THE HONG KONG POLYTECHNIC UNIVERSITY

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Qualitative Bond Graph Approach to Intelligent Supervisory Coordinator

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CERTIFICATE OF ORIGINALITY

I hereby declare that this thesis is my own work and that, to the best of my knowledge and belief, it reproduces no material previously published or written nor material which has been accepted for the award of any other degree or diploma, except where due acknowledgement has been made in the text.

____________________ (Signed)

LO, CHI HANG (Name of Student)

To my Parents

Abstract

In recent years, the increasing complexity of process plants and other engineered systems has extended the scope of interest in control engineering that was previously focused on the development of controllers for specified performance criteria such as stability and precision. Modern industrial systems require a higher demand of system reliability, safety and low-cost operation which in-turn call for sophisticated and elegant fault detection and isolation algorithms. In this thesis, three basic aspects of the Intelligent Supervisory Coordinator (ISC) for fault detection and localization have been studied. Among the problems addressed in the thesis are: (a) Hybrid simulation; (b) Automatic fault detection; and (c) Qualitative model-based fault diagnosis. Hybrid simulation is a novel simulation technique for dynamic systems that utilizes both qualitative and quantitative knowledge. The automatic fault detection deals with the on-line system monitoring method for system performance classification. Qualitative model-based fault diagnosis is a qualitative method for localizing faulty components in process plants. Based on these studies, an integrated real-time ISC that assist human operators to manage process plants is developed. The studies are accomplished in three phases.

In the first phase, a novel hybrid simulation technique is proposed, that alleviates the difficulty in establishing precise mathematical representations of process plants. Dynamic system behaviors are predicted through this hybrid simulation technique. Qualitative representation of bond graph model is adopted to model a dynamic

system. System measurements are represented by real numbers rather than qualitative values to improve accuracy. The integration of qualitative and quantitative information enhances the accuracy and effectiveness of qualitative simulation, and at the same time reduces the need for a precise mathematical model. The effectiveness of the proposed hybrid simulation approach is demonstrated by simulation studies of both linear and non-linear systems.

In the second phase, the tasks of automatic fault detection and diagnosis are addressed. Fuzzy-genetic algorithm (FGA) is proposed to effect automatic fault detection. The automatic fault detection system (AFD) monitors the system states continuously by fuzzy logic. The optimization capability of genetic algorithms allows the generation of optimal fuzzy rules. System behaviors are represented as four states: normal, malfunction, load disturbance and faulty, and are distinguished by fuzzy logic after tuning its rule table. When a faulty behavior is detected, the AFD triggers the fault diagnosis algorithm. With the previously derived qualitative bond graph model of the system, Genetic Algorithm (GA) is then proposed to search for possible fault components among the system. The proposed fault diagnosis algorithm is tested on an in-house designed and built floating disc experimental set-up.

In phase three, the development of the integrated real-time ISC will be discussed and applied to the servo-tank liquid system. The ISC integrates artificial intelligence techniques, like, fuzzy logic and GA; with control engineering in order to perform system simulation, fault detection and diagnosis.

Acknowledgement

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Qualitative Bond Graph Approach to Intelligent Supervisory Coordinator

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List of Abbreviations

AFD	Automatic Fault Detection
AI	Artificial Intelligence
COMPS	System Components
FES	Fuzzy Evaluation System
FGA	Fuzzy-Genetic Algorithm
FGA-AFD	Fuzzy-Genetic Algorithm based Automatic Fault Detection
GA	Genetic Algorithms
IE	Integral Error
IPDI	Increasing Precision with Decreasing Intelligence
IPS	Integrated Process Supervision
ISC	Intelligent Supervisory Coordinator
ISE	Integral Squared Error
MIMO	Multi-Input Multi-Output
MISO	Multi-Input Single Output
OBS	Observations
PM	Performance Measure
QBG	Qualitative Bond Graph
QDE	Qualitative Differential Equation
QM	Qualitative Modeling
QPT	Qualitative Process Theory
QR	Qualitative Reasoning
SCAP	Sequential Causal Assignment Procedure

SD	System Description
SISO	Single Input Single Output
SSWOD	Steady State WithOut Duplicates

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Chapter 1

Introduction

Sir Arthur C. Clark in his recent book *"3001 The Final Odyssey"* best portrays the distinct link between the scientific and technological development and control systems: "*The biggest difference, though, is the control systems.*" Important as it has been in the last century, the significance of the control systems in this century is by far greater. Diminishing natural resources, environmental considerations, and highly complex systems provide challenging problems for humans. In this regard, the role of control engineering as a catalyst for implementing safe, plausible, and efficient solutions to alleviate these problems is paramount. Meanwhile, the emergence of multi-dimensional-multi-objective systems has imposed a fundamental paradigm shift from a single layer control to a multi-layer and hierarchical coordinator. In addition, the growing demand for system safety, reliability, efficiency, and low-cost operation has extended the scope of interest in control engineering. The integration of artificial intelligence (AI) techniques with control theory is believed to provide solutions to industrial, economic, and perhaps social systems. In this context, the concept of *Intelligent Supervisory Coordinator (ISC)* has been formed to address the ever-increasing plethora of problems associated with design and control of complex systems. In a nutshell, ISC is a suite of elaborate, intelligent, and autonomous algorithms for system modeling, robust real-time process control, supervision, and fault diagnosis. The crux of the studies undertaken in this thesis concerns the development and implementation of an integrated real-time ISC by integrating AI techniques with control engineering.

In particular, the following objectives are addressed:

- To propose a novel hybrid qualitative and quantitative simulation approach for overcoming both quantitative and qualitative simulation shortcomings.
- To design an automatic fault detection algorithm via a fuzzy-genetic approach.
- To suggest a qualitative fault diagnosis method for localizing faulty components of dynamic systems.
- To develop and implement an integrated real-time ISC.
- To examine the applications of the ISC to process supervision, fault diagnosis and coordination of different strategies for managing various system situations.

1.1 Background and Motivation

In the late 1980s, Saridis [1989] proposed the general architecture of intelligent supervisory systems that consisted of three levels: organization level, coordination level, and execution level, ordered according to the *principle of increasing precision with decreasing intelligence* (IPDI). The organization level is the highest level that imitates functions of human behavior and is where the knowledge base rests. The coordination level receives commands from the organization level and feedback information from the process, and coordinates the execution at the lowest level. The execution level executes the appropriate control functions. The essential feature of this architecture that makes it different from conventional approaches is the separation of the knowledge base, the inference mechanism, and algorithms. This allows the incorporation of AI techniques to represent the knowledge base for higher-level reasoning. This heuristic knowledge makes the intelligent supervisory systems more robust, flexible, and intelligent.

Currently, the success of intelligent supervisory systems does not rely on the use of new mathematical approaches but on the progress of AI techniques. The *Qualitative Reasoning Environment for Modeling and Simulation* (QREMS) provides an economic way for acquiring knowledge for building the knowledge base. QREMS combined with AI techniques and bond graph theory can be used to build qualitative models that are represented by the constitutive physical laws of process components and their interconnections. Qualitative reasoning techniques are further employed to analyze the behavior of individual components of a process and their functional relations. This idea, qualitative bond graph reasoning, is adopted as the basis for the intelligent supervisory coordinator developed in this thesis.

The qualitative bond graph approach provides an integrated framework for building a model that represents both qualitative and quantitative information. A set of qualitative equations representing the components' physical variables, locations, and their functional relations can be stated directly from the model. This is particularly suitable for model-based fault diagnosis since possible faults can be localized via analyzing the interrelations of the component states and abnormal behavior observed. The model describes qualitative information only since fault diagnosis usually relies on cause-effect inference rather than on numerical computation. Moreover, these equations can be abstracted to represent the relations between input and output variables. This allows numerical values of process parameters and variables to be included for system simulation or feedback control.

Historically, feedback control, process supervision, fault detection, and diagnosis are developed separately, using different approaches, often with fundamentally different assumptions on the model. However, as the complexity of the systems increase these methods as standalone and fragmented may not be appropriate any longer. Motivated by this observation and in order to study the feasibility of a more holistic approach, the studies reported in this thesis suggest an alternative approach. This promising viewpoint advocates a contrasting approach than the conventional approaches. With the aid of AI techniques and within the integrated framework of qualitative bond graph (QBG) approach, it is possible to combine these control activities for building intelligent supervisory systems. In response to this requirement, this thesis develops and implements an integrated real-time intelligent supervisory coordinator based on the QBG approach. Soft computing techniques (e.g. fuzzy system, GA) are used to supervise the process behavior and a GA-based qualitative fault diagnosis is developed for localizing faulty process components. The QBG approach is adopted to construct the knowledge based of the ISC, providing necessary information for supervision and fault analysis.

1.2 Research Outline

This thesis consists of three phases. The first phase focuses on the development of the hybrid qualitative and quantitative simulation technique based on the qualitative bond graph. Based on the outcome of phase one, the design issues of the automatic fault detection system via the integration of fuzzy systems and genetic algorithms are pursued. Moreover, a GA-based qualitative fault diagnosis algorithm for dynamic physical systems is introduced in the second phase. Finally, the development of an integrated real-time ISC will be discussed and implemented on a servo-tank liquid process rig. The research outline is graphically depicted in Figure 1-1.

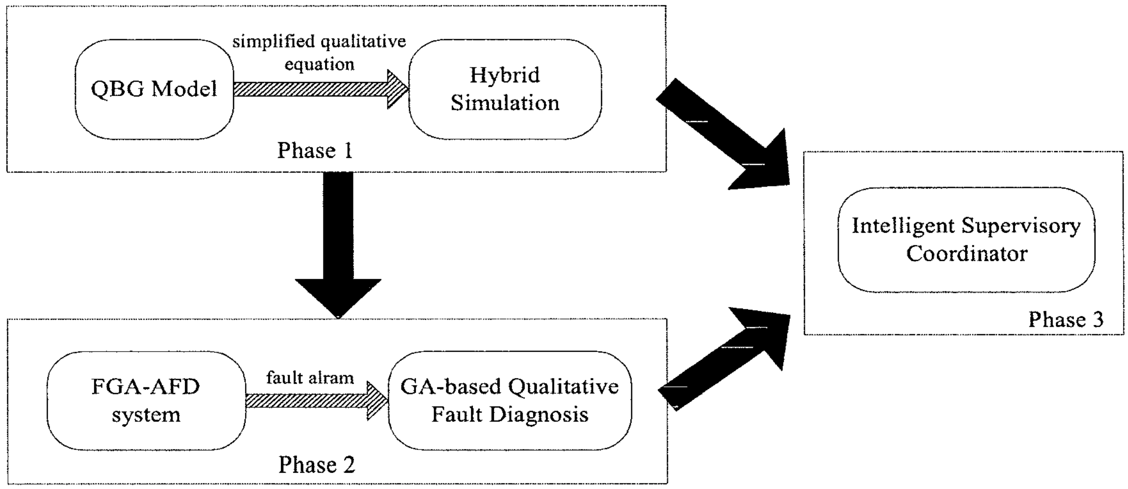

Figure 1-1 Research outline of this thesis.

1.3 Organization of the Thesis

The thesis is organized as follows. The first Chapter states the background, objectives, outline of the thesis, main contributions and research outputs generated. It lays out the foundation of this thesis.

Chapter 2 reviews previous research in intelligent supervisory coordinator. The scope and functions of the ISC are first presented. Qualitative reasoning, bond graph theory and qualitative bond graph formalism for knowledge representation and acquisition in the ISC are discussed next. Then, methodologies for process supervision and fault analysis are classified and given including qualitative reasoning and modeling, fuzzy qualitative simulation, fuzzy systems and GA. It should be noted that due to the extensive literature available, the treatment in this chapter is very selective and only those relevant topics are included.

In Chapter 3, the author proposes a novel hybrid qualitative and quantitative simulation technique for predicting behaviors of dynamic systems. A set of qualitative equations generated from a bond graph model is simplified to an input-output qualitative equation. This simplified qualitative equation describes the interaction of system input, system output and states of system parameters. Quantitative information (e.g. system inputs, time step, etc.) is inserted to the simplified model for performing the hybrid simulation. Simulation studies on both linear and non-linear dynamic systems illustrate the applications of the proposed approach.

Chapter 4 introduces an automatic fault detection system (AFD) for process supervision via fuzzy-genetic algorithm (FGA). Residual is computed as the difference between the observed system behavior and the predicted normal behavior from hybrid simulation (Chapter 3). Fuzzy system together with other process information (e.g. error signal, control action, etc.) is employed to evaluate the residual and determine the process state as normal, malfunction, under load disturbance or faulty. With the aid of GA, an optimal fuzzy rule base of the AFD system is obtained. Experimental results show that the proposed FGA-AFD system is suitable for process supervision and fault detection.

In Chapter 5, the qualitative fault diagnosis method based on GA and qualitative bond graph model is illustrated. Qualitative bond graph model provides a formal representation of the system structure and its components' locations. GA is then employed to search for possible faulty components via qualitative inference mechanism among a set of qualitative equations. The experiment on an in-house designed and built floating disc system reveals that correct and complete fault candidates are obtained by the proposed GA-based qualitative fault diagnosis algorithm.

Chapter 6 integrates all the techniques developed in Chapters 3 to 5 to construct an ISC. The architecture of this ISC, which consists of knowledge level, supervisory level and execution level, is described. The qualitative bond graph methodology is employed to build the knowledge base situated in the knowledge level of the ISC. A supervisor in the supervisory level is designed to choose suitable strategies for dealing with various system situations. A controller and fault diagnosis mechanism in the execution level provide feedback control and faulty components localization. Implementation of the ISC is illustrated by experiments on a laboratory scale servo-tank liquid process rig operating in real-time.

Chapter 7 draws the conclusions for this thesis. It summarizes the contributions and makes recommendation for future research in this area.

1.4 Statement of Originality

The original contributions or important developments made by the author in this thesis are stated below:

1. Proposing a novel hybrid qualitative and quantitative simulation technique based on qualitative bond graph model for predicting system behaviors of dynamic processes (Chapter 3).
2. Suggestion of an automatic fault detection system to distinguish system behaviors on-line via the integration of fuzzy system and genetic algorithms

(Chapter 4).

3. Designing a GA-based qualitative fault diagnosis algorithm for localizing faulty components of dynamic physical systems (Chapter 5).
4. Integrating the techniques developed in the preceding chapters to construct an intelligent supervisory coordinator for process supervision and fault diagnosis (Chapter 6).
5. Application of the ISC to supervise a laboratory scale servo-tank liquid process rig.

1.5 Publications

At the time of writing this thesis, four journal papers have been published/accepted and nine conference papers have been presented. In addition, six journal papers have been submitted and are under review.

Published/Accepted Journal Papers

1. Lo, C.H., Chow, K.M., Wong, Y.K. and Rad, A.B. "Qualitative system identification with the use of on-line genetic algorithms". *Simulation Practice and Theory*, Vol. 8, Issue 6/7, pp.415-431 (2001)

2. Lo, C.H., Wong, Y.K., Rad, A.B. and Chow, K.M. "Fusion of qualitative bond graph and genetic algorithms: a fault diagnosis application". *ISA Transactions*, Vol. 41, Issue 4, pp.445-456 (2002)

3. Lo, C.H., Wong, Y.K. and Rad, A.B. "Hybrid simulation of qualitative bond graph model". *WSEAS Transactions on Systems*, Vol. 3, Issue 1, pp.78-83 (2004)

4. Lo, C.H., Wong, Y.K. and Rad, A.B. "Knowledge-based automatic fault detection for dynamic physical systems". *WSEAS Transactions on Systems,* Vol. 3, Issue 1, pp.72-77 (2004)

Journal Papers under Review

5. Lo, C.H., Chan, P.T., Wong, Y.K., Rad, A.B. and Cheung, K.L. "Fuzzy-genetic algorithm for automatic fault detection in HVAC". *International Journal of Intelligent Automation and Soft Computing (AutoSoft)* (Revised for second review, Paper No. EC-2002-112)

6. Lo, C.H., Wong, Y.K. and Rad, A.B. "Hybrid qualitative and quantitative simulation with dynamic systems". *Simulation Modeling Practice and Theory* (Submitted).

7. Lo, C.H., Wong, Y.K. and Rad, A.B. "Bond graph based bayesian network for fault diagnosis". *The International Journal of Computers and Their Applications (IJCA)* (Submitted).

8. Lo, C.H., Wong, Y.K. and Rad, A.B. "Qualitative bond graph simulation using fuzzy parameters". *International Journal of Modeling and Simulation* (Submitted).

9. Lo, C.H., Wong, Y.K. and Rad, A.B. "Model-based fault diagnosis in continuous dynamic systems". *ISA Transactions* (Submitted).

10. Lo, C.H., Wong, Y.K. and Rad, A.B. "Real-time intelligent supervisory coordinator for dynamic physical systems". *IEEE Transactions on Systems, Man, and Cybernetics – Part A: Systems and Humans* (Submitted).

Published Conference Papers

11. Lo, C.H., Wong, Y.K., Rad, A.B. and Lo, W.L. "Supervisory intelligent qualitative controller". *The 6th International Conference on Soft Computing (Iizuka 2000)*, Iizuka, Japan, 1-4 October, 2000, pp.562-568 (2000)

12. Lo, C.H., Wong, Y.K. and Rad, A.B. "Application of self-tuning fuzzy logic controller on process control". *IFAC/IEEE Symposium on Advances in Control Education 2000,* Gold Coast, Queensland, 17-19 December, 2000, pp.281-286 (2000)

13. Lo, C.H., Wong, Y.K., Rad, A.B. and Ip, Y.L. "Fault diagnosis based on qualitative bond graph and genetic algorithms". *IFAC Conference on New Technologies for Computer Control 2001 (NTCC2001),* Hong Kong, 19-22 November, 2001, pp.431-436 (2001)

14. Lo, C.H., Wong, Y.K., Rad, A.B. and Yu, C.W. "Incipient fault diagnosis using bond graphs". In *Proceedings of Summer Computer Simulation Conference SCSC'02*, San Diego, California, U.S.A., 14-18 July, 2002, pp.339-344 (2002)

15. Lo, C.H., Wong, Y.K. and Rad, A.B. "Simulation of qualitative bond graph model using fuzzy arithmetic". In *Proceedings of International Conference on*

Bond Graph Modeling and Simulation (ICBGM' 03), Orlando, F.L., 19-23 January, 2003, pp.9-14 (2003)

16. Lo, C.H., Wong, Y.K. and Rad, A.B. "Automatic fault detection for dynamic physical systems". *Regional Inter-University Postgraduate Electrical and Electronic Engineering Conference 2003 (RIUPEEEC 2003)*, The Hong Kong Polytechnic University, Hong Kong, 29-30 August, 2003 (in Press)

17. Lo, C.H., Wong, Y.K. and Rad, A.B. "Bayesian network for fault diagnosis". *European Control Conference (ECC2003)*, University of Cambridge, U.K., 1-4 September, 2003 (in Press)

18. Lo, C.H., Wong, Y.K. and Rad, A.B. "Hybrid simulation of qualitative bond graph model". *The 3rd WSEAS International Conference on Soft Computing, Optimization, Simulation and Manufacturing Systems (SOSM'03)*, Malta, 1-3 September, 2003 (in Press)

19. Lo, C.H., Wong, Y.K. and Rad, A.B. "Knowledge-based automatic fault detection for dynamic physical systems". *The 3rd WSEAS International Conference on Soft Computing, Optimization, Simulation and Manufacturing Systems (SOSM'03)*, Malta, 1-3 September, 2003 (in Press)

Chapter 2

Literature Review

2.1 Introduction

Early works in control engineering were concentrated on the development of versatile controllers for specified performance criteria such as stability and precision. The use of analytical models (e.g. state-space equations) led to the development of optimal control, multivariable control, and Lyapunov stability, etc. These studies have provided a rich and sound foundation for mathematical-based control theory. Among the most prolific works are the following: Ziegler and Nichols [1942], Bode [1945], Bellman [1957, 1961], Kalman [1960a, 1960b, 1962, 1963], Brockett [1965], Athans [1966, 1968, 1971], Åström [1970], Kailath [1974, 1980], Åström and Wittenmark [1995, 1997].

In a parallel development but at a slower pace, some researchers advocated that mathematical-based control theory might have limitations in dealing with the emerging complex systems. In late sixties, few individuals did not follow the *status quo* and resisted heavy criticism from the control community and the AI techniques and fuzzy systems were born. All this is history now. Currently, there is a strong belief that mathematical-based control theory along with the AI techniques and soft computing methods are able to provide efficient solutions to many problems. The growing demands for product quality, cost efficiency, reliability and safety, the call for intelligent supervisory systems is gaining more and more important among the control engineering community [Ignova *et al.* 1996, Junior and Martin 2000, Martin 1994, Quek and Wahab 2000, Wang and Linkens 1996]. The intelligent supervisory system is an integration of the disciplines of control engineering and artificial intelligence (AI). The system will execute intelligent tasks operating in uncertain disturbances and fault conditions with minimum interaction with a human operator. The adoption of AI techniques (such as fuzzy system, genetic algorithms, etc) reduces the burdens on exact numeric information and automates the human intelligence for process supervision.

The studies undertaken in this thesis focus on the development of the intelligent supervisory coordinator (ISC). It should be remarked that the ISC is interpreted within the context of *process control*. Hence, the literature survey is directed towards the applications in process control. Main functions of the ISC are depicted in Figure 2-1. Process knowledge for the derivation of a simulation model is acquired in the knowledge acquisition module. Fault detection and performance monitoring are conducted in the supervision module while fault analysis module performs fault diagnosis. The ISC is implemented through the coordination of these modules.

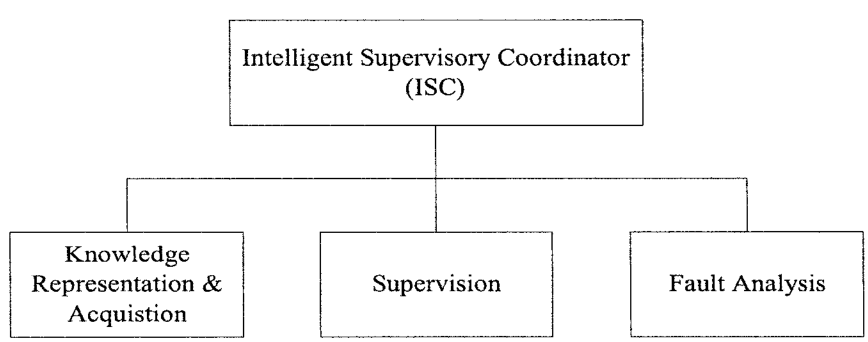

Figure 2-1 The ISC schematic.

This chapter provides an effective and comprehensive coverage of underlying principles, techniques, and architecture of implementation of the ISC. It gives the scope of the ISC in order to set the scene and to present the background materials relevant to the thesis. Since the literature in this area is exhaustive, this review is highly selective and covers only parts of the ISC and AI techniques that are essential in the following chapters. Any specific details related to a particular topic that is not covered here will be included in the respective chapter.

The rest of the chapter is organized as follows. The scope of the ISC will be addressed in Section 2.2. Section 2.3 describes the knowledge representations in the ISC. Qualitative reasoning, bond graph theory and qualitative bond graph (QBG) modeling will be outlined. In Sections 2.4 and 2.5, supervision and fault analysis algorithms are covered, and finally, Section 2.6 concludes the chapter.

2.2 Scope of Intelligent Supervisory Coordinator

The supervision of complex dynamic physical systems typically involves a number of control tasks: feedback control, process supervision, fault detection and diagnosis. It can be well argued that the AI techniques have had a significant impact on the way we view the control and modeling of complex physical systems. In particular, the development of other modeling paradigms [Bobrow 1984b, Weld and de Kleer 1990] provides a substantial expansion in the tools and techniques available for representing complex physical systems. Therefore, an integrated framework for the aforementioned control tasks can be established which allows the AI techniques and control theory to coexist.

The intelligent supervisory system is an integration of the disciplines of control engineering and AI. The basic ideas and methods of integrating control theory and AI were formed around 1970. Early intelligent supervisory system was mainly focused on improving the performance of a controller, and this led to a branch of research area termed "intelligent supervisory control" or "intelligent control" for short. The purpose of the intelligent control was to transfer as much as possible the human operator's intelligence that is relevant to the specified tasks to a machine controller. Hence, this "intelligent machine" would operate automatically with minimum interaction with a human operator. Fu [1971] suggested that the intelligent control system should be composed of two controllers: primary and supervisory. Activities requiring relatively lower intelligence such as data acquisition, routine decisions, and on-line computations, could be accomplished by the primary controller. On the other hand, decisions requiring higher intelligence such as recognition of environmental situations, setting sub-goals for the primary controller, and correcting improper decisions made by the primary controller, were assigned to the supervisory controller.

A generalized hierarchical architecture for intelligent robotic control was proposed by Saridis in 1977 [Saridis 1977 and 1983]. The aim of this approach was to develop an intelligent system that could perform all the tasks of a primary controller (e.g. regulation) and human operators (e.g. planning, decision making, and learning). With this purpose, the system's structure was composed of three levels namely, organization level, coordination level, and execution level, and was hierarchically distributed according to the "*principle of increasing precision with decreasing intelligence*" [Saridis 1989]. The functions in the organization level were to imitating functions of human behaviors, while the coordination level received commands from the organizer and feedback information from different subtasks, and coordinated the execution at the lowest level. The execution level consisted of several controllers designed for effective optimal control.

Another intelligent control technique was the expert system approaches which were motivated by the research work of Åström *et al.* [1986]. They had observed that the actual implementation of PID control often required substantial amount of heuristic logic, which was more important in multivariable and self-tuning regulators. Further, they stated that knowledge representation was a key issue in intelligent control systems. In their system, knowledge was described as if-then rules. A well-known example of expert system usage is the Foxboro EXACT [Kraus and Myron 1984], which was focused on control heuristics but implemented via conventional techniques based on pattern identification of transients in the control error. Furthermore, Liu *et al.* [1987] proposed a supervisory control structure using heuristic rules for the supervision of adaptive controllers.

The aforementioned intelligent supervisory systems mainly focused on supervisory control, i.e., monitoring the performance of a controller and seldom concerned the issues of fault detection and diagnosis. The incorporation of fault detection and diagnosis processes to the intelligent supervisory system was proposed by Leitch and Quek in 1992 [Leitch and Quek 1992]. They proposed architecture for integrating the control tasks (e.g. feedback control, adaptation, fault detection and diagnosis) within a scheme for integrated process supervision (IPS). The IPS consisted of a primary control regime, an adaptive control regime, and fault diagnosis regime. A boundary detection mechanism was employed to monitor system behaviors according to a supervisory cost function. The cost function was evaluated by comparing the observed behaviors with the reference behaviors that were generated through simulating the reference model. Then, the system supervisor initiated appropriate generic control regime whenever there was a transition across a behavior boundary. From then on, the term "intelligent supervisory system" was used to describe a system that could perform feedback control, adaptive control, system supervision, and fault analysis under an integrated framework between control theory and AI techniques [Isermann 1998, Linkens and Abbod 1992, Sohlberg 1998, Quek and Wahab 2000].

There was also a branch from the intelligent supervisory system that was primarily concentrated on knowledge representation (i.e. process modeling and simulation), system supervision, and fault analysis [Corea *et al.* 1993, Ignova *et al.* 1996, Junior and Martin 2000, Leyval *at al.* 1994b, Montmain and Gentil 1999]. This branch of systems is also referred to as "intelligent supervisory system" or more precisely "intelligent supervisory coordinator (ISC)" since the adaptation mechanism for optimizing the performance of a primary controller is omitted. The ISC schematic for its functional blocks is shown in Figure 2-1.

2.2.1 Remarks on Intelligent Supervisory Coordinator

Most existing approaches of ISC can be seen as knowledge-based systems [Corea *et al.* 1993, Ignova *et al.* 1996, Isermann 1998, Linkens and Abbod 1992, Wang and Linkens 1996], although their architectures, inference methods, and knowledge representation may be different. The block diagram shown in Figure 2-2 depicts a typical architecture of an ISC.

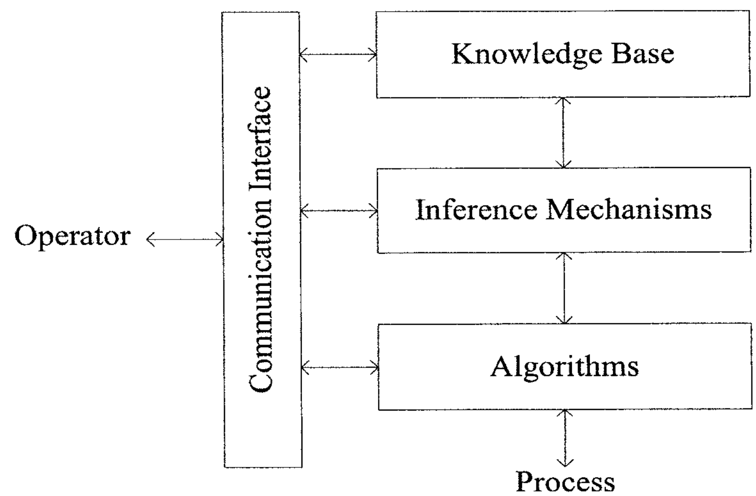

Figure 2-2 General architecture of an ISC.

The coordination modules consist of control algorithms, monitoring algorithms, and fault diagnosis algorithms, which can be quantitative or qualitative. The control algorithms compute control actions according to the desired value given by the inference mechanisms and measurement signals. The control algorithms can be seen as "primary controller" as described in [Nilsson 1969]. The monitoring and fault diagnosis algorithms supervise system behavior and localizing faulty components once a faulty system behavior is observed. The inference mechanisms treat quantitative and qualitative knowledge, and the processing of qualitative information may be performed by methods of soft computing [Zadeh 1994], including fuzzy logic, artificial neural network and genetic algorithms. The inference mechanisms receive the information and apply the knowledge stored in the knowledge base to deduce a proper control strategy and initiate the fault diagnosis process. In learning systems, the inference mechanisms can also update the stored knowledge according to the observed system behaviors [Bellazzi *et al.* 1998, Coiera 1989, Cordón *et al.* 2003, Kay *et al.* 2000, Petridis *et al.* 1998, Say and Kuru 1996].

The core of an ISC is a knowledge base that contains the problem-solving knowledge of a particular application. This knowledge can be expressed qualitatively or quantitatively in the form of process models, if-then rules, graphs, objects, etc. Performance criteria, reference inputs, process specifications, and relevant information that cannot be inferred by the inference mechanisms but is necessary for operating a system are also embedded in the knowledge base. Communication interface provides a bridge for exchanging information with different functional modules in the ISC and allows the operator to maintain or modify the system in a user-friendly environment.

The separation of problem-solving knowledge base, inference mechanisms, and algorithms is a crucial feature of the ISC's architecture which makes ISC different from conventional control systems. This allows the knowledge to be expressed in a more natural form (e.g. if-then rules) rather than profoundly lower-level computer code [Isermann 1998, Linkens and Abbod 1992, Wang and Linkens 1996]. Heuristic knowledge can be embedded in the knowledge base but the algorithms cannot. This heuristic knowledge supports higher-level reasoning and makes the ISC more robust and flexible than conventional ones. Furthermore, the separation allows the inference mechanisms and algorithms to be generalized for a variety of processes. In some learning systems, an intelligent process supervisor begins to monitor a process with an empty knowledge base and create a new knowledge base appropriate to the process (Chapter 4).

The success of the ISC does not rely on the use of new mathematical techniques but on the progress of AI techniques. Using heuristic knowledge to infer possible solutions for problems makes the supervisory coordinators intelligent. Here, knowledge representation plays an important role in an efficient system, because, after the knowledge representation has been decided, the corresponding inference mechanisms are more or less easily implemented to apply the knowledge [Wang and Linkens 1996]. The representation scheme must allow system builders to express the knowledge required for inferring a problem solution. The ability of an ISC to resolve problems also depends on how much knowledge can be articulated by the representation scheme.

