Preprints of the 10th IFAC International Symposium on Dynamics and Control of Process Systems
The International Federation of Automatic Control
December 18-20, 2013. Mumbai, India

A Hybrid Method for Process Fault Detection and Diagnosis

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Abstract: For process fault detection and diagnosis, a real time hybrid method based on Principle component analysis (PCA) and Bayesian belief network (BBN) is described. Upon successful identification of fault from PCA residual plot and Q statistics, information from the PCA contribution of each variable is passed to the BBN for root cause analysis. Pearl's message passing algorithm is used for belief updating. Early detection of fault, makes the methodology more reliable and robust during the process fault occurrence. The aim of this monitoring tool is to incorporate prior process knowledge along with the present observed evidence to come up with most plausible explanation of how the process is behaving. The effectiveness of the proposed method is demonstrated for a Dissolution tank model for different simulated scenarios by detecting and diagnosing the fault accurately.

Keywords: Fault Detection and Diagnosis (FDI), Principle component analysis (PCA), Bayesian belief network (BBN), Hybrid model, Prior probability, Posterior probability, Contribution plot, Residual, Q-statistics.

1. INTRODUCTION

According to Himmelblau (1978), the term fault in process, is generally defined as a departure of an observed variable or a calculated parameter from an acceptable range. The underlying cause of this abnormality is called the basic event or the root cause. In the recent years significant research has been done on process monitoring. This analysis includes qualitative, quantitative and multivariate statistical approaches, excellent review of these methods can be found in Venkatasubramanian et al. (2003c,a,b). Although, these methods are very effective for detecting the fault early but they are not as effective for pinpointing the root cause of the fault.

Modern processes are complex with large number of variables and it needs complex analysis for the operators to detect the root cause of a process fault. According to the industrial statistics, human error is the main reason for about 70% of the industrial accidents which have significant economic, safety and environmental impact. Therefore, an automated fault diagnosis method is desired during the process fault condition to aid the human operators to steer the process to a safe operating condition.

In this work, a PCA-BBN based automated hybrid fault detection and diagnosis method is described. PCA is very efficient for fault detection however not as efficient in diagnosing the fault and cannot provide the root cause of the fault. In a process once a fault is detected by a monitoring scheme, in addition to the diagnosis report an operator uses the process knowledge to pinpoint the root cause. Process knowledge is introduced into BBN to perform this diagnosis task by mimicking exactly what an operator does during the process fault to find the root cause.

The paper is structured as follows: background and motivation of research is in section 2, Next in section 3, a brief description of the PCA-BBN based hybrid algorithm, then simulation case study Dissolution tank model in section 4, After that, performance and efficiency of the proposed method is shown with simulated result in the section 5 followed by conclusion in the section 6.

2. BACKGROUND AND MOTIVATION

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 diagnosis models such as signed directed graph (SDG) based methods tend to be good for root cause analysis rather than being early detectors. SDG models are less sensitive to the process parameter change or noise but they are not efficient for large processes. 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, often referred to as analytical models or observer-based or parity-based approaches, are very efficient and sensitive to process fault. They are built with deep process knowledge, however requires significant computational effort. 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. However, they 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 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 positive features of various methods hybrid methods have been proposed. Becraft et al. (1991) have 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 is 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 based hybrid model proposed by Mylaraswamy and Venkatasubramanian (1997) for process fault detection and diagnosis. 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. 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 have proposed by Enrique E. Tarifa (2003). The SDG model of the process is 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. Sun et al. (2012) used a first-principle 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.

Introduction of process knowledge into an expert model to perform diagnosis has been recent interest of research. Leung and Romagnoli (2000) developed an process knowledge based diagnosis method (PCEG) for fault diagnosis. In this context, 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. S. Dey (2005) showed that pearl's direct message passing algorithm can find root cause of process fault successfully in which posterior probability of each node is updated from evidence.

In this work a PCA-BBN based hybrid fault detection and diagnosis method is described where BBN takes detection and diagnosis results of PCA and further refines it based on process knowledge to accurately pinpoint the root cause of fault.

