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Timed automaton models for fault diagnosis of the drilling process on a CNC machine

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Abstract

Fault diagnosis is a crucial task to guarantee reliability, and reduce losses and production cost in smart machining. In order to do so, it is necessary to implement a fault diagnoser that does not use a large amount of memory and that is capable of detecting the occurrence of a fault in a fast manner. In this paper, we propose timed automaton models, which represent the drilling process on a CNC machine, that are suitable for fault diagnosis. The fault diagnoser uses only the spindle power and Z axis displacement read directly from the system controller, and does not need any additional sensors. The proposed diagnoser is capable of identifying the occurrence of a wrong sequence of events executed by the system and the use of a material different from the expected.

keywords: Industry 4.0, Fault diagnosis, Discrete-event systems, CNC machine

1 Introduction

With the advances of the Industry 4.0, it is expected a more integrated operation between humans and machines. In order to do so, it is necessary to provide a safe environment where humans can better visualize the operations that the machines are performing, and the system must report alarms when there is some kind of fault in the system in order to the operator to actuate the system with a view to mitigating possible damages. Thus, an automatic fault diagnosis system is crucial to guarantee reliability, and reduce losses and production cost in smart machining.

Computer numerically controlled (CNC) machines perform the machining processes in the industry due to their high precision, repeatability, flexibility and lower production costs. The CNC machine can be programmed through a CAM software that produces an ISO program using simple commands to obtain a desired product, and it is very important that any abnormal condition can be rapidly identified by the operator in order not to waste the workpiece or cause an excessive wear of the cutting tool. Thus, the implementation of a fault diagnoser would

help the operator in his decision to recover the system from the fault and it is the first level for developing smart manufacturing systems [4]. Indeed, smart machining refers to real time diagnosis, alert to the operator and adaptation of cutting parameters for process optimization based on a data base [1]. For example, thousands of holes has to be drilled for assembling stack layers in an aircraft, so smart drilling is a key point for performance maximization because each layer should be machined with different parameters to have a proper tool life [18, 10]. Thus, the identification of the material is mandatory for adapting the proper cutting parameters, as feed rate and cutting speed, in real time for process optimization [11].

Several works in the literature address the problem of fault diagnosis of CNC machines using different strategies and objectives. In [9], a method of diagnosis of multiple faults in the flood coolant system of a CNC vertical milling machine tool is presented. In [12], an intelligent integrated diagnosis system is proposed based on neural networks and expert systems, and, in [14], a method for fault diagnosis of temperature sensors along with the recovery for faulty data is presented. In [25], a method for data acquisition of CNC machine tools based on OPC specification, the communication framework of state data, and application of data mining are presented. Using the method, the user is able to build a monitoring platform which can provide fault warnings. More recently, in [5], the use of expert knowledge-based systems is proposed for identifying machine tool failures caused by accidental events such as cable disconnection or impact events, and in [27], a fault diagnosis strategy based on cascading failures is proposed. The fault propagation model, which models the process of fault propagation, is constructed, and can be used to locate the source of the fault.

A different approach for fault diagnosis has been presented in the seminal work by [20] in which the system is abstracted as a Discrete-Event System (DES), *i.e.*, a system with discrete set of states and whose state evolution depends entirely on the occurrence of discrete events over time [3], and the fault is said to be diagnosable when it can be detected and isolated within a bounded number of event occurrences. Thus, the fault diagnoser must observe the sequence of events generated by the system and compare it with the sequences which have the same observation that can be generated by the corresponding model. If the observed sequence corresponds only to sequences containing a specific fault type, then this fault is diagnosed. Since then, several strategies for fault diagnosis of DES have been presented in the literature for untimed and timed system models [21, 2, 17, 6, 8, 23, 24, 26].

In some cases, however, obtaining the DES model may be a difficult or even impossible task, since the number of states of the system grows with its complexity. In order to overcome this problem, several works in the literature present methods of identification of DES with the aim of fault diagnosis [19, 13, 15, 16]. In addition, some faults cannot be detected by only observing the sequence of events executed by the system, such as faults that lead the system to a deadlock. This problem is circumvented in [22] and [7], by adding the time information of the occurrence of events to the model, increasing therefore the number of faults that can be diagnosed. The main advantage of the DES approach for fault diagnosis is that the diagnoser can be easily implemented in a computer or a programmable logic controller (PLC), and the fault can be detected as soon as an unexpected event occurs in the system or if it occurs in a time instant different from the expected.

