

# Distributed Machining Control and Monitoring

## Using Smart Sensors/Actuators

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**Abstract.** The study of smart sensors and actuators led, during the past few years, to the development of facilities which improve traditional sensors and actuators in a necessary way to automate production systems. In an other context, many studies are carried out aiming at defining a decisional structure for production activity control and the increasing need of reactivity leads to the autonomization of decisional levels close to the operational system. We suggest in this paper to study the natural convergence between these two approaches and we propose an integration architecture dealing with machine tool and machining control that enables the exploitation of distributed smart sensors and actuators in the decisional system.

**Key words:** smart sensors and actuators, multiagent architecture, production management, machine tool monitoring, machining control

### 1. Introduction

The productive organizations nowadays face with new obligations because of more and more competitive markets. In this context the ability to produce at the right time various products of good quality at low cost is a major issue for their development. The flexibility and reactivity of firms is therefore required in order to adapt to rapidly changing environments.

- flexibility is a consequence of the presence of freedom degrees in the managed system,
- reactivity represents the ability of the system to use these freedom degrees in order to adapt to changes.

Automation of production systems is a way to improve flexibility and many efforts carried out at the operational system level aim at improving the automation of production devices. In order to achieve this objective, several studies have shown the interest of sensors and actuators able to process information (calibration, fault detection, diagnosis and so on). The concept of smart sensor or actuator (Isermann 1993, Robert et al. 1993) takes into

account this additional processing capability with respect to the “traditional” sensors and actuators. The global structure of a smart sensor is illustrated in figure 1 and an example of a detailed structure of a smart actuator is given in figure 2.

The studies carried out in the context of smart instruments are led, in most cases, to develop sensors or actuators dedicated to a complex function of a given system. A major trend in the field of smart sensors and actuators is to use an object-oriented approach for the specification and development (Filali et al. 1994, Luttenbacher et al. 1996). Generally, smart sensors are designed to ensure the observation of processes in a more reliable way than with "traditional" ones by processing validation and self-diagnosis treatments and by providing their results to other units. Smart actuators are able to give local responses to a process change since the information given by other instruments, their own observation onto the process and the results of their self-diagnosis.

However, the use of smart sensors and actuators is not entirely satisfying especially for the reaction to disturbances that perturb the nominal functioning of the production system since the behavior of a smart sensors and actuators is strongly predetermined.

A way to improve this situation is to increase the autonomy of the decisional levels that are close to the operational system in order to make quickly the appropriate decisions when a disturbance occur. The complexity of the production system and of its interactions with the environment has led to a hierarchization of the decision making. We therefore consider in this study, as in GRAI method (Doumeingts et al. 87), the decisional system as a hierarchical structure of decision centers having a longer decisional horizon of decision at the top of the hierarchy. In general, the more one goes down in the decisional hierarchy structure, the more restricted the autonomy of the decision centers is. That is why the decisional part of the system, which is close to the operational system, is very sensitive to disturbances. A present tendency, induced by reactivity concern, is to autonomize low level decision centers in order to make them more reactive to environment fluctuation (Grobot & Geneste 1998) or to develop the notion of decisional agent (Ouzrout et al. 1994).

So, on one hand, in the context of the production system automation, studies aim at solving the problems of physical architecture and equipment organization linked to the automation itself without considering the control strategies or decision models that are applied to the production system. On the other hand, research studies about the decisional structure, which supports the production activity control, are generally carried out at an abstract and generic level. The proposed models do not take into account the physical configuration of the production system that is to control. The objectives of the research study presented in this paper are the following ones:

- to show the convergence of the two approaches described above,

- to develop, in the context of production systems an architecture and a methodology aiming at integrating the orientations followed in both approaches,
- to propose and to bring into operation a simulation platform using the defined architecture and methodology.

The platform is developed in order to model and simulate the control structure of a machine tool, which is a basic component of the physical architecture of production systems, thanks to a distributed architecture of Smart Sensors/Actuators (SSA). We wish to propose an experimental framework that enable, at the end, to federate the physical and decisional points of view in a common representation.

## **2. Proposal of architecture for the integration**

The organization of the traditional manufacturing machine should be set into question in order to apply the proposed ideas. We therefore propose to introduce a new decisional level in the classical decisional structure. This additional level is based on elements directly linked to the process: smart sensors and actuators.

### **2.1 Organization of the traditional machine**

A production machine aims at achieving a task in an industrial process. It is generally divided into two parts: the control part and the operative part. The operative part of the machine receives orders from the control part. These orders are applied to the actuators and information is sent back thanks to sensors. The operative part has no decisional role.

The control part should be able to:

- receive, identify and process information from the environment,
- store the information and the results of the process,
- monitor and dispatch information to the environment.

The processed information belongs to two different categories:

- orders from other intelligent devices (cell pilots, human operator...),
- state information about the machine.

The treatments generally correspond to the execution of algorithms and depend on the integration degree of the production system. In the case of numerically controlled machine tools, the control system is centralized as shown in figure 3.

There is a single decision center represented by the numerical controller. It gives to the other instruments the instructions (spindle velocity reference to the spindle regulator, position references to the axis cards, ...) since the work-piece program and parameters that can be changed thanks to the man/machine interface or sent to the numerical controller. Some binary indicators, often provided by the PLC, help the numerical controller to make decisions that can be to change a worn tool, to stop machining operation and so on. The other devices do not have any decision ability.

