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Fault Diagnosis of Metro Traction Power Systems Using A Modified Fuzzy Reasoning Spiking Neural P System

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Abstract. This paper presents the application of a modified fuzzy reasoning spiking neural P systems (MFRSN P system, for short) to fault diagnosis of metro traction power supply systems. In MFRSN P systems, three types of neurons are used to represent operation information of protection devices including protective relays and circuit breakers; a reasoning algorithm associated with MFRSN P systems is introduced to fulfill fault reasoning; fault diagnosis rules for metro traction power supply systems and their MFRSN P systems are described. Case studies show the feasibility and effectiveness of the presented method.

Key-words: Membrane computing, probabilistic fuzzy reasoning spiking neural P system, metro traction power supply system, fault diagnosis.

1. Introduction

Membrane computing, formally introduced by Gh. Păun in [1], is an attractive research field of computer science aiming at abstracting computing models, called membrane systems or P systems, from the structures and functioning of living cells, as well as from the way cells are organized in tissues or higher order structures [2, 3]. As a main type of P systems, a spiking neural P system (SN P system) is a type of P system inspired by the neurophysiological behavior of neurons sending electrical impulses (spikes) along axons from presynaptic neurons to postsynaptic neurons in a distributed and parallel manner [4]. Recently, SN P systems have become a hot topic in membrane computing [7–29], among which there are several investigations focus on the use of SN P systems and their variants to solve fault diagnosis problems [14–22].

An overview of different types of fuzzy reasoning spiking neural P systems (FRSN P systems), differences between FRSN P systems and SN P systems and newly obtained results on these FRSN P systems in solving fault diagnosis problems can be found in [14]. In [15], a fuzzy reasoning spiking neural P system with real numbers (rFRSN P system) was presented to fulfill diagnosis knowledge representation and reasoning and then the rFRSN P system was used for fault diagnosis of a transformer. In [16] and [17], the rFRSN P system was used for fault diagnosis in power systems and several different applications verified its effectiveness. In [18], the rFRSN P system was used to perform fault diagnosis of electric locomotive systems. In [19], an adaptive fuzzy spiking neural P system (AFSN P system) was proposed to fulfill fault diagnosis of a local power system with four cases. Furthermore, a fuzzy reasoning spiking neural P system with trapezoidal fuzzy numbers (tFRSN P system) was proposed in [20] and the fault diagnosis of power transmission networks based on tFRSN P systems was investigated in [20], [21]. Besides, in [22], a weighted fuzzy reasoning spiking neural P system (WFSN P system) was proposed to diagnose faults occurring in a traction power supply system of high-speed railways with three cases.

Metro traction power supply systems (MTPSSs, for short) are a kind of special distribution networks with direct current (DC) power supply. As usual, the fault diagnosis of a MTPSS is quite difficult and challenging, due to its two-way feeding power supply approach and a complex protection system caused by the DC power supply mode. FRSN P systems are a class of distributed and parallel computing models with good understandability and dynamics [14–22]. The fault occurrence in power systems is a discrete and dynamical process [20]. From the aforementioned studies [14–22], FRSN P systems are feasible and effective in solving fault diagnosis problems of different kinds of power systems as well as show great potential. Thus, this study proposes to use FRSN P systems to diagnose the faults occurring in metro traction power supply systems.

In the rFRSN P systems proposed in [15], new ingredients such as fuzzy truth value, new firing rule, pulse value, proposition neuron and rule neuron were added to the original definition of SN P systems. However, two kinds of rule neurons in rFRSN P systems are not enough to well represent status information of protective devices. To use rFRSN P systems to solve fault diagnosis problems in MTPSSs, a modified fuzzy reasoning spiking neural P system (MFRSN P system) is discussed by considering three kinds of rule neurons, a reasoning algorithm associated with MFRSN P systems, fault diagnosis rules for MTPSSs and corresponding MFRSN P systems. The parameter setting with respect to MFRSN P systems is also discussed. Case studies show the effectiveness of the presented method.

The remainder of this paper is organized as follows. Section 2 states the problem to solve. The definition of MFRSN P systems and their reasoning algorithm as well as the MFRSN P system models for fault diagnosis rules of MTPSSs are presented in Section 3. In Section 4, case studies on fault diagnosis of a MTPSS are used to test the effectiveness of MFRSN P systems. Finally, conclusions are drawn in Section 5.

2. Problem Description

Metros are important parts of public transport systems. Traction power supply systems are the energy systems of rail transportation systems and have a great significance to ensure the safety and reliable operations of trains. However, impacted by various factors such as equipment failures, interruption of power service may happen in traction power supply systems of metros. Thus, when a fault occurs in a metro traction power supply system, it is crucial to design a method to help dispatchers judge where the faults are and which sections fail so as to restore power supply of the metro as soon as possible. Thus, this study focuses on the application of FRSN P systems to fault diagnosis of metro traction power supply systems. For the convenience of description, fault diagnosis of metro traction power supply systems is abbreviated by FDMTPSS.

The framework of fault diagnosis in power systems using reasoning model-based method is shown in Fig. 1 [20]. Metro traction power supply systems (MTPSSs) are a special kind of power systems. Thus, FDMTPSS can be considered in the framework in Fig. 1. In this paper, a modified fuzzy reasoning spiking neural P systems with real numbers (MFRSN P systems) is used for FDMTPSS within this framework. The aim of fault diagnosis is to identify the faulty sections by using status information of protection devices (protective relays and CBs) which are read from SCADA systems.

