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Abnormal Condition Identification for the Electro-fused Magnesia Smelting Process

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Abstract: To improve the performance of the abnormal condition identification, the multi-source information of the abnormal conditions in the electro-fused magnesia smelting process is analyzed in this paper. An intelligent abnormal condition identification method is proposed based on Bayesian network (BN). By analyzing three main abnormal conditions and the experience of the operators, the characteristics related with the abnormal conditions are extracted. The BNs are established to identify the abnormal conditions by fusing the multi-source information. The simulation results show that the proposed method can realize abnormal condition identification, distinguish the degree of the abnormal condition, and obtain better performance.

Keywords: Abnormal condition identification, Bayesian network, Electro-fused magnesium furnace, multi-source information extraction, information fusion

1. INTRODUCTION

The electro-fused magnesia has been applied in a variety of fields, which is an important refractory, such as aerospace industry, cement industry, glass industry, and electric apparatus, etc. In China, the magnesite usually is used as the raw material of the electro-fused magnesia. However, due to the low grade of the raw material and the complex composition, the electro-fused magnesia has to be produced by the special equipment. Therefore, the three-phase ac fused magnesium furnace (FMF) is applied to produce high-purity electro-fused magnesia. The related researches on the FMF have been provided from different angles (Zhang and Zhang, 2011, Dong et al., 2008, Yang and Chai, 2016, Zhang et al., 2010, Wu et al., 2009, Ma and Zhu, 2014).

For the electro-fused magnesia smelting process, the operators adjust the setpoints of the currents based on the different conditions. The control system tracks the setpoints of the current by changing the position of the electrode. When the raw material granule size and the impurity constituent change, the previous setponit will not adapt to the changed condition any more. When the operators do not change the setpoints of currents in time, the abnormal conditions will happen. However, it is very difficult even impossible for the operators to predict the changes of the raw material granule size and the impurity constituent and make the corresponding adjustments. The operators need to make suitable decisions to decrease the high energy consumption and avoid the safety threat when the abnormal conditions happen. Before making the suitable decisions, the abnormal condition identification becomes the very important task. If the abnormal condition can be identified when it is slight rather than serious, it will be dealt with to avoid more serious results. The general thought is to establish the models of the abnormal conditions. However, due to the strong nonlinearity and coupling among the variables, and the existence of random disturbances in the electro-fused magnesia production process, only the qualitative relationship between the abnormal conditions and the all kinds of variables can be obtained. It is very difficult to obtain accurate mechanism models for the abnormal conditions. Until now the abnormal condition identification is carried out by the manual way based on the experience, memory, and knowledge of the operators. The observed information includes the change of the current information, the change of the furnace body colour and the change of the sound signal which is from the arcs between the electrodes and the molten pool. The change of the furnace body colour can be reflected by the image processing. The change of the sound signal can be obtained by the sound signal processing. The manual operation way is susceptible to human errors. The ability of the operators to deal with multi-source information is limited. They always ignore the interactions between the variables and only focus on the main and obvious information. The paper (Zhang and Ma, 2011) proposes nonlinear fault diagnosis methods based on multi-scale contribution plots, which is applied to the process monitoring of the FMF. However, the proposed method cannot identify the fault types for FMF. The identification method based on the current information has been proposed in the paper (Wu et al., 2015). However, the proposed method only can identify the abnormal conditions when they have developed into serious degree, which do not combine the multi-source information.

As an important intelligent tool, the Bayesian network (BN) is effective for the probabilistic knowledge representation and reasoning, especially when the researched background includes a large number of uncertain information. BN has been applied to solve many practical problems (Fienen et al., 2016, Jia et al., 2016, Mujalli et al., 2016, Pascual et al., 2016). When the online information is regarded as evidence, the BN can obtain the posterior probability of the target problem by reasoning. In the electro-fused magnesia smelting process, a large amount of uncertain information exists and the qualitative experience of the operators can be utilized. Therefore, the BN is an effective and suitable method to deal with this problem.

