Application of Weighted Fuzzy Reasoning Spiking Neural P Systems to Fault Diagnosis in Traction Power Supply Systems of High-speed Railways

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Summary. This paper discusses the application of weighted fuzzy reasoning spiking neural P systems (WFRSN P systems) to fault diagnosis in traction power supply systems (TPSSs) of China high-speed railways. Four types of neurons are considered in WFRSN P systems to make them suitable for expressing status information of protective relays and circuit breakers, and a weighted matrix-based reasoning algorithm (WMBRA) is introduced to fulfill the reasoning based on the status information to obtain fault confidence levels of faulty sections. Fault diagnosis production rules in TPSSs and their WFRSN P system models are proposed to show how to use WFRSN P systems to describe different kinds of fault information. Building processes of fault diagnosis models for sections and fault region identification of feeding sections, and parameter setting of the models are described in detail. Case studies including normal power supply and over zone feeding show the effectiveness of the presented method.

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 the cells are organized in tissues or higher order structures. 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]-[19], among which there are several investigations focus on the use of SN P systems and their variants to solve engineering problems.

In [14], a fuzzy reasoning spiking neural P system with real numbers was presented to fulfill diagnosis knowledge representation and reasoning. In [15], the FRSN P system was used for fault diagnosis in power systems and three different applications verified its effectiveness. Adaptive fuzzy spiking neural P systems (AFSN P systems) for fuzzy inference and learning were presented in [16] and the work in [17] focused on the application of AFSN P systems in fault diagnosis of power systems. The aforementioned investigations verify the feasibility and effectiveness of extended SN P systems in fault diagnosis of power systems.

Traction power supply systems (TPSSs) of high-speed railways are a kind of special power systems. In recent decades, the most studied intelligent fault diagnosis method for TPSSs of China high-speed railways is expert system (ES) [20]-[22]. ES expresses operation logic of protective relays and circuit breakers easily, and makes full use of experts knowledge, but it has a slow inference speed due to its sequential search nature, and the difficulties of designing and maintaining a rule-based knowledge system. In [23], fuzzy Petri nets (FPNs) are applied in the fault diagnosis of TPSSs to avoid the weakness of ESs and a second reasoning method was designed to improve the reliability of diagnosis results when status information of protections contains uncertainty and incompleteness. However, the second reasoning adds the complexity of computation in reasoning process and makes the fault diagnosis need more time. So, how to improve the aforementioned methods and explore new ones to solve fault diagnosis problems in TPSSs is worth further discussing.

This paper discusses the application of a novel and bioinspired model, weighted fuzzy reasoning spiking neural P systems (WFRSN P systems), to fault diagnosis in TPSSs. WFRSN P systems were first proposed in [18] and new ingredients, such as fuzzy truth value, weighted fuzzy logic, output weight, threshold and two types of neurons, were added to the original definition of SN P systems. Besides, a weighted fuzzy backward reasoning algorithm was developed for the WFRSN P systems to fulfil dynamic fuzzy reasoning. However, two types of neurons in WFRSN P systems can not express status information of protections completely. Moreover, the weighted fuzzy backward reasoning algorithm is too complex to use it to diagnose faults in TPSSs directly. To adapt WFRSN P systems to solve fault diagnosis problems in TPSSs, four types of neurons are considered in this study and a weighted matrix-based reasoning algorithm (WMBRA) is introduced to fulfill the reasoning of fault information. WFRSN P system models for fault diagnosis production rules in TPSSs are proposed to show how to describe different kinds of fault information by using them. How to build fault diagnosis models for sections and set parameters in the models are described in detail. Besides, owing to the special power supply manner of TPSSs, a WFRSN P system model for fault region identification of feeding sections is also built. 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 WFRSN P systems and WMBRA are defined in Section 3. Section 4 presents the key issues of fault diagnosis based on WFRSN P systems, and the application of WFRSN P systems to fault diagnosis in TPSSs is discussed in Section 5. Conclusions are finally drawn in Section 6.

2 Problem Description

When faults occur in a power system, protective relays detect the faults and trip their corresponding circuit breakers (CBs) to isolate faulty sections from the operation of this power system and guarantee the other parts can operate normally. The aim of fault diagnosis in this paper is to identify the faulty sections by using status information of protective relays and CBs which are read from supervisor control and data acquisition (SCADA) systems. The framework of fault diagnosis in power systems using reasoning model-based method is shown as in Fig. 1 [15, 24]. There are three important parts in this framework: real-time data, static data and a flowchart of identification fault sections. The real-time data, protective relay operation information and circuit breaker tripping information, are used to estimate the outage areas to obtain candidate faulty sections using a network topology analysis method, so as to reduce the subsequent computational burden [24]. The static data, network topology and protection configuration of a power system, are used to build a fault diagnosis model for each candidate section in each outage area. The inputs of each diagnosis model are initialized by both real-time data and static data. Then, each diagnosis model performs reasoning algorithm to obtain fault confidence levels of candidate faulty sections to determine faulty sections. The diagnosis results include the faulty sections and their fault confidence levels.

TPSSs of high-speed railways are a kind of special power systems. Thus, the fault diagnosis of TPSSs of China high-speed railways can keep the framework of fault diagnosis in Fig. 1. Meanwhile, it is important to describe the characteristics and protection configuration of TPSSs because of their particularity.

The electrical principle schematic illustration for TPSSs of China high-speed railways is shown in Fig. 2. Power systems supply TPSSs with three-phase alternating currents (three-phase ACs) (220 kv or 330 kv) which are converted to single-phase alternating currents (single-phase ACs) (25 kv) by traction substations (TSSs) [25, 26]. Then, the single-phase ACs are supplied to electric locomotives by feeding sections. Subsection posts (SSPs) usually are built near pivotal station yards who need to output multipath feeder lines. The SSPs only has power distribution equipments because they are used only for the redistribution of power supply and do not convert the voltage. Thus, the function of SSPs is the same as power distribution stations. In order to increase the flexibility of power supply as well as to improve the reliability of electric power operation, section posts (SPs) usually are built between two TSSs. Over zone feeding is fulfilled by using over zone switches in SPs, and up and down line parallel power supply is fulfilled by using an up and down line interconnection switch, which can improve the reliability of TPSSs. Feeder lines connect TSSs and contact wires to transmit the electricity

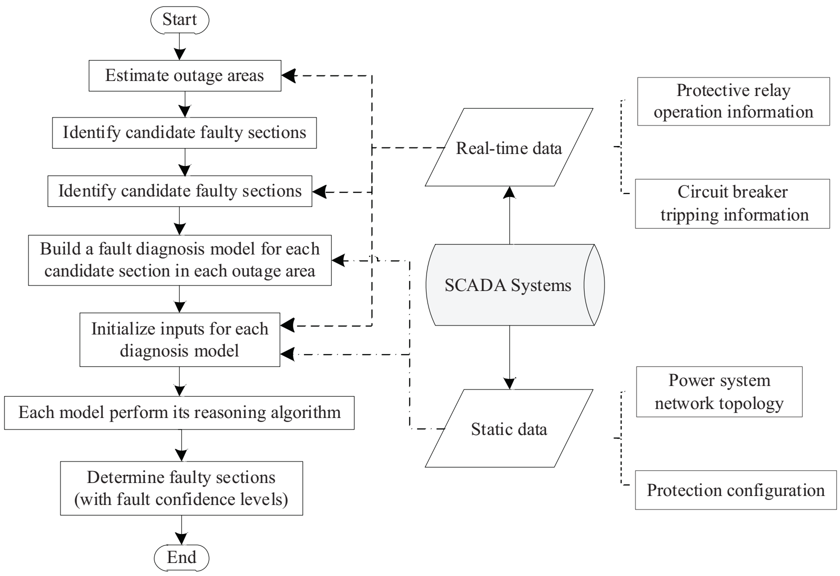

Fig. 1. Framework of fault diagnosis in power systems using reasoning model-based method.

