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A Co-operative Fault Detecton System with Multiple Detectors for Smart Factory Based on Fuzzy Petri Net

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***Abstract*—Petri net can accurately simulate the dynamics of the system running process and can reflect the inherent characteristics of the fault for complex system. In a smart factory, different types of fault detector are deployed to detect different faults. However, as a failure occurred in a smart factory with complexity production process, detection systems cannot analyze the type for the fault. As a result, the fault cannot be processed by the suitable detector. To solve the problem, we propose a co-operator fault detection system based on fuzzy Petri net to organize several different fault detectors. The fuzzy Petri net based fault detect system can infer which detector can be used to detect the suitable faults. To improve the detection efficiency, we adopt the load balance among the same type of detectors. We apply the fuzzy Petri net based detection system in a smart factory Experiment results show that the fault detection algorithm can effectively find the suitable detectors for the occurring faults.**

Keywords—smart factory, fuzzy petri net, fault detection, load balance

I. INTRODUCTION

Nowadays, advanced manufacturing technologies and management experience have been adopted widely in smart factories to optimize production development and manufacturing process [1]. An effect method to improve the productive efficiency is the reduction of the defective rate for products by predicting the failure of the equipment condition. The key technology lies in the fault detection that can facility recognitions of the defects and notifies in the production and manufacturing process [2]. However, the faults occurrence in the manufacturing process are significantly complex, which results in a low detection rate. Another problem is that these complex faults are caused by multiple devices and equipment, which cannot be diagnosed by a single detector. How to combine heterogeneous detectors in a system to cooperatively detect different complex faults is a great challenge. To solve the problem, we propose a Petri net based fault detection system.

Petri-based fault detection has captured intensive attentions and imaginations in both academia and industry. Initially, [3] have proposed a fault detection system with hierarchical Petri nets, where different detectors are distributed in different hierarchies. Furthermore, to detect the complex fault in the factories, [4] design a Petri-base fault detection framework, and the detection algorithm for the complex faults are put forth. By taking the advantage of the fault tolerate approach, [5] describe a fault detection approach to detection and diagnose abnormal accidents in the smart factories. Then, combined with other approaches, the Petri-net has been used in different areas to detection the fault occurred in the factories [6-9].

Recent fuzzy Petri is emerging as a cutting-edge technique in fault detection in industries. For example, [10] proposed a fuzzy Petri net to detect and diagnose the fault in the power grid, where applications may take the uncontainable actions and commends. Similarly, [11] propose to improve the performance of the fuzzy Petri-net by adopting neuro networks. According to their experiments, the detection rate is can be improved significantly after adopting the neuro network aided fuzzy Petri net. Moreover, [12] design a iteration inferring algorithm with the fuzzy Petri net to detect the fault, which is occurred with an unknown reason.

In this paper, we propose a cooperatively fault detection system for smart factories based on fuzzy Petri net. This system can improve the detection accuracy for complex faults. According to the fault events, the detection system can migrate the fault detection task to the suitable detectors by the inference rules, which thereby results in a high correct detection rate. The contributions are listed as follows.

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We propose a fault detection model with multi-detector co-operation with the fuzzy Petri net, where fault events can be migrated to suitable fault detectors automatically.

We formulate the inferring scheme aided by the fuzzy Petri Net, the previous experience on faults can be used to detect the faults of the equipment and devices.

We develop a fault detection algorithm with the fuzzy Petri net. Furthermore, we apply the fault detection algorithm in a smart factory to detect practical complex faults.

The rest of this paper is organized as follows. Section II describes the system model. Section III presents the fault detection algorithm. Section IV presents numerical results. Finally, Section IV concludes this paper.

II. SYSTEM MODEL

A. Cooperative Deteion Model

Fig.1 demonstrate a fault detection system in a smart factory, where different fault detectors are deployed in various to monitor the equipment and devices. In this system, each fault detector can only find out one type of faults of devices or equipment. For example, a detector can be used to detect the fault of the motor for a machine, which however cannot be used to detect abnormal accident of chain for the machine. Similarly, a fault detector used to detect error an elevator cannot be used to detect the abnormal accident of a robot. Therefore, we propose to combine heterogeneous detectors to detect different faults in one system. To combine different detectors in one system, we first connect these detectors with a network, where each detector is equipped with a wired or wireless interface.

