FUZZY BASED NONLINEAR PRINCIPAL COMPONENT ANALYSIS FOR PROCESS MONITORING

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ABSTRACT

Nowadays, process monitoring to improve product quality and safety has become an important issue in control engineering. One of the most used methods in process monitoring is principal component analysis. This method uses process data to make process model with lower dimension than original dimension. In this paper, a new PCA based monitoring is proposed that uses fuzzy logic capability. The reason to use fuzzy logic is its good ability to approximate nonlinear function with arbitrary accuracy. The new method is tested on Tennessee Eastman Process.

KEYWORDS

PCA, Nonlinear PCA, Process Monitoring, Fuzzy Logic

1. INTRODUCTION

Principal component analysis (PCA) is a basic method in the framework of the multivariate analysis techniques. It has been successfully used in numerous areas including data compression, feature extraction, image processing, pattern recognition, signal analysis, and process monitoring [1]. Thanks to its simplicity and efficiency in processing huge amount of process data, PCA is recognized as a powerful tool of statistical process monitoring and widely used in the process industry for fault detection and diagnosis [2-4].

Nowadays, development in electronics and networks has made us able to use a lot of sensors in process. So there are a lot of measurements and a huge amount of data available. But in most often cases, many of these measurements have same information. Indeed, the real dimension of process is lower than the dimension of measured variables. The most important goal to use PCA is reducing dimension of process without losing much information [5]. Less the dimension of process, more ease in analysis and decision making.

There are many extended form of PCA to match it with different processes. One of these extended forms is MPCA[1] that used for monitoring batch process [6]. Considering dynamic behaviours of processes, DPCA[2] is proposed in [7] with ARMAX model idea.

One important branch in extended form of PCA is NLPCA[3] to deal with nonlinear properties in process. KPCA[4] is proposed in [8] based on kernel functions. In [9], neural network based is used to learn nonlinearity of process.

There are some reported using fuzzy logic in PCA but they more limited than neural networks. In [10] a combination of classic PCA and ANFIS and in [11-12] two combination of classic PCA and fuzzy C-mean are used. In these methods, classic PCA reduces process data dimension and then dimension reduced data is used in a fuzzy system for fault detection. In [13-14] fuzzy logic is used for pre-processing process data and reducing negative effect of outliers and missing data in PCA. In all of these methods fuzzy logic is used beside classic PCA to improve its Quality. Indeed, fuzzy logic is added to PCA and there is not a fuzzy based PCA.

In this paper a new fuzzy based PCA is proposed to deal with nonlinearity in process. Fuzzy based nonlinear PCA is discussed in section 2 and in section 3 new approach is tested on the Tennessee Eastman Benchmark.

2. Fuzzy Based NLPCA

Suppose that there are n measurement samples of m variables of process. So the data matrix will be $X_{n\times m}$ .PCA makes a model based on good data of the process. Meaning of good data is the situation that product has good quality and there is no fault in process. From this model, two monitoring parameters is extracted and their situation are considered. When model is made, it is given the online data and monitoring parameters are extracted again and compared with the good data situation. If these parameters are so different, there is a problem in process.

2.1. Fuzzy system

Fuzzy systems for major parts:

- Fuzzifier
- Fuzzy inference Engine
- Fuzzy rule base
- Defuzzifier

It is proved that a fuzzy system with Singleton fuzzifier, Product inference system, Center Average defuzzifier and Gaussian membership function, can approximate any nonlinear function with arbitrary accuracy [15]. Suppose that there are n pair (x, t) and there is need to a fuzzy system for approximation function g in a way that

$$t = g(x)$$

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[1] Multi-Way PCA
[2] Dynamic PCA
[3] Nonlinear PCA
[4] Kernel PCA

Rule base consists of n rules corresponding to n pair data like this:

Rule (l): If Input is x^l Then Output is t^l. $\qquad l = 1,\dots,n$

x^l and t^l are input and output Gaussian membership functions. Indeed, for each point one membership function is used.

