Monitoring Systems Modeling and Analysis Using Fuzzy Petri Nets

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Abstract: In this paper, we propose a unitary tool for modeling and analysis of discrete event systems monitoring. Uncertain knowledge of such tasks asks for specific reasoning and adapted fuzzy logic modeling and analysis methods. In this context, we propose a new fuzzy Petri net called Fuzzy Reasoning Petri Net: the FRPN. The modeling consists in a set of two collaborative FRPN. The first is used for the fault dynamic state of the system by temporal spectrum of the marking. A monitoring fuzzy Petri (MFPN) net represents the fault tree. The second model, RFPN (recovery fuzzy Petri net), corresponds to recovering activities. The two models form a dynamic loop for production system monitoring and recovery. Production system is supposed to be modelized using various types of Petri nets, with the assumption that the primary fault symptoms are known. These symptoms are considered in the monitoring FRPN and evolve in relation with all other derived faults of the system. Synchronizing signals, corresponding to different warning levels and alarms, form the interface between these two tools.

Keywords: Discrete event system, Fuzzy logic, Fuzzy Petri nets, Monitoring, Recovery, Diagnosis, Fault tree.

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1. Fuzzy LOGIC Approach FOR Monitoring and Recovery

The complex analysis of re-configurable discrete event systems requires specific flexible, fast reasoning and modeling methods. The field of the artificial intelligence seems very appropriate for monitoring and renewal applications. In the class of modeling tools, fuzzy Petri nets [4, 6, 7] are very interesting tools for discrete event systems characterized by an imprecise knowledge. J. Cardoso, R.Valette and D. Dubois have published in [3] a very complete overview of the existing fuzzy Petri nets (FPN) approaches.

Chen [4] and Gao, Zhou, & all [8] have some important research contributions in fuzzy reasoning Petri nets. For monitoring tasks modeling, we complete this approach by defining an extension of the FPN able to integrate, by a fuzzy temporal approach, the instant of occurrence of a default or degradation of a discrete event system. The recovery is the consequence of a reasoning based on a fuzzy logical rule basis, modelized by another FPN tool with a similar typology. This FPN recovery model has a double interface, one with the monitoring (detection and diagnosis) system and the second one with the studied (supervised) discrete event system. In theses interfaces, information is transmitted by an emission/reception protocol, using a representation inspired by the synchronized Petri nets [11], adapted to the fuzzy variables transmission.

In the next paragraph, we define the fuzzy Petri net for monitoring. Following, the recovery fuzzy Petri net is introduced. An example of industrial study is presented at the end, for illustrate the interest of the proposed modeling and analysis algorithms.

2. Fuzzy Petri nets for Monitoring

2.1. Fuzzy Monitoring

Fuzzy Petri nets are used for fuzzy reasoning modeling, based on the static logic rules [4, 6, 7] according to their evolution in time. In this sense, we propose a fuzzy Petri net for monitoring (MFPN – monitoring fuzzy Petri net). By a fuzzy temporal approach, this tool permits us to model the dynamic behavior of a monitoring system. The MFPN treats a fuzzy logic rule base obtained from the logic expression of the supervised system fault tree. Inadequate for linear logical reasoning [8], the MFPN doesn't apply to the resources state modeling [2, 3, 12]. MFPN represents the union or the intersection of logical reasoning, while respecting the specific concepts of the fuzzy logic [1, 4, 6, 7]. Analysis possibilities of such a tool offers us refined information of every basic and derived defect, by the transfer of fault signals temporally synchronized. We also show the impact of critical cases and strategies (represented by the critical path in fault tree) to the strategy of the prognosis function.

2.2. Monitoring Fuzzy Petri Nets Definition

In the first part of our study, we treat the problem of a discrete event system monitoring. We suppose that the surveyed system is modelized by a high-level temporal Petri net, able to include the fault symptom detection, using appropriate devices like watching dogs [5].

