$$\begin{cases} W^T Z + b \geq 1 & if\ C_n = 1 \\ W^T Z + b \leq -1 & if\ C_n = -1 \end{cases} \tag{8}$$

The equation (8) can be written as follows:

$$C_n(W^T Z + b) \geq 1 \tag{9}$$

Let W be the gradient vectorg(Z). After that there is the inversely proportional between the margin square and

$$||W||^2 = W^T W \tag{10}$$

The minimization of $||W||^2$ is found by maximizing the margin.

The constraints of equation (8) are incorporated by the Lagrange multipliers to minimize function (11).

$$L = \frac{1}{2}||W||^2 + \sum_{n=1}^{N_s} \alpha_n [C_n(W^T Z + b) - 1]\ , \alpha_n \geq 0 \tag{11}$$

The partial of L equation with W and b is derivated to zero results, given as (12):

$$\begin{cases} W = \sum_{n=1}^{N_s} \alpha_n C_n Z_n \\ \sum_{n=1}^{N_s} C_n\ \alpha_n = 0 \end{cases} \tag{12}$$

The minimization of L equation means that W and b are respected, on the other hand $\alpha_n$is respected for maximizingL equation.

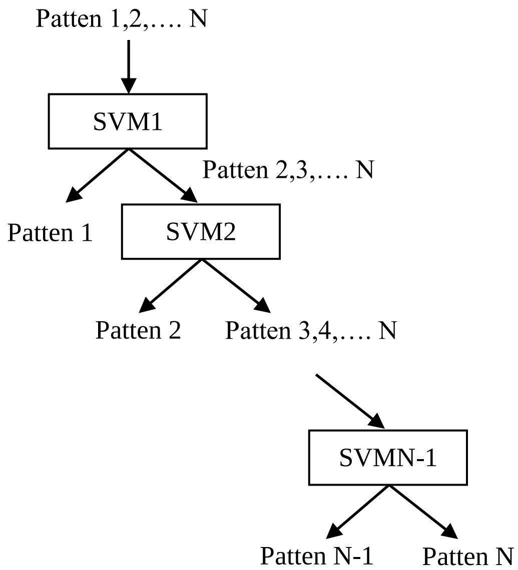


Fig. 2. Layer by layer classification model of SVM [25].

This is a quadratic optimization problem, after optimization,α_n are used in the equation (11) to find.

The typical problems have the sparse solution with many α_n equal zero, but the samples Z_n have $\alpha_n > 0$, called the support vectors machine.

One of the solutions of the multiclass classification used the N-1 SVM classifiers to classify N types of fault that make layer by layer [25], as presented in Figure 2.

3. Wind Turbine Benchmark and its Faults

3.1. Benchmark model

The benchmark model of wind turbine is based on three blades, horizontal axial and variable speed with a full converter, and an output power of 4.8 Mw [29].

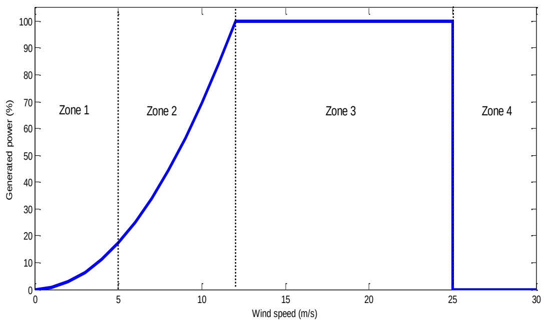


Fig. 3. Operate zones of wind turbine (Power curve) [29]

This model is composed by five parts: Blades, drive train, generator, converter, and controller.

Figure3 shows four operate zones: the first is start-up, the second is crowned, the third is constant, and the last is no power production. This work focuses on zones 2 and 3.

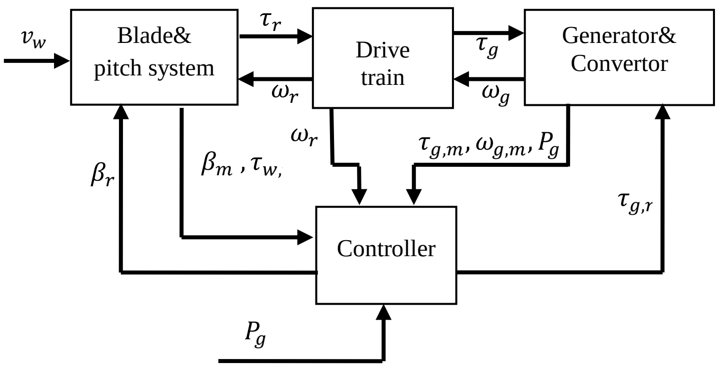


Fig. 4. System overview of the wind turbine benchmark model [29].

