2008 American Control Conference
Westin Seattle Hotel, Seattle, Washington, USA
June 11-13, 2008

Data-driven Bayesian Approach for Control Loop Diagnosis

Fei Qi, Biao Huang

Abstract— **Many methods and algorithms have been proposed for control performance monitoring and process monitoring. However, there are few methods available for synthesis of different monitoring algorithms to form a control loop diagnostic system. Determination of the underlying reason of poor control performance is challenging. In this paper, we investigate a novel data-driven Bayesian approach for control loop diagnosis. The new approach can synthesize information from different monitoring techniques to give an appropriate inference even if the performance of each individual monitor may be low. Some other merits of the new approach include, for example, probabilistic inferences which can be easily used by optimal decision making system, robustness to missing data, and ability to incorporate *a priori* knowledge. Simulation of Bayesian diagnostic system for a binary distillation column is presented. Data missing handling feature using causality structure and marginalization is discussed. Performance of the Bayesian diagnostic system is examined under different operating modes to demonstrate the information synthesizing ability of the proposed approach.**

I. INTRODUCTION

The main objective of control performance monitoring and diagnosis is to provide an online automated procedure that delivers information to plant personnel for determining whether specified performance targets are being met by the controlled process variables and that evaluates the performance of control loop [1], as well as suggesting possible problem sources and troubleshooting sequences.

A number of methods for control performance monitoring have been proposed, such as minimum variance control (MVC) benchmark, historical performance benchmark, user-specified benchmark, etc [1], [2], [3], [4]. Some algorithms can be found from a MATLAB based control performance assessment toolbox [5]. Significant progress has also been achieved in the development of process monitors, including sensor monitors, actuator monitors, model validation monitors, etc. However, most of the monitoring algorithms target specific problems in control loops. The common practice was that one monitoring algorithm was developed for one specific problem [6].

There are also literatures discussing control loop diagnosis, which can be classified into quantitative model based, qualitative model based, and process history based [7], [8], [9]. These existing methods mainly focus on specific problem sources, such as actuator problem, sensor bias, and process model mismatch. Few have been reported for a systematic way for control loop diagnosis [1], [10], [11].

This work was supported by the Natural Sciences and Engineering Research Council of Canada (NSERC)

The authors are both with Department of Chemical and Materials Engineering, University of Alberta, Edmonton, Alberta, Canada.

According to [6], there are several challenging issues in synthesizing problem of control loop diagnosis. First, although problem sources may be different, the symptoms can be similar. Second, all processes operate in uncertain environment to some extent, and the symptoms have probabilistic interconnections with different problem sources. Thus a solution should be built on a probabilistic framework. Last but not least, how to incorporate *a priori* knowledge in the diagnostic system to improve diagnosis performance is also worth considering. Most of the existing monitoring methods are data based. However, incorporating *a priori* knowledge is not only helpful, but sometimes also necessary for a meaningful diagnosis [6].

This paper develops a data-driven algorithm for control loop diagnosis based on the novel framework proposed in [6]. A general description of the control loop diagnosis problem is given in section II, and some presumptions of the monitors are also made in this section. By following the data-driven Bayesian method for fault detection [12], a systematic way for control loop performance diagnosis and related issues are discussed in section III. Simulation results of the proposed Bayesian diagnostic system for a binary distillation column are presented in section IV. Section V concludes this paper with discussion on the simulation results obtained and future work.

II. PROBLEM DESCRIPTION

Generally, a control loop consists of the following components: controllers, actuators, process, and sensors, all subject to disturbances. These components may all suffer from certain problems. For example, a valve acting as an actuator may suffer from stiction problem; the output of a sensor may have bias error. All these problems may cause degradation of the overall control performance, such as large variation, oscillation, etc. Our goal is to determine the underlying reason of poor control performance based on the results of the monitors.

In this work, measurements of manipulated variables (MVs) and controlled variables (CVs), nominal process model, nominal disturbance model, and the nominal operating point are assumed to be available. We further assume that monitors are available for all components in the control loop. They are control performance monitors, valve stiction monitors, process model validation monitors, and sensor bias monitors. These monitors, however, are subject to disturbances and thus false alarms, and each monitor can be sensitive to other abnormalities that it is not intended to monitor.

978-1-4244-2079-7/08/$25.00 ©2008 AACC.

