ROMANIAN JOURNAL OF INFORMATION SCIENCE AND TECHNOLOGY
Volume **20**, Number 1, 2017, 5–17

Fault Diagnosis of Power Systems Using Fuzzy Reasoning Spiking Neural P Systems with Interval-valued Fuzzy Numbers

Wenping YU[1,2], Jun WANG[1,2], Hong PENG[3], Jun MING[1,2], Chengyu TAO[1,2], Tao WANG[1,2]

[1] School of Electrical Engineering and Electronic Information, Xihua University, Chengdu 610039, P. R. China

[2] Key Laboratory of Fluid and Power Machinery, Ministry of Education, Xihua University, Chengdu 610039, P. R. China

E-mail: 745257101@qq.com

[3] School of Computer and Software Engineering, Xihua University, Chengdu 610039, P. R. China

Abstract. Combining interval-valued fuzzy numbers with spiking neural P systems (SN P systems, in short), an extended SN P system model is developed for fault diagnosis of power systems, called fuzzy reasoning spiking neural P systems with interval-valued fuzzy numbers (ivFRSN P systems, in short). The ivFRSN P systems can better characterize uncertain alarm information in power systems. Firstly, the modeling approach and fuzzy reasoning algorithm are developed. Secondly, the corresponding fault diagnosis models are discussed. Finally, the fault diagnosis of a six-bus 69kV distribution system is used as an example, including single fault with device failure and multiple faults, to demonstrate the availability and effectiveness of the proposed fault diagnosis model based on ivFRSN P systems.

Key-words: Power system; Fault diagnosis; Fuzzy reasoning spiking neural P systems; Interval-valued fuzzy numbers

1. Introduction

Nowadays, with gradually expanding of the power system scale and increasing complexity of the power system structure, the number of power system components is increasing. Protection elements of these components (such as generators, transformers, bus bars, transmission lines, etc.) are mainly composed of the protective relays, circuit breakers (CBs) and communication equipment sections [1]. Once a fault occurs, dispatchers must isolate the influenced branches quickly and accurately, and take the necessary measures to restore the normal supply of electricity as soon as possible. The fault diagnosis of power system is a process of identifying faulty system elements by reading tripping signals of protective relays and CBs [2]. When a fault occurs, a lot of alarm information from supervisor control and data acquisition (SCADA) system will be immediately transferred to the dispatch center system to provide data source for fault diagnosis. However, these alarm messages are often incomplete and uncertain [3, 4]. Therefore, a good fault diagnosis method should provide the accurate and effective diagnosis information to dispatch operators [5], and help them identify the fault location and elements in order to guarantee the secure and stable operation of power systems.

In recent decades, many methods have been applied to fault diagnosis, such as expert systems (ES) [3, 5], fuzzy logic (FL) [4, 5], Petri nets (PNs) [1, 5], artificial neural networks (ANNs) [2] and so on. ES is a mature approach for fault diagnosis of power systems. However it has slow inference speed and poor tolerance ability [3]. FL expresses the imprecision and uncertainty by using the concept of fuzzy membership, but it needs to be combined with other methods [6, 8]. For PNs applied to the fault diagnosis, bad tolerance and difficulty to identify false alarm massages are their weaknesses [5]. ANNs have the advantages of good tolerance and strong learning ability, but the disadvantages are the need for numerous samples and poor generally interpreting ability [4, 8]. Therefore, it is necessary to develop new methods to avoid the problems and serve as a good model for fault diagnosis of power systems.

Spiking neural P systems (SN P systems, for short) are membrane computing models inspired by the way the neurons communicate by means of electrical impulses [9–13]. In recent years, different variants of SN P systems were proposed [14–18]. Among them, both fuzzy spiking neural P systems and fuzzy reasoning spiking neural P systems [19–22] were applied to solve the problem of fault diagnosis and got better results. However, how to handle the incompleteness and uncertainty of the alarm information in different power systems is worth further discussing [22]. Interval valued fuzzy set is an extension of traditional fuzzy sets theory, which is used to indicate the parameter values of real world processes. Taking into account that interval-valued fuzzy number (IVFN, in short) not only contains more uncertainty, but also has the ability to reflect the fuzziness of subjective judgment easily, it seems that IVFN is suitable to deal with the incomplete and uncertain fault alarm information in power systems. It was mainly used in risk analysis and group multi-criteria decision making [23, 24], but there is no relevant work in power system fault diagnosis.

Combining interval-valued fuzzy numbers with SN P systems, an extended SN P system model is developed for fault diagnosis of power systems, called fuzzy reasoning spiking neural P systems with interval-valued fuzzy numbers (ivFRSN P systems, in short). The use of interval-valued fuzzy numbers is helpful to express potential values of spikes contained in neurons and the fuzzy values of the neurons, and furthermore allows us to handle incompleteness and uncertainty in power systems. The diagnosis model based on ivFRSN P systems is discussed, including the modeling method and fuzzy reasoning algorithm.

The remainder of this paper is organized as follows. The ivFRSN P systems are introduced in Section 2. Section 3 presents the fault diagnosis method by using ivFRSN P systems and provides two case studies of the fault diagnosis of power systems. Conclusions are finally drawn in Section 4.

