MODELING OF FAULTS FOR CHEMICAL BATCH REACTOR USING ARTIFICIAL NEURAL NETWORK AND FUZZY LOGIC

SYED AZHAR BIN SYED AB. RAHMAN

UNIVERSITI SAINS MALAYSIA

2009

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by

SYED AZHAR BIN SYED AB. RAHMAN

Thesis submitted in fulfillment of the requirements for the degree of Master of Science

June 2009

ACKNOWLEDGEMENT

In the Name of ALLAH, the Most Gracious and the Most Merciful. Peace is upon to Muhammad S.A.W., the messenger sending to guide people for the truth way. All praises to Almighty Allah for giving me the strength and inspiration to finish my master within the time given.

First and foremost, I would like to thank to my supervisor, Associate Professor Dr. Mohamad Zailani for his enthusiastic supervision on this research, his valuable ideas and his understanding always make me feel that the work was worthwhile and important. I would like to thank to my co-supervisor, Dr. Zainal Ahmad for his guidance and advice especially when it deals with the state-of-art of neural network modeling and also to Dr. Suhairi Sata for the beauty of fuzzy logic. Not forgetting to all Control Group lecturers and students for helping me when difficulty comes around.

Alhamdulillah, with the financial support from MARA and study release from Universiti Kuala Lumpur everything finally goes to the end. I would like to thank to the Dean of UniKL MICET, Professor Azanam Shah, Head of Section, Mr Zulhafiz Tajuddin, my colleagues and students because always standing behind me when a support is needed.

Finally, this thesis is especially dedicated to my beloved parents, Syed Ab. Rahman and Sharifah Aminah for their pray, love and encouragement to see their son succeed. To my brother and sisters, I love you all. Last but not least, to master and PhD friends, thank you for struggler, laughter and share together with me before we finally reach the final steps.

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LIST OF ABBREVIATIONS

Symbols	Description
AIBN	Azobisisobutyronitrile
ANN	Artificial Neural Network
ASM	Abnormal Situation Management
BPN	Back Propagation Network
CSTR	Continuous Stirred Tank Reactor
DC	Direct Current
EKF	Extended Kalman Filter
FD	Fault Detection
FDD	Fault Detection and Diagnosis
FIS	Fuzzy Inference System
FL	Fuzzy Logic
GUI	Graphical User Interface
ICA	Independence Component Analysis
KBES	Knowledge Based Expert System
LM	Levenberg-Marquardt
LR	Learning rate
MF	Membership Function
MLP	Multilayer Perceptron
MMA	Methylmethacrylate
MPCA	Multiway Principal Component Analysis
MKPCA	Multiway Kernel Principal Component Analysis
MSKPCA	Multi-Scale Kernel Principal Component Analysis
NN	Neural Network
PCA	Principal Component Analysis
PMMA	Polymethymethacrylate
RBFN	Radial Basis Function Network
SCADA	Supervisory Control and Data Acquisition
SSE	Sum Square Error
USA	United State of America

LIST OF SYMBOLS

Symbols	Description	Unit
r-value	Correlation Coefficient	
C_{A0}	Initial Concentration	mol/l
C_A	Final Concentration	mol/l
d	Disturbances	-
f	Fault	
k	Fault Number	
F	Faulty Vector	-
ΔH	Heat of Reaction	kJ/mol
u	Input	
U	Input Vector/ Input Signal	-
y_M	Model Output	-
F_o	Normal State	-
y	Output/Real Measured Signal	
y_{ref}	References Output	
Y	Output Vector/ Output Signal	-
Θ	Parameter Estimated	-
r	Residual	-
x	State Estimated/Features	-
X	Conversion	%
s	Symptoms	-
T	Actual Temperature	°C
T-1	Past Temperature	°C
z	Neural Network Output	

PERMODELAN KEGAGALAN UNTUK REAKTOR KELOMPOK KIMIA MENGGUNAKAN RANGKAIAN NEURAL BUATAN DAN LOGIK KABUR

ABSTRAK

Setiap proses kimia cenderung untuk mengalami kegagalan. Situasi ini memaksa industri dan penyelidik mencari teknik bersesuaian bagi mengesan kegagalan secepat yang mungkin. Kaedah yang terbaik adalah dengan mengaplikasi sistem pengesanan kegagalan dan pengenalan (FDD). Di dalam kajian ini, sepuluh kegagalan proses telah direka untuk ujikaji. Data bagi suhu dan konduktiviti direkodkan semasa ujikaji dan penukaran dan kepekatan hasil diperolehi secara pengiraan. Data ini kemudiannya akan bertindak sebagai masukan ke dalam sistem permodelan. Sebaliknya, keadaan normal dan sepuluh kegagalan akan bertindak sebagai keluaran bagi sistem permodelan. Bagi permodelan menggunakan Rangkaian Neural Buatan (ANN), 'perceptron' berbilang lapisan (MLP) dengan satu lapisan tersembunyi telah digunakan. Bagi kajian pengekstrakan sifat, pertalian kepekatan hasil-penukaran-suhu lepasan menghasilkan keputusan yang terbaik dengan nilai SSE, 133.38 dan nilai r, 0.999. Nombor optimum bagi lapisan tersembunyi diperolehi pada 21 neuron dengan nilai SSE terendah pada 117.65 dan nilai r, 0.99. Pembangunan ANN telah berjaya mengesan dan mengasingkan 10 kegagalan semasa sessi pengesanan dan pengasingan. Pembangunan permodelan ini kemudiannya dioptimumkan dan disahkan dengan data ujikaji yang mana ianya tidak digunakan semasa latihan dan ujian. Sekali lagi, ANN yang dibangunkan telah berjaya menghasilkan corak kegagalan dan mengasingkan kegagalan. Penggunaan amaran lajakan dan ambang diagnosis dengan had 0.2 dan 0.8 akan memberikan amaran lajakan dan diagnosis terhadap data latihan dan ujian. Selain dari itu, 10 rekaan

kegagalan juga telah berjaya dikesan dengan menggunakan Logik Kabur (FL). Perbandingan Fungsi Keahlian (MF) mendapati bahawa 5 MF mempunyai keupayaan yang lebih baik untuk mengesan kegagalan berbanding dengan 3 MF. Keputusan juga menunjukkan bahawa bentuk Segitiga dan Gaussan akan menghasilkan keputusan yang sama. Bagaimanapun, bentuk Gaussan mempunyai keupayaan mengesan dan mengasingkan 40% lebih kegagalan tunggal berbanding dengan Segitiga. Selepas penghapusan peraturan lebihan, pengesanan dan pengasingan kegagalan tunggal meningkat sebanyak 12% dan kegagalan berpasangan berkurang sebanyak 76%. Akhir sekali, Sistem Taabir Kabur (FIS) dicadangkan untuk kajian terkini bagi menggantikan FIS yang sedia ada di dalam MATLAB® atau yang telah dicadangkan oleh penyelidik terdahulu. Sebagai kesimpulan, ANN dan FL merupakan kaedah yang berpotensi di dalam kajian FDD. Kedua-duanya mempunyai keupayaan mengesan dan mengasingkan pelbagai kegagalan seperti yang dipertimbangkan di dalam kajian ini. Ini menunjukkan bahawa ANN dan FL boleh diaplikasi untuk pengawasan sebarang kegagalan proses di dalam reaktor kelompok kimia.

