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Fault Diagnosis and Fault Propagation Traceability of Chemical Process Based on Complex Network Method

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Abstract: In order to ensure the safe production of chemical handicrafts, it is necessary to monitor the process variables of the chemical system in order to deal with the failures. In order to improve the accuracy and accuracy of the monitoring process, the whole process is modeled to find out the key variables that cause the fault, and at the same time, the impact of the key variables in the system is analyzed to find out the propagation path of the key variables. Based on the complex network theory, the fault node set is obtained by combining the measured data with the horizontal visibility map; At the same time, the fault propagation complex network is constructed, and the fault propagation source node is identified according to the topology characteristics of the complex network. A traceback algorithm is proposed to determine the propagation path of the source node; The importance ranking (IR) is used to quantify the impact of the propagation path on the system and focus on monitoring the key nodes in the path. By taking the Tennessee Eastman process as the verification object, the results show that the method can identify the occurrence of the fault and control the propagation path of the fault, which proves the effectiveness of the method.

1. Introduction

The production hazard factors related to the chemical production process include hazardous chemicals, production process and operating conditions requirements, and the increasingly wide application range of large-scale and automatic continuous equipment, which are all important factors leading to the occurrence of production failures in the chemical industry. The operating conditions (temperature, pressure) commonly used in chemical processes may represent risks and may lead to deviations, which may lead to hazardous events. Plant equipment, including pumps, compressors and control equipment, may fail even with correct maintenance policies [1]. The failures of chemical systems are often not easy to detect, so fault diagnosis of chemical production has become an important tool to ensure the safety of enterprises, and has always been a hot topic of research. After decades of development, the fault diagnosis process technology has combined the research contents of many fields; The current fault diagnosis technology includes: data-driven method [2], analytical model-based method [3,4] and qualitative knowledge-based method [5,6].

The huge structure and production process of industrial system make it more and more difficult to describe the system operation and fault conditions; On the other hand, the complex characteristics between faults in industrial engineering set obstacles for fault diagnosis path diagnosis. For the problems caused by these factors, complex network can realize the topology analysis of device variable attributes and complex interaction system. Complex networks, as a powerful tool to describe the relationship between multiple process variables in complex systems, are widely used in psychology, electricity, social networking, disease transmission, meteorology and other aspects [7-12]. In practice, most of the research on complex networks is to simply abstract many individuals into a single node, so as to discuss their various nonlinear functions and connections [13]; This method cannot reflect the correlation structure between them in time and space, and multi-layer network can meet this requirement. As a hotspot of research in recent years, multi-layer network takes into account the relationship between various types of nodes and connections, and reflects its differences by abstracting different types of nodes and connection modes into different network layers [14]. At present, the research on multi-layer network includes the theoretical research of multi-layer network, the propagation of multi-layer coupling network, and the time series network. The multi-layer network composed of a single network changing with time is called a sequential network [15]. The study of time series network is applied to the situation that a single network changes with time. With the evolution of time, the structural relationship between nodes and connecting edges in the network will also change when the system changes and extends to the fault due to some factors.

Fault propagation is a kind of distributed diffusion behavior [16], which is very common in the actual system. When a component fails, it will quickly spread to other components through the boundary; There are several fault propagation paths from one component to another, and there are many factors affecting the fault propagation behavior. The models describing fault propagation include petri nets [17], cellular automata [18], complex network topology models [19], etc; These analysis methods focus on different factors affecting the propagation of the evaluation indicators describing the behavior of fault propagation, but at present, the impact of these factors on the dynamics of fault propagation is difficult to define. The research results in recent years show that there is a linkage relationship between the scope of fault propagation and key components [20], that is, in the fault propagation model, in addition to affecting adjacent nodes, it will also affect some distant important nodes in some ways. At present, the traditional model of fault propagation is mainly to study the relationship between the fault probability and the maximum withstand threshold of the circuit [21]. we should also find out the critical path of fault propagation based on the impact of the fault, and focus on monitoring the key nodes on the critical path and the propagation source nodes of the fault, so as to improve the accuracy of diagnosis.

