Sensor Optimal Configuration Method for Sensor Fault Detection

Wen Yang
Key Laboratory of Space Launching
Site Reliability Technology
Xichang Satellite Launch Center
XiChang, Sichuan, China
whutyw@126.com

***Abstract*—For the limited number of sensors, an optimized sensor configuration method for sensor fault detection is proposed. By defining the concept of the sensor information redundancy and its measurement, the performance evaluation criteria for different configuration modes are given, and a sensor optimal placement strategy for ensuring maximum information redundancy is designed. The estimation of the number of sensors satisfying the minimum estimation requirement for the unmeasured state is given.**

***Keywords*—Sensor Optimal Configuration, fault detection,**

I. INTRODUCTION

In power, chemical, and manufacturing systems, a large number of sensors need to be deployed or configured for measurement and control [1]. Due to many reasons, the sensor may malfunction, manifested as a failure, decreased accuracy, drift, and stuck [2]. Different sensor configurations have different effects on the sensor's own fault diagnosis [3]. It is particularly important to consider the fault detection of sensors during the system design stage. The optimal configuration of sensors discussed in this article mainly analyzes different configuration schemes from the perspective of sensor fault diagnosis. Compared with classic fault diagnosis, the research on the optimal configuration of sensors is still relatively preliminary, and the theory is immature [4]. Part of the research work starts from the description of the structure of the system under test and selects the smallest sensor set by analyzing the contribution of sensors to diagnosability[5-7]. However, these methods lack a quantitative description in evaluating the contribution of sensors. For this reason, people have proposed a variety of quantitative evaluation methods based on cross-entropy (Kullback-Leibler, K-L) divergence, which calculates the log-likelihood ratio, and combines hypothesis testing to quantify the data, thereby quantifying the system's diagnosability[8,9]. Redundant information between sensor measurements is the basis of sensor fault detection. If more redundant information can be obtained under limited sensor conditions, it will be more conducive to sensor fault detection [10]. There is a kind of network system, such as a power grid, HVAC, water network, gas network, and so on, which always satisfies the material and energy balance in the operation process. A large number of sensors are deployed in such networked systems. Although the physical attributes and dimensions measured by these sensors are different, the measured values of these sensors can be equivalent to energy units through certain transformation, and corresponding constraints can be established, which can be used for sensor fault detection [11,12].

The rest of the paper is organized as follows. In section II, we will introduce the energy network model and formal description. In section III, We will present the concept of the sensor information redundancy and its measurement, the performance evaluation criteria for different configuration modes are given. The sensor configuration strategy to maximize measurement redundancy will be discussed in Section IV. In section V, we will propose the new method that how to determine the number of sensors that meet the minimum estimation requirements. Finally, we discuss and conclude in Section VI.

II. ENERGY NETWORK MODEL

According to the characteristics of energy transmission, conversion, and distribution in the physical system, a physical system is modeled as a directed graph $D(V;A)$. Among them, the nodes $v \in V$ of the graph correspond to the equipment that transforms and distributes energy in the physical system. The edges $a \in A$ in the figure correspond to various pipes for energy transmission in the physical network, such as cables, liquid Tube, etc. The direction of the edge corresponds to the direction of energy flow. w is a real-valued function on A, called the weight function of D, and its value is the amount of energy flowing on the edge $w(a)$.

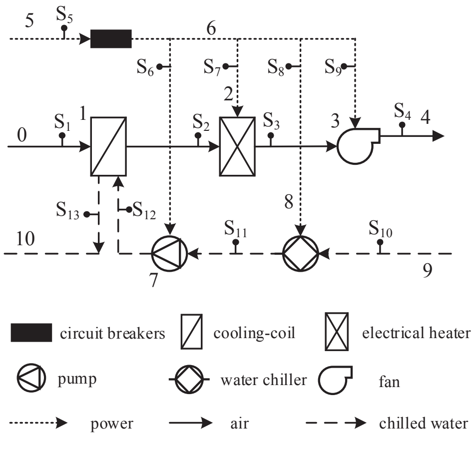

Fig .1. The physical network of air conditioning system

Fig1 is a structural diagram of a typical air conditioning system, including air supply, water supply, power supply, and other subsystems, consisting of 6 types of equipment including water pumps, fans, cooling-coil, electrical heater, water chiller, and circuit breakers. In addition, the system has 13 sensors. Among them, S_1~S_4 measures the heat and mechanical energy contained in the air, S_5~S_9 measures the electrical energy delivered to the air conditioning equipment, and S_{10}~S_{13} measures the chilled water cooling capacity and mechanical energy. According to the above modeling method,