In this paper, we propose timed automaton models to represent the drilling operation on a CNC machine that are suitable for fault diagnosis. The models are inspired by the one proposed in [7] with the difference that in [7] all inputs and outputs of the system controller

are binary signals, whereas in this work we use analogical continuous signals as the spindle power and the Z displacement read directly from the system controller. The CNC signals are the key to obtain the events and the time that they occur in the system, necessary for the fault diagnosis. The diagnoser obtained using the proposed method can be easily implemented in a computer or PLC, leading to a fast fault detection. The faults that can be detected by using the method proposed in this work are an incorrect programming code inserted in the machine by the operator, an incorrect cutting velocity, and an incorrect workpiece material.

This work is organized as follows. In Section 2, some preliminary concepts are presented. Then, in Section 3, we present the drilling operation on a CNC machine, and the need for a fault diagnoser in the system. In Section 4, the timed automaton models of the drilling operation on a CNC machine are presented. Finally, the conclusions are drawn in Section 5.

2 Preliminaries

Let G be a Timed Automaton with Timing Intervals (TATI) defined as follows [3, 7]. A timed automaton with timing intervals is a six-tuple:

$$G = (X, \Sigma, f, c_g, guard, x_0),$$

where X is the set of states, Σ is the finite set of events, $f : X \times \Sigma \rightarrow X$ is the transition function, c_g is the global clock with value $c_g(t) \in \mathbb{R}^+$, $t \in \mathbb{R}^+$, $guard : X \times \Sigma \rightarrow \mathcal{A}$ is the guard function, where \mathcal{A} is the set of admissible timing intervals for the global clock c_g , and $x_0 \in X$ is the initial state of the system. \square

The domain of the transition function f can be extended to $X \times \Sigma^*$, where Σ^* denotes the Kleene-closure of Σ , as usual: $f(x, \varepsilon) = x$, and $f(x, s\sigma) = f(f(x, s), \sigma)$, for $s \in \Sigma^*$, and $\sigma \in \Sigma$, where ε denotes the empty sequence [3]. The feasible event function $\Gamma : X \rightarrow 2^\Sigma$ is defined as $\Gamma(x) = \{\sigma \in \Sigma : f(x, \sigma) \text{ is defined}\}$. In this case, $guard(x, \sigma)$ is defined if, and only if, $f(x, \sigma)$ is defined.

Function $guard : X \times \Sigma \rightarrow \mathcal{A}$ specifies the timing conditions that need to be satisfied on the global clock for the transition to occur, and \mathcal{A} are the admissible clock constraints defined as timing intervals. In the TATI, the global clock is reset to zero each time an event occurs. Let t' denote the time that a state $x \in X$ is reached in the timed automaton, and let τ denote the time that has elapsed after reaching state x . Then, transition (x, σ, x') , where $x' = f(x, \sigma)$, is executed in the TATI if event σ occurs at time $t' + \tau$ and $\tau \in guard(x, \sigma)$.

Let $\Sigma_t := \Sigma \times \mathbb{R}^+$. Then, the set of all sequences formed of elements $\sigma_t \in \Sigma_t$, including the empty sequence ε , is denoted by Σ_t^* . A timed sequence is denoted as $s_t = (\sigma_1, \tau_1)(\sigma_2, \tau_2) \dots (\sigma_l, \tau_l) \in \Sigma_t^*$, where τ_1 is the time elapsed between initiating the system and the occurrence of σ_1 and τ_j , $j \in \{2, \dots, l\}$, is the time elapsed between the occurrence of σ_{j-1} and σ_j . With a slight abuse of notation, let $(\sigma, \tau) \in s_t$ denote that (σ, τ) is one of the timed events that form s_t .

The length of a sequence s , timed or not, is denoted by $\|s\|$.