With mentioned fuzzy system, function g will be:

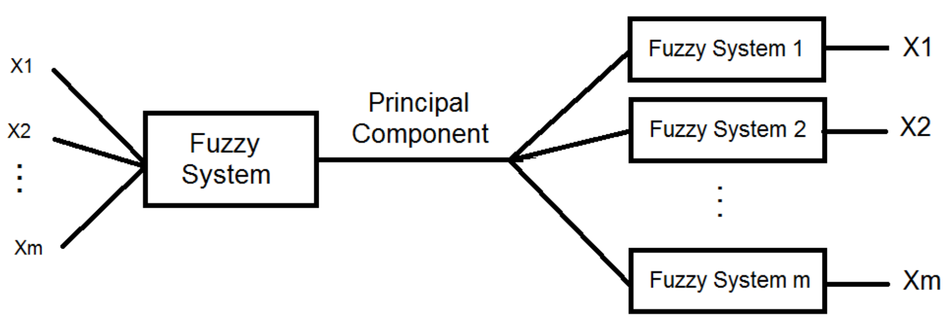
$$g(x) = \frac{\sum_{l=1}^{n} \bar{t}^l e^{-\left(\frac{x - x_0{}^l}{\sigma}\right)^2}}{\sum_{l=1}^{n} e^{-\left(\frac{x - x_0{}^l}{\sigma}\right)^2}}$$

$\bar{t}^l$ is center of output functions, $x_0{}^l$ is input data used for modelling and σ is standard deviation for input membership functions.

2.2. Fuzzy modelling

Suppose there are m variables for making model. Fuzzy model will be as figure 1. This monitoring system has two parts :

1. One fuzzy system to make principal component from m input variables.
2. m fuzzy systems to make original variable from principal component.



Figyre 1. Fuzzy based PCA

If input data is $X_{n\times m}$, output of first fuzzy system will be $T_{n\times l}$ (principal component) and output of second part will be $\hat{X}_{n\times m}$. With this model two monitoring parameter is made called "$T^2{}_{n\times l}$" from $T_{n\times l}$ and "$SPE_{n\times l}$" from $\hat{X}_{n\times m}$ and two monitoring chart are made from them respect to time:

$$T^2(l) = T(l)^2 \qquad l = 1,\dots,n$$

$$\mathrm{E}_{n\times m} = X_{n\times m} - \hat{X}_{n\times m} \quad \& \quad SPE(l) = \sum_{k=1}^{m} E(l,k)^2 \qquad l = 1,\ldots,n$$

To make monitoring system, good data of process ($\mathrm{X}_{n\times m}$) is given to model and principal component ($\mathrm{T}_{n\times l}$) is calculated with nonlinear optimization in a way that original variables is generated at output of model ($\hat{\mathrm{X}}_{n\times m} = \mathrm{X}_{n\times m}$). So cost function of nonlinear optimization will be:

$$J = \sum_{l=1}^{n} SPE(l)^2$$

In this manner, process model for good situation and limits for monitoring charts are made. This limit are used for online monitoring.

2.3. Online test

After making fuzzy model of process, online data is given to model and monitoring parameters are made as mentioned before and compared to ones made with good data. If there is difference, there is a fault in process.

3. SIMULATION

The Tennessee Eastman (TE) Plant-wide Industrial Process Control Problem was proposed by Downs and Vogel (1993) as a challenge test problem for a number of control related topics, including multivariable controller design, optimization, adaptive and predictive control, nonlinear control, estimation and identification, process monitoring and diagnostics, and education [16]. The TE process is a realistic simulation environment of a real chemical process. As shown in Figure 2, the TE process includes following units: an exothermic, a two-phase reactor, a flash separator, and a reboiled striper. There are a total of 41 measured output variables (22 continuous and 19 discrete) and 12 manipulated variables.

