Fuzzy Petri-net Approach to Fault Diagnosis in Power Systems Using the Time Sequence Information of Protection System

Myong-Gyun Roh, and Sang-Eun Hong

Department of Information Technology Engineering
College of Engineering, Soonchunhyang University, Asan 336-745, Korea
(Tel : +82-41-530-1367; E-mail: myongno@orgio.net, sehong@sch.ac.kr)

Abstract: In this paper we proposed backward fuzzy Petri-net to diagnoses faults in power systems by using the time sequence information of protection system. As the complexity of power systems increases, especially in the case of multiple faults or incorrect operation of protective devices, fault diagnosis requires new and systematic methods to the reasoning process, which improves both its accuracy and its efficiency. The fuzzy Petri-net models of protection system are composed of the operating process of protective devices and the fault diagnosis process. Fault diagnosis model, which makes use of the nature of fuzzy Petri-net, is developed to overcome the drawbacks of methods that depend on operator knowledge. The proposed method can reduce processing time and increase accuracy when compared with the traditional methods. And also this method covers online processing of real-time data from SCADA (Supervisory Control and Data Acquisition)

Keywords: Fuzzy Petri-nets(FPN), fault diagnosis, protection systems, modeling, power systems

1. INTRODUCTION

As the complexity of power systems increases, especially in the case of multiple faults or incorrect operation of protective devices, fault diagnosis requires new and systematic methods to the reasoning process, which improves both its accuracy and its efficiency.

To reduce outage time and to enhance service reliability, it is essential for operators to find the fault location in power system. However, an increasing number of system variables and alarms can now be monitored and processed. Few operators now handle system control. After the fault occurrence, operators would have to respond to an avalanche of alarm messages and the fault diagnosis can be very difficult.

We consider fault protection system as discrete event system. Even though power systems are continuous-time systems from a macro point of view, some operating procedures, such as system change from one state to another state, relay or circuit breaker operation, can be viewed as a set of discrete event. Therefore, the systems consisting of those procedures can consider as discrete event systems, such as protection system and switching sequence operation, from micro operating point of view. [1]

When fault occurs, the automatic fault diagnosis system suggests the possible way to remove fault and assists an operator to protect the systems with the best way in that situation. Fault diagnosis is also to identify fault location in power system by using the time sequence information on operation of relay and circuit breakers, which is available from SCADA systems. [2]

Many methods have been adopted to solve this problem. Among these, the logic based method, the expert system approach, and the artificial neural network were researched earlier. [3][4][5]

This paper describes a new method of the modeling of protection system and fault diagnosis in power systems using fuzzy Petri-net. The fuzzy Petri-net models of protection system are composed of the operating process of protective devices and the fault diagnosis process. Fault diagnosis model, which makes use of the nature of fuzzy Petri net, is developed to overcome the drawbacks of methods that depend on operator knowledge. The proposed method can reduce processing time and increase accuracy when compared with the traditional methods. And also this method covers online processing of real-time data from SCADA (Supervisory Control and Data Acquisition).

2. FUZZY PETRI-NET (FPN)

2.1 Petri-net

A Petri-net is a directed graph consisting of two types of nodes, places and transitions. The places are always followed by transitions, and vice versa. The places that signify activities represent by circles. The transitions which imply events are represented by bar. The state of Petri-net (its current marking) is denoted by the distribution of tokens in the places. Each token represents an instance of entity and the place where it is located is its current state. A place containing n tokens describes the fact that n instances of the same class of entity are in the same state. A Petri-net structure can be defined as a 5-tuple [6]:

$$PN = (P, T, I, O, M_0)$$

where

$P = \{p_1, p_2, \cdots, p_m\}$ is a finite set of places,
$T = \{t_1, t_2, \cdots, t_n\}$ is a finite set of transitions,
I: P ?   T: input function,
O: T ?   P: output function,
M_0: initial marking,

2.2 Firing rule of Petri-net

A firing results in removing one token from each of its input places and adding one token to each of its output places. A transition may fire if it is enabled. A transition is enabled if each of its input places has many token in it as arcs from the place to the transition: P? T. A transition fires by removing its entire output places one token for each arc from the transition to the place: T? P.