III. Data-driven Bayesian approach for control loop performance diagnosis

Applications of Bayesian methods have been reported in medical science, image processing, target recognition, pattern matching, information retrieval, reliability analysis, and engineering diagnosis [12], [13]. In the presence of noise and disturbances, Bayesian inference provides a well suited way to solve the process monitoring and diagnosis problem, providing quantifiable measures of the uncertainty. Following fault diagnosis approach of [12], this section introduces a data-driven algorithm for control loop performance diagnosis.

A. Preliminaries

Before the Bayesian method is introduced, some concepts need to be defined.

1) Mode m: Assume that the control loop under diagnosis consists of components $c_1, c_2, \cdots, c_n$. All the components are subject to malfunctions or errors. Each component is said to have a set of possible operating status. For instance, the sensor might be "biased" or "unbiased". The control loop diagnosis problem is to determine the true underlying problem source of poor control performance. An assignment of operating status to all components in the control loop is called a mode, and denoted as m, for example, m:=(c_1=*well tuned controller*, c_2=*valve with stiction*, $\cdots$). Mode in normal operation is denoted as NF (normal functioning), which means that all the components in the control loop function normally.

2) Evidence e: The monitor readings, called evidence or observation, are inputs to the control loop diagnostic system, and are denoted as $e = (e_1, e_2, \cdots, e_L)$, where e_i is the output of the ith monitor, and L is the total number of monitors. The vector e is also called the evidence vector.

Often the monitor readings, which are generally continuous, are discretized owing to thresholding of residuals to reduce false alarms. Also, the distribution of continuous evidence may be difficult to describe with standard ones. For example, the controller performance monitor may indicate "optimal", "normal", or "poor", depending on the thresholds adopted. The evidence vector e may be e=(e_1=*optimal control performance*, e_2=*no sensor bias*,$\cdots$). In this work, monitor readings are all discretized.

3) Historical data D: Each sample D_i in the historical data set D consists of the evidence e and the underlying mode m. This can be denoted as $D_i = (e, m)$, and the set of all historical data samples available is denoted as $D = \{D_i\}, i = 1, 2, \cdots, N$, where N is the number of historical data samples. Historical data are retrieved from the past data when both the mode of control loop and the monitor readings are known, whether it is abnormal or normal. However, even for medium sized systems there are many possible combinations of abnormalities; thus it is infeasible to collect data from all the possible modes of a large-scale system. Further, there may be problems, or combination of problems, which have not occurred before, and hence no historical data are available for them. These modes are all categorized as unconsidered (UC) mode.

Given current evidence e, historical data D, Bayes' rule can be stated as following:

$$p(m|e, D) = \frac{p(e|m, D)p(m|D)}{p(e|D)}, \qquad (1)$$

where $p(m|e, D)$ is conditional probability of existence of mode m in the control loop given current evidence e, historical data D, which is also known as posterior probability; $p(e|m, D)$ is conditional probability of having current evidence e, conditioning on mode m with historical data D, also known as likelihood probability; $p(m|D)$ is the prior probability of mode m; and $p(e|D)$ is a scaling factor, $p(e|D) = \sum_m p(e|m, D)p(m|D)$. Note that historical data are selectively collected when control loop operates under different modes, i.e. selective data collection; therefore they provide no information of prior probabilities of the abnormalities, and the priors of different modes are independent of D [12], $p(m|D) = p(m)$.

B. Estimation of likelihood probability

Since prior probabilities are determined by *a priori* information, and the scaling factor $p(e|D)$ can be calculated readily if the likelihood probabilities are known, the main task of building a Bayesian diagnostic system is the estimation of the likelihood probabilities with historical data D, whose objective is to make the likelihood probabilities be consistent with historical data D. Pernestal [12] presented a Bayesian algorithm for fault detection and isolation. The method can be extended to control loop performance diagnosis. According to the derivations of [12], the following result can be obtained as the likelihood:

$$p(e = j|m = M, D) = \frac{n_{j,M} + \alpha_{j,M}}{N_M + A_M}, \qquad (2)$$

where $n_{j,M}$ is the number of samples with the evidence $e = j$, and mode $m = M$; $\alpha_{j,M}$ is the number of prior samples that fall into the discretized evidence bin j under mode M, and generally the prior samples are assumed to be uniformly distributed with $\alpha_{j,M} = 1$; $N_M = \sum_j n_{j,M}$, $A_M = \sum_j \alpha_{j,M}$. See Fig. 1 for illustration.

