FAULT DETECTION AND MONITORING SYSTEM USING ENHANCED PRINCIPAL COMPONENT ANALYSIS FOR THE APPLICATION IN WASTEWATER TREATMENT PLANT

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To my beloved *Mak* and *Ayah* and those encourage me to finish this thesis

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ABSTRACT

Fault detection and monitoring is essentially important in wastewater treatment to ensure that safety, environmental regulations compliance, maintenance and operation of the Wastewater Treatment Plant (WWTP) are under control. Many researchers have developed methods in fault detection and monitoring such as fuzzy logic, parameter estimation, neural network and Principal Component Analysis (PCA). In studies involving data and signal model approach, PCA is the most appropriate method used in this work. Besides when using PCA, the dimensionality of the data, noise and redundancy can be reduce. However, PCA is only suitable for data with mean constant or steady state data. The use of PCA can also increase false alarm and produce false fault in a plant such as WWTP. Modifications of PCA need to be done to overcome the problems and hence, enhanced methods of PCA are proposed in this work. The enhanced methods are Multiscale PCA (MSPCA) and Recursive PCA (RPCA), which are appropriate for offline monitoring test and online monitoring test, respectively. To see the effectiveness of the methods, they were applied into the european Co-operation in the field of Scientific and Technical Research (COST) simulation benchmark WWTP. The results from the simulation plant were then applied in a real WWTP, IWK Bunus Regional Sewage Treatment Plant (RSTP). The data of WWTP involved are Dissolved Oxygen (DO), Biochemical Oxygen Demand (BOD), Chemical Oxygen Demand (COD) and Nitrate (SNO). In analysis for both plants, faults were detected when the confidence limit is over 95% and confidence limits in the range of 90-95% were considered for alarm region in the data, using Hotelling"s T^2 and residual. Finally, simulation results of the proposed methods were compared and it was found that the enhanced methods of PCA (MSPCA and RPCA) were able to reduce false alarm and false fault in the analysis of fault detection by 70% for steady state influence and dynamic influence and hence provides more accurate results in detecting faults in the process data.

ABSTRAK

Kerosakan pengesanan dan pemantauan kini dianggap sebagai asas penting dalam rawatan sisa air bagi memastikan keselamatan, peraturan-peraturan alam sekitar, penyelenggaraan dan operasi loji rawatan sisa air (WWTP) adalah di bawah kawalan. Ramai penyelidik telah membangunkan kaedah mengesan kerosakan dan pemantauan seperti logik kabur, anggaran parameter, rangkaian neural dan komponen analisis utama (PCA). Di dalam kajian yang melibatkan data dan pendekatan model isyarat, PCA adalah kaedah yang sesuai digunakan dalam kajian ini. Selain itu, apabila menggunakan PCA kedimensian data, bunyi dan pemberhentian dapat dikurangkan. Walau bagaimanapun,PCA hanya sesuai untuk data dengan purata seragam atau data yang stabil. Penggunaan PCA di dalam loji seperti WWTP boleh menimbulkan masalah, antaranya pengesanan penggeraan palsu dan kerosakan palsu. Pengubahsuaian kepada PCA perlu dilakukan untuk menyelesaikan masalah ini dengan mengubah suai pengiraan purata, maka peningkatan PCA diperkenalkan dalam kajian ini. Kaedah peningkatan PCA yang diperkenalkan adalah komponen analisis utama berskala berbilang (MSPCA) dan rekursif komponen analisis utama (RPCA) yang mana sesuai untuk ujian pemantauan luar talian dan ujian pemantauan dalam talian. Untuk melihat keberkesanan kaedah tersebut, aplikasi peningkatan PCA dilakukan ke atas loji rawatan air sisa menggunakan Kerjasama persatuan eropah dalam bidang Penyelidikan Saintifik dan Teknikal (COST) penanda aras simulasi WWTP. Kemudian keputusan simulasi digunakan ke atas WWTP sebenar, IWK loji rawatan kumbahan wilayah Bunus. Data WWTP yang terlibat ialah oksigen terlarut (DO), permintaan oksigen biokimia (BOD), permintaan oksigen kimia (COD) dan nitrat (SNO). Dalam analisis untuk kedua-dua loji, kesilapan dikesan apabila had keyakinan adalah melebih 95% dan had keyakinan dalam lingkungan 90-95% telah dipertimbangkan untuk rantau penggera dalam data menggunakan T^2 Hotelling dan sisa analisis. Akhir sekali, hasil dari simulasi yang dicadangkan di dalam kajian ini dibandingkan dan didapati kaedah PCA yang dipertingkatkan (MSPCA dan RPCA) berjaya dalam mengurangkan penggera palsu sebanyak 50% untuk input seragam dan 80% input dinamik dan memberi ketepatan yang jitu di dalam mengesan kerosakan di dalam data proses.