Wind turbine generated the electrical energy from the wind power. There are two kinds of wind turbines: a vertical axis, and a horizontal axis.

When the wind turns, the wind turbine blades transfer the movement to the rotor shaft, a generator converts the mechanical energy to electrical energy after introducing the drive train.

The conversion from wind energy to mechanical energy is controlled by pitching the blades or by controlling the rotational speed of the turbine relative to the wind speed.

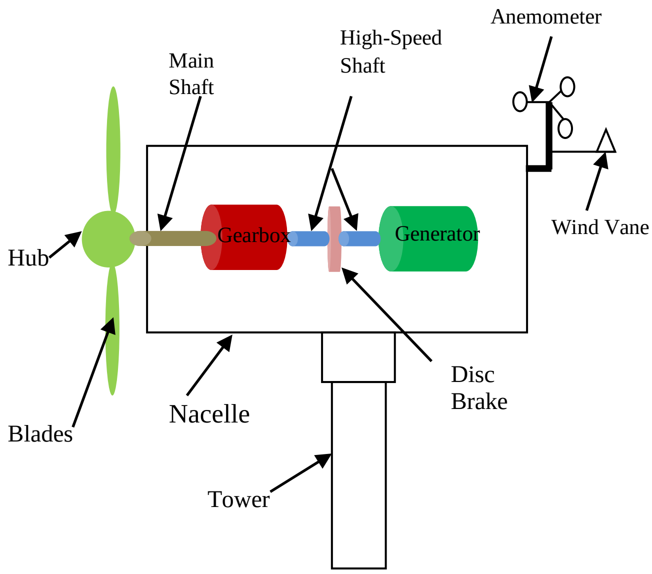


Fig. 5. Conceptual schema of components of the wind turbine.

The structure of model is presented in Figure4. Table 2 describes its symbols:

Table 2. Description of the symbols of the benchmark [29]

Sym	Description	Sym	Description
v_w	wind speed	β_m	Measured pitch angles
τ_r	Rotor torque	ω_r	Rotor speed
τ_g	Generator torque	$\omega_{r,m}$	Measured rotor speed
$\tau_{g,m}$	Measured generator torque	ω_g	Generator speed
$\tau_{g,r}$	generator torque reference	$\omega_{g,m}$	Measured generator speed
$\tau_{w,m}$	Measured wind torque	P_g	Measured generated electrical power
β_r	pitch angle control reference	P_r	Power reference

3.2. Faults of wind turbine benchmark

The wind turbine benchmark has many types of faults, as the actuators, the system, and sensors. The faults 1 to 5 do not concern actuators.

In this work, it was focused on actuators and the system faults:

- Fault 6 represented by a changed pitch system response in pitch actuator 2 as a result of high air content in oil, in period of2900s-3000s.
- Fault 7represented by a changed pitch system response in pitch actuator 3 as a result of low pressure, in period of 3400s-3500s.

- Fault 8 represented by an offset in converter torque control, in period of 3800s-3900s.

- Fault 9 represented by a Changed dynamics drive train, in period of 4000s-4100s.

Table 3 summarizes these faults and their duration

Table 3. Faults of benchmark model [29]

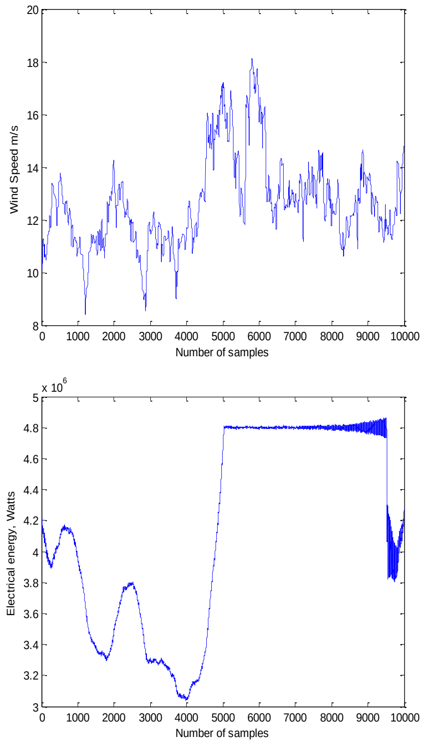
No.	Description	Duration
Fault6	Changed pitch system response pitch actuator 2 - high air content in oil	2900-3000 sec.
Fault7	Changed pitch system response pitch actuator 3 – low pressure	3400-3500 sec.
Fault8	Offset in converter torque control	3800-3900 sec.
Fault9	Changed dynamics drive train	4000-4100 sec.

