

# Safety Analysis of Level Crossing Surveillance Systems Using Fuzzy Petri Nets

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## Abstract

*A backward safety analysis model that can deal with dangerous status by virtue of fuzzy theory is proposed in this paper. Fuzzy Petri Nets (FPN) is developed and applied to the safety analysis for three types of level crossing surveillance systems of Taiwan Railway Administration. The numerical results of proposed FPN models are fairly plausible.*

## 1. Introduction

Complex component-based systems used in mission- or safety-critical domains, including defense applications, air traffic control, railway signaling and medical applications play an important role in our modern society. One important task in the development of these systems is the construction of safe cases and risk assessment models that are used to determine quantitative measures for failure or hazard probabilities. These safety analysis models should be intuitive, compositional and have the expressive power to model both software and hardware behavior [1]. In industrial projects, currently event-based models such as Fault Trees or state-based models such as Markov chains are used. Each of these models has its limitations [2]. State Event Fault Trees (SEFTs) are a hierarchical and visual model that integrates elements from stochastic state-based models (Markov-chains) with Fault Trees [3]. A model that combines elements from Fault Trees and Markov Models was proposed to improve expressive power of safety cases [4].

Recently Petri nets have been used to model and analyze for such complex component-based systems regarding properties as safety and failure-tolerance [5, 6]. Many fairly good results of real case studies proved the advantages of Petri nets since hardware, software, and human behavior can be modeled using the same model. However, complex component-based systems themselves are required to handle fuzzy information for safety critical issues. It is strongly recommended

that fuzziness must be taken into account for safety analysis. Combining with Petri net and knowledge representation, a Fuzzy Petri Nets (FPN) can be used to depict fuzzy generating rules that can be taken as rules of fuzzy relationships between two propositions.

Using the hazardous states and fuzzy information that have been identified in the preliminary stage, it may be possible to analyze backward to the system, that is, hardware, software, and human, using FPN and thus to derive safety requirements. In this paper, we propose a safety analysis method using a FPN model which can handle fuzzy information. The effectiveness of this method is demonstrated with a case of level crossing surveillance systems that are already in operation or will be installed in near future by Taiwan Railway Administration (TRA).

The structure of this paper is organized as follows. In section 2, we describe fundamental principles of FPN. Section 3 illustrates the safety models of three scenarios of level crossing surveillance systems, and numerical tests are conducted to calculate fuzzy numbers to validate the proposed approach. Finally, the conclusions are drawn in section 4.

## 2. Fundamental Principles

FPN expanded from a Petri net is a bidirectional graph that has place and transition nodes like the Petri net. However, in FPN a token incorporated with a place is associated with a real value between 0 and 1; a transition is associated with a certain factor (CF) between 0 and 1. At the same time enabling and firing rules of a transition are also updated. There are nine elements in the structural definition of FPN [7]. The definition is follows:

$$FPN = (P, T, F, I, O, D, \mu, \alpha, U) \quad (1)$$

where,

$P = \{p_1, p_2, \dots, p_n\}$  is a finite set of places; corresponding to the propositions of fuzzy production rules;

$T = \{t_1, t_2, \dots, t_m\}$  is a finite set of transitions,  $P \cap T = \emptyset$ ; corresponding to the execution of fuzzy production

rules;

$F$  is a set of directional arcs,  $F \subseteq (P \times T) \cup (T \times P)$ ;

$I$ : is the input incidence matrix and  $I = \{\delta_{ij}\}$ , where  $\delta_{ij}$  is a logical value,  $\delta_{ij} \in [0,1]$ ,  $\delta_{ij} = 1$  when  $P_i$  is the input of  $T_j$ , otherwise,  $\delta_{ij} = 0$ ,  $i=1,2,\dots,n, j=1,2,\dots,m$ ;

$O$ : is the output incidence matrix and  $O = \{\gamma_{ij}\}$ , where  $\gamma_{ij}$  is a logical value,  $\gamma_{ij} \in [0,1]$ ,  $\gamma_{ij} = 1$  when  $P_i$  is the output of  $T_j$ , otherwise  $\gamma_{ij} = 0$ ,  $i=1,2,\dots,n, j=1,2,\dots,m$ ;

$D = \{d_1, d_2, \dots, d_n\}$  is a finite set of propositions of fuzzy production rules.  $|P| = |D|$ ;  $| \cdot |$  denotes the number of its elements;

$\mu: T \rightarrow [0,1]$  is the function which assigns a threshold  $\mu_i$  between 0 and 1 to transition  $t_i$ ;

$\alpha: P \rightarrow [0,1]$  is the function which assigns the degree of truth between 0 and 1 to each place;

$U = U\{u_1, u_2, \dots, u_m\}$ , where  $u_i$  denotes the certainty factor (CF) of  $R_i$ , which indicates the reliability of the rule  $R_i$ , and  $u_m \in [0,1]$ .