MODELING OF FAULTS FOR CHEMICAL BATCH REACTOR USING ARTIFICIAL NEURAL NETWORK AND FUZZY LOGIC

ABSTRACT

Every chemical processes prones to failure. This situation enforces the researchers and industrial to find the appropriate techniques to detect a process failure as early as possible. The best solution is by implementing fault detection and diagnosis system (FDD). In these studies, ten process faults have been designed for the experimental work. The temperature and conductivity data were collected during the experiment and the conversion and concentration of the products were calculated. These data were then acted as an input into the modeling system. In the other hand, the normal and ten faulty situations acted as an output for the modeling system. In the modeling by using Artificial Neural Network (ANN), Multilayer Perceptron (MLP) with single hidden layer was implemented. For the feature extraction study, the correlation of concentration-conversion-past temperature produced the best result with sum square error (SSE) of 133.38 and r-value of 0.999. The optimum number of the hidden layer was found to be 21 neurons with the lowest SSE value of 117.65 and r value of 0.99. The developed ANN was successfully detected and isolated the 10 prescribed faults during the detection and isolation session. This developed modeling then has been further optimized and validated with another set of experimental data which were not used during the training and testing. Again, the developed ANN was successfully produced fault patterns and isolated the faults. The application of an advanced warning and diagnosis threshold with the limit of 0.2 and 0.8 could give an advanced warning and diagnosis on the training and testing data. The 10 designed faults were also successfully detected by using Fuzzy Logic (FL) approach. Comparison on the

different Membership Function (MF) indicated that 5 MFs have better ability to detect the faults compared to 3MFs. The result also shows that Triangular and Gaussian shape MF produced similar the results. However, the Gaussian has the ability to detect and isolate 40% more single fault compared than the Triangular. After eliminating some redundancies rules, the detection and isolation of single fault detected increased about 12% and paired-fault reduces about 76%. Finally, a new Fuzzy Inference System (FIS) has been proposed in the present study to replace the existing FIS in the MATLAB® or proposed from previous researchers. As for the conclusion, the ANN and FL have potential methods in FDD studies. Both these methods were able to detect and isolate various faults considered in the study. It shows that ANN and FL can be implemented for monitoring any process faults in chemical batch reactor.

CHAPTER 1

INTRODUCTION

1.0 Introduction

This chapter presents the introduction to fault detection and a few definitions related to this area. It covers some fault terminologies, types of faults, the importance of fault detection, problem statement, project objectives and thesis organization.

1.1 Definition of Faults

A fault can be defined as any non-permitted deviation from an acceptable behavior (Isermann & Balle, 1996). Frank and Koppen-Seliger gave their own perspective of fault definition (Frank and Koppen-Seliger, 1997a, b). Fault according to their definition is an additional input that can disturb the system's performance. Normally, a fault can be classified by temporary or permanent physical changes in the system (Leger *et al.*, 1998). The physical changes are either incipient (soft) or abrupt (hard) (Bocaniala and Sa da Costa, 2006).

1.2 Type of Faults

Faults or any additional inputs can be categorized into three main types; *actuators faults, process faults* and *sensor faults* (Frank and Koppen-Seliger, 1997a, b; Guglielmi *et al.*, 1995). The illustration of faults can be seen in Figure 1.1. Actuator faults are deviations between the intended control and its realization by the actuators. Process faults are disturbances on the process causing shift in the plant's outputs and may describe plant leaks, overloads and broken down components.

Sensor faults are discrepancies between the measured and true values of the process output or input variables (Luo, 2006).

Suppose in an automatic control system, the known input vector *U* and the output vector *Y*, a fault is something that disturbs functional devices of a plant and may lead to undesired or intolerable performance (failure) of the control system.

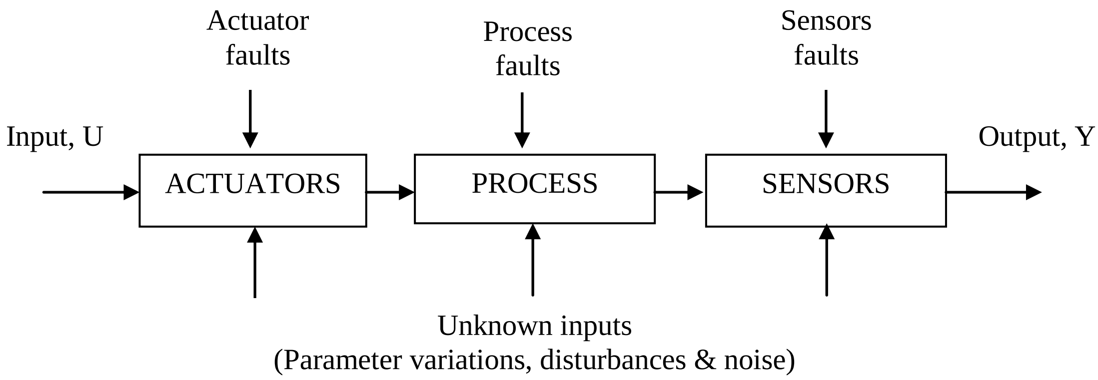

Figure 1.1: Definition of faults (Frank and Koppen-Seliger, 1997a, b)

In order to get a clear definition of faults, Frank and Koppen-Seliger have listed various examples of faults such as structural damage, abnormal parameter variations and external obstacles. In addition, there is always a modeling uncertainty, noise and model mismatch which are unknown input. Even though these inputs are not critical, they can create a false alarm in the detection system.