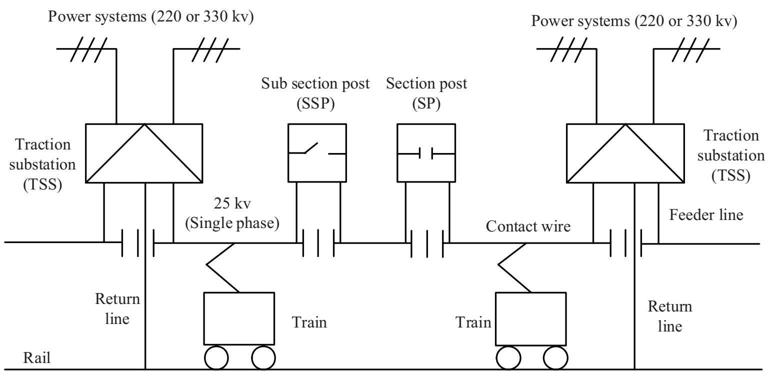

Fig. 2. Electrical principle schematic illustration of TPSSs.

from TSSs to contact wires. Return lines connect TSSs and rails to return loop currents in rails into TSSs. Traction networks are composed of feeder lines, contact wires, return lines, rails and earth ground.

If a TPSS uses autotransformer (AT) feeding manner, then one autotransformer is installed along rails every other 10 to 15 kilometers [25]. Fig. 3 shows a composition diagram of TPSSs in AT feeding manner considered in this study. Typical feeding sections in AT feeding manner consist of TSSs, ATPs and SPs. In this kind of TSS-ATP-SP feeding sections, lines in SPs are connected in an up and

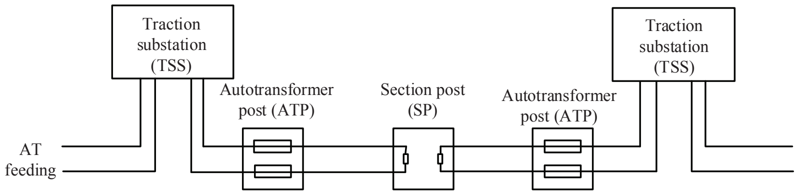

Fig. 3. Composition diagram of TPSSs in AT feeding manner.

Table 1. Protection configuration of feeder lines in AT TPSSs with normal power supply

Posts	Protection configurations		Automatic devices
TSSs	Main	One impedance protection Overcurrent protection of low voltage starting	One shot automatic reclosing
	Backup	$\triangle\ I$ current increment protection	
SPs	Main	No-voltage protection	Voltage checking for automatic reclosing
ATPs	Main	No-voltage protection	Voltage checking for automatic reclosing

down line paralleling manner while lines in ATPs are not. It is worth pointing out that if a feeding arm is very long, then SSPs are built between TSSs and SPs to reduce the power failure scope when faults occur in traction networks.

In this study, a feeding section fed by a same traction substation is considered as one fault diagnosis unit because the feeding section works in a relatively independent way in its operation, protection, etc. The faults on feeder lines, buses, traction transformers and autotransformers, in TSSs, ATPs and SPs, are diagnosed by using the status information read from SCADA systems, as shown in Fig. 1. Tables 1 and 2 show the protection configuration of feeder lines in AT TPSSs with normal power supply and over zone feeding, respectively [25]-[28]. Table 3 shows the protection configuration of transformers (traction transformers and autotransformers) in AT TPSSs [25]-[28].

When an AT traction power supply system is in the over zone feeding manner, the feeding section fed by the faulty TSS is temporarily fed by its adjacent TSS through over zone switches. When remote backup protections of feeder lines in TSSs operate, in order to distinguish which autotransformer (the one in the original TSS or in the temporary TSS) has a fault, main protections and primary backup protections of this autotransformer and their corresponding CBs are considered as reasoning conditions of the results obtained according to the remote backup protections.

Table 2. Protection configuration of feeder lines in AT TPSSs with over zone feeding

Posts	Protection configurations		Automatic devices
TSSs	Main	Two impedance protection Overcurrent protection of low voltage starting	One shot automatic reclosing
	Backup	$\triangle\ I$ current increment protection	
SPs	Main	One impedance protection Overcurrent protection of low voltage starting	Voltage checking for automatic reclosing
	Backup	$\triangle\ I$ current increment protection No-voltage protection	
ATPs	Main	No-voltage protection	Voltage checking for automatic reclosing

Table 3. Protection configuration of transformers in AT TPSSs

Transformers	Protection configurations	
Traction transformers	Main	Differential current quick-break protection Ratio-restrained differential protection of second harmonic lock Non-electrical protection
	Backup	Overcurrent protection of low voltage starting
Autotransformers	Main	Differential current quick-break protection Non-electrical protection
	Backup	Overcurrent protection of low voltage starting Shell collision protection

3 WFRSN P systems

3.1 Definitions

Definition 1: A WFRSN P system of $m \geq 1$ is a construct $\Pi = (O, \sigma_1, \ldots, \sigma_m, syn, in, out)$, where:

(1) $O = \{a\}$ is a singleton alphabet (a is called spike);
(2) $\sigma_1, \ldots, \sigma_m$ are neurons, of the form $\sigma_i = (\theta_i, c_i, \overrightarrow{\omega_i}, \lambda_i, r_i), 1 \leq i \leq m$, 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 truth value associated with neuron σ_i;

c) $\overrightarrow{\omega_i} = (\omega_{i1}, \ldots, \omega_{iN_i})$ is a real number vector in (0,1] representing the output weight vector of neuron σ_i, where ω_{ij} $(1 \leq j \leq N_i)$ represents the weight on jth output arc (synapse) of neuron σ_i and N_i is a real number representing the number of synapses starting from neuron σ_i.
d) λ_i is a real number in [0,1) representing the firing threshold of neuron σ_i;
e) r_i represents a firing (spiking) rule contained in neuron σ_i with the form $E/a^{\theta} \rightarrow a^{\beta}$, where θ and β are real numbers in [0,1], $E = \{a^n, \theta \geq \lambda_i\}$ is the firing condition. The firing condition means that if and only if neuron σ_i receives at least n spikes and the potential value of spikes is with $\theta \geq \lambda_i$, then the firing rule contained in the neuron can be applied, otherwise, the firing rule cannot be applied;

(3) $syn \subseteq \{1, \ldots, m\} \times \{1, \ldots, m\}$ with $i \neq j$ for all $(i, j) \in syn, 1 \leq i, j \leq m$; that is, syn provides a (weighted) directed graph whose set of nodes is $\{1, \ldots, m\}$;
(4) $in, out \subseteq \{1, \ldots, m\}$ indicate the input neuron set and the output neuron set of Π, respectively.