Knowledge rules of FPN are summarized as follows:

R1: IF  $d_i$  THEN  $d_j \Rightarrow (CF = u_i) \Rightarrow d_i \rightarrow d_j$

R2: IF  $d_i$  AND  $d_j$  THEN  $d_k \Rightarrow (CF = u_i) \Rightarrow d_i \cap d_j \rightarrow d_k$

R3: IF  $d_i$  OR  $d_j$  THEN  $d_k \Rightarrow (CF = u_i) \Rightarrow d_i \cup d_j \rightarrow d_k$

In these rules,  $d_i$  and  $d_j$  represent precondition set,  $d_k$  represents an action or conclusion.  $u_i \in [0,1]$  is a CF of a rule.

During fuzzy inferring and, we should establish three sets ( $RS, IRS, AP$ ) for each place. For a specific place  $p_i$ :

$RS(p_i)$ : a reachable place set of  $p_i$ , no matter how many transitions are fired.

$IRS(p_i)$ : a place set that  $p_i$  can reach through one transition.

$AP(p_i)$ : all the places that through one transition can reach the place that  $p_i$  can reach through one transaction.

In order to enhance inferring efficiency, backward inference mechanism shown in Fig. 1 is used.

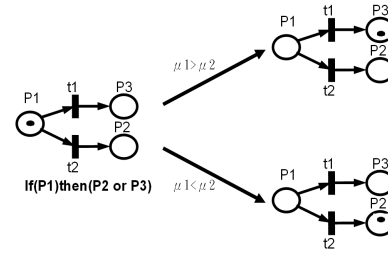


Figure 1. Backward fuzzy inference mechanism

### 3. FPN Models of Level Crossing Surveillance Systems

The existing level crossing surveillance system of TRA is based on infrared detection technology. It is now in progress that a video image processing-based surveillance system will be installed at several level crossings. TRA has, therefore, three types of level crossing surveillance systems in the future, i.e. the infrared, the video image processing and both of them (hybrid one). Three Petri nets models are hence constructed for these level crossing surveillance systems. An example of Petri nets model of the hybrid system combining the infrared and the video image processing technologies is shown in Fig. 2. The states of place and transition for this hybrid system can be summarized in Table 1.

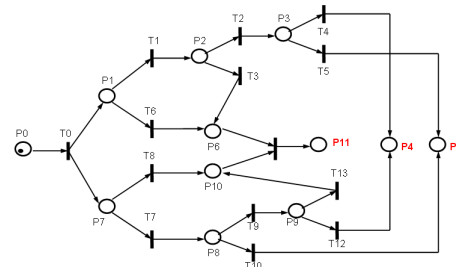
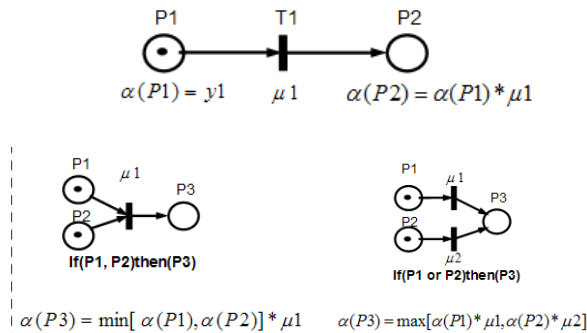


Figure 2. Fuzzy petri nets of the hybrid system

Table 1. States of place and transition of the hybrid system

State of place	Description	State of transition	Description
$P_0$	Receive radio commands	$T_0$	Transmit starting commands
$P_1$	Start video image surveillance	$T_1$	System is normal
$P_2$	Transmit video images	$T_2$	Video images are recognizable
$P_3$	Receive messages from the train	$T_3$	Video images are not recognizable
$P_4$	Train Stops	$T_4$	Train can not pass
$P_5$	Train passes	$T_5$	Train can pass
$P_6$	Video image surveillance fails	$T_6$	System is abnormal
$P_7$	Start infrared surveillance	$T_7$	System is abnormal
$P_8$	Send infrared signals	$T_8$	System is normal
$P_9$	Transmit train stop signals	$T_9$	Incident occurs
$P_{10}$	Infrared surveillance fails	$T_{10}$	No incident
$P_{11}$	Dangerous status	$T_{11}$	Protection system fails
		$T_{12}$	Signals are receivable
		$T_{13}$	Signals are not receivable



The fuzzy analysis of the hybrid system which is the standard type 3A of TRA's level crossing surveillance system can be performed by defining fuzzy functions and fuzzy rules.

