INTELLIGENT CONTROL APPLICATION FOR INDUSTRIAL SAFETY

A DISSERTATION

Submitted in partial fulfillment of the requirements for the award of the degree
of
MASTER OF TECHNOLOGY
in
CHEMICAL ENGINEERING
(With Specialization in Industrial Safety and Hazard Management)

By

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JUNE, 2006

CANDIDATES'S DECLARATION

I hereby declare that the report which is being presented in this dissertation work "**INTELLIGENT CONTROL APPLICATION FOR INDUSTRIAL SAFETY**" in partial fulfillment of the requirements for the award of the degree of **Master of Technology** in Chemical Engineering, specialization in **Industrial Safety and Hazard Management** submitted in Chemical Engineering Deptt. , Indian Institute of Technology, Roorkee is an authentic record of my own work carried out during a period from Dec 2005 to June 2006 under the supervision of **Dr. Nidhi Bhandari**, Assistant Professor, Chemical Engineering Deptt Indian Institute of Technology, Roorkee.

I have not submitted the matter embodied in this report for the award of any other degree or diploma.

Atif Hussain

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This is to certify that the above statement made by the candidate is correct to the best of my knowledge.

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ACKNOWLEDGEMENT

It is with great pleasure that I take this opportunity to bow my head in respect and gratitude for all those who helped me in making this dissertation a great success. I am in dearth of words to express myself in such a joyous moment

I take this opportunity to grace myself from the benign self of my teacher and guide, Dr.Nidhi Bhandari, for ushering me from theoriticality to practicality and from plutonic to pragmatic ideas. No rhapsody or rhetoric eloquence can replace of what she had done for me and the way she has helped me in bringing out this dissertation. I will always be indebted to her all our long life.

I would also like to thank my friends for patiently bearing me and helping me in what ever way possible through their expert advices and encouraging me to go deeper in my dissertation.

Last impact is more lasting, so at the last I would like to thank all those who have directly or indirectly helped me in making this project a success. I would feel the bliss of a beneficiary by the showers of their benevolent blessings.

ATIF HUSSAIN

ABSTRACT

Chemical processes are systems that include complicated networks of material, energy and signal flow. As time passes, the performance of chemical process equipment gradually degrades due to deterioration of process components. In addition, ambient disturbances endanger the process upsets. Both factors lead to values of process variables at variance with those expected under normal operating conditions. Early detection and diagnosis of process faults while the process is still operating in a controllable region can help avoid normal event progression and reduce productivity. Hence fault detection and diagnosis is an important problem with respect to safety and productivity in process engineering.

Over the last decade an extensive search has been carried out in the area of Intelligent Control. Emerging technologies such as Fuzzy Logic have received much attention in the control area. In recent years Fuzzy logic has emerged as a mathematical tool to deal with faults in the process at incipient stage. It also provides a frame work for an inference mechanism that allows for approximate human reasoning capabilities to be applied to knowledge based systems. This technique has been claimed to yield excellent results for some applications.

The distillation column is probably the most popular and important process studied in chemical engineering literature, it is usually controlled by conventional proportional integrative derivative (PID) controller. The project "Intelligent Control Application for Industrial Process Safety" proposes application of Fuzzy Logic in Fault detection and diagnosis for distillation column safety.

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INTRODUCTION

1.1 GENERAL

With the ever increasing competition in the global market, process industries are faced with a situation where continuous improvement in process condition, production techniques, equipments, machinery etc. is the necessasity. The quest for making the process cost efficient often draws a process condition which is not only severe but may often abet abnormal (hazardous) situation unless a good safety policy and a sound risk analysis is observed.

The growth of an industry is also reasonably dependent upon technological advances. This is especially true in the Chemical Industry, which is entering an era of more complex process: higher pressure, more reactive chemicals and exotic chemistry. More complex process requires more complex safety technology. Many industrialists even believe that the development and application of safety technology is actually a constraint on the growth of the chemical industry.

As chemical process technology becomes more complex safety becomes paramount in the minds of those responsible for the design and operation of process plant. Until the 1960's most organizations had their own methods of safety assurance, relying very much on in house experience and expertise. The whole structure of process industries has changed dramatically in the last thirty years and much of the accumulated experience and expertise has now been lost. It is therefore essential that formal methods of safety analysis are available to the process industries to ensure the safe and efficient operation of their processes.

Today, safety is equal in importance to production and has developed into a specific discipline, which includes many highly technical and complex theories and practices. Recent advances in chemical plant safety emphasize the use of appropriate technological tools to provide information for making safety decisions with respect to plant design and operation.

1.2 FAULT DETECTION AND DIAGNOSIS AS IMPORTANT SAFETY ASPECT

One of the primary aspects of safety is the fault detection and diagnosis. Abnormal situations occur when processes deviate significantly from their normal regime during on-line operation. Abnormal situation management (ASM) deals with timely detection and diagnosis, assessment of the abnormal situation and countermeasure planning. Process fault diagnosis (PFD) is the first step in ASM dealing with detection and isolation of abnormal events, i.e. analysis of root causes that result in abnormal behavior. The area of fault detection and diagnosis is an important aspect of process engineering. Not only is it important from a safety viewpoint, but also for the maintenance of yield and quality in a process. This area has received considerable attention from industry and academia alike because of the economic and safety impact involved. The early detection of faults can help avoid system shut-down, breakdown and even catastrophes involving human fatalities and material damage. A system which includes the capacity of detecting, isolating, identifying or classifying faults is called a fault diagnosis system

1.3 INTELLIGENT CONTROL (SYSTEM)

In May 1993, a task force was created at the invitation of the Technical Committee on Intelligent Control of the IEEE Control Systems Society to look into the area of Intelligent Control and define what is meant by the term. Its findings are aimed mainly towards serving the needs of the Control Systems Society and on deriving working characterizations of Intelligent Control. Many of the findings however may apply to other disciplines as well. The charge to the task force was to characterize intelligent control systems, to be able to recognize them and distinguish them from conventional control systems; to clarify the role of control in intelligent systems; and to help identify problems where intelligent control methods appear to be the only viable avenues.

Deregulation requires that utilities exercise less conservative operation regimes and more precise power-flow control. This is possible only by monitoring and controlling the system in much more detail than is, or has been, the case in present and past practice. The large quantity of information required can be provided in many cases through advances in telecommunications and computing techniques. There is still the need for evaluation techniques that extract the salient information from the large amount of raw data to use for higher-order processing. Up until now, the extraction of qualitative information is still done by the human expert, who can be overwhelmed in emergency situations when fast decisions are needed. The future operators also need to have the ability to specify the operating strategy in qualitative form, which is then translated into quantitative form in order to be processed by the computer control.

An intelligent system has the ability to act appropriately in an uncertain environment where an appropriate action is that which increases the probability of success, and success is the achievement of behavioral sub-goals that support the system's ultimate goal. In order for a man-made intelligent system to act appropriately, it may emulate functions of living creatures and ultimately human mental faculties. An intelligent system can be characterized along a number of dimensions. There are degrees or levels of intelligence that can be measured along the various dimensions of intelligence. At a minimum, intelligence requires the ability to sense the environment, to make decisions and to control action. Higher levels of intelligence may include the ability to recognize objects and events, to represent knowledge in a world model and to reason about and plan for the future.

Intelligent Systems can be categorized as:

- **Expert Systems** which process qualitative as well as quantitative knowledge with emphasis on the qualitative results.
- **Fuzzy Systems** which quantify qualitative knowledge including uncertainties.
- **Artificial Neural Networks** which infer quantitative information through approximation techniques and classify quantitative data into higher-order qualitative categories.

- **Decision Trees (DT)** which classifies quantitative data into discrete sets of qualitative categories.

The concepts of intelligence and control are closely related and the term "Intelligent Control" has a unique and distinguishable meaning. An intelligent system must define and use goals. Control is then required to move the system to these goals and to define such goals. Consequently, any intelligent system will be a control system. Conversely, intelligence is necessary to provide desirable functioning of systems under changing conditions, and it is necessary to achieve a high degree of autonomous behavior in a control system. Since control is an essential part of any intelligent system, the term "Intelligent Control Systems" is sometimes used in engineering literature instead of "Intelligent Systems" or "Intelligent Machines". The term "Intelligent Control System" simply stresses the control aspect of the intelligent system.

1.4 OBJECTIVE OF DISSERTATION

Fault diagnosis of control engineering systems can be based upon the generation of signals which reflect inconsistencies between the fault-free and faulty system operation so called residual signals. The large quantity of information required can be provided in many cases through advances in instrumentation and computing techniques. There is still the need for evaluation techniques that extract the salient information from the large amount of raw data to use for higher-order processing. Up until now, the extraction of qualitative information is still done by the human expert, who can be overwhelmed in emergency situations when fast decisions are needed. The future operators also need to have the ability to specify the operating strategy in qualitative form, which is then translated into quantitative form in order to be processed by the computer control. One of the main motivations for using intelligent systems is to provide this important interface between qualitative and quantitative information.

Artificial intelligence approaches to fault diagnosis can be very effective in enhancing the powerful detection and isolation capabilities of quantitative model-based methods. The objective of the dissertation is to demonstrate the application of Intelligent Control (through Fuzzy Logic) in the integration of qualitative and quantitative strategies in a fault diagnostic system. The Fuzzy Logic fault diagnostic system can minimize the probability of false-alarms and missed-alarms in fault decision making, while improving the level of heuristic information available for the human operator.

LITERATURE REVIEW

There are a lot of literatures available on Intelligent Control, Fuzzy Logic (FL) as well as Distillation Column Control. For the preparation of the project report many papers and books have proved beneficial, some of the literatures which have been beneficial in preparation of this report along with the features incorporated are discussed below.

For the basic understanding of the distillation column control, the book by **Buckley, P.S., Luyben, W.L., Shunta, J.P., "*Design of Distillation Column Control Systems*", Instruments Society of America 1985**, has been very helpful. The book is useful primarily from the stand point of an engineering design organization and is written keeping in view the drawbacks in the conventional control design of distillation column.

Looking at background information that forms the motivation of dissertation, there have been a number of recent papers in the fuzzy literature showing that fuzzy systems are universal approximations. For basic concept of fuzzy logic, **Horowitz, I., "*Fuzzy logic tutorial*", IEEE Trans. SMC, Vol. 17, No 6, Nov/Dec 1989, pp. 1085-1087** has been used. In the paper Fuzzy Logic was conceived as a better method for sorting and handling data but has proven to be an excellent choice for many control system applications since it mimics human control logic. It can be built into anything from small, hand-held products to large computerized process control systems. It uses an imprecise but very descriptive language to deal with input data more like a human operator.

Dash, S., Rengaswamy, R., Venkatasubramanian, V., "*Fuzzy-logic based trend classification for fault diagnosis of chemical process*", Computers and Chemical Engineering, Vol. 27, 2003, pp. 347-362, considered fault diagnosis based on patterns exhibited in the sensors measuring the process variables. The temporal patterns that a process event leaves on the measured sensors, called event signatures, have been utilized to infer the state of operation. They employed a two staged strategy using a pattern-matching approach. The first stage identifies the most likely fault candidates based on a similarity measure between the observed trends and the event-signatures in the knowledge base. The second stage is the estimation of the fault magnitude.

Elnemr, H., A., Elewa, M., M., "*Expert failure detection technique for distillation column*", IEEE, Vol. 6, 1996, pp. 1323 -1328, described an expert system for diagnosis of faults in a distillation column. The faults are in the incipient stage but may lead to serious situations in the near future. To demonstrate the feasibility of applying expert system in fault detection and diagnosis, they illustrated a numerical example. The results demonstrate the effectiveness of expert systems for real time fault diagnosis.

Venkatasubramanian, V., et al. reviewed process fault detection and diagnosis in three paper series. In the first paper of the series, **Venkatasubramanian, V., Rengaswamy, R., Kavuri, "*A review of process fault detection and diagnosis Part I: Quantitative model-based methods*", Computers and Chemical Engineers, Vol. 27, 2003, pp. 293-311,** they discussed a general diagnostic framework. The desirable characteristics of a fault diagnostic system have also been discussed. The paper also describes the various Quantitative model based fault diagnostic methods in detail.
The second paper by **Venkatasubramanian, V., Rengaswamy, R., Kavuri, "*A review of process fault detection and diagnosis Part II: Qualitative models and search strategies*", Computers and Chemical Engineers, Vol. 27, 2003, pp. 313-326,** reviewed qualitative model representations and search strategies used in fault diagnostic systems. Qualitative models are usually developed based on some fundamental understanding of the physics and chemistry of the process. Various forms of qualitative models such as causal models and abstraction hierarchies are discussed. The relative advantages and disadvantages of these representations are highlighted. In terms of search strategies, we broadly classify them as topographic and symptomatic search techniques. Topographic searches perform malfunction analysis using a template of normal operation, whereas, symptomatic searches look

for symptoms to direct the search to the fault location. Various forms of topographic and symptomatic search strategies are discussed.

In the final part of the series, **Venkatasubramanian, V., Rengaswamy, R., Kavuri, S.N., Yin, K., "*A review of process fault detection and diagnosisPart III: Process history based methods*", Computers and Chemical Engineers, Vol. 27, 2003, pp. 327-346**, discussed fault diagnosis methods that are based on historic process knowledge. We also compare and evaluate the various methodologies reviewed in this series in terms of the set of desirable characteristics we proposed in Part I. This comparative study reveals the relative strengths and weaknesses of the different approaches. The important role of fault diagnosis in the broader context of process operations is also outlined.

Book by **Bequette, B., W., "*Process Control- Modeling, Design and Simulation*", Eastern Economy Edition, Prentice Hall India,** has been useful in analyzing dynamic chemical processes and developing automatic control strategies to operate them safely and economically. The contents of the book are written in lucid language and also uses interactive learning through computer based simulation exercises. The popular MATLAB software package, including SIMULINK block-diagram simulation environment, is used.

Wood, R., K., Berry, M., W., "Terminal composition control of a binary distillation column", Chemical Engineering Science, Vol. 28, 1973, pp. 1707-1717, studied terminal composition control of a pilot scale binary distillation column operated under the control of an IBM 1800 digital computer for disturbances in feed flow rate. Conventional two point control, whereby the overhead composition is controlled by reflux flow rate and bottom composition by means of steam rate, was demonstrated to be unsatisfactory. Two alternate control systems, namely a non-interacting control system and a ratio control system were evaluated. The results show that a very significant improvement in the control of both compositions is achieved by using non interacting control.

Skogestad, S., and Morari, M. in "Control configuration selection for distillation columns", AIChE Journal, Vol. 33, No. 10, 1987, pp. 1620 – 1635, discussed the main issues that must be addressed when designing a composition control system. The paper outlines simplified control system design of two product distillation column by means of the following procedure.

- Choosing two manipulated inputs for composition control (corresponding to specific control configuration).
- Designing the level and pressure control system (usually three SISO controllers).
- Designing a 2×2 controller for composition control.

The paper provides guidelines for step1, which is considered the most important. Differences between control configurations have been discussed elaborately. The illustration of a distillation column fault diagnosis using fuzzy logic tool in the dissertation report has been taken from this paper.

