

Optimal Fault Diagnosis of Electric Power Systems Using MSE Learning



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Abstract. The electric power systems (EPSs) is a complex system with lots of bus bars, transmission lines, and transformers. The primary goal of maintaining an EPS is providing sustainable and stable power supply for customers. However, the quality of service of an EPS suffers from the failures of its system sections. Fast and accurate fault diagnosis is the prerequisite to bring the system back in normal state, thus has attracted much attentions from power engineers. In this paper, we present a minimum square error (MSE) learning based optimal fault diagnosis algorithm, in which the operation state of system sections and protections are formulated using matrices representations. Optimization model is developed to find most probably state of the system sections. The method requires no complex logic designing, nor any historical operation records, and it is simple and fast for implementation. Test results prove that the proposed method has satisfactory diagnosis performance compared with other existing methods.

Keywords: electric power systems, fault diagnosis, matrix representation, MSE learning

1 Introduction

In smart grid, the electric power system (EPS) is a complex system composed of different system sections, including power generators, transformers, bus bars and transmission lines [1]. EPS aims at supplying stable and uninterrupted power sources to remote customers. However, due to reasons, such as bad weather, equipment failure, and malicious attack, power transmission in EPS may be interrupted or even blackout, which cause huge economic losses. To avoid damage on the system sections, a protective system is adopted by using protective relays and circuit breakers (CBs) [2]. Fault diagnosis helps the dispatchers to find out faulty system sections, which is the prerequisite to take measures to repair the system [3]. When the system is in faulty state, the operation state of the protections will be uploaded to supervisor control and data acquisition (SCADA) system, and fault diagnosis tasks can be realized by utilizing intelligent algorithms, but not just relies on judgements of experts.

Many methods have been proposed to deal with the fault diagnosis problem in EPSs [4]. The expert system (ES) is the first one for failure identifying in EPS, which utilizes the experts' professional knowledge to design inference rules for fault diagnosing. However, designing such a complex rule-based knowledge system is a high-cost project, and the diagnosis efficiency is not satisfactory.

Since the information of the protective relays and CBs are always incomplete and uncertain, fuzzy systems (FS) [5-8] becomes a popular direction for its advantage in dealing with information uncertainty. however, designing a fuzzy reasoning system for a complex EPS still needs heavy efforts on designing the membership functions and combinational rules, thus it is inefficiency in designing process. Optimization methods (OMs), such as genetic algorithm-tabu search (GATS) [9], binary particle swarm optimization (BPSO) [10], and genetic algorithm (GA) [11], also have been proposed to utilizing intelligent searching strategies to obtain globally optimal solutions. However, due the non-linearity of the

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objective function and the complexity of EPSs, developing optimization model automatically is not an easy task. Moreover, the result may not be stable due to the local optimum property of the objective function.

To overcome the designing cost and improve the diagnosis efficiency, machine learning methods have been proposed, including artificial neural networks (ANNs) [12-14] and Bayesian networks (BNs) [15-16]. However, a well-trained ANN needs sufficient training data to obtain the parameters of the network structure. Training a BN also needs lots of prior information. This needs the designer to collect sufficient operation sample data, which limits their practicability. Cause-effective networks (CE-Nets) [17-18] is another method with high efficiency by using parallel information processing, but its fault tolerance still needs to be improved.

In this paper, we present a simple, fast, and effective method for fault diagnosis in EPSs. Although EPS is a system with complex topologies, it still can be represented using matrix, which lays a foundation for mathematical analysis. We formulate system structure by using matrix representation, and the fault diagnosis problem are formulated as a simple minimum square error (MSE) learning problem. Complex inference logics and prior information of system operation are not required. Test results prove that the proposed MSE learning method is able to correctly identify faulty sections.

The remainder of this paper is organized as follows. Section 2 gives an introduction on the fault diagnosis problem in EPS. Sections 3 illustrates the principles of the proposed method. Tests results are provided in Section 4. Section 5 finally concludes this paper.

2 Fault Diagnosis in Electric Power Systems

As aforementioned, fault diagnosis in EPS is based on collecting information of the protective relays and circuit breakers (CBs). System sections, including bus bars, transformers, transmission lines, are protected by these protections, as shown in Fig. 1. Except the buses, a protective relay of a system section has three entities: main protective relay (MPR), first backup protective relay (FBPR), and second backup protective relay (SBPR) [19]. A bus line will be only protected by MPR and SBPR. The CBs are controlled by the protective relays. Usually, a transformer or a transmission line has two protective adjacent CBs, and a bus line has three CBs.

