A DIAGNOSIS FRAMEWORK OF HYBRID DYNAMIC SYSTEMS BASED ON TIME FUZZY PETRI NETS

E. Rocha Loures[1][2], J. C. Pascal[1]

[1] Laboratory for Analysis and Architecture of Systems – LAAS/CNRS, Toulouse-France
[2] Graduate Program in Production System Engineering – PUCPR, Curitiba-Brazil
e-mail addresses: loures@laas.fr, jcp@laas.fr

Abstract: This paper presents a diagnosis framework based on a qualitative model of the process. Starting from a dynamic abstraction procedure under a defined operating mode a fuzzy partitioning of the variables evolution is made, defining for each measured or observable variable a number of qualitative states. Then time Fuzzy intervals representing the moment of state change are defined. The process behaviour of the operating mode is represented by Time Fuzzy Petri nets (TFPN) model and its evolution is the consequence of events detection due to the partitioning bounds crossing. According to the membership possibility of an event to the estimated time interval and to fuzzy influence knowledge, it is possible to reason about a fault occurrence. The fuzzy data issue from the TFPN components allows evaluating the causes of the fault or failure mode. A model-based diagnosis of a hybrid system is presented. *Copyright © 2005 IFAC*

Keywords: Time fuzzy Petri nets, qualitative modelling, possibility theory, detection, diagnosis, hybrid systems.

1 INTRODUCTION

The supervision of an industrial process has the aim of applying operating sequences and adapting the control if a fault is detected (Pascal, 2000). The detection can be made through a reference model of the process which describes its expected behaviour. It is neither always possible nor necessary to have a precise mathematical representation of the process dynamics through algebraic-differential equations. Thus, the qualitative approaches (Bourseau et al., 1995) become an interesting solution. They allow the representation of the process behaviour with a degree of abstraction that offers more robustness and a better suitability with the supervision needs. However, certain approaches do not consider the time explicitly. The time modelling allows a real time monitoring of the process evolution and a more precise diagnosis. Based on a qualitative model the supervision must be able to detect the deviations of the normal functioning, isolate the fault and diagnose the causes.

In the domain of monitoring various models of qualitative representation were developed for continuous, discrete and hybrid systems. Moreover, the problem of correspondence between the continuous and discrete models has been constantly raised by the dynamic hybrid system community. Concerning the continuous systems, the qualitative models are frequently based on the causal graphs, temporal causal graphs, symbolic representation and episodes, signed direct graph and others (Bourseau et al., 1995).

Supported by the formalism found in discrete-event systems (DES) and in the Supervision theory, we find the '*discrete*' or qualitative models representing the continuous behaviours. This representation is based on an abstraction of the continuous dynamics through qualitative states as in (Fanni and Giua, 1998), (Peleties and DeCarlo, 1994) and (Raisch, 2000). In this field, various approaches based on automata and Petri Nets (stochastic, timed, fuzzy, hybrid) are proposed taking into account the criteria like determinism, reachability, controllability and diagnosability (Blanke et al., 2003), (Koutsoukos et al., 2000), (Zaytoon, 1998).

Other researches propose an integration of discrete and continuous models: hybrid automata, hybrid Petri nets, differential predicate-transition Petri nets (DPT-PN) (Benazera et al., 2002), (Alla and David, 1998), (Champagnat et al., 1998). The latter combines the differential equation systems and Petri nets. However, these approaches require the precise knowledge of physical relations between the variables of the continuous part (mathematical model based on algebraic-differential equations).

To avoid this requirement, notably in complex process, the methods based on rules, associations and experimental data are explored (Bourseau et al., 1995). We can mention the methods based on pattern recognition such as clustering and classification, episodes, neural networks, etc. Moreover, we can refer to the methods of chronicle recognition (Ghallab, 1996) adapted by (Supavatanakul et al., 2003) where a timed discrete automata is obtained by means of the measured variables of the process (identification process).