The knowledge representation usually adopted for the ISC is if-then rules. Although if-then rules are very good at representing heuristic knowledge, they do not provide information about subsystems interactions and they are shallow knowledge, which can only tell "what" to do but cannot explain "why" to do so. To overcome these difficulties, model-based approaches as in qualitative reasoning [Voss 1988] were developed to represent deep-level knowledge for the ISCs. A deep model describes the behavior of various components of a system and their functional relationships, hence causalities and interactions between components can be considered. Moreover, since the deep-level model is constructed on the basis of physical laws, it can be verified objectively. Leyval *et al.* [1994a, 1994b] used qualitative causal graph model and qualitative transfer functions to represent deep-knowledge for a supervisory system. Their implementation demonstrated that the supervisory system capable of providing action advice and explanations via reasoning about a causal model.

Reasons for adopting deep-level knowledge representation for the ISC are given above, but how to acquire this deep-level knowledge is yet another problem. The problem of knowledge acquisition comes from the complexity of industrial processes. Structuring and representing complicated knowledge for efficient computation require a strong background in AI programming, such as using the high-level languages LISP and PROLOG, and object-oriented methods, which a domain expert is usually not possessed. Automatic knowledge based editor is an approach developed in helping domain experts to cope with the problem of building the knowledge base. The program named Teiresias [Davis and Lenat 1982] is an example developed for the MYCIN expert advisor to help doctors add new rules to the system. Another way to tackle the problem is to build a system that can learn its own knowledge base via operating a process. Techniques of neural networks [Frank 1996, Linkens and Nyongesa 1999] and fuzzy-genetic algorithm [Khoo *et al.* 2000, Thrift 1991] have promising results in this area.

Furthermore, an automatic modeling method based on qualitative bond graph (QBG) reasoning was proposed in [Linkens *et al.* 1993, Xia *et al.* 1993] to resolve the problem of knowledge acquisition. Based on their works, [Wang and Linkens 1996], a representation method to describe deep models have evolved. This representation allows deep models to be described explicitly, and can incorporated readily with the ISC without considering the details of computer implementation. Hence, domain experts can use it to build the knowledge base by themselves. Here, the bond graph modeling language is employed for model building and representation, while qualitative reasoning is used as the basic strategy for reasoning about the deep-level knowledge embedded in bond graph models. Once the knowledge base has been constructed, the inference mechanisms and algorithms of system supervision and fault analysis can be developed to utilize the knowledge represented in the QBG pragmatism.

In the following sections, an outline of knowledge representation and acquisition of qualitative reasoning, bond graph theory and QBG will be given. Subsequently, techniques on system supervision and fault analysis used in the ISC will be reviewed.

2.3 Knowledge Representation and Acquisition

Knowledge base plays a crucial role in the ISCs and a careful choice of its representation becomes a paramount issue. As mentioned previously, a deep model based on QBG formalism is chosen to construct the knowledge base. It is because qualitative reasoning shows strong power in deep-level knowledge representation and utilization, while bond graph provides a systematic way for building deep models, in which system structure and its interactions can be represented explicitly. In this subsection, background information on qualitative reasoning, bond graph theory, and QBG formalism are briefly described.

2.3.1 Qualitative Reasoning

Qualitative reasoning has attracted much interest from the AI research community in the last two decades. Every year since 1986, the US's National Conference on Artificial Intelligence has devoted two to three technical sessions to qualitative reasoning and the modeling of physical devices. Also, an International Workshop on Qualitative Reasoning has been held every year since 1987. Broadly speaking, qualitative reasoning aims to develop representation and reasoning techniques that permits a program to reason about the behavior of physical systems, without using precise quantitative information. It simulates the intelligence of engineers and scientists in solving physical problems.

The works of de Kleer [1975, 1977] marked the beginning of qualitative reasoning research. Their main scope was the formalization of "pre-physics" knowledge. Rather than to solve the quantitative equations, it was important to comprehend the problem, formulate a plan for solving the problem, to know when and how to apply which formula or model and to interpret the results of quantitative analysis qualitatively. A further, and until today one of the most important applications is the simulation of electronic circuits' behavior or their diagnosis in the case of faulty behavior [de Kleer 1979]. Significant effort is required to codify this "pre-physics" knowledge [de Kleer 1993].

Haye's Naive Physics Manifesto [1979, 1985], proposed a formalism of the ordinary knowledge of physical common sense to reason about situations happening between events. A crucial difference between the naive physics and the mainstream approaches of qualitative reasoning is in the use of common sense knowledge. The mainstream approaches represented physical systems in terms of physical laws rather than common sense. The standpoint taken here is that there should be no fundamental difference between "naive" physics and "ordinary" physics. The differences were only in areas such as resolution of detail and presentation, not in the phenomena themselves.

1984 was a fruitful year for the research in qualitative reasoning. In this year, the

Journal *Artificial Intelligence* published a special volume entitled "*Qualitative Reasoning about Physical Systems*" [Bobrow 1984a], in which a number of significant contributions to the development of qualitative reasoning were published. Thus, qualitative reasoning has been promoted as an independent and established filed in AI. Most papers in this special volume focused on the development of qualitative causal explanations for time-evolved behavior to explain how devices work. The best known of these include de Kleer and Brown's [1984] *device-centered* approach, Forbus' [1984] *process-centere*d approach, and Kuipers' [1984, 1986] *constraint-centered* approach, which provided a computational framework for qualitative analysis. Each of these is briefly discussed below.

- *Device-centered* approach [de Kleer and Brown 1984]: It determined the behavior of a composite device from laws governing the behavior of its components, and introduced causality as an ontological commitment for explaining how devices behave. Three basic principles were established for performing the qualitative inference: (1) No-Function-in-Structure, (2) Class-wide assumptions, and (3) Locality. Device components were connected via simple interactions, resembling the constitutive relationships of system dynamics. Qualitative differential equations called "confluences" were used to express the device's behavior. Three qualitative values {[+], [0], [−]} were assigned to confluences associated to each component. These values represented physical quantities and were manipulated through qualitative operations shown in Table 2-1. The possible behavior of a device could thus be predicted though the operations on the confluences of the device. The use of qualitative values and their operations has now become accepted as standard, and appears in most qualitative reasoning approaches.

Table 2-1 Qualitative operations for qualitative space {[+], [0], [–]} (*: undefined value).

		[X] + [Y]	[X]			[X] – [Y]	[X]	
		+	0	–		+	0	–
	+	+	+	?		?	–	–
[Y]	0	+	0	–		+	0	–
	–	?	–	–		+	+	?
		[X] × [Y]			[X] / [Y]			
	+	+	0	–		+	0	–
[Y]	0	0	0	0		*	*	*
	–	–	0	+		–	0	+

- *Process-centered* approach [Forbus 1984]: This approach was widely known as Qualitative Process Theory (QPT). It concentrated on reasoning about how things change in physical systems, where physical processes initiated the changes. "Individual Views" were adopted to model a set of active processes. An Individual View was defined to record the individuals concerned (the objects existing in a process), the preconditions that must hold (the conditions must be true for a view), quantity conditions (comparisons between quantities of individuals or between an individual's quantity and a certain value), and relations (physical laws among objects). A process (e.g. heat flow) was similar to an Individual View, except that it also contained influences. The dynamics of a process were come from the influences, which were qualitative equations indicating the directions of quantities' changes in a process. The descriptions of behavior have much the same characteristics as [de Kleer and Brown 1984] in their use of qualitative variables.

- *Constraint-centered* approach [Kuipers 1984, 1986]: This approach was intended to simulate the behavior of physical systems using qualitative values, rather than providing explanations for behaviors of physical processes. The program *QSim* was produced by Kuipers [1984, 1986] for qualitative simulation of physical systems. A simulation began with a description of system's structure and initial behavior, and then resulted a directed graph consisting of all possible future behaviors of the system. The structure of a system was described by a set of constraint equations describing how physical parameters interacted with each other. Constraint equations were obtained from the qualitative abstraction of ordinary differential equations governing the system.

Early research in qualitative reasoning was devoted to formalize qualitative representation and reasoning techniques mathematically. A well-known difficulty with qualitative descriptions is the large numbers of solutions that can be produced, due to ambiguities caused by loss of magnitude information. With the aim of incorporating magnitude information into the relationships between variables, Raiman [1986] has proposed the Order of Magnitude reasoning approach to resolve the problem of ambiguity. In this approach, three basic relationships were used:

A Ne B means that A is negligible with respect to B.

A Vo B means that A is close to B.

A Co B means that A has the same sign and order of magnitude as B.

Based on these relations, 30 inference rules were defined for relation interpretations. For example, R_{21}: A Co B, C Co D $\rightarrow$ A·C Co B·D. A later paper [Dague *et al.* 1987] illustrated the use of order of magnitude reasoning. Although Raiman's ideas are promising, there are practical difficulties in applying his method. Now, consider R_{21}, if A = 1, B = 9, C = 100 and D = 900, then the interpretation will become 1 Co 9, 100 Co 900 $\rightarrow$ 100 Co 8100. The values 100 and 8100 will normally be considered different orders of magnitude.

Mavrovouniotis and Stephanopoulos [1988] offered an alternative formulation in the same sprit as Raiman for resolving the above-mentioned interpretation problem. In their method, the representation for the relations between variables was enhanced (e.g. A is much smaller than B, A is slightly smaller than B, and so on). However, it is difficult to explain explicitly the linguistic terms "much smaller", "slightly smaller", etc. Fuzzy logic, based on the work of Zadeh [1973], is a formal methodology to reason about relationships using linguistic terms. It seems to be an appropriate tool for representing the qualitative relations between variables. Shen and Leitch [1990, 1993a] have integrated the fuzzy logic and qualitative reasoning techniques to increase qualitative precision.

Morgan [1988], Cheung and Stephanopoulos [1990a, 1990b] proposed a method for improving the accuracy for process trend prediction. In this approach, the qualitative vector represented a qualitative state (*QS*) of a continuous variable (x) with qualitative values drawn from the set $\{[+], [0], [-], [?]\}$:

$$QS(x,t) = \langle [x(t)],[\partial x(t)],[\partial\partial x(t)] \rangle . \tag{2-1}$$

Time-domain characteristics were expressed by a sequence of qualitative vectors which distinguished the under-damped, critical-damped, and over-damped responses of a system.

Fault diagnosis and automatic modeling are two active applications that are benefited from the development of qualitative reasoning techniques. Approaches that contribute to the fault diagnosis will be given in next section, while the significant researches in automatic modeling are described below.

As techniques for reasoning with imprecise information became fairly well established, the problem of model formulation emerged as an important topic. Automatic modeling in qualitative reasoning attempts to develop algorithms to assist the user abstract appropriate information from the domain knowledge, and to construct a model that is appropriate for a given analysis purpose. The qualitative reasoning community has devoted much attention and effort to automatic modeling research [Falkenhainer and Forbus 1991, Iwasaki and Levy 1994, Nayak *et al.* 1992, Rickel and Porter 1994].

An important paradigm in automatic modeling is "compositional modeling" [Falkenhainer and Forbus 1991], based on Forbus' Qualitative Process Theory. In compositional modeling approach, domain knowledge was decomposed into a library of model fragments. Each model fragment represented a conceptually independent physical phenomenon such as a physical process, specified combinations of physical objects, and behavior characteristics of objects. A qualitative model was built through relating a minimal set of model fragments in response to the user's task definitions. Compositional modeling is effective for automatically formulating a behavior model of a physical system that can be adequately modeled as lumped-parameter model.

There are three difficulties in compositional modeling approach that hinder its application. One is that a physical system must be decomposed into several independent modules for model building. But, the system decomposition is problem specific which depends on operating conditions and the purpose analysis [Falkenhainer 1992]. Determining the appropriate system decomposition requires detailed user understanding of the domain knowledge. The other difficulty is choosing the appropriate set of model fragments for a given problem. Knowledge acquisition for building a large library of model fragments is another difficulty. A large library of model fragments covering a substantial portion of the domain is essential to construct a model that can reason about a variety of problems in a given domain. However, building and maintaining such a large library is labor-intensive and time-consuming, researchers are developing facilities for enabling collaborative construction and reuse of knowledge [Iwasaki *et al.* 1997].

Another approach to automatic modeling builds model from system structures. Linkens *et al.* [1991] developed the *qualitative reasoning environment for automatic modeling and simulation* of dynamic physical systems (QREMS). In their approach, bond graph was employed as formal modeling language, where models of physical systems were represented by a set of physical primitives (e.g. resistance, capacitance, inertia, etc.) interacting by two interconnections (parallel and serial junctions). A set of qualitative equations relating the effort and flow variables of the system was generated according to the bond graph model for conducting qualitative analysis.

Qualitative reasoning shows a strong power in deep-knowledge representation and utilization, e.g. device-centered, process-centered, and constraint-centered approaches. Automatic modeling provides a systematic and formal way for knowledge acquisition. Efforts on qualitative reasoning have provided a solid foundation for the development of ISCs. This section introduced the basic concept and approaches of qualitative reasoning. A more detailed survey can be seen in [Werthner 1994].

2.3.2 Bond Graph

Bond graph was devised by Paynter at MIT in April 1959 [Paynter 1959] and subsequently developed into a methodology by Rosenberg and Karnopp [1972]. Currently, bond graph has become a formal modeling language of dynamic systems. It provides a systematic and formal way for modeling dynamic systems with different energy domain, such as, electrical, hydraulic, mechanical, etc, in a unified framework. Table 2-2 shows the effort and flow variables for individual energy domain. The success of bond graph modeling reflects in a number of sub-conferences within IMACS conferences, an international SCS conference (ICBGM) explicitly dedicated to bond graph modeling held every two years since 1993, invited plenary session papers on bond graph modeling [Cellier 1990], and a number of textbooks that was published in the past decades [Brown 2001, Gawthrop and Smith 1996, Karnopp *et al.* 2000, Mukherjee and Karmakar 2000, Thoma 1990].

Rosenberg [1971] proposed a formal procedure for the systematic generation of linear state-space equations in terms of energy variables. Later, Martens [1973] extended the equation formulation method to include non-linear systems. The notion of causality was introduced by Karnopp [1975] to maneuver the state space formulation. After then, a fast and complete method for automatically assigning causality to bond graph models was developed by Hood *et al.* [1989]. Barreto [1988] showed how bond graphs and the sequential causality assignment algorithm (SCAP) could be used in building a qualitative model of a physical system. Qualitative model in the form of if-then-else form, expressing the causal relationship between variables, was formulating from an augmented bond graph model [Barreto 1988]. Bond graph modeling approach provides a systematic causality assignment method that can be adopted to resolve the causal ordering problem for qualitative modeling.

Table 2-2 Effort and flow variables for individual energy domain.

Domain	Effort	Flow	Momentum	Displacement
Electric	Voltage	Current	Flux linkage variable	Charge
	e (V)	i (A)	λ (V-s)	q (C)
Hydraulic	Pressure	Volume flow rate	Pressure momentum	Volume
	P (N/m^2)	$\dot{V}$ (m^3/s)	P (N-s/m^2)	V (m^3)
Mechanics	Force	Velocity	Momentum	Displacement
(Trans.)	F (N)	V (m/s)	p	x (m)
Mechanics	Torque	Angular velocity	Angular momentum	Angle
(Rotation)	τ (N-m)	ω *(rad/s)*	H (N-m-s)	θ (rad)
Thermo-	Temperature	Entropy flow rate	–	Entropy
dynamics	T (K)	$\dot{S}$ (J/(K-s))		S (J/K)

Initially, bond graph method was applied to mechanical, electrical and hydraulic systems. In recent years, its applications have been extended to cover chemical, thermodynamics, economics, and biological systems. A number of computer-aided modeling and simulation programs based on bond graph theory, such as ENPORT

[Rosenberg 1973], CAMP [Granda 1985], CAMAS [Broenink and Nijen Twilhaar 1985], Modelica [Broenink 1997], and Kalibond [Jörgl *et al.* 1997], have been developed extensively through scientific and engineering communities (see a survey in [Filippo *et al.* 1991]). The bond graph modeling technique has been applied to various energy domain systems that demonstrated it is a useful and versatile tool for modeling and simulation. This is due to the fact that the semantic of bond graph theory is simple and systematic which facilitates modeling of different energy domain systems in a unified way.

2.3.2.1 Bond Graph Primitives

Bond graph represents the interactions of power variables with interconnected links, i.e. "bonds". It simply consists of subsystems linked together by lines representing power bonds as shown in Figure 2-3. The half arrow indicates the direction of actual power flow (positive power flow). The product of power variables, effort or across variable (e) and flow or through variable (f), is the power on the bond. Usually, flow represents either: current, flow rate or velocity; effort represents either: force, voltage or pressure. Bonds are numbered and the numbered effort and flow correspond to the respective numbered bond.

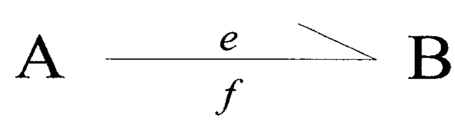

Figure 2-3 A power bond. Positive power flows from element A to B.

The bond graph modeling language consists of nine primitive entities: three passive elements, resistance (R), capacitance (C), and inertia (I); two distribution elements, transformer (TF) and gyrator (GY); two ideal sources, effort source (S_e) and flow source (S_f); and two kind of junctions, serial junction (1-junction) and parallel junction (0-junction). Ideal sources are 1-port active elements. Passive elements are also 1-port elements: R for power dissipation, both C and I for energy storage and their constitutive laws are defined by Eq. (2-2), respectively.

$$e_i = \mathrm{R} \times f_i; \quad f_i = \mathrm{C}\frac{d}{dt}e_i; \quad e_i = \mathrm{I}\frac{d}{dt}f_i \tag{2-2}$$

where i represents the number of bond.

The 2-port elements, TF and GY, transfer energy between two parts of a system and their constitutive laws are defined by Eqs. (2-3) and (2-4) respectively (in both cases power are conserved).

$$\text{For TF}: \quad e_{in} = ae_{out}, \qquad f_{in} = \frac{1}{a}f_{out} \tag{2-3}$$

$$\text{For GY}: \quad e_{in} = bf_{out}, \qquad f_{in} = \frac{1}{b}e_{out} \tag{2-4}$$

The parameters a and b are called transformer modulus and gyrator modulus respectively. Transformer relates the effort at one port to the other port, while gyrator relates the effort at one port to the flow at the other port.

Bond graph consists of two types of connections: serial and parallel junctions, and are classified as multi-port elements as they can connect n elements in a node. For the serial junction (1-junction), the flow is common to all bonds while the algebraic sum of all efforts on the bonds is zero, as in Eq. (2-5). For the parallel junction (0-junction), the algebraic sum of all flows on the bonds is zero while the effort is common to all bonds, as in Eq. (2-6). In both Eqs. (2-5) and (2-6), m is the number of input elements and n is the number of output elements.

$$\begin{aligned} e_{in\,1} + e_{in\,2} + \cdots + e_{inm} &= e_{out\,1} + e_{out\,2} + \cdots + e_{outn} \\ f_{in\,1} = f_{in\,2} = \cdots = f_{inm} &= f_{out\,1} = f_{out\,2} = \cdots = f_{outn} \end{aligned} \tag{2-5}$$

$$\begin{aligned} f_{in\,1} + f_{in\,2} + \cdots + f_{inm} &= f_{out\,1} + f_{out\,2} + \cdots + f_{outn} \\ e_{in\,1} = e_{in\,2} = \cdots = e_{inm} &= e_{out\,1} = e_{out\,2} = \cdots = e_{outn} \end{aligned} \tag{2-6}$$

These nine primitive entities are employed as a set of general conventions to represent engineering systems. Their interactions are expressed in terms of their energy transformations. Differential or state space equations are generated after causality assignment for simulation and analysis. Details on the procedure for building bond graph models based on these primitive entities can be found in [Karnopp *et al.* 2000, Mukherjee and Karmakar, 2000].

2.3.3 Qualitative Bond Graph

Qualitative reasoning is a paradigm which represents system knowledge based on the governing physical laws of the system, and describes system structure information for high-level cause-effect reasoning in supervisory systems. Bond graph methodology is a formal modeling scheme used to build models for all engineering systems from limited primitives. Qualitative bond graph (QBG) reasoning is then developed based on the integration of qualitative reasoning and bond graph theory in order to benefit from both approaches. Xia and his colleagues were pioneers to the development of QBG methodology [Xia *et al.* 1992]. Xia *et al.* also developed an automatic modeling method based on QBG reasoning in 1993 [Xia *et al.* 1993]. Based on Xia's works, Wang and Linkens [1996] have evolved a representation method to describe deep models and applied for qualitative fault diagnosis [Linkens and Wang 1994] and feedback control. In this thesis, Wang and Linkens' idea on QBG representation has been adopted for deep model construction (Chapter 3), process supervision (Chapter 4), qualitative fault diagnosis (Chapter 5) and building the ISC (Chapter 6).

2.4 Supervision and Fault Analysis

Process supervision and fault diagnosis are two essential functions of the ISCs that are closely related to each other. When the knowledge base of an ISC is established, algorithms for process supervision and fault diagnosis can be formulated. Process supervision monitors the performance of a dynamic physical system and determines the present of faults. Fault diagnosis determines the location, types and sources of a fault. The procedure of process supervision and fault diagnosis is illustrated in Figure 2-4. Process information such as system input, system output, etc., are input to the process supervision for residual generation and evaluation. Residual is computed as the difference between measured system output (y) and predicted system output ($\hat{y}$). Fault analysis is activated for localizing sources and types of faults when a faulty behavior is detected in the supervision module.

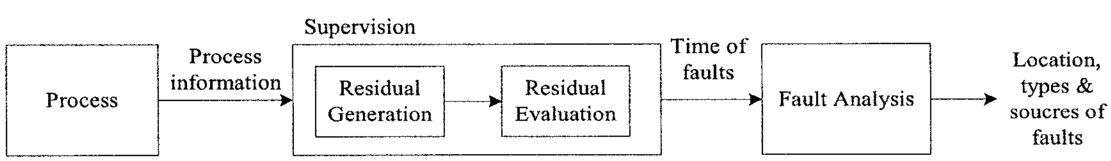

Figure 2-4 Schematic representation of the procedure of process supervision and fault diagnosis.

A wide range of process supervision and fault diagnosis approaches has been proposed in the literature which can be broadly divided into model-based techniques and signal-based techniques. A classification of supervision and fault diagnosis methods is shown in Figure 2-5. The studies undertaken in this thesis focus on qualitative approaches on process supervision and fault diagnosis. Therefore, the details of quantitative model-based approaches and signal-based techniques are not in the scope of this thesis and only brief review is given for the sake of completeness.

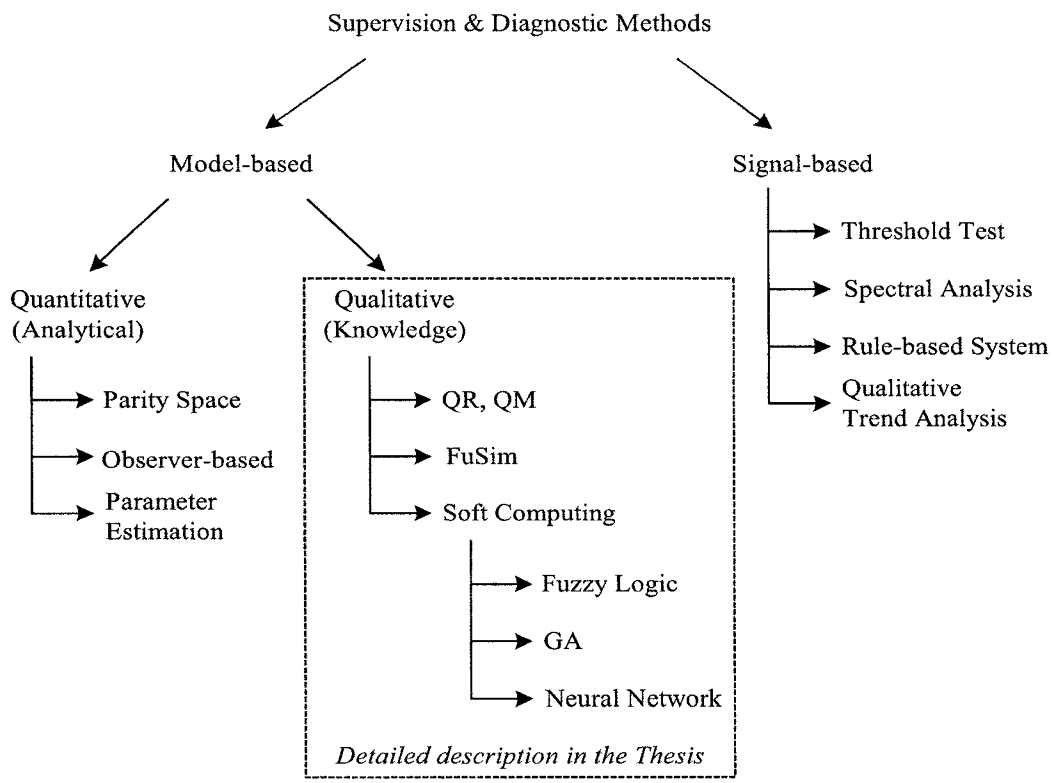

Figure 2-5 Classification of process supervision and fault diagnosis methods.

2.4.1 Signal-based Approaches

Signal-based techniques without model application such as threshold test, spectral analysis, rule-based system and qualitative trend analysis can be used in supervision and fault diagnosis process. In rule-based systems, simple production rules are used to provide mapping between the symptoms of a system and possible faults, e.g. MYCIN [Shortliffe 1976]. They provide an effective and efficient diagnosis performance, but they all suffered from incompleteness and inflexibility. Qualitative trend analysis utilizes the trend information present in sensor measurements [Bakshi and Stephanopoulos 1994, Cheung and Stephanopoulos 1990a and 1990b, Janusz and Venkatasubramanian 1991, Rengaswamy and Venkatasubramanian 1995]. But the problems of determination of the length of the trend-window to identify the trend at different scale and mapping between identified process trends and possible faults, hinders the applicability of the approach.

2.4.2 Model-based Approaches

Better approaches to process supervision and fault diagnosis are based on a model of a device's structure and behavior. Models provide structural, functional, and behavioral information and their relationships, which are essential for complex cause-effect reasoning so that more powerful and robust monitoring and diagnostic systems can be built. There are two classes of model-based approaches, quantitative and qualitative.

2.4.2.1 Quantitative Model-based

In the quantitative approach, analytical models (differential equations, state space methods, transfer functions, etc.) are used and based upon parameter estimation, state estimation, observed-based method or parity space concepts. However, this approach requires a prior knowledge about the relationships between system behaviors and faults and model parameters or states. Comprehensive theoretical models for complex systems (e.g. chemical processes) are difficult to obtain, and some situations impossible to derive. The development of mathematical models can be very time-consuming and rarely replicate the functions of the entire process. Without precise numerical models, the quantitative approach cannot be applied. For literature on the quantitative model-based approaches, the reader is referred to comprehensive papers as, [Frank 1990 and 1996, Gertler 1991, Isermann 1984, 1993 and 1997, Lo *et al.* 2002, Willsky 1976] or books by [Gertler 1998, Patton *et al.* 1989 and 2000, Sohlberg 1998, Simani *et al.* 2003].

2.4.2.2 Qualitative Model-based

A qualitative model-based approach is more applicable and effective when numerical models are not available. It makes use of a qualitative causal analysis that links individual component malfunctions expressed in a qualitative form with deviations in the measurement values. The sensitivity of the diagnostic system to modeling errors and measurement noise may be alleviated by qualitative approaches [Ghiaus 1999].

The most widely known qualitative model-based process supervision and fault diagnosis approach is based on Kuipers' *QSim* [Kuipers 1986]. [Dvorak and Kuipers 1989] and [Kuipers 1987] used *QSim* to simulate a set of fault models, and then compared the faulty behavior observed with that predicted by the fault models. The fault model whose predicted behavior matched with the observed faulty behavior then determined the set of faults that would be present in the system. This "hypothesize-and-match" cycle is illustrated in Figure 2-6. Note that observations from the dynamic physical systems evoke fault hypotheses via a decision tree induced off-line by qualitatively simulating the known fault models, with each hypothesis corresponding to a particular fault model. The set of fault models needs to be determined a priori, and to be explicitly specified.

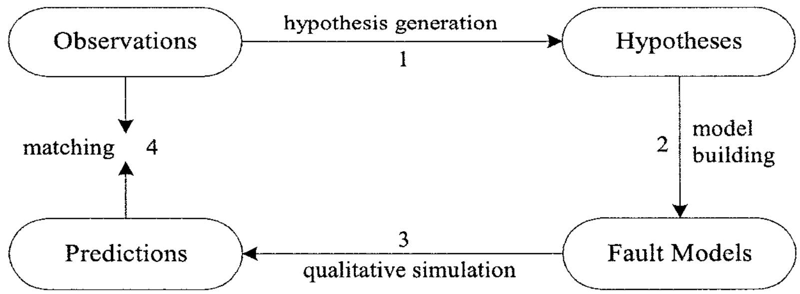

Figure 2-6 Hypothesize-and-match cycle [Dvorak and Kuipers 1989].

An alternative approach to use qualitative simulation but without the employment of faulty models adopts Reiter's idea of "reasoning from first principles" [Reiter 1987]. The early works in this area, such as DART [Genesereth 1984], HT [Davis 1984], and GDE [de Kleer and Williams 1987], presented several prototypes of diagnostic systems for diagnosing digital circuits. In Reiter's theory, a system is defined as a triple (SD, COMPS, OBS), where SD (system description) and OBS (observations) are finite sets of first-order sentences, and COMPS (system components) is a finite set of constant. If the OBS shows an abnormal behavior, then there must be a number of conflict sets (subsets of COMPS) that will cause "SD $\cup$ OBS $\cup$ $\{\neg AB(c) \mid c \in$ COMPS $- \Delta\}$" to be inconsistent, where AB(c) means that component c is abnormal or faulty and $\Delta \subseteq$ COMPS is a minimal set of a diagnosis. Thus, fault candidates can be obtained from these conflict sets. The "reasoning from first principles" has been extended to diagnose dynamic systems, e.g. DIAMON [Lackinger and Nejdl 1991] and Inc-Diagnose [Ng 1990], where qualitative simulation acts as an inference engine to predict possible system behaviors during the monitoring and diagnosis processes. However, it is difficult to generate a set of complete and consistent first-order sentences for system description, especially for complex engineering systems, which obstructs its utilization.

[Shen and Leitch 1992] proposed a fuzzy qualitative simulation (FuSim) algorithm for diagnosing continuous dynamic systems. The system performance is monitored via a synchronous tracking of system behavior by the so-called behavior simulator. If the observed behavior cannot match the predicted one, the candidate generator will then search for modified models that can generate behavior to match the observations. Thus, fault candidates can be determined from the modified models. In addition, FuSim provides more precise information than QSim. The adoption of fuzzy sets allows a more precise representation of time which is essential for monitoring and diagnosing continuous dynamic systems. However, the choice of the number of fuzzy sets and their memberships, and the determination of appropriate modeling dimensions to search for candidate generation are problems to be faced for building an efficient FuSim monitoring and diagnostic system.

2.5 Soft Computing techniques

A large area of process supervision and fault diagnosis work within the AI domain, applicable to dynamic systems, makes use of neural networks, fuzzy systems and GA. They are attractive because they do not require explicit mathematical models of the process being monitored. Here, fuzzy systems and GA will be briefly described. Artificial neural networks approach will not be presented since it is outside the scope of this thesis.