2020 Chinese Automation Congress (CAC) | 978-1-7281-7687-1/20/$31.00 ©2020 IEEE | DOI: 10.1109/CAC51589.2020.9327092

circuit breaker and air-conditioning equipment as the nodes of the network, and the cables, water pipes, and air ducts as the edges of the network, and then the corresponding energy network is obtained as shown in Fig 2.

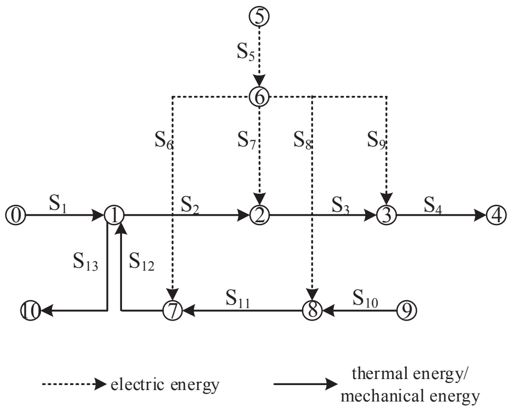

Fig .2. The energy network of air conditioning system

The network $D(V;A)$ can be described by an incidence matrix $Q_a=[q_{ij}]\in\mathbb{N}^{(n-k)\times b}$, Among them, n is the number of network nodes, k is the total number of source nodes and sink nodes in the network, b is the number of edges in the network, $n-k$ represents the number of intermediate nodes in the network. The value range of a_{ij} is 1, -1, 0, and the specific rules are shown in (1).

$$a_{ij}=\begin{cases}1, & \text{edge } a_j \text{ is associated with node } i \text{ and its direction} \\ & \text{starts from } i; \\ -1, & \text{edge } a_j \text{ is associated with node } i \text{ and its direction} \\ & \text{is pointing to } i; \\ 0, & \text{edge } a_j \text{ is not associated with node } i.\end{cases} \tag{1}$$

According to the law of conservation of energy, the energy flowing into the node is equal to the energy flowing out of the node. Therefore, for the node i , there is

$$\sum_{j=1}^{b} a_{ij}x_{ij}=0 \tag{2}$$

where, x_{ij} is the energy transmitted between nodes i and j .

III. Redundancy of Sensor Measurement

According to the energy balance between input and output of nodes, the balanced relationship between sensor measurements in the network can be established in different numbers and forms. However, the balanced relationship is closely related to the number and deployment location of sensors. Even if the number of sensors is the same, the redundant information obtained by different installation locations is different. Therefore, it is necessary to define criteria for evaluating information redundancy in different configurations. Now, we discuss the problem of information redundancy on the basis of node association edge. For a given network, if the number of edges of the network is b , the number of sensors is m , the total number of source nodes and sink nodes is k , and $g=n-k$ is the number of common nodes in the network. Under the condition of complete measurement, that is $b=m$, and according to the node energy balance (2), the sum of the product of each row of the incidence matrix and the measured value of the corresponding sensor is 0. The measured value vector of each side of the network is defined as $\boldsymbol{x}=\left[x_1,x_2\cdots,x_b\right]^{\mathrm{T}}$, so g equations can be constructed and written in matrix form as below.

$$\begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1b} \\ a_{21} & a_{22} & \cdots & a_{2b} \\ \vdots & \vdots & \ddots & \vdots \\ a_{g1} & a_{g2} & \cdots & a_{gb} \end{bmatrix}\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_b \end{bmatrix}=0 \tag{3}$$