In the field of hybrid dynamic system supervision, notably the batch systems, the modelling of the control must consider continuous aspects (continuous nature matter – continuous operations), as well as discrete aspects management of plant's different configurations). Those aspects are closely interconnected and may be represented by DPT-PN based models (Pascal, 2000). The representation of continuous complex operations (for instance, distillation and reaction) by mathematical models requires a large number of variables linked through complex algebraic-differential relations. This kind of representation leads to complex models difficult to manipulate and with high degree of accuracy that is not suitable for the supervision level. Therefore, we propose a qualitative abstraction of the continuous operations that is appropriate for detection and diagnosis. The obtained qualitative model must be able to be integrated in the hierarchical structure of control system whose description is essentially supported by discrete models.

Based on this context we propose an abstraction of the continuous dynamics of a hybrid system and its description by time fuzzy Petri nets (TFPN) (Cardoso, 1999), (Loures and Pascal, 2004).

In Section 2, we present the process abstraction method and explain the fuzzy partitioning aspects in detail. In Section 3, the obtained TFPN model representing the evolution of the process variables is detailed. The detection and diagnosis mechanisms are described in Section 4 by means of a coupled tanks process (Benchmark problem of hybrid systems diagnosis used by the French community of dynamic hybrid systems). Finally, conclusions are presented in Section 5.

2 ABSTRACTION PROCESS

The process of obtaining our qualitative model is based on the abstraction process of the plant continuous dynamic. The experimental realization is carried out in a time horizon (τ_h) established according to the needs of the supervision from the measured or observable variables. The process is characterised by its input U(0... τ_h) (defined as set-point related to the operating mode), output Y (0... τ_h) and state measurable or observable variables X(0... τ_h), where $X = [x_1...x_I]^T$, $U = [x_1...x_J]^T$, $Y = [x_1...x_W]^T$ represent the vectors of the variables. In a general way these variables may be defined by $\mathbf{V}(0...\tau_h) = \{\mathbf{U},\mathbf{Y},\mathbf{X}\}$ where $\mathbf{V}=[v_1...v_K]^T$. This realization or historical data represents a normal behaviour related to the operating mode.

The Fig. 2 shows the temporal evolution of two variables v_1 (level of tank *a*) and v_2 (level of tank *b*) of the process (Fig. 1) submitted to a set-point step change (upon the outflow *Qp* from the pump *Pp*) related to an operating mode.

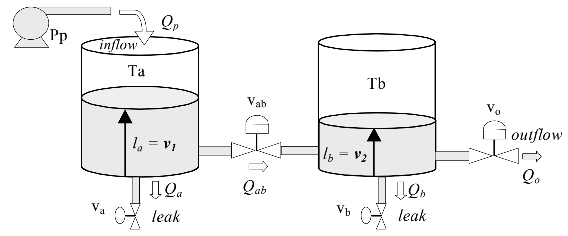

Fig. 1. Coupled tanks process

2.1 The fuzzy partitioning

Due to the dynamics of each one of the variables, a fuzzy partitioning is realised by establishing their qualitative states. Let us consider Fig. 2, where the qualitative state of a variable is given by $v_{kQm} \in Q_{vk} = \{v_{kQ1},\ldots,v_{kQM}\}$, where M is the number of partitions that are associated to that variable. This way, we get for v_1 the qualitative states $v_{1Qm} \in Q_{v1} = \{v_{1Q1},\ldots,v_{1QM1}\}$, where $M_1 = 4$, and for v_2 the qualitative states $v_{2Qm} \in Q_{v2} = \{v_{2Q1},\ldots,v_{2QM2}\}$, where $M_2=4$. This partitioning is made up by the fuzzy sets ψ_m, which delimits the qualitative states v_{kQm} described by trapezoidal membership functions μ_{vkQm}, thus allowing the representation of uncertainties and imprecision of the variable states (Fig. 2) and of the boundaries between these states.

Let Φ be a fuzzy set associated to the set Q_{vk}, which is defined by a membership function μ_Φ that associates the degree $\mu_\Phi(v_{kQm}) \in [0,1]$ to each qualitative state v_{kQm} of Q_{vk}. Let π_{vk} be the possibility distribution that delimits the fuzzy set Φ of the more or less possible values of v_k. One can approximate the unknown possibility distribution π_{vk} by means of the fuzzy set Φ : $\forall\ v_{kQm} \in Q_v$, $\pi_{vk}(v_{kQm}) = \mu_\Phi(v_{kQm})$ (Dubois and Prade, 1999).

