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Dynamic Bayesian Network Based Networked Process Monitoring for Fault Propagation Identification and Root Cause Diagnosis of Complex Dynamic Processes

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Abstract: In this article, a novel dynamic Bayesian network based networked process monitoring approach is proposed for fault detection, propagation pathway identification and root cause diagnosis. First, process network structure is designed according to the prior process knowledge including process flow sheets and used to characterize the causal relationships among different measurement variables. Then, the dynamic Bayesian network model parameters including the conditional probability density functions of different nodes are learned from historical process data to quantify the causality among those variables. Further, the new monitoring index is derived from the likelihoods of the entire process network for detecting abnormal operating events. With the captured process abnormality, the novel probabilistic contribution indices within Bayesian network are proposed to identify the major fault effect variables. Subsequently, the fault propagation pathways from the downstream backwards to upstream process are isolated through the variable contribution indices and hence the ending nodes of the identified pathways are determined as the root-cause variables of the abnormal events. The proposed approach is applied to the Tennessee Eastman Chemical process and the results show that the presented method can accurately detect abnormal events, identify fault propagation pathways, and diagnose the root-cause variables.

Keywords: Networked process monitoring, dynamic Bayesian network, fault detection, fault propagation pathway identification, root cause diagnosis

1. INTRODUCTION

Process monitoring, fault detection and diagnosis are becoming critically important in order to improve product quality, yields, plant safety, energy efficiency and eco-sustainability (Venkatasurbramanian et al., 2003). The approaches fall into the two major categories, which are the model-based and the data-driven techniques (Gertler, 1988). Performance of model-based process monitoring methods heavily relies on the accuracy of mechanistic models. However, the development of mechanistic models requires in-depth process knowledge to characterize the complex physical, chemical, and biological phenomena in processes. In addition, it can be time-consuming to build precise mechanistic models for complex processes.

In order to address these challenges, multivariate statistical process monitoring (MSPM) techniques have been proposed by extracting latent variables and hidden features from a large number of highly correlated process variables and the corresponding historical data sets (Nomikos and MacGregor, 1995). Principal components analysis (PCA) and partial least squares (PLS) methods are widely used in the MSPM field to build the data-driven models within the low-dimensional subspace that retains most of variance or covariance structure (Qin, 2003). Statistical indices such as T^2 and SPE are then developed to detect abnormal operating events. Moreover, once a fault is detected, variable contribution plots can be generated to identify the major fault effect variables without prior process knowledge. Nevertheless, variable contribution methods are unable to identify the root causes of faulty operations without in-depth process knowledge because the operational faults can propagate throughout the process due to the intricate variable interactions, process dynamics, closed-loop control systems, etc. Machine learning techniques including support vector machines (SVM), artificial neural networks (ANN) and Gaussian mixture model (GMM) methods are successfully applied to process monitoring (Sorsa and Koivo, 1993; Yélamos et al., 2009; Yu and Qin, 2008; Yu, 2012). However, these methods are also data-driven but exclude preliminary process knowledge. Therefore, they may not be able to identify the root-cause variables particulary when the fault propagation pathways include sophisticated variable interactions across different process units.

Alternately, signed directed graph (SDG) approach for incipient fault diagnosis has been developed. SDG method may capture the cause-effect relationship and the direction of the fault effect (Maurya et al., 2004). Moreover, it can be integrated with data driven approaches such as qualitative trend analysis (QTA) in order to reduce the

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number of spurious alarms (Maurya et al., 2007). However, the above method identifies candidate faults from the prior fault database and thus it can be challenging to diagnose abnormal events that the prior fault database does not include. In addition, these methods cannot trace the fault propagation pathways and especially the root-cause variables. A method for the fault source identification, propagation analysis and time delay estimation is also developed (Stockmann et al., 2012). Nevertheless, when the process sampling frequency is high, the online implementation of process monitoring becomes difficult due to its heavy computational load. More recently, Granger causality methods are proposed for diagnosing the root causes of plant oscillations (Yuan and Qin, 2012). Granger causality is based on linear prediction of time series and can extract useful dynamic information including the cause-effect relationship in processes. However, the industrial processes are often characterized by significant nonlinearity so that this approach may not be valid in identifying the root causes.