If $m<b$, that is, only m edges can deploy sensors in the network, m edges can be selected from b edges for sensor deployment. So there are C_b^m different deployment modes. Without loss of generality, assume that the sensor is deployed on the edge corresponding to the last m column of the matrix $\boldsymbol{A}$, (3) can be rewritten as

$$\begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1(b-m)} & a_{1(b-m+1)} & \cdots & a_{1m} \\ a_{21} & a_{22} & \cdots & a_{2(b-m)} & a_{2(b-m+1)} & \cdots & a_{2m} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ a_{g1} & a_{g2} & \cdots & a_{g(b-m)} & a_{2(b-m+1)} & \cdots & a_{gm} \end{bmatrix}\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_{b-m} \\ \mu_{b-m+1} \\ \mu_{b-m+2} \\ \vdots \\ \mu_m \end{bmatrix}=0$$

wherein, the edge corresponding to $x_1,x_2,\cdots,x_{b-m}$ does not have a sensor deployed, and $\boldsymbol{x}=[x_1,x_2,\cdots,x_{b-m}]^{\mathrm{T}}$ is an unknown measurement vector, and $\mu_{b-m+1},\mu_{b-m+2},\cdots,\mu_m$ corresponds to the side where the sensor is deployed, which is a measured value of a known sensor. Write the block matrix in the form

$$[\boldsymbol{C}\quad\boldsymbol{D}]\begin{bmatrix}\boldsymbol{x}\\ \boldsymbol{\mu}\end{bmatrix}=0 \tag{4}$$

where $\boldsymbol{C}$,$\boldsymbol{D}$ are data matrices, $\boldsymbol{\mu}$ is the sensor measurement vector, and $\boldsymbol{x}$ is the unknown vector.

As $\boldsymbol{C}$,$\boldsymbol{D}$ are completely determined by how the sensor is deployed in the network, that means one deployment method corresponds to a combination of $\boldsymbol{C}$ and $\boldsymbol{D}$. After the transformation of (4), there is

$$\boldsymbol{Cx}=-\boldsymbol{D\mu} \tag{5}$$

Equation (5) is the measurement equation of the network, which is a non-homogeneous linear equation system. Where $\boldsymbol{C}$ is the $g\times(b-m)$ data matrix. When $\mathrm{Rank}(\boldsymbol{C})\leqslant b-m<g$, according to the matrix theory, (5) is an overdetermined equation, and each equation contains redundant information. At this time, an $\boldsymbol{x}$ cannot be found to make the equation hold, but we can find an $\boldsymbol{x}$ that minimizes $(\boldsymbol{Cx}+\boldsymbol{D\mu})^{\mathrm{T}}(\boldsymbol{Cx}+\boldsymbol{D\mu})$.

In fact, when $g>b-m$, according to the least squares method, the measurement equation is transformed into

$$\boldsymbol{C}^{\mathrm{T}}\boldsymbol{C}\boldsymbol{x} = -\boldsymbol{C}^{\mathrm{T}}\boldsymbol{D}\boldsymbol{\mu} \tag{6}$$

If $\mathrm{Rank}(\boldsymbol{C}) = b - m$, since $\boldsymbol{C}^{\mathrm{T}}\boldsymbol{C}$ is non-singular, the equation has a unique solution under least squares

$$\boldsymbol{x} = -(\boldsymbol{C}^{\mathrm{T}}\boldsymbol{C})^{-1}\boldsymbol{C}^{\mathrm{T}}\boldsymbol{D}\boldsymbol{\mu} \tag{7}$$

If $\mathrm{Rank}(\boldsymbol{C}) < b - m$, then the least squares solution is

$$\boldsymbol{x} = -(\boldsymbol{C}^{\mathrm{T}}\boldsymbol{C})^{\dagger}\boldsymbol{C}^{\mathrm{T}}\boldsymbol{D}\boldsymbol{\mu} \tag{8}$$

where $\boldsymbol{C}^{\dagger}$ represents the Moore-Penrose inverse matrix of matrix $\boldsymbol{C}$.

It can be seen that the degree of redundancy of the measurement system is closely related to the data matrix $\boldsymbol{C}$ of the measurement equation. The definition of network measurement redundancy is given below.

Definition 1: For a given network $\boldsymbol{D}$ with b edges and m sensors are deployed in it. $\boldsymbol{C} \in \mathbb{N}^{g\times(b-m)}$ and $\boldsymbol{D} \in \mathbb{N}^{g\times m}$ are data matrix determined by (5). Let g' is the number of non-zero rows in $\boldsymbol{C}$, then the redundancy of the measurement system is

$$R = g' - \mathrm{Rank}(\mathbf{C}) \tag{9}$$

that means the measured redundancy is the difference between the number of equations in (5) and the rank of the coefficient matrix $\boldsymbol{C}$.

