

MONITORING ONLINE TO DETECT FAULTS INTO DISCRETE EVENT SYSTEMS

Hernández Rueda Karen, Meda Campaña María Elena

University of Guadalajara - University Center for Economic and Administrative Sciences

PhD in Information Technologies

Norte N° 799 Mod L305, Núcleo Universitario Los Belenes. C.P. 45100. Zapopan, Jalisco.

Phone +52 (33)37703430 , Fax

khernandez@cucea.udg.mx, emeda@cucea.udg.mx

1. ABSTRACT.

This paper addresses the fault diagnosis problem of Discrete Event Systems that is modeled with Interpreted Petri nets, based on the online diagnosis approach. The aim of this work is to propose an alternative to face up the fault detection problem, considering the cases to be taken into account for online monitoring of faults and the methodology's diagram that is used.

2. INTRODUCTION.

Fault diagnosis is an important function of a fault tolerant system that allows preserving the system integrity, minimizing risks to humans, and improving the reliability of the system. Also, this considers the stages of detection, localization, and identification of the faults. In order to solve this problem, the Discrete Event Systems (DES) research community has used the model-based approach for fault diagnosis in DES because it no requires detail in-depth the model system to be diagnosed [16]; several works on the matter use finite automata (FA) or Petri nets (PN) as modeling formalism. The use of FA is limited to small size systems [13], [12], [15] and the exponential state growth (particularly with the concurrent behavior). To cope with the state explosion problem, research groups throughout the world are increasingly adopting PN as a modeling formalism for DES [2]. Information to make the diagnosis is obtained from the inputs and outputs generated by the system in [9]. Ramirez in [3] works with the diagnosability of event-detectable live and safe PNs under a structural approach. In [5] is proposed a diagnoser based on the PN paths and causality relationships for determining the presence of faults in a system. In [11], fault monitoring for hybrid PN is addressed; monitoring PN are used to supervise when tasks start, finish and are interrupted, or resumed. In [10] it is assumed that there exist not unobservable cycles no blocked firing sequences after the firing of any faulty transition; necessary and sufficient conditions are given for

diagnosability based in a basis reachability diagnoser. Then, in [4] fault detection technique based on an identified model is proposed, the online detection and location are done; however, it does not study the diagnosability property. Although, there are works dealing with the diagnosability problem for some classes of PNs as mentioned, the proposition of an efficient algorithm for verifying the diagnosability of general PNs is still an open problem.

In this work, the DES is modeled with Interpreted Petri nets (IPN) containing the normal and failure behaviors. The IPN relating the input with actuators and the output with sensors is binary, live and safe. In the system some sensors are measurable, a transition symbol is activated into the system when the transition is enabled or it was disabling by the firing of a faulty transition and the online monitoring never fails (follows the evolution system). The online monitoring takes into account the normal and current behaviors of the DES. If there exists difference between them, then, is detected an error and in turn, this detected a fault. However, it is necessary consider some requirements and here are presented some of them. Also, is presented a methodology's diagram and a scheme of the diagnoser model used in the online monitoring.

The paper is distributed as follows; first is introduced the IPN, after that is defined the methods that is used in this work and considers the modeling of DES, the modeling of permanent and control faults, the diagnosis scheme (system model and diagnoser model) that is used for the monitoring the faults and the calculation of an error in order to detect the faults. Then the results are presented as the requirements that are needed to monitoring the faults. Finally, the conclusions are shown.

3. INTERPRETED PETRI NET.

The Interpreted Petri nets are an extension to the PN [14] that induces the input and output signal of a DES. The IPN is composed by a PN model together with input and output alphabets; the input and output symbol are assigned to transitions (t_1, t_2) and places (p_1, \dots, p_4), respectively. An IPN can model the commands sequences given by the signals from actuators and sensors each time a new state is reached. A graphic IPN is represented in the figure 1.