This is an concise yet intuitive result. The likelihood probability is determined by both prior samples and historical data. As the number of historical data increases, the likelihood probability will converge to the relative frequency determined by historical data samples, and the influence of prior samples will decrease. The number of prior samples is another interesting issue. Actually the prior samples come from the likelihood derivation procedures. It can be interpreted as prior belief of the likelihood distribution, where uniform distribution indicates that prior likelihoods are equal for all evidences of a given underlying mode. It is important to set nonzero prior sample numbers; otherwise the diagnostic system may yield unexpected results [12]. The larger the prior sample number is, the stronger belief for the prior likelihood distribution.

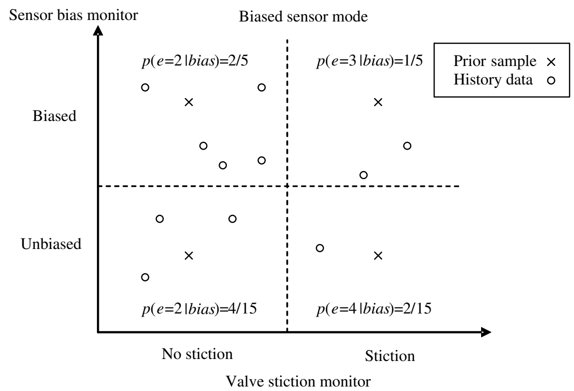

Fig. 1. Updated likelihood with historical data

Consider a SISO control loop under diagnosis with two possible problematic components: a valve subject to possible stiction problem, and a sensor subject to possible bias problem. Each possible problematic component is assigned with a monitor. Readings of both monitors are discretized into two bins with predefined thresholds; therefore the overall evidence space is discretized into four bins, as shown in Fig. 1. The underlying system mode is set with m=(*no vale stiction, sensor bias*). Each discretized evidence bin is assigned with one prior sample, under the assumption of uniformly distributed prior samples. Hence, $\alpha_{j,bias} = 1$, $A_{bias} = 4$. With the historical data collected under the same mode, the likelihood probabilities can be updated using eqn. (2), illustrated in Fig. 1.

C. Causality structure

In a control system, there might be some problems that have never occurred before or did not occur when the historical data were sampled, and therefore no historical data are available for them. Diagnosis performance for these problems may be poor, since all the likelihood probabilities for the corresponding modes are the same. However, if *a priori* knowledge of the control system structure is applied to the diagnosis, the results can be improved dramatically.

A concept called causality structure [12] is introduced here. Let $e = (e_1, \cdots, e_L)$ be an evidence vector, Q the number of modes, L the number of monitors, and $\mathfrak{C} \in (Q \times L)$ a matrix. $\mathfrak{C}$ is called a causality structure for the probability distribution $p(e_1, \cdots, e_L|m)$, if for each $\mathfrak{C}_{j,i} = 0$, $p(e_i|m = m_j) = p(e_i|m = NF)$, which means that distribution of a monitor reading e_i is the same between mode NF and mode m_j, i.e., monitor e_i is insensitive to mode m_j. For instance, the variance-based control performance monitor is insensitive to the sensor bias. This provides us an opportunity to reuse historical data from NF, which is quite easy to obtain.

We study a simple example to illustrate how to use the causality structure. Consider the causality structure for a SISO control loop. Assume that the sensor bias monitor is insensitive to the controller tuning problem, and the variance-based controller performance monitor is insensitive to a biased sensor. Thus we can derive the causality structure shown in Table I.

TABLE I

A TYPICAL CAUSALITY STRUCTURE

	Sensor bias monitor $e1$	Controller performance monitor $e2$
sensor bias m_1	$\times$	0
poorly tuned controller m_2	0	$\times$

Each monitor reading is discretized into two bins, and thus there are totally four possible evidence bins. Suppose historical data from mode m_1 and m_2 are not available, and readings of the sensor monitor and controller performance monitor are independent, so

$$p(e|M, D) = p((e_1, e_2)|m_1, D) = p(e_1|m_1, D)p(e_2|m_1, D).$$

Since the causality structure for m_1 only implies that $p(e_2|m_1, D) = p(e_2|NF, D)$, historical data from NF can be reused for e_2, but not for e_1, and the likelihood probability can be computed as (assuming uniformly distributed prior samples with one sample in each of the four discretized evidence bins):

$$\begin{aligned} p(e|m_1, D) &= p(e_1|m_1, D)p(e_2|NF, D) \\ &= \frac{n_{e_1,m_1} + \alpha_{e_1,m_1}}{N_{m_1} + A_{m_1}} \frac{n_{e_2,NF} + \alpha_{e_2,NF}}{N_{NF} + A_{NF}} \\ &= \frac{0+2}{0+4} \frac{n_{e_2,NF} + 2}{N_{NF} + 4}. \end{aligned} \tag{3}$$