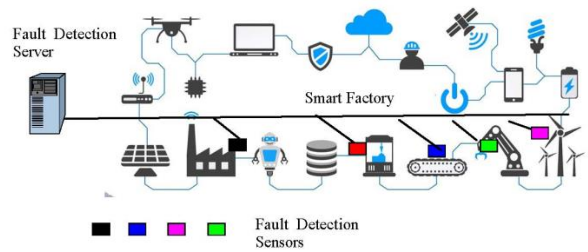

Fig. 1. System model of the co-operative detection system with petri-net

In the cooperative fault detection system, there are many sensors that can monitor the devices and equipment to generate the running data. These data can be transmitted to the detection server equipped with an inference algorithm based on fuzzy Petri net. Once a fault event is found, the data collection node infers what kind of detector to use by inference algorithm and then sends these fault events to the suitable target detector. As a result, the detection task can be migrated to this detector. Furthermore, in this system, we adopt a load balance scheme to alleviate the heavy detection tasks for detectors. For example, we deploy several same type of detectors to detect the running flow faults. If there are to many running flow fault events are found, the detectors with smaller detection tasks will be selected as the migrating target. To support this scheme, the cooperative fault detection system can use the fuzzy Petri net to represent the knowledge of the faults, and then infer an appropriate target detector according to the obtained knowledge.

B. Knowledge-based Fuzzy Petri Net

The fuzzy Petri net (FPN) is an extension of Petri net, which is suitable for knowledge inference and artificial intelligence. In this paper, we define a fuzzy Petri net as follows.

Definition 1: Six tuples (P, T, I, O, τ (t), S0 (p)) are fuzzy Petri net (FPN), where: P={p_1, p_2,..., p_n} is a finite set of nodes in fuzzy proposition, which represents fuzzy propositions={t1, t2,... tm} is a finite set of fuzzy transition nodes, which represents the realization of rules, I is a fuzzy relationship with a label defined on P×T, which represents the connection between the proposition node and transition node. Note that the weight coefficient of each connection satisfies 0<I (p_i, t_j)<1;O is the fuzzy relationship with a label defined on T×P, which represents the connection between the transition node and proposition node. Note that the credibility of each output connection satisfies 0<O (t_j , p_i) <1;

τ(t) is a real function defined on transition set. $\tau(t)\in[0,1]$ represents the trigger threshold of transition node;

S0(p) is a real function defined on the proposition set P and $S_0(p)\in[0,1]$ represents the initial state of the proposition nodes at the beginning [13].

Based on this definition, we can be inferring the fault knowledge with fuzzy Petri net. In addition, the fuzzy derivation rules are corresponded to the T of FPN. A transition in fuzzy Petri net indicate that the corresponding inference rule are triggered.

In this paper, there are three basic forms of fuzzy derivation rules, as shown in Fig 2. These three basic derivations represent three basic logics, which can be combined to express all logics defined in Definition 1. These three forms can be written as the following statement.

R1: if $p_1 \wedge p_2 \wedge p_3 \ldots \wedge p_n$, then p_k (cf$=\mu$)

R2: if p_1 then p_k (cf$=\mu_k$)$\wedge p_{k+1}$(cf$=\mu_{k+1}$)$\ldots \wedge p_{k+m}$(cf$=$ μk+2)

R3: if $p_1 \vee p_2 \vee p_3 \ldots \vee p_n$ then p_k(cf$=\mu$)

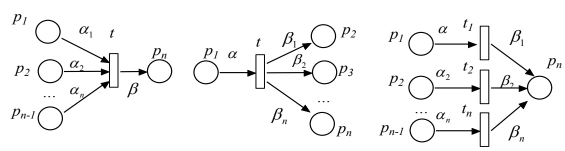

Fig. 2. Knowledge elements in fuzzy petri net

In this rules, $p_i(i=1,\ldots,n)\in[0,1]$ is a proposition, which contains fuzzy variables to describe the behavior or state, $cf\in[0,1]$ is the credibility of the fuzzy rule, which corresponds to αp of FPN, and T is used as the threshold of rule establishment. These rules can be triggered only when the credibility αp of pi is larger than the threshold τ. With the represented knowledge by the derivation rules of fuzzy Petri net, we design the inference algorithm.

