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RESEARCH ON FAULT DIAGNOSIS OF POWER SUPPLY CONTROL SYSTEM ON BEPCII*

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Abstract

The reliable and stable operation of the accelerator is the premise and foundation of physics experiments. For example, in the BEPCII, the fault of the magnet power supply front-end electronics devices may cause accelerator energy instability and even lead to beam loss. Therefore, it is very necessary to diagnose and locate the device fault accurately and rapidly, that will induce the high cost of the accelerator operation. Faults diagnosis can not only improve the safety and reliability of the equipment, but also effectively reduce the equipment's cycle costing. The multi-signal flow model [1] proposed by Pattipati K.R is considered as the preferred method of industrial equipment faults detection. However, there are still some problems about fault probability conflict in the processing of correlation matrix diagnosis due to the hierarchical nature of multi-signal flow modelling. Thus we develop the fault diagnosis strategy based on the important prior knowledge of the fault. This method is applied to the front-end electronic devices of BEPCII magnet power supply control system and improves the fault diagnosis and analysis ability of magnet power supply control system.

MULTI - SIGNAL FLOW GRAPH METHOD

The basic principle of magnet power supply front-end electronics system modelling is based on the idea of multiple signal flow dependencies. Multi-signal flow graph model is a hierarchical model you can directly see the impact of a fault mode of transmission to other modules. The multi-signal flow graph model does not need to establish the exact quantitative relationship of the system. It only needs to determine the important functional attributes of the system. Since the multi-signal flow graph model covers multiple information flow models, the model is closer to the physical structure of the system. In addition, the signals in the model are independent and will not influence each other. These features make the modelling of multi-signal flow graphs simple, and the integration and verification of the models are relatively simple too.

Testing model analysis firstly performs FMECA(Failure Mode, Effects and Criticism Analysis) to determine all possible fault mode of various components of the system during the designing and manufacturing process through system analysis, and the causes and effects of each fault mode. According to this, the function and structure of the UUT (Unit under Test) are divided, and the correlation graph model is established by using the available test points. Then, the first-order correlation is established, furthermore the D-matrix model (also called the diagnosis matrix or dependency matrix) is acquired. After establishing the D-matrix model, the test points can be calculated, and the diagnosis tree and the fault dictionary can be established. Then the generated diagnosis strategy can be used to predict the system's fault detection rate and fault isolation rate [2].

APPLICATION OF MULTI - SIGNAL MODEL IN FAULT DIAGNOSIS

Supposing the correlation matrix of the simplified multi-signal model D = [d_{ij}] (1≤i≤m,1≤j≤n, where m and n denotes the totality of the source of failure and the set of testing respectively), y={y_1, y_2, ..., y_m} is the possible set of fault sources for the system, T={t_1, t_2, ..., t_n} is the set of testing. The essence of fault diagnosis is to find the most likely candidate set of faults ($X \subseteq Y$) based on the structure of multi-signal model. And it is consistent with the test results, with the formula described as :

$$\max_{X \subseteq Y} \Pr ob(X \mid T_p, T_f) . \tag{1}$$

In the above formula, Prob() represents probability function and T_p represents success and T_f represents fault during tests.

For the sake of description, we define a vector, x={x_1, x_2, …, x_m }, if x_i=1,that means $y_i \in X$; if x_i=0, that means $y_i \notin X$. After deleting the constant term $\Pr ob(T_p, T_f)$ according to the Bayesian theory, the question turns to find the max value of the formula below:

$$\Pr ob(T_p \mid X) \Pr ob(T_f \mid X) \Pr ob(X) \tag{2}$$

Among them,

$$\Pr ob(X) = \prod_{i=1}^{m} p(y_i)^{x_i} (1 - p(y_i))^{(1-x_i)} \tag{3}$$

According to [3] ,after negating the left and taking natural logarithm and then deleting the constant term, this problem can be converted to an optimal set covering problem (SCP) :

$$\frac{\min}{X \subseteq Y^-} \left(\sum_{y_i \subseteq Y^-} c_i x_i \right) \tag{4}$$

Where Y^- is the set of the source of failure which excluded the normal components. The restriction is : D_x≥e,