Gani, R., Rurz, C., A. and Camerons, I., T., "A generalized model for distillation columns-I" generalized model for the dynamic simulation of distillation columns. The model allows the solution of a wide variety of problems, from open- and closed-loop responses of single (and multiple) columns to operability studies (of feed changeover and start-up operations) and column instability studies (effect of plate hydraulics during transient operations). Results are given for single columns (including industrial) as well as multiple columns for different types of operations. The problems include thermodynamically close to ideal systems to highly non ideal systems. Efficient and robust numerical integrators are used to obtain reliable solutions even for difficult discontinuous operations. Results are given for single columns (including industrial) as well as multiple columns for different types of operations

Koyuncu, M., and Yazici, A., in their paper "A Fuzzy Knowledge-Based System for Intelligent Retrieval" discussed the importance of developing an environment that permits flexible modeling and fuzzy querying of complex data and knowledge including uncertainty. With such an environment, one can have intelligent retrieval of information and knowledge, which has become a critical requirement for those applications. In this paper, we introduce a fuzzy knowledge-based (FKB) system along with the model and the inference mechanism. The inference mechanism is based on the extension of the Rete algorithm to handle fuzziness using a similarity- based approach. The proposed FKB system is used in the intelligent fuzzy object-oriented database environment, in which a fuzzy object-oriented database is used to handle large scale of complex data while the FKB system is used to handle knowledge of the application domain. Both the fuzzy object-oriented database system and the fuzzy knowledge-based system are based on the object-oriented concepts to eliminate data type mismatches.

FAULT DETECTION AND DIAGNOSIS

The term fault is generally defined as a departure from an acceptable range of an observed variable or a calculated parameter associated with a process. This defines a fault as a process abnormality or symptom, such as high temperature in a reactor or low product quality and so on. The underling cause(s) of this abnormality, such as a failed coolant pump or a controller, is (are) called the basic event(s) or the root cause(s). The basic event is also referred to as a malfunction or a failure. Since one can view the task of diagnosis as a classification problem, the diagnostic system is also referred to as a diagnostic classifier.

Fig. 3.1 depicts the components of a general fault diagnosis framework. The figure shows a controlled process system and indicates the different sources of failures in it. In general, one has to deal with three classes of failures or malfunctions as described below:

3.1 GROSS PARAMETER CHANGES IN A MODEL

In any modeling, there are processes occurring below the selected level of detail of the model. These processes which are not modeled are typically lumped as parameters and these include interactions across the system boundary. Parameter failures arise when there is a disturbance entering the process from the environment through one or more exogenous (independent) variables. An example of such a malfunction is a change in the concentration of the reactant from its normal or steady state value in a reactor feed. Here, the concentration is an exogenous variable, a variable whose dynamics is not provided with that of the process. Another example is the change in the heat transfer coefficient due to fouling in a heat exchanger.

3.2 STRUCTURAL CHANGES

Structural changes refer to changes in the process itself. They occur due to hard failures in equipment. Structural malfunctions result in a change in the information flow between various variables. To handle such a failure in a diagnostic system would require the removal of the appropriate model equations and restructuring the other equations in order to describe the current situation of the process. An example of a structural failure would be failure of a controller. Other examples include a stuck valve, a broken or leaking pipe and so on.

3.3 MALFUNCTIONING SENSORS AND ACTUATORS

Gross errors usually occur with actuators and sensors. These could be due to a fixed failure, a constant bias (positive or negative) or an out-of range failure. Some of the instruments provide feedback signals which are essential for the control of the plant. A failure in one of the instruments could cause the plant state variables to deviate beyond acceptable limits unless the failure is detected promptly and corrective actions are accomplished in time. It is the purpose of diagnosis to quickly detect any instrument fault which could seriously degrade the performance of the control system.

3.4 DESIRABLE CHARACTERISTICS OF A FAULT DIAGNOSTIC SYSTEM

Whenever an abnormality occurs in a process, a general diagnostic classifier would come up with a set of hypotheses or faults that explains the abnormality. Completeness of a diagnostic classifier would require the actual fault(s) to be a subset of the proposed fault set. Resolution of a diagnostic classifier would require the fault set to be as minimal as possible. Thus, there is a trade-off between completeness and resolution. The trade-off is in the accuracy of predictions. These two concepts would recur whenever different classifier designs are compared. The following presents a set of desirable characteristics one would like the diagnostic system to possess.

3.4.1 Quick Detection and Diagnosis

The diagnostic system should respond quickly in detecting and diagnosing process malfunctions. However, quick response to failure diagnosis and tolerable performance during normal operation are two conflicting goals. A system that is designed to detect a failure (particularly abrupt changes) quickly will be sensitive to high frequency influences. This makes the system sensitive to noise and can lead to frequent false alarms during normal operation, which can be disruptive. This is analogous to the trade-off between robustness and performance noticed in the control literature.

3.4.2 Isolability

Isolability is the ability of the diagnostic system to distinguish between different failures. Under ideal conditions free of noise and modeling uncertainties, this amounts to saying that the diagnostic classifier should be able to generate output that is orthogonal to faults that have not occurred. Of course the ability to design isolable classifiers depends to a great extent on the process characteristics. There is also a trade-off between isolability and the rejection of modeling uncertainties. Most of the classifiers work with various forms of redundant information and hence there is only a limited degree of freedom for classifier design. Due to this, a classifier with high degree of isolability would usually do a poor job in rejecting modeling uncertainties and vice versa.

3.4.3 Robustness

One would like the diagnostic system to be robust to various noise and uncertainties. One would like its performance to degrade gracefully instead of failing totally and abruptly. Robustness precludes deterministic isolability tests where the thresholds are placed close to zero. In the presence of noise, these thresholds may have to be chosen conservatively.

3.4.4 Novelty Identifiability

One of the minimal requirements of a diagnostic system is to be able to decide, given current process conditions, whether the process is functioning normally or abnormally, and if abnormal, whether the cause is a known malfunction or an unknown, novel, malfunction. This criterion is known as novelty identifiability. In general, sufficient data may be available to model the normal behavior of the process. However, one typically does not have such historic process data available for modeling the abnormal regions satisfactorily (off course, if one has access to a good dynamic model of the process, then generating such data is much easier). Only a few data patterns may be available covering portions of the abnormal region. Thus, it is possible that much of the abnormal operations region may not have been modeled adequately. This will pose serious challenges in achieving novelty identifiability. Even under these difficult conditions, one would like the diagnostic system to be able to recognize the occurrence of novel faults and not misclassify them as one of the other known malfunctions or as normal operation.

3.4.5 Classification Error Estimate

An important practical requirement for a diagnostic system is in building the user's confidence on its reliability. This could be greatly facilitated if the diagnostic system could provide a priori estimate on classification error that can occur. Such error measures would be useful to project confidence levels on the diagnostic decisions by the system giving the user a better feel for the reliability of the recommendations by the system.

3.4.6 Adaptability

Processes in general change and evolve due to changes in external inputs or structural changes due to retrofitting and so on. Process operating conditions can change not only due to disturbances but also due to changing environmental conditions such as changes in production quantities with changing demands, changes in the quality of raw material etc. Thus the diagnostic system should be adaptable to changes. It should be possible to gradually develop the scope of the system as new cases and problems emerge, as more information becomes available.

3.4.7 Explanation facility

Besides the ability to identify the source of malfunction, a diagnostic system should also provide explanations on how the fault originated and propagated to the current situation. This is a very important factor in designing on-line decision support systems. This requires the ability to reason about cause and effect relationships in a process. A diagnostic system has to justify its recommendations so that the operator can accordingly evaluate and act using his/her experience. One would like the diagnostic system to not only justify why certain hypotheses were proposed but also explain why certain other hypotheses were not proposed.

3.4.8 Modeling requirements

The amount of modeling required for the development of a diagnostic classifier is an important issue. For fast and easy deployment of real-time diagnostic classifiers, the modeling effort should be as minimal as possible.

3.4.9 Storage and Computational Requirements

Usually, quick real-time solutions would require algorithms and implementations which are computationally less complex, but might entail high storage requirements. One would prefer a diagnostic system that is able to achieve a reasonable balance on these two competing requirements.

3.4.10 Multiple Fault Identifiability

The ability to identify multiple faults is an important but a difficult requirement. It is a difficult problem due to the interacting nature of most faults. In a general nonlinear system, the interactions would usually be synergistic and hence a diagnostic system may not be able to use the individual fault patterns to model the combined effect of the faults. On the other hand, enumerating and designing separately for various multiple fault combinations may not be possible for large processes.

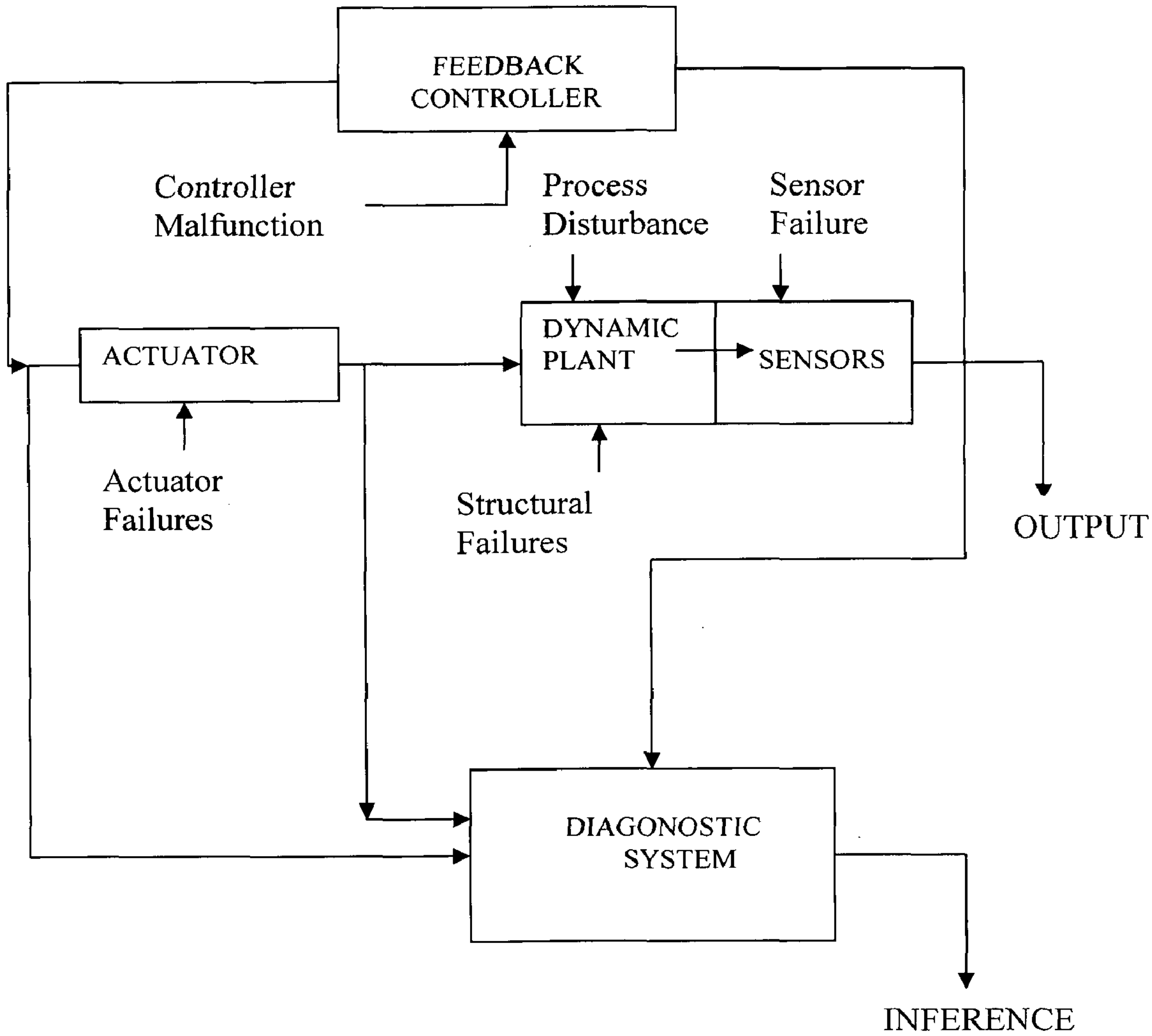


Figure 3. 1 A General Fault Diagnostic System.

FUZZY LOGIC AND FAULT DIAGNOSIS

4.1 GENERAL

The concept of Fuzzy Logic (FL) was conceived by Lotfi Zadeh, a professor at the University of California at Berkley, and presented not as a control methodology, but as a way of processing data by allowing partial set membership rather than crisp set membership or non-membership. This approach to set theory was not applied to control systems until the 70's due to insufficient small-computer capability prior to that time. Professor Zadeh reasoned that people do not require precise, numerical information input, and yet they are capable of highly adaptive control. If feedback controllers could be programmed to accept noisy, imprecise input, they would be much more effective and perhaps easier to implement. Unfortunately, U.S. manufacturers have not been so quick to embrace this technology while the Europeans and Japanese have been aggressively building real products around it.

In this context, FL is a problem-solving control system methodology that lends itself to implementation in systems ranging from simple, small, embedded micro-controllers to large, networked, multi-channel PC or workstation-based data acquisition and control systems. It can be implemented in hardware, software, or a combination of both. FL provides a simple way to arrive at a definite conclusion based upon vague, ambiguous, imprecise, noisy, or missing input information. FL's approach to control problems mimics how a person would make decisions, only much faster.

4.2 WORKING PRINCIPLE OF FUZZY LOGIC

FL requires some numerical parameters in order to operate such as what is considered significant error and significant rate-of-change-of-error, but exact values of these numbers are usually not critical unless very responsive performance is required in which case empirical tuning would determine them. For example, a simple temperature control system could use a single temperature feedback sensor whose data is subtracted from the command signal to compute "error" and then time-differentiated to yield the error slope or rate-of-change-of-error, hereafter called "error-dot". Error might have units of degs F and a small error considered to be 2F while a large error is 5F. The "error-dot" might then have units of degs/min with a small error-dot being 5F/min and a large one being 15F/min. These values don't have to be symmetrical and can be "tweaked" once the system is operating in order to optimize performance. Generally, FL is so forgiving that the system will probably work the first time without any tweaking.

FL was conceived as a better method for sorting and handling data but has proven to be a excellent choice for many control system applications since it mimics human control logic. It can be built into anything from small, hand-held products to large computerized process control systems. It uses an imprecise but very descriptive language to deal with input data more like a human operator. It is very robust and forgiving of operator and data input and often works when first implemented with little or no tuning.

4.3 NECESSITY OF FUZZY LOGIC

FL offers several unique features that make it a particularly good choice for many control problems.

a) It is inherently robust since it does not require precise, noise-free inputs and can be programmed to fail safely if a feedback sensor quits or is destroyed. The output control is a smooth control function despite a wide range of input variations.
b) Since the FL controller processes user-defined rules governing the target control system, it can be modified and tweaked easily to improve or drastically alter system performance. New sensors can easily be incorporated into the system simply by generating appropriate governing rules.
c) FL is not limited to a few feedback inputs and one or two control outputs, nor is it necessary to measure or compute rate-of-change parameters in order for it to be implemented. Any sensor data that provides some indication of a system's actions

and reactions is sufficient. This allows the sensors to be inexpensive and imprecise thus keeping the overall system cost and complexity low.

d) Because of the rule-based operation, any reasonable number of inputs can be processed (1-8 or more) and numerous outputs (1-4 or more) generated, although defining the rule base quickly becomes complex if too many inputs and outputs are chosen for a single implementation since rules defining their interrelations must also be defined. It would be better to break the control system into smaller chunks and use several smaller FL controllers distributed on the system, each with more limited responsibilities.

e) FL can control nonlinear systems that would be difficult or impossible to model mathematically. This opens doors for control systems that would normally be deemed unfeasible for automation.

