Fault Diagnosis Models for Electric Locomotive Systems Based on Fuzzy Reasoning Spiking Neural P Systems

Tao Wang[1], Gexiang Zhang[1], and Mario J. Pérez-Jiménez[2](✉)

[1] School of Electrical Engineering, Southwest Jiaotong University, Chengdu 610031, People's Republic of China
wangtaocdu@gmail.com, zhgxdylan@126.com

[2] Department of Computer Science and Artificial Intelligence, Research Group on Natural Computing, University of Sevilla, 41012 Sevilla, Spain
marper@us.es

Abstract. This paper discusses the application of fuzzy reasoning spiking neural P systems with real numbers (rFRSN P systems) to fault diagnosis of electric locomotive systems. Relationships among breakdown signals and faulty sections in subsystems of electric locomotive systems are described in the form of fuzzy production rules firstly and then fault diagnosis models based on rFRSN P systems for these subsystems are built according to these rules. Fuzzy production rules for diagnosing electric locomotive systems are abstracted from the fault diagnosis analysis of the subsystems and the causality among faulty sections, faulty subsystems and electric locomotive systems. Finally, a diagnosis model based on rFRSN P systems for electric locomotive systems is proposed.

Keywords: Fuzzy reasoning spiking neural P system · Fault diagnosis · Electric locomotive system · Real number · SS4 electric locomotive systems

1 Introduction

Spiking neural P systems (SN P systems), introduced in [2] in the framework of membrane computing, is a new class of computing devices which are inspired by the neurophysiological behavior of neurons sending electrical impulses (spikes) along axons to other neurons. Since then, SN P systems have become a hot topic in membrane computing [3]-[21], including investigations focusing on the use of SN P systems and their variants to solve engineering problems in power systems [18]-[21].

In [18], fuzzy reasoning spiking neural P systems with real numbers (rFRSN P systems) were introduced in order to capture the diagnosis knowledge representation and reasoning. The merits of rFRSN P systems lie in visually describing fuzzy production rules in a fuzzy diagnosis knowledge systems, where they effectively model the relationships among breakdown signals and faulty sections and represent and handle fuzzy knowledge/information. This paper discusses the

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application of rFRSN P systems to the fault diagnosis of the Shaoshan4 (SS4) electric locomotive systems (always indicate SS4 electric locomotive systems).

Electric locomotive systems are composed of several subsystems with different functions; meanwhile, these subsystems consist of numerous sections. Thus, a locomotive system can be viewed as a hierarchical tree structure of sections and subsystems [22,23]. To build fault diagnosis models based on rFRSN P systems for different subsystems, relationships among breakdown signals and faulty sections in subsystems are abstracted and described in the form of fuzzy production rules firstly. Then, fault diagnosis models for these subsystems are built based on these rules. Fuzzy production rules for diagnosing electric locomotive systems are derived in accordance with causality rules among faulty sections, faulty subsystems and SS4 electric locomotive systems. It is worth pointing out that rFRSN P systems used in this paper contain three types of rule neurons, i.e., $GENERAL$, AND and OR, while the ones in [18] only contain two types: AND and OR.

This paper is structured as follows. Section 2 introduces preliminary definitions and concepts utilsed in this work. The fault diagnosis models for key subsystems and electric locomotive systems are presented in Section 3. Conclusions are drawn in Section 4.

2 Preliminaries

In this section, we briefly review the basic concepts of rFRSN P systems [18]. Here, only the necessary prerequisites are introduced.