III. FAULT DETECTION ALGORITHM

The fuzzy inference algorithm employs the uncertain inference method-MYCIN confidence method [14]. The main idea lies in that the truth value of the combination of fuzzy propositions takes the minimum value of the truth value of each sub formula. Furthermore, the truth value of the disjunction of fuzzy propositions takes the maximum value of the truth value of each sub formula. Then, we introduce $\oplus$ and $\otimes$ in algebra as the maximum and minimum operators, which are given as

$\oplus$: $a \oplus b = c$. If a, b, c are n-dimensional vectors, $c_i = \max\ (a_i,\ b_i)$.

$\otimes$: $a \oplus b = c$. If a is the (n×m)-dimensional vector and b is the m-dimensional vector, $c_i = min\ (a_i,\ b_i)$.

The goal of migration is designed for fault detectors. As the load of these detectors exceeds a certain threshold, the detection tasks cannot be accomplished. In this case, we present the information of detector as the Definition 2 based on fuzzy Petri net with matrix.

Definition 2 The matrix of fuzzy Petri net FPN is as follows

(1) IN $\{\delta_{ij}\}$ is the input matrix, where $\delta_{ij} \in [0,1]$ represents the input relation and weight from p_i to t_j. When pi is the input of t_j, δ_{ij} is equal to the weight coefficient α_{ij} from p_i to t_j input arc. When pi is not the input of t_i, δ_{ij}=0, where *i*=1,2,3, …, *n* and *j*=1, 2, 3, …, *m*.

(2) $\gamma=\{\gamma_{ij}\}$ is the output matrix, where $\gamma_{ij} \in [0,1]$ represents the output relation from T_j to P_i. When P_i is the output of T_j, γ_{ij} is equal to the credibility β_{ij} of P_i inferred by transition T_j. When Pi is not the output of T_j, γ_{ij}=0, where *i*=1,2,3, …, *n* and *j*=1, 2, 3,…, *m*.

(3) $S=[s_1, s_2,\cdots,s_n]T$ is the state vector defined on the fuzzy proposition set P and represents the credibility of each proposition, $s_i \in [0,1]$, *i*=1,2,3,···, *n*. $S0=[s_{10}, s_{20},...,s_{n0}]T$ represents the initial real function credibility of the proposition.

(4)$\tau=[\tau_1, \tau_2,..., \tau_m]$ T is the threshold of the transition, $\tau_j \in [0,1]$, *j*=1,2,3,...*m*.

(5) $L=[l_1, l_2, l_3,..., l_m]$ T is the load of each migration target, which is determined by the migration target detector memory, CPU and the number of packets being detected [14,15].

Suppose that there are nth propositions and mth inference rules in a certain inferring process. Thus, there will be nth libraries and mth transitions in the fuzzy Petri net. Then, the input matrix is given as In×m, output matrix is given as Γn×m. Moreover, we define a transition threshold vector as τ and a state vector as S according to Definition 2. Accordingly, we design the main algorithm.

Algorithm 1: Fault Detection Algorithm (FDA)

Step 1 Calculate the credibility of the input

$$F = IN \times S_0, \tag{1}$$

where $F=[f_1, f_2,…, f_m]$.

Step 2 compare between the credibility fuzzy of input and transition threshold, and the results save as an m-dimensional vector R. When the credibility of equivalent fuzzy input is larger than or equal to the transition threshold, $R_j=f_j$. Otherwise, R_j=0, where *j*=1, 2, *m*.