How WFRSN P systems are extended from SN P systems are described as follows. First, the definition of neurons are extended. WFRSN P systems consist of two kinds of neurons, i.e., proposition neurons and rule neurons, where rule neurons contain three subcategories: *general*, *and* and *or*. Second, the pulse value θ_i contained in each neuron σ_i is a real numbers in [0,1] representing potential value of spikes contained in this neuron instead of the number of spikes in SN P systems. Third, each neuron is associated with either a proposition or a production rule, and $c_i \in [0, 1]$ represents the truth value of this proposition or the certainty factor (CF) of this production rule. Fourth, each weighted directed synapse has an output weight. In other words, each synapse in $syn \subseteq \{1, \ldots, m\} \times \{1, \ldots, m\}$ has a weight. The output weights of neurons represent the importance degree of their values in contributing to the computing results in output neurons. Fifth, each neuron contains only one firing (spiking) rule of the form $E/a^{\theta} \rightarrow a^{\beta}$. When the firing condition of one neuron is satisfied, the firing rule is applied, which means that the potential value θ is consumed and then this neuron produces a new spike with potential value of β. These different types of neurons aforementioned handle the potential values θ and β in different ways (see definition *Definition 2-5*). If the firing condition of one neuron is not satisfied, then the potential value of the spikes received by this neuron is updated via logical *and* or *or* operators. Finally, time delay is ignored in WFRSN P systems, thus all neurons are always open.

The definitions of different types neurons in WFRSN P systems are described as follows.

Definition 2: A *proposition neuron* is associated with a proposition in a fuzzy production rule. Such a neuron is represented by a circle and symbol P, as shown is Fig. 4.

If a *proposition neuron* is an input neuron of a WFRSN P system Π, then its potential value θ is received from the environment; otherwise, θ equals to the result of logical *or* operation on all weighted potential values received from its presynaptic rule neurons, i.e., $\theta = max\{\theta_1 * \omega_1, \ldots, \theta_k * \omega_k\}$. The firing rule of

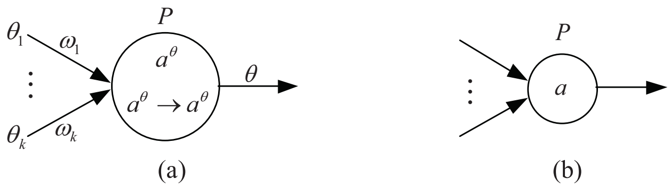

Fig. 4. A *proposition neuron* (a) and its simplified form (b).

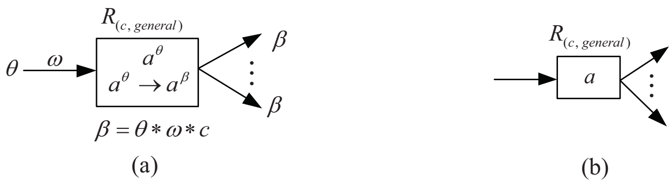

Fig. 5. A *general rule neuron* (a) and its simplified form (b).

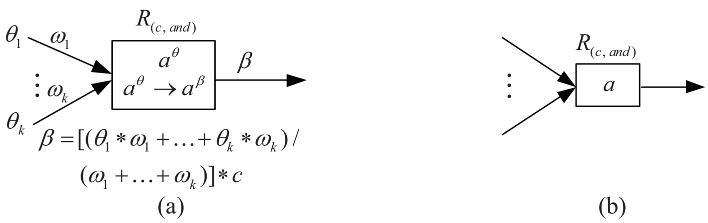

Fig. 6. An *and rule neuron* (a) and its simplified form (b).

a *proposition neuron* is of the form $E/a^\theta \to a^\theta$, in other words, the parameter β of the firing rule contained in such a neuron is identical to θ. When the firing condition E of a *proposition neuron* is satisfied, the potential value θ of spikes contained in this neuron is consumed and then a new spike with potential value θ is produced and emitted.

Definition 3: 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 and symbol $R_{(c,\ general})$, as shown is Fig. 5.

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 $\beta = \theta * \omega * c$.

Definition 4: An *and rule neuron* is associated with a fuzzy production rule which has more than one propositions with an *and* relationship in the antecedent part of the rule. Such a neuron is represented by a rectangle and symbol $R_{(c,\ and)}$, as shown is Fig. 6.

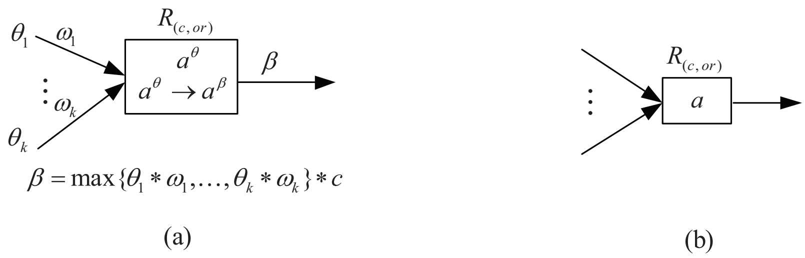

Fig. 7. An *or rule neuron* (a) and its simplified form (b).

An *and rule neuron* has more than one presynaptic proposition neurons and only one postsynaptic proposition neuron. If an *and rule neuron* receives k spikes from its k presynaptic proposition neurons and its firing condition is satisfied, then the neuron fires and produces a new spike with the potential value $\beta = [(\theta_1 * \omega_1 + \ldots + \theta_k * \omega_k)/(\omega_1 + \ldots + \omega_k)] * c$.

Definition 5: An *or rule neuron* is associated with a fuzzy production rule which has more than one propositions with an *or* relationship in the antecedent part of the rule. Such a neuron is represented by a rectangle and symbol $R_{(c,\ or)}$, as shown is Fig. 7.

An *or rule neuron* has more than one presynaptic proposition neurons and only one postsynaptic proposition neuron. If an *or rule neuron* receives k spikes from its k presynaptic proposition neurons and its firing condition is satisfied, then the neuron fires and produces a new spike with the potential value $\beta = max\{\theta_1 * \omega_1, \ldots, \theta_k * \omega_k\} * c$.

3.2 WMBRA

In order to clearly present a weighted matrix-based reasoning algorithm (WMBRA), we first introduce some parameter vectors and matrices as follows.

(1) $\boldsymbol{\theta} = (\theta_1, \ldots, \theta_s)^T$ is a real truth value vector of the s proposition neurons, where θ_i $(1 \leq i \leq s)$ is a real number in [0, 1] representing the potential value contained in the ith proposition neuron. If there is not any spike contained in a proposition neuron, its potential value is 0.