Definition 1: An rFRSN P system of degree $m \geq 1$ is a tuple $\Pi = (O, \sigma_1, \ldots, \sigma_m, syn, in, out)$, where:

(1) $O = \{a\}$ is a singleton alphabet (a is called spike);
(2) $\sigma_1, \ldots, \sigma_m$ are neurons, of the form $\sigma_i = (\theta_i, c_i, r_i), 1 \leq i \leq m$, where:
  (a) θ_i is a real number in [0, 1] representing the potential value of spikes (i.e. value of electrical impulses) contained in neuron σ_i;
  (b) c_i is a real number in [0, 1] representing the fuzzy truth value corresponding to neuron σ_i;
  (c) r_i represents a firing (spiking) rule contained in neuron σ_i with the form $E/a^\theta \to a^\beta$, where E is the firing condition and its form will be specified below, θ and β are real numbers in [0, 1];
(3) $syn \subseteq \{1, 2, \ldots, m\} \times \{1, 2, \ldots, m\}$ with $i \neq j$ for all $(i, j) \in syn, 1 \leq i, j \leq m$, is a directed graph of synapses between the linked neurons;
(4) $in, out \subseteq \{1, 2, \ldots, m\}$ indicate the input neuron set and the output neuron set of Π, respectively.

In rFRSN P systems, each neuron associates with either a fuzzy proposition or a fuzzy production rule, and $c_i \in [0, 1]$ is used to express a truth value of this fuzzy proposition or confidence factor (CF) of this fuzzy production rule. Each neuron σ_i contains only one firing (spiking) rule, of the form $E/a^\theta \to a^\beta$, where $E = a^n$ and n is the number of input synapses from other neurons to the neuron. It can be applied if and only if σ_i contains at least n spikes, otherwise, the rule cannot be enabled until n spikes are received. For neuron σ_i, if its firing rule is applied, then its pulse value θ_i is consumed and a new spike with value β is produced in σ_i. Once the spike with value β is emitted from σ_i, each neuron σ_j with $(i, j) \in syn$ immediately receives this spike.

In rFRSN P systems, the neurons are extended to four types (proposition neurons and three kinds of rule neurons: $GENERAL$, AND and OR) and the pulse value contained in each neuron is no longer the number of spikes represented by a real value, but a real number in [0, 1] representing the potential value of spikes contained in neuron σ_i. For neuron σ_i, if $\theta_i > 0$, then the neuron contains a spike with pulse value θ_i; otherwise, it contains no spike and its pulse is 0. For different types of neurons, their definitions and the operations for pulse values are different. We only introduce the definition of GENERAL rule neurons. Details about the other three types of neurons can be found in [18].

Definition 2: A $GENERAL$ rule neuron is associated with a fuzzy production rule which has only one proposition in the antecedent part of the rule. Such a neuron is represented by a rectangle, as shown is Fig. 1.

A $GENERAL$ rule neuron has only one presynaptic proposition neuron and one or more postsynaptic proposition neurons. If a $GENERAL$ rule neuron receives a spike from its presynaptic proposition neuron and its firing condition is satisfied, then the neuron fires and produces a new spike with the potential value $\beta = \theta * c$, where β, θ and c are real numbers in [0, 1].

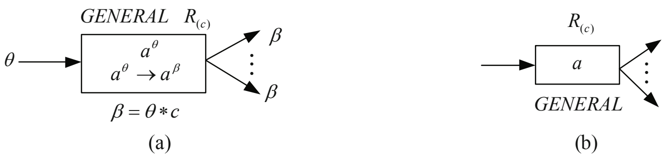

Fig. 1. A $GENERAL$ rule neuron (a) and its simplified form (b)

3 Fault Diagnosis Models for Electric Locomotive Systems Based on rFRSN P Systems

In this section, fault diagnosis models based on rFRSN P systems for SS4 electric locomotive systems and their main subsystems, i.e., main circuit systems, power supply systems, traction and breaking systems, are proposed. Since an SS4 electric locomotive system can be viewed as a hierarchial tree structure of subsystems and sections shown in Fig. 2, we can build the diagnosis models from leaves to the top (that is, the root) of the tree. Thus, we firstly build the models for subsystems and then analyze these models and relationships among an electric locomotive system, its subsystems and faulty sections in these subsystems. Finally, a fault diagnosis model for SS4 electric locomotive systems is proposed.