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LIST OF ABBREVIATIONS

ASM1	-	Activated sludge model no.1
BOD	-	Biochemical Oxygen demand
COST	-	The European Co-operation in the field of Scientific and Technical Research
COD	-	Chemical oxygen demand
DO	-	Dissolved oxygen
FDM	-	Fault detection and monitoring
MSPCA	-	Multiscale PCA
PCA	-	Principal component analysis
RPCA	-	Recursive PCA
RSTP	-	Regional sewage treatment plant
SPE	-	Squared prediction error
WWTP	-	Wastewater treatment plant

LIST OF SYMBOLS

b	-	mean
α	-	Level of significant
į^2	-	Squared prediction error limit confidence
I	-	Identity matrix
m	-	Variable
n	-	Sample
P	-	Loadings
R	-	Correlation matrix
T	-	Score
T^2	-	Hotelling‟s T^2
ϑ	-	T^2 confidence limit
V	-	Eigenvector
X	-	Data from WWTP
ˆ	-	PCA data
˜	-	Residual
Λ	-	Eigenvalue
$\varphi_{j,n}$	-	Scaling function
$\psi_{j,n}$	-	Wavelet function

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CHAPTER 1

INTRODUCTION

1.1 Research Background

Fault detection and monitoring in wastewater treatment plant (WWTP) has been applied decades ago to control and prevent any abnormality in the plant. The fault is detected in the WWTP system and monitoring will be performed to confirm the presence of the fault. When the fault is identified, fault location can be determined. Therefore, the presence of the fault can be controlled by reducing or eliminate the existence fault and prevent the next fault happen at the same place. The benefit of earlier fault detection is to reduce disturbances within the plant system.

For the WWTP which is continuously monitored from fault, the operational risk and the cost of maintenance of the plant can be reduced. If the WWTP operation fails to be constantly monitored, it can contribute to environmental pollution and increases the general cost to operate the WWTP. Therefore in WWTP, monitoring of the plant is important to ensure the operational output can be carried out smoothly such as, Chemical Oxygen Demand (COD), pH, Biochemical Oxygen Demand (BOD) and Nitrogen.

In addition, the Malaysia Government has issued a regulation that WWTP is responsible for the effluent discharged to ensure that no harm will be subjected on humans and thus avoiding environmental pollution. This is due to the fact that WWTP could inadvertently produce water pollution instead of treated water should they not adhere to the prescribed regulations. Therefore, wastewater treatment plants must be constantly monitored so that any abnormality in the control processes can be detected.

Fault or abnormality in WWTP is unwanted signal that occurs in a standard condition system of plant [1]. Fault detection and monitoring determine the fault that occurs in the monitoring system. Fault can be in three types which are sensors [2], actuators [3] and processes [4] fault. Based on the three faults, process fault is chosen in this work. Process faults can be in a form of single fault or multiple faults. For both cases, multiple faults are more complicated because if the faults have different signs it can cancel each other, thus to detect the fault, enhanced method is needed [5] and is considered in this work. The enhanced method in fault detection can detect fault more specifically and more accurately. The method is an improvement of conventional method of fault detection by combining with other technique such as principal component analysis (PCA) with Wavelet Transform. In fault detection and monitoring system, three main methods are widely implemented. The first is knowledge based method. For example, fuzzy logic is a knowledge based method representing form of production rules and it is quite difficult and requires deep understanding of the overall process behaviour [6]. The second is process model based method such as parameter estimation [7], [8]. In this method, the essence of this concept is analytical redundancy by comparing the actual output and the output that is obtained from the mathematical model. The third method, is data and signal model approach. In this method, the most often used is PCA whereas the exploitation of data is formed from the experimental work [6], [9], [10]. In this thesis, the third method is preferable to first and second methods.