2. ivFRSN P systems

2.1. Interval-valued fuzzy numbers

An interval-valued fuzzy number A can be denoted as $A = [A^L, A^U] = [(a_1^L, a_2^L, a_3^L, a_4^L), (a_1^U, a_2^U, a_3^U, a_4^U)]$, where A^L and A^U are the lower and upper interval-valued fuzzy numbers [23]. The two lower and upper interval-valued fuzzy numbers can be expressed by two trapezoidal fuzzy numbers, $(a_1^L, a_2^L, a_3^L, a_4^L)$ and $(a_1^U, a_2^U, a_3^U, a_4^U)$, where $a_1^L \leq a_2^L \leq a_3^L \leq a_4^L$ and $a_1^U \leq a_2^U \leq a_3^U \leq a_4^U$, and a_1, a_2, a_3, a_4 are the real numbers in [0,1].

It is obvious that if $A^L = A^U$, then A becomes a generalized fuzzy number; if $a_1 = a_2 = a_3 = a_4$, then A becomes a non-negative real number; if $a_1 < a_2 = a_3 < a_4$, then A becomes a triangular interval-valued fuzzy number.

Suppose that $A = [(a_1^L, a_2^L, a_3^L, a_4^L), (a_1^U, a_2^U, a_3^U, a_4^U)]$ and $B = [(b_1^L, b_2^L, b_3^L, b_4^L), (b_1^U, b_2^U, b_3^U, b_4^U)]$ are two interval-valued fuzzy numbers. Then, four arithmetic operations for interval-valued fuzzy numbers can be defined as follows:

(1) $A \oplus B = [(a_1^L + b_1^L, a_2^L + b_2^L, a_3^L + b_3^L, a_4^L + b_4^L), (a_1^U + b_1^U, a_2^U + b_2^U, a_3^U + b_3^U, a_4^U + b_4^U)]$.

(2) $A \otimes B = [(a_1^L \times b_1^L, a_2^L \times b_2^L, a_3^L \times b_3^L, a_4^L \times b_4^L), (a_1^U \times b_1^U, a_2^U \times b_2^U, a_3^U \times b_3^U, a_4^U \times b_4^U)]$.

(3) $A \owedge B = [(a_1^L \wedge b_1^L, a_2^L \wedge b_2^L, a_3^L \wedge b_3^L, a_4^L \wedge b_4^L), (a_1^U \wedge b_1^U, a_2^U \wedge b_2^U, a_3^U \wedge b_3^U, a_4^U \wedge b_4^U)]$.

(4) $A \ovee B = [(a_1^L \vee b_1^L, a_2^L \vee b_2^L, a_3^L \vee b_3^L, a_4^L \vee b_4^L), (a_1^U \vee b_1^U, a_2^U \vee b_2^U, a_3^U \vee b_3^U, a_4^U \vee b_4^U)]$.

2.2. ivFRSN P systems

In the following description, ivFRSN P systems are introduced, which can be regarded as an extension of the original SN P systems introduced in [11].

Definition 1: An ivFRSN P system of degree $m \geq 1$ is a construct

$$\Pi = (A, \sigma_1, \sigma_2, \ldots, \sigma_m, syn, I, O) \tag{1}$$

where:

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

(2) $\sigma_1, \sigma_2, \ldots, \sigma_m$ are neurons, and $\sigma_i = (\theta_i, c_i, r_i)$, $i \in \{1, 2, \ldots, m\}$, where

a) θ_i is an interval-valued fuzzy number representing the value of spikes contained in neuron σ_i at the beginning of the calculation;

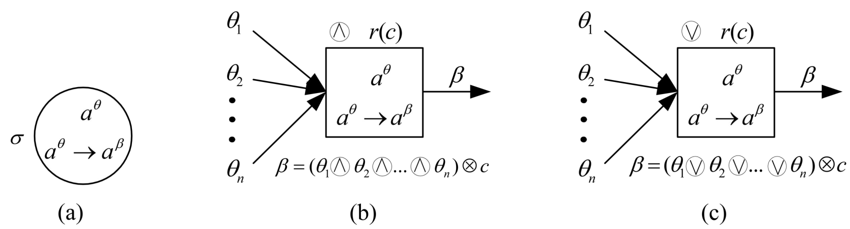

Figure 1: (a) proposition neuron, (b) "*and*"-type rule neuron, and (c) "*or*"-type rule neuron.

b) c_i is an interval-valued fuzzy number representing the fuzzy value corresponding to neuron σ_i;

c) r_i represents a firing rule associated with neuron σ_i of the form $a^\theta \to a^\theta$ or $a^\theta \to a^\beta$, where θ and β are two interval-valued fuzzy numbers.

(3) $syn \subseteq \{1, 2, \ldots, m\} \times \{1, 2, \ldots, m\}$, a directed graph of synapses between the linked neurons.

(4) I and O indicate the input neuron set and the output neuron set of Π, respectively.

In general, a fuzzy knowledge base can be represented by the following two forms of fuzzy production rules.