Generally, the nature of fault can be classified into two categories; *abrupt* and *incipient*. Abrupt faults are dramatic and persistent due to significant deviations from steady state operation; however, incipient faults occur relatively slowly over time and they are linked to wear and tear of components and drift in control parameters.

1.3 Fault Detection System

In general, the system consists of three major steps; *fault detection*, *fault isolation* and *fault diagnosis*.

1.3.1 Fault Detection

Fault detection is a binary decision making process; either the system is functioning properly or there is a fault occurrence. This step determines the presence of faults in a system and the time of detection.

1.3.2 Fault Isolation

Fault isolation is a process of isolating several faults based on the symptoms. Generally, this step is taken after the fault detection process.

1.3.3 Fault Diagnosis

Fault diagnosis is more difficult compared to fault detection and isolation because it finds and diagnoses the root cause of the problem. The task consists of determining the type, size and location of fault as well as its time of detection based on the symptoms.

1.4 Advantages of Fault Detection System

Any process system is liable to faults. Although a good design is implemented to minimize the faults from occurring, the situation cannot be fully removed. The only way to overcome the growing faults phenomena is by using the detection system. Numerous applications of faults detection system are reported in the literature mainly in the area of aeronautical and aerospace systems, automotive and traffic systems, chemical processes, electrical and electronic systems, nuclear plants, power systems and transportation systems (Isermann and Balle, 1996).

Currently, the fault detection system is very important in the chemical industry because of the demand on finding the appropriate method that covers safety and reliability. The purpose of the detection system is generally to generate an alarm to inform the operators that there is at least one fault has occurred in the system (Wang and Daley, 1996). The detection of fault should be as early as possible before it slowly propagates elsewhere (Jamsa-Jounela *et al*., 2003; Avoy, 2002; Frank and Koppen-Seliger, 1997a, b; Isermann, 1997; Patton *et al*., 1994). The detection at an early stage will help the operators to counteract the problem by reconfiguring, maintaining and repairing the faulty system (Isermann, 1997). The only way to get an earlier detection is by obtaining as much information as possible related to the process or system.

In most of the chemical industries, there are two main problems that are always interrupting the operators to get an accurate reading and more information. This is caused by equipment malfunctions or process disturbances. Of these two, process disturbances are usually more difficult to detect (Wang and Daley, 1996). Detection of process disturbances is important since it reduces the occurrence of production that does not meet the quality criteria. The reduction of the product quality will contribute to the economic impact.

1.5 Problem Statement

In practice, the ideal fault detection system must include detection, isolation and diagnosis. However, the majority of previous works addressed only on the detection step, giving little emphasis on isolation and diagnosis. Among the three steps, diagnostic is far more complicated because it requires the determination of the location and magnitude of the plant faults (Isermann, 1996; Jiang, 1996, Wang and Daley, 1996).

In a real process, there are many fault scenarios which may produce similar characteristics and it is rather difficult to pinpoint the exact cause of the problem with a limited amount of data. Currently, the fault diagnosis mainly depends on the operator's experience to assimilate a large amount of information from different sources and react rapidly to avoid any hazardous or any costly consequences (Benkhedda and Patton, 1996). Hence, a proper fault detection system that includes the isolation of fault is required.

Another problem in fault detection system is the utilization of the simulation data instead of real experimental data. This application of the simulation data is not significant, very difficult, undesirable and inconvenient to apply into the real process (Afonso *et al.*, 1998a; Brydon *et al.*, 1997 and Chang *et al.*, 1993). According to Afonso *et al.*, (1998a), the simulation environment that was commonly applied never included a number of practical realities. The real failure data and experience in the real operating environment are needed because the validation of method cannot just simply depend on the simulation results (Ruokonen, 1995). Some other researchers applied the steady-state simulation to develop and test the diagnosis model.

However, the results could not give the insight into real-time dynamic behavior under the closed-loop system (Armengol *et al.*, 2000).

1.6 Scope of Present Study

The present study focuses on the development of fault detection system, that includes both detection and isolation stages. The normal and various fault situations will be detected and isolated based on their characteristics. This condition will help the operators to recognize and differentiate the pattern of normal and various faulty situations.

In this study, the data for the fault detection and isolation development were collected from a series of experimental works from an esterification process in pilot scale batch reactor. Before the experimental data were collected, the normal and faulty operations were designed by changing the process parameters. The conductivity, temperature, conversion and concentration were recorded and calculated during the experiment. This data then acted as the input whereas the operation condition acted as output into the modeling system. The utilization of the real data is more significant, desirable and convenient because it gives an insight into the real operations. Those data can also be used directly for the validation method.

Two different methods are applied for fault detection and isolation study which is artificial neural network (ANN) and fuzzy logic (FL). Both of method are independent each other. The main reason is to study the feasibility for the both two method for an esterification process.

1.7 Project Objectives

This research is carried out to develop a fault detection system using two different methods which consist of the artificial neural network and fuzzy logic. To achieve the overall aim of the research objectives, several specific objectives were defined:

1. To develop a modeling off-line fault detection and isolation system using the artificial neural network and fuzzy logic.
2. To optimize an off-line fault detection and isolation system in the artificial neural network by removing some of a fault.
3. To validate an off-line fault detection and isolation system in the artificial neural network based on pattern generated between normal and faulty situations.
4. To propose the Fuzzy Inference System in off-line fault detection and isolation system in the fuzzy logic.
5. To validate the proposed Fuzzy Inference System in the fuzzy modeling.

1.8 Thesis Organization

This thesis structure is organized in six main chapters;

Chapter 1 The outline of the fault detection terminology, types of faults and the importance of fault detection study are included here. The limitation of current study and the scope of present study are also included in this chapter. At the end of the chapter, the specific research objectives are mentioned.

Chapter 2 Provides the theoretical description of fault detection and diagnosis including their importance, requirement to a good detection system and classification of the methods. Detailed discussion of methods which covers model-based is covered in this section. The theory of artificial neural network and fuzzy logic as well as the previous study will also be included. The applications of chemical reactor in FDD are explained before ending of the chapter.

Chapter 3 Describes the methodology applied in the development of fault detection and isolation system. The explanation consists of experimental and modeling work. The experimental covers the process selection, materials and chemicals, equipment description and design of faults. On the other hand, the modeling works was covers the development of fault detection and isolation using artificial neural network and fuzzy logic.

Chapter 4 Presents the results and discussion of the study. Results from experimental as well as modeling works are presented in this chapter.

Chapter 5 Presents the overall conclusions, summary of results and contribution of this research. The recommendation and avenue for the further research is suggested in this chapter.

