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Co-Author(s) : Chouaib Chakour. Abdelhafid Benyounes.

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Fault Detection and Isolation of Wind Turbine using Minimal Learning Machine

1st Zakaria Bouzid
LAGE laboratory
University of Ouargla
Ouargla, Algeria
bouzid.zakaria@univ-ouargla.dz

2nd Chouaib Chakour
Electrical Engineering Department
20 August 1955 University of Skikda
Skikda, Algeria
chakour.chouaib@gmail.com

3rd Abdelhafid Benyounes
Department of Electrical Engineering
University of M'sila
M'sila, Algeria
benyounes.abdelhafid@gmail.com

***Abstract*—Wind turbines, as one of the fastest-growing renewable energy technologies, require advanced fault detection and diagnostic methods to maintain cost-effective and reliable energy production. The field of fault detection includes model-based and data-driven approaches, with recent advancements emphasizing data-driven techniques that leverage machine learning for more robust performance. In this paper, we aim to apply the Minimal Learning Machine (MLM) for fault detection and isolation (FDI) in wind turbines. MLM is a supervised machine learning technique that relies on distance-based learning to predict outputs by approximating relationships in the input space. This approach offers a simpler and computationally efficient alternative to traditional machine learning methods while still providing accurate fault detection capabilities. For the fault detection phase, we employ indices to identify anomalies, SPE index (Squared Prediction Error) for indicating potential sensor/ actuator faults in the system. Fault isolation is achieved through structured residuals, using the principle of reconstruction to pinpoint specific faults. Our application concerned the benchmark Wind Turbine Supervisory Control and Data Acquisition (SCADA) system, which provides a comprehensive set of variables to evaluate MLM's performance in terms of fault prediction and isolation.**

***Index Terms*—wind turbines, supervisory control and data acquisition (SACADA), fault detection and isolation, Fault reconstruction, machine learning**

I. Introduction

Fault diagnosis has gained significant attention in recent years due to the deteriorating characteristics of industrial processes, which can result in severe social and economic consequences. Ensuring a high level of safety, performance, and reliability in controlled systems requires the prompt detection of system errors and abnormal operations, enabling timely corrective actions to prevent escalation [1]. Fault Detection and Diagnosis (FDD) methods can be classified into two categories: model-based and data-driven [2]. Model-based methods rely on mathematical representations of system dynamics, using physical laws and observer-based techniques like the Kalman filter and Luenberger observers to detect and diagnose faults [3]. Data-driven methods, on the other hand, leverage historical or real-time data to identify patterns, anomalies, and faults without requiring a detailed physical model of the system [4]. In the data-driven techniques, statistical methods such as Principal Component Analysis (PCA) are used in many applications to detect faults based on residual analysis such as [5] [6]. Machine learning techniques, also used widely in FDD field using classification and regression including Support Vector Machines (SVM) [7], and Neural Networks [8], have gained prominence for their ability to model complex, nonlinear systems and adapt to diverse fault scenarios, Minimal Learning Machine (MLM) [9], also used in faults classification. These methods are particularly suitable for applications where large amounts of sensor data are available, such as in wind turbine systems.

