ROMANIAN JOURNAL OF INFORMATION SCIENCE AND TECHNOLOGY
Volume **18**, Number 3, 2015, 240–255

Fault Section Estimation of Power Systems with Optimization Spiking Neural P Systems

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Abstract. An optimization spiking neural P system (OSNPS) provides a novel way to directly use a P system to solve optimization problems. This paper discusses the practical application of OSNPS for the first time and uses it to solve the power system fault section estimation problem formulated by an optimization problem. When the status information of protective relays and circuit breakers read from a supervisory control and data acquisition system is input, the OSNPS can automatically search and output fault sections. Case studies show that an OSNPS is effective in fault sections estimation of power systems in different types of fault cases: including a single fault, multiple faults and multiple faults with incomplete and uncertain information.

Key-words: Membrane computing, optimization spiking neural P system, fault section estimation, power systems, fault diagnosis.

1. Introduction

Membrane computing is an attractive branch of natural computing, initiated by Gh. Păun in [1], aiming at abstracting innovative computing models or computing ideas from functioning and structures of living cells, as well as from the way the cells are organized in tissues or other higher order structures [2]. The obtained models, called membrane systems or P systems, are distributed and parallel computing models. Currently, there are three basic types of P systems: cell-like P systems, tissue-like P systems and neural-like P systems [3, 4].

In recent years, the research on neural-like P systems mainly focused on spiking neural P systems (SN P systems), which were introduced in [5]. An SN P system is a class of distributed and parallel computing devices which are inspired by the way neurons communicate by means of electrical impulses (spikes). Since then, SN P systems have become a hot topic in membrane computing [6–21] and an overview of this field can be found in [3], with up-to-date information available at the membrane computing website (`http://ppage.psystems.eu`).

In [18], an extended spiking neural P system (ESNPS) was proposed by introducing the probabilistic selection of evolution rules and multi-neurons output and correspondingly a novel way to design a P system for directly obtaining the approximate solutions of combinatorial optimization problems without the aid of evolutionary operators was introduced. Besides, a family of ESNPS, called optimization spiking neural P systems (OSNPS), were further designed by introducing a guider to adaptively adjust rule probabilities to approximately solve combinatorial optimization problems. This is the first time that a strategy to design SN P systems capable of solving optimization problems is proposed. Experimental results on knapsack problems in [18] proved the viability and effectiveness of OSNPS. Moreover, the proposed future work in [18] pointed out that OSNPS can be used to solve various application problems, such as fault diagnosis of electric power systems.

Strictly speaking, fault diagnosis of power systems includes fault detection, fault section estimation, fault type identification, failure isolation and recovery [19, 22]. Among the five processes, fault section estimation is especially important [19, 23]. Fault section estimation (FSE) identifies the fault section in power systems by using the status information of protective relays and circuit breakers (CBs) obtained from supervisory control and data acquisition (SCADA) systems [24]. So far, various approaches have been proposed to solve this problem, such as expert systems (ES) [25], fuzzy logic (FL) [26], fuzzy Petri nets (FPN) [23], artificial neural networks (ANN) [27], multi-agent systems (MAS) [28], optimization methods (OM) [22], [29–31]. Each method has its own pros and cons [19]. Therefore, improving the aforementioned methods and developing new ones to solve fault section estimation problems is a hot topic in the research field of electrical power systems.

The power system fault section estimation problem can be effectively solved by formulating it into a 0-1 integer programming problem. In [18], only the widely used benchmark problems, knapsack problems, were applied to verify the OSNPS effectiveness and the authors pointed out that OSNPS can be used to solve various application problems. However, until now there is not any work about the real application of OS-

NPS. This paper discusses the application of OSNPS to fault section estimation of power systems. This is the first time to use OSNPS to solve real application problems. When the status information of protective relays and circuit breakers read from a supervisory control and data acquisition system is input, OSNPS can automatically search and output fault sections. Case studies show that OSNPS is effective in fault sections estimation of power systems in different types of fault cases including single fault, multiple faults and multiple faults with incomplete and uncertain information.

This paper is structured as follows. Section 2 states the problem to solve. Section 3 presents the fault section estimation method based on OSNPS. Subsequently, three case studies are provided in Section 4. Conclusions are finally drawn in Section 5.

