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Chemical Production Fault Detection Technology Based on Computer Process Control Software

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Chemical production safety is the only way to ensure the economic benefits and development and the life safety of employees in a company. For any company, the safety production is a subject which cannot be ignored. To get early warning of the potential risks, the troubleshooting technology in the process of chemical production is no doubt vital to the modern business. For this purpose, this paper, by ways of literature investigation, comparative analysis and case analysis, and on account of chemical fault detection mechanism model, proposes a chemical production fault detection model with process simulation based on computer process control software. In the other way, the availability and the feasibility of the model also have a sound verification with simulation case analysis.

1. Introduction

The dramatic development of chemical production industry is attributed to the constant growth of the national economy. However, due to the facts that some combustible and explosive chemicals are often used in the chemical production process, and the chemical production process is complicated and highly automated (Yu, 2012), it seems more dangerous to work in this industry and the accidents occurred are generally more severe than those in other industries. Today, the safety of chemical production has aroused people’s wider concern.
Troubleshooting and diagnosis technology, as an important means to ensure the safety of chemical production, can timely detect and diagnose the possible faults occurred in the production process and identify it for isolation (Jiang et al., 2013), thus to ensure the safe operation of equipment, reduce or avoid personal injury and even casuality, as well as property losses, greatly improve the safety and reliability of chemical production.
Currently, the troubleshooting technologies for chemical production include signal processing, knowledge representation and analytical models (Pierri et al., 2008), each of which has its own advantages and disadvantages. In this paper, we build a chemical production fault detection model with process simulation based on the computer process control software by applying the integrated technology of the Aspen Dynamics developed in America and Simulink simulation tool, which derives from the chemical fault detection model based on mechanism model. And beyond that, an experiment is conducted with simulation cases in order to make sure what is the effect this model plays in the chemical production process. This survey can help achieve chemical production process inspection, timely discover the fault source for the sake of safety production.

2. Chemical production fault detection model with process simulation based on computer process control software

2.1 Introduction of fault detection technology

Fault detection technology enables the monitoring of production process to discover the potential risks that may cause accidents in the production, in order to inform staff of relevant information, help them timely take measures against risks, ensure the safe operation of equipment and reduce potential safety hazards (Yu, 2013). Currently, Chemical production fault detection technologies usually include three types, i.e. signal processing, knowledge representation and analytical model.

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The signal processing uses computer to mine data acquired for the purpose of fault detection, no need to depend on operation process and knowledge (Neumann et al., 2003), but this technology is still in its infancy, mainly based on a mass of history data as collected. Not only that, data compression technology has to be further developed. The knowledge-based approach does not require a mathematic model with accurate results, can incorporate some knowledge about experts and process inspection of the diagnostic object model (Liu et al., 2010) to complement each other. In relation to the above two, the analytical model provides a mechanism-based detection technology which can more comprehensively and profoundly detect the mechanism of chemical processes and equipment operations, and has a more extensive application. However, there are still gaps in some respects, such as difficult to modelling, poor university of model, low computer capacity and data storage capacity and poor veracity (Pei et al., 2008), so that it has many limitations in application.

2.2 Chemical production fault detection model with process simulation based on computer process control software

As described above, the main limitation of the mechanism based model is that it is difficult to modelling more accurately. If we can solve this problem and achieve real-time data acquisition and detection on the detection objects, set up a reasonable threshold, a more accurate detection will be available for chemical production faults by analyzing the relationship between the residue error and the threshold.
The state-of-the-art computer technology makes it possible to use chemical engineering software to quickly modelling and improve the computation accuracy. To achieve the dynamic monitoring on chemical production faults and eliminate the limitations of mechanism-based models, this paper, on account of the mechanism-based fault detection technology (Tian et al., 2012), adopts Simulink to implement the dynamic modeling, simulation, comprehensive analysis, data acquisition and calling functions integrated with the dynamic modeling software Aspen Dynamics (Tian et al., 2012), whereby a chemical production fault detection with process simulation based on computer process control software is proposed. The specific monitoring procedure for this model is shown in Fig. 1 (Jiang et al., 2013).