2.5.1 Fuzzy Systems

Fuzzy sets and theory [Zadeh 1965] has been widely exploited and studied by scientists and engineers [Isermann 1998, Mendel 1995, Ross 1995, Tong 1977, Wang 1997, Yager and Filez 1994]. Many research works of fuzzy systems have been focused on the design and implementation of fuzzy controllers [Kickert and van Nauta Lemke 1976, Mamdani 1974, Mamdani and Assilian 1975, Verbruggen and Babuška 1999, Wang 1997]. However, as industrial processes become more complex and sophisticated, there is a growing demand for their reliability, safety, and low cost operation. This is partly being met by the use of robust automated monitoring and fault diagnosis systems. Several researchers [Frank and Köppen-Seliger 1997, Isermann 1998, Kiupel and Frank 1993, Patton and Lopez-Toribio 1998, Sauter *et al.* 1993, Schneider 1993] have exploited process supervision and fault diagnosis approaches based on fuzzy systems. Here, the fuzzy system embeds the relationships between system behavior and the causes of faults in the form of "if-then" relations (or rules). The architecture of the fuzzy system (Figure 2-7), which is used in this thesis, is briefly reviewed.

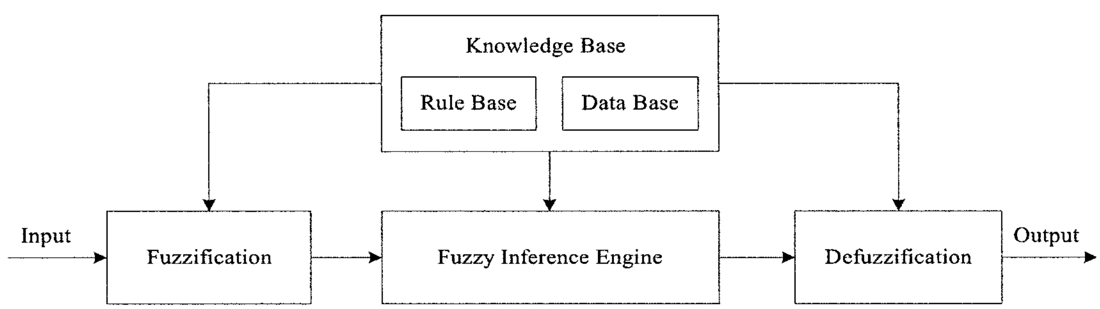

Figure 2-7 Basic configuration of the fuzzy system.

Fuzzy systems are knowledge-based systems which consist of four modules as shown in Figure 2-7.

- Fuzzification module: It is the process of mapping from crisp inputs to fuzzy sets described in linguistic terms (e.g. ***PB***, ***NB***, etc.). Each fuzzified crisp inputs is associated with a membership value.
- Fuzzy inference engine: It provides approximate reasoning for the fuzzy system. It infers the output values contributed from each rule and then aggregated them to produce the final result according to the knowledge base.
- Defuzzification module: It is the process of mapping from fuzzy sets to crisp outputs, an inversion of fuzzification.
- Knowledge base: It consists of a rule base and a data base. The rule base is the heart of the fuzzy system and comprises a set of fuzzy if-then rules. The data base defines the fuzzy membership functions for fuzzification and defuzzification.

Consider a fuzzy system with multi-input-single-output, where $U = U_1 \times U_2 \times \cdots \times U_n \subset R^n$ is the input space and $V \subset R$ is the output space, comprises the following fuzzy rules,

$$Ru^i\text{: } \mathbf{IF}\ (x_1\ is\ \boldsymbol{L}_1^i)\ \mathbf{AND}\ \ldots\ \mathbf{AND}\ (x_n\ is\ \boldsymbol{L}_n^i),\ \mathbf{THEN}\ (y\ is\ \boldsymbol{K}^i) \tag{2-7}$$

,where $\boldsymbol{L}_j^i$ and $\boldsymbol{K}^i$ are fuzzy sets in $U_j \subset R$ and $V \subset R$, respectively, and $X = (x_1, x_2, \ldots, x_n) \in U$ and $y \in V$ are the input and output linguistic variables of the fuzzy system, and M is the number of rules in the fuzzy system, that is, $i = 1, 2, \ldots, M$ in Eq. (2-7).

According to the individual-rule based inference, each rule in the form of Eq. (2-7) can be represented as a fuzzy relation, $Ru^i = \boldsymbol{L}_1^i \times \cdots \times \boldsymbol{L}_n^i \rightarrow \boldsymbol{K}^i$, in $U \times V$. The membership is determined as,

$$\mu_{Ru^i}(X,y) = \min[\mu_{\boldsymbol{L}_1^i \times \cdots \times \boldsymbol{L}_n^i}(X), \mu_{\boldsymbol{K}^i}(y)] \tag{2-8}$$

where $\mu_{\boldsymbol{L}_i^i \times \cdots \times \boldsymbol{L}_n^i}(X) = \min[\mu_{\boldsymbol{L}_1^i}(x_1), \ldots, \mu_{\boldsymbol{L}_n^i}(x_n)]$ (2-9)

Let $\boldsymbol{A}$ be an arbitrary fuzzy set in U. Then, the output fuzzy set $\boldsymbol{B}_i$ in V for each individual fuzzy rule Eq. (2-7) is computed as,

$$\mu_{\boldsymbol{B}_i}(y) = \sup_{X \in U} \min[\mu_{\boldsymbol{A}}(X), \mu_{Ru^i}(X,y)], \text{ for } i = 1, 2, \ldots, M. \tag{2-10}$$

where $\mu_{Ru^i}(X,y)$ is given in Eq. (2-8). The output of the inference engine is the combination of the M fuzzy sets $\{\boldsymbol{B}_1, \boldsymbol{B}_2, \ldots, \boldsymbol{B}_M\}$ by union, that is,

$$\mu_{\boldsymbol{B}}(y) = \max_{i=1}^{M}[\sup_{X \in U} \min(\mu_{\boldsymbol{A}}(X), \mu_{\boldsymbol{L}_1^i}(x_1), \ldots, \mu_{\boldsymbol{L}_n^i}(x_n), \mu_{\boldsymbol{K}^i}(y))]. \tag{2-11}$$

Eq. (2-11) is the well-known max-min inference method. Throughout this thesis, the fuzzy systems are implemented with trapezoidal membership function, max-min inference and center of area defuzzification. Following is the center of area defuzzifier,

$$y^* = \frac{\sum_{i=1}^{M} \bar{y}^i (\mu_{\boldsymbol{B}_i}(\bar{y}^i))}{\sum_{i=1}^{M} (\mu_{\boldsymbol{B}_i}(\bar{y}^i))} \tag{2-12}$$

where $\bar{y} = \arg\sup[\mu_{\boldsymbol{K}^i}(y)]$, i.e. $\bar{y}^i$ is the point in V at which $\mu_{\boldsymbol{K}^i}(y)$ achieves its maximum value.

In Chapter 4, a process supervision module based on fuzzy system is proposed to distinguish different system behaviors, such as, normal, faulty, malfunction, and load disturbance, according to process information (such as, residual, system input and output, etc.).

2.5.2 Genetic Algorithms

GA is a search algorithm based on the mechanism of natural selection and genetic reproduction. GA searches its potential solution through a population of chromosomes. As analogy to the survival of the fittest law, fittest chromosomes will have a higher probability to survive and generate offspring. This allows GA to improve or optimize its solution.

Holland [Holland 1975] proposed the GA in 1975, and in 1980s, Goldberg [1989] and Davis [1991] further elaborated and formulated the mechanisms of GA. With the advances in electronics and computational powers in 1990s, there has been an explosion of GA research. GA has been studied in the traveling salesman problem [Jang *et al.* 1997], robot trajectory generation [Tzafesta *et al.* 1999], and power systems optimization and planning [Fung *et al.* 2000, Song *et al.* 1996, Wong and Wong 1997], etc.

GA consists of four principles components: Initialization module, Evaluation module, Reproduction module, and Selection module. Figure 2-8 illustrates the interaction between each module in GA. GA first encodes the optimization problem's variables into its chromosome and the length of a chromosome is pre-defined. Depending on the nature of variables and applications, different coding methods (e.g. binary, gray code, real number [Wright 1991], etc.) can be used. The size of the population is chosen to be big enough to preserve diversity while small enough to reduce computational burden (fast convergence).

The Evaluation module contains a fitness function that computes the fitness value of each chromosomes of the problem to be solved. Chromosomes with higher fitness values receive a higher proportion of the roulette wheel selection scheme and thus have a higher chance of being selected for reproduction. The fitness function is problem specific and related to the objective of the optimization problem in hand.

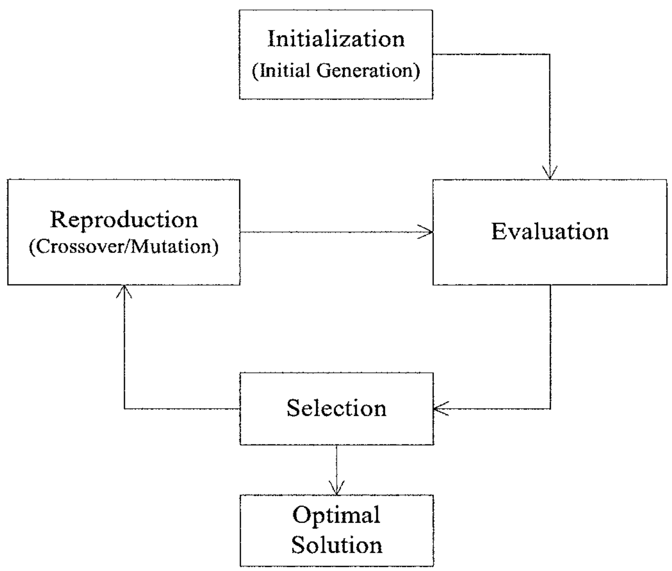

Figure 2-8 Schematic diagram of GA.

The Reproduction module carries out genetic operations (e.g. crossover, mutation) for generating new offspring. Crossover allows the exchange of genetic materials between two parent chromosomes. The purpose is to maintain the "fittest" genes while eliminating the worst one. Mutation changes a randomly chosen gene in a selected chromosome. It helps maintaining the diversity of the population and is especially important after several generations. Mutation introduces new genetic material in the population that facilitates the search process to escape from a trap of local optimum. Figure 2-9 shows the single-point crossover and mutation operations respectively. The occurrence of crossover or mutation is a random process while the probability of crossover is much higher than mutation. The Reproduction module repeatedly generates the offspring from the selected parents until the offspring's population size is the same as their parent's population size.

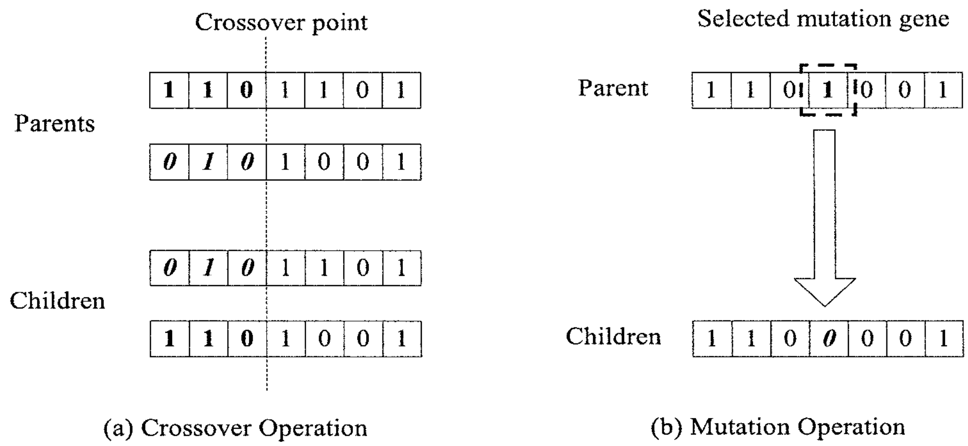

Figure 2-9 Crossover and mutation operations.

The Selection module selects the next generation population according to the fitness values of the parent and offspring populations. Based on the survival of the fittest law, only the "fittest" chromosomes are able to survive in the next generation and those "worst" chromosomes are being discarded. Steady-State-Without-Duplicates (SSWOD) [Goldberg 1989] is employed to discard chromosomes that are duplicates of current chromosomes in order to ensure a maximum usage of the population.

Fault diagnosis involves a global search through a space of possible fault candidates. GA is such a global searcher that performs large search spaces of complex systems without performing an exhaustive search [Goldberg 1989, Khoo *et al.* 2000]. In

Chapter 5, GA is used to search for fault candidates based on the QBG model of a dynamic physical system. More often, fuzzy systems and GA are integrated to complement each other [Cordón *et al.* 2003, Karr 1991, Thrift 1991]. GA is used to optimize the design of fuzzy systems and equip them with learning ability, whereas fuzzy systems provide GA with a structural framework with if-then rules to capture human knowledge and reasoning. Most applications of this hybrid technique are focused on the optimization of fuzzy logic controllers but seldom apply to the process supervision. In Chapter 4, the hybrid fuzzy-genetic algorithm is employed to perform process supervision. Fuzzy rule base is derived by GA which extracts knowledge describing the system behavior from the data sets.

2.6 Conclusions

In this chapter, a literature survey on various aspects for building an ISC has been presented. The scope of the ISC is first determined to include knowledge representation and acquisition, process supervision, and fault analysis (diagnosis). Then different approaches to perform the specified tasks are discussed. This chapter provides background material for the algorithms to be presented in later chapters. It should be reiterated that this survey has been selective and inevitably, some general references on these topics may have been omitted.

Chapter 3

Hybrid Simulation of Qualitative Bond Graph Model*

3.1 Introduction

Computer simulation provides a virtual environment for designers to see, test, and evaluate a product or a system before it is physically realized. As such, it has played a crucial role in understanding how systems work in all areas of science and engineering. Whereas most attention has been directed towards quantitative methods, the qualitative approaches have gained some popularity in the last decade. Qualitative simulation with traditional quantity space {[+], [0], [−], [?]} is often inaccurate and ambiguous, while quantitative simulation is often subjected to the difficulty in establishing a precise mathematical model. Motivated by shortcomings of qualitative and quantitative simulations, the author, in this chapter, proposes a hybrid qualitative and quantitative simulation algorithm for applications in the simulation of dynamic systems.

[Kuipers *et al.* 1988] proposed using quantitative knowledge in qualitative simulation in order to reduce the inherent ambiguity and computational time. The qualitative model adopted in their work was derived by inclusion of intuition in derivation of physical laws. In contrast, the author formulates the qualitative model schematically by qualitative bond graph (QBG). Bond graph methodology provides a systematic and formal way for modeling dynamic systems with different energy domains, such

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* Some of the result in this chapter has been published in papers 3, 15 and 18 on pages 8, 10 and 11 in this thesis.

as, electrical, hydraulic, mechanical, etc, in a unified framework [Karnopp *et al.* 2000]. Its integration with qualitative reasoning results a deep-level knowledge model that is suitable for fault diagnosis since the model indicates components' locations and their interactions. Instead of using a numeric interval to express a qualitative variable [Kuipers *et al.* 1988] or extending the qualitative space in fuzzy sets [Shen and Leitch 1993b], an exact numeric value is used to represent a qualitative variable. The proposed hybrid simulation approach is also different from [Mosterman and Biswas 2002] in the way that they are focused on the formalism of hybrid model rather than real-time system simulation. Their proposed hybrid model encompasses both discrete- and continuous-time behaviors' transition. The proposed hybrid simulation approach can be employed for system monitoring, supervision and on-line simulation which also is the main objective of the first phase of the studies reported in this thesis.

The chapter is organized as follows. In Section 3.2, the formalism of qualitative bond graph for modeling dynamic physical systems is presented. Section 3.3 presents the hybrid qualitative and quantitative simulation algorithm. The performance of the hybrid simulation algorithm is given and discussed in Sections 3.4 and 3.5 through simulation studies of linear and non-linear dynamic systems. Finally, conclusions are drawn in Section 3.6.

3.2 Qualitative Bond Graph Modeling

Bond graph theory was reviewed in Chapter 2. In this section, we focus on QBG formalism. When qualitative values {[+], [0], [−]} are used to represent the quantities of power variables (effort and flow) in bond graph formalism, the resulting modeling approach is termed qualitative bond graph (QBG) that is proposed by [Wang and Linkens, 1996]. Instead of generating state space or differential equations, a set of qualitative equations is derived from the QBG formalism. Simulation and analysis of the physical systems can be accomplished by these qualitative equations.

3.2.1 Qualitative Bond Graph Representations

Besides using qualitative values for representing the quantities of power variables, a set of qualitative operators should be defined to describe the qualitative behavior of bond graph primitives for mathematical consideration. The qualitative operators are drawn from the set {+, −, ×, /, =} which have the same definitions as standard operators for real numbers. The computation of qualitative values through these operators has been defined in many papers as has been discussed in Chapter 2. Throughout this thesis, the qualitative variables of effort, flow, resistance, capacitance, and inertial elements are represented by capital and italic letters E, F, R, C, I respectively. Qualitative representations of bond graph primitives are established with these symbols.

Based on the qualitative operators, Eqs. (2-2) to (2-6) can be converted to qualitative form. Clearly, the qualitative notion for R elements can be directly converted from its quantitative counterpart and becomes (where i represents the number of bond):

$$E_i = R \times F_i \tag{3-1}$$

Similar to R element, the qualitative representations of 1-junction and 0-junction can be directly obtained from their quantitative counterparts (Eqs. (2-5) and (2-6)). For the 1-junction, the equation will be:

$$\begin{aligned} E_{in\,1} + E_{in\,2} + \cdots + E_{inm} &= E_{out\,1} + E_{out\,2} + \cdots + E_{outn} \\ F_{in\,1} = F_{in\,2} = \cdots = F_{inm} &= F_{out\,1} = F_{out\,2} = \cdots = F_{outn} \end{aligned} \tag{3-2}$$

For the 0-junction, the equation will be:

$$\begin{aligned} F_{in\,1} + F_{in\,2} + \cdots + F_{inm} &= F_{out\,1} + F_{out\,2} + \cdots + F_{outn} \\ E_{in\,1} = E_{in\,2} = \cdots = E_{inm} &= E_{out\,1} = E_{out\,2} = \cdots = E_{outn} \end{aligned} \tag{3-3}$$

However, the qualitative representations of C and I elements are different from their quantitative forms. The equation of C elements in discrete form can be approximated from Eq. (2-2) as:

$$F_i(k \cdot \Delta t) = C \times \frac{[E_i(k \cdot \Delta t) - E_i((k-1)\Delta t)]}{\Delta t} \tag{3-4}$$

In a discrete-time representation (3-4), Δt is the sampling period and can be regarded as unity without loss of generality. The symbol k denotes a certain number of time steps while $(k-1)$ denotes the previous time step of k. The qualitative representation for C elements then becomes:

$$F_i(k) = C \times [E_i(k) - E_i(k-1)] \tag{3-5}$$

Similar reasoning, the qualitative representation of I elements is:

$$E_i(k) = I \times [F_i(k) - F_i(k-1)] \tag{3-6}$$

In real systems, the moduli a and b in Eqs. (2-3) and (2-4) are always positive. Therefore, they can be neglected in the qualitative forms. Thus, the qualitative descriptions for transformer (TF) and gyrator (GY) can be generalized as shown in Eqs. (3-7) and (3-8), respectively:

For TF: $E_{in} = E_{out}$, $F_{in} = F_{out}$ (3-7)

For GY: $E_{in} = F_{out}$, $F_{in} = E_{out}$ (3-8)

With the above qualitative representations of constitutive relations, a set of qualitative equations can be generated as will be discussed in the next Section. The parameters *R*, *C*, and *I* are not neglected in the representations because they will be employed to represent fault states for their corresponding in the later presented model-based fault diagnosis algorithm (Chapter 5). The following table summarizes the qualitative representations of bond graph primitives to be used in this thesis in order to model all dynamic physical systems.

Table 3-1 Summary of the qualitative bond graph primitives and their representations.

Primitive	Symbol	Qualitative Representation
Effort	E	-
Flow	F	-
Resistance	R	$E(k) = R \times F(k)$
Capacitance	C	$F(k) = C \times [E(k) - E(k\text{-}1)]$
Inertial	I	$E(k) = I \times [F(k) - F(k\text{-}1)]$
Transformer	TF	$E_{in}(k) = E_{out}(k)$, $F_{in}(k) = F_{out}(k)$
Gyrator	GY	$E_{in}(k) = F_{out}(k)$, $F_{in}(k) = E_{out}(k)$
1-Junction	-1-	$E_{in1} + \ldots + E_{inm} = E_{out1} + \ldots + E_{outn}$
(Serial)		$F_{in1} = \ldots = F_{inm} = F_{out1} = \ldots = F_{outn}$
0-Junction	-0-	$E_{in1} = \ldots = E_{inm} = E_{out1} = \ldots = E_{outn}$
(Parallel)		$F_{in1} + \ldots + F_{inm} = F_{out1} + \ldots + F_{outn}$

3.2.2 Qualitative Bond Graph Equations Generation

Typically, bond graph models are employed to generate differential equations, state space equations or block diagram for physical systems. Here, with QBG formalism, a set of qualitative equations describing the interaction of different elements and their energy transformations is produced. These equations connect constitutive element equations and contain structural, behavioral and functional information about a physical system. Since qualitative equations relate components' behaviors to the behaviors of the entire system, the interactions between components and their system can be analyzed. Hence, a deep-level knowledge model can be obtained by using the QBG formalism.

A schematic procedure is developed in [Wang and Linkens 1996] to guarantee the completeness for generating the qualitative equations from a bond graph model. Using QBG notion, qualitative equations for the coupled-tank system shown in Figure 3-1 are formulated as follows:

$$
\begin{array}{ll}
F_1 = F_2 + F_3, & E_1 = E_2 = E_3 \\
F_2(t) = C_1 \times (E_2(t) - E_2\,(t-1)), & E_3 = E_4 + E_5 \\
F_3 = F_4 = F_5, & E_4 = R_{12} \times F_4 \\
E_5 = E_6 = E_7, & F_5 = F_6 + F_7 \\
F_6(t) = C_2 \times (E_6(t) - E_6(t-1)), & E_7 = R_{out} \times F_7
\end{array}
\qquad (3\text{-}9)
$$

All the power variables are considered at time t unless specified. Each passive element, like, R and C, will contribute one equation. For junction elements, two equations will be generated, one describing efforts property while the other relating flows property. In this subsection, only a brief account on qualitative equation generation is given and details can be found in [Wang and Linkens 1996].

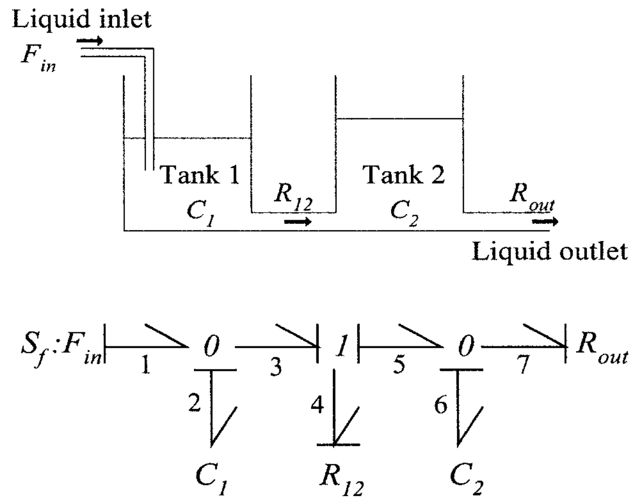


Figure 3-1 Coupled-tank system and its bond graph.

3.2.3 Deep-Level Knowledge Representation

So far the qualitative bond graph representation and a way to generate qualitative equations from the physical structure of a system have been treated. In this subsection, how the qualitative equations represent deep-level knowledge will be presented.

Bond-1 does not receive energy from any other junctions since variables E_1 and F_1 in Eq. (3-9) do not appear on the right hand side of the operator "=". In other words, energy is fed into the system from bond-1. Next, energy is distributed to bond-2 and bond-3 via a common-effort (-0-) junction. Then, part of the energy is stored by the element C_1 and some of it is distributed to other elements through the common-flow (-1-) junction. Furthermore, the input flow F_1 is branched to F_2 and F_3 flows where F_2 and F_3 are passed through a lag component via C_1 and R_{12} respectively. This describes the structural information about the coupled-tank system illustrated in Figure 3-1 and shows that the qualitative equations indicate the components' locations and their interactions.

If we would like to increase the liquid level in Tank 2 (E_6) without changing any value of system components, then, from Eq. (3-9), the flow to the Tank 2 (F_6) should be increased since $E_6(t)$ is now larger than $E_6(t-1)$. Hence, the flows F_5 and F_3 should also be increased. Finally, the input flow F_1 should be increased with increasing F_3. Thus, if we want to increase the liquid level in Tank 2, we must increase the input flow to the system. Here, the qualitative equations provide the conceptual function of the entire system in terms of the individual functions of its components and junctions.

Next, let us assume the pressure of Tank 2 (E_6) is decreasing, with $E_6(t) < E_6(t-1)$. Hence, the flow of the tank 2 (F_6) is negative and the output flow of R_{out} (F_7) is larger than the output flow of R_{12} (F_5). If we keep the pressure of Tank 2 constant, the effort E_6 will be constant ($E_6(t) = E_6(t-1)$). Thus, the flow F_6 is zero, and the output flow F_7 is equal to the output flow F_5. Following this inference route, it can be demonstrated that the output flow F_7 will be smaller than the output flow F_5 when the pressure of Tank 2 is increasing. Besides, we see that the flow F_6 depends on the component C_2. Hence, the value of C_2 will affect the flow difference between F_5 and F_7. This inference mechanism can be extended to the entire system to reason about system behaviors. The qualitative equations here provide a formal representation for reasoning about the relationships between the system components' behaviors and the system behavior.

From the above description for the construction of deep-level knowledge models, the

QBG representation provides an effective systematic method, which is suitable to build the knowledge base of the intelligent supervisory coordinator (Chapter 6).

3.3 Hybrid Qualitative and Quantitative Simulation

Simulation predicts the dynamic behaviors of a physical system and provides a means to system monitoring or supervision [Aguilar-Martin 1994, Sohlberg 1998, Vinson and Ungar, 1995]. Traditionally, quantitative information is used to establish a precise mathematical model that best described the physical system at hand. However, the difficulties to obtain a precise mathematical model and accurate numerical information from physical systems impair the accuracy and effectiveness of quantitative simulation. In this circumstance, qualitative simulation seems to be useful because it possesses the ability to infer results from incomplete and weak numerical information.

Kuiper's *QSim* [Kuipers 1986 and 1994] is a formal algorithm utilizing qualitative information to do simulation. Qualitative differential equations (QDE*s*) derived from system structure act as constraints that govern the inference process for predicting qualitative states. However, ambiguous and spurious states are also inferred together with the actual states for any real system since traditional qualitative space {[+], [0], [−]} lack of ordinal information. An extended version of *QSim* named *Q2* is then proposed [Kuipers and Berleant 1988] which introduces numeric interval to each qualitative state and eliminates some of the ambiguities by filtering out impossible qualitative states (spurious states). Based on step size refinement technique, *Q*3 is employed to replace *Q2* in order to refine a qualitative simulation progressively by providing increasingly specific quantitative information [Berleant and Kuipers 1997].

However, computational burden is also increased.

Qualitative simulation of physical systems is often inaccurate and ambiguous, while quantitative simulation is often subjected to the difficulty in establishing a precise mathematical model. Shortcomings of both simulations motivate the development of a hybrid qualitative and quantitative simulation that presents the strengths of both.

In this section, the development of the proposed hybrid qualitative and quantitative simulation algorithm is presented. The simulation model of a physical system is formulated by the QBG methodology as previously mentioned.

3.3.1 Implementation

The set of qualitative equations derived from QBG semantic (in Section 3.3.1) contains many internal states that are necessary for high-level reasoning, such as fault diagnosis; but not required for predicting system behaviors. For simulation purpose, this set of qualitative equations requires simplification to describe directly the relationship between system inputs and outputs. According to this simplified input-output equation, many ambiguous states can be avoided during the prediction of system behaviors.

A generic procedure for simplifying the set of qualitative equations is developed by [Wang and Linkens 1996]. The input and output variables from the qualitative equations are first identified. Numeric information about system parameters can be inserted into the qualitative equations if available. By repetitive substitution and replacement of equations that either input or output variable is not presented, a simplified input-output qualitative equation can be obtained. Since the simplified qualitative equation will not infer the internal states of a system, the computational burden is alleviated so that on-line simulation becomes possible.

Let us take the coupled-tank system in Section 3.3.1 as an illustration. From Figure 3-1 and Eq. (3-9), taking F_1 as the input variable representing input flow rate (F_{in}) and E_6 as the output variable representing the liquid level in Tank 2 (since the liquid level in a tank is a function of pressure), the set of qualitative equations in Eq. (3-9) can be simplified to,

$$\begin{aligned} F_1(t) &= (C_1 + C_2 + C_1C_2R_{12} + \frac{C_1R_{12}}{R_{out}} + \frac{1}{R_{out}})E_6(t) \\ &\quad - (C_1 + C_2 + 2C_1C_2R_{12} + \frac{C_1R_{12}}{R_{out}})E_6(t-1) \\ &\quad + (C_1C_2R_{12})E_6(t-2) \end{aligned} \tag{3-10}$$

If system parameters of the coupled-tank system are of interest, they can be retained in the simplified qualitative equation. The simplified equation describes the relationship between input and output variables and is in discrete form, on-line prediction of system behaviors can be achieved once the state of input and interested system parameters are given.

The simplified qualitative equation developed above represents the relations between interested system parameters, input and output variables, which is suitable for predicting system behaviors. Instead of using qualitative values, quantitative information about system inputs and system parameters (if any) are used to do simulation. This hybrid qualitative and quantitative simulation of dynamic systems improves the accuracy of the predicted behaviors and reduces the computational burden. Figure 3-2 shows an overview of the proposed hybrid qualitative and quantitative simulation algorithm.

A dynamic system is first modeled by bond graph. From the bond graph model, a set of qualitative equations can be formulated and then simplified into an input-output qualitative equation as mentioned before. Hybrid simulation can be conducted once quantitative information, such as, system parameters, system input(s) and time step, are inserted to the simplified qualitative equation.

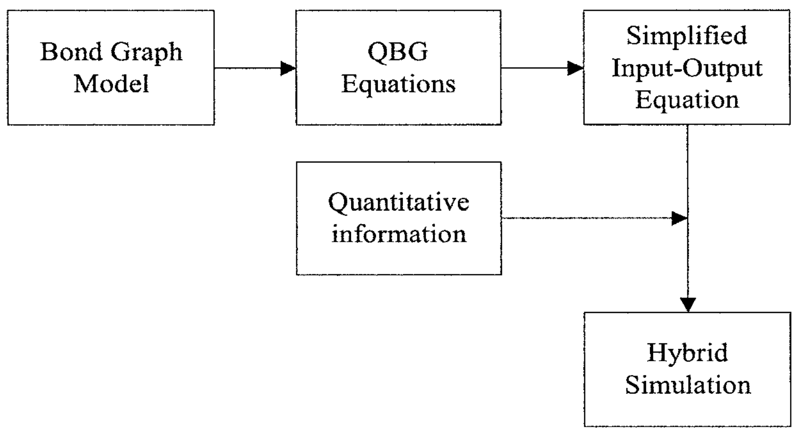


Figure 3-2 Overview of the hybrid qualitative and quantitative simulation algorithm.

3.4 Simulation Analysis

The effectiveness of the proposed hybrid qualitative and quantitative simulation can be demonstrated through the following linear and non-linear systems simulation:

- Coupled-tank system (SISO) with varying R_{out} value at 1200s.
- Mass-Spring-Damper system (MISO).
- Quarter car active suspension system (MIMO) with noise.

