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A Hybrid Approach for Complex Industrial Process Monitoring

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This study proposes a multi-agent system with several intelligences for complex industrial process monitoring. The suggested multi-agent system combines a set of techniques which are: multivariate control charts, neural networks, and Bayesian networks. The proposed approach has been evaluated on the TEP (Tennessee Eastman Process). The obtained results have been compared with set of methods that were applied to the Tennessee Eastman Process in the literature; our system performs better on the faults diagnosis.

Keywords: Complex Industrial Process, Multi-Agent System, Hotelling T2 Control Chart, Bayesian Network, Neural Network

Introduction

Currently, the process monitoring is an important task in all industrial companies. For this reason; the most important purpose of companies is the optimisation of their process monitoring methods. Three principal methods of process monitoring have been proposed[1]: (i) the analytical methods which are based on mathematical models. These methods compare the real system outputs with the mathematical model outputs; hence they are excellent and give good results. However, the most shortcoming of these first methods is the difficulty to obtain and manage the model for the big systems, (ii) the methods based on knowledge, which use the human knowledge (risk analysis, Failures Modes Effects and Critically Analysis- FMECA, decision trees)[2-3]; their disadvantages reside in the difficulty to own all the knowledge about the faults, and (iii) the data based methods which focus on statistical process control. The last kind of methods apply, generally, the methods which are based on univariate control charts (x-bar chart[4], CUSUM (Cumulative SUM)[5], or EWMA (Exponentially Weighted Moving Average weighted moving average)[6], and multivariate control charts (the Hotelling T2 control chart)[7], the MCUSUM (Multivariate Cumulative SUM)[8], and the MEWMA (Multivariate Exponentially Weighted Moving Average)[9] for the faults detection in industrial process. Currently, the industrial processes become more and more complex and multivariate. In these systems, the operator recuperates a vast data amount to be analysed. The high volume of data and the big number of process variables make the operator task fastidious. To avoid such problems, and simplify the complex process monitoring tasks the data based methods are more suitable for a complex process monitoring. The multivariate control charts (Hotelling T2 control chart, MCUSUM, and MEWMA) have been used in the monitoring of multivariate process and have proved their adequacy in reducing the complexity of such process monitoring. The monitoring of a multivariate process is a complex task which can be devised into four subtasks that are: the detection of abnormal situation, the diagnosis of the faults that appeared in the process, the identification of variables that caused this situation, and finally the reconfiguration of the process[1]. In literature, lot of researches have used the control charts for process monitoring[10-12]. To identify the variables that make an out of control in T2, a decomposition of the statistic T2 into independent terms[13] has been suggested. Moreover, the Bayesian networks have been applied for variables identification[14-19]. Our contribution consists to combine in one multi agent system different intelligences (multivariate control charts, neural networks, and Bayesian networks) for multivariate process monitoring. The developed agents use multivariate control chart for abnormal detection, neural network for faults diagnosis, and Bayesian network for variables identification. We use the multi-agent system because it:

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- simplifies the communication between the different intelligences (control chart, neural network, and Bayesian network),
- manages the intelligence diversity,
- optimises the time of the monitoring process tasks,
- offers a cooperative supervised approach for complex industrial process.

The proposed multi-agent system

The proposed multi-agent system is composed by three principal agents: the Multivariate Control Chart Executor Agent (MCCEA), the Diagnosis Artificial Neural Network Agent (DANNA), and the Identification Bayesian Network Agent (IBNA). The following paragraphs describe each of these used agents. We model agent diagram for the proposed system as shown in Figure 1.

The interface agent (IA)

The IA is a reactive agent which is the bridge between the multi-agent system and the operator. It is an interface for the human operator; hence it receives the request from the users (monitoring the process state). Besides this, the IA transforms the agent's responses to the users. If the IA receives a request from the user, to control the process state, it sends a message to the MCCEA. If the process is stable, the IA informs the operator that the process is under control. Otherwise, the process is unstable; the IA waits the response of the IBNA and displays it for the operator.

The multivariate control charts executor agent (MCCEA)

This agent is responsible on the execution of the multivariate control charts (Hotelling T2 control chart, MCUSUM, MEWMA). The control charts detect successfully the process instability. To monitor successively the process, we suggest using a software agent that executes simultaneously a set of multivariate charts and detects easily the process instability. The different control charts are used in the design of the MCCEA. This agent receives request from the IA about the process state, it executes the control charts. After that, if the process is under control, it sends report to the IA. If not, it informs the DANNA that the process is not stable.