Wind turbines, particularly those located offshore, face tough conditions that can lead to sensor and component failures [10]. It's crucial to diagnose these faults accurately and swiftly to keep performance up, minimize downtime, and maintain safety standards. Several studies have addressed FDD in wind turbines, employing methods such as PCA for fault detection [1]. Also, Santos et al [7] proposed a solution to use Support Vector Machin SVM for Fault Detection of a Wind turbine, and using Neural Networks, Zhang et al [11], presents a review of artificial neural networks used in wind energy. However, faults in sensor measurements can compromise the safety and performance of wind turbines due to the harsh environmental conditions. To ensure continuous operation, robust FDD methods are essential. In this paper, we propose a methodology for fault detection and isolation using the Minimal Learning Machine (MLM). MLM is a new supervised machine learning technique, based on the existence of a linear mapping among the distance points between the input and output spaces [12], as outlined in the first section. MLM is used in this work in predictive diagnosis, which can deal with multi-response regression, in the second section we proposed a methodology to adapt the square prediction error (SPE) index and the reconstruction principle to use with MLM for fault detection and isolation FDI. Reconstruction Principle proposed by Dunia et al. [13] in detail. This method relies on the SPE index for isolation and localization. It assumes that each sensor can be suspected and reconstructed. And SPE is calculated after reconstructing each variable. The comparison of the SPE before and after reconstruction makes it possible to identify the faulty variable [14]. In the last section, the proposed methodology was applied on a Wind Turbine Benchmark provided by Leahy, et al. [15]. Six sensors were used, including wind speed, torque, generated energy, and blade angles. After preprocessing and normalizing the data, we apply MLM to estimate sensor values and calculate the Squared Prediction Error (SPE) index for fault detection. For fault isolation, the reconstruction principle is utilized, which identifies the faulty sensor by replacing sensor values with their reconstructed estimates and analyzing the SPE. This study contributes to the growing field of machine learning-based FDD by integrating MLM with SPE and reconstruction principles, offering a novel and efficient method for identifying and isolating sensor faults in wind turbines.

II. Minimal Learning Machine

The Minimal Learning Machine (MLM) is a novel distance-based supervised learning technique that builds predictive models by mapping input distances to output distances. MLM achieved promising results on many applications like [17] [9]. In MLM, a linear mapping is constructed between input and output distance matrices. During prediction, this learned distance mapping estimates the distances from a set of K output reference points to the unknown target output. The final output estimate is then derived by solving a multilateration problem, using the predicted output distances along with the known positions of these reference points [12]. Building an MLM model involves three main steps. Before starting, the dataset should be divided into training and test sets. In the first step, select the number of reference points, K, which is the only hyperparameter required by MLM. K reference points are randomly chosen from the training samples, each containing both input attributes and the corresponding output. The next step, a linear mapping is constructed between the distances from each point to each reference point in the input space and the corresponding distances in the output space. In the estimation step, the model calculates distances to the reference points in the input space and then maps these distances using the linear mapping to estimate the output space distance matrix. Finally, this estimated output distance matrix, together with the reference points, is used to determine the final output by solving a convex optimization problem. In the next subsections, more details about MLM will be discussed.

A. Formulation

Let's give a set of N input points $X = \{x_i\}_{i=1}^{N}$ and $Y = \{y_i\}_{i=1}^{N}$ the set of N output points, with $x_i \in \mathbb{R}^D$ and $y_i \in \mathbb{R}^S$.

Assuming the existence of a continuous mapping $f : X \to Y$ between the input and the output space, the learning problem can be defined as the task of estimating f from data with the multi-response model $\mathrm{Y} = f(X) + E$

Where, the matrices $X \in \mathbb{R}^{N\times D}$ and $\mathrm{Y} \in \mathbb{R}^{N\times S}$, and the matrix $E \in \mathbb{R}^{N\times S}$ correspond to the residuals. In the next two subsections, we will discuss reconstructing the mapping existing between input and output distances and then estimating the response from the output points.

B. Training Phase

Let $R = \{r_k\}_{k=1}^{K}$ be a non-empty subset of X, and $T = \{t_k\}_{k=1}^{K}$ be such that t_i is the output of r_i, where K is the number of reference points. Moreover, let $D_x, \Delta_y \in \mathbb{R}^{N\times K}$ be euclidean distance matrices such that their k-th columns are respectively $\left[\|x_1 - r_k\|_2, \cdots, \|x_N - r_k\|_2\right]^T$ and $\left[\|y_1 - t_k\|_2, \cdots, \|y_N - \ t_k\|_2\right]^T$.