The purpose to specify that g' is the number of non-zero lines in $\boldsymbol{C}$ is to ensure that more balanced relationships can be established by using the row vectors in $\boldsymbol{C}$.

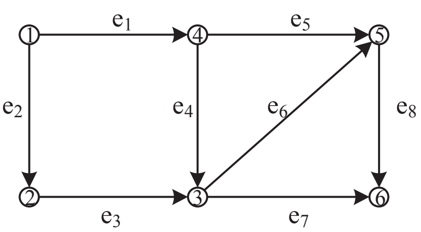

Fig. 3. A typical network example

The network shown in Fig. 3, the incident matrix $\boldsymbol{A}$ is

$$\boldsymbol{A} = \begin{array}{c} \\ v_2 \\ v_3 \\ v_4 \\ v_5 \end{array} \begin{array}{c} \begin{array}{cccccccc} e_1 & e_2 & e_3 & e_4 & e_5 & e_6 & e_7 & e_8 \end{array} \\ \begin{bmatrix} 0 & -1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & -1 & -1 & 0 & 1 & 1 & 0 \\ -1 & 0 & 0 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & -1 & -1 & 0 & 1 \end{bmatrix} \end{array} \tag{10}$$

Suppose there are 5 sensors to be deployed to e_4, e_5, e_6, e_7, e_8, $m = 5$, the data matrices $\boldsymbol{C}$ and $\boldsymbol{D}$ are respectively

$$\boldsymbol{C} = \begin{array}{c} \\ v_2 \\ v_3 \\ v_4 \\ v_5 \end{array} \begin{array}{c} \begin{array}{ccc} e_1 & e_2 & e_3 \end{array} \\ \begin{bmatrix} 0 & -1 & 1 \\ 0 & 0 & -1 \\ -1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \end{array} \quad \boldsymbol{D} = \begin{array}{c} \\ v_2 \\ v_3 \\ v_4 \\ v_5 \end{array} \begin{array}{c} \begin{array}{ccccc} e_4 & e_5 & e_6 & e_7 & e_8 \end{array} \\ \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ -1 & 0 & 1 & 1 & 0 \\ 1 & 1 & 0 & 0 & 0 \\ 0 & -1 & -1 & 0 & 1 \end{bmatrix} \end{array}$$

then the number of non-zero rows of the matrix $g' = 3$ and $\mathrm{Rank}(\boldsymbol{C}) = 3$, the redundancy of the measurement system is $R = 0$.

If these sensors are deployed to e_2, e_4, e_6, e_7, e_8, the data matrices $\boldsymbol{C}$ and $\boldsymbol{D}$ are respectively

$$\boldsymbol{C} = \begin{array}{c} \\ v_2 \\ v_3 \\ v_4 \\ v_5 \end{array} \begin{array}{c} \begin{array}{ccc} e_1 & e_3 & e_5 \end{array} \\ \begin{bmatrix} 0 & 1 & 0 \\ 0 & -1 & 0 \\ -1 & 0 & 1 \\ 0 & 0 & -1 \end{bmatrix} \end{array} \quad \boldsymbol{D} = \begin{array}{c} \\ v_2 \\ v_3 \\ v_4 \\ v_5 \end{array} \begin{array}{c} \begin{array}{ccccc} e_2 & e_4 & e_6 & e_7 & e_8 \end{array} \\ \begin{bmatrix} -1 & 0 & 0 & 0 & 0 \\ 0 & -1 & 1 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & -1 & 0 & 1 \end{bmatrix} \end{array}$$

The number of non-zero rows of the $\boldsymbol{C}$ is 4 and $\mathrm{Rank}(\boldsymbol{C}) = 3$, the redundancy of the measurement system is $R = 0$.

IV. Sensor Configuration to Maximize Measurement Redundancy

After get the performance evaluation criteria for different configuration modes, we now discuss how to deploy sensors to form the greatest measurement redundancy. According to the definition of information redundancy, see (9), the number of non-zero rows of matrix $\boldsymbol{C}$ should be as large as possible, and column $\boldsymbol{C}$ should be full rank. Therefore, when the number of non-zero rows of $\boldsymbol{C}$ maximized, and the maximum value is g. Therefore, the maximum redundancy configuration strategy can be obtained through two steps as shown below.