Let us consider a qualitative state v_{1Qm} of v_1, and $\pi_{v1}(v_{1Qm})$ the possibility that v_1 is in qualitative state v_{1Qm}. The values of $\pi_{v1}(v_{1Qm})$ will be interpreted as follows:

- $\pi_{v1}(v_{1Qm})=1$: v_{1Qm} is a possible state of v_1 ;
- $\pi_{v1}(v_{1Qm})=0$: it is certain that v_1 is not in state v_{1Qm} ;
- $\pi_{v1}(v_{1Qm})=1$, $\pi_{v1}(v_{1Qm+1}) = 1$: it is possible that v_1 is in state v_{1Qm} or v_{1Qm+1} ;
- If $\pi_{v1}(v_{1Qm})=1$ and $\forall\ v_{1Qm'} \neq v_{1Qm}$, $v_{1Qm'} \in Q_{vm}$ $\pi_{v1}(v_{1Qm'})=0$, we can be sure that v_1 is in state v_{1Qm}.

In our approach, for each variable, the possibility degrees $\pi_{v1}(v_{1Qm}) \neq 0$ are only applied to two successive states, thus representing the qualitative state transition uncertainty. At the moment of the qualitative state transition, the possibility distribution π_{v1} is updated: $\pi_{v1}(v_{1Qm})$, $\pi_{v1}(v_{1Qm+1}) \in (0,1]$ and $\pi_{v1}(v_{1Qm'}) = 0$, where $v_{1Qm'} \neq v_{1Qm}$ and v_{1Qm} , v_{1Qm+1}, $v_{1Qm'} \in Q_{v1}$.

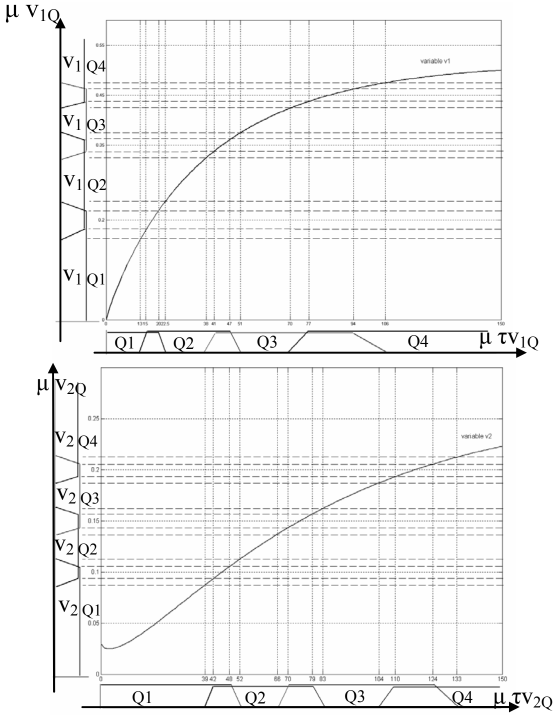

Fig. 2. Fuzzy partitioning of v1 and v2

The partitioning that is made up by the fuzzy sets ψ_m, which delimits the qualitative states v_{1Qm}, results in the definition of fuzzy time windows that represent the possible instants in which a change of qualitative state may occur (Fig. 3).