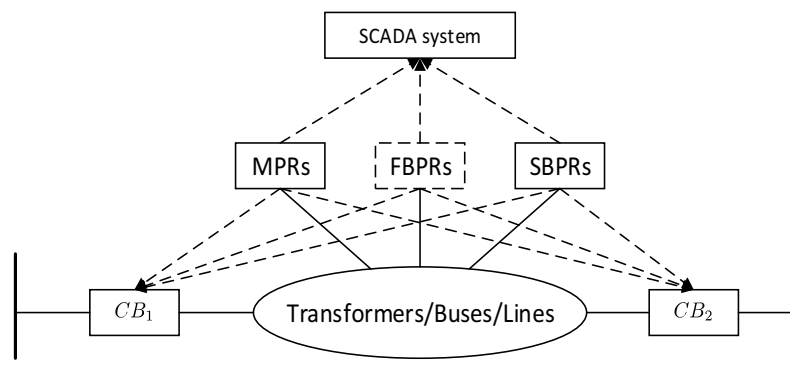


Fig. 1. The protection system of an EPS

When a system section fails to operate, the monitoring MPR will try to operate to CBs to protect it from damage. If MPR fails to operate, then FBPR tries to work. SBPR is the last protection if both of them fail to operate. Subsequently, the faulty alarms will be uploaded to the SCADA system. The dispatchers conduct the fault diagnosis operation to find out which system sections are in faulty state, and further steps will be taken to repair the faults to make the system back in normal state.

Let us look at the example in Fig. 2, in which there are 5 system sections, including 1 single bus A_1 , 2 transformers T_1, T_2 , and a double bus B_1, B_2 . If T_1 fails to operate, its protective relays will give orders to trip CB_2 and CB_4 , thus T_1 is isolated from the system. However, information of fault monitoring are usually incomplete, or uncertain. For example, when MPR of A_1 operates to trip CB_2 . In this case, we are not sure of which one is faulty. The results can be A_1 or T_1 . If we know CB_4 are also tripped, then

we are confident that T_1 fails to operate. Therefore, how to deal with the uncertainty and incompleteness of protective information is vital for dealing with fault diagnosis in EPS.

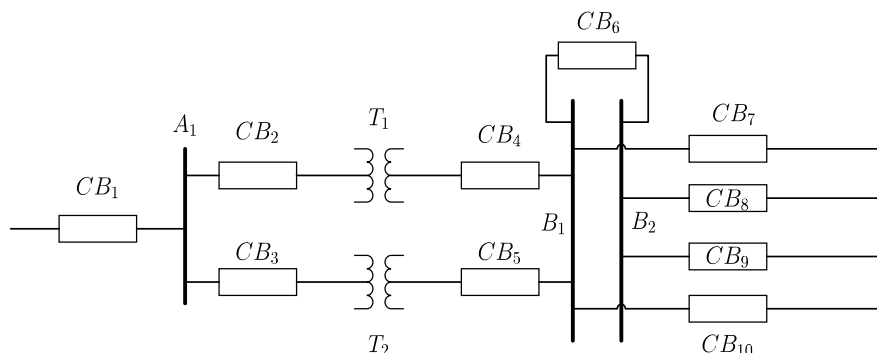


Fig. 2. An example of the protection system of an EPS

3 Proposed Optimal Fault Diagnosis Method

In this section, we introduce the proposed optimal fault diagnosis method for electrical power systems. For better understanding, examples will also be provided.

3.1 Matrix Representation of EPS

Suppose there are n system sections $S = \{s_1, s_2, \dots, s_n\}$ and m CBs $V = \{CB_1, CB_2, \dots, CB_n\}$ in an electric power system. Note that for all the backup protective relays and the corresponding main protection are regarded as one protective relays, and a double bus has two protective relays. Let S be the vertex set, an electric power system can be regarded as a undirected graph $G = \{S, E\}$, in which $E = \{e_1, e_2, \dots, e_m\}$ is the edge set of the graph G . For $e_k \in E (1 \leq k \leq m)$, $e_k = \{s_i, s_j\}$ is called an edge of two adjacent vertex nodes s_i to s_j .