Dynamic Bayesian networks (DBN) are a class of graphical models of stochastic processes for characterizing time-varying dynamics and variable causality under system uncertainty. DBNs and their static version, Bayesian networks (BN), have been successfully applied to various fields including medical diagnostics, speech recognition, target tracking, and reliability analysis. For instance, DBN is applied for control loop performance diagnosis and makes it possible to synthesize various existing monitoring methods (Huang, 2008). However, each hidden node represents a type of faults, which must be specified in advance. In this study, a dynamic Bayesian network based networked process monitoring and diagnosis approach is proposed to detect the abnormal operating events, identify fault propagation pathways and capture root-cause variables in dynamic processes without any specifications of fault types. First, the network structure is designed from prior process knowledge and analysis. Then, the network parameters including the conditional probability density functions of all nodes are estimated from process data for quantifying the causal relationships among process variables. Further, the likelihood based monitoring indices are proposed for detecting faulty operations. After the abnormal event is alarmed, the novel dynamic Bayesian contribution indices are developed to capture the major fault cause and effect variables. Moreover, according to the Bayesian contribution indices and network inference rules, the fault propagation pathways from the downstream backward to the upstream process are traced so that the ending nodes along the pathways can be diagnosed as the root-cause variables resulting in process upsets.

The organization of this article is as follows. Section 2 briefly reviews the dynamic Bayesian networks. Section 3 describes the proposed dynamic Bayesian network based process monitoring approach for fault detection and root cause diagnosis. The presented method is applied to the Tennessee Eastman Chemical process in Section 4. Finally, the conclusions are drawn in Section 5.

2. PRELIMINARIES

Bayesian networks are graphical models to represent complex causal relationships among a set of random variables and their conditional dependencies. A BN is essentially a directed acyclic graph (DAG) consisting of hidden and observed nodes, each of which is connected to the various nodes in the same time slice. The nodes that have arcs directed into are termed as child nodes while the ones with departing arcs are parent nodes. Meanwhile, the nodes without any parent nodes are called root nodes. As a kind of extension of BN, dynamic Bayesian networks are designed to characterize the dynamic relationships among variables by tracking the transitional probabilities between the parent and child nodes across different time slices (Murphy, 2002).

The structure of DBN can be designed from prior knowledge and then the qualitative causal reasoning is conducted within the network models. Further, the conditional probability distributions with model parameters $\theta_i \in \Theta$ can be estimated from historical data to infer the quantitative causal relationships among variables.

Given all the multivariate measurements $X_t = \left[X_t^1, X_t^2, \ldots, X_t^N\right]$ with X_t^i being the i-th node at time t, the probabilistic transition model from the previous state to the current state for all variables is expressed as

$$p(X_t|X_{t-1}) = \prod_{i=1}^{N} p(X_t^i|Pa(X_t^i)) \tag{1}$$

where $Pa(X_t^i)$ are the parent nodes of X_t^i. Thus the joint probability density function from $t = 1$ to T is given by

$$p(X_{1:T}) = \prod_{t=1}^{T}\prod_{i=1}^{N} p(X_t^i|Pa(X_t^i)) \tag{2}$$

Once the network structure is determined, model parameters Θ can be identified from expectation-maximization (EM) algorithm. The details on DBN model learning procedure can be found in literature (Murphy, 2002).

3. DYNAMIC BAYESIAN NETWORK BASED NETWORKED PROCESS MONITORING APPROACH FOR FAULT DETECTION AND DIAGNOSIS

As DBN is a type of graphical model to characterize the stochastic non-steady-state processes using conditional probability based dynamic state transition, it is possible to determine the operational status of processes, identify the fault propagation pathways and diagnose the root causes of abnormal event using the time-varying transitional probability among different variables.