2. Problem Description

The aim of *fault section estimation* (FSE, for short) problem in power systems based on optimization methods (OM) is to obtain a fault hypothesis which can explain warning signals (status information) with a maximum degree of confidence. Specifically, fault section estimation can be abstracted as a 0-1 programming problem with an objective function (error function), as shown in (1), which is obtained according to the causality between a fault and the statuses of protection devices including protective relays and circuit breakers (CBs) [30]. Then, an optimization method is used to find the fault hypothesis, i.e. the minimal value of the expression:

$$E(S) = \sum_{j=1}^{n_c} \left| c_j - c_j^*(S,R) \right| + \sum_{k=1}^{n_r} |r_k - r_k^*(S)|, \tag{1}$$

where:

(1) n_c and n_r represent the numbers of circuit breakers (CBs) and protective relays, respectively;

(2) $E(S)$ represents a status function of all the sections in a power system;

(3) S is an n-vector representing the status of sections in a power system and n represents the number of sections: if section i is faulty, then $s_i = 1$; otherwise, $s_i = 0$, $i = 1, \ldots, n$;

(4) c_j $(1 \leq j \leq n_c)$ is the jth element of an n_c-vector and represents the real status of the jth circuit breaker in a protection system. If CB_j trips, then $c_j = 1$; otherwise, $c_j = 0$;

(5) $c_j^*(S,R)$ $(1 \leq j \leq n_c)$ is the jth element of an n_c-vector and represents the expected status of the jth circuit breaker in a protection system. If CB_j should trip, then $c_j^* = 1$; otherwise, $c_j^* = 0$;

(6) r_k $(1 \leq k \leq n_r)$ is the kth element of an n_r-vector and represents the real status of the kth protective relay in a protection system. If the kth protective relay operates, then $r_k = 1$; otherwise, $r_k = 0$;

(7) $r_k^*(S)$ $(1 \leq k \leq n_r)$ is the kth element of an n_r-vector and represents the expected status of the kth protective relay in a protection system. If the kth protective relay should operate, then $r_k^* = 1$; otherwise, $r_k^* = 0$.

In this study, OSNPS is used to fulfill fault section estimation in power systems by minimizing $E(S)$ in (1). Specifically, the expected status of protective relays and CBs can be obtained according to their operation principles and the protection structure of a power system. The real status of protective relays and CBs are normally read from a power SCADA system. When all the expected status and real status of protections are obtained, we can use an OSNPS to find the minimal value of $E(S)$ in (1). The aim of fault section estimation is to obtain vector elements of S corresponding to the minimum value of (1).

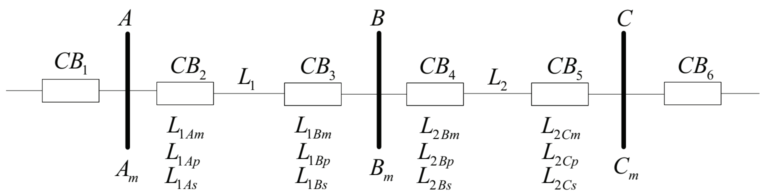

Fig. 1. A simple power network.

Table 1. Labels of sections and protective devices

Sections/devices	A	B	C	L_1	L_2	A_m	B_m	C_m	L_{1Am}
Labels	S_1	S_2	S_3	S_4	S_5	r_1	r_2	r_3	r_4
Devices	L_{1Bm}	L_{2Bm}	L_{2Cm}	L_{1Ap}	L_{1Bp}	L_{2Bp}	L_{2Cp}	L_{1As}	L_{1Bs}
Labels	r_5	r_6	r_7	r_8	r_9	r_{10}	r_{11}	r_{12}	r_{13}
Devices	L_{2Bs}	L_{2Cs}	CB_1	CB_2	CB_3	CB_4	CB_5	CB_6	-
Labels	r_{14}	r_{15}	C_1	C_2	C_3	C_4	C_5	C_6	-