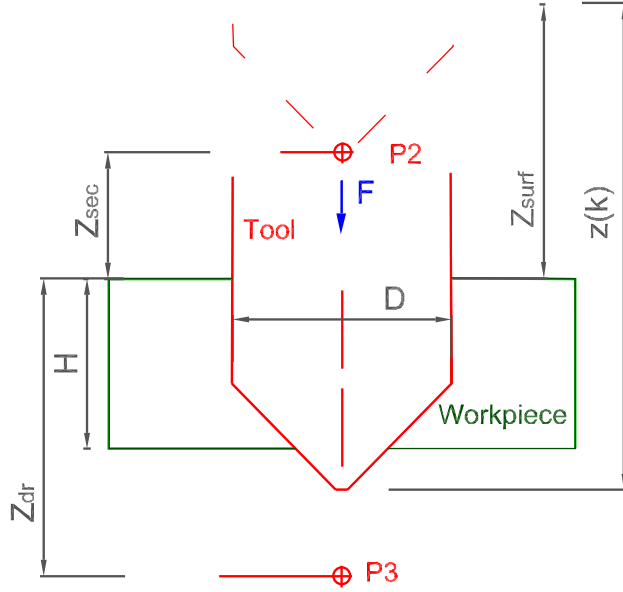


Figure 1: Drilling coordinates

3 Drilling operation on a CNC machine

A complete CNC program includes several machining steps for producing complex geometries. For the drilling phase of the workpiece (H thickness), the workpiece material defines a proper range of the two basis cutting parameters: cutting speed, denoted by V_c (m/min), and the feed per revolution f (mm/rev). Based on these parameters and on the nominal tool diameter D (mm), shown in Fig. 1, the spindle speed S (rpm) and feed velocity F (mm/min) are calculated : $S = \frac{1000}{\pi D} V_c$ and $F = f.S$.

The drilling part of the CNC program is composed of a sequence of lines, where each line represents one event described by ISO codes: G0 represents fast movement, G1 controlled feed and M3/M5 that turns on and off the tool rotation spindle. The drilling tool moves fast to the security position Z_{sec} , and then with controlled feed F from P2 to P3 ($Z_{sec} + Z_{surf} > H$). The Z absolute coordinate of the surface Z_{surf} is identified on the machine for coding and the machine-tool controls the real-time Z axis position. The following code represents the commands used in the example of this work:

```
G0 Z200 (Z upper position for drilling operation)
G0 X_hole Y_hole (Tools move to XY hole position)
M3 S=S_drill (The spindle turns on with a peek on spindle power)
G0 Z=Z_surf+Z_sec (The tool moves fast to point P2)
G1 Z=Z_surf-Z_dr F=F_dr (The tool moves face to the sheet, until point P3)
G1 Z=Z_sec F=5*F_dr (Back movement with controlled feed 5*F)
G0 Z200 (Returns upper position)
M5 (Stop spindle, peek of power identifies this event)
```

The machine-tool sensors measure the Z position, $z(k)$, and spindle power, $p(k)$. A different from the expected workpiece material for a specific cutting speed is considered a fault in this process, since it impacts directly the tool life and represents a different power consumption. In this work, we consider the drilling of aluminium and titanium, which are materials commonly used in the aeronautical industry, with the considered cutting speed for drilling aluminum $V_c = 100m/min$, and for drilling titanium $V_c = 50m/min$.

4 Timed automaton model

In this paper, we present a timed automaton model inspired by the Timed Automaton with Outputs and Conditional Transitions (TAOCT) presented in [7]. As in [7], the timed model has conditions related with the time that the events must be observed to allow the transitions to occur. The set of possible times is obtained by identification after observing the system for a sufficient long time at different conditions. Differently from [7], the sequences of events are already known, since it is assumed that the programming code that must be inserted in the machine is known. Thus, the number of sequences r that are considered for obtaining the models depends on the number of materials of the workpieces, and also on the defined cutting speed V_c . In this case, the outputs associated with the states of the automaton model are used to indicate to the operator the last event that the system has executed. Hence, the operator can verify if the system is executing the programming code correctly at any time, since the automaton model is played in real-time in parallel with the execution of the machine. The timed automaton with outputs (TAO) is defined as follows.