Figure 3-1 shows the coupled-tank system and its bond graph. The simplified input-output qualitative equation is described in Eq. (3-10) and the system is assumed to be linear. The input flow rate F_1 is the system input and is shown in Figure 3-3. System output is the liquid level in Tank 2 (E_6). Comparison of conventional simulation and the proposed hybrid simulation of the coupled-tank system with square input flow rate is shown in Figure 3-4 (upper half). In this thesis, conventional simulation stands for numerical simulation of differential equations and assumes to be the actual system response. The value of R_{out} is increased to twice at 1200s and the time step for the simulation is 0.1s. The difference between conventional and hybrid simulation is also shown in Figure 3-4 (lower half).

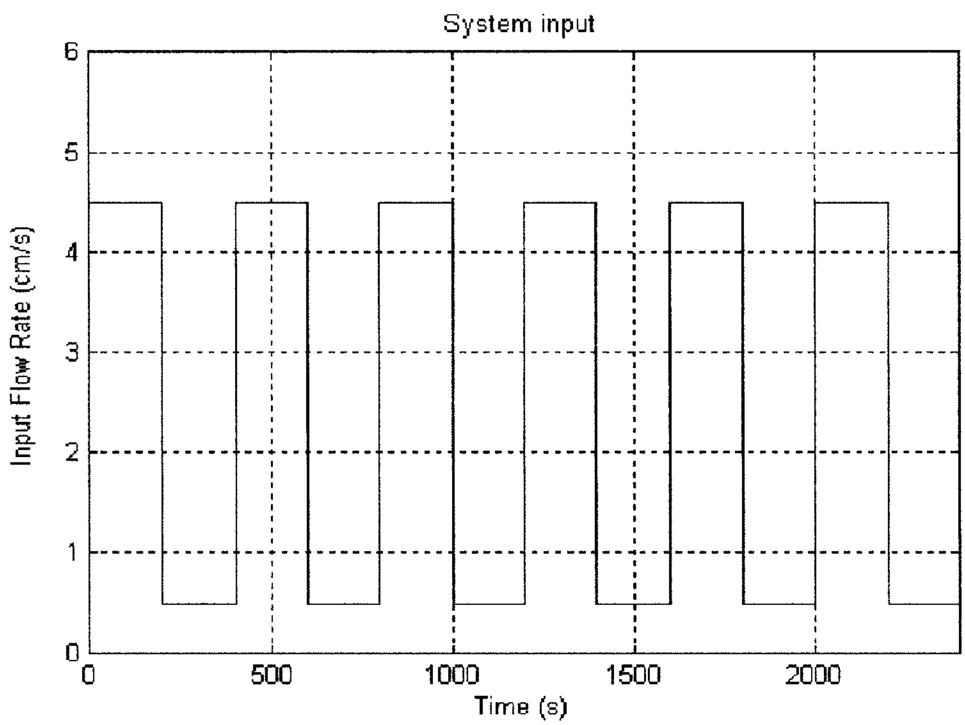


Figure 3-3 System input of the coupled-tank system.

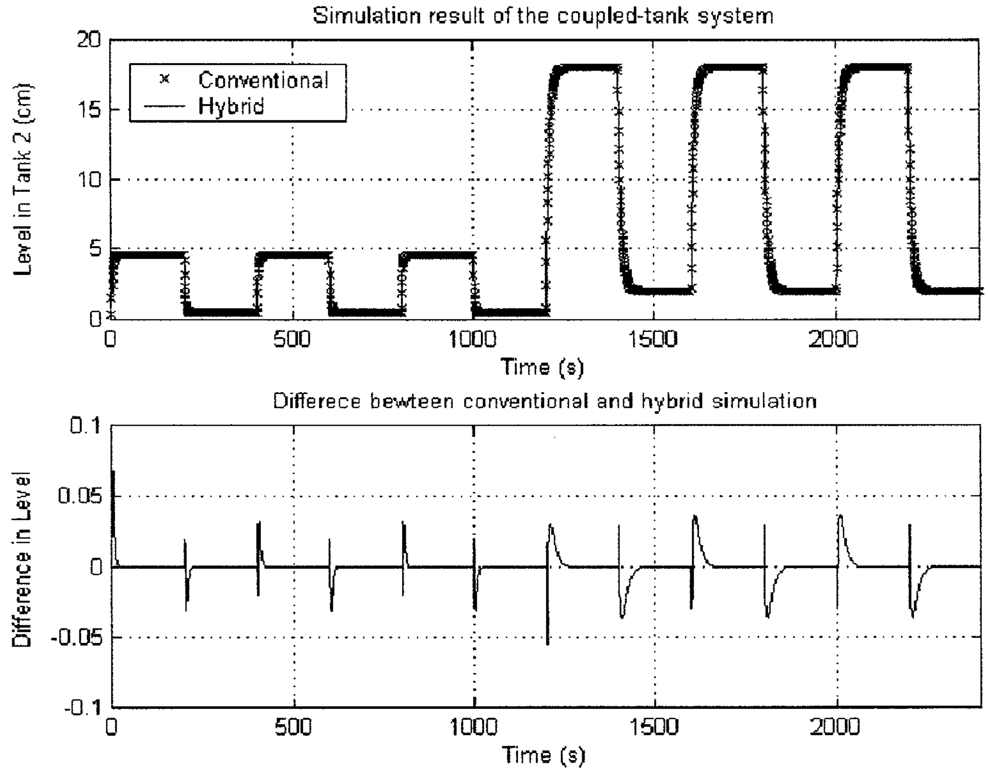
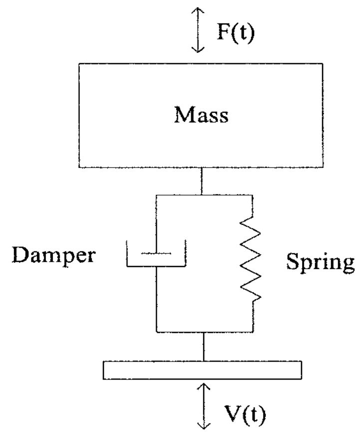


Figure 3-4 Conventional and hybrid simulations of coupled-tank system (SISO) and their difference.

The second system is a linear mass-spring-damper mechanical system (MISO) that is shown in Figure 3-5. The system inputs are the force on mass ($F(t)$), E_1, and the velocity ($V(t)$), F_5 and the system output is the force on the spring, E_6. The simplified input-output qualitative equation describing the system is given in Eq. (3-11). System inputs (E_1 and F_5) are shown in Figure 3-6. Comparison of conventional and hybrid simulations of the mass-spring-damper system with time step of 0.01s is shown in Figure 3-7 (upper half). The difference between conventional and hybrid simulation is also shown in Figure 3-7 (lower half).

$$(1+RC+CI)E_6(t) = I(F_5(t)-F_5(t-1)) - E_1 + (2CI+RC)E_6(t-1) - (CI)E_6(t-2) \tag{3-11}$$



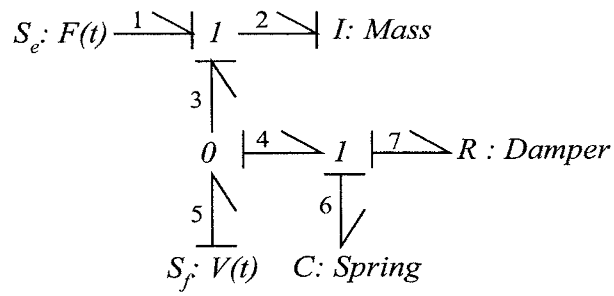


Figure 3-5 The mass-spring-damper system and its bond graph.

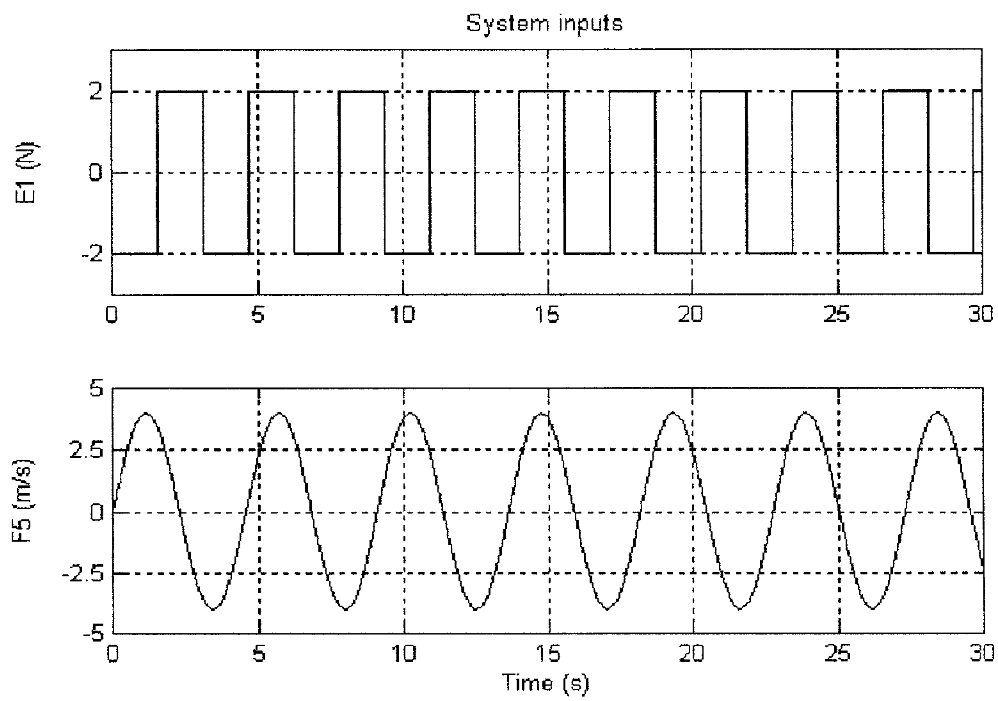


Figure 3-6 System inputs of the mass-spring-damper system.

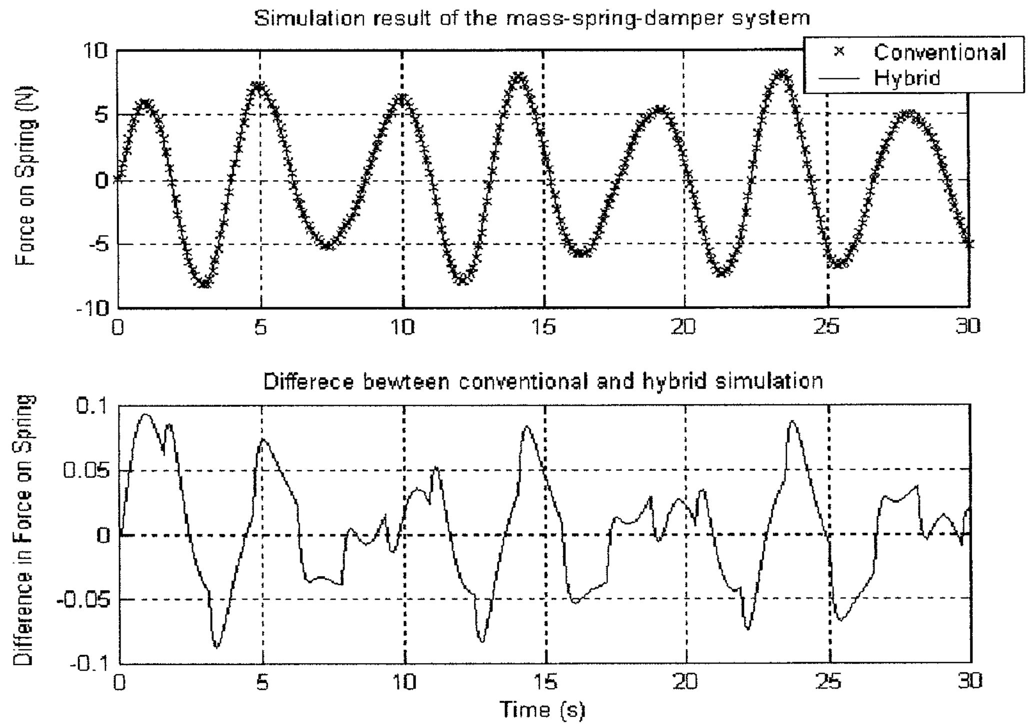


Figure 3-7 Conventional and hybrid simulations of mass-spring-damper system (MISO) and their difference.

Finally, the effectiveness of the proposed hybrid simulation is demonstrated through simulation of a non-linear quarter car active suspension system (MIMO) [Jamei *et al.* 2001]. The quarter car model (Figure 3-8) consists of a sprung mass (M_s) supported on a suspension system, which has suspension spring rate (K_s), damper coefficient (B_s) and an actuator (S_e). The suspension system is connected to the unsprung mass (M_{us}) and the tire is modeled by a spring (K_t) and a damper (B_t). The non-linearity of the system comes from the damper element (B_s) in the suspension system which is a function of its velocity and taken different values during the rebound and jounce processes. The system inputs are the road profile (F_1) and the actuator force (E_{10}) which are shown in Figure 3-9; and the system outputs are the body acceleration ($\dot{F}_8$)

and damper displacement ($E_{11}*C_2$). Figure 3-10 compares the conventional and hybrid simulation of the quarter car system; and Figure 3-11 shows their difference.

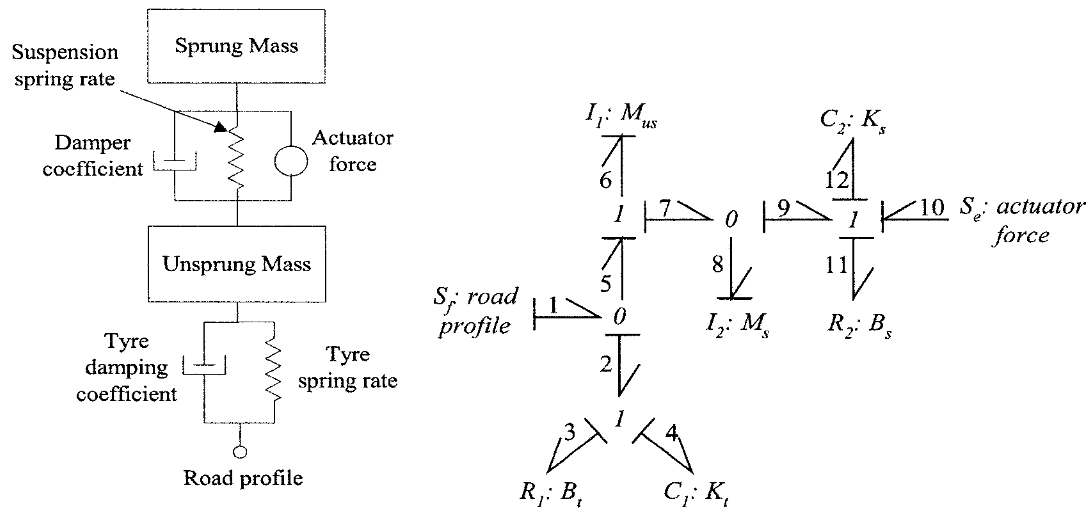


Figure 3-8 The quarter car active suspension system and its bond graph.

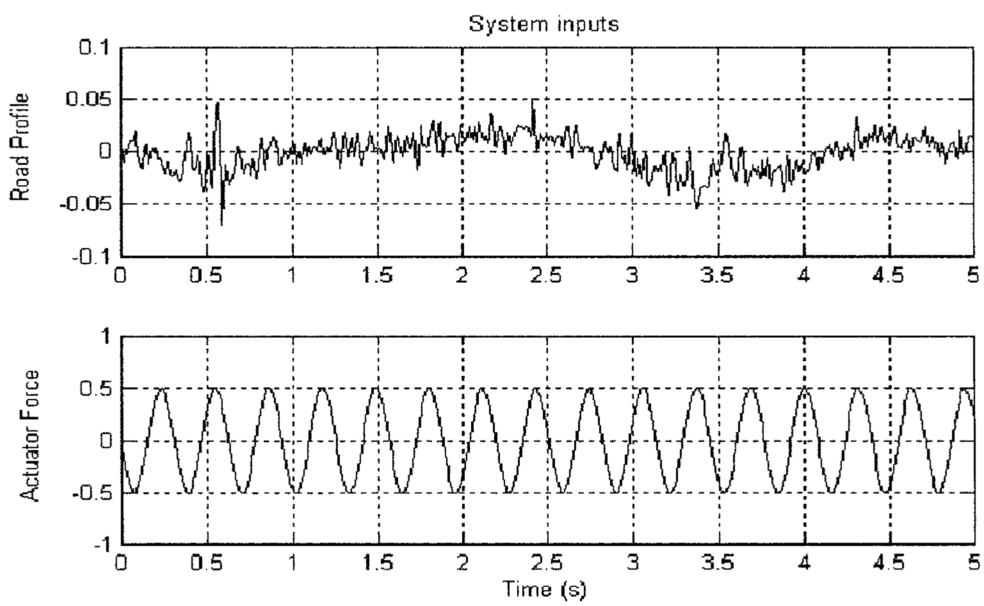


Figure 3-9 System inputs of the quarter car active suspension system.

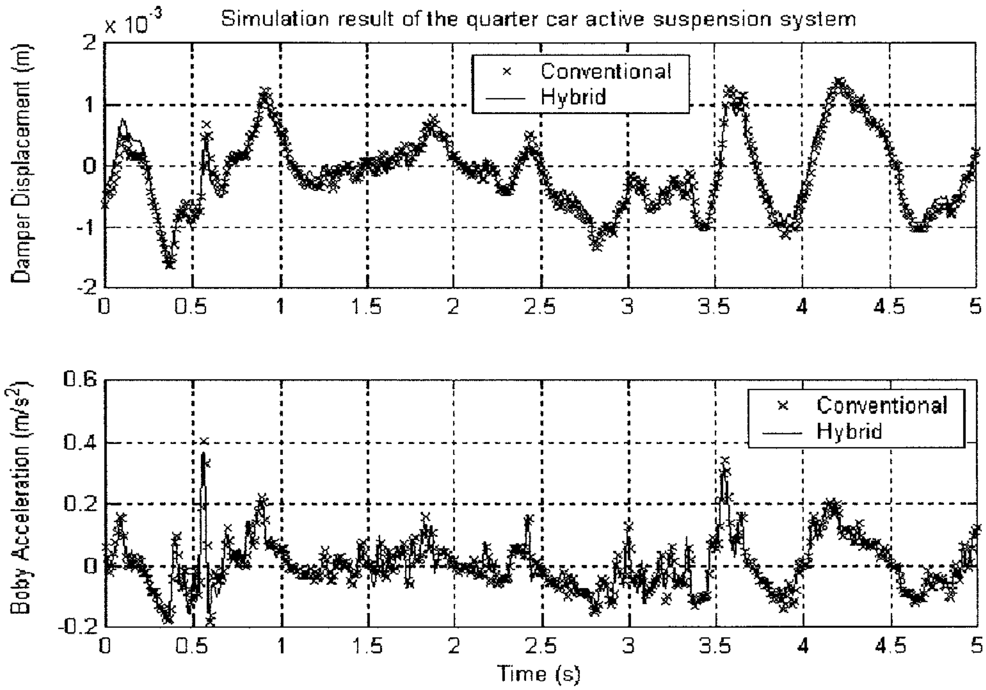


Figure 3-10 Conventional and hybrid simulations of non-linear quarter car active suspension system (MIMO).

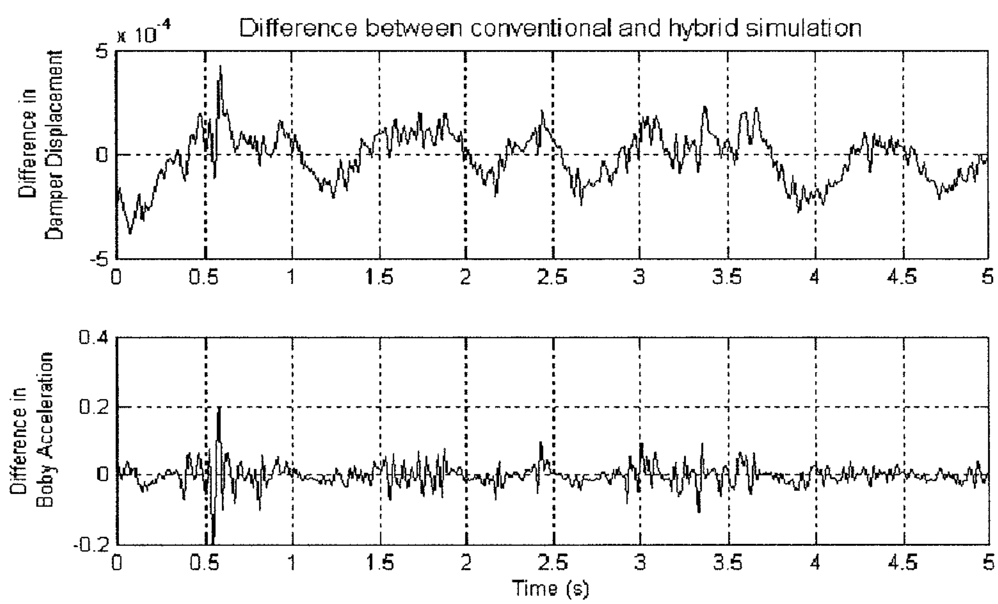


Figure 3-11 Difference between conventional and hybrid simulation for the car suspension system.

3.5 Discussions

The above simulation results demonstrate the effectiveness of the proposed hybrid qualitative and quantitative simulation. The proposed hybrid simulation performs well and its performance is comparable to conventional simulation with small difference in both linear (SISO, MISO) and non-linear (MIMO) systems. Unlike qualitative simulation, the proposed hybrid simulation generates a unique behavior at one time point instead of generating tree-like behaviors. Hence, the accuracy and speed of the simulation is enhanced and the filtering of spurious behaviors is avoided. Conventional simulation techniques require a precise mathematical model that describes the dynamic behaviors of a system in differential equations. The derivation of these differential equations is non-trivial, time-consuming, and sometimes impossible. Fusion of bond graph theory and qualitative reasoning to generate system model for simulation is shown to be feasible and provided an alternative to mathematical model.

There is an obvious difference between conventional and hybrid simulation around the inflection points. This can be shown in Figure 3-4 (lower half) for the coupled-tank system. When the input flow rate is changed, the difference between conventional simulation and hybrid simulation is varied from steady. This is due to the qualitative representation of C and I elements which possess a very coarse time step, assumed to be one second. Improved simulation can be obtained by time step refinement that means reducing the step size, for example, from 1s to 0.1s. Figure 3-12 shows the relationship between simulation accuracy and time step for the mass-spring-damper system. Simulation accuracy is computed as the inverse of the integral absolute difference between conventional and hybrid predicted results.

Similar observation can be found for the other two systems. Since more distinct states can be predicted at the inflection point when small time step is used, the accuracy of the hybrid simulation is improved. The improvement to the accuracy of hybrid simulation becomes steady even with further reduction in time step.

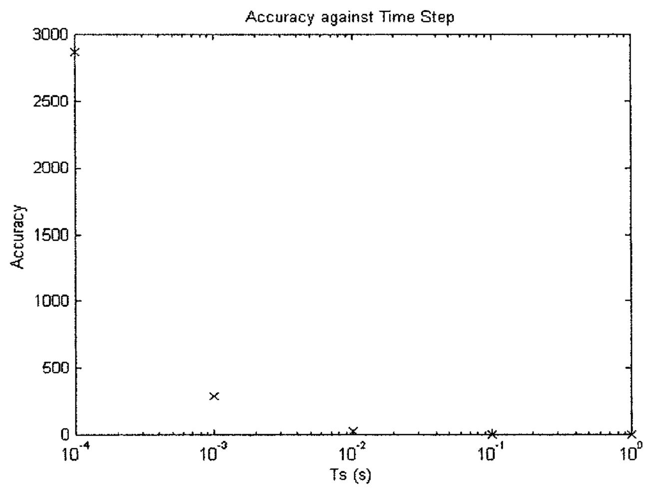


Figure 3-12 The relationship between simulation accuracy and time step for the mass-spring-damper system.

Using a small time-step can improve the accuracy of the hybrid simulation with the expense of increasing the computational time. Figure 3-13 shows the relationship between simulation accuracy and computational time (CPU time) for the mass-spring-damper system. Similar observations can also be found for the other two systems. In this thesis, the computational time is measured as CPU time in second that is required to complete the hybrid simulation at specified simulation time. Since more states are predicted with small time-step, the computational time required to perform the simulation will then be increased. Depending on the application of the hybrid simulation, the performance of the simulation will be in favor of accuracy, speed or both. Since the hybrid simulation algorithm will not predict spurious states, the consistency of the simulation algorithm can be achieved. Accurate dynamic behaviors of a system can be predicted through hybrid simulation with different input signals which ensures the completeness of the algorithm.

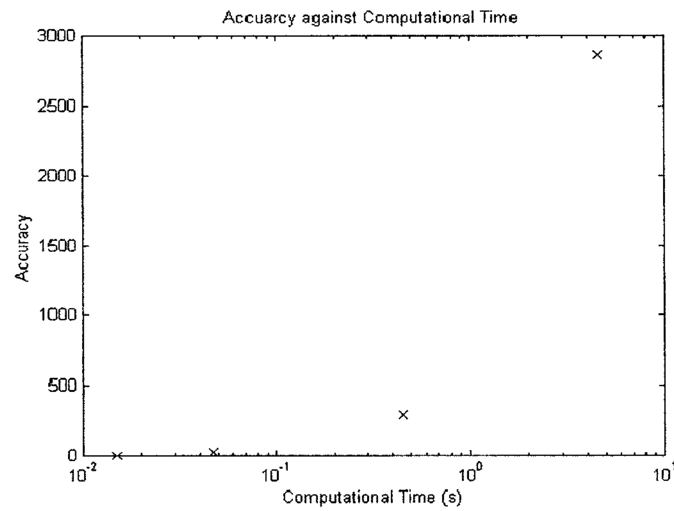


Figure 3-13 The relationship between simulation accuracy and computational time (CPU time) for the mass-spring-damper system.

3.6 Conclusions

In this chapter, the author has presented a novel hybrid qualitative and quantitative simulation algorithm for predicting behaviors of dynamic systems. The feasibility and effectiveness of the proposed hybrid simulation is demonstrated through simulation studies of both linear and non-linear systems. Qualitative bond graph theory is adopted as the modeling language to formulate the model used in the hybrid simulation. For system inputs, quantitative information is employed, and numerical data instead of qualitative values is applied in order to improve the accuracy and speed of the simulation. From simulation results, the proposed hybrid simulation algorithm ensures the completeness and consistency of the predicted system behaviors and allows for on-line simulations.

The chapter reported the first phase of this research project. The next chapter begins the second phase of this thesis, which focuses on the development of an automatic fault detection and diagnosis algorithm based on the qualitative model developed in this chapter.

Chapter 4

Automatic Fault Detection*

4.1 Introduction

Detecting fault before it deteriorates the system performance is imperative for the reliability and safety of all engineering systems. Fault detection is usually initiated with the so-called residual generation through which a signal or symptom (termed as residuals, r) is produced that reflects the faults. Next, a residual evaluation assesses the nature of the event and labels the state of process as faulty or otherwise. In case of fault detection, an alarm is triggered when the residual surpasses a predefined limit (threshold). Traditionally, residual generation is conducted by a mathematical model that describes the normal operation of the system [Frank 1996, Gertler 1998, Patton *et al.* 2000]. Many engineering systems are complicated and non-linear and it is rather difficult to derive mathematical models for such systems. Without accurate and reliable mathematical model, the chance of false alarms is increased. Constant threshold evaluation strategy is one possible solution but it is generally unreliable and inflexible [Quek and Wahab 2000]. Adaptive threshold evaluation strategy was proposed to improve the constant threshold counterpart [Ding and Frank 1991, Emami *et al.* 1988, Patton *et al.* 1989]. However, it only overcomes the problem to a certain extent and with great effort.

Traditional approaches to fault detection suffer from the fact that under real

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* This chapter is based on the papers 4, 5 and 19 on pages 9 and 11in this thesis.

situations, no accurate mathematical model of a system is available. Knowledge-based techniques [Frank 1996] become a suitable strategy towards automatic fault detection (AFD) to address drawbacks of threshold test methods. Fuzzy logic is among the knowledge-based techniques to address the fault detection problem. Several researchers [Isermann 1998, Kiupel and Frank 1993, Sauter *et al.* 1993, Schneider 1993] have proposed fault detection and diagnosis approaches based on fuzzy systems. Fuzzy systems are rule-based approaches where the rules are usually learned from experts or prior knowledge of the system. The process of fault detection can be seen as a classification problem and hence the fuzzy system acts as a classifier to distinguish different system behaviors according to its rules. The success of the fault detection process hence depends on the accuracy of the fuzzy rules.

Typically, fuzzy rules are generated by intuition and expert's knowledge. However, for complex systems, the derivation of fuzzy rules is tedious and inaccurate. Researchers have continuously tried to find efficient and effective methods to generate these fuzzy rules. Neural networks have been proposed to solve the problem but they are suitable in building fuzzy systems with relatively small number of numerical variables. The trapping of local optimal in the learning process is a weakness of using neural networks [Yuan and Zhuang 1996]. Genetic algorithms (GA) has also been proposed to optimize the fuzzy rule table which finds many control applications [Karr 1991, Thrift 1991], such as pH control, level control, etc.

In this chapter, a fuzzy-genetic algorithm (FGA) is proposed to construct the automatic fault detection (AFD) system for monitoring dynamic system behaviors. Residual is computed as the difference between observed process outputs (y) and predicted normal system outputs ($\hat{y}$), which is predicted through hybrid simulation (Chapter 3). A fuzzy system is then employed to evaluate the residual and determine the process state as normal, malfunction, under load disturbance or faulty. Genetic algorithms (GA) are used to generate an optimal fuzzy rule set based on the training data. Fitness function in GA is evaluated by fuzzy system. Once an optimal fuzzy rule set and system inputs are available, different system states of a dynamic system can be classified. The Fuzzy-Genetic Algorithm-based Automatic Fault Detection (FGA-AFD) system is more flexible, efficient, and accurate than the threshold test method since the effects of noise and measurement inaccuracies can be alleviated by fuzzy system.

This and the next chapters address the second phase of this project on model-based fault detection and diagnosis. The focus of this chapter is on the fault detection based on the simplified input-output qualitative equation derived from QBG pragmatism (Chapter 3). In Chapter 5, the attention will be devoted to a model-based fault diagnosis algorithm. These two chapters collectively address the design of an Intelligent Supervisory Coordinator (ISC) which constitute the second phase of the thesis.

The chapter is organized as follows: Section 4.2 introduces different system behaviors to be classified by the FGA-AFD system. In Section 4.3, the architecture of the FGA-AFD system is presented. Experimental results on a laboratory scale servo-tank liquid process rig will be given and discussed in Section 4.4, and finally, the conclusions are drawn in Section 4.5.

4.2 Behavioral Classification

In the past decades, most research works [de Kleer and Williams 1987, Hamscher *et al.* 1992] were aimed at detecting and diagnosing faults for discrete systems, such as, finite state machines, digital circuits, etc. Little work is reported on the continuous dynamic systems. For discrete systems, the definition of "faulty behavior" is straightforward: either the system is working correctly or not. However, the condition of "faulty behavior" for continuous dynamic systems is not easy to define. For example, a condition known as "intermediate behavior" that cannot be classified as either "normal" or "faulty", may exist during the transition from a "normal behavior" to a "faulty behavior". This "intermediate behavior" may be caused by the degradation of the system, i.e. due to the wear and tear of system components that drift the system behavior away from the optimal but still can be corrected by re-tuning the controller. Load disturbance is another possible cause provided that the specified set point can be attained again by the controller.

When a continuous dynamic system produces behaviors that meet the specified performance criteria under normal operating conditions, these behaviors are termed as acceptable or normal behaviors. Those behaviors that do not fulfill the performance specifications will be termed unacceptable behaviors. Unacceptable behaviors are the result of a poorly designed controller, an insufficient and incomplete model, or the characteristics of the physical system and controller are varied in an unanticipated way. These possibilities show that there will be a lack of knowledge about the physical system during the modeling stage (e.g. operating temperature or voltage limit) or insufficient design effort is endeavored. Unexpected external disturbances on a system is a further cause of an unacceptable behavior

[Leitch and Quek 1991].