To illustrate the operational rules of different levels of protections and how to compute protective expected values $c_j^*(S, R)$ $(1 \leq j \leq n_c)$ and $r_k^*(S)$ $(1 \leq k \leq n_r)$ in (1), a simple power network is used and is shown in Figure 1. This power network includes five system sections, six CBs and fifteen protective relays. For the convenience of description, some notations are described as follows. The five sections are A, B, C, L_1 and L_2, which are labeled as $S_1, \ldots, S_5$. The six CBs are $CB_1, CB_2, CB_3, CB_4, CB_5, CB_6$, which are labeled as $C_1, \ldots, C_6$. The fifteen protective relays are composed of seven main ones $(A_m, B_m, C_m, L_{1Am}, L_{1Bm}, L_{2Bm}, L_{2Cm})$, which are labeled as $r_1, \ldots, r_7$, four first backup ones $(L_{1Ap}, L_{1Bp}, L_{2Bp}, L_{2Cp})$, which are labeled as $r_8, \ldots, r_{11}$ and 4 second backup ones $(L_{1As}, L_{1Bs}, L_{2Bs}, L_{2Cs})$, which are labeled as $r_{12}, \ldots, r_{15}$. All the labels of sections and protective devices are shown in Table 1. The detail operational rules of different types of protective devices, please see [19], [22]. For the simple system in Figure 1, the operational rules of main protections and backup protections are shown in Table 2 and Table 3, respectively.

Table 2. Operational rules of main protections

Main protections	Operational rules
A_m	when A has a fault, A_m operates to trip CB_1 and CB_2
B_m	when B has a fault, B_m operates to trip CB_3 and CB_4
C_m	when C has a fault, C_m operates to trip CB_5 and CB_6
L_{1Am}	when L_1 has a fault, L_{1Am} operates to trip CB_2
L_{1Bm}	when L_1 has a fault, L_{1Bm} operates to trip CB_3
L_{2Bm}	when L_2 has a fault, L_{2Bm} operates to trip CB_4
L_{2Cm}	when L_2 has a fault, L_{2Cm} operates to trip CB_5

Table 3. Operational rules of main protections

Main protections	Operational rules
L_{1Ap}	when L_1 has a fault and its main protections fail, L_{1Ap} operates to trip CB_2
L_{1Bp}	when L_1 has a fault and its main protections fail, L_{1Bp} operates to trip CB_3
L_{2Bp}	when L_2 has a fault and its main protections fail, L_{2Bp} operates to trip CB_4
L_{2Cp}	when L_2 has a fault and its main protections fail, L_{2Cp} operates to trip CB_5
L_{1As}	when B has a fault and CB_3 fails or L_2 has a fault and CB_3 and CB_4 fail, L_{1As} operates to trip CB_2
L_{1Bs}	when A has a fault and CB_2 fails, L_{1Bs} operates to trip CB_3
L_{2Bs}	when C has a fault and CB_5 fails, L_{2Bs} operates to trip CB_4
L_{2Cs}	when B has a fault and CB_4 fails or L_1 has a fault and CB_3 and CB_4 fail, L_{2Cs} operates to trip CB_5

In this study, the protective relays consist of main protective relays (MPRs), first backup protective relays (FBPRs) and second backup protective relays (SBPRs). According to the operational rules of main and backup protections, we obtain the computational formulas of expected values of protective relays (r_k^*, $1 \leq k \leq 15$) and CBs ($c_j^*(S,R)$, $1 \leq j \leq 6$) and are shown in Table 4. Therefore, according to Table 4, the respected value for every protective relay or circuit breaker is acquirable.

3. Fault Section Estimation Based on OSNPS

3.1. Optimization Spiking Neural P Systems

First, let us recall the concept of extended spiking neural P systems introduced in [18] (it is depicted in Figure 2).

Table 4. Computational formulas of expected values of protective relays and CBs

Protective devices	Computational formulas
MPRs	$r_1^*(S) = s_1$
	$r_2^*(S) = s_2$
	$r_3^*(S) = s_3$
	$r_4^*(S) = s_4$
	$r_5^*(S) = s_4$
	$r_6^*(S) = s_5$
	$r_7^*(S) = s_5$
FBPRs and SBPRs	$r_8^*(S) = s_4(1 - r_4)$
	$r_9^*(S) = s_4(1 - r_5)$
	$r_{10}^*(S) = s_5(1 - r_6)$
	$r_{11}^*(S) = s_5(1 - r_7)$
	$r_{12}^*(S) = 1 - [1 - s_2(1 - c_3)][1 - s_5(1 - c_3)(1 - c_4)]$
	$r_{13}^*(S) = s_1(1 - c_2)$
	$r_{14}^*(S) = s_3(1 - c_5)$
	$r_{15}^*(S) = 1 - [1 - s_2(1 - c_4)][1 - s_4(1 - c_3)(1 - c_4)]$
CBs	$c_1^*(S, R) = s_1 r_1$
	$c_2^*(S, R) = max\langle s_1 r_1, s_4 r_4, s_4(1 - r_4) r_8,$ $\{1 - [1 - s_2(1 - c_3)][1 - s_5(1 - c_3)(1 - c_4)]\} r_{12}\rangle$
	$c_3^*(S, R) = max\langle s_2 r_2, s_4 r_5, s_4(1 - r_5) r_9, s_1(1 - c_2) r_{13}\rangle$
	$c_4^*(S, R) = max\langle s_2 r_2, s_5 r_6, s_5(1 - r_6) r_{10}, s_3(1 - c_5) r_{14}\rangle$
	$c_5^*(S, R) = max\langle s_3 r_3, s_5 r_7, s_5(1 - r_7) r_{11},$ $\{1 - [1 - s_2(1 - c_4)][1 - s_4(1 - c_3)(1 - c_4)]\} r_{15}\rangle$
	$c_6^*(S, R) = s_3 r_3$