The focus of this paper will be on fault diagnosis and fault propagation path tracing. By introducing the data mapping method with time series characteristics, the horizontal visibility algorithm can be used as the mapping between time series and complex networks, and can distinguish the randomness of time series; The numerical simulation experiment shows that even in the case of a large amount of noise, it is not necessary to use the method of replacing data or reducing noise [22]. The data-driven method is used to build complex network model for fault identification and internal volatility transmission analysis;

Use the horizontal visibility diagram to map the time series data to the single-layer network. After establishing the model, use the fluctuation degree of network correlation reflected by mutual information to identify the fault, and use the identified results and the relevant network characteristics of the complex network to find the node most affected by the fault; The backtracking algorithm is used to analyze the transmission fault error of sum importance ranking (IR) to find out the most seriously affected link and node set, and finally play a role in improving the fault detection accuracy.

2. Generation of complex networks

2.1 Complex network composition of case 1

Tennessee-Eastman process (TE) is a simulated chemical process, often used as a case of fault diagnosis. Its process model is derived from the simulation program of a chemical plant. The process model is divided into five parts, including reactor, condenser, compressor, separator and stripper. The main components of this reaction are the addition of A, C, D and E to produce products G and H, as well as by-products F and inert substances B.

The process includes 12 operation variables and 41 measurement variables; Among the measured variables, there are 22 variables that can be continuously measured; Their types include temperature, pressure, liquid level, etc. The fault types mainly include four types, with a total of 21 types. The 22 continuous observation variables in Case 1 are regarded as the basic elements of the network.

2.2 Complex network process data of case 1

The network model constructed above is a directed weighted network. Generally, when considering the weight and direction of the network connection, the network is divided into: undirected weighted network, undirected weighted network, directed weighted network and directed weighted network.

Complex network is a scale network with complex topological characteristics and dynamic behavior based on points and edges [23]. In general, the topological structure and characteristics of complex networks can be described by statistical methods, such as degree distribution, clustering coefficient, shortest path, etc.

The dynamic behavior of the network can be reflected by the process time data. For example, considering the problem of calculation accuracy, 200 data of the normal operation state of 22 continuous observation variables and 200 data observed after the introduction of fault are extracted as the basis of fault detection research.

2.3 Construction method of fault propagation complex network in case 1

In order to study the influence of faults on different parts of the system and the tracing of fault transmission, it is necessary to establish a complex network of fault transmission as the basis of research.

The characteristic of complex networks is that through the statistical physics characteristics of graph theory, it focuses on describing the structure of each basic constituent element in a simple way, and is more inclined to represent the relationship structure of complex systems.

In order to reflect the dynamic correlation of the system itself, the randomness of fault transmission and other factors, data mining is a solution. Mining the comprehensive information in the system, using a new form of expression (complex network model) for subsequent analysis, and finally reaching the purpose of deeper understanding and analysis.

In order to complete the construction of fault propagation complex network; A group of time series data of a single variable in a certain state for a period of time is regarded as the attribute of a single observation variable. The time series data is abstracted into a single layer network using the horizontal visibility graph method; At the same time, according to the correlation of different single-layer networks, the matrix is constructed to represent that the whole system is in a sequential network.

3. Fault diagnosis

3.1 Horizontal visibility diagram of fault propagation complex network

The horizontal visibility graph method is a graph method that describes the change trend of the variable in a period of time by taking a measure with time series characteristics as a period of time.

This kind of method was first proposed by Lacasa et al. as a fast and simple mathematical method to map the time series into the network, called visibility graph [24]. Its definition is that for any two time segment in the time series.

The two samples are considered visible and are called the two connected nodes of the visibility graph.

Fioriti et al. proposed a new visibility graph algorithm called horizontal visibility graph method [25] based on the above algorithm and through modification and adjustment.

This graph method reflects the changes of variables in the form of matrix. After selecting the measurement unit of unit time interval, the variable itself is specified to be network generated. After meeting the definition of visibility, the attributes of the measured variable are saved in the matrix.For measured variables, the matrix storing relevant information is defined as a single-layer network. Every system composed of M variables will have M single-layer networks. The research of correlation between multiple single-layer networks needs to study the degree distribution within each single-layer network in order to obtain the correlation information between them.