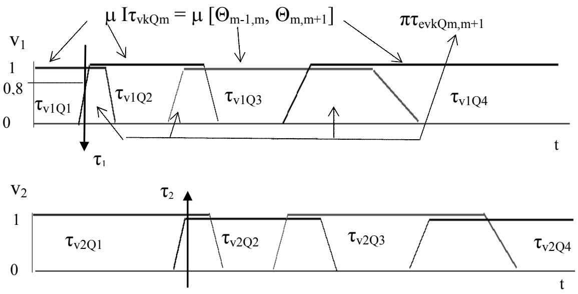

Fig. 3. Fuzzy time windows associated to v_1 and v_2

Let us consider the qualitative states of v_1: v_{1Qm} and v_{1Qm+1}; the time window of possible instants in which a change of qualitative state may occur is defined by the possibility distribution $\pi\tau_{ev1Qm,m+1}$, which is delimited by the fuzzy set $\Theta_{m,m+1}$. The set of dates, possibly after $\Theta_{m-1,m}$ and possibly before $\Theta_{m,m+1}$, where v_1 is possibly in qualitative state v_{1Qm}, is defined by the conjunctive set of instants $I\tau_{v1Qm} = [\Theta_{m-1,m}, \Theta_{m,m+1}]$. In the same way, we can define the conjunctive set of instants $]\Theta_{m-1m}, \Theta_{m,m+1}[$, where v_1 is necessarily in a qualitative state v_{1Qm}. The 3-uple ($\Theta_{m-1,m}$, $\Theta_{m,m+1}$, L) describes the temporal location of the state of the variable [8], where L is the interval length given by $L = \Theta_{m-1,m} \,\theta\, \Theta_{m,m+1}$, and θ is an extended subtraction operation.

2.2 Identification method of the dynamic

Once the partitioning of each variable and the state change time windows are established, we determine the time relations between the different variables by means of a causal knowledge (Mosterman, 2001), (Benazera et al., 2002). In order to do that, the qualitative states of other variables are considered when the qualitative state of a certain variable changes. This leads to the definition of the state transition condition CTv_k. In a first moment, we consider two variables v_1 and v_2 with an influence relation, prior to a generalisation:

$$CTv_1 = \{e_{v1Qm,m+1},\ \pi\tau_{ev1Qm,m+1}(\tau),\ \{\pi_{v2}(q)_{(\tau)}\}\} \qquad (1)$$

where $e_{v1Qm,m+1}$ represents an event at instant τ indicating the passage of state v_{1Qm} to state v_{1Qm+1} (change of qualitative state), $\pi\tau_{ev1Qm,m+1}$ represents the fuzzy time window of possible instants for change of variable v_1, and $\pi v_{2Q_n}(q)$ represents the evaluation of possibility that variable v_2 associated may be in the qualitative states $q \in Q_{v2}$, at this instant. The same way, the transition condition of v_2 is:

$$CTv_2 = \{e_{v2Qm,m+1},\ \pi\tau_{ev2Qm,m+1}(\tau),\ \{\pi_{v1}(q)_{(\tau)}\}\} \qquad (2)$$

In general, the transition condition CT_{vk} is:

$$CTv_k = \{e_{vkQm,m+1},\ \pi\tau_{evkQm,m+1}(\tau),\ \{\pi_{vk'}(q)_{(\tau)}\}\} \qquad (3)$$

where CT_{vk} represents the transition relation of a variable $v_k \in V$, associated to variables $v_{K'} \neq v_K \in V \in \{V_I\}$. $\{V_I\} \subset V$ represents the set of associated variables issue from the influence knowledge.

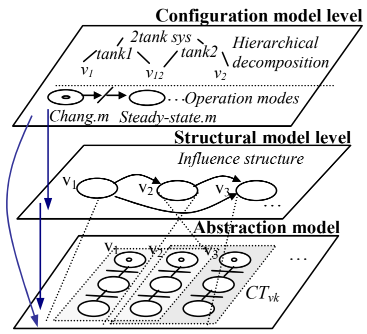

Fig. 4. Modelling structure

The modelling structure shown in Fig. 4 considers some important hybrid aspects of the process. This organization guided the definition of our abstraction model in a way to better integrate these aspects for the purpose of monitoring and diagnosis:

– *Configuration model level*: the hierarchical decomposition of the process by means of sub-systems and systems allows a finer identification of the implicated variables as well as its internal relations according to the operating mode. Thus a component-oriented modelling becomes possible. Under fault conditions the isolation process of the cause may be oriented through physic components.

– *Structural model level*: the possibility degree $\{\pi_{v1}(q)_{(\tau)}\}$ of the CTs define the relation between the variables (influences) or sub-systems. It is issue from a causal knowledge and verifies the consistency degree of the temporal evolution of the associated variables.

– *Abstraction model*: the considerations above led us to an abstraction model of the process continuous dynamic by means of the FTPN described in the following.

3 TIME FUZZY PETRI NET MODEL

The time fuzzy Petri net used in our approach is defined as the tuple:

$$FTPN = \langle P,T,Pre,Post,Mo,\Theta \rangle$$

where : P is a non-empty set of places, T is a non-empty set of transitions, Pre is a multi-set over P x T - a backward function, Post is a multi-set over T x P – a forward function, Mo the initial marking, $\Theta : T \rightarrow CT$ the transition function CTv_k (eq.3), previously described.

