VOLUME - 12, ISSUE - 06, JUNE - 2023 • PRINT ISSN No. 2277 - 8160 • DOI : 10.36106/gjra

Original Research Paper

Electronic Engineering

HEATING TANK SYSTEM FAULT DIAGNOSTIC MECHANISM USING KERNEL PRINCIPAL COMPONENT ANALYSIS

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ABSTRACT Nowadays, global industry is witnessing the explosion of flexible manufacturing systems considered as key role for the fourth industrial revolution. Almost hardware and software producers tried their best to assure the best performance for those system. However, some chemical processes in particular requires more strict conditions beside high-accuracy operation of actuators. Chemical reactions may lead to a poor quality for output product even a small change. Therefore, beside the necessary of high-performance integrated control system, monitoring operation should be fast and correct enough to detect and isolate faults when any problems happened in system. In this paper, a method for process fault detection and diagnostic based on data-driven estimation is investigated. In this method, the process fault is detected based on the error between process model response and process response. The Kernel Principal Component Analysis (KPCA) is utilized to classify errors for fault diagnostic. In this research, the method is verified on Stirred-Tank Heating Process. The simulation results demonstrate the effectiveness of proposed method.

KEYWORDS : Faults diagnostic, PCA, KPCA, non-linear system.

INTRODUCTION

Up to now, there are a lot of choices for data processing algorithm aiming to analyze data as efficient as possible. Each method has its own advantages and disadvantages. In general, we can divide them into two group: qualitative and quantitative method. Qualitative method requires developers have to understand comprehensively about system and it is really difficult to apply for real process. Therefore, this study will concentrate on quantitative method with statistical algorithm (PCA, KPCA, MD,…).

Conventional PCA (principal component analysis) was apply successfully to monitor and diagnose system by Qin in 2006 [1]. In 2010, T.V. Villegas et al [2] developed fault detection model based on simple PCA algorithm for Two-tank system. Harru [3] introduce solution to improve this operation with CSTR model. In 2018, T.Ait et al [4] proposed new method to apply PCA for MIMO systems. MÁRQUEZ-Vera et al [5] introduced Adaptive threshold PCA model for fault detection and isolation. However, this method based on linearization technique while almost real processes are non-linear and complex.

Therefore, based on conventional PCA, KPCA (Kernel principal component analysis) model is considered as the best choices. Kernel function is non-linear transformation aiming to project data on hyperplane to be linear separated. Viet Ha Nguyen [6] (2010) proposed solution to detect faults in mechanical system applying KPCA. Similarly, M.Mansouri [7] (2016) introduce faults detection model of chemical process based on standard T^2 and Q. Besides, we also have others statistical method such as: Euclidean distance (ED), mahalanobis distance,… However, PCA in general and KPCA in particular is also one of the most efficient data processing tool in multivariable systems. Dimensional reduction ability and kernel function allow this method extract only necessary features as well as removing disturbances in complex raw data. Recently, F. Bencheikh [8] (2020) develop new RKPCA to detect fault in cement rotary kiln. In this research, KPCA suffers from high computing time and large storage space when a large-sized training dataset is used. Therefore, a new Reduced KPCA (RKPCA) approach is developed to extract and select the more relevant observations in training samples. Afterwards, the obtained reduced training dataset is used to build a KPCA model for Fault detection and diagnosis (FDD) purposes. Similarly, R.Li and Y.Liu [9] (2019) proposed a hybrid dimension reduction algorithm based on feature selection and KPCA to recognize faults for the planetary gearbox.

This study will propose a general process to develop fault diagnostic model using kernel principal component analysis (KPCA) based on data-driven estimation.

2. METHOD

In general situation, system identification is primary step to investigate characteristics of specific system considered as black box model. All predicted data are collected simultaneously with system output to analyze correlation between two data sets based on statistical algorithm. Therefore, the accuracy of previous step will decide the quality of fault diagnostic mechanism during real operation.