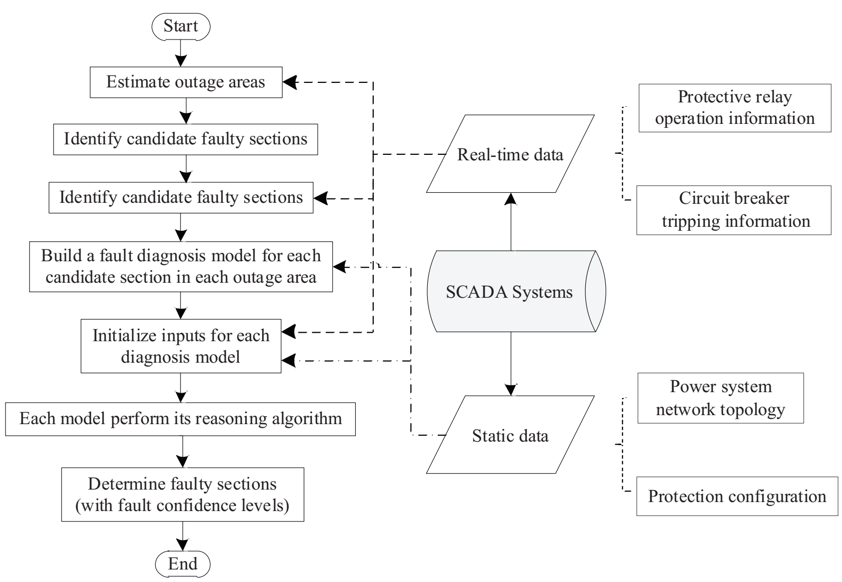

Fig. 1. Framework of fault diagnosis in power systems using reasoning model-based method.

2.1. Metro Traction Power Supply Systems

To easily understand FDMTPSS based on MFRSN P systems, this section describes basic components and operational principles of metro traction power systems. A metro traction power system consists of two parts:

(1) metro traction substations;

(2) overhead contact systems (OCS), which are usually set up along with the metro route. We will introduce them in the following.

Figure 2 shows metro traction substation electrical connection relationship, where three traction substations (identified by 1, 2 and 3) form a traction power supply section. Traction substation 1 receives 35 kV alternating current (35 kV AC) from the main substation, then feeds 35 kV AC power to traction substation 2. Traction substation 2 receives 35 kV AC power from traction substation 1 and then feeds 35 kV AC power to traction substation 3. The electrical principle schematic illustration of metro traction substation is shown in Fig. 3, where metro traction substations use single-bus sections which can be partitioned into two parts: Bus I and Bus II. Bus I and Bus II access different powers, respectively. Two traction rectifier transformers are connected to Bus II. These transformers receive three phases 35 kV AC power from section Bus II and then step-down and rectification is down to convert 35 kV AC power to 1500 V DC power. The OCSs are connected to the 1500 V DC Bus. It is worth pointing out that metro traction power systems adopt two-way feeding. So OCSs should be accessed to a left traction substation and a right traction substation at the same time.

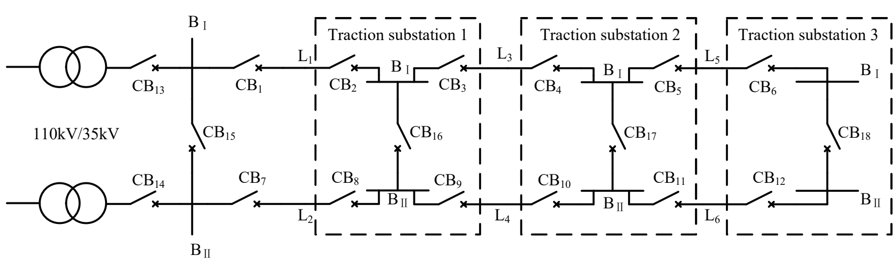

Fig. 2. Metro traction substation electrical connection relationship.

2.2. Protection Devices of Metro Traction Power Supply Systems

The fault diagnosis of FDMTPSS in this paper is based on SCADA data (statuses of protective relays and CBs). According to SCADA data, fault diagnosis models based on MFRSN P systems reason out fault confidences of candidate fault sections. So it is necessary to describe operational rules of protective relays and CBs.

In this study, the protective relays consist of main protective relays (MPRs), first backup protective relays (FBPRs) and second backup protective relays (SBPRs). It is worth pointing out that there is no FBPR for buses. When a section has a fault, MPRs of this section operate immediately to trip their associated CBs. If these MPRs fail to operate or their associated CBs do not trip, then FBPRs of this section operate to trip their associated CBs. If both MPRs and FBPRs of this section fail to operate, then SBPRs of this section operate to trip the CBs of its adjacent section. It is worth pointing out that the MPRs and FBPRs control the operation of CBs associated with the faulty sections while SBPRs control the operation of CBs associated with adjacent sections of the faulty sections.

We will take some examples to illustrate operation rules of aforementioned protection devices.

(1) If L_3 in Fig. 2 has a fault, then MPRs of L_3 will operate to trip CB_3 and CB_4 to protect L_3. If MPRs of L_3 fail to operate, then FBPRs will operate to trip CB_3 to protect L_3. If MPRs and FBPRs fail to operate or the CB_3 does not trip, then SBPRs of L_3 operate to trip CB_1 to protect L_3.

(2) If the DC 1500 V Bus in Fig. 4 has a fault, then the MPRs of the DC 1500 V Bus will operate to trip CB_1, CB_7 and CB_9 to protect this Bus.

(3) For each level of protective relays for a transformer, if a protective relay operates, then it will trip the CBs of the transformer on both its primary winding and secondary winding. If T_1 in Fig. 3 has a fault, then its MPRs or FBPRs or SBPRs will operate to trip CB_5 and CB_9.