Type 1: IF p_1 AND p_2 AND ... AND p_{k-1} THEN p_k $(CF = c)$

Type 2: IF p_1 OR p_2 OR ... OR p_{k-1} THEN p_k $(CF = c)$

where $p_1, p_2, \ldots, p_{k-1}$ are the $k-1$ propositions of the rule's antecedent parts, and p_k is the proposition of the rule's consequent part, and c is an interval-valued fuzzy number representing the certainty factor (CF) of the fuzzy production rule.

In order to make ivFRSN P systems suitable for modeling the fuzzy production rules, the neurons are divided into three types: proposition neurons, "*and*"-type rule neurons and "*or*"-type rule neurons. Proposition neurons are associated with the propositions in fuzzy production rules. Fig. 1(a) shows a proposition neuron. The fuzzy production rule of type 1 can be represented by an "*and*"-type rule neuron, shown in Fig. 1(b). When such a rule neuron receives spikes with pulse values $\theta_1, \theta_2, \ldots, \theta_{k-1}$ from other proposition neurons, it will fire and produce a spike with pulse value $\beta = (\theta_1 \textcircled{\wedge} \theta_2 \textcircled{\wedge} \ldots \textcircled{\wedge} \theta_{k-1}) \otimes c$. Similarly, "*or*"-type rule neuron can be used to model the fuzzy production rule of type 2, shown in Fig. 1(c). When the "*or*"-type rule neuron receives spikes with pulse values $\theta_1, \theta_2, \ldots, \theta_{k-1}$ from other proposition neurons, it will fire and produce a spike with pulse value $\beta = (\theta_1 \textcircled{\vee} \theta_2 \textcircled{\vee} \ldots \textcircled{\vee} \theta_{k-1}) \otimes c$.

2.3. Fuzzy reasoning algorithm based on ivFRSN P systems

Based on the firing mechanism of ivFRSN P systems, a fuzzy reasoning algorithm is developed as follows. Assume that the ivFRSN P system contains s proposition neurons and t rule neurons, each of which may be "*and*"-type or "*or*"-type rule neurons. Thus, the total number of neurons is $m = s + t$. To explain this reasoning algorithm, some vectors and matrices are introduced as follows.

(1) $\theta = (\theta_1, \theta_2, \ldots, \theta_s)^T$ is a vector containing the fuzzy values of the s proposition neurons, where θ_i represents the pulse value contained in the ith proposition neuron, $1 \leq i \leq s$. If there is no spike contained in a proposition neuron, its pulse value is "*unknown*" or $[(0.0, 0.0, 0.0, 0.0), (0.0, 0.0, 0.0, 0.0)]$.

(2) $\delta = (\delta_1, \delta_2, \ldots, \delta_t)^T$ is a vector containing the fuzzy values of the t rule neurons, where δ_j represents the pulse value contained in the jth rule neuron, $1 \leq j \leq t$. If there is no spike contained in a rule neuron, its pulse value is "*unknown*" or $[(0.0, 0.0, 0.0, 0.0), (0.0, 0.0, 0.0, 0.0)]$.

(3) $C = diag(c_1, c_2, \ldots, c_t)$ is a diagonal matrix, where $c_j (1 \leq j \leq t)$ is an interval-valued fuzzy number representing the certainty factor of the jth fuzzy production rule.

(4) $D_1 = (d_{ij})_{s \times t}$ is a synaptic matrix representing the directed connection from proposition neurons to "*and*"-type rule neurons. If there is a directed synapse from the proposition neuron σ_i to rule neuron σ_j, $d_{ij} = 1$; otherwise, $d_{ij} = 0$.

(5) $D_2 = (d_{ij})_{s \times t}$ is a synaptic matrix representing the directed connection from proposition neurons to "*or*"-type rule neurons. If there is a directed synapse from the proposition neuron σ_i to rule neuron σ_j, $d_{ij} = 1$; otherwise, $d_{ij} = 0$.

(6) $E = (e_{ji})_{t \times s}$ is a synaptic matrix representing the directed connection from rule neurons to proposition neurons. If there is a directed synapse from the rule neuron σ_j to the proposition neuron σ_i, $e_{ji} = 1$; otherwise, $e_{ji} = 0$.

Next, three multiplication operations are introduced as follows.

(1) $C \circledcirc \delta = (c_1 \otimes \delta_1, c_2 \otimes \delta_2, \ldots, c_t \otimes \delta_t)^T$.

(2) $D^T \odot \theta = (\widetilde{d}_1, \widetilde{d}_2, \ldots, \widetilde{d}_t)^T$, where $\widetilde{d}_j = d_{1j}\theta_1 \owedge d_{2j}\theta_2 \owedge \ldots \owedge d_{sj}\theta_s$, $j = 1, 2, \ldots, t$.

(3) $E^T \circledast \delta = (\widetilde{e}_1, \widetilde{e}_2, \ldots, \widetilde{e}_s)^T$, where $\widetilde{e}_i = e_{1i}\delta_1 \ovee e_{2i}\delta_2 \ovee \ldots \ovee e_{ti}\delta_t$, $i = 1, 2, \ldots, s$.

According to previous discussion, a fuzzy reasoning algorithm for the ivFRSN P system can be described as following. Here, the input is the fuzzy values of the propositions corresponding to the input proposition neurons and the output is the fuzzy values of the propositions corresponding to the output proposition neurons.