1.2 Problem statement

Wastewater treatment plant is generally known as highly nonlinear system subject to various forms of internal and external disturbances. For the internal disturbance, there is a higher possibility of change in the parameter value which may affects the growth of the microorganisms (aerobic growth and anoxic growth) responsible for treating the wastewater. External disturbance such as environmental and weather factors affect the condition of the plant. Therefore, the plant must be constantly monitored to avoid unnecessary complications in the plant such as low dissolved oxygen and prevent toxic leak in the effluent, as these could lead to faulty conditions in the process, which may deteriorate the quality of the data.

Principal component analysis has been used to monitor and detect fault in the wastewater treatment plant (WWTP). However, the main limitation of the PCA method is poor fault detection for dynamic data.

To solve this problem for effective monitoring and fault detection in WWTP this thesis provides enhanced PCA (which are Multiscale PCA and Recursive PCA) technique using process history based method.

1.3 Objective

1. To improve the PCA method by using Multiscale PCA by improving the mean calculation for the detection and monitoring fault in off-line monitoring.

2. To develop the recursive PCA in fault detection and monitoring by enhancing the PCA performance in on-line monitoring.

3. To validate and evaluate the performance of the developed algorithms into the COST simulation benchmark WWTP and IWK Bunus regional sewage treatment plant (IWK Bunus RSTP).

1.4 Scope of work

The scopes of work in this thesis are listed below.

i. Study the behaviour of fault in the domestic WWTP. This work involved with data collections such as dissolved oxygen (DO), biochemical oxygen demand (BOD), chemical oxygen demand (COD), pH and oil and grease (O&G) from IWK Bunus RSTP and COST simulation benchmark WWTP.

ii. Developing PCA algorithm for detecting and monitoring fault in the COST simulations benchmark WWTP.

iii. Reducing the false detection in fault and alarm at the COST simulation benchmark WWTP by applying enhanced PCA which are MSPCA and RPCA algorithms.

iv. Applying results analysis of PCA, Multi-scale PCA (MSPCA) and Recursive PCA (RPCA) in the COST simulation benchmark WWTP and IWK Bunus RSTP.

1.5 Research contribution

1. The contribution in this work is false detection of fault and alarm in PCA analysis had been reduced by applying MSPCA. In MSPCA, the procedure of mean calculation is improved by applying wavelet decomposition to separate data into several scales before mean was calculated. MSPCA is then used for off-line monitoring in WWTP.
2. However in on-line monitoring, MSPCA cannot be applied because of limitation in wavelet decomposition to update the data. Therefore RPCA is used, to reduce the false detection in online monitoring. In RPCA the false detection is reduced by updating the mean, standard deviation and variance.
3. Both methods for off-line and on-line monitoring are successfully applied in the COST simulation benchmark WWTP and IWK Bunus RSTP in order to detect and monitor the fault.
4. Three methods of fault detection in this thesis, which are PCA, MSPCA and RPCA have been used to develop toolbox for fault detection and monitoring in WWTP.

1.6 Thesis Outline

This thesis consists of six chapters. Chapter 2 provides explanation on the fundamental concept of domestic WWTP and literature review on fault detection and monitoring focuses on PCA and the enhanced PCA method, which are MSPCA and RPCA.

Chapter 3 covers the method used in fault detection and monitoring in WWTP. The case study plants utilized in this research are COST simulation benchmark WWTP and IWK Bunus RSTP.

Chapter 4 presents the simulation results and discussion of fault detection and monitoring in COST simulation benchmark WWTP and IWK Bunus RSTP based on PCA, Multiscale PCA and Recursive PCA.

Chapter 5 presents Fault Detection and Monitoring Toolbox and its applications. This chapter also describes the procedure in Fault Detection and Monitoring Toolbox to detect the fault in the input data.

Chapter 6 concludes the thesis and suggests several possible future works of the fault detection and monitoring in WWTP. This chapter also provides list of paper published under this work.

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