3.1 A Fault Diagnosis Model for the Main Circuit Systems

Fuzzy production rules ($Rules$ 1 to 16), describing the relationships between breakdown signals detected and candidate faulty sections, for main circuit

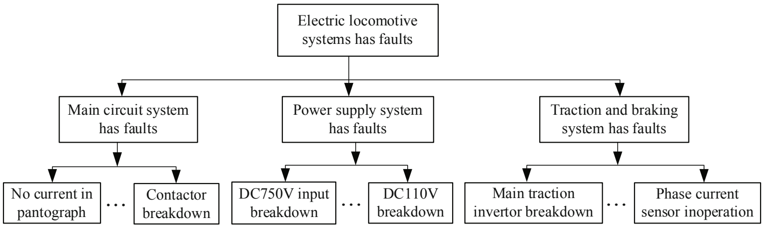

Fig. 2. A hierarchial tree structure of components in an SS4 electric locomotive system

systems of electric locomotives are described as follows, where CF represents the certainty (confidence) factor of a rule, $P_1, \ldots, P_{18}$ are propositions whose meanings are shown in Table 1. According to these fuzzy production rules, a fault diagnosis model based on rFRSN P systems for main circuit systems $\Pi_1 = (O, \sigma_1, \ldots, \sigma_{34}, syn, in, out)$ is built, as shown in Fig. 3, where:

(1) $O = \{a\}$ is the singleton alphabet (a is called spike);
(2) $\sigma_1, \ldots, \sigma_{18}$ are proposition neurons associated with propositions $P_1, \ldots, P_{18}$, respectively;
(3) $\sigma_{19}, \ldots, \sigma_{28}, \sigma_{30}, \ldots, \sigma_{34}$ are *GENERAL* rule neurons associated with fuzzy production rules $R_1, \ldots, R_{10}, R_{12}, \ldots, R_{16}$, respectively; σ_{29} is an *OR* rule neuron associated with fuzzy production rule R_{11};
(4) $syn = \{(1,19), (2,20), (3,21), (4,22), (5,23), (6,24), (7,25), (8,26), (9,27), (10,28), (11,29), (12,29), (13,30), (14,31), (15,32), (16,33), (17,34), (19,13), (20,13), (21,13), (22,14), (23,14), (24,14), (25,15), (26,15), (27,16), (28,16), (29,17), (30,18), (30,15), (31,18), (31,15), (32,18), (33,15), (34,18)\}$;
(5) $in = \{\sigma_1, \ldots, \sigma_{12}\}$, $out = \{\sigma_{18}\}$.

Rule 1: IF P_1 THEN P_{13} (CF=0.95); *Rule* 9: IF P_9 THEN P_{16} (CF=0.95)
Rule 2: IF P_2 THEN P_{13} (CF=0.85); *Rule* 10: IF P_{10} THEN P_{16} (CF=0.9)
Rule 3: IF P_3 THEN P_{13} (CF=0.9); *Rule* 11: IF P_{11} OR P_{12} THEN P_{17} (CF=0.9)
Rule 4: IF P_4 THEN P_{14} (CF=0.8); *Rule* 12: IF P_{13} THEN P_{15} AND P_{18}(CF=1.0)
Rule 5: IF P_5 THEN P_{14} (CF=0.85); *Rule* 13: IF P_{14} THEN P_{15} AND P_{18}(CF=0.9)
Rule 6: IF P_6 THEN P_{14} (CF=0.8); *Rule* 14: IF P_{15} THEN P_{18} (CF=0.9)
Rule 7: IF P_7 THEN P_{15} (CF=0.95); *Rule* 15: IF P_{16} THEN P_{15} (CF=0.85)
Rule 8: IF P_8 THEN P_{15} (CF=0.8); *Rule* 16: IF P_{17} THEN P_{18} (CF=0.85)

Table 1. Meaning of each proposition in fuzzy production rules for main circuit systems

P_1	pantograph bounce	P_{10}	nonlinear resistor sparkwear
P_2	mechanical part damaged	P_{11}	coil/main contact sparkwear
P_3	scratching of pantograph	P_{12}	contact in poor contact
P_4	insulating oil damp	P_{13}	no current in pantograph
P_5	cooling system breakdown	P_{14}	traction transformer breakdown
P_6	transformer internal breakdown	P_{15}	pulling motor inoperation
P_7	electrical strength reduction	P_{16}	circuit breaker inoperation
P_8	electromotor overload	P_{17}	contactor breakdown
P_9	isolating switch sparkwear	P_{18}	main circuit breakdown