Definition 1. An *extended spiking neural P system* (ESNPS, for short) of degree $m \geq 1$, is a tuple $\Pi = (O, \sigma_1, \ldots, \sigma_{m+2}, syn, I_0)$, where:

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

(2) $\sigma_i, 1 \leq i \leq m$, are neurons $\sigma_i = (1, R_i, P_i)$, where $R_i = \{r_i^1, r_i^2\}$, $r_i^1 = \{a \to a\}$, $r_i^2 = \{a \to \lambda\}$, and $P_i = \{p_i^1, p_i^2\}$ is a finite set of probabilities (p_i^j is associated with rule r_i^j, $1 \leq j \leq 2$) such that p_i^1+p_i^2=1;

(3) $\sigma_{m+1} = \sigma_{m+2} = (1, \{a \to a\})$;

(4) $syn = \{(i, j) \mid (i = m + 2 \wedge 1 \leq j \leq m + 1) \vee (i = m + 1 \wedge j = m + 2)\}$;

(5) $I_0 = \{\sigma_1, \ldots, \sigma_m\}$ is a finite set of *output* neurons, i.e., the output is a spike train formed by concatenating the outputs of $\sigma_1, \ldots, \sigma_m$.

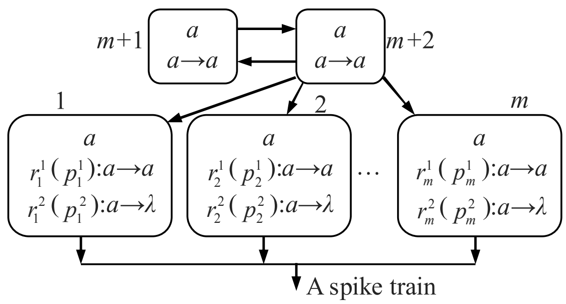

Fig. 2. The ESNPS structure.

This system contains the subsystem consisting of neurons σ_{m+1} and σ_{m+2}, and this subsystem is used as a step by step supplier of spikes to neurons $\sigma_1, \ldots, \sigma_m$. In the subsystem, there are two identical neurons, each of which fires at each moment of time and sends a spike to each of neurons $\sigma_1, \ldots, \sigma_m$, and reloads each other continuously. At each time unit, each of neurons $\sigma_1, \ldots, \sigma_m$ performs the firing rule r_i^1 by probability p_i^1 and the forgetting rule r_i^2 by probability p_i^2, $i = 1, 2, \ldots, m$. If the ith neuron spikes, we obtain its output 1, i.e., we obtain 1 by probability p_i^1, otherwise, we obtain its output 0, i.e., we obtain 0 by probability p_i^2, $i = 1, 2, \ldots, m$. Thus, this system outputs a spike train consisting of 0 and 1 at each moment of time. If we can adjust the probabilities $p_1^1, \ldots, p_m^1$, we can control the output spike train. So, a method to adjust the probabilities $p_i^1, \ldots, p_m^1$ by introducing a family of ESNPS is presented and described as follows.

A certain number of ESNPS can be organized into a family of ESNPS (called OSNPS) by introducing a guider to adjust the selection probabilities of rules inside each neuron of each ESNPS. The structure of OSNPS is shown in Figure 3, where OSNPS consists of H ESNPS, ESNPS$_1$, ESNPS$_2$, ..., ESNPS$_H$. Each ESNPS is identical with the one in Figure 2 and the pseudocode algorithm of the guider algorithm is illustrated in Figure 4. For detail explanation about the guider algorithm and more information about ESNPS and OSNPS, please see [18].