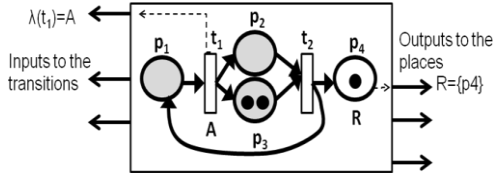


Figure 1. Interpreted Petri net

The places are presented by circles, the transitions by bars and the marks by black points into the places. These are connected between them, considering I and O functions of the PN. The measurable places ($R=\{p_4\}$) of IPN are transparent circles while the no-measurable places are dark circles. The transitions that are no-controllable, have not labeled (t_2) or are labeled with $\lambda(t_j)=\varepsilon$. The formal definition is as follows:

Definition 2.a A Interpreted Petri Net denoted by (Q, Mo) is the 4-tuple $Q=(N, \Sigma, \Phi, \lambda, \varphi)$ where,

- $N=(P, T, I, O, Mo)$ is a structure of PN composed by finite set of n places $P=\{p_1, p_2, \dots, p_n\}$, finite set of m transitions $T=\{t_1, t_2, \dots, t_m\}$, input arcs to transitions $I: P \times T \rightarrow \{0, 1\}$, output arcs from transitions $O: T \times P \rightarrow \{0, 1\}$ and Mo is the initial marking of PN.
- $\Sigma = \{\alpha_1, \alpha_2, \dots, \alpha_r\}$ is an alphabet of the input symbols, where α_i is the i -th symbol of the input alphabet.
- $\Phi = \{\Phi_1, \Phi_2, \dots, \Phi_v\}$ is an output alphabet.
- $\lambda: T \rightarrow \Sigma \cup \{\varepsilon\}$ is a labeling transition function with the restriction: $\forall t_j, t_k \in T, j \neq k$ if $\forall p_i I(p_i, t_j) = I(p_i, t_k) \neq 0$ and both $\lambda(t_j) \neq \varepsilon, \lambda(t_k) \neq \varepsilon$, then $\lambda(t_j) \neq \lambda(t_k)$. In this case ε represents a null event.
- $\varphi: R(N, Mo) \rightarrow \{\Phi \cup \{\varepsilon\}\}^q$ is a output lineal function that is represented by a matrix φ of $q \times n$ dimensions, where $R(N, Mo)$ is the set of possible states that the IPN reaches and q is the total of outputs. The output vector $y_k = \varphi M_k$ is the map of marking M_k in a observation q -dimensional vector. The column $\varphi(\bullet, i)$ is the elemental vector e_h if the place p_i has associated the sensor h ; or the null vector if p_i has no associated sensor. In this

case an elemental vector e_h is the q -dimensional vector with all entries equal to zero, except the entry h , which is equal to 1. A null vector has all entries equal to 0.

Definition 2.b If $\lambda(t_i) \neq \varepsilon$ the transition t_i is said **manipulable**; in other case there is no manipulable. A place $p_i \in P$ is **measurable** if the i -th column of the column vector of φ is no null, i. e. $\varphi(\bullet, i) \neq \vec{0}$; otherwise it is no measurable.

Definition 2.c A transition $t_j \in T$ of a IPN is **enabled** in the marking M_k if $\forall p_i \in P, M_k(p_i) \geq I(p_i, t_j)$. If $\lambda(t_j) = \alpha_i \neq \varepsilon$ is present and t_j is enabled, then t_j must be fired. If $\lambda(t_j) = \varepsilon$ and t_j is enabled then t_j can be fired. When an enabled transition t_j is fired in a marking M_k , then a new marking M_{k+1} is reached. This means: $M_k \xrightarrow{t_j} M_{k+1}$.

Definition 2.d A **firing sequence of IPN** is a sequence $\sigma = t_{i_1} t_{i_2} \dots t_{i_k}$ such that $Mo \xrightarrow{t_{i_1}} M_1 \xrightarrow{t_{i_2}} \dots \xrightarrow{t_{i_k}} M_k$.