In this paper, the operation state of an EPS is represented as following four matrices

$$Z = \{C, D, X, Y\} \quad (1)$$

where

- (1) C is an $n \times n$ matrix representing the original normal connectivity state of CBs and system sections.
- (2) D is an $m \times n$ matrix representing the faulty connectivity state of CBs and system sections.
- (3) X is an $n \times 1$ vector representing the operation state indicators of system sections. A system section s_i is in normal state if its corresponding operation state indicator is $x_i \leq 0.5$, otherwise it is in faulty state.
- (4) Y is a $m \times 1$ vector representing the failure degrees of the lost connections of CBs. When the system section of a CB is normal, its failure degree is 0. However, if both two of the CB's adjacent system section are faulty, then the corresponding failure degree is 2.

Next we illustrate how to obtain the values of the elements in above four matrices. Firstly, matrix C can be obtained according to original sketch map of the EPS. We denote $c_{ij} = 1$ if CB_i and system section s_j are connected, and $d_{ij} = 0$ if they not adjacent. Note that two arbitrary system sections can not be directly connected, thus a CB has at least one connected system section.

Matrix D is the real time faulty connectivity state of the system. Apparently, if $D = C$, the system is in normal condition. On the contrary, if $D \neq C$, it is in faulty state. Therefore, values of elements in C are fixed, while the ones in D is dynamic with the real-time system condition. For a tripped CB_i , suppose it is the output end of s_i and the input end of s_k . The values of d_{ij} and $d_{ik} = 0$ are obtained as the following strategy: If there is at least one CB in the input end of s_i and at least one CB in the output end of s_k are tripped, then $d_{ij} = 0$ and $d_{ik} = 0$ which means CB_i is not connected with s_i and s_k in this

scenario. In other situations $d_{ij} = 0.5$ and $d_{ik} = 0.5$, since we are not sure which one of the two system relays is in faulty state.

Again, let us look at the example system given in Fig. 2. In this situation, the vertex set is $V = \{s_1 = A_1, s_2 = T_1, s_3 = T_2, s_4 = B_1, s_5 = B_2\}$. There are 10 CBs and 5 protective relays in this EPS, and we can get the values of the elements in the corresponding adjacent matrix C , e.g. $d_{11} = 1$ because CB_1 and A_1 are directly connected. Particularly, matrix C representing the original connectivity condition of the system, and it is given by

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 \\ 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix} \quad (2)$$

Now suppose the system is in faulty state, and the SCDA system observes that CBs CB_2, CB_3, CB_4, CB_5 are tripped. In this situation, the faulty connectivity state matrix D is given by

$$D = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0.5 & 0.5 & 0 & 0 & 0 \\ 0.5 & 0 & 0.5 & 0 & 0 \\ 0 & 0.5 & 0 & 0.5 & 0 \\ 0 & 0 & 0.5 & 0.5 & 0 \\ 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix} \quad (3)$$

Assume that CBs $CB_1, CB_2, CB_3, CB_4, CB_5$ are tripped, then the corresponding matrix D is

$$D = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix} \quad (4)$$

We define $Y = [y_1, \dots, y_m]$ as the failure degree vector of the CBs, and the values of its elements is defined as

$$y_i = \sum_{j=1}^n (c_{ij} - d_{ij}) \quad (5)$$

We can see that, for arbitrary rows in C and D , the sum of the elements of the rows equal to 1 or 2. Therefore, any element in matrix Y has one of three values: 0, 1, 2. For example, $y_i = 2$ means that CB_i lose connections with its two adjacent protective relays. In Fig. 2, when CBs CB_2, CB_3, CB_4, CB_5 are tripped, the corresponding operation state vector of CBs is $Y = [0, 1, 1, 1, 1, 0, 0, 0, 0, 0]$. When CBs $CB_1, CB_2, CB_3, CB_4, CB_5$ are tripped, the corresponding operation state vector of CBs is $Y = [1, 2, 2, 1, 1, 0, 0, 0, 0, 0]$.

3.2 Optimal Diagnosis

Now we define vector $X = [x_1, x_2, \dots, x_n]^T$ to represent the operation state of the protective relays. When protective relay s_i is in faulty state, we have $x_i = 1$, otherwise $x_i = 0$. Apparently, when the system is in normal state, $X = [0, 0, \dots, 0]^T$. If the all the CBs are in good functional conditions, i.e. when a protective relay is in faulty condition, its adjacent CBs are all tripped. Then we have the following equations

$$CY = Y \quad (6)$$

the operating state vector X of protective relays can be easily obtained by

$$X = (C^T C)^{-1} C^T Y \quad (7)$$

However, as aforementioned, information of fault diagnosis in EPS are always incomplete and uncertain, and equation (6) are not always true in real practice. The alternative way is using optimization model to find out the most solutions with minimum square error (MSE) to the above equations. as given by