CHAPTER TWO

LITERATURE SURVEY

2.0 Introduction

This chapter presents the literature study in the area of fault detection research. It begins with the importance of fault detection system. Then, the discussion on the requirement for fault detection system is followed by the classification of fault detection method which is model-based and data-driven. After that, two most commonly used techniques in modeling of fault known as the Artificial Neural Network (ANN) and Fuzzy Logic (FL) are discussed. Finally, the literature is concluded with the overall summary.

2.1 The Importance of Fault Detection System

The complexities of most chemical industries always tend to create a problem in monitoring and supervising a system. The problem or upset experienced in one area of the plant will give an impact to the operations of other sections (Shin and Venkatasubramanian 1996). The fault tolerance in automatic control systems has a potential to solve this problem (Frank and Koppen-Seliger, 1997a, b).

According to Frank and Koppen-Seliger (1997a, b), the fault tolerance can be achieved either by passive or active strategies. The passive approach makes use of robust control techniques to ensure that the closed-loop system becomes insensitive with respect to the faults. On the other hand, the active approach provides fault accommodation such as the configuration of the control system when a fault has occurred. The fault tolerance is not just to detect any incipient faults in sensors and actuator but preserves a performance in a good quality and safety manner (Bonivento, Isidori et al. 2004).

Figure 2.1 shows the architecture of fault tolerance control. Generally, it consists of two steps with fault diagnosis and control re-designs. In the fault diagnosis step, existing faults will be detected and identified whereas the controller will be adapted with the faults in the control re-design stage. Both steps will be carried out by a supervision system that prescribes the control structure and selects the algorithm and parameters of the feedback controller.

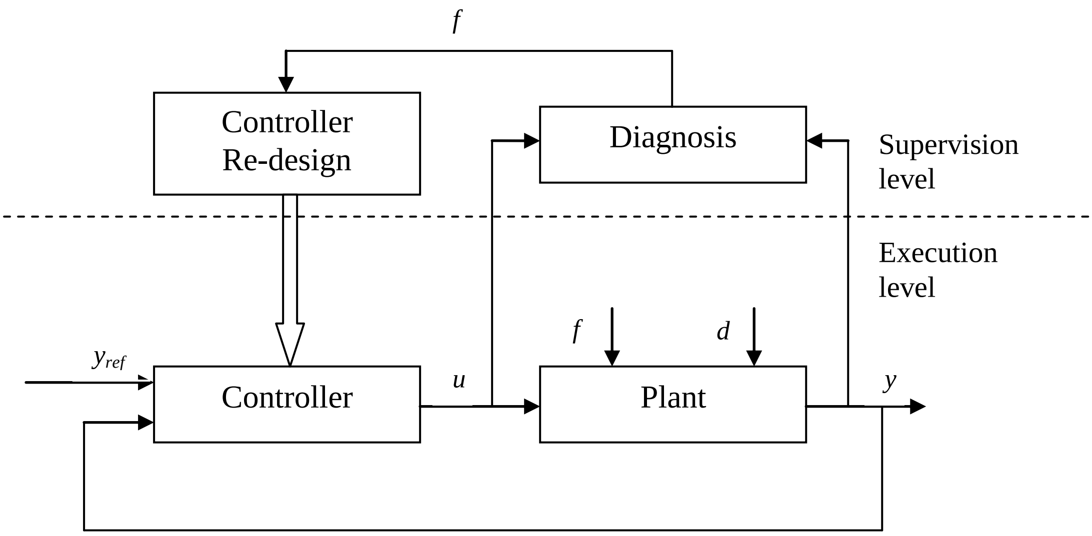

Figure 2.1: Architecture of fault tolerance control

Fault detection, isolation and diagnosis are very important in the chemical process industry. It is a step of the maintenance process (Aubrun, Robert et al. 1995). By applying scheduled maintenance, it will help the process to run in a good condition and safely manner. The study of fault detection is very important not just to the maintenance of the equipment and process but also to the maintained yield and quality of the process (Dash and Venkatasubramaniam, 2000). The appropriate system and method of fault detection can avoid product deterioration, performance degradation, major damage to the equipment and human health even cause casualty (Garcia, Izquierdo et al. 2000). For obvious reasons of safety and economics, fault detection and diagnosis have become an integral part of process design (Ralston, DePuy et al. 2001).

The Abnormal Situation Management (ASM) is a system that deals with timely detection and diagnosis, assessment of the abnormal situation and countermeasure planning. The first step in the ASM is the Fault Detection and Diagnosis (FDD). According to Dash and co-worker (2000) and Nimmo (1995), abnormal situation management will help avoid event progression and hence reduce the amount of productivity loss during abnormal events.

Inadequate managing of abnormal situations caused annual losses of $20 billion for petrochemical industry in the USA (Nimmo 1995). This cost was caused by premature shutdowns, suboptimal operation of the process and violation of safety and environmental regulations. Similar accidents also cost a lost to British economy, around $27 billion dollars every year (Laser 2000). These considerations provide a strong motivation for the development of methods for the design of advanced fault detection system to enhance the fault recovery and prevent faults from propagating into the total faults.

The design of fault monitoring system is a challenging research area especially when considering the practical significance (Chang *et al*., 1993). Avoy *et* *al*., (2004) and Avoy (2002) mentioned that the latest intelligent control should not just focus on modeling and optimization, but also cover the area of fault detection and isolation. Traditional approach of fault detection involves checking of some variables or the application of redundant sensors (Garcia *et al*., 2000; Frank 1990; Isermann,1984). This method is based on mathematical models and has a link between input and output variables. Nowadays, the study on the fault detection can be considered as already at a matured stage even though a suitable and appropriate method is still under development. The report emphasized on the fault detection was reported by Dochain *et al*., (2006). Isermann and Balle (1996) in their work gave a review of fault detection and diagnosis applications.

2.2 Fault Detection Methods

There are an abundance of work on process fault diagnosis ranging from analytical methods to artificial intelligence and statistical approaches. From the modeling perspectives, there are a few methods that require accurate process model and a few of them applies qualitative models. On the other hand, there are methods that only rely on process history data.

A survey from Venkatasubramaniam *et al*., (2003a, b, c) classified fault detection methods into two categories: model-based and data driven methods. The hierarchy of fault diagnosis approaches is shown in Figure 2.2. This classification is based on the process knowledge that is required a priori (Yang, 2004). The priori process knowledge is used to distinguish the features for classifying fault diagnosis system. Normally, the basic a priori knowledge is a set of failure and relationship between the symptoms and the failures (Yang, 2004).