It is possible to define three categories from unacceptable behavior namely, malfunction, load disturbance and faulty behavior. If the performance of a physical system is deviated from the specified performance criteria, the system is classified as exhibiting malfunction behavior. Malfunction behavior is usually caused by drifting of system parameter values from their nominal ranges during the operational lifetime. This may be due to the components' aging or degradation of the physical system. The system may be brought back to within the acceptable/normal region via "redesigning" or "re-tuning" the existing controller. Load disturbance behavior is used to describe a system under load disturbances. The controller is able to maintain system output to the specified set point both before and after load disturbances. For both behaviors, there is no structural change to the physical system. As malfunction and load disturbance behaviors are neither normal nor faulty behaviors, they can be further classified as the "intermediate behavior". Further degradation of physical system or drastic change of parameter values may force the controller to fail, and thus, the system is considered to exhibit faulty behavior. Permanent structural changes (e.g. blocked pipe or a liquid tank bursting) are additional causes of the faulty behavior.

In this section, four system behaviors are considered for continuous dynamic systems: normal, malfunction, load disturbance and faulty. Table 4-1 summarizes the four system behaviors and their causes. Hence, the AFD system is functioning as a classifier in order to distinguish these behaviors. Once the system behavior is classified as faulty, the model-based fault diagnosis (Chapter 5) module will be activated to infer fault candidates that explain the faulty behavior.

Table 4-1 Summary of the four detectable system behaviors and their causes.

Behaviors			Causes
Acceptable (Normal)			meets specified performance criteria
Unacceptable	Intermediate	Malfunction	components' aging or un-tuned controller
		Load Disturbance	load disturbances applied to the system
	Faulty		further degradation of system or faulty components, e.g. blocked pipe, a tank bursting

4.3 Fuzzy-Genetic Algorithm for Automatic Fault Detection

In this section, an automatic fault detection system based on the fuzzy-genetic algorithm is proposed to monitor continuously the behavior of a dynamic system. The resulting fuzzy-genetic algorithm-based automatic fault detection (FGA-AFD) system is capable of distinguishing the four types of system behaviors (Section 4.2) accurately and efficiently. The effects of modeling error, system noise and measurement inaccuracies can be alleviated compare to other analytical fault detection methods [Frank 1996, Gertler 1998].

4.3.1 Overview of the Automatic Fault Detection System

The block diagram illustrated in Figure 4-1 shows the configuration of the proposed FGA-AFD system. The FGA-AFD system consists of a fuzzy evaluation system (FES) and residual generation block. The hybrid simulation algorithm developed in

Chapter 3 predicts normal system behaviors from the QBG model. Residual (r) is computed as the difference between observed process outputs (y) and predicted normal system outputs ($\hat{y}$) in the residual generation block. System error (e), reference input (y_r), control action (u) and residual are used to infer system behaviors in the fuzzy evaluation system (FES) according to its fuzzy rule table that is optimized by GA. As discussed in Section 4.2, the FES is capable of classifying four different system behaviors namely, normal, malfunction, load disturbance and faulty behaviors.

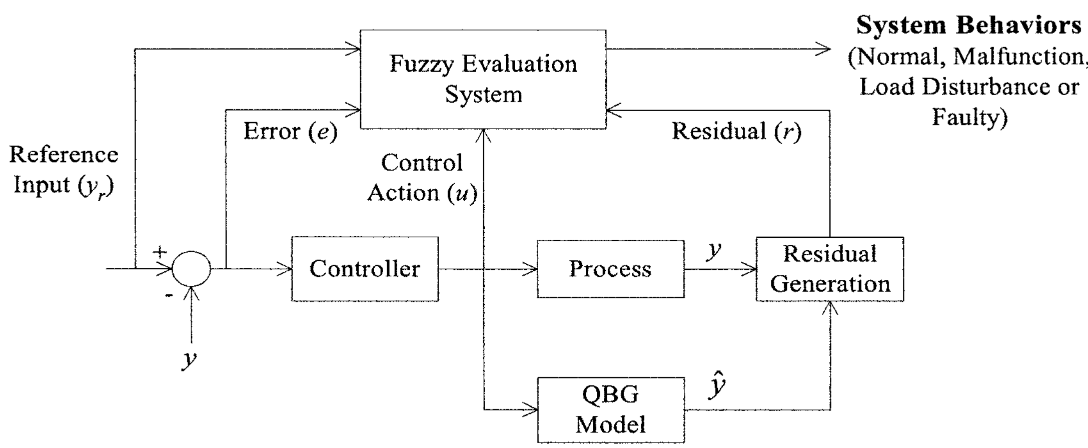


Figure 4-1 Configuration of the FGA-AFD system.

The FGA provides an alternative method to generate fuzzy rule table in an accurate and efficient fashion. It takes care of vague and imprecise input data by using the advantage of fuzzy logic. The selection of fuzzy rule table by GA is an off-line process. Once the rule table is optimized, the fuzzy system is ready to perform continuous monitoring of the dynamic physical system. Hence, the proposed FGA-AFD system optimizes the fuzzy rule table off-line, while performs on-line fault detection.

4.3.2 Fuzzy Evaluation System (FES)

The fuzzy evaluation system (FES) is a logic decision-making process that transforms quantitative knowledge into qualitative conclusions (e.g. normal or faulty behavior, etc). It can also be interpreted as a classification problem that distinguishes different system behaviors from residuals and auxiliary measurements (such as, error, control action and reference input). FES provides a flexible and accurate way to effect fault detection since no prior knowledge about the causes of faults is required. Additionally, the rate of false detection (or alarm) is lower than crisp threshold detection system since the effects of modeling uncertainty and measurement noise to the AFD system is alleviated by FES.

The FES consists of three steps as illustrated in Figure 4-2. Firstly, the residuals and auxiliary measurements are fuzzified, and then they are evaluated by an inference mechanism using fuzzy **IF-THEN** rules. Finally, fuzzy results are defuzzified to a crisp system behavior.

a. Fuzzification

The fuzzification of residuals and auxiliary measurements is the mapping from real-valued quantities to fuzzy sets. According to Wang [1997], there are three design criteria for the fuzzification process. First, the fuzzy set should have large membership value at the crisp point of the variable. Second, if the fuzzy system is corrupted by noise, then it is desirable to surpass the noise during fuzzification.

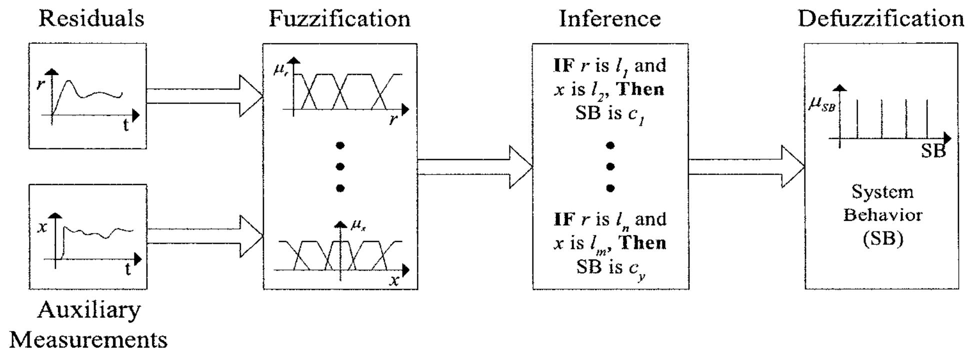


Figure 4-2 General scheme of the FES.

Finally, fuzzification should help simplify the computations involved in the fuzzy inference mechanism. In this chapter, trapezoidal fuzzy sets are used to fuzzify the residuals and auxiliary measurements. The supports of the trapezoidal fuzzy sets help to surpass noise and the plateau provides the largest membership value of a variable at its crisp point. The computations involved in the fuzzy inference mechanism is similar to other fuzzy sets such as the triangular fuzzy sets.

Another consideration to the fuzzification is the definition of fuzzy-membership functions. The definition of fuzzy-membership functions can be assigned on the basis of heuristic process knowledge or statistical distribution functions or by learning with the aid of neural nets or GA.

b. Inference Mechanism

The task of the FES is to infer system behavior of the set ***SB*** of four possible system behaviors (Section 4.2) from residual and auxiliary measurements (e.g. u, e, y_r). In our FES, the residual (r), control action (u) and error (e) are defined by their fuzzy sets $\boldsymbol{R_k}$, $\boldsymbol{U_m}$ and $\boldsymbol{E_n}$, respectively, and the relationships between them and system behavior are given by **IF-THEN** rules. For example, the i^{th} fuzzy rule (Ru^i) in a fuzzy rule table (with L fuzzy rules) can be written in the form:

$$Ru^i\text{: } \textbf{IF } (u \textit{ is } \boldsymbol{U_m}) \textbf{ AND } (e \textit{ is } \boldsymbol{E_n}) \textbf{ AND } (r \textit{ is } \boldsymbol{R_k}), \quad \text{(4-1)}$$

$$\textbf{THEN } (\text{System Behavior } \textit{is } \boldsymbol{SB_a}).$$

An output fuzzy set is determined from each rule in the fuzzy rule table and the fuzzy output of the FES is the aggregation of L individual fuzzy sets. There are different aggregation (or inference) methods (e.g. max-min, max-product, etc) [Ross 1995] in order to complete this task.

c. *Defuzzification*

Finally, the fuzzy output of system behavior from FES has to be converted into crisp sets (normal, malfunction, load disturbance or faulty). Many defuzzification methods are known from the literature [Ross 1995, Wang 1997]. In our FES, center-of-average (Eq. (4-2)) defuzzification technique is adopted to obtain the crisp system behavior. This technique is the most commonly used in fuzzy systems and fuzzy control. It is computational simple and intuitively plausible.

$$\text{System Behavior} = \frac{\sum_{i=1}^{L} \boldsymbol{SB}_i \cdot \mu_i}{\sum_{i=1}^{L} \mu_i} \quad \text{(4-2)}$$

,where μ is the degree of membership of ***SB***. Singleton fuzzy membership functions of the system behaviors are used in the FGA-AFD system as illustrate in Figure 4-3. From Figure 4-3, the fuzzy sets $\boldsymbol{SB_1}$, $\boldsymbol{SB_2}$, $\boldsymbol{SB_3}$ and $\boldsymbol{SB_4}$ represent the normal, malfunction, load disturbance and faulty system behaviors respectively.

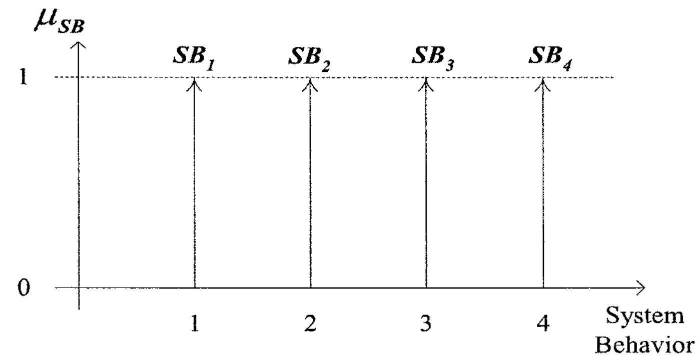


Figure 4-3 Singleton membership functions of the system behaviors used in the FGA-AFD system.

The set of fuzzy **IF-THEN** rules is often obtained by expert's knowledge and tuned manually which result in an inaccurate and non-optimal rule set. Since the quality of a fuzzy rule table greatly affects the accuracy and performance of the classification system, an effective approach has to be employed to generate the rule table. In next section, GA is employed to extract the knowledge from a training data set of system inputs whose system behaviors of a dynamic system in a specific time period is known in order to formulate the fuzzy rule table. The ability to search solution globally in a parallel fashion for reducing the probability of being trapped in a local optimum make GA to be a good option for fuzzy rules generation.

4.3.3 Fuzzy Rules Generation by Genetic Algorithms

Genetic algorithms (GA) are search algorithm based on the mechanism of natural selection and genetic reproduction [Goldberg 1989]. Potential solution is being searched by GA through a population of chromosomes. As analogy to the survival of the fittest law, fitness of each chromosome is evaluated within a population by the fitness (objective) function. Chromosomes with the highest fitness values will have a higher probability to survive and generate offspring. This allows GA to improve or optimize its solution. GA can be applied to solve non-linear, discontinuous, multi-objective optimization problems [Bolc and Cytowski 1992, Goldberg 1989]. The abilities of GA to search complex and large search space globally and efficiently, and locate near optimal solutions are suitable for the generation of fuzzy rules for a fuzzy system.

In this section, various implementation issues about using GA to optimize fuzzy rule table in the FGA-AFD system will be presented. A clear description of how GA optimizes the FES's rule table is illustrated in Figure 4-4.

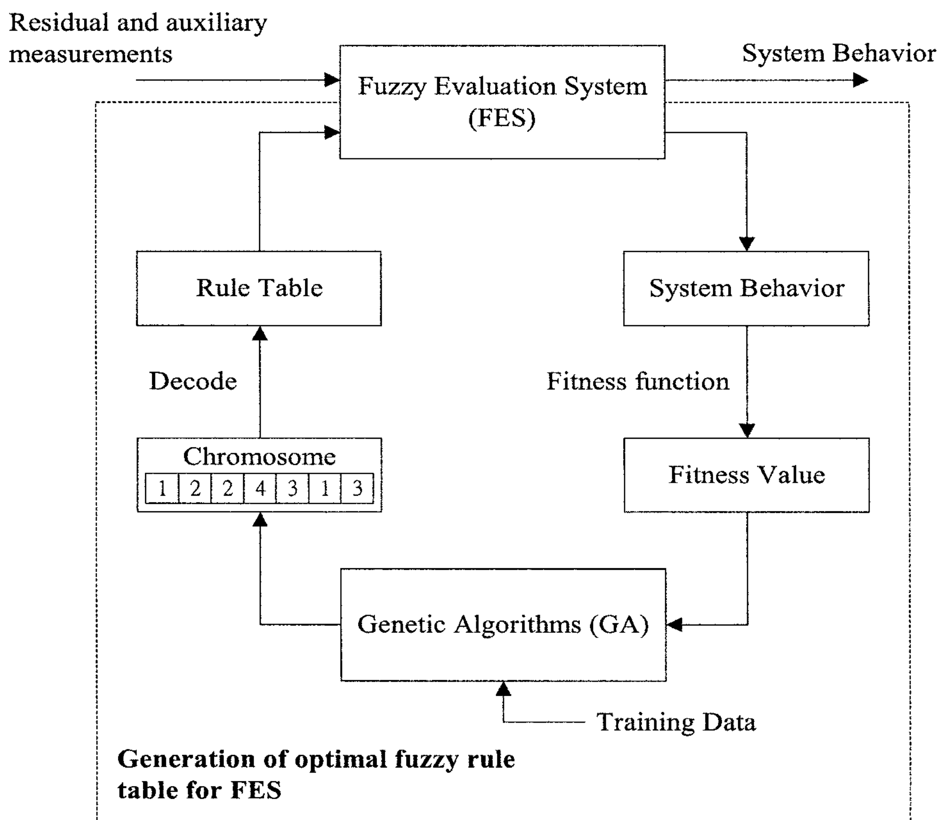


Figure 4-4 Integration of GA and FES for fuzzy rule table optimization.

a. Coding of Fuzzy Rule Table

The fuzzy rule table of the FES is coded into a chromosome and integer number encoding method is adopted for easier understanding and manipulation than binary encoding method. In our FES (Figure 4-1), the fuzzy variable (System Behavior) consists of 4 fuzzy sets, {$\boldsymbol{SB_1}$ (normal), $\boldsymbol{SB_2}$ (malfunction), $\boldsymbol{SB_3}$ (load disturbance), $\boldsymbol{SB_4}$ (faulty)}, that is coded as 1, 2, 3 and 4, respectively (Figure 4-3). Let error (*e*) and residual (*r*) both consist of 5 fuzzy sets as {***PB*** (Positive Big), ***PS*** (Positive Small), ***ZE*** (Zero), ***NS*** (Negative Small), ***NB*** (Negative Big)}, and control action (*u*) comprises 4 fuzzy sets as {***ZE*** (Zero), ***S*** (Small), ***M*** (Medium), ***L*** (Large)}. Then, the coding of the fuzzy rule table into a chromosome is illustrated in Figure 4-5.

From Figure 4-5, the length of a chromosome is equal to the size of the fuzzy rule table (i.e. $5\times5\times4$) and each gene of a chromosome represents the fuzzy output of a fuzzy rule. Integer encoding method helps to reduce the length of a chromosome, as the size of the rule table is going large. Population size is problem specific and depends on the length of a chromosome. It is selected such that it is large enough to preserve diversity while small enough to reduce computational time (fast convergence). Initial population is generated randomly in the FGA-AFD system.

b. Evaluation of Fitness Function

After population initialization, each chromosome is decoded into fuzzy rule table for the FES and is evaluated by a pre-defined fitness function. A fitness value is then generated and it is used as selecting criterion for chromosomes to undergo reproduction, crossover and mutation. The choice of fitness function depends on the nature of the search and is problem specific. In our FGA-AFD system, searching an

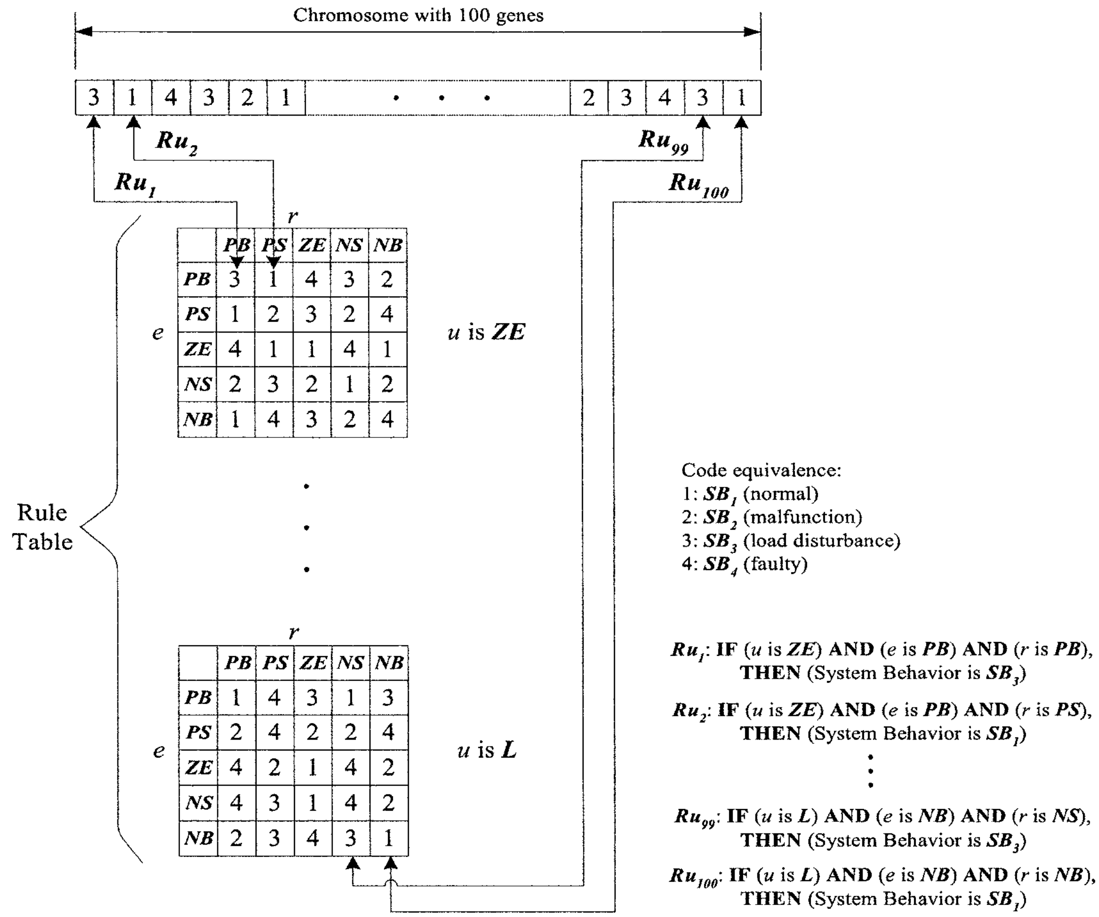


Figure 4-5 Illustration of the coding method used in the optimization of fuzzy rule table.

optimal rule table for the classification of system behavior in dynamic systems is the objective. Fuzzy system is applied to evaluate the fitness of each chromosome. System behavior (β) will be computed by fuzzy system for each chromosome. Hence, the following fitness function is formulated to determine the fitness value of chromosomes:

Fitness Function: $FF = \left(\frac{1}{k} \sum_{i=1}^{k} \left| \alpha_i - \beta_i \right| + 1 \right)^{-1}$, (4-3)

where α is the reference system behavior from the training data; β is the system behavior of a chromosome computed by FES and k is the number of training data.

There are two termination conditions for terminating GA's searching. From the fitness function (Eq. (4-3)), if the computed system behavior of a chromosome is equal to the reference behavior for all training data, the fitness value of that chromosome is equal to 1. Then, the GA will be terminated since this fitness value is the highest value that a chromosome can reach. Second, once a pre-defined maximum number of generations is reached, GA will also be terminated. In this case, a chromosome with the highest fitness value among others will be selected as the optimal output. This method terminates GA from an exhaust search, but the generated fuzzy rule table will not be accurate. It indicates the training data is not "rich" enough to generate accurate solution. Choice of GA's parameters (such as population size, crossover and mutation probabilities, or number of generations) may also affect the accuracy of the generated fuzzy rule table. For both cases, the optimal chromosome will decode back to form the fuzzy rule table.

c. Reproduction

Chromosomes with highest fitness value will have a higher probability of being selected for reproduction through randomly performed crossover or mutation to generate offspring. Eq. (4-4) is the parent selection probability function (PS_i) for each chromosome. During each parent selection cycle, two parent chromosomes are being selected to generate their offspring. The population sizes of both parent and offspring are kept constant.

$$PS_i = \frac{FF_i}{\sum_{i=1}^{n} FF_i}, \qquad i = 1, 2, \ldots, n;\ n = \text{population size} \tag{4-4}$$

During crossover, a randomly selected crossover point between parents produces their offspring. Crossover is a critical accelerator of the search processes to create offspring with only good features that are better than any other members in the population. However, only crossover alone cannot avoid the loss of promising genetic materials in the presence of other genetic structures, which could lead to local optimal. Mutation is an operator with the role of restoring the lost genetic materials. Randomly selected mutating gene of parent chromosomes can either be increased or decreased by 1. Verification is required to check whether the mutated gene is within the pre-defined limit or not. Mutation is also critical in keeping the population's genetic heterogeneous. Mutation process introduces new genetic material in the population by randomly modifying genes that facilitates the search process to escape from a trap of local optimum.

d. Generation Selection

The formation of new generation is based on fitness values of the parent population and its offspring population. According to the survival of the fittest law, only those chromosomes with the highest fitness values can survive in the next generation. Steady-State-Without-Duplicates (SSWOD) [Goldberg 1989] is employed to discard chromosomes that are duplicate of current chromosomes in order to ensure a maximum usage of the population.

4.3.4 Summary of the FGA-AFD System

In this section, implementation issues about the proposed FGA-AFD system is presented. The fuzzy rule table used in the FES is first optimized by GA. After the optimization, the FES is ready to classify different system behaviors from residual, system error, control action and reference input. The FGA-AFD system continuously monitors the system's state and fault alarm is triggered once a faulty behavior is detected. A flow chart for the optimization of fuzzy rule table by GA is shown in Figure 4-6 and the procedures can be summarized as follows:

Step 1: Population initialization.

Step 2: Evaluation of each chromosome by FES and fitness function, Eq. (4-3).

Step 3: Termination checks.

Step 4: Parents selection, Eq. (4-4)

Step 5: Crossover, mutation, reproduction and viability check.

Step 6: Generation selection according to SSWORD. Back to Step 2.

4.4 Experimental Results

The proposed FGA-AFD system is applied to detect fault in a laboratory scale Servo-Tank Liquid Process Rig. An introduction to the process rig will first be given. Then, experimental results with the proposed FGA-AFD system on this process rig will be presented and its performance is discussed.

4.4.1 The Servo-Tank Liquid Process Rig

The servo-tank liquid process rig is shown in Figure 4-7. Liquid in the sump tank is pumped to the process tank through the servo system and pipe work. The pump can either be switched on or off, and the flow rate is controlled by varying the voltage applied to the servo system. The servo system consists of a d.c. motor and gear box for varying the orifice of the servo valve. Voltage from 0 to 5V is applied to the servo system in order to vary the orifice of the servo valve from fully close to fully open. A maximum of 4.4L/min flow rate can be achieved by applying 5V to the servo system. The maximum liquid level that the process tank can hold is 13cm. An

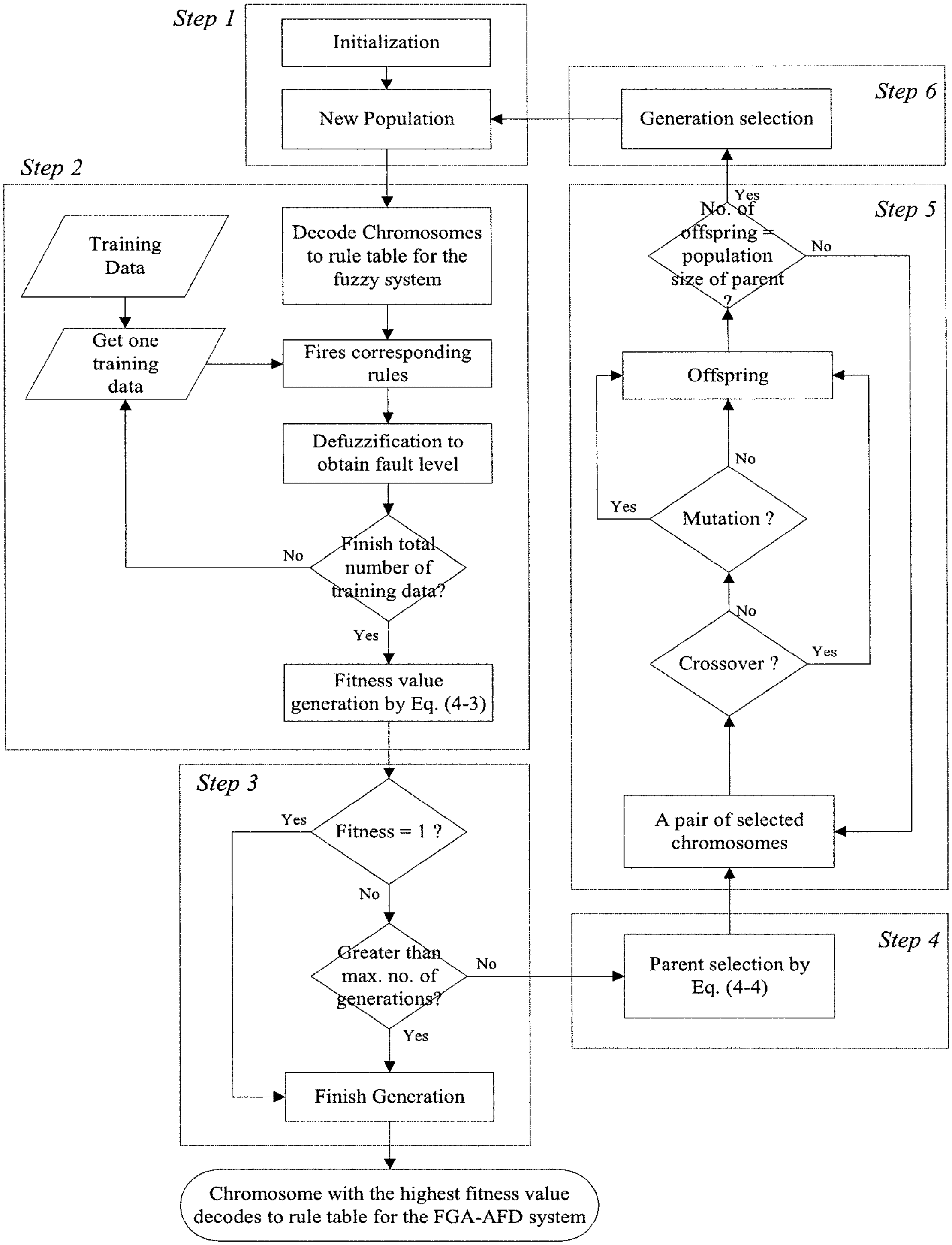


Figure 4-6 Flow chart of the fuzzy rule table generation in the FGA-AFD system.

overflow pipe is situated in the process tank for overflowing the excessive liquid. Since both dynamics of the liquid level and servo valve opening are not linear, and the time lag for the movement of gears in the servo system to the desired position (to attend the desired flow rate), thus it is a challenging system for control, modeling and fault diagnosis.

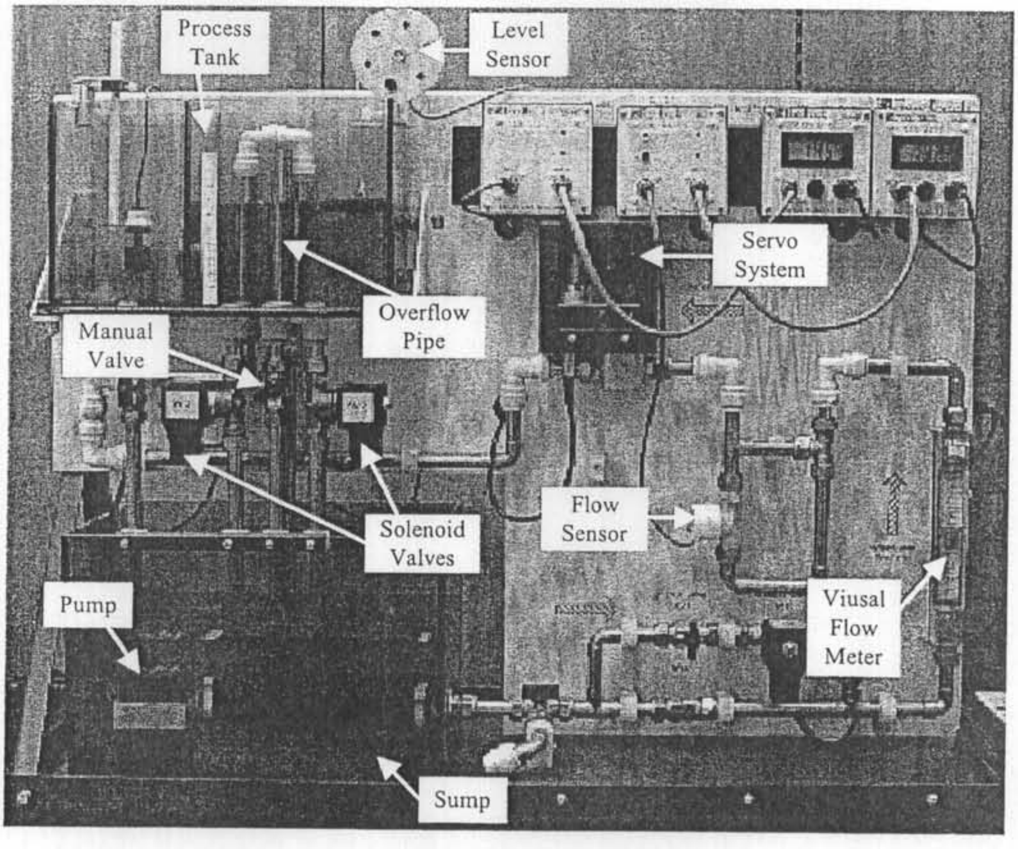


Figure 4-7 The Servo-Tank Liquid Process Rig.