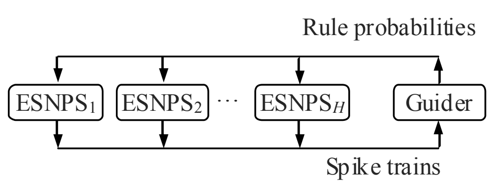

Fig. 3. OSNPS.

Input: Spike train T_s, p_j^a, Δ, H and m

Rearrange T_s as matrix P_R
  $i = 1$
while $(i \leq H)$ **do**
    j=1
  while $(j \leq m)$ **do**
    if $(rand < p_j^a)$ **then**
      $k_1, k_2 = ceil(rand * H)$, $k_1 \neq k_2 \neq i$
      if $(f(C_{k_1}) > f(C_{k_2}))$ **then**
        $b_j = b_{k_1}$
      else
        $b_j = b_{k_2}$
      end if
      if $(b_j > 0.5)$ **then**
        $p_{ij}^1 = p_{ij}^1 + \Delta$
      else
        $p_{ij}^1 = p_{ij}^1 - \Delta$
      end if
    else
      if $(b_j^{max} > 0.5)$ **then**
        $p_{ij}^1 = p_{ij}^1 + \Delta$
      else
        $p_{ij}^1 = p_{ij}^1 - \Delta$
      end if
    end if
    if $(p_{ij}^1 > 1)$ **then**
      $p_{ij}^1 = p_{ij}^1 - \Delta$
    else
      if $(p_{ij}^1 < 0)$ **then**
        $p_{ij}^1 = p_{ij}^1 + \Delta$
      end if
    end if
    $j = j + 1$
  end while
  $i = i + 1$
end while

Output: Rule probability matrix P_R

Fig. 4. Guider Algorithm

3.2. Fault Section Estimation Based on OSNPS

The process of OSNPS applied to the FSE problem can be illustrated by the sketch map in Figure 5, which depicts how to estimate fault sections using OSNPS.

To clearly present the process in Figure 5, a detailed description is given as follows.

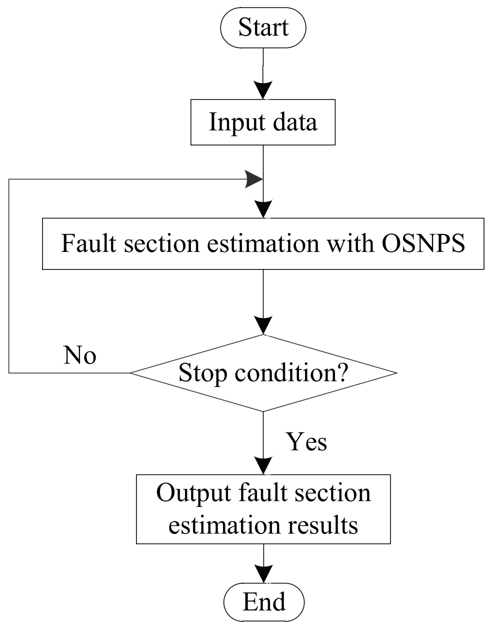

Fig. 5. The sketch map of fault section estimation based on OSNPS.

Step 1: Input data

To start the method, SCADA data, parameters of OSNPS and initial value of the fitness function are required. Thus, the input data block/process consist of three parts which are described as follows.

1) Read SCADA data. The status information including the status of protective relays and CBs, the topological connection of a given power system and its protection system structure information are read from an SCADA system;

2) Set parameters of OSNPS. The parameters refer to the number of ESNPS (H), the dimension of each ESNPS (m), the learning probabilities, the learning rate, the rule probability matrix, maximum iterations and so on;

3) Initial fitness function. Above mentioned data are used to initial fitness function of the FSE problem according to (1).

Step 2: Fault section estimation with OSNPS

Perform OSNPS to produce and update spike trains to find the minimum value of (1). As mentioned in Subsection 3.1, each ESNPS can produce a spike train, which stores the needed result in binary encoding. H ESNPS are organized into an OSNPS by a guider to adjust the selection probabilities of rules inside each neuron of each ESNPS. The guider algorithm, as shown in Figure 4 and described in [18] in detail, is used to help OSNPS getting the spike train which brings the minimum value of (1).

Step 3: Stopping condition

The optimization process is terminated when either reaching the maximum iterations or concluding that no better solution would appear in the following iterations.

Step 4: Output fault section estimation results

The spike train corresponding to the minimum value of (1) is outputted in an n-vector S and $S_i = 1$ is the ith faulty section, $i = 1, \ldots, n$.

