Automatic Acquisition and Update of a Causal Temporal Signatures Base- for Faults Diagnosis in Automated Production Systems

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Abstract: Causal Temporal Signatures (CTS) is an efficient formalism for behaviors description and recognition of fault diagnosis in Discrete Event Systems (DES). The main advantages of this formalism are the readability and the expressivity. Indeed, it is able to describe clearly all desired behaviors and it is understandable and readable by an expert in the field. However, it raises the problem of acquisition and updating of expert knowledge stored in a CTS base. In this paper, we suggest an incremental learning approach based on the simulation to acquire and update automatically a consistent CTS base. The proposed approach is illustrated with an example applied to the turntable helps to understand the different modules of the method.

1 INTRODUCTION

Over the recent decades, the automation of industrial systems has aimed at increasing the production performance, enhancing product quality, reducing its cost and making its equipments more available in the market. Indeed, the Automated Production Systems (APS) can be considered from three different views depending on their dynamics: Continuous Systems, Discrete-Event Systems (DES) and Hybrid Systems.

In this context, on-line diagnosis systems are necessary to detect, locate, and identify as soon as possible the potential failure at the system on run. In this paper, we are interested in an online diagnosis of APS considered as DES.

In fact, when the system is running, a large number of observations come forward regularly and should be considered. These amounts of data cannot be processed online by a human operator due to their complexity and / or their large number. From this observation, the need for proposing specific support tools used to analyze and process these data has emerged in order to recognize both normal and faulty behaviors. These tools are able to first describe and represent the possible evolutions of the systems in form of rules or predicates and secondly to recognize these behaviors in a flow of events.

The literature distinguishes several description and recognition tools, such as chronicles with different definitions (Dousson et al., 1993), (Boufaied et al., 2002), (Bertrand et al., 2007), (Carle et al., 2011), (Subias et al., 2014), (Cram et al, 2012) and Causal Temporal Signatures (CTS) (Toguteni et al., 1991), (Saddem et al., 2011), (Saddem et al., 2014), etc. The main advantage of these tools is their high efficiency due to the symptom to fault knowledge they rely on (Cordier et al., 2000). However, the common problem is the difficulty of acquiring and updating this expert knowledge. The literature shows two types of approaches on this problem: model based approaches (Guerraz and Dousson, 2004) (Saddem and Philippot, 2014) and data-based approaches (Dousson and duong, 1999) (Cordier and Dousson, 2000) (Cram et al., 2012), (Subias et al., 2014). A key limitation of data-based approaches is the need of human expert (analyst) intervention. Indeed, they require its presence either for the qualification of the chronicles (Dousson and duong, 1999) (Cordier and Dousson, 2000) or for the definition of constraints to guide the algorithm of the discovery of the chronicles of interests (Cram et al., 2012), (Subias et al., 2014). This article offers a solution for CTS formalism that is very close to chronicle formalism. It presents a new approach based on past experiences and couples simulation with learning to automatic acquisition and updating of a CTS base. The coupling between simulation and learning (AI technique) is a promising solution where

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simulation is used as a technique for generating empirical knowledge for learning. On the one hand we propose a Representation of Observations in form of CTS Algorithm (ROCTSA) which describes the possible evolutions of the system to diagnose as a set of CTS. The algorithm allows to model normal behavior of the system as normal CTS and faulty behavior as abnormal CTS. This set constitutes the learning base. On the other hand, an incremental learning module is introduced to learn new CTS and to update the CTS base based on past experiences. The remainder of this paper is organized as follows. In section 2, problem background, definitions and concepts of CTS are detailed. In section 3, we describe an example of APS on which we will rely to illustrate our approach. Section 4 is devoted to present our proposed method. In section 5, we present the results of applying our approach to the described example. A conclusion and a perspective for future works are presented in section 6.

2 PROBLEM BACKGROUND, DEFINITIONS AND CONCEPTS

We begin this section by presenting a short state of the art on knowledge building approaches for chronicle and CTS formalisms and providing concepts and definitions that explain CTS formalism.

2.1 State of the Art on Knowledge Building Approaches for Chronicles and CTS

In the literature, several approaches have been suggested for acquiring and updating chronicles or CTS base either from models or data.