The monitoring fuzzy Petri net - MFPN is defined as being the n-uplet: MFPN = < **P**, **T**,**D**, I, O, f, F, **?S**, **!R**, α, β, λ > , with:

$P = \{ p_1, p_2, ... p_n \}$ - the finite set of places modeling possible faults, identified at the discrete event system level. Two types of faults characterize this fault set: basic faults and derived faults. The considered faults can be as well transient that persistent;

$T = \{ t_1, t_2, ... t_n \}$ - the finite set of transitions, representing the fault evolution, corresponding to the set of logical fuzzy rules *R*. Every transition is associated to a fuzzy rule;

$D = \{ d_1, d_2, ... d_n \}$ - the finite set of logical propositions that defines the rule basis *R*;

$I : T \rightarrow P$ - the input function of places;

$O: P \rightarrow T$ - the output function of places;

$f: T \rightarrow F$ - the function that associates to the every rule modelized by a transition, a function *F* describing the credibility degree $\mu = F(t)$ of the rule. The instant t corresponds to the detection of a fault symptom in the surveyed discrete event system;

?S $= \{ s_1, s_2, ..., s_l \}$ - the set of fuzzy symptoms (signals) received by the monitoring system from the surveyed discrete event system;

!R $= \{ r_1, r_2, ..., r_l \}$ - the set of fuzzy recovery information (signals) emitted by the monitoring system. These signals will be used by the recovery tool;

α: **P** → [0,1] - the function giving a fuzzy value α_j of credibility for each place p_i corresponding to the logic proposition $d_i \in D$. This parameter represents the possibility of apparition of the corresponding fault;

β : **P** → **D** - the bijective function that associates a logic proposition d_i to each place $p_i \in P$;

λ : **P** → [0,1] - the function that associates an acceptance/permissiveness warning threshold λ_i of the fault corresponding to each $p_i \in P$ of the critical path of the fault tree. These thresholds represent the starting point of all recovery policy.

M_0 - the basic faults places initial marking. Every token of the marking M_0 is associated to the fuzzy number 1 that means the certainty of the basic fault occurrence. By convention, places associated to the basic faults are not represented in the global model of the MFPN.

Each transition of the MFPN represents a fuzzy logic elementary proposition: $d_i \rightarrow d_j$. The transition is associated to a function *F(t)* describing the degree of credibility of the corresponding proposition at the time *t* (firing possibility at time *t*). The function $\mu_i = F(t)$ represents the membership function of the fuzzy variable *t* to the fuzzy set defined by the linguistic variable: "occurrence of the fault d_j" (fig.1). Being variable in time, the value of credibility μ gives to every rule, a *dynamic credibility* character. The interval [0 ΔT] represents the total studied period. A fault is producing if it occurs in the interval $[t_0, t_{max})$ and it is fully produced if its occurrence instant belongs to $[t_{max}, \Delta T]$ (fig.1).

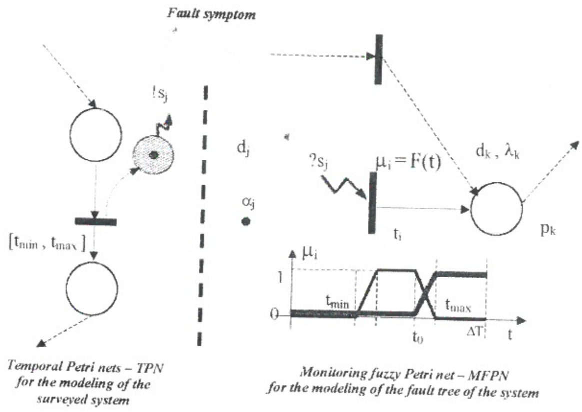

Figure 1: Fault Propagation Modeling Using MFPN.

Every place of the MFPN is related to a (basic or derived) fault of the supervised system. The marking of a place is associated to a fuzzy credibility value α in the interval [0, 1]. For the MFPN represented in the figure 1, the place p_j is associated to the observed fault (new experience) and the place p_k to the derived fault (conclusion). The fuzzy value α_k, associated to the marking of the exit place, will be calculated using the generalized modus ponens [1]. In our approach, we consider the operators: $T(u,v)=\min(u,v)$, $\perp(u,v)=\max(u,v)$ and the generalized modus-ponens operator $\mathbf{T}_{probabilistic}(u, v)= u \cdot v$. The value α_k of credibility of the conclusion will be calculated using the next formula (1) [4, 6, 7]:

$$\alpha_k = \alpha_j \cdot \mu_i \Rightarrow \mu_i = \frac{\alpha_k}{\alpha_j} \qquad (1)$$

We suppose [6] that a transition firing consumes copies of tokens of the places of the M_0. This hypothesis is justified by the respect of the logical reasoning principle: if a hypothesis is true, it always remains true.