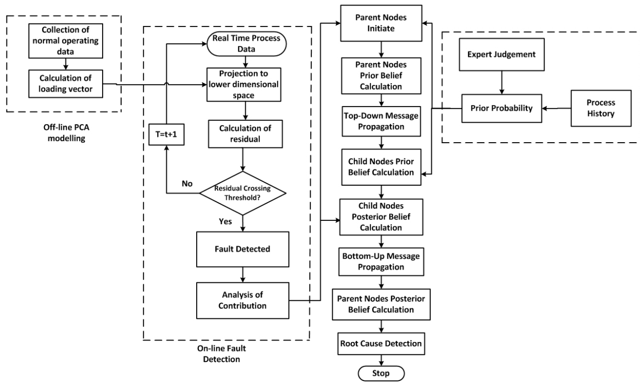

Fig. 1. FDD algorithm

3. PCA-BBN HYBRID METHOD

Detail algorithm for this hybrid FDI model is shown in Fig. 1. This algorithm has two essential parts. They are online fault detection using PCA, fault diagnosis using BBN and process knowledge incorporation into BBN for fault diagnosis.

3.1 Fault Detection using PCA

For online fault detection, PCA model is built from the normal operating condition data. The PCA model (the loading vectors) is used for process monitoring by projecting the on-line data onto the model.

For a given data matrix of dimension $X \epsilon R^{N \times m}$ where N is the number of sample data and m is the number of the correlated variables in the data set. From SVD analysis of covariance matrix, the original variables decomposes as follows:

$$cov(X) = P \Lambda P^T + \tilde{P} \tilde{\Lambda} \tilde{P}^T \tag{1}$$

where Λ is a diagonal matrix with significant eigenvalues and P contains the respective eigenvectors also known as loading vector. The $\tilde{\Lambda}$ and $\tilde{P}$ are the residual eigenvalues and eigenvectors respectively.

Then the PCs can be expressed by the following equation

$$t_i = X P_i \tag{2}$$

Here, $i = 1, 2, 3......m$ and $P_i \epsilon R^{m \times 1}$

$\hat{X}$ is the underlying noise free signal given by,

$$\hat{X} = \sum_{i=1}^{r} t_i P_i \tag{3}$$

Where r is the number of principle component $r \leq m$. Then the residual, between the projected data and model predictions, is estimated. Residual R, is calculated according to the following formula,

$$\begin{aligned} R &= (X - \hat{X})^T (X - \hat{X}) \\ &= X^T \tilde{P} \tilde{P}^T X \end{aligned} \tag{4}$$

Whenever the residual exceeds its threshold limit, the fault is detected. Upon successful detection of fault, PCA contribution of each variable is analysed and passed to the

BBN for fault diagnosis known as evidence. Contribution of i th variable to the Q-statistic can be calculated as

$$C_i = (X^T \tilde{P}\tilde{P}^T \beta_i)^2 \tag{5}$$

Here β is a column vector i th element is one and the others are zero. 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 leads to an ambiguity in root cause analysis. The contributions of the each variable is calculated by a matrix multiplication. The effect of faulty variables may smear out over the other non-faulty variables. This will mislead a diagnosis of the correct root causes of the faults. Therefore, to mitigate this smearing effect, process knowledge along with contribution of each variable is used as evidence for the BBN for fault diagnosis.

3.2 Fault Diagnosis using BBN

BBN can be built from the process dynamics or differential equation of the process variables or cause effect relationship among the process variables. Analysing the historical data of the process, both prior probability and conditional probability can be calculated. One can rely on expert judgement if historical data is not reliable. BBN is a graphical representation of the cause and effect relationship among the process variables. Parent nodes are casual or root nodes where child nodes are the effect nodes. For example a network with two nodes X and Y, where X is the parents node and Y is the child node can be expressed as

$$BEL(X) = \alpha P(X)\lambda(X) \tag{6}$$

where $BEL(X) = P(X|Y)$, $\alpha = [P(e)]^{-1}$ and $\lambda(X) = P(e|X) = P(Y|X)$ is the likelihood vector or the conditional probability of the corresponding nodes.