Note in this equation, the prior sample number of a single monitor is two, but not one. This can be seen from Fig. 1. There are, for example, two prior samples for either $e_1 = unbiased$ or $biased$.

Similarly, the likelihood under mode m_2 is

$$p(e|m_2, D) = \frac{2}{4} \frac{n_{e_1,NF} + 2}{N_{NF} + 4}. \tag{4}$$

If the causality structure is not considered, the likelihoods would be $\alpha_{k,M}/(N_M + A_M) = 1/4$. We can see that by using causality structure, it is possible to distinguish the two modes. Otherwise, both the likelihood probabilities of m_1 and m_2 would have been the same, providing no difference between the two modes in diagnosis.

In view of the above procedure, it can be seen that the idea of causality structure is to reconstruct part of the evidence distribution of a problematic mode by independency assumption of certain monitors, *a priori* knowledge of insensitive monitors to this mode, and then reuse of historical data from *NF* mode. Although the overall joint distribution of monitor readings is unknown, partly available distributions of some monitor readings will distinguish one mode from other modes even without sufficient historical data. Therefore, the reconstructed mode can have different likelihood from the other modes, and hence the diagnosis performance can be improved.

The concept of causality structure can also be extended to two problematic modes, not merely between NF mode and a problematic mode. For instance, it is readily to know that the same sensor monitor should have the same distributions under *sensor bias* mode and *sensor bias plus valve stiction* mode, if the sensor shows the same bias under these two modes. Thus the historical data from these two problematic modes can also be reused for each other.

D. Partially missing data handling

It is not unusual that a variable may have missing data in the historical data record. In the method derived in [12], only complete historical data samples are considered. If any variable has missing data, then the corresponding samples in all other variables have to be omitted, which can affect the diagnosis performance negatively. We solve this problem by marginalization over all possible missing values. Due to limitation of space, the detail of the derivation procedure is not presented here. Instead, an example is used to illustrate the result. Suppose that there are two monitors e_1 and e_2, both with possible output 0 and 1, and part of the historical data are missing in e_2. By using the portion of the complete data only, the likelihood of evidence (0,0), for example, is

$$p((0,0)|m,D) = \frac{n_{(0,0)} + \alpha_{(0,0)}}{N_m + A_m}, \quad (5)$$

where $n_{(0,0)}$ is the number of complete data samples with evidence (0,0), and $\alpha_{(0,0)}$ is the prior sample number. When the portion of the incomplete data samples is also used, the likelihood can be shown to be

$$p((0,0)|m,D) = \frac{n_{(0,0)} + \alpha_{(0,0)}}{N_m + A_m} \cdot \left(1 + \frac{n_{(0,\times)}}{\sum_{e_2} n_{(0,e_2)} + \alpha_{(0,e_2)}}\right), \quad (6)$$

where $n_{(0,\times)}$ is the number of incomplete evidence corresponding to $(0,\times)$, where $\times$ stands for monitor readings of e_2 that are missing. It can be seen that information from the incomplete evidences $(0,\times)$ is useful when estimating the likelihood probabilities.

The above procedure establishes an approach for control loop diagnosis. Results from different monitors and *a priori* knowledge of the control system structure can be synthesized to give a more effective probabilistic diagnosis. Thus, the Bayesian approach provides an appropriate solution for control loop diagnosis, even in the presence of problematic monitors, which will be demonstrated in next section through a simulation example.

IV. Simulation Example

A. Process description

To investigate performance of the Bayesian diagnostic system for MIMO processes, we apply the algorithm to a simulated binary distillation column [14]. The column has five inputs, four of which are manipulated variables (MVs) operated by a MPC controller. Of the ten outputs, three are controlled quality variables (CVs). They are: top product (distillate) quality measured as final boiling point (FBP top), bottom product (pressure compensated) temperature (PCT bottom), and column pressure. The system is subject to several different problems. All the possible modes, and the corresponding problematic components, are listed in Table II.