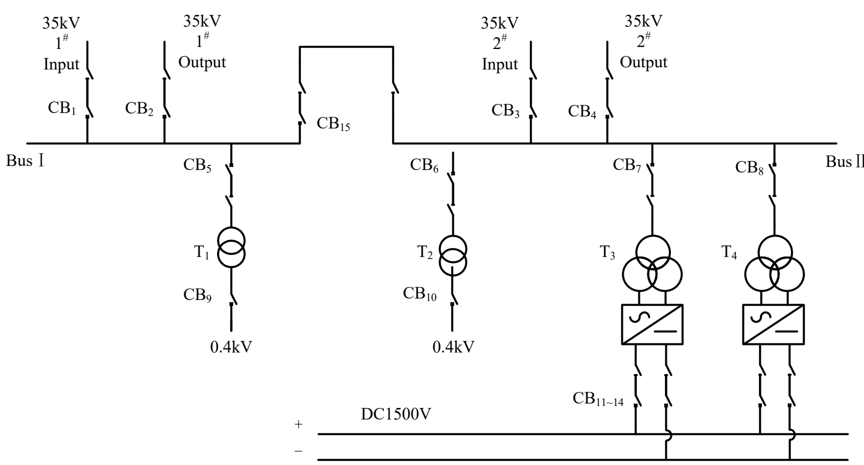

Fig. 3. Schematic illustration for traction substation of metro.

A metro traction network has transfer inter-trip (TIP) protection devices (main protection devices) because its power supply technique is two-way feeding. When a TIP protection device of a DC feeder line detects a tripping single of a CB associated with this TIP protection device, it will operate to trip all its associated CBs. For example, if the protective relays associated with CB_1 in Fig. 4 operate to trip CB_1, then the TIP protection device TIP_1 of OCS will operate to trip CB_2.

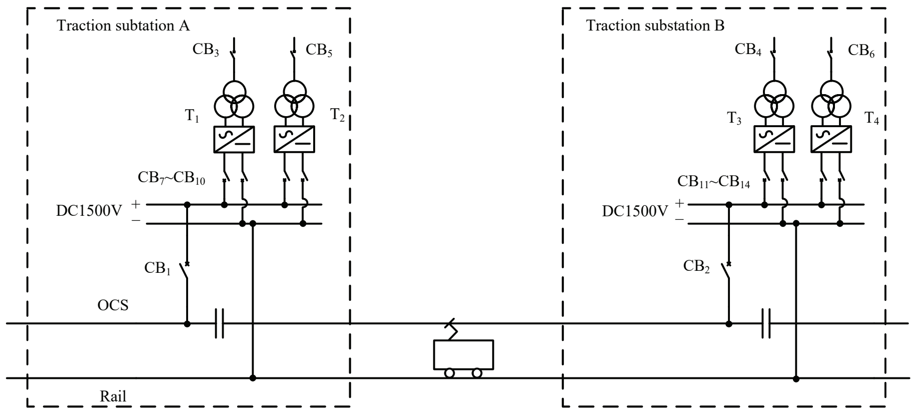

Fig. 4. Metro two-way feeding diagram

3. MFRSN P systems

In this section, a modified fuzzy reasoning spiking neural P systems (MFRSN P systems, for short) are first presented, and then a reasoning algorithm for MFRSN P systems is described. Finally, fault diagnosis rules for MTPSS and a MFRSN P system model are discussed.

3.1. MFRSN P systems

On the basis of the work in [15] and [22], we introduce a MFRSN P system, which considers one more kind of rule neurons, $general$ rule neurons, compared with rFRSN P systems in [15], and does not consider weighted synapses compared with WFRSN P systems in [22].

Definition 1. A *MFRSN P system of degree* m is a tuple

$$\Pi = (O, \sigma_1, ..., \sigma_m, syn, in, out),$$

where:

(1) $O = \{a\}$ is a singleton alphabet (a is called spike);

(2) $\sigma_1, \ldots, \sigma_m$ are neurons such that $\sigma_i = (\theta_i, c_i, r_i, \lambda_i)$, $1 \le i \le m$, where:

- (a) θ_i is a real number in [0, 1] representing the potential value of spikes contained in neuron σ_i;
- (b) c_i is a real number in [0, 1] representing the truth value of neuron σ_i;
- (c) r_i represents a firing (spiking) rule associated with neuron σ_i of the form $E/a^\theta \to a^\beta$, where θ and β are real numbers in [0,1], $E = \{a^\theta, \theta > \lambda_i\}$ represents the firing condition. The firing condition means that if and only if neuron σ_i receives at least n spikes and $\theta > \lambda_i$, then the firing rule contained in the neuron can be

applied; otherwise, the firing rule cannot be applied. If the firing rule is applied, then it means that neuron σ_i will consume a spike a with potential value θ and then send out a spike a with potential value β;

(d) λ_i is a real number in [0,1) representing the firing threshold of neuron σ_i;

(3) $syn \subseteq \{1,...,m\} \times \{1,...,m\}$ with $i \neq j$ for all $(i,j) \in syn$, $1 \leq i,j \leq m$; that is, syn is a directed graph of synapses that provides the links between neurons;

(4) $in, out \subseteq \{1,\ldots,m\}$ indicate the input neuron set and the output neuron set of Π, respectively.

MFRSN P systems include two types of neurons: proposition neurons and rule neurons. For both proposition neurons and rule neurons, their firing rules have an identical form and there is only one firing rule in each neuron. According to different computing methods of spikes, rule neurons are divided into three different kinds: $General$ rule neurons, And rule neurons and Or rule neurons, which are shown in Figure 5 (a), (b) and (c), respectively.

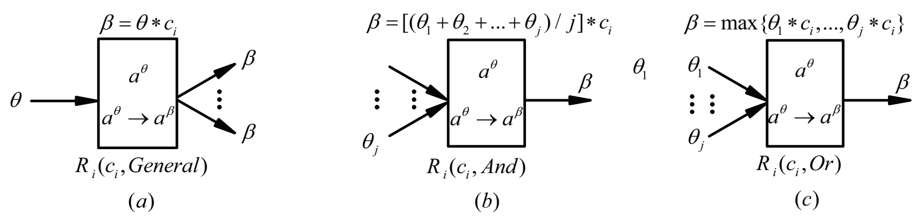

Fig. 5. Rule neurons. (a) $General$ rule neurons; (b) And rule neurons; (c) Or rule neurons.