Table 4. Used data [29]

	v_w (m/s)	β_r (deg)	β_{1m} (deg)	β_{2m} (deg)	β_{3m} (deg)	ω_r (rad/s)	ω_g (rad/s)	τ_r ($x10^6$Nm)	τ_g ($x10^4$ Nm)	P_g ($x10^6$W)
Fault 6	8.41-18.13	(-2)-13.94	(-3.94)-12.85	(-3.50)-12.79	(-3.74)-12.97	0-1	136.63-164.43	1.22-6.60	2.26-3.30	3.04-4.86
Fault 7	10.72-18.92	(-2)-14.79	(-3.50)-13.86	(-3.39)-13.80	(-3.78)-12.96	1	149.24-164.28	1.84-5.89	2.97-3.28	4.75-4.83
Fault 8	10.78-25.50	(-2)-22.22	(-3.46)-21.35	(-3.65)-21.13	(-3.49)-21.24	1	155.93-164.10	1.88-6.02	2.99-3.15	4.80-4.83
Fault 9	10.38-20.06	(-2)-15.36	(-3.58)-14.59	(-3.39)-14.59	(-3.42)-14.54	0-1	144.60-163.74	2.03-5.48	2.53-3.32	3.59-4.83
Normal	7.65-21.39	(-2)-14.25	(-3.31)-13.72	(-3.39)-13.58	(-3.51)-13.75	0-1	130.78-165.21	0.925-7.23	2.07-3.32	2.66-4.81

Figure 6 represents the benchmark data of wind speed and electrical energy.

a)



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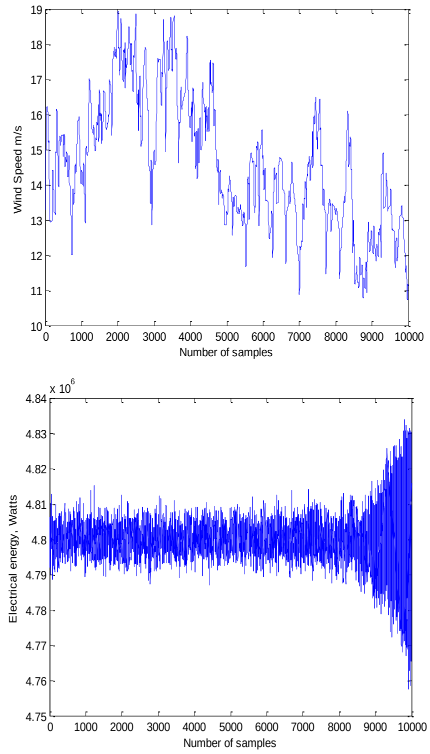

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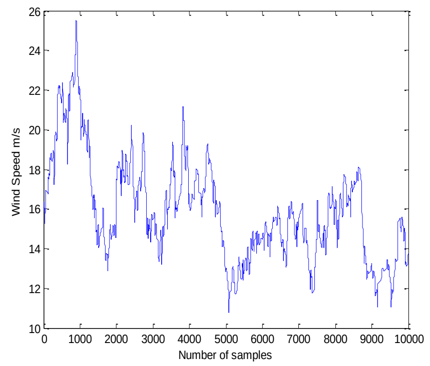

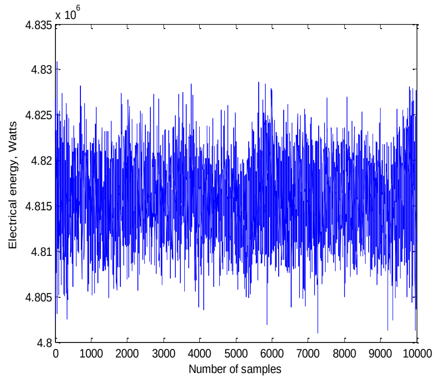

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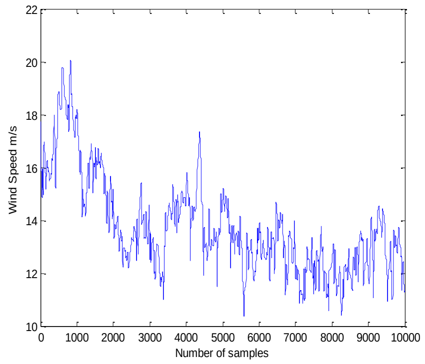
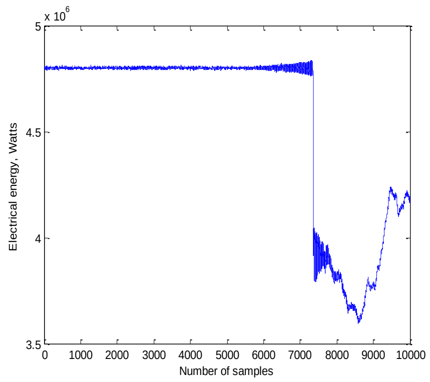
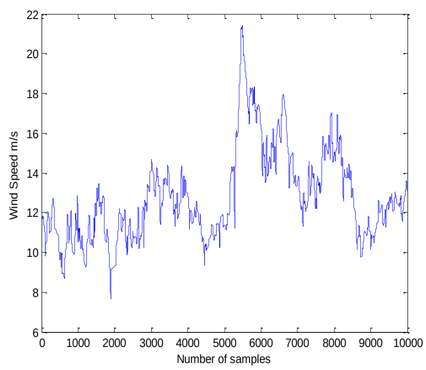




e)



