HYBRID METHOD FOR PROCESS FAULT DETECTION AND DIAGNOSIS

MD RAIHAN MALLICK

Hybrid Method For Process Fault Detection and Diagnosis

by

©MD RAIHAN MALLICK

A thesis submitted to the School of Graduate Studies in partial fulfillment of the requirements for the degree of

Master of Engineering

Faculty of Engineering and Applied Science

Memorial University of Newfoundland

October, 2013

St. John's Newfoundland

Abstract

This thesis demonstrates a real time automated hybrid method for process monitoring. Motivation of this research comes from the fact that there is hardly any single techniques available which is decent enough for process fault detection and diagnosis simultaneously. Process history based methods are well known as early fault detectors but operators require complex analysis to find out the root cause of the fault. Knowledge based qualitative models are worthy for root cause analysis but mostly done in off-line fashion. Moreover, modern processes are equipped with thousands of variables and structurally they are very complex in nature. All these influences make manual diagnostic task more complicated for the operators. Therefore, there is a need for automated process monitoring tool that has good detection and diagnosis performance.

In this work, a hybrid method based on principal component analysis (PCA) and Bayesian belief network (BBN) is described for process monitoring. PCA is very proficient as early fault detector but not for fault diagnosis. On the other hand, BBN is good for diagnosis. This hybrid method combines the strong features of both PCA and BBN to an automated monitoring system that can detect fault early as well as diagnose the root cause precisely. Upon successful detection of fault from PCA, diagnostic information from the PCA is passed to the BBN for root cause analysis. Pearl's message passing algorithm is used for belief updating. This monitoring tool

integrates prior process knowledge along with the present observed evidence processed by the multivariate statistical method to come up with the most probable explanation of process fault. Efficacy of the proposed method is verified by simulating different scenarios on a simulated dissolution tank model. The monitoring tool is also validated using industrial data from a pure terephthalic acid (PTA) plant.

Acknowledgements

Foremost, I would like to express my sincere gratitude to my supervisor Dr. Syed A Imtiaz for all his generous help, support and valuable suggestions. Since the first day, he had been guiding me in this difficult voyage. There were times of frustration in research, when his patience, motivation, enthusiasm and immense knowledge provided me the right directions.

Throughout the tenure at Memorial University of Newfoundland, I was lucky to have Professors like Dr. Syed A Imtiaz, Dr. Faisal I Khan, Dr. Benjamin Jayasuria and Dr. Yan Zhang as my course teachers. They helped me a lot to build my analytical skill and enhanced my knowledge in control and safety engineering. My sincere thanks also goes to my fellow lab-mates Musfiqur Rahman and Mohammad Aminul Islam Khan for helping me in simulation. My gratitude goes to all my friends for offering me help to understand Matlab and LaTeX. I also want to take this opportunity to express my gratitude to few friends and whose company made my stay in St. John's a soothing experience.

I would like to express the highest gratitude to my wife Shayma Sattar Shathi and family in Bangladesh, especially my mother Laila Akhter and sister Samia Mallick, as well as my other siblings and relatives for their encouragement and support. I would like to dedicate this thesis to my father Late Mohiuddin Mallick who was an inspiration from my childhood for higher studies.

Finally, Research and Development Corporation(RDC), School Graduate Studies(SGS) Memorial University of Newfoundland and Faculty of Engineering and Applied Science are much appreciated for the financial support they provided.

Table of Contents

List of Tables

List of Figures

Chapter 1

Introduction

1.1 Motivation

Although large scale accidents do not happen frequently in the industries but these accidents can have significant consequences. It has been reported in the literature that petrochemicals industry alone losses estimated 20 billion dollars every year due to such accidents [Venkatasubramanian et al., 2003c]. In the recent era, researchers from both academic and industries are concentrating more on the topics like early fault detection and correct diagnosis of the root cause of a process fault. While the plant is still operating in a controllable region early detection and diagnosis can help to avoid abnormal event progression and reduce productivity loss.

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 [Himmelblau, 1978]. For example, no coolant flow rate resulting in high temperature in a reactor can be considered as process fault. The underlying cause of this abnormality could be a failed coolant pump or a poorly tuned controller, is called the basic event or the root cause. The main sources of process faults are mainly parameter changes in a system due to the disturbance, process structural change due to hard failure of the equipment, malfunctioning sensors and actuators. Monitoring is established to detect and diagnose such faults. Process monitoring is served in two steps: first step is to detect the process fault; in second step, the root cause of the fault is diagnosed to help the operators to take the most appropriate corrective action. Many automated fault detection and diagnosis methods are available. But human operators play a very important role both in control task and monitoring the process plants during both the normal and abnormal conditions.

Success of the diagnostic tasks largely depends on the operators expertise. Responding to the abnormal events in a process is crucial as erroneous judgement of an operator can lead to a catastrophic accident. Complexity and the size of the modern process plants add more hurdle in monitoring task. In addition, quick diagnosis is desired to successfully mitigate the abnormal condition in the process plants. According to the industrial statistics, human error is the main reason for about 70% of the industrial accidents. These abnormal events have significant economic, safety and environmental impact [Venkatasubramanian et al., 2003c].

To avoid the human error and help the operators during process fault, automation in detection and diagnosis is the first step in abnormal event management. Various computer aided approaches have been developed over the years to solve the process fault diagnosis problem. They cover a wide variety of techniques including multi-variate statistical techniques (e.g. principal component analysis (PCA), partial least square (PLS)), observer based methods (e.g. Kalman filter, particle filter), fault trees and digraphs, analytical approaches, knowledge-based systems, neural networks etc. In general the multivariate statistical techniques are successful in detecting fault early and knowledge based methods are preferred for fault diagnosis. There is a lack of a comprehensive fault detection and diagnosis tool that can detect the fault early, diagnose the root cause and guide the operator in the recovery of the process. In this thesis, this problem has been investigated and a hybrid method is proposed as a solution of this problem.

1.2 Objective

The main objective of this research is to build an automated fault diagnostic tool for process plants that can use both on-line measurements and process knowledge to find root cause of the fault precisely. The aim of this monitoring tool is to minimize the human error in the diagnosis of fault and improve the overall safety of the process.

The objectives of the current research is summarized as below

i Develop an automated monitoring tool that can detect fault early and diagnose the root cause precisely. Thus help operators to steer the process to safe operating condition, prevent loss in productivity and accidents in process.

ii Minimize complex analysis by operators for root cause analysis and to reduce both human error and ambiguity in diagnosis.

iii Incorporate on-line measurement with process knowledge for precise diagnosis.

1.3 Thesis Structure

This thesis consists of six chapters. This first chapter provides a brief description about process fault and its consequences followed by motivation and objectives of this thesis.

Chapter 2 covers extensive literature review on process fault detection and diagnosis. The advantages and deficiencies of the different methods are discussed and the gap in the research is identified.

Chapter 3 describes the method to construct a Bayesian belief network (BBN) for process systems. The BBN is mapped from signed directed graph (SDG). The methodology is validated by simulation.

Chapter 4 introduces the hybrid methodology for process fault detection and diagnosis. This hybrid tool is a combination of PCA and BBN. Detailed steps of the algorithm are discussed in this chapter.

Implementation of the proposed method is described in Chapter 5 with both simulation and industrial case studies. The results confirm competence of the monitoring tool by detecting and diagnosing the fault precisely.

Chapter 6 concludes the thesis with critical findings of this research followed by recommendations for future work.

Chapter 2

Literature Review

On-line process monitoring is one of the most important research topic in process industries. Researchers developed various amount of methodologies for process monitoring from different perspectives. The most popular FDD methods used in the process industries are discussed in the following sections.

2.1 Quantitative Model Based FDD

Quantitative model based methods use explicit system models developed either from laws of physics or identified models from identification experiment. The most widely used approaches for quantitative model based algorithms are diagnostic observers, parity relations, Kalman filters, state-space models, input-output relationship, first Principal models, frequency response models etc are reported in different literatures [Venkatasubramanian et al., 2003c, Venkatasubramanian et al., 2003a].

The observer-based FDD algorithms use a bank of observers to generate residuals [Frank and Ding, 1997]. Each one of this residual is sensitive to a particular type of fault while it remains insensitive to the remaining faults and unknown inputs. During normal operating condition, observers track the process closely and the residuals from the unknown inputs will be small. However, when a fault occurs, all observers which are made insensitive to the fault by design, continue to develop small residuals. On the other hand, observers which are sensitive to the fault will deviate from the process significantly and result in residuals of large magnitude. Fault isolation become easy since these observers are designed for particular faults. [Yoon and MacGregor, 2000] applied this observer based methodology successfully for a CSTR plant for detecting fault. More application of observer based FDD methods can be found in [Frank, 1994]. The fault signal might get obscured due to sensor noise and disturbance. Filters are designed to separate the effect of faults and noise from the residual signal so that they can be easily differentiated [P.M. Frank, 1989].

Parity equation relations check is one of popular method for model based FDD and application of this method can be found in [Gertler and Monajemy, 1995]. The main idea is to check the inconsistency of the plant models prediction compare to the sensor outputs (measurements).

$$r(s) = (\frac{A(s)}{B(s)} - \frac{\hat{A}(s)}{\hat{B}(s)})u(s) \tag{2.1}$$

Eqn. 2.1 is called the parity equation where $r(s)$ is the residual generated by the parity equation. Process is described by $\frac{A(s)}{B(s)}$ where $A(s)$ is the output parameters and $B(s)$ is the input parameter of the process. Model is described by $\frac{\hat{A}(s)}{\hat{B}(s)}$ where $\hat{A}(s)$ is the output parameters and $\hat{B}(s)$ is the input parameter of the process model.

Assumptions associated with the parity equation method are no process uncertainty, no modelling errors and explicit model can explain all faults. If any of these assumptions is violated, the performance will be degraded. Another assumption is that parity relations are considered as linear model. Linear models are valid only around the operating conditions at which the non-linear process is approximated as linear. The parity relation approach thus cannot be easily applied to batch or non-linear processes where operating conditions vary continuously.

Kalman filter is very popular in chemical industries as state estimator. Kalman filter estimates all process states and can be used for residual generation for measured process states. Generated residuals indicate the presence of fault [Benkouider et al., 2009, Chang and Chen, 1995].

[Isermann, 1997] proposed a model parameter estimation method for fault detection. Model parameters are also affected by process faults. Through parameter estimation method model parameters for the normal operating condition are determined initially. These parameters are compared to the parameters obtained from the on-line process measurements. Any significant change from the normal operating range is denoted as fault.

In the early days hardware redundancy was mainly used for fault detection. Measurements from the redundant sensors were compared for variation. If inconsistency is found in the measurement, sensor fault is reported. This technique is for sensor fault detection is known as voting scheme [Willsky, 1976]. If hardware redundancy is available, voting schemes can quickly identify sensor fault. The advantage is that the faulty sensors are removed smoothly from consideration reducing the number of false alarms. Application of this type of FDD method can be found in aircraft space vehicles and nuclear power plants. Due to the extra cost and additional space required, hardware redundancy is less popular and more interest is shifting towards analytical redundancy [Frank, 1990].

Analytical redundancy uses functional dependency of the process variables. Input-output relation of the process variables are expressed in terms of algebraic relation. This is useful for computing the value of a particular variable given that the states of the process variable and the measurements of the other sensors are known. Difference between the measured signal and the calculated value from the algebraic relation is known as residual. If significant deviation is found between the measured value and calculated value, fault is identified [Chow and Willsky, 1984].

The problem associated with model based FDD is an explicit mathematical model of the system is required to generate the diagnostic residual. Most of the FDD model is constructed assuming the process to be linear which is seldom in practical life. Their application to a non-linear system requires a model linearisation around the operating point. On top of that these models include some modelling error. Another lapse of the model based FDD approach is if the fault is not modelled properly then the fault may not be detected by the residual. All this can reduce the effectiveness of the method drastically. Often computational cost associated with deriving a model is very high and most of all very few mathematical models for a process can be found.

2.2 Qualitative Knowledge based FDD

Knowledge based models are usually developed from the fundamental understanding of process dynamics. Signed directed graph (SDG), Baysian Network, Possible cause and effect graph (PCEG) etc are most common knowledge based model FDD approaches.

Prior process knowledge is the key ingredient to build a knowledge based model. These models capture the cause and effect relationship among different process variables. and are expressed in terms of qualitative functions. These knowledge based systems are often computer aided programs which consists of various logics and conditional reasoning (If-else) [Venkatasubramanian et al., 2003a].

Rule based expert systems applied for fault diagnosis are reported in a number of papers. These expert systems are often if-else rule based system with process knowledge extracted from the first principal of the process. The main objective of the expert system is to diagnosis a process fault and make a suggestion for the human operator to handle the fault properly. [Chen and Modarres, 1992] proposed an expert system which is capable of process fault diagnosis and suggestive to the operators for correct action during the abnormal condition in the process. The main advantages of expert systems as a diagnostic tool are ease of development and the ability to provide explanations for the solutions provided.

Fault tree analysis (FTA) is the most popular method in the industries for root cause analysis. FTA is a top down deductive failure analysis. Boolean logic and lower-level events are combined to analyse an undesired state of a system in FTA [Sklet, 2004]. Logical "AND" and "OR" gates are used to describe basic events propagation up to top-events. The qualitative structure of how fault occurs can be analysed using cut set analysis. The smallest number of events that leads to top-event is known as minimal cut set. Minimal cut sets can imply the safety of the system qualitatively [Woodward and Pitbaldo, 2010]. Fault tree is used mainly for analysing system reliability and risk analysis along with detecting root cause of an abnormal condition.

Cause-effect relationship of the process variables or models can be represented in the form of signed directed graphs (SDG). SDG was first introduced for process fault diagnosis by Iri, Aoki, O'Shima, and Matsuyama [Iri et al., 1979]. Digraph consists of directed arcs between the nodes which represent each process variables. In SDG each directed arcs have a positive or negative sign attached to them. The directed arcs lead from the cause nodes to the effect nodes. Each node in the SDG represents the steady state of a process variable. SDG is relatively easy and simple to implement. The causal information can easily be converted into rules. SDG can be obtained either from the mathematical model of the process or from the operational data or differential equation of the process model [Umeda et al., 1980]. SDGs are very efficient way of representing qualitative models graphically. It has been the most widely used as causal knowledge based process fault diagnosis algorithm [Yang et al., 2010]. Once a process fault has been detected, knowledge based model can find the root cause.

Several enhanced version of SDG are developed, such as, possible cause effect graph (PCEG), to overcome some of the limitations of SDG is proposed by [Leung and Romagnoli, 2000]. In traditional SDG approach, state of each node is restricted to the high, normal and low states. In PCEG, more meaningful state description about the nodes are used. This makes knowledge representation more user-friendly and flexible. Another major improvement in PCEG over SDG is the distinct definition of root causes. PCEG diagnose the root cause with the proper process knowledge.

Although all the above methods are very easy to set up but one of the main limitations of these diagnosis methods is they do not give a measure of the uncertainty in the diagnostic information. Since in a diagnosis numerous noisy and incomplete sources of evidence are assimilated, it is important to quantify the uncertainty in the decision. In this context, Bayesian belief network (BBN) can overcome some limitation of the above stated knowledge based methods. A Bayesian belief network is a probabilistic graphical model (a type of statistical model) that represents a set of random variables and their conditional dependencies via a directed acyclic graph (DAG) in terms of conditional probability table. BBN can represent the probabilistic relationships among the causal variables. Given effects, the network can be used to compute the probabilities of the presence of various causes [Krieg, 2001, Neapolitan and Jiang, 2010, Neapolitan, 2004]. This allows to diagnose the root cause for abnormal conditions. Bayesian belief networks are very popular in process reliability assessment and root cause analysis [Wilson and Huzurbazar, 2007].

BBN is a probabilistic approach and thus it can capture the uncertainty in the diagnosis. Some of the benefits are capability to model complex systems, make predictions as well as diagnose the root cause, compute the occurrence probability of an event, update the calculations according to evidences, represent multi-modal variables and to help modelling user-friendly by a graphical and compact approach [Bobbio et al., 2001]. An early warning system for root cause analysis using BBN is developed by [Pradhan et al., 2007]. Since it is difficult to represent process knowledge directly in a BBN an equivalent model was built from first principle of the system and used for probabilistic reasoning and root cause analysis. [Azhdari and Mehranbod, 2010] showed application of BBN for industrial fault diagnosis. Tennessee Eastman process was selected for testing the effectiveness of BBN as an industrial diagnostic tool. BBN was developed from the process knowledge of the system and it diagnosed some known faults successfully. However, it is assumed that faults do not occur simultaneously. A comprehensive review on BBN as a fault diagnosis tool can be found in [Weber et al., 2012, Guo and Hsu, 2002].

[S. Dey, 2005] used BBN for fault diagnosis. Pearl's direct message passing algorithm was implemented to update probability of each node in BBN. Posterior probability of each node is updated from evidence. To explain very simply, when new evidence is introduced into the network, each node updates its own belief, based on message received from its parents and children and correspondingly generate message to be sent to its children. This process is repeated until the network is stabilized.

The successive stages of belief propagation is shown in Fig. 2.1. Here, it is assumed that evidences $e1$ and $e2$ are introduced. Initially the BBN is in equilibrium Fig. 2.1(a). As soon as two evidences are introduced Fig. 2.1(b) belief propagation is initiated. At this stage belief of the child node (evidence entering node) is updated and a message to the corresponding parent node is sent. Then in Fig. 2.1(c) the intermediate node updates its belief and sent message to its parent and child node.

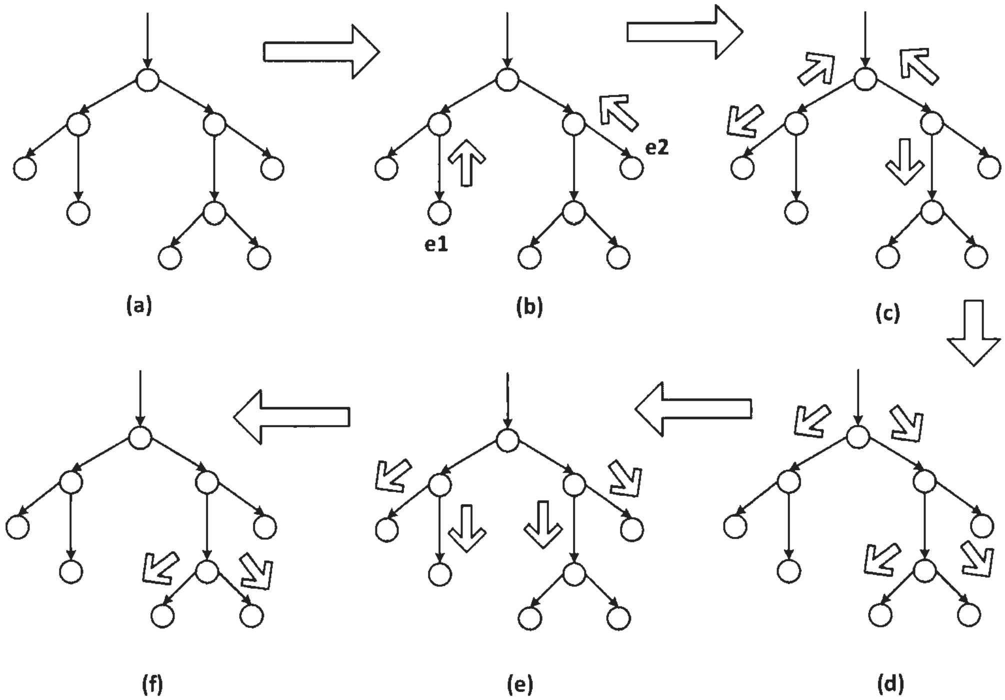


Figure 2.1: Impact of new evidence on belief propagation

The top root node receive two messages from its children and updates its belief. This process continues for the six cycles, at which point all messages are propagated and the network reaches a new equilibrium. After that the network is ready to take another new evidence. However, this diagnosis method is not applicable for cyclic process since BBN is acyclic [Pearl, 1988].

Introduction of process knowledge to perform diagnose a fault has been recent interest of research. BBN brings value as it quantifies the uncertainty in the diagnosis and it can incorporate process knowledge. More recently BBN has been used to combine various fault detection and diagnosis methods. [Huang, 2008] used BBN to unite diagnostic information from various diagnostic tools to calculate the overall control loop performance. [Khakzad et al., 2013] proposed BBN for dynamic safety analysis. Although bow tie is very popular method but they can not handle the process uncertainty due to their static nature. Mapping bow tie into BBN helps to overcome the limitation. A case study from the U.S. Chemical Safety Board has been used to illustrate the application BBN techniques as a fault diagnosis tool.