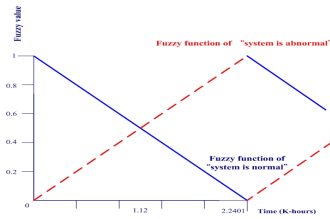
### 3.1. Fuzzy functions

The relative situations of Petri nets conflicts in this paper are: "system is normal or abnormal", "video images are recognizable or not recognizable", "incident occurs or not occur", "signals are received or not received" and "train can pass or not pass". The paired fuzzy functions are defined with common indexes shown in table 2.

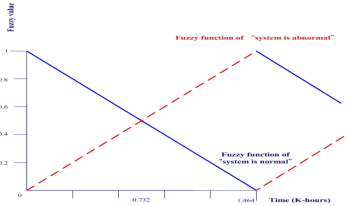
**Table 2. Fuzzy functions and indexes**

Function	Index
System is normal or abnormal	Time
Video images are recognizable or not recognizable	Transmitting intervals of video images
Incident occurs or not occur	Seconds of infrared interrupts
Signals are receivable or not receivable	Ratio of signal noise
Train can pass or not pass	Distance from level crossing gate

The upper limit values of fuzzy index for video image processing surveillance system and infrared surveillance system are set as 2.2401 K-hours and 1.464 K-hours, respectively (shown in Fig. 3 and Fig.4).

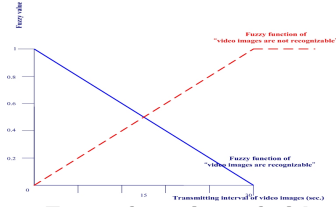


**Figure 3. Fuzzy function of video image system**

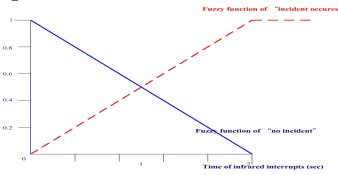


**Figure 4. Fuzzy function of infrared system**

The warning time of a level crossing device till the train arrives is at least 30 seconds based on TRA's operation rules. The upper limit value of fuzzy index for video recognition is hence set as 30 seconds (shown in Fig. 5). As to the time to detect incident whether occurs or not, it needs at least 2 seconds for infrared surveillance system to identify. The upper limit value of fuzzy index for infrared interrupts is set as 2 seconds (shown in Fig. 6).

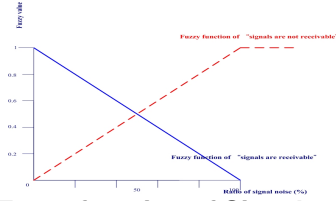


**Figure 5. Fuzzy function of video image recognition**

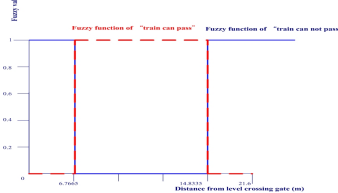


**Figure 6. Fuzzy function of incident occurring**

The upper limit value of fuzzy index for signal receiving is represented by ratio of signal noise in percentage (shown in Fig. 7). When train driver receives signals to stop the train, the distance from level crossing gate for car approaching is set as 21.6 meters according to TRA's 3A type level crossing manual (shown in Fig. 8).



**Figure 7. Fuzzy function of Signal receiving**



**Figure 8. Fuzzy function of train passing**

### 3.2. Fuzzy rules

The fuzzy rules for Petri nets model of Fig.2 are summarized in Table 3.

**Table 3. Fuzzy functions and indexes**

Rule	Description
R1	if (P <sub>0</sub> ) then (P <sub>1</sub> and P <sub>7</sub> )
R2	if (P <sub>1</sub> ) then (P <sub>2</sub> or P <sub>6</sub> ) ⇒ μ <sub>6</sub> ≥ μ <sub>1</sub> → T <sub>6</sub> , μ <sub>6</sub> < μ <sub>1</sub> → T <sub>1</sub>
R3	if (P <sub>2</sub> ) then (P <sub>3</sub> or P <sub>6</sub> ) ⇒ μ <sub>3</sub> ≥ μ <sub>2</sub> → T <sub>3</sub> , μ <sub>3</sub> < μ <sub>2</sub> → T <sub>2</sub>
R4	if (P <sub>3</sub> ) then (P <sub>4</sub> or P <sub>5</sub> ) ⇒ μ <sub>4</sub> ≥ μ <sub>3</sub> → T <sub>4</sub> , μ <sub>4</sub> < μ <sub>3</sub> → T <sub>5</sub>
R5	if (P <sub>7</sub> ) then (P <sub>8</sub> or P <sub>10</sub> ) ⇒ μ <sub>8</sub> ≥ μ <sub>7</sub> → T <sub>8</sub> , μ <sub>8</sub> < μ <sub>7</sub> → T <sub>7</sub>
R6	if (P <sub>6</sub> ) then (P <sub>9</sub> or P <sub>5</sub> ) ⇒ μ <sub>9</sub> ≥ μ <sub>6</sub> → T <sub>9</sub> , μ <sub>9</sub> < μ <sub>6</sub> → T <sub>10</sub>
R7	if (P <sub>8</sub> and P <sub>3</sub> ) then (P <sub>3</sub> ) ⇒ μ <sub>9</sub> < μ <sub>10</sub> and μ <sub>4</sub> < μ <sub>5</sub> → T <sub>10</sub>
R8	if (P <sub>9</sub> ) then (P <sub>10</sub> or P <sub>4</sub> ) ⇒ μ <sub>13</sub> ≥ μ <sub>12</sub> → T <sub>13</sub> , μ <sub>13</sub> < μ <sub>12</sub> → T <sub>12</sub>
R9	if (P <sub>9</sub> and P <sub>3</sub> ) then (P <sub>4</sub> ) ⇒ μ <sub>13</sub> < μ <sub>12</sub> and μ <sub>4</sub> ≥ μ <sub>5</sub> → T <sub>12</sub>
R10	if (P <sub>6</sub> and P <sub>10</sub> ) then (P <sub>11</sub> )