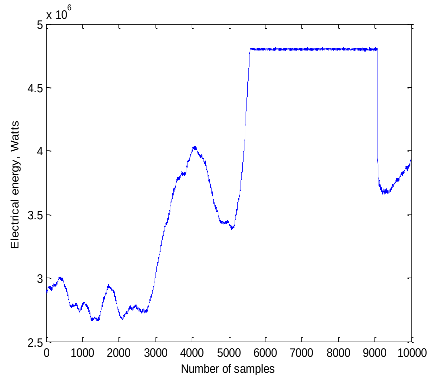


Fig. 6. Benchmark data of wind speed and electrical energy respectively: a) Fault 6, b) Fault 7, c) Fault 8, d) Fault 9, e) Normal state.

The Figures 6.a, 6.b, 6.c, 6.d and 6.e are presented the data of wind speed and electrical energy respectively for four kinds of fault and normal state, the values of wind speed are between 7.65 to 25.50 m/s corresponding to the generated power of zone 3 of Figure 3 (Power curve).

4. The fault diagnosis approach

State vector: is a feature set of the system parameters presenting the state of system on time variation which are ordered in a column or row matrix.

The wind turbine system is characterized by very important two parameters, the power energy and the wind speed, so this approach is based on the power energy as key parameter.

Figure 7 presents the proposed approach of fault diagnosis in this work:

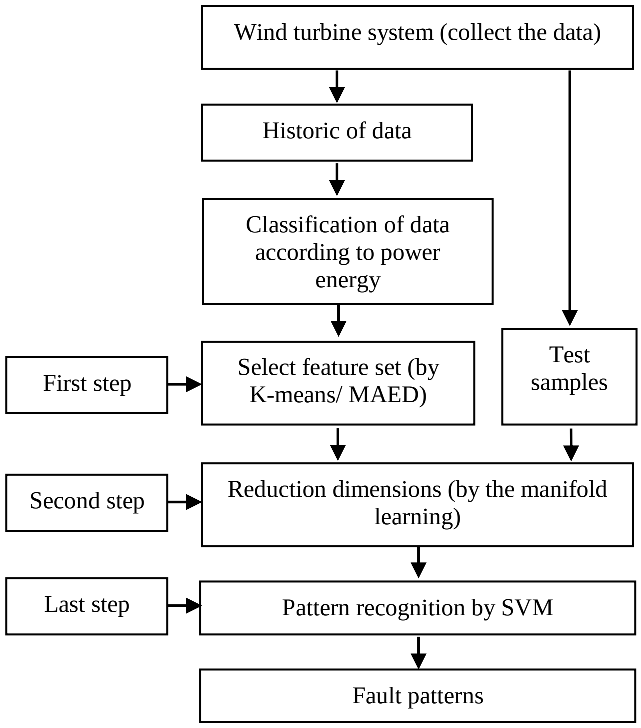


Fig. 7. Conceptual schema of Implementation process of fault diagnosis for the proposed approach.

The main steps of fault diagnosis approach (data-based model) are:

➢ The first step is the extraction of feature set from a huge historical data, so the best feature should be extracted from sample representing this data, with the K-means then the MAED algorithm.

➢ The second step is the reduction of dimension of the state vector containing parameters of feature set (output of first step), because the dimension of feature set is big (superior to three). To be exploited easily, it should be reduced.

This approach uses the LPP algorithm in the first time then the NPE algorithm.

➢ The last step is pattern recognition by SVM classifier and finding fault patterns.

5. Faults Diagnosis and Obtained Results

5.1. Application of the proposed fault diagnosis approach on benchmark model

This approach is used to diagnosis the normal state and four kinds of faults (fault 6, fault 7, fault 8, fault 9), so the state vector is constructed as showed in (13):

$$V = \left[v_w, \beta_r, \beta_{1m}, \beta_{2m}, \beta_{3m}, \omega_r, \omega_g, \tau_r, \tau_g, P_g\right] \qquad (13)$$

Where the feature set has ten elements for each type and test samples too.

In the first time, the k-means was applied on 1000 vectors to obtain 10 elements for each type and a matrix of 60x10. After reduction of the last matrix (so the LPP is characterized by nearest neighbors k=3, Heat kernel t=3 and dimension d=3), another matrix of 60x3 will be obtained.

