INTELLIGENT FAULT DETECTION AND DIAGNOSIS BASED ON OPTIMIZED FUZZY MODEL FOR PROCESS CONTROL RIG

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ABSTRACT

This thesis focuses on the application of artificial intelligent techniques in fault detection and diagnosis. Fault detection and diagnosis scheme is a technique used in supervisory systems. The function of the supervisory system is to indicate unnecessary process states and to take the most appropriate actions to maintain continuous operation and to avoid damages. There are two main methods in fault detection and diagnosis: model free and model-based. In this thesis, model-based fault detection and diagnosis is used. One of the research challenges in model-based fault detection and diagnosis of a system is to find the accurate models. The objective of this thesis is to detect and diagnose the faults to a process control rig. A technique for the modeling of nonlinear control processes using fuzzy modeling approach based on the Takagi–Sugeno fuzzy model with a combination of genetic algorithm and recursive least square is proposed. This thesis discusses the identification of the parameters at the antecedent and consequent parts of the fuzzy model. For the antecedent fuzzy parameters, genetic algorithm is used to tune them while at the consequent part, recursive least squares approach is used to identify the system parameters. The proposed method is used to develop fault model and to detect the fault where this task is performed by using residual signals. When the residual signal is zero or nearly zero, the system is in normal condition, and when the fault occurs, residual signals should distinctively diverge from zero. Meanwhile, neural network is used for fault classification where this task is performed by identifying the fault in the system. This approach is applied to a process control rig with three subsystems: a heating element, a heat exchanger and a compartment tank. Experimental results show that the proposed approach provides better modeling when compared with Takagi Sugeno fuzzy modeling technique and the linear modeling approach. The overall accuracy for classification results also shows the best performance of around 93%.

ABSTRAK

Tesis ini memberi tumpuan kepada aplikasi teknik-teknik kepintaran buatan untuk pengesanan dan diagnosis kerosakan. Skim pengesanan dan diagnosis kerosakan adalah teknik yang digunakan dalam sistem penyeliaan. Fungsi sistem penyeliaan adalah untuk menunjukkan keadaan proses yang tidak perlu dan untuk mengambil tindakan yang paling sesuai untuk mengekalkan operasi yang berterusan dan untuk mengelakkan kerosakan. Terdapat dua kaedah utama dalam pengesanan dan diagnosis kerosakan: model-bebas dan berasaskan model. Dalam tesis ini berasaskan model pengesanan dan diagnosis kerosakan digunakan. Salah satu cabaran kajian kepada berasaskan model pengesanan dan diagnosis kerosakan sistem adalah mencari model yang tepat. Objektif tesis ini adalah untuk mengesan dan mendiagnosis kerosakan kepada pelantar kawalan proses. Satu teknik untuk pemodelan proses kawalan tak lelurus berdasarkan model samar Takagi-Sugeno dengan gabungan algoritma genetik dan rekursi kuasa dua terkecil dicadangkan. Tesis ini membincangkan pengenalpastian parameter bahagian anteseden dan akibat langsung pada model samar. Bagi parameter anteseden samar, algoritma genetik digunakan untuk pelarasan parameter tersebut, manakala pada bahagian akibat langsung pendekatan rekursi kuasa dua terkecil digunakan untuk mengenalpasti parameter sistem. Kaedah yang dicadangkan digunakan untuk membangunkan model yang rosak untuk mengesan kerosakan di mana tugas ini dilakukan dengan menggunakan isyarat sisa. Apabila isyarat sisa adalah sifar atau hampir sifar, sistem ini dalam keadaan normal, dan apabila kerosakan berlaku, isyarat sisa akan menyimpang dari sifar. Sementara itu, rangkaian neural digunakan untuk pengkelasan kerosakan di mana tugas ini dilakukan dengan mengenal pasti kerosakan dalam sistem. Pendekatan ini digunakan untuk pelantar kawalan proses dengan tiga subsistem: elemen pemanas, penukar haba dan ruang tangki. Keputusan eksperimen menunjukkan bahawa pendekatan yang dicadangkan menyediakan pemodelan yang lebih baik apabila dibandingkan dengan teknik pemodelan kabur Takagi Sugeno dan pendekatan pemodelan lelurus. Keseluruhan keputusan ketepatan bagi pengkelasan juga menunjukkan prestasi terbaik di sekitar 93%.