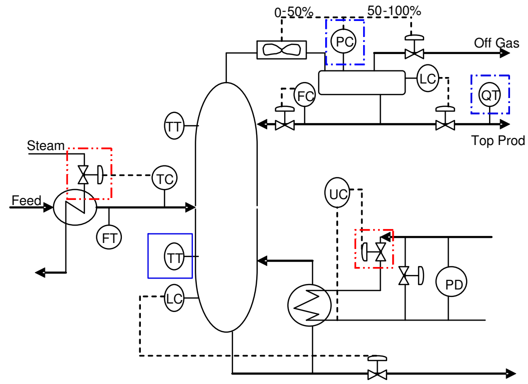

Fig. 2. Distillation column simulation system

TABLE II
Operating Modes

Mode	Problematic components
NF	None
m_1	Poorly tuned MPC controller
m_2	Feed temperature valve stiction
m_3	Duty valve stiction
m_4	FBP top & PCT bottom model mismatch
m_5	PCT bottom model mismatch
m_6	PCT bottom disturbance dynamic change
m_7	Pressure disturbance dynamic change
m_8	FBP top sensor bias
m_9	Pressure sensor bias
UC	Other unknown errors or combinations of errors

B. Monitor selection

To evaluate the synthesizing ability of the Bayesian diagnosis approach, monitors are chosen, some of which may have high false-alarm/misdetection rate.

1) Controller performance monitor: The minimum variance control benchmark is adopted to evaluate control performances for both univariate and multivariate cases. The FCOR algorithm [2] is employed to compute control performance indices based on both univariate CVs and multivariate CVs.

Note that the process delay d should be known to evaluate control performance of univariate CV, but it is not well defined under an MIMO system. Therefore, for univariate performance monitoring of MIMO system, we select the process delay d as the longest time delay between all the MVs and that CV, and use this value to evaluate the univariate control performance. Note that in this way, the univariate performance index does not precisely reflect the performance of the target CV. However, since the univariate performance index reflects the predictability of a univariate time series [15], we use it as a part of the predictability monitoring scheme. Although imprecise, it is demonstrated that this information will be useful under the proposed synthesizing approach.

2) Valve stiction monitor: For illustration purposes, we consider the following simplified scenario: if a control loop has oscillation, then the oscillation is caused either by valve stiction or by external oscillatory disturbance. The latter has the sinusoid form while the former does not.

If the CV and the MV oscillate sinusoidally, by plotting CV versus MV, an ellipse will be obtained. It has been observed that an ellipse will be distorted if the oscillation is caused by valve stiction. The method adopted here is based on the evaluation of how well the shape of the CV versus MV plot can be fitted by an ellipse. An empirical threshold of distance between each data point and the ellipse is used to determine goodness-of-fit, and thereafter the valve stiction.

3) Process model validation monitor: The local approach based on the output error (OE) method [16] is employed to validate nominal process model. This method applies to MISO systems. A MIMO system can be separated into several MISO subsystems. Models of each MISO part can be validated with the local approach.

4) Disturbance dynamics monitor: According to the assumption made in section II, the nominal model for the output disturbance, namely G_l, is available. Multiplying residual of the process model with inverse of the disturbance model yields input to the disturbance model $\tilde{e}(t)$,

$$\tilde{e}(t) = G_l^{-1}[y(t) - \hat{y}(t)], \qquad (7)$$

where $y(t)$ is the process output, and $\hat{y}(t)$ is the simulated output. If there is no disturbance model mismatch, the generated sequence should be white noise. So the disturbance model validation problem can be transformed into a whiteness test problem. The index $\tilde{e}^T(t)R_{\tilde{e}}^{-1}\tilde{e}(t)$, which should follow χ^2 distribution, is used as the output of the disturbance dynamics monitor, where $R_{\tilde{e}}$ is variance of $\tilde{e}(t)$.

5) Sensor bias monitor: A state space model based analytical redundancy method which eliminates the unknown states is applied to detect sensor bias [17].

C. Diagnosis settings and results

Since the three quality CVs are of main interest, the selected monitors mainly target these CVs, as shown in Table III.