In this section, there are two comparisons:

The first comparison is between:

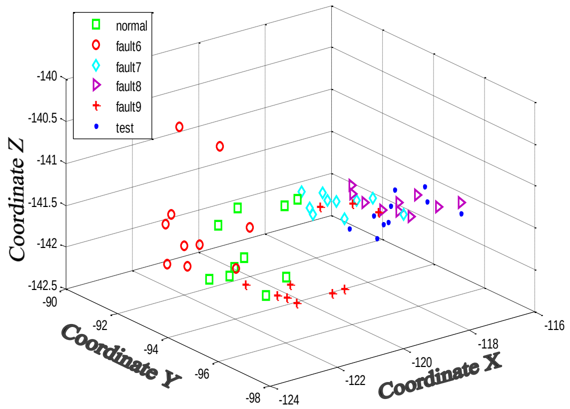
➢ Over the state vector in same time (k=10).

➢ And over the wind speed (important factor with k=10), and then affect the other parameters to each element of state vector, finally the k-means was applied again over new matrix (k=1).

Figure 8.a shows that feature set is not separated from each other and test samples are very scattered in the cases of fault 7 and fault 8.

But in figure 8.b, there is separation from each other, which means that the wind speed is the key factor for the wind turbine system.

a)



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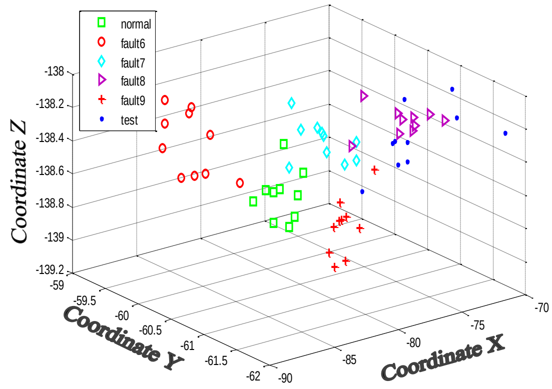


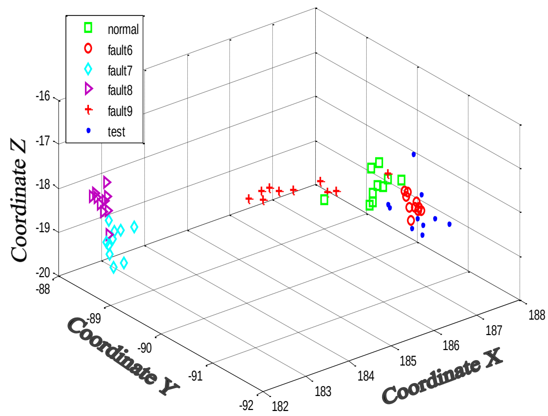
Fig. 8. Low dimensional feature set with LPP: (a)- k-means applied to all state vector, (b)- k-means applied to wind speed.

In second time, a comparison between LPP and LPP-SVD was done, then linear SVM for fault classification was applied with c=1.

➢ Outputs of LPP are eigenvectors with (10x6), just the first 3 elements were used among 6 which are with dimensions (10x3) only, so the low dimensions were obtained (60x10)x(10x3)=(60x3),

➢ But here, the SVD was applied to eigenvectors with (10x6), so the dimension of eigenvectors is reduced (outputs of LPP), the low dimension is obtained from (10x6)x(6x3)=(10x3). Finally, the new low dimension is (60x10)x(10x3)=(60x3).

a)