The Timed Automaton with Outputs is an eight-tuple:

$$\text{TAO} = (X, \Sigma, f, c_g, \lambda, R, g, x_0),$$

where X is the finite set of states, Σ is the finite set of events, $f : X \times \Sigma \rightarrow X$ is the transition function, c_g is the global clock, with value $c_g(t) \in \mathbb{R}^+$, $t \in \mathbb{R}^+$, $\lambda : X \rightarrow \Sigma$ is the state output function, $R = \{1, 2, \dots, r\}$ is the set of indexes associated with the different conditions of the experiments for identification, $g : X \times \Sigma \times R \rightarrow \mathcal{C}$ is the guard function, and $x_0 \in X$ is the initial state. \square

The set of admissible constraints \mathcal{C} is formed of all sets $I \subset \mathbb{R}^+$, that represent time intervals. As in the TATI, presented in Definition 2, in the TAO a unique global clock c_g is used, and it is reset every time a transition occurs. Function $g(x, \sigma, k)$ specifies a subset of \mathbb{R}^+ to which the clock value $c_g(t)$ must belong so that transition from state x labeled with σ can occur. Differently from [7], in this paper, the output function λ associates the last event occurred with a state of the model.

It is important to remark that, differently from [7], the signals that are observed for identification of the time intervals for the occurrence of the events are not binary signals. In the case of the CNC machine, we record the spindle power, $p(k)$, and the Z displacement, $z(k)$, of the machine tool. Thus, only continuous variables are read from the PLC, and these variables must be used to observe the occurrence of the events of the system. In the sequel, we show how events can be obtained from $z(k)$ read from the PLC.

At the top of Figure 2, we present the Z displacement curve $z(k)$ obtained using the Siemens software SinuCom NC for drilling titanium with $V_c = 50 \text{ m/min}$. Note that each change in the slope of the curve represents a command to the CNC machine. Thus, if we compute the approximate second order derivative of $z(k)$, we obtain, approximately, the time instant where the command has been sent to the machine. The curve of the approximate second order derivative of $z(k)$, $z''(k)$, is depicted at the bottom of Figure 2. The finite-difference approximation used to compute $z''(k)$ is given by

$$z''(k) = \frac{z(k+1) - 2z(k) + z(k-1)}{h^2}, \quad (1)$$

where $h = 4 \text{ ms}$ is the sample time of the data recorded by the software SinuCom NC. Thus, by measuring the time where there is a peak in the curve of $z''(k)$, we can define approximately the time instant in which each command of the code to move the tool occurs. Note that for each desired cutting speed, by measuring $z(k)$, we can identify if the correct speed is being executed by the machine, *i.e.*, we can detect a wrong command inserted by the operator for drilling a specific material.

In order to obtain the TAO of the Z displacement, we have made 16 tests with a new drilling tool. Eight drilling tests using the correct cutting speeds: four experiments in titanium using $V_c = 50 \text{ m/min}$ and four in aluminium using $V_c = 100 \text{ m/min}$, and eight using the undesired speeds: four in titanium using $V_c = 100 \text{ m/min}$ and four in aluminium using $V_c = 50 \text{ m/min}$. Thus, we have obtained 8 timed sequences $s_i^1 = (\sigma_1, \tau_{i,1}^1), (\sigma_2, \tau_{i,2}^1), \dots, (\sigma_l, \tau_{i,l}^1)$, $i = 1, \dots, 8$, associated with cutting speed 100 m/min , and 8 timed sequences $s_i^2 = (\sigma_1, \tau_{i,1}^2), (\sigma_2, \tau_{i,2}^2), \dots, (\sigma_l, \tau_{i,l}^2)$, $i = 1, \dots, 8$, associated with cutting speed 50 m/min , with number of events equal to 10, *i.e.*, $l = 10$. It is important to remark that $\tau_{i,1}^1$ and $\tau_{i,1}^2$ are defined as the times for the occurrence of the first event σ_1 after reaching the initial state of the system.