The motivation of this paper is to fuse the multi-source information and obtain the better abnormal condition identification results for the electro-fused magnesia smelting process. Even if the abnormal condition is slight, the proposed method also can identify it, which lays the foundation for the self-healing control scheme to avoid more serious damage. At the same time, the proposed method is more consistent with the practical behaviour of the operators and can obtain more accurate identification results, because the computer replaces the qualitative analysis of the operators. Firstly, this paper proposes a general abnormal condition identification framework based on BN. Furthermore, three main abnormal conditions are analyzed, and the corresponding characteristics of the abnormal conditions are extracted based on the experience of the operators. The BNs are established to identify the abnormal conditions. Finally, the simulation result shows that the proposed method is effective to identify the abnormal condition, which conforms to the practical experience. By the comparison, the proposed method can obtain better identification results than the traditional method which only includes the current information.

The organization of this paper is as follows. Section 2 analyzes the general abnormal condition identification framework based on BN. In Section 3, the electro-fused magnesia smelting process is described. Three main abnormal conditions are analyzed and the corresponding characteristics are extracted. The BNs are established. In Section 4, the simulation results of the abnormal condition identification are shown. Finally, the conclusions are presented in Section 5.

2. THE GENERAL ABNORMAL CONDITION IDENTIFICATION FRAMEWORK BASED ON BN

For the abnormal condition identification, the general framework based on BN is summarized, which includes the following steps.

Step 1: analyze the abnormal conditions, obtain the expert knowledge and collect the related variables.

Step 2: figure out the causal or correlated relationships among the variables and determine the root nodes, the intermediate nodes, and the leaf nodes.

Step 3: BN structure learning.

Step 4: BN parameter learning.

In the step 1, the researched background needs be understood and the expert knowledge needs to be collected by extracting the related variables of the abnormal condition. These variables can be divided into different categories, such as, semantic variables, operational variables, and the variables which characterize phenomena, and so on. In the step 2, all the variables are divided into different layers, which is the base of the BN structure learning. In the step 3, the BN structure learning algorithms can be used to obtain the BN structure based on the data analysis. When the expert knowledge is available for the relationships among the BN nodes, the BN structure can be obtained by the expert knowledge. If only some relationships are known, other relationships are learned by the dataset information. In the step 4, the BN parameter learning algorithms are used to obtain the probability distribution among the nodes, or the conditional probability tables (CPTs) can be obtained by calculating each type of event accounted for the proportion of the overall events. In the end, based on the above steps, the BN is established, and the identification results can be obtained by reasoning.

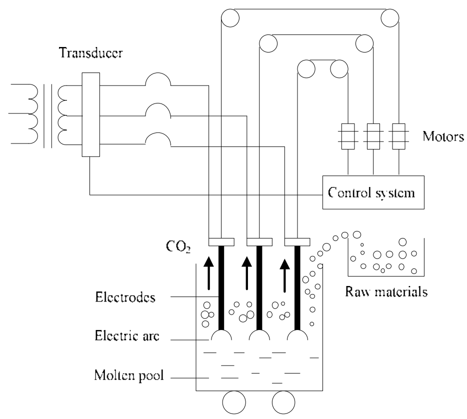


Fig. 1. The electro-fused magnesia smelting process

3. THE ABNORMAL CONDITION IDENTIFICATION OF THE ELECTRO-FUSED MAGNESIA SMELTING PROCESS

In this section, the electro-fused magnesia smelting process will be described in detail. Three main abnormal conditions will be analyzed based on the experience of the operators. The related variables will be determined and extracted. The BNs will be established.

3.1 Process description

The electro-fused magnesia smelting process is depicted in Fig. 1 (Wu et al., 2015). In general, the smelting process mainly includes the following three operating conditions: heating and melting, feeding, and exhausting (Wu et al., 2009). The control process is carried out by the control system tracking the setpoints of the current. For the different conditions, the corresponding setpoints of the current are different. When the abnormal conditions appear, the pervious setpoints of the current will be not suitable. The abnormal conditions will result that a great deal of energy is wasted even the safety threat. The operators have to adjust the setpoints of the current to adapt to the change of the environment and make sure the process run smoothly based on their experience. Therefore, whether the abnormal conditions can be identified or not influences the decisions of the operators on the setpoints of the current. When the abnormal condition is identified by the manual way, the identification results will depend heavily on the experience and responsibility of operators. Therefore, it is necessary to propose a method to identify the abnormal condition, replace the manual way and obtain the better identification results.