The pseudocode algorithm of the OSNPS fault section estimation algorithm is illustrated in Algorithm 1, where m represents the number of neurons in every ESNPS, M represents iteration, $p_j^a, 1 \leq j \leq m$ represents learning probabilities, Δ represents learning rate and H represents the numbers of ESNPS.

4. Case studies

Figure 6 shows a typical 4-substation system including 28 system sections, 40 CBs and 84 protective relays [19], [22]. For the convenience of description, some notations are described as follows. The 28 sections are $A_1, \ldots, A_4, T_1, \ldots, T_8, B_1, \ldots, B_8, L_1, \ldots, L_8$ which are labeled as $s_1 \sim s_{28}$ and the 40 CBs are $CB_1, \ldots, CB_{40}$ which are labeled as ($C_1 \sim C_{40}$). The 84 protective relays are composed of 36 main ones ($A_{1m}, \ldots, A_{4m}, T_{1m}, \ldots, T_{8m}, B_{1m}, \ldots, B_{8m}, L_{1Sm}, \ldots, L_{8Sm}, L_{1Rm}, \ldots, L_{8Rm}$) which are labeled as $r_1, \ldots, r_{36}$ and 48 backup ones: $T_{1p}, \ldots, T_{8p}, T_{1s}, \ldots, T_{8s}, L_{1Sp}, \ldots, L_{8Sp}, L_{1Rp}, \ldots, L_{8Rp}, L_{1Ss}, \ldots, L_{8Ss}, L_{1Rs}, \ldots, L_{8Rs}$) which are labeled as $r_{37}, \ldots, r_{84}$.

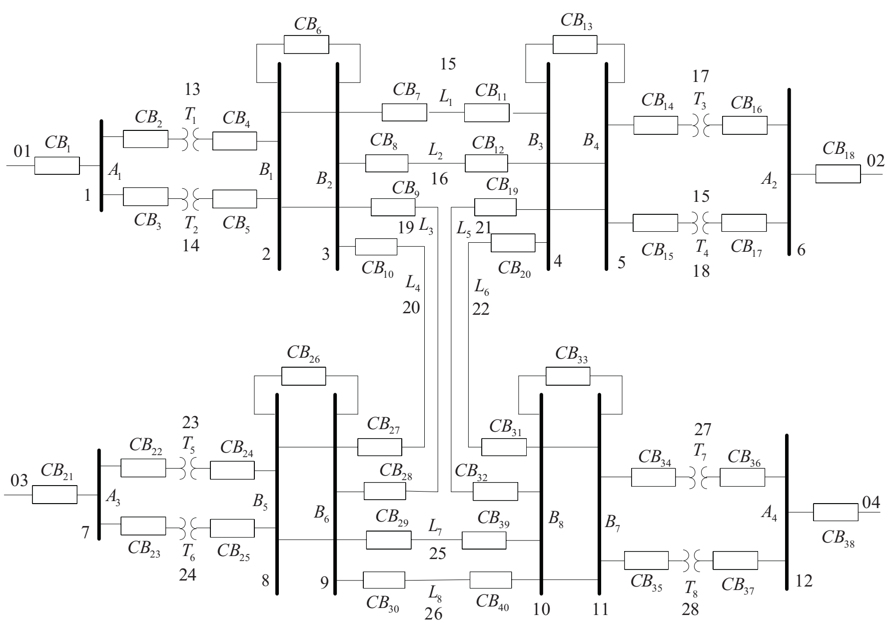

Fig. 6. A local sketch map of the protection system of an EPS.