1) Let $g = 0$ when initial reasoning step begins;

2) Set D_1, D_2, E, C, and termination condition is $O_1 = (unknown, unknown, \ldots, unknown)_t^T$. The initial values of θ and δ are set to $\theta_0 = (\theta_{10}, \theta_{20}, \ldots, \theta_{s0})$ and $\delta_0 = (\delta_{10}, \delta_{20}, \ldots, \delta_{t0})$ respectively;

3) Let g increase 1;

4) The firing condition of input neurons ($g = 1$) or proposition neurons ($g > 1$) is evaluated. If the condition is satisfied and there is at least a postsynaptic rule neuron, the neurons fire and transmit a spike to the next rule neuron.

5) Compute the fuzzy value vector δ_g:

$$\delta_g = (D_1^T \odot \theta_{g-1}) \oplus (D_2^T \circledast \theta_{g-1}) \tag{2}$$

6) If $\delta_g = O_1$, the algorithm stops and exports the reasoning results in output neurons; otherwise, it will go to step 7).

7) Evaluate the firing condition of rule neurons. If the condition is satisfied, the rule neurons fire and each transmit a spike to the next proposition neuron.

8) Compute the fuzzy value vector θ_g according to (3), and then it goes to step 3)

$$\theta_g = E^T \circledast (C \circledcirc \delta_g) \tag{3}$$

3. Fault diagnosis of power systems using ivFRSN P systems

3.1. Problem description

The fault diagnosis of power systems is a process of identifying faulty components by using the tripping information of protection relays and circuit breakers (CBs). In order to quickly and selectively remove the faulty components, when a fault occurs in power systems, the main measure is three-section current protection, i.e., main protection, nearby (first) backup protection and remote (second) backup protection. In this paper, three types of fault diagnosis are mainly considered: lines, buses and transformers.

Fig. 2 shows a six-bus 69kV distribution system, which is adopted from [7]. This system includes 10 system sections, 10 CBs and 26 protective relays. For the convenience of description, some notations are described as follows. A bus, line, CB and transformer are represented by $A/B/C, L, CB$ and T, respectively. The 10 system sections are labeled as $A_1, A_2, B_1, B_1, C_1, C_2, L_1, L_2$ and T_1, T_2. The 10 CBs are labeled as $CB_1, CB_2, \ldots, CB_9, CB_{10}$. The 26 protective relays are composed of 12 main relays, i.e., $A_{1m}, A_{2m}, B_{1m}, B_{2m}, C_{1m}, C_{2m}, T_{1m}, T_{2m}$, $L_{1Bm}, L_{2Bm}, L_{1Cm}, L_{2Cm}$, 8 nearby backup relays ($T_{1p}, T_{1s}, T_{2p}, T_{2s}, L_{1Bp}$,$L_{2Bp}$, L_{1Cp}, L_{2Cp}), and 6 remote backup relays ($T_{1t}, T_{2t}, L_{1Bs}, L_{2Bs}, L_{1Cs}, L_{2Cs}$).

The operational principles of protective relays in power systems are described as follows.

(1) Protective relays of lines: When a fault occurs on a line, the main protective relays (MPRs) of the line operate, and the corresponding CBs of both ends of the line are tripped. For example, if line L_1 fails, MPRs L_{1Bm}, L_{1Cm} operate to trip CB_7 and CB_9. Likewise, when the main protections of the line fail to operate,

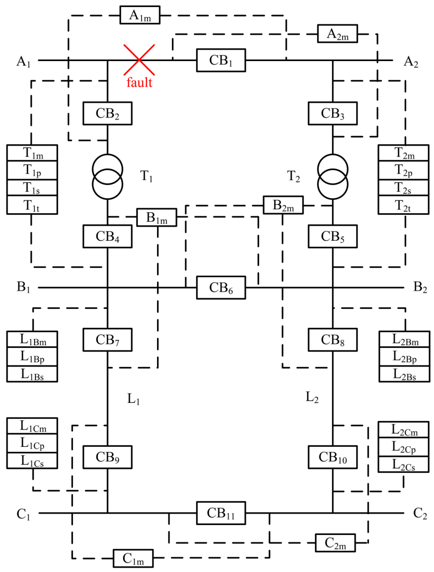

Figure 2: A six-bus 69kV distribution system, where symbol "m" refers to the main protective relay, "p" represents the backup relay (nearest region), "s" represents the backup relay (second nearest region), and "t" is the backup relay (in the opposite direction to "s").

the nearby backup protective relays (NBPRs) operate to trip CBs connected to this line. For example, if line L_1 fails and MPR L_{1Bm} fails to operate, NBPR L_{1Bp} operate to trip CB_7. If line L_1 fails and MPR L_{1Cm} fails to operate, NBPR L_{1Cp} operates to trip CB_9. In addition, when a section of adjacent region of a line fails and its protections fail to operate, the remote protective relays (RBPRs) of the line operate to protect the section. For example, if section B_1 fails and CB_7 fails to trip off, RBPR L_{1Bs} operates to trip CB_7. If section C_1 fails and CB_9 fails to trip off, RBPR L_{1Cs} operates to trip CB_9.