Aimed at designing DBN structure, the intra-slice topology within a time slice and the inter-slice topology between two slices should be defined. First, the intra-slice structure is determined from the prior process knowledge including process flow sheets. The idea is to sort out the monitored variables in terms of process flow order from the upstream to the downstream process. Then cause-effect relationships can be analyzed from process flow order as well as physical or chemical interactions among monitored variables. In this way, network arcs can be connected between the parent and child nodes based on the qualitative cause-effect relationships among process variables.

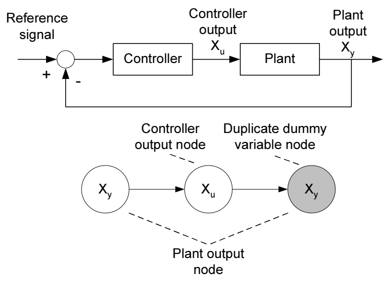

Fig. 1. Illustrative Diagram of Duplicate Dummy Node for Feedback Controller

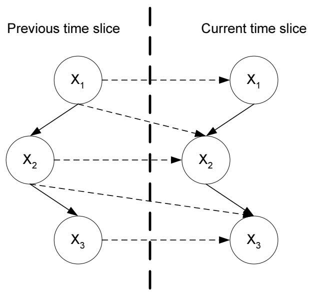

Fig. 2. Illustrative Example of Dynamic Bayesian Network

For processes with recycle loops or feedback controllers, DBN cannot handle directly as they are essentially acyclic graphs. In this situation, duplicate dummy variables are designed and added to the network structure for representing the recycle or manipulated variables. As shown in Fig. 1, a duplicate dummy node X_y for manipulated variable is designed in the network structure to take into account the feedback effect of a controller. Similarly, the impact of process recycles can be captured by adding a duplicate dummy node to represent a recycle variable.

With the defined intra-slice topology, the inter-slice topology can be determined to account for the process dynamics. In this study, each node in the previous time slice is connected to the same one in the current time slice. Moreover, in order to take into consideration the scenario when time-delays are present in process, each parent node in the previous time slice is connected to it child nodes in both the previous and current time slices. An illustrative diagram of a simple three-node DBN is shown in Fig. 2.

After the dynamic bayesian network structure is defined, the model parameters in terms of conditional probability distributions of different nodes are estimated from historical process data. In this work, all monitored variables are assumed to be continuous random variables with approximately Gaussian distributions and thus the parameters of the conditional probability distributions are their means and variances. With the DBN model obtained, the likelihood for the new observation X_t can be derived for fault detection and propagation pathway identification. The conditional probability function of the i-th node at time t is estimated as follows

$$p(X_t^i|Pa(X_t^i)) = N\left(X_t^i \left| \mu_t^i, v_i\right.\right) \tag{3}$$

with

$$\mu_t^i = \sum_{j \in Pa(X_t^i)} w_{ij} X_t^j + b_i \tag{4}$$

where w_{ij} and b_i are parameters governing the mean while v_i is the variance of the conditional distribution. The log likelihood function for the new observation of the network nodes X_t at time t is expressed as

$$\ln\, p(X_t) = \sum_i^N \ln\, p(X_t^i|Pa(X_t^i)) \tag{5}$$

which represents the overall probability of all the network nodes under normal operational conditions. In other words, the smaller value the log likelihood function is, the higher possibility that the abnormal event occurs. Thus, the following abnormal likelihood index (ALI) is proposed

$$\zeta(t) = -\ln\, p(X_t) \tag{6}$$

The corresponding confidence limit can be estimated from kernel density estimation (KDE) algorithm (Bishop, 2006). Given observations $(\zeta(1), \zeta(2), \ldots, \zeta(T))$ from unknown probability distribution f, the density function can be estimated as follows

$$f(\zeta) = \frac{1}{TD}\sum_{t=1}^{T} K\left\{\frac{\zeta - \zeta(t)}{D}\right\} \tag{7}$$

where ζ denotes ALI under consideration, D represents the kernel window width and K is a kernel function. The following Gaussian kernel function is commonly used

$$f(\zeta) = \frac{1}{T}\sum_{t=1}^{T} \frac{1}{\sqrt{2\pi}D}\exp\left\{-\frac{(\zeta - \zeta(t))^2}{2D^2}\right\} \tag{8}$$

After a probability density function is estimated, the corresponding point with cumulative density function value at $1-\alpha$ is the confidence limit under the confidence level of $(1-\alpha)\times 100\%$.