Step 3 Calculate the credibility of fuzzy output proposition

$$S_1 = \Gamma \times R \tag{2}$$

where S1 represents the credibility of conclusion proposition obtained from the first round of inference. Specially, if a proposition that cannot be inferred directly, the credibility is set as zero.

Step 4 Obtain the load $L=[l_1,l_2,…,l_k]$ of each detector. If the transition target $l_j > \tau$, the detector with the least load can be found out from L for detection.

Step 5 Calculate the credibility of all propositions that can be obtained as

$$S = S \oplus S_1 \tag{3}$$

Step 6 Substitute S0 in (1) with S1 in (3), and iterate repetitively with Step 1-Step 5. If S_K is the conclusion inferred, the credibility of all propositions will be after inference of Step K:

$$S_K = S_{K\text{-}1} \oplus S^K \tag{4}$$

Step 7 When the credibility of propositions is not changed, that is $S_K=S_{K-1}$, then the algorithm exits.

From the inference algorithm, we can judge whether the migration target is overloaded. If the overload is occurred, the migration target will be changed. Therefore, the proposed mechanism can ensure the load balance for fault detectors [16].

IV. Experiments and Result Analysis

To evaluate the proposed algorithm, we implement a Petri net for the fault detection system in a typical smart factory, where a cigarette transportation system is deployed. The failure knowledge is extracted based on the electrical equipment and mechanical machines in the finished product warehouse by analyzing collected data. The structure of the factory is shown as in Fig. 3.

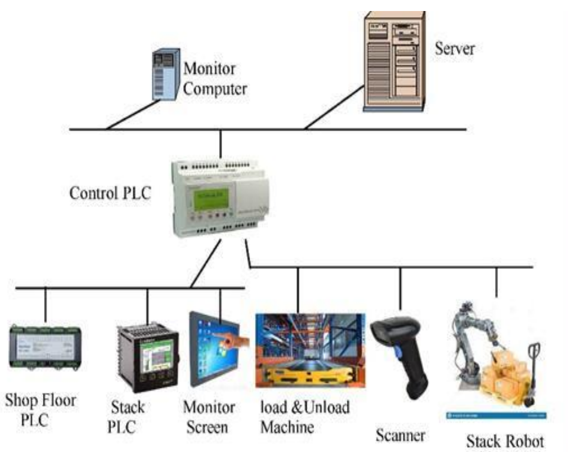

Fig. 3. A cigarette transportation system in factory

We summarize seven fault types in the cigarette factory: mechanical failure detector, load overload detector, running component detector, track failure detector, motor error detector, and chain error detector. The fault data are inputted of the fuzzy inference algorithm. Fault data are collected in the following ways: (1) develop a program to collect fault data from the all machines; (2) collect the fault report from monitoring devices; (3) Collect the error running parameters.

A. Detection Rule

According to the training data and the expert opinions on mechanical devices with FPN, we represent the detection flow, as shown in Fig. 4.

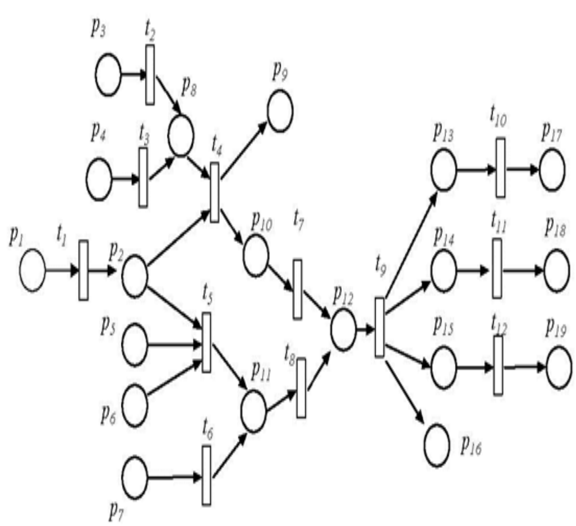

Fig. 4. Fault detection process in a smart factory

First, we employ a flow detector to detects abnormities. The detector will exit immediately as soon as the detection is successful. If an abnormality detected, the algorithm checks whether the road is normal. If it is normal, we migrate to the mechanical detection process to detect mechanical errors. Second, the detect on stack error. If the stack detection is abnormal, then the detection system exit and return a error code to indicate the stack error. Otherwise, the detector checks whether the motor is error. If the motor is not error, the detection will migrate to the gear detectors.