(2) Protective relays of buses: When the MPRs of a bus operate, all CBs directly connected to the bus will be tripped. For instance, if bus A_1 fails, MPR A_{1m} operates to trip CB_1 and CB_2. It is worth pointing out that there are not any NBPRs for buses. When the MPRs of a bus fail to operate, the RBPRs of all the adjacent regions of the bus, which can protect the bus, operate to trip off the relevant CBs.

(3) Protective relays of transformers: When a fault occurs on a transformer, the MPRs of the transformer operate, and the corresponding CBs of both ends of the transformer are tripped. For example, if transformer T_1 fails, MPR T_{1m} operates to trip CB_2 and CB_4. Likewise, when the MPRs of the transformer fail to operate, the NBPRs operate to trip CBs connected to the transformer. For example, if transformer T_1 fails and MPR T_{1m} fails to operate, NBPR T_{1p}

Table 1: Linguistic values and the corresponding interval-valued fuzzy numbers.

linguistic terms	interval-valued fuzzy number (IVFN)
Absolutely-low(AL)	$[(0.0, 0.0, 0.0, 0.0), (0.0, 0.0, 0.0, 0.0)]$
Very-low(VL)	$[(0.0075, 0.0075, 0.015, 0.0525), (0.0, 0.0, 0.02, 0.07)]$
Low(L)	$[(0.0875, 0.12, 0.16, 0.1825), (0.04, 0.10, 0.18, 0.23)]$
Fairly-low(FL)	$[(0.2325, 0.255, 0.325, 0.3575), (0.17, 0.22, 0.36, 0.42)]$
Medium(M)	$[(0.4025, 0.4525, 0.5375, 0.5675), (0.32, 0.41, 0.58, 0.65)]$
Fairly-high(FH)	$[(0.65, 0.6725, 0.7575, 0.79), (0.58, 0.63, 0.80, 0.86)]$
High(H)	$[(0.7825, 0.815, 0.885, 0.9075), (0.72, 0.78, 0.92, 0.97)]$
Very-high(VH)	$[(0.9475, 0.985, 0.9925, 0.9925), (0.93, 0.98, 1.0, 1.0)]$
Absolutely-high(AH)	$[(1.0, 1.0, 1.0, 1.0), (1.0, 1.0, 1.0, 1.0)]$

Table 2: Confidence levels of the operated protective devices.

Sections	Protective devices					
	Main		Nearby		Remote	
	Relays	CBs	Relays	CBs	Relays	CBs
L	VH	VH	H	H	FH	FH
B	VH	VH	–	–	FH	FH
T	VH	VH	H	H	FH	FH

operates to trip CB_2 and CB_4. In addition, when a section of the adjacent regions of a transformer and its protections fail to operate, the RBPRs of the transformer can operate to protect this section. For example, if section A_1 fails and CB_2 fails to trip off, RBPR T_{1t} operates to trip CB_2 and CB_4 so that this bus can be protected.

3.2. Setting of fault diagnosis using ivFRSN P systems

The cause and effect relationship of a fault and its protective devices can be described by fault fuzzy production rules for main components including lines, buses and transformers in power systems. The fault fuzzy production rules consist of certainty factors. A certainty factor represents the degree of confidence that a fault occurs, and each rule has one certainty factor. Owing to the uncertainty of the knowledge of experts and senior dispatchers, we use linguistic terms to describe certainty factors, which are denoted by interval-valued fuzzy numbers [23] and provided in Table 1.

In this paper, the provisions can be illustrated as follows according to the experience and the levels of protection. Firstly, all the certainty factors of rule neurons which are related to main protections and nearby backup protections are set to AH. Secondly, all the certainty factors of rule neurons which are related to remote backup protections are set to VH. If it involves multiple levels of protections, the certainty factors can be set to the value corresponding to the highest level of protections. Thirdly, if the confidence level θ of a section satisfies the condition $\theta \geq [(0.65, 0.6725, 0.7575, 0.79), (0.58, 0.63, 0.80, 0.86)]$, the section is faulty; if $\theta \leq [(0.2325, 0.255, 0.325, 0.3575), (0.17, 0.22, 0.36, 0.42)]$, the section is not faulty;

Table 3: Confidence levels of the non-operated protective devices.

Sections	Protective devices					
	Main		Nearby		Remote	
	Relays	CBs	Relays	CBs	Relays	CBs
L	L	L	L	L	L	L
B	FL	L	–	–	FL	L
T	FL	L	FL	L	L	L

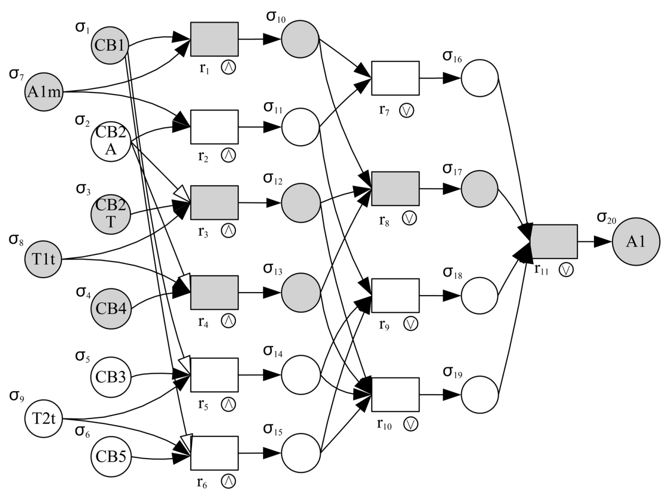

Figure 3: The fault diagnosis model of bus A_1 based on ivFRSN P systems.

otherwise, the section may be faulty.