Definition 2.e A **Parikh vector** is $\sigma^-: T \rightarrow (Z^+)^m$, where $m=|T|$, considering that $\sigma = t_{i_1} t_{i_2} \dots$ is a firing sequence, σ^- maps each transition $t \in T$ in the occurrences number of t in σ . Then, the marking reached from Mo when σ is fired can be calculated through the state equation of an IPN as:

$$M_{k+1} = M_k + C\sigma^- \text{ and } y_k = \varphi(M_k) \quad (1)$$

Where C is the incidence matrix and $y_k \in (Z^+)^q$ is the k -th observation vector, defined as a PN [14]. Some dynamic properties of PN (IPN) that are used to ensure the firing of a transitions sequence are considered in the diagnosis problem and are defined below[14]: a) a PN (N, Mo) is cyclic if $\forall M_i \in R(N, Mo)$ it is true that $\exists \sigma$, such that $M_i \xrightarrow{\sigma} M_o$. b) A PN (N, Mo) is live is $\forall M_i \in R(N, Mo)$ and $\forall t \in T$ it is true that $\exists M_j$, such that $M_i \xrightarrow{\sigma} M_j \xrightarrow{t}$. c) A PN (N, Mo) is k -safe (k -bounded) is $\forall M \in R(N, Mo)$ and $\forall p \in P, M(p) \leq k$. If it is true that $\forall M \in R(N, Mo)$ and $\forall p \in P, M(p) \leq 1$, then the net is called 1-safe (safe or binary).

4. MONITORING ONLINE TO DETECT FAULTS.

The method that is used in this works is presented in the next diagram. First, the DES is modeled with IPN as in [3] to ensure that the net is live and safe. Then the IPN needs pass the test of event-detectability [8] in order to identify the events occurrence. After that, the faults are modeled into the IPN model [6]. Again, the IPN needs pass the test of event-detectability.

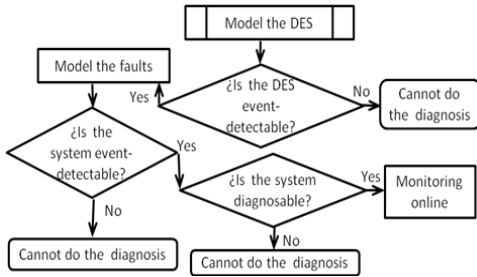


Figure 2. Diagram of the procedure used

Also, it is necessary to review if the IPN is diagnosable in order to detect failures. Finally, the monitoring is implemented in order to detect if there exists an error during the evolution of the DES. In the next lines an explanation of each stages of this diagram is described.

4.1. Model the DES with Interpreted Petri Net.

The model of DES with IPN is based on the Ramirez' methodology [3]. Using this methodology a bounded and live IPN can be constructed; first, it is necessary to identify the components of the system, the variables range, and codifications of these variables in order to have an IPN model. Then, it is obtained the modules and after make compositions between them (includes, label the places that are measurable and the transitions that are manipulable), these are synchronized in order to obtain the final model. An example of this can see in the figure 3. The figure 3a shows two cars (1 and 2) that are controlled by the switch M, these are the systems components and the modules of the models. When the switch is oppressed the cars are going to move at the same time (simultaneously to the right).

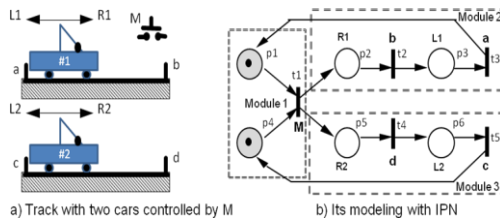


Figure 3. Modeling with IPN

The cars can be moved from left (L_1 or L_2) to right (R_1 or R_2), moving from point "a" or "c" to point "b" or "d", respectively. These are considered the variables ranges. When the end position is reached, their motion is the inverse. When the initial position is detected, every car stops. In the figure 3b, the set of places is $P=\{p_1, p_2, p_3, p_4, p_5, p_6\}$ and the set of transitions is $T=\{t_1, t_2, t_3, t_4, t_5\}$, that are the