In the proposed detecting model, some detectors are often overwhelmed. In this scenario, we adopt several similar type detectors to cooperatively detect failure for one equipment. Then, we establish the following inference rules.

R1 if p_1 then p_2 (cf=0.97);

R2 if $p_4 \vee p_5$ then p_8;

R3 if $p_2 \wedge p_8$ then p_9 (cf =0.7)$\wedge p_9$ (cf=1);

R4 if p_8 then $p_9 \wedge p_{10}$ (cf=0.76)

R5 if $(p_2 \wedge p_5 \wedge p_6) \vee p_7$ then p_{11} (cf=0.97)

R6 if p_{11} then p_{12}(cf=0.84);

R7 if p_{13} then p_{14}(cf=0.85)$\vee p_{13}$(0.70)$\vee p_{16}$ (cf=0.20)$\vee$ (cf=0.15)$\vee p_{19}$ (cf=0.92);

R8 if p_{13} then p_{17}(cf=0.96);

R9 if p_{15} then p_{18} (cf=0.89);

R10 if p_{16} then p_{19}(cf=0.97).

The processing and fault types of propositions are shown in TABLE I.

B. Experimental Results Analysis

In this paper, we define the truth degree of state as untrue, some true, relatively true, true, and very true, where the fuzzy degree are set as 0.1, 0.3, 0.6, 0.75, 0.95 [17]. We use 400 typical fault recorders to analyze the system state with the above propositional trusted classification rules. We set the transition threshold as τ = (0.78, 0.50, 0.70, 0.9, 0.56, 0.77, 0.54, 0.68, 0.78, 0.67, 0.80 and 0.42). The initial proposition set is {p_1, p_3, p_4, p_5, p6 and p_7}. According to the initial state of system, the truth degree of the propositions in these initial databases can be inferred from the system. The simulation algorithm runs in Windows 2010 with Visual C++. After simulating the above 7 typical faults, we plot the detecting results as Fig. 5.

Fig. 5. shows that when multiple data recorders with fault information enter the detecting system. Then, all detectors cooperatively analyze the recorder to find out faults. With the increase of inputting recorders, the number of correctly detected faults also increases. However, when the data recorders increase to a certain value, the detecting task of the detector increase dramatically. For the motor error and chain error detectors, as the data recorder increases, the correctly mitigate fault numbers increase slowly. The reason is due to the fact that mort and chain error are really occurred. However, the running flow detector is chains linearly with the recorder number, since all data are analyzed by the detector. As a result, we deplorer multiple running flow detectors. Third, we observed that the detection running components and load detector increase gradually due to the increase of data recorders.

TABLE I. FUZZY PROPOSITION TABLE

Proposition	Processing and Detection Results
p^1	The running flow detecting process
p_2	Mechanical failure detector
p_3	Electromagnetic fault detection
p_4	High tempter
p_5	Load overload
p_6	Production overload
p_7	Track deviation
p_8	Environment error
p_9	Main circuit Error
p_{10}	Control circuit error
p_{11}	Running component failure
p_{12}	Production error
p_{13}	Engine mechanism fault
p_{14}	Loading and unloading machine error
p_{15}	Speed Reducer failure
p_{16}	Motor error occurrence
p_{17}	Clutch failure occurrence
p_{18}	Gear error occurrence
p_{19}	Chain error occurrence