Once the abnormal operation is detected, it is needed to identify fault propagation pathways and diagnose root-cause variables. In this study, a dynamic Bayesian probability index (DBPI) is developed from the conditional probability function $p(x|Pa(X_t^i))$ of the i-th node at time t as follows

$$\gamma_i(t) = \int_{x_i^1(t)}^{x_i^2(t)} p(x|Pa(X_t^i))dx \tag{9}$$

where

$$x_i^1(t) = \begin{cases} X_t^i & \left(X_t^i < \mu_t^i\right) \\ 2\mu_t^i - X_t^i & \left(X_t^i \geq \mu_t^i\right) \end{cases} \tag{10}$$

$$x_i^2(t) = \begin{cases} 2\mu_t^i - X_t^i & \left(X_t^i < \mu_t^i\right) \\ X_t^i & \left(X_t^i \geq \mu_t^i\right) \end{cases} \tag{11}$$

This time-varying index is a type of cumulative distribution function and can be used to quantify the effect of each monitored variable on the abnormal event by its directly connected upstream variables in a probabilistic manner. Once a faulty event is detected, the DBPI can be averaged as a new dynamic Bayesian contribution index (DBCI) Γ_i for each variable as follows

$$\Gamma_i = \frac{1}{t_1 + t' - 1}\sum_{t=t_1}^{t_1+t'-1} \gamma_i(t) \tag{12}$$

where t_1 is the time when the abnormal event is first detected, t' is the period used to diagnose the faulty operation and should be specified by users. Γ_i is the mean of DBPI from t_1 to $t_1 + t' - 1$ and it represents the likelihood of each process variable with significantly abnormal behavior and can be utilized as an indicator identifying the major effects given process faults.

Because of intricate variable interactions, process dynamics and closed-loop control, the fault can often propagate throughout the process from upstream to downstream operations. Therefore, identifying the fault propagation pathways and diagnosing the root-cause variables of abnormal operations are highly desirable. In our work, with above the dynamic Bayesian contribution index, the following probabilistic inference rules are further designed to identify fault propagation pathways by searching from the downstream backwards to the upstream process within the network.

The proposed search for fault propagation pathways starts from all the leaf nodes that do not have any child nodes. First, among all the leaf nodes within the network, the ones satisfying the following criteria are selected as the nodes at which the fault propagation pathway $S = [\eta_1, \eta_2, \ldots, \eta_M]$ starts

$$\eta_1 = \arg_{\eta \in Z_L} \{\Gamma_\eta \geq \epsilon\} \tag{13}$$

where η_1 is the starting nodes in the fault propagation pathway, Z_L represents the sets of leaf nodes in the network, Γ_η is the dynamic Bayesian contribution index of the node η, ϵ is the threshold value that should be set at the confidence level $(1-\alpha)100\%$, and M is the total number of nodes within the identified fault propagation pathway. With the starting node identified, the fault propagation pathway can be determined gradually. The node $\eta_j (j \geq 2)$ in the propagation pathway is inferred from the previous node η_{j-1} along the reversed arc. The ones whose dynamic Bayesian contribution index values are no less than the threshold ϵ are selected in the fault propagation pathway as follows

$$\eta_j = \arg_{\eta \in Pa(X^{j-1})} \{\Gamma_\eta \geq \epsilon\} \tag{14}$$

where η_j denotes the j-th node in the fault propagation pathway and $Pa(X^{j-1})$ represents all the parents nodes of the previous node η_{j-1}. If the DBCI values of all the parent nodes are less than the threshold, the one that has the largest DBCI value among all the parent nodes is selected in the fault propagation pathway

$$\eta_j = \arg\max_{\eta \in Pa(X^{j-1})} \Gamma_\eta \tag{15}$$

The above search for the fault propagation pathway continues until there are no remaining nodes whose DBCI values are no less than the threshold vaue. Otherwise, the pathway search does not terminate until it reaches one of the root nodes that do not have any parent nodes. The ending node in the identified fault propagation pathway is thus determined as the root-cause variables leading to process upsets.