4.4 LINGUISTIC VARIABLES

In 1973, Professor Lotfi Zadeh proposed the concept of linguistic or "fuzzy" variables. Think of them as linguistic objects or words, rather than numbers. The sensor input is a noun, e.g. "temperature", "displacement", "velocity", "flow", "pressure", etc. Since error is just the difference, it can be thought of the same way. The fuzzy variables themselves are adjectives that modify the variable (e.g. "large positive" error, "small positive" error, "zero" error, "small negative" error, and "large negative" error). As a minimum, one could simply have "positive", "zero", and "negative" variables for each of the parameters. Additional ranges such as "very large" and "very small" could also be added to extend the responsiveness to exceptional or very nonlinear conditions, but aren't necessary in a basic system.

Thus, FL does not require precise inputs, is inherently robust, and can process any reasonable number of inputs but system complexity increases rapidly with more inputs and outputs. Distributed processors would probably be easier to implement. Simple, plain-language IF X AND Y THEN Z rules are used to describe the desired system response in terms of linguistic variables rather than mathematical formulas. The number of these is dependent on the number of inputs, outputs, and the designer's control response goals.

4.5 THE RULE MATRIX

The fuzzy parameters of error (command-feedback) and error-dot (rate-of-change-of-error) were modified by the adjectives "negative", "zero", and "positive". To picture this, imagine the simplest practical implementation, a 3-by-3 matrix. The columns represent "negative error", "zero error", and "positive error" inputs from left to right. The rows represent "negative", "zero", and "positive" "error-dot" input from top to bottom. This planar construct is called a rule matrix. It has two input conditions, "error" and "error-dot", and one output response conclusion (at the intersection of each row and column). In this case there are nine possible logical product (AND) output response conclusions. Although not absolutely necessary, rule matrices usually have an odd number of rows and columns to accommodate a "zero" center row and column region. This may not be needed as long as the functions on either side of the center overlap somewhat and continuous dithering of the output is acceptable since the "zero" regions correspond to "no change" output responses the lack of this region will cause the system to continually hunt for "zero". It is also possible to have a different number of rows than columns. This occurs when numerous degrees of inputs are needed. The maximum number of possible rules is simply the product of the number of rows and columns, but definition of all of these rules may not be necessary since some input conditions may never occur in practical operation. The primary objective of this construct is to map out the universe of possible inputs while keeping the system sufficiently under control.

4.6 FUZZY KNOWLEDGE-BASE (FKB)

The knowledge base of the FKB system includes intelligent objects having fuzzy attributes and rules. A fuzzy inference method is used for deduction of fuzzy conclusions. The objects with deduction capability are called as intelligent objects in this study.

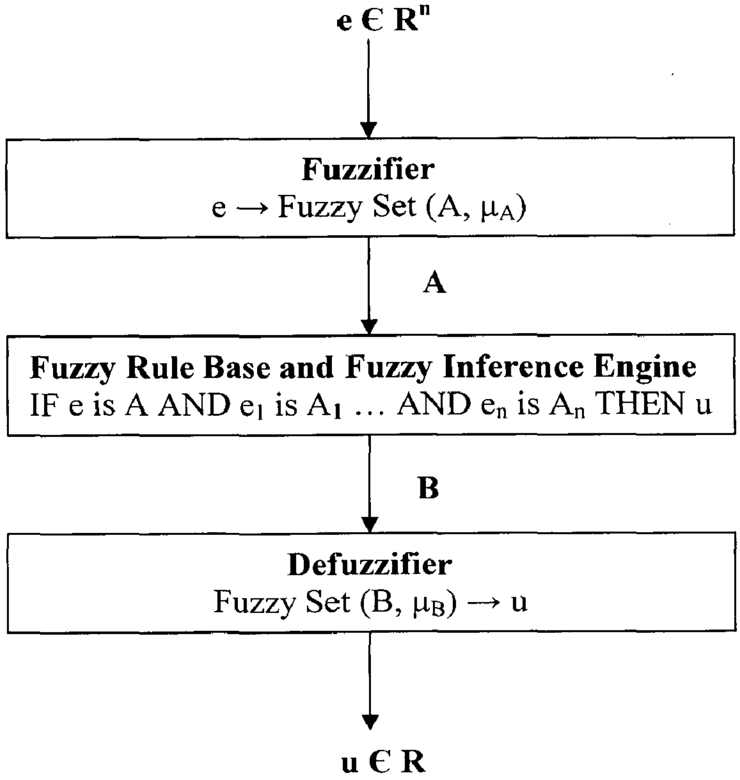


Figure 4. 1 Working of Fuzzy Logic.

4.6.1 STRUCTURE OF FUZZY RULES

In FKB, knowledge is represented by IF–THEN rules in which the antecedent and the consequent involve linguistic variables.

For example

IF x is A THEN y is B

where x and y are linguistic variables, and are fuzzy sets. The antecedent of a rule may be composed of more than one clause connected by the fuzzy logical operators AND and OR.

For example

IF dose is high OR dose is VeryHigh AND exposureTime is long

THEN pollution is very Dangerous

Fuzzy rules are used to derive new attributes or to specify some constraints using not only crisp but also fuzzy attributes of different objects. The variables of rules represent attributes of objects or objects themselves. For example, consider the domain of the following fuzzy attributes of the pollutants class.

Domain (dose): {VeryHigh, High, Medium, Low}.

Domain (exposure Time): {VeryLong, Long, Medium, Short}.

Domain (status): {VeryDangerous, Dangerous, LessDangerous}

Fuzzy rules are defined using these linguistic values as follows:

IF pollutants dose is VeryHigh

AND pollutants exposure Time is VeryLong

THEN pollutants status is VeryDangerous

The rule given here exemplifies the exact syntax of the fuzzy IF–THEN rules utilized in the IFOOD language.

(R-1) defrule X.status ([VeryDangerous], Y)

:- pollutants (X), X.dose ([VeryHigh], 0.7)

X exposureTime ([VeryLong], 0.6)

where, X.status ([VeryDangerous], Y) is the consequent of the rule (the THEN part or the left-hand side (LHS) of the rule) and the right-hand side (RHS) of the ":-" sign is the antecedent of the rule (the IF part). In the consequent of the rule, Y is the membership degree of the rule conclusion, which is computed by using the matching degrees of the rule antecedent conditions, the matching degree of the rule conclusion and the implication function.

4.6.2 SIMILARITY MATCHING

In the intelligent fuzzy object-oriented database environment, there are no sharp boundaries among fuzzy terms. We use similarity relations to define similarities between pairs of elements in the fuzzy domain. Even when there is no exact matching, similar rule(s) may still be activated. Normally, when the matching degrees of predicates in the rule's antecedent are greater than 0, a rule will be activated. However, in order to eliminate undesired effects and increase the efficiency of querying, a threshold value is used. For example, the threshold levels are 0.7 for the dose attribute and 0.6 for the exposure Time attribute in the rule (R-1). Users can specify any threshold levels in their queries. We support this flexibility because one user may prefer more restricted values as output while another may request all the possible values. A default threshold value is employed when the user does not specify it.

For example, consider the rule (R-1) given above. If there is a pollutant's object matching exactly with the rule antecedent (i.e., dose is VeryHigh and exposure Time is VeryLong), the rule will succeed. However, if the values of an object do not exactly match with a rule's antecedent, there can still be matching in our FKB system, since it employs the similarity matching approach. Here, by similarity matching we mean that not only the rule with exact matching is activated but also any other rule may be activated when the fuzzy values of objects are similar to the corresponding predicates in the rule's antecedent. For example, the similarity between high and VeryHigh and the dose attribute of an object are specified as follows:

$$\mu_s \text{(high, Very High)} = 0.8 \text{ and Object.dose} = \text{[high]}.$$

Even though the object value of the dose attribute is High, instead of VeryHigh, the antecedent of the rule is satisfied with a matching degree of 0.8 (for dose), since the similarity of high to VeryHigh is greater than the given threshold value. Since the model permits to represent both fuzzy and crisp values, some objects may have fuzzy values and some may have crisp values for the same attribute. If the value of an object attribute is fuzzy, the rules are activated using similarity matching. If the value of an object attribute is crisp, then the membership degree of this crisp value to the fuzzy set in the rule is determined by using a predefined fuzzy membership function. If that membership value, which is in [0, 1], is greater than or equal to the specified threshold value, then the rule condition is satisfied.

A rule's antecedent may be composed of more than one condition. Each condition in a rule antecedent may have its own matching degree with a corresponding object value. Therefore, we compute an overall matching degree of the rule antecedent. Here, we use the operator for combining the degree of matching of conjunction (AND) conditions and the operator for combining the degree of matching of disjunction (OR) conditions, as shown as follow:

For AND operator: $\mu_{antecedent} = \mathrm{Min}(\mu_1,\mu_2,\ldots\ldots,\mu_n)$

For OR operator: $\mu_{antecedent} = \mathrm{Min}(\mu_1,\mu_2,\ldots\ldots,\mu_n)$.

Considering the rule (R-1) given above, each object term is matched with a matching degree (i.e., X.dose ([VeryHigh], 0.7) and X.exposureTime ([VeryLong], 0.6)). In addition to object terms, the rule also includes a class term (i.e., pollutants(X)). The matching degree of this term is the object inclusion degree which represents the degree of membership of the object to the class that it belongs to. This degree is computed during the object creation and stored with the object. This matching degree is directly obtained from the database when needed.

For example, consider the rule (R-1) given previously and calculate its overall matching degree using the following values:

$\mu\sigma$	=	0.8
σ1.dose	=	[high]
σ1.exposureTime	=	medium
μ_s(high, VeryHigh)	=	0.9
μ_s (Medium, VeryLong)	=	0.6

The overall matching degree of the rule (R-1)

$$\mu_{antecedent} = \min(0.8, 0.9, 0.6) = 0.6$$

Another issue related to the rule definitions is the usage of fuzzy and crisp attributes together in the rule definitions. If an antecedent predicate is defined using a crisp attribute, then the traditional pattern matching is applied and the matching degree of this predicate is one (1) in case of successful matching, otherwise the rule fails.

4.6.3 FUZZY INFERENCE METHOD

Fuzzy implication rules are generalization of two-valued logic. We use the generalized modus ponens for fuzzy implications in the knowledge base. Fuzzy inference mechanism produces a conclusion that is both qualified and quantified. The conclusion is qualified using modus ponens (MP) inference method as follows:

Rule : x is A $\rightarrow$ y is B

Fact : x is A′

Infer : y is B′ where $\mu_s(A', A) > 0$

Fuzzy inference mechanism quantifies the conclusion with a membership degree using an implication function. There are different implication functions proposed in literature. One such implication function is the Godelian's fuzzy implication function. It is easy and efficient to calculate the membership degrees of the conclusions by this function.

$$t\,(x_i \text{ is } A \rightarrow y_i \text{ is } B) = \begin{cases} 1, & \mu_A(x_i) \leq \mu_B(y_i) \\ \mu_B(y_i), & \mu_A(x_i) > \mu_B(y_i) \end{cases}$$

For example, assume that similarity of High to VeryHigh is given as 0.9 and similarity of Dangerous to VeryDangerous is given as 0.7

Rule : IF pollutant dose is high THEN pollutant.status is dangerous.

Fact : pollutant.dose is VeryHigh

Infer : pollutant.status is VeryDangerous.

Matching degree of antecedent is:

μ_{dose}(High, VeryHigh) = 0.9

Matching degree of consequent is:

μstatus (Dangerous, VeryDangerous) = 0.7

Since the matching degree of antecedent (i.e., 0.9) is greater than the matching degree of consequent (i.e., 0.7), the membership degree of the rule conclusion is 0.7. Therefore, the status of the object is VeryDangerous with a membership degree 0.7.

In the given example, the rule's antecedent includes only one condition. If a rule antecedent consists of more than one condition, then the overall matching degree of the rule's antecedent is calculated as explained before.

Another important issue related to the fuzzy inference is that implication itself may be specified as fuzzy in addition to the fuzziness in the rule antecedent and consequent. Fuzziness in the implication is formulated as follows:

$$x \text{ is } A \xrightarrow{\theta} y \text{ is } B,$$

where θ is the uncertainty level given to the implication.

For example, if we say that the intelligence level of a person more or less determines the success of the person. The implication here is specified by a fuzzy term and can be represented with the θ value in [0, 1], i.e., 0.5. We may assign different values to the following fuzzy terms:

Definitely: 1.0

Almost: 0.9

Very: 0.7

More or less: 0.5.

The fuzziness level of the obtained conclusion will be reduced proportional to the fuzziness level specified in the implication itself. For example, if we fuzzify implication using more or less, then its implication level is 0.5. The conclusion can be obtained by taking algebraic product of the value obtained from the rule antecedent and consequent, and the value assigned to the implication itself. If we modify the example given above, the conclusion is computed as follows:

Rule: IF pollutant dose is high

THEN pollutant status is dangerous (0.5).

Fact: pollutant.dose is VeryHigh

Infer: pollutant.status is VeryDangerous.

Notice that 0.5 is the uncertainty level assigned to the implication. That is, if pollutant.dose is high, than we can more or less infer that pollutant.status is dangerous.

$$\mu_{conclusion} = 0.7 \times 0.5 = 0.35$$

where 0.7 is the value obtained from the rule antecedent and consequent as computed in the previous example.

Since all the similar rules will be activated during fuzzy inference, we combine the conclusions of the activated rules to produce the final output of inference. We combine the conclusion by using the maximum operator as follows:

$$\mu_{FINAL} = \text{Max}\ (\mu_{R1}, \mu_{R2}, \ldots, \mu_{Rn}).$$

FUZZY LOGIC BASED FAULT DIAGNOSTIC SYSTEM

5.1 PROCESS FAULT SIGNATURES AND PATTERN RECOGNITION

The temporal patterns that a process event leaves on the measured sensors are called event signatures. The event signatures can be represented by language based on trend exhibited by the signatures or any mathematical tool.

The first step is the pattern recognition process. The process signatures retrieved online from the sensors are related with the characteristic trends in the knowledge-base of the diagnostic system. The signature trend to event mapping process is an important issue. In real life systems, precision tends to be vague or more so, when dealing with qualitative features like signature trends. An important factor in their consideration is that unlike crisp and definitive measures such as numbers, there is some latitude i.e. degree of fuzziness associated with them, both in the identification and matching stages. Trends present scope of variation even for the same underlying event. It is important to understand the concept of a trend as understood when visually seen can be different from what results when a particular trend identification scheme is employed.

In the case study for matching of signature trend with characteristic fault signatures simple least square error technique is employed.