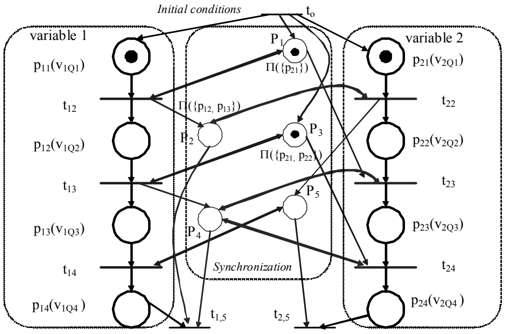

Fig. 5. FTPN as the reference model

The qualitative states of a variable correspond to the places of the Petri net (left and right parts of the net in Fig. 5). The transition conditions *CT* are associated to the transitions. The middle part of the net in Fig. 5 represents the time relation (influence structure) between variables. This relation is described by the synchronization places. An algorithm to the Petri net construction may be easily implemented based on this information.

The place P_2, for instance, indicates that at the firing moment of transition t_{22} – to which the possibility distribution time window $\pi\tau_{ev2Q1,2}$ (passing of v_2 from its qualitative state v_{2Q1} to qualitative state v_{2Q2}) is associated - the v_1 can be in qualitative states v_{1Q2} or v_{1Q3} (ref. Fig. 3). For this, the necessity and possibility measures are evaluated:

$$\Pi(v_{1Q}) = \max_{q \in v1Q} \pi_{v1}(q),$$

$$\text{where } v_{1Q} = \{v_{1Q2}, v_{1Q3}\},\ v_{1Q} \subseteq \mathcal{Q}_{vk}$$

$$\text{then } \Pi(v_{1Q}) = \max_{q \in v1Q} (\pi(v_{1Q2}), \pi(v_{1Q3})),$$

$$N(v_{1Q}) = 1 - \Pi(v_{1Q})' = 1 - \max_{q \in v1Q'} \pi_{v1}(q),$$

$$\text{where } v_{1Q}' = \{v_{1Q1}, v_{1Q4}\},\ v_{1Q} \subseteq \mathcal{Q}_{vk}$$

At instant τ_0, the qualitative states of variables (v_{1Qm} and v_{2Qn}) are known. Therefore, we can say that $\Pi(v_{1Qm}) = \Pi(v_{2Qm}) = 1$ and $N(v_{1Qm}) = N(v_{2Qm}) = 1$, once $\pi_{v1}(v_{1Qm}) = 1$ and $\forall\ v_{1Qm'} \neq v_{1Qm}$, $v_{1Qm'} \in \mathcal{Q}_{vm}$ $\pi_{v1}(v_{1Qm'}) = 0$, and also for v_2. Thus, it is possible to characterise the certainty of state that will correspond to the precise marking Mo = $\{p_{11}, p_{21}\}$, shown in Fig. 5. An external event issue from the process at the instant τ leads to the evaluation of the transition conditions *CT* associated to the enabled transitions (marking of the input places of the transition $\neq 0$), which leads to a fuzzy marking $\pi_{v1}(v_{1Qm})$, $\pi_{v1}(v_{1Qm+1}) \in (0,1]$ and $\pi_{v1}(v_{1Qm'}) = 0$, where $v_{1Qm'} \neq v_{1Qm}$ and v_{1Qm}, v_{1Qm+1}, $v_{1Qm'} \in \mathcal{Q}_{v1}$, according to the fuzzy time evaluation carried out by the *CT*.