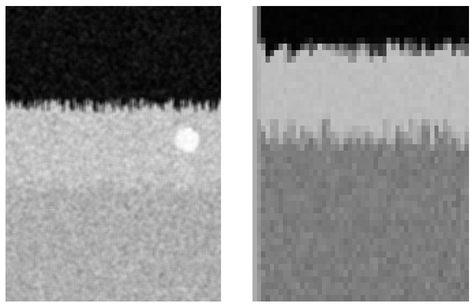
3.2 The analysis of three main abnormal conditions and the characteristics extraction

For the FMF, there are three main abnormal conditions: semimolten condition, overheating condition and abnormal exhausting condition. In the following section, we will analyze three abnormal conditions and the corresponding characteristics.

In the related research results, only the current information is used to identify the abnormal conditions (Wu et al., 2015). However, based on the expert knowledge and the experience of the operators, other than the current information, the operators also observe the changes of the image signal and the sound signal. The main sound sources of FMF are from the arcs between the electrodes and the molten pool. To improve the performance of the abnormal condition identification, the multi-source information should be fused to simulate the abnormal condition identification process of the operators on site. Based on the research results in the paper (Wu et al., 2015), the current tracking errors and the current change rates are chosen to identify the abnormal condition. Therefore, in this paper, we still use these characteristics of the current information. In the following part, the image information and sound information related with the abnormal conditions will be analyzed.

During the heating and smelting, due to the increase of the melting point of the raw materials, the raw materials will not be melted fully using the original setpoints of the current. This condition will lead to the rapid increase of the temperature at some local area of the furnace body and the production of the bright spots, even melting the furnace body. Once the furnace body is melted, the smelting process has to be stopped. This abnormal condition is called as the semimolten condition. The image information of the furnace body can be extracted to identify the semimolten condition. In the image processing, the change of the gradation reflects the change of the brightness. The red component plays the main role in the three primary colours of the image. Therefore, the following image characteristics are chosen to reflect the semimolten condition: the change of the average gradation; the energy in a short time for the average gradation; the change of the gradation variance; the abundance of the gradation; the change of the average red component. Among the characteristics, the abundance of the gradation refers to the percentage of exceeding the average gradation in the normal image signal. Because the position of the bright spots is uncertain, the image of the furnace body is divided into some parts. Above image characteristics are extracted from every part, and the characteristics of the part with the most obvious change will be regarded as the final characteristics to identify the semimolten condition.

During the heating and smelting, when the melting point of raw materials decreases, the molten pool level will rise too fast to satisfy the allowable range of the smelting process. This condition will influence the purity of the product and make the quality decline. This abnormal condition is called as the overheating condition. The temperature of the molten pool is rather high. The brightness of this section is higher than other sections of the furnace body. The change of the molten pool level can be obtained by the image information. Therefore, the following image information is used to identify the overheating condition: the speed of the molten pool level and the abundance of the gradation. By processing the images over a period of time, the speed of the molten pool level can be obtained. During the overheating condition, the operators can hear different sound information compared with the normal smelting process. Therefore, the sound information also can be used to identify the overheating condition. The energy in a short time and the amplitude for the characteristic frequency are used. When the abnormal condition is slight, the sound information plays the main role. When the abnormal condition changes to moderate degree, the sound and the current information reflects the main characteristics. When the abnormal condition changes to serious degree, the sound, current, and image information all reflects the main characteristics. The gradation images of the semimolten condition and the overheating condition are shown in the Fig.2.



