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

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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 \( \tau_0 \) established according to the needs of the supervision from the measured or observable variables. The process is characterised by its input \( U(0...\tau_0) \) (defined as set-point related to the operating mode), output \( Y(0...\tau_0) \) and state measurable or observable variables \( X(0...\tau_0) \), where \( X = [x_1...x_J]^T, Y = [x_{1...x_W}]^T \) represent the vectors of the variables. In a general way these variables may be defined by \( V(0...\tau_0) = [U,Y,X] \) where \( V = [v_1...v_K]^T \).

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.

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 \( v_{km} \in \mathcal{Q}_k = \{v_{k1},...,v_{kM_k}\} \), where \( M_k \) is the number of partitions that are associated to that variable. This way, we get for \( v_1 \) the qualitative states \( v_{1km} \in \mathcal{Q}_1 = \{v_{11},...,v_{1M_1}\} \), where \( M_1 = 4 \), and for \( v_2 \) the qualitative states \( v_{2km} \in \mathcal{Q}_2 = \{v_{21},...,v_{2M_2}\} \), where \( M_2 = 4 \). This partitioning is made up by the fuzzy sets \( \psi_{km} \), which delimits the qualitative states \( v_{km} \) described by trapezoidal membership functions \( \mu_{\psi_{km}} \), thus allowing the representation of uncertainties and imprecision of the variable states (Fig. 2) and of the boundaries between these states.

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

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

- \( \pi_{1km}(v_{1km}) = 1 : v_{1km} \) is a possible state of \( v_1 \);
- \( \pi_{1km}(v_{1km}) = 0 : \) it is certain that \( v_1 \) is not in state \( v_{1km} \);
- \( \pi_{1km}(v_{1km}) = 1, \pi_{1km}(v_{1km+1}) = 1 : \) it is possible that \( v_1 \) is in state \( v_{1km} \) or \( v_{1km+1} \);
- \( \pi_{1km}(v_{1km}) = 1 \) and \( \forall v_{1km} \neq v_{1km} : v_{1km} \in \mathcal{Q}_{km} \), \( \pi_{1km}(v_{1km}) = 0 \), we can be sure that \( v_1 \) is in state \( v_{1km} \).

In our approach, for each variable, the possibility degrees \( \pi_{1km}(v_{1km}) = 0 \) 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 \( \pi v_1 \) is updated: \( \pi v_1(v_{1Qm}) \), \( \pi v_1(v_{1Qm+1}) \in (0,1] \) and \( \pi v_1(v_{1Qm^*}) = 0 \), where \( v_{1Qm^*} \not\subset v_{1Qm} \) and \( v_{1Qm^*}, v_{1Qm+1}, v_{1Qm^*} \in Q_{v_1} \).

The partitioning that is made up by the fuzzy sets \( \psi_m \), 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).

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 (Fig. 3).

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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 \( CT_v \). In a first moment, we consider two variables \( v_1 \) and \( v_2 \) with an influence relation, prior to a generalisation:

\[
CT_v = \{ e_{v1Qm,m+1}, \pi_{v1Qm,m+1}(t), \{ \pi_{v2Q}(q) \} \} \quad (1)
\]

where \( e_{v1Qm,m+1} \) represents an event at instant \( t \) indicating the passage of state \( v_{1Qm} \) to state \( v_{1Qm+1} \) (change of qualitative state), \( \pi_{v1Qm,m+1} \) represents the fuzzy time window of possible instants for change of variable \( v_1 \), and \( \pi_{v2Q}(q) \) 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:

\[
CT_v = \{ e_{v2Qm,m+1}, \pi_{v2Qm,m+1}(t), \{ \pi_{v2Q}(q) \} \} \quad (2)
\]

In general, the transition condition \( CT_{v_k} \) is:

\[
CT_{v_k} = \{ e_{v_kQm,m+1}, \pi_{v_kQm,m+1}(t), \{ \pi_{v_kQ}(q) \} \} \quad (3)
\]

where \( CT_{v_k} \) represents the transition relation of a variable \( v_k \in V \), associated to variables \( v_k \neq v_k \in V \in \{ V_1 \}, V_1 \subset V \) represents the set of associated variables issue from the influence knowledge.

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 \( \{ \pi_i(Q_{t[i]} \} \) 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:

\[ FTPN = <P,T,Pre,Post,Mo,Θ> \]

where: \( P \) is a non-empty set of places, \( T \) is a non-empty set of transitions, \( Pre \) is a multi-set over \( P \times T \) - a backward function, \( Post \) is a multi-set over \( T \times P \) - a forward function, \( Mo \) the initial marking, \( Θ : T → CT \) the transition function \( CT_vk \) (eq.3), previously described.

