Fault Diagnosis with Stacked Sparse AutoEncoder for Multimode Process Monitoring

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Abstract: Traditional process monitoring generally assumes that process data follow a Gaussian distribution with linear correlation. Nevertheless, this sort of restriction cannot be satisfied in reality since many industrial processes are nonlinear in nature. This work provides an enhanced multivariate statistical process monitoring technique based on the Stacked Sparse AutoEncoder and K-Nearest Neighbor (SSAE-KNN). This approach consists of developing a model by using Stacked Sparse AutoEncoder (SSAE) to get the residual space, which is the main tool in detecting and reconstructing the potential missing data by residual space. The monitoring statistics in this space are constructed using KNN rules; the threshold values for SSAE-KNN process monitoring are estimated utilizing the Kernel Density PDF Estimation (KDE) method, and an enhanced Sensor Validity Index (SVI) is proposed to detect faulty data based on the reconstruction approach. The experimental results using actual data from a photovoltaic power station connected at the site of OuedKebrit, located in north-eastern Algeria, reveal the effectiveness of the proposed scheme and show its capacity to detect and identify sensor failures.

1 INTRODUCTION

Data mining can extract hidden and usable information from massive datasets, where possible correlations may be utilized for automated anomaly detection and associated issue root cause identification. In general, Statistical Process Control (SPC) charts enable the visualization of process development and the identification of abnormal changes (Qin S. J., 2012 and Yin S. et al, 2014). However, most standard SPC methods like PCA (Principal Components Analysis) work well only if the correlations are linear, which is a poor approximation of the real world. Deep learning is an unsupervised approach that can provide a better representation using a deep learning algorithm and has recently proved extremely effective in several fields (Hinton G. E. et al, 2006). As part of deep learning approaches, we present the Stacked Sparse AutoEncoder (SSAE) to reconstitute the input data (Xu J. et al 2016). The K-nearest neighbor rule is one of the population-based learning strategies, which uses the closest samples to classify objects in an n-dimensional feature space. It is the simplest way of learning; the number of k defines how numerous nearest neighbors will be grouped for classification with the Euclidean distance metric commonly used to compute the distance between data points (Wang G. et al, 2015). The Squared Prediction Error (SPE) index is used to identify detection. It is developed by introducing the KNN rule and its associated control limits established by Kernel Density Estimation (KDE) (Odiowei P. E. et al, 2010). Additionally, the Sensor Validity Index (SVI) is proposed as a way of detecting faulty sensors. The findings reveal that, when compared to the contribution plot, the proposed technique is more effective at diagnosis the faulty sensor. In this paper discusses the application of a Stacked Sparse AutoEncoder (SSAE) that has been trained to recreate the input data acquired during normal operation. Then, using KNN, create monitoring statistics in the residual space of the

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SSAE model. The paper is structured as follows: A brief overview of basic concepts is presented in Section 2. The recommended approaches for multimode process monitoring are shown in Section 3. The validation of the methods is realized by experiments conducted in section 4, utilizing real data from solar power plants. The last section concentrates on a discussion of the results obtained and conclusions.

2 METHODS USED

2.1 Stacked Sparse AutoEncoder

Deep Learning has recently demonstrated outstanding performance on a variety of tasks. It has been utilized in the past for visual analysis and picture identification, but not for process monitoring. Models of deep neural networks with a hidden layer called the bottleneck layer are used to extract features. To begin, the input data X_i = 1, 2, 3,....N is translated as follows into a hidden layer represented by the function h_i shown as follows:

$$h_i = f(x_i) = sigm(W_1x+b_1) \quad (1)$$

Where b1 and W_1 are respectively the bias and the weight between the input part and the hidden layer and *sigm(x)* is a sigmoid function chosen to get more bounded and uniformly distributed embedding. In the decoding layer, h_i is translated to the output represented by x. In this stage, we employ the activation function shown below:

$$x_i = g(h_i) = sigm(W_2h+b_2) \quad (2)$$

Where W_2 and b_2 are respectively the bias and the weight between the hidden layer and the output layer *(x)*. The bottleneck network whose learning criteria contain a sparsity penalty in the bottleneck part is named Stacked Sparse AutoEncoder (SSAE) (Yin J. et al, 2019). The aim of this network is to estimate its output (prediction of the input) as similarly as possible to its input, thus through optimizing the cost function described by:

$$J = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{1}{2}(\|x_i - \hat{x}_i\|^2\right) + \frac{\lambda}{2}\sum_{i=1}^{N}\|W_i\|^2 + \beta\sum_{j=1}^{m}KL(\rho\|\hat{\rho}_j) \quad (3)$$

Where λ and β are respectively the coefficient that establishes the weight decay and the sparsity penalty terms, m: is the number of the hidden nodes.