In addition, the status information obtained from SCADA system may include operation failure, mal-operation and misinformation, so it is necessary to use a confidence level to describe the operation accuracy of each section [22]. Therefore, an empirical confidence level is assigned to each protective device including the protective relays and its corresponding CBs. Tables 2 and 3 list the confidence levels of the operated protective devices and the non-operated protective devices, respectively.

3.3. Case studies

In this subsection, the cases of single faulty section with failure device and multiple faulty sections in the six-bus 69kV distribution system are considered to demonstrate the effectiveness of ivFRSN P systems.

Case 1 (single fault): Suppose that a fault occurs at the bus A_1, and it leads to the operation of MPR A_{1m} and the tripping of both CB_1 and CB_2. However, CB_2 fails to open, leading to the operation of RBPR T_{1t} which opens CB_2 again and trips off CB_4. Status information obtained from the SCADA system indicates: operated relays are A_{1m} and T_{1t}, and tripped CBs have CB_1, CB_2 and CB_4.

Firstly, the fault diagnosis model of bus A_1 including 20 proposition neurons and 11 rule neurons is constructed by the ivFRSN P systems, shown in Fig. 3. In this figure, there are four assistant synapses, i.e.,(σ_1, r_5), (σ_1, r_6),(σ_2, r_3) and (σ_2, r_4), marked by hollow tips. The synapse from σ_1 to r_5 can be taken as an example to explain the meaning of these assistant synapses: if CB_1 opens, the operation of T_{2t},CB_3 and CB_5 is invalid and then the their values are set as $[(0.0, 0.0, 0.0, 0.0), (0.0, 0.0, 0.0, 0.0)]$; otherwise, the operation of them is valid.

Secondly, the detailed fuzzy reasoning process is described as follows. The interval-valued fuzzy numbers θ_0 and δ_0 can be obtained according to the status information and Tables 1, 2 and 3. Note that θ is a 20-dimension vector and δ is an 11-dimension vector.

$$\theta_0 = \begin{bmatrix} [(0.9475, 0.985, 0.9925, 0.9925), (0.93, 0.98, 1.0, 1.0)] \\ [(0.0875, 0.12, 0.16, 0.1825), (0.04, 0.10, 0.18, 0.23)] \\ [(0.65, 0.6725, 0.7575, 0.79), (0.58, 0.63, 0.80, 0.86)] \\ [(0.65, 0.6725, 0.7575, 0.79), (0.58, 0.63, 0.80, 0.86)] \\ [(0.0, 0.0, 0.0, 0.0), (0.0, 0.0, 0.0, 0.0)] \\ [(0.0, 0.0, 0.0, 0.0), (0.0, 0.0, 0.0, 0.0)] \\ [(0.9475, 0.985, 0.9925, 0.9925), (0.93, 0.98, 1.0, 1.0)] \\ [(0.65, 0.6725, 0.7575, 0.79), (0.58, 0.63, 0.80, 0.86)] \\ [(0.0, 0.0, 0.0, 0.0), (0.0, 0.0, 0.0, 0.0)] \\ O \end{bmatrix}, \delta_0 = [O]\,;$$

When $g = 1$, we get the results

$$\delta_1 = \begin{bmatrix} [(0.9475, 0.985, 0.9925, 0.9925), (0.93, 0.98, 1.0, 1.0)] \\ [(0.0875, 0.12, 0.16, 0.1825), (0.04, 0.10, 0.18, 0.23)] \\ [(0.65, 0.6725, 0.7575, 0.79), (0.58, 0.63, 0.80, 0.86)] \\ [(0.65, 0.6725, 0.7575, 0.79), (0.58, 0.63, 0.80, 0.86)] \\ O \end{bmatrix},$$

$$\theta_1 = \begin{bmatrix} O \\ [(0.9475, 0.985, 0.9925, 0.9925), (0.93, 0.98, 1.0, 1.0)] \\ [(0.0875, 0.12, 0.16, 0.1825), (0.04, 0.10, 0.18, 0.23)] \\ [(0.6159, 0.6624, 0.7518, 0.7841), (0.5394, 0.6174, 0.80, 0.86)] \\ [(0.6159, 0.6624, 0.7518, 0.7841), (0.5394, 0.6174, 0.80, 0.86)] \\ O \end{bmatrix};$$