4.4.2 Results

The performance of the proposed FGA-AFD system was appraised through two experiments with different load disturbance and faults on the servo-tank liquid process rig. A manual tuned fuzzy logic controller was used to control the liquid level in the process tank by varying the voltage applied to the servo system. During both experiments, the sampling time was kept at 1 second and the manual valve below the process tank was partially open, allowing liquid to flow out. As mentioned in the previous section, the FGA-AFD system's fuzzy rule table was first optimized by GA. After the optimization, the FGA-AFD system was ready to classify the four types of system behaviors. The fitness value over 49 generations for the fuzzy rule optimization in the FGA-AFD system is shown in Figure 4-8.

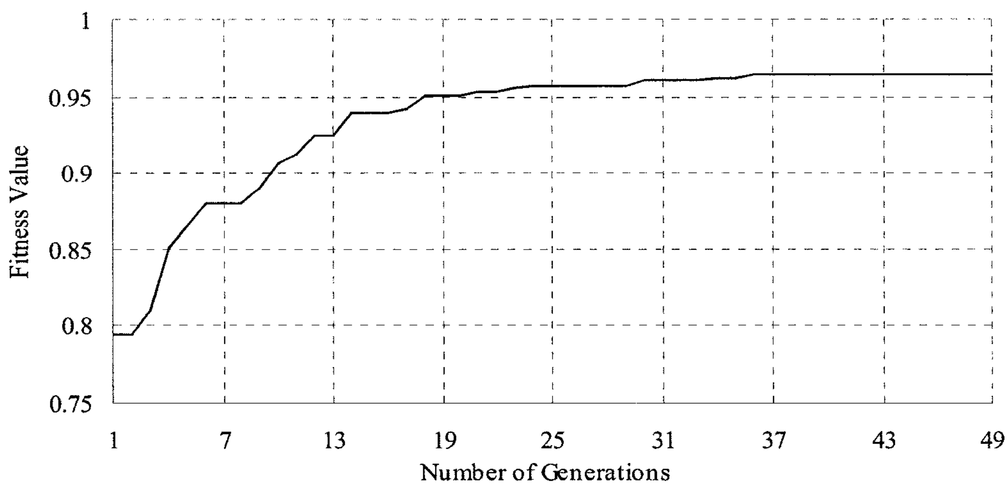
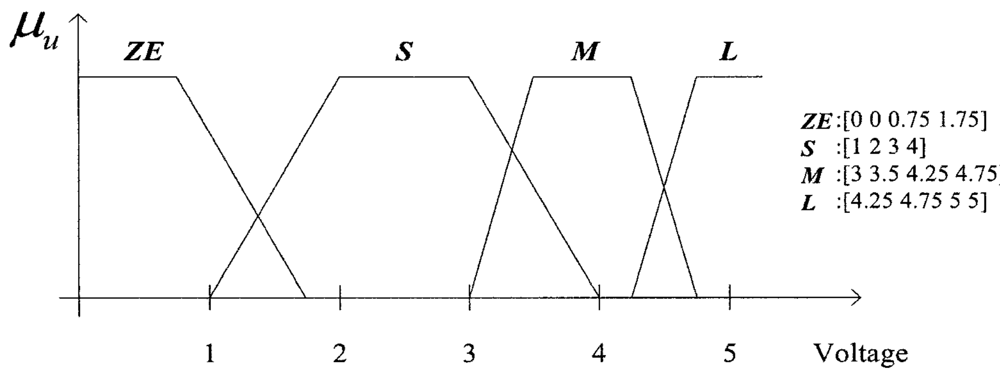


Figure 4-8 Fitness value over 49 generations for fuzzy rule optimization.

Residual (r), system error (e) and control action (u) were used to classify different system behaviors in the FGA-AFD system and their membership functions were shown in Figure 4-9. Once an unacceptable system behavior was detected by the FGA-AFD system, the system should check for any change applied to the reference input (y_r). If y_r was changed, the system would then start a new detection and ignore the previous result. Figures 4-10 and 4-11 show the system responses and input signals of the FGA-AFD system for experiments 1 and 2 respectively. The parameter settings for the FGA-AFD system are summarized in Table 4-2.



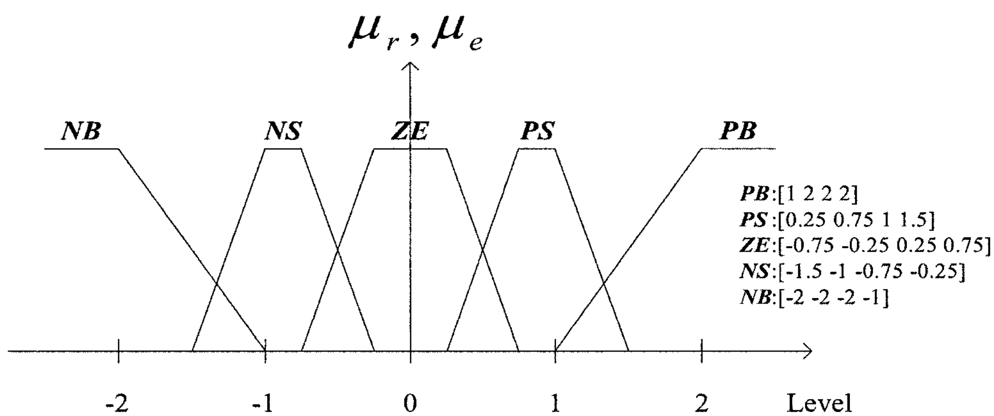


Figure 4-9 Fuzzy membership functions for input variables.

Table 4-2 Parameter settings for the FGA-AFD system.

For FES			
Number of fuzzy sets for u		4, {***ZE***, ***S***, ***M***, ***L***}(Figure 4-9)	
Number of fuzzy sets for r and e		5, {***PB***, ***PS***, ***ZE***, ***NS***, ***NB***} (Figure 4-9)	
For GA			
Population size	200	Crossover rate	0.8
Length of chromosome	100	Mutation rate	0.05
Generation iterated	49		
Defuzzification method	$\frac{\sum_{i=1}^{L} \boldsymbol{SB}_i \cdot \mu_i}{\sum_{i=1}^{L} \mu_i}$	Fitness function	$(\frac{1}{k}\sum_{i=1}^{k}\lvert\alpha_i - \beta_i\rvert + 1)^{-1}$

In experiment 1 (Figure 4-10), the pump was switched off at 269 sec in order to simulate a faulty situation that the liquid level in the process tank was decreasing. After 7 sec, our AFD system was able to detect this faulty behavior. In experiment 2 (Figure 4-11), a load disturbance was first applied to the process rig by closing one of the solenoid valves underneath the process tank at 235 sec. Then, the manual valve was closed also to simulate an increasing liquid level faulty behavior. Again, our AFD system detected both unacceptable behaviors during the monitoring period. The load disturbance and faulty system behaviors were detected at 244 sec and 394 sec respectively. The detection results for both experiments are summarized in Table 4-3.

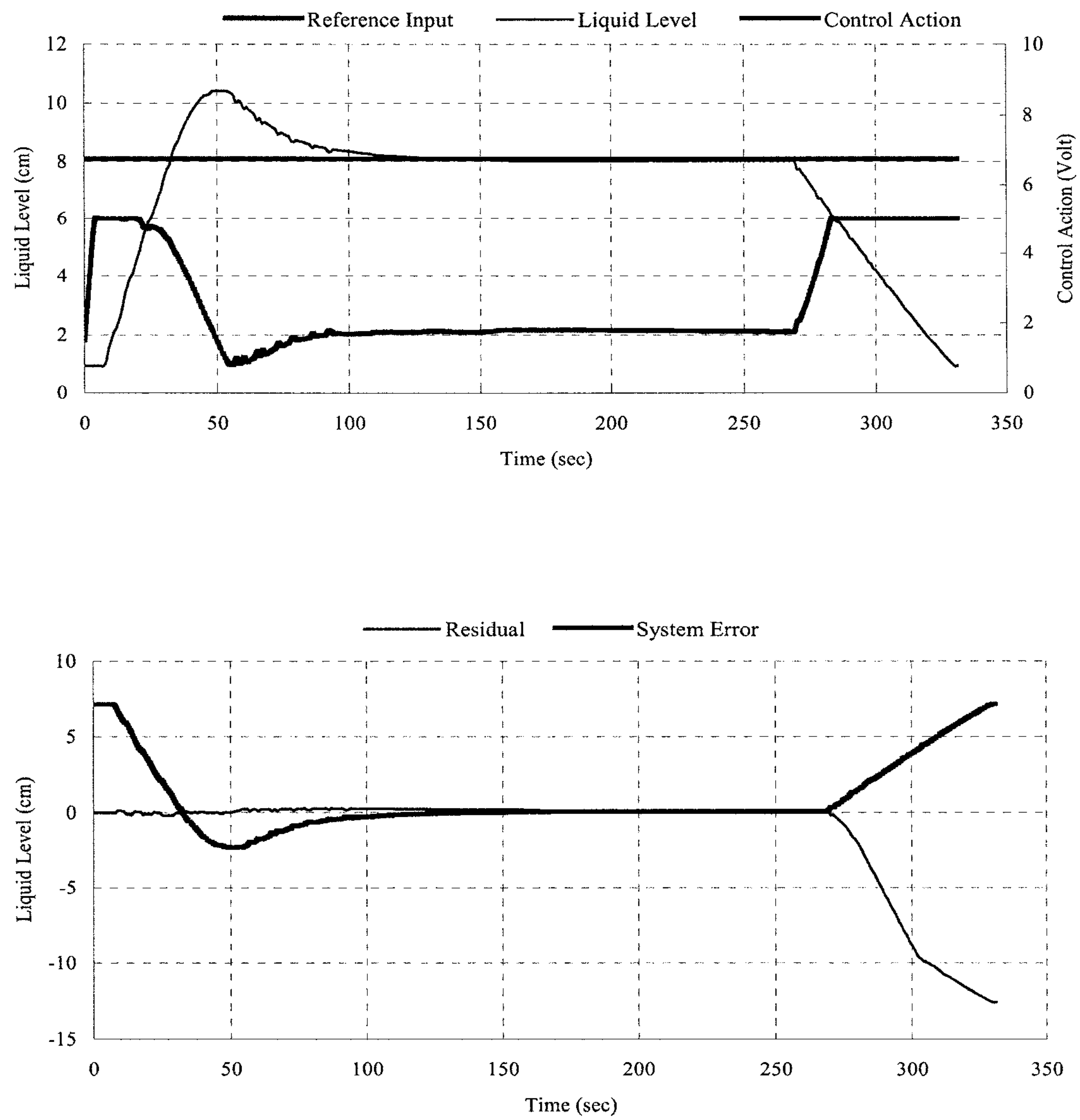
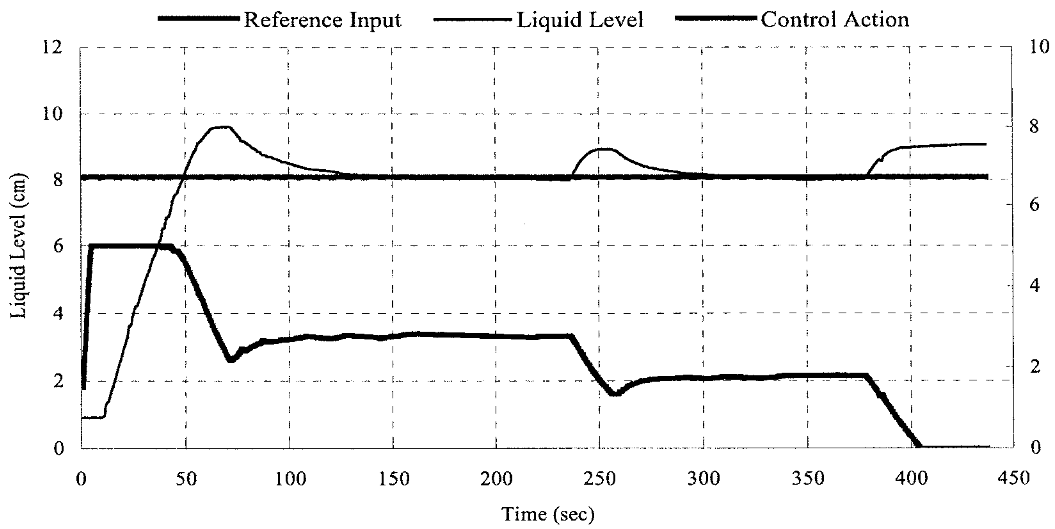


Figure 4-10 System responses and input signals of the FGA-AFD system for experiment 1.



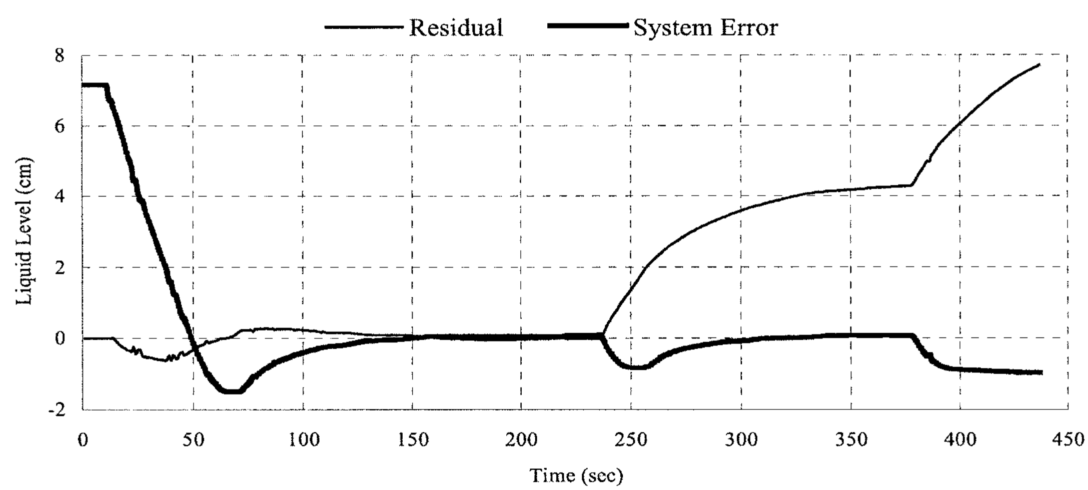


Figure 4-11 System responses and input signals of the FGA-AFD system for experiment 2.

Table 4-3 Summary of the results for experiments 1 and 2.

	Experiment 1	Experiment 2
Load disturbance	-	Solenoid valve close at 235 sec
Time for detection	-	9 sec
Fault	Pump switched off at 269 sec	Manual valve closed at 377 sec
Time for detection	7 sec	17 sec

4.4.3 Discussions

Both experiments verified that the FGA-AFD system could classify different system behaviors based on residual (r), control action (u) and system error (e). Checking for any changes in the reference input (y_r) is a measure in order to avoid false detection. The proposed FGA-AFD system continuously monitors the dynamic physical system (the process rig) and presents the system's state to the operator. For every detection system, there is a time lag between the time for applying the fault and the time for detection. Since the fault requires some time to build up its effect, the characteristic of the fault and the controller tries to correct the fault which in turn, reduces the effect of fault to the system's performance in the earlier stage. These explain why the detection time for faulty behavior in experiment 2 is much longer than experiment 1. Since the pump is switched off in experiment 1, there will be no longer flow of liquid throughout the process rig, and the effect of this fault cannot be corrected or reduced by the controller. Hence, the changes in residual and system error are much drastic than in experiment 2 with the manual valve closed. With obvious signal variation, the AFD system can detect the fault in a relatively shorter time.

The nature of fault is also an important factor that may lengthen the time for detection and sometimes even affect the detection of the AFD system. As for incipient faults, the gradual deterioration towards a dynamic system may be masked by the controller and only be detected when the faults have accumulated to a certain extend. The design of our proposed FGA-AFD system is focused on detecting abrupt faults.

Since training the fuzzy rule table is an off-line process. Regular training of rule table is then necessary to reduce the chance of false detection. Fuzzy system alleviates this problem since it can tolerate a certain degree of system parameter variations. This is not the case when using mathematical model to formulate the AFD system. The selection of optimal fuzzy rule table can be extended on-line based on the segmentation of fuzzy rule table. According to the training data, a segment of rule table can be identified based on the fired fuzzy rules at single time step. Only this segment is coded and trained instead of the whole rule table and hence the computational time and search space is reduced. Further improvements to the FGA approach can be achieved by increasing the number of linguistic variables in order to improve resolution and accuracy, and the assignment of the membership function parameters can also be optimized by GA.

4.5 Conclusions

In this chapter, we proposed a fuzzy-genetic algorithm (FGA) to address the problem of automatic fault detection. Early fault detection methods are either based on constant threshold test or adaptive threshold strategy. FGA systems have been used widely in many other applications, such as, synthesis of fuzzy control rules, fuzzy classification rules, but limited use in automatic fault detection. With the strengths of fuzzy reasoning and global optimization from genetic algorithms, the FGA system is a promising technique to perform automatic fault detection. Genetic algorithms are used to train the fuzzy rule table by training data. Hence, the workload for the design of the AFD system is reduced. A fuzzy-genetic system is used to evaluate the fitness of chromosomes. Once the fuzzy rule table is optimized, the FGA is ready for fault detection. The proposed approach is evaluated on the Servo-Tank Liquid Process Rig. Experimental results show the ability of the proposed approach to detect and distinguish different system behaviors with only residuals, system error and control action. Correct faulty behaviors detection is achieved for the FGA-AFD system.

Once a faulty behavior is detected, the model-based fault diagnosis process should be activated for localizing faulty components. In the next chapter, qualitative reasoning and QBG modeling pragmatism are employed to develop model-based fault diagnosis algorithm. Design and implementation issues will be discussed and the developed diagnosis algorithm will be tested with an in-house designed and built floating disc system.

Chapter 5

Qualitative Model-Based Fault Diagnosis*

5.1 Introduction

As the complexity of modern industrial systems increases, the problem of fault diagnosis becomes even more important and its efficient solution plays an essential part in the overall management and control hierarchy. Modern industrial systems require a higher demand of system reliability, safety and low-cost operation which in-turn call for sophisticated and elegant fault diagnosis algorithms [Biswas *et al.* 1996, Chen and Patton, 1999, Ghiaus, 1999, Khoo *et al.* 2000, Mosterman and Biswas 1999, Patton *et al.* 2000, Wang and Linkens 1996, Zhou *et al.* 2000]. The process of fault diagnosis starts when a discrepancy between an observed abnormal behavior and the expected behavior or desired behavior is detected. An initial set of fault candidates is then generated and additional measurements are suggested to help refine the initial candidate set.

In the last chapter, the FGA-AFD system was proposed as an alternative algorithm to fault detection for dynamic physical systems. The fault diagnosis mechanism would be activated once a faulty behavior was detected. In this chapter, the theory and implementation issues of the qualitative model-based fault diagnosis mechanism are addressed for completing the second phase of the thesis.

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* Some of the result in this chapter has been published in papers 2 and 13 on pages 8 and 10 in this thesis.

Quantitative and qualitative approaches constitute the mainstream trends towards model-based fault diagnosis. The quantitative approach relies on physical laws and precise mathematical models [Chen and Patton 1999, Patton *et al.* 1989 and 2000]. The idea is to estimate model parameters either on-line or off-line, and compare with their "fault-free" or nominal values. The main problems with such methodology are the intricacy and overheads of obtaining precise numerical models and the sensitivity of the diagnostic system to modeling errors. Usually, the effect of modeling errors obscures the effect of faults and thus causes false alarms [Wang and Linkens 1996].

The qualitative approach [Biswas *et al.* 1996, Ghiaus 1999, Linkens and Wang 1994, Mosterman and Biswas 1999, Wang and Linkens 1996] is based on both physical laws and expert knowledge/rules and is more applicable when mathematical models are either difficult to obtain or unavailable. Qualitative reasoning [de Kleer and Brown 1984, Forbus 1984, Kuipers 1986 and 1994] can be employed to construct a deep-level knowledge model which represents the relationship between system structure and behavior. However, heuristic rules or a prior knowledge of faults are usually required along with the qualitative model to generate the fault candidates [Lee *et al.* 1985].

Fault diagnosis using a QBG model is based on qualitative reasoning and physical laws, and has the merit of inferring faults directly without the use of fault models or fault trees (i.e. without a prior knowledge of faults). Unanticipated faults can be inferred by solving a set of qualitative equations derived from the bond graph model. Biswas *et al.* [1996] and Wang *et al.* [1994 and 1996] both use QBG to model systems for fault diagnosis. The QBG model explicitly describes the locations of system components and their interconnections. Hence, the diagnosis mechanism easily localizes system faults via this structural information. Finally, the effect of modeling errors is alleviated since the qualitative model contains no numerical information.

Diagnosis is accomplished along a set of qualitative equations. The method of solving the qualitative equations is different from their numerical counterpart. For example, if $a = b + c$, then in the case that both a and b are known values, c cannot be calculated by simply reasoning the equation as $c = a - b$. This characteristic requires testing all the possible candidates repeatedly when solving the equations. However, as the system becomes more complex, the number of qualitative equation increases and the testing process becomes inefficient. In this chapter, genetic algorithms (GA) are used as the search engine for possible fault candidates. Components' fault states are coded into a chromosome and through genetic operations, a set of fault candidates is generated.

The chapter is organized as follows. Section 5.2 provides a general framework of the qualitative model-based fault diagnosis method. The inference process for fault candidates via QBG model and qualitative operations is presented in Section 5.3. In Section 5.4, implementation issues of the proposed GA-based qualitative fault diagnosis method are given. Experimental results of the proposed fault diagnosis method on an in-house designed and built floating disc system are reported and discussed in Section 5.5. Finally, conclusions are drawn in Section 5.6.

5.2 Schematic Representation of Fault Diagnosis

Figure 5-1 shows the schematic diagram for the qualitative model-based fault diagnosis mechanism. QBG formalism is used to model the dynamic physical system as presented in Chapter 3 for the hybrid qualitative and quantitative simulation algorithm, but the modeling result, a set of qualitative equations, need not be simplified since the un-simplified qualitative equations provide the system structural information (components' locations and interconnections) and internal states which are necessary for qualitative fault diagnosis. The relations between the whole system's behaviors and components' behaviors can be analyzed through qualitative reasoning among the set of qualitative equations. Thus, fault candidates can be inferred by qualitative reasoning with the relations between faulty component's behavior and the observed abnormal system behavior.

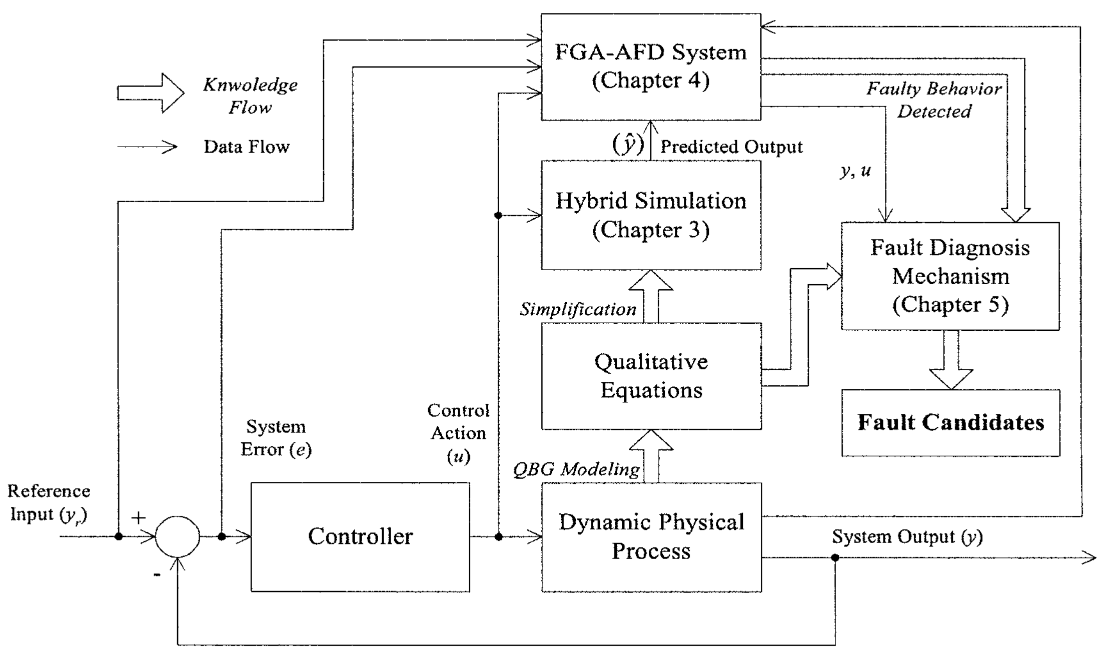


Figure 5-1 Schematic diagram of the qualitative model-based fault diagnosis mechanism.

The main function of the fault diagnosis mechanism is fault localization. Hybrid simulation (Chapter 3) predicts normal system behaviors (i.e. fault-free behaviors) for residual generation in the FGA-AFD system. The FGA-AFD system developed in Chapter 4 classifies different system behaviors for dynamic physical systems. When a faulty behavior is detected, the fault diagnosis mechanism presumes that some faults are occurred in the system. Then, system observations (e.g. u, y) will be converted into their corresponding qualitative values for localizing fault candidates through the qualitative inference mechanism.

The strategy for the fault localization searches fault locations through several different fault hypotheses of particular components to see how their faulty behaviors affect the observed system behaviors. When a faulty behavior is detected, the inference mechanism will assume a component is faulty and assign a fault type in qualitative value to that component. Then, the assumed component's fault type and measured system behaviors (in qualitative values) are inserted into the qualitative equations to infer all the qualitative values of unknown variables via operations on qualitative equations. If all the qualitative equations are satisfied with the inferred qualitative values, then the fault hypothesis is sensible and the component can be regarded as a fault candidate. Otherwise, the component is not a fault candidate. This "hypothesis-test" strategy is reiterated until all components in the physical system have been investigated.

In the next section, a detailed description of the qualitative inference mechanism among the set of qualitative equations will be presented and illustrated through a tank system.

5.3 Qualitative Bond Graph for Fault Diagnosis

Fault diagnosis is performed based on the cause-effect inference via operations on a set of qualitative equations as previously discussed. This is in contrast to feedback control tasks that rely on accurate numeric computations. Thus, the qualitative space and operations used in the qualitative equations must be defined for the cause-effect inference. Traditional quantity space {[+], [0], [−], [?]} representing the measurement space is a coarse division. It is not fine enough to distinguish abnormal and normal system behaviors for the need of fault diagnosis, since a same qualitative value can be used to represent both abnormal and normal behaviors. Hence, a finer division for the measurement space and its corresponding qualitative operations is needed.

For the simplicity and effectiveness reasons, an extended qualitative space {[+1], [+], [0], [−], [−1], [?]} is adopted to represent system behaviors and component states for qualitative fault diagnosis. For system measurements, [+] and [−] denote the positive and negative values in the measurement space, respectively. [0] denotes the boundary between [+] and [−], while [?] represents an uncertain value. [+1] and [−1] represent very large positive and negative values, respectively. For power variables, E and F, [+1], [−1] and [0] represent different abnormal states caused by system faults, while [+] and [−] denote the normal behaviors. For system components, R, C and I, [+1] denotes component blocked (i.e. obstruct power delivery), and [0] denotes component leakage or short circuit (i.e. power loss) [Ghiaus 1999, Wang and Linkens 1996], and [+] denotes normal behavior.

As the operations on qualitative variables are different from numerical ones, it is necessary to define qualitative operations to handle the arithmetic operations of addition (+), subtraction (–), multiplication (×), division (/) and equal (=) processes. The qualitative operations are worked by qualitative operators, which are drawn from the set {+, –, ×, /, =} and have the same mathematical meanings as their corresponding operators on numerical values. Their definitions are shown in Table 5-1 [Wang and Linkens 1996]. The inference mechanism on qualitative equations is different from normal equations. For example, with the qualitative equation: [+1] = [+1] + [Y]; a set of solutions results: [Y] = {[0], [+], [+1]} since from Table 5-1, [+1] = [+1] + [0], [+1] = [+1] + [+] and [+1] = [+1] + [+1] are both valid. However, solving the equation with standard mathematical operation, the equation becomes: [Y] = [+1] – [+1], and only one solution is reached, i.e. [Y] = [0]. Hence, special inference method is employed to solve qualitative equations.

Table 5-1 Qualitative operations (*: undefined state).

[X] + [Y]			[X]			
[Y]	+1	+	0	–	–1	?
+1	+1	+1	+1	+	0	?
+	+1	+	+	?	–	?
0	+1	+	0	–	–1	?
–	+	?	–	–	–1	?
–1	0	–	–1	–1	–1	?
?	?	?	?	?	?	?

[X] – [Y]			[X]			
[Y]	+1	+	0	–	–1	?
+1	0	–	–1	–1	–1	?
+	+	?	–	–	–1	?
0	+1	+	0	–	–1	?
–	+1	+	+	?	–	?
–1	+1	+1	+1	+	0	?
?	?	?	?	?	?	?

[X] × [Y]			[X]			
[Y]	+1	+	0	–	–1	?
+1	+1	+1	?	–1	–1	?
+	+1	+	0	–	–1	?
0	?	0	0	0	?	?
–	–1	–	0	+	+1	?
–1	–1	–1	?	+1	+1	?
?	?	?	?	?	?	?

[X] / [Y]			[X]			
[Y]	+1	+	0	–	–1	?
+1	+	+	0	–	–	?
+	+	+	0	–	–	?
0	*	*	*	*	*	*
–	–	–	0	+	+	?
–1	–	–	0	+	+	?
?	?	?	?	?	?	?

5.3.1 Qualitative Inference Mechanism for Fault Localization

The qualitative equations were defined in Chapter 3 and a bond graph model was formulated for qualitative model-based fault diagnosis. In this subsection, a tank system [Ghiaus 1999], is used to demonstrate the qualitative inference mechanism for fault localization among a set of qualitative equations. Figure 5-2 shows the structure of the tank; with an input flow source Q_{in}, an output control valve R and the capacity of the tank C, and its bond graph. The measured variable is the liquid height h in the tank which is related to the pressure as $P = f(h)$ and corresponds to the effort variable E_2. In this example, volume flow rate and pressure are the flow and effort variables respectively. Using QBG notion, the qualitative equations describing the system are formulated as in Eq. (5-1). Each passive element contributes one equation, while for junction elements, two equations are generated, one describing efforts property while the other relating flows property. Detailed account on qualitative equation generation can be found in [Wang and Linkens 1996]. All power variables in Eq. (5-1) are considered at time t unless specified.

$$E_1 = E_2 = E_3, \qquad F_1 = F_2 + F_3$$

$$F_2(t) = C \times (E_2(t) - E_2(t-1)), \qquad E_3 = R \times F_3 \tag{5-1}$$

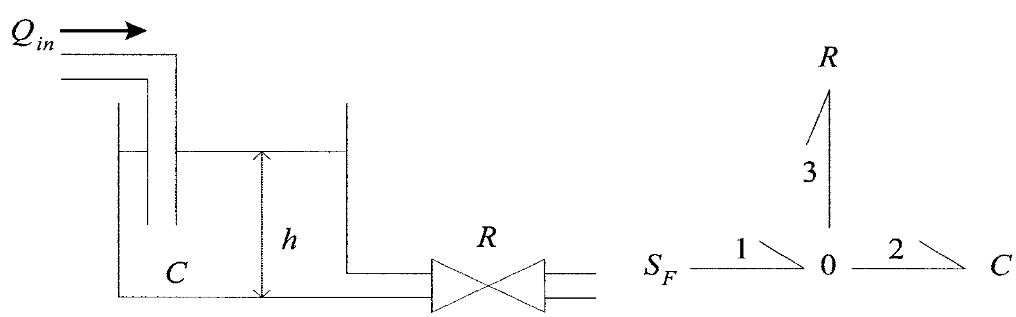


Figure 5-2 The tank system and its bond graph.