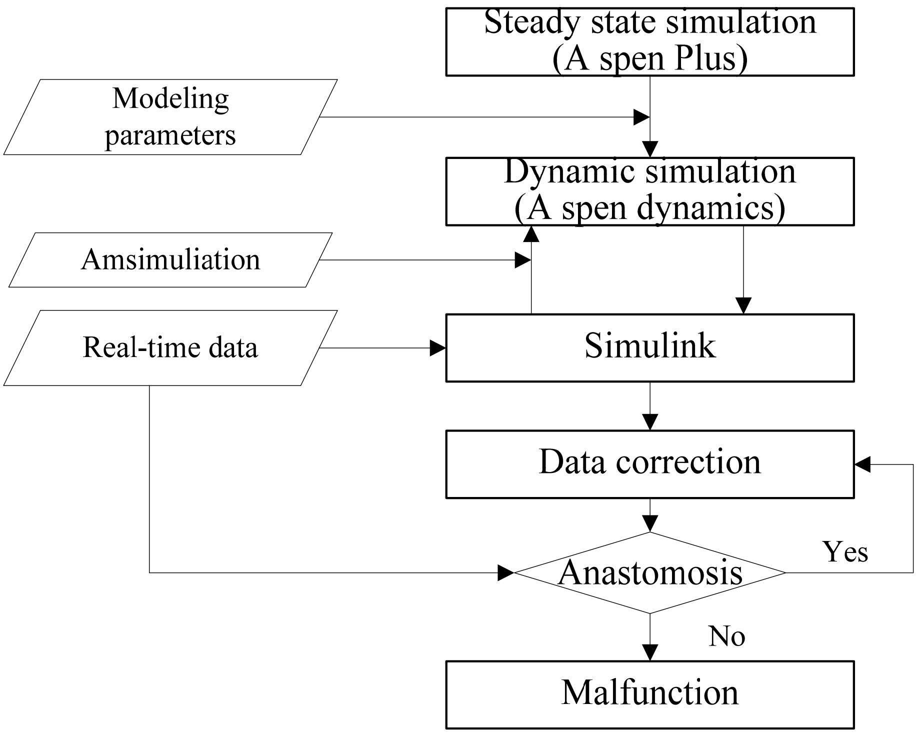

Figure 1: Process failure detection steps

The model mainly includes the following four procedures (Zumoffen et al., 2007): (1) use Aspen Dynamics, a dynamic simulation software, to build an accurate dynamic model for the monitored object. (2) Use Simulink to implement dynamic modeling, simulation and analysis of the environment, the acquisition system of chemical production process can be combined to achieve real-time data acquisition and data correction. (3) Simulink is

used with Aspen Dynamics by data interface, Simulink can timely invoke the Aspen Dynamics model to input and output data on demand in order to complete the fault detection of the chemical production process. (4) According to the comparison between residual error and preset threshold, identify the safety status of the whole production process.
The detection approach also involves the option of two key parameters: (1) inputs, used to analyze that the establishment of the model underlies chemical process surveillance, (2) monitoring, as a key procedure for implementing the surveillance of chemical process, and easy to discover exceptional cases. These two key parameters are chosen by analyzing how they are sensitive to common faults.

3. Analysis of simulation cases

Methanol, as an important organic raw material commonly used in the chemical industry, can be applied to produce formaldehyde, paint, cleaning degreasers, etc. Distillation is one of the major processes for the synthesis of methanol in the industry. In this paper, the simulation process of Formaldehyde water coupled distillation is taken as an study case to test the availiabilty and the feasibility of chemical production fault detection model with process simulation based on the computer process control software.

3.1 Simulation process

3.1.1. Dynamic simulation
The schematic diagram of Formaldehyde water coupled distillation is shown in Fig. 2 (Olivier-Maget et al., 2010), where C1 and C2 are high-pressure and low-pressure columns, respectively; FEED is a mixture of CH_4O and H_2O; D_1, D_2 and $B_{1,}$ B_2 represent CH_4O and H_2O on the top and at the bottom of column, respectively; the flow test can be conducted at the initial state of simulation to further determine the FEED flow distributions in columns C1 and C2, and ends in simulation of coupled rectification. The detailed logistics information acquired in the distillation process can be available from Table 1, which reflects the steady-state operation after the steady-state model is built for the whole process with Aspen Plus. Then the results are imported into Aspen Dynamics in the pressure-driven mode for dynamic simulation. In order to more truly reflect the chemical process, it is required to modify and add the control points in the simulation. In the end, the dynamic simulation is established successfully (Wang et al., 2016).