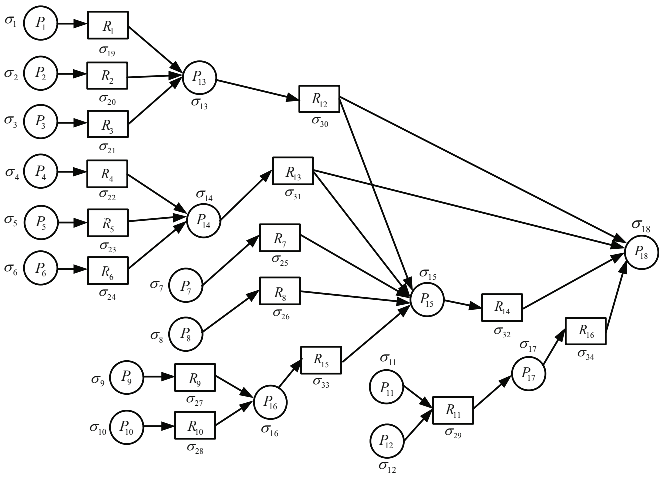

Fig. 3. A fault diagnosis model based on rFRSN P systems for the main circuit systems

3.2 A Fault Diagnosis Model for the Power Supply Systems

Fuzzy production rules (*Rules* 1 to 13), describing the relationships between breakdown signals detected and candidate faulty sections, for power supply systems of electric locomotives are described as follows, where CF represents the certainty (confidence) factor of a rule, $P_1, \ldots, P_{17}$ are propositions whose meanings are shown in Table 2. According to these fuzzy production rules, a fault diagnosis model based on rFRSN P systems for power supply systems $\Pi_2 = (O, \sigma_1, \ldots, \sigma_{30}, syn, in, out)$ is built, as shown in Fig. 4, where:

(1) $O = \{a\}$ is the singleton alphabet (a is called spike);
(2) $\sigma_1, \ldots, \sigma_{17}$ are proposition neurons associated with propositions $P_1, \ldots, P_{17}$, respectively;
(3) $\sigma_{18}, \ldots, \sigma_{21}, \sigma_{23}, \sigma_{24}, \sigma_{26}, \ldots, \sigma_{30}$ are $GENERAL$ rule neurons associated with fuzzy production rules $R_1, \ldots, R_4, R_6, R_7, R_9, \ldots, R_{13}$, respectively; σ_{22} is an OR rule neuron associated with fuzzy production rule R_5; σ_{25} is an AND rule neuron associated with fuzzy production rule R_8;
(4) $syn = \{(1,18), (2,19), (3,20), (4,21), (5,22), (6,23), (7,24), (8,25), (9,26), (10,27), (11,22), (12,28), (13,25), (14,29), (16,30), (18,17), (19,10), (20,10), (21,11), (22,12), (23,14), (23,13), (24,13), (25,15), (26,16), (27,17), (27,11), (27,13), (27,14), (28,14), (28,17), (29,16), (30,17)\}$;
(5) $in = \{\sigma_1, \ldots, \sigma_9\}$, $out = \{\sigma_{15}, \sigma_{17}\}$.

Rule 1: IF P_1 THEN P_{17} (CF=0.9)
Rule 2: IF P_2 THEN P_{10} (CF=0.8)
Rule 3: IF P_3 THEN P_{10} (CF=0.85)
Rule 4: IF P_4 THEN P_{11} (CF=0.9)
Rule 5: IF P_5 OR P_{11} THEN P_{12} (CF=0.85)
Rule 6: IF P_6 THEN P_{13} AND P_{14} (CF=0.8)
Rule 7: IF P_7 THEN P_{13} (CF=0.95)
Rule 8: IF P_8 AND P_{13} THEN P_{15} (CF=0.85)
Rule 9: IF P_9 THEN P_{16} (CF=0.9)

Table 2. Meaning of each proposition in fuzzy production rules for power supply systems