3.2. Fault diagnosis rules for MTPSSs and their MFRSN P systems

In this subsection, we will first describe three different kinds of fault diagnosis rules for MTPSS and then we propose their MFRSN P system models, which are shown in Fig. 6.

(1) $General\ Rule\ R_i$: IF $p_j(\theta_j)$ THEN $p_k(\theta_k)$ (CF = c_i), where p_j and p_k are propositions, c_i is a real number in [0,1] representing the certainty factor of such rule R_i, θ_j and θ_k are real numbers in [0,1] representing the truth values of p_j and p_k, respectively. The truth value of p_k is $\theta_k = \theta_j * c_i$.

(2) $And\ Rule\ R_i$: IF $p_1(\theta_1)$ and $\ldots$ and $p_{k-1}(\theta_{k-1})$ THEN p_k (θ_k) (CF = c_i), where $p_1, \ldots, p_k$ are propositions, C_i is a real number in [0,1] representing the certainty factor of such rule R_i, $\theta_1, \ldots, \theta_k$ are real numbers in [0,1] representing the truth values of $p_1, \ldots, p_k$, respectively. The truth value of p_k is $\theta_k = [(\theta_1 + \ldots + \theta_{k-1})/(k-1)] * c_i$.

(3) $Or\ Rule\ R_i$: IF $p_1(\theta_1)$ or $\ldots$ or $p_{k-1}(\theta_{k-1})$ THEN $p_k(\theta_k)$ (CF = c_i), where $p_1, \ldots, p_k$ are propositions, c_i is a real number in [0, 1] representing the certainty factor of such rule R_i, $\theta_1, \ldots, \theta_k$ are real numbers in [0, 1] representing the truth values of $p_1, \ldots, p_k$, respectively. The truth value of p_k is $\theta_k = max\{\theta_1 * c_i, \ldots, \theta_{k-1} * c_i\}$.

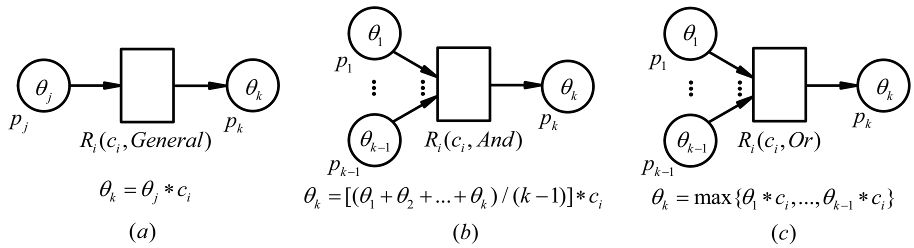

Fig. 6. Diagnosis models for MTPSS based on MFRSN P systems. (a) $General\ Rules$; (b) $And\ Rules$; (c) $Or\ Rules$

3.3. Reasoning algorithm

To make MFRSN P systems have better knowledge representation and reasoning ability, a reasoning algorithm for MFRSN P systems is introduced in this subsection. In order to clearly describe the reasoning algorithm, we will introduce some parameter vectors and matrices as follows where s represents the number of proposition neurons, t represents the number of rule neurons and $s + t = m$.

(1) $\boldsymbol{B}_p = (b_{ji})_{s\times t}$. If there is a directed arc from rule neuron σ_i to proposition neuron σ_j, then $b_{ji} = 1$; otherwise, $b_{ji} = 0$;

(2) $\boldsymbol{B}_1 = (b_{ij})_{t\times s}$. If there is a directed arc from proposition neuron σ_j to $General$ rule neuron σ_i, then $b_{ij} = 1$; otherwise, $b_{ij} = 0$;

(3) $\boldsymbol{B}_2 = (b_{ij})_{t\times s}$. If there is a directed arc from proposition neuron σ_j to And rule neuron σ_i, then $b_{ij} = 1$; otherwise, $b_{ij} = 0$;

(4) $\boldsymbol{B}_3 = (b_{ij})_{t\times s}$. If there is a directed arc from proposition neuron σ_j to Or rule neuron σ_i, then $b_{ij} = 1$; otherwise, $b_{ij} = 0$;

(5) $\boldsymbol{\theta} = (\theta_1, ..., \theta_s)^T$. θ_i $(1 \leq i \leq n)$ is a real number in [0, 1] representing the potential value of spikes in proposition neurons $\sigma_1, \ldots, \sigma_n$;

(6) $\boldsymbol{\delta} = (\delta_1, ..., \delta_t)^T$. δ_i $(1 \leq i \leq n)$ is a real number in [0, 1] representing the potential value of spikes in rule neurons $\sigma_1, \ldots, \sigma_n$;

(7) $\boldsymbol{C} = diag(c_1, ..., c_t)$. c_i $(1 \leq i \leq n)$ is a real number in [0, 1] representing the certainty factor of rule neurons $\sigma_1, \ldots, \sigma_n$;

(8) $\boldsymbol{\lambda_p} = (\lambda_{p1}, ..., \lambda_{ps})^T$. λ_{pi} $(1 \leq i \leq n)$ is a real number in [0, 1] representing the firing threshold of proposition neuron σ_i;

(9) $\boldsymbol{\lambda_r} = (\lambda_{r1}, ..., \lambda_{rt})^T$. λ_{ri} $(1 \leq i \leq m)$ is a real number in [0, 1] representing the firing threshold of rule neuron σ_i.

The reasoning algorithm contains three types of multiplication operations as follows:

(1) $\otimes$: $(b_{ij})_{t\times s} \otimes (\theta_1, ..., \theta_s)^T = (a_1, ..., a_t)^T$, where $a_i = b_{i1} * \theta_1 + ... + b_{is} * \theta_s$;

(2) $\oplus$: $(b_{ij})_{t\times s} \oplus (\theta_1, ..., \theta_s)^T = (a_1, ..., a_t)^T$, where $a_i = \frac{b_{i1}*\theta_1+...+b_{is}*\theta_s}{b_{i1}+...+b_{is}}$;

(3) $\odot$: $(b_{ij})_{t\times s} \odot (\theta_1, ..., \theta_s)^T = (a_1, ..., a_s)^T$, where $a_i = max\{b_{i1} * \theta_1, ..., b_{is} * \theta_s\}$.