For our proposed method PCA contribution of each variable is used as evidence for the BBN for fault diagnosis. Depending upon this on-line evidence, BBN updates its belief of each node. If evidence is introduced from the head and tail of a BBN shown in Fig. 2 $BEL(X)$ can be calculated as a function of the incoming evidences e^+ and e^-. Here, e^+ and e^- represents evidence coming into BBN, to node X, from its parent node and child node respectively.

$$\begin{aligned} BEL(X) &= P(x|e^+, e^-) \\ &= \alpha P(e^-|x, e^+)P(x|e^+) \\ &= \alpha P(e^-|x)P(x|e^+) \\ &= \alpha\lambda(X)\pi(X) \end{aligned} \tag{7}$$

here

$$\begin{aligned} \pi(X) &= P(x|e^+) \\ &= \sum_u P(x|u, e^+)P(u|e^+) \end{aligned} \tag{8}$$

since node U separates node X from e^+

$$\begin{aligned} \pi(X) &= \sum_u P(x|u)\pi(u) \\ &= \pi(u) * M_{x|u} \end{aligned} \tag{9}$$

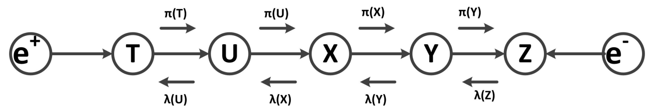

Fig. 2. Introduction of evidence in BBN

here $M_{x|u}$ is a matrix defining conditional probability table for $P(X|U)$. Similarly $\lambda(X)$ can be calculated as

$$\begin{aligned} \lambda(X) &= \sum_y P(y|x)\lambda(Y) \\ &= \lambda(Y) * M_{y|x} \end{aligned} \tag{10}$$

Now each node of the network can compute its own π and λ based on the evidence it receives.

Belief propagation between the parent nodes and child nodes follows Peral‘s message passing algorithm shown in Fig. 3 can be found in Pearl (1988). Each parent node is initiated by prior probability. Prior belief of parent nodes are calculated by evidence from the PCA and initially calculated prior probability. By top-down propagation parent nodes prior belief are passed to the child nodes. Then child nodes calculate the prior belief with the help of the conditional probability table and the prior belief of the parent nodes. Each child node updates its prior belief to posterior belief based on the evidence coming from PCA. Posterior belief of the child node is sent to the parent node by bottom up belief propagation. Then each parent node updates its prior belief to posterior belief based on the posterior belief of the child nodes. 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.

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. Belief propagation can be summarized as below

Step 1 - Belief Updating When a node X is activated to update its parameters, it simultaneously inspects the message from its parent nodes $\pi(X)$ and the messages from its child nodes $\lambda(X)$. Using these inputs, a initiated node updates its belief

$$BEL(X) = \alpha\lambda(X)\pi(X) \tag{11}$$

where

$$\lambda(X) = \prod_j \lambda_{y_j}(X) \tag{12}$$

$$\pi(X) = \sum_u P(X|u)\pi_x(u) \tag{13}$$

and α is a normalizing constant and for all states of X

$$\sum_x BEL(X) = 1 \tag{14}$$

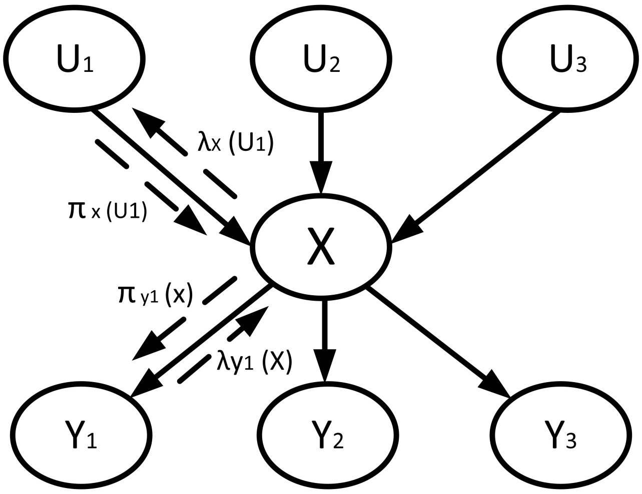

Fig. 3. Message passing in BBN after evidence coming to the nodes

Step 2 - Bottom-Up Propagation Using the λ message, child nodes communicate with the parent nodes, which is known as Bottom-Up propagation of belief. Node X computes a new message $\lambda_x(u)$ which is sent to its parents U