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LIST OF SYMBOLS AND ABBREVIATIONS

q	-	volumetric flowrate
U	-	heat transfer coefficient
A	-	area of heat transfer
ρ	-	density
V	-	volume
C	-	specific heat capacity
T_{he}	-	temperature of heating element
T_h	-	temperature of hot water of heat exchanger
T_c	-	temperature of cold water of heat exchanger
h	-	level of compartment tank
FDD	-	Fault Detection and Diagnosis
GA-RLS	-	Genetic Algorithm and Recursive Least Square
ANN	-	Artificial Neural Network
DAQ	-	Data Acquisition
GA	-	Genetic Algorithm
RLS	-	Recursive Least Square
PCA	-	Principle Component Analysis
ICA	-	Independent Component Analysis
IC	-	Independent Component
DICA	-	Dynamic Independent Component Analysis
FDA	-	Fisher Discriminant Analysis
MLP	-	Multilayer Perceptron
AI	-	Artificial Intelligence
TS	-	Takagi Sugeno
TSK	-	Takagi Sugeno Kang
COG	-	Centre of Gravity
MISO	-	Multi Input Single Output

MIMO	-	Multi Input Multi Output
FCCU	-	Fluidised Catalytic Cracking Unit
ARX	-	Auto Regression with eXogenous
BPR	-	Basic Process Rig
TPR	-	Temperature Process Rig
VI	-	Virtual Instrument
FLT	-	Float Level Transmitter
PI	-	Process Interface
PFT	-	Pulse Flow Transmitter
NTC	-	NegativeTemperature Coefficient
PWM	-	Pulse Width Modulation
MSE	-	Mean of Squared Error

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CHAPTER 1

INTRODUCTION

1.1 General

Monitoring system that can monitor process control system component and diagnose fault detected is important to develop since the performance of computers into daily activities is growing fastest. This will provide the solutions without human intervention. The increasing demand of quality in production processes has encouraged the research and development on fault detection and diagnosis (FDD) in industrial plant. An unexpected change of system functionality may call a "fault" which it is maybe related to a failure in a physical component or in a system sensor or actuator.

Fault detection and fault diagnosis are the two main tasks that should perform in monitoring system. The first task is to determine whether a fault has occurred in the system. To achieve this goal, all the available information from the system should be collected and processed to detect any changes from nominal behaviour of the process. The second task is classifying the fault into several categories of faults such as the location and type of faults.

There are several methods that may solve the problem of FDD. Classical methods also called model-free FDD methods used physical redundancy, limit sensors, frequency spectrum and logic reasoning (Gertler, 1998). Eventhough the methods is easy to implement, the disadvantages are high cost, extra space and complex computation.

Model-based FDD is the innovative methods in recent years. The classical model-based FDD used dynamic models of the process. Because faults are supposed to appear as state changes caused by malfunctions, they are often monitored using estimation techniques (Willsky, 1976; Isermann, 1984; Baseville, 1988; Trank, 1990), or parity equations (Gertler, 1991; Patton et al., 1991). The basic idea is very simple: the behaviours such as input-output time series of the model and real system are compared to generate residual signals, which, in the presence of faults, take non-zero values. Rule-based expert systems have also been investigated very intensively for FDD problems (Kramer, 1987; Rich et al., 1987; Patton et al., 1989). However, these systems need an extensive database of rules and the accuracy of diagnosis depends on the rules. Therefore, the less number of rules with accurate model is represented in this research.

In order to get accurate fault diagnosis, the optimized model is developed. In this research, fuzzy model with genetic algorithm and recursive least square (GA-RLS) is proposed. This fuzzy model is developed to representing the process control rig sub-model. Four sub-models is proposed from the test bed of process control rig which are heating element, heat exchanger for hot water, heat exchanger for cold water and compartment tank models. In this proposed fuzzy model, the mean squared error is used as a performance index. The minimum error will produced the optimized model of the system. The model for every fault occurred is also developed by using the same approach. The residual is generating based on the differences between fault model and system model. Then, artificial neural network (ANN) is used to classify the fault. The highest accuracy is the best classification.