(2) $\boldsymbol{\delta} = (\delta_1, \ldots, \delta_t)^T$ is a real truth value vector of the t rule neurons, where δ_j $(1 \leq j \leq t)$ is a real number [0, 1] representing the potential value contained in the jth rule neuron. If there is not any spike contained in a rule neuron, its potential value is 0.

(3) $\boldsymbol{C} = diag(c_1, c_2, \ldots, c_t)$ is a diagonal matrix, where c_j $(1 \leq j \leq t)$ is a real number in [0,1] representing the certainty factor of the jth fuzzy production rule,

(4) $\boldsymbol{W}_{r1} = (\omega_{ij})_{s\times t}$ is a synaptic weight matrix representing the directed connection with weights among *proposition neurons* and *general rule neurons*. If there is a directed arc (synapse) from *proposition neuron* σ_i to *general rule neuron* σ_j, then ω_{ij} is identical to the output weight of synapse (i, j), otherwise, $\omega_{ij} = 0$.

(5) $\boldsymbol{W}_{r2} = (\omega_{ij})_{s\times t}$ is a synaptic weight matrix representing the directed connection with weights among *proposition neurons* and *and rule neurons*. If there is a directed arc (synapse) from *proposition neuron* σ_i to *and rule neuron* σ_j, then ω_{ij} is identical to the output weight of synapse (i, j), otherwise, $\omega_{ij} = 0$.

(6) $\boldsymbol{W}_{r3} = (\omega_{ij})_{s\times t}$ is a synaptic weight matrix representing the directed connection with weights among *proposition neurons* and *or rule neurons*. If there is a directed arc (synapse) from *proposition neuron* σ_i to *or rule neuron* σ_j, then ω_{ij} is identical to the output weight of synapse (i, j), otherwise, $\omega_{ij} = 0$.

(7) $\boldsymbol{W}_p = (\omega_{ji})_{t\times s}$ is a synaptic weight matrix representing the directed connection with weights among rule neurons and proposition neurons. If there is a directed arc (synapse) from rule neuron σ_j to proposition neuron σ_i, then ω_{ji} is identical to the output weight of synapse (j, i), otherwise, $\omega_{ji} = 0$.

(8) $\boldsymbol{\lambda_p} = (\lambda_{p1}, \ldots, \lambda_{ps})^T$ is a threshold vector of the s proposition neurons, where λ_{pi} $(1 \le i \le s)$ is a real number in [0, 1) representing the firing threshold of the ith proposition neuron.

(9) $\boldsymbol{\lambda_r} = (\lambda_{r1}, \ldots, \lambda_{rt})^T$ is a threshold vector of the t rule neurons, where λ_{rj} $(1 \le j \le t)$ is a real number in [0, 1) representing the firing threshold of the jth rule neuron.

Subsequently, we introduce some multiplication operations as follows.

(1) $\otimes$: $\boldsymbol{W}_{rl}^T \otimes \boldsymbol{\theta} = (\bar{\omega_1}, \bar{\omega_2}, \ldots, \bar{\omega_t})^T$, where $\bar{\omega_j} = \omega_{1j} * \theta_1 + \ldots + \omega_{sj} * \theta_s$, $j = 1, \ldots, t$, $1 \le l \le 3$.

(2) $\oplus$: $\boldsymbol{W}_{rl}^T \oplus \boldsymbol{\theta} = (\bar{\omega_1}, \bar{\omega_2}, \ldots, \bar{\omega_t})^T$, where $\bar{\omega_j} = (\omega_{1j} * \theta_1 + \ldots + \omega_{sj} * \theta_s)/(\omega_{1j} + \ldots + \omega_{sj})$, $j = 1, \ldots, t$, $1 \le l \le 3$.

(3) $\odot$: $\boldsymbol{W}_{rl}^T \odot \boldsymbol{\theta} = (\bar{\omega_1}, \bar{\omega_2}, \ldots, \bar{\omega_t})^T$, where $\bar{\omega_j} = max\{\omega_{1j} * \theta_1, \ldots, \omega_{sj} * \theta_s\}$, $j = 1, \ldots, t$, $1 \le l \le 3$. Likewise, $\boldsymbol{W}_p^T \odot \boldsymbol{\delta} = (\bar{\omega_1}, \bar{\omega_2}, \ldots, \bar{\omega_s})^T$, where $\bar{\omega_i} = max$ $\{\omega_{1i} * \delta_1, \ldots, \omega_{ti} * \delta_t\}$, $i = 1, \ldots, s$.

Next, we list the pseudocode of WMBRA.

4 Fault Diagnosis Based on WFRSN P systems

The diagnosis strategy based on WFRSN P systems is to build a WFRSN P system fault diagnosis model for each candidate faulty section in outage areas. Each model performs WMBRA from a set of SCADA data to the diagnosis results in the form of faulty sections and their fault confidence levels. If the confidence level of a candidate faulty section is larger than 0.5, then this section is a faulty section. This section presents the key issues of fault diagnosis based on WFRSN P systems. We first present WFRSN P system models for fault diagnosis production rules in TPSSs. Subsequently, how to build WFRSN P system fault diagnosis models for sections in TPSSs and set parameters in the models are described in detail. Finally, a WFRSN P system model for fault region identification of feeding sections is built.

Algorithm WMBFRA

Input: $\boldsymbol{W}_{r1}$, $\boldsymbol{W}_{r2}, \boldsymbol{W}_{r3}$, $\boldsymbol{W}_{p}$, $\boldsymbol{\lambda}_p$, $\boldsymbol{\lambda}_r$, $\mathbf{C}$, $\boldsymbol{\theta}_0$, $\boldsymbol{\delta}_0$

Set the termination condition $\boldsymbol{0} = (0, \ldots, 0)_t^T$
Let $g = 0$, where g represents the reasoning step
while $\boldsymbol{\delta}_g \neq \boldsymbol{0}$ **do**
    for each input neuron ($g = 0$) or each proposition neuron ($g > 0$) **do**
        if the firing condition $E = \{a^n, \theta_i \geq \lambda_{pi}, 1 \leq i \leq s\}$ is satisfied **then**
            the neuron fires and compute the real truth value vector $\boldsymbol{\delta}_{g+1}$ via $\boldsymbol{\delta}_{g+1} = (\mathbf{W}_{r1}^T \otimes \boldsymbol{\theta}_g) + (\mathbf{W}_{r2}^T \oplus \boldsymbol{\theta}_g) + (\mathbf{W}_{r3}^T \odot \boldsymbol{\theta}_g)$
            if there is a postsynaptic rule neuron **then**
                the neuron transmits a spike to the next rule neuron
            else
                just accumulate the value in the neuron
            end if
        end if
    end for
    for each rule neuron **do**
        if the firing condition $E = \{a^n, \delta_j \geq \lambda_{rj}, 1 \leq j \leq t\ \}$ is satisfied **then**
            the rule neuron fires and computes the real truth value vector $\boldsymbol{\theta}_{g+1}$ via $\boldsymbol{\theta_{g+1}} = \mathbf{W}_p^T \odot (\mathbf{C} \otimes \boldsymbol{\delta_{g+1}})$ and transmits a spike to the next proposition neuron
        end if
        $g = g + 1$
    end for
end while

Output: $\boldsymbol{\theta}_g$, which represents the final states of pulse values contained in proposition neurons.