3. Research Plant

In this study, a Heating Tank Process will be investigated to deploy the proposed method. Firstly, the model input-output relationship will be summarized. Secondly, the Matlab Simulink model is developed to simulate process input-output response. Finally, the numerical model is integrated into proposed method to identify, detect and classify process faults.

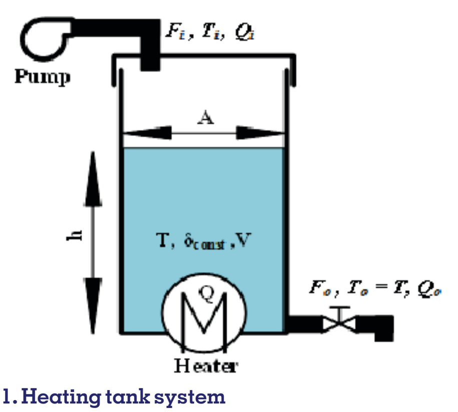

Figure 1. Heating tank system

Where:

δ: density of liquid

F_i, F_o : input and output flow

T_i, T_o : input and output temperature

Q_i, Q_o: represent for the enthalpy of the inlet and outlet

stream(s).
Q : heater energy
h : water level height
A : tank area

Table 1. Single tank's parameters

Parameters	Value
Tank area (A)	1500 cm2
Exhausted coefficient (C)	0.6
Exhausted valve area (b)	7 cm2
Power coefficient of pump (K)	150 cm3/Vs
Gravity coefficient (g)	9.81 m/s2

In this study, behaviors of heating tank system based on below assumptions:

1. Material of liquid is homogeneous
2. System's parameters are constant with time.
3. Perfect mixing, the exit temperature T is also the temperature of the tank content.
4. Heat losses are negligible .

Changes in potential energy and kinetic energy can be neglected, because they are small in comparison with changes in internal energy.

4. KPCA-BASED Process Monitoring

Considered as a conventional linear transformation technique, PCA transfer high-dimensional data into low-dimensional with maximum data information. When the algorithm is executed in the feature space, KPCA is obtained. In data science, KPCA is known as kernel-based learning machine. The basic idea of KPCA algorithm is to project the input data set into feature space **F** via non-linear mapping , and then apply PCA in **F**. However, it is difficult to do directly because the dimension *h* of the feature space **F** can be arbitrarily large or even infinite. In implementation, the implicit feature vector in **F** does not need to be computed explicitly, while it is just done by computing the inner product of two vectors in **F** with a kernel function [10].

In fault diagnostic application, new data set will be investigated based on feature space of standard data.
Given a standard data matrix, X, representing n observations of m variables as:

$$X = (x_1, x_2, ..., x_n) = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{pmatrix}$$

And testing data set X' with same dimension:

$$X' = (x'_1, x'_2, ..., x'_n) = \begin{pmatrix} x'_{11} & x'_{12} & \cdots & x'_{1n} \\ x'_{21} & x'_{22} & \cdots & x'_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x'_{m1} & x'_{m2} & \cdots & x'_{mn} \end{pmatrix}$$

In this study, the main flow of the algorithm is as follows seven steps:

Step 1: Choose kernel function, there are some popular kernel function below:

Gaussian kernel: $k(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|_2^2),\ \gamma > 0$
Linear kernel: $k(x_i, x_j) = x_i^T x_j$
Polynomial kernel : $k(x_i, x_j) = (r + \gamma x_i^T x_j)^d$
Sigmoid kernel : $k(x_i, x_j) = \tanh(\gamma x_i^T + x_j)$

Step 2: Calculate kernel matrix K of dimension *n x n* :

$K_{i,j} = \langle \Phi(x_i), \Phi(x_j)^T \rangle = k(x_i, x_j)$

Where $k\ (x_i, x_j)$ is the calculation of the inner product of two vectors in **F** with a kernel function.