$$\begin{aligned} \min_X \quad & \|CX - Y\| \\ \text{s.t.} \quad & 0 \leq x_i \leq 1, 1 \leq i \leq n \end{aligned} \quad (8)$$

where $\|\cdot\|$ denotes the l_2 norm operation. Without considering the constraint, the optimal solution is $X = C^\dagger Y$, where C^\dagger is the Moore-Penrose generalized inverse of matrix C . However, the above equation is not applicable in most situations, since elements in X may not distributed in $[0, 1]$ when using the above equation. Solving the above optimization model can be realized by any proper optimal algorithms, such as a commonly used gradient descent method, and we don't repeat it again. With the obtained vector X , now we have the decision rule

$$CB_i = \begin{cases} \text{faulty,} & \text{if } x_i > 0.5 \\ \text{normal,} & \text{if } x_i \leq 0.5 \end{cases} \quad (9)$$

Again, let us look at the example in Fig. 2, when CB_2, CB_3, CB_4, CB_5 are tripped, we can obtain the state vector of protective relays as $X = [0, 1, 1, 0, 0]$, which means that the two transformers T_1 and T_2 are in faulty state. Although 2/3 of the connected CBs of A_1 are tripped, but it is caused by T_1, T_2 , and A_1 will not be regarded as faulty.

We can see that, in our method, we just need to get the operation state vector Y when fault happens. And the fault diagnosis results can be easily calculated by using the above optimization model. Finally, the diagnosis decisions can be obtained via the decision rule. The whole process is simple, fast, and requires no prior information except the original normal condition C . In next section, simulation results will be provided prove the high fault diagnosing performance of the proposed method.

4 Experimental Results

In this section, experiments will be conducted with several single and multiple fault cases in the EPS shown in Fig. 3, which includes 28 system sections and 40 CBs. The 24 system sections have 84 protective relays. The system sections are marked by circled numbers, and single bus, double bus, transformer, and line are denoted by A, B, T, L , respectively. Subscripts S and R represent sending and receiving ends of a line, respectively. Subscripts m, p, s designate the main protection, the first backup protection and the second backup protection, respectively. The 40 CBs are labeled as $CB_1 \sim CB_{40}$. The 28 system sections are marked as $S_1 \sim S_{28}$, including $A_1 \sim A_4, T_1 \sim T_8, B_1 \sim B_8, L_1 \sim L_8$. There are 36 main protective relays $r_1 \sim r_{36}$, including $A_{1m} \sim A_{4m}, T_{1m} \sim T_{8m}, B_{1m} \sim B_{8m}, L_{1Sm} \sim L_{8Sm}, L_{1Rm} \sim L_{8Rm}$. The others are backup protections $r_{37} \sim r_{84}$, including $T_{1p} \sim T_{8p}, T_{1s} \sim T_{8s}, L_{1Sp} \sim L_{8Sp}, L_{1Rp} \sim L_{8Rp}, L_{1Ss} \sim L_{8Ss}, L_{1Rs} \sim L_{8Rs}$.