(a) (b)

Fig. 2. (a) The gradation image of the semimolten condition; (b) The gradation image during the overheating condition

During the smelting process, a certain amount of CO_2 gas produces in the FMF. The gas needs to be exhausted from the furnace to keep the internal and the external pressure consistent. By moving the electrodes to track the new setpoint, the gap between the raw materials and the electrodes will make the gas out of the FMF. The gap is determined by the particle size of the raw materials. When the particle size of the raw materials changes and exceeds the normal range, the previous setpoint will not adapt to produce suitable gap and exhaust the gas. The pressure inside the FMF will not balance with the atmospheric pressure, even the high-temperature melts will spurt out of the furnace together with the gas. This abnormal condition is called as the abnormal exhausting condition, which will produce serious threat for the equipment and the operators on site. Before the splashing happens, the operators will hear different sound information compared with the normal exhausting condition. Therefore, the sound information can be used to identify the abnormal exhausting condition. Based on the research results in the paper (Fu et al., 2017), the following sound characteristics are chosen to identify the abnormal exhausting condition: the energy in a short time for the splattering characteristic frequency; the amplitude for the splattering characteristic frequency. When the splashing happens, the operators will observe that the high-temperature melts spurt out of the furnace and the brightness of the image in the range of the furnace opening increases. Therefore, the following characteristics are chosen to reflect the abnormal exhausting condition: the change of the average gradation; the energy in a short time for the average gradation; the change of the gradation variance; the abundance of the gradation; the change of the average red component. When the abnormal exhausting condition is slight, the sound information reflects the main characteristics; when the abnormal exhausting condition changes to moderate degree, the sound and the current information reflect the main characteristics; when the abnormal exhausting condition changes to serious degree, the current and the image information reflect the main characteristics.

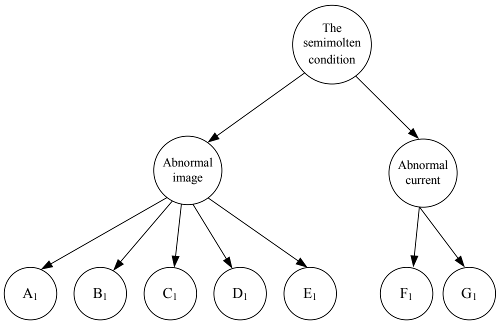


Fig. 3. The established BN for the semimolten condition

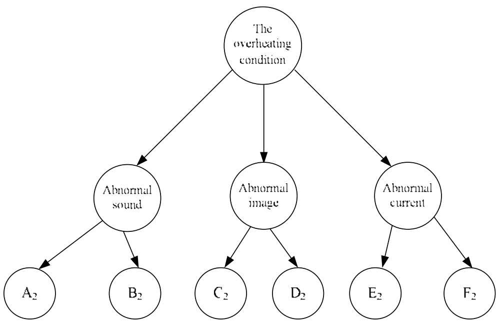


Fig. 4. The established BN for the overheating condition

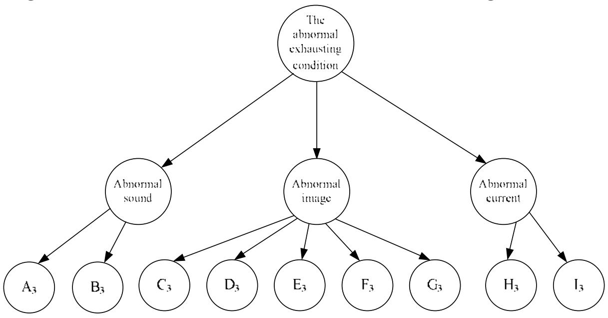


Fig. 5. The established BN for the abnormal exhausting condition

3.3 *The abnormal condition identification method based on BN*

Applying the general abnormal condition identification framework based on BN proposed in Section 2, the BNs can be established for three main abnormal conditions. The extracted characteristics in Section 3.2 are used as the BN nodes. For the structure learning, the relationships between the characteristics and the abnormal conditions are used to establish the structure of the BN, which come from the expert knowledge. For the parameter learning, all the characteristics are divided into different degrees in a qualitative way. The number and the thresholds of the degrees are decided based on the experience of the operators. The CPTs can be obtained by calculating each type of event accounted for the proportion of the overall events. The established BNs are shown in the Figures 3-5, where the meanings of the nodes can be found in the Tables 1-3.