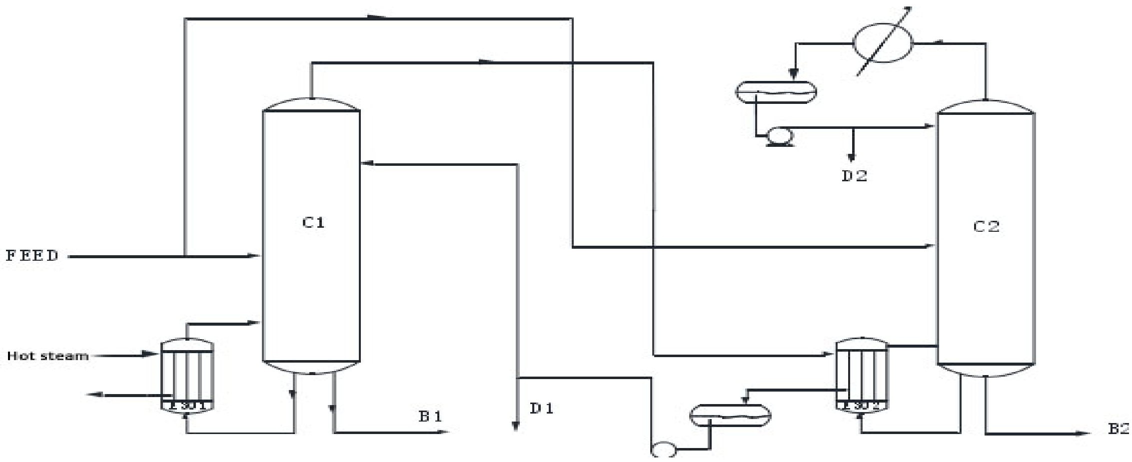

Figure 2: Formaldehyde a coupled distillation schematic

Table 1: logistics information of distillation process

Logistics Name.	Flow/t·h-1	Pressure/kPa	Temperature/°**C**	Methanol (%)	Water (%)
FEED	95.14	810.59	25.0	71.73	26.27
D1	34.26	814.75	111.6	98.67	98.96
B1	12.47	851.55	153.95	1.32	98.68
D2	35.37	368.74	52.66	98.45	1.53
B2	13.01	390.09	90.08	1.27	98.35

3.1.2. Fault data generation

The setting of the faults in this paper uses Task module in Aspen Dynamics (Chilin et al., 2012). The specific procedure is shown in Figure 3. To simulate practical production process in chemical industry and get fault data to verify the fault detection model, two types of faults, i.e. faults 1, 2, 3 and 4, are set up respectively under normal conditions without changes in production conditions and when the production status is adjusted (Lee et al., 2004), see Table 2 for detailed fault information.

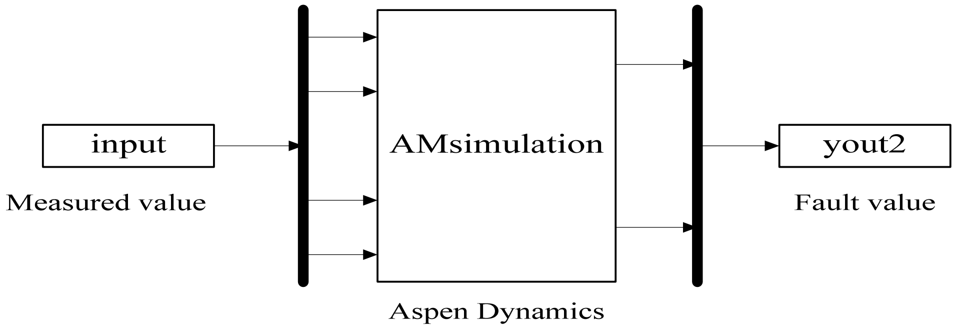

Figure 3: Use simulation program to generate fault data

Table 2: Fault information

Fault	Fault description	Operating status change
1	Logistics FEED leak (24h)	no
2	Logistics FEED temperature decreased by 10	no
3	C2 tower liquid outflow(20h)	Increase logistics FEED traffic(18-28h)
4	R1 / F1 failure	Increase logistics FEED traffic(18-28h)

3.1.3. Fault detection

The Simulink invokes the dynamic model of formaldehyde-water coupled rectification which is derived from Aspen Dynamics, where input data exactly coincides with above fault setting data. The monitoring time is 48 hours and the frequency is 0.1h/time. The basis of fault judgment is whether the measurement values remain above or below theoretical values (Tian et al., 2015).