Proposition 1 : The degree of truth μ corresponding to a transition associated to proposition

$$\left(D_1^x \wedge D_2^x \wedge \ldots . \wedge D_k^x\right) \rightarrow D^y$$

which receive in a synchronous way the signals $\{?s_1, ?s_2, \ldots, ?s_k,\}$ is :

$$\mu = \frac{\min(\alpha_1 \cdot \mu_1, \alpha_2 \cdot \mu_2, \ldots, \alpha_m \cdot \mu_k)}{\min(\alpha_1, \alpha_2, \ldots, \alpha_k)}$$

if the transition receives temporal synchronized signals for the input positions and

$\mu = 0$, if the transition does not receive any signal $?s_i$.

We specify that signals $\{?s_1, ?s_2, \ldots, ?s_k,\}$ represent instants of elementary implication validation:

$$D_1^x \rightarrow D^y, \quad D_2^x \rightarrow D^y, \quad . \quad . \quad D_k^x \rightarrow D^y$$

Proposition 2 : If a fuzzy implication transition doesn't receive its corresponding fuzzy symptom signal, we consider the degree of truth $\mu = 0$ for the transition representing the elementary logical proposition $D_i^x \rightarrow D^y$.

The synchronization information between the supervised discrete event system model (temporal Petri net – TPN) and the fault propagation corresponding model (monitoring fuzzy Petri net - MFPN) are illustrated in figure 1 using a fuzzy signal representation inspired by the synchronized Petri nets [11].

3. Fuzzy Petri Nets for Recovery

3.1. The recovery problem in monitoring

The recovery action requests a new tool, able to integrate temporal synchronous fuzzy information of the monitoring system, related to a base of fuzzy logic rules. This detailed information can describe the critical faults associated to the critical path of the MFPN model.

We propose thus a second tool called recovery fuzzy Petri net (RFPN), representing a fuzzy expert system. Using the fuzzyfication of the embedded variable (the marking value of the place that receives the signal), the fuzzy signals represent input variables for a mechanism of inference to a base of fuzzy logic rules (fig.2). This base $\boldsymbol{R}$ is designed according to the strategy adopted for an optimal recovery. The so obtained RFPN model represents a variant of a fuzzy controller for discrete event systems. The transitions of the model materialize the generalized modus ponens operator, by the composition of input variables and the base of rules $\boldsymbol{R}$. The outputs of the RFPN are also synchronized fuzzy temporal signals. They are correction controls for the supervised system, either fuzzy recovery signals for the subsystems of the next decision level.

3.2. RFPN definition

The recovery fuzzy Petri net - RFPN is defined as being the n-uplet :

$$RdPFR = \langle \boldsymbol{P}, \boldsymbol{T}, \boldsymbol{x}, y, \boldsymbol{D}, \boldsymbol{X}_k, \boldsymbol{Y}_q, \boldsymbol{R}, ?!\boldsymbol{S}, \boldsymbol{M}_0, \partial, I, O, f, \lambda, \dagger_x, \dagger_y \rangle$$

with:

$\boldsymbol{P} = \boldsymbol{P}^k \cup \boldsymbol{P}^q$ - the finite set $\{p_1, p_2, ...p_{k\times q}\}$ of input $\boldsymbol{P}^k$ and output $\boldsymbol{P}^q$ places;

$\boldsymbol{T} = \{tf_1, tf_2, ...tf_n\}$ - the finite set of transitions specialized in inference/aggregation operations of logic rules and fuzzy variables defuzzyfication;

$\boldsymbol{x} = \{x_1, x_2, ..x_k\}$ - the finite set of markings of $p_i \in P^k$ places;

$y = \{y_1, y_2, ...y_q\}$ - the finite set of output normalized variables, associated to the markings of $p_j \in \mathbf{P^q}$ places;

$\boldsymbol{D} = \boldsymbol{D}^x \bigcup \boldsymbol{D}^y$ - the finite set of the logic variables. D^x, D^y are subsets of variables that are respectively in the antecedence and in the consequence of the base of rules $\boldsymbol{R}$;

$\boldsymbol{R} = \bigcup_{w=1}^{r} \boldsymbol{R}^w$, $\boldsymbol{R}^w : \boldsymbol{D}^x \rightarrow \boldsymbol{D}^y$ - the fuzzy logic rules set. We supposes that the set $\boldsymbol{R}$ of rules can be incomplete from the point of view of the possibilities of exhaustive combination of the logical variables associated to the $\boldsymbol{D}^x$ and respectively $\boldsymbol{D}^y$;