Step1: Construct an incidence matrix $\boldsymbol{A}$ according to the network structure.

Step2: Perform elementary column transformation on matrix $\boldsymbol{A}$, and then select b column vectors among them to form matrix $\boldsymbol{C}$ so that the number of non-zero rows of $\boldsymbol{C}$ is the largest and the columns are full rank. Then the edges corresponding to the remaining m column vectors are the edges where sensors need to be deployed.

Take the diagram shown in Fig 3 as an example, there are 6 sensors to be deployed. The incidence matrix $\boldsymbol{A}$ is shown in (10). Perform elementary column transformation on matrix $\boldsymbol{A}$ to get

$$\tilde{\boldsymbol{A}} = \begin{array}{c} \\ v_2 \\ v_3 \\ v_4 \\ v_5 \end{array} \begin{array}{c} \begin{array}{cccccccc} e_2 & e_3 & e_7 & e_4 & e_1 & e_5 & e_6 & e_8 \end{array} \\ \begin{bmatrix} -1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & -1 & 1 & -1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & -1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & -1 & -1 & 1 \end{bmatrix} \end{array}$$

Select columns e_3 and e_5 construct matrix $\boldsymbol{C} = (e_3, e_5)$ which is full rank, and the number of rows that are not all 0 is the largest, then the edges where sensors are deployed are $e_2, e_7, e_4, e_1, e_6, e_8$. The maximum redundancy can be obtained 2.

$$\boldsymbol{C} = \begin{array}{c} \\ v_2 \\ v_3 \\ v_4 \\ v_5 \end{array} \begin{array}{c} \begin{array}{cc} e_3 & e_5 \end{array} \\ \begin{bmatrix} 1 & 0 \\ -1 & 0 \\ 0 & 1 \\ 0 & -1 \end{bmatrix} \end{array} \quad \boldsymbol{D} = \begin{array}{c} \\ v_2 \\ v_3 \\ v_4 \\ v_5 \end{array} \begin{array}{c} \begin{array}{cccccc} e_2 & e_7 & e_4 & e_1 & e_6 & e_8 \end{array} \\ \begin{bmatrix} -1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & -1 & 0 & 1 & 0 \\ 0 & 0 & 1 & -1 & 0 & 0 \\ 0 & 0 & 0 & 0 & -1 & 1 \end{bmatrix} \end{array}$$

The deployment result is shown in Fig 4.

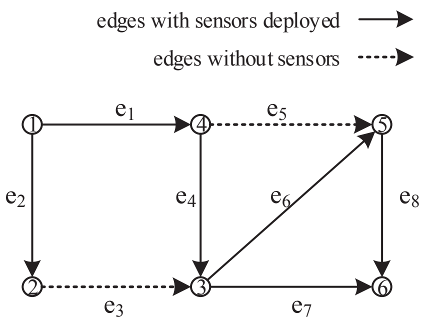

Fig.4. Maximum information redundancy configuration mode

V. MINIMUM NUMBER OF SENSORS REQUIRED FOR ESTIMATION

Given the network structure, in the case of a limited number of sensors and assuming that the sensors are not faulty, the measured value on the side where the sensors are not deployed can be estimated according to the known measured values and measurement equations. Note that the minimum estimate here refers to the minimum number of sensors required. Therefore, it is necessary to determine the number of sensors and the deployment location at the same time, so that the value of the unmeasured edge can be estimated when the number of sensors is the smallest.

Recalling the measurement equation (5), to calculate the unknown measurement $\boldsymbol{x}$ from the known measurement $\boldsymbol{\mu}$, the measurement equations must have a solution. According to the nature of the solution of the inhomogeneous linear equations, the necessary and sufficient condition for the measurement equation to have a unique solution is $\mathrm{Rank}(\boldsymbol{C}) = \mathrm{Rank}(\boldsymbol{C},\boldsymbol{D\mu}) = b-m$. Since the number of edges b of the network is fixed, to minimize the number of sensors m, it is necessary to maximize $b-m$. The possible maximum value of $b-m$ is discussed below.