The linear mapping between D_x and Δ_y, giving rise to the following regression model:

$$\Delta_y = D_x\beta + \boldsymbol{E} \tag{1}$$

where $\boldsymbol{E} \in \mathbb{R}^{N\times K}$ is a matrix of residuals and $\beta \in \mathbb{R}^{K\times K}$ is the matrix of regression coefficients. β can be estimated using Ordinary Least Squares (OLS):

$$\hat{\beta} = \left(D_x^T D_x\right)^{-1} D_x^T \Delta_y \tag{2}$$

The training phase will involve learning these relationships, while the prediction phase will use the model to estimate sensor data and detect any differences. As we have described earlier in the principle of Minimal Learning Machine (MLM), the first step is splitting the sensors into two sets $S = [X, Y]$ (S is the set of sensors). This division allows us to model the relationship between sensors data effectively. After selecting K reference points from both the input and output sensor sets, the next step is to calculate the distance between input and its reference points D_x and the same with output and reference points Δ_y. This distance is used to measure the relationship between the two sets of sensors.

Once calculating the distances, finding the matrix $\hat{\beta}$ can be done by solving the (1), which represents the transformation that best maps the input reference points to the corresponding output reference points. we obtain the optimal matrix $\hat{\beta}$, (2)

C. Prediction Phase

The last step, estimation of the output done by giving a new input X, we can obtain an estimate $\hat{\delta y} = \left[\hat{\delta y_1}, \cdots, \hat{\delta y_K}\right]$ of the distance between the output of X and the K points in T, given by:

$$\hat{\delta_y} = \left[\|X - R_1\|_2, \cdots, \|X - R_K\|_2\right]\hat{\beta} \tag{3}$$

In other words, we expect that the output Y of X to be such that:

$$\|Y - T_i\|_2 \approx \hat{\delta} y_i \forall i \in \{1, \cdots, K\} \tag{4}$$

Therefore, an estimate $\hat{Y}$ of Y can be obtained by any minimizer $\hat{Y} = \operatorname{argmin}\{J(Y)\}$ like the nonlinear least-squares estimates from standard gradient descent methods.

$$J(Y) = \sum_{k=1}^{K}\left((Y - T_k)^T (Y - T_k) - \hat{\delta y_k^2}\right)^2 \tag{5}$$

Using the obtained matrix $\hat{\beta}$, we can now estimate the distances for both sets of sensors. To estimate the distances for the second set of sensors based on the first set, we use the matrix $\hat{B}$ as follows: - Estimating the second set from the first set:

Given a test point x from the first sensor set, we calculate its distance $d(x, R)$ to the K reference points:

$$\hat{\delta}(y, T) = d(x, R)\hat{B} \tag{6}$$

where $\hat{\delta}(y, T)$ represents the estimated distances of the corresponding point y in the second sensor set to the reference output points T. - Estimating the first sensors set from the second sensors set:

To predict the first sensor set from the second, we use the inverse of $\hat{B}$:

$$\hat{d}(x, R) = \delta(y, T)\hat{B}^{-1} \tag{7}$$

This relationship allows us to recover the distance vector $\hat{d}(x, R)$ for the first set of sensors based on the distances $\delta(y, T)$ from the second set.

By applying these equations, we can estimate the sensor data in both directions. Hence, an estimate $\hat{Y}$ of Y and $\hat{X}$ of X can be obtained by minimizing $\hat{Y} = \mathrm{argmin}\{J(Y)\}$, and $\hat{X} = \mathrm{argmin}\{J(X)\}$ respectively, Levenberg-Marquardt algorithm used in our application.

Here, $S = [X, Y]$ represents the set of measurements, and is $\hat{S} = [\hat{X}, \hat{Y}]$, represents the corresponding set of estimated values. In the next section, we will demonstrate how these two sets are used for fault detection and isolation.

III. Fault Detection and Isolation Methodology

In this section, we outline the Fault Detection and Isolation (FDI) methodology for wind turbine dataset using the Minimal Learning Machine (MLM). The MLM technique is used to train a model from healthy data, and it learns the relationships between different sets of sensor data. By comparing predicted and actual sensor readings, we can detect faults through indices that highlight significant deviations between real and estimated sensor values. Once a fault is detected, we proceed to isolate it using a principal reconstruction approach.

A. Fault Detection

In our Fault Detection method using the Minimal Learning Machine (MLM), we split the sensor data into two sets. First, we trained a model to predict the readings of one set based on the other, capturing their relationship. By comparing the actual and predicted values in both directions, we can detect any differences that might indicate faults in the wind turbine's operation.