2.3 History based FDD

Process data based historical methods rely on the availability of large amount of historical data. When the process is under control, the observations have distributions corresponding to the normal mode of operation. This distribution changes when the process is out of control. If a monitored variable is in normal operating condition, then its statistical parameters like mean and the standard deviation will be close to their normal values. But for faulty conditions, either the mean or the standard deviation or both may deviate from their nominal values. In on-line statistical approach, samples are taken sequentially and decisions are made based on the observations up to the current time [Venkatasubramanian et al., 2003b].

History based method includes both univariate and multivariate methods. In univariate analysis process measurements are compared to the threshold values for detecting fault. Probability of fault increases as the process moves away from the normal operating condition [Mah and Tamhane, 2004]. Univariate statistical techniques are easy to implement. But they cannot distinguish between normal operational changes and abnormal changes which leads to significant number of false alarms. Also operators need to monitor trend of each variable separately this can easily overwhelm an operator.

Compared to the univariate analysis, multivariate techniques are more robust to false alarm and successfully reduces the dimensionality of the system. Multivariate techniques monitor the correlation among different variables as well as the variables in a lower dimensional space. They are also robust to the changes in the process due to controller actions, set point change or noise in the process. These techniques are capable of compressing data so that the original huge data set can be analysed easily with essential information is retained. For these reasons multivariate statistical methods such as principal component analysis (PCA), independent component analysis (ICA), partial least squares (PLS), Fisher discriminant analysis (FDA), subspace aided approach (SAP) are very popular in industries. [Yin et al., 2012] applied different data driven techniques such as standard PCA, Dynamic PCA (DPCA), TPLS, MPLS, ICA,Subspace aided(SAP) to the bench-mark Tennessee Eastman process to compare their performance in fault detection.

Multi-scale PCA (MPCA) is commonly used to monitor batch process. MPCA that combines wavelet filtering with PCA is proposed by [Misra et al., 2002] for process fault diagnosis. Multi-scale PCA is widely used for condition monitoring to detect equipment fault such as compressor, pump etc.

Several variation of PCA has been developed to fulfill different needs for process monitoring. Dynamic PCA (DPCA) has been developed to account for the dynamic variation in the system. For non-linear systems, several non-linear PCA methods have been developed. [Choi et al., 2005] proposed non-linear PCA-based method that uses kernel functions and showed better results.

These statistical methods use contribution plots for fault diagnosis [Miller et al., 1998, Kourti and MacGregor, 1996a]. The contributions are very easy to calculate. When the square prediction error (SPE), T^2 or Q-statistics violates its threshold limit the fault is detected. The contributions of the individual variables can be analysed for diagnosis. Those variables having large contributions to the fault are examined. The maximum contribution is indicated as possible causes [Jackson and Mudholkar, 1979, Joe Qin, 2003]. Application of the contribution plots as a diagnostic tool in an industrial batch processes can be found in [Kourti and MacGregor, 1996b, Westerhuis et al., 2000]. For a more complex and realistic process, the operator needs to employ his experience to determine whether he should look at the magnitude or the sign of the contributions, or a combination of both sign and magnitude. Monitoring hundreds of variables can be overwhelming to examine and it requires a complex analysis to find out the root cause from this contribution plot. Two common problems associated with the contribution plots are

- A fault of small magnitude may not have the largest contribution. However, when fault magnitude is very large significant contribution is observed. This can be a source of misdiagnosis.
- Often more than one variables are shown as faulty since the contribution of the each variable is calculated by a matrix multiplication [He et al., 2005]. This is known as "smearing" effect and can reduce the significance between contributing and non-contributing variables. This can insert ambiguity in diagnosis task [CHEN et al., 2011, Alcala and Qin, 2009].

Data based process monitoring methods are very easy to implement and effective in detecting faults early but the diagnosis is not precise. The residual analysis is not enough to aid the operator in identifying the root cause. This is because, for a large process with many variables, the interpretation of measured variable contributions is difficult. It needs complex analysis for the operators to detect the root cause from the contribution plot. Moreover, for the diagnosis task there is no mechanism to incorporate the expert knowledge. Therefore, recognizing the inadequacy of single-method based approaches, researchers are now giving more attention to the hybrid methods.

2.4 Hybrid FDD

Hybrid FDD models are the combination of two or more than two independent FDD models. The motivation for designing hybrid diagnostic systems arises due to the fact that there is no single method that meets all the requirements of a good diagnostic system, [Mylaraswamy and Venkatasubramanian, 1997]. Qualitative knowledge based diagnosis models such as signed directed graphs (SDGs) are good for root cause analysis rather than being early detectors. For large-scale or non-linear process, building a SDG based diagnosis model is tedious, [Yang et al., 2010]. On the other hand, quantitative model-based methods are very efficient and sensitive to process fault. However requires significant computational effort and often explicit models for the process are not available. Computational cost associated with developing statistical classifiers and neural networks are very low. They are relatively robust to noise and other model uncertainties present in the process but cannot provide adequate explanations about the diagnostic reasoning. For example, PCA/PLS based FDI scheme are efficient and quick at fault detection but from the contribution plot it requires a complex analysis to find out the root cause. Sometimes more than one variable is shown as faulty due to the smearing effect in the PCA which leads to an ambiguity in root cause analysis, [Yoon and MacGregor, 2000, Liu, 2012].

It is evident from the above discussion that one single method is not enough to develop an efficient FDI scheme. To combine the strength features and to complement for the shortcomings of various methods, hybrid methods have been proposed. [Becraft et al., 1991] proposed an integrated methodology for fault diagnosis with a neural network and an expert system. To diagnose the most commonly encountered faults in chemical process plants, a neural network was used. Once the faults are detected within a particular process by the neural network, a deep knowledge expert system analyse the result and suggests mitigating action.

A DKit (combination of neural network and SDG) based hybrid model was proposed by [Mylaraswamy and Venkatasubramanian, 1997]. The inability of SDG for timely fault detection is overcome by the strength of early detection abilities of neural networks and the inability of neural networks to provide insights for diagnosis was compensated by the SDG's accurate diagnostic power. The salient features of the DKit and its performance was demonstrated successfully by simulating 13 different scenarios with Amoco FCCU process.

[Vedam and Venkatasubramanian, 1999] proposed a PCA-SDG based hybrid methodology for fault detection and diagnosis. In order to perform diagnosis using SDGs alone, each measured variable need to be compared against the high and low thresholds to identify its deviation which is very difficult for a large process. PCA plays a vital role in dimension reduction of the analysis.

A hybrid system with signed directed graphs (SDG) and fuzzy logic was proposed by [Enrique E. Tarifa, 2003]. The SDG model of the process was used to perform qualitative simulation to predict possible process behaviour for various faults. Those predictions are used to generate if-else rules that are evaluated by an expert system using information about the actual process state.

[Weiqing et al., 2012] proposed an abnormal root cause diagnosis method combining Kernal PCA (KPCA) and fuzzy probabilistic SDG (FPSDG). KPCA-FPSDG based hybrid model has the multivariate monitoring characteristics of KPCA and fault explanation capability of SDG. All the variables are monitored using KPCA. When a fault is detected, the abnormal variable is isolated from the FPSDG. Case studies show that the KPCA-FPSDG method can effectively monitor the thermal system process and find the anomaly source promptly.

Although these SDG hybrid based models are efficient for the standard process but its application for the complex process is limited. To overcome this limitation [Özyurt and Kandel, 1996] introduced a hybrid FDD technique combining neural network and expert fuzzy logic. Author suggested hierarchical multilayer neural network structure to deal with the complex process. Fault is discovered by the neural network by pattern recognition comparing to the normal operating condition pattern. The fuzzy expert system diagnose the fault using process knowledge and input from the supervisory network and sub-networks. The result shows effectiveness of the proposed hybrid system and adaptive capability to deal with noise in the process. A hybrid system with signed directed graphs (SDG) and fuzzy logic have been proposed by Tarifa and Scenna. The SDG model of the process is used to perform qualitative simulation to predict possible process behaviours for various faults. Those predictions are used to generate if-else rules that are evaluated by an expert system using information about the actual process state [Enrique E. Tarifa, 2003]. [Sun et al., 2012] used a first-principle knowledge based model combined with a data-driven artificial neural network model for process fault detection and diagnosis. It demonstrates good performance both in process monitoring and fault diagnosis.

Extended Kalman filter (EKF) and neural network based hybrid FDD is proposed by [Benkouider et al., 2012]. The EKF estimates the state of reactor as well as the overall heat transfer coefficient and χ^2 test is conducted on residual for the fault detection. The identification of the fault is based on a probabilistic neural network model. Estimated EKF states of the reactor along with the overall heat transfer coefficient are the inputs for the neural network model. The neural network model, with the help of process knowledge diagnoses the root cause precisely. This hybrid model is validated both for simulated and experimental data sets for a chemical process reactor. Although this method is effective, it requires an explicit process model and neural network needs to be trained with process faults which limits its applicability.

2.5 Conclusion

It is evident from the review that each method has its own strength and shortcomings.

i PCA can detect the fault early and has overwhelming popularity in process industries for fault detection.

ii BBN is convenient for capturing process knowledge and the associated uncertainty.

iii Combining more than one method can complement each other to over come limitations. Combination of knowledge based and data driven methods can deliver best result. Thus hybrid methods are becoming popular as FDD tool. These hybrid models could be a solution for automated process fault detection and diagnosis.

iv Though many hybrid methods are available but they are not hybrid in true sense. The knowledge based diagnostic tools are not utilizing the limited diagnostic information from the quantitative methods. Also in many cases the diagnostic tools (e.g. neural network) requires huge database of faulty data which are difficult to obtain.

v Considering the above facts hybrid method which combines PCA and BBN together is proposed in this thesis. PCA is very efficient for early fault detection and BBN captures process knowledge with uncertainty which can give accurate diagnosis of the root cause. This hybrid method combines the strong features of both PCA and BBN to overcome their individual limitations.

Chapter 3

Development of BBN for Process Systems

In this chapter a method to develop a BBN for process system is described. Signed Directed Graph(SDG) is well known for representing cause and effect relation among the different variables. The method described here, maps a SDG to a BBN. First a brief overview on SDG is provided. Methods of obtaining SDG from mathematical equations and process knowledge are discussed. The mapping of SDG to a BBN is described.

3.1 Signed Graph

Signed graphs were first introduced by Harary to handle a problem in social psychology [Cartwright and Harary, 1956]. Since then it has been applied in many fields of study such as physics, data clustering, diagnosis of root causes etc. In graph theory, a signed graph refers to a graph in which each edge has a positive or negative sign. This is a graphical representation of cause effect relation among different variables. The graph

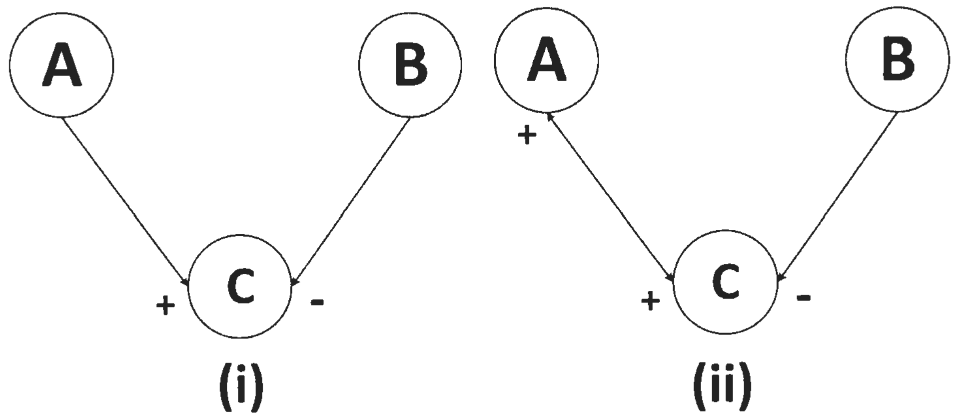


Figure 3.1: Signed Graph

may have loops and multiple edges as well as half-edges (with only one endpoint) and loose edges (with no endpoints). Half and loose edges do not receive signs. In formal terms a digraph is a pair $G = (X, Y)$ Where

- X is a set whose elements are called vertices or nodes,
- Y is a set of ordered pairs of vertices, called arcs, directed edges, or arrows.

Two signed graphs are shown in Fig. 3.1. Both graphs have three nodes A, B and C. Both A and B are connected to C by two arcs.

In Fig. 3.1(i) Edges of these two arcs have a positive and a negative sign representing the types of relations between nodes $A - C$ and $B - C$ respectively. The positive sign at the edge of the arc $A - C$ means, if there is an increase in A, this will result in an increase in C. The negative sign at the edge of arc $B - C$ indicates an inverse relationship. An increase in A will result in a decrease in C or vice versa. This type of causal relations can be graphically represented by signed graphs. Both A and B nodes are called root nodes or causal nodes and node C is the effect node. This is shown by the arc direction from the root nodes to the effect node.

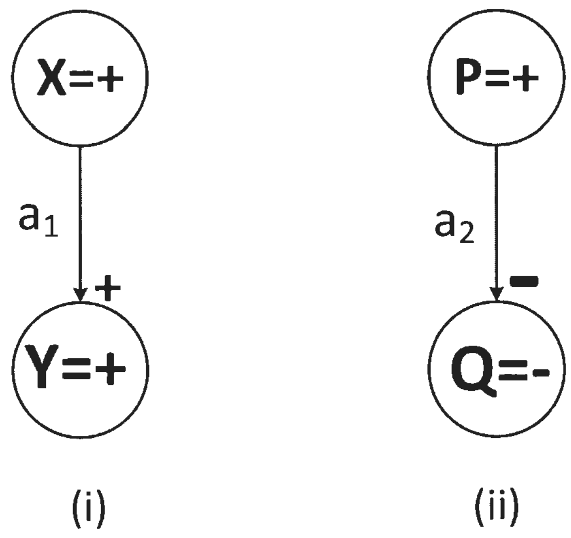


Figure 3.2: Signed Directed Graph (SDG)

In Fig. 3.1(ii) $A - C$ edge is a multi edge arc which has two positive signs. This multi edge represents that both nodes A and C can now act as cause and effect nodes simultaneously. The signs assigned to the arc represents the relation between the nodes.

3.2 Signed Directed Graph

An extended version of signed graph is signed directed graph(SDG) which deals with only single edge arcs. Nodes of the SDGs are assigned with positive, negative or a zero state. These represent the states of a nodes higher than, lower than or normal operating condition respectively. The SDG can be defined as below

In Fig. 3.2 two simple SDG is shown. Fig. 3.2 (i) shows relation between variable X and Y and Fig. 3.2 (ii) shows relation between variable P and Q.

Sign of node Sign of SDG nodes can be defined as below

$$\begin{aligned} \psi(v) &= 0 \; for \; \mid x_v - \bar{x_v} \mid < \varepsilon_v, \\ \psi(v) &= + \; for \; (x_v - \bar{x_v}) \geq \varepsilon_v, \\ \psi(v) &= - \; for \; (\bar{x_v} - x_v) \geq \varepsilon_v. \end{aligned} \tag{3.1}$$

where x_v is the measurement of the variable v, $\bar{x_v}$ is the normal value, and ϵ_v is the threshold.

Sign of arc This can be illustrated by Fig. 3.2(i) node X and node Y is connected by an arc from node X to Y. When X increases, Y also increases. Deviation of X and Y in the same direction. This relation is shown by the positive sign arc a_1. On the other hand, in Fig. 3.2(ii) node P and node Q is connected by an arc from node P to Q. When P increases, Q decreases. Deviation of P and Q in the opposite direction. This relation is shown by the negative sign arc $a_2 = -$.

3.3 Modelling of SDG

SDGs can be constructed either from operational data and system knowledge, or mathematical models of the system. Various methods for building SDG are discussed below.

3.3.1 SDG Modelling from Mathematical Equations

SDG can be derived from the differential and algebraic equations of the system. The structure as well as signs of the graph can be derived from the differential equations. An arc is drawn from the variables in the right hand side of an equation to the variables in the left hand side of that equation. The sign of the arc between the

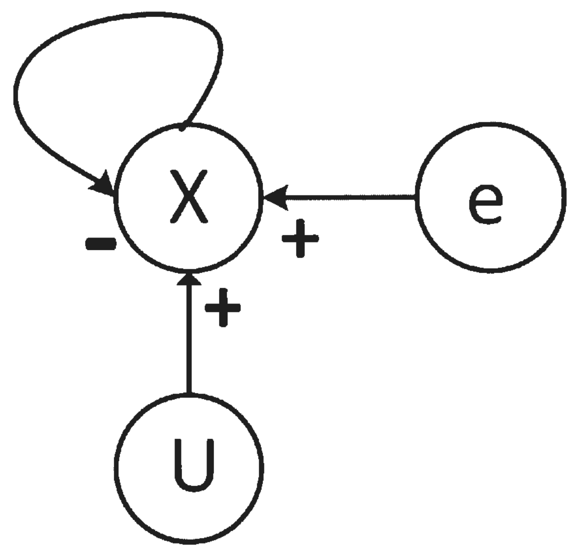


Figure 3.3: SDG of a system with first order differential equation

variables depends on the sign of the variables in the equation [Maurya et al., 2003]. A typical dynamic system can be expressed as a set of ODEs,

$$\frac{dx_i}{dt} = f(x_1, x_2, ...x_n, u_1, u_2. u_3, ...u_n, e). \tag{3.2}$$

where $(x_1, x_2, ...x_n)$ are state variables of the system, $u_1, u_2, u_3, ...u_n$ are input variables of the system and e is the disturbance.

A first order system state variable x, input u and disturbance e,

$$\frac{dx}{dt} = -(\frac{a_0}{a_1})x + k\ u + (\frac{1}{a_1})e. \tag{3.3}$$

For the system defined by the Eqn. (3.3), SDG can be constructed as shown in Fig. 3.3. An arc is constructed from e to x with a sign $sgn[1/a_1] = +$, an arc from u to x with a sign $sgn[k] = +$ and a self-cycle on the node x with a sign $-sgn[a_0/a_1] = -$ on the arc.

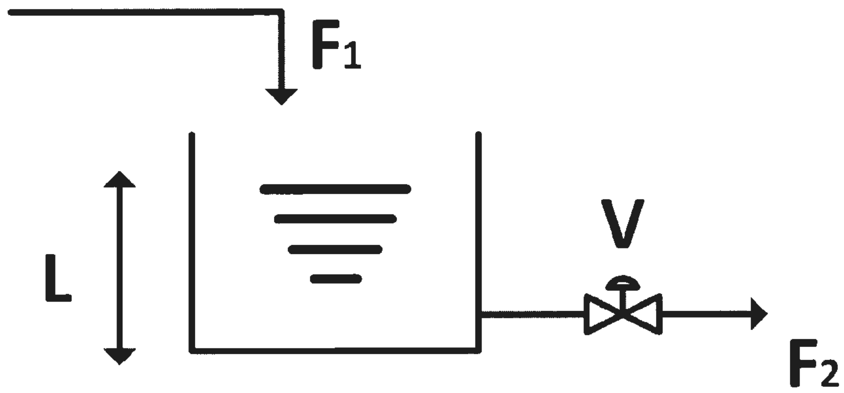


Figure 3.4: Simple tank model

3.3.1.1 SDG Modelling of a Simple Tank System from Mathematical Equations

A simplified tank model is shown In Fig. 3.4. Water flows into the tank with flow rate F_1. The flow coming out of the tank, F_2 is controlled by a flow valve V and level of water accumulation is denoted as L.

Governing equations for the system are as below

$$A\frac{dL}{dt} = F_1 - F_2, \tag{3.4a}$$

$$F_2 = \sqrt{L}/V, \tag{3.4b}$$

here, A is the cross sectional area of the tank and V is the valve resistance acting on the flow.

SDG derived from the Eqn. (3.4) is shown in Fig. 3.5. Water flow F_1 and F_2 have direct influence to water level accumulation in the tank described by Eqn. (3.4a). Any positive change in F_1, will make positive change to L. This means that if inflow increases the accumulation will increase. To capture this process dynamics in SDG,

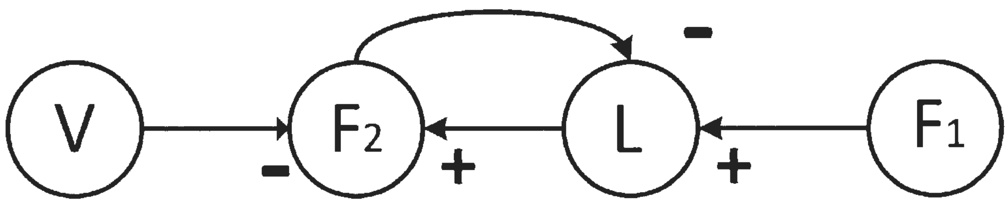


Figure 3.5: SDG of a simple tank model

an arc from F_1 (right side of equation)to L (left side of equation) with a positive sign is constructed. Again, a positive change in F_2, will make negative change to L. When outflow increases the accumulation will decrease. To capture this process dynamics in SDG, and an arc from F_2 to L with a negative sign is drawn.