Now the reasoning algorithm is presented as follows.

Step 1: Initialization parameters. Set zero-matrix $\boldsymbol{O}$ termination condition. According to MFRSN P system fault diagnosis models rules for MTPSS, information of protection devices from SCADA systems and Table 1, vectors $\boldsymbol{\theta_0}$, $\boldsymbol{\delta_0}$, $\boldsymbol{\lambda_p}$, $\boldsymbol{\lambda_r}$ and matrices $\boldsymbol{B}_p$, $\boldsymbol{B}_1$, $\boldsymbol{B}_2$, $\boldsymbol{B}_3$, $\boldsymbol{C}$ are initialized;

Step 2: Set $g = 0$, which presents the reasoning step;

Step 3: If the firing condition of a proposition neuron is satisfied and there is a postsynaptic neuron, then the proposition neuron will transmit a new spike to the next rule neuron through directed arc;

Step 4: According to fault diagnosis rules for MTPSS, rule neurons compute the vector $\boldsymbol{\delta}_{g+1}$ according to $\boldsymbol{\delta}_{g+1} = (\boldsymbol{B}_1 \otimes \boldsymbol{\theta}_g) + (\boldsymbol{B}_2 \oplus \boldsymbol{\theta}_g) + (\boldsymbol{B}_3 \odot \boldsymbol{\theta}_g)$;

Step 5: If $\boldsymbol{\delta}_{g+1} = \boldsymbol{O}$, then the reasoning algorithm stops and outputs the reasoning results;

Step 6: $g = g + 1$;

Step 7: The new spikes are transmitted to the next proposition neurons through directed arc and the pulse value of each spike is equal to $\boldsymbol{\theta}_{g+1}$, where $\boldsymbol{\theta}_{g+1} = \boldsymbol{B}_p \odot (\boldsymbol{C} \otimes \boldsymbol{\delta}_g)$;

Step 8: Go to Step 3.

4. Case Studies

4.1. Parameter setting

The operation information of protective relays and CBs may contain uncertainty or incompleteness. So it is necessary to use a parameter to describe the accuracy of the information and confidence levels of protection devices. Table 1 shows the confidence levels of operated and non-operated feeder lines, buses and transformers [22]. According to the protection devices operation information from SCADA systems and confidence levels for sections in Table 1, we can initialize the input spikes of MFRSN P system models. It is worth pointing out that both main protective relays (MPRs) and first backup protective relays (FBPRs) control the same CBs. Thus, if both MPRs and FBPRs operate, then the values of the CBs is set according to their corresponding MPRs.

Table 1. Operation and non-operation confidence levels of the protective devices

Sections	Protective devices (operated)						Protective devices (non-operated)					
	Main		Primary backup		Remote backup		Main		Primary backup		Remote backup	
	Relays	CBs	Relays	CBs	Relays	CBs	Relays	CBs	Relays	CBs	Relays	CBs
FL	0.9913	0.9833	0.8	0.85	0.7	0.75	0.2	0.2	0.2	0.2	0.2	0.2
B	0.8564	0.9833	-	-	0.7	0.75	0.4	0.2	-	-	0.4	0.2
T	0.7756	0.9833	0.75	0.8	0.7	0.75	0.4	0.2	0.4	0.2	0.4	0.2

To make sure every kinds of fault problems can be diagnosed, the firing threshold value of each neuron in an MFRSN P system should be smaller than the minimum pulse value of spikes appearing in the neurons. So according to Table 1 and three different diagnosis models in Section 3.2, we set the firing threshold value to 0.1. There are three kinds of protection devices for sections in power systems. Correspondingly, there are three kinds of fault diagnosis rules which are associated with main protection, first backup protection and second backup protection, respectively. In this study, according to the experience, the certainty factors c_i of different kinds of rules (main, first backup and second backup protection) are set to 0.975, 0.95 and 0.9, respectively.

Besides, a criterion for determining which section has a fault should be given. If the confidence level θ of a section obtained by a reasoning algorithm satisfies condition $\theta \geq 0.5$, then the section has a fault; otherwise, the section is not faulty.

4.2. Cases

Three cases are considered as examples to test the effectiveness of MFRSN P systems in fault diagnosis of metro traction power systems. In Case 1, the protection devices operation information from the SCADA system does not contain uncertainty and incompleteness while the information in Cases 2 and 3 have uncertainty and incompleteness.

Case 1: The 35 kV medium-voltage network has a fault and the electric diagram of the diagnosed local power system is shown in Fig. 2. Operated protective relays: L_{3m}. Tripped CBs: CB_3 and CB_4. A fault diagnosis model for L_3 based on an MFRSN P system is built and is shown in Fig. 7, which contains 14 proposition neurons and 8 rule neurons.

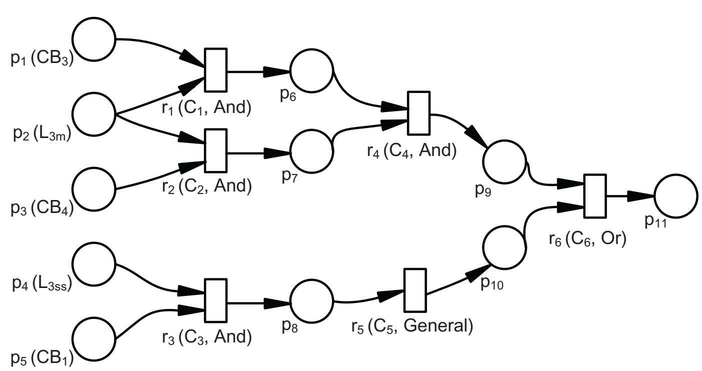

Fig. 7. A fault diagnosis model for L_3 based on MFRSN P system.