The process of qualitative fault diagnosis uses the "hypothesis-test" strategy. Assume that the liquid height h in the tank is measured to be smaller than normal, and so, set the effort variable: E_2 = [0]. Assign normal values to all component parameters in the system before hypothesizing a fault. Set the past state of C component to [+]. Then, assume a faulty component causes the abnormality. Now, let the output valve leaks, i.e. R = [0]. A component with fault type [0] will have its effort tends to zero, while a component with fault type [+1] will have its flow tends to zero. Therefore, E_3 will be [0]. Insert the above qualitative values to Eq. (5-1). The qualitative inference mechanism will start to evaluate the unknown variables among the qualitative equations sequentially with the qualitative operations defined in Table 5-1.

		First Inference		Second Inference
$E_1 = E_2 = E_3$	$\rightarrow$	[0] = [0] = [0]		
$F_1 = F_2 + F_3$	$\rightarrow$	[+] = [?] + [?]	$\rightarrow$	[+] = [−] + [+1]
$F_2(t) = C \times (E_2(t) - E_2(t-1))$	$\rightarrow$	[−] = [+] × ([0] − [+])		
$E_3 = R \times F_3$	$\rightarrow$	[0] = [0] × [?]	$\rightarrow$	[0] = [0] × [+1]

In the first inference, one can observe that the state of F_2 in the second equation of Eq. (5-1) is uncertain [?], however, in the third equation of Eq. (5-1), F_2 = [−]. It is because the inference process is sequential, i.e. from top to bottom. Therefore, for this example, it takes two inference steps to solve the problem. It can be seen that all the equations are satisfied. Therefore, the hypothesis R = [0] is recognized as a fault candidate. Other faults being tested are: R = [+1], C = [+1], C = [0], ... etc. The other faults that satisfy all qualitative equations are C = [0] and F_1 = [0]. Additional measurements or direct inspection are required to refine the fault candidates.

Procedures for localizing fault candidates through qualitative inference mechanism is summarized as follows:

1. Generate a set of qualitative equations through QBG formalism.
2. Convert system inputs and outputs into their corresponding qualitative values from the extended quantity space and then insert into the qualitative equations.
3. Assume that a component is faulty and assign its fault type.
4. Hold all other components as normal.
5. Infer the qualitative values for all unknown power variables via qualitative operations.
6. If all the qualitative equations are satisfied, then the component is recognized as a fault candidate.
7. Reiterate until all system components are investigated.

As the system becomes more complex, the number of components grows and this one-by-one testing method becomes inefficient. Wang and Linkens [1996] suggested decomposing the bond graph model into several segments in order to improve efficiency. When a component is considered as a fault candidate, the other components within the segments are fault candidates as well. Another fault diagnosis and system reliability analysis method is fault tree analysis [Lee *et al.* 1985]. A fault tree, which embeds the logical relation between system failure and component faults, is used to obtain the causes of a system failure. However, the development of fault tree is time-consuming and needs a prior knowledge of faults. The fault tree itself is inflexible and problem specific. Hence, in fault tree analysis, unanticipated faults cannot be localized. It is not the case of using a QBG model that actually infers the faulty components from measured variables. A similar approach to the QBG was proposed by Mosterman and Biswas [1999]. Fault diagnosis is based on qualitative reasoning and temporal causal graph that is derived from the causally augmented bond graph. Faults are localized through the "hypothesis-test" cycle along the temporal causal graph. However, problems of causality assignment and algebraic loop manipulation [Dijk 1994] of the bond graph approach overburden the modeling task and a correct temporal causal graph may not be derived. In this chapter, fusion of QBG and genetic algorithms is then proposed to preserve the simplicity of modeling task, infer fault candidates correctly and completely.

5.4 Fault Diagnosis Algorithm

In this section, the author proposes a GA-based qualitative fault diagnosis algorithm to address the problem of fault diagnosis as stated previously. The algorithm is formulated via integration of genetic algorithms (GA) and qualitative bond graph (QBG) formalism. GA is adopted to search globally for possible fault candidates of a physical system via operations on a set of qualitative equations, while QBG provides deep-level knowledge about the relations between faulty component's behaviors and system behaviors.

5.4.1 GA based Search Engine

Fault diagnosis involves a global search through a space of possible fault candidates. GA is a global searcher that performs large search spaces of complex systems without having to perform exhaustive search [Goldberg 1989, Khoo *et al.* 2000]. The construction of GA to cope with the task of fault diagnosis consists of four major modules: initialization and encoding method, evaluation, reproduction and generation selection.

a. Initialization and Encoding Method

In this chapter, a set of fault candidates means a collection of faulty components of a physical system. Hence, the states of all components (*R*, *C* and *I*) of the bond graph model are encoded into a chromosome as shown in Figure 5-3. Qualitative values [+], [+1] and [0] are assigned to each component in order to represent component normal state, block state and leakage state respectively. Integer number coding of qualitative values is adopted, so, integer numbers 0, 1 and 2 represent qualitative states [0], [+1] and [+], respectively. The length of the chromosome is equal to the number of components in bond graph model. The restriction of chromosome is that at least one component is being assigned a faulty state when a fault situation is observed. During the search, each chromosome represents a potential solution to the fault diagnosis process.

$[Com_1]$	$[Com_2]$	$[Com_3]$	$[Com_4]$	----------	$[Com_n]$

n: number of components in the model

Figure 5-3 State of system components (*R*, *C* and *I*) is encoded in the chromosome ($[Com_i]$ denotes the qualitative state of the i^{th} component).

The population size is problem specific and depends on the number of components in the bond graph model. It is chosen to be big enough to preserve diversity while small enough to reduce computational time (fast convergence). Usually, the initial population is generated randomly. Alternatively, commonsense reasoning and heuristic knowledge of faulty components can be used to initialize the population [Elhadef and Ayeb 2000].

b. Evaluation

After population initialization, each chromosome is evaluated by a pre-defined fitness function and a fitness value is then generated. Fitness value is used as selecting criterion for chromosomes to undergo reproduction, crossover or mutation. The choice of the fitness function depends on the nature of the search and is problem specific. In this problem, searching all potential fault candidates from the bond graph model is the objective of the GA. The set of qualitative equations acts as constraints in the genetic search for possible fault candidates. Since a gene location represents a component fault type (Figure 5-3), when the assumed fault type of a component satisfies all qualitative equations (as the reasoning in subsection 5.3.1), the component is assigned a performance measure (PM) of "1" (faulty), otherwise, its performance measure (PM) is set "0" (fault-free). Hence, the following fitness function is formulated to determine the fitness value of chromosomes:

$$\text{Fitness Function: } FF_j = \frac{\sum_{i=1}^{n} \mathrm{PM}_i}{n} \tag{5-2}$$

where PM_i is the performacne measure of the i^{th} component of the j^{th} chromosome and n is the number of components in a chromosome. From the fitness function Eq. (5-2), if all the potential fault candidates are included in the chromosome (i.e., the complete and correct fault candidates set), the chromosome will have the highest fitness value.

c. Reproduction

Chromosomes with the highest fitness value will have a higher probability of being selected for reproduction through randomly performed crossover or mutation to generate offspring. Eq. (5-3) is used as the parent selection probability function (PS_j).

In each parent selection process, two different chromosomes are selected to generate their offspring. For simplicity, the pair of selected chromosomes either perform crossover or mutation according to the crossover probability (p_c) and the mutation probability (p_m). The population sizes of both parent and offspring are kept constant.

$$PS_j = \frac{FF_j}{\sum_{j=1}^{m} FF_j}, \quad j = 1, 2, \ldots, m;\ m = \text{population size} \tag{5-3}$$

d. Generation Selection

Chromosomes with the highest fitness values are retained in the next generation, while those with the lowest fitness values are being discarded. Steady-State-Without-Duplicates (SSWOD) [Goldberg 1989] is employed to discard those identical offspring in the population in order to ensure a maximum usage of the population.

5.4.2 Implementation

A pseudo-code describing the implementation of the proposed GA-based qualitative fault diagnosis algorithm is shown in Figure 5-4. The algorithm terminates when a set of fault candidates (*FS*) are identified. The physical system to be diagnosed is described by a bond graph model together with a set of qualitative equations. Qualitative values of measured variables are inserted into the qualitative equations when faulty behavior is detected. The initial population is generated randomly where each chromosome represents a potential set of fault candidates [$FS(i)$]. Fitness function, Eq. (5-2) is used to evaluate the fitness value [$FF(i)$] of each chromosome in the population (*Pop*). After evaluating all chromosomes in *Pop*, offspring's population is generated based on the reproduction module. Since a pair of selected chromosomes generates two offspring, the ***For**-loop* (within the ***While**-loop* in Figure 5-4) is computed up to half the population size in order to maintain a constant population size (*Pop_Size*) for the offspring. Each chromosome in the offspring's population is also evaluated by the fitness function as their parents. After evaluating all the offspring chromosomes, those offspring chromosomes with the highest fitness values are selected to replace those parent chromosomes with the lowest fitness values among the *Pop*. The GA terminates when the set of fault candidates is obtained correctly and completely, and the best-fit chromosome (solution chromosome, i^*) is decoded back to the fault states of each component in the model.

GA-based Qualitative Fault Diagnosis Algorithm

Input: Bond graph model and its qualitative equations, and the qualitative values of the measured variables.

Output: A set of fault candidates (*FS*).

Begin

$Pop\_Size \leftarrow$ population size

Randomly initialize the population (*Pop*)

For $i \leftarrow 1 \ldots Pop\_Size$

Evaluate fitness values $FF(i)$ for each chromosome according to Eq. (5-2)

Endfor

$i^* \leftarrow$ a chromosome $\in Pop$ and represents FS, a solution chromosome

While $FS \neq FS(i^*)$ **do**

For $i \leftarrow 1 \ldots (Pop\_Size/2)$

Select a pair of chromosomes from *Pop* according to Eq. (5-3);

$r \leftarrow$ a randomly generated number from the range [0, 1]

$p_c \leftarrow$ crossover probability

If $r < p_c$ **then** crossover;

Else mutation

Endif

Endfor

For $i \leftarrow 1 \ldots Pop\_Size$

Evaluate fitness values $FF(i)$ (Eq. (5-2)) of the offspring

Endfor

Select chromosomes with the highest fitness values to form *Pop*

Endwhile

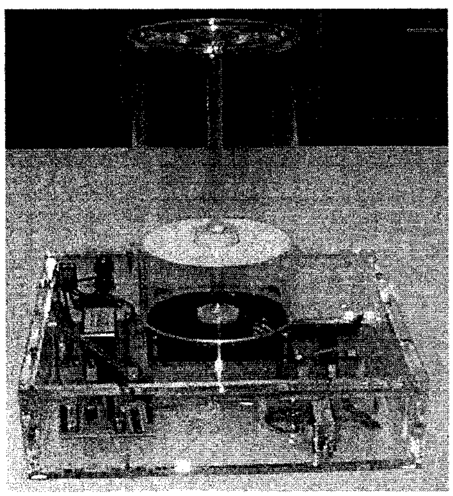
$FS \leftarrow FS(i^*)$; $i^* \in Pop$

End

Figure 5-4 Pseudo code for the proposed GA-based qualitative fault diagnosis algorithm.

5.5 Floating Disc System Application

The proposed fault diagnosis algorithm was tested on a floating disc system. Figure 5-5 shows the floating disc system and its cross-sectional view. This system was designed and constructed in-house. The system consists of a power supply circuit, a control circuit, a dc motor-driven fan, an analogue infra-red distance sensor, and the disc. The objective of this system is to maintain the disc at any desired position by varying the duty cycle of the input voltage to the fan. The average output power decreases when the off-time period is longer than the on-time period provided that the period of the pulse is constant, and vice versa.



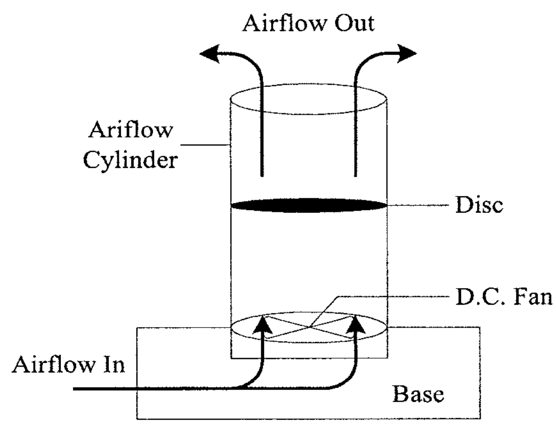


Figure 5-5 The floating disc system and it cross-sectional view.

The position of the disc is regulated by the speed of the fan. When the fan speed increases (decreases), the disc moves upwards (downwards). An infrared sensor is used to measure the height of the disc in centimeters. It should be noted that such a system is highly non-linear except in a narrow range at the middle of the cylinder that exhibits a linear relation. A standard fuzzy logic controller [Ross 1995, Yager and Filez 1994] was used to control the disc position. Figure 5-6 shows the bond graph of the system and its qualitative equations are given as follow:

$E_1 = E_2 + E_3 + E_4$

$F_1 = F_2 = F_3 = F_4$

$E_2(t) = I_1 \times (F_2(t) - F_2(t-1))$

$E_3 = R_1 \times F_3$

$E_4 = F_5$

$F_4 = E_5$

$E_5 = E_6 + E_7 + E_8$

$F_5 = F_6 = F_7 = F_8$

$E_6(t) = I_2 \times (F_6(t) - F_6(t-1))$

$E_7 = R_2 \times F_7$

$E_8 = E_9 = E_{10}$

$F_8 = F_9 + F_{10}$

$F_9(t) = C \times (E_9(t) - E_9(t-1))$

$E_{10} = E_{11} + E_{12}$

$F_{10} = F_{11} = F_{12}$

$E_{11}(t) = I_{disc} \times (F_{11}(t) - F_{11}(t-1))$

$E_{12} = R_{cover} \times F_{12}$

where I_1 and R_1 are the armature inductance and resistance respectively, R_2 is the axial friction, I_2 is rotor inertia, C is the capacitance of the airflow cylinder, I_{disc} is the inertia of the disc and R_{cover} is the flow resistance of the cylinder. The measured variable is the effort E_9, the height of the disc.

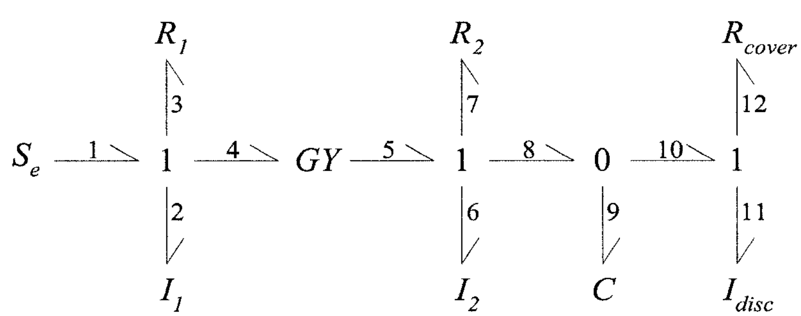


Figure 5-6 The bond graph of the floating disc system.

5.5.1 Experimental Results

The fault states of the system components (either [+], [+1] or [0]) were encoded into the chromosome as shown in Figure 5-7. The initial population was randomly selected and the size of the population was set to 10. The inference method of qualitative values among the set of qualitative equations was presented in subsection 5.3.1. We assumed that the disc was positioned at 13 cm, i.e. E_9 = [+1], which was caused by a faulty component. Figure 5-8 shows the control response results with the desired level at 8 cm. The resistance of the motor was then lowered at 38 sec (i.e., R_1 = [0]) by varying a rheostat which was connected in series with the motor in order to simulate a fault state. The GA parameters and the set of fault candidates are shown as below:

Population size	10	Number of generations	30
Crossover probability (p_c)	0.9	Length of Chromosome	7
Mutation probability (p_m)	0.1	Fault candidates [$FS(i^*)$]	R_1, I_1, R_2, I_2

[I_1]	[R_1]	[I_2]	[R_2]	[C]	[I_{disc}]	[R_{cover}]

Figure 5-7 Chromosome represents fault state of different components in the floating disc system ([.] denotes qualitative fault state of components).

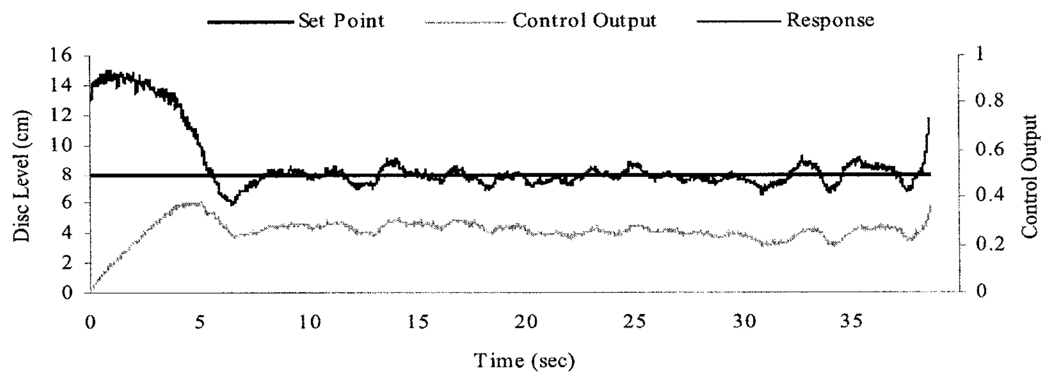


Figure 5-8 Control response of the floating disc system and fault is applied at 38 sec.

In this experiment, decreasing the resistance of the rheostat simulated a leakage or short circuit state of the armature resistance of the motor (R_1). Since the armature resistance was lowered, more voltage (effort) could be applied to the motor; hence the speed of the motor was increased and more power was applied to the motor. As the speed increased, the disc level was also increased (i.e., E_9 = [+1]) which caused the abnormal behavior of the system. Besides the actual fault (R_1), more fault candidates were inferred.

5.5.2 Discussions

From the experiment, one can observe that a prior knowledge of a fault is not necessary. This is not the case for rule-based fault diagnosis and fault tree analysis. Fault candidates are searched through the set of qualitative equations by GA. The QBG model embedded deep-level knowledge of the system is employed as the model for our proposed fault diagnosis algorithm instead of using a shadow-level knowledge model, like a mathematical model. Components' states are represented in qualitative values and located in the model. Hence, the interpretation of components' states is convenient for human operators understanding and the location of faulty component(s) can be obtained easily.

The computational time for evaluating chromosomes' fitness depends on the complexity of the system and the number of measured variables. It is obvious that when the number of measured variable increases, the number of inference steps will be reduced since the number of unknown states is decreased and hence more qualitative states can be inferred during the first inference step. When the system is complex such as present-day industrial processes, the number of components and qualitative equations are increased, which may overload the evaluation process as well. Hence, our algorithm is proposed to run off-line. To make on-line search realistic, one possibility is to increase the number of measured variables or employ compositional modeling framework [Falkenhainer and Forbus 1991] to assist the derivation of the bond graph model. The bond graph model is segmented into different compartments based on compositional modeling. Once a compartment is regarded as the cause of faulty behavior, the components in the compartment can be coded into the chromosome to perform the GA search. Since the number of components within a compartment should be smaller than the whole system, the time for searching the fault candidates set can be shortened.

Model quality plays an important role in the success of model-based fault diagnosis. The quality of the QBG model depends on the detail-level employed to abstract the system in a qualitative way. Different detail-level abstraction will result in a different qualitative model which in terms generate a different set of qualitative equations.

Hence, a component will be regarded as faulty in this modeling level, but will be fault-free in another modeling level. A deep understanding of the system and more time will be necessary in order to develop an appropriate detail-level QBG model when using our proposed algorithm. Ambiguity is another problem that may limit the performance of the proposed fault diagnosis algorithm. Uncertain states may be generated during qualitative operations (Table 5-1). Sometimes an uncertain state will be preferred since any qualitative states can make a qualitative equation satisfactory. However, most of the time, an uncertain state will increase the processing time during qualitative fault inference (subsection 5.3.1). In order to improve efficiency, quantitative information can be employed in the qualitative inference mechanism. Order-of-magnitude reasoning [Olivier 1991] is one of the approaches that can be used to solve the uncertain state by qualifying the relative importance of different qualitative variables.

5.6 Conclusions

In this chapter, the author proposes the use of genetic algorithms as the search engine to find a set of fault candidates. The approach can diagnose a fault without any prior knowledge of possible faults. The QBG formalism is used as the formal modeling scheme which provides a unified approach to model different energy domain subsystems together. The proposed approach is tested on a newly constructed floating disc system and the fault can be inferred correctly. Additional measurements are necessary to refine the set of fault candidates automatically.

This and the previous chapters complete the second phase of this thesis, which is centered on the model-based fault detection and diagnosis. The next chapter begins the third phase, which focuses on the development of the Intelligent Supervisory Coordinator (ISC) based on QBG paradigms for the supervision and fault diagnosis of the dynamic physical systems.

Chapter 6

Intelligent Supervisory Coordinator*

6.1 Introduction

The key building block of an intelligent supervisory coordinator is a knowledge base that contains the indicative information regarding a particular application. The AI techniques have produced a plethora of tools and methods for representing the knowledge embedded in complex physical systems. The qualitative bond graph modeling approach, integrating AI techniques with control engineering, is a promising technique to build the knowledge base for the ISC. In QBG semantics, qualitative reasoning is used as general reasoning strategy and bond graph theory is employed as the knowledge representation. Together, they are capable of building deep-level knowledge models for representing the structural, behavioral and functional information about complex engineering systems.

In the first phase, based on the abstraction of knowledge from the deep-level models, a hybrid qualitative and quantitative simulation algorithm was proposed (Chapter 3) for applications in the simulation of dynamic systems. In the second phase, the FGA-AFD system was developed as an alternative algorithm to fault detection, and the qualitative model-based fault diagnosis mechanisms are described for localizing faulty components. In this phase, an ISC is constructed by integrating the techniques developed in the preceding phases. The resulting ISC assists human operators to

* This chapter is based on the paper 10 on page 9 in this thesis.

manage dynamic physical systems and acts like human operators in control rooms to execute the tasks of regulation, process monitoring, and decision-making.

In this chapter, a supervisor is developed under the ISC's architecture. The supervisor is used to select appropriate control tasks, according to its monitoring results, to cope with different system situations (e.g. faulty, under load disturbance, etc.). It coordinates different control tasks and communicates system states to human operators.

The rest of this chapter is arranged as follows. Section 6.2 develops an architecture for the proposed ISC based on QBG models. In Section 6.3, a demonstration of the ISC is implemented on a Servo-Tank Liquid Process Rig that was also used in Chapter 4. Discussions on the ISC are included in Section 6.4, and finally, Section 6.5 concludes the chapter.

6.2 An Architecture for Intelligent Supervisory Coordinator

The architectural (or structural) approach is a central task in the categories of AI and automatic control. A proper architecture makes a machine imitate human intelligence effectively and efficiently. Intelligent supervisory systems usually adopt a hierarchical structure that is capable of autonomous operation in known or unknown environments in response to qualitative instructions, with minimum or no human operators' intervention [Ravindranathan and Leitch 1994]. For example, Saridis [1983 and 1989] built an architecture for robotic systems with three levels, organization, coordination and execution (as discussed in Chapter 2), and Rasmussen [1986] constructed a multi-level decision-making structure with the knowledge level on the top. All these architectures represent their structure by a finite set of tasks, functions, or modules. Hence, the intelligent supervisory systems determine the best sequence of a finite set of tasks in response to changes in the observed dynamic physical processes.

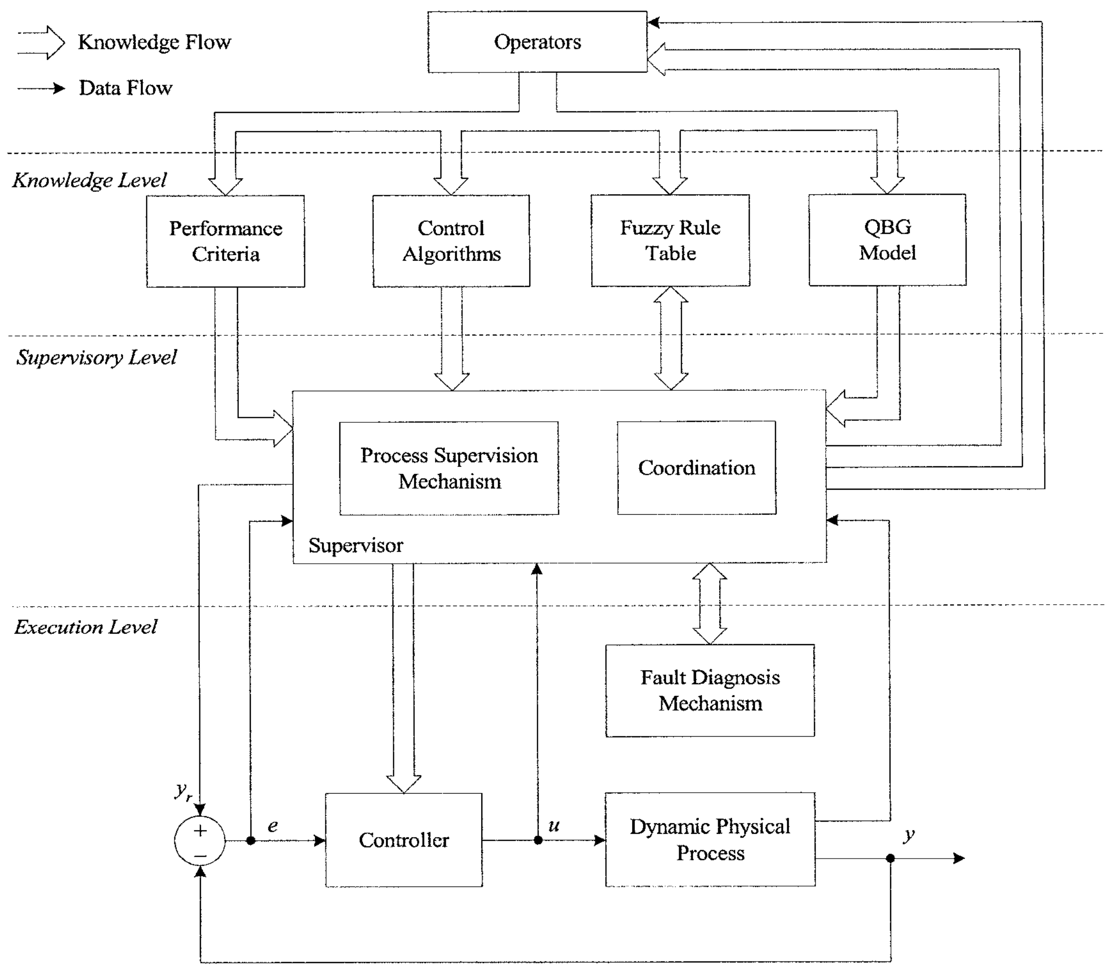


Figure 6-1 The architecture of the proposed intelligent supervisory coordinator based on qualitative bond graph models.

The architecture developed for the proposed ISC based on QBG models is depicted in Figure 6-1. The architecture is comprised three levels, *knowledge level*, *supervisory level* and *execution level*. This separation of problem-solving knowledge base, the inference mechanisms and algorithms is an essential feature that makes the ISC intelligent, autonomous and robust. Above these levels are human operators who have the responsibility to control and monitor the ISC.

In this section, details of the architecture for the proposed ISC are presented. The role of human operators in the ISC will be first presented, and then, functions and structures of the three levels will be discussed accordingly.

6.2.1 The Role of Human Operators in the ISC

Although it is preferable to exclude the intervention of human operators to the ISC for a greater degree of automation, there are still several reasons for retaining the human operators in command. Firstly, the process model should be built on the basis of control goal, the purpose of the model, relevant variables determination (e.g. feedback variables, system input and output variables, etc.) and model detail-level abstraction. Human operators are capable of addressing these requirements in order to build an appropriate and complete model for the process under concern.

Secondly, human operators should provide specifications, i.e., set-point and performance criteria, for governing the dynamic system operation. This is because the specifications for an engineering system may be changed to produce different products, and human operators are quite flexible in determining appropriate specifications for various mission goals. Besides specifications, knowledge (e.g.

operational constraints), which cannot be obtained from logical inferences but are necessary for the normal and safety system operation, should also be provided by human operators. For example, in logical inference, either opening the switch of a pump or close a valve can stop the liquid flow through a pipe. However, we know that long-term operating a pump with zero output flow rate will overload the pump and cause damage. In such circumstance, operators can specify some rules for the ISC to avoid dangerous movements. In the above case, a safety rule can be given as "avoid the building of excessive pressure along the pipe". On the other hand, "closing a valve long-term for stopping the liquid flow through a pipe rather than switching off the pump will cause excessive pressure" can be logically inferred. Hence, the ISC can prevent this dangerous operation because the inference result violates the safety rule.

Finally, when the result of a fault diagnosis involves operating a process component (e.g. opening or closing a valve, opening a circuit breaker), it is imperative to let these movements be monitored by human operators. This is because human operators are knowledgeable than the ISC to judge whether a movement is dangerous. Moreover, human operators can take the control of the ISC in case of any emergency situation occurred.

6.2.2 Knowledge Level

Right after a human operator is the knowledge level which usually regards as the top level in the ISC. It consists of two kinds of knowledge: one is relating to the process structure and data, and the other is the knowledge that cannot be inferred from the process structure. The structural information of a dynamic physical system is obtained via the qualitative bond graph modeling approach and is represented in qualitative equations. These equations are used to derive simulation model for hybrid simulation (Chapter 3). Furthermore, qualitative equations provide a knowledge representation for the fault diagnosis mechanism to generate cause-effect inference (Chapter 5). Besides, Wang and Linkens [1996] suggested an approach to derive control algorithms from the qualitative equations for the basic feedback control. However, in our architecture, the operators supply the control algorithms since the development of feedback controller is not within the scope of this thesis. Operators are able to decide the detail-level of the qualitative models, and known values of system parameters can be inserted into the qualitative equations to improve the accuracy of the structural information.

In the proposed ISC architecture, a fuzzy rule table in the knowledge level can either be given by human operators or generated by the process data. The fuzzy rule table is used by the supervisor in the supervisory level to detect faulty behavior and distinguish different system behaviors (Chapter 4).

On the other hand, the knowledge that cannot be logically inferred from the qualitative structural information and process data is given by human operators. This knowledge includes reference inputs, input and output variables, operational constraints, performance criteria and locations of auxiliary measurements. This knowledge is essential for the normal and safety operation of a dynamic physical system. All the knowledge are assigned to the supervisor first and then allocated to the inference mechanisms and modules in the execution level. The reference inputs are given to the feedback controller, and locations of auxiliary measurements are sent to the fault diagnosis mechanism to refine the initial set of fault candidates.

6.2.3 Supervisory Level

Next to the knowledge level is the supervisory level and is where the supervisor is placed. In the proposed ISC, the supervisor monitors the system behaviors and coordinates different inference mechanisms for a safety and normal system operation. The FGA-AFD system developed previously (Chapter 4) forms the backbone of the supervisor. The supervisor assesses the system behavior via fuzzy evaluation of residual (r), error signal (e) and control action (u). Then, the system behavior is classified into normal, malfunctioning, under load disturbance and faulty. The supervisor results are validated when there are no changes observed in the reference inputs. Besides process supervision, the supervisor allocates the underlying knowledge stored in the knowledge level for inference mechanisms as shown in Table 6-1.

Table 6-1 Knowledge allocations to inference mechanisms by the supervisor.