Outflow F_2 is a function of both accumulated level and valve resistance V. An arc from V to F_2 and another arc from L to F_2 is drawn according to the Eqn. (3.4b). When the valve is open, valve resistance V on the flow is low, and there will be high out flow F_2. This will decrease the water level L. Because the type of the relations among the variables V, F_2 and L are opposite, the arcs are assigned with negative signs.

3.3.2 SDG Modelling of a Simple Tank System from Process Knowledge

In most cases SDGs are built with process knowledge and experience. Often mathematical equation or model for a process is not available. Process dynamics and qualitative process knowledge remains as last resource to build a SDG.

A simple tank model with controlled flow rates is shown in Fig. 3.6. Inflow F_1 is controlled by a valve with flow resistance V_1. Since there is no controller F_1 does not

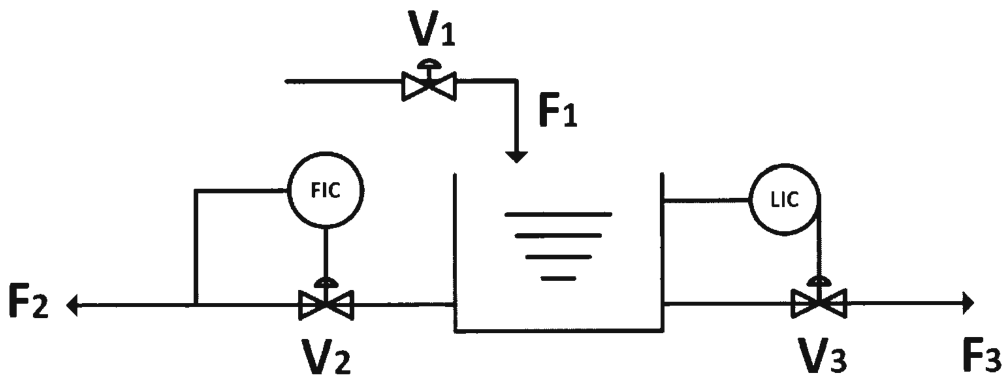


Figure 3.6: Simple tank model with controlled flow rates

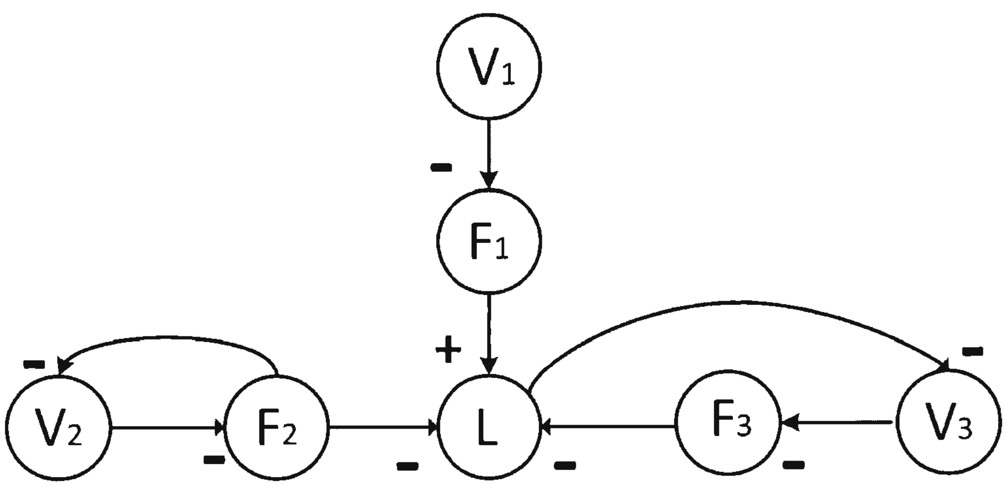


Figure 3.7: SDG with controlled flow rates

affect V_1. The relationship is unidirectional from V_1 to F_1. Inflow F_1 depends on the V_1, hence V_1 is the cause and F_1 is the effect of that. An arc from the V_1 to F_1 is draw with a negative sign. Accumulation is directly influenced by both inflow and outflow rates F_1, F_2 and F_3. When inflow increases the accumulation increases. Therefore, a positive signed arc is drawn from F_1 to L. Two arcs with negative sign are drawn from F_2 to L and F_3 to L. Because both out flow F_2 and F_3 will reduce accumulation in the tank. Both outflow F_2 and F_3 is controlled by two flow valves with flow resistance V_2 and V_3 respectively. When valve resistance V_2 decreases, outflow F_2 increases. Flow controller regulates the valve (resistance) to control the flow F_2. Similarly, when valve resistance V_3 decreases, outflow F_3 increases. Level controller regulates the valve (resistance) to control the flow F_3. Flow control and level control is shown by the other two negative arcs from F_2 to V_2 and L to V_3. Thus SDG can be obtained from only process dynamics without any process model or governing equation shown in Fig. 3.7.

3.4 Mapping of SDG to BBN

In SDG the type of relation among the variables is expressed in terms of arc sign where in BBN this relation is expressed in terms of conditional probability table.

Mapping of SDG to BBN is shown in Fig. 3.8. Mapping of the SDG into BBN is done in two steps. First, SDG is developed from either process knowledge or mathematical equations described in section 3.3. After a SDG has been developed, it is mapped to the BBN based on both graphical and numerical translation. The structure of BBN is obtained from the graphical translation. The nodes are connected in the same way as they are connected in the SDG. The root nodes, intermediate nodes and effect nodes are mapped into the BBN as parent nodes, intermediate nodes

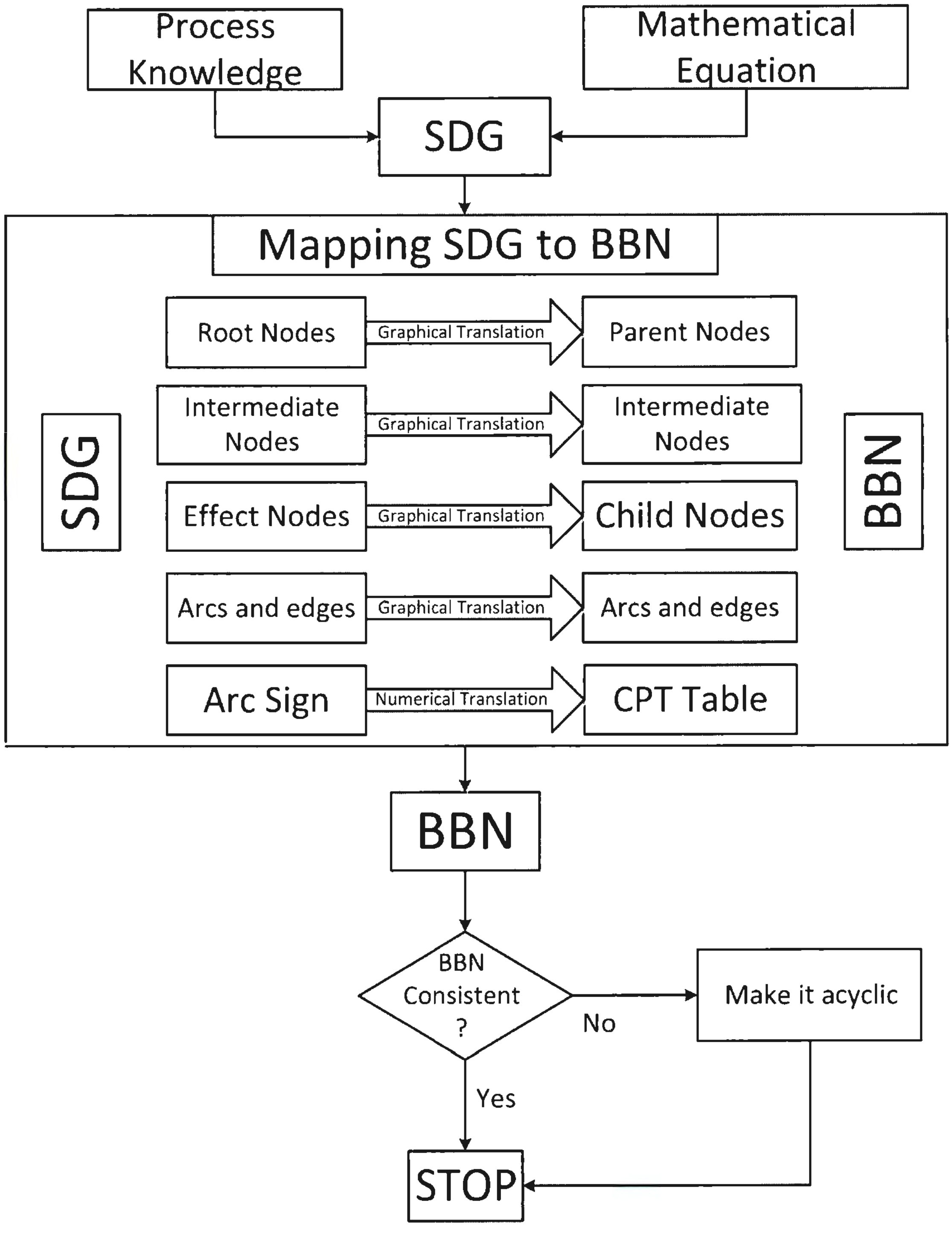
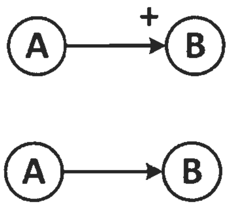


Figure 3.8: Mapping SDG to BBN



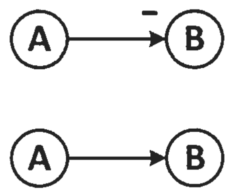
	B	
A	TRUE	FALSE
TRUE	0.95	0.05
FALSE	0.1	0.9

Figure 3.9: Mapping SDG to BBN

and child nodes. On the other hand, in the numerical translation, the conditional probability tables of the BBN nodes are filled up based on the signs of the arcs in SDG.

An arc with positive sign between the two nodes in the SDG refers that the direction of change in the causal node, will be followed by the effect node. This behaviour is mapped in BBN conditional probability table (CPT) between the same two nodes. In the CPT those two variables will be assigned with high probability value (greater than 0.5) for the same state. Fig. 3.9 a SDG with two variables A and B is shown. With the graphical translation the structure of the BBN is obtained. The CPT for node B is obtained from the numerical translation. The arc from A to B is denoted with positive sign. In the CPT, when both A and B are in the same state, high probability value is assigned. $P(B|A) = 0.95$ with both A and B in the $True$ state and $P(\bar{B}|\bar{A}) = 0.9$ with both A and B in the $False$ state.

On the other hand, an arc with negative sign between the two nodes in the SDG refers that the direction of change in the causal node, will be opposite to the effect node. In the BBN CPT those two variables will be assigned with higher probability



	B	
A	TRUE	FALSE
TRUE	0.15	0.85
FALSE	0.92	0.08

Figure 3.10: Mapping SDG to BBN

value (greater than 0.5) for the opposite state. The probability values can be obtained from the frequency analysis or expert judgement. Conditional probability tables illustrate how intermediate nodes are related to precedent intermediate or root nodes which is similar to the arc sign in the SDG. Fig. 3.10 a SDG with two variables A and B is shown. The CPT for node B is obtained from the numerical translation. The arc from A to B is denoted with negative sign. In the CPT, when both A and B are in the opposite state, high probability value is assigned. $P(\bar{B}|A) = 0.85$ with A in $True$ state and B in the $False$ state and $P(B|\bar{A}) = 0.92$ with A in the $False$ state and B in the $True$ state.

Often exact graphical translation of SDG into BBN may result in cyclic network. This is not consistent for BBN analysis. Therefore the cyclic network need to be converted to acyclic network without altering the process behaviour captured by the network. To avoid a loop, indirect relationship between the variables may be useful. This is demonstrated with example in the next section.

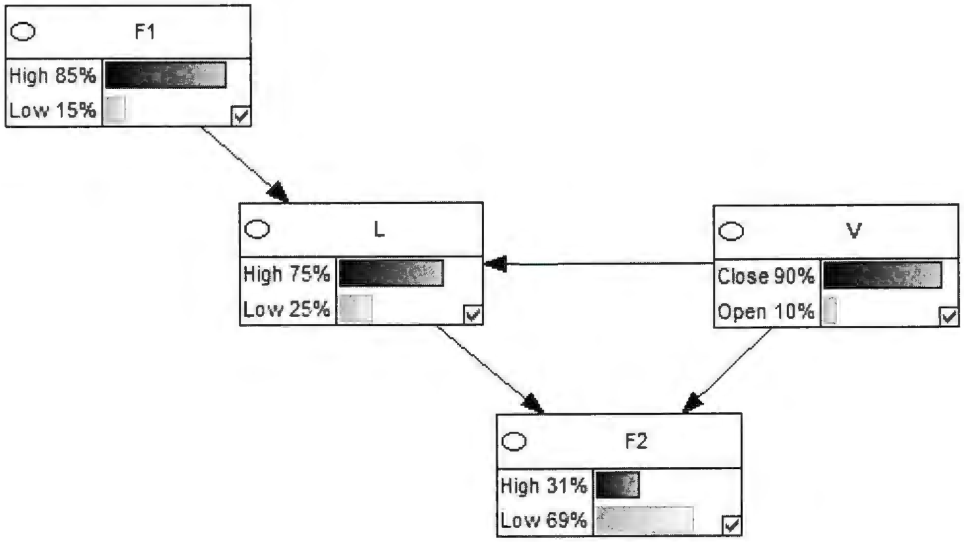


Figure 3.11: Scenario 1: BBN of simple tank

3.4.1 Mapping of BBN Model for Simple Tank System

BBN for the simple tank model shown in the Fig. 3.4 can be drawn as Fig. 3.11. The BBN structure is same as the SDG shown in Fig. 3.5, except for the arc from V to L. Since BBN is acyclic by the definition, to make the network consistent an arc from F_2 to L is avoided. Instead of that, an arc from the V to L is drawn. From Eqn. (3.4) it is evident that L is a function of both F_1 and F_2. Outflow F_2 depends on V. Therefore, L has a dependency with V. This process knowledge is used to avoid the cyclic loop in BBN to make it consistent.

Relation among the different variables are quantitatively expressed in terms of conditional probability. Prior probability and conditional probability table is shown in Table.(3.1, 3.2, 3.3 and 3.4).

Accumulation of water in the tank is function of both inflow rate F_1 and valve state (open or close). When inflow increases and valve is closed, accumulation is

	F1
High	0.85
Low	0.15

Table 3.1: Prior probability of inflow F_1

F1		High		Low	
	V	Close	Open	Close	Open
L					
High		0.95	0.05	0.15	0.02
Low		0.05	0.95	0.85	0.98

Table 3.2: Conditional probability table for level L

higher. These relations are shown with different signs in the SDG. In BBN, positive and negative relation can be defined by the conditional probability table (CPT) shown in Table.(3.2). Accumulation is 0.95 when F_1 has higher flow rate and the valve is closed. But accumulation is 0.02 when F_1 has lower flow rate and the valve is open. This is how the positive or negative relation among the variables in the SDG can be transformed to the CPT to map a BBN from SDG.

L		High		Low	
	V	Close	Open	Close	Open
F2					
High		0.3	0.95	0.05	0.8
Low		0.7	0.05	0.95	0.2

Table 3.3: Conditional probability table for outflow F_2

Probability inserts uncertainty into consideration. Prior probability of F_1 and V is set according to the Table.(3.1 and 3.4).

3.4.1.1 Scenario 1: Validation of Conditional Probability

From the process knowledge it is evident that if the inflow F_1 is high and valve V is closed outflow F_2 will be lower and it will result in high accumulation of level L. This

	V
Close	0.9
Open	0.1

Table 3.4: Prior probability of valve V

process dynamics is justified by the BBN in Fig. 3.11. When inflow is set to high probability 85% and the valve is close with high probability of 90%, outflow F_2 is low with 69%. The chance of accumulation of water in the tank is higher with 75%.

3.4.1.2 Scenario 2: Validation of Conditional Probability

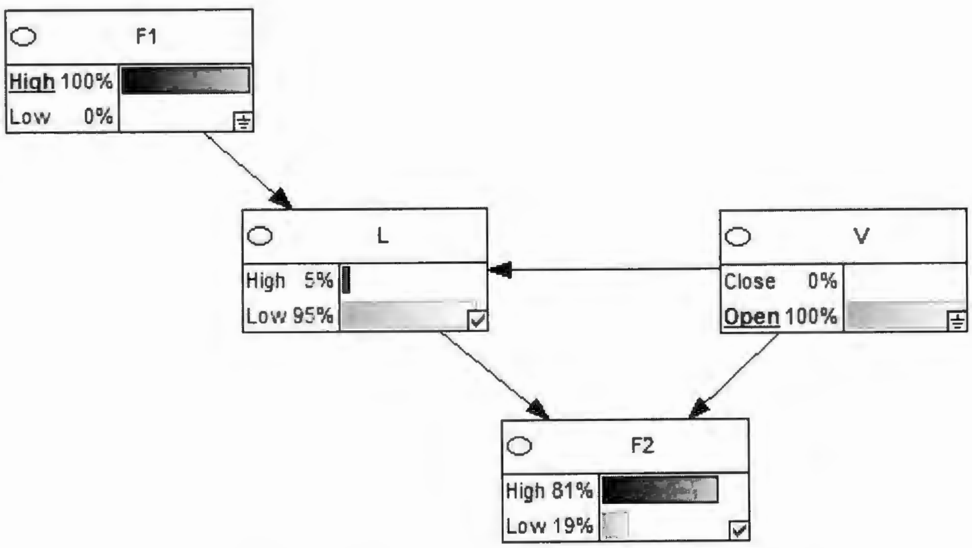


Figure 3.12: Scenario 2: BBN of simple tank

A different scenario where inflow rate is high and the outlet valve is fully open is shown in Fig. 3.12. Here F_1 has very high probability 100% and the valve opening has very high probability of 100%.

It is evident from process dynamics, there will be very low amount of water accumulation in the tank. Because outlet valve is kept open. This will result in

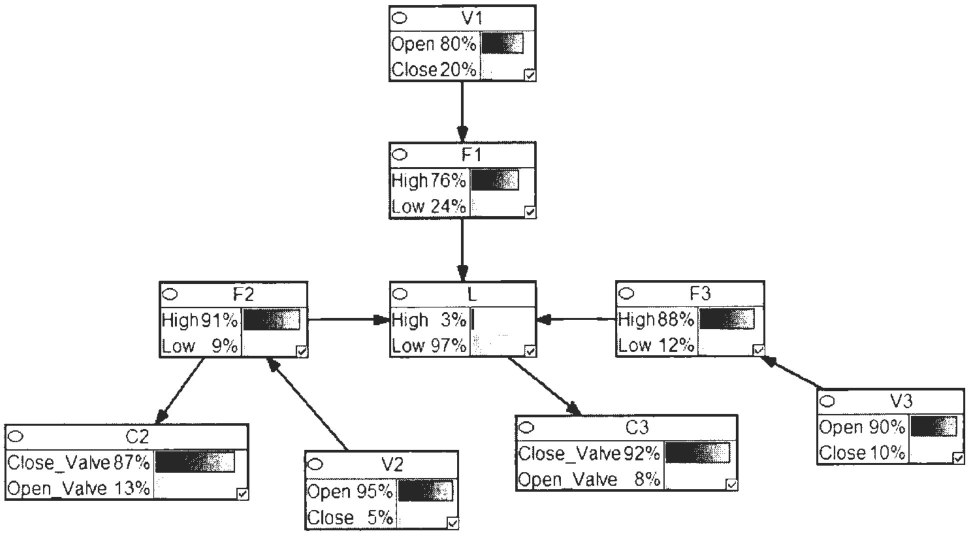


Figure 3.13: Validation of Conditional Probability for controlled tank model 1

high out flow rate F_2. This process dynamics is illustrated by the BBN. L has low accumulation probability of 85% and F_2 has high flow rate probability of 81%.

It can be concluded that a BBN can be constructed from SDG if process model is available. If process model is not available, BBN can be built from process knowledge itself. Positive or negative arc which express the type of relations among the variables in SDG, can be defined in terms of conditional probability in BBN.