Set the data sample length of each single-layer network as S, randomly select two single-layer networks k and j,As a basic concept of complex network, degree refers to the number of edges between nodes and other nodes in the network.

In Example 1, there are 22 continuous observation variables in total. Under the condition of normal operation of the system, the 11th variable product separator temperature and the ninth variable reactor temperature generate the adjacency matrix of the single-layer network according to the definition of the horizontal visibility diagram, and the matrix specification is 200*200.The degree distribution of single-layer network refers to the number of edges connected by nodes in the network matrix formed by each variable. This indicator can reflect the internal correlation of the network. The intra-layer degree distribution of the single-layer network of variable 9 is defined as the expression, where is the degree of the single-layer network of variable 9; The degree distribution collects the degree of each node in the single-layer network.

3.2 Node mutual information of fault propagation complex network

In order to quantify the connection mode of different nodes in the system, two different single-layer networks with the same data samples will be used: the two single-layer networks have the same number of nodes. The degree values of different nodes are related to the topology of the single-layer network. Taking variable 9 as an example, the degree distribution of the single-layer network is as Figure 1 follows:

The algorithm in the above formula is based on the probability distribution function of X and Y, and calculates the relationship between their joint probability distribution and independent probability distribution to determine the relationship between them. In [26], it is proposed to use the degree correlation between single-layer networks to calculate the mutual information of single-layer networks.

The calculated mutual information is the weight of the edge of the fault propagation complex network. The edge weight value between the two nodes of the fault propagation complex network represents the tightness of the connection between the two nodes, and can also represent the degree of influence between the nodes.

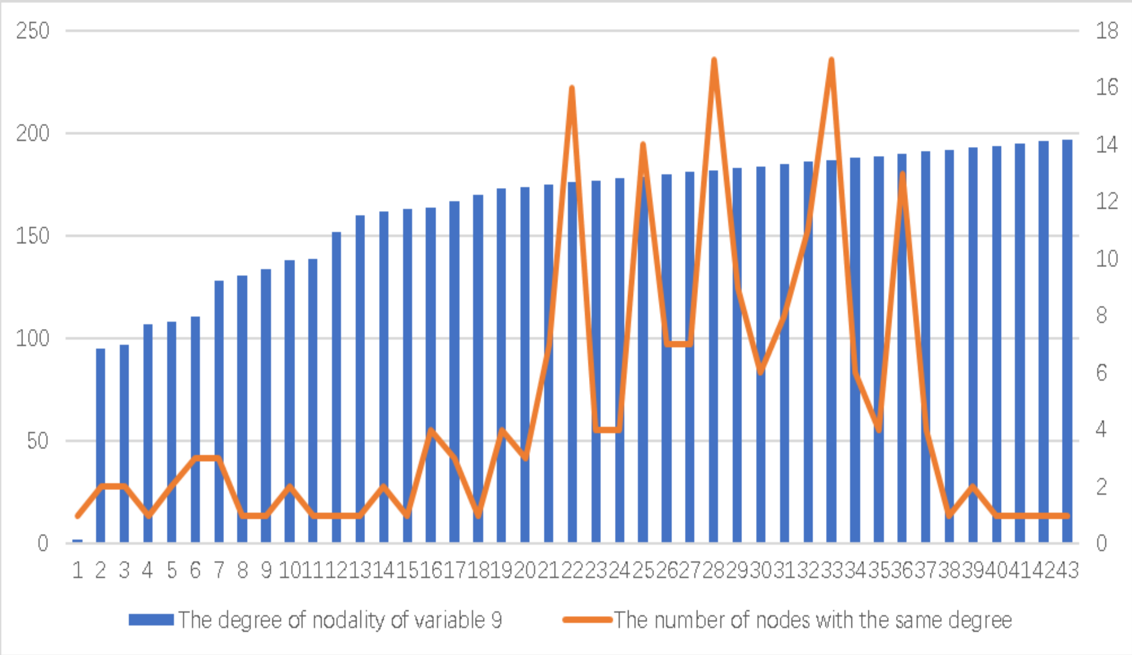

Figure 1: Degree distribution for a single-layer network.