- Model based approaches:

Are problem solving techniques based on models representing either the system to diagnose or the faults that may exist in the system. For example, (Guerraz and Dousson, 2004) developed a petri nets based method for the generation of chronicles necessary for diagnosis from the fault model of the system to diagnose. The proposal does not require knowledge of the global behavior of the system. Another solution is described in (Saddem and Philippot, 2014) to translate a timed Atomaton model of a diagnoser into CTS. The method ensures the completeness of the CTS data base but it is done manually.

- Data based approaches:

They rely on historical data by extracting significant features using temporal data mining techniques. One of the first examples is suggested in (Dousson and Duong 1999), (Cordier and Dousson, 2000). It introduced FACE (Frequency Analyzer for Chronicle Extraction) which is a technique for analyzing log files of alarms (i.e. events) inspired from data mining techniques. It allows analyzing log files of alarms in order to determine the most frequent alarms and to reduce their number displayed to the operator. The negative point of FACE is that during the generation of chronicles (candidates), there is only one time constraint that is taken into account.

To fill this limit, (Cram et al., 2012) proposed a process of discovering chronicles from a trace (i.e. temporal sequence). The learning process is based on two steps:

(i) Construction of a database of time constraints. It allows to associate for each pair of events, a set of temporal constraints represented in a graph called constraint graph. The graph is constructed through the Complete Constraint-Database Construction (CCDC) algorithm.

(ii) A Heuristic Chronicle Discovery Algorithm (HCDA) that generates a set of chronicles (candidates) from a set of chronicles that are frequent and uses the temporal constraint database to explore the chronicle space.

The latest solution is described in (Subias et al., 2014). It improved the proposal of (Cram et al., 2012) to learn frequent chronicles for several temporal sequences (not only one temporal sequence) in order to represent variants of a single situation.

The intervention of human experts (i.e. analysts) represents a major drawback to these data-based methods. Indeed, they require their presence either for the qualification of chronicles (Dousson and Duong, 1999), (Cordier and Dousson, 2000) or for the definition of constraints to guide the algorithm of discovery of chronicles of interests (Cram et al . 2012), (Subias et al., 2014).

In this work, we present a new approach based on past experiences to automatic acquisition and updating of a CTS base. Construction and CTS labeling are purely automatic (they don't require a human expert). The following section details the basic concepts of CTS formalism.

2.2 Definitions and Concepts

CTS were proposed in the early 90s by (Toguyeni et al., 1991). Then, they were improved by (Saddem et al., 2011). Like chronicles, a CTS is a formalism for the description and recognition of behaviors applied to the DES diagnosis. It was defined in the work of Saddem (Saddem et al., 2011) as *"a subset of partially-ordered observable events that characterizes the system faulty behavior"* and as "*the description of a temporal pattern defining a partial order on events determined by their type and date of occurrence"*.

Diagnosis based on CTS consists in interpreting online the event occurrence to instantiate the pattern to be recognized. In fact, a CTS is recognized when all its events occur while respecting their temporal constraints. This determines if the system is operating normally or not. The literature shows a variety of algorithms for chronicle and CTS recognition (Dousson et al., 1993), (Bertrand et al., 2007), (Saddem and Phillippot, 2014). In this paper, we are interested in the acquisition and the update of a set of CTS (CTS base) that will be the input of recognition algorithm. We present (in the rest of the section) the basic concepts of CTS formalism in the rest of the section.

Definition 1 (Event)
Let *EN* be a finite set whose elements are called by the observable events names. Let *E* be a finite set whose elements are observable events. A naming function is a total function *H: E -> EN* that assigns a name to each observable event.

Definition 2 (Occurrence of an event)
E is a finite set whose elements are observable events. Let *F* be a set of times corresponding to the times of events production. An occurrence function is a function *O*: *E-> F* that associates to each observable event a time at which it occurs.

Definition 3 (CTS triplet)
Let t_i be a CTS triplet defined by: (e_r, e_c, Ct_{rc}) where e_r is the name of a reference observable event, e_c is the name of an observable constrained event expected compared to e_r, and Ct_{rc} is a temporal constraint.

Definition 4 (Temporal constraint)
Let Ct_{rc} be a temporal constraint which corresponds to a relative time separating the occurrence of an event having e_r reference and an expected one e_c. The time constraint can be a date, a period or a duration.