Inference Mechanism	Knowledge
Process supervision mechanism	Performance criteria, Fuzzy rule table, Simulation model abstracted from QBG model, Operational constraints
Fault diagnosis mechanism	Qualitative equations derived from QBG model, Locations of system inputs, outputs, and auxiliary measurements
Controller	Control algorithms

When inference mechanisms are allocated with corresponding knowledge, the supervisor select appropriate inference mechanisms for different control problems. If a normal system behavior is resulted from the supervisor, the controller is commanded to regulate the system. If the system behavior is regarded as malfunctioning or under load disturbance, the controller will be kept working and suggestions are given to the human operators, such as, re-tuning the controller, using different control algorithms, etc. When faulty behavior is detected, the controller will be stopped and then the fault diagnosis mechanism is enable to localize faulty system components. The supervisor coordinates different inference mechanisms for performing an appropriate sequence of tasks to cope with various system situations.

Finally, the supervisor communicates system states to inference mechanisms and human operators. An inference mechanism will ask the supervisor for current states once it is activated. The information needed for inference mechanisms is summarized in Table 6-2. Inference mechanisms will also return their results to the supervisor. All the information, including system states and inference results, are displayed to human operators.

Table 6-2 Information needed for inference mechanisms.

Inference Mechanism	Information
Process supervision mechanism	Observed system outputs (y), error signal (e), control action (u), reference inputs (y_r)
Fault diagnosis mechanism	Qualitative states of inputs, outputs, and control action
Controller	Reference inputs (y_r)

6.2.4 Execution Level

The lowest level is the execution level which contains a fuzzy logic controller, the controlled dynamic physical system, the fault diagnosis mechanism, and a feedback loop. The execution level executes an appropriate control function. The fuzzy logic controller is employed to regulate the dynamic physical system according to the reference input provided by the supervisor. Triangular membership functions are adopted for controller inputs because of their simplicity and computational efficiency. The fuzzy rule table for the controller is obtained by expert knowledge and trial-and-error. The fuzzy rule table can also be generated by QBG model [Linkens *et al.* 1992] which can extend the proposed ISC architecture to include an auto-tuning mechanism. The fault diagnosis mechanism localizes faulty components qualitatively when the process structure changes accidentally, or controller fails. The possible fault candidates are then reported to the supervisor which assists human operators to make appropriate decisions or actions.

6.3 Experimental Results

In this section, the hybrid qualitative and quantitative simulation technique, the FGA-AFD system and the GA-based qualitative fault diagnosis methodology developed in earlier chapters are integrated together through the supervisor to supervise the servo-tank liquid process rig.

6.3.1 The Servo-Tank Liquid Process Rig

The servo-tank liquid process rig is shown in Figure 4-7 and its schematic diagram is depicted in Figure 6-2. The process rig consists of two subsystems: Servo system, and Pump and Liquid Tank system. The servo system comprises a d.c. motor and a gear box for varying the orifice of the servo valve with various voltage applied. Hence, the flow rate (L/min) to the process tank can be altered. Electrical energy is transformed into mechanical energy in the servo system. The pump and liquid tank system contains a pump with constant pump rate and a process tank. The liquid level in the process tank can be controlled by the input flow rate to the process tank.

The bond graph of the process rig is shown in Figure 6-3. The two subsystems are connected through an active bond (the full arrow that links the 1-junction and the MTF) that transfers signals from the servo system to the pump and liquid tank system. Since both dynamics of the liquid level and servo valve opening are not linear, and the time lag for the movement of gears in the servo system to the desired position (to attend the desired flow rate), thus it is a challenging system for control, modeling and fault diagnosis.

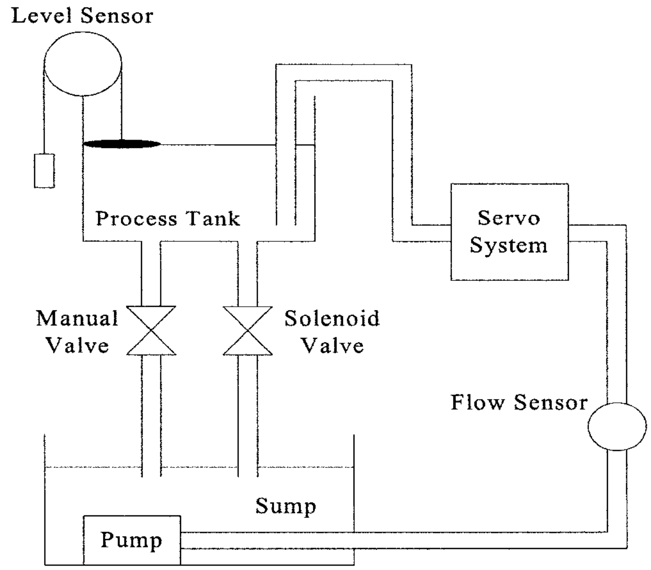


Figure 6-2 Schematic diagram of the servo-tank liquid process rig.

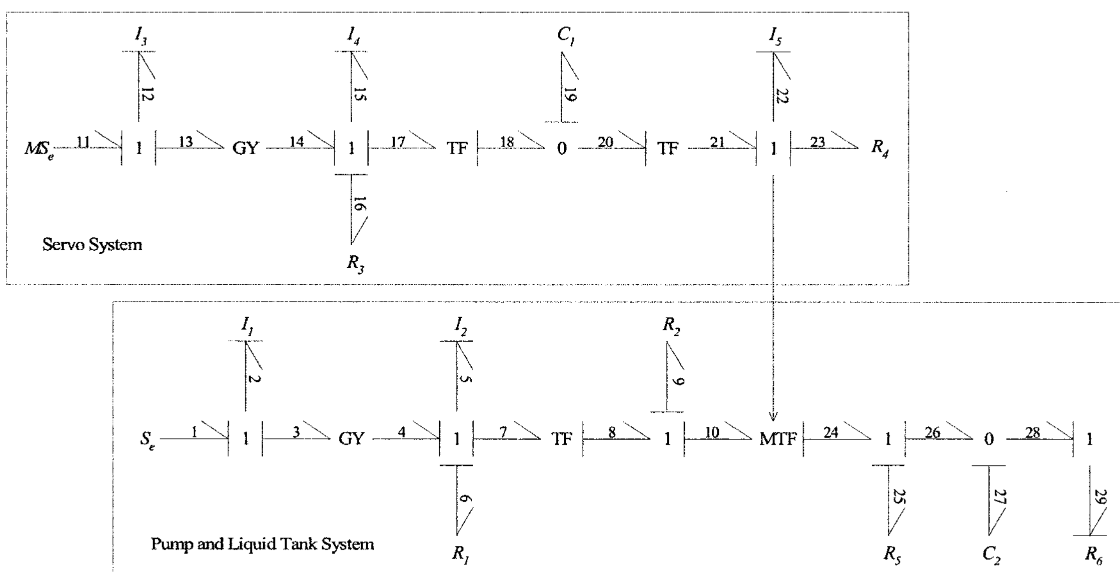


Figure 6-3 The bond graph model of the servo-tank liquid process rig.

The symbols used in the bond graph model and the established qualitative equations are listed as follows.

I_1: Armature inductance of the motor in the pump.

I_2: Inertia of the pump

I_3: Armature inductance of the motor in the servo system

I_4: Inertia of the motor in the servo system

I_5: Inertia of the servo valve

R_1: Axial friction of the pump

R_2: Inlet pipe resistance to the servo system

R_3: Axial friction of the motor in the servo system

R_4: Resistance of the servo valve

R_5: Inlet pipe resistance to the process tank

R_6: Resistance of the manual valve

C_1: Gear box

C_2: Process tank

Qualitative equations for the Pump:

$E_1 = E_2 + E_3$, $\quad F_1 = F_2 = F_3$

$E_2 = I_1 \times (F_2(t) - F_2(t-1))$, $\quad E_3 = F_4$

$F_3 = E_4$, $\quad E_4 = E_5 + E_6 + E_7$

$F_4 = F_5 = F_6 = F_7$, $\quad E_5 = I_2 \times (F_5(t) - F_5(t-1))$

$E_6 = R_1 \times F_6$, $\quad E_7 = E_8$

$F_7 = F_8$, $\quad E_8 = E_9 + E_{10}$

$F_8 = F_9 = F_{10}$, $\quad E_9 = R_2 \times F_9$

Qualitative equations for the servo system:

$E_{11} = E_{12} + E_{13}$, $F_{11} = F_{12} = F_{13}$

$E_{12} = I_3 \times (F_{12}(t) - F_{12}(t-1))$, $E_{13} = F_{14}$

$F_{13} = E_{14}$, $E_{14} = E_{15} + E_{16} + E_{17}$

$F_{14} = F_{15} = F_{16} = F_{17}$, $E_{15} = I_4 \times (F_{15}(t) - F_{15}(t-1))$

$E_{16} = R_3 \times F_{16}$, $E_{17} = E_{18}$

$F_{17} = F_{18}$, $E_{18} = E_{19} = E_{20}$

$F_{18} = F_{19} + F_{20}$, $F_{19} = C_1 \times (E_{19}(t) - E_{19}(t-1))$

$E_{20} = E_{21}$, $F_{20} = F_{21}$

$E_{21} = E_{22} + E_{23}$, $F_{21} = F_{22} = F_{23}$

$E_{22} = I_5 \times (F_{22}(t) - F_{22}(t-1))$, $E_{23} = R_4 \times F_{23}$

Qualitative equations for the process tank:

$\phi(.) \times F_{10}(t) = F_{24}(t)$, with $\phi(.) = \mathrm{f}(E_{11}, F_{22})$

$F_{24} = F_{25} = F_{26}$, $E_{24} = E_{25} + E_{26}$

$E_{25} = R_5 \times F_{25}$, $E_{26} = E_{27} = E_{28}$

$F_{26} = F_{27} + F_{28}$, $F_{27} = C_2 \times (E_{27}(t) - E_{27}(t-1))$

$E_{28} = E_{29}$, $F_{28} = F_{29}$

$E_{29} = R_6 \times F_{29}$

$\phi(.)$: A function of the modulated transformer (MTF) that depends on the applied voltage to the servo system (E_{11}) and the opening velocity of the servo valve (F_{22}).

6.3.2 Performance of the ISC

The performance of the ISC is demonstrated through a series of experiments with different load disturbances and faults. During these experiments, the sampling time was kept at 1 second and the manual valve underneath the process tank was partially opened, allowing liquid to flow out. A manual tuned fuzzy logic controller was used to control the liquid level in the process tank by varying the voltage applied to the servo system. In these experiments, the controller stopped tracking and regulating the liquid level when a faulty behavior was identified by the supervisor.

Figures 6-4, 6-5 and 6-6 show three experimental results (experiment 1 to 3) performed by the proposed ISC, with the upper one shows the system response under load disturbance or faults and the lower one shows the supervisor's output. System behaviors were classified by the supervisor and coded in integer number as, 0 (normal), 1 (malfunction), 2 (under load disturbance) and 3 (faulty). The symbols printed in bold denote the actual faults unanticipated. In these experiments, the observed system states are, applied voltage to the pump (E_1), applied voltage to the servo system – controller output (E_{11}), measured liquid level in the process tank (E_{27}). An auxiliary measurement, the flow rate in the process rig (F_{24}), is used to refine the initial set of fault candidates. The settings for the GA-based qualitative fault diagnosis algorithm in the ISC were kept constant during these experiments and shown as follows:

Population Size	20	Crossover probability (p_c)	0.9
Length of Chromosomes	13	Mutation probability (p_m)	0.1

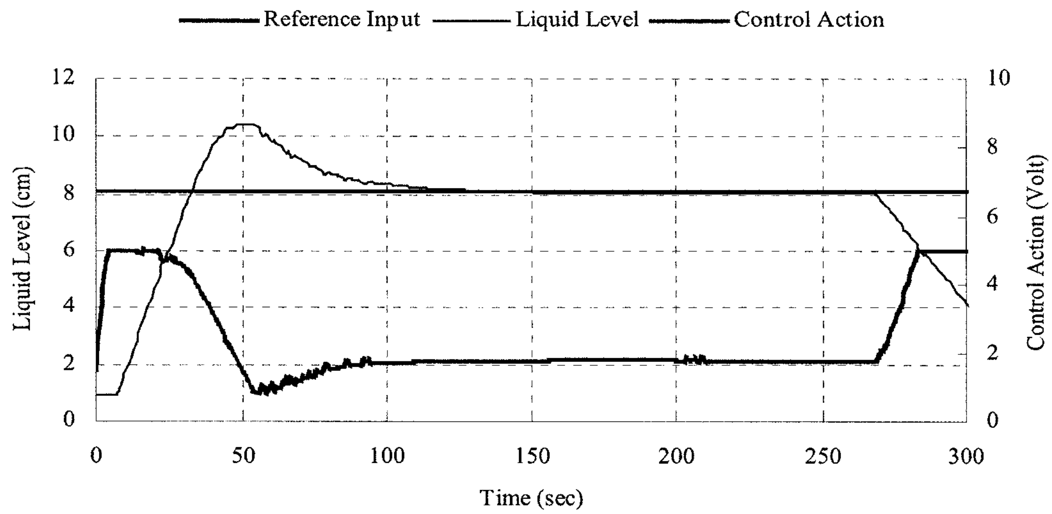
Experiment 1

Actual Fault : $\boldsymbol{R_2}$ blocked at 269 sec.

Observed System State : E_1 = [+], E_{11} = [+1], E_{27} = [0] (F_{24} = [0]).

Time for Fault Detection: 7 sec.

Diagnosis Result : C_1, I_2, I_4, I_5, R_1, $\boldsymbol{R_2}$, R_3, R_4.



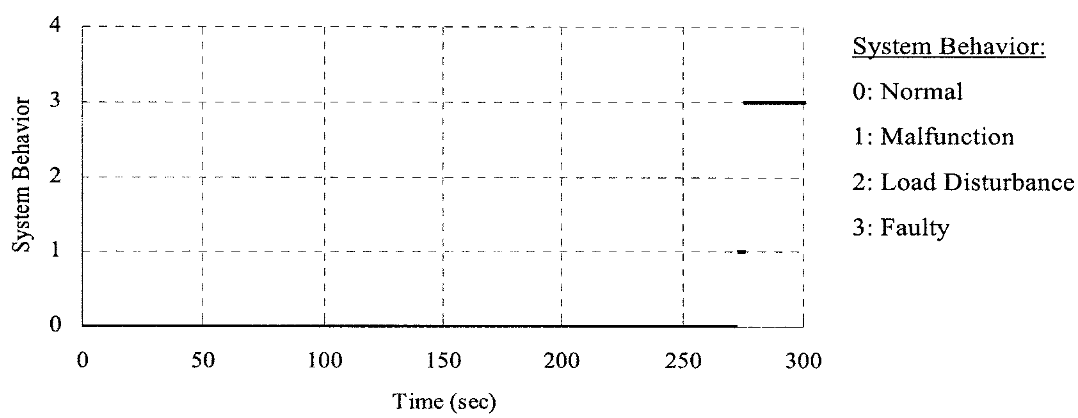
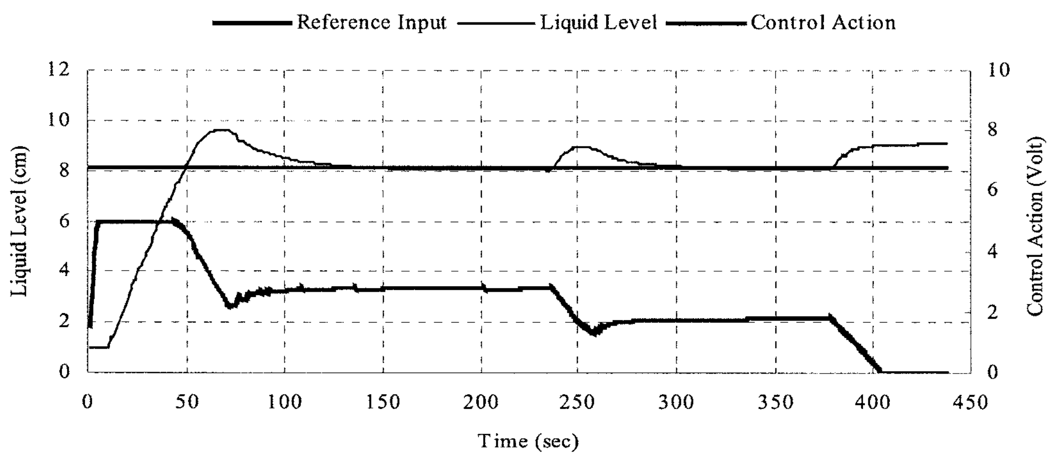


Figure 6-4 Performance of the ISC for experiment 1.

Experiment 2

Load Disturbance	: Solenoid valve closed at 235 sec.
Actual Fault	: $\boldsymbol{R_6}$ blocked at 377 sec.
Observed System State	: $E_1 = [+]$, $E_{11} = [0]$, $E_{27} = [+1]$ ($F_{24} = [0]$).
Time for Load Disturbance Detection	: 9 sec.
Time for Fault Detection	: 17 sec.
Diagnosis Result	: C_2, $\boldsymbol{R_6}$.



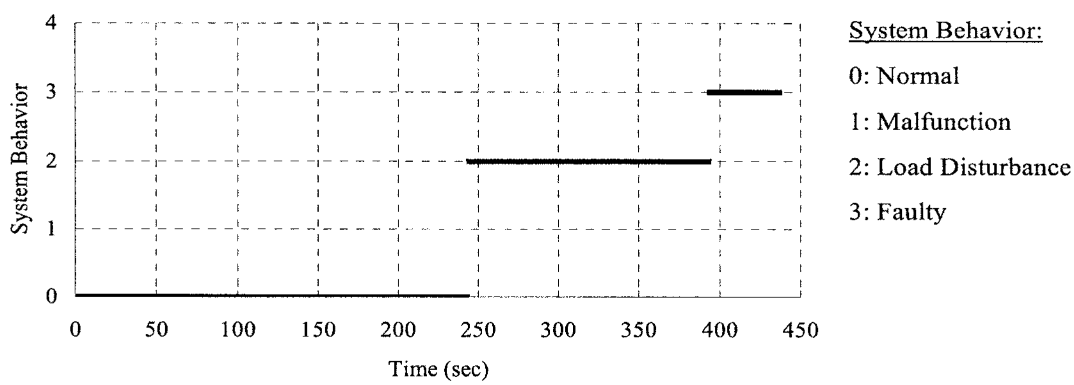
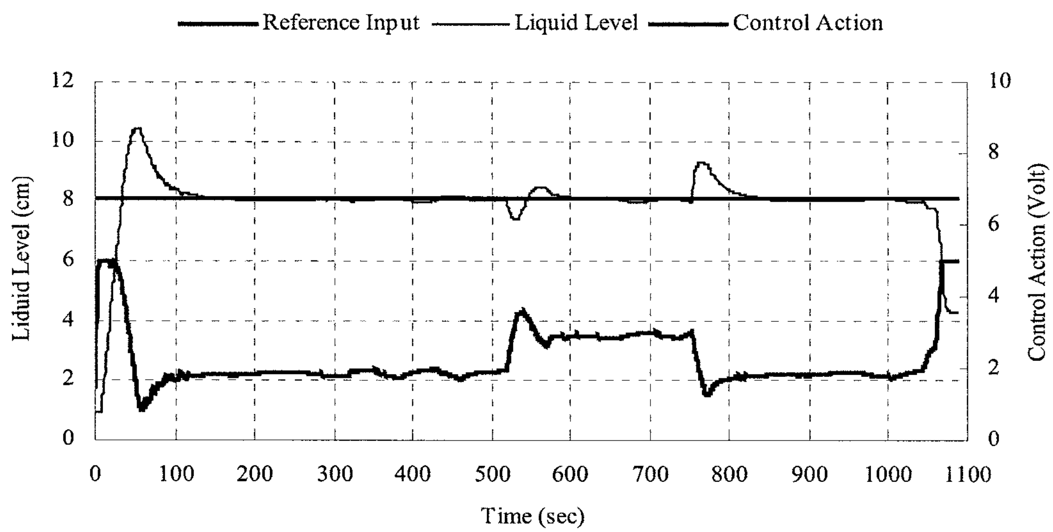


Figure 6-5 Performance of the ISC for experiment 2.

Experiment 3

Load Disturbance	: Solenoid valve opened at 252 sec Solenoid valve closed at 758 sec.
Actual Fault	: C_2 leaking at 1059 sec.
Observed System State	: $E_1 = [+]$, $E_{11} = [+1]$, $E_{27} = [0]$ ($F_{24} = [+1]$).
Time for Load Disturbance Detection	: 6 sec (opened) & 5 sec (closed).
Time for Fault Detection	: 9 sec.
Diagnosis Result	: C_2, R_5, R_6.



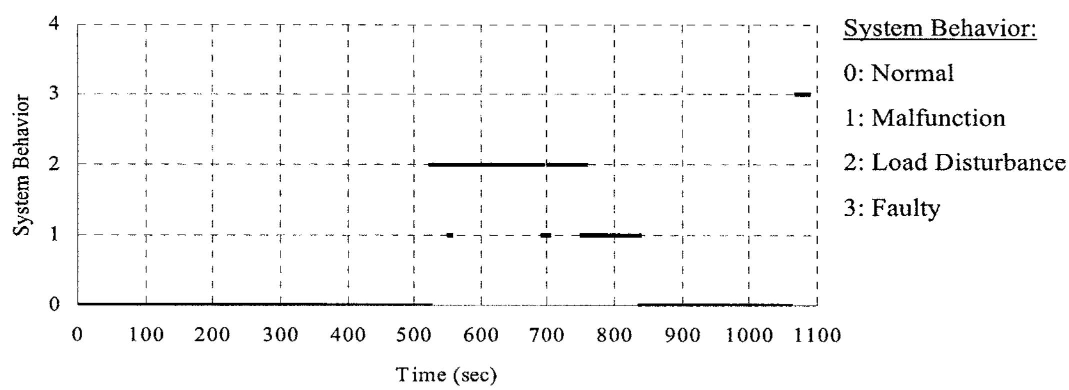


Figure 6-6 Performance of the ISC for experiment 3.

6.4 Discussions

These experiments demonstrated that the ISC could supervise the process rig well. Different system behaviors can be distinguished and actual faulty components are identified with other possible fault candidates. Unlike fixed threshold method using performance indices (e.g. IE, ISE, etc.) [Quek and Wahab 2000, Wang and Linkens, 1996], the FGA-based supervisor provides a flexible and "soft" classification of system behaviors. Thus, the difficulty in choosing appropriate performance indexes and their limits for a system in order to distinguish clearly normal and abnormal system behaviors is avoided. This can help to reduce the chance of false detection and allow supervising the more complex systems (e.g. chemical system with serious non-linearity).

With the FGA-based supervisor, it is possible to update the knowledge embedded in the fuzzy rule table at the knowledge level. This provides a means for the ISC to be more "intelligent" by learning new knowledge from system data as time past. The learning process can be activated when the times of false detection is higher than a threshold and the residuals are significantly deviated from zero under normal system operation.

The sensitivity of the ISC to fault detection is affected by the choice of membership functions for the supervisor. In these experiments, the universe of discourse for the ISC's input variables, u, r and e, were [0,5], [-2, 2] and [-2, 2], respectively (Figure 4-9), and were manually selected. With larger universe of discourse for these variables, a fault with small size will not be detected. But, using smaller universe of discourse will make the ISC over-sensitive. Hence, there is a compromise between the sensitivity of faults and the range of universe of discourse.

Generally, more measurements lead to a more accurate diagnosis result. However, in certain circumstances, further measurements cannot effectively reduce the number of fault candidates. It is because measurements are represented qualitatively and thus cannot be used to distinguish slight differences caused by different faults. Consequently, some measurements are synonymous for the fault diagnosis inference mechanism. For example, if the values of F_{24} and F_{28} are known, additional measurement on F_{27} is useless since it can be inferred from the qualitative equations. In this circumstance, the human operator should decide which additional measurements are necessary.

Unlike fault tree analysis and fuzzy logic-based fault diagnosis, the proposed ISC is capable of localizing unanticipated faults and a *priori* knowledge about the cause-effect relationships of system faults is not required. This makes the ISC more robust in order to accommodate different unforeseeable faults. However, due to the imprecise characteristic of qualitative representation, the ISC is difficult to detect and localize incipient faults. Incipient faults occur slowly over time, and are linked to the wear and tear of system components and drift of control parameter. Lo *et al.* [2002] proposed a method based on the parameter estimation method and bond graph model to identify incipient faults. Since the difference in fault characteristics requires different schemes for effective and reliable detection and localization, the proposed ISC aims on the abrupt fault analysis in dynamic physical systems.

6.5 Conclusions

In this chapter, the author proposes an integrated real-time ISC, via a hybrid qualitative and quantitative simulation technique, the FGA-AFD system, and the GA-based qualitative fault diagnosis algorithm developed in the previous chapters have been integrated to handle different classes of system behaviors. A supervisor is used to schedule an appropriate sequence of control regimes for various system behaviors. A hierarchical architecture of the proposed ISC is given for explanation and implementation purposes. The experiments show that this ISC can supervise the laboratory scale servo-tank liquid process rig successfully.

This chapter completes the third phase of this thesis with the focus on the development and implementation of an integrated real-time ISC based on QBG model.

Chapter 7

Conclusions and Suggestions for Future Developments

The studies reported in this volume encapsulate author's contributions to enhance the characteristic of ISC. The thesis's objective has been developing a real-time intelligent supervisory coordinator to provide a robust semi-autonomous system using qualitative design. In Chapters 3 to 6, the author presented a number of methodologies for hybrid qualitative and quantitative simulation, AFD system, qualitative fault diagnosis, and system supervision. Incorporating these methods, under a unified framework provided by qualitative bond graph modeling scheme, led to a real-time ISC for system simulation, process supervision and fault diagnosis.

Much of the previous work in process control has focused on the formulation of control algorithms for the intelligent supervisory systems. As such, those attempts examined a microscopic and fragmented view of the entire plant operation and control. The thesis, on the other hand, devotes to integrate and coordinate different control tasks, such as, fault diagnosis, process supervision, system modeling, and simulation, for determining an appropriate sequence of control tasks to cope with various system behaviors by the ISC. This is motivated by a holistic and macroscopic view of the plant operation and control. Implementation of the integrated real-time ISC has been illustrated by experiments on a laboratory scale servo-tank liquid process rig. The contributions of the thesis have been discussed in great detail in the preceding chapters. The aim of this chapter is to summarize the findings and outline some future directions.

7.1 Main Contributions

This thesis has made the following contributions:

- The author has re-visited the QBG modeling scheme for the possibility of building qualitative model for real-time system simulation. A novel hybrid qualitative and quantitative simulation technique is proposed for applications in the simulation of dynamic physical systems. It is motivated by the difficulty in establishing a precise mathematical model for quantitative simulation and the inaccurate and ambiguous predicted results during qualitative simulation. Qualitative model of a physical system, in the form of a simplified input-output qualitative equation, is derived from the QBG modeling scheme. Quantitative information, e.g. system inputs, time step, etc., are then inserted to the qualitative equation for conducting the hybrid simulation. The feasibility and effectiveness of the proposed hybrid simulation technique is demonstrated through simulation studies of both linear and non-linear systems. The proposed technique ensures the completeness and consistency of the predicted system behaviors and allows for real-time simulation.

- A new automatic fault detection system based on the integration of fuzzy system and GA is designed to distinguish different system behaviors. The resulting AFD system is called Fuzzy-Genetic Algorithm based Automatic Fault Detection (FGA-AFD) system. The FGA systems have been used widely in the synthesis of fuzzy control rules, fuzzy classification rules, but limited application in automatic fault detection. The proposed FGA-AFD system provides a flexible and robust fault detection to address the problems of inflexibility, threshold determination, and the derivation of accurate mathematical models of quantitative fault detection approaches. In the FGA-AFD system, GA is used to optimize the rule table of the fuzzy system and equip it with the learning ability, whereas fuzzy system provides GA with a structural framework with if-then rules to capture the knowledge embedded in system data. Beside faulty behavior detection, the FGA-AFD system is capable of distinguishing system behavior that is normal, malfunction and under load disturbance.

- A GA-based qualitative model-based fault diagnosis algorithm is presented to localize faulty components in physical systems. Qualitative model of a system for fault diagnosis is expressed by a set of qualitative equations from QBG formalism. GA is adopted to search globally for possible fault candidates of a physical system via qualitative operations on a set of qualitative equations, while QBG formalism provides deep-level knowledge about the relations between faulty component's behaviors and system behaviors. The proposed algorithm eliminates the intricacy and overheads of obtaining precise numerical models, the sensitivity of the diagnostic system to modeling errors, a prior knowledge of the cause-effect relations of component faults, and the need of fault models. The proposed algorithm has been applied to localize faulty components in the floating disc system.

- Having the formation of different control tasks for system simulation, process supervision and fault diagnosis, the author integrates these control tasks for building a real-time ISC under the QBG approach. The proposed ISC is hierarchically structured which consists of knowledge level, supervisory level and execution level. This separation of problem-solving knowledge base, the inference mechanisms and algorithms is an essential feature that makes the ISC intelligent, autonomous and robust. The needs of human operators are pointed out for building a process model, setting control goals and performance criteria, and monitoring the operation of the ISC. A supervisor based on the FGA-AFD system is suggested to monitor system behaviors and coordinates different inference mechanisms (control tasks) for a safety and normal system operation. The supervisor is able to update the knowledge base from system data. Unlike other intelligent supervisory control systems, our proposed ISC can be used for process supervision, fault detection and diagnosis, and real-time system simulation.

- Finally, the implementation of the proposed ISC has been demonstrated with application to the servo-tank liquid process rig. The experimental results have shown that this ISC supervises the process rig successfully. Actual faulty component can be identified together with other possible fault candidates. Time for fault detection is lengthened when controller is presented in the system because the controller attempts to correct the faults.

7.2 Outlooks

Research of this scale is obviously, insufficient to cover every aspect of our target topics. This work has left much opportunity for further development, including:

- *Developing an on-line auto-tuning mechanism for controller*. The function of the ISC can be extended to perform real-time auto-tuning of controller parameters when malfunction behavior is detected. QBG reasoning is able to derive rule table for a fuzzy logic controller [Linkens *et al.* 1992]. Thus, it is possible to extend its application for scaling factors adjustment.

- *Determining the detail-level of qualitative models.* The quality of qualitative model is the key success to the ISC and the detail-level decides the accuracy of a qualitative model. The detail-level of a QBG model can be determined via system simulation. The process begins with the most detailed model of the system and then abstracts away the irrelevant details according to the simulation results until an appropriate model for a given task is obtained. In future, a general method to determine an appropriate detail-level of a QBG model should be developed to improve the ability of QBG modeling.

- *Enhancing the qualitative representation.* Ambiguities generated from qualitative operations limit the inference capability of the ISC. For example, the qualitative inference mechanism for fault diagnosis (Chapter 5) could suggest too many fault candidates because of the uncertain situations of internal variables. Study on the concepts of stochastic, fuzzy set theory, and order-of-magnitude reasoning may find a possible method to improve the qualitative inference mechanism.

- *Applying the ISC to detect and localize different fault types.* The ISC has applied to localize faulty components for causing abrupt faults. It is our future goal to increase the application area by applying the ISC to detect and localize incipient and intermittent faults.

7.3 Closing Remarks

The development of intelligent supervisory systems has a long history since 1960s. The concept was naturally originated from observing two phenomena: increasing trends for systems complexity and a desire to fully automate systems. Advances in AI techniques for bringing common sense and intuition into control systems, unprecedented and rapid growth in computing technology and evolving control theory have all contributed towards implementation of a true ISC. However, there are still many challenges. Control of complex and multi-dimensional systems leave no room for mistakes for any mistake might cost human life as well as material loss. The AI techniques motivated by the need to build a machine (an "intelligent machine") that would execute intelligent tasks (e.g. decision-making) operating in uncertain environments with minimum interaction with human operators have still not realized all the promises advocated by their die hard supporters. The view taken by the author is that we have come a long way and a holistic framework is available to address problems of process management. We have the necessary will and tools to provide solutions to complete process management and control for the ultimate goal of improving the quality of life for humans!

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