2.3 Linear algebra of Petri-net

In modeling of discrete event systems, transition firing is represented system operation. Place is the condition of system. Change of marking can be obtained from the state transition matrix. [7][8]

Marking vector M(k) is defined in time k as below,

$$M(k) = [p_1(k), p_2(k), \cdots, p_n(k)]^T \qquad (1)$$

where

$p_j(k)$ is marking state of p_j in time k (j=1,2,…,n).

Control vector U(k) is defined in time k as below.

$$U(k) = [t_1(k), t_2(k), \cdots, t_m(k)]^T \qquad (2)$$

where

$t_i(k)$ is fireable (1) or not (0) in time k (i=1,2,…,m)

In any marking state, after firing of some transition, is represented for the next equation.

$$M(k+1) = M(k) + [B^{-} - B^{+}] \cdot U(k) \qquad (3)$$

where

M(K+1) : Marking vector in time k+1, after U(k) fired in time k.

B^+: Incidence matrix, place to transition

B^-: Incidence matrix, transition to place

$B = B^+ - B^-$: incidence matrix

2.4 Fuzzy Petri-net (FPN)

The concept of fuzzy Petri-net is derived from Petri-nets. A fuzzy Petri-net structure can be defined a 7-tuple [8]:

FPN = (P, T, D, I, O, CF, M)

where

$P = \{p_1, p_2, \cdots, p_m\}$ is a finite set of places,
$T = \{t_1, t_2, \cdots, t_n\}$ is a finite set of transitions,
$D = \{d_1, d_2, \cdots, d_n\}$ is a finite set of proposition
d_i: proposition of place p_i
$I: P \to T$: Input function,
$O: T \to P$: Output function,
CF: $[cf_1, cf_2, \cdots, cf_m]^T$ is vector for certainty factor
cf_i: certainty factor of transition t_i
$cf_i \in [0, 1]$,
M: $[m_1, m_2, \cdots, m_3]^T$ is token vector
m_i: Value of token in the place p_i
$m_i \in [0, 1]$,
The t_i can be fired when $p_j \in I(t_i)$ and $n_j > \lambda$, λ is threshold value.

2.5 Fuzzy Reasoning using FPN

We can use not only a fuzzy Petri-net to represent the fuzzy production rules (FRR) of a rule-based system but also fuzzy reasoning algorithm based on the fuzzy Petri-net model (FPN) [8][9][10]. In this paper, we could be solved the uncertainty problem by applying fuzzy reasoning algorithm and the two types of fuzzy production rule as following:

- Type 2: IF d_j THEN d_{k1} and d_{k2} and … and d_{kn} (CF=μ_i)
  FPN Model of type 2 is represented Fig. 1.

- Type 3: IF d_{j1} or d_{j2} or … d_{jn} THEN d_k (CF=μ_i)
  FPN Model of type 3 is represented Fig. 1.

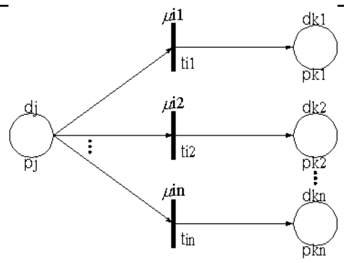


Fig. 1. FPN model of FPR type 2.

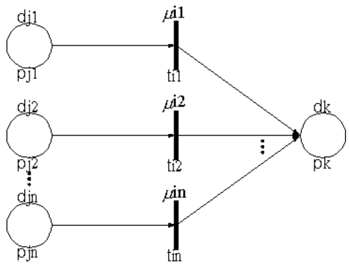


Fig. 2. FPN model of FPR type 3.

2.6 State transition of FPN

According to [11], if the transitions remain fired at each step, then the vector M satisfies the following equation of state transition.

$$M(t+1) = P \cdot [\overline{(Q \cdot \overline{M(t)})} \circledcirc CF] \qquad (4)$$

where

$\cdot$: Fuzzy multiplication of m×n and n×1 matrices
$\circledcirc$: Fuzzy AND (Minimum of inputs) operator
P: Incidence matrix, from transition to place
Q: Incidence matrix, from place to transition
$M(t) = [m_1(t), m_2(t), \ldots, m_n(t)]^T$
n: number of places

3. MODELING

In this section, we describe a modeling strategy and fault diagnosis method for protection scheme of simple power system. [12][13]

3.1 Operating process of protective device

Since the fault occurrence and clearance process in power systems can be regarded like as discrete event system, Petri-net can model series of that operation. In the Petri-net model, the places denote the state of relay, circuit breaker, and bus and line fault, the transitions are formed by the operation of relay and circuit breaker.