4.1 WFRSN P system models for fault diagnosis production rules in TPSSs

In what follows, we describe fault diagnosis production rules in TPSSs and their WFRSN P system models, as shown is Fig. 8.

Type 1 (*Simple Rules*) 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 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 weight of proposition p_j is ω_j, where $\omega_j = 1$ because there is only one proposition in the antecedent of this kind of rules. The truth values of p_k is $\theta_k = \theta_j * \omega_j * c_i = \theta_j * c_i$.

Type 2 (*Compound And Rules*) R_i: IF $p_1(\theta_1)$ and ... 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 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 weights of propositions $p_1, \ldots, p_{k-1}$ are $\omega_1, \ldots, \omega_{k-1}$, respectively. The truth values of p_k is $\theta_k = [(\theta_1 * \omega_1 + \ldots + \theta_{k-1} * \omega_{k-1})/(\omega_1 + \ldots + \omega_{k-1})] * c_i$.

Type 3 (*Compound Or Rules*) R_i: IF $p_1(\theta_1)$ or ... 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] rep-

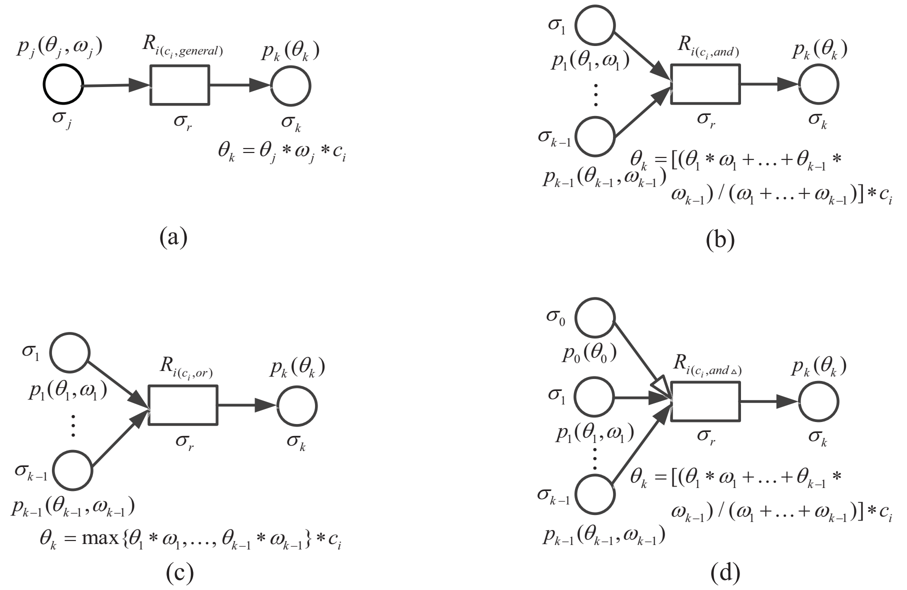

Fig. 8. WFRSN P system models for fault diagnosis production rules in TPSSs. (a) *Type 1*; (b) *Type 2*; (c) *Type 3*; (d) *Type4*.

resenting the certainty factor of 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 weights of propositions $p_1,\ldots,p_{k-1}$ are $\omega_1,\ldots,\omega_{k-1}$, respectively. The truth values of p_k is $\theta_k = max\{\theta_1*\omega_1,\ldots,\theta_{k-1}*\omega_{k-1}\}*c_i$.

Type 4 (*Conditional And Rules*) R_i: WHEN $p_0(\theta_0)$ is true, IF $p_1(\theta_1)$ and $\ldots$ and $p_{k-1}(\theta_{k-1})$ THEN $p_k(\theta_k)$ (CF = c_i), where $p_0,\ldots,p_k$ are propositions, c_i is a real number in [0,1] representing the certainty factor of rule R_i, $\theta_0,\ldots,\theta_k$ are real numbers in [0,1] representing the truth values of $p_0,\ldots,p_k$, respectively. The proposition p_0 is used to judge whether the reasoning condition of rule R_i is satisfied and its truth value θ_0 is not used in reasoning process. Thus, the weight of θ_0 is not considered in the model. The weights of propositions $p_1,\ldots,p_{k-1}$ are $\omega_1,\ldots,\omega_{k-1}$, respectively. The truth values of p_k is $\theta_k = [(\theta_1*\omega_1+\ldots+\theta_{k-1}*\omega_{k-1})/(\omega_1+\ldots+\omega_{k-1})]*c_i$.

4.2 WFRSN P system fault diagnosis models for sections

A good WFRSN P system fault diagnosis model should be able to intuitively describe the causality between a fault and the the statues of its protective devices. Moreover, all kinds of protective devices including main protective relays, backup protective relays and their corresponding CBs of a faulty section should be considered in its diagnosis model. In order to show how to build models and set parameters, we take bus A in a TSS and its WFRSN P system fault diagnosis

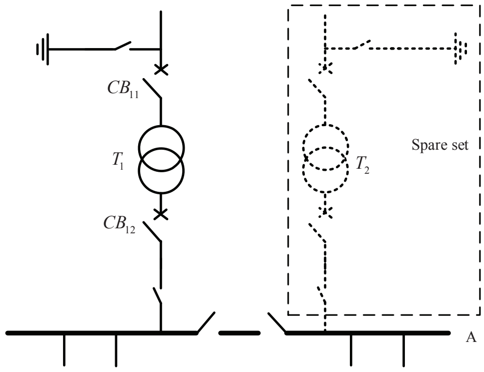

Fig. 9. Single line diagram of bus A in a TSS.

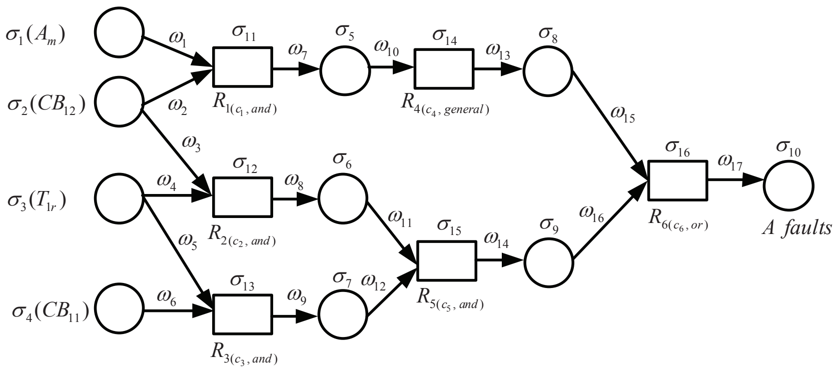

Fig. 10. A WFRSN P system fault diagnosis model for bus A.

model as examples which are shown in Fig. 9 and Fig. 10, respectively, where T represents a transformer, dotted line part represents a spare section set, m, p, r represent main protection, primary backup protection and remote backup protection, respectively.