Step 3: Standardize Kernel matrix into centroid

$$K_{Zmean} = K - (1_{1/n})K - K(1_{1/n}) + (1_{1/n})K(1_{1/n})$$

Step 4: Calculate eigenvectors α and eigenvalues λ:

$$K_{Zmean}\alpha_i = \lambda_i \alpha_i$$

Step 5: Project standard data (normal data or training data) into new space

$$\hat{y}_j = \sum_{i=1}^{n} \alpha_{i,j} k(x_i, x_j),\ j = 1, 2, ..., n$$

Step 6: Standardize new data (fault data or testing data) based on standard data space

$$\hat{y}'_j = \sum_{i=1}^{n} \alpha_{i,j} k(x'_i, x'_j),\ j = 1, 2, ..., n$$

Step 7: Detect fault bases on Hotelling *T-Square* standard with *T_UCL* threshold.

Hotelling T-Square statistical method is considered as general method to verify statistic data processing as PCA and KPCA. With KPCA model, [2] and [12] we can calculate T^2 for data samples x_j :

$$T_j^2 = y_j^T \Delta_L^{-1} y_j$$

$\Delta_L = diag\ (\lambda_1, \lambda_2, ... \lambda_n)$ is diagonal matrix correspond to *L* eigenvalues of *L* Kernel PCs calculated before.

5. EXPERIMENTAL RESULTS

5.1 System in normal operation

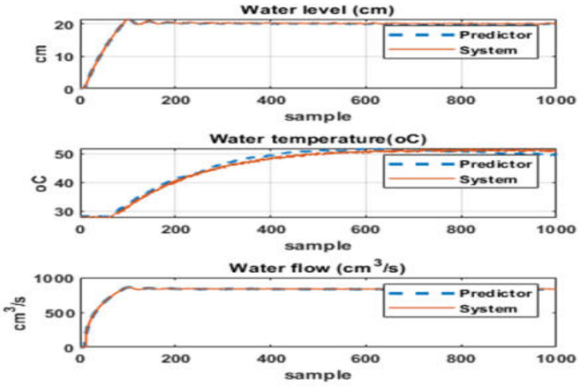

Figure 2. Normal system

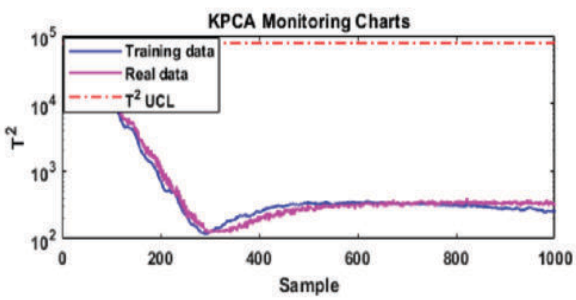

Figure 3. Normal system diagnose

In this situation, training data (predicted output) and real data (system's output) is processed follow figure 8. Experimental results in figure 9 and figure 10 shows that in normal condition, real data from system is compatible with training data and distribute ***under*** T^2-UCL line. On the other hand, when system falls into fault cases in below experiments, real data will distribute ***above*** T^2-UCL line in KPCA monitoring chart.