3.3 Judgment matrix of fault propagation complex network

According to the work in the above chapters, use Example 1 to build a complex fault propagation network.

First, calculate the mutual information of the correlation matrix of each node, taking node 22 as an example; Nodes connected to node 22 include nodes 9, 11, 16, 18, 20, and 21.

According to the definition of visibility graph, the single-layer network matrix of multiple nodes can be obtained. This process is realized by matlab programming. First, the degree distribution of the single-layer network is calculated, taking node 22 as an example: after the visibility graph algorithm

After processing the data under normal operation, The 200 data recorded after the introduction of the fault are processed to obtain a new single-layer matrix; The fault type introduced here is a step fault with the number of 3, which is the change of the temperature of logistics D. The degree distribution of single-layer matrix under fault condition is also obtained. Calculate the mutual information between nodes according to the formula.Combine the degree distribution of all nodes in the correlation matrix of node 22 to form a 7 * 200 matrix. Calculate the mutual information of connecting nodes one by one according to the sequence. The calculation process is realized by matlab.Similarly, the mutual information between other nodes in the system network is calculated as the edge weight of the complex network for fault propagation.

Solve the mutual information in the correlation matrix of each node in the normal state, and calculate the variance of the mutual information in the matrix under the two states. The ratio of the calculated different correlation coefficients is formed into a proportion matrix, which can reflect the change trend and degree of the system process variables in the unknown state and the correlation information in the normal operation state.By calculating and comparing the change trend of different node variables in the scale matrix, the most significant type of node is the node that is most likely to cause failure.After calculation, the corresponding variance of node 22 under normal operation is 0.03356; The corresponding variance in the unknown test state is 0.398238. The relative coefficient of node 22 is 0.077721.

Similarly, the relative coefficients of all nodes in the whole network can be determined. The meaning represented in the following figure2 is the change of variance in the normal state and the detection state. Sum the two, take the variance in the normal operation state as the numerator, and the sum of the two as the denominator to obtain the relative coefficient. The smaller the relative coefficient is, the more obvious the change of the variable in the detection state is compared with the normal state. The system is in a stable state under normal operation, and the single-layer network structure of all nodes is in a relatively stable state. If a fault occurs, it will have a direct impact on the data, and the data change trend will inevitably have a certain degree of change trend; Therefore, compared with other nodes, the relative coefficient of fault nodes will have more obvious fluctuations.