The rules above are based on single condition, multiple conditions of fuzzy inferences are therefore not necessary to be discussed here.

#### 4. Numerical Tests

Based on fuzzy rules above, the fuzzy values of final states for three FPN models are computed according to various scenarios if the input value  $\alpha(P_0) = 1$ . For instance, the fuzzy values are 0.64287 and 0.54644, respectively when video image surveillance system is normal while infrared surveillance system is abnormal under the condition of 0.8 K-hours. Table 3 shows the input values of fuzzy functions under various scenarios.

**Table 3. Input values of fuzzy functions under various scenarios**

Scenario	Time (K-hours)	Transmitting interval of video images (sec)	Distance from level crossing gate (m)	Time of infrared interrupts (sec)	Ratio of signal noise (%)
A	0.6	14	6	0.5	--
B	0.6	14	10	1.5	45
C	0.6	14	10	0.5	--
D	0.6	14	6	1.5	45
E	0.8	14	6	--	--
F	0.8	14	10	--	--
G	2	--	--	0.5	--
H	2	--	--	1.5	45
I	1.2	--	--	--	--
J	0.6	16	--	1.5	55
K	0.8	16	--	--	--
L	2	--	--	1.5	55

The computed fuzzy values of final states of FPN models for “train can pass”, “train stops” and “dangerous status” under various scenarios are summarized in Table 4.

**Table 4. Numerical results of various scenarios**

Scenario	Video image processing			Infrared			Hybrid system		
	Train can pass	Train stops	Dangerous status	Train can pass	Train stops	Dangerous status	Train can pass	Train stops	Dangerous status
A	0.39045	0	0	0.44262	0	0	0.44262	0	0
B	0	0.39045	0	0	0.24344	0	0	0.39045	0
C	0	0.39045	0	0.44262	0	0	0	0.39045	0
D	0.39045	0	0	0	0.24344	0	0.39045	0	0
E	0.34286	0	0	0	0	0.54644	0.34286	0	0
F	0	0.34286	0	0	0	0.54644	0	0.34286	0
G	0	0	0.89281	0.47541	0	0	0.47541	0	0
H	0	0	0.89281	0	0.26147	0	0	0.26147	0
I	0	0	0.53569	0	0	0.81967	0	0	0.53569
J	0	0	0.39045	0	0	0.24344	0	0	0.24344
K	0	0	0.34286	0	0	0.54644	0	0	0.34286
L	0	0	0.89281	0	0	0.26147	0	0	0.26147

Except scenario A and H the infrared system performs better than the video image surveillance system in “train can pass” and “train stops”, it is found that the final state of video image surveillance system significantly differs from the infrared system under most scenarios. A train driver can simply judge whether to stop the train with the help of video images

which reliability is naturally higher than the infrared system.

#### 5. Conclusions

The dangerous status of the hybrid level crossing surveillance system can be detected under following necessary condition:

$$\text{IF } \{\mu_6 > \mu_1 \text{ OR } \mu_3 > \mu_2\} \text{ AND } \{\mu_8 > \mu_7 \text{ OR } [\mu_9 > \mu_{10} \text{ AND } \mu_{13} > \mu_{12}]\}$$

In addition, the fuzzy values of final states of three FPN models are also computed under various scenarios to identify the safety or risk status of certain level crossing surveillance system by constructing customized fuzzy rules.

However, it is recommended that multiple rules of fuzzy inferences are taken into account and the thresholds of several fuzzy values should be also specified to enhance the reliability of presented FPN models. In the future we'll develop a model based on Fuzzy Colored Petri net (FCPN) which is expected to have more expressive power than other Fuzzy Petri nets.

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