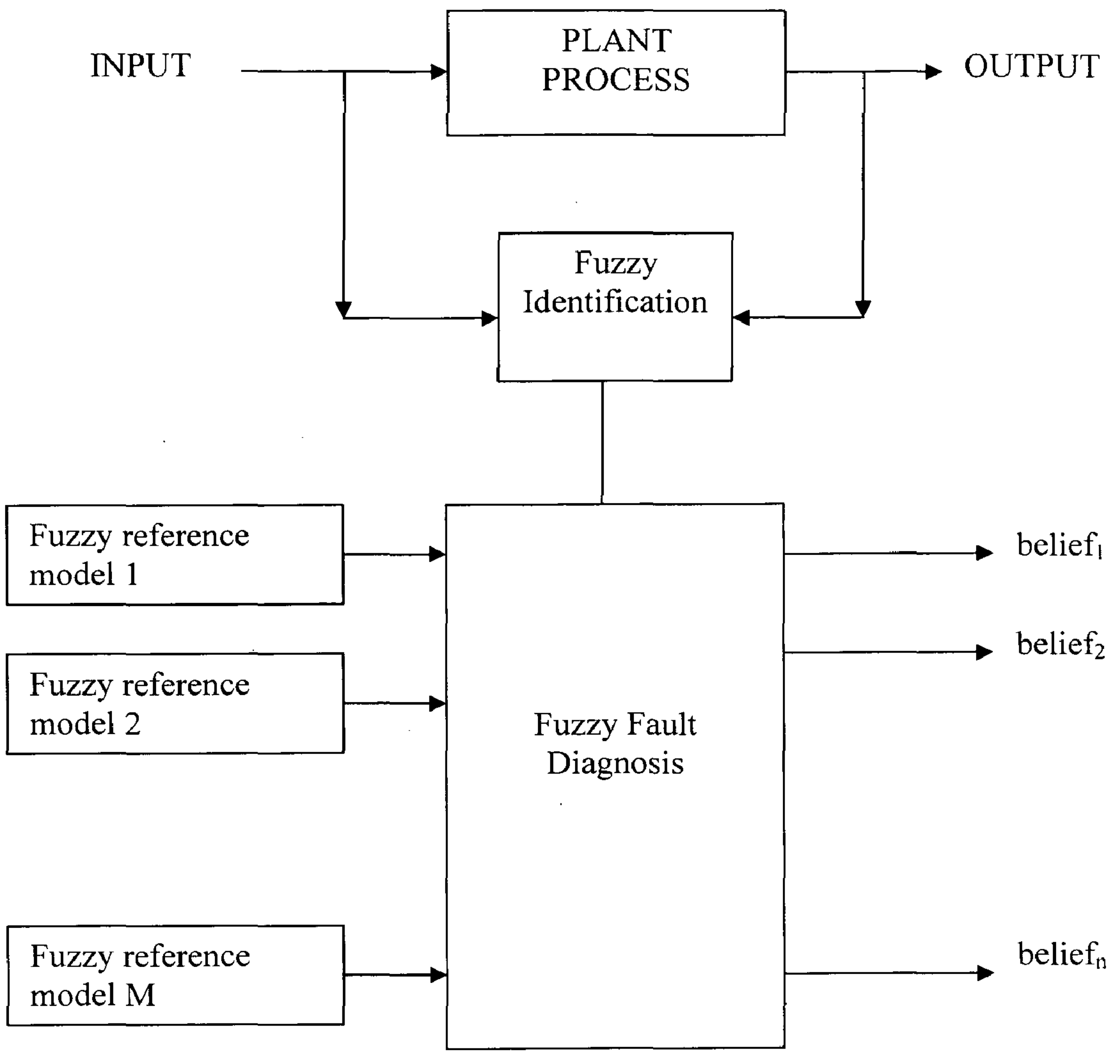


Figure 5.1 Fuzzy Logic Based Fault Diagnostic System

5.2 RULE-BASED KNOWLEDGE-BASE

To identify faults in the system knowledge base is used in mapping fault signatures to the faults in the form of if – then rules. The fault signatures are patterns that are exhibited by the sensors in response to a fault, obtained either from dynamic simulations or historical databases. An example of the *i* th rule (*i* th fault) is shown below.

If sensor S1 $\rightarrow$ trend Tr^*_{1i} AND

sensor S2 $\rightarrow$ trend Tr^*_{2i} AND........ then

Fault is Fi

where I =1,2,....M rules relating sensor trends to the M fault scenarios. Tr^*_{1i} refers to the fault signature exhibited by sensor S1 for fault Fi. The inferencing here is multivariable in nature due to conjunction operator and used here.

According to the effectiveness in classification and broadness in identification representative signature for each sensor for each fault with varying magnitude is required to be stored.

5.3 RULES EVALUATION

To evaluate the rules for an observed trend Tr, fuzzy inferencing is employed. By comparing Tr fuzzily with the signature trend Tr* in each part j of the antecedent in the I th rule, a similarity index SI^j_i is obtained. This is the degree of match between the observed trend Tr and that in the knowledge – base Tr*. Once all the SI^j_i are evaluated, the overall confidence index CI_i of the ith rule's consequent is calculated. The fuzzy logic interpretation of AND as minimum is employed, thus CI_i is given by the minimum over all the antecedent parts j

$$CI_i = \min_j [SI^j_i]$$

This evaluation is physically intuitive. The truth value of a hypothesis takes a value between 0 and 1, and the strength of a rule is considered equivalent to the weakest link i.e. the part of the antecedent with the smallest SI^j_i value. Once all the CI_i are obtained, the faults are ranked in the decreasing order of their confidences.

One important issue here is about fault resolution. If all the faults can be qualitatively resolved i.e., distinguishable* based only on the measured sensor signatures, then this would result in a high degree of accuracy in pin pointing the actual fault. However if this is not the case i.e. the CI_i are close, it is necessary to add more discriminating sensors to resolve the conflict.

Once the most likely fault candidate F* is identified, it is passed to the next stage to evaluate the severity (fault magnitude).

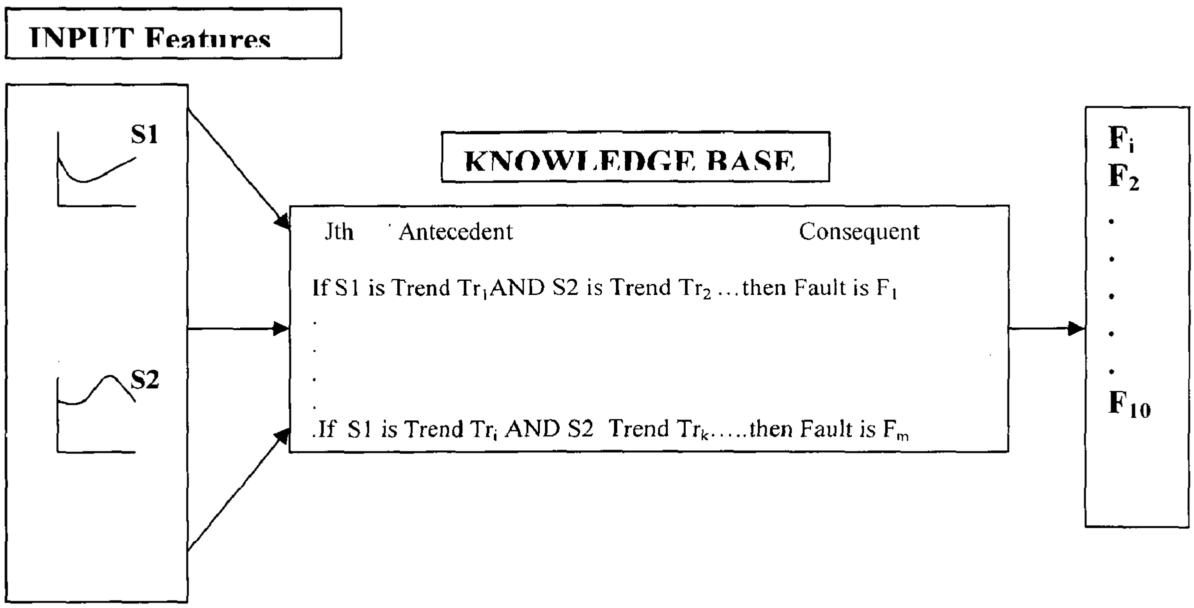


Figure 5. 2 Trend matching based on Fuzzy Inferencing using Similarity Indices.

5.4 DISTILLATION COLUMN- CASE STUDY

In this section the application of the Fuzzy Logic Fault Diagnostic strategy will be studied for Distillation Column. The main control objective of the distillation column is to maintain the top and bottom product compositions. The mathematical model of the distillation column is based on mass – energy balances. The model of the distillation column is expressed in a linear constant multivariable system.

$$\begin{bmatrix} dy_D \\ dx_B \end{bmatrix} = \begin{bmatrix} \dfrac{0.878}{75s+1} & \dfrac{-0.864}{75s+1} \\ \dfrac{1.082}{75s+1} & \dfrac{-1.096}{75s+1} \end{bmatrix} \begin{bmatrix} dL \\ dV \end{bmatrix} + \begin{bmatrix} \dfrac{0.394}{75s+1} & \dfrac{0.881}{75s+1} \\ \dfrac{0.586}{75s+1} & \dfrac{1.119}{75s+1} \end{bmatrix} \begin{bmatrix} dF \\ dz_F \end{bmatrix}$$

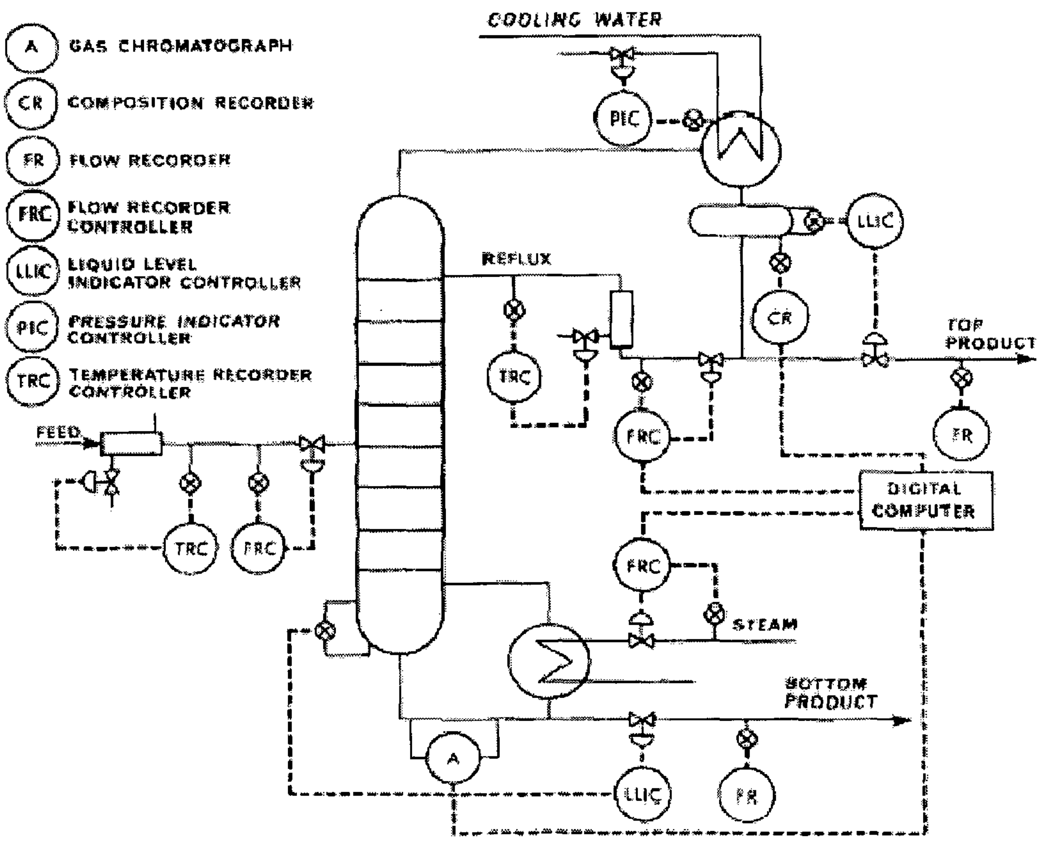


Figure 5. 3 Schematic Diagram of the column.

Assumptions and conditions:

- Constant molar flows.
- Binary separation is observed
- Relative volatility of the system does not change along the column temperature.
- The column control is one to one PI control configuration.

Table 5. 4. 1 Data for Distillation Column

Feed Condition	**Saturated liquid**
Relative volatility, α	**1.5**
No. of theoretical trays, N	**40**
Feed tray location, N_F (reboiler = 1)	**21**
Feed rate, F (kmol/min)	**1**
Feed composition, z_F	**0.5**
Distillate Composition, y_D	**0.99**
Bottom product compositon, x_B	**0.01**
Distillate rate, D (kmol/min)	**0.5**
Bottom product rate, B (kmol/min)	**0.5**
Minimum reflux rate, Lmin (kmol/min)	**1.39**
Reflux rate, L (kmol/min)	**2.71**