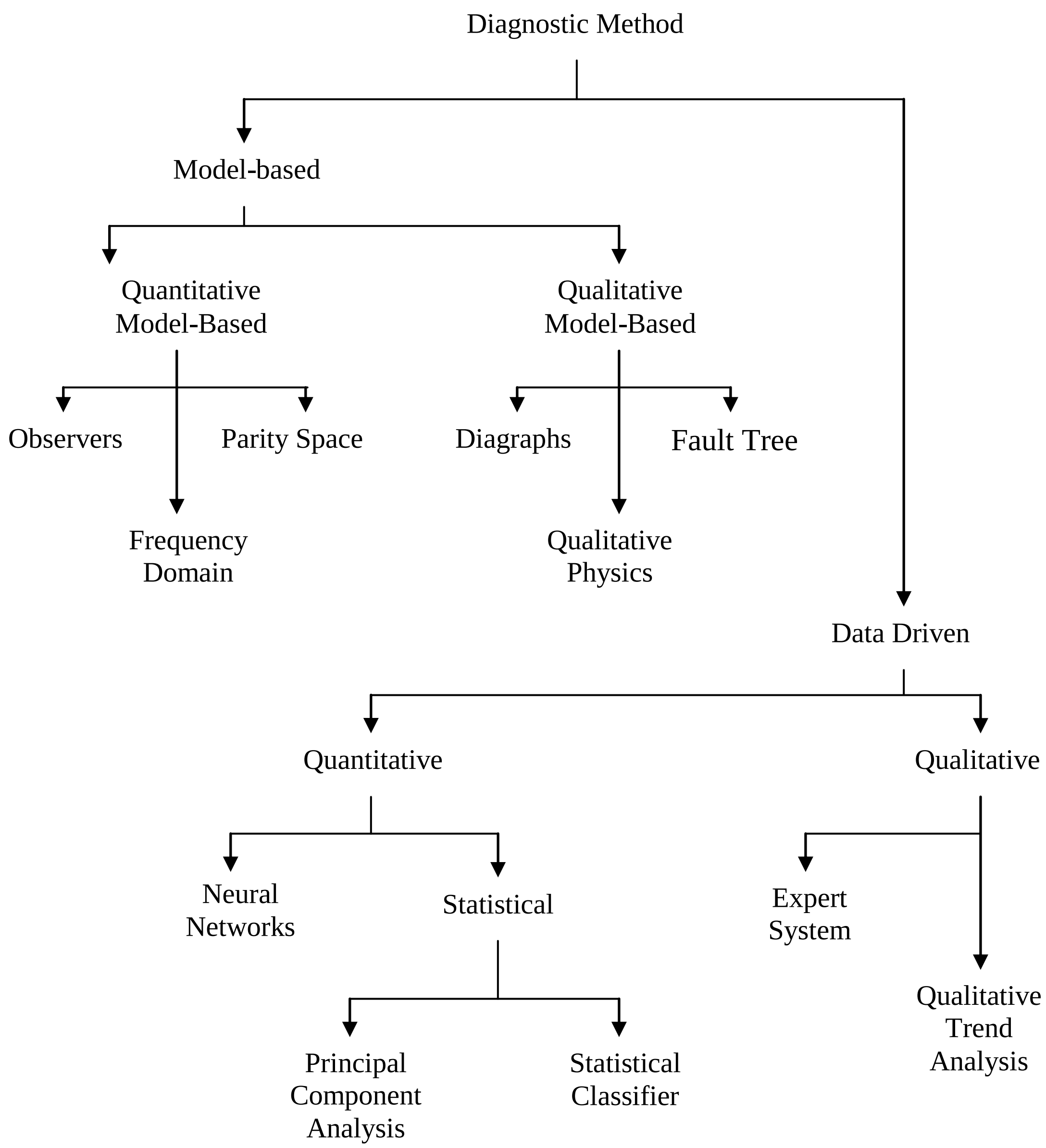

Figure 2.2: Classification of fault detection methods (Venkatasubramaniam *et al*., 2003a)

For model-based methods, the model is classified as qualitative and quantitative. This model is currently being developed by considering the fundamental understanding of the physical law of the process. Thus, the model based method is known as white box model. In a quantitative model, the relationships between the inputs and outputs of the system are expressed in terms of mathematical function; whereas qualitative model is expressed in terms of qualitative functions. As examples of quantitative methods are observers, frequency domain and parity space and diagraph method, fault tree and qualitative physics are method for qualitative method.

For data-driven approaches, a large amount of historical data is required to develop relationship between input and output data. The data driven method does not rely on mathematical models, yet capable in detecting the process malfunction.

The data can be transformed and presented as a priori knowledge to diagnostic systems. This is known as feature extraction. In term of data driven, it can be classified by either qualitative or quantitative feature extraction. Two of the major methods in qualitative methods include expert system and qualitative trend analysis. Methods that extract quantitative information can be non-statistical classifier or statistical methods. Neural network is an important class of non-statistical quantitative method; and principal component analysis/partial least square and statistical classifier are examples of statistical methods. The key advantage of data driven fault detection is generating concise and accurate detection model from a large amount of data (Luo, 2006).

There might be some overlapping between the model-based and data-driven approaches. It depends on whether or not the knowledge about process characteristics are required (Yang, 2004). Artificial neural network for example are classified as data driven method but it is normally applied in residual generation and residual evaluation in model-based method such as in Koscielny (2004a, b), Patan and Korbicz (2004), Simani *et al*., (2003) and Koppen-Seliger and Frank (1996). The study between the model-based and neural network is done by Rengaswamy *et al*., (2001). In this study, the implementations of neural network and fuzzy logic are based on model-based approach.

2.3 Model-Based Fault Detection System

2.3.1 Overview

As mentioned by Frank (1990), fault detection system can be implemented by using various methods. Among them, model-based is a very popular method and powerful tool to detect a system failure at an early stage (Dochain *et al*., 2006; Isermann, 2005, 1997, 1996; Amman *et al*., 2001; Frank *et al*., 2000; Frank and Ding, 1997; Frank and Koppen-Seliger, 1997a, b). This method has been available for the past 30 years (Isermann, 2005; 1997; 1996; Benkhedda and Patton, 1996; Patton *et al*., 1994; Frank, 1990).