TABLE III

MONITORS SUMMARY

Evidence	Monitor description
e_1	Overall control performance monitor
e_2, e_3, e_4	Univariate control performance monitors for three quality variables
e_5, e_6	Valve stiction monitors for the two possible problematic valves
e_7, e_8, e_9	Process model validation monitors for three quality variables
e_{10}, e_{11}, e_{12}	Disturbance change detection monitors for three quality variables
e_{13}, e_{14}, e_{15}	Sensor bias detection monitors for three quality variables

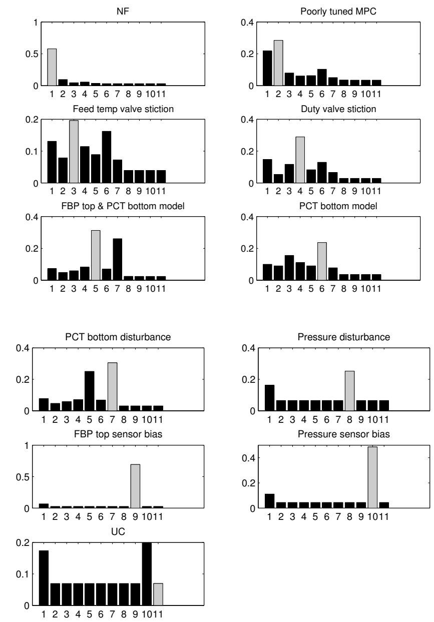

Fig. 3. Average posterior probability assigned to each mode

The parameter settings of the Bayesian diagnostic system are summarized in Table IV. Note that UC represents both unknown problems and combination of two or more problems occurring simultaneously, so data from *PCT bottom sensor bias*, which represents unknown problems, and data from *simultaneous poorly tuned controller and pressure sensor bias*, which represents combination of two or more problems, are represented by the UC mode.

TABLE IV

SUMMARY OF BAYESIAN DIAGNOSIS PARAMETERS

Discretizaion	$k_i = 3, K = 3^{15} = 14348907$
Training data	300 samples for each mode, except UC
Prior sample	Uniformly distributed with prior sample, $\alpha_{k,B} = 1, A_{k,B} = 14348907$
Prior probabilities	$p(NF) = 0.1, p(m_{other}) = 0.09$
Evaluation data	300 samples for each mode, from training modes and UC

With the Bayesian diagnostic system, diagnosis results in Fig. 3 are obtained for the evaluation data. In Fig. 3, the title of each plot denotes the true underlying mode, and the numbers on the horizontal axis stand for the diagnosed eleven possible modes numbered according to the sequence shown in Table II. In each plot, the probability corresponding to true underlying mode is shown with gray bars, while others are in dark bars. The final diagnosis result is determined by identifying the mode with the largest probability. If the largest probability happens to be the grayed one, then the problem source is correctly identified. From Fig. 3, we can see that all the true underlying modes are assigned with the largest probabilities, except UC. Even in the presence of low

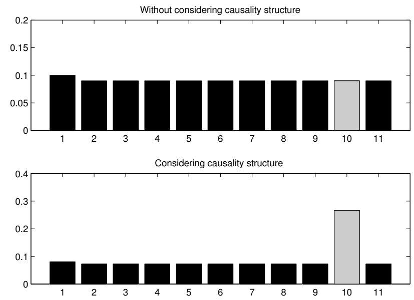

Fig. 4. Diagnosis result of *pressure sensor bias* mode without considering causality structure

performance monitors, the Bayesian approach can synthesize information from these monitors to provide a good diagnosis result. Performance of the diagnostic system for the UC mode, however, is poor, which is due to lack of historical data under that mode.

Furthermore, assume that historical data from *pressure sensor bias* mode are not available. If causality structure is not considered, the diagnosis result for *pressure sensor bias* mode is shown in the upper panel of Fig. 4. Since there is no historical data available for this mode, all the likelihood probabilities are the same, and the diagnostic system can not distinguish the true underlying mode from the other modes.