5.2 System in abnormal operation

5.2.1 Pump not working at the beginning

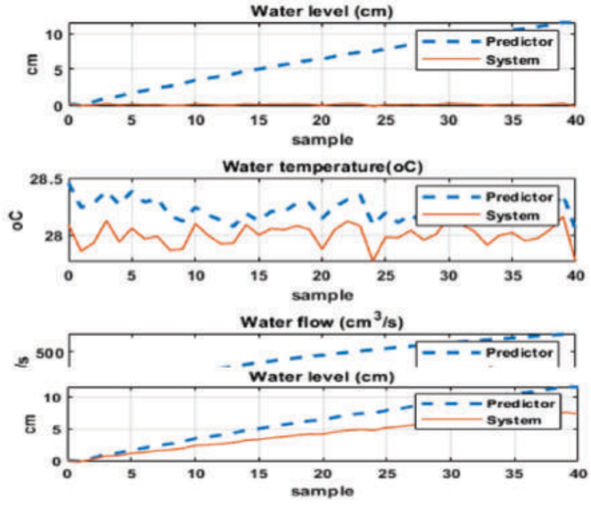

Figure 4. System respond

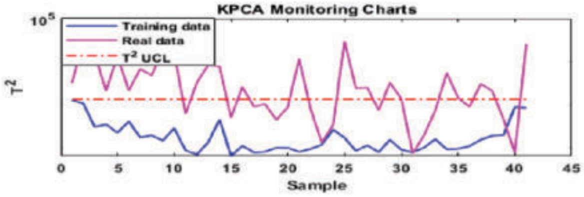

Figure 5. Fault detection result

5.2.2 Pump efficientcy loss

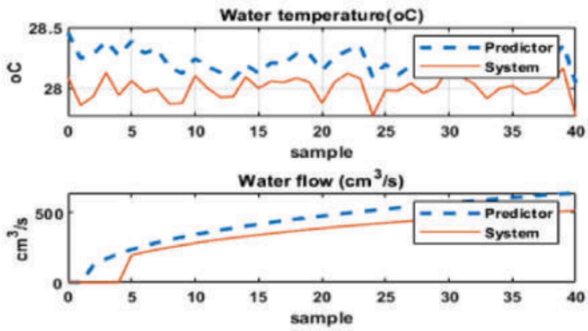

Figure 6. System respond

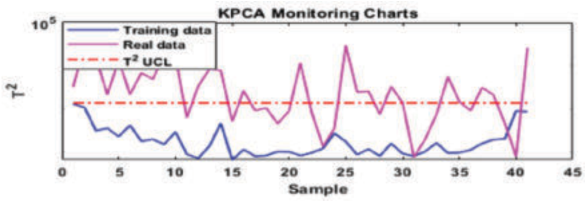

Figure 7. Fault detection result

5.2.3 Water level sensor fault

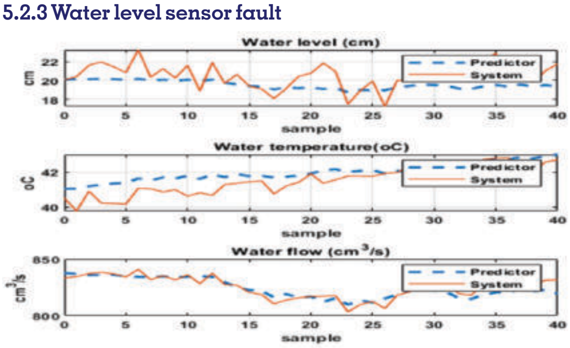

Figure 8. System respond

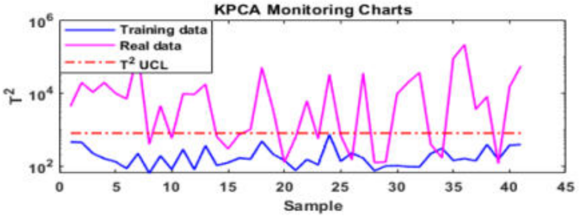

Figure 9. Fault detection result

5.2.1 Heater not working at the beginning

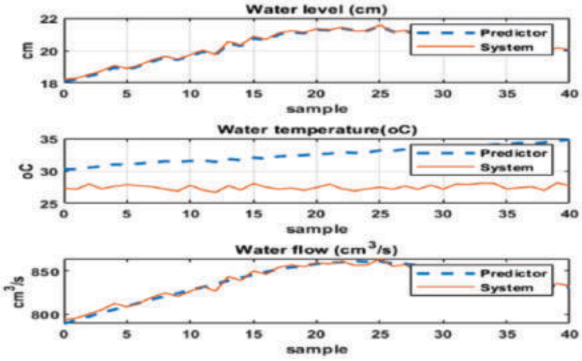

Figure 10. System respond

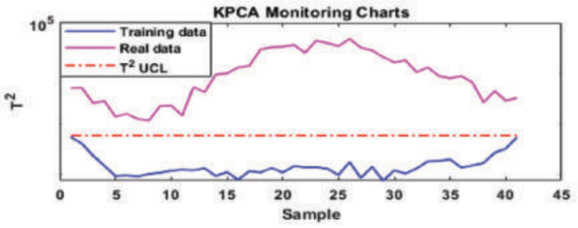

Figure 11. Fault detection result

5.2.8 Heater efficiency loss

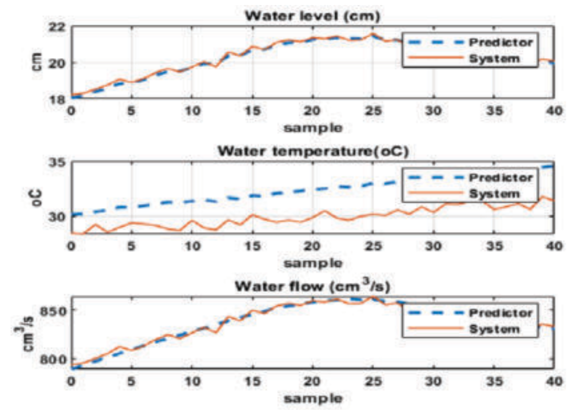

Figure 12. System respond

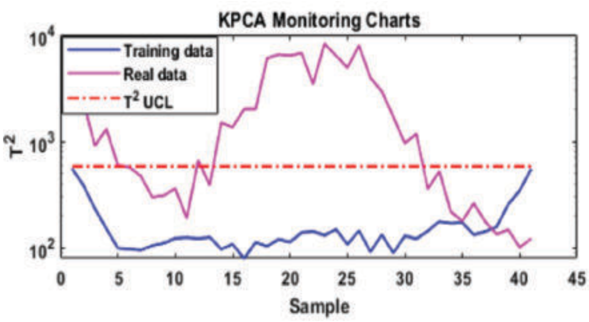

Figure 13. Fault detection result

5.2.8 Temperature sensor fault