Model-based can be used as a monitoring system for fault detection and isolation system. By comparing the system's measurement and mathematical model, process error signal will be generated. This procedure is called the analytical redundancy. It is different with the hardware redundancy where replication hardware such as computers, sensor, actuators and other component are used to generate a signal. Analytical redundancy is more reliable and cost effective compared to hardware redundancy (Isermann, 1997; Isermann and Balle, 1996). Figure 2.3 illustrates the analytical and hardware redundancy concepts.

The understanding of physical fundamental is needed when developing a model-based method. In the early applications, most of the processes were based on the observation with a linear system and analytical redundancy (Balle and Fuessel, 2000; Genovesi *et al*., 1999). The method such as parameter estimation, observer schemes and parity schemes were commonly applied (Isermann and Balle, 1996). The objective of analytical redundancy was to generate residual by comparing the actual output with predictions obtained by mathematical model. The residual is acts as fault indications of the system. The examples of residuals include disturbances, noise and modeling errors.

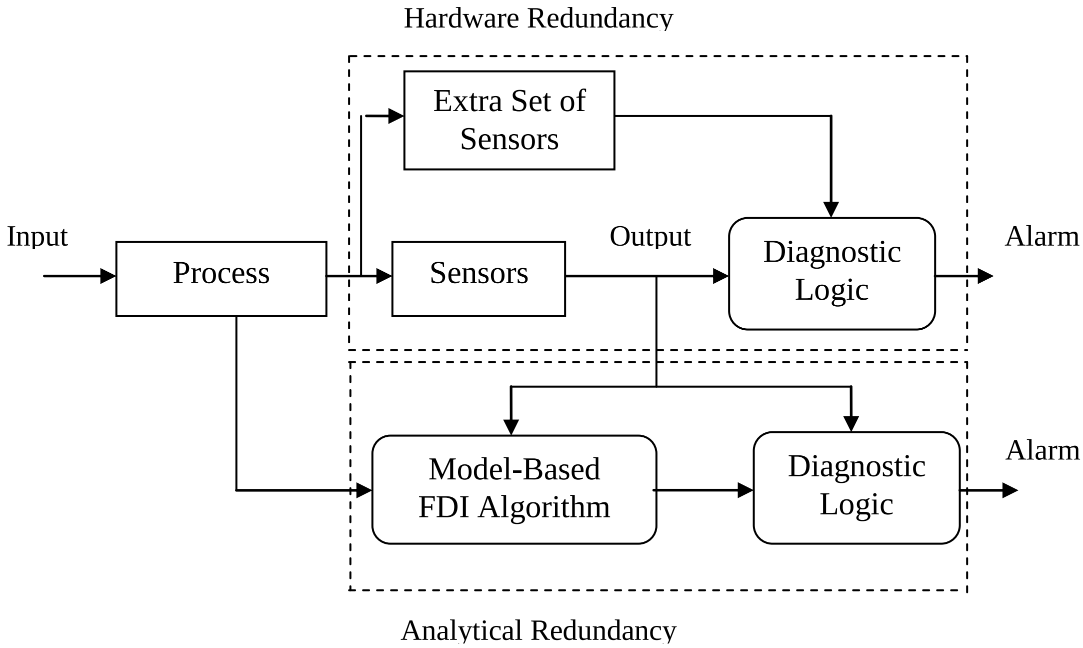

Figure 2.3: Hardware and analytical redundancy

Model-based can be classified into two categories *qualitative* or *quantitative* (Venkatasubramaniam *et al*., 2003a). The quantitative model can be developed using the terms of mathematical relationships function between the inputs and the outputs of the system. On the other hand, qualitative model are expression in qualitative terms.

There are various works which concentrate on the application of model-based studies. This includes the study from Cheng *et al*.,(2003), Afonso *et al*., (1998b), Pfeufer (1997), Chang *et al*., (1995), Chang *et al*., (1994), Chang *et al*., (1993) and Schuler and Schmidt (1993).

2.3.2 Model-Based Scheme

According to Leonhardt and Ayobi (1997), the fault diagnosis system can be viewed as a sequential process involving two steps; the residual generation and residual evaluation. Figure 2.4 illustrates the general and conceptual structure of a model-based fault diagnosis system comprising of two stages: residual generation and residual evaluation.

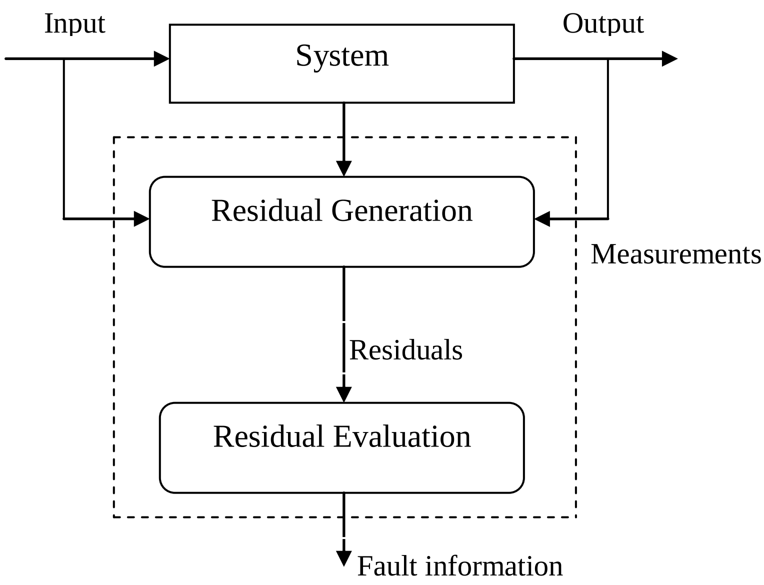

Figure 2.4: General structure of model-based scheme

Residual generation is a process of comparing the measurement and predicted value from the available input and output data. It acts as an indicator to represent the fault in the system. If the fault is not present, the residual value will normally be zero or close to zero, whilst different from zero when faults are present. The algorithm or processor to generate residual is known as residual generator. In ideal condition, the residual should carry only fault information and are independent of the system operating state.

According to Genovesi and co-workers (1999), the residual generation algorithm should work even if these problems arise:

- the time evolution of the fault is unknown
- the mathematical model of the nominal system is uncertain (with unknown tolerance)
- there are system and measurement noises (with unknown characteristic)

In a normal system, an existing residual generation is more dependent on a few factors such as:

- the knowledge of the normal and abnormal behavior
- a good definition of the faulty behavior
- the existence of analytical redundancy relations
- a satisfactory reliability of the redundant information

Residual evaluation is a process to examine the likelihood of faults. Decision rule is used to determine the types of faults. The decision process may consist of a simple threshold test on the instantaneous value or moving average of the residuals.