Models building

When a fault occurs on a section in a TPSS, protective devices of this section will reach certain statues accordingly to protect the system. The observed status information, protective relay operation information and circuit breaker tripping information, obtained from SCADA systems are used as inputs of the WFRSN P system fault diagnosis model of the section. For example, in Fig. 10, main protective relay A_m, remote backup protective relay T_{1r} and their corresponding CBs, CB_{11} and CB_{12}, are used as the inputs of the diagnosis model of bus A. The other parts of the model are built according to relationships between the protective devices and the fault occurrence on bus A. For example, the relationships about

Table 4. 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

bus A can be described as follows: IF A_m operates and CB_{12} trips THEN bus A fails; IF T_{1r} operates and $(CB_{11}, CB_{12}$ trip) THEN bus A fails. Then proposition neurons and different types of rule neurons are chosen, and their links are created according to the relationships to obtain the WFRSN P system fault diagnosis model in Fig. 10. Output neuron σ_{10} will export the fault confidence level of bus A once WMBRA stops.

A WFRSN P system for the model in Fig. 10 can be formally described as $\Pi_1 = (O, \sigma_1, \ldots, \sigma_{16}, syn, in, out)$, where:

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

(2) $\sigma_1, \ldots, \sigma_{10}$ are *proposition neurons* corresponding to the propositions with truth values $\theta_1, \ldots, \theta_{10}$; that is, $s = 10$.

(3) $\sigma_{11}, \ldots, \sigma_{16}$ are rule neurons, where σ_{11}, σ_{12}, σ_{13} and σ_{15} are *and rule neurons*, σ_{14} is a *general rule neuron* and σ_{16} is an *or rule neuron*; that is, $t = 6$.

(4) $syn = \{(1, 11)$, $(2, 11)$, $(2, 12)$, $(3, 12)$, $(3, 13)$, $(4, 13)$, $(5, 14)$, $(6, 15)$, $(7, 15)$, $(8, 16)$, $(9, 16)$, $(11, 5)$, $(12, 6)$, $(13, 7)$, $(14, 8)$,$(15, 9)$,$(16, 10)\}$.

(5) $in = \{\sigma_1, \ldots, \sigma_4\}$, $out = \{\sigma_{10}\}$.

Parameters setting

Since the protections of sections in TPSSs are designed in single-ended manner, the status information of protective devices obtained form SCADA systems may contain uncertainty and incompleteness caused by abnormal situations such as operation failure, malversation and misinformation. Thus, it is necessary to use a probability value to describe the operation confidence level of each section. In consideration of the generality of the reliability of protective relays and CBs in TPSSs and ordinary power systems, the operation confidence levels of these protective devices are set the same as those in [17, 23, 29]. Table 4 shows the confidence levels of operated protective devices and non-operate protective devices, where FL, B and T represent the feeder line, bus and transformer, respectively.

Initially, each input neuron of a WFRSN P system fault diagnosis model contains only one spike assigned a real number, which is identical with the confidence level of the protective device associated with this input neuron. The other neurons in the model do not contain spikes at the very beginning and their pulse values are 0. For example, in Fig. 10, if bus A_m and CB_{12} operate, and T_{1r}, CB_{11} do not operate, then the spikes contained in $\sigma_1, \ldots, \sigma_4$ are given the values of 0.8564, 0.9833, 0.4, 0.2, respectively. The pulse values of $\sigma_5, \ldots, \sigma_{16}$ are given the same value 0.

Each rule neuron of a WFRSN P system fault diagnosis model has a truth value which represents the certainty factor of the fault diagnosis production rule associated with this rule neuron. Usually, a main protection has a higher reliability than that of a primary backup protection while a primary backup protection has a higher reliability than that of a remote backup protection. The truth values of neurons associated with main, primary backup and remote backup protections are set as 0.975, 0.95, 0.9, respectively. It is worth pointing out that for *or rule neurons*, their truth values are set according to their highest protection. In Fig. 10, the truth values of $\sigma_{11}, \ldots, \sigma_{16}$ are set as 0.975, 0.9, 0.9, 0.975, 0.9, 0.975.

Since the protective relay operation information and circuit breaker tripping information are both important to a fault diagnosis production rule, the output weights of proposition neurons associated with protective relays and CBs are set as the same value 0.5. If a neuron has only one presynaptic neuron, then the output weight of its presynaptic neuron is set as 1. Besides, the weight of a protection type is also set as 1. The weighs $\omega_1, \ldots, \omega_{17}$ in Fig. 10 are set as 0.5, 0.5, 0.5, 0.5, 0.5, 0.5, 1, 1, 1, 1, 0.5, 0.5, 1, 1, 1, 1, 1.

The firing threshold value of each neuron in WFRSN P system fault diagnosis models should be smaller than the minimum pulse value appeared in the neurons in the whole reasoning process. According to Table 4 and the operation of pulse values in different types of neurons, the firing threshold value of each neuron is set as 0.1.

4.3 Fault region identification for feeding sections

Lines in section posts (SPs) are connected in an up and down line paralleling manner in a TSS-ATP-SP feeding section (FS). So, when faults confirmed occur in a feeding section, one important task of fault diagnosis for taction power supply systems is to identify fault regions (which parts fail) in FSs. Fig. 11 shows a single line diagram of a TSS-ATP-SP feeding section and its WFRSN P system fault diagnosis model for fault region identification is shown in Fig. 12, where neurons σ_1 and σ_2 are associated with the propositions that current directions of I_{34} and I_{35} are positive, respectively; neurons σ_3 is associated with the proposition that current is detected in SP2; neurons σ_4 and σ_5 are associated with the propositions that current directions of I_{42} and I_{43} are negative, respectively; a small circle on an arrow tip represents an inverse proposition associated with its presynaptic neuron; a hollow tip represents an assistant synapse, i.e., the proposition associated with its presynaptic neuron is used as a judgement condition; output neuron σ_6 is associated with the proposition that first part of up direction feeding section in FS2, i.e., $FS2_{1\ up}$ has a fault. The meanings of output neurons σ_7, σ_9, σ_9 are similar. Here, clockwise direction is the positive current direction while counter-clockwise direction is the negative one.

Fig. 11 and Fig. 12 show a typical feeding section and its WFRSN P system fault diagnosis model for fault region identification, the models for other feeding

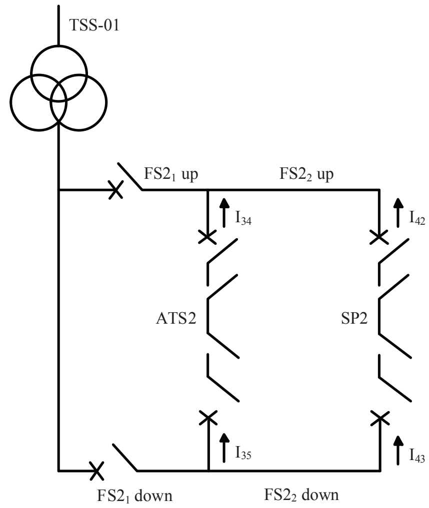

Fig. 11. Single line diagram of a TSS-ATP-SP feeding section.