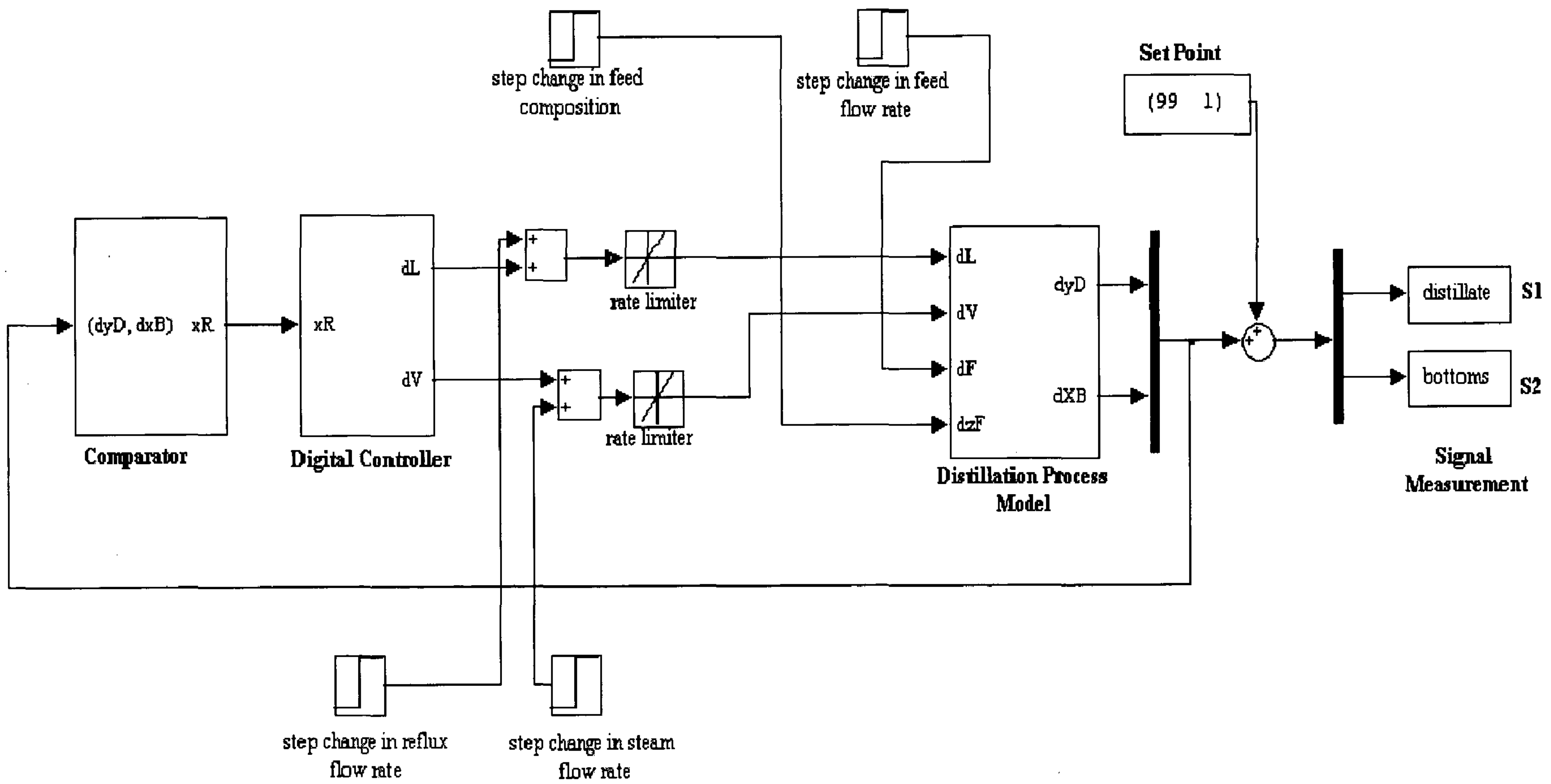


Figure 5. 3. 1 Terminal Composition Control in a Binary Distillation Column

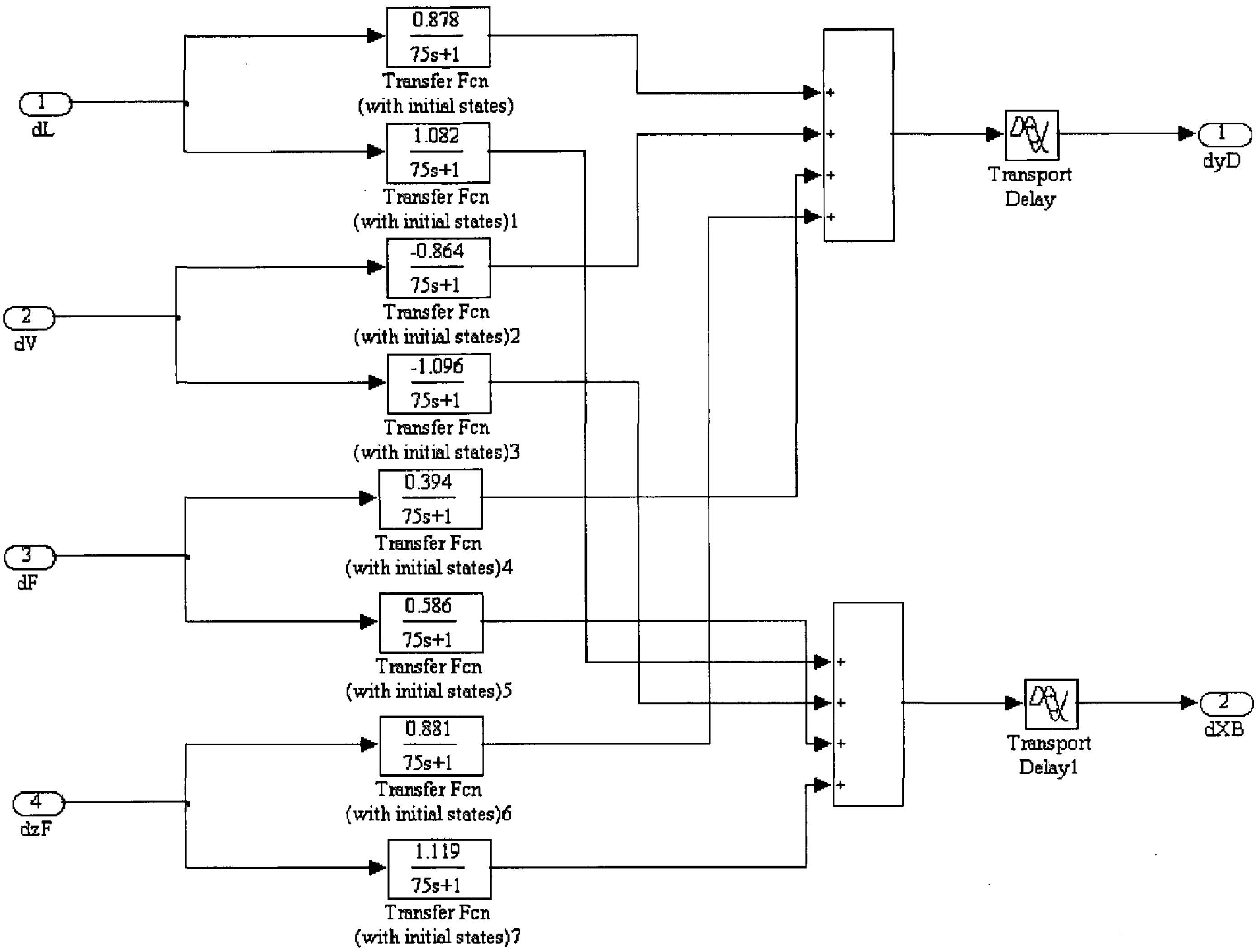
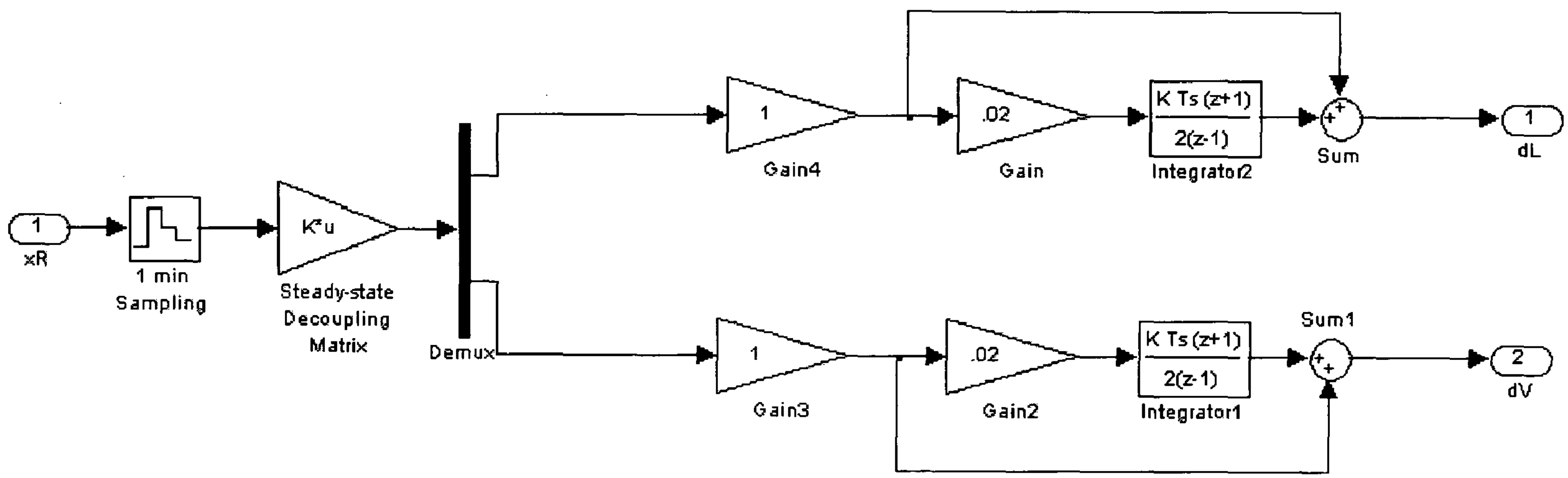


Figure 5. 3. 2 Distillation Process Model



Single-loop PI Controllers

Figure 5. 3. 3 Digital Controller

5.5 SIMULATED STEP FAULT SCENARIOS

To evaluate the proposed strategy fault scenarios are simulated for knowledge-base construction and testing. The measurement sensors and the fault variables for the case study are shown in Table 5. 4. 2. To construct the knowledge-base we carry out fault simulations in positive and negative deviations for all the 4 input fault variables. Three levels of step faults (low, medium and high) are simulated in each direction for all the fault variables (totaling 4 ×3 ×2 = 24 scenarios) as shown in Table 5.5.1 through 5.5.4. The level of the fault is treated as a fuzzy variable with fuzzy values low, medium and high.

Table 5. 4. 2 Measurement and fault variables for Distillation Column.

MEASUREMENT SENSORS	MEASURED VARIABLE
S1	Distillate composition, y_D
S2	Bottom product composition, x_B
No.	**DISTURBANCE VARIABLE (FAULTS)**
1	Feed flow rate, F
2	Feed concentration, z_F
3	Reflux rate, L
4	Steam flow rate, V

Table 5. 5. 1 Fault scenario for varying feed flow rate, F.

LEVEL	FAULT
+0.2	$HighF^+$
+0.08	$MedF^+$
+0.01	$LowF^+$
-0.01	$LowF^-$
-0.08	$MedF^-$
-0.2	$HighF^-$

Table 5. 5. 2 Fault scenario for varying Feed Composition, z_F.

LEVEL	FAULT
+0.15	$Highz_F^+$
+0.1	$Medz_F^+$
+0.04	$Lowz_F^+$
-0.04	$Lowz_F^-$
-0.1	$Medz_F^-$
-0.15	$Highz_F^-$

Table 5. 5. 3 Fault scenario for varying reflux flow rate, R.

LEVEL	FAULT
+1.0	$HighL^+$
+0.5	$MedL^+$
+0.1	$LowL^+$
-0.1	$LowL^-$
-0.5	$MedL^-$
-1.0	$HighL^-$

Table 5. 5. 4 Fault scenarios for varying steam flow rate, V.

LEVEL	FAULT
+0.75	$HighV^+$
+0.40	$MedV^+$
+0.10	$LowV^+$
-0.10	$LowV^-$
-0.40	$MedV^-$
-0.75	$HighV^-$

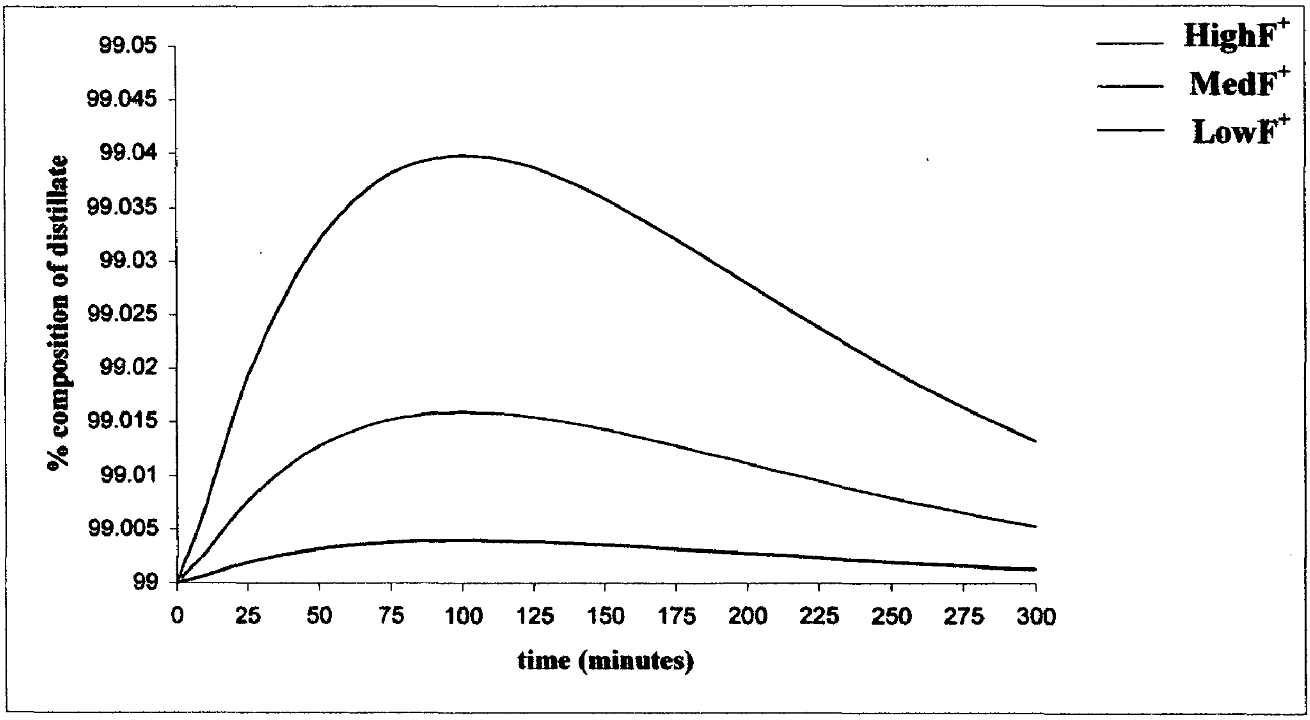


Figure 5. 4 (a) Fault Signatures for increasing feed flow rates as obtained by S1.

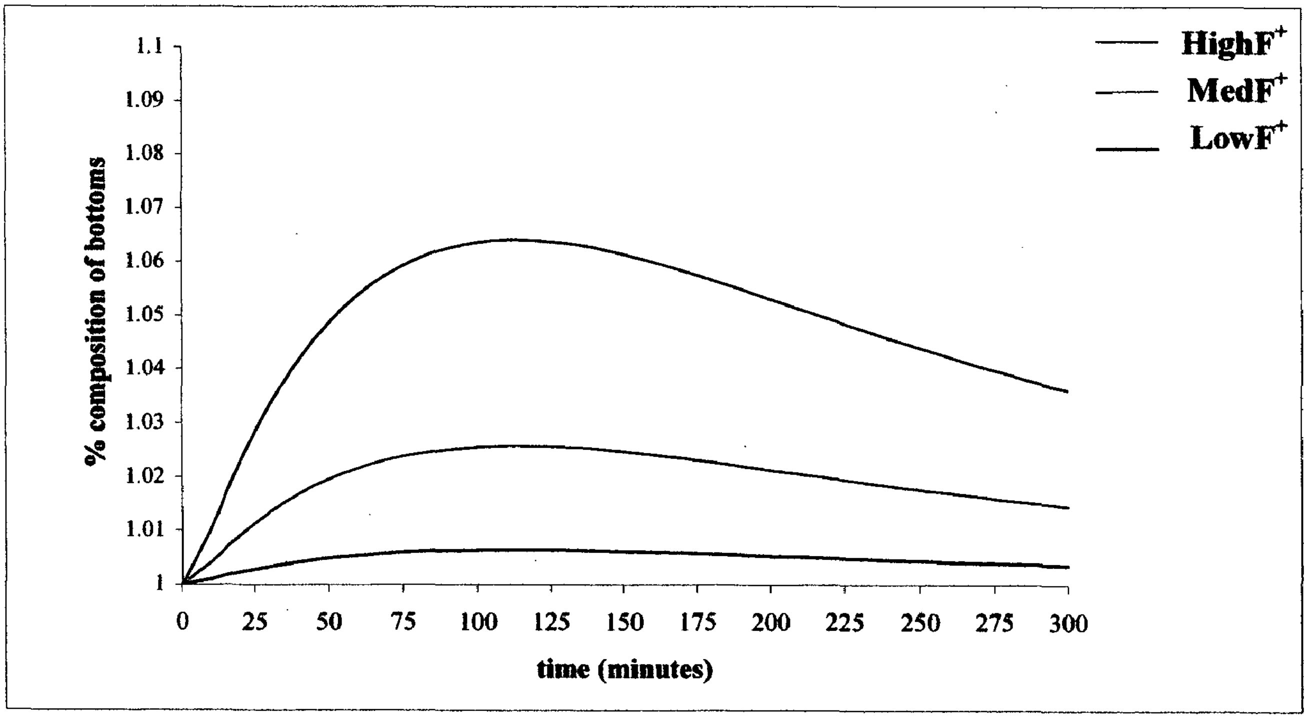


Figure 5. 4 (b) Fault Signatures for increasing feed flow rates as obtained by S2.