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$x_i \in \{0,1\}$, i = 1, 2, …, m. D is the result matrix consisting of a series of fault sources tested. $e=[1,1,\ldots,1]^T$. c_i represents the source of failure based on the probability of failure.

$$c_i = -\ln\left(\frac{p(y_i)}{1-p(y_i)}\right), \quad i = 1,2,\ldots,m \tag{5}$$

The optimal set covering problem is a kind of NP-hard problem, which can't acquire a complete solution in polynomial time. But we can obtain the lower bound of the SCP problem which can be generated by using the Lagrangian relaxation algorithm, and then the solution satisfying the requirements can be generated. The solution of the problem is obtained by a series of steps. The solution in detail is described in the paper [4,7] .

IMPROVED MULTI - SIGNAL FLOW DIAGNOSIS APPLICATION BASED ON FAULT MODE'S FAULT PROBABILITY

In the modelling of multi-signal models discussed in the previous section, it is considered that the reliability of every constituent unit is the same. But in practice it is difficult to occur, and the reliability of the constituent units is usually not the same. Low probability of fault of the component unit should be a priority detection, and give it high detection weights and isolation weights. However, considering the reliability of the impact of fault mode's fault probability, the signal fault probability, which comes from different sources compared to fault mode's fault probability, will conflict with the fault probability. Therefore, it is necessary to amend the fault mode's fault probability to prevent the bias of synthesis diagnosis.

In order to formally describe the processing method when fault probability of a fault mode and the signal probability occur conflicts, these elements involved are defined as follows in paper [8]:

1) F is the set of fault mode, $F=\{f_1, f_2, \ldots, f_u\}$, f_i ($1 \le i \le m$) represents fault mode;

2) S is the set of signal , $S=\{s_1, s_2, \ldots, s_v\}$, s_j ($1 \le j \le n$) represents signal;

3) $\lambda(f_i)$ is the fault probability of fault mode f_i, which equals the number of faults in this fault mode/the number of faults in all fault mode, we have:

$$\sum_{i=1}^{u} \lambda(f_i) = 1 \tag{6}$$

4) $P(s_j)$ is the fault probability of signal s_j ,which equals this signal's frequency/all the signal's frequency

$$\sum_{j=1}^{u} P(s_j) = 1 \tag{7}$$

5) $FM(s_j)$ is the set of fault mode related to signal s_j , $SN(f_i)$ is the set of signal related to fault mode f_i .

Fault Mode Probability Equalization Method

The method recalculates the signal reliability data by the fault probability of all fault modes associated with the aliased signal (the fault probability of the fault mode remains unchanged). The method is simple, although the original signal reliability data is completely ignored. But the adjusted signal probability comes entirely from the fault mode associated with the signal. This correction method is suitable for the case where the probability of the signal is in error and the reliability is too low or the signal probability can't be calculated.

We assume $Pd(s_j, f_i)$ is the probability of $s_j (s_j \in SN(f_i))$ when $\lambda(f_i)$ is assigned at $SN(f_i)$,thus the equation below is the number of $SN(f_i)$.

$$Pd(s_j, f_i) = \tfrac{1}{v_i} \lambda(f_i), n_i \tag{8}$$

Then the probability $P'(s_j)$ of the corrected signal s_j is

$$P'(s_j) = \sum_{f_i \in FM(s_j)} Pd(s_j, f_i) \tag{9}.$$

Fault Mode Probabilistic Priority Method

Fault Mode Probabilistic Priority Method differs from the Probabilistic Equalization of fault Mode, which takes into account the raw signal probability data but still prioritizes the fault probability of the fault mode. This method gives priority to the reliability data of the fault mode, but also emphasizes the reliability of the signal. This probabilistic update method fits the reliability data of the signal with a certain degree of confidence, but is lower than the fault mode reliability data. And the fault mode probabilistic priority method considers that the different fault modes associated with the same signal contribute to the signal differently. This approach is implemented in the following four steps:

1)According to s_j ($s_j \in S$) and $\lambda(f_i)(f_i \in FM(s_j))$, we can calculate the relevant proportion $c(f_i, s_j)$ between f_i and s_j

$$c(f_i, s_j) = \frac{\lambda(f_i)}{\sum_{f_k \in FM(s_j)} \lambda(f_k)} \tag{10}$$