$\boldsymbol{X}^k = \{X_{11}, X_{12}, ...X_{k1}, X_{k2}, ..X_{ki}\}$ - the finite set of membership functions, defined on the universe $[0,1]$ of the variables $\{x_1, x_2, ..x_k\}$ associated to the logic variables of $\boldsymbol{D}^x$. k represents the number of input variables;

$\boldsymbol{Y}^q = \{Y_{11}, Y_{12}, ...Y_{q1}, Y_{q2}, ..Y_{qj}\}$ - the finite set of membership functions, definite on the universe of variable $\{y_1, y_2, ...y_q\}$, partners to the logical variable $\{y_1, y_2, ...y_q\}$ of $\boldsymbol{D}^y$. q is the number of output variables;

$?!\ \boldsymbol{S} = \{r_1, r_2, ...r_{k\times q}\}$ - the set of received/emitted (fuzzy) signals for recovery/control. The signal r_i induces a vector of fuzzy numbers in the input places;

$\boldsymbol{M}_0 : P^k \rightarrow \{v_i = \langle 0, 0, ..0 \rangle\}_{i=1:k}$ - the initial marking of the input places $p_i \in P^k$ representing the corresponding null vectors;

$\partial : P \rightarrow \{v_1, v_2, ...v_{k\times q}\}$ - function that associates a dimension v_i to every input place. For an input place, v_i is the number of membership functions defined on the universe of the variable x_i. For an output places, v_i will be equal to 1;

$I : T_f \rightarrow P$ and $O : T_f \rightarrow P$ - (places) input and output functions;

$f : \boldsymbol{P} \rightarrow \bigcup_{w=1}^{k\times q} F^w$ - function that associates to every place p_i, the membership function v_i corresponding to the fuzzy description F^i of the variable x_i;

$\lambda : \boldsymbol{P}^k \rightarrow [0,1]$ - function that associates to a place $p_i \in P^k$ a threshold value of acceptance/permissiveness warning

λ_i of the corresponding fault, from the point of view of the recovery. The parameter λ_i is associated to places belonging to the critical path of the fault tree;

$\dagger_x : \boldsymbol{X}^k \rightarrow \boldsymbol{D}^x$ - a bijective function that associates a fuzzy set X_{ij} to a logic proposition D_{ij}^x being in the antecedence of a logic implication ;

$\dagger_y : \boldsymbol{Y}^q \rightarrow \boldsymbol{D}^y$ - a bijective function that associates a fuzzy set Y_{ij} to a logic proposition D_{ij}^y being in the consequence of a logic implication.

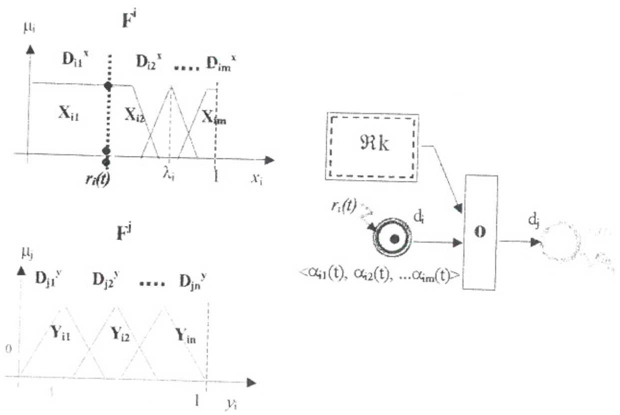

Figure 2: Recovery Modeling Using RFPN.

For the complex systems, the recovery action permits a modular approach (fig.3).

Proposition 3 : If a fuzzy signal represents the input of several modular recovery subsystems, it will be multiplied by a simple transition.

Remark : The RFPN model is open and can have input interface places with elaborated information obtained with other intelligent sensors. The presence of these places permits us to develop, by the different techniques of the artificial intelligence, a distributed monitoring platform.