P_1	main traction invertor breakdown	P_9	fan breakdown
P_2	current collector breakdown	P_{10}	DC750V input breakdown
P_3	locomotive current collector breakdown	P_{11}	110V DC/DC chopper inoperation
P_4	110V DC/DC chopper breakdown	P_{12}	DC110V breakdown
P_5	110V accumulator breakdown	P_{13}	280V DC/DC chopper inoperation
P_6	auxiliary inverter breakdown	P_{14}	auxiliary inverter inoperation
P_7	280V DC/DC chopper breakdown	P_{15}	DC280V breakdown
P_8	280V accumulator breakdown	P_{16}	fan inoperation
P_{17}	main traction invertor inoperation		

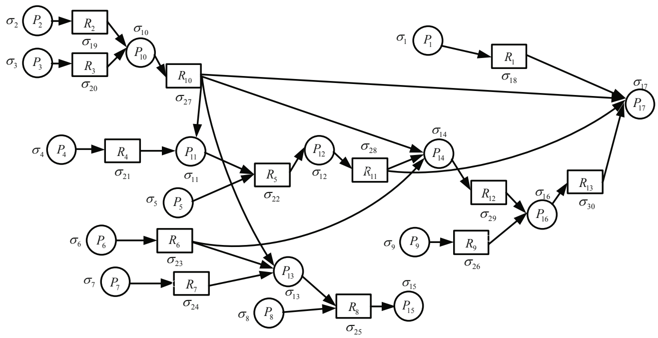

Fig. 4. A fault diagnosis model based on rFRSN P systems for the power supply systems

Rule 10: IF P_{10} THEN P_{11} AND P_{13} AND P_{14} AND P_{17} (CF=0.85)
Rule 11: IF P_{12} THEN P_{14} AND P_{17} (CF=0.8)
Rule 12: IF P_{14} THEN P_{16} (CF=0.95)
Rule 13: IF P_{16} THEN P_{17} (CF=0.9)

3.3 A Fault Diagnosis Model for the Traction and Braking Systems

Fuzzy production rules (*Rules* 1 to 10), describing the relationships between breakdown signals detected and candidate faulty sections, for traction and braking systems of electric locomotives are described as follows, where CF represents the certainty (confidence) factor of a rule, $P_1, \ldots, P_{16}$ are propositions whose meanings are shown in Table 3. According to these fuzzy production rules, a fault diagnosis model based on rFRSN P systems for traction and braking systems $\Pi_3 = (O, \sigma_1, \ldots, \sigma_{26}, syn, in, out)$ is built, as shown in Fig. 5, where:

(1) $O = \{a\}$ is the singleton alphabet (a is called spike);
(2) $\sigma_1, \ldots, \sigma_{16}$ are proposition neurons associated with propositions $P_1, \ldots, P_{16}$, respectively;
(3) $\sigma_{17}, \sigma_{18}, \sigma_{23}, \ldots, \sigma_{26}$ are *GENERAL* rule neurons associated with fuzzy production rules $R_1, R_2, R_7, \ldots, R_{10}$, respectively; $\sigma_{20}, \ldots, \sigma_{22}$ are *OR* rule neurons associated with fuzzy production rules $R_4, \ldots, R_6$, respectively;
(4) $syn = \{(1, 17), (2, 18), (3, 19), (4, 19), (5, 19), (6, 20), (7, 20), (8, 21), (9, 22), (10, 23), (11, 22), (12, 24), (13, 25), (14, 26), (15, 21), (17, 16), (18, 16), (19, 13), (20, 14), (21, 16), (22, 16), (23, 16), (24, 16), (25, 15), (26, 16)\}$;