$$\lambda_x(u) = \sum_x \lambda(X) P(X|u) \tag{15}$$

Step 3 - Top-Down Propagation Using the π message, parent nodes communicate with the child nodes, which is known as top-down propagation of belief. Node X computes a new message $\pi_{y_j}(x)$ which is sent to its $j-th$ child Y_j is computed by

$$\pi_{y_j}(X) = \alpha \pi(X) \prod_{k \neq j} \lambda_{y_k}(x) \tag{16}$$

Here

$$\begin{aligned} \lambda_X(u) &= P(e_X^-|u) \\ \pi_y(X) &= P(x|e_y^+) \end{aligned} \tag{17}$$

4. SIMULATION CASE STUDY

4.1 Dissolution Tank Model

A simplified process diagram for the dissolution tank system can be found in Mallick and Imtiaz (2011), is shown in Fig. 4. In this system solid PTA crystals is dissolved in a tank with water. Water is pumped into the tank under flow control. PTA crystal is 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 measured variables. The main control objectives of the system are to maintain the tank level and maintain the concentration at desired set point. However, both the concentration and the water level at the outlet are subject to frequent large disturbances when the operators have to take control of the process to ensure safe operation during abnormal condition. Objective of the monitoring scheme is to develop an automated method for this process that will detect the fault early along with the root cause.