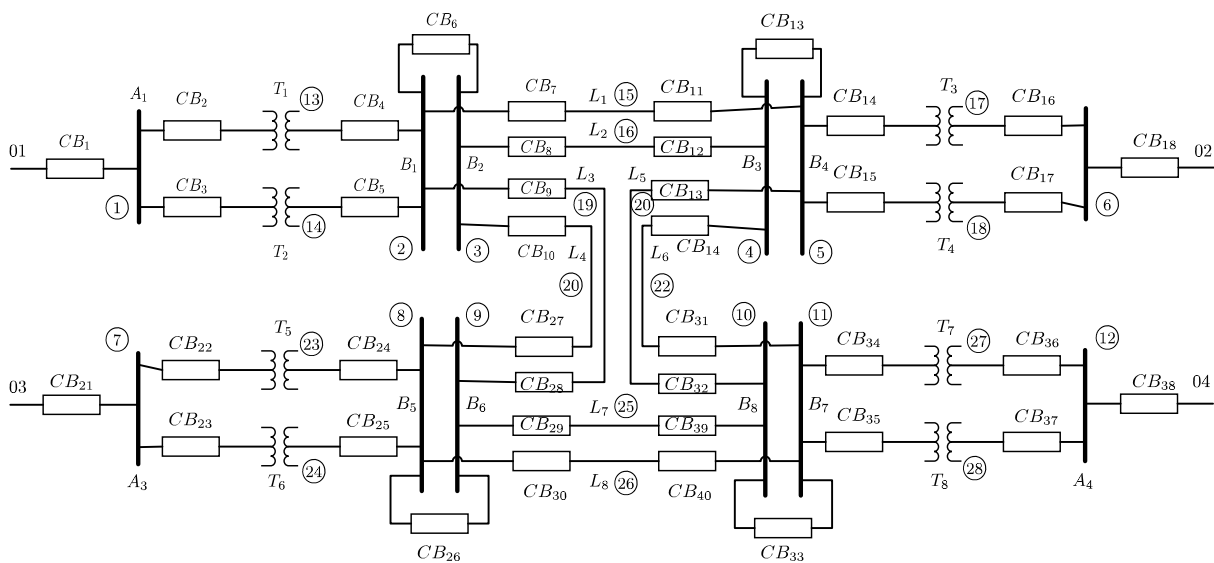


Fig. 3. The local sketch map of the EPS used in simulation

The status information of protective relays and CBs of the seven faulty cases are shown in Table 1, in which cases 1 and 2 are single fault situations, the others are multiple faults situations. Note that the operated relays are not equivalent to the faulty sections. Usually, the faulty sections are included in the operated protections, but sometimes when the status information are incomplete and uncertain, the faulty sections may not be appeared in the operated relays.

Table 1. The status information of 7 faulty cases

No.	Operated Relays	Operated CBs
1	B_{1m}, L_{2Rs}, L_{4Rs}	$CB_4, CB_5, CB_7, CB_9, CB_{12}, CB_{27}$
2	L_{2Rs}, L_{4Rs}	$CB_4, CB_5, CB_7, CB_9, CB_{12}, CB_{27}$
3	B_{1m}, L_{1Sp}, L_{1Rm}	$CB_4, CB_5, CB_6, CB_7, CB_9, CB_{11}$
4	$B_{1m}, L_{1Sm}, L_{1Rp}, B_{2m}, L_{2Sp}, L_{2Rm}$	$CB_4, CB_5, CB_6, CB_7, CB_9, CB_{10}, CB_{11}, CB_{12}$
5	T_{3p}, L_{7Sp}, L_{7Rp}	$CB_{14}, CB_{16}, CB_{29}, CB_{39}$
6	$L_{1Sm}, L_{1Rp}, L_{2Sp}, L_{2Rp}, L_{7Sp}, L_{7Rm}, L_{8Sm}, L_{8Rm}$	$CB_7, CB_8, CB_{11}, CB_{12}, CB_{29}, CB_{30}, CB_{39}, CB_{40}$
7	$T_{7m}, T_{8p}, B_{7m}, B_{8m}, L_{5Sm}, L_{5Rp}, L_{6Ss}, L_{7Sp}, L_{7Rm}, L_{8Rs}$	$CB_{19}, CB_{20}, CB_{29}, CB_{30}, CB_{32}, CB_{33}, CB_{34}$ $CB_{35}, CB_{36}, CB_{37}, CB_{39}$

In this step, we have the system's original connectivity condition matrix $C_{40 \times 28}$, as given in Fig. 4, in

which the non-zero elements are marked with grey background. The failure degree vector of CBs in faulty state are given in Table 2. Subsequently, the optimal solution can be obtained using the proposed optimization model, and the results are provided in Table 3.

Fig. 4. The original connectivity matrix of normal state of the EPS

Table 2. Operation state vector of CBs of the 7 fault cases

No.	Failure degree vector of CBs
1	[0 0 0 1 1 0 1 0 1 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0]ᵀ
2	[0 0 0 1 1 0 1 0 1 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0]ᵀ
3	[0 0 0 1 1 1 2 0 1 0 1 0]ᵀ
4	[0 0 0 1 1 2 2 2 1 1 1 1 0]ᵀ
5	[0 1 0 0 0 0 0 0 0 0 0 1 0]ᵀ
6	[0 0 0 0 0 0 1 1 0 0 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 1 1]ᵀ
7	[0 1 0 2 2 2 2 1 1 0 2 0]ᵀ