According to the reasoning algorithm proposed in Section 3.3, the steps of the reasoning process are described as follows.

Step 1: $\boldsymbol{\theta}_0 = (0.9833, 0.9913, 0.9833, 0.2, 0.2, 0.2, 0, 0, 0, 0, 0, 0, 0, 0)^T$, $\boldsymbol{C} = diag(0.975, 0.975, 0.95, 0.9, 0.975, 0.95, 0.9, 0.975)$, $\boldsymbol{\delta}_0 = \boldsymbol{O}$.

$$\boldsymbol{B}_p = \begin{bmatrix} 0&0&0&0&0&0&0&0\\ 0&0&0&0&0&0&0&0\\ 0&0&0&0&0&0&0&0\\ 0&0&0&0&0&0&0&0\\ 0&0&0&0&0&0&0&0\\ 0&0&0&0&0&0&0&0\\ 1&0&0&0&0&0&0&0\\ 0&1&0&0&0&0&0&0\\ 0&0&1&0&0&0&0&0\\ 0&0&0&1&0&0&0&0\\ 0&0&0&0&1&0&0&0\\ 0&0&0&0&0&1&0&0\\ 0&0&0&0&0&0&1&0\\ 0&0&0&0&0&0&0&1 \end{bmatrix}$$

$$\boldsymbol{B}_1 = \begin{bmatrix} 0&0&0&0&0&0&0&0&0&0&0&0&0&0\\ 0&0&0&0&0&0&0&0&0&0&0&0&0&0\\ 0&0&0&0&0&0&0&0&0&0&0&0&0&0\\ 0&0&0&0&0&0&0&0&0&0&0&0&0&0\\ 0&0&0&0&0&0&0&0&0&0&0&0&0&0\\ 0&0&0&0&0&0&0&0&1&0&0&0&0&0\\ 0&0&0&0&0&0&0&0&0&1&0&0&0&0\\ 0&0&0&0&0&0&0&0&0&0&0&0&0&0 \end{bmatrix}$$

$$\boldsymbol{B}_2 = \begin{bmatrix} 1&1&0&0&0&0&0&0&0&0&0&0&0&0\\ 0&1&1&0&0&0&0&0&0&0&0&0&0&0\\ 0&0&1&1&0&0&0&0&0&0&0&0&0&0\\ 0&0&0&0&1&1&0&0&0&0&0&0&0&0\\ 0&0&0&0&0&0&1&1&0&0&0&0&0&0\\ 0&0&0&0&0&0&0&0&0&0&0&0&0&0\\ 0&0&0&0&0&0&0&0&0&0&0&0&0&0\\ 0&0&0&0&0&0&0&0&0&0&0&0&0&0 \end{bmatrix}$$

$$\boldsymbol{B}_3 = \begin{bmatrix} 0&0&0&0&0&0&0&0&0&0&0&0&0&0\\ 0&0&0&0&0&0&0&0&0&0&0&0&0&0\\ 0&0&0&0&0&0&0&0&0&0&0&0&0&0\\ 0&0&0&0&0&0&0&0&0&0&0&0&0&0\\ 0&0&0&0&0&0&0&0&0&0&0&0&0&0\\ 0&0&0&0&0&0&0&0&0&0&0&0&0&0\\ 0&0&0&0&0&0&0&0&0&0&0&0&0&0\\ 0&0&0&0&0&0&0&0&0&0&1&1&1&0 \end{bmatrix}$$

$\boldsymbol{\lambda}_p = (0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1)^T$,
$\boldsymbol{\lambda}_r = (0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1)^T$;

Step 2: The firing condition of proposition neurons is satisfied and there is a postsynaptic neuron, the proposition neuron will transmit a new spike to next rule neuron through a directed arc.

Step 3: $\boldsymbol{\delta}_{g+1} = (\boldsymbol{B}_1 \otimes \boldsymbol{\theta}_g) + (\boldsymbol{B}_2 \oplus \boldsymbol{\delta}_g) + (\boldsymbol{B}_3 \odot \boldsymbol{\theta}_g)$, $\boldsymbol{\delta}_1 = [0.9873, 0.9873, 0.5917, 0.2, 0, 0, 0, 0]^T$.

Step 4: $\boldsymbol{\delta}_1 \neq \boldsymbol{O}$. Continue the reasoning algorithm.

Step 5: $g = 1$.

Step 6: $\boldsymbol{\theta}_g = \boldsymbol{B}_p \odot (\boldsymbol{C} \otimes \boldsymbol{\delta}_g)$, $\boldsymbol{\theta}_1 = [0, 0, 0, 0, 0, 0.9626, 0.9626, 0.5621, 0.18, 0, 0, 0, 0]^T$.

Step 7: $\boldsymbol{\delta}_{g+1} = (\boldsymbol{B}_1 \otimes \boldsymbol{\theta}_g) + (\boldsymbol{B}_2 \oplus \boldsymbol{\delta}_g) + (\boldsymbol{B}_3 \odot \boldsymbol{\theta}_g)$, $\boldsymbol{\delta}_2 = [0, 0, 0, 0, 0.9626, 0.5621, 0.18, 0]^T$.

Step 8: $\boldsymbol{\delta}_2 \neq \boldsymbol{O}$. Continue the reasoning algorithm.

Step 9: $g = 2$.

Step 10: $\boldsymbol{\theta}_g = \boldsymbol{B}_p \odot (\boldsymbol{C} \otimes \boldsymbol{\delta}_g)$, $\boldsymbol{\theta}_{(2)} = [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0.9385, 0.54, 0.162, 0]^T$.

Step 11: $\boldsymbol{\delta}_{g+1} = (\boldsymbol{B}_1 \otimes \boldsymbol{\theta}_g) + (\boldsymbol{B}_2 \oplus \boldsymbol{\delta}_g) + (\boldsymbol{B}_3 \odot \boldsymbol{\theta}_g)$, $\boldsymbol{\delta}_3 = [0, 0, 0, 0, 0, 0, 0, 0.9385]^T$.