3.4.2 BBN of Controlled Tank Model

The tank model and corresponding SDG shown in the Fig. 3.6 and 3.7 is mapped to the BBN shown in the Fig. 3.13. The structure of the BBN is obtained from the graphical translation of the SDG model. To avoid loops in the BBN and to make it consistent, control loops are made acyclic. This is done by introducing two controller nodes C_2 and C_3. One arc from the F_2 to C_2 is drawn to denote the flow control action. Depending on the flow F_2 the controller will take action to maintain the optimal flow by opening or closing the valve which is shown by the *Close Valve* and *Open Valve* states of V_2. Another arc from the L to C_3 is drawn to represent level control action. Depending on the level L the controller will take action to maintain the optimal level by opening or closing the valve which is shown by the *Close Valve* and *Open Valve* states of V_3. Here, no controller action is implemented since it will make the network a cyclic one. The controller action can be implemented by superposition to replicate the process behaviour. The following simulation results show how dynamic process behaviour was captured in BBN.

In Fig. 3.13 shows that accumulation L is very low 97% due to high flow rate of both of F_2 and F_3 respectively 91% and 88%. To maintain the desired flow rate of F_2, controller 2 needs to close the valve. To implement this action, an arc from the C_2 to V_2 is needed. But the arc will make the BBN cyclic. Therefore to avoid this loop and make the BBN an acyclic model In Fig. 3.14 the controller 2 action is implemented. Valve V_2 is closed a bit to make flow rate F_2 to optimum level. Therefore, accumulation is raised and controller action C_2 is also minimised. The control loop of the level controller was avoided similarly.

3.5 Conclusion

The simulation results show that BBN for a system can be deduced from the governing equation of the model. The complete methodology is demonstrated with several simulation examples using GeNIe 2.0. Various faults were assumed to calibrate the BBN and to verify cpt table and prior probability values. The cpt table values and the prior probability values are the inputs for BBN constructed in GeNIe 2.0. These faults were assumed from the process dynamics. Often the model or the equations are not available. In that case system dynamics and process knowledge can be helpful to

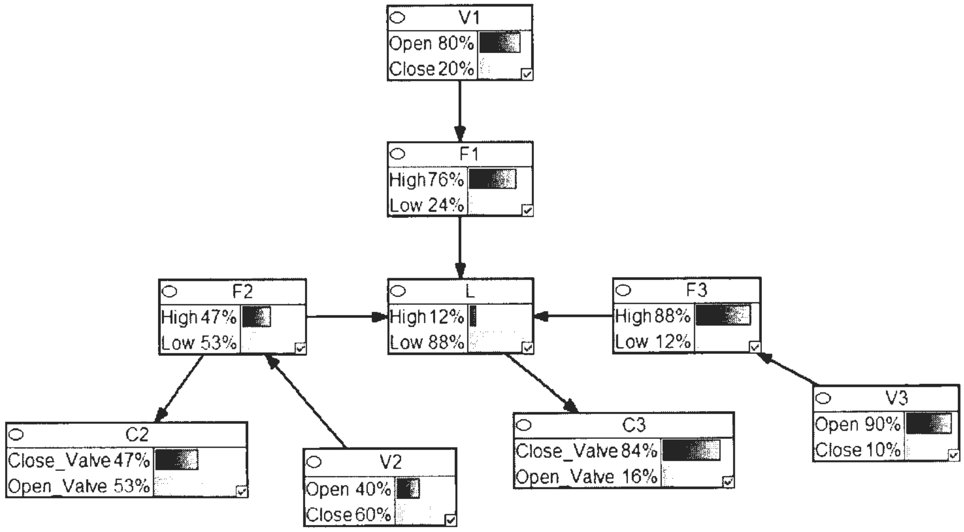


Figure 3.14: Validation of Conditional Probability for controlled tank model 2

build a BBN model. First SDG is built, than SDG can be mapped into BBN discussed in Fig. 3.8. The prior probability and conditional probability tables can be obtained by expert judgement where enough historical data is not available. In addition to that, BBN can be useful for diagnosis or in root cause analysis. For process with complex structure, operators often performs very complex analysis to find the root cause of a fault. Often due to lot of factors (Mental pressure, Working conditions etc.) this manual diagnosis is erroneous during the process fault conditions. In this context BBN provide solution in need for an automated diagnostic tool.

Chapter 4

PCA-BBN Based Hybrid Method for Process Fault Detection and Diagnosis

In this chapter an automated fault detection and diagnosis tool is described. This hybrid tool is the combination of PCA and BBN. PCA detects the fault and preliminarily diagnose the root cause. BBN takes detection and diagnosis results of PCA and further refines it based on the process knowledge to accurately pinpoint the root cause of a fault.

4.1 PCA-BBN Hybrid Method

The PCA-BBN hybrid FDD algorithm is shown using a flowchart in Fig. 4.1. This algorithm has two essential parts. They are fault detection using PCA. Once fault is detected, diagnosis is done using BBN. The loop execution will occur at each sampling instant of the available data set.

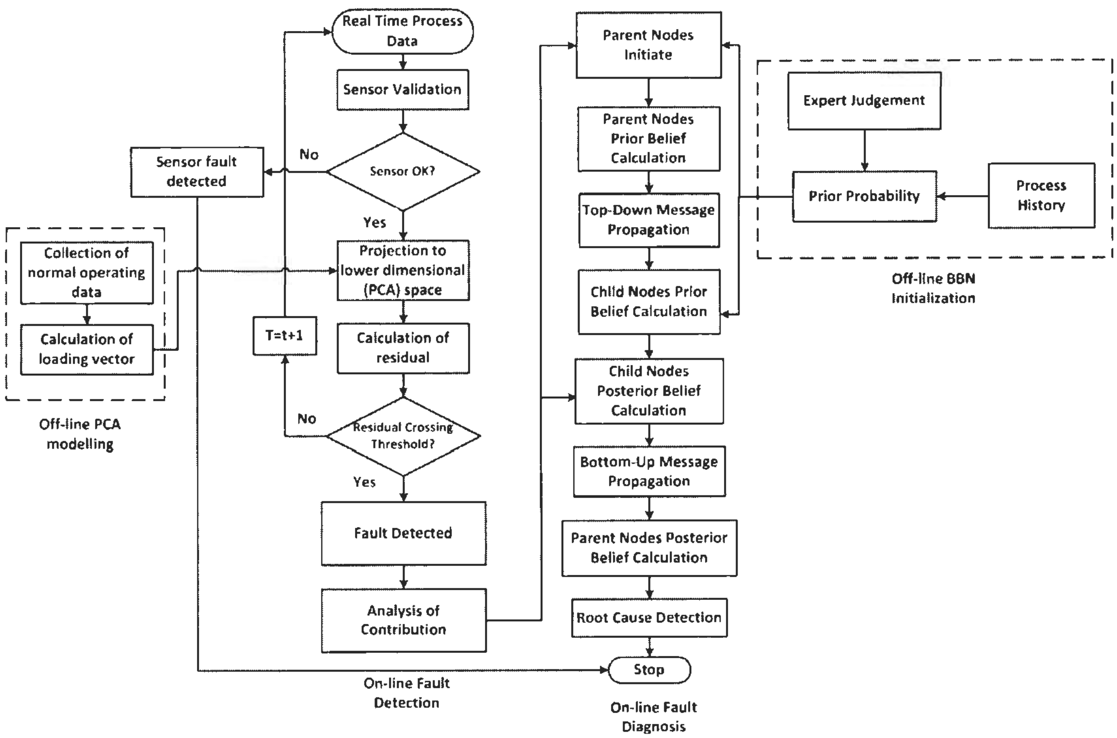


Figure 4.1: PCA-BBN hybrid fault detection and diagnosis method

Before a sensor measurement is fed to the PCA-BBN, it needs to be validated. Sensor validation allows to detect sensor faults locally and does not require any further analysis. Typically in a process system measurement will always show small random variations due to the fluctuation in the system and measurement noise of the sensors. If the a sensor does not shown any movement for an extended period that is indication of sensor malfunction. Simple logic check is implemented here to detect the sensor fault. For example, If no variation is found in the measurement for the seven consecutive samples (i.e. less than 10^{-6}) compare to the present measurement, the sensor is said to be faulty.

$$v_t = |x_t - x_{t-i}| \tag{4.1}$$

Here $i = 1, 2, 3, ..., 7$.

Again, if the change in the measured data is unusually high or low the sensor is said to be faulty. This can only happen when measured variable has a sharp rise or sharp fall. For a slow system like process these sharp changes are unusual.

A faulty sensor can be pinpointed correctly through sensor validation. This sensor authentication makes the diagnostic tool more robust. Whenever a fault is detected for a variable, sensor validation algorithm ensures the integrity of sensor measurement.

If sensor is found to be operating, The PCA model (the loading vectors) is used for process monitoring by projecting the on-line data onto the PC subspace. On-line data set X_t is projected by linear transformation and PCs of on-line data set can be expressed by the following equation,

$$S_i = X_t P_i. \tag{4.2}$$

Here, S is the PC or score vectors of on-line data, $i = 1, 2, 3......m$, $P_i \epsilon R^{m\times r}$ and r is the number of principal component $r \leq m$.

Each of the Principal components or score vectors capture as much variation as possible which has not been explained by the former PCs. The maximum number of principal components are equal to the total number of the variables.

For on-line fault detection, PCA model is built from the normal operating condition data. Off-line PCA model is built from a given data matrix X, of normal operating condition, of dimension $\epsilon R^{N\times m}$ where N is the number of sample data and m is the number of the correlated variables in the data set. Initially data set X is pre-processed by auto-scaling (mean zero and variance one). Then off-line PCA model is obtained from the SVD analysis of covariance matrix of auto-scaled data set [Jackson, 2005, Afifi and Clark, 2004].

The covariance matrix of X can be defined as

$$cov(X) = \frac{X^T X}{N-1}. \tag{4.3}$$

SVD analysis of covariance matrix X decomposes as follows:

$$SVD[cov(X)] = P\Lambda P^T. \tag{4.4}$$

where Λ is a diagonal matrix with significant eigenvalues and P contains the respective eigenvectors also known as loading vectors and the basis vector of the principal subspace [Smith, 2002]. This obtained eigenvectors P is the PCA model is used for on-line process monitoring. This principal subspace has a lower dimension than the original data set X and yet is able to capture or explain significant portion of the information content (or the variance) in the original data set.

PCA model prediction for all variables can be expressed by as follows,

$$\hat{x}_t = \sum_{i=1}^{r} S_i P_i. \tag{4.5}$$

$\hat{x}_t$ is the model prediction.

Residual is calculated from the difference between the model projection and projected data set [Jolliffe, 2005]. Residual E for an on-line sample x_t, is calculated according to the following formula,

$$E \quad = (x_t - \hat{x}_t)^T (x_t - \hat{x}_t), \tag{4.6}$$

A confidence limit for E can be calculated as follows

$$\begin{aligned} Q &= \theta_1 (\tfrac{C_\alpha \sqrt{2\theta_2 h_0^2}}{\theta_1} + 1 + \tfrac{\theta_2 h_0 (h_0 - 1)}{\theta_1^2})^{(\frac{1}{h_0})}, \\ \theta_i &= \textstyle\sum_{j=r+1}^{n} (\lambda_j)^i, \\ h_0 &= 1 - \tfrac{2\theta_1\theta_3}{3\theta_2^2}. \end{aligned} \tag{4.7}$$

where C_α is obtained from the normal distribution limits for the upper $(1 - \alpha)$ percentile [Jackson and Mudholkar, 1979].

During the normal operating condition threshold defined by Eqn. (4.7) is not violated and data for new time instant is monitored for fault. But for the abnormal condition the residual exceeds its threshold limit. Upon successful detection of fault, PCA contribution of each variable is analysed.

Contribution of $i - th$ variable to the Q-statistic can be calculated as

$$C_i = (X_t^T P P^T \beta_i)^2. \tag{4.8}$$

Here β is a column vector i-th element is one and the others are zero and

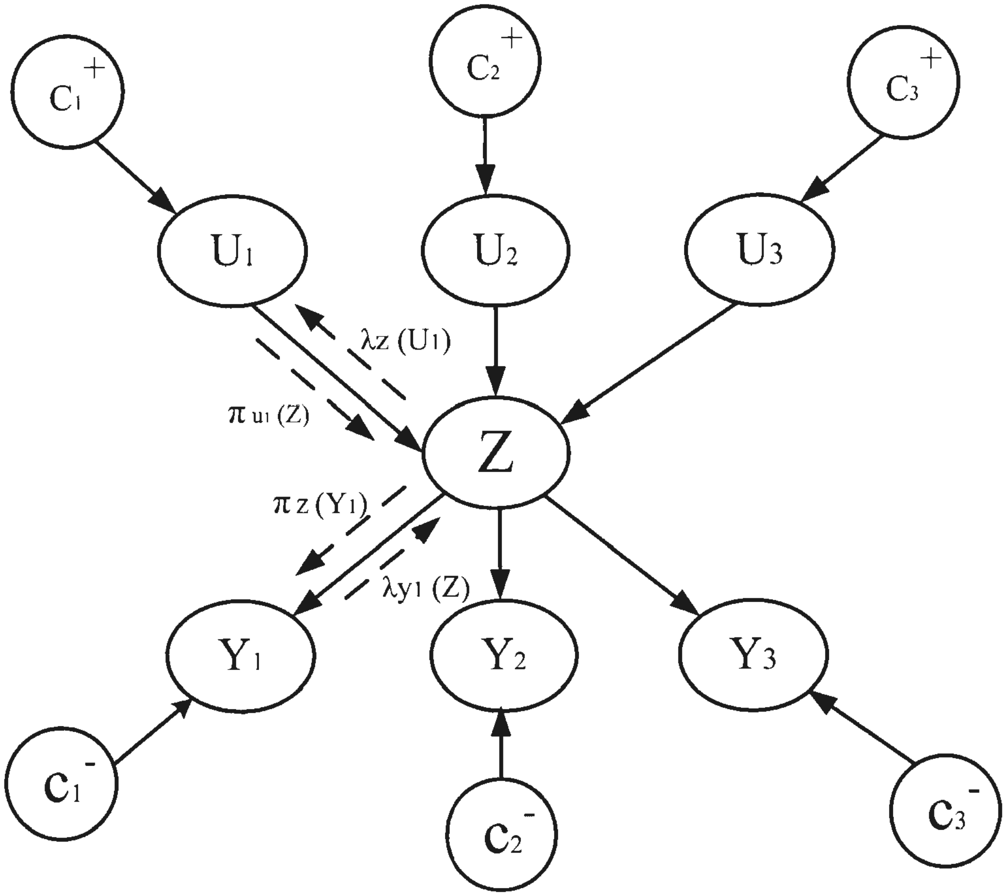


Figure 4.2: Message passing in BBN after evidence coming to the nodes

$i = 1, 2, 3.....m$ [Liu, 2012].

For on-line fault diagnosis contribution of each variable is used as evidence for the BBN. Depending upon this on-line evidence, BBN updates its belief of each node. Contribution as evidence input for the parent nodes is denoted as c^+ and contribution as evidence input for the child nodes is denoted as c^-. The contribution matrix is

$$C = \begin{bmatrix} c^+ & c^- \end{bmatrix} \tag{4.9}$$

In Fig. 4.3 a BBN with tree structure is shown. U_1, U_2 and U_3 are parent nodes and Y_1, Y_2 and Y_3 are child nodes. Message from the parent nodes to the child nodes are denoted as π messages and message from the child nodes to the parent nodes are denoted as λ message.

Initially each parent node in BBN is initiated by prior probability. Prior belief of parent nodes is calculated by evidence from the PCA and initially calculated prior probability.

$$\begin{aligned} bel(U_i) &= \tfrac{P(c_i^+|U_i)P(U_i)}{P(c_i^+)}, \\ &= \pi_{U_i}(Z). \end{aligned} \tag{4.10}$$

here $P(U_i)$ is prior probability of node U_i, $bel(U_i)$ is prior belief of node U_i and $i = 1, 2, 3...., p$ number of the parent nodes.

By top-down propagation parent nodes prior belief is passed to the child nodes. Child nodes calculate the prior belief with the help of the conditional probability table and the prior belief of the parent nodes.

$$\begin{aligned} bel(Y_j) &= \alpha_j \pi_Z(Y_j) P(Y_j|Z), \\ &= BEL(Z)P(Y_j|Z) \end{aligned} \tag{4.11}$$

here α_j is a normalizing constant and for all states of Y_j, $bel(Y_j)$ is prior belief of node Y_j and $j = 1, 2, 3...., c$ number of the child nodes.

Belief of node Z is calculated simultaneously inspecting the message from its parents $\pi(Z)$ and the messages from its children $\lambda(Z)$. Using this inputs, it updates its belief

$$BEL(Z) = \alpha_z \lambda(Z) \pi(Z). \tag{4.12}$$

here α_z is a normalizing constant and for all states of Z

$$\sum_z BEL(Z) = 1. \tag{4.13}$$

where

$$\pi(Z) = \sum_{i=1}^{p} \pi_{U_i}(Z) P(Z|U_i). \tag{4.14}$$

$$\lambda(Z) = \sum_{j=1}^{c} \lambda_{Y_j}(Z) P(Y_j|Z). \tag{4.15}$$

Then each child node updates its prior belief to posterior belief based on the evidence coming from PCA.

$$BEL(Y_j) = \alpha_j bel(Y_j) P(c_j^-). \tag{4.16}$$

Posterior belief of the child node in sent to the parent node by bottom up belief propagation.

$$\lambda_{Y_j}(Z) = \alpha_j BEL(Y_j) P(Y_j|Z). \tag{4.17}$$

Then each parent node updates its prior belief to posterior belief based on the posterior belief of the child nodes.

$$BEL(U_i) = \alpha_i bel(U_i) \lambda_Z(U_i). \tag{4.18}$$

$$\lambda_Z(U_i) = BEL(Z) P(Z|U_i). \tag{4.19}$$

This updating process continues until each node is updated to the posterior belief. At next time instant each node receive new evidence from the PCA and posterior belief of the previous time instant becomes prior belief for next time instant. Belief propagation start again until the network is converged.

Belief propagation between the parent nodes and child nodes follows Pearl's message passing algorithm. Prior belief of every node is rectified by both PCA evidence and process knowledge. Initially some non-faulty variables may show up as faulty in the PCA contribution plot. But when they are updated based on the evidence and current process knowledge in the BBN, their posterior belief reflects the real condition of the variable and removes the ambiguity of diagnosis. In this fashion the inference network can track a changing environment and provide the most updated possible condition.

A real time hybrid process monitoring technique based on PCA and BBN for process fault detection and diagnosis is described here. The proposed hybrid method uses the diagnostic results from PCA and combines with process knowledge captured in a BBN. Thus the method is able to accurately pinpoint the root cause of a fault which is shortcomings of PCA and other statistical fault detection and diagnosis approaches.

4.2 Diagnosis using Sensor Measurement as Evidence

Sensor measurements can be used as evidence instead of PCA contribution information. The complete algorithm for this is shown in Fig. 4.3. Initially measurement is validated by sensor validation algorithm. If sensor is found normal operating then sensor measurement is further processed.

Sensor measured data is compared with the corresponding set point value to obtain the residual. Residual of each variable is used as evidence input for the BBN.

$$X_r = |X_m - X_s| \tag{4.20}$$

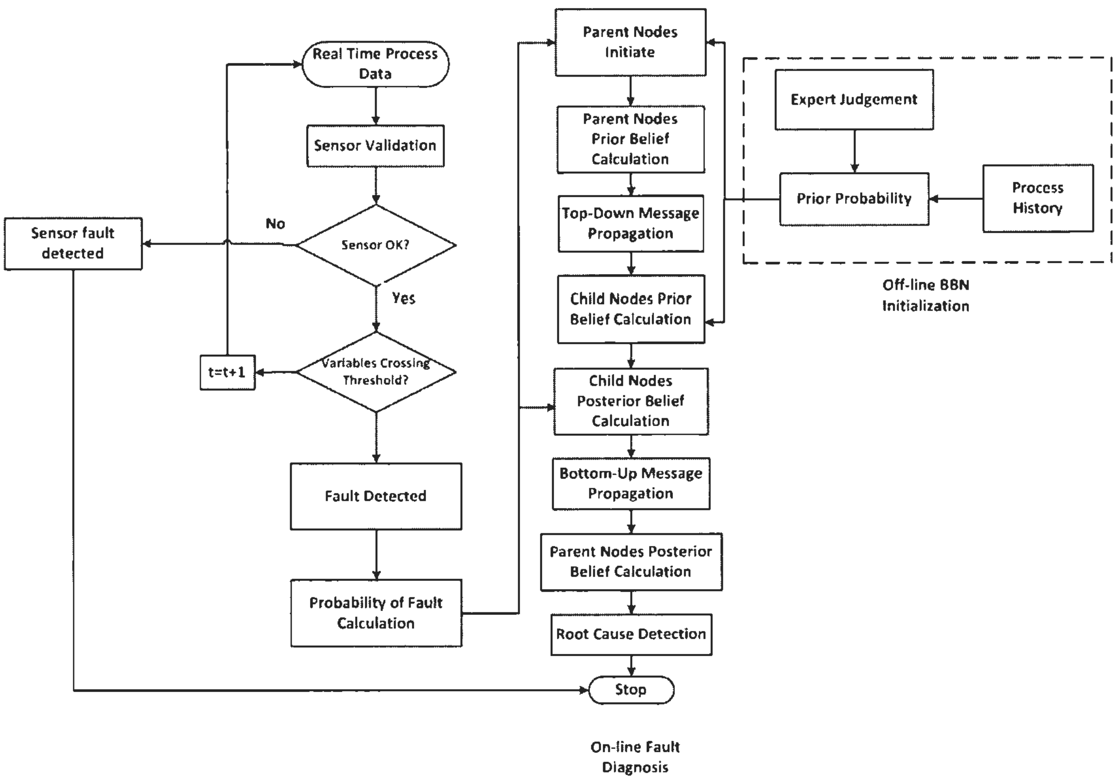


Figure 4.3: Diagnosis using sensor measurement as evidence

Here, X_r is the residual of variable X, X_m is the measurement from the sensor and X_s is the set point of X.