Table 1. The characteristics of the semimolten condition

The multi-source information	The characteristics of the semimolten condition
The abnormal image signal	A_1: the change of the average gradation B_1: the energy in a short time for the average gradation C_1: the change of the gradation variance D_1: the abundance of the gradation E_1: the change of the average red component
The abnormal current signal	F_1: the current change rates G_1: the current tracking errors

Table 2. The characteristics of the overheating condition

The multi-source information	The characteristics of the overheating condition
The abnormal sound signal	A_2: the energy in a short time for the splattering characteristic frequency B_2: the amplitude for the splattering characteristic frequency
The abnormal image signal	C_2: the speed of the molten pool level D_2: the abundance of the gradation
The abnormal current signal	E_2: the current change rates F_2: the current tracking errors

4. THE APPLICATION RESULTS OF THE PROPOSED METHOD

4.1 *The simulation platform*

The simulation platform for the electro-fused magnesia smelting process is designed and constructed in our team, which is shown in the Fig. 6. The simulation platform can simulate the electro-fused magnesia smelting process based on mechanism analysis and actual data. For the simulation platform, we can design and verify the proposed method including the abnormal condition identification, optimal control and safe control for the smelting process. The data in the simulation platform come from the practical production process. Therefore, the verified methods by testing in the simulation platform can be applied in the practical production process. The related equipment includes all kinds of computers, embedded control system, data sever, sensing equipment and transferring equipment. The sensing equipment includes the current detection instrument, the image measuring instrument, and the sound detection instrument. At first, these sensing instruments transfer the collected multi-source signals to the local data sever. These signals are transferred to the simulation platform by the Ethernet in a certain time interval. The collected data is used to identify the abnormal conditions. To avoid the influence of the noise, the related filtering methods are adopted to eliminate the noise in the data.

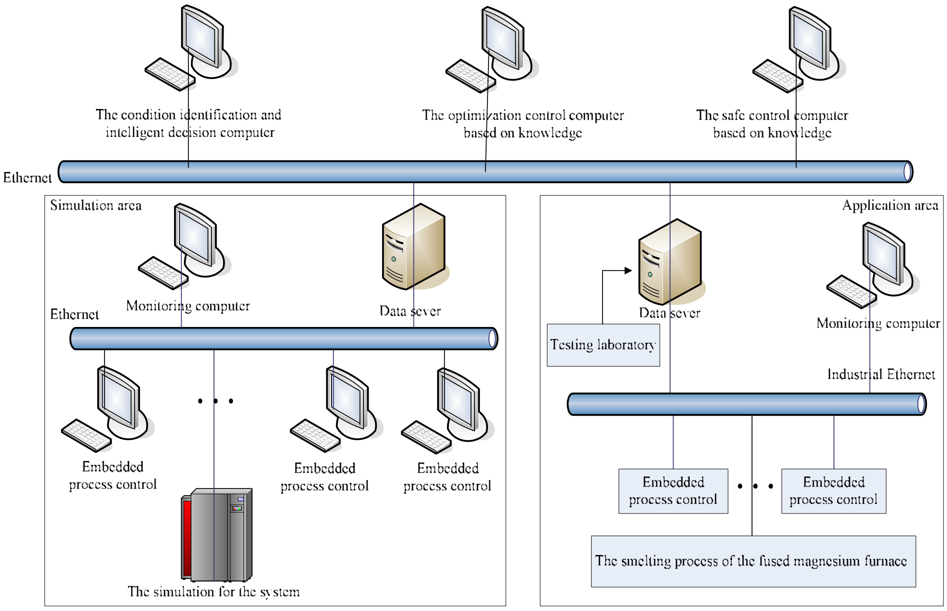


Fig. 6. The simulation platform for the electro-fused magnesia smelting process

In this paper, we use the simulation platform to verify the proposed method.