In sensor faults detection using the MLM (Minimal Learning Machine), faults can be recognized by observing the residuals between estimated and actual data. Here, the detection using index $\mathrm{SPE}_{\mathrm{MLM}}$ (squared prediction error in MLM) quantifies the difference between the MLM model's predictions and the observed sensor data. At observation k, this index is defined as follows [18]:

$$\mathrm{SPE}_{MLM}(k) = \|\hat{S}(k) - S(k)\|^2 \tag{8}$$

where $\hat{S}(k)$ is the MLM-predicted output for time k and $S(k)$ is the actual sensor output. An abnormal situation is indicated when:

$$\mathrm{SPE}_{MLM}(k) > \delta \tag{9}$$

where δ is a control limit for the MLM detection index, it is determined by calculating the 95% confidence level of the residuals from fault-free data.

B. Fault Isolation

Fault isolation is an important and crucial phase in Fault Detection and Diagnosis (FDD), Dunia et al [13] proposed a fault isolation technique based on reconstruction principle using the Squared Prediction Error (SPE) index for fault localization. The reconstruction principle involves estimating one of the variables of the vector $s(k)$at a given time, denoted as $s_i(k)$, using all other variables $s_j(k)$ at the same time, based on a pre-established model, such as PCA. This method assumes that each suspected sensor can be reconstructed [18]. In this work, we adapt the reconstruction principle to the Minimal Learning Machine (MLM) for effective fault isolation. Figure 1 shows that the process starts with a pre-trained MLM model, as previously explained, the estimated variables $\hat{S}$ are obtained in two parts: one using the direct model and the other using its inverse. This involves reconstructing one set of variables based on another, and vice versa. These predicted sensor values are considered as reconstructed variables, representing an estimation of the faulty data using all other measurements for example the reconstructed value of sensor 1 is $z_1 = \hat{s_1} = f(s_2, \ldots, s_m)$. To isolate the fault, a data block is built where each dataset matches to a scenario where one sensor's variable is replaced by its reconstructed value z_i, it means for each sensor s_i, its reconstructed value $z_i = \hat{s}_i$ is placed into the dataset while all other variables are retained directly from the original measurements, which creates a block of datasets, each reflecting a different sensor reconstruction scenario.

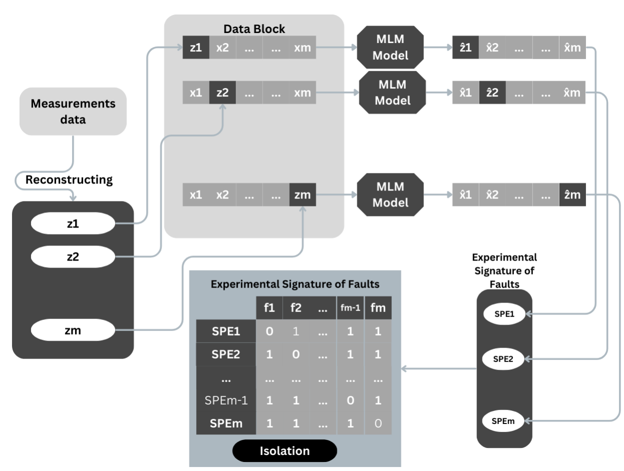

Fig. 1. Isolation based on Reconstruction Principle

The MLM is then applied to each dataset in the block to estimate the sensor values, enabling the calculation of the Squared Prediction Error (SPE) index for each case. The SPE index measures the deviation between the actual and reconstructed data. Fault isolation is achieved by comparing the SPE index for each reconstructed dataset to a predefined threshold. The faulty variable is identified as the one whose SPE does not exceed the threshold $SPE_i(k) <= \sigma$. This approach leverages the predictive accuracy of MLM for fault reconstruction and uses the SPE index as a diagnostic tool to pinpoint the faulty sensor. In the next section, we will demonstrate this methodology using the Wind Turbine Benchmark dataset.