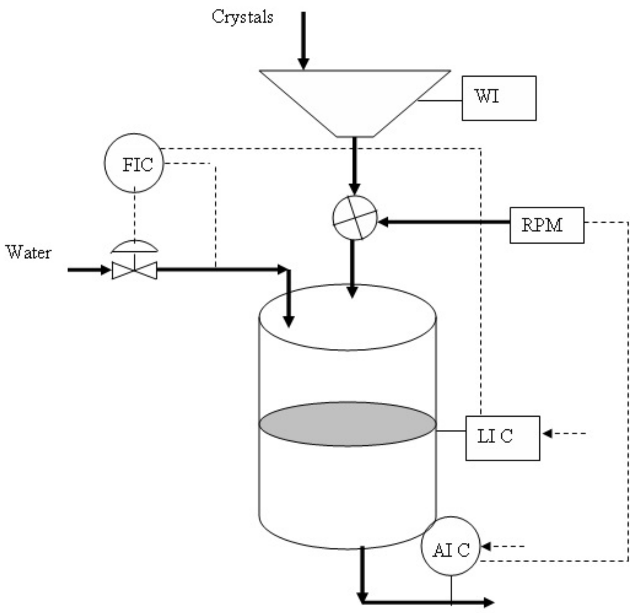

Fig. 4. Process flow diagram with the existing control strategy

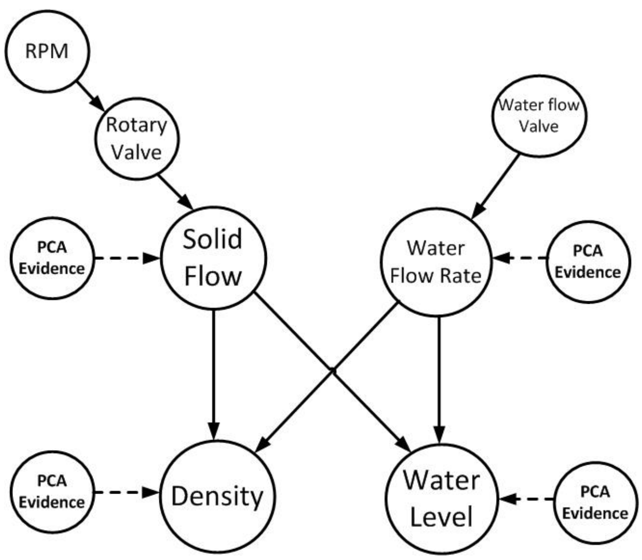

Fig. 5. Dissolution Tank Model BBN

4.2 BBN of Dissolution Tank Model

BBN for the Dissolution tank model is constructed from the process dynamics shown in Fig. 5. Solid flow is controlled by a rotary valve which is driven by an actuator. An arc from the RPM of the actuator to rotary valve and rotary valve to solid flow is drawn. Precise control of both solid flow and water flow rate keeps the concentration of the output product in desired level. So, density node has two arcs incoming from the solid flow and water flow rate nodes. On the other hand, water flow rate has a direct influence from water flow valve which is shown by an arc from the water flow valve node to the water flow rate node. Uniform water flow is desired to have water level in control. Again to give more flexibility to control density water level is controlled depending on the solid flow. Therefore, water level node has two incoming arcs from the solid flow node and water flow node. PCA contribution for each variable is used as evidence to the corresponding nodes shown by broken arcs. Process dynamics is introduced to the BBN by prior probability and conditional probability. Both prior probability and conditional probability table filled up for each node based on expert judgement.

The BBN is initiated with prior probability calculated from the expert judgement. When ever new evidence come to solid flow node, the node update its own belief and propagates its belief according to the propagation method described in the Section 3.2 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 is propagated between water flow, water level and solid flow node. When belief of all node is updated network stabilizes and wait for the next evidence. This cycle repeats at each time instant until all nodes update its belief to the posterior belief.

Two faulty scenarios are created and hybrid method is applied. PCA detected the fault early but diagnosis was not precise since PCA contribution plot showed more than one variables to be faulty since the contributions are transformed from the process variables through a matrix multiplication, the faulty variables may smear out over the other variables, which will mislead a diagnosis of the correct root causes of the faults. BBN resolve this diagnosis problem. Here, PCA evidence and process knowledge plays a vital role. Successful diagnosis is shown in the result section.

5. RESULT

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

5.1 Case Study 1

A fault is introduced in the solid flow at $t = 3100\ min$, as a result a fault in density is observed at $t = 3160\ min$ in Fig. 6. This fault is detected early at $t = 3130\ min$ from PCA residual plot, as it violates Q-statistic threshold level shown in Fig. 7. From PCA contribution plot Fig. 8 its 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 3.1. With process knowledge the BBN correctly diagnose the solid flow as root cause of the fault in Fig. 9. Evidence from both density and water level updates the posterior probability of both water flow rate and solid flow node. Because fault in density has more strong relation with solid flow than water flow rate the root cause of the fault was pinpointed correctly.

5.2 Case Study 2

A fault is introduced in the water flow at $t = 3100\ min$, as a result a fault in water level is observed at $t = 3190\ min$