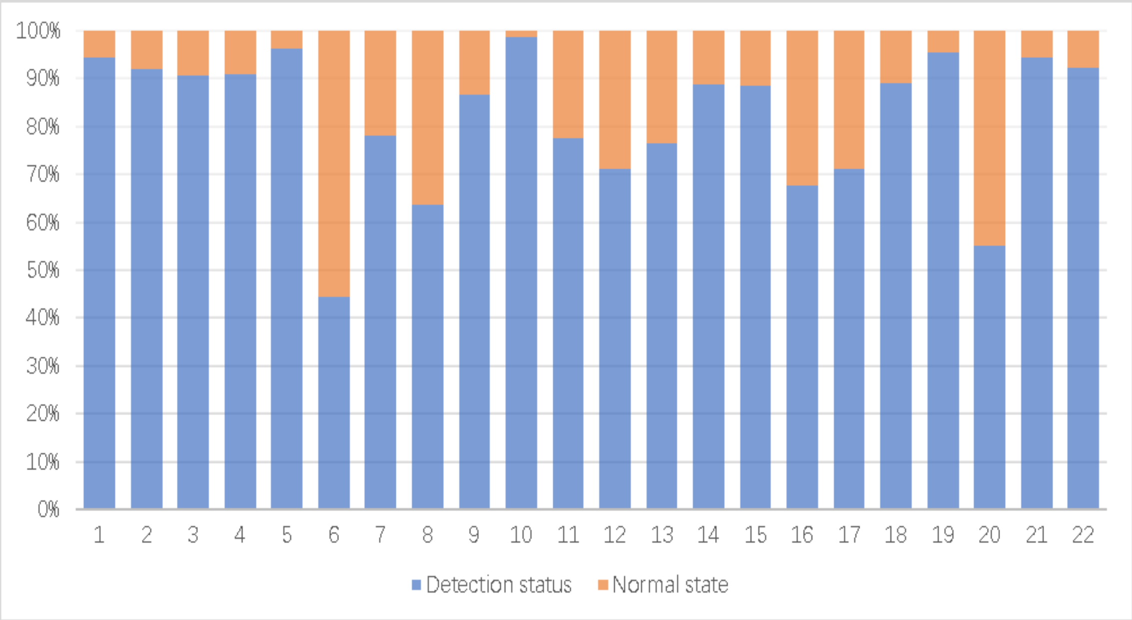

Figure 2: Status detection results for variable 22.

3.4 Fluctuation results of fault propagation complex network

According to the above definition and analysis of the figure, it is obvious that the nodes with obvious fluctuations include nodes 1, 2, 3, 5, 10, 19, 21 and 22. According to the specific quantitative numerical analysis, it is found that the node with the most obvious fluctuation is node 10. That is, node 10 is the node with the largest change in the topology of the single-layer network of all nodes after the fault is introduced. This method effectively identifies the fault; At the same time, the fault node set is obtained.

4. Fault path propagation and tracing

4.1 Topological characteristics of complex network with fault propagation

When the fault actually occurs, it will spread through different paths, thus spreading the impact of the fault to the entire network. The statistical characteristics of complex networks can reflect the characteristics of nodes. After identifying the faults of complex networks, find out the key source nodes that transmit the faults, and trace their location in the network and the impact caused by the fault propagation path, so as to realize the quality control of production and processing links.

In the previous chapter, the result of fault diagnosis can be obtained, which reflects the impact of the node during the fault occurrence; At the same time, it is necessary to consider the application of complex network systems to the interaction between components, and take into account some relevant characteristics, such as degree, degree distribution, clustering coefficient, community structure and other factors; The entropy weight method is used as the standard to measure the importance of these factors. The degree distribution of nodes, CLD clustering coefficient and fault diagnosis results can be selected as the important basis to measure the critical fault nodes.

At the same time, the relative coefficient of nodes in the previous chapters is taken as the influence of network fault propagation; The smaller the value of the relative coefficient, the greater the degree of the measured node affected by the fault.

In combination with the influence effect of neighboring nodes in the network, the fault transmission effect between nodes, and the influence degree of the nodes' own faults, the entropy weight method is used to select the nodes with higher efficiency and greater impact on the fault propagation and select the node set of the fault propagation source, so as to prepare for the fault tracing of the complex network with fault propagation.

Standardize the edge weights of the constructed fault propagation complex network, and use the min-max standardization method to process the data to obtain the standard fault propagation complex network.

4.2 Propagation node set of fault propagation complex network

In case 1, it is detected that nodes 1, 2, 3, 5, 10, 19, 21 and 22 should be faulty nodes compared with other nodes. These nodes form a set of fault nodes. In order to improve the efficiency and accuracy of studying the fault propagation path, we must take the network topology property as an important parameter to select the fault propagation source node. In this paper, CLD clustering coefficient and node degree are selected as important reference for selecting propagation source nodes.

Consider them as a set, and calculate their CLD coefficients and node degrees respectively. The results are shown in the following table.

In the solution process, it was found that the number of nodes connected to node 19 was too small to meet some characteristics of the propagation source node, so 19 was removed from the set.The results are shown in the table1

Table 1: Assessment of key nodes.

Node name	CLD clustering	Node degree	Relative
1	13.1379	2.233503	0.055123
2	13.2826	1.995765	0.081444
3	13.8553	1.662538	0.094188
5	10.5987	0.949855	0.037177
10	17.9122	1.844555	0.014696
21	15.0812	1.835239	0.05729
22	21.9144	3.617122	0.077721

Use the entropy weight method Empower indicators，The weight of the final CLD coefficient is 0.2305; The weight of node degree is 0.1976.The weight of the relative coefficient is 0.5719. Finally, the fault propagation node set is selected according to the selected indicators for comprehensive evaluation. Since the positive indicators are used, nodes 1, 10, 21 and 22 are used as the propagation source nodes for fault tracing.The results are shown in the table2

Table 2: The comprehensive score of the fault propagation node.