IV. Application to benchmark Wind Turbine SCADA

To evaluate the performance of MLM based Fault Detection and Isolation (FDI) method for wind turbines, in [15] K. Leahy et al. have proposed a wind turbine benchmark dataset, serving as a valuable tool for those in the field of fault diagnosis. This wind turbine benchmark dataset offers a comprehensive view of data collected by turbine control systems, covering SCADA (Supervisory Control and Data Acquisition), alarms, and availability data, which.

The SCADA data provides various operational metrics collected at each 10 minutes. Key data include Generated power by the Wind Turbine, wind speed and its maximum and standard deviation, and blade pitch angles, Table I.

TABLE I
Ten-minute SCADA data.

TimeStamp	Wind Speed (Avg.) $\mathbf{m/s}$	Wind Speed (Std.) $\mathbf{m/s}$	Power (Avg.) $\mathbf{kW}$
9 06 2015 14:10:00	5.8	0.1	367
9 06 2015 14:20:00	5.7	0.1	378
9 06 2015 14:30:00	5.6	0.5	384
9 06 2015 14:40:00	2.8	0.9	0

The alarms data records alerts from the turbine's control system, categorized as information, warning, or fault alarms. Each alarm includes a start/end time, code, description, and severity. In the meantime, availability data logs the turbine's operational status every 10 minutes, marking it as OK, down (fault-related), grid (grid issues), maintenance (scheduled downtime), or Repair (unplanned repairs). Together, alarms and availability data provide a comprehensive dataset for analyzing turbine performance, reliability, and maintenance.

In our application, we collected normal data using the criteria outlined above, focusing on periods where the turbine works under normal conditions. This dataset includes SCADA data, as well as availability and alarms records, ensuring that we capture standard operational behavior without fault interruptions. Now, we can effectively train the model to recognize any deviations that may indicate potential faults.

In applying this methodology to the benchmark, we utilize several key parameters to train the model. These include wind speed, generated energy (in kilowatts), torque, and the actual angles of the three blades. These variables are critical for understanding the turbine's performance. Wind speed and generated energy provide insights into the turbine's energy production, while torque offers a measure of the mechanical load. By including these variables, the model can learn the turbine's normal behavior and identify potential deviations that may signal faults.

A. Training Model and Estimation

The Minimal Learning Machine (MLM) was employed in this study to model the relationships between input and output sensor data, chosen for its simplicity and effectiveness in capturing nonlinear relationships. In this application, we utilize six sensors from the Wind Turbine Benchmark dataset: wind speed, torque, generated energy, and blade angle $S = [s_1 s_2 s_3 s_4 s_5 s_6]$, Then split S into two sets $X = [s_1 s_2 s_3]$ and $Y = [s_4 s_5 s_6]$. A subset of the data, consisting of 1000 randomly chosen observations, was selected as reference points. These points were used to compute distance matrices in the input and output spaces. The linear mapping between these spaces was determined using the Levenberg-Marquardt optimization method, minimizing the mean squared error (MSE) during training. Preprocessing steps included normalizing the data to ensure consistency across features and improve model performance.

The trained MLM achieved an MSE of $5.7318e-05$ on the test set, determining its capability to reconstruct sensor data accurately. The performance metrics, including MSE and the number of reference points, show up the model's effectiveness in balancing simplicity and accuracy. Figure 2 shows the comparison between the estimated and actual sensor data under healthy conditions, showcasing the model's ability to reproduce system behavior.

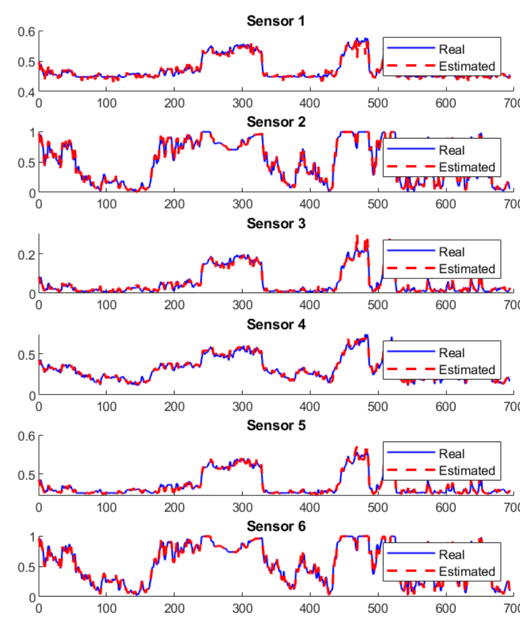

Fig. 2. Estimation of healthy data.