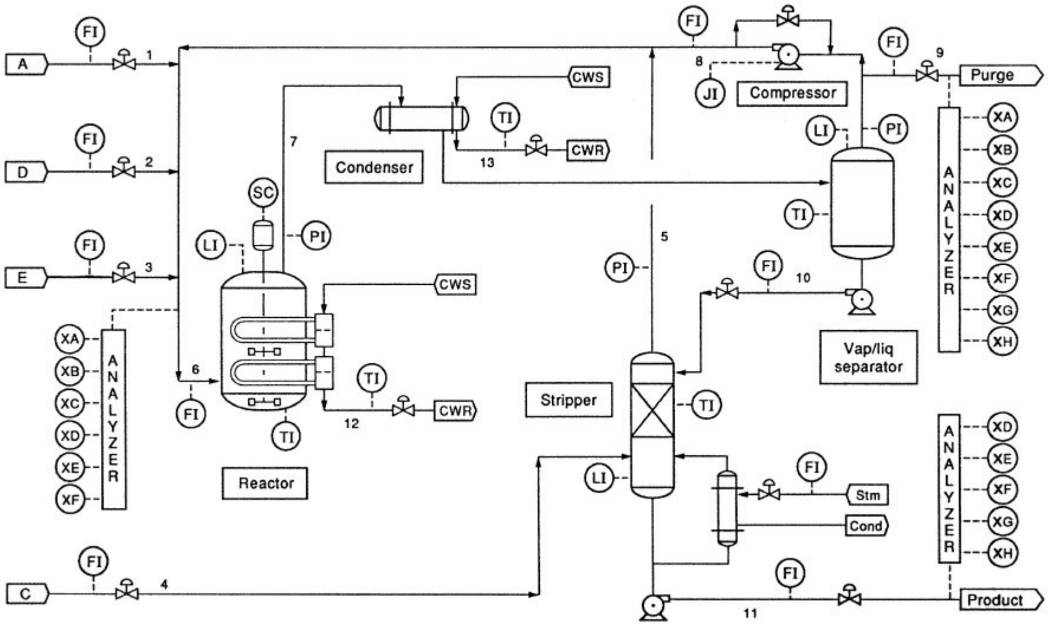


Figure 2. The Tennessee Eastman (TE) Challenge Process

The process produces two products from four reactants. Also present are an inert and a by-product making a total of eight components: A, B, C, D, E, F, G, and H. The reactions are:

$$A + C + D \rightarrow G$$

$$A + C + E \rightarrow H$$

$$A + E \rightarrow F$$

$$3D \rightarrow 2F$$

To implement new approach on this process, 22 continuous variables are used for model making. monitoring system is tested with defined faults is [16]. For these purpose 24 hours data (2400 samples) is used which at 15th hour (at sample 1500) the fault is created. For most of faults, monitoring system clearly shows. For one of them monitoring system is weak. Because variable change was small. The results for some of them:

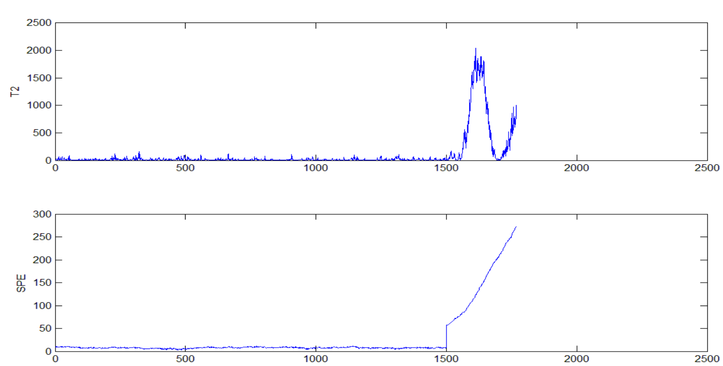


Figure 3. "A" feed loss

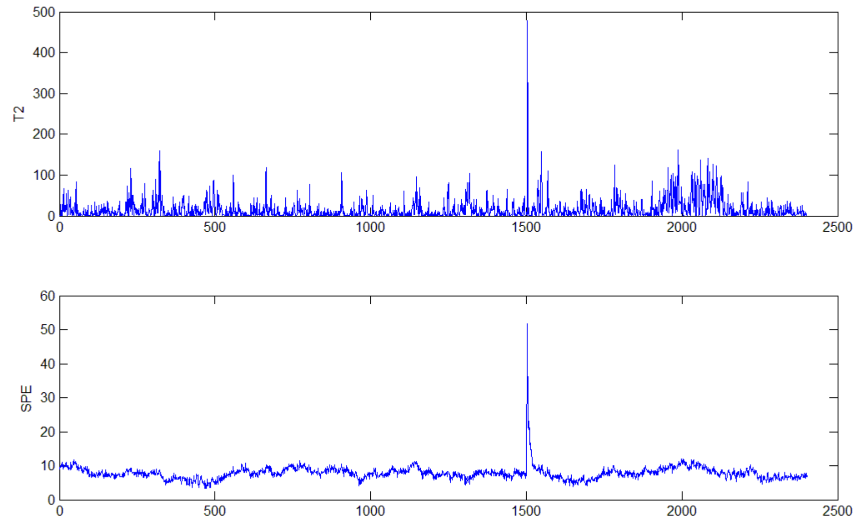


Figure 4. Step change in Reactor cooling water inlet temperature

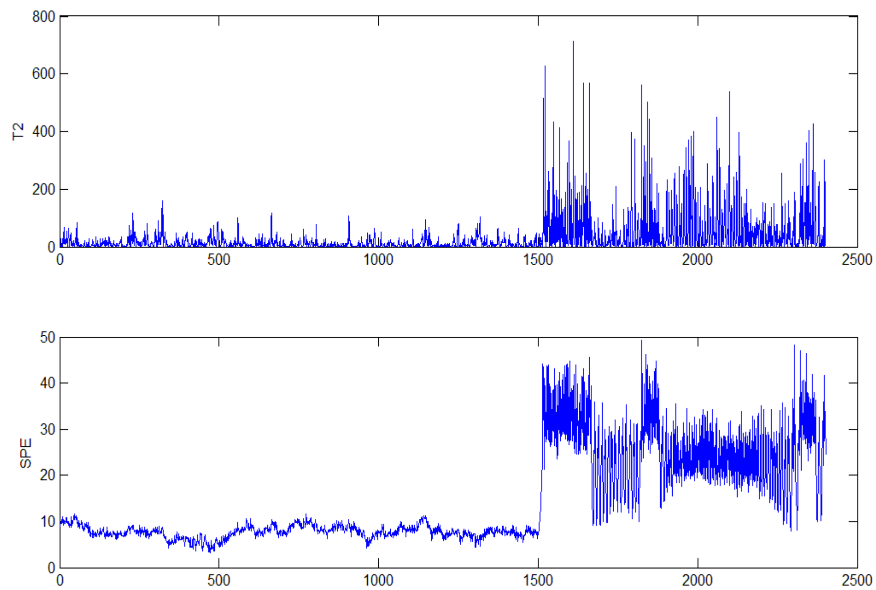


Figure 5. Reactor cooling water valve Stiction

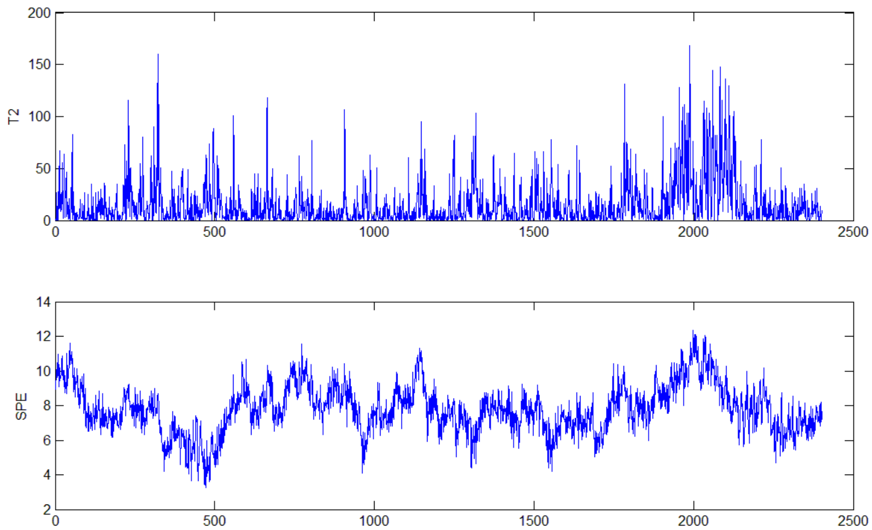


Figure 6. Step change in Condensor cooling water inlet temperature

4. CONCLUSION

In this paper a new approach for process monitoring was proposed. This approach was a kind of principal component analysis based on fuzzy logic. The reason for using fuzzy system was the power of this system in approximating nonlinearity with arbitrary accuracy. At the end, new method was tested on the Tennessee Eastman Benchmark.

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