After obtaining the elapsed time between events, $\tau_{i,j}^k$, we compute the sets $T_j^k = \{\tau_{i,j}^k \in \mathbb{R} : i \in \{1, 2, \dots, 8\} \wedge (\sigma_j, \tau_{i,j}^k) \in s_i^k\}$, for $j = 2, 3, \dots, 10$. Then, the interval in which event σ_j can be observed is obtained as

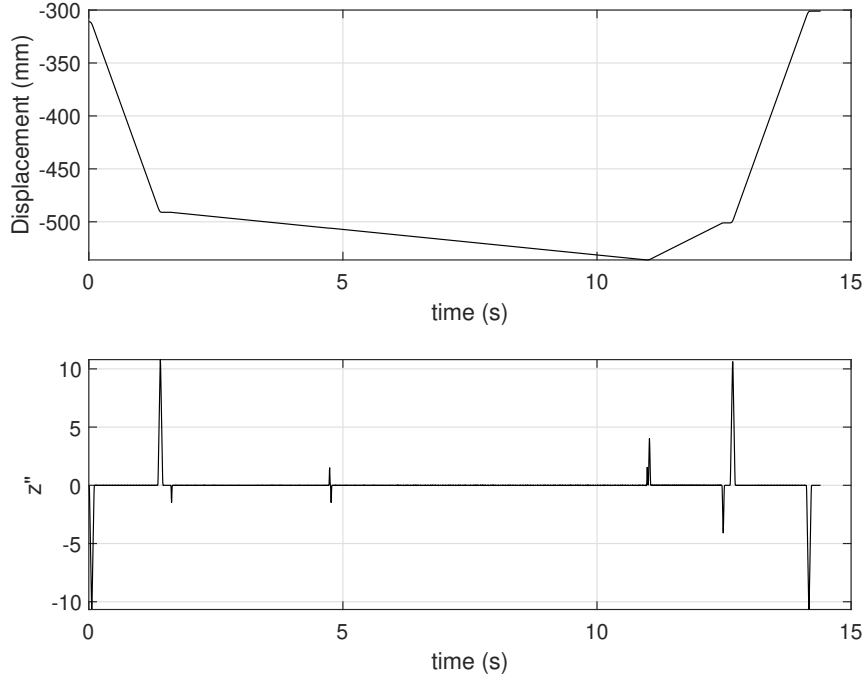


Figure 2: Z displacement curve for drilling with cutting speed $V_c = 50 \text{ m/min}$ ($P2 \approx -480 \text{ mm}$).

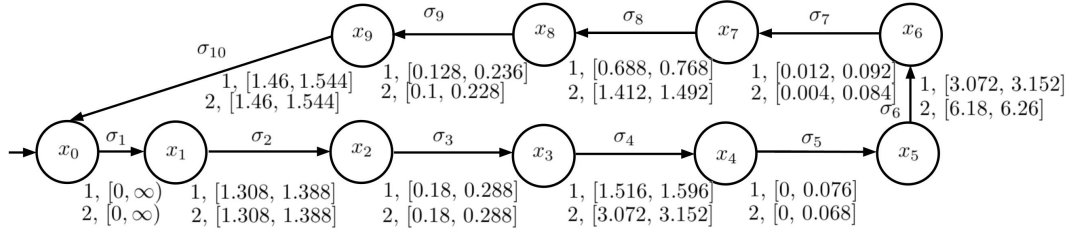


Figure 3: TAO model for the Z displacement (the guards 1, I_j^1 are associated with the time-interval sequence for $V_c = 100 \text{ m/min}$, and 2, I_j^2 are associated with the time-interval sequence for $V_c = 50 \text{ m/min}$).

$I_j^k = [\min(T_j^k) - \delta, \max(T_j^k) + \delta]$, $j = 2, \dots, 10$, where the uncertainty $\delta \in \mathbb{R}_+$ is defined to take into account possible errors in measuring the time values. We have chosen in this work 10 sample times to define δ , *i.e.*, $\delta = 40 \text{ ms}$. Since the first event can be observed at any time after reaching the initial state, then the time intervals for σ_1 are defined as $I_1^1 = I_1^2 = [0, \infty)$.