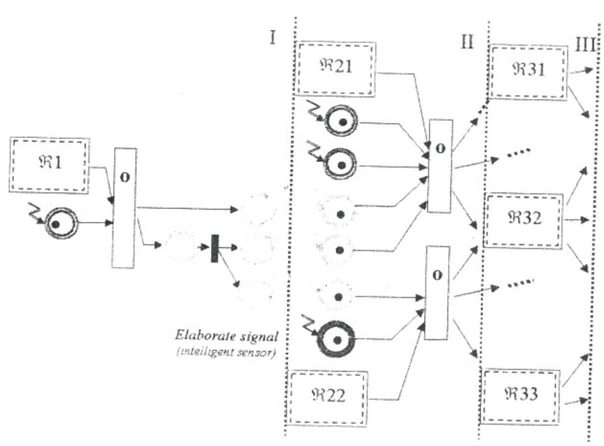

Figure 3: Modular Recovery System.

Each input or output place of the RFPN is associated to a fuzzy description. For the input places, we describe the marking variable of the place, whereas for the output places we describe the normalized control.

For each subsystem modelized by RFPN, we identify a transition specialized in a complex operation of input variables composition. Each base of logic rules $\boldsymbol{R}$ represents the fuzzy implications describing the knowledge base of the expert. Each implication respects the "if-then" model represents the logical dependence of linguistic variable $\{\boldsymbol{D}^x \bigcup \boldsymbol{D}^y\}$ associated to the fuzzy sets $\{\boldsymbol{X}^k, \boldsymbol{Y}^q\}$. The composition of K rules, requires an aggregation mechanism using intersection or means. Two methods of approximate reasoning exist: the AI (the aggregation of rules followed by the inference) method and the IA (the inference of the every rule followed by the aggregation) method, that give almost the same results. We chose the first approach $\mathbf{R} = \bigcap_{k=1}^{K}{}_{T,\Sigma} R^k$, where

$\bigcap_{T,\Sigma}$ represents the operation of aggregation using the T - triangular norm or Σ - mean.

Proposition 3 : In order to obtain the fuzzy variable associated to the rule base **R**, we apply the ZMA approach (Zadeh-Mamdani-Assilian) [1]. In this approach, a fuzzy rule $\mathbf{R^u}$ is generally interpreted like a superposition of simultaneously true logical propositions:

$$R^u \Leftrightarrow \Omega(X_{1u}, \Omega(X_{2u}, \Omega(\ldots, \Omega(X_{k-1,u}, X_{ku})))) \otimes (Y_{1u}) \Rightarrow \mathbf{R} = \mathbf{D}^x (\dagger_x \circ \dagger_y \circ \otimes) \mathbf{D}^y$$

For an arbitrary input variable, modelized by a fuzzy set X', while applying the concept of generalized modus ponens, we obtain a fuzzy exit set Y', that will be obtained by the composition between fuzzy sets **R** and X'.

$$Y' = R \circ X' \qquad Y' = \sup_{x \in X} \mathbf{T}(X', \mathrm{R}),$$

where **T** is the generalized modus ponens operator.

A defuzzyfication operation f^{-d} will be necessary to get the exact value of **Y**. In fact, a specialized transition of the RFPN is associated to the operations:

$$\mathbf{Y} = f^{-d}(\sup_{x \in X} \mathbf{T}(X', \bigcap_{k=1}^{K}{}_{T\Sigma} R^k)) \Rightarrow \mathbf{Y} = f^{-d}\left(\sup_{x \in X} \mathbf{T}(X', \mathbf{R})\right)$$

4. Industrial Application

We considers the logic expression F of the fault propagation in a failure tree of a flexible production system of our partner, the "Institut de Productique" of Besançon [10] :

$$F = [(a+b+c+d) * e] + b + c$$

where + and * operators represent the union or the intersection of the logic variables {a, b, c, d, e}. This expression corresponds to the previous failure tree with the set of associates of rules (fig.4). The critical path indicates places that send warning signals in the recovery model (fig.6). Output variables u_1 and u_2 represent controls of the system. The logic reasoning between the MFPN model and the RFPN model, constitute the base of the fuzzy logic rules (fig.5).