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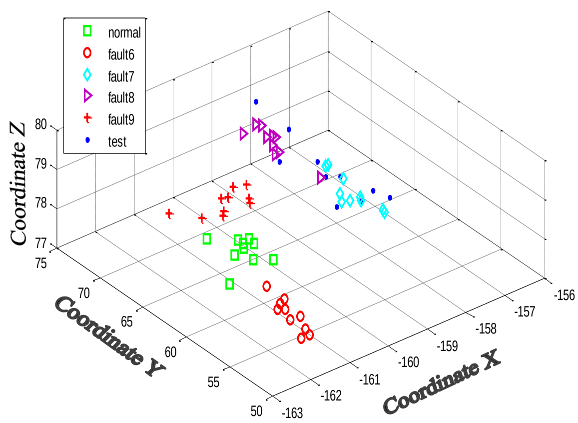
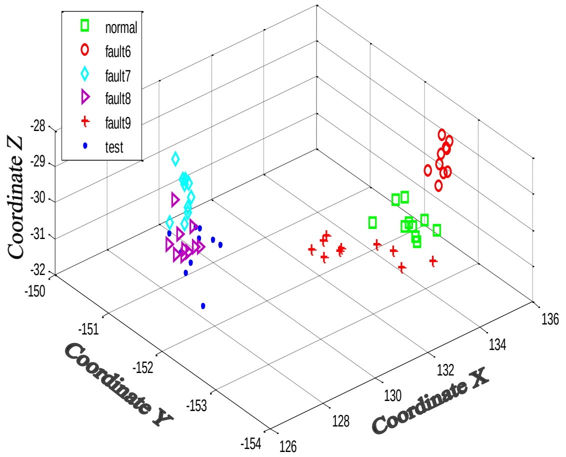
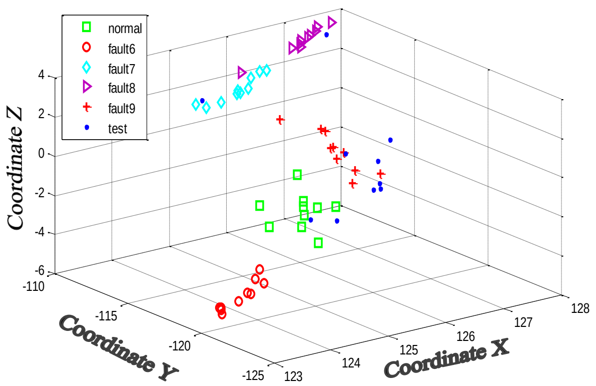


c)



d)



e)

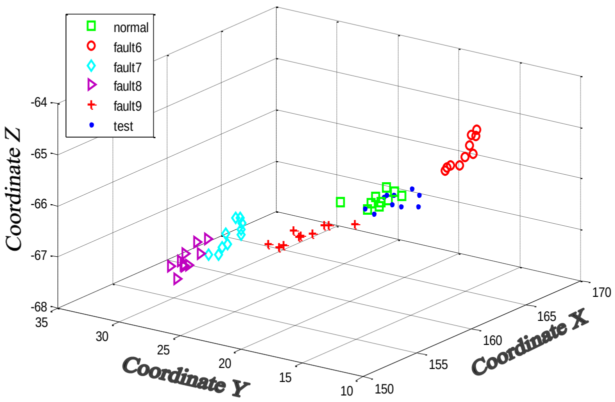


Fig. 9. Low dimensional of feature set with LPP-SVD: (a) fault6, (b) fault7, (c) fault8, (d) fault9 and (e) Normal state.

As shown in Figure 9 and Figure 8.b, the elements of feature set are well separated from each other, and it gives for the test samples of fault 8 recognition approximately equal to 90% (9/10 samples), contrarily to a recognition of 70% in the first time (LPP only). But the normal state percentage is 100% (good performance). Also there is difficulty in the fault 9 because its performance is low related to the other results.

Table 5summarizes and compares the results.

Table 5. Comparison of the fault diagnosis results using LPP and LPP-SVD

Recognition Accuracy	Normal	Fault 6	Fault 7	Fault 8	Fault 9	Average
LPP	70%	70%	50%	70%	50%	62%
LPP-SVD	100%	90%	70%	90%	60%	82%

Table 5 presents the results of comparison between two reduction dimension algorithms used by the proposed fault diagnosis approach. The first one is LPP algorithm, it gives the result of 62% accuracy, but the LPP-SVD algorithm gives the result of 82% accuracy obtained when the SVD algorithm was applied (the second reduction dimensions). The last result could be increased to reach better and high performance of recognition accuracy, which is the objective presented in section 5.2.

5.2. Improvement of the fault diagnosis approach

To improve the performance of recognition accuracy of the proposed approach, there is a lot of ways to do it. In this section, the NPE and MAED algorithms are applied on the feature set algorithm and the directional reduction method.

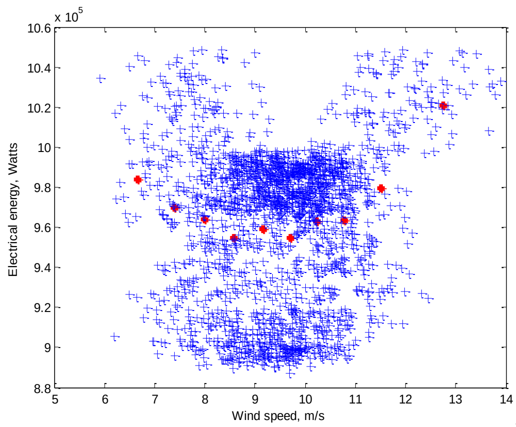
In this step of proposed approach the feature set will be extracted, the same data are saved (Fault6, Fault7, Fault8, Fault9) and the MAED algorithm is applied for the normal state and the four kinds of faults.

In the first time, the state vector of each fault should be constructed (the same parameters of equation (13) in section 5.1).