Then the performance of Bayesian diagnostic system with the consideration of the causality structure is evaluated. The causality structure in Table V can be obtained for the *pressure sensor bias* mode. From the causality structure, we

TABLE V
CAUSALITY STRUCTURE FOR *pressure sensor bias* MODE

	e_1	e_2	$\cdots$	e_{11}	$\cdots$	e_{15}
m_9	0	0	$\cdots$	$\times$	$\cdots$	0

have

$$
\begin{aligned}
&p(e|m_9, D) \\
&= p(e_1 \cdots e_{10} e_{12} e_{13} e_{15} | m_9, D) p(e_{11} | m_9, D) \\
&= p(e_1 \cdots e_{10} e_{12} e_{13} e_{15} | NF, D) p(e_{11} | m_9, D) \quad (8)
\end{aligned}
$$

Applying eqn. (8) to compute likelihood probabilities yields the diagnosis result for *pressure sensor bias*, shown in the lower panel of Fig. 4. Clearly, the performance is much better than the case without considering the causality structure.

V. CONCLUSIONS

In this paper, a novel Bayesian approach for control loop diagnosis is presented. Bayesian inference is employed to synthesize results of control and process monitors, together with *a priori* knowledge of the control loop, to generate an appropriate probabilistic diagnostic system. The method is applied to a simulated binary distillation column, where the feature of the Bayesian approach to incorporate *a priori* knowledge, as well as to synthesize results from a variety of low-performance monitors, is demonstrated. Diagnosis results considering causality structure are shown to be better than that without considering causality structure when the historical data is incomplete. It is concluded that the Bayesian approach is an appropriate solution for control loop diagnosis. Our future work will include some related theocratical problems, such as cross correlation between monitor outputs, and temporal dependency of historical data samples. Also, some practical implementation issues will be investigated.

REFERENCES

[1] M. Jelali, An overview of control performance assessment technology and industrial applications, *Control Engineering Practice* 14(5)(2006), pp. 441-466.

[2] B. Huang, S.L. Shah, *Performance assessment of control loops*, Springer-Verlag(1999).

[3] S.J. Qin, Control performance monitoring: a review and assessment, *Computers and Chemical Engineering* 23(2)(1998), pp. 173-186.

[4] T.J. Harris, C.T. Seppala, L.D. Desborough, A review of performance monitoring and assessment techniques for univariate and multivariate control systems. *Journal of Process Control*, 9(1)(1999), pp. 1-17.

[5] http://www.ualberta.ca/~bhuang/Research/Research.htm

[6] B. Huang, Bayesian methods for control loop monitoring and diagnosis, in *2007 DYCOPS*, June 6-8, 2007, Cancun, Mexico.

[7] V. Venkatasubramanian,R. Rengaswamy, K. Yin, S.N. Kavri, A review of process fault detection and diagnose part I: quantitative model based methods, *Computers and Chemical Engineering*, 27(3)(2003), pp. 293-311.

[8] V. Venkatasubramanian,R. Rengaswamy, K. Yin, S.N. Kavri, A review of process fault detection and diagnose part II: qualitative models and search strategies, *Computers and Chemical Engineering*, 27(3)(2003),pp. 313-326.

[9] V. Venkatasubramanian,R. Rengaswamy, K. Yin, S.N. Kavri, A review of process fault detection and diagnose part III: process history based methods, *Computers and Chemical Engineering*, 27(3)(2003), pp. 327-346.

[10] J. Schafer, A. Cinar, Multivariable MPC system performance assessment, monitoring, and diagnosis, *Journal of process control*, 14(2)(2006), pp. 113-129.

[11] R.S. Patwardhan, S.L. Shah, Issues in performance diagnostics of model-based controllers, *Journal of Process Control*, 12(3)(2002), pp. 413-427.

[12] A. Pernestal, *A Bayesian approach to fault isolation with application to diesel engine diagnose*, PhD thesis, KTH School of Electrical Engineering, 2007.

[13] S. Dey and J.A. Stori, A Bayesian network approach to root cause diagnosis of process variations, *International Journal of Machine Tools & Manufacture*, 45(1)(2005), pp. 75-91.

[14] U. Volk, D.W. Kniese, R. Hahn, R. Haber, U. Schmitz, Optimized multivariable predictive control of an industrial distillation column considering hard and soft constrains, *Control Engineering Practice*, 13(7)(2005), pp. 913-927.

[15] B. Huang, S.X. Ding, N. Thornhill, Alternative solutions to multivariate control performance assessment problems, *Journal of Process Control*,16(5)(2006),pp. 457-471.

[16] S. Ahmed, B. Huang, S.L. Shah, Validation of continuous-time models with delay, *In preparing*.

[17] S.J. Qin, W. Li, Detection and identification of faulty sensors in dynamic processed,*AIChE Journal*, 47(7)(2001),pp. 1581-1593.