B. Fault Detection and Isolation

To evaluate the fault detection and isolation capability of the Minimal Learning Machine (MLM), we introduced a simulated fault in Sensor 1. This fault was designed to affect the sensor by a 10% deviation from their actual values, occurring between time steps 100 and 400. The goal was to analyze how the MLM captures this deviation in its predictions and isolate it. Figure 3 depicts the measured data for Sensor 1, showing the healthy sensor readings alongside the faulty data during the fault interval. The clear distinction between the two determines the magnitude of the created fault.

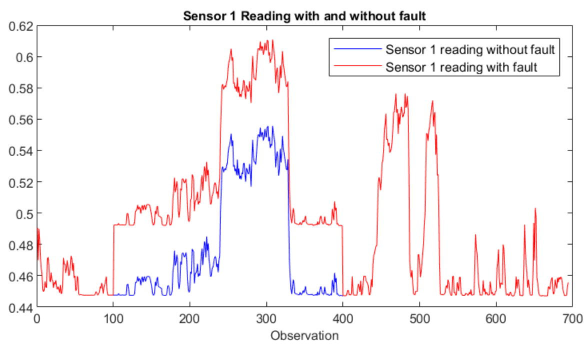

Fig. 3. Evolution of the SPE with a fault affecting sensor 1 s_1 with 10% from time step 100.

To detect faults, the Squared Prediction Error (SPE) index was computed, comparing the reconstructed data from the MLM to the actual sensor readings. The SPE was used to identify anomalies, A threshold was set based on the healthy data to detect faults. we calculate the SPE for each observation by measuring the difference between the actual sensor values S and their estimated values $\hat{S}$. $\text{SPE}(k) = \|\hat{S}(k) - S(k)\|^2 >$

As illustration in Figure 4, the SPE values for both a fault free scenario and a fault introduced in Sensor 1. The sharp increase in SPE values when the fault occurs highlights the MLM's sensitivity and effectiveness in detecting faults. These results will help us on fault isolation.

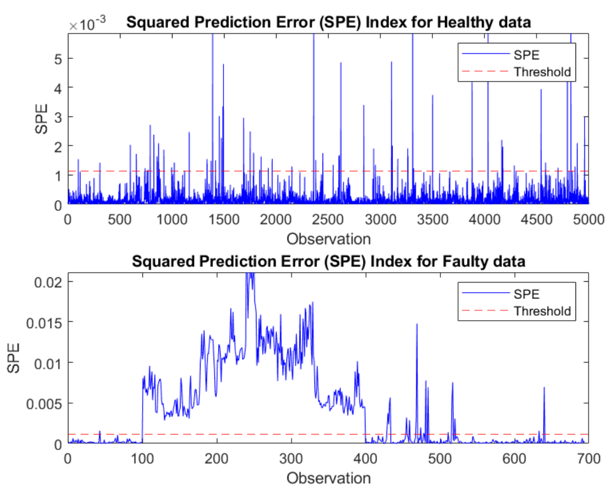

Fig. 4. Evolution of the SPE with a fault affecting sensor 1 s_1 with 10% from time step 100.

The reconstruction principle is employed to isolate faults in the six sensors by replacing each sensor with its reconstructed estimate z_i and analyzing the impact on the Squared Prediction Error (SPE). For each sensor s_i, a modified dataset D_i is created where the value of s_i is replaced with its reconstructed estimate $z_i = \hat{s}_i$, while the other sensor values remain unchanged. The SPE is recalculated for each dataset $D_i (i = 1, ;6)$, if the SPE exceeds the threshold, it is marked with a value of 1; otherwise, it is marked with a 0. This binary representation forms the structural residuals for all sensors in the system. By analyzing these residuals, If the SPE for a particular dataset SPE_i drops significantly below the threshold after reconstruction, it indicates that the replaced sensor s_i is the source of the fault.