✓ Date constraint:
A date constraint (figure 1) allows modeling the exact time separating the occurrence of two events. It is defined by:

$$O(e_c) - O(e_r) = \Delta t \qquad (1)$$

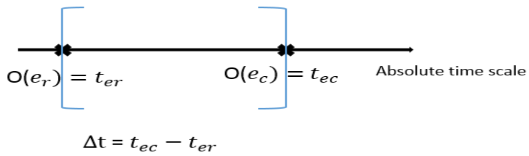


Figure 1: Date constraint.

✓ Period constraint:
A period constraint (figure 2) allows the modeling, with uncertainty degree, of the time between the occurrence of two events. It expresses that e_C must occur after e_r in a time interval [*α*, *β*] where *α* and *β* ∈Q⁺.

$$\alpha \le O(e_c) - O(e_r) \le \beta \qquad (2)$$

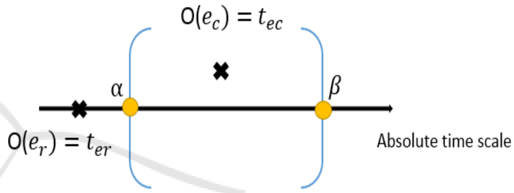


Figure 2: Period constraint.

✓ Duration constraint
A duration constraint is generally used to characterize an event which persists in time. It shows that an event e_i occurs for the date Δt_1 to the date $\Delta t_1 + \Delta t_2$.

Note 1:
In order to describe the dynamics of DES that we are studying, we consider time as a set of discrete linearly-ordered instants and we use only the period constraint in our examples.

Definition 5 (CTS)
Let *T* be a countable set whose elements are triplets of CTS. Indeed, a CTS represents a rule that can be formally defined as follows:

$$X \rightarrow Y \qquad (3)$$

✓ X consists of a sequence of a subset of triplets *TR* included in *T* where $t_i * t_j$ describes the recognition of triplet t_i followed by that of triplet t_j .

✓ Y represents the state of the system following this signature (normal or faulty behavior).

✓ We choose to identify each CTS by a unique identifier which is an integer.

Definition 6 (Normal CTS)
It is a CTS that describes a normal behavior in the system. It is defined by:

$$X \to N \tag{4}$$

N denotes a normal behavior in the system.
Definition 7 (Abnormal CTS)
It is a CTS that describes a faulty behavior in the system. It is defined by:

$$X \to Fi \tag{5}$$

Fi presents a system failure.

We note that APS study is carried out from the point of view of the operative part (OP). That's why we only treat internal failures, those caused by the OP, such as the stuck-off to 1 or 0 of a sensor or an actuator.

Example 1:

$$(In, A, nct)*\ (A, B, [t1, t2])\ *\ (A, D, [t3, t4])\ -> F1 \tag{6}$$

In is the name of an observable event that is always occurring. It is used as the reference of events that are not constrained. *nct:* implies the absence of time constraint. The rule (6) implies that if event *A* (not limited by any temporal constraint) occurs followed by the occurrence of event *B* satisfying the period constraint [*t1*, *t2*] with respect to *A* and the occurrence of event *D* satisfying the period constraint [*t3*, *t4*] with respect to A, then we can deduce the system is faulty and *F1* is the fault.

3 STUDY FRAMEWORK

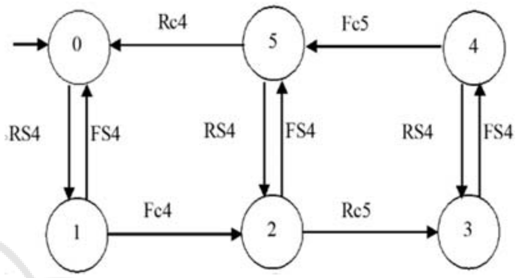
In this section, we describe an example of APS which we will rely on to illustrate our approach presented later. We chose the sorting system which brings boxes of entry conveyor to exit conveyor by sorting them according to their size. The system has 11 sensors to determine boxes size (small or large) and the box entry or exit in different conveyors (feeding, intermediate, and evacuation) or turntable. It also has 7 actuators to activate the various conveyors and the turntable. In our case, we only present our results for the turntable, a component of the sorting system. It has 2 sensors (c4, c5) and 1 actuator (S4). The specifications retained are presented through a state automaton with 6 states and 10 transitions (figure 3). Normal behavior of the component can be described through two paths:

Path A: State 0 -> State 1 -> State 2 -> State 3 -> State 4 -> State 5 -> State 0

From the initial state '0', the turntable is in the c4 loading position. If the S4 actuator is activated, the turntable is moving and sensor c4 is deactivated (transition from state "1" to "2"). From there, if the command is still active, the turntable returns to the unloading position (transition from state "2" to "3"). Disabling the S4 actuators allows returning to the original position (states "4" after "5" then "0").

Path B: State 0 -> State 1 -> State 2 -> State 5 -> State 0

From state '2', during the movement, and if the S4 actuator is deactivated, the turntable returns directly to state '0'.



c4: Detector of the turntable loading position
c5: Detector of the turntable unloading position
S4: Turntable

Figure 3: Model of turntable.

An expert work allowed to obtain the following internal failures that may occur in the turntable: F1: c4 stuck at 0, F2: c4 stuck at 1, F3: c5 stuck at 0, F4: c5 stuck at 1, F5: S4 stuck at 0, F6: S4 stuck at 1, F7: unexpected passage of c4 from 0 to 1, F8: unexpected passage of c4 from 1 to 0, F9: unexpected passage of c5 from 0 to 1, F10: unexpected passage of c5 from 1 to 0.

In the following sections, we will try to formulate automatically CTS which are able to describe these normal and faulty behaviors of the turntable. Our approach is presented in the next section.

4 PROPOSED APPROACH

The main idea of our approach (figure 4) is to couple simulation with learning (AI technique) (Monostori et al., 2000), (Belisario et al., 2015). The simulation describes the evolution of the studied model over time in order to provide useful information on its dynamic behavior in different situations (including situations of dysfunctioning). This information can be exploited by an expert system or a decision maker (Pierreval and Ralambondrainy, 1992).

In our proposal, this information (i.e. signals of sensors and actuators) is the input of the proposed Representation of Observations in form of CTS Algorithm (ROCTSA) which allows to model the normal behavior of the system as a set of normal CTS and the faulty behavior as a set of abnormal CTS. From these CTS examples (i.e learning base), an incremental learning is introduced to learn new CTS and to update the CTS base based on past experiences.

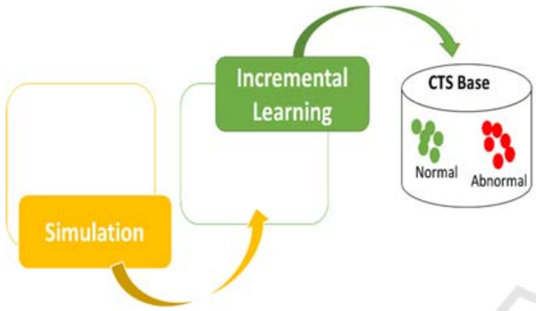


Figure 4: Proposed approach.

4.1 Simulation

Simulation is a necessary module to generate examples of CTS from which it will be possible to learn new knowledge and update the knowledge base. It consists in:

a) Operating the model of the real system in a normal mode (absence of failures) and abnormal mode (triggering failures).
b) Collecting for each mode the relevant information (values of the sensors +actuators+ dates) from the model.
c) Generating from these information causal temporal signatures through the proposed Representation of Observations in form of CTS Algorithm (ROCTSA) which will be presented in the following paragraph.

4.1.1 Principle of ROCTSA

For each PLC cycle (T), the algorithm constructs a triplet (e_r, e_c, Ct_{rc}) from a binary signature which represents the signals of sensors and actuators of the system to be diagnosed and from a binary signature which represents the signals during the previous PLC cycle (T-1). A CTS is the concatenation of *at least two triplets*.