Location of the token in each place is represented available state of protective relay, operated state of circuit breaker, and fault state on transmission line and bus bar.

In general, protection systems are composed of main protective relay and some backup protective relays. Backup protective relays consist of primary and secondary protective relay. The operating process of protective devices (relay and circuit breaker) has some operating logic. For instance, when a fault occurs, main protective relays are operated. If main protective relays are failed operation, then backup protective relays operate to clear the fault.

3.2 Protection system modeling using FPN

Sample system in Fig. 3 is examined to this paper. This system is composed of 7 sections, 19 protective relays and 6 circuit breakers.

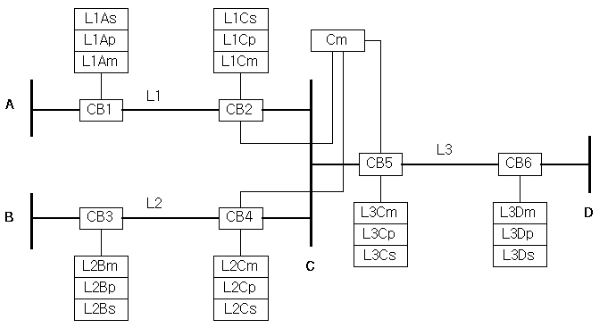


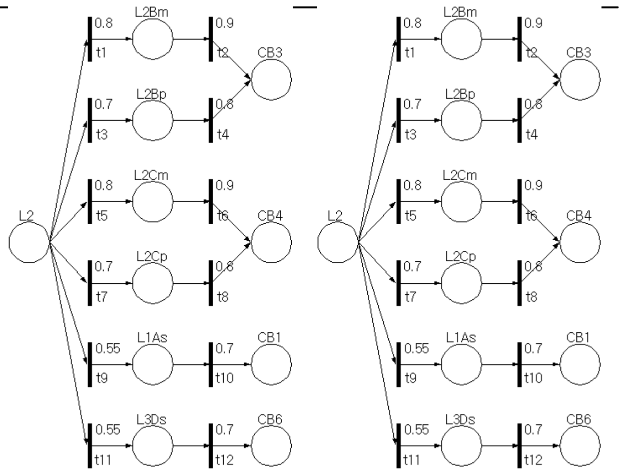
Fig. 3. Sample system.

Table 1. Operating logic of protective relays (bus A).

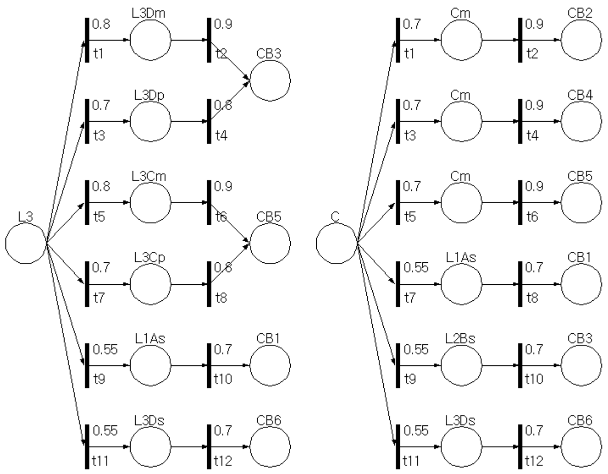
Protective relay	Operating logic
Am	Fault occurred on A; Normal operation: Am Trip operation: CB1.
L1Am	Fault occurred on L1; Normal operation: L1Am Trip operation: CB1.
L1Ap	Fault occurred on L1, Normal operation: Failed Non-operation: L1Am; Backup operation: L1Ap Trip operation: CB1.
L1As	Fault occurred on C, Normal operation: Failed Non-operation: CB2; Fault occurred on L2, Normal operation: Failed Non-operation: CB4; Fault occurred on L3, Normal operation: Failed Non-operation: CB5; Backup operation: L1As Trip operation: CB1.