Probability of fault increases as residual of a variable goes away from the normal operating limit. In this case absolute value of residual is considered and the normal operating condition limit is defined as $\mu + 3\sigma$ of normal operating data. When the residual exceeds this limit the process is said to be in faulty condition. The probability that X is faulty is calculated from the following equation

$$P(X) = \begin{cases} 0 & X_r = 0 \\ 1 & X_r > 0 \end{cases} \tag{4.21}$$

Here, X_r is the absolute residual value of variable X.

These obtained values are introduced as evidence for the BBN nodes. BBN diagnosed the fault using message passing algorithm discussed in the previous section.

4.3 Conclusions

A PCA-BBN based hybrid monitoring tool is proposed in this chapter. Performance of the proposed method is demonstrated using a PTA tank model. Various fault scenarios were considered. Results are shown in the next Chapter.

Chapter 5

Results and Discussions

In this chapter the performance of the proposed diagnostic tool is demonstrated using simulation and industrial case study. The system is a model of a dissolution tank to dissolve terephtalic acid crystals in order to remove impurities to form pure terephtalic acid (PTA). After testing the diagnostic tool in simulation environment, data was collected from the real process. The diagnostic tool was validated using industrial data. The organization of this chapter is as follows, first the construction of the BBN for the dissolution tank system is described. Prior probability and conditional probability were assigned and verified by simulating several different scenarios. Next, with various simulated faults in the system the proposed hybrid method was applied to detect and diagnose the root cause of the fault. Performance of the proposed method was compared with the BBN where sensor measurements were used as evidence. Finally, the PCA-BBN hybrid method is validated using industrial data from the PTA dissolution tank for a known fault condition.

5.1 Dissolution Tank Model

A simplified process diagram for the dissolution tank system, is shown in Fig. 5.1 [Mallick and Imtiaz, 2011]. In this system solid terepthalic acid crystals are dissolved in a tank with water. Water is pumped into the tank under flow control. PTA crystals are fed to the dissolution tank from a hopper using a rotary feeder. The feed rate of solid crystals to the mixing vessel is controlled by the speed of the rotary feeder (RPM). The water level in tank and the concentration of the liquid going out of the tank are continuously measured variables. The solid flow is calculated intermittently from loss of weight of the load-cell.The control objectives of the system are to maintain the concentration at desired set point and prevent overflow or dry out in the tank. Under the existing control strategy, two PID controllers are used to meet these objectives, the concentration of the outlet stream is controlled by manipulating the rotary valve rpm, while the flow controller under cascade control maintains the tank level.

However, the concentration at the outlet is subject to frequent large disturbances when the operators have to take control of the process and manually drive the process out of the abnormal condition. Major cause of the disturbance is the difficulty in solid dispensing. Occasionally because of the variation in moisture content the solid gets lumped in the rotary feeder. As a result solid does not dispense from the feeder uniformly. After a while when the lump gets too big it falls into the tank creating a big disturbance in the concentration which causes a further problem in the downstream process. The other causes include disturbances in the water level due to the poor control of water flow sensor malfunction, stiction of water flow valve etc. Objective of the monitoring scheme is to develop an automated fault detection and diagnosis system that will detect the fault early and will also precisely point to root cause of

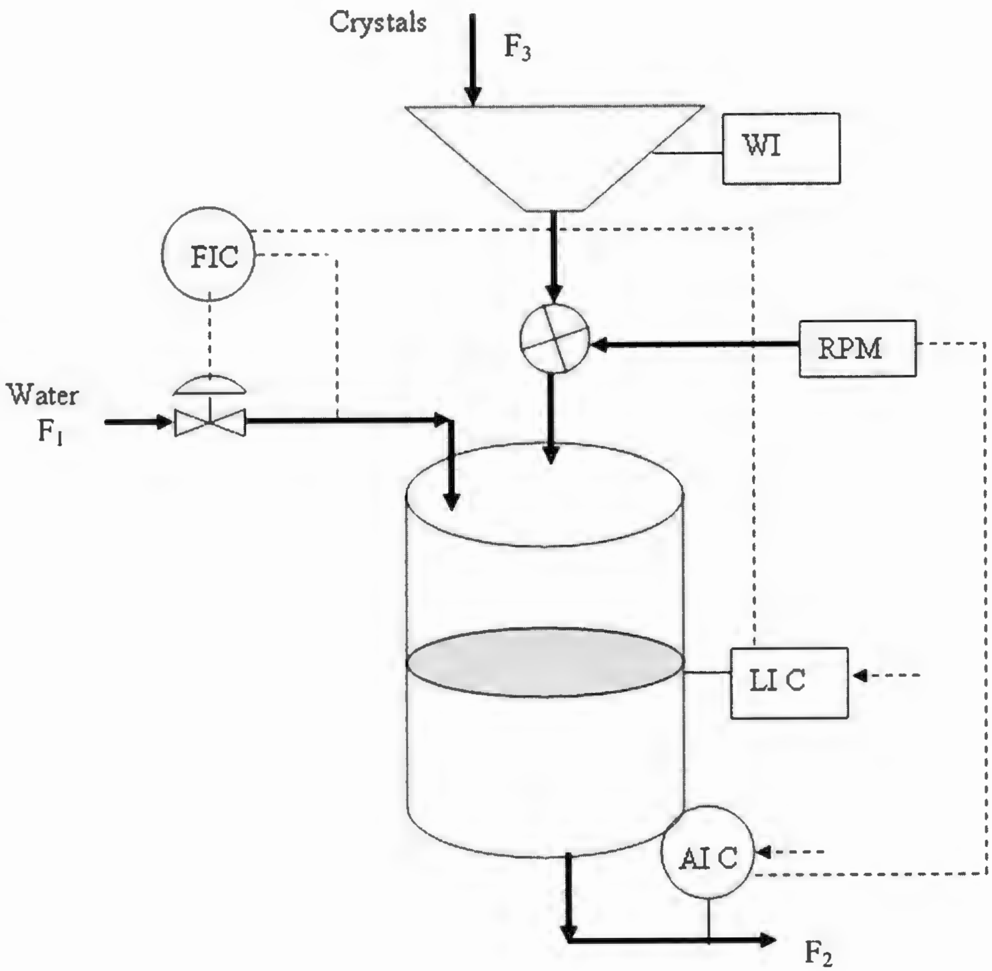


Figure 5.1: Dissolution tank model with existing control strategy

fault.

5.2 SDG for Dissolution Tank Model

First order differential equations for the PTA dissolution tank model are as below,

$$A\frac{dL}{dt} = (F_1 - F_2 + \frac{F_3}{1.52}), \tag{5.1a}$$

$$V\frac{dC}{dt} = (F_1\alpha_1 + F_3\alpha_2 - F_2C). \tag{5.1b}$$

Here, F_1 is inflow of water into the tank, F_2 is the outlet flow. Solid inflow rate is F_3 and C is the output concentration. A is the cross sectional area of the tank, V volume of the tank, α_1 and α_2 are process constants.

With these governing Eqn. (5.1) SDG model for the dissolution tank model can be developed following the methodology discussed in Section. 3.3. Three arcs from node F_1, F_2 and F_3 to node L are drawn. The sign of the arcs are positive, negative and positive respectively according to Eqn. (5.1a). Three arcs from node F_1, F_2 and F_3 to node C are drawn. The signs of the arcs are positive, negative and positive respectively according to Eqn. (5.1b). Rest of the network is developed based on the process knowledge. The simplified SDG model is shown in Fig. 5.2.

Since RPM drives the solid flow rotary valve RV, a positive arc from the RPM node to the RV node is drawn. The solid flow rate is proportional to rotary valve revolution which is denoted by a positive arc from the RV node to the solid flow rate S node. Solid flow has direct impact on concentration. This relation is shown by an arc drawn form S node to node C. Water flow is controlled by the flow valve FV and water flow is directly related to the water level L. These relations are captured

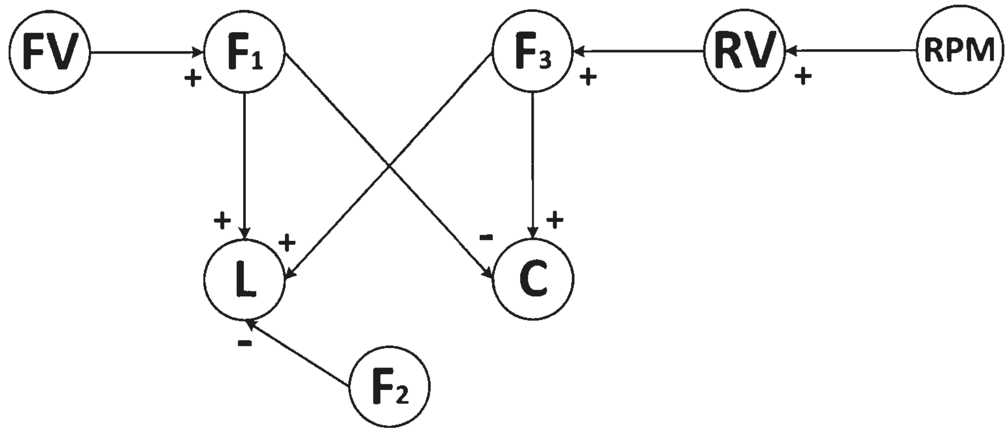


Figure 5.2: SDG for dissolution tank model

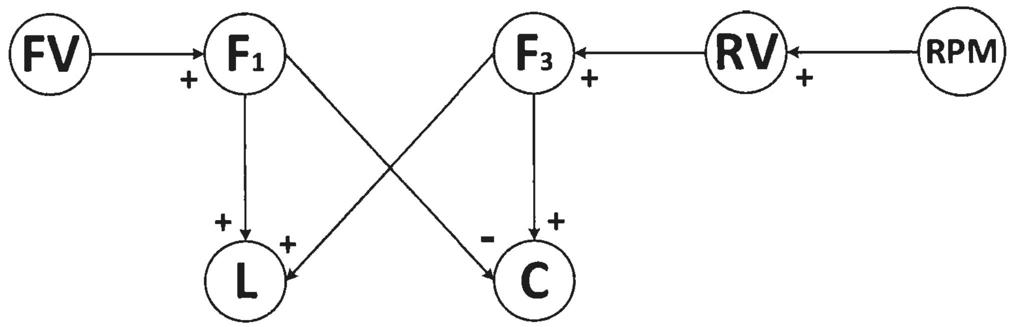


Figure 5.3: SDG for dissolution tank model

in the SDG by arcs drawn from FV to F_1 node and from F_1 to L node respectively. Outflow F_2 has inverse impact on the water level L. This is shown by a negative arc from F_2 to L. For this process outflow F_2 was maintained controlled manually and there was no flow sensor for F_2. Therefore, the impact of F_2 can be neglected and a simplified SDG can be obtained as shown in Fig. 5.3.

5.3 Mapping of Dissolution Tank SDG to BBN

The SDG for dissolution tank model shown in Fig. 5.3 is mapped to BBN shown in Fig. 5.4 following the methodology described in Section. 3.4. In this case there

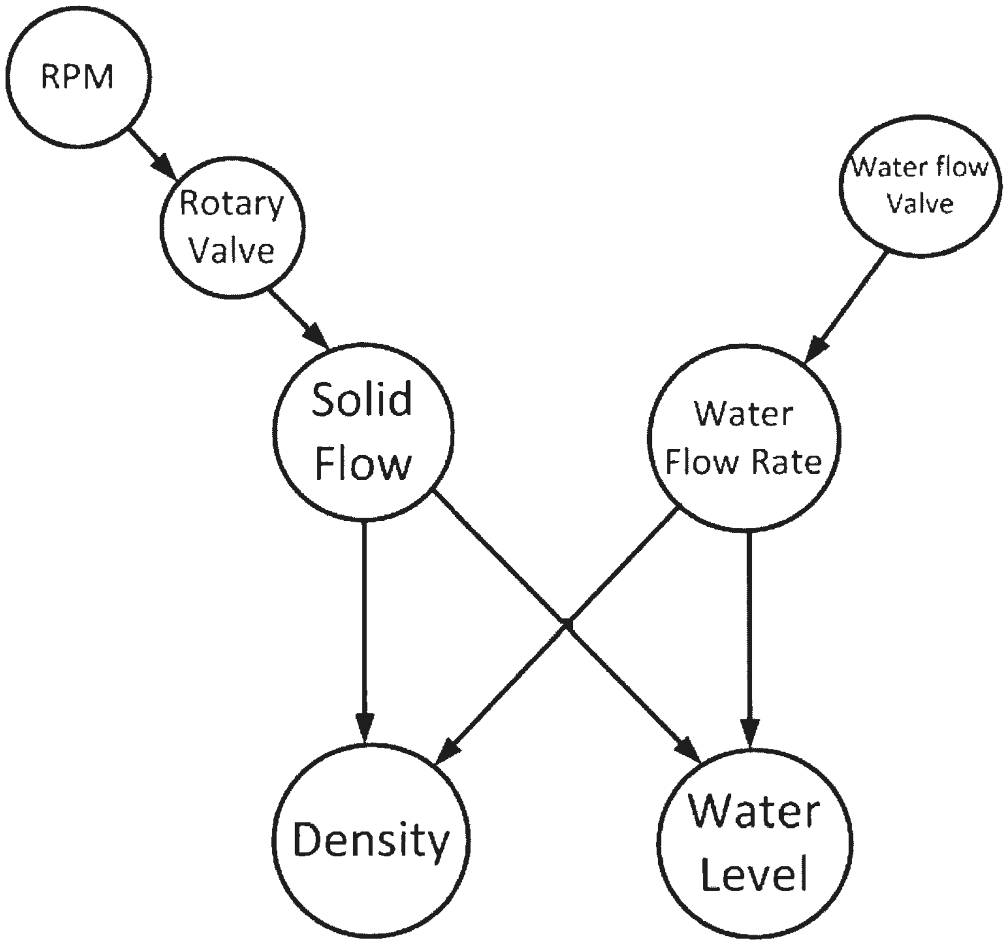


Figure 5.4: BBN for dissolution tank model

is no cycle in the SDG therefore the graphical structure for BBN is same as the SDG. Conditional probability values and prior probability values for the BBN were assigned based on process knowledge and expert judgement. The network is initiated with the probability values given in Table. 5.1-5.7. The numerical translation requires conversion of signed relationships to conditional probability tables. These assigned probability values were validated by simulating various scenarios described in the following sections.

	OK	NOT OK
RPM	0.8	0.2

Table 5.1: Prior probability of RPM

	RPM	
Rotary Valve	OK	NOT OK
OK	0.9	0.05
Not OK	0.1	0.95

Table 5.2: Conditional probability table for rotary valve

	OK	NOT OK
Water Flow Valve	0.85	0.15

Table 5.3: Prior probability of water flow rate

	Water Flow Valve	
Water Flow	OK	NOT OK
OK	0.93	0.08
Not OK	0.07	0.92

Table 5.4: Conditional probability table for water flow

	Rotary Valve	
Solid Flow	OK	Not OK
OK	0.85	0.1
Not OK	0.15	0.9

Table 5.5: Conditional probability table for solid flow

	Water Flow	OK		Not OK	
	Solid Flow	OK	Not OK	OK	Not OK
Density					
OK		0.95	0.1	0.65	0.01
Not OK		0.05	0.9	0.35	0.99

Table 5.6: Conditional probability table for density

	Solid Flow	OK		Not OK	
	Water Flow	OK	Not OK	OK	Not OK
Water Level					
OK		0.9	0.05	0.75	0.01
NOT OK		0.1	0.95	0.25	0.99

Table 5.7: Conditional probability table for water level

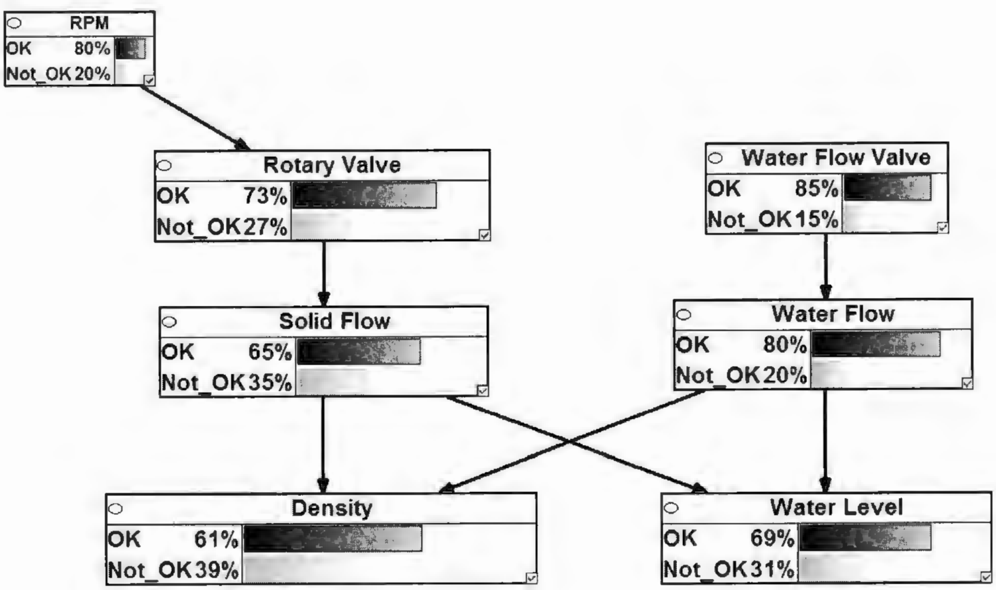


Figure 5.5: Scenario 1: No fault condition

	State in BBN	Actual State
Variable		
RPM	OK Not OK	RPM tracking set point Controller or Sensor Fault
Rotary Valve	OK Not OK	Smooth operating valve Sticky valve or other faults in the valve
Water Flow Valve	OK Not OK	Smooth operating valve Sticky valve or other faults in the valve
Solid Flow	OK Not OK	Uniform flow of solid Uneven flow due to clogging of solid
Water Flow	OK Not OK	Uniform flow of water Non uniform water flow due to the faulty valve
Density	OK Not OK	Density tracking the set point (no fault condition) Density not tracking the set point (fault condition)
Water Level	OK Not OK	Water Level tracking the set point (no fault condition) Water Level not tracking the set point (fault condition)

Table 5.8: Variable states in BBN

5.3.1 Validation of Conditional Probability

The mapped BBN captures the process cause and effect relationship between different variable. Several simulations are shown to demonstrate validation of conditional probability values assignment.

5.3.1.1 Scenario 1: No fault condition

Fig. 5.5 shows BBN for dissolution tank model initiated with prior probability values given in Tables 5.1-5.7. Here, RPM node is initiated with 80% OK state and $Water\ Flow\ Rate$ node is initiated with 85% OK state. $Rotary\ Valve$ node has high probability for being in the operating state as RPM node has high value of OK states. This results in uniform solid flow of 65%. Since water flow directly depends on the performance of water flow valve which is held at OK state cause water flow to be at OK state with 80% of probability. Consequently the probability of both $Density$ and $Water\ Level$ are at desired level is high 61% and 69% respectively. This result reflects the causality between process variables in terms of probability values correctly.