Another method such as pattern signatures can also be applied in the decision process. Isermann and Balle (1996), lists the methods that are commonly used in this stage such as neural network, fuzzy logic, Bayes classification and hypothesis testing.

Frank and Koppen-Seliger (1997a, b) and Patton (1997) proposed a structure of model-based scheme. In this structure, the model-based consists of three stages: residual generation, residual evaluation and fault analysis. Residual generation can be determined by computing the difference between the measured output and the estimated output obtained from the model of the system (Chang *et al*., 1995). At this stage, any signal generated is reflected by the faults. The seconds stage in the model-based is the residual evaluation: a logical decision making on the time of occurrence and the location of a fault. The model-based and knowledge-based are applied in this scheme to improve decision making and assist in residual generation. The final stage is a fault analysis where it is defined as the determination of the type and size of the faults. The first two stages implement system theory for instance the artificial intelligence based method. Nonetheless, stage three requires in general either a human expert or knowledge-based system for the fault analysis (Frank and Koppen-Seliger, 1997a, b; Patton 1997). The structural diagram of the residual generation and evaluation is shown in Figure 2.5.

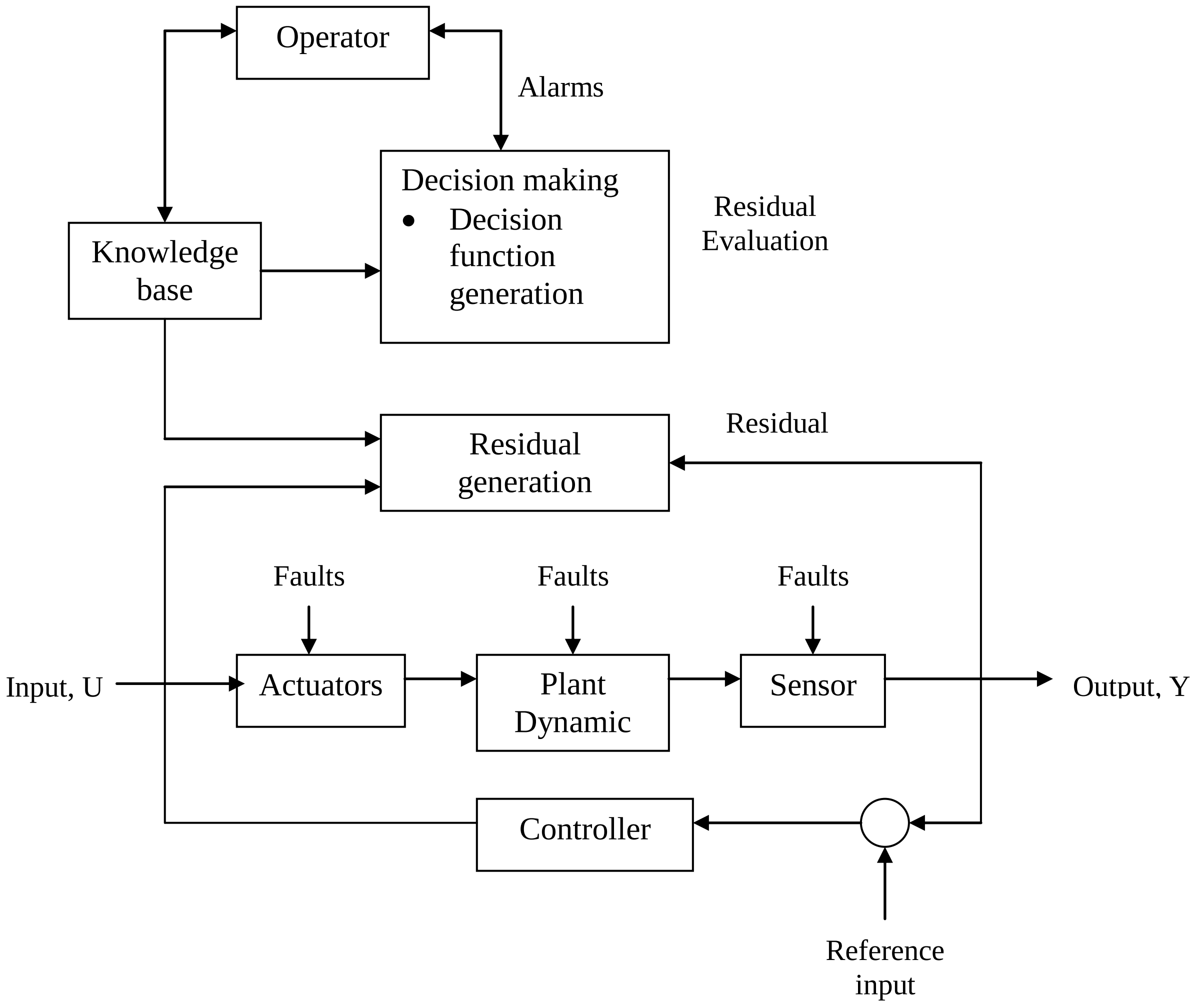

Figure 2.5: Model-based scheme (Frank and Koppen-Seliger, 1997a, b; Patton 1997)

Isermann (1996) proposed another scheme for model-based fault detection system. In this task, detection of faults in processes, actuators and sensors were conducted based on the dependencies between different measurable signals. The scheme is shown in Figure 2.6. Using the input signal, (*U)* and output signal (*Y)*, the detection method will generate features that consist of residual (*r*), parameter estimate (Θ), or state estimates (*x*). Any differences in these features can be detected by simply comparing them between the normal and abnormal changes in the process conditions. This procedure will lead to the analytical symptoms (*s*).