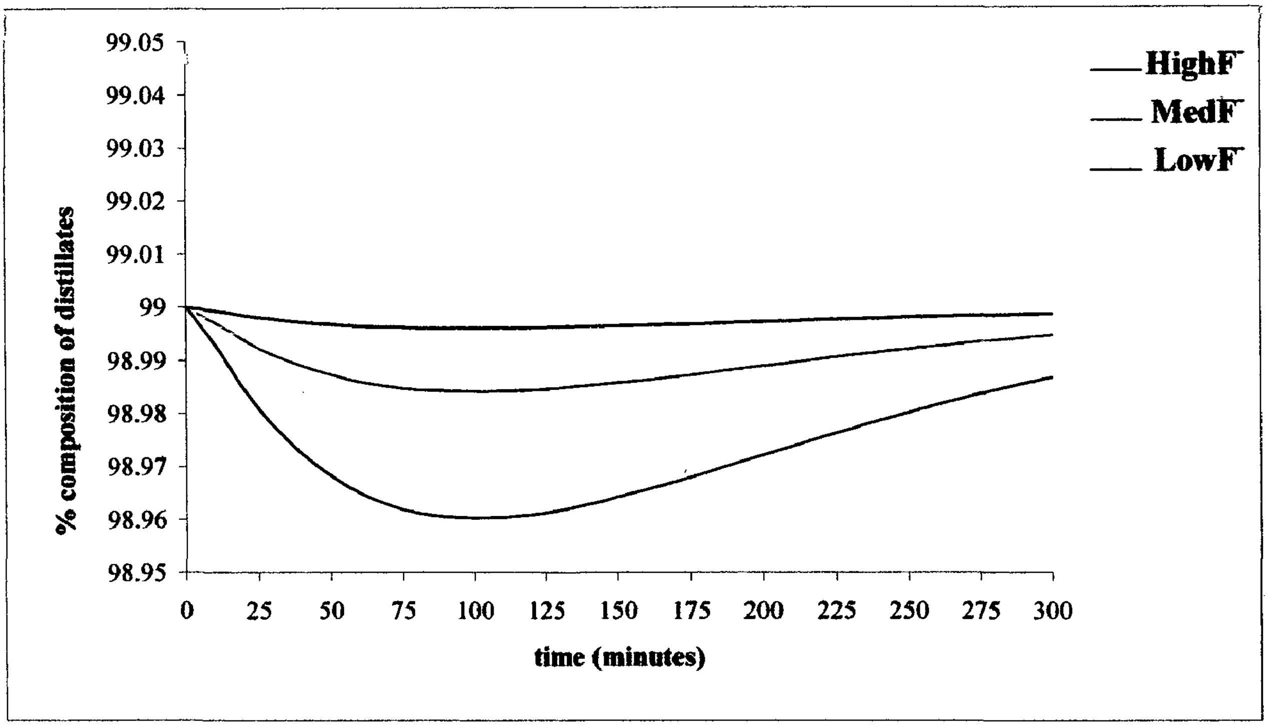


Figure 5. 4 (c) Fault Signatures for decreasing feed flow rates as obtained by S1.

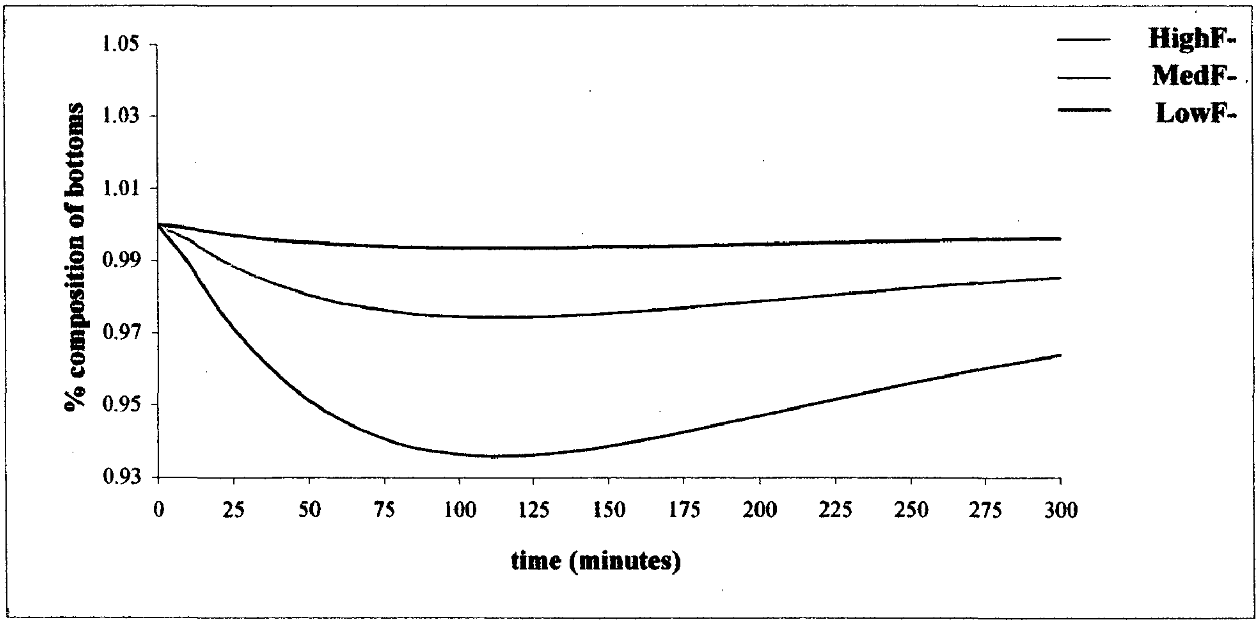


Figure 5. 4 (d) Fault Signatures for decreasing feed flow rates as obtained by S2.

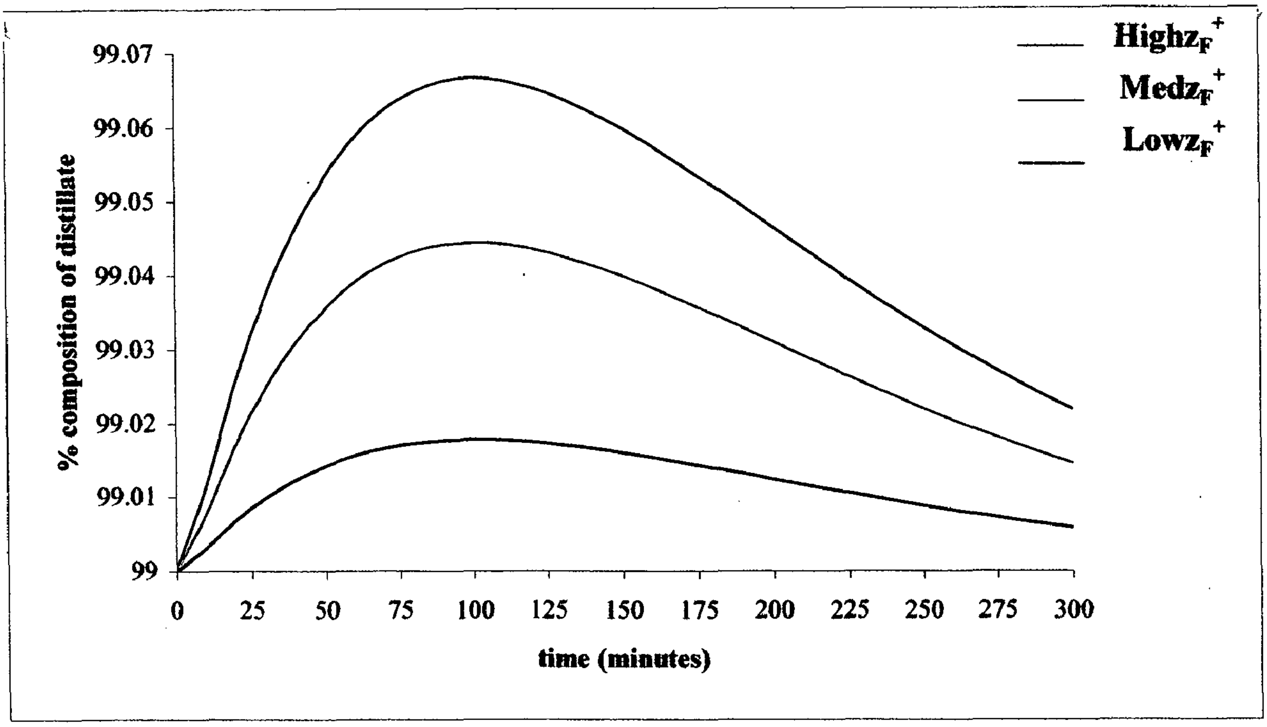


Figure 5. 5 (a) Fault Signatures for increasing feed composition as obtained by S1.

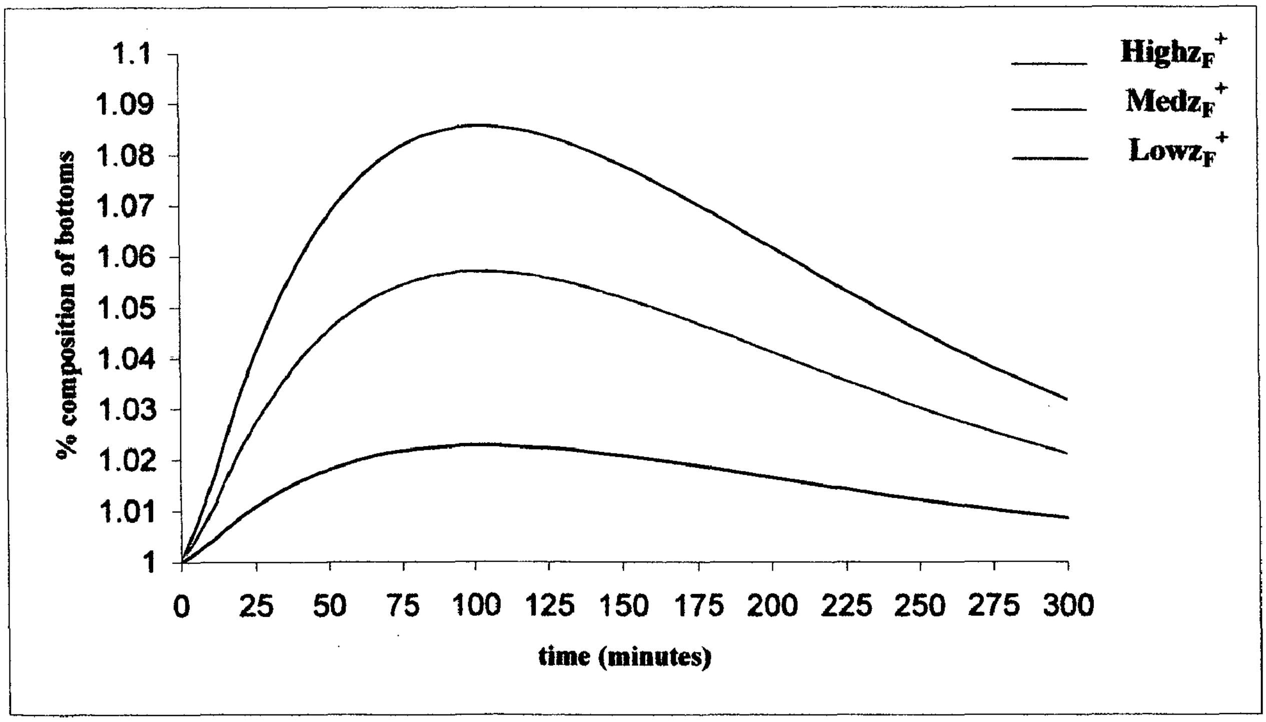


Figure 5. 5 (b) Fault Signatures for increasing feed composition as obtained by S2.

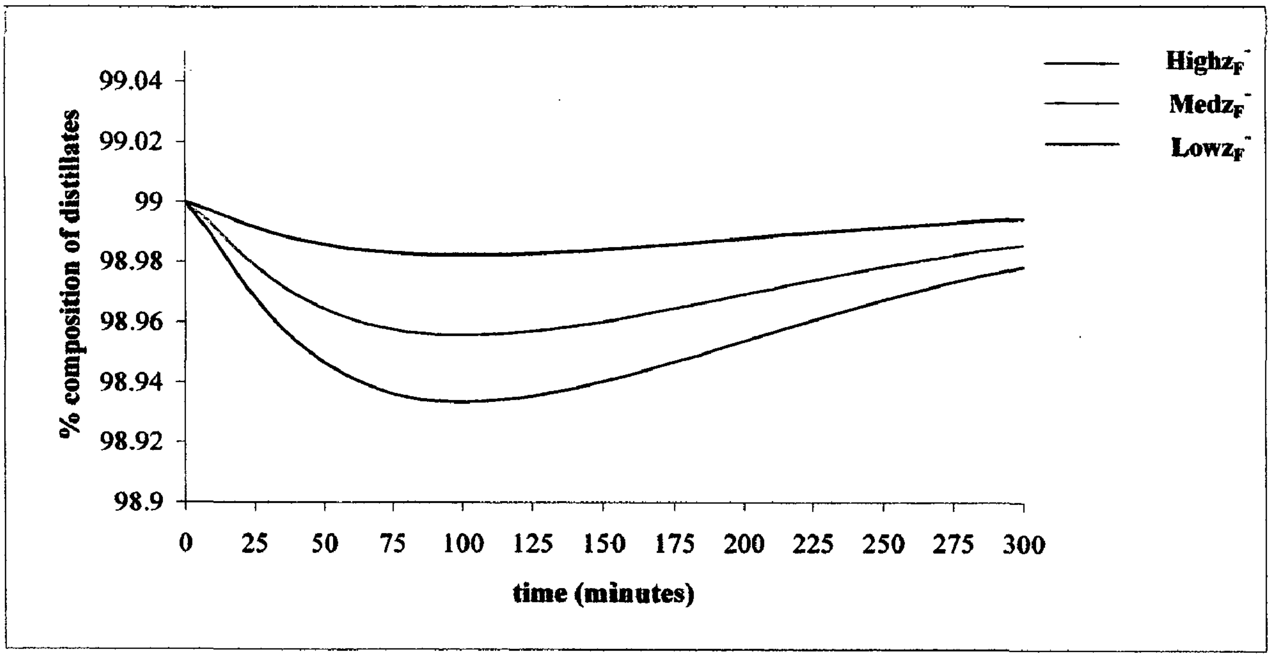


Figure 5. 5 (c) Fault Signatures for decreasing feed composition as obtained by S1.