The proposed DBN based networked process monitoring and diagnosis approach is illustrated in Fig .3. Moreover, the step-by-step procedure of the presented method is listed below

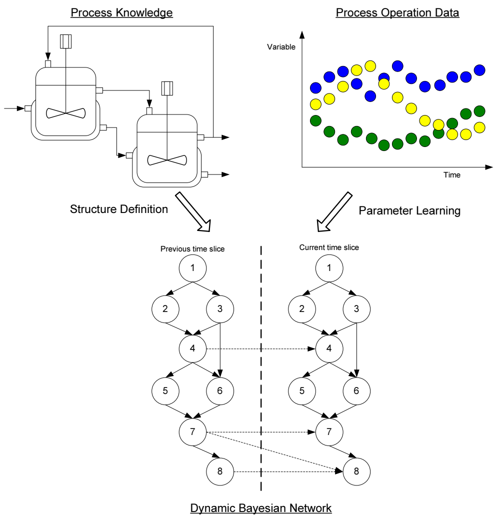

Fig. 3. An Illustration of Networked Process Monitoring

(1) Determine the intra-slice topology of the dynamic Bayesian network based on prior process knowledge and process flow sheets with the network nodes representing process variables and arcs denoting the causal relationships.
(2) Add duplicate dummy nodes representing manipulated variables of controllers or recycled variables in the network structure.
(3) Connect each node in the previous time slice to the same one in the current time slice.
(4) Connect each parent nodes in the previous time slice to all its child nodes in the current time slice.
(5) Learn the network model parameters in terms of conditional probability density functions of all nodes from the historical process data.
(6) Compute the abnormal likelihood index values of training data and determine its confidence limit using kernel density estimation.
(7) Calculate the values of ALI for new process data and detect abnormal operations with ALI values above the confidence limit.
(8) Calculate the dynamic Bayesian contribution index values of the detected faulty samples for all network nodes and generate the corresponding DBCI contribution plots.
(9) Search for the fault propagation pathway using the proposed DBCI and statistical inference rules.
(10) Identify the ending nodes in the propagation pathways as the root-cause variables responsible for the abnormal events.

4. CASE STUDY

In this work, the Tennessee Eastman Chemical process is utilized to examine the performance of the DBN based networked process monitoring approach. The diagram of the Tennessee Eastman Chemical process is shown in Fig. 4 and this process has five major units including a exothermic 2-phase reactor, a product condenser, a vapor-liquid separator, a recycle compressor and a product stripper (Downs and Vogel, 1993). The process has total 41 measurement variables and 12 manipulated variables. The process involves a plant-wide decentralized control implementation with different feedback control loops. For process