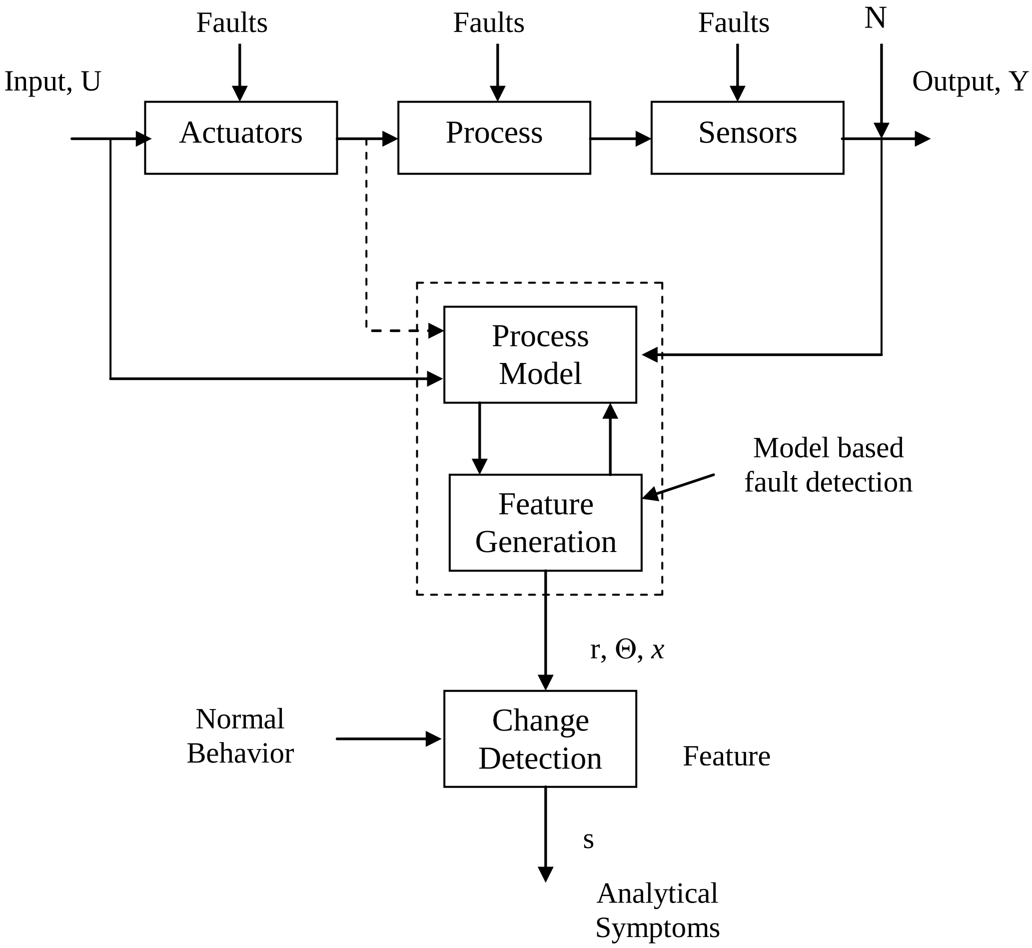

Figure 2.6: Model-based scheme (Isermann 2005; 1997 and 1996)

2.3.3 Assumptions of Model-Based Method

Model-based fault detection method is built upon a number of idealized assumptions (Patton 1997; Patton and Chen 1997). One of the assumptions is that the developed mathematical model is a replica of the plant dynamics. However, it is impossible to model a system as accurate and complete as a mathematical system. It is because at times, the mathematical structure of a dynamical system is not fully known. There are a few cases where the system parameter is unknown or the parameter is with limited range of values. This situation will create a “model-reality mismatch” between the plant dynamics and the model developed.

As the complexity in chemical process plant increases, it is often difficult to model a system that fulfills the entire requirement and simultaneously tolerates the disturbances. More attentions are now given to the study of robustness of process models. Report from Patton (1997) noted that early studies on robustness focused more on local sensitivity requirements rather than producing truly robust solution. The main goal is to discriminate between the effects of faults, uncertain signal and system perturbations. But, recently the increasing development of truly robust methods shows promising developments. The studies are now focusing on both in order to create robustness in residual generation and decision-making stage.

2.3.4 Problems of Model-Based Method

Model-based approaches require accurate mathematical models of the plant. However, the model development task using the first principles is often difficult and time consuming, particularly for complex nonlinear processes (Balle and Fuessel, 2000).

The main problems in the model-based system are the implementation and maintenance in a real process environment (Lautala *et al.*, 1996; Benkhedda and Patton *et al.*, 1996). Processes usually have several modes and operating points and for this reason large and complex models are required. Most of the existing automation system do not support tasks needed such as modeling and visualizing dynamics of multivariable systems. Such a problem will later increase when dealing with a non-linear system.

A model-based system has several problems that should be minimized. Ma and co-workers (2007) have stated the two main problems faced in applying the model-based system and they are:

- potential *fragile*: mismatch between actual plant and the model used algorithm can result in false alarm.
- the difficulty in isolating the exact location of the fault and in detecting simultaneous faults.

Since the model-based system is highly dependent on the mathematical model; therefore, they are a few disadvantages when applying this method. Among others are the sensitivity to model errors, parameter variations, noise, and disturbances (Patton 1994). The success of the model-based depends on the quality of models and this is often difficult to achieve in practice.

Rengaswamy *et al*., (2001) mentioned that most of the model-based methods developed generally focused on the linear system. This system is difficult to apply in practice especially in engineering system where most of the processes are nonlinear with such complex terms (Frank and Koppen-Seliger 1997a). In reality, modeling of linear system is difficult in many cases especially in chemical process industry (Rengaswamy, Mylaraswamy et al. 2001).

The model-based qualitative model approach in the form of qualitative differential equations, signed diagraph, qualitative functional and structural models are poor in diagnostic process especially when it involves the process transitions

(Rengaswamy, Mylaraswamy et al. 2001). Such models require a large number of hypotheses since they give poor resolution when applied with on-line systems (Power and Bahri, 2004).

2.4 Artificial Neural Networks (ANN)

2.4.1 Introduction

The ANN has been previously used to study the interconnection of neurons in human brain. These interconnections allow the implementation of pattern recognition computation in an attempt to mimic the human brain. Artificial neural network is generally a nonlinear mapping between the input and output which consists of interconnected "neurons" between layers. These layers are connected such that the signals at the input of the neural net are propagated through the network. The choice of neuron nonlinearity, network topology and the weights of connections between neurons actually specify the behavior of neural network.

The application of ANN in fault detection and diagnosis are based on model approximation and pattern recognition (Lipnickas, 2006; Simani *et al*., 2003; Zhou *et al*., 2003). Among these methods, pattern recognition has been formed to be more adequate based on the difficulty to perform the ANN training on the dynamic patterns. Pattern recognition method is a convenient approach to solve the fault identification problem for instance in determining the size of the fault (Simani *et al*., 2003). Pattern recognition classification is typically an off-line procedure where the information regarding normal and faulty situation can be obtained from the training. In recent years, successful implementation of ANN as pattern recognition in fault identification and diagnosis were highlighted and reported by a number of previous