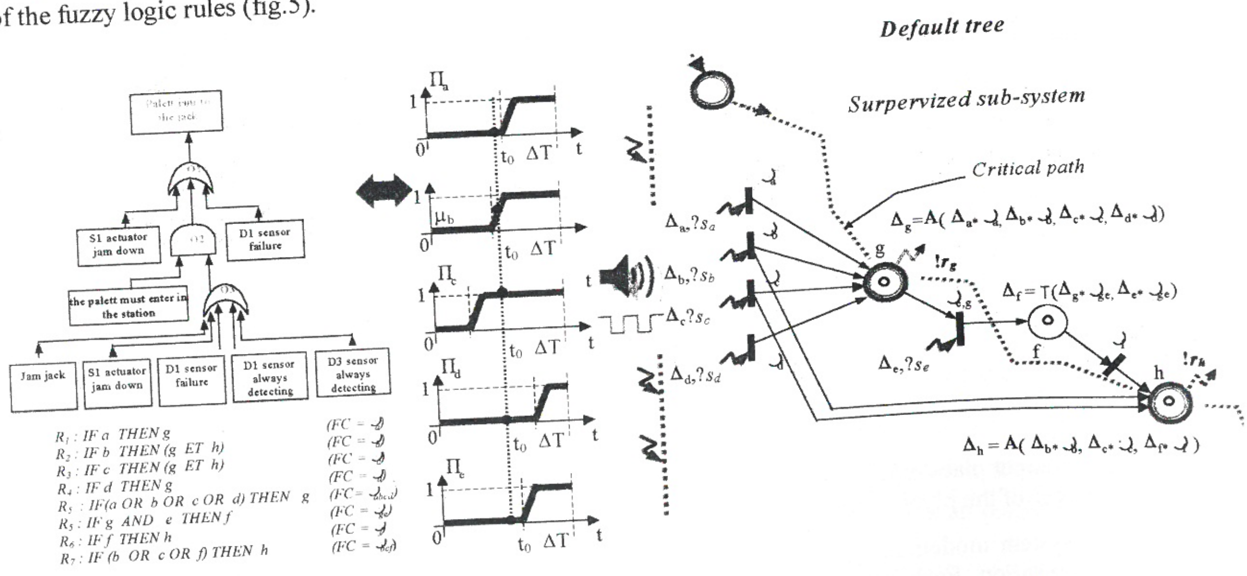

Figure 4: Representation of the Function F Using Logic Blocks and MFPN.

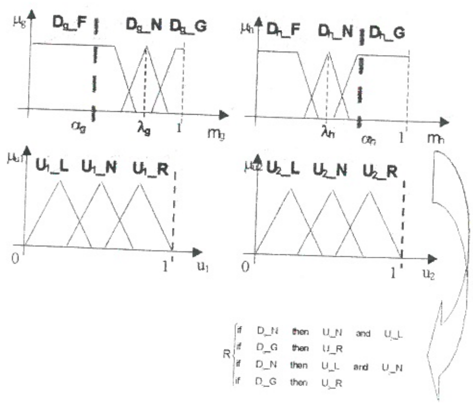

Figure 5: Fuzzy Rule Base for the Recovery.

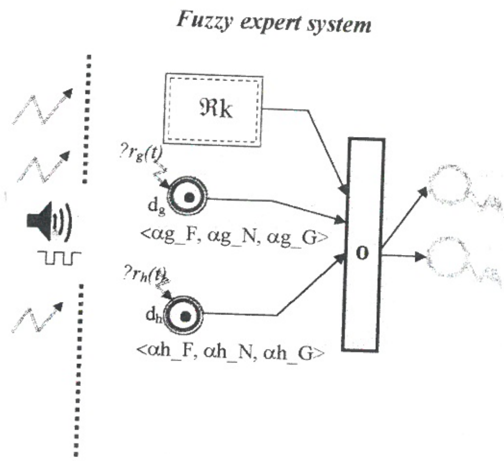

Figure 6: Modeling of the Real-Time Recovery System.

5. Conclusions

In this paper, we have proposed two fuzzy Petri net tools, MFPN - monitoring fuzzy Petri nets and RFPN - recovery fuzzy Petri nets, able to modeling and analyze monitoring and recovery tasks of a discrete event system, using a temporal fuzzy approach. The discrete event system and the monitoring and recovery models communicate using fuzzy synchronous information. This approach permits us to give a finer spectrum of the discrete event system failures. The use of the fuzzy logic and of the associated degree of credibility for a failure event/evolution includes a prognosis point of view in the monitoring fuzzy tool.

For complex systems monitoring, our results permit the use of a modular approach. The proposed tools form an open monitoring system and give also the possibility to integrate some other monitoring modules using other diagnosis and prognosis techniques. The open architecture can thus integrate a more complete maintenance platform.

In order to improve our fuzzy Petri net tool, a future research is represented by the extension including the negation and other logical operations as suggested in [8], by keeping our temporal specification.

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