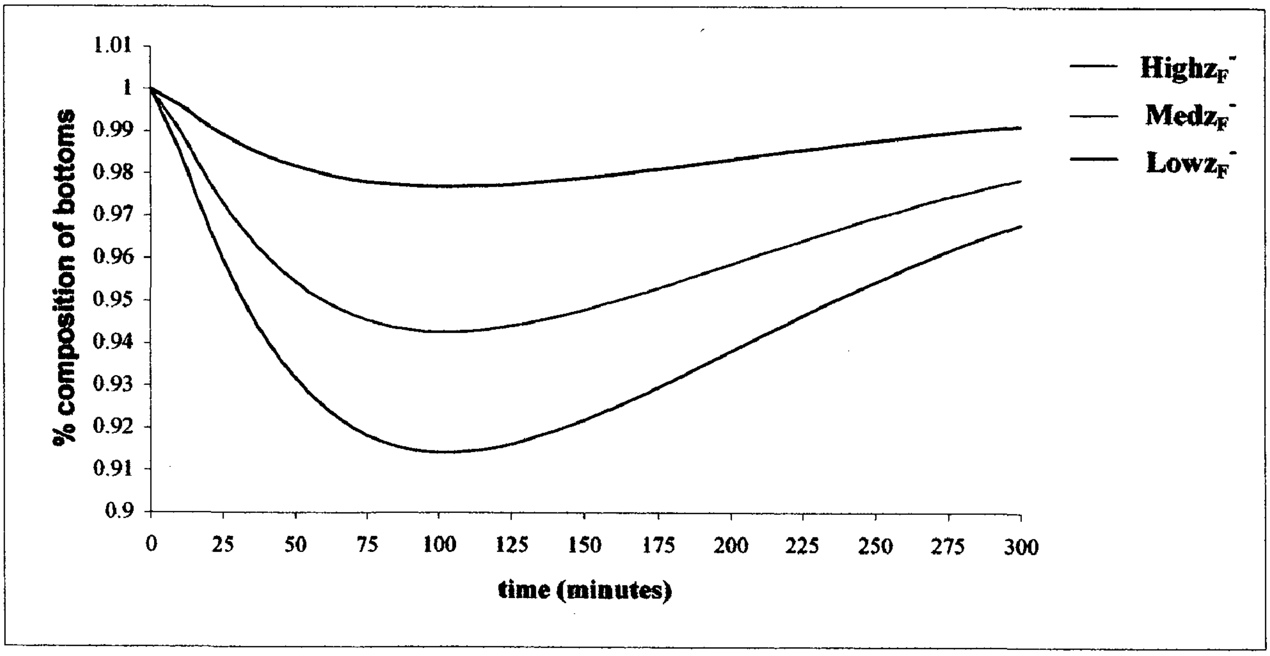


Figure 5. 5 (d) Fault Signatures for decreasing feed composition as obtained by S2.

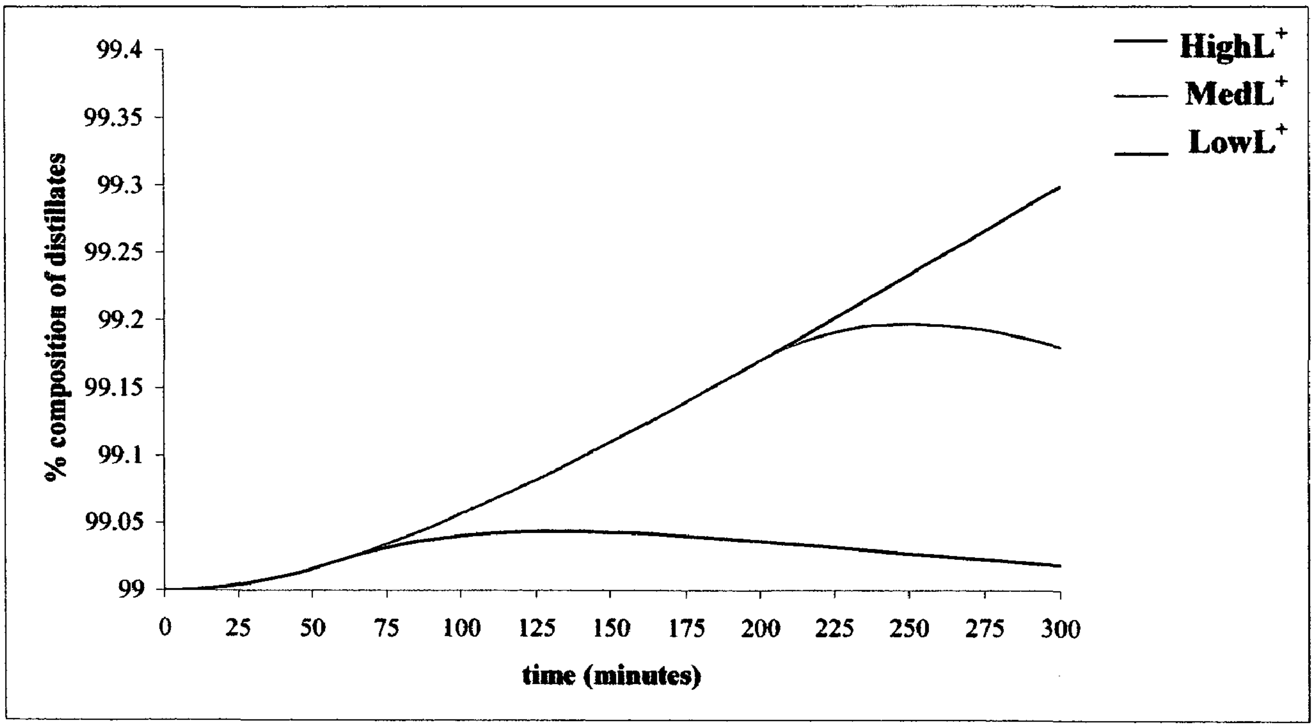


Figure 5. 6 (a) Fault Signatures for increasing reflux flow rates as obtained by S1.

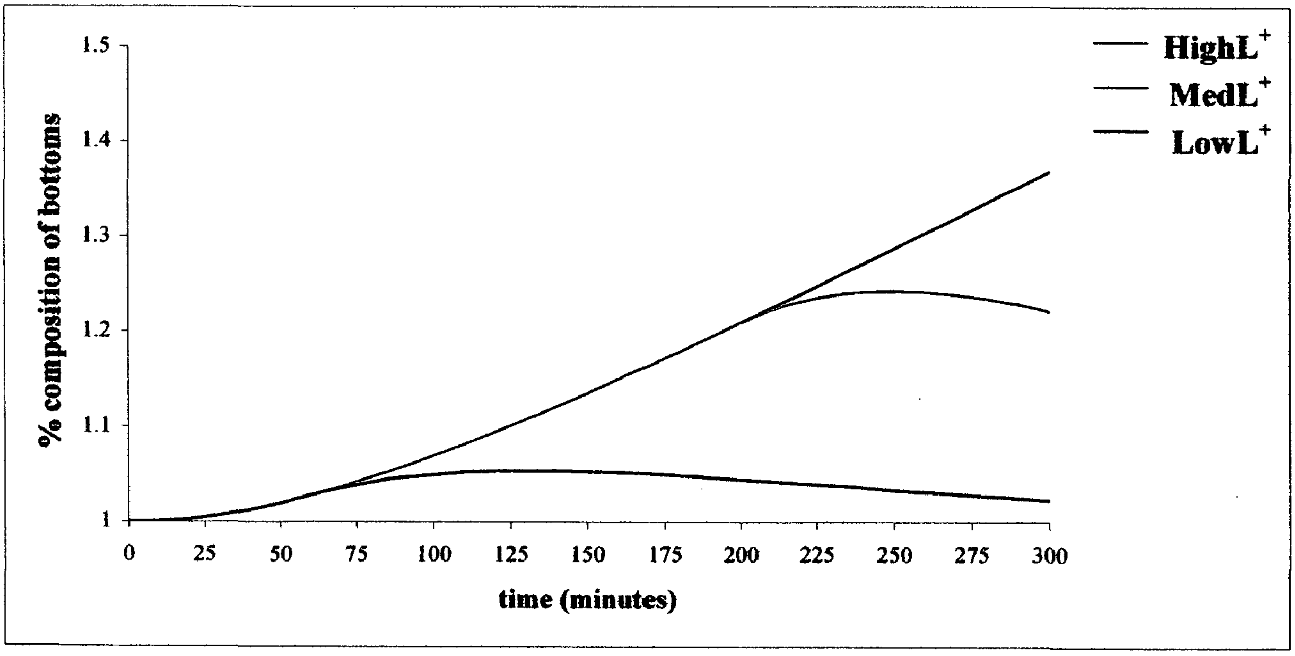


Figure 5. 6 (b) Fault Signatures for increasing reflux flow rates as obtained by S2.

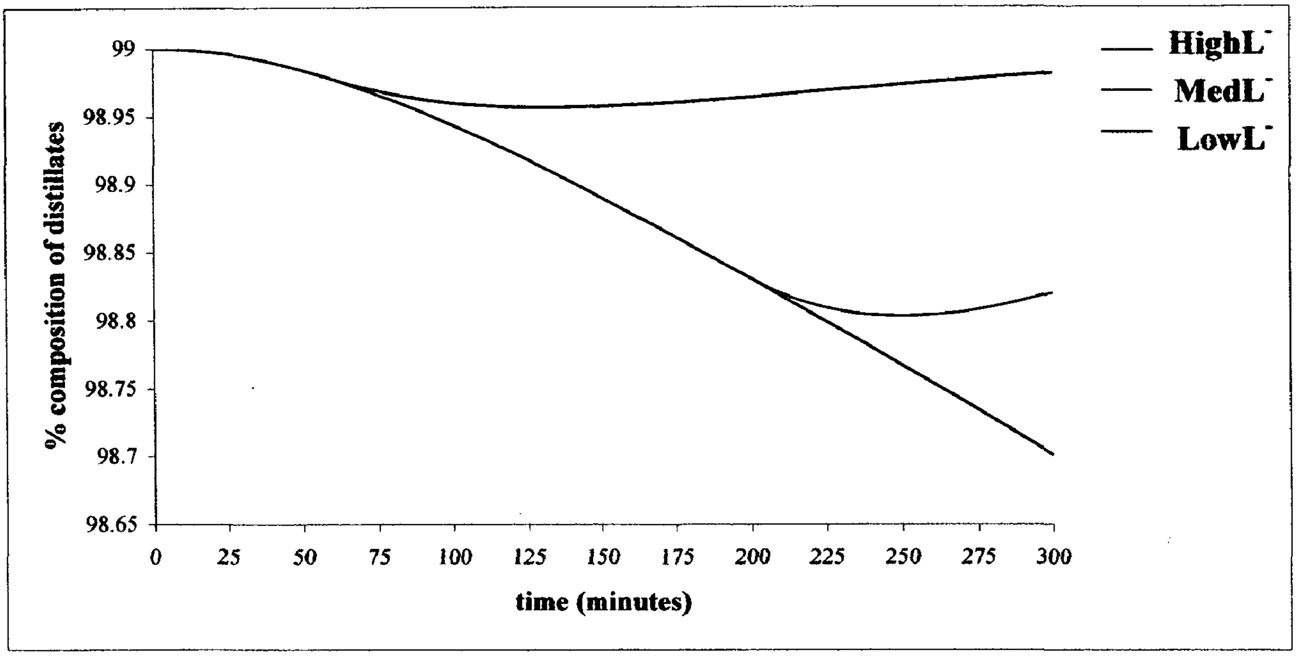


Figure 5. 6 (c) Fault Signatures for decreasing reflux flow rates as obtained by S1.

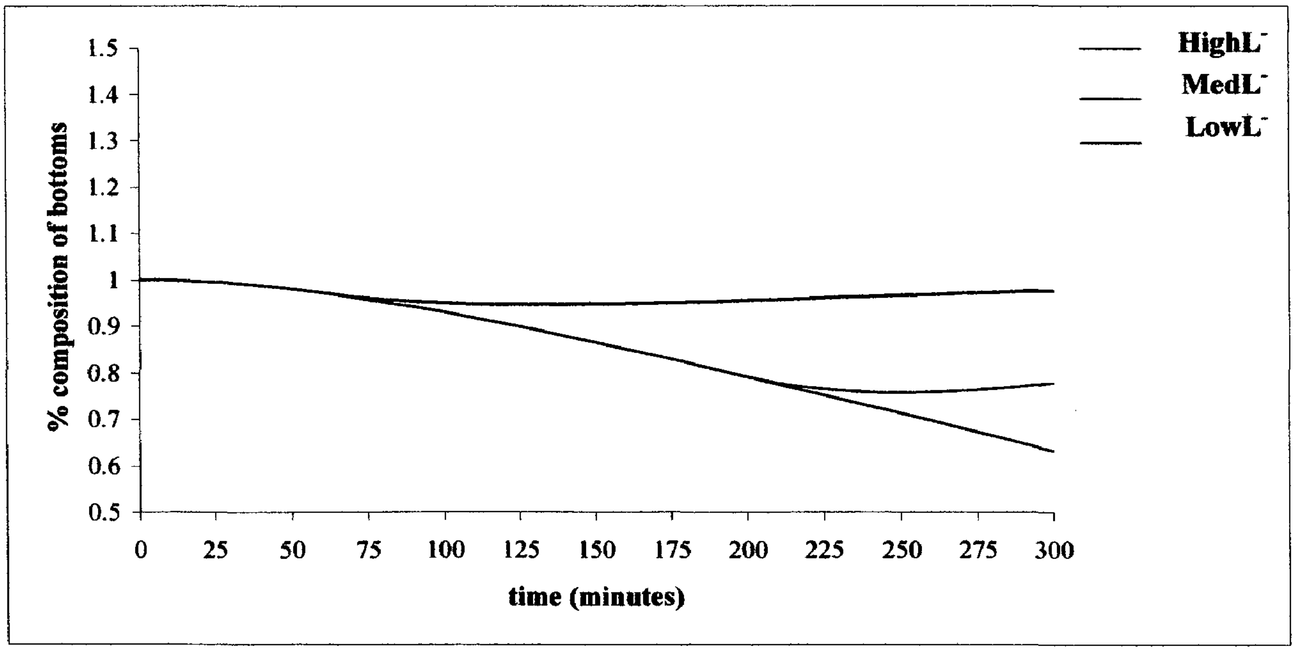


Figure 5. 6 (d) Fault Signatures for decreasing reflux flow rates as obtained by S2.