4.2 The abnormal condition identification results

For the abnormal condition identification, the filtered online data is divided into different degrees to enter the BN as the evidence. By the reasoning, the degree of the abnormal condition with the maximum posteriori probability will be regarded as the identification result. For the sake of limited space, in the following part, we will mainly analyze the identification results of the overheating condition. The processes of the analysis for the semimolten condition and the abnormal exhausting condition are similar to it.

Table 3. The characteristics of the abnormal exhausting condition

The multi-source information	The characteristics of the abnormal exhausting condition
The abnormal sound signal	A_3: the energy in a short time for the splattering characteristic frequency B_3: the amplitude for the splattering characteristic frequency
The abnormal image signal	C_3: the change of the average gradation D_3: the energy in a short time for the average gradation E_3: the change of the gradation variance F_3: the abundance of the gradation G_3: the change of the average red component
The abnormal current signal	H_3: the current change rates I_3: the current tracking errors

For the overheating condition, some possible abnormal scenarios are extracted and shown in the Table 4. Only typical scenarios are considered and other similar scenarios can be analyzed in the same way. In the Table 4, every abnormal scenario includes six characteristics with different degrees. The characteristics are divided into three (or four) degrees. We use the numbers 1-3 (or 1-4) to represent the different degrees. For the characteristics A_2-D_2, we divided them into three degrees: small, medium, and large; the characteristic E_2 is divided into three degrees: small, large, and very large; the characteristic F_2 is divided into four degrees: very small, small, large, and very large. Taking the abnormal scenario 10 as the example, the physical meaning is that the states of the characteristics A_2-D_2 are large; the state of the characteristic E_2 is small; the state of the characteristic F_2 is very large. The listed abnormal scenarios in the Table 4 will be regarded as the evidences to enter the established BN. The identification results are shown in the Table 5. The overheating condition is divided into four degrees: normal, slight abnormal, moderate abnormal, and serious abnormal, which is represented by numbers 1-4. By the analysis of the identification results in the Table 5, it can obtain that the identification results conform to the practical experience of the operators. To reflect the strength of the proposed method, the proposed identification method is compared with the method in the paper (Wu et al., 2015), and the results are shown in the Fig. 7. It can obtain that the proposed method can distinguish the degree of the abnormal condition. When the abnormal condition is slight, the proposed method can identify it, which has better performance than the traditional method and lays the foundation for making effective measures to remove the abnormal condition in advance.

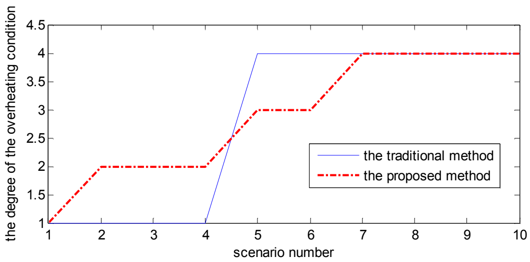


Fig. 7. The identification results of the proposed method and the traditional method

Table 4. Some possible abnormal scenarios for the overheating condition

Scenario number	A_2	B_2	C_2	D_2	E_2	F_2
1	1	1	1	1	1	1
2	2	2	1	1	1	1
3	3	3	1	1	1	1
4	3	3	1	1	1	2
5	3	3	1	1	1	3
6	3	3	1	1	1	4
7	3	3	2	2	1	3
8	3	3	2	2	1	4
9	3	3	3	3	1	3
10	3	3	3	3	1	4

Table 5. The identification results of the abnormal scenarios

Scenario number	1	2-4	5-6	7-10
Identification result	1	2	3	4

5. CONCLUSIONS

This paper proposes an intelligent abnormal condition identification method for the electro-fused magnesia smelting process by fusing the multi-source information. The simulation results show that the proposed method is effective to identify the abnormal condition, which owns better performance than traditional method which only includes current information. The obtained identification results with different degrees lay the foundation for making the elaborate safe control scheme.

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