(5) $in = \{\sigma_1, \ldots, \sigma_{12}\}$, $out = \{\sigma_{16}\}$.
Rule 1: IF P_1 THEN P_{16} (CF=0.85)
Rule 2: IF P_2 THEN P_{16} (CF=0.8)
Rule 3: IF P_3 OR P_4 OR P_5 THEN P_{13} (CF=0.9)
Rule 4: IF P_6 OR P_7 THEN P_{14} (CF=0.95)
Rule 5: IF P_8 OR P_{15} THEN P_{16} (CF=0.9)
Rule 6: IF P_9 OR P_{11} THEN P_{16} (CF=0.8)
Rule 7: IF P_{10} THEN P_{16} (CF=0.7)
Rule 8: IF P_{12} THEN P_{16} (CF=0.85)
Rule 9: IF P_{13} THEN P_{15} (CF=0.95)
Rule 10: IF P_{14} THEN P_{16} (CF=0.75)

Table 3. Meaning of each proposition in fuzzy production rules for traction and braking systems

P_1	DC110V breakdown	P_9	main protective relay breakdown
P_2	control source converter plate breakdown	P_{10}	traction power controller breakdown
P_3	U-phase current sensor breakdown	P_{11}	A/D breakdown
P_4	W-phase current sensor breakdown	P_{12}	25/5V breakdown
P_5	V-phase current sensor breakdown	P_{13}	more than one among P_3, P_4 and P_5 happen
P_6	first linear electromotor group breakdown	P_{14}	linear electromotor inoperation
P_7	second linear electromotor group breakdown	P_{15}	phase current sensor inoperation
P_8	main traction invertor breakdown	P_{16}	traction and braking system inoperation

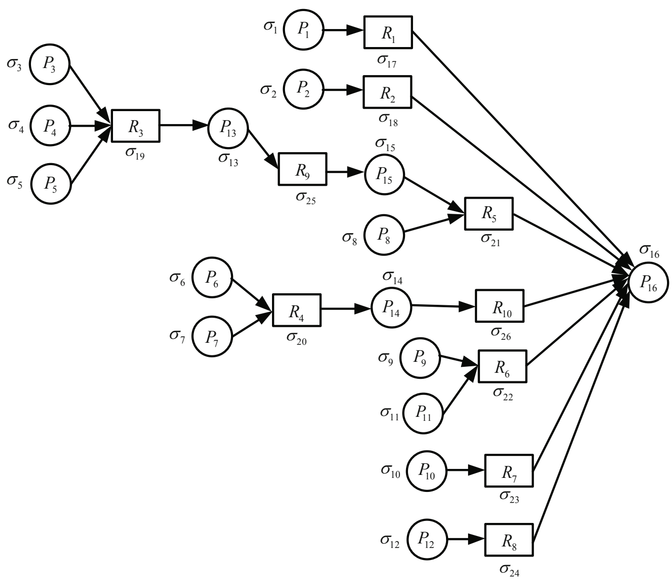

Fig. 5. A fault diagnosis model based on rFRSN P systems for the traction and braking systems

3.4 A Fault Diagnosis Model for the Electric Locomotive Systems

From Fig. 3 to Fig. 5, we know that if there is no current in pantograph or traction transformers breakdown or pulling motors inoperation or contactors breakdown, then the main circuit system of electric locomotive systems has faults; if DC750V input breakdown or fan inoperation or main traction invertor breakdown or DC110V breakdown, then the power supply system of electric locomotive systems has faults; if DC750V input breakdown or fan inoperation or main traction invertor breakdown or DC110V breakdown, then the power supply system of electric locomotive systems has faults; if the main traction invertor breakdown or DC110V breakdown or control source converter plate breakdown or main protective relay breakdown or traction power controller breakdown or A/D breakdown or 25/5V breakdown or linear electromotor inoperation or phase current sensor inoperation, then the traction and braking system of electric locomotive systems has faults.

Table 4. Meaning of each proposition in fuzzy production rules for electric locomotive systems

P_1	no current in pantograph	P_{10}	main protective relay breakdown
P_2	traction transformer breakdown	P_{11}	traction power controller breakdown
P_3	pulling motor inoperation	P_{12}	A/D breakdown
P_4	contactor breakdown	P_{13}	25/5V breakdown
P_5	DC750V input breakdown	P_{14}	linear electromotor inoperation
P_6	fan inoperation	P_{15}	phase current sensor inoperation
P_7	main traction invertor breakdown	P_{16}	main circuit system has faults
P_8	DC110V breakdown	P_{17}	power supply system has faults
P_9	control source converter plate breakdown	P_{18}	traction and braking system has faults
P_{19}	electric locomotive systems has faults		