2)According to $c(f_i, s_j)$, we assign the fault probability $P(s_j)$ of s_j into $FM(s_j)$,then we can obtain the distribution probability of f_i correlated to s_j .

$$Pd(f_i, s_j) = c(f_i, s_j) P(s_j) \tag{11}$$

3) The distribution probability correlated to f_i of $s_j \in SN(f_i)$ is re-adjusted in the same proportion to get partial fault probability $P'd(s_j, f_i)$

$$\sum_{s_j \in SN(f_i)} P'd(s_j, f_i) = \lambda(f_i) \tag{12}$$

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4) Calculate the updated $\mathrm{P}'(s_j)(s_j \in S)$

$$p'(s_j) = \sum_{f_i \in FM(s_j)} \mathrm{P}' d(s_j, f_i) \tag{13}$$

MODELING AND SIMULATION OF MAGNET POWER SUPPLY INTERFACE EQUIPMENT

There are about 400 various power supply for many types of magnets in the BEPCII accelerator storage, which provide a stable magnetic field for the beam. Power Supply Interface (PSI) is a key electronic device for controlling and monitoring the output and status of magnet power supply, which includes power supply, interface cards and other parts [9]. Schematic diagram shown in Fig. 1 and Fig. 2.

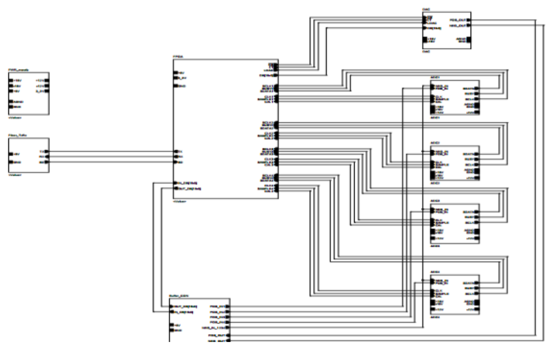

Figure 1: Interface card diagram.

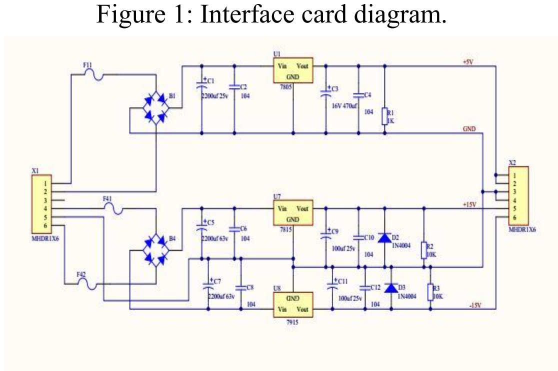

Figure 2: Power supply diagram.

After performing the structure and function analysis of the power interface device, the multi-signal flow modelling of each functional module and components of the interface device is carried out. The modelling process is not described in detail because of the large number of internal components and the large number of component fault mode effects and hazard analysis categories. The overall model and the power supply model are showed below in Fig. 3 and Fig. 4 after the multi-signal flow diagram of the power control system is modelled [10] .

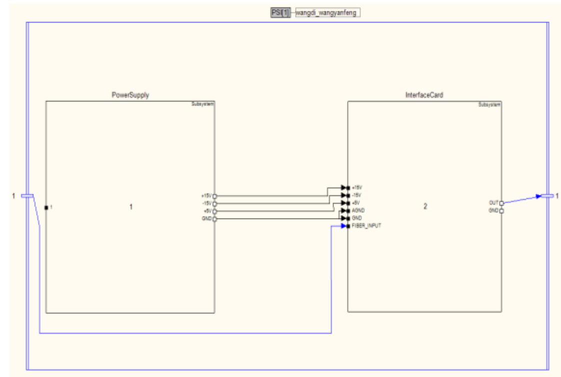

Figure 3: Multi-signal flow graph of the whole system.