Equation (3) consist of the reconstruction error, the regularization term and the last term is sparsity penalty, where $KL(\rho\|\hat{\rho}_j)$ is the Kullback-Leibler divergence, it is used to compute the difference between ρ and $\hat{\rho}_i$, those are the constraint utilized during learning. The back propagation algorithm is utilized to find the appropriate parameters W_1, W_2, b_1, b_2 and to minimize the cost function.

2.2 K-Nearest Neighbor

Firstly, the KNN rule is a supervised classification algorithm that is nonparametric. The goal of supervised classification is to predict the unknown sample of data using a set of labeled samples. The detection approach works on the assumption that a sample under control will take values in the neighborhood of the training data. Then, if a new sample deviates too much from the data under control, it considers out-of-control. A cumulative distance between new sample and its k closest neighbors included in the learning sample is computed to analyze the distance between each new sample and the data under control. Because the KNN rule is a nonlinear classifier, it could address many limitations such as process nonlinearity.

Furthermore, since the FD-KNN technique finds flaws based on local neighbors of comparable batches, it is ideally suited for multimodal data sets in which batches may be divided into subgroups with distinct characteristics (Ren Z. et al, 2021).

2.3 Kernel Density Estimation

KDE is a method for generating a smooth PDF (Probability Density Function) from a collection of random samples and fitting it to a data set. It's often used to estimate PDFs, particularly for univariate random data. The KDE may be used with the Q and T^2 statistics since they are both univariate, despite the fact that the process they describe is multivariate. The PDF $g(y)$ of a random variable y may be estimated from its m samples, y_j, j = 1,...,m, as follows:

$$g(y) = \frac{1}{mh}\sum_{j=1}^{m}K\left(\frac{y-y_j}{h}\right) \quad (4)$$

Where h is the bandwidth while K is a kernel function. The significance of bandwidth selection and strategies for achieving an optimal value are detailed in (Xiong L. et al, 2007). The probability is obtained by integrating the density function across a continuous range. Assuming the PDF $g(y)$, the likelihood of y being smaller than c at a given significance level, *a is* given by:

$$P(y < c) = \int_{-\infty}^{c} g(y)dy = \alpha \quad (5)$$

As a result, the threshold of the monitoring statistics Q can be determined using their corresponding PDF estimates:

$$\int_{-\infty}^{Q\alpha} g(Q)dQ = \alpha \tag{6}$$

2.4 Contribution Plot

There are numerous approaches for fault isolation. Contribution plots may be used for this purpose (Bougheloum W. et al, 2019). This technique is often based on the contribution rate from each variable to determine which variable contributes the most to the Q statistic; the contribution of variable j is computed as follows:

$$C_{ijk}^{Q} = e_{ijk}^{2} \tag{7}$$

Where : $e = (x_i - \hat{x}_i)$

2.5 Sensor Validity Index

This method is based on the principle of reconstructing all the variables from the moment of detection by calculating the validity indexes of the sensors. The reconstructed measuremen $\hat{x}_j$ can be obtained iteratively, estimated, and re-estimated until convergence, as indicated in Figure 1. This is why, and similarly, in order to restructure the faulty data, it is essential to detect the fault in a unique.

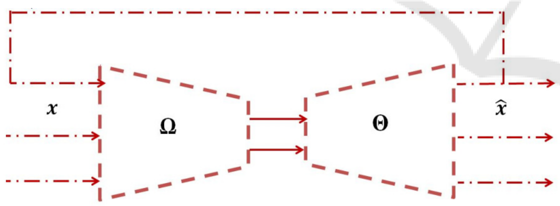


Figure 1: The schema of the reconstruction principal used.

The method requires predicting the process measurement $\hat{x}_j$ by substituting the j^{th} process variable with the predicted one and continuing the procedure until the algorithm converges as follows:

$$\hat{x}_j = \varphi_j^T \Theta(\Omega(x_j)) \tag{8}$$

Where: $\hat{x}_j = (x_1, x_2, \ldots, x_i, \ldots, x_n)$,

φ_j^T is the j^{th} column of the identity matrix.