5.3.1.2 Scenario 2: Fault in the Rotary Valve

We need the same probability values given in Table. 5.1-5.7 and use those to investigate the diagnosis ability of the network in case of a fault in the rotary valve. When rotary valve is not operating properly due to valve stiction , density at the outlet is affected. This may results in non-uniform solid flow at 90% probability. The probability for $Density$ and $Water\ Level$ to be at the desired level are 16% and 62% respectively are affected by high probability of non-uniform solid flow. This is expected process behaviour because solid flow has more influence on density and disturbance in solid

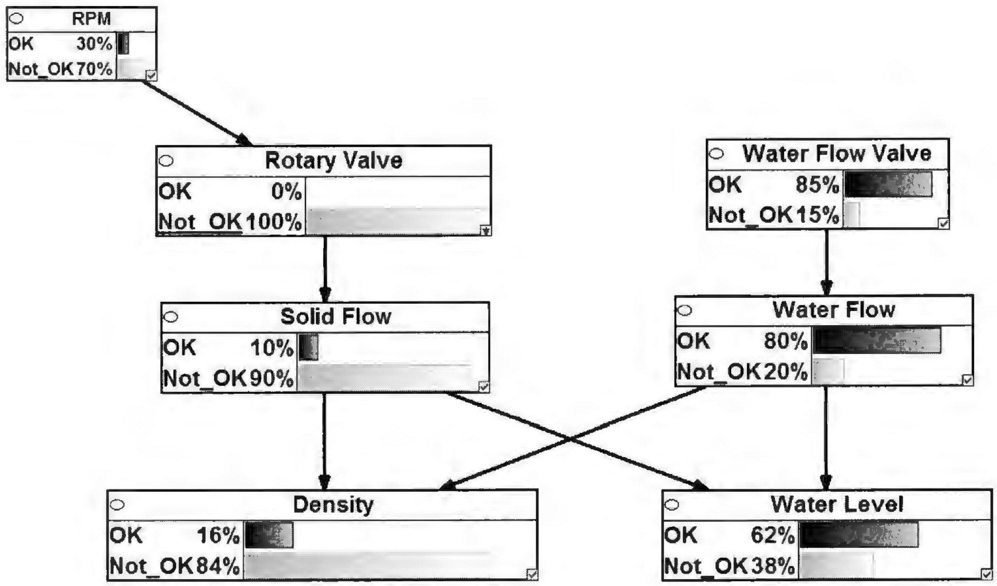


Figure 5.6: Scenario 2: Fault in the Rotary Valve

flow has significant effect on density. On the other hand, water flow and water flow valve are in OK state. Therefore, fault in solid flow should not affect the tank level significantly as shown in Fig. 5.6.

5.3.1.3 Scenario 3: Fault in the Water Flow Valve

In this case we consider fault in water flow valve. To simulate this scenario BBN for dissolution tank model shown in Fig. 5.7 is initiated with prior probability given in the Tables 5.1-5.7. Since $Water\ Flow\ Valve$ node is set at $Not\ OK$ state, this will result in non-uniform water flow of 92%. Solid flow is not affected as rotary valve is held at the operating state with 73% probability. The probability for both *Density* and $Water\ Level$ to be at desired set points drops to 44% and 10% respectively. In a process we expect similar behaviour as water flow is a strong handle for the controller. The density will also be impacted but to lesser degree.

BBN can be very handy diagnostic tool. Root cause of any incident can easily

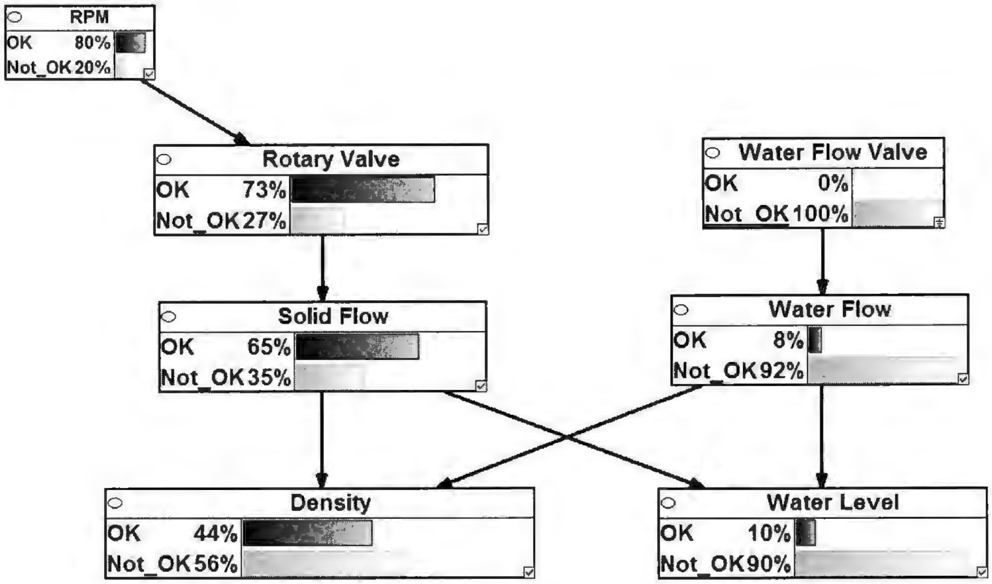


Figure 5.7: Scenario 3: Fault in the Water Flow Valve

be detected using BBN. The following simulation results demonstrate the power of BBN as diagnostic tool.

5.3.2 Scenario 4: Fault in Density Node

To demonstrate the power of diagnosis, a simulation case study for the dissolution tank model is shown in Fig. 5.8. A fault in density was introduced by setting *Density* node at *Not OK* with 100% probability. Solid flow has more influence on the density than water flow. Therefore, *Not OK* state of *Density* must be the result of non-uniform solid flow 82% probability. The nature of solid flow whether it will be uniform or not, will completely depend on the rotary valve performance. Simulation result shows that non-uniform solid flow is because of *Rotary Valve* malfunction with 57% probability.

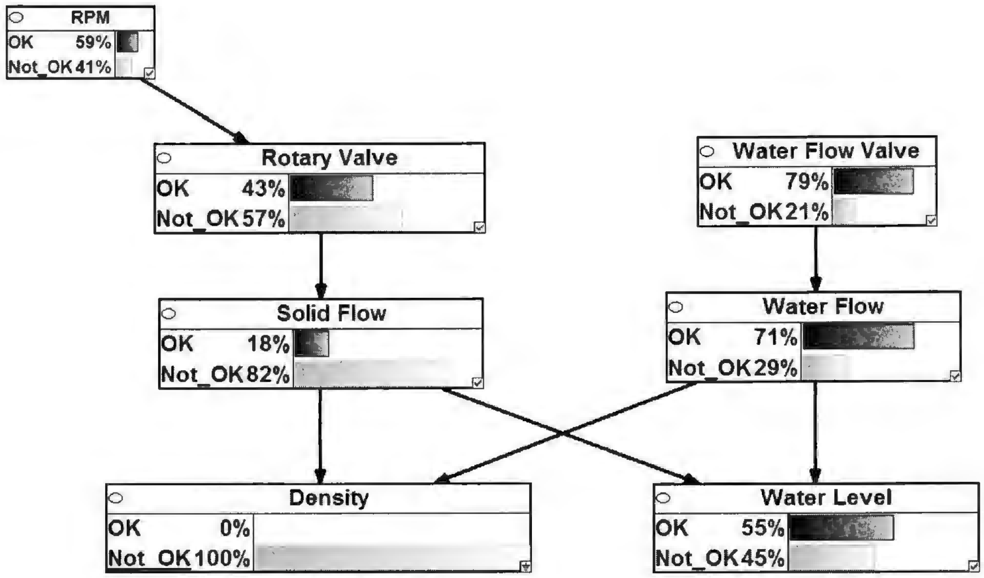


Figure 5.8: Scenario 4: Fault in Density Node

5.3.3 Scenario 5: Fault in Water Level Node

A fault in water level was introduced by setting *Water Level* node at *Not OK* state with 100% probability. This simulation case study is shown in Fig. 5.9. Water flow has more influence on the water level than solid flow. Therefore, *Not OK* state of *Water Level* must be the result of non-uniform 55% probability water flow. The nature of water flow whether it will be uniform or not, will completely depend on the water flow valve performance. Simulation result shows that non-uniform water flow is because of *Water Flow Valve* in *Not OK* condition with 52% probability.

5.4 PCA-BBN Hybrid Method as a Diagnostic Tool

The hybrid method was successfully implemented on the dissolution tank model for simulated faults. First, in case study 1, a fault is introduced in water flow and in case study 2 a fault is introduced in solid flow rate. In both cases fault was detected and

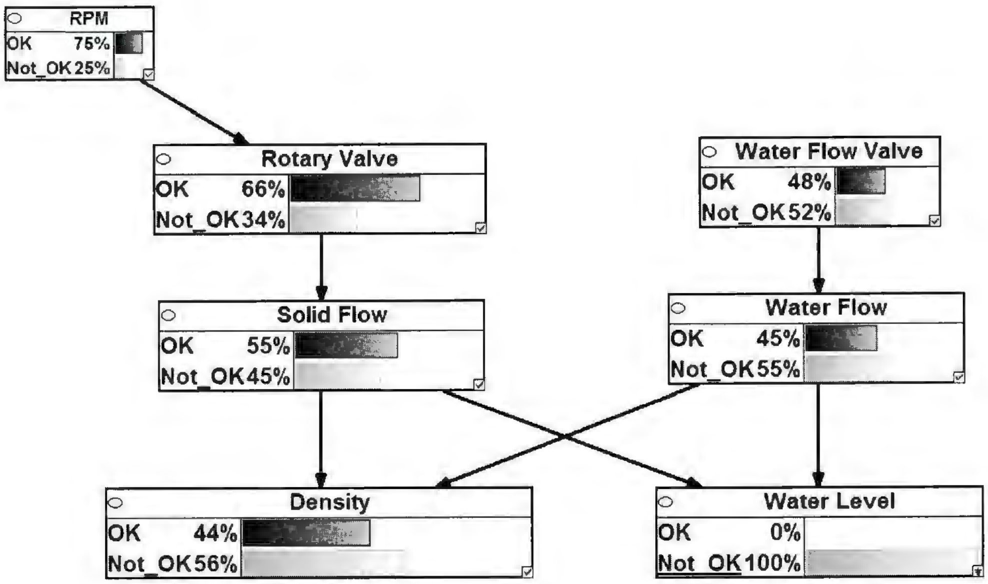


Figure 5.9: Scenario 5: Fault in Water Level Node

diagnose correctly. Sampling rate for this data was 1 sec.

5.4.1 Diagnosis of Simulated Fault

5.4.1.1 Scenario 1: Fault in Water Flow

A ramp type fault of maximum magnitude which is about 6% of the nominal signal variation was introduced in water flow at $t = 3100\ min$ as a result water level exceeded threshold level at $t = 3190\ min$ in Fig. 5.10. This fault is detected at $t = 3160\ min$ from PCA residual plot, as it violates Q-statistic threshold level shown in Fig. 5.11. From PCA contribution plot Fig. 5.12 its difficult to diagnose the fault correctly, as it is seen that all the variables have significant contribution for the fault except density. This is due to the smearing effect discussed in Section 4.1. This preliminary diagnosis information was supplied to the calibrated BBN which correctly diagnose the water flow as root cause the fault in Fig. 5.13. Evidence from both density and water level

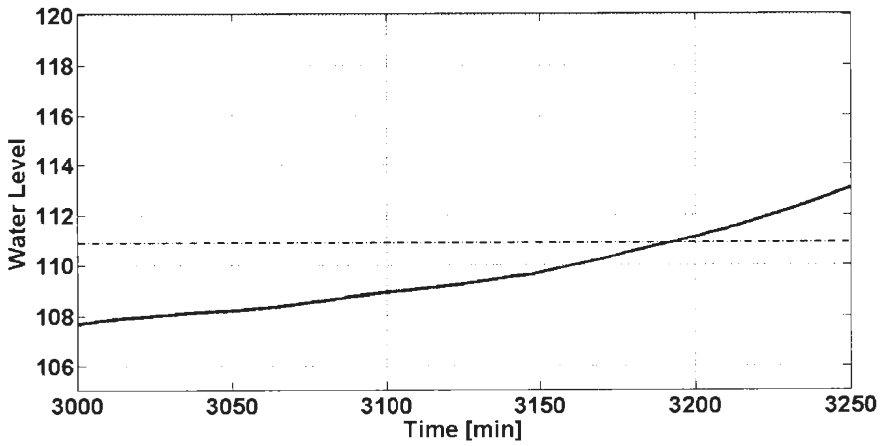


Figure 5.10: Scenario 1: A ramp type fault in water level

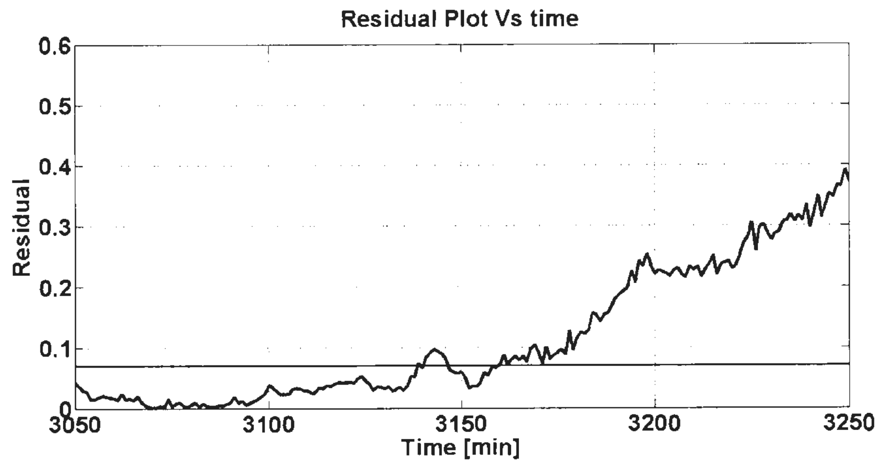


Figure 5.11: Scenario 1: PCA residual plot detecting the fault in water level

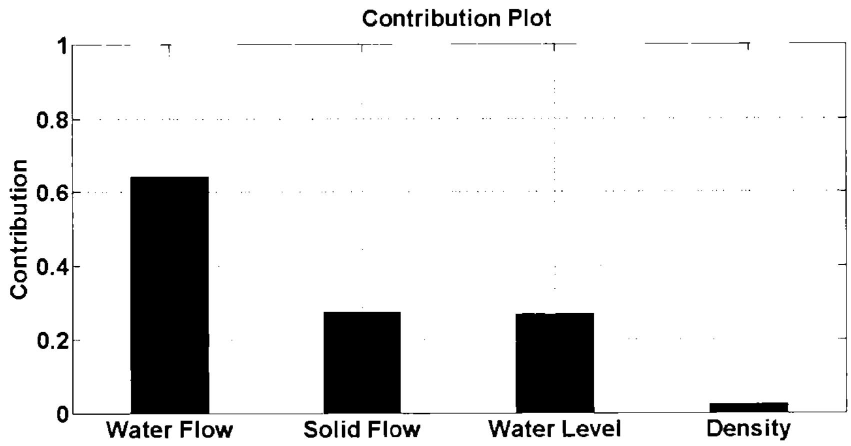


Figure 5.12: Scenario 1: PCA contribution plot

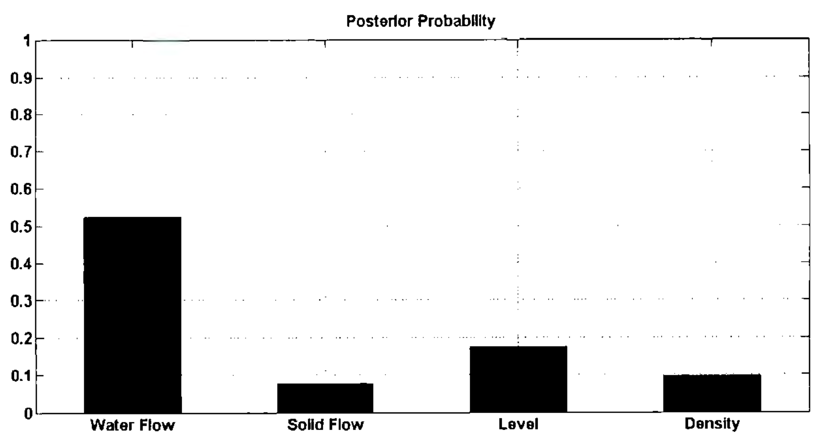


Figure 5.13: Scenario 1: Root cause diagnosis from BBN

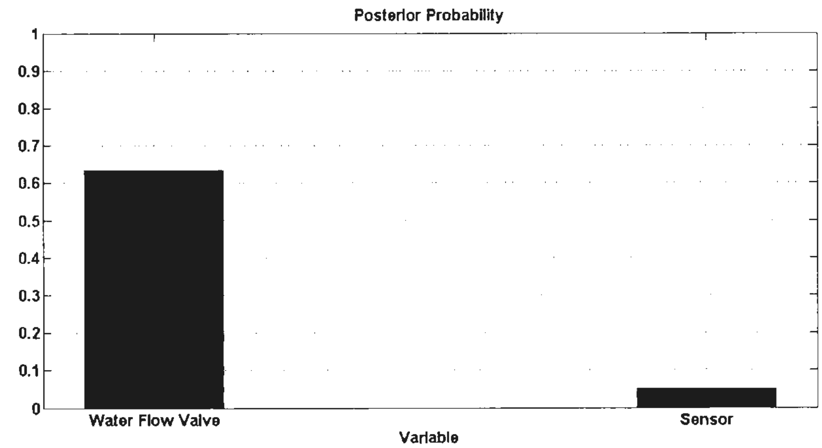


Figure 5.14: Root cause diagnosis from BBN within the water flow loop

updates the posterior probability of both water flow rate and solid flow node. Because fault in water level has stronger relation with water flow rate than solid flow, the root cause of the fault was diagnosed correctly. Further to find out whether the fault is associated with the sensor or valve, diagnosis in the water flow loop is conducted. Sensor validation provided a very little chance of sensor fault. Since the measurement instruments was no faulty, the only remaining cause for the water flow fault is found to be the water flow valve (Fig.5.14).