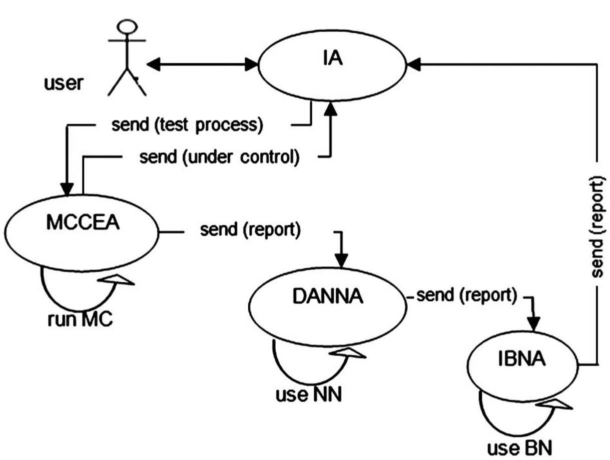

Fig. 1 — Agent diagram

The diagnosis artificial neural network agent (DANNA)

We use the neural network in the diagnosis task. The neural network has been implemented and integrated into the DANNA development in order to obtain a good diagnosis of the process faults. The objective of this neural network is to provide classification of the faults that appeared in the process. We create a classical Multi Layer Perceptron (MLP), with three layers:

- The input layer: the number of neurons in this layer is the number of the process parameters,
- The output layer: in this layer, the number of the neurons represents the number of classes (faults of the process),
- The hidden layer: it is generally known that the number of neurons in this layer is problematic research. After a set of tests, we find that the optimal number is equal to: *(number of neurons in the input layer + the number of neurons in the output layer)/2*. When the process is unstable, the DANNA receives report from the MCCEA. Its principle objective is to find the fault that appeared in the process. After, it sends a report to the IBNA.

The identification bayesian network agent (IBNA)

As with neural network, a Bayesian network has been integrated in the IBNA development. The IBNA receives report from DANNA about the fault that appeared in the process. It builds a Bayesian network using the causal decomposition of T2. After, the probabilistic values provided by the Bayesian net will be used by the IBNA in order to find the variables that are involved in the faults.

Application of the proposed model on the tennessee eastman process

Introduction to the tennessee eastman process

The Tennessee Eastman process[20] (TEP) is proposed, to provide a simulated model and to evaluate the monitoring methods of industrial complex process. The process consists of five principal units: a condenser, a