Let us consider the evolution of the net from the initial marking shown in Fig. 5, from an event $e_{v1Q1,2}$ related to v_1, at instant τ_1 (Fig. 3). The possibility distribution values at this instant (just before τ_1, τ_1^-) corresponds to the initial condition $\pi_{\tau 1^-}(p_{11}) = 1$ and $\forall\ p_{1m} \neq p_{11}$, $\pi_{v1}(p_{1m}) = 0$, determining a precise marking $M_{\tau 1^-}\{p_{11}\}$. The evaluation of the possibility degree $\pi_{v2}(v_{2Q1})$ (eq.1) is done through the place P_1, to which are related the possibility and necessity measurements $\Pi(v_{2Q1})$, $N(v_{2Q1}) = 1$ (v_2 is certainly in state 1). Transition t_{12} is enabled. The evaluation of the possibility degree $\pi\tau_{ev1Q1,2}(\tau_1)$ (possibility that τ_1 is the expected date for a state change) leads to the firing of transition t_{12} (just after τ_1, τ_1^+), to the fuzzy marking M'=$\{p_{11}, p_{12}\}$ and to the updating of the values of possibility distribution $\pi_{\tau 1^+}(p_{12}) = \pi_{v1}(v_{1Q2}) = 0{,}8$ and $\pi_{\tau 1^+}(p_{11}) = \pi_{v1}(v_{1Q1}) = 1$.

Assuming that at instant τ_2 a new event ($e_{v2Q1,2}$) occurs (Fig. 3). The same evolution process as described above is carried out, leading to the fuzzy marking M'=$\{p_{21}, p_{22}\}$. The place P_1 is unmarked at the moment of the firing of t_{23}, where $\Pi(v_{2Q1}) = \Pi(v_{2Q1}) = 0$, and it is certain that v_2 in no longer in state 1. A more detailed analysis may be found in (Loures and Pascal, 2004).

4 DETECTION AND DIAGNOSIS

The qualitative model based on FTPN is utilized as prediction model of the process in the context of model-based diagnosis (MDB). According to the FTPN evolution mechanism described previously, we have a monitoring and detection of a misbehaving trajectory assigning a consistency-based diagnosis (Blanke et al., 2003). The temporal evaluation of the process events lead us also to a context of chronicles recognition (Ghallab, 1996).

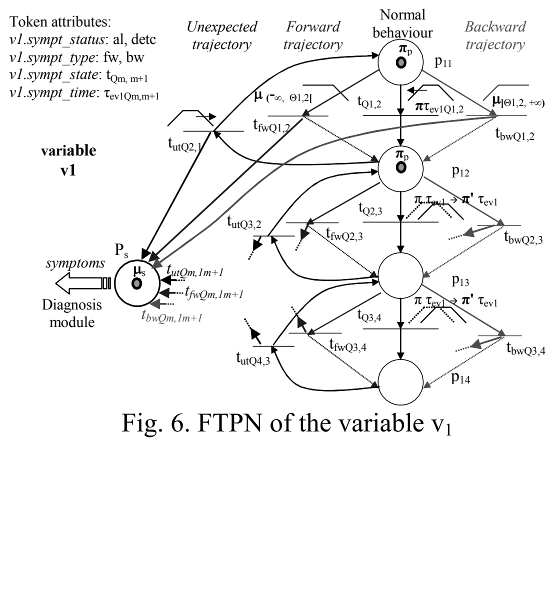

Fig. 6. FTPN of the variable v_1

4.1 Monitoring and detection

For simplicity and clearness we will only analyse variable v_1. The initial Petri net for this variable (Fig. 5) is reproduced in bold lines at the centre, as shown in Fig. 6. This Petri net receives a complementary development, so as to represent deviations with respect to the normal behaviour (alarm or fault detection conditions) as shown in Fig. 6. The place P_s (symptom place) presents a fuzzy evaluation when the trajectory of the variable is no longer normal (a symptom is detected) through the transitions (t_{ut}, t_{fw}, t_{bw}). This fuzzy marking, updated at the moment of each event, is taken into account by the diagnosis module to hypothesis revision inference:

– *Backward trajectory* (transitions $tbw_{Qm,m+1}$): corresponds to the case in which a state transition event e_2 occurs at instant τ_2, after the time window related to transition $t_{Q2,3}$ ($\pi\tau_{ev1Q2,3}(\tau_2) = 0$) (Fig. 7 and 8). For this, let $\Theta_{2,3}$ be the fuzzy set that delimits $\pi\tau_{ev1Q2,3}$. An association is made between transition $tbw_{Q2,3}$ and the fuzzy set $]\Theta_{2,3},+\infty)$ of instants that occur necessarily after $\Theta_{2,3}$, which is determined by the membership function $\mu_{]\Theta 2,3,+\infty)}(t) = \inf_{s\geq t}$ $(1 - \pi\tau_{ev1Q2,3}(s))$. This transition allows the detection of a misbehaving and the evolution of the model towards the following fuzzy marking M'=$\{p_{12},p_{13}\}$ with the possibility distribution updating: $\pi(v_{1Q2})= 1$, $\pi(v_{1Q3})= 0$ (in spite of the state transition occurrence, it is certain that the variable remains in the state v_{1Q2}). This discrepancy is treated by the fuzzy marking of the place P_s obtained by the $((\Theta_{2,3} \cap \mu_{]\Theta 2,3,+\infty)})(\tau_2) = 1)$ evaluation leading to $\mu P_s(\tau_2) = 1$. The token attributes are updated (*v_1.symp_status= detc, v_1.sympt_type=fw, v_1.sympt_state*=$v1_{Q2,3}$, *v_1.sympt_time* = τ_2) and sent to the diagnosis module.

– *Forward trajectory* (transitions $tfw_{Qm,m+1}$): considering the same reasoning detailed above, a state transition event e_1 occurs at τ_1, before the time window related to transition $t_{Q2,3}$ ($\pi\tau_{ev1Q2,3}(\tau_1) = 0$) (Fig. 7 and 8). An association is made between transition $tfw_{Q2,3}$ and the fuzzy set $(-\infty, \Theta_{2,3}[$ of instants that occur necessarily before $\Theta_{2,3}$, which is determined by the membership function $\mu_{(-\infty,\ \Theta 2,3[}(t) = \inf_{s\leq t}$ $(1 - \pi\tau_{ev1Q2,3}(s)) = 1 - \mu_{[\Theta 2,3,+\infty)}(t)$. At the moment of this transition firing, the token attributes are updated (*v_1.detec_fw =1*). The place P_s evaluation leads to $\mu P_s(\tau_1) = 1$. The token attributes are updated (*v_1.symp_status = detc, v_1.sympt_type =bw, v_1.sympt_state*=$v1_{Q2,3}$, *v_1.sympt_time* = τ_1)

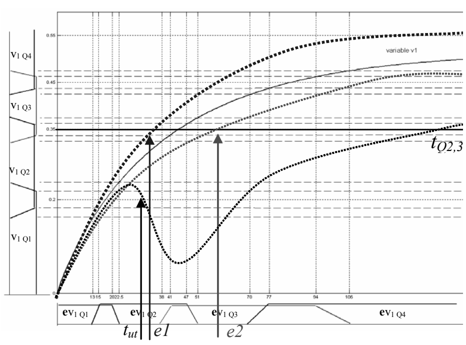

Fig. 7. *Possible trajectories of the variable v_1*

– *Unexpected trajectory* (transitions $tut_{Qm,m-1}$): this is the case in which a state transition event does not represent the expected trajectory, when considering the evolution of the variable towards the previous qualitative state (v_{1Q1}).

These situations lead to fault detection and the triggering of diagnosis. Certain situations can lead the process to a marginal deviation from its normal operation. This is the case in which $\pi e_{v1Q2,3}(\tau) \in\ ]0,1[$ (events e_3 and e_4). In such a case, an alarm situation is established (respectively *v_1.symp_status = al*) and the diagnosis module is adverted through the symptom place P_s with $\mu(P_s) \in (0,1]$. At τ_3, for instance, we have $\mu P_s(\tau_3) = 0.8$ (Fig. 8).

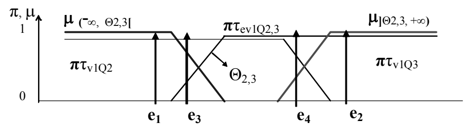

Fig.8. Possibility and necessity

4.2 Diagnostic

The fuzzy information propagation mechanism allows the qualitative time evaluation of the variables evolution. If there is a deviation over a variable v_1 in $e_{v1Qm,m+1}(\tau)$, it is possible to check its evolution in time up to instant τ, tracing back until the causes of the fault.