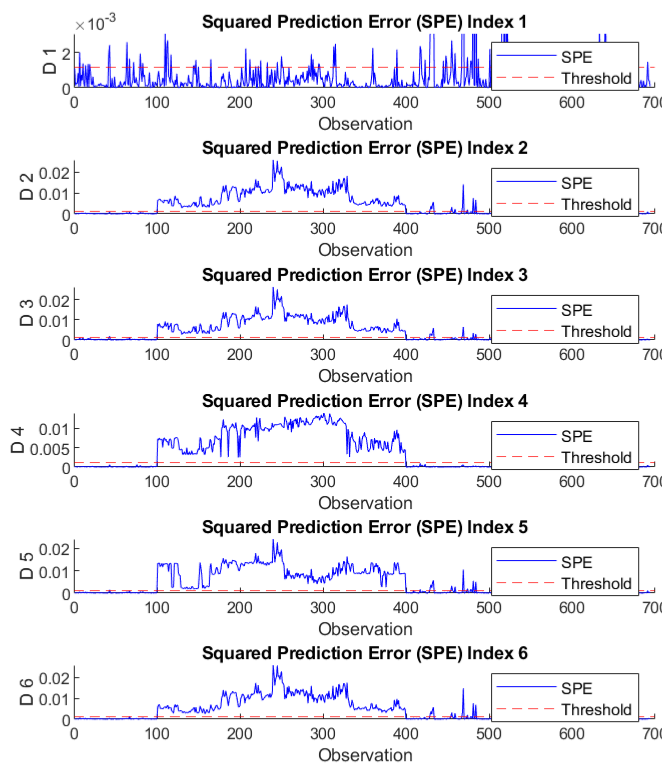

Fig. 5. Evolution of the different SPE values obtained with a fault affecting sensor 1 s_1 with 10% from time step 100 to 400.

The figure 5 illustrates the SPE values for all six sensors during the fault occurs in Sensor 1 s_1. For each sensor, the SPE was calculated based on its reconstructed data block, and the threshold determined from healthy data was applied. The figure clearly shows that the SPE for Sensor 1 stays below the threshold, representing that its reconstruction was impacted by the fault. Conversely, the SPE values for the other sensors exceed the threshold, signifying successful reconstruction and confirming their healthy state.

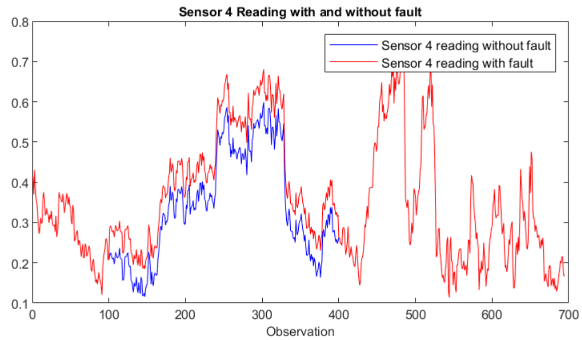

Fig. 6. Evolution of the SPE with a fault affecting sensor 4 s_4 with 15% during a 300-time interval.

To further explain the ability of the Minimal Learning Machine (MLM) to detect and isolate faults, we produced a new fault in Sensor 4 Fig 6. This fault affects the sensor readings by a 30% deviation during a 300-time interval. The detection process was carried out using the SPE index (see Fig 7), calculated based on the estimated data compared to the actual data.