When $g = 2$, we get the results

$$\delta_2 = \begin{bmatrix} O \\ [(0.9475, 0.985, 0.9925, 0.9925), (0.93, 0.98, 1.0, 1.0)] \\ [(0.9475, 0.985, 0.9925, 0.9925), (0.93, 0.98, 1.0, 1.0)] \\ [(0.0875, 0.12, 0.16, 0.1825), (0.04, 0.10, 0.18, 0.23)] \\ [(0.6159, 0.6624, 0.7518, 0.7841), (0.5394, 0.6174, 0.80, 0.86)] \\ O \end{bmatrix},$$

$$\theta_2 = \begin{bmatrix} O \\ [(0.9475, 0.985, 0.9925, 0.9925), (0.93, 0.98, 1.0, 1.0)] \\ [(0.9475, 0.985, 0.9925, 0.9925), (0.93, 0.98, 1.0, 1.0)] \\ [(0.0875, 0.12, 0.16, 0.1825), (0.04, 0.10, 0.18, 0.23)] \\ [(0.6159, 0.6624, 0.7518, 0.7841), (0.5394, 0.6174, 0.80, 0.86)] \\ [(0.0, 0.0, 0.0, 0.0), (0.0, 0.0, 0.0, 0.0)] \end{bmatrix};$$

When $g = 3$, we get the results

$$\delta_3 = \begin{bmatrix} O \\ [(0.9475, 0.985, 0.9925, 0.9925), (0.93, 0.98, 1.0, 1.0)] \end{bmatrix},$$

$$\theta_3 = \begin{bmatrix} O \\ [(0.9475, 0.985, 0.9925, 0.9925), (0.93, 0.98, 1.0, 1.0)] \end{bmatrix};$$

When $g = 4$, we get the result

$$\delta_4 = [O].$$

Thus, the termination condition is satisfied and the reasoning process ends. The reasoning result is $[(0.9475, 0.985, 0.9925, 0.9925), (0.93, 0.98, 1.0, 1.0)]$ from output neuron σ_{20}. According to the condition in Section 3.2, A_1 is a faulty section with a confidence level VH. While CB_2 refused to operate, the failure extended. Similarly, it can be obtained that T_1 has the reasoning result [(0.0875,0.12,0.16,0.1825),(0.04,0.10,0.18, 0.23)]. According to the condition in Section 3.2, T_1 is not faulty section with a confidence level L.

Case 2 (multiple faults): Suppose that multiple faults occur at buses C_1, C_2 and line L_1. The fault at line L_1 leads to the operations of MPRs L_{1Bm} and L_{1Cm}, and the tripping of both CB_7 and CB_9. For buses C_1 and C_2, they lead to the operations of MPRs C_{1m} and C_{2m} and trip circuit breakers CB_9, CB_{10} and CB_{11}. Status information obtained from the SCADA system indicates: operated relays are L_{1Bm}, L_{1Cm}, C_{1m} and C_{2m}, and tripped CBs have CB_7, CB_9, CB_{10} and CB_{11}.

Owing to the model-building of C_1, C_2 and L_1 are similar to A_1 and space limitations, they are omitted here. Since Case 2 and Case 1 have a similar reasoning procedure, it is also omitted here. After reasoning, it can be obtained that C_1, C_2 and L_1 have the same value $[(0.9475, 0.985, 0.9925, 0.9925), (0.93, 0.98, 1.0, 1.0)]$. According to the condition in Section 3.2, C_1, C_2 and L_1 all are identified as the faulty sections with the confidence level VH. Case 1 and Case 2 show that the proposed method not only can deal with single fault with device failure, but also can handle multiple faults.

3.4. Comparison analysis with other methods

Case 1 and Case 2 have been studied in [7] using the CTPN method. For Case 1 and 2, ivFRSN P systems and CTPN method can diagnose the faults A_1, C_1, C_2 and L_1. Compared with the CTPN method, ivFRSN P systems can express imprecision and uncertainty by using the concept of fuzzy membership. Furthermore it can be seen that fault confidence levels are represented by interval-valued fuzzy numbers, which provide a quantitative description of the fault components and make the diagnosis results more reliable. In addition, from Case 1, it is obvious that the fault diagnosis model and model-building process based on ivFRSN P systems are easier to handle and more intuitive than CTPN method.

Moreover, IVFN contains more uncertainty than trapezoidal fuzzy numbers. So compared with the FRSN P systems in [22], ivFRSN P systems can handle incomplete and uncertain messages from the SCADA system in a more flexible and effective way by using IVFN. Therefore, from the two case studies, the relevance and effectiveness of ivFRSN P systems are illustrated.

4. Conclusions

In this paper, ivFRSN P systems with a graphic modeling description is proposed to diagnose main faulty sections in power systems. This approach provides a good accuracy of diagnosis solution and has a parallel computing ability by calculating the components membership separately. Besides, ivFRSN P systems can handle incomplete and uncertain messages from the SCADA system in a more flexible and effective way by using interval-valued fuzzy numbers, which adequately displays the fault-tolerant capacity of the method. In the end, the case studies verify the validity and feasibility of proposed approach in diagnosing the faults in a typical power system.

Acknowledgements. This work was partially supported by the National Natural Science Foundation of China (No.61472328), Chunhui Project Foundation of the Education Department of China (No.Z2016143) and Research Fund of Sichuan Science and Technology Project (No.2015HH0057).