![Fig. 5. FTPN as the reference model](image)

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 \( π_{v2Q1,2} \) (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:

\[ Π(v_{1Q}) = \max_{q} v_{1Q} π_v(q), \]

where \( v_{1Q} = (v_{1Q1},v_{1Q2}), v_{1Q} \subseteq Q_k \)

then \( Π(v_{1Q}) = \max_{q} v_{1Q} π_v(q), N(v_{1Q}) = 1 - Π(v_{1Q}) = \max_{q} v_{1Q} π_v(q), \)

where \( v_{1Q} = (v_{1Q1},v_{1Q2}), v_{1Q} \subseteq Q_k \)

At instant \( τ_0 \), the qualitative states of variables \( (v_{1Qm} \text{ and } v_{2Qm}) \) are known. Therefore, we can say that \( Π(v_{1Qm}) = Π(v_{2Qm}) = 1 \) and \( N(v_{1Qm}) = N(v_{2Qm}) = 1 \), once \( \pi_v(v_{1Qm}) = 1 \) and \( v_{1Qm} \neq v_{1Qm} \in Q_m \pi_v(v_{1Qm}) = 0 \), 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 \( ≠ 0 \)), which leads to a fuzzy marking \( π(v(1Qm)), π(v(1Qm+1)) = (0,1] \) and \( π(v(1Qm)) = 0 \), where \( v(1Qm) ≠ v(1Qm) \text{ and } v(1Qm), v(1Qm+1), v(1Qm) ∈ G_{14} \), 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 \( π_{v1}(p_{11}) = 1 \) and \( π_{v1}(p_{12}) = 0 \), determining a precise marking \( M_{11} = \{p_{11}\} \). The evaluation of the possibility degree \( π_{a}(V_{2Q1}) \) (eq.1) is done through the place \( P_1 \), to which are related the possibility and necessity measurements \( Π(v_{2Q1}), N(v_{2Q1}) = 1 \) (\( v_2 \) is certainly in state 1). Transition \( t_{12} \) is enabled.

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 \( Π(v_{2Q1}) = Π(v_{2Q1}) = 0 \), and it is certain that \( v_2 \) in no longer in state 1. A more detailed analysis may be found in (Loureis 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 evolution mechanism (Fig. 5).

![Fig. 6. FTPN of the variable v1](image)
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) over flow of the pump. For simplicity and clearness we will only analyse variables \( v_1 \) and \( v_2 \) the following hypothesis, are defined and implemented in the diagnosis module:

1. Hypothesis \( h_{31} = \{ \text{output valve is closed blocked; over flow of the pump} \} \); the level growth rate increases

\( e_2 \) occurs at instant \( t_2 \) after the time window related to transition \( t_{Q2,3} \) (Fig. 7 and 8). For this, let \( \Theta_{2,3} \) be the fuzzy set that delimits \( \pi_{\text{ev1Q2,3}} \). An association is made between transition \( t_{Q2,3} \) and the fuzzy marking \( \mu_{\Theta_{2,3}}(t) = \inf_s (1 - \pi_{\text{ev1Q2,3}}(s)) \). This transition allows the detection of a misbehaving 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 \( \pi_{\text{ev1Q2,3}}(t) \in [0,1] \) (events \( e_3 \) and \( e_4 \)). In such a case, an alarm situation is established (respectively \( v_1.\text{sympt\_status} = \text{fault} \) and the diagnosis module is adverted through the symptom place \( P_s \) with \( \mu_{P_s}(t) = 0.8 \) (Fig. 8).

\[ \mu_{P_s}(t) = 0.8 \quad (\text{Fig. 8}) \]

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 \( h_i = \{ f_i \} \subseteq \mathcal{P}_{\text{symptoms}} \) where \( f_i \in \mathcal{F} = \{ f_1, \ldots, f_n \} \) are the set of faults and \( \mathcal{F} \) fuzzy operations over the symptoms \( \mathcal{P}_{\text{symptoms}} \). The hypotheses are updated at each state transition occurrence (\( \tau_{\text{symptoms}} \)).

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 \( \mathcal{F} = \{ f_1, \ldots, f_n \} \), it is possible to check its evolution in time up to instant \( \tau_{\text{symptoms}} \) tracing back until the causes of the fault.

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

2. \textbf{Hypothesis} \( h_{2i} = \{\text{connexIon valve closed blocked}\}: \) the level growth rate increases in tank 1 while the level growth rate decreases in tank 2 \( (v_1 \text{ forward and } v_2 \text{ backward trajectories}) \Rightarrow (v_1, \text{sympt\_type} = \text{fw}) \wedge (v_2, \text{sympt\_type} = \text{bw}) = \max(\mu P_{sv1}(t), \mu P_{sv2}(t))=1 \) where \( \mu P_{sv1}(t), \mu P_{sv2}(t) \neq 0. \)

3. \textbf{Hypothesis} \( h_{3i} = \{\text{leakage tank 1, leakage tank 2, pump closed blocked}\}: \) the level growth decreases in tank 1 and tank 2 (backward trajectory) \( \Rightarrow (v_1, \text{sympt\_type} = \text{bw}) \wedge (v_2, \text{sympt\_type} = \text{fw}) = \max(\mu P_{sv1}(t), \mu P_{sv2}(t))=1 \) where \( \mu P_{sv1}(t), \mu P_{sv2}(t) \neq 0. \)

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 \( (t_{ab}, t_{bc}, t_{ba}) \) (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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