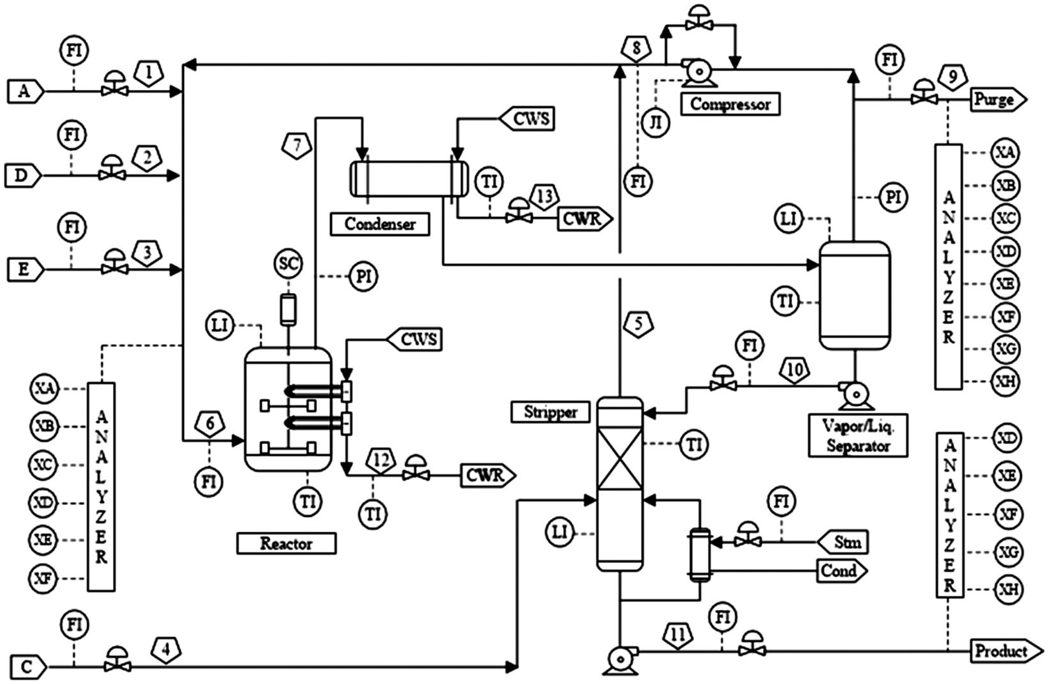

Fig. 2 — Tennessee Eastman control problem

separator, a reactor, a compressor, and a stripper Figure 2. Four gaseous reactants (A, C, D, and E) and inert B are fed to the reactor. It produces two components (G and H), and the undesired by-product F. The reaction equations are listed from (1 to 4). All the reactions are irreversible, exothermic, and approximately first-order with respect to the reactant concentrations. The reaction rates are expressed as Arrhenius function of temperature. The reaction producing G has higher activation energy than that producing H, thus resulting in more sensitivity to temperature.

$$A\ (g) + C\ (g) + D\ (g) \rightarrow G\ (l) \quad \dots (1)$$

$$A\ (g) + C\ (g) + E\ (g) \rightarrow H\ (l) \quad \dots (2)$$

$$A\ (g) + E\ (g) \rightarrow F\ (l) \quad \dots (3)$$

$$3D\ (g) \rightarrow 2F\ (l) \quad \dots (4)$$

The TEP process[20], is open loop unstable and it should be operated under closed loop. In this article, we use this control structure to evaluate the performance of our approach on fault diagnosis. The reactor product stream is cooled through a condenser and fed to a vapour-liquid separator. The vapour exits the separator and recycles to the reactor feed through a compressor. A portion of the recycle stream is purged to prevent the inert and by-product from accumulating. The condensed component from the separator is sent to a stripper, which is used to strip the remaining reactants. Once G and H exit the base of the stripper, they are sent to a downstream process which is not included in the diagram. The inert and by-products are finally purged as vapour from vapour-liquid separator. The process provides 41 measured and 12 manipulated variables, denoted as XMEAS (1) to XMEAS (41) and XMV (1) to XMV (12), respectively. Twenty faults IDV (1) to IDV (20) of TEP are given to represent different conditions of the process operation (Fifteen faults are pre-programmed and four are unknowns).

Simulation and Results

Approach implementation tools

The proposed approach has been implemented using the Java environment Net beans IDE and the platform JADE (Java Agent Development framework). JADE is a software framework that simplifies the implementation of multi-agent systems. To simplify the development of the neural network and Bayesian network with Netbeans, java offers many libraries. In this work, we use FIPA Agent Communication specifications that deal with Agent Communication Language (ACL) messages, message exchange interaction protocols and content language representations.

Used data set for simulation

In this section we evaluate the performances of the proposed approach on a concrete example which is the TEP. The used data represent 480 training observations and 960 tests observations for each fault, in addition to the normal period. The observations of training have been obtained with the simulation of each fault in a period of 24 hours; moreover the observations of the test set have been obtained through a period of 48 hours. Variables are sampled every three minutes.

Application of the proposed model on the TEP

Detection

The MCCEA runs the Hotelling T2 control chart and sends message to the DANNA when it detects the instability of process. The false alarm rate is 0,01%. The performance of detection system is evaluated by calculating its reliability. The last is defined as: (*the number of obtained alerts in the test period/the total number of sample in the period test*)[21]. Generally, the reliability detection is the same that been obtained by Sylvain[19].

Results analyses

As we see in the Table 1

- Some faults are easily detectable which are: IDV (4), IDV (5), IDV (6), IDV (7), IDV (14), IDV (1), IDV (2), IDV (8), IDV (10), IDV (12) (reliability of detection= 100%),
- Other faults are difficult to detect which are: IDV (3), IDV (9), and IDV (15) (reliability of detection < 40%), For example, the fault IDV (8) is generally detectable (reliability of detection = 97, 95), because the first samples (33 first samples) of this faults are not detectable.

Table 1 — Reliability of detection by MCCEA

Fault	Detection reliability
IDV(1)	99.75 %
IDV(2)	98.5%
IDV(3)	35%
IDV(4)	100%
IDV(5)	100%
IDV(6)	100%
IDV(7)	100%
IDV(8)	97.75%
IDV(9)	15.88%
IDV(10)	97%
IDV(11)	90.88%
IDV(12)	99.88%
IDV(13)	95.5%
IDV(14)	100%
IDV(15)	30.5%

Diagnosis

This task is realised by the DANNA. It receives massage from the MCCEA that the process is unstable. It was decided to use the MLP neural network with the training algorithm ”Backpropagation”. The inputs data represent the process parameters (52 variables, the agitator speed is constant), and the outputs parameters correspond to the process faults. The input data of the neural network must be normalized (using theoretical minimum and maximum).