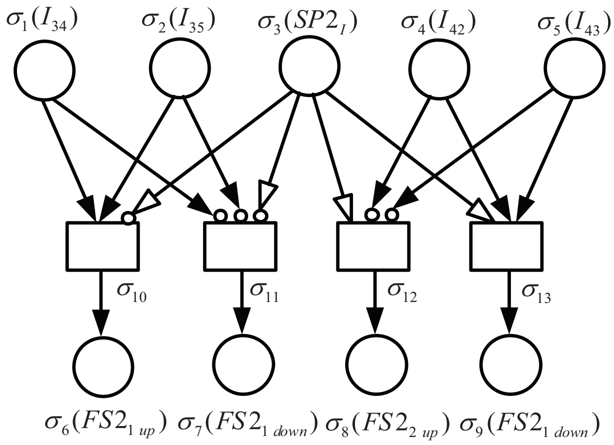

Fig. 12. A WFRSN P system fault diagnosis model for fault region identification of a feeding section.

sections can be built in a similar way. Causality between currents detected and fault regions is described by a WFRSN P system fault diagnosis model to get the fault regions of feeding sections and no numerical calculation is involved in this identification process. Thus, parameter setting of WFRSN P system fault diagnosis models for fault region identification of feeding sections is not considered.

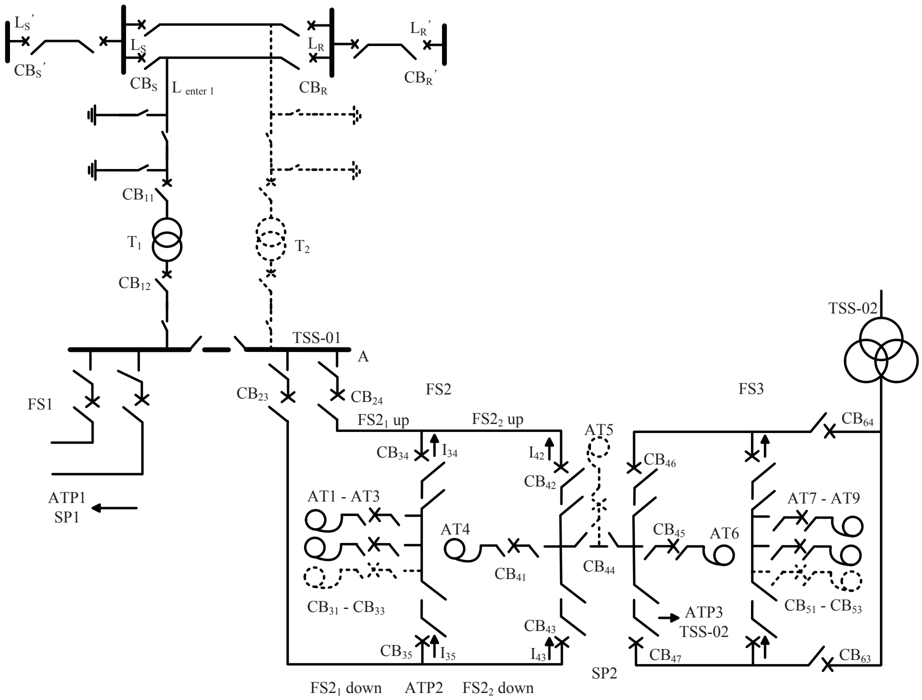

Fig. 13. A local single line sketch map of a TPSS.

5 Applications

In this section, three cases from the local system of a TPSS chosen in [23], as shown in Fig. 13, are considered as examples to test the effectiveness of WFRSN P systems in fault diagnosis, where S and R represent the sending end and receiving end of transmission lines, L represents transmission lines. The first two cases are in normal power supply and the third case is in over zone feeding. It is worth pointing out that, the complete line connection of FS1, ATP1, SP1, FS3, ATP3 and TPS-02 is the same as that of TSS-01, FS2, SP2 and ATP2 in Fig. 13.

Case 1: normal power supply. $FS2_{1\ up}$ and AT1 have faults.

Status information from the SCADA system (in time order): $AT1_m$ operated, CB_{31} tripped, $AT3$ auto switched over; $FS2_m$ operated, CB_{23} and CB_{24} tripped; feeder lines auto reclosed, $FS2_{up\ m}$ operated quickly, CB_{23} tripped again. When faults occur, current directions of I_{34} and I_{35} are positive, and current is not detected in SP2.

A WFRSN P system for $FS2_{up}$ is Π_2 and its corresponding WFRSN P system fault diagnosis model is shown in Fig. 14. $\Pi_2 = (O, \sigma_1, \ldots, \sigma_{16}, syn, in, out)$, where:

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

(2) $\sigma_1, \ldots, \sigma_9$ are proposition neurons corresponding to the propositions with truth values $\theta_1, \ldots, \theta_9$; that is, $s = 9$.

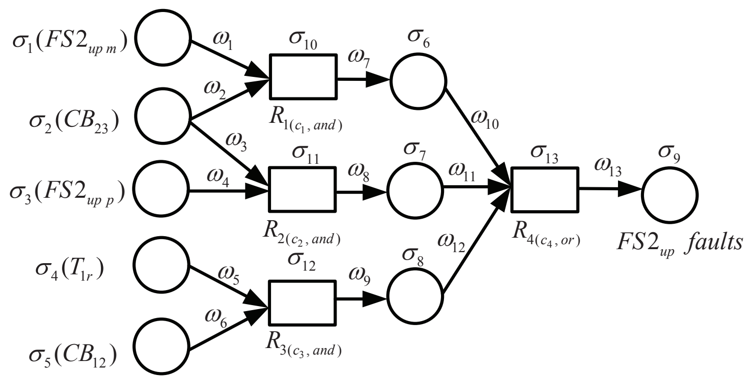

Fig. 14. A WFRSN P system fault diagnosis model for $FS2_{up}$.

(3) $\sigma_{10}, \ldots, \sigma_{13}$ are rule neurons, where σ_{10}, σ_{11} and σ_{12} are *and* rule neurons, σ_{14} is an *or* rule neuron; that is, $t = 4$.

(4) $syn = \{(1,10)\ ,(2,10), (2,11), (3,11),(4,12), (5,12), (6,13), (7,13), (8,13), (10,6), (11,7), (12,8), (13,9)\}$.

(5) $in = \{\sigma_1, \ldots, \sigma_5\}$, $out = \{\sigma_9\}$.