When fault occur at C in fig. 3, Cm should operate to trip CB2, CB4, and CB5. If CB2 do not operate, then backup protective relay L1As should operate to trip circuit breaker CB1. In case of non-operation circuit breaker CB4 and CB5, each of backup protective relays removes fault sections automatically. When a fault has occurred at line L1, main protective relays L1Am and L2Cm should actuate to trip CB1 and CB2. If CB2 did not trip, then L1Cp should operate to trip CB2. And also if normal operation failed, then L2Bs and L3Ds should operate to trip CB3 and CB 6. Table 1 is shown operating logic of protective relays.

Fig. 4 shows FPN model of Fig 3. CF is statistical value for abnormal operation of protective devices. In case of node, primary protective relay's CF value is 0.8, secondary protective relay's CF value is 0.7, and CF value of protective



(a) FPN model of node L_1 (b) FPN model of node L_2



(c) FPN model of node L_3 (d) FPN model of node C

Fig. 4. FPN models of sample system.

relay to zone-2 is 0.55. In case of main node, connected node is increased then uncertainty is more than more. In this reason smaller CF value is assigned.

Fig 4 is modeled from fault to operating of circuit break. We need not state of circuit break. In other words, we need from circuit breaker state to get fault location information.

3.3 Backward FPN

When faults occur in power system, the protective relays corresponding to the faulty sections should actuate to take the faulty sections out of operation. Using the real time information of circuit breakers, we can develop an efficient method to diagnoses the fault sections. However, because the time sequence information has the forward characteristic, we need to have reverse concept.

In this paper, we propose backward FPN model to fault diagnosis. It makes use of the same FPN model with the directions of all the arrows reversed.

4. CASE STUDY

Case study on the sample system as shown in fig. 3 is performed to demonstrate performance of the proposed backward FPN model. Table 2 is listed the time sequence information.

Table 2. the time sequence information.

step	Operating logic
First	Fault occurred on C, Normal operation: Cm Trip operation: CB5, Non-operation: CB2 and CB4; Backup operation: L1As and L2Bs Trip operation: CB1 and CB3.
Second	After fault section removed, Abnormal operation: L3Ds Trip operation: CB6

4.1 Case of L1, L2 and L3

Several places and transitions are removed in fig. 5, fig. 6, and fig. 7. The fault operation procedures on L1, L2 and L3 are similar with the equations as following:

$$\mathbf{P} = \begin{array}{c|cccc} & \multicolumn{4}{c}{\text{From Transitions}} \\ \text{To Place} & t9 & t10 & t11 & t12 \\ \hline L1 & 1 & 0 & 1 & 0 \\ L2Bs & 0 & 1 & 0 & 0 \\ CB3 & 0 & 0 & 0 & 0 \\ L3Ds & 0 & 0 & 0 & 1 \\ CB6 & 0 & 0 & 0 & 0 \end{array}$$

$$\mathbf{Q} = \begin{array}{c|ccccc} & \multicolumn{5}{c}{\text{From Places}} \\ \text{To Trans.} & L1 & L2Bs & CB3 & L3Ds & CB6 \\ \hline t9 & 0 & 1 & 0 & 0 & 0 \\ t10 & 0 & 0 & 1 & 0 & 0 \\ t11 & 0 & 0 & 0 & 1 & 0 \\ t12 & 0 & 0 & 0 & 0 & 1 \end{array}$$

$$\boldsymbol{M}(0) = [0\ 0\ 1\ 0\ 1]^T$$

$$\boldsymbol{CF} = [0.55\ \ 0.3\ \ 0.55\ \ 0.3]^T$$

$$\boldsymbol{M}(1) = P \cdot [(Q \circ M^c(0))^c \circledcirc CF] = [0\ 0.3\ 0\ 0.3\ 0]^T$$

$$\boldsymbol{M}(2) = P \cdot [(Q \circ M^c(1))^c \circledcirc CF] = [0.165\ 0\ 0\ 0\ 0]^T$$

Backward FPN models for searching fault section of each case are shown in Figs. 5 – 7.