For an electric locomotive system, if one or more than one of its subsystems (main circuit systems, power supply systems, and traction and braking systems) have faults, then this electric locomotive system has faults. According to the analysis, fuzzy production rules (*Rules* 1 to 4) for electric locomotive systems are described as follows, where CF represents the certainty (confidence) factor of a rule, $P_1, \ldots, P_{19}$ are propositions whose meanings are shown in Table 4. According to these fuzzy production rules, a fault diagnosis model based on rFRSN P systems for electric locomotive systems $\Pi_4 = (O, \sigma_1, \ldots, \sigma_{23}, syn, in, out)$ is built, as shown in Fig. 6, where:

(1) $O = \{a\}$ is the singleton alphabet (a is called spike);
(2) $\sigma_1, \ldots, \sigma_{19}$ are proposition neurons associated with propositions $P_1, \ldots, P_{19}$, respectively;
(3) $\sigma_{20}, \ldots, \sigma_{23}$ are OR rule neurons associated with fuzzy production rules $R_1, \ldots, R_4$, respectively;
(4) $syn = \{(1,20), (2,20), (3,20), (4,20), (5,21), (6,21), (7,21), (7,22), (8,21), (8,22), (9,22), (10,22), (11,22), (12,22), (13,22), (14,22), (15,22), (16,23), (17,23), (18,23), (20,16), (21,17), (22,18), (23,19)\}$;
(5) $in = \{\sigma_1, \ldots, \sigma_{15}\}$, $out = \{\sigma_{19}\}$.

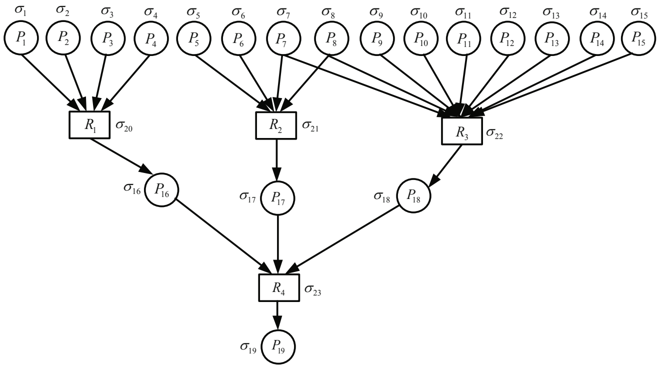

Fig. 6. A fault diagnosis model based on rFRSN P systems for the electric locomotive systems

Rule 1: IF P_1 OR P_2 OR P_3 OR P_4 THEN P_{16} (CF=0.95)
Rule 2: IF P_5 OR P_6 OR P_7 OR P_8 THEN P_{17} (CF=0.95)
Rule 3: IF P_7 OR P_8 OR P_9 OR P_{10} OR P_{11} OR P_{12} OR P_{13} OR P_{14} OR P_{15} THEN P_{18} (CF=0.95)
Rule 4: IF P_{16} OR P_{17} OR P_{18} THEN P_{19} (CF=0.98)

4 Conclusions

In this study, rFRSN P systems are applied in fault diagnosis of electric locomotive systems. This study focuses on describing relationships among breakdown signals, faulty sections, faulty subsystems and faulty electric locomotive systems in the form of fuzzy production rules by using syntactical ingredients provided by rFRSN P systems. It proposes fault diagnosis models based on rFRSN P systems for SS4 electric locomotive systems. These models can visually and formally describe relationships among breakdown signals detected and candidate faulty sections or faulty systems. This work is an important theoretical basis for proposing a novel bio-inspired method for fault diagnosis of electric locomotive systems by using rFRSN P systems. To test and verify the practical implementation and scalability of the proposed method, our future work includes the development of diagnosis algorithms for the models proposed in this paper and model reduction algorithms for the models used in specific cases. Experiments with a tool we aim to develop will prove the effectiveness of these algorithms and the approach presented in this paper.

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