Theorem 1: For a given network, the number of nodes is n, the number of source nodes and sink nodes is k, and the measurement equation is $\boldsymbol{Cx} = -\boldsymbol{D\mu}$, the maximum value of the rank of the coefficient matrix $\boldsymbol{C}$ is $\max(\mathrm{Rank}(\boldsymbol{C})) = n-k$.

Proof: The graph theory has been proved that for a connected graph with n nodes, the rank of incidence matrix is $\boldsymbol{A}$ is $n-1$, that means the row vectors remaining after removing any row in $\boldsymbol{A}$ is linearly independent. Then, after removing the rows corresponding to the k source nodes and sink nodes in the incidence matrix $\boldsymbol{A}$, the matrix obtained must be row full, that is, $\mathrm{Rank}(\boldsymbol{A}) = g$. Moreover, because the row rank of the matrix is equal to the column rank, the maximum number of independent column vectors that can be obtained from $\boldsymbol{A}$ is $\max(\mathrm{Rank}(\boldsymbol{C})) = g = n-k$. □

We further consider its existence. Since $\mathrm{Rank}(\boldsymbol{A}) = g < b$, that means the column vectors of $\boldsymbol{A}$ are linearly related, a set of linearly independent column vectors $q_1,\cdots,q_g$ can be found in $\boldsymbol{A}$, so that the rest column vectors can be represented by this group of column vectors. The matrix $\boldsymbol{C}$ and $\boldsymbol{D}$ formed by this column vector have $\mathrm{Rank}(\boldsymbol{C}) = \mathrm{Rank}(\boldsymbol{C},\boldsymbol{D\mu}) = b-m = g$. Then maximum value of $b-m$ is g. Also $g = n-k$, so the minimum number of sensors is

$$m = b-g = b+k-n \tag{11}$$

Based on the above discussion, the deployment strategy that minimizes m can be obtained by two steps as shown below.

Step1: Perform elementary row transformation on matrix $\boldsymbol{A}$ and become row-echelon form.

Step2: Select g linearly independent column vectors, and the edges corresponding to the remaining columns are the edges on which sensors need to be deployed. The number of sensors required is $b+k-n$.

Also take the network shown in Fig. 3 as an example, wherein $b=8, k=2, n=6$. According to (11), the minimum number of sensors required is 4. Perform elementary row transformation to get

$$\begin{array}{c} \begin{array}{cccccccc} e_1 & e_2 & e_3 & e_4 & e_5 & e_6 & e_7 & e_8 \end{array} \\ \boldsymbol{A} \sim \begin{bmatrix} 1 & 0 & 0 & -1 & 0 & 1 & 0 & -1 \\ 0 & 1 & 0 & 1 & 0 & -1 & -1 & 0 \\ 0 & 0 & 1 & 1 & 0 & -1 & -1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 0 & -1 \end{bmatrix} \end{array}$$

a) Suppose four sensors are deployed to e_4, e_6, e_7, e_8, the two data matrices of $\boldsymbol{C}$ and $\boldsymbol{D}$ are respectively

$$\begin{array}{c} \begin{array}{cccc} e_1 & e_2 & e_3 & e_5 \end{array} \\ \boldsymbol{C} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \end{array} \qquad \begin{array}{c} \begin{array}{cccc} e_4 & e_6 & e_7 & e_8 \end{array} \\ \boldsymbol{D} = \begin{bmatrix} -1 & 1 & 0 & -1 \\ 1 & -1 & -1 & 0 \\ 1 & -1 & -1 & 0 \\ 0 & 1 & 0 & -1 \end{bmatrix} \end{array}$$

The value of x_1, x_2, x_3, x_5 are obtained by solving the measurement equation, and the sensor deployment result is shown in Fig 5.