The synaptic weight matrices of Π_2 are shown in Fig. 15 and other parameter matrices associated with the model in Fig. 14 are described as follows: $\boldsymbol{\theta_0} = (0.9913\ 0.9833\ 0.8\ 0.4\ 0.2\ 0\ 0\ 0\ 0)^T$, $\boldsymbol{\delta_0} = (0\ 0\ 0\ 0)^T$, $\boldsymbol{C} = diag(0.975\ 0.95\ 0.9\ 0.975)$. In order to succinctly describe the matrices, let us denote $\boldsymbol{O_l} = (x_1, \ldots, x_l)^T$, where $x_i = 0, 1 \le i \le l$. When $g = 0$, we get the results: $\boldsymbol{\delta_1} = (0.9873\ 0.8917\ 0.3\ 0)^T$, $\boldsymbol{\theta_1} = (0\ 0\ 0\ 0\ 0\ 0.9626\ 0.8471\ 0.27\ 0)^T$. When $g = 1$, we get the results: $\boldsymbol{\delta_2} = (0\ 0\ 0\ 0.9626)^T$, $\boldsymbol{\theta_2} = (0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0.9385)^T$. When $g = 2$, we get the results: $\boldsymbol{\delta_3} = (0\ 0\ 0\ 0)^T$. Thus, the termination condition is satisfied and the reasoning process ends. We obtain the reasoning results, i.e., the truth value 0.9385 of the output neuron σ_9. The feeding section $FS2_{up}$ has a fault with a fault confidence level 0.9385. The fault region of $FS2_{up}$ can be further identified according to the fault current detected and the WFRSN P system fault diagnosis model for fault region identification in Fig. 12, and then we get the result that $FS2_{1\ up}$ has a fault with a fault confidence level 0.9385.

For AT1, a WFRSN P system can be constructed in a similar way and its corresponding WFRSN P system fault diagnosis model is shown in Fig. 16. The diagnosis process of AT1 is similar. According to the SCADA data and Table 4, the parameter matrices of WFRSN P system fault diagnosis model for AT1 is established to perform WMBRA. After the reasoning, the fault confidence level of AT1 is obtained, i.e., 0.8361. So the autotransformer AT1 has a fault with a fault confidence level 0.8361.

Case 2: normal power supply. $FS2_{1\ up}$ *has faults.*

$$\boldsymbol{W_{r1}} = [\mathbf{O}]_{9\times 4}, \boldsymbol{W_{r2}} = \begin{bmatrix} 0.5 & 0 & 0 & 0 \\ 0.5 & 0.5 & 0 & 0 \\ 0 & 0.5 & 0 & 0 \\ 0 & 0 & 0.5 & 0 \\ 0 & 0 & 0.5 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}, \boldsymbol{W_{r3}} = \begin{bmatrix} 0&0&0&0 \\ 0&0&0&0 \\ 0&0&0&0 \\ 0&0&0&0 \\ 0&0&0&0 \\ 0&0&0&1 \\ 0&0&0&1 \\ 0&0&0&1 \\ 0&0&0&0 \end{bmatrix}, \boldsymbol{W_{p}} = \begin{bmatrix} 0&0&0&0&0&1&0&0&0 \\ 0&0&0&0&0&0&1&0&0 \\ 0&0&0&0&0&0&0&1&0 \\ 0&0&0&0&0&0&0&0&1 \end{bmatrix}.$$

Fig. 15. Synaptic weight matrices of WFRSN P system fault diagnosis model for $FS2_{up}$.

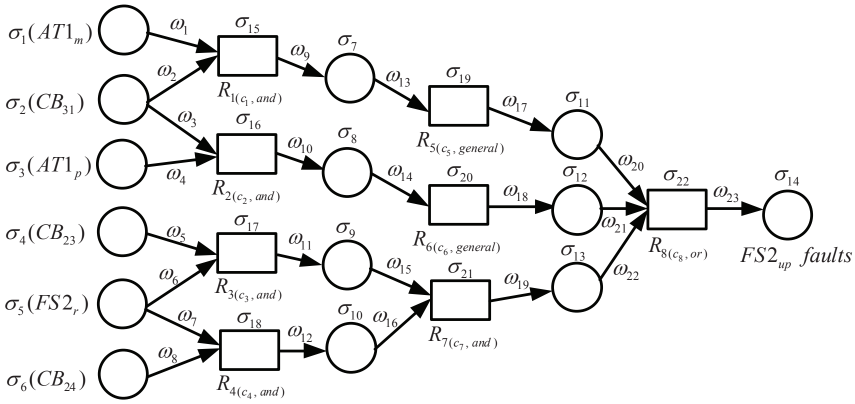

Fig. 16. A WFRSN P system fault diagnosis model for AT1.

Status information from the SCADA system (in time order): $FS2_m$ operated, CB_{24} tripped; T_{1r} operated, CB_{11} and CB_{12} tripped. When faults occur, current directions of I_{34} and I_{35} are positive, and current is not detected in SP2. In this case, CB_{23} refused operation.

According to the SCADA data and Table 4, the WFRSN P system fault diagnosis model for $FS2_1$ and its parameter matrices are established to perform WMBRA. After the reasoning, the fault confidence level of $FS2_{up}$ is obtained, i.e., 0.7439. The fault region of $FS2_{up}$ can be further identified according to the fault current detected and the WFRSN P system fault diagnosis model for fault region identification in Fig. 12, and then we get the result that $FS2_{1\ up}$ has a fault. So the feeding section $FS2_{1\ up}$ has a fault with a fault confidence level 0.7439.

Case 3: FS2 is over zone fed by TPS-02. AT7 and $FS2_{2\ up}$ have faults.

Status information from the SCADA system (in time order): primary backup protections of feeder lines in SP2 operated, CB_{42} tripped; meanwhile, CB_{51} tripped, AT9 auto switched over; remote backup protection $FS3_s$ of feeder lines in TSS-02 operated, CB_{63} and CB_{64} tripped. When faults occur, current directions of I_{34} and I_{35} are positive, and current is detected only in SP2 and ATP2. In this case, main protection of feeder lines in SP2, CB_{43} and main protection of AT7 refused operation, and status information of primary backup protection of AT7 lost.

According to the SCADA data and Table 4, the WFRSN P system fault diagnosis modelS for AT7 and $FS2_2$ and their parameter matrices are established to perform WMBRA, respectively. After the reasoning, the fault confidence levels AT7 and $FS2_{up}$ are obtained, i.e., 0.6946 and 0.6123. The fault region of $FS2_{up}$ can be further identified according to the fault current detected and the WFRSN P system fault diagnosis model for fault region identification in Fig. 12, and then we get the result that $FS2_{2\ up}$ has a fault. So the autotransformer AT2 has a fault with a fault confidence level 0.6946 and the feeding section $FS2_{2\ up}$ has a fault with a fault confidence level 0.6123.

The results of *Cases 1-3* give evidence of that the proposed fault diagnosis approach can obtain satisfying results both in the situation in normal power supply and over zone feeding with complete/incomplete alarm information. In addition, the proposed method can obtain the satisfying result as that in [23] by using only once simple reasoning while the method in [23] needs a second reasoning.

6 Conclusions

In this study, WFRSN P systems are applied in fault diagnosis of TPSSs and WMBRA is proposed to perform weighted matrix-based reasoning to obtain a fault confidence level for each candidate faulty section. The definitions of neurons in the WFRSN P system proposed in [18] are extended and more types of neurons are considered to express different types of status information of protection obtained form SCADA systems. Building processes and parameter setting of fault diagnosis models for sections and fault region identification of feeding sections are described in detail. Case studies show effectiveness of the presented method in diagnosing faulty sections in TPSSs. Considering the high requirement of TPSSs for diagnosing speed, how to improve WFRSN P systems to adapt themselves to online fault diagnosis is our future work.

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