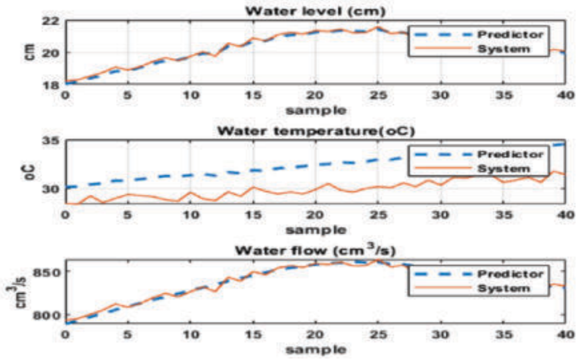

Figure 14. System respond

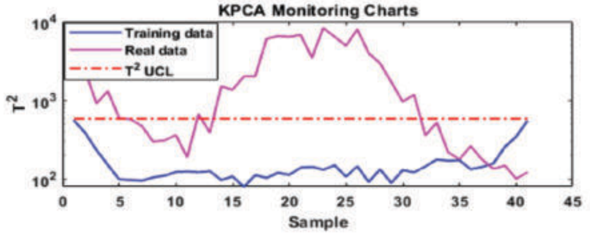

Figure 15. Fault detection result

Figure 4 to figure 15 show all fault operation with KPCA monitoring method. Although in two situation E2 and E6 the distribution distance between training data and real data on KPCA chart is not clear as the others, fault diagnostic mechanism works correctly.

CONCLUSIONS

This study proposes a method to develop faults diagnosing for industrial process based on statistical method KPCA. With a little information about new system, KPCA can detect almost all abnormal problems. Tanks to its capability to process data in a nonlinearfeature map, KPCA presents some advantages with respect to other methods like PCA, MD, EE,… which are basically linear procedures.

The simulation results are the evidence for the applicability and the effectiveness of the proposed approach in reality.

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