The proposed algorithm can be illustrated through these steps:

- ✓ *Step 1*: Group the signals of the sensors and actuators of the system to be diagnosed during the PLC cycle (T) in order to construct a binary signature and associate a cycle time to it. (Note: tampon is the binary signature of the previous PLC cycle (T-1) and PreviouscycleTime is its cycle time).
- ✓ *Step 2:* Formulate the reference event (e_r): If this is the first PLC cycle executed then er <- "IN" otherwise the constrained event of the previous PLC cycle (T-1) becomes the reference event of the PLC cycle T.
- ✓ *Step 3:* Formulate the constrained event (e_c): Each element of the binary signature is transformed into an event that can be either the *rising edge* (denoted by *R*) or the *falling edge* (denoted by *F*) of a sensor or actuator. This event is defined as a constrained event.
- ✓ Step 4: Formulate the temporal constraint (temporalC): If the referent event(er) is equal to IN then absence of the temporal constraint (nct) otherwise the temporal constraint is constructed from two times [DateMin, DateMax].

DateMin<- CurrentcycleTime- PreviouscycleTime
DateMax<- DateMin +d

with "d" is the duration of the PLC cycle, DateMin is the lower bound of the period constaint and DateMax is the upper bound of the period constraint.

- ✓ *Step 5:* Group the result of the 3 previous steps to construct a triplet of the CTS.

The complexity of the algorithm is a linear complexity with respect to the size of the binary signature: O (K (n + m)) where K is the number of PLC cycles performed by the automated production system, n is the number of sensors and m is the number of actuators.

4.1.2 Labeling of CTS

The operation of the model in a normal mode and abnormal mode (triggering failures) allows the labeling of each instance of CTS automatically without the need for an expert accompanying the data formatting process and it does not need to give advice (normal or faulty behavior). The normal functioning of the model is represented as a set of normal CTS, while the faulty one is defined as a set of abnormal CTS. Both types of CTS are stored in a CTS Base. This base is the learning base.

4.2 Learning Module

For new CTS learning, we rely on the learning data stored in the CTS base obtained during the simulation module. Each new observation is transformed into a new CTS (nCTS) through ROCTSA. The principle of this module consists in extracting, for each nCTS, the similar or nearest CTS from the CTS Base. The research is based on the use of a similarity metrics that calculates the degree of similarity between the new CTS and the past CTS.

For this reason, we use a similarity calculator that has as input a nCTS and the CTS base. Its outputs are the similarity values between the nCTS and all the past CTS (pCTS) stored in the base. Then, the new CTS will inherit the result of the CTS having the greatest similarity and will be stored in CTS Base.

4.2.1 Similarity Calculator

Let *S* be the similarity relation defined by:

$$S = \text{CTS} \times \text{CTS} \to [0, 1]$$

-If CTS_i and CTS_j are equal, then S (CTS_i, CTS_j) =1

-If CTS_i and CTS_j are not equal, then S (CTS_i, CTS_j) =0

Calculate the similarity between two CTS is to calculate the distance:

$$D(CTS_i, CTS_j) = 1 - S(CTS_i, CTS_j) \quad (7)$$

To calculate the distance between two CTS, we must compute the distance separating its triplets. The triplets consist of different types of elements (event of chain type, time constraint of interval type), which makes the distance calculating a difficult step.

To solve this problem, we propose to discretize the values of the triplets' elements as follows:

- To events, we assign the value 1 if Val $(e_{t_{i,k}})$ = Val $(e_{t_{j,k}})$ and the value 0 if Val $(e_{t_{i,k}}) \neq$ Val $(e_{t_{j,k}})$ where Val is the value of the event, $(e_{t_{i,k}})$ denotes an event of a triplet t_k of a CTS_i and $(e_{t_{j,k}})$ represents an event of a triplet t_k of CTS_j.
- To temporal constraints of interval type, we assign the value 1 if Val (lower bound $(C_{t_{i,k}})$) >= Val (lower bound $(C_{t_{j,k}})$) and Val (upper bound $(C_{t_{i,k}})$) <= Val (upper bound $(C_{t_{i,k}})$), otherwise 0, where Val is the value of the lower or upper bound of the temporal constraint, $(C_{t_{i,k}})$ is a time constraint of a triplet t_k of a CTS_i and $(C_{t_{j,k}})$ is a time constraint of a triplet t_k of a CTS_j. Thus, the value of a triplet t_k of a CTS_i $(Vt_{i,k})$ is calculated by the aggregation of values of its events and its temporal constraint.