1.2 Problem Statement and Importance of Research

In the process plant application, many variables and instruments involved needs to monitor to make sure the process functioning and running accordingly. If there is just a small problem or faults occurred, sometimes it is undetected by the operator. Normally, only expert personnel know about the fault and will cause the late action to detect the fault. The late detection of fault may result in high maintenance cost because may be the fault is already spread to other system. Therefore, a good and intelligent fault monitoring and diagnosis system is needed. In order to do that, the fault detection and diagnosis software with the optimized fuzzy model was developed to overcome the problem of the tedious process of detecting fault in the process control application.

1.3 Research Objectives and Scope

1.3.1 Objectives

The objectives of the thesis are:

1. To derive a mathematical model for process control rig.
2. To develop an optimized fuzzy model using genetic algorithm and recursive least square.
3. To use optimized fuzzy in development of fault detection and diagnosis system.
4. To develop an intelligent fault detection and diagnosis for process control rig.

1.3.2 Research Scope

The scopes of the research are

1. To use Labview 8.6 as the computation platform for developing of data acquisition (DAQ), fuzzy modeling and fault detection and diagnosis software.
2. To use the process control rig as test bed system as a reference system for model development.
3. To model and validate the system using input and output data from experiments on the process control rig.

4. To model and classify the fault through simulated or offline process for fault detection and diagnosis.

1.4 Methodologies

There are two methods proposed in this research which in general depend on the scopes and objectives of the work as follows:

1.4.1 Part 1

Fuzzy model with GA-RLS is proposed to model the process control rig to represent the real system. Because of the fuzzy model is the blackbox model, the input and output data is required to model the system. To acquire the data, the data acquisition software for the process needs to be done. In this research, there are three sub-systems, which are heating element, heat exchanger and compartment tank. The heat exchanger contents of two mathematical models such as heat exchanger for hot water and heat exchanger for cold water. Therefore, there is four model developed in this research. The input and output variables to the fuzzy model is depending on the mathematical model of the system. In fuzzy modeling, genetic algorithm (GA) is used for tuning the antecedent parts parameters and recursive least square (RLS) is used for tuning the consequents part parameters of fuzzy model.

1.4.2 Part 2

In this part the fault model is develop by using the proposed technique fuzzy modeling. The input and output data of the faults is obtained from the experiments based on the fault injection discussed in Chapter 3. The residuals are generated by comparing this fault model and system model obtained in Part 1. Then the residuals are fed into ANN to classify the fault.

1.5 Contribution of Thesis

The most important contributions of this thesis are the development of a fuzzy model with GA-RLS applied to process control rig and to classify the fault by using ANN. It can be summarized as follows:

1. Mathematical derivation for modeling of process control rig.
2. Optimized model by using fuzzy model with GA-RLS.
3. Development of FDD software.

1.6 Outline of Thesis

The thesis is divided into five chapters:

- Chapter 1 introduces the thesis which covers some background information on FDD problems. The proposal to resolve the phenomena is also described. Fuzzy model with GA-RLS is identified to model the system in this research. The chapter consists of scope and objective, research methodology, the contribution and layout of the thesis.
- Chapter 2 reviews the FDD, fuzzy modeling and optimization techniques through literature search. A summary on the previous research dealing with FDD and fuzzy model is described in this chapter. It also covers the traditional and the intelligent FDD and the achievements made by other researchers in this field.
- Chapter 3 presents the methodology of this research. The mathematical models of process control rig are derived for each-subsystem in this chapter. The techniques used on the developments of the three softwares such as DAQ, fuzzy modeling and FDD are described. The optimization techniques such as GA and RLS are also discussed. In FDD, the method how the residual is generated and classified is presented.
- Chapter 4 discusses the results and discussion of the fuzzy modeling and FDD application on process control rig. In the modeling part, the

proposed model, fuzzy model with GA-RLS is used to model the system and then compared with another two methods such as conventional fuzzy model and linear model. In FDD, the residual is generated by comparing the system model and fault model. Then it is classified by using ANN. The used of three softwares are also discussed in this chapter.

- Chapter 5 concludes the thesis on a fuzzy model with GA-RLS and the FDD applied to process control rig. It also summarizes the achievements made in this research and further work recommended to be carried out.

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