This vector has the fault specification, the very important parameters are the v_w (wind speed) and P_{gm} (power energy), but when applying the K-means algorithm on these parameters for extraction, the feature set do not represent the best fault specification.

The two schemas of Figure 10 represent the difference between feature set when the K-means algorithm (schema a) and MAED algorithm (schema b) are applied.

a)



b)

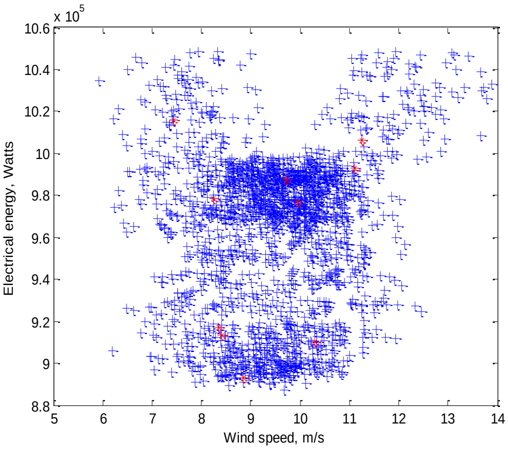


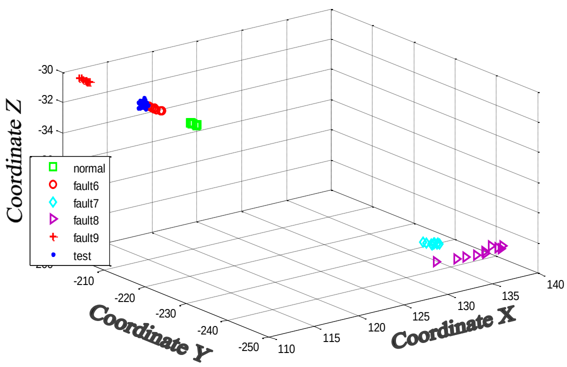
Fig. 10. Feature set of normal state, a) K-means and, b) MAED

In Figure 10.a the data class of normal state (number of elements of the sample is 1000) and feature set with the k-means algorithm (k=10, the ten red points), are shown.The feature set is located in the center of data, because this algorithm is based on the mean of each set, and the values of the electric energy (between 8.8x105 and 10.6x105Watts) are very large relatively to values of the wind speed and the K-means algorithm application. It gives a very close average values between them as shows Figure 10.a.

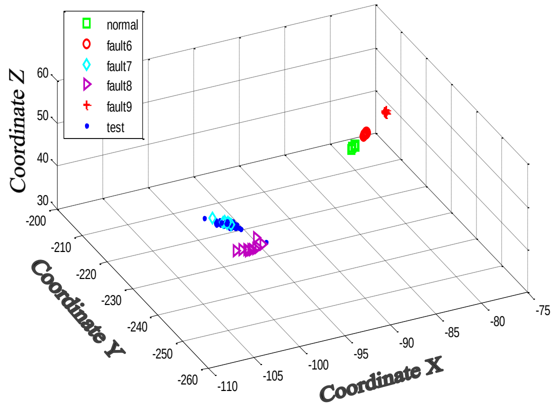
But Figure 10.b, presents the best scattering of feature set (n=10) when the K-means algorithm is applied to extract very important information of faults.

The comparison concerns the feature set algorithm and the dimension reduction methods; the first and second steps of proposed approach. This comparison is established between the K-means and the MAED algorithms, because step 1 is very important for fault diagnosis. On the other hand, a second comparison is established between the reduction dimension methods (LPP and NPE) and their parameters nearest neighbors k=3 and dimension d=3.Then, the feature set is selected with the K-means algorithm.

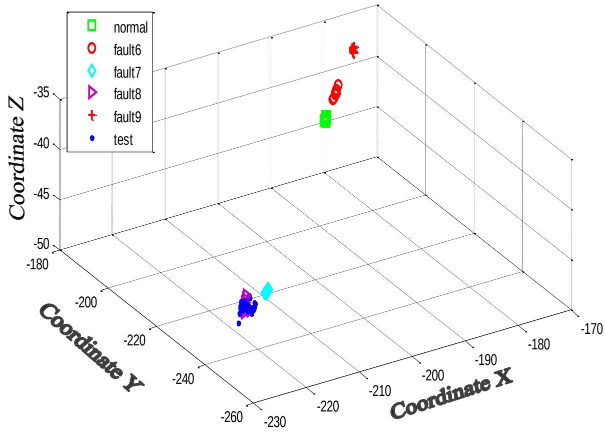
a)