4.2.2 Distance Metric

The choice of distance metric depends on data type to compare (nominal, ordinal, continuous or binary). Indeed, values of triplets are numerical. Therefore we choose the Manhattan distance (Stahl, 2003) to calculate the distance between two CTS.

$$D(CTS_i, CTS_j) = \frac{1}{3m} \times \sum_{k=1}^{m} \left| Vt_{i,k} - Vt_{j,k} \right| \quad (8)$$

Where *TR* is the set of triplets representing a CTS defined by $TR = \{t_1, t_2, t_3, ..., t_m\}$, m is the triplets number of a CTS, *m*>=2 and $Vt_{i,k}$, $Vt_{j,k}$ are the triplet values.

5 EXPERIMENTATION

To validate our proposal, we exploit the Interactive Training System for PLC (ITS PLC) proposed by the Portuguese company Real Games (www.realgames.pt). ITS PLC is an education and training tool dedicated to programming the PLC and validating the control algorithm through a real time interactive experience (Riera et al., 2010). It offers 3D simulations of Operative Parts (OP) of 5 industrial systems (sorting, batching, palletizer, pick and place and automatic warehouse). Each system a graphical simulation of an operative part including its sensors and its actuators and allowing a PLC to control it.

We use the beta version of ITS PLC in this study which allows: (a) using scripts in IronPyton (http://ironpython.net) to write its own controllers in a language close to the ST (Structured Text). (b) accessing to an Interactive IronPython Interpreter allowing the user to interact with each simulated system by accessing for example to its inputs / outputs through the IO object. IO.Actuators and IO.Sensors respectively return the actuators and sensors signals. (c) simulating failures in sensors and actuators. Our proposal was led through the development of 2 scripts:

- ✓ The first one allows controlling the sorting system without the need for a real API
- ✓ The second one allows access to the inputs / outputs of the simulated system each the 16ms (ITSPLC cycle duration), to implement the

ROCTSA (simulation module) and the similarity calculator (learning module).

Note: we chose the duration of a temporal constraint of period type (d) is 5ms.

During the simulation module, the set of normal and abnormal CTS are recorded in the CTS base to form the learning base. Figure 5 shows various examples of CTS instances with the different attributes of the learning base. It describes 10 instances labeled as normal behaviors of the turntable and 7 instances labeled by the various failures as previously described.

Instance 5 of the learning base is a normal CTS which corresponds to this rule:

(In, ↑S4, nct)* (↑S4, ↓c4, [80, 85])* (↓c4, ↑c5, [2816, 2821])* (↑c5, ↓S4, [6912, 6917])* (↓S4, ↓c5, [80, 85])* (↓c5, ↑c4, [2816, 2821]) -> N

This signature describes the passage through the different states of path A (introduced above). It implies that if the rising edge of the S4 actuator (↑S4) occurs followed by the occurrence of the falling edge of sensor c4 (↓c4) satisfying the time constraint [80, 85] with respect to ↑S4, the occurrence of the rising edge of the sensor c5 (↑c5) satisfying the constraint [2816, 2821] with respect to ↓c4, the occurrence of the falling edge of the S4 actuator (↓S4) satisfying the constraint [6912, 6917] with respect to ↑c5 of the falling edge of the sensor (↓c5) satisfying the constraint [80, 85] with respect to ↓S4 and the rising edge of sensor c4 (↑c4) satisfying the constraint [2816, 2821] with respect to ↓c5, then we
the normal behavior of the system.

Instance 11 of the learning base is an abnormal CTS which corresponds to this rule:

(In, ↑S4, nct)*(↑S4, ↑c5, [2896, 2901])-> F2

It implies that if the rising edge of the S4 actuator (↑S4) occurs followed by the occurrence of the rising edge of sensor c5 (↑c5) satisfying the time constraint [2896, 2901], then we can deduce the faulty behavior F2. The learning module uses these past experiences to add new CTS to the CTS base (to promote learning).