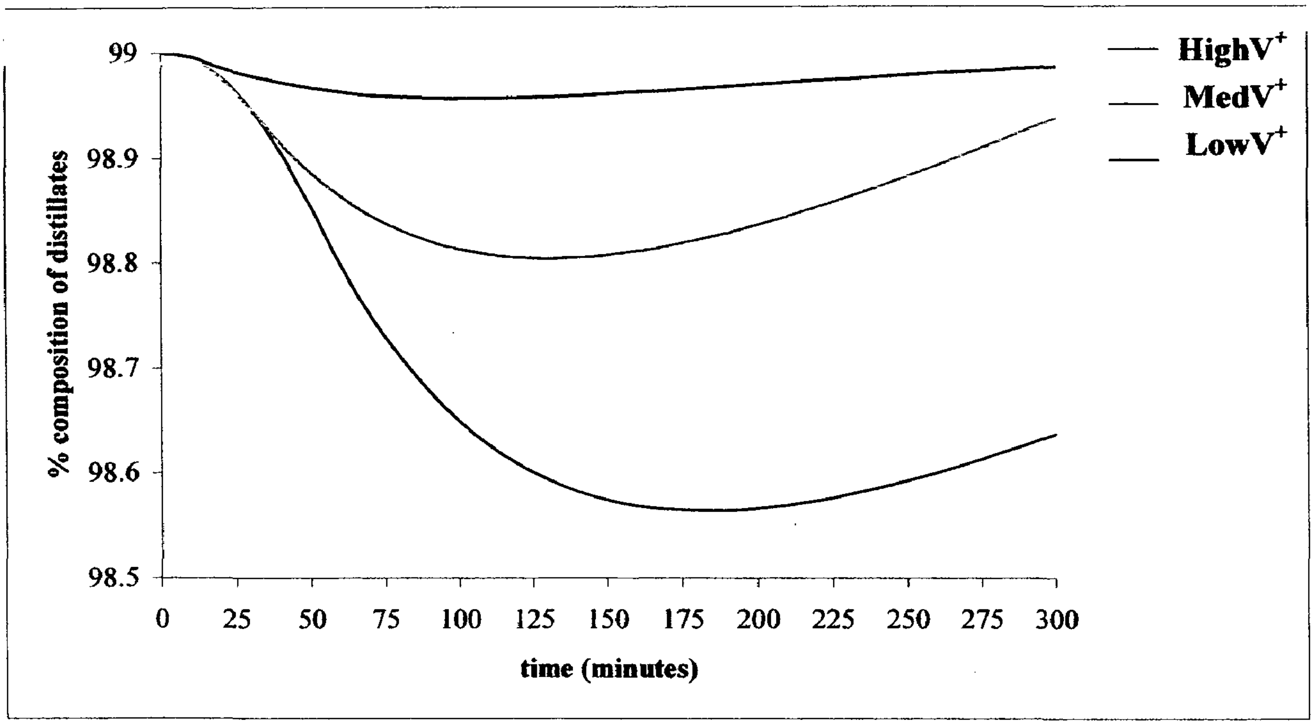


Figure 5. 7 (a) Fault Signatures for increasing steam flow rates as obtained by S1.

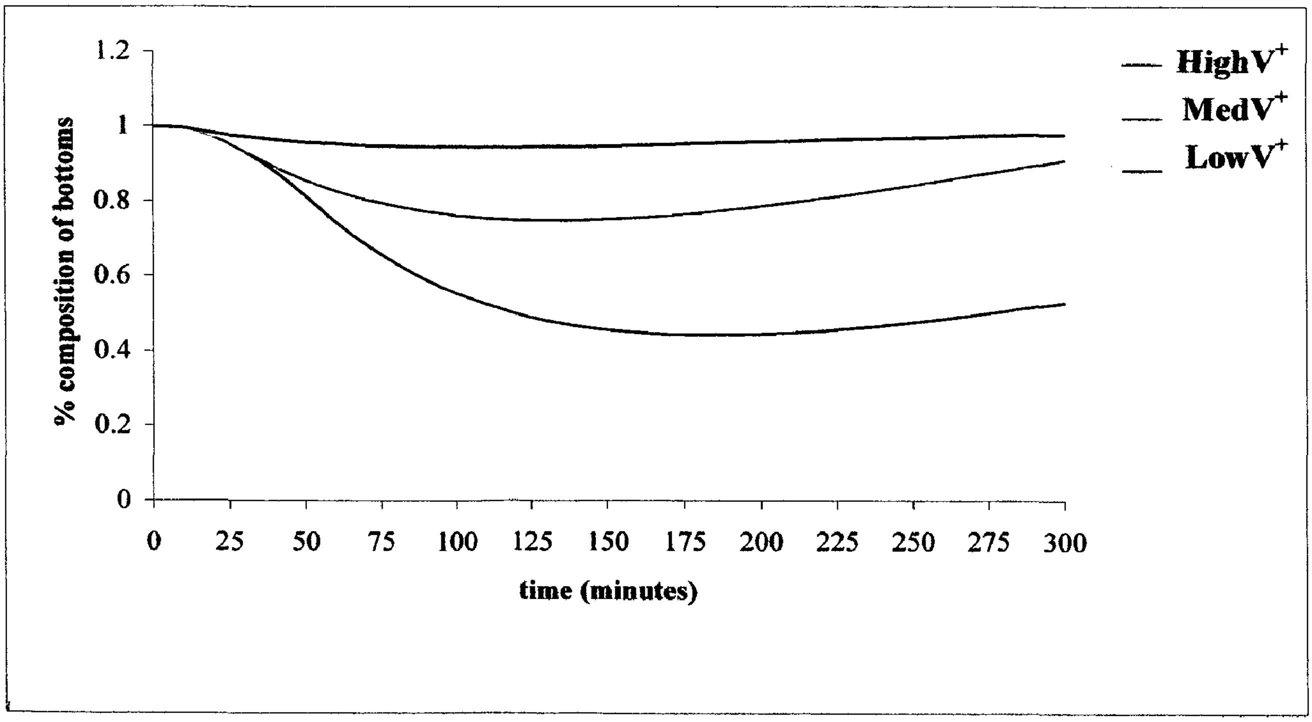


Figure 5. 7 (b) Fault Signatures for increasing steam flow rates as obtained by S2.

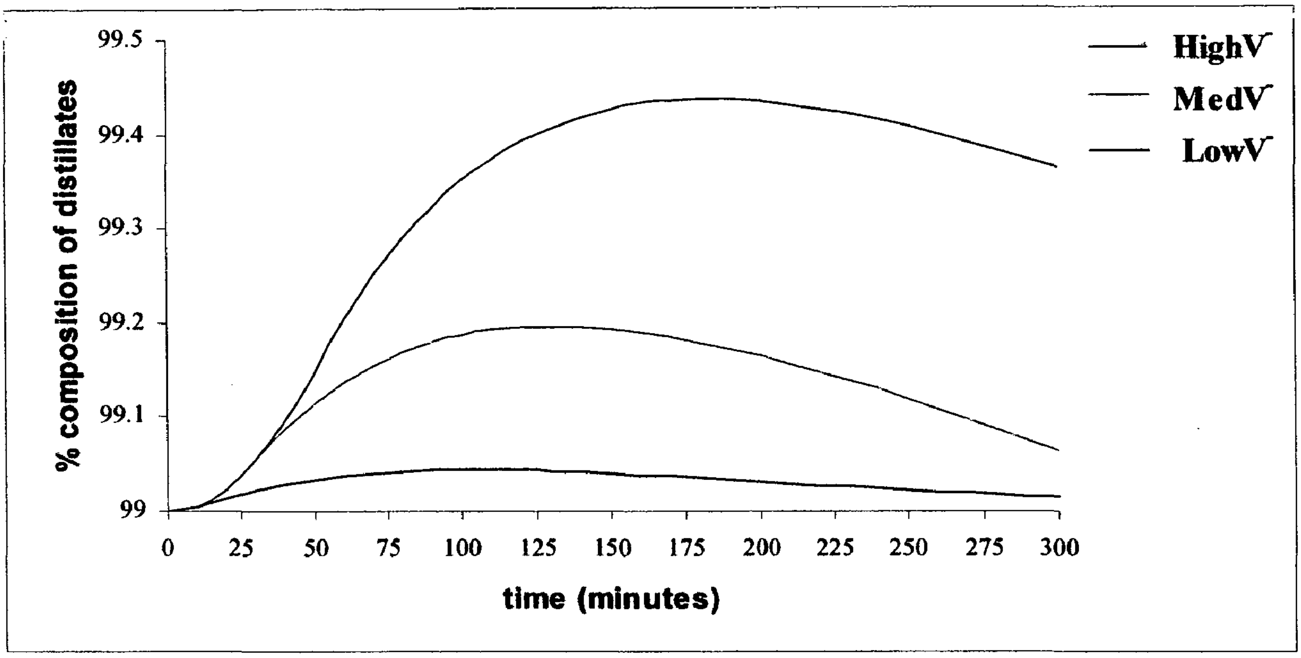


Figure 5. 7 (c) Fault Signatures for decreasing steam flow rates as obtained by S1.

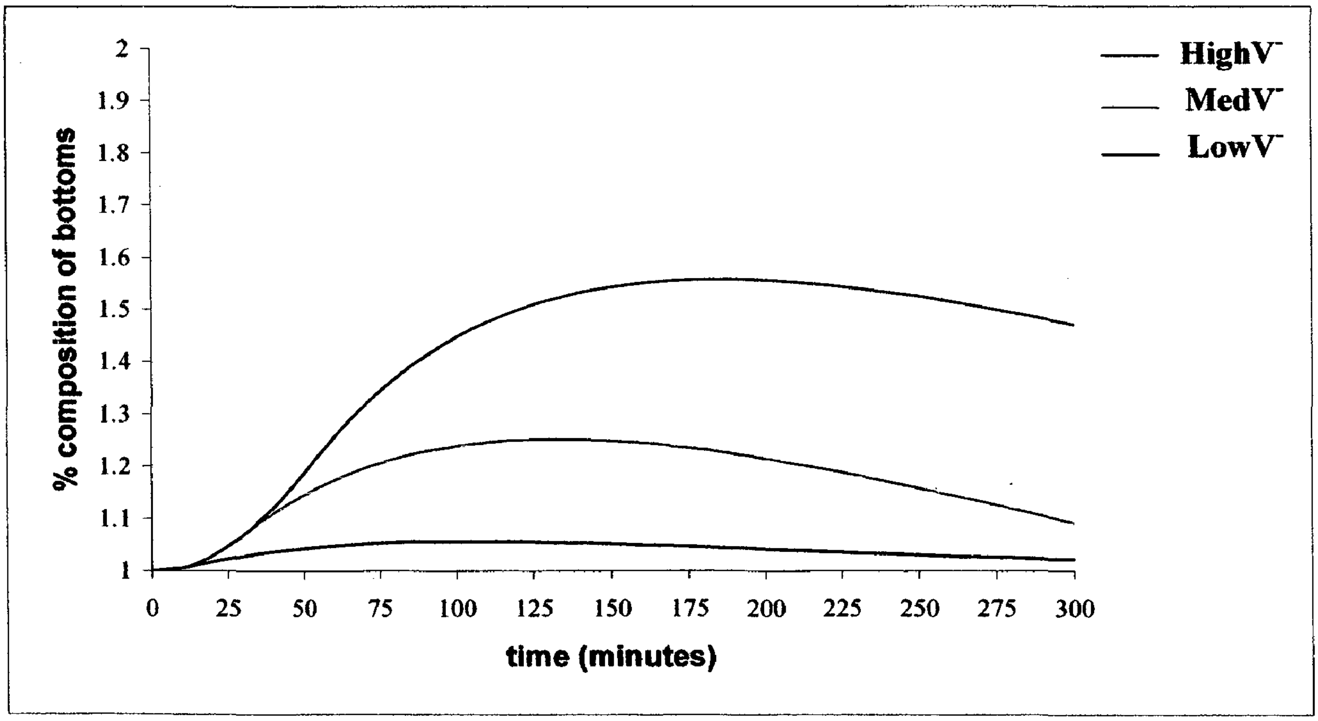


Figure 5. 7 (d) Fault Signatures for decreasing steam flow rates as obtained by S2.

5.6 KNOWLEDGE BASE

The Plots, fault signatures left by various simulated faults, forms the knowledge base of the Fuzzy Fault Diagnostic System. The data so obtained from the plots can be stored as array of points with small interval time. The simulation time for obtaining the fault signatures is kept as 300 minutes. This depends upon the process sluggishness to change in input conditions. The more sluggish the process to respond for input variations, the more will be the simulation period and vice – versa.. However the plots can be stored in the knowledge base in array format with small time interval depending upon the degree of resolution. The various fault signatures obtained by the simulation of process model are as given in the plots.

5.7 TESTING OF FAULT CASES

A test fault scenario is simulated; to be tested with the fuzzy logic based proposed diagnostic system.

For the case study a variation of +0.1 kmol/min in feed supply rate is affected. The event signature so obtained from sensors for the fault $F^+ = +0.1$, is fuzzily matched with the knowledge base of the diagnostic system.

5.8 RESULT AND DISCUSSION

5.8.1 Result

Upon Fuzzy matching the following result is obtained.

The array structure of the fault signature is compared with fault signature arrays in the knowledge base of the diagnostic system. The matching technique applied here is least square error method.

The test fault F+ = +0.1 yields the following result.

For the fault signature $MedF^+$ ($F^+ = +0.08$)

Sensor Trend S1 gives a fuzzy matching with similarity index SI = 0.59

Sensor Trend S2 gives a fuzzy matching with similarity index SI = 0.29

CI = min [SI] = 0.29

The test fault does not find match with the other fault signatures in the Fuzzy logic knowledge base.

Simulated Fault	Fault 1^{st}	SI	CI = min[SI]	Fault2^{nd}	SI	CI=min[SI]
$F^+ = +0.1$	$MedF^+$	0.59	0.29	-	-	-

5.8.2 Discussion

As the test fault fits only with the $MedF^+$ fault signature within the fuzziness range, it is the only viable fault that may have occurred. Hence it can be concluded that with 29 % confidence index fault $MedF^+$ has occurred.

5.9 CONCLUSION

The whole technique is data driven that is no fundamental understanding of the process is incorporated. Hence the performance is limited by the quality of the knowledge base. A poor fault resolution in this technique can thus arise when trends exhibited are similar for all the measured sensors across different faults thus leaving little or no evidence for distinguishability. To overcome this problem either additional discriminating sensors need to be added or finer features may help distinguish the faults needs to be emphasized.

5.10 SCOPE FOR FUTURE WORK

Artificial Intelligence in the form of Fuzzy Logic, Neural Network etc, is increasingly becoming an useful tool to model and reason about process behavior and hence Fault Diagnosis. There has been plenty of research work in the field of artificial intelligence to make it a more practical tool for Fault Detection and Diagnosis. The Dissertation report attempts to showcase one such application of Fuzzy Logic in Fault Diagnosis.

Among the various Fault Diagnostic techniques, fault diagnosis based on patterns exhibited in the sensors measuring the process variables is considered in this report. The temporal patterns that a process event leaves on the measured sensors are utilized to infer the state of operation using a pattern matching approach. A fuzzy reasoning approach is worked out to ensure robustness to the inherent uncertainty in the identified trends and to provide succinct mapping.

In the dissertation report process trend based matching is done with simple numerical technique. However, better Process Trend Analysis techniques can improve resolution in the identification of various faults. Research is being carried out to bring more feasible process trend analysis techniques which are more acceptable to Intelligent Diagnostic Systems.

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