4.2 Case of C

Fig. 8 shows backward FPN model for marking state of main node C. The fault operation procedures on C are the equations as following:

$$\boldsymbol{M}(0) = [0\ 0\ 0\ 0\ 0\ 0\ 1\ 0\ 1\ 0\ 1\ 0\ 1]^T$$

$$\boldsymbol{CF} = [0.7\ \ 0.1\ \ 0.7\ \ 0.1\ \ 0.7\ \ 0.1\ \ 0.55\ \ 0.3\ \ 0.55\ \ 0.3\ \ 0.55\ \ 0.3]^T$$

$$\boldsymbol{M}(1) = P \cdot [(Q \circ N^c(0))^c \circledcirc CF]$$

$$= [0\ 0\ 0\ 0\ 0\ 0.1\ 0\ 0.3\ 0\ 0.3\ 0\ 0.3\ 0]^T$$

$$\boldsymbol{M}(2) = P \cdot [(Q \circ N^c(1))^c \circledcirc CF] = [0.07\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0]^T$$

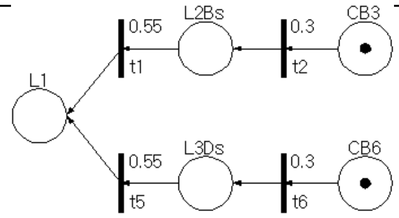


Fig. 5. Marking state of node L1.

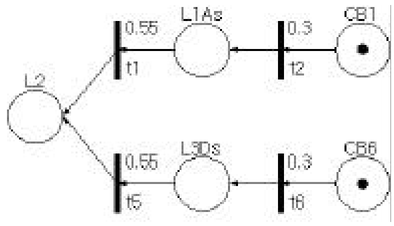


Fig. 6. Marking state of node L2.

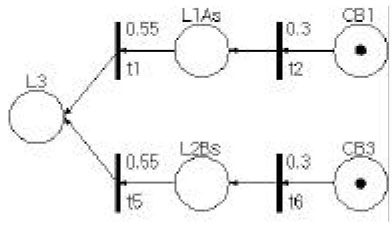


Fig. 7. Marking state of node L3.

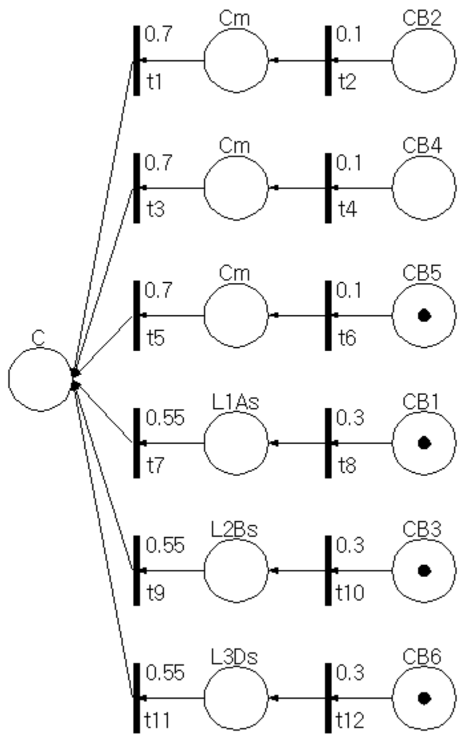


Fig. 8. Marking state of node C.

4.3 Result of fault diagnosis

Result of fault section C is 0.07 in Table 3. It has the smallest value against other case (L1, L2 and L3). From this result, we can estimate the fault section having the high possibility of occurrence.

Table 3. Result of fault diagnosis.

Fault section	Results	Priority
C	0.07	1
L1	0.165	2
L2	0.165	2
L3	0.165	2

5. CONCLUSION

In this paper, we proposed strategy of diagnosis for detecting the fault location in power system. At First, we focused on the fault procedure models of power system using fuzzy Petri-net. And then, we constructed the backward fuzzy Petri-net model for the fault diagnosis by using the time sequence information on protection system.

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