The Sensor Validity Index (SVI) is a sensor effectiveness assessment in which, regardless of the number of principal components of the faults, a specified range should be present (Bouzenad K. et al., 2017), it is defined as follows:

$$\eta_j^2(k) = \frac{SPE_j(k)}{SPE(k)} \tag{9}$$

SPE_j is the j^{th} quadratic prediction error calculated after reconstruction, while SPE is the quadratic global prediction error computed before reconstruction. A faulty sensor's validity index must converge towards zero.

3 FAULT DETECTION BASED ON SSAE-KNN

The suggested technique is consisted of offline modelling and online monitoring. The specified stages are explained as follows:

3.1 Offline Modeling

Offline modeling steps' include the following:

1. Training data is collected and normalized under normal conditions.
2. The model is trained using the SSAE cost function, deep nonlinear and dynamic features are extracted from the input data.
3. The monitoring statistic is built using the extracted feature with the model's reconstruction error.
4. In the extracted feature, finding k nearest neighbors for input data x.
5. Calculate the KNN squared for each sample. The KNN squared distance of sample i (D_i^2) is described as:

$$D_i^2 = \sum_{j=1}^{k} d_{ij}^2 \tag{10}$$

Where d_{ij}^2 indicates the squared Euclidean distance between sample i to its j^{th} closest neighbor.

6. KDE establishes a D_i^2 threshold for fault detection. The threshold D_α^i with a significance level α may be established because the distribution of D_i^2 can be approximated by a noncentral chi-square distribution (Verdier G. et al., 2011).

3.2 Online Monitoring

The fault detection section for an incoming unclassified sample x has five steps:

1. The samples used for the test is standardized.
2. The dynamic enhanced data are transmitted into a well-trained SSAE, which calculates the residual feature and reconstruction error.
3. D^2 and SPE statistical quantities are calculated.
4. The problem is detected using the threshold

determined in step 6. If the statistical quantity exceeds the threshold, the fault has occurred.

5. Using the contribution plot and sensor validity index SVI to identify the faulty sensor. To provide a more intuitive picture, the flow chart of the proposed multimode process monitoring technique based on the Stacked Sparse AutoEncoder and K nearest neighbour scheme is summarized in Figure 2.

4 CASE STUDY OF IMPLEMENTATION

4.1 Process Description Used

The case study is about the solar power plant of Oued Keberit, which is located near the city of Souk-Ahras in north-eastern Algeria; close the Tunisian border, shown in Figure 3. It is located in latitude 35°55'28" north and longitude 7°55'1" East (Toumi R. et al, 2019). The temperature varies between 22.9 and 26.3 degrees Celsius in the summer and as low as 10.2 degrees Celsius in the winter. This gives an ideal setting for solar energy project development. In our study, the model inputs consist of solar power plant parameters, the hidden layer that represents learned features, and the output layer with the same dimension of the input layer that represents reconstruction (Soualmia A. et al., 2016).

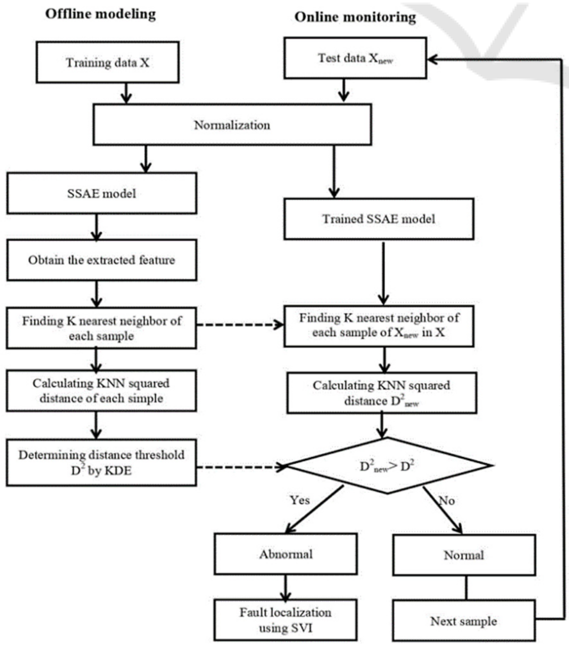


Figure 2: Flow chart of proposed fault detection method.

Figure 3: Photovoltaic Power Station of Oued Kebrit.