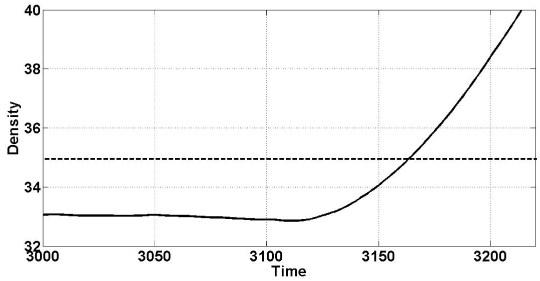

Fig. 6. Case study 1: Fault in density

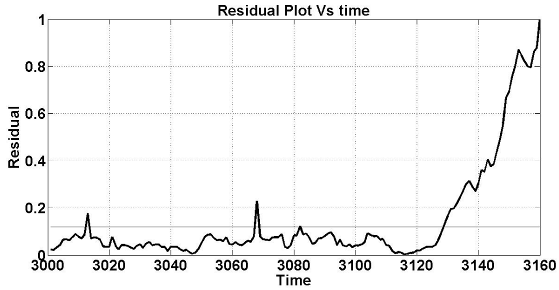

Fig. 7. Case study 1: PCA early fault detection

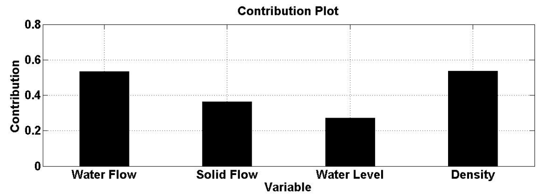

Fig. 8. Case study 1: PCA contribution plot

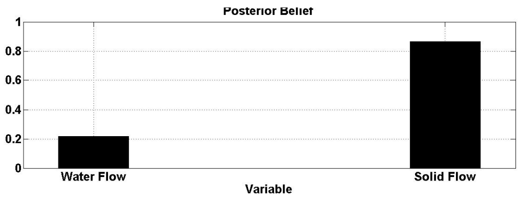

Fig. 9. Case study 1: Root cause diagnosis from BBN

in Fig. 10. This fault is detected early at $t = 3160\ min$ from PCA residual plot, as it violates Q-statistic threshold level shown in Fig. 11. From PCA contribution plot Fig. 12 its difficult to diagnose the fault correctly, as it is seen that all the variables have significant contribution for the fault except density due to the smearing effect discussed in Section 3.1. With process knowledge the BBN correctly diagnose the water flow as root cause the fault in Fig. 13. Evidence from both density and water level updates the posterior probability of both water flow rate and solid flow node. Because fault in water level has more strong relation with water flow rate than solid flow, the root cause of the fault was pinpointed correctly.

6. CONCLUSIONS

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 outputs from PCA and combines with process

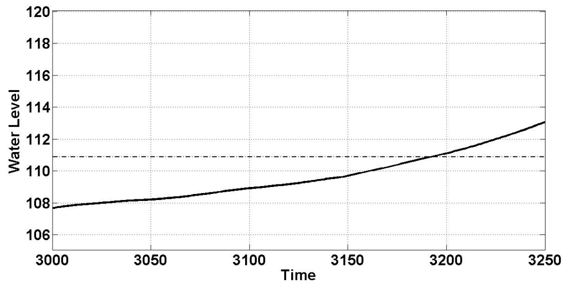

Fig. 10. Case Study 2: Fault in Water Level

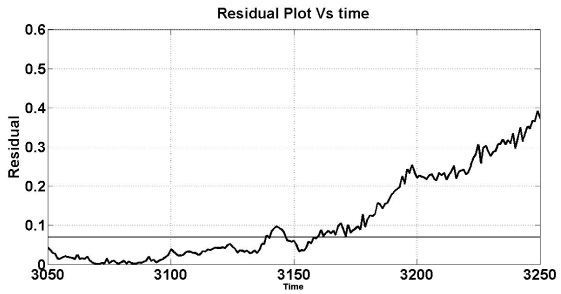

Fig. 11. Case Study 2: PCA early fault detection

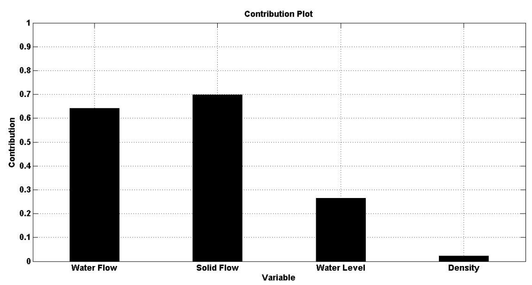

Fig. 12. Case Study 2: PCA contribution plot

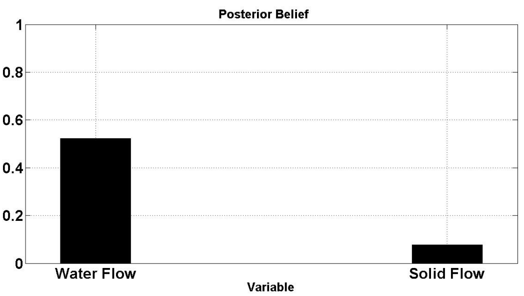

Fig. 13. Case Study 2: Root cause diagnosis from BBN

knowledge captured in a BBN. Thus 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. The method successfully detected the fault early allowing the operator to take corrective action. Also, it diagnose the root cause precisely. 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.

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