codifications of the variables ranges. The synchronization of the three modules forms the final model of figure 3b. Its initial marking is $M_0 = [1 \ 0 \ 0 \ 1 \ 0 \ 0]^T$ because the marks are in p_1 and p_4 initially. For this case, the manipulated transitions are $\lambda(t_1)=M$, $\lambda(t_2)=b$, $\lambda(t_3)=a$, $\lambda(t_4)=d$, $\lambda(t_5)=c$, and the measurable places are $R_1=\{p_2\}$, $R_2=\{p_5\}$, $L_1=\{p_3\}$, $L_2=\{p_6\}$. These are the interpretations of the net. It is incidence matrix C and the output function ϕ , are defined as follows:

$$C = \begin{bmatrix} t_1 & t_2 & t_3 & t_4 & t_5 \\ p_1 & -1 & 0 & 1 & 0 & 0 \\ p_2 & 1 & -1 & 0 & 0 & 0 \\ p_3 & 0 & 1 & -1 & 0 & 0 \\ p_4 & -1 & 0 & 0 & 0 & 1 \\ p_5 & 1 & 0 & 0 & -1 & 0 \\ p_6 & 0 & 0 & 0 & 1 & -1 \end{bmatrix} \quad (2) \quad \phi = \begin{bmatrix} p_1 & p_2 & p_3 & p_4 & p_5 & p_6 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} L_1 \\ L_2 \\ R_1 \\ R_2 \end{bmatrix} \quad (3)$$

The PN is cyclic because for any reachable marking M_i there exists a firing sequence σ that it can lead to the initial marking M_0 ; it is live because always it can reach a marking M_k it enables any transition of the net; is 1-safe, because for any reachable marking, every place can only have at most a mark (token).

4.2. Verify if the IPN is event-detectable.

A DES may be diagnosed (i.e to determine if there exists or not a failure in it) through the diagnosability property [13], which is related to the ability to infer, based on sequences of observable events the occurrence of certain events that are not observable (failure events). So to be able to make inferences based on observable events is used the event-detectable property. An IPN is called event-detectable if the sequences can be detected using only the output and structural information of the IPN. The following lemma in [7] defines a polynomial characterization of the event-detectability property of an IPN.

Lemma 3.2a A live IPN (Q, M_0) is event-detectable if and only if

- $\forall t_i, t_j \in T$ such that $\lambda(t_i) = \lambda(t_j)$ or $\lambda(t_i) = \varepsilon$ it holds that $\phi C(\bullet, t_i) \neq \phi C(\bullet, t_j)$ and
- $\forall t_k \in T$ it holds that $\phi C(\bullet, t_k) \neq 0$.

4.3. Model the faults into the IPN.

The events to be diagnosed are referred to as "faults", hereafter are modeled as unobservable events in the respective system modules. Events are unobservable when they are not directly recorded by the sensors attached to the system. The objective is to diagnose the occurrence of fault events based on the sequence of observed events and on the structure

of the respective PN modules. Some faults that can be present into the system are control failure and permanent failure [1]. These faults are modeled based on [6]:

- Permanent Failures (P^{PF}, T^{PF}): $\forall p_i^N$ that represents an operation that can fail, add an uncontrollable transition t_f (T^{PF}), a place of failure p_j^N (P^{PF}), and the arcs (p_i^N, t_f) and (t_f, p_j^N) . The new place of failures p_i^F must be equal of measurable that the normal place.
- Control Failures (P^{CF}, T^{CF}): $\forall p_i^N$ (P^{CF}) that represents an operation of control failure f_c that can occur, add a no manipulable transition t_c (T^{CF}), which must be connected to another place p_j^N (same place that will be affected by the firing of the transition from control failures) and add the arcs (p_i^N, t_c) and (t_c, p_j^N) .