Node name	score
1	0.221853
2	0.148806
3	0.119243
5	0.162228
10	0.787247
21	0.225104
22	0.450628

4.3 Tracing algorithm for complex network of fault propagation

The node seriously affected by the fault was detected in the previous work. Considering the connection and strength between nodes, the propagation strength of fault nodes will gradually decrease with the expansion of the propagation loop; In the process of fault propagation, the relationship between its propagation intensity and the distance of propagation is a power-law decreasing relationship [20]. Generally, the fault propagation range is defined according to the threshold of the fault propagation probability [29]. Considering the size of the network and the accuracy and accuracy of the fault propagation calculation, the propagation step t of the fault node is defined as 3.In the previous chapters, nodes 1, 10, 21 and 22 are propagation nodes through calculation; Taking node 1 as an example, the propagation path of node 1 can be found according to the adjacency matrix above. First, the propagation intensity L of nodes 6, 7, 9 and 10 connected to node 1 is calculated; Through calculation, the maximum propagation intensity of node 9 is 0.9296; Next, continue the above process for nodes 8, 11, 18, 21, and 22 connected to node 9, and the node to be propagated is 8; Node 8 is connected to node 7, and the final node for propagation is 7.

For other nodes, use the same method; The propagation paths of all propagation nodes are shown in the following table 3:

Table 3: The propagation path of all propagation nodes.

propagation path	Propagation node	Step 1 node	Step 2 Node	Step 3 Node
Path 1	1	9	8	7
Path 2	10	21	11	22
Path 3	21	11	22	18
Path 4	22	11	18	19

Calculate the IR value of nodes in the propagation path, and use the formula to calculate the node ranking in each path as shown in the following table. It can be seen in Table 4 that the node IR value of propagation path 1 with node 1 as the propagation source node is significantly higher; It can be seen from the table that the key propagation paths are 1-9-8-7 and 10-21-11-22. The impact of 21-11-22-18 and 22-11-18-19 on the whole system is not so obvious compared with the former; The ranking of path communication influence should be path 1, path 2, path 4, and path 3. Among them, the node variables on path 1 and path 2 need to be monitored, and path 3 and path 4 have less profound impact on the subsequent node propagation than path 1 and path 2; For path 3 and path 4, the propagation nodes overlap, which indicates that the node has been affected many times, and this type of node should be monitored. Finally, we can get two sets of loop and node variables for key monitoring [9,8,7,21,12,18].

Table 4: The value of the node IR in the propagation path.

propagation path	Step 1 node	IR	Step 2 Node	IR	Step 3 Node	IR	Average IR
Path 1	9	1.7910	8	0.6755	7	2.6929	1.720
Path 2	21	0.6783	11	0.9707	22	1.4370	1.029
Path 3	11	0.2450	22	0.3627	18	0.7263	0.445
Path 4	11	0.2898	18	0.8590	19	0.2133	0.454

5. Conclusion

In this paper, we use the theory of complex network, combined with the specific chemical process characteristics of the case, and use the horizontal visibility graph algorithm and network model to do network fault diagnosis; At the same time, the weight value of the constructed fault propagation complex network is given.

It is proposed to combine the topological characteristics of complex network with the fault diagnosis results, and calculate the fault propagation node set by using entropy weight method.

The fault propagation node set is regarded as the source node of the fault propagation. The fault tracing algorithm is used to identify and evaluate the influence of the propagation path in the constructed fault propagation complex network, and select the path and node to be monitored.

The feasibility and effectiveness of the proposed method are verified by studying the different operation states of typical chemical models, which provides a certain degree of theoretical basis for the safe operation, monitoring and control of chemical production process.

In the next step of research work, in view of an actual chemical production case and considering the network formed by adapting to a larger production system, consider forming a community with a key node as the core in the node cluster of the complex network, change the basic unit of fault propagation into a community, and the transmission process of the fault will first spread within the community, and then transfer to the next community. By studying the community, it is helpful to simplify the steps, reduce the amount of calculation, and improve the efficiency and accuracy.

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