5.4.1.2 Scenario 2: Fault in Solid Flow

A fault was introduced in solid flow at $t = 3100$ min, as a result a fault in density is observed at $t = 3160$ min in Fig. 5.15. This fault is detected early at $t = 3130$ min from PCA residual plot, as it violates Q-statistic threshold level shown in Fig. 5.16. From PCA contribution plot Fig. 5.17 its difficult to diagnose the fault correctly contributions of all variables are comparable. This is due to the smearing effect discussed in Section 4.1. Using this preliminary diagnosis information the BBN correctly diagnose the solid flow as root cause of the fault in Fig. 5.18. Evidence from both

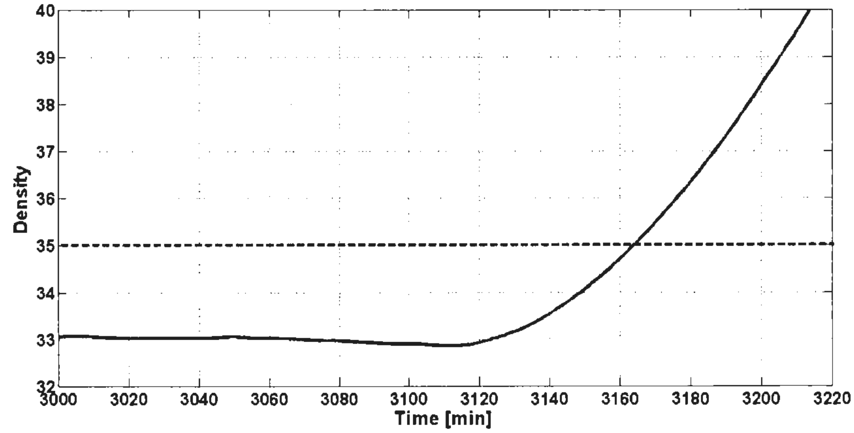


Figure 5.15: Scenario 2: Fault in density

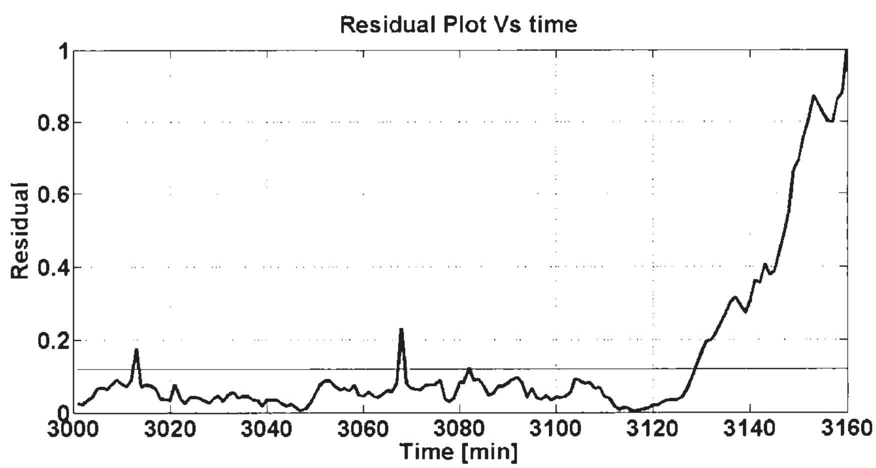


Figure 5.16: Scenario 2: PCA early fault detection

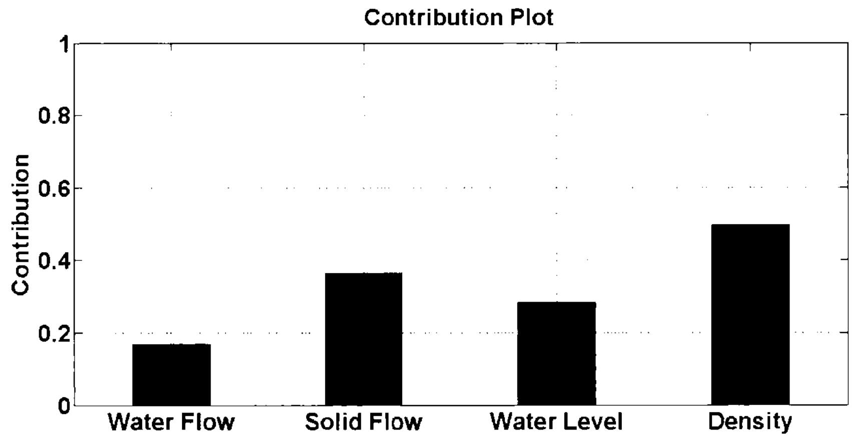


Figure 5.17: Scenario 2: PCA contribution plot

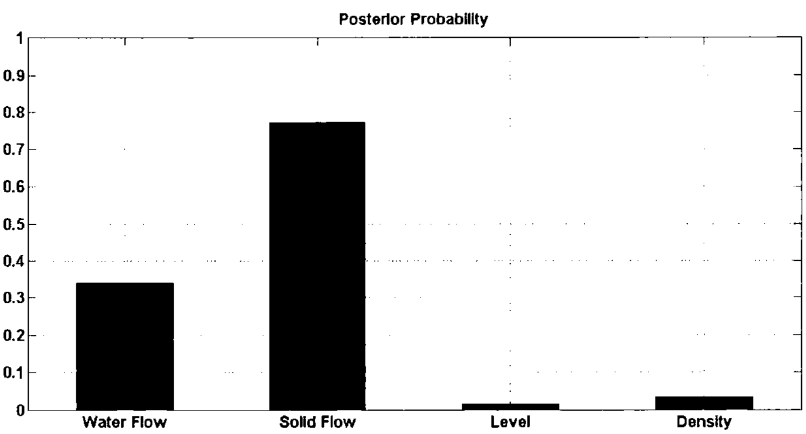


Figure 5.18: Scenario 2: Root cause diagnosis from BBN

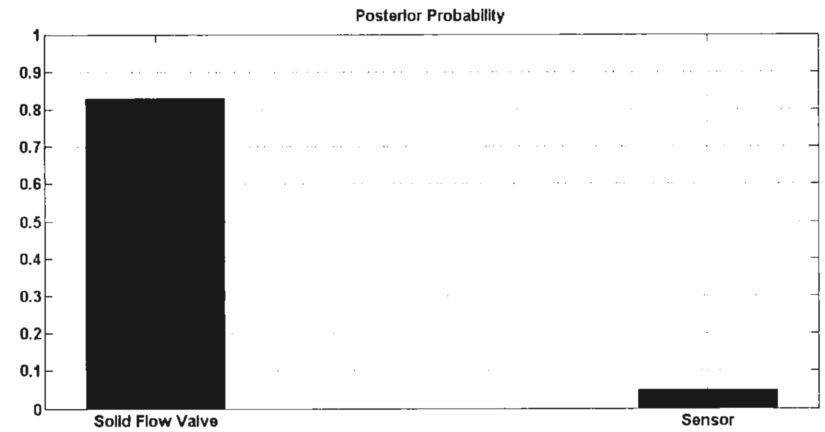


Figure 5.19: Root cause diagnosis from BBN within solid flow loop

density and water level updates the posterior probability of both water flow rate and solid flow node. Because fault in density has stronger relation with solid flow than water flow rate the root cause of the fault was diagnosed correctly. Further to find out whether the fault is associated with the sensor or valve, diagnosis in the solid flow loop was conducted. Sensor validation provides a very little chance of sensor fault. Since the solid flow sensor was not faulty, the only remaining cause for the solid flow fault is found to be the solid flow valve (Fig.5.19).

5.4.2 Comparison of PCA-BBN Method with BBN using Sensor Data Directly as Evidence

In order to compare the hybrid PCA-BBN with the traditional use of BBN, a fault was introduced in the solid flow at $t = 3100\ min$, as a result a fault in density was observed at $t = 3160\ min$ in Fig. 5.15 when it violates the threshold limit. Residuals are calculated from difference between set point (desired value) and observed value of each variable. The BBN correctly diagnosed the solid flow as root cause of the fault as shown in Fig. 5.20. Evidence from density and water level update the posterior

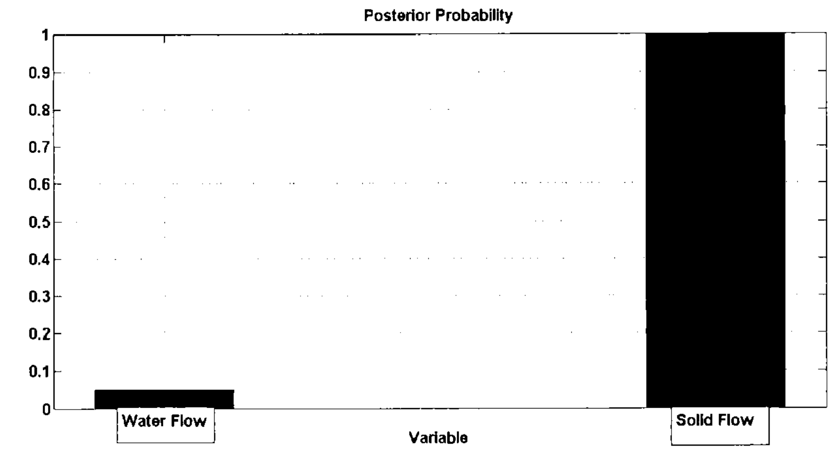


Figure 5.20: Root cause diagnosis from BBN

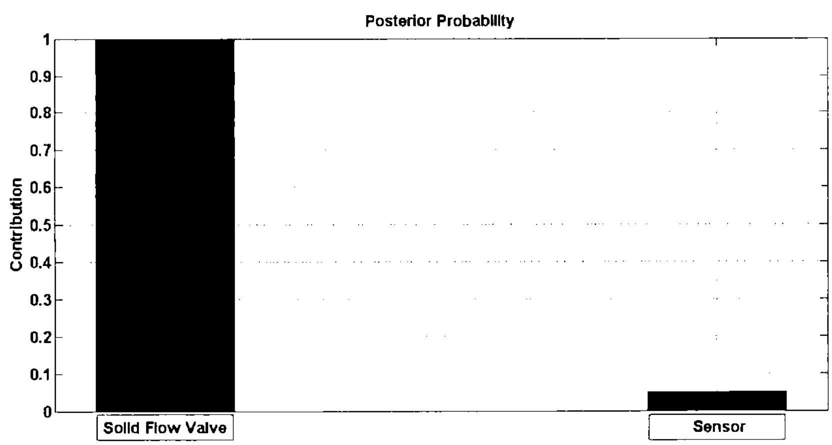


Figure 5.21: Root cause diagnosis from BBN within solid flow Loop

probability of both water flow rate and solid flow node. Because fault in density has stronger relation with solid flow than water flow rate the root cause of the fault was pinpointed correctly. Further to find out whether the fault is associated with the sensor or valve, diagnosis within the solid flow loop was conducted. Sensor validation provides a low probability of sensor fault. Since the measurement instruments are validated successfully, the only remaining cause for the solid flow fault is found to be the solid flow valve shown in Fig. 5.21.

From the above results it is seen that for both cases (PCA contribution as evidence and sensor data as evidence) root cause of the fault was detected successfully. When sensor data was used as evidence, the fault was detected at $t = 3160$ *min* shown in Fig. 5.15 compare to the hybrid case where fault was detected at $t = 3130$ *min* shown in Fig. 5.16. PCA Q-statistic detects the fault earlier. This early fault detection initiates the root cause analysis earlier compare to the sensor data as evidence case. This lead time in diagnosis can provide the operators an opportunity to steer the process to the normal operating condition during the process fault.

5.5 Industrial Case Study: PTA Dissolution Tank

Industrial data from the dissolution tank of a PTA plant was collected. The data set contained normal operational data as well as a known process fault in the solid discharge. The data set consists of measurements of four process variables. They are water flow rate, solid flow rate, tank water level and solution density at the outlet of the tank. The sampling frequency of the data was 15 *sec*. This data set was used to validate PCA-BBN hybrid algorithm and the traditional BBN with sensor data as evidence.

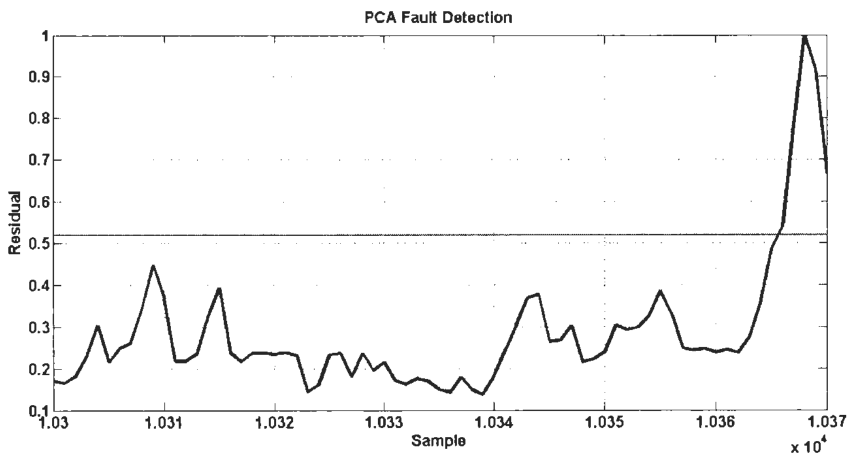


Figure 5.22: PCA early fault detection

5.5.1 Diagnosis using Hybrid Method: Industrial Case Study

Due to the actuator problem a chunk of solid drops into the tank at 10352 *sample*, as a result a fault in density is observed at 10512 *sample* in Fig. 5.26. This fault is detected early at 10383 *sample* from PCA residual plot, as it violates Q-statistic threshold level shown in Fig. 5.22. From PCA contribution plot Fig. 5.23 it is difficult to diagnose the fault correctly as it is seen that all the variables have significant contribution for the fault due to the smearing effect discussed in Section 4.1. These contributions were used as evidence to update the BBN. The BBN is initiated with prior probability calculated from the expert judgement. The trained BBN correctly diagnosed the solid flow as root cause of the fault as shown in Fig. 5.24. When ever new evidence come to solid flow node, the node update its own belief and propagates its belief to the density node and the water level node. Evidence coming to the density node updates the prior belief of density to the posterior belief and propagates its belief to the both water flow node and solid flow node. Solid flow node then updates its belief based on the information it gets from the density node. With the similar process belief

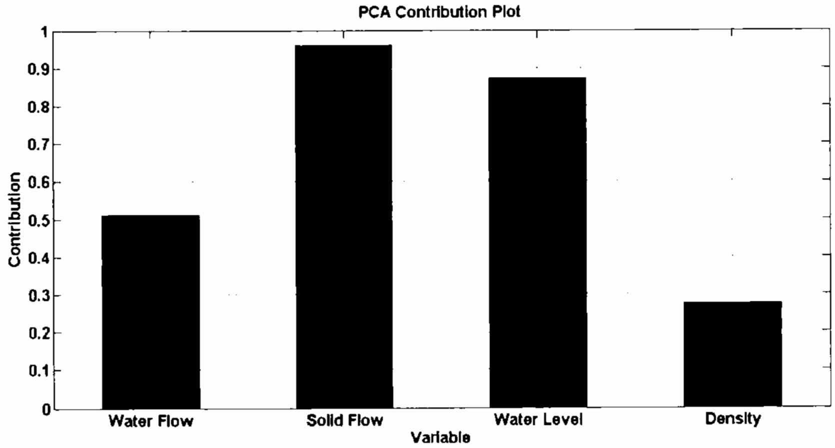


Figure 5.23: PCA Contribution to fault

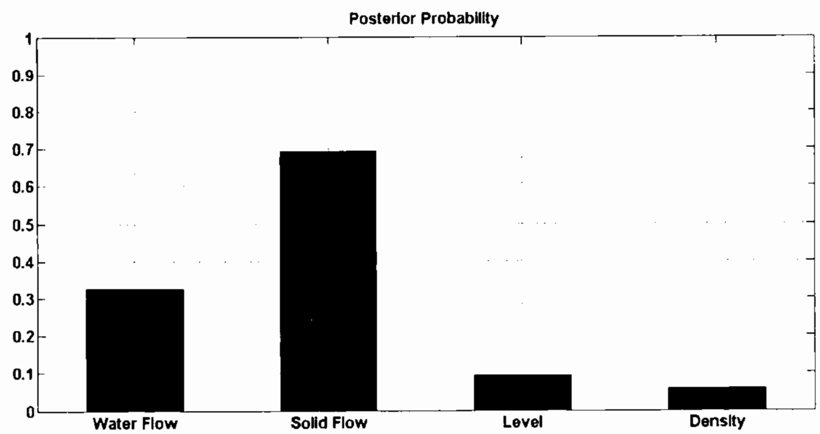


Figure 5.24: Root cause diagnosis from BBN

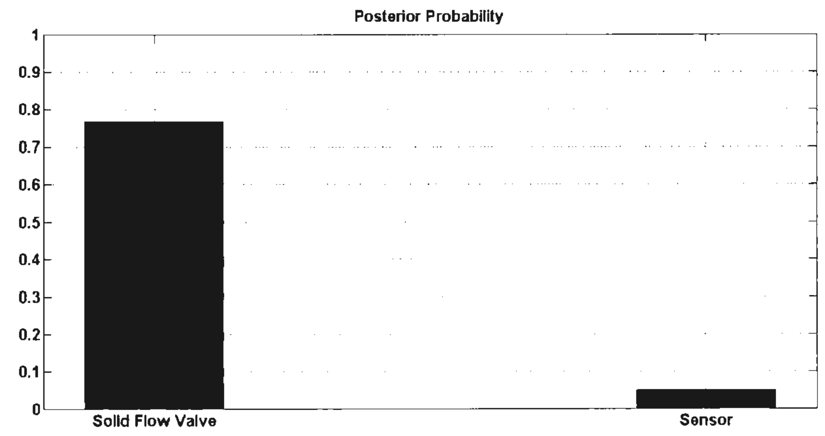


Figure 5.25: Root cause diagnosis from BBN within solid flow loop

is propagated among water flow, water level and solid flow node. When belief of all node is updated network stabilizes and wait for the next evidence. Further to find out whether the fault is associated with the sensor or valve, diagnosis in the solid flow loop is conducted. Sensor validation provided a small probability for sensor fault. Since the measurement instruments are validated successfully, the only remaining cause for the solid flow fault is found to be the solid flow valve as shown in Fig.5.25.

5.5.2 Industrial Case Study: Comparison of PCA-BBN Method with BBN using Sensor Data Directly as Evidence

Residuals are calculated from the difference between set point (desired value) and observed value of each variable was used to detect fault. Residuals were calculated for density water flow rate and water level. Solid flow was a calculated signal from the loss of weight of the load cell and such residual could not be calculated for solid flow. The fault was detected by the density residuals at 10512 *sample*. After the fault was detected the posterior probability of density node was set to 1. The BBN correctly diagnose the solid flow as root cause of the fault in Fig. 5.29. Evidence from density