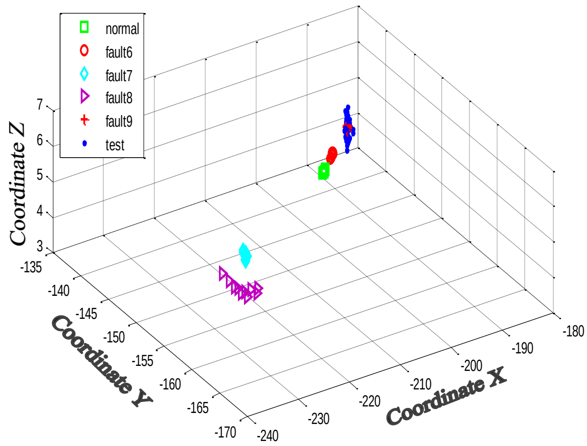
b)



c)



d)



e)

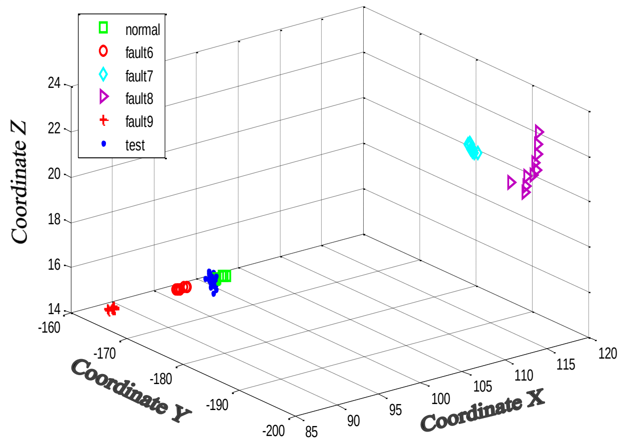


Fig. 11. Feature sets with the MAED algorithm and the reduction of dimensions with the NPE: (a) fault 6, (b) fault 7, (c) fault 8, (d) fault 9, (e) Normal state.

When the MAED and the NPE algorithms were applied, they give better performance (Figure 11) than section 5.1, where the set of each fault is well separated as shows Figure9.e.

The main step in proposed approach is extraction of the feature set and MAED gives higher performance than k-means. Also this step reinforces dispersion and centralization of feature set in the same fault.

But the dimension reduction method (NPE) gives a higher separation between classes of defaults (e.g. class fault and class of fault b) than LPP.

These two comparisons are summarized in Figure 12:

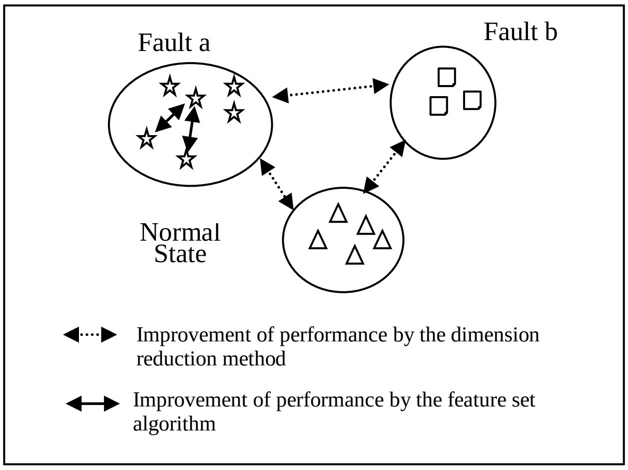


Fig. 12. Schema of improvement of performance by the reduction dimension methods

The results are summarized of this comparison in table 6:

Table 6. Comparison of recognition accuracy of the fault diagnosis results.

Recognition Accuracy	Normal	Fault 6	Fault 7	Fault 8	Fault 9	Average
K-means LPP-SVD	100%	90%	70%	90%	60%	82%
Proposed MAED algorithm	100%	100 %	92%	100 %	100 %	98.4%

Finally, the efficiency of the proposed approach appears in the case of the fault 9, the accuracy reached 100% where it was 60%. On the other hand, the higher average result of performance is (98.4%).

6. Conclusion

The proposed fault diagnosis approach is based on three steps, the first step is the extraction feature set, the second step is the directional reduction and the last step is the fault recognition. Three important algorithms were applied respectively for each step, the MAED algorithm, NPE algorithm and the SVM classifier. They were implemented on the wind turbine benchmark and gave the best feature set and better performance of dimension reduction.

The extraction algorithm of the feature set reinforces dispersion and centralization of feature set in the same fault, where MAED algorithm gives the highest performance, and the dimension reduction method (NPE) gives the highest separation between classes of defaults.

When this approach is applied to the actuators and system faults of wind turbine benchmark, it gives 98.4% recognition accuracy of the fault diagnosis result; it is the best result when it is compared to other methods (k-means, LPP).

The next work will concentrate on the blades faults (actuators) of wind turbine, because there are variations of speed and direction wind.This last is considered as input of wind turbine, it is very important key to improve the power energy

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