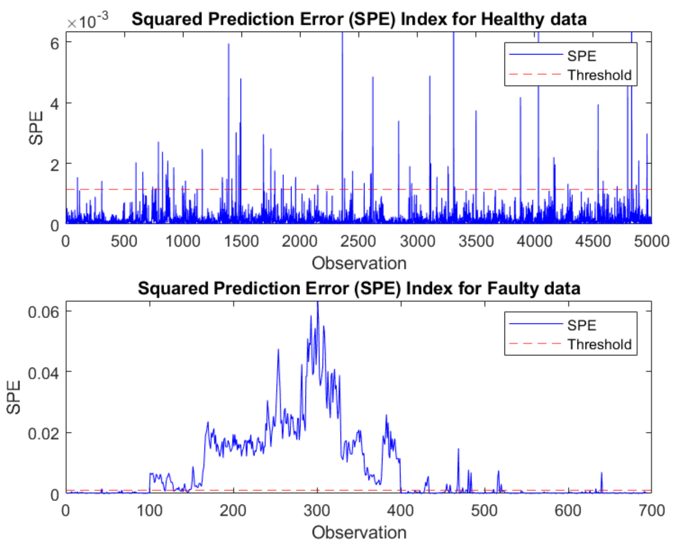

Fig. 7. Evolution of the SPE with a fault affecting sensor 4 s_4 with 30% during a 300-time interval.

For fault isolation, the SPE values for each reconstructed sensor data block were analyzed. The figure 8 illustrating this analysis reveals that the SPE for Sensor 4 remains below the threshold, proving it as the faulty sensor. In the other side, the SPE values for the other sensors exceed the threshold, indicating accurate reconstruction and their healthy state. This isolation process supports the MLM's capability to systematically pinpoint the faulty sensor in multi-sensor systems, ensuring precise fault diagnosis.

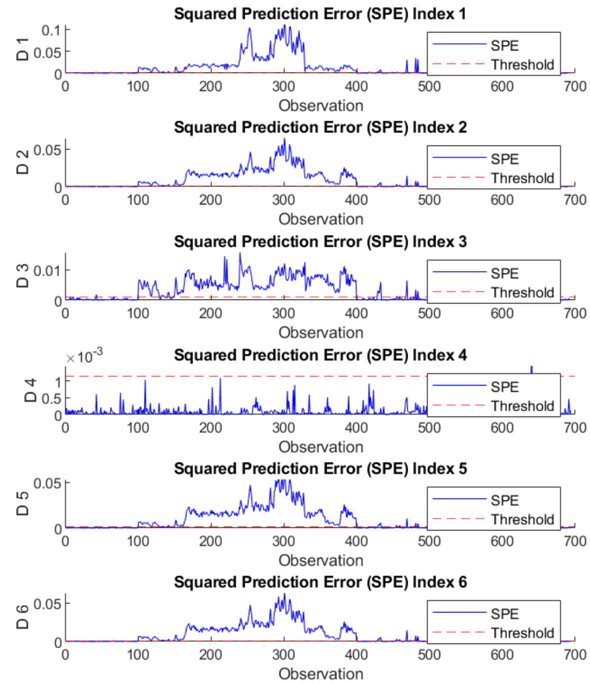

Fig. 8. Evolution of the different SPE values obtained with a fault affecting sensor 4 s_4 with 30% during a 300-time interval.

This demonstrates MLM as a viable and effectiveness approach in isolating the faulty sensor by leveraging the structural residuals and SPE index. These results underline MLM's potential for both fault detection and isolation applications at same time.

V. Conclusion

This paper presented a novel approach for Fault Detection and Diagnosis in wind turbines using the Minimal Learning Machine (MLM). By leveraging six critical sensors and integrating data normalization, SPE-based fault detection, and reconstruction principles for fault isolation, the proposed methodology demonstrated its capability to identify and isolate sensor faults effectively.

The results highlight the robustness of MLM in modeling the complex relationships among sensor measurements and detecting anomalies. Also, the reconstruction principle proved to be an efficient method for pinpointing the specific faulty sensor by reducing the SPE for the reconstructed dataset. The application of this technique on the Wind Turbine Benchmark dataset emphasizes its practical relevance and adaptability to real-world conditions.

Future work could explore investigating the integration of other machine learning techniques with MLM could provide deeper insights and improved fault diagnosis performance in more complex scenarios.

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