Table 3. The diagnostic operation state vector of system sections

No.	Failure degree vector of CBs
1	[0 0.667 0 0 0.111 0 0 0.111 0 0 0 0 0.167 0.167 0.167 0.444 0 0 0.167 0.444 0 0 0 0 0 0 0 0]ᵀ
2	[0 0.667 0 0 0.111 0 0 0.111 0 0 0 0 0.167 0.167 0.167 0.444 0 0 0.167 0.444 0 0 0 0 0 0 0]ᵀ
3	[0 1 0]ᵀ
4	[0 1 1 0]ᵀ
5	[0 0]ᵀ
6	[0 0]ᵀ
7	[0 0 0 0.316 0 0 0 0 0.316 1 0.579 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 1 0.053 1 1]ᵀ

Next, by using the decision rule, the final diagnosis results can be obtained, and they are shown in Table 4. For performance comparison, the results of 5 existing methods are provided, including fuzzy reasoning spiking neural P systems (FDSNP), fuzzy logic (FL), fuzzy petri networks (FPN), genetic algorithm-tabu search (GATS), and genetic algorithm (GA). The above five methods have provided the diagnosis results of the 7 faulty states by in the same EPS considered in this simulation. The “-” symbol means that the corresponding faulty case is not provided in their original works.

Table 4. Comparison of diagnosis results

No.	MSE(proposed)	FDSNP	FL	FPN	GATS	GA
1	B_1	B_1	B_1	B_1	-	B_1
2*	B_1	B_1	-	-	-	-
3	B_1, L_1	B_1, L_1	B_1, L_1	B_1, L_1	-	B_1, L_1
4	B_1, B_2, L_1, L_2	B_1, B_2, L_1, L_2	B_1, B_2, L_1, L_2	B_1, B_2, L_1, L_2	-	B_1, B_2, L_1, L_2
5	T_3, L_7	T_3, L_7	T_3, L_7	T_3, L_7	T_3, L_7	(1) T_3, L_7 , (2) T_3 , (3) L_7 , (4)No
6	L_1, L_2, L_7, L_8	L_1, L_2, L_7, L_8	L_1, L_2, L_7, L_8	L_1, L_2, L_7, L_8	L_1, L_2, L_7, L_8	(1) L_1, L_2, L_7, L_8 (2) L_1, L_7, L_8
7*	L_5, L_7, B_7, B_8 T_7, T_8	L_5, L_7, B_7, B_8 T_7, T_8	L_5, L_7, B_8 T_7, T_8	L_5, L_7, L_8, B_7, B_8 T_7, T_8	L_5, L_7, B_7, B_8 T_7, T_8	(1) L_5, L_7, B_7, B_8 T_7, T_8 (2) L_5, L_7, T_7, B

In Table 3, only $S_2(B_1)$ in fault cases 1 and 2 has the state value larger than 0.5, thus the diagnosis result is B_1 . We can see that the state values of $S_{16}(L_2)$ and $S_{20}(L_4)$ are all 0.444, which means that they maybe in faulty state. The reason is that CB_{12} and CB_{27} are tripped in the two cases. However, CB_8 and CB_{10} remain unchanged, thus this is insufficient to prove $S_{16}(L_2)$ and $S_{20}(L_4)$ are faulty, which is consistent with the diagnosis results. In case 2, the operated relays are L_{2Rs}, L_{4Rs} , but actually the faulty section is B_1 , this is because the information in EPS protection systems may be incomplete, the faulty sections may not be included in the operated ones.

The test results of cases 1-6 are almost the same with each other, except the GA method. We can see that the results of GA method are not robust, and sometimes the results are not reliable, thus it is incompetent with other methods. Case 7 has several different diagnosis results. In this case, the results of the proposed method, FDSNP method and GATS method are the same with each other. Since L_5, L_7, B_8, T_7, T_8 are all detected by the 6 methods, and the difference is that, B_7 is not found in FL, and L_8 is regarded as faulty in FPN. For B_7 , we can see that CB_{33}, CB_{34} and CB_{35} are tripped, which mean more than half of the its connected CBs are tripped, thus B_1 is more likely to be a fault section. In Table 3, $x_{11} = 0.579$, which is also consistent with this result. For L_8 , just CB_{30} is tripped, and it is not enough to prove that L_8 is fault. In conclusion, the results of the proposed MSE method, the FDSNP and GATS are more reasonable. As a conclusion, we can see that the proposed method is more fast, effective, and feasible compared with the existing methods.

4 Conclusions

This paper presents a new way for fault diagnosis in EPS. Operation states of system sections and CBs are represented by using matrices, and the fault diagnosis problem is formulated as a MSE learning problem. Test results demonstrate the diagnosis performance of the propose MSE method. Besides, it is also easy for implementation, and no prior results are needed. Our future work is applying the method for more complex situations, and consider prior information to improve its effectiveness.

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