Where $P = \{P^{NUP^{PF}}\}$, $P^N \in P^{CF}, P^R$ and $T = \{T^N, T^{PF}, T^{CF}, T^R\}$. $P^R = T^{PF}$ is a places set of risk and $T^R = \{P^R \cap T^N\}$ the transitions set post-risk.

4.4. Verify if the IPN continues being event-detectable.

Again is used the Lemma 3.2a. First is necessary to add the places (p_6) and transitions (t_6, t_7) of faults in the matrices C and ϕ . Then, it can review the columns of these matrices.

4.5. Verify if the IPN is diagnosable.

Fault diagnosis considers the detection, localization and identification steps of faults. Fault detection and location must be included in systems, since even assuming that during the system design stage no errors were introduced, external events or malfunctioning system components could lead the system to risky states. It is a common practice to assume that a set of potential faults occurring within the system is a priori known; the fault diagnosis system must detect real fault occurrences during system execution [2]. As the objective of diagnosis problem is to identify the occurrence and type of, if any, failure events, based on the observable traces generated by the system, then the detection of the failure needs to be done within finite steps of observation after the occurrence of the failure. So it is necessary to know if the system is diagnosable to detect these failures applying the following theorem [6]:

Theorem 3.5a Let (Q, Mo) be an IPN safe with the permanent and control faults, where (Q^N, M^N_0) together with the control faults transitions is a safe, live and event-detectable IPN. If

- $\forall t_i \in T^R, \forall t_j \in T^N$ where $t_i \neq t_j$, the maximum relative distance D_H between these transitions is finite. $D_H(t_i, t_j) = \max\{D_R(t_i, t_j), D_R(t_j, t_i)\}$ where $D_R(t_i, t_j)$ is the number of firing of t_i , when a token is held in the input place $\bullet t_j$ (the token cannot be used to fire any other transition).
- $\forall t_k \in T^R, \bullet(t_k) = \{p_i^N\}$, it must fulfill that $|\bullet(t_k)|=1$ and $\lambda(t_k) \neq \varepsilon$. Then (Q, Mo) is input-output diagnosable.

4.6. Monitoring online of faults.

The monitoring is based-on the diagnosis approach [12] presented in the figure 4, it needs a diagnosis scheme and the system model (DES modeled with IPN in normal behavior (Q^N, M^N_0)).

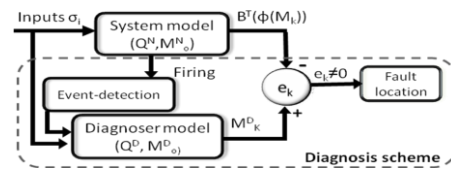


Figure 4. Monitoring scheme

The diagnosis scheme needs; a module of event-detection, a reduced diagnoser model, a calculation of the error (difference between outputs of DES model and diagnoser model) when the DES is working in order to detect faults in the system and a fault locate module to determine where the fault was occurred. In case that any fault occurs in the system, the computed error (e_k) will be different from zero ($e_k \neq 0$), indicating that a fault is present in the system.

Diagnoser model

The structure of the reduced diagnoser model based on [3] is a net (Q^D, M^D_0) , with $P^D = P^N$ and $T^D = T^N$. It has an incidence matrix $C^D = C^D - B^T \phi^N C^N$ (where $C^N = C$ of (Q^N, M^N_0) , $\phi^N = \phi$ of (Q^N, M^N_0) and $B^T = [b^0 \ b^1 \ \dots \ b^{q-1}]$, $q = \#P$ measurable and $b = 2 \max((\text{abs}(c_{ij})) + 1)$) and the initial marking $M^D_0 = B^T \phi M_0$. The diagnoser model is shown in the figure 5. The number of elements of C^D corresponds with the number of elements of T^N .

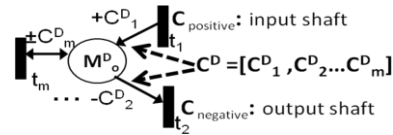


Figure 5. Diagnoser model

Error calculation

The error e_k is calculated as in [6] as it can be seen in the figure 4: $e_k = M^D_k - B^T \phi(M_k)$. When there is not any fault, then $e_k = 0$, but when a fault occurs, $e_k \neq 0$. After the error is detected by the diagnoser it is necessary to locate the fault.