Algorithm 1 OSNPS fault section estimation algorithm

Input: m, M, p_j^a, Δ and H
set the generation counter $t = 1$
initial fitness function E(S) according to (1)
while $(t \leq M)$ **do**
  generate dematrix B according to rule probability matrix P_R: $B_{H\times m} = rand() < P_R$,
  for $(j = 1; j \leq H; j++)$ **do**
    calculate the fitness function value of ith ESNPS according to (1)
  end for
  update individual optimal value B_{best}^i. B_{best}^i represents historical optimal value of ith ESNPS
  update global optimal value G_{best}. G_{best} represents historical optimal value among H ESNPSs in previous t iterations
  i=1
  while $(i \leq H)$ **do**
    j=1
    while $(j \leq m)$ **do**
      if $(rand < p_j^a)$ **then**
        perform individual learning:
        (1) choose two distinct individuals k_1 and k_2 among H ESNPSs, where $1 \leq k_1 \neq k_2 \neq i \leq H$
        (2) Compare historical optimal fitness function values corresponding to $B_{best}^{k_1}$ and $B_{best}^{k_2}$. If the fitness function value of k_1 is better, then record the jth bits of k_1; otherwise, record the jth bit of k_2
        (3) update rule probability matrix P_R
        if $(b_j == 1)$ **then**
          $P_{ij}^t = P_{ij}^t + \Delta$
        end if
        if $(b_j == 0)$ **then**
          $P_{ij}^t = P_{ij}^t - \Delta$
        end if
      else
        perform global learning:
        Learning global optimal value G_{best} and update rule probability matrix P_R
        if $(G_{best}^j == 1)$ **then**
          $G_{best}^j == P_{ij}^t + \Delta$, where G_{best}^j represents the jth bit of G_{best}
        end if
        if $(b_j == 0)$ **then**
          $P_{ij}^t = P_{ij}^t - \Delta$, where G_{best}^j represents the jth bit of G_{best}
        end if
      end if
    end while
    $i = i + 1$
  end while
  $t = t + 1$
end while
Output: global optimal value G_{best} which is a m-vector and represent status of sections. If $G_{besti} = 1$, then the ith section is faulty; otherwise, it is not faulty.

To test the effectiveness and superiority of OSNPS in fault section estimation, three cases of the local power system in Figure 6 are considered. The status information about protective relays and CBs of these cases is shown in Table 5, where *Case 1* has a single fault, *Case 2* has multiple faults and *Case 3* has multiple faults with incompleteness and uncertainty. OSNPS is used to estimate fault sections for the three cases, the estimation results are shown in Table 6 with a comparison with three other fault section estimation methods, where " – " means that this case was not considered in the corresponding reference.

From Table 6, we can see that the estimation results of OSNPS, in *Cases 1-2*, are the same as those of fuzzy logic [FL], genetic algorithm (GA) and FDSNP in [26], [22] and [19], respectively. In other words, OSNPS is effective in fault section estimation of power systems for single and multiple faults. In *Case 3*, the estimation result of OSNPS is different from those in [26] and [22]. According to the results in [19] and [30], we know that the result of OSNPS is correct. Therefore, from the three typical cases, OSNPS is effective in fault section estimation of power systems for a single fault, multiple faults and multiple faults with incomplete and uncertain alarm information.

Table 5. Status information about protective relays and CBs

Cases	Status information	
	Operated relays	Tripped CBs
1	B_{1m}, L_{2Rs}, L_{4Rs}	CB_4, CB_5, CB_7 CB_9, CB_{12}, CB_{27}
2	B_{1m}, L_{1Sm}, L_{1Rp} B_{2m}, L_{2Sp}, L_{2Rm}	CB_4, CB_5, CB_6 CB_7, CB_8, CB_9 $CB_{10}, CB_{11}, CB_{12}$
3	T_{7m}, T_{8P}, B_{7m} B_{8m}, L_{5Sm}, L_{5Rp} $L_{6Ss}, L_{7Sp}, L_{7Rm}, L_{8Ss}$	$CB_{19}, CB_{20}, CB_{29}, CB_{30}$ $CB_{32}, CB_{33}, CB_{34}, CB_{35}$ $CB_{36}, CB_{37}, CB_{39}$

Table 6. Comparisons between OSNPS and three fault diagnosis methods

Cases	Diagnosis results				
	OSNPS	FL [15]	GA [23]	FDSNP [13]	GATS [21]
1	B_1	B_1	B_1	B_1	-
2	B_1, B_2 L_1, L_2	B_1, B_2 L_1, L_2	B_1, B_2 L_1, L_2	B_1, B_2 L_1, L_2	-
3	L_5, L_7 B_7, B_8 T_7, T_8	L_5, L_7 B_8, T_7 T_8	$(1) L_5, L_7, B_7, B_8$ T_7, T_8 $(2) L_5, L_7, T_7, B_8$	L_5, L_7 B_7, B_8 T_7, T_8	L_5, L_7 B_7, B_8 T_7, T_8

In what follows, we use *Case 1* as an example to illustrate how to use OSNPS estimating fault section.

Case 1: SCADA data. Operated relays: B_{1m}, L_{2Rs} and L_{4Rs}. Tripped CBs: CB_4, CB_5, CB_7, CB_9, CB_{12} and CB_{27}.

The fault section estimation process is described as follows.