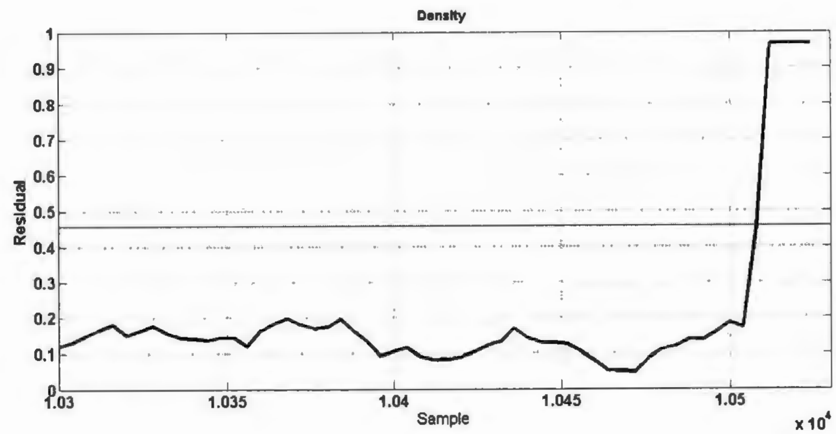


Figure 5.26: Fault detected in density

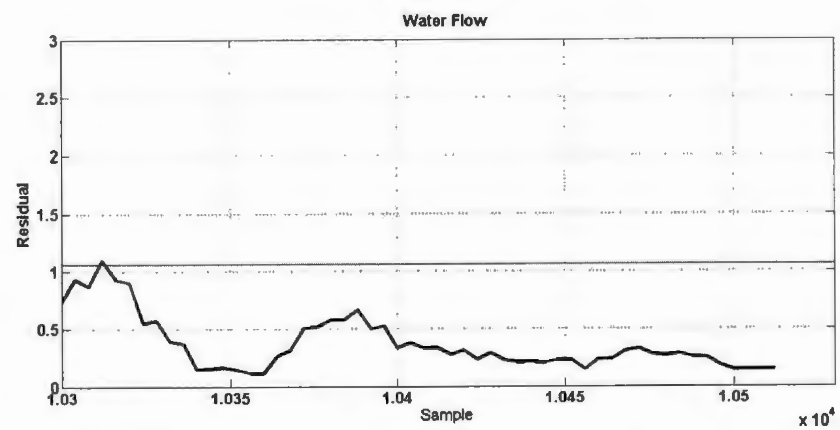


Figure 5.27: Water flow rate

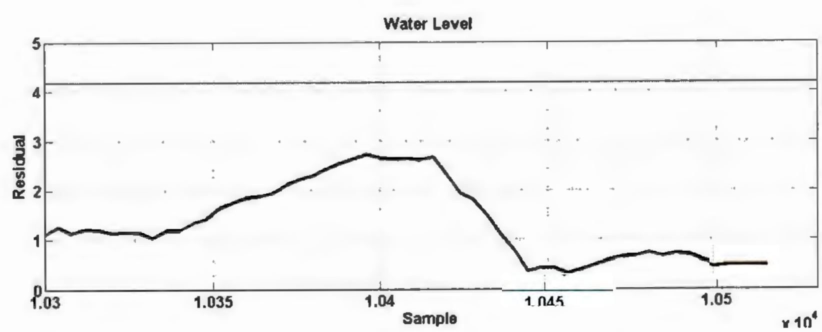


Figure 5.28: Water level

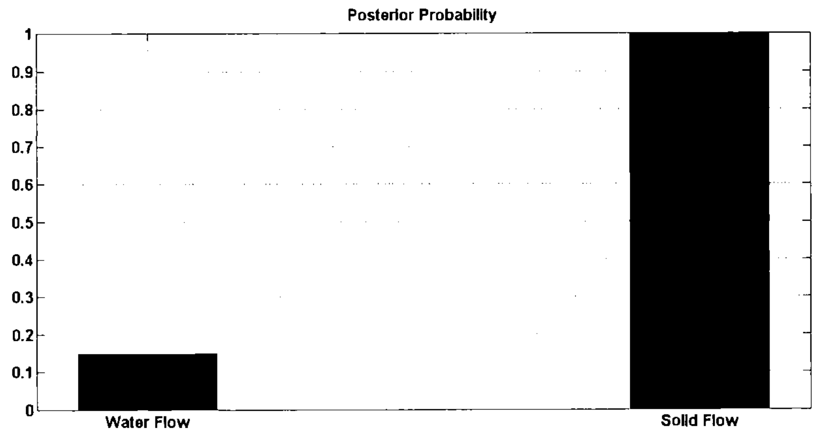


Figure 5.29: Root cause diagnosis from BBN

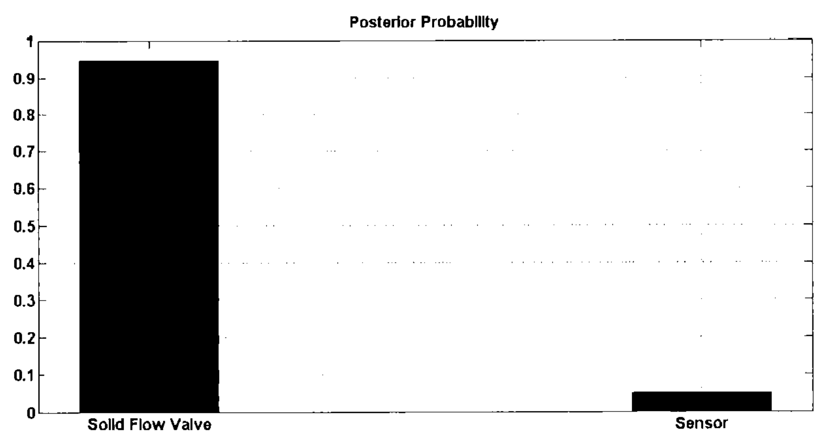


Figure 5.30: Root cause diagnosis from BBN within solid flow loop

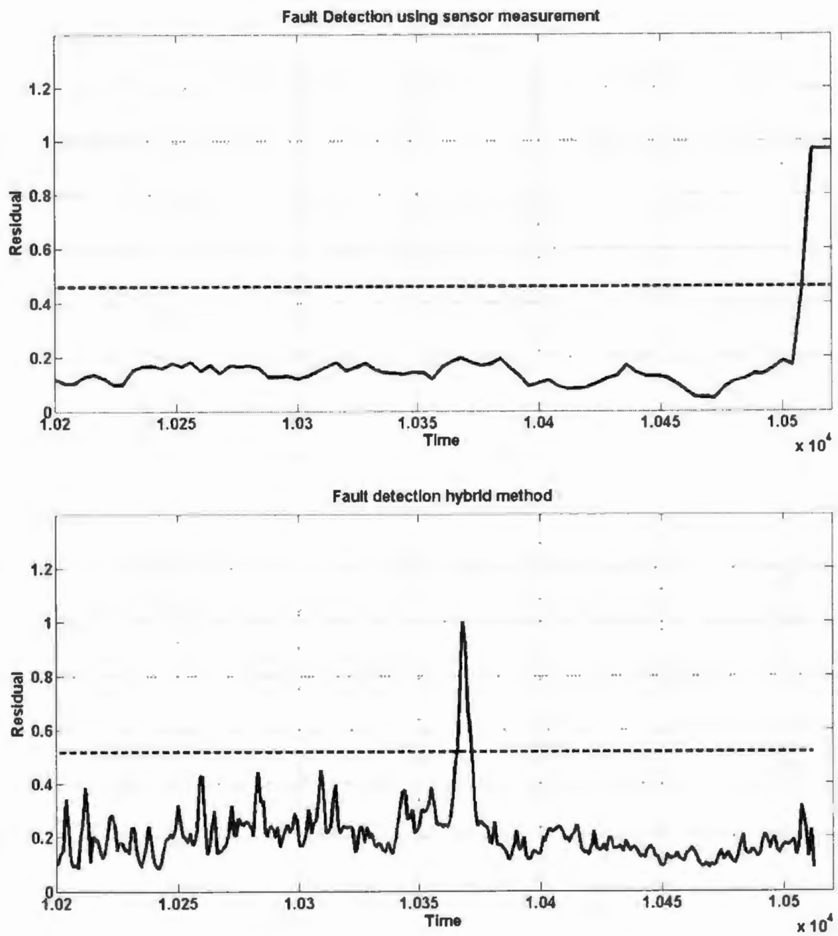


Figure 5.31: Comparison of PCA-BBN Method with BBN using Sensor Data Directly as Evidence

and water level updated the posterior probability of water flow and solid flow node. Because fault in density has stronger relation with solid flow than water flow the root cause of the fault was identified as solid flow problem correctly. Further to find out whether the fault is associated with the sensor or valve, diagnosis in the solid flow loop is conducted. Sensor validation provides a very low probability of sensor fault. Since the measurement instruments are validated successfully, the only remaining cause for the solid flow fault is found to be the solid flow valve Fig.5.30.

From the above results it is seen that for both cases (PCA contribution as evidence and sensor data as evidence) root cause of the fault was detected successfully. When sensor data was used as evidence, the fault was detected at 10512 *sample* compared to the hybrid case where fault was detected at 10383 *sample* in Fig. 5.31. This early fault detection initiates the root cause analysis earlier for the hybrid model compared to the sensor data as evidence case. This lead time for diagnosis can provide the operators an opportunity to steer the process to the normal operating condition during the process fault.

5.6 Conclusion

Hybrid method is applied for both simulated faulty scenarios and industrial case study. PCA detected the fault early but diagnosis was not precise since PCA contribution plot showed more than one variables to be faulty. BBN resolve this diagnosis problem with the help of both PCA evidence and process knowledge. Again the proposed hybrid method detects and diagnose the fault early compare to the existing methods where sensor measurements are use as evidence for the BBN. It is assumed for this case study that quality of input material and temperature will not change. Moreover, these parameters were considered to be constant in the dataset provided by the industry. Multivariate analysis (PCA) is used to taken care of any input changes.

Chapter 6

Conclusion and Future Work

6.1 Conclusion

An automated fault detection and diagnosis method is developed. This hybrid method is a combination of both PCA and BBN. The proposed hybrid method uses the diagnostic outputs from PCA and combines with process knowledge captured in a BBN. The method is able to accurately pinpoint the root cause of a fault which is lacking in PCA and other statistical fault detection and diagnosis approaches. The methodology is demonstrated using a solid crystal dissolution tank example. Various fault scenarios were considered along with a industrial case study. The method successfully detected the fault early allowing the operator to take corrective action. Also, it diagnose the root cause precisely.

The outcome of the current research can be summarized as below

i A methodology to construct BBN for process fault detection and diagnosis is developed. The proposed network is slightly different from the BBN found in the literature. Typically a separate BBN is built for each fault. In the proposed approach we built one universal network that can be used for multiple fault.

ii A method of mapping BBN from the SDG is proposed.

iii A method of calibrating BBN using simulation scenarios is proposed. Calibration is pivotal in diagnosing different faults using single BBN.

iv Updating mechanism of BBN using evidence from PCA is described in the thesis.

v A real time automated hybrid methodology based on Principal Component Analysis (PCA) and Bayesian Belief Network (BBN) for fault detection and diagnosis is described. The proposed hybrid method detected fault early and diagnosed the root cause precisely. BBN overcome the limitations of PCA in diagnosis fault accurately. The effectiveness of the proposed methodology is demonstrated using both simulated and industrial data.

vi This proposed monitoring tool can detect and diagnose the fault ahead of time. This lead time can be significant for ensuring safe operation of a process plant.

6.2 Future Work

i Since BBN is a directed acyclic graph, this method is applicable for acyclic process only. Further research is required to represent a general class of systems (process systems with cycles) using BBN.

ii This hybrid tool can work as building block for fault tolerant controller. Once root cause of a fault is diagnosed correctly with sufficient confidence that information can be processed by a decision making tool to take the appropriate corrective action and the whole process can be automated.

iii This method is verified for single fault scenarios. Further research is required to investigate multiple fault scenarios.

iv Further research is required to evaluate performance of this proposed method in case of process knowledge.

v The SDG can be developed from either mathematical equations or first principle model of the process. In case where the first principle model is not available SDG can be built from the mathematical equations. For a large system this could be complicated. To overcome this, the system can be divided into few subsystems and for each subsystem a different SDG can be built and further mapped to a BBN.

Bibliography

[Afifi and Clark, 2004] Afifi, A. A. A. and Clark, V. A. (2004). *Computer-aided multivariate analysis*, volume 62. CRC Press.

[Alcala and Qin, 2009] Alcala, C. F. and Qin, S. J. (2009). Reconstruction-based contribution for process monitoring. *Automatica*, 45(7):1593 – 1600.

[Azhdari and Mehranbod, 2010] Azhdari, M. and Mehranbod, N. (2010). Application of bayesian belief networks to fault detection and diagnosis of industrial processes. In *Chemistry and Chemical Engineering (ICCCE), 2010 International Conference on*, pages 92–96.

[Becraft et al., 1991] Becraft, W. R., Lee, P. L., and Newell, R. B. (1991). Integration of neural networks and expert systems for process fault diagnosis. In *In Proc. of the 12 th IJCAI*, pages 832–837. Morgan Kaufmann.

[Benkouider et al., 2009] Benkouider, A., Buvat, J., Cosmao, J., and Saboni, A. (2009). Fault detection in semi-batch reactor using the ekf and statistical method. *Journal of Loss Prevention in the Process Industries*, 22(2):153 – 161.

[Benkouider et al., 2012] Benkouider, A., Kessas, R., Yahiaoui, A., Buvat, J., and Guella, S. (2012). A hybrid approach to faults detection and diagnosis in batch and semi-batch reactors by using ekf and neural network classifier. *Journal of Loss Prevention in the Process Industries*, 25(4):694 – 702.

[Bobbio et al., 2001] Bobbio, A., Portinale, L., Minichino, M., and Ciancamerla, E. (2001). Improving the analysis of dependable systems by mapping fault trees into bayesian networks. *Reliability Engineering and System Safety*, 71(3):249 – 260.

[Chang and Chen, 1995] Chang, C.-T. and Chen, J.-W. (1995). Implementation issues concerning the ekf-based fault diagnosis techniques. *Chemical Engineering Science*, 50(18):2861 – 2882.

[CHEN et al., 2011] CHEN, D.-S., LEE, M.-W., and LIU, J. (2011). Isolating multiple sensor faults based on self-contribution plots with adaptive monitoring. *China steel technical report*, 24:64–73.

[Chen and Modarres, 1992] Chen, L. and Modarres, M. (1992). Hierarchical decision process for fault administration. *Computers & Chemical Engineering*, 16(5):425 – 448. An International Journal of Computer Applications in Chemical Engineering.

[Choi et al., 2005] Choi, S., Lee, C., Lee, J., Park, J., and Lee, I. (2005). Fault detection and identification of nonlinear processes based on kernel pca. *Chemometrics and intelligent laboratory systems*, 75(1):55–67.

[Chow and Willsky, 1984] Chow, E. and Willsky, A. (1984). Analytical redundancy and the design of robust failure detection systems. *Automatic Control, IEEE Transactions on*, 29(7):603 – 614.

[Enrique E. Tarifa, 2003] Enrique E. Tarifa, N. J. S. (2003). Fault diagnosis for a msf using a sdg and fuzzy logic. *Desalination*, 152:207 – 214.

[Frank, 1994] Frank, P. (1994). On-line fault detection in uncertain nonlinear systems using diagnostic observers: a survey. *International journal of systems science*, 25(12):2129–2154.

[Frank and Ding, 1997] Frank, P. and Ding, X. (1997). Survey of robust residual generation and evaluation methods in observer-based fault detection systems. *Journal of Process Control*, 7(6):403 – 424.

[Frank, 1990] Frank, P. M. (1990). Fault diagnosis in dynamic systems using analytical and knowledge-based redundancy: A survey and some new results. *Automatica*, 26(3):459 – 474.

[Gertler and Monajemy, 1995] Gertler, J. J. and Monajemy, R. (1995). Generating directional residuals with dynamic parity relations. *Automatica*, 31(4):627 – 635.

[Guo and Hsu, 2002] Guo, H. and Hsu, W. (2002). A survey of algorithms for real-time bayesian network inference. In *AAAI/KDD/UAI02 Joint Workshop on Real-Time Decision Support and Diagnosis Systems*. Edmonton, Canada.

[He et al., 2005] He, Q. P., Qin, S. J., and Wang, J. (2005). A new fault diagnosis method using fault directions in fisher discriminant analysis. *AIChE Journal*, 51(2):555–571.

[Himmelblau, 1978] Himmelblau, D. M. (1978). *Fault detection and diagnosis in chemical and petrochemical processes*. Elsevier Scientific Publishing Company.

[Huang, 2008] Huang, B. (2008). Bayesian methods for control loop monitoring and diagnosis. *Journal of Process Control*, 18(9):829 – 838.

[Iri et al., 1979] Iri, M., Aoki, K., O'Shima, E., and Matsuyama, H. (1979). An algorithm for diagnosis of system failures in the chemical process. *Computers & Chemical Engineering*, 3(1–4):489 – 493.

[Isermann, 1997] Isermann, R. (1997). Supervision, fault-detection and fault-diagnosis methods — an introduction. *Control Engineering Practice*, 5(5):639 – 652.

[Jackson and Mudholkar, 1979] Jackson, J. and Mudholkar, G. (1979). Control procedures for residuals associated with principal component analysis. *Technometrics*, 21(3):341–349.

[Jackson, 2005] Jackson, J. E. (2005). *A user's guide to principal components*, volume 587. Wiley. com.

[Joe Qin, 2003] Joe Qin, S. (2003). Statistical process monitoring: basics and beyond. *Journal of Chemometrics*, 17(8-9):480–502.

[Jolliffe, 2005] Jolliffe, I. (2005). *Principal component analysis*. Wiley Online Library.

[Khakzad et al., 2013] Khakzad, N., Khan, F., and Amyotte, P. (2013). Dynamic safety analysis of process systems by mapping bow-tie into bayesian network. *Process Safety and Environmental Protection*, 91(1–2):46 – 53.

[Kourti and MacGregor, 1996a] Kourti, T. and MacGregor, J. F. (1996a). Multivariate spc methods for process and product monitoring. *Journal of Quality Technology*, 28(4).

[Kourti and MacGregor, 1996b] Kourti, T. and MacGregor, J. F. (1996b). Multivariate spc methods for process and product monitoring. *Journal of Quality Technology*, 28(4).

[Krieg, 2001] Krieg, M. L. (2001). A tutorial on bayesian belief networks. Technical report, DTIC Document.

[Leung and Romagnoli, 2000] Leung, D. and Romagnoli, J. (2000). Dynamic probabilistic model-based expert system for fault diagnosis. *Computers & Chemical Engineering*, 24(11):2473 – 2492.

[Liu, 2012] Liu, J. (2012). Fault diagnosis using contribution plots without smearing effect on non-faulty variables. *Journal of Process Control*, 22(9):1609 – 1623.

[Mah and Tamhane, 2004] Mah, R. and Tamhane, A. (2004). Detection of gross errors in process data. *AIChE Journal*, 28(5):828–830.

[Mallick and Imtiaz, 2011] Mallick, M. and Imtiaz, S. (2011). A mpc based fault tolerant control strategy for actuator fault. *ICECE 2011*, pages 3777–3780.

[Maurya et al., 2003] Maurya, M. R., Rengaswamy, R., and Venkatasubramanian, V. (2003). A systematic framework for the development and analysis of signed digraphs for chemical processes. 1. algorithms and analysis. *Industrial & Engineering Chemistry Research*, 42(20):4789–4810.

[Miller et al., 1998] Miller, P., Swanson, R. E., and Heckler, C. E. (1998). Contribution plots: a missing link in multivariate quality control. *Applied Mathematics and Computer Science*, Vol. 8, no 4:775–792.

[Misra et al., 2002] Misra, M., Yue, H., Qin, S., and Ling, C. (2002). Multivariate process monitoring and fault diagnosis by multi-scale pca. *Computers & Chemical Engineering*, 26(9):1281 – 1293.

[Mylaraswamy and Venkatasubramanian, 1997] Mylaraswamy, D. and Venkatasubramanian, V. (1997). A hybrid framework for large scale process fault diagnosis. *Computers & Chemical Engineering*, 21, Supplement:S935 – S940.

[Neapolitan, 2004] Neapolitan, R. E. (2004). *Learning bayesian networks.* Pearson Prentice Hall Upper Saddle River.

[Neapolitan and Jiang, 2010] Neapolitan, R. E. and Jiang, X. (2010). *Probabilistic methods for financial and marketing informatics.* Morgan Kaufmann.

[Pearl, 1988] Pearl, J. (1988). *Probabilistic reasoning in intelligent systems: networks of plausible inference.* Morgan Kaufmann.

[P.M. Frank, 1989] P.M. Frank, J. W. (1989). *Robust fault diagnosis using unknown input observer schemes Fault diagnosis in dynamic systems: theory and applications.* Prentice Hall, NY.

[Pradhan et al., 2007] Pradhan, S., Singh, R., Kachru, K., and Narasimhamurthy, S. (2007). A bayesian network based approach for root-cause-analysis in manufacturing process. In *Computational Intelligence and Security, 2007 International Conference on*, pages 10–14.

[S. Dey, 2005] S. Dey, J. S. (2005). A bayesian network approach to root cause diagnosis of process variations. *International Journal of Machine Tools and Manufacture*, 45(1):75 – 91.

[Sklet, 2004] Sklet, S. (2004). Comparison of some selected methods for accident investigation. *Journal of Hazardous Materials*, 111:29 – 37.

[Smith, 2002] Smith, L. I. (2002). A tutorial on principal components analysis. *Cornell University, USA*, 51:52.

[Sun et al., 2012] Sun, D., yun Lu, N., Guo, Y., and Jiang, B. (2012). Process monitoring and fault diagnosis based on a hybrid modeling technique. *31st Chinese Control Conference (CCC), 2012*, pages 5357 –5362.

[Umeda et al., 1980] Umeda, T., Kuriyama, T., O'Shima, E., and Matsuyama, H. (1980). A graphical approach to cause and effect analysis of chemical processing systems. *Chemical Engineering Science*, 35(12):2379 – 2388.

[Vedam and Venkatasubramanian, 1999] Vedam, H. and Venkatasubramanian, V. (1999). Pca-sdg based process monitoring and fault diagnosis. *Control Engineering Practice*, 7(7):903 – 917.

[Venkatasubramanian et al., 2003a] Venkatasubramanian, V., Rengaswamy, R., and Kavuri, S. N. (2003a). A review of process fault detection and diagnosis: Part ii: Qualitative models and search strategies. *Computers & Chemical Engineering*, 27(3):313 – 326.

[Venkatasubramanian et al., 2003b] Venkatasubramanian, V., Rengaswamy, R., Kavuri, S. N., and Yin, K. (2003b). A review of process fault detection and diagnosis: Part iii: Process history based methods. *Computers & Chemical Engineering*, 27(3):327 – 346.

[Venkatasubramanian et al., 2003c] Venkatasubramanian, V., Rengaswamy, R., Yin, K., and Kavuri, S. N. (2003c). A review of process fault detection and diagnosis: Part i: Quantitative model-based methods. *Computers & Chemical Engineering*, 27(3):293 – 311.

[Weber et al., 2012] Weber, P., Medina-Oliva, G., Simon, C., and Iung, B. (2012). Overview on bayesian networks applications for dependability, risk analysis and maintenance areas. *Engineering Applications of Artificial Intelligence*, 25(4):671 – 682. Special Section: Dependable System Modelling and Analysis.

[Weiqing et al., 2012] Weiqing, Z., Fengqi, S., Zhigao, X., Zongliang, Q., and Jianxin, Z. (2012). An investigation on system anomaly source diagnosis using kpca-fpsdg.

Power and Energy Engineering Conference (APPEEC), 2012 Asia-Pacific, pages 1 –4.

[Westerhuis et al., 2000] Westerhuis, J. A., Gurden, S. P., and Smilde, A. K. (2000). Generalized contribution plots in multivariate statistical process monitoring. *Chemometrics and Intelligent Laboratory Systems*, 51:95 – 114.

[Willsky, 1976] Willsky, A. S. (1976). A survey of design methods for failure detection in dynamic systems. *Automatica*, 12(6):601–611.

[Wilson and Huzurbazar, 2007] Wilson, A. G. and Huzurbazar, A. V. (2007). Bayesian networks for multilevel system reliability. *Reliability Engineering and System Safety*, 92(10):1413 – 1420.

[Woodward and Pitbaldo, 2010] Woodward, J. L. and Pitbaldo, R. (2010). *LNG risk based safety: modeling and consequence analysis*. John Wiley & Sons.

[Yang et al., 2010] Yang, F., Xiao, D., and Shah, S. (2010). Qualitative fault detection and hazard analysis based on signed directed graphs for large-scale complex systems. *Fault Detection*, pages 15–50.

[Yin et al., 2012] Yin, S., Ding, S. X., Haghani, A., Hao, H., and Zhang, P. (2012). A comparison study of basic data-driven fault diagnosis and process monitoring methods on the benchmark tennessee eastman process. *Journal of Process Control*, 22(9):1567 – 1581.

[Yoon and MacGregor, 2000] Yoon, S. and MacGregor, J. F. (2000). Statistical and causal model-based approaches to fault detection and isolation. *AIChE Journal*, 46(9):1813–1824.

[Özyurt and Kandel, 1996] Özyurt, B. and Kandel, A. (1996). A hybrid hierarchical neural network-fuzzy expert system approach to chemical process fault diagnosis. *Fuzzy Sets and Systems*, 83(1):11 – 25.