Diagnosis of the faults in the TEP

We have done the diagnosis of the known faults, i.e., IDV (1) to IDV (15) in TEP. A network of three layers obtained the best results on the performed tests:

- Input layer: contains 52 neurones that represent the process parameters,
- Output layer: contains 15 neurons that represent the process faults,
- Hidden layer: contains 34 neurones ((52 + 15)/2 = 34).

Table 2 represents a comparison between the diagnosis realised by DANNA and some other approaches that proposed for the diagnosis of the TEP faults. The Bayesian Network (BN) has been used for the faults classification by Sylvain[19]; however the approach proposed by Li & Xiao[22] is a supervised pattern classification method which uses one dimensional adaptive rank-order morphological filter

Identification

The IBNA is the responsible on the realisation of on the identification task. It receives a message about the

Table 2 — Rate of correct classification

The faults of TEP	Classification rate		
	DANNA	Bayesian net [19]	PC1DARMF[22]
IDV(1)	97.01%	97.5%	30%
IDV(2)	95.34%	98.125%	95%
IDV(3)	82.10%	22%	0.00%
IDV(4)	97.34%	82.375%	25%
IDV(5)	96.67%	98%	100%
IDV(6)	100%	100%	65%
IDV(7)	97.67%	100%	0.00%
IDV(8)	100%	97%	5%
IDV(9)	79.06%	22.625%	0.00%
IDV(10)	71.42%	86.875%	15%
IDV(11)	69.1%	75.5%	0.00%
IDV(12)	96.67%	98.25%	5%
IDV(13)	100%	76.125%	5%
IDV(14)	93.02%	98.75%	5%
IDV(15)	92.69%	23.5%	0.00%

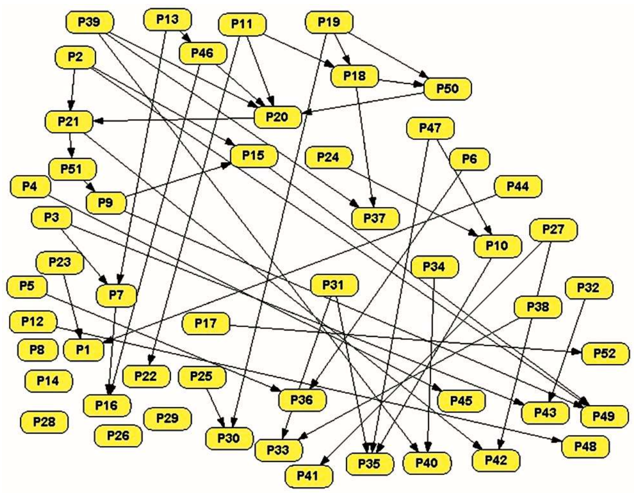

Fig. 3 — The BN used in the development of IBNA

fault that appeared in the process. To develop the BN, we use the approach proposed by Sylvain[19] which is causal decomposition of $T2$. The Figure 3 presents the BN that is created with normal situation of process functionality. We take rate of false alarm $\alpha = 0,005$. The IBNA takes the observation that represents the fault, and then it gives its identification of the variables. All the variables that have probability under to *0,995* are out of control.

Conclusion

The multivariate process monitoring is a complex procedure that is devised into four principal tasks: detection, diagnosis, identification and reconfiguration of the process. For this reason a complete multi-agent system has been implemented. Three principal agents have been developed and equipped with different intelligences. The first agent is: MCCEA which is responsible on the detection task (execution and interpretation of multivariate control charts). The second agent is the DANNA, which utilises the ANN classifier (MLP algorithm) to do the diagnostic of process faults. The IBNA agent exploits the BN that has been proposed by Sylvain[19] to do the identification task. From the development of this system that combines different intelligences, the use of this intelligences diversity enables a system to be able to give an effective detection, a high rate of diagnosis, good variables identification. The proposed model has been evaluated on a multivariate process (TEP). From the simulation results, we find that the proposed classifier gives a good result compared with some works applied to the TEP. The suggested integrated model seems to be effective for process monitoring of the proposed case study and may be used to monitor other similar processes as well. In this work, we have seen that some faults are difficult for detecting, so our future works will concentrate on the development of the detection task. We concentrate also on the adding of the reconfiguration agent which will be responsible on the correction tasks. Our future work will focus on this issue and try to minimize the number of false classification.

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