Step 12: $\boldsymbol{\delta}_3 \neq \boldsymbol{O}$. Continue the reasoning algorithm.

Step 13: $g = 3$.

Step 14: $\boldsymbol{\theta}_g = \boldsymbol{B}_p \odot (\boldsymbol{C} \otimes \boldsymbol{\delta}_g)$, $\boldsymbol{\theta}_3 = [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0.915]^T$.

Step 15: $\boldsymbol{\delta}_{g+1} = (\boldsymbol{B}_1 \otimes \boldsymbol{\theta}_g) + (\boldsymbol{B}_2 \oplus \boldsymbol{\delta}_g) + (\boldsymbol{B}_3 \odot \boldsymbol{\theta}_g)$, $\boldsymbol{\delta}_4 = \boldsymbol{O}$.

Step 16: $\boldsymbol{\delta}_4 = \boldsymbol{O}$. The reasoning algorithm ends. We can get the reasoning results from output neurons p_{14}. The pulse value of the spike in p_{14} is 0.915. Thus, the fault confidence level of L_3 is 0.915. So L_3 is a faulty section.

Case 2: The OCS has a fault and the electric diagram of the diagnosed local power system is shown in Figure 4. Operated protective relays: TIP_1, T_{1s}, T_{2s}. Tripped CBs: CB_2, CB_3 and CB_5. The information from the SCADA system is incomplete: the OCS_{CB2-m} operated information is missing. A fault diagnosis model for OCS based on an MFRSN P system is built and is shown in Figure 8, which contains 28 proposition neurons and 15 rule neurons. It is worth to point out the TIP_1 represent the transfer intertrip protections associated with the CB_1 and CB_2. OCS_{CB1-m} and OCS_{CB2-m} represent the OCS main protective devices associated with CB_1 and CB_2, respectively.

According to the fault diagnosis model and the protective relays and CB_s information from SCADA and Table 1, the column vectors $\boldsymbol{\theta}_0$, $\boldsymbol{\delta}_0$, $\boldsymbol{\lambda}_p$, $\boldsymbol{\lambda}_r$ and matrix $\boldsymbol{B}_p, \boldsymbol{B}_1, \boldsymbol{B}_2, \boldsymbol{C}$ can be initialized and we get:

$\boldsymbol{\theta}_1 = [\theta_1, ..., \theta_{13}, \theta_{14}, \theta_{15}, \theta_{16}, \theta_{17}, \theta_{18}, \theta_{19}, \theta_{20}, \theta_{21}, \theta_{22}, ..., \theta_{28}]^T = [0, ..., 0, 0.195, 0.577, 0.581, 0.963, 0.653, 0.653, 0.27, 0.27, 0, ..., 0]^T$

$\boldsymbol{\theta}_2 = [\theta_1, ..., \theta_{21}, \theta_{22}, \theta_{23}, \theta_{24}, \theta_{25}, \theta_{26}, \theta_{27}, \theta_{28}]^T = [0, ..., 0, 0.376, 0.376, 0.565, 0.239, 0.612, 0.415, 0]^T$

$\boldsymbol{\theta}_3 = [\theta_1, ..., \theta_{27}, \theta_{28}]^T = [0, ...0, 0.597]^T$ and $\boldsymbol{\delta}_4 = \boldsymbol{O}$;

According to the reasoning algorithm, the fault confidence level of OCS is 0.597. So, OCS is a faulty section.

Case 3: The transformer T_3 has a fault and the electric diagram of the diagnosed local power is shown in Figure 3. Operated protective relays: T_{3m}, T_{3p}, T_{3s}. Tripped CBs: CB_3 and CB_{11}. CB_4 and CB_7 refuse to trip. CB_4 refusing trip is misinformation and the information about CB_{12} is missing. Based on the introduction above, the diagnosis model is shown in Figure 9. According to the fault diagnosis model and the protective relays and CB_s information from SCADA and Table 1, the column vectors $\boldsymbol{\theta}_0$, $\boldsymbol{\delta}_0$, $\boldsymbol{\lambda}_p$, $\boldsymbol{\lambda}_r$ and matrix $\boldsymbol{B}_p$, $\boldsymbol{B}_1, \boldsymbol{B}_2, \boldsymbol{C}$ can be initialized and we get:

$\boldsymbol{\theta}_1 = [\theta_1, ..., \theta_8, \theta_9, \theta_{10}, \theta_{11}, \theta_{12}, \theta_{13}, \theta_{14}, \theta_{15}, \theta_{16}, \theta_{17}, ..., \theta_{20}]^T = [0, ..., 0, 0.476, 0.857, 0.476, 0.451, 0.823, 0.451, 0.652, 0.405, 0, ..., 0]^T$

$\boldsymbol{\theta}_2 = [\theta_1, ..., \theta_{16}, \theta_{17}, \theta_{18}, \theta_{19}, \theta_{20}]^T = [0, ..., 0, 0.588, 0.546, 0.452, 0]^T$

$\boldsymbol{\theta}_3 = [\theta_1, ..., \theta_{19}, \theta_{20}]^T = [0, ..., 0, 0.573]^T$ and $\boldsymbol{\delta}_4 = \boldsymbol{O}$.