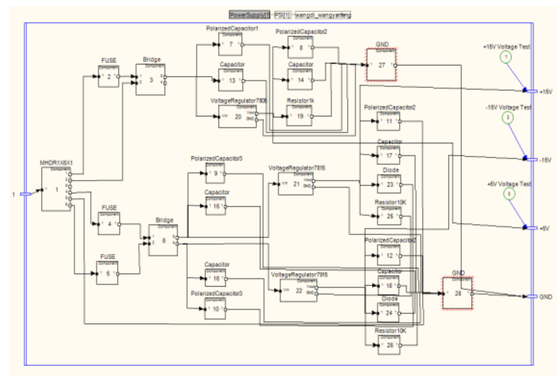

Figure 4:Multi-signal flow graph of power supply.

After modelling power control system for multi-signal flow diagram, the resulting model is showed in Fig. 5 and Fig. 6. The TEAMS toolbox can be used to test the testability of this model without considering the fault mode reliability. Considering the reliability of the components and adding the probability of the fault mode, the fault mode probabilistic priority method can comprehensively consider the different reliability data compared with the fault mode probabilistic equalization method, so this model is corrected by using the probabilistic priority method of the fault mode , The FDR (fault detection rate) increases from 97.37% to 97.47%, and the FIR (fault isolation rate) increases from 97.52% to 97.62% (see from Fig. 5 and Fig. 6) by comparing the analysis results of the interface models. Due to the simpler structure and simpler function of the power control system, the accuracy of the fault detection is limited, but the accuracy of FDR and FIR will be greatly improved for complex systems.

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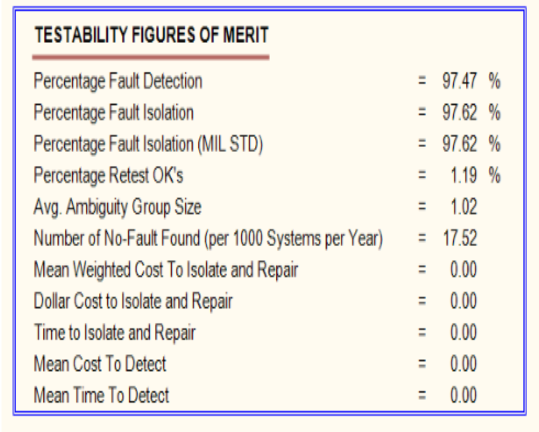

TESTABILITY FIGURES OF MERIT		
Percentage Fault Detection	=	97.47 %
Percentage Fault Isolation	=	97.62 %
Percentage Fault Isolation (MIL STD)	=	97.62 %
Percentage Retest OK's	=	1.19 %
Avg. Ambiguity Group Size	=	1.02
Number of No-Fault Found (per 1000 Systems per Year)	=	17.52
Mean Weighted Cost To Isolate and Repair	=	0.00
Dollar Cost to Isolate and Repair	=	0.00
Time to Isolate and Repair	=	0.00
Mean Cost To Detect	=	0.00
Mean Time To Detect	=	0.00

Figure 5: Testability figures of merit.

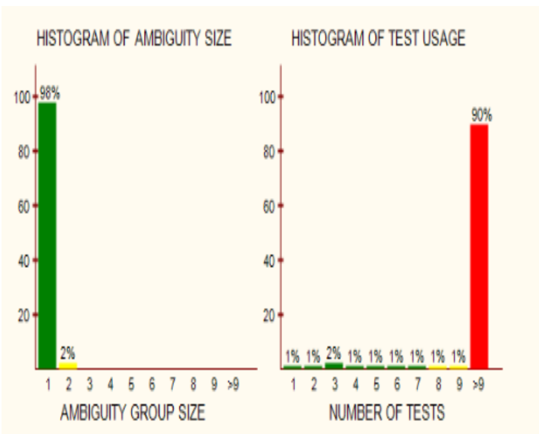

Figure 6: Histogram of ambiguity group and test usage.

CONCLUSION

This paper first introduces the application of the multi-signal flow method in fault diagnosis, and proposes the idea of improving the multi-signal flow diagnosis based on the fault probability of the fault mode. The confidence level of the latter is improved by modifying the probabilistic data with high confidence to the probability of the other confidence, and the multi-signal model is modified to improve the accuracy of the system's testability analysis and fault diagnosis strategy generation. At last, this method is used to the modeling and simulation of the front-end electronic devices, Power Supply Interface. It can be seen that the improved multi-signal model based on fault mode fault probability can effectively improve the testability of the system when dealing with system fault, which provides a new idea for fault diagnosis of multi-level and complex systems.

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