From the timed sequences s_i^k , $i = 1, 2, \dots, 8$, we compute the time-interval sequences $s^k = (\sigma_1, I_1^k)$, $(\sigma_2, I_2^k), \dots, (\sigma_l, I_l^k)$, $k = 1, 2$, and compute the TAO model for the Z displacement, depicted in Figure 3, where the events σ_j are placed above the transition and the guards are placed below them in the form k, I_j^k . Note that both time-interval sequences are generated by the TAO model, and that only this two sequences of length 10 can be generated. In addition, note that the cutting speed leads to disjoint time intervals in the fourth event executed by the system. Thus, if an incorrect order of events is executed, or a different from the expected cutting speed is used, then, we can identify the faulty behavior by playing the model in parallel with the system execution.

In order to diagnose faults associated with a different material of the workpiece, we use the power curve.

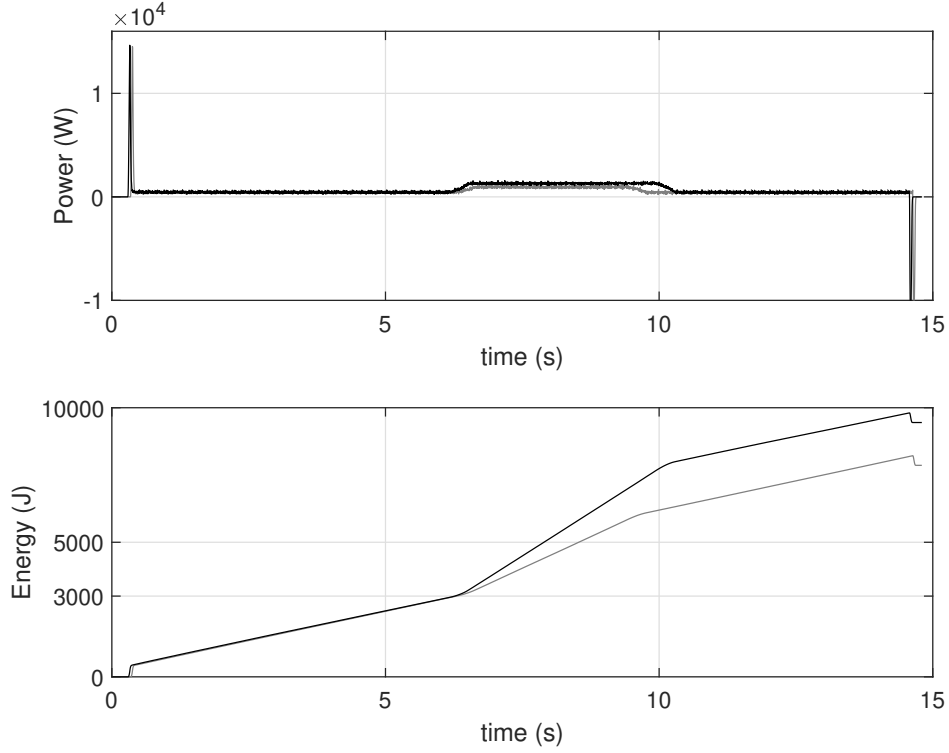


Figure 4: Power $p(k)$ at the top and energy at the bottom of the figure for drilling titanium (black) and aluminium (grey), both obtained using $V_c = 50 \text{ m/min}$.

At the top of Figure 4 we present the power curves for drilling titanium in black and aluminium in grey, with cutting speed $V_c = 50 \text{ m/min}$ in both cases. As it can be seen from the curves, the power needed for drilling titanium is greater than the power needed for drilling aluminium. This fact becomes more evident when we integrate the two curves, obtaining the curves at the bottom of Figure 4. The curve in black represents the energy consumed for drilling titanium and the curve in grey represents the energy for drilling aluminium. At it can be seen, the energy behaviors start to become different when they reach approximately 3000 J, which shows that the materials can be distinguished using the energy curves.