5. RESULTS.

The IPN of the figure 3 passes the test of event-detectability property, since the φC matrix has all the columns different between them and from zero. It fulfills the lemma 3.2a:

$$\varphi C = \begin{bmatrix} 0 & 1 & -1 & 0 & 0 \\ 0 & 0 & 0 & 1 & -1 \\ 1 & -1 & 0 & 0 & 0 \\ 1 & 0 & 0 & -1 & 0 \end{bmatrix} \quad (4)$$

Assuming that there may be a permanent fault into car #1 when is oppressed the switch M and a control fault when the car #1 returns to the initial place. The model with the normal and fault behavior is obtained as shown in the figure 6. The set of places and transitions are $P^N=\{p_1, p_2, \dots, p_6\}$, $T^N=\{t_1, t_2, \dots, t_5\}$, $P^R=\{p_1\}$, $T^R=\{t_1\}$, $P^{PF}=\{p_7\}$, $T^{PF}=\{t_6\}$, $P^{CF}=\{p_2\}$ and $T^{CF}=\{t_7\}$.

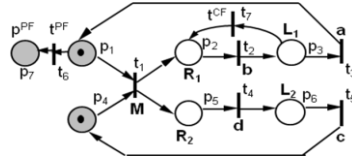


Figure 6. The IPN with normal and fault behavior: a) case $\bullet T^{CF} = P_2$.

In other case, if is considered that can exist a permanent fault when the car #2 returns to the initial place and a control fault when the car #1 returns to the initial place. The model with the normal and fault behaviors is shown in the next figure 7. The set of places and transitions for this IPN are $P^N=\{p_1, p_2, \dots, p_6\}$, $T^N=\{t_1, t_2, \dots, t_5\}$, $P^R=\{p_6\}$, $T^R=\{t_5\}$, $P^{PF}=\{p_7\}$ and $T^{PF}=\{t_6\}$, $T^{CF}=\{t_7\}$ and $P^{CF}=\{p_2\}$.

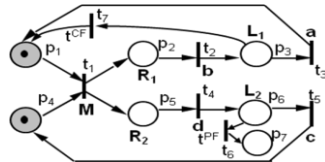


Figure 7. The IPN with normal and fault behavior: a) case $\bullet T^{CF} = P_1$.

Again, the IPN passes the test of event-detectability property. For the case a) case $\bullet T^{CF} = P_2$ (shown in the matrix 5) all its columns of φC matrix are different between them (the column equal to zero correspond to the permanent fault) then this IPN passes this test.

$$\varphi C = \begin{bmatrix} 0 & 1 & -1 & 0 & 0 & 0 & -1 \\ 0 & 0 & 0 & 1 & -1 & 0 & 0 \\ 1 & -1 & 0 & 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & -1 & 0 & 0 & 0 \end{bmatrix} \quad (5)$$

For the case b) case $\bullet T^{CF} = P_1$ (shown in the matrix 6), the φC matrix fulfills the lemma 3.2a so this IPN is an event-detectable too.

$$\varphi C = \begin{bmatrix} 0 & 1 & -1 & 0 & 0 & 0 & -1 \\ 0 & 0 & 0 & 1 & -1 & -1 & 0 \\ 1 & -1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & -1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \quad (6)$$

However, when this system needs pass the test of diagnosability, there exist different results for the two cases of the faults that were shown in the figure 6 and figure 7:

- Applying theorem 3.5a to the IPN depicted on the figure 6, case $\bullet T^{CF} = P_2$, with $t_1 \in T^R$ and $t_2, \dots, t_5 \in T^N$ it shows that $D_H(t_1, t_2) = D_H(t_1, t_3) = D_H(t_1, t_4) = D_H(t_1, t_5) = D_H(t_2, t_1) = D_H(t_3, t_1) = D_H(t_4, t_1) = D_H(t_5, t_1) = 1$, $\lambda(t_1) \neq \epsilon$ but $|\bullet(t_1)| \neq 1$. So the IPN of figure 6 is not diagnosable.
- However, this theorem applied to the IPN depicted on the figure 7, case $\bullet T^{CF} = P_1$, with $t_5 \in T^R$ and $t_1, \dots, t_4 \in T^N$ shows that $D_H(t_5, t_3) = 1$, $D_H(t_2, t_5) = 1$, $D_H(t_5, t_2) = 1$, $D_H(t_3, t_5) = 1$, $D_H(t_5, t_4) = D_H(t_4, t_5) = D_H(t_5, t_1) = 0$, $D_H(t_1, t_5) = 1$, and $\lambda(t_5) \neq \epsilon$ and $|\bullet(t_5)| = 1$. So the IPN is diagnosable.

As the IPN of the figure 7 is diagnosable, then it can construct the diagnoser model of this DES. The diagnoser model of figure 3, can see in the next figure 8a.

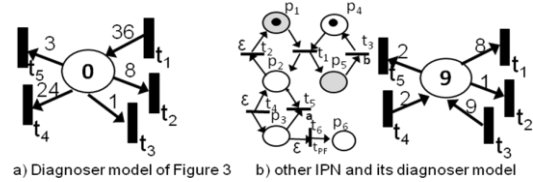


Figure 8. Diagnoser model of DESs

The diagnoser 8a has the following data $P^D=\{p_1, p_2, \dots, p_6\}$, $T^D=\{t_1, t_2, \dots, t_5\}$, $C^D = [36 \ -8 \ -1 \ -24 \ -3]$ and $M_o^D=0$, since $B^T = [1 \ 3 \ 9 \ 27]$. Suppose that the transitions t_1, t_4 , and t_5 are fired then $e_k=[9] - [1]=8$. The error is different from zero this means that a fault has occurred in the system. However, unless that the transition t_6 or t_7 is fired the systems cannot has a fault. This happened because there is only one input transition and some elements are contained in both T-semi-flows of the IPN: $X_1=\{1111100\}$ and $X_2=\{1101101\}$. For example, the diagnoser model of figure 8b that pass the event-detectable and diagnosability properties has two input transitions and tree output transitions. This has the following data $P^D=\{p_1, \dots, p_5\}$, $T^D=\{t_1, \dots, t_5\}$, $C^D=[-8 \ -1 \ 9 \ 2 \ -2]$, $M_o^D=[9]$ and $B^T=[1 \ 3 \ 9]$. Also, its elements are not contained in both T-semi-flows of IPN: $X_1=\{00011\}$ and $X_2=\{11100\}$. This considers one permanent fault transitions (t_6) with its permanent place p_6 . Suppose that the transitions

t_1 and t_4 are fired then $e_k=[3]-[3]=0$. There is no a fault. However, if is activated a permanent fault t_6 the place p_6 is marked but this is no detected because there no exist into the system model. If after that, the transition t_5 is fired, then the diagnoser model changes its marking and $e_k=[2]-[3]=-1$. So a fault is detected, the permanent fault.

6. CONCLUSIONS.

It was described the methodology used to detect a fault in DES modeled with IPN and was presented the requirements to monitoring online. Also, it was illustrated two cases in order to understand the process of fault diagnosis in DES and the situations that should be considered. Here was shown how to construct the system model with IPN and the monitoring online to detect faults. It is necessary to have a diagnosis scheme that uses the normal behavior model and the normal with the failure model. Then, the system must pass the analysis of the diagnosability property. After that, it is made the design of diagnosis that considers two important steps: 1) a diagnoser model and 2) an error calculation. It will be necessary to find a new definition of diagnosability property in order to include small and large system. Also, modify the event-detectable definition to consider different kind of IPN. Future research therefore should also to modify this diagnoser model to avoid that the error be different from zero without a failure has occurred.

7. REFERENCES.

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