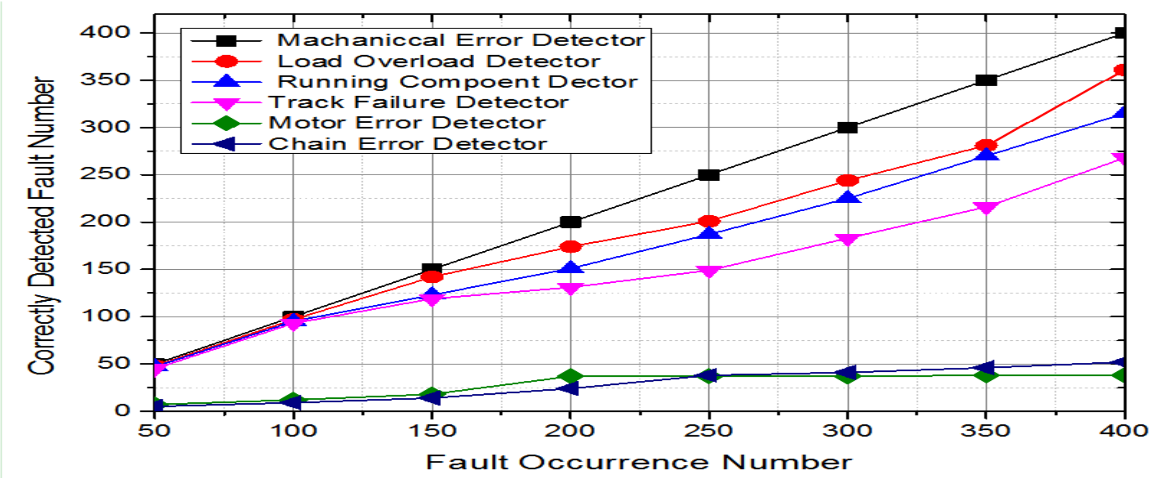

Fig. 5. Detection rate of faults

In this experiment, we select 200 fault recorders that contain 5 different faults. The inferring results are shown as Fig. 6. We observe that with the above inference algorithm 92 of 100 faults can be correctly migrated to the correct detector. The experimental result shows that the cooperative fault detection system based on fuzzy Petri net can integrate multiple detectors into one network. Second, we observe that the algorithm can infer which type of detector to use according to the network features. Third, when a detector detects overload, load can be migrated to similar detectors with the load-balancing algorithm. The parallel capability of Petri net can be used to detect multiple detection loads, improve the throughput capacity of detection and reduce the detection time.

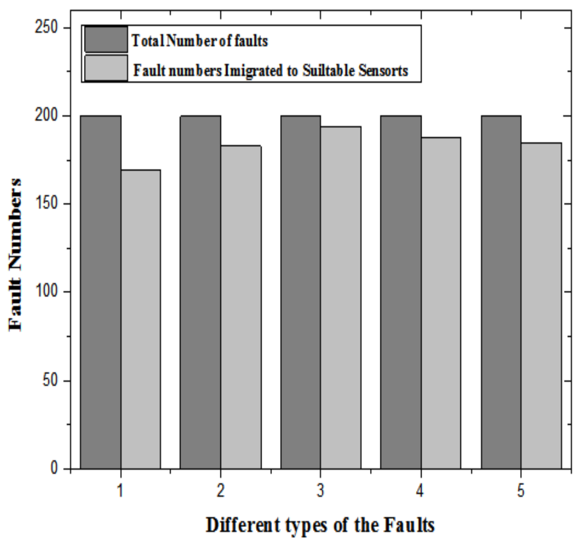

Fig. 6. The numbers of correctly migrating faults

V. Conclusion

In this paper, we propose a cooperative fault detection system, where different fault detector simultaneously detect faults with fuzzy Petri net for smart factories. The cooperative fault detection system is a fault detection system that can detect different kinds of faults. The fuzzy Petri net inference and parallel mechanism can accurately find the detector for the detection load according to their features. By improving the accuracy of fault detection, the detection system can intelligent allocate suitable detector for the occurred faults. Moreover, we use a fuzzy Petri net with matrix model to implement load balance among the same type of detectors.

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