To demonstrate the usefulness of the suggested technique, we examine data from the grid-connected photovoltaic solar plant at Oued Kebrit. This data includes the following parameters: Total Radiation, Temperature, Wind Speed, Humidity, and Pressure, we have a total of 05 parameters, indicating that we have five sensors monitoring the observations throughout a thirty-day period (2018). To develop the SSAE model, a data matrix X was constructed using N = 633 observations indicating the process normal functioning. The data in such a matrix are centered and scaled using the data means and standard deviations. For the monitoring model, a vector of measures comprised of the 05 variables described previously was selected.

4.2 Simulations Results

In this context, we will present the results of the suggested multimode process monitoring technique, which is primarily used to identify sensor problems. To show the monitoring method's validity and the advantages of fault detection, we created a multimode monitoring model using a dataset from a

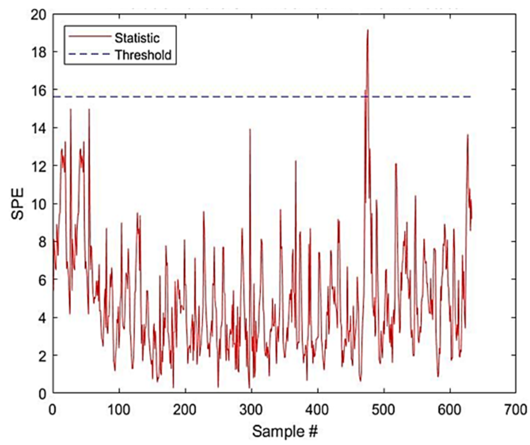


Figure 4: Evolution of the SPE index in normal state.

solar power plant that had five variables and 633 samples. Under normal conditions, both the standard technique based on SPE statistics and the SSAE-KNN monitoring statistics suggest that all samples are contained within the relevant zones depicted in Figure 4-5.

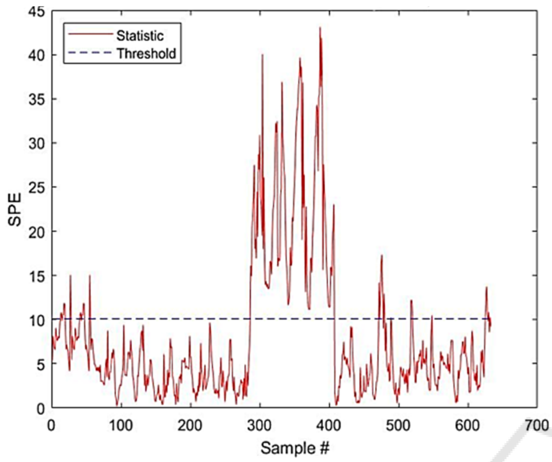


Figure 5: Evolution of the SPE index in faulty state.

After discovering a fault, it is required to determine which sensor is faulty; this is accomplished using the contribution plot. The evolution of the contribution plots in the presence of a problem affecting the first sensor measuring total radiation and the fourth sensor measuring humidity is shown in Figure 8(a)-(b). The usual technique fails to identify the infected fourth sensor. Then, using the reconstruction approach, we used the enhanced sensor validity index (SVI). The fault localization of all faulty variables is depicted in Figure 9(a)-(b). Consequently, SVI based on reconstruction approaches of the offending variable measures is effectively used and gives better performance compared to the conventional approach.

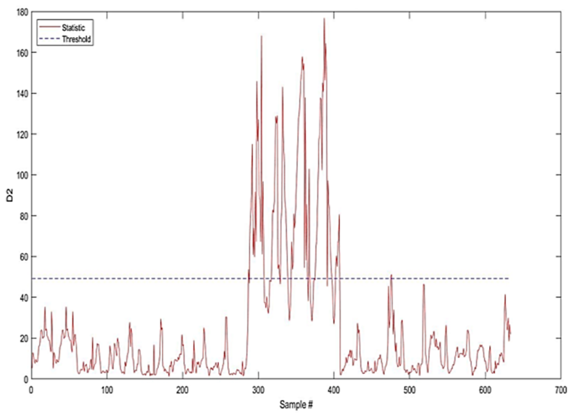


Figure 6: Evolution of the monitoring index based on KNN in normal state.