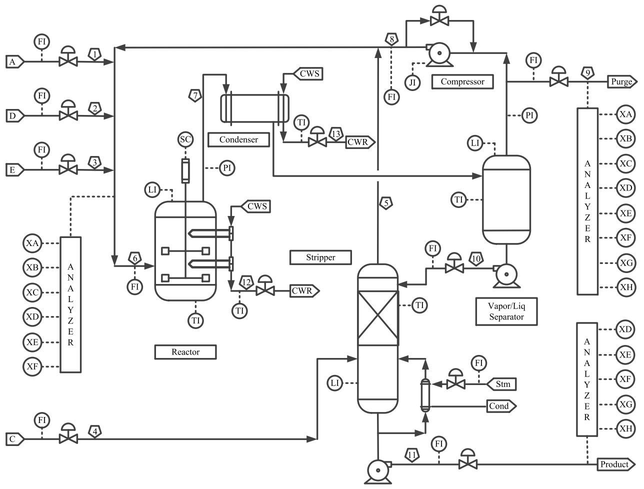

Fig. 4. Process Flow Diagram of the Tennessee Eastman Chemical Process

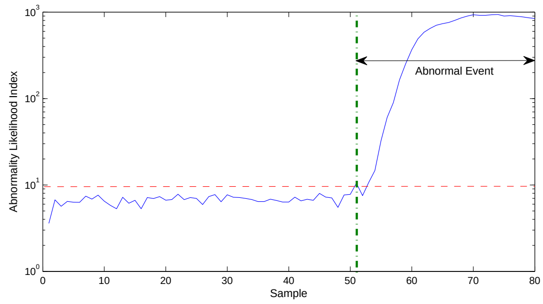

Fig. 5. Fault Detection Results of the DBN Based Networked Process Monitoring Approach in the Tennessee Eastman Chemical Process

monitoring purpose, 22 continuous variables among the 41 measurement variables are selected, as shown in Table 1. The variable symbols shown in the table are used later in this section. The sampling time of this process is set to 3 min. The training data set consisting of 500 samples is generated under normal operations for network model parameter learning. Furthermore, a test case is designed to evaluate the effectiveness of the networked process monitoring and diagnosis method. In the test scenario, the process begins with normal operating conditions from the first through the 50-th samples and then is followed by the process fault of increased random variations in D feed temperature for the remaining 30 samples.

Table 1. Monitored Variables of the Tennessee Eastman Chemical Process

Variable no.	Symbol	Variable description
1	F1	A Feed
2	F2	D Feed
3	F3	E Feed
4	F4	Total Feed
5	F5	Recycle Flow
6	F6	Reactor Feed Rate
7	P7	Reactor Pressure
8	L8	Reactor Level
9	T9	Reactor Temperature
10	F10	Purge Rate
11	T11	Separator Temperature
12	L12	Separator Level
13	P13	Separator Pressure
14	F14	Separator Underflow
15	L15	Stripper Level
16	P16	Stripper Pressure
17	F17	Stripper Underflow
18	T18	Stripper Temperature
19	F19	Stripper Steam Flow
20	J20	Compressor Work
21	T21	Reactor Coolant Temperature
22	T22	Separator Coolant Temperature

The first task in the proposed approach is to determine the intra-slice network structure from the prior process knowledge and process flow sheet. The monitored variables can be sorted in terms of process flow order from upstream to downstream units and then placed into network hierarchy as nodes without any arcs. Then the interactions among the monitored variables are analyzed based on the prior process knowledge and used to determine the node connections. The intra-slice network defined in this work includes 22 nodes corresponding to all the monitored variables and one duplicate dummy node for the recycle flow that is the only cyclic loop containing monitored variables. After the inter-slice network is defined, the entire dynamic Bayesian network structure is obtained. Then, the network model parameters in terms of the conditional probability density functions of all nodes are estimated from the training data. With the network model constructed, the abnormal likelihood index values for new process data are computed for detecting the abnormal operation. Once the faulty event is captured, the fault propagation pathway is searched and the root-cause variable for process abnormality is identified.

The trend plot of the abnormality likelihood index is shonw in Fig. 5. It can be readily observed that the ALI values are less than the confidence limit line during the normal operation while exceed the confidence limit line once the process fault of increased random variations in D feed temperature occurs from the 51-st sample.