3.2 Simulation results and analysis

The simulation data monitoring discloses that the faults occurred in reality coincides with those preset in this paper. This paper only describes the fault 1 without changes in production conditions and the fault 3 with the change in production conditions in detail. The detection result of fault 1 is shown in Figure 4. It is obvious that, at 24h, the theoretical value and the actual value show a significant deviation, which is consistent with the preset fault design. It is proved that the model can detect the operation process under normal conditions, that is, the production conditions remain unchaged.

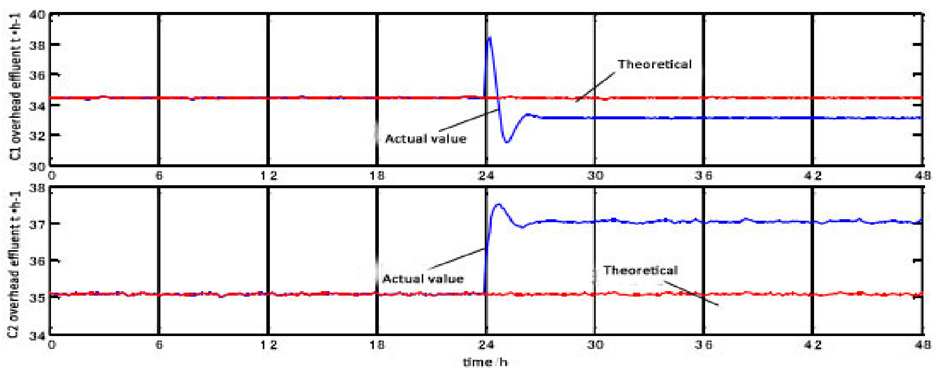

Figure 4: Fault 1 test results

The test results of fault 3 are shown in Figure 5. We can see that when the operating procedures are changed at 18-28h, and logistics FEED flow is increased, the fault occurs at 20-23h. This also coincides with the previous fault settings, However, the other way, when the parameters are changed, the theoretical and actual value fluctuate greatly. It is suggested that the changes of production parameters make the modeling harder. The model overcomes this difficulty after a transient adjustment, which also implies that the model can detect faults occurred when the production conditions change.

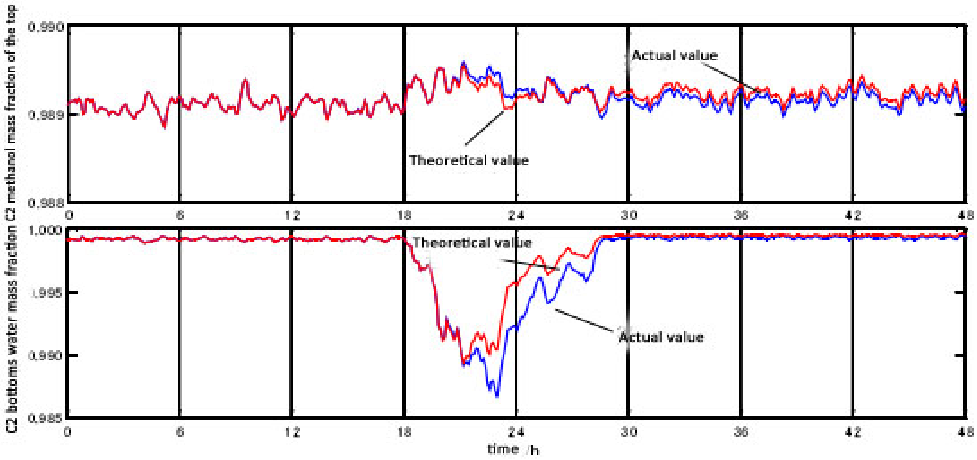

Figure 5: Fault 3test results

4. Conclusion

In recent years, the continuous expansion in the scale of chemical production has exacerbated the safety risks in chemical production. The fault detection technology for chemical production has gradually become a hotspot, while the rapid development of computer technology provides a brand-new perspective for fault detection and modelling in chemical production process.
This paper aims to the application of computer technology in fault detection of chemical production, and put forward a chemical production fault detection model based on computer process control software, by which the following conclusions are drawn:
(1) Based on the comparative analysis of the advantages and disadvantages of various commonly used detection methods, a chemical production fault detection model with process simulation based on computer process control software was proposed.
(2) Dynamic system modeling, simulation, comprehensive analysis, data acquisition and call function were carried out by Simulink simulation tool, combining with Aspen Dynamics to realize the process detection of chemical faults.
(3) With the simulation case of Formaldehyde water coupled distillation, this model has achieved the fault detection in the case when the production conditions are normal and changeable. Then the feasibility and the availability of this model have been proven to be high.

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