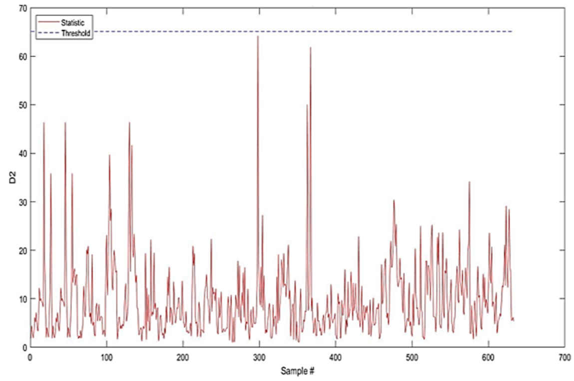
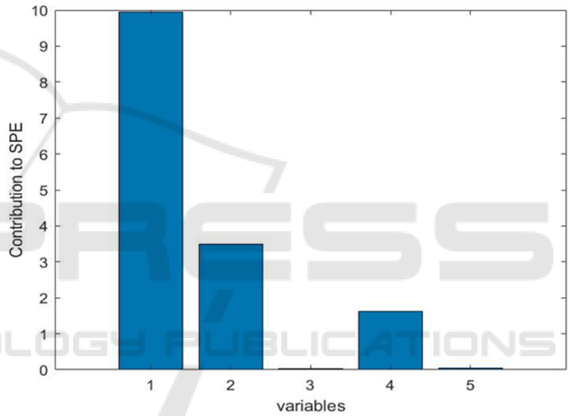
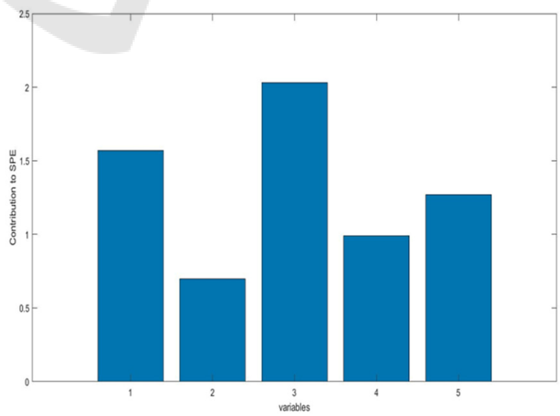


Figure 7: Fault detection using SSAE-KNN.

The proposed SSAE-KNN method gives better performance in fault detection, which appears clearly in false alarm detection in the validation and the test steps.

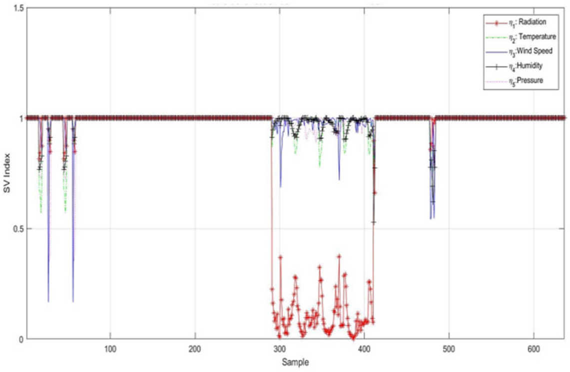


(a) Evolution of Contribution plot of the 1st sensor.

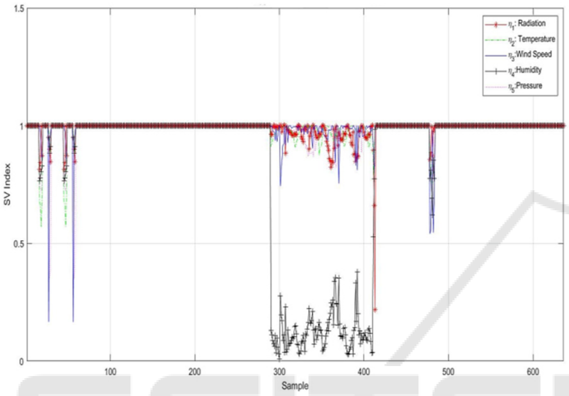


(b) Evolution of Contribution plot of the 4th sensor.

Figure 8: Localization of fault based on Contribution plot.



(a) Evolution of Sensor validity index of the 1^{th} sensor.



(b) Evolution of Sensor validity index of the 4^{th} sensor.

Figure 9: Localization of fault based on Sensor Validity Index.

5 CONCLUSIONS

This work proposes a multimode process monitoring approach based on the Stacked Sparse AutoEncoder (SSAE) and K-Nearest Neighbour (KNN). The input data is rebuilt using SSAE, and monitoring statistics are generated using the KNN rule, with their related thresholds determined using Kernel Density Estimation (KDE). To detect malfunctioning sensors, an improved Sensor Validity Index (SVI) based on the reconstruction technique is proposed. The experimental findings from a solar power plant indicate the usefulness of the proposed system and its ability to detect and diagnose sensor failures.

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