From the experiments drilling titanium and aluminium with different speeds V_c , we have obtained the discrete event models of Figure 5(a), for $V_c = 50 \text{ m/min}$, and Figure 5(b), for $V_c = 100 \text{ m/min}$, where we have discretized the energy within levels, and observed the elapsed time between two levels of energy for each material in order to obtain timed automaton models. The timed automaton model of Figure 5(a) generates the time-interval sequences $s^3 = (s_{on}, I_1^3), (e_{3000}, I_2^3), (e_{4000}, I_3^3), (s_{off}, I_4^3)$ for aluminium with cutting speed $V_c = 50 \text{ m/min}$, and $s^4 = (s_{on}, I_1^4), (e_{3000}, I_2^4), (e_{4000}, I_3^4), (s_{off}, I_4^4)$ for titanium with cutting speed $V_c = 50 \text{ m/min}$, where s_{on} represents the command to turn on the spindle, e_{3000} and e_{4000} represent that the energy has reached 3000 J and 4000 J, respectively, and s_{off} represents the command to turn off the spindle. Note that the elapsed time between the reach of energy 3000 J and 4000 J with speed $V_c = 50 \text{ m/min}$ is different for drilling aluminium and titanium. Thus, the TAO model of Figure 5(a) can be used for distinguishing the workpiece material in a fast way.

The TAO model of Figure 5(b) is similar to the TAO model of Figure 5(a), with the difference that the time interval sequences s^5 and s^6 represent the discrete event behavior of drilling aluminium and titanium, respectively, with cutting speed $V_c = 100 \text{ m/min}$. In this case, the workpiece materials can be distinguished by measuring the elapsed time between the reach of energies 5000 J and 6000 J, represented by events e_{5000} and e_{6000} , respectively.

It is important to remark that after observing a sudden decrease in the energy, associated with turning

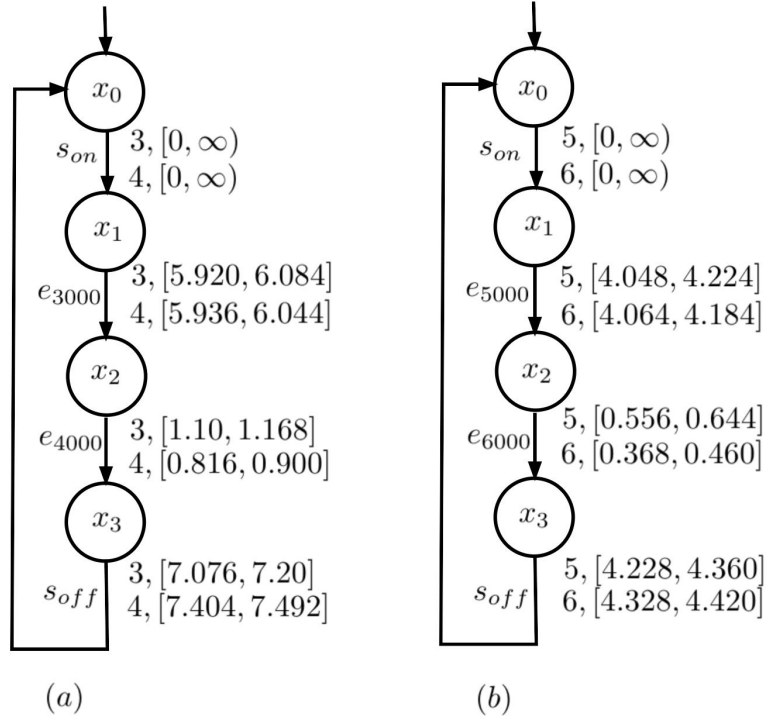


Figure 5: TAO models for drilling aluminium and titanium with cutting speeds (a) $V_c = 50$ m/min (the guards $3, I_j^3$ are associated with drilling titanium and $4, I_j^4$ with aluminium) and (b) $V_c = 100$ m/min (the guards $5, I_j^5$ are associated with drilling titanium and $6, I_j^6$ with aluminium).

the spindle off, represented by event s_{off} , the models return to the initial state, and the accumulated energy is reset. The power is integrated again only after observing the sudden increase in the power, which indicates that the spindle has been turned on again, represented by event s_{on} .

5 Conclusions

We have presented in this work timed automaton models for the Z displacement of the tool and consumed energy of a CNC machine drilling aluminium and titanium. The models are suitable for fault detection and can be played in parallel with the system to identify the faults in a fast and easy to implement way. The results show that the proposed method is able to identify if an incorrect cutting speed for a specific material is used, which certainly increase the drilling tool life. We are currently investigating if the method can also be applied to automatically determine the tool wear and identify when the tool life is achieved.

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