References

[1] LUO X., KEZUNOVIC M., *Implementing fuzzy reasoning Petri-nets for fault section estimation*, IEEE Transactions on Power Delivery, **23**(2), pp. 676-685, 2008.

[2] THUKARAM D., KHINCHA H.P., VIJAYNARASIMHA H.P., *Artificial neural network and support vector machine approach for locating faults in radial distribution systems*, IEEE Transactions on Power Delivery, **20**(2), pp. 710-721, 2005.

[3] PARK Y.M., KIM G.W., SOHN J.M., *A logic based expert system for fault diagnosis of power system*, IEEE Transactions on Power Systems, **12**(1), pp. 363-369, 1997.

[4] MIN S.W., SOHN J.M., PARK J.K., KIM K.H., *Adaptive fault section estimation using matrix representation with fuzzy relations*, IEEE Transactions on Power Systems, **19**(2), pp. 842-848, 2004.

[5] SUN J., QIN S.Y., SONG Y.H., *Fault diagnosis of electric power systems based on fuzzy Petri nets*, IEEE Transactions on Power Systems, **19**(4), pp. 2053-2059, 2004.

[6] CHEN W.H., TSAI S.H., LIN H.I., *Fault section estimation for power networks using logic cause-effect models*, IEEE Transactions on Power Delivery, **26**(2), pp. 963-971, 2011.

[7] YANG C.L., YOKOYAMA A., SEKINE Y., *Fault section estimation of power system using colored and timed Petri nets*, Electrical Engineering in Japan, **115**(2), pp. 89-101, 1995.

[8] LIN S., HE Z.Y., QIAN Q.Q., *Review and development on fault diagnosis in power grid*, Power System Protection & Control, **38**(4), pp. 140-150, 2010.

[9] PĂUN G., *Computing with membranes*, Journal of Computer & System Sciences, **61**(1), pp. 108-143, 2000.

[10] PĂUN G., ROZENBERG G., SALOMAA A.(eds.), *The oxford handbook of membrane computing*, Oxford University Press, New York, 2010.

[11] IONESCU M., PĂUN G., YOKOMORI T., *Spiking neural P systems*, Fundamenta Informaticae, **71**(2-3), pp. 279-308, 2006.

[12] PĂUN G., PÉREZ-JIMÉNEZ M.J., *Membrane computing: brief introduction, recent results and applications*, Biosystems, **85**(1), pp. 11-22, 2006.

[13] WANG T., ZHANG G.X., PÉREZ-JIMÉNEZ M.J., *Fuzzy membrane computing: theory and applications*, International Journal of Computers, Communications and Control, **10**(6), pp. 904-935, 2015.

[14] ZENG X.X., ZHANG X.Y., SONG T., PAN L.Q., *Spiking neural P systems with thresholds*, Neural Computation, **26**(7), pp. 1340-1361, 2014.

[15] SONG T., PAN L.Q., PĂUN G., *Asynchronous spiking neural P systems with local synchronization*, Information Sciences, **219**, pp. 197-207, 2013.

[16] PAN L.Q., WANG J., HOOGEBOOM H.J., *Spiking neural P systems with astrocytes*, Neural Computation, **24**(3), pp. 805-825, 2012.

[17] ZHANG G.X, RONG H., NERI F., PÉREZ-JIMÉNEZ M.J., *An optimization spiking neural P system for approximately solving combinatorial optimization problems*, International Journal of Neural Systems, **24**(5), pp. 1-16, 2014.

[18] WANG J., SHI P., PENG H., PÉREZ-JIMÉNEZ M.J., WANG T., *Weighted fuzzy spiking neural P system*, IEEE Transactions on Fuzzy Systems, **21**(2), pp. 209-220, 2013.

[19] PENG H., WANG J., PÉREZ-JIMÉNEZ M.J., WANG H., SHAO J., WANG T., *Fuzzy reasoning spiking neural P system for fault diagnosis*, Information Sciences, **235**(6), pp. 106-116, 2013.

[20] WANG T., WANG J., PENG H., WANG H., *Knowledge representation and reasoning based on FRSN P systems*, in Proceedings WCICA, China, pp. 255-259, 2011.

[21] WANG J., PENG H., TU M., PÉREZ-JIMÉNEZ M.J., SHI P., *A fault diagnosis method of power systems based on an improved adaptive fuzzy spiking neural P systems and PSO algorithms*, Chinese Journal of Electronics, **25**(2), pp. 320-327, 2016.

[22] WANG T., ZHANG G.X., ZHAO J.B., HE Z.Y., WANG J., PÉREZ-JIMÉNEZ M.J., *Fault diagnosis of electric power systems based on fuzzy reasoning spiking neural P systems*, IEEE Transactions on Power Systems, **30**(3), pp. 1182-1194, 2015.

[23] CHEN S.M., SANGUANSAT K., *Analyzing fuzzy risk based on similarity measures between interval-valued fuzzy numbers*, Expert Systems with Applications, **38**(7), pp. 8612-8621, 2011.

[24] CHEN T.Y., *Multiple criteria group decision-making with generalized interval-valued fuzzy numbers based on signed distances and incomplete weights*, Applied Mathematical Modelling, **36**(7), pp. 3029-3052, 2011.