Based on fault knowledge some fault scenarios are constructed so as to support the hypothesis inference (preference criteria) and thus, helping the isolation and identification of the faults. This approach is supported by the diagnosis module shown in figure 9. The hypotheses are $h_y = \{f_i\} = \Im(P_{svk})$ where $f_i \in F=\{f_1,\ldots,f_n\}$ are the set of faults and $\Im$ fuzzy operations over the symptoms P_{svk}. The hypotheses are updated at each state transition occurrence (τ_{vk}).

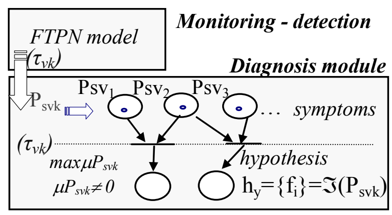

Fig. 9. Possibility and necessity

In a way to describe the diagnosis mechanism let us consider the following scenario under a defined operation mode of the coupled tank process (Fig. 1):

– *Instrumentation (known variables)*: level sensors in tank 1 and tank 2.

– *Faults*: single fault (within the time horizon) and no-varying with the time.

Based on fault knowledge and upon the measured variables (v_1 and v_2) the following hypothesis, are defined and implemented in the diagnosis module:

1. *Hypothesis h_{y1} = {output valve is closed blocked; over flow of the pump}*: the level growth rate increases

in tank 1 and tank 2 assigning a temporal misbehaving (forward trajectory) $\Rightarrow$ (v_1.sympt_type = fw) $\wedge$ (v_2.sympt_type = fw) = max($\mu P_{sv1}(\tau)$, $\mu P_{sv2}(\tau)$)=1 where $\mu P_{sv1}(\tau)$, $\mu P_{sv2}(\tau) \neq 0$

2. *Hypothesis* h_{y2} *= {connexion valve closed blocked}:* the level growth rate increases in tank 1 while the level growth rate decreases in tank 2 (v_1 forward and v_2 backward trajectories) $\Rightarrow$ (v_1.sympt_type = fw) $\wedge$ (v_2.sympt_type = bw) = max($\mu P_{sv1}(\tau)$, $\mu P_{sv2}(\tau)$=1) where $\mu P_{sv1}(\tau)$, $\mu P_{sv2}(\tau) \neq 0$.

3. *Hypothesis* h_{y3} *= {leakage tank 1, leakage tank 2, pump closed blocked}:* the level growth decreases in tank 1 and tank 2 (backward trajectory) $\Rightarrow$ (v_1.sympt_type = bw) $\wedge$ (v_2.sympt_type = bw) = max($\mu P_{sv1}(\tau)$, $\mu P_{sv2}(\tau)$)=1 where $\mu P_{sv1}(\tau)$, $\mu P_{sv2}(\tau) \neq 0$.

The revision or resolution of the conflicts from the scenarios 2 and 3 will be treated by means of a fault trajectory search method. The fault trajectories are represented by new branches of the FTPN transitions (t_{ut}, t_{fw}, t_{bw})(Fig. 6). The branch which better re-establish the consistency between the observations and the predictions (minimal discrepancy) during the monitoring, represents the faults behaviour and the solution of the fault identification $f_i \in F=\{f_1,\ldots,f_n\}$. A discrepancy decision criteria based on a fuzzy distance as in (Shen and Leitch, 1993) may be implemented.

5 CONCLUSION

In the field of supervision of hybrid dynamic systems, especially the batch treating systems, the modelling of continuous operations (e.g., distillation) is complex. It demands a high number of complex differential equations that are difficult to obtain in some cases.

Within this context, we proposed a method to identify the process dynamics of a process by means of a fuzzy partitioning of the variables trajectory. This way, qualitative states and a fuzzy temporal evaluation are obtained. The association of this information to a FTPN allows us to consider the uncertainties issues from qualitative models as well as the representation of the process behaviour, with an abstraction level that is adequate for supervision. These FTPN models are organized in a hybrid framework where the configuration, operating modes and causal knowledge are taken into account so as to support the diagnosis process.

Now existing works consist in proposing recovery state mechanisms that will allow the refining of fuzzy information about the qualitative states between two successive events. The study of the partitioning criterion is also evaluated as to refine the qualitative representation with respect to diagnosability. Moreover, concerning the diagnosis a deeper development of search fault trajectory method is done allowing a refined fault hypothesis. At last, the commutation of signals and models will be targeted.

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