After the fault is detected, the dynamic Bayesian contribution index values are calculated to identify the fault cause and effect variables, as shown in Fig. 6. One can easily see that the DBCI plot can rank the variables in terms of the effects from the abnormal event but is unable to point out the root-cause variables directly. With the DBCI values and probabilistic inference rules, the fault propagation pathways can be further identified, as shown in Fig. 7. The determined fault propagation pathway includes reactor pressure (P7), reactor temperature (T9), separator temperature (T11) and condenser cooling water outlet temperature (T22). As a result of increased random variations in D feed temperature, the reactor stream is significantly affected so that the abnormal behavior can be observed in reactor pressure. Subsequently, the abnormal variations in reactor pressure leads to abnormal reactor temperature. Furthermore, the downstream condenser and separator temperature are influenced by the upset in reactor temperature. Therefore, the identified fault propagation pathway correctly captures the actual fault propagations in the process and the ending node of reactor pressure in the pathway is precisely determined as the root-cause variable of faulty operation.

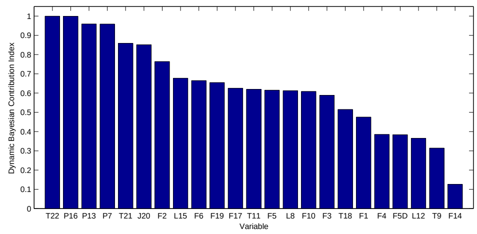

Fig. 6. Dynamic Bayesian Contribution Plot of the Tennessee Eastman Chemical Process

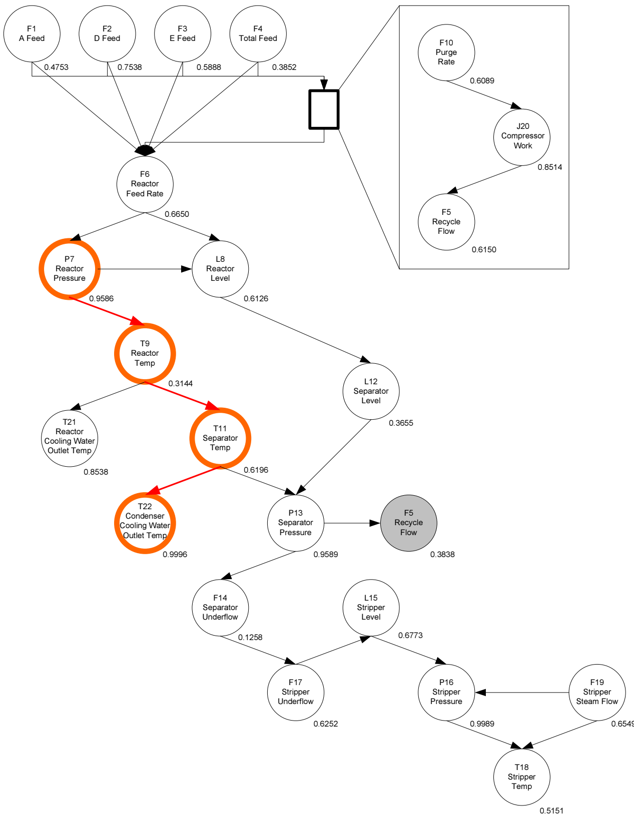

Fig. 7. Fault Propagation Pathway Identification and Root Cause Diagnosis Results of the Tennessee Eastman Chemical Process

5. CONCLUSION

In this paper, a novel dynamic Bayesian network based networked process monitoring approach for fault detection, fault propagation pathway identification and root cause diagnosis is proposed. First, Bayesian network structure is defined from prior process knowledge and process flow sheets. Then, network model parameters including conditional probability density functions of all different nodes are estimated from historical process data. Further, a new abnormality likelihood index is developed to quantify the likelihood of the whole process to be under abnormal operating conditions. Once the fault is detected, dynamic Bayesian contribution index is developed to identify the major faulty effect variables. With the DBCI values and statistical inference rules, the fault propagation pathways are identified throughout the process and the ending nodes in the pathways are determined as the root-cause variables responsible for process abnormalities. The proposed approach is applied to the Tennessee Eastman Chemical process, and the results demonstrate that it can accurately detect faults, identify fault propagation pathways and ultimately diagnose root-cause variables leading to process faults. Future work can be focused on extending the proposed method to automatic network structure learning for more desirable utility.

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