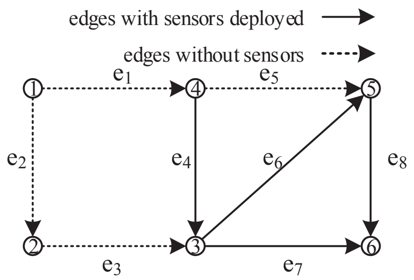

Fig 5. Minimum number of sensors deployment mode 1

b) If the edges e_3, e_5, e_7, e_8 are selected for sensor deployment, the two data matrices of $\boldsymbol{C}$ and $\boldsymbol{D}$ are respectively

$$\begin{array}{c} \begin{array}{cccc} e_1 & e_2 & e_4 & e_6 \end{array} \\ \boldsymbol{C} = \begin{bmatrix} 1 & 0 & -1 & 1 \\ 0 & 1 & 1 & -1 \\ 0 & 0 & 1 & -1 \\ 0 & 0 & 0 & 1 \end{bmatrix} \end{array} \qquad \begin{array}{c} \begin{array}{cccc} e_3 & e_5 & e_7 & e_8 \end{array} \\ \boldsymbol{D} = \begin{bmatrix} 0 & 0 & 0 & -1 \\ 0 & 0 & -1 & 0 \\ 1 & 0 & -1 & 0 \\ 0 & 1 & 0 & -1 \end{bmatrix} \end{array}$$

The deployment result is shown in Fig 6.

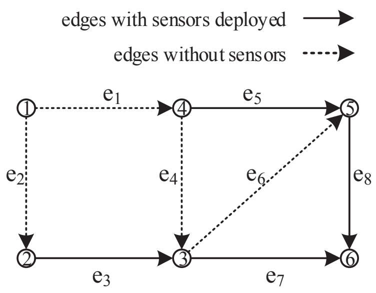

Fig 6. Minimum number of sensors deployment mode 2

It can be seen that there are many ways to construct matrix $\boldsymbol{C}$, that means the minimum number of sensors deployment method exists but is not unique.

VI. Conclusion

Because different configuration methods will affect the effect of fault detection, optimizing the configuration of sensors in the system design phase will help to improve the effect of sensor fault detection. In view of the limited number of sensors, an optimal configuration method for sensor fault detection is proposed. Both measurements of redundancy of sensor measurement information and the performance evaluation criteria of different configurations are given. An optimal sensor configuration strategy is designed to ensure maximum redundancy of measurement information, and an estimation of the number of sensors is given to meet the minimum estimation requirement for unmeasured states.

References

[1] Li J Q, Yu F R, Deng G, et al. Industrial internet: A survey on the enabling technologies, applications, and challenges. IEEE Communications Surveys & Tutorials, 2017, 19(3):1504–1526.

[2] Reppa V, Polycarpou M M, Panayiotou C G. Sensor fault diagnosis. Foundations and Trends in Systems and Control, 2016, 3(1-2):1–248.

[3] Lu W, Wen R, Teng J, et al. Data correlation analysis for optimal sensor placement using abond energy algorithm. Measurement, 2016, 91:509–518.

[4] Krysander M, Frisk E. Sensor placement for fault diagnosis. IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans, 2008, 38(6):1398–1410.

[5] Debouk R, Lafortune S, Teneketzis D. On an optimization problem in sensor selection. Discrete Event Dynamic Systems, 2002, 12(4):417–445.

[6] Rosich A, Yassine A A, Ploix S. Efficient optimal sensor placement for structural model based diagnosis. 21st Annual Workshop Proceedings, 2010.

[7] Frisk E, Krysander M, Åslund J. Sensor placement for fault isolation in linear differential-algebraic systems. Automatica, 2009, 45(2):364–371.

[8] Harmouche J, Delpha C, Diallo D. Incipient fault amplitude estimation using kl divergence with a probabilistic approach. Signal Processing, 2016, 120:1–7.

[9] Youssef A, Delpha C, Diallo D. An optimal fault detection threshold for early detection using kullback–leibler divergence for unknown distribution data. Signal Processing, 2016, 120:266–279.

[10] Yin S, Ding S X, Xie X, et al. A review on basic data-driven approaches for industrial process monitoring. IEEE Transactions on Industrial Electronics, 2014, 61(11):6418–6428.

[11] YANG Wen, ZHAO Qianchuan. Fault detection in HVAC systems based on energy balances. Journal of Tsinghua University (Science and Technology), 2017, 57(12): 1272-1279. (In Chinese)

[12] YANG Wen, ZHANG Bang shuang, YE Xin,et al. Sensor Fault Detection in Distribution Network Based on Energy Balanc. Automation of Electric Power System, 2018,42(12):154-159. (In Chinese).