Example**:** We propose to add an nCTS and search the most similar using our similarity calculator. ROCTSA starts generating an nCTS:

nCTS: (↑c4, ↑S4, [65664,65669])* (↑S4, ↓c4, [80, 85])-> **?**

It does not exist in the CTS base. Consequently, the similarity calculator can be launched. The nCTS inherits the (normal or faulty) behavior of the CTS which has the minimum distance and will be stored in the CTS Base. In this example, CTS 6 has the minimum distance (D=0.166). Therefore, the nCTS inherits the normal behavior of CTS 6 and is stored in the CTS Base.

6 CONCLUSIONS

In the context of diagnoses, we suggest a new approach based on past experiences which couples a simulation with learning for automatic acquisition and update of a set of CTS. We present ROCTSA algorithm allowing to model the normal behavior of the system to diagnose as a set of normal CTS and the faulty behavior as a set of abnormal CTS. A learning module is introduced to learn new CTS and to update the CTS base. The proposed approach has many advantages: (i) An easy update for the CTS Base. Indeed, when a new behavior occurs in the APS, a new CTS will be added to the CTS base that models this new behavior. (ii) It is a generic approach that can be applied to any APS. (iii) It does not require the presence of an expert who might be reluctant to acquire a CTS base. As a prospect, to improve the expressiveness of ROCRSA, we will express the absence of events (negation operators). Then, we will use this work to introduce a distributed approach for complex system diagnoses. It will be based on a multi-agent architecture which decomposes the system to be diagnosed into subsystems. Each subsystem will be supervised through an agent which is responsible for the acquisition of its CTS Base and its local diagnosis.

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I_D	X																								Y
	t1				t2				t3				t4				t5				t6				
	e_r	e_c	L	U	e_r	e_c	L	U	e_r	e_c	L	U	e_r	e_c	L	U	e_r	e_c	L	U	e_r	e_c	L	U	
1	In	RS4	0	0	RS4	FC4	80	85																	N
2	In	RS4	0	0	RS4	FC4	80	85	FC4	RC5	2816	2821													N
3	In	RS4	0	0	RS4	FC4	80	85	FC4	RC5	2816	2821	RC5	FS4	6912	6917									N
4	In	RS4	0	0	RS4	FC4	80	85	FC4	RC5	2816	2821	RC5	FS4	6912	6917	FS4	FC5	80	85					N
5	In	RS4	0	0	RS4	FC4	80	85	FC4	RC5	2816	2821	RC5	FS4	6912	6917	FS4	FC5	80	85	FC5	RC5	2816	2821	N
6	RC4	RS4	21760	21765	RS4	FC4	80	85																	N
7	RC4	RS4	21760	21765	RS4	FC4	80	85	FC4	RC5	2816	2821													N
8	RC4	RS4	21760	21765	RS4	FC4	80	85	FC4	RC5	2816	2821	RC5	FS4	6864	6869									N
9	RC4	RS4	21760	21765	RS4	FC4	80	85	FC4	RC5	2816	2821	RC5	FS4	6864	6869	FS4	FC5	80	85					N
10	RC4	RS4	21760	21765	RS4	FC4	80	85	FC4	RC5	2816	2821	RC5	FS4	6864	6869	FS4	FC5	80	85	FC5	RC5	2816	2821	N
11	In	RS4	0	0	RS4	RC5	2896	2901																	**F2**
12	In	RS4	0	0	RS4	FC4	80	85	FC4	RC5	2816	2821	RC5	FS4	6928	6933	FS4	FC5	80	85	FC5	RC5	2496	2501	**F4**
13	In	RS4	0	0	RS4	FC4	80	85	FC4	RC5	1616	1621													**F9**
14	In	RS4	0	0	RS4	FC4	80	85	FC4	RC5	2816	2821	RC5	FC5	720	725									**F6**
15	In	RS4	0	0	RS4	FC4	80	85	FC4	RC5	2816	2821	RC5	RC4	1376	1381									**F7**
16	In	RS4	0	0	RS4	FC4	80	85	FC4	RC5	2816	2821	RC5	RC4	656	661	RC4	FS4	6240	6245					**F5**
17	In	RS4	0	0	RS4	FC4	80	85	FC4	RC5	2816	2821	RC5	FC5	192	197									**F10**

ID : identifier of the instance, X: sequence of triplets, Y: state of the system, ti : CTS triplet,
er: reference event, ec: constrained event, L: lower bound of the period constraint, U: upper bound of the period constraint.

Figure 5: Learning base.