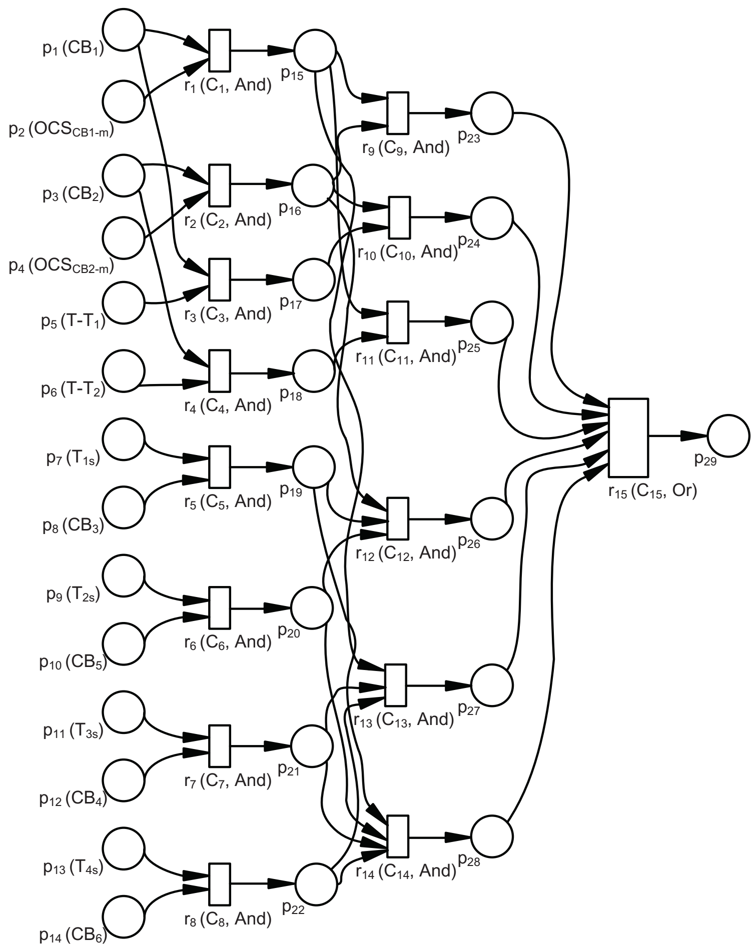

Fig. 8. A fault diagnosis model for OCS based on MFRSN P system

According to the reasoning algorithm, the fault confidence of T_3 is 0.573. So T_3 is a faulty section.

For Case 1, certain and complete operate information of protective relays and CBs is used as fault diagnosis reasoning data and the reasoning result is that L_3 is a faulty section with a high fault confidence level 0.915. In Case 2, OCS_{CB2-m} operated information is missing and in case 3, CB_4 refuses to trip and the information about CB_{12} is missing. So, for Cases 2-3, uncertain and incomplete operate information of protective relays and CBs is used as fault diagnosis reasoning data. The reasoning result for Case 2 is that OCS is a faulty section with a low fault confidence level 0.597 while the result for Case 3 is T_3 is a faulty section with a low fault confidence level 0.573. According to these results, we

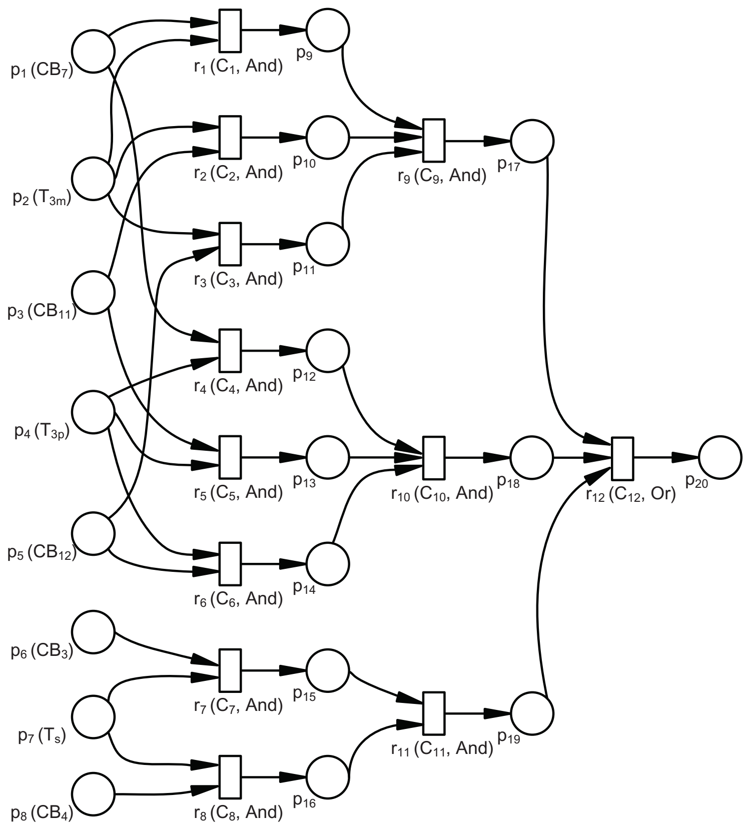

Fig. 9. A fault diagnosis model for T_3 based on MFRSN P system

know that although uncertain and incomplete operate information have influences on fault confidences of candidate faulty sections, MFRSN P system can diagnose right faulty sections with certain/uncertain and complete/incomplete operate information.

5. Conclusions

In this study, MFRSN P systems are introduced for fault diagnosis of MTPSSs. In MFRSN P systems, four kinds of neurons (one kind of proposition neurons and three kinds of rule neurons) are considered and a reasoning algorithm for MFRSN P systems to fulfill fault information reasoning is presented. Besides, fault diagnosis rules for MTPSSs and their MFRSN P system based fault diagnosis models are described. Moreover, how to set the parameters of these models is discussed. Finally, three case studies are considered according to whether operation information of protection devices from the SCADA system contains uncertainty and/or incompleteness. These cases show the presented method is effective in fault diagnosis of MTPSSs. This study focus on applying MFRSN P systems in diagnosing faults of MTPSSs and testing their validity and feasibility. Thus, the following work about verifying the performance superiority of MFRSN P systems compared with other classical diagnosis methods is now in progress. Furthermore, we will consider either the use of electric information or both operation information of protection devices and electric information in fault diagnosis of MTPSSs to improve fault tolerance ability of MFRSN P systems.

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