1. Passive networks are searched according to network topology analysis method which is descried in detail in [19]. The passive network is shown in Figure 7, where B_1, B_2, L_2 and L_4 are candidate faulty sections and their corresponding status vector is $S = [s_1, s_2, s_3, s_4]$.

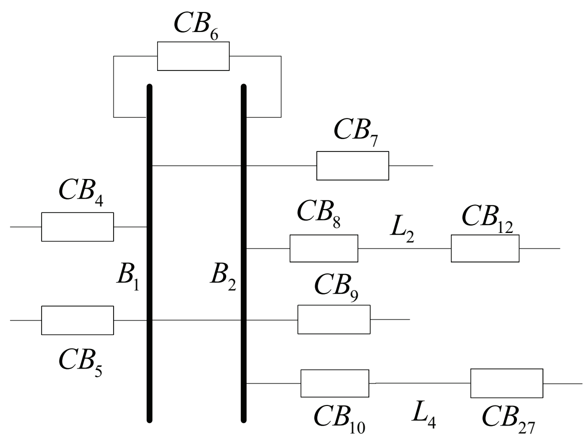

Fig. 7. Passive network.

2. According to SCADA data, the real status vector of CBs is $C = [c_1, c_2, c_3, c_4, c_5, c_6, c_7, c_8, c_9] = [1, 1, 0, 1, 0, 1, 0, 1, 1]$, where $c_1 \sim c_9$ represent CB_4, CB_5, CB_7, CB_9, CB_{12}, respectively. The real status vector of protective relays is $R = [r_1, r_2, r_3, r_4, r_5, r_6, r_7, r_8, r_9, r_{10}, r_{11}, r_{12}, r_{13}, r_{14}] = [1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1]$, where $r_1 \sim r_{14}$ represent B_{1m}, B_{2m}, L_{2Sm}, L_{2Rm}, L_{4Sm}, L_{4Rm}, L_{2Sp}, L_{2Rp}, L_{4Sp}, L_{4Rp}, L_{2Ss}, L_{2Rs}, L_{4Ss}, L_{4Rs}, respectively.

3. Compute expected status of protective relays and CBs. According to the operational rules of main and backup protections described in Section 2, we obtain the computational formulas of expected values of protective relays (r_k^*, $1 \leq k \leq 14$) and CBs ($c_j^*(S, R)$, $1 \leq j \leq 9$) and are shown in Table 4.

4. According to the real status vector C of CBs, the real status vector R of protective relays and computational formulas in Table 4, we get that $E(S) = \sum_{j=1}^{9} \left|c_j - c_j^*(S, R)\right| + \sum_{k=1}^{14} |r_k - r_k^*(S)| = (1-s_1)+s_2+s_3+s_3+s_4+s_4+s_3+s_3+s_4+s_4+0+(1+s_2)+0+(1+s_2)+(1-s_1)+(1-s_1)+max\langle\{s_1r_1, s_2r_2\}+(1-s_1)+0+(1-s_1)+0+s_2(1-c_5)+s_1(1-c_7) = 7 - 3s_1 + 4s_2 + 4s_3 + 4s_4$.

5. Perform *OSNPS fault section estimation algorithm* in *Section 3* to get the 0-1 vector S. If $s_i = 1$, then ith section has a fault; otherwise, the ith section is not faulty.

5. Conclusions

In this study, an optimization spiking neural P system (OSNPS) is applied to fault section estimation of power systems. When status information of protection devices (protective relays and CBs) are obtained from the SCADA system, OSNPS can automatically get the minimal value of the objective function of the FSE problem and accordingly determine fault sections. Three typical case studies show that OSNPS is effective in fault section estimation of power systems. On the one hand, this study provides an alternative method for solving the fault section estimation problem in power systems. On the other hand, this study advances the work in [18] forward and is of great significance in extending the application of P systems and variant SN P systems.

This work focuses on the effectiveness of OSNPS in fault section estimation of power systems. In the future, we will pay attention to explore superiority of OSNPS in fault diagnosis of power systems and its availability in large-scale power grid and complex power systems.

Acknowledgments. The work of T. Wang, S. Zeng and G. Zhang is supported by the National Natural Science Foundation of China (61170016, 61373047). The work of J. Wang is supported by the National Natural Science Foundation of China (61472328). The work of M.J. Pérez-Jiménez is supported by Project TIN2012-37434 of the Ministerio de Economía y Competitividad of Spain.

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