One major drawback of this centralized numerical control system is that it can hardly be enlarged with new functions without the help of the manufacturer. Indeed, numerical control systems are nowadays offered as closed manufacturer-specific solutions (Pritschow et al. 1993). The fact that only non-open controllers are proposed by manufacturers have led to a demand for the development of open and modular control systems expected by the users of flexible manufacturing systems (Mehrabi et al. 2002). The modularity enables the users to implement the devices and functions they really need. That is why many studies are carried out aiming at defining such structures (Altintas et al. 1996, Pritschow et al. 1993, Schofield & Wright 1998). Different frameworks are proposed but, although they define modular and open control systems, they are still centralized systems. This is not relevant in the objective of autonomization of a machine and a hierarchical structure should be created by adding a decisional level leading to a new definition of the decisional structure of a machine tool. This decisional level is based on SSA and is called CAID ("Capteurs et Actionneurs Intelligents Distribués": distributed intelligent sensors and actuators).

## 2.2. Integration of the additional decision level

In order to create the additional decision level, CAID level, we rely upon elements that make the interface between the control and the operative part of the machine (SSA) by endowing them with decisional abilities. The organization of the machine is therefore modified and is made of a two level hierarchized control structure, the machine level and the CAID level, as described in figure 4. The communication between the two decisional levels and between the components of the same level is achieved thanks to a local network. The interface is divided into two elements:

- the first one is integrated with the physical process and corresponds to the classical functions of smart sensors and actuators,
- the other one is devoted to the CAID decisional level and corresponds to the additional decision making functions.

The CAID level becomes the lowest decisional level of the production system. It is connected to the upper level made of the general control of the machine that is usually the last decomposition level. The problem is at this stage to define how the various elements of the CAID level and of the machine will interact in order to ensure an appropriate decision making.

### 2.3. Distributed control structure at the CAID level

Each SSA of the CAID level is a decision center that ensures a local response to events that may happen on the controlled physical device. However some situations may lead a SSA to require help of other SSA to make an appropriate decision. The need may be for instance an information on the state of another SSA or the decision achieved by another SSA... The architecture of the control must enable the communication and cooperation between SSA. The distributed architecture is therefore the most appropriate one in this case as illustrated in figure 5. The machine decisional level is made of a set of decisional centers that aim at controlling each machine and to cooperate with other machines. The decision centers of the machine level send orders that the SSA of the CAID level execute. Each SSA, local decision center, makes decisions according to information that stem from the controlled process and from the other SSA. Each SSA is in charge of the control of a specific physical device such as spindles and feed-drives.

A distributed architecture is relevant to materialize this cooperation by exchange of information between SSA at the same level and between the two decisional levels. In this architecture, no entity is in charge of the decision making, which is carried out by cooperation of the various SSA and the control of the corresponding Machine decision center. The reactivity of the system is therefore improved since only situations that require to stop the machining operation are transmitted to the upper decisional level.

The distributed architecture requires specific features for its components, the CAID level part of the SSA. They have for instance a decisional autonomy, an ability to choose a behavior according to internal and external information, an ability to communicate and to cooperate with other SSAs and with upper level decision centers. The classical smart sensors and actuators are able, thanks to some of these features, to process complex data, to communicate, ... but they do not support the most important one for distributed control: decisional autonomy. In this aim, we modified the internal organization of smart instruments in order to integrate these new possibilities by using the notion of intelligent agent (Jennings & Wooldridge 1995), which extends the notion of smart sensors and actuators with decision capabilities. Studies have already been led in the domain of distributed

process control using agents like the ones presented in (Velasco et al. 1996, Iung 2003) but the agents are rarely embedded in the treatment units of low level components like smart sensors and actuators.

### **3. Application to machining control and monitoring**

The previous section defines the context and principles of this work. In order to study the relevance of the implementation of a distributed architecture in machine tools, we developed a simulator of Numerically Controlled (NC) lathes. The simulator imitates a disturbed cutting process presenting a tool wear without risking to damage physical devices. It is also a way to validate the operational and decisional coordination at the CAID level.

#### **3.1. Control principles**

NC lathes are often used in flexible production cells. They permit to obtain shapes generated by revolution of the work-piece like cylinders, cones... These machines are made of two axes or feed-drives (Z: longitudinal, and X: transversal), that drive the tool trajectory, and generally one spindle which holds the work-piece. The spindle and feed-drives also interact during the machining process.

Other components of the machines, dedicated to auxiliary functions (chuck locking, protection bay opening...) are not taken into account in the simulator.

This study can be generalized for more complex NC machines like machining centers for which only the process model has to be reconsidered.

According to the operative part, the CAID level is organized into several decision centers. The role of each decision center is to drive one component of the operative part (feed-drive or spindle) and involves additional functions that constitute the facilities of SSA: data processing, communication, data storage, monitoring, self-diagnosing...

Therefore, the control of an operative part, devoted to one SSA, involves two levels (see figure 6). At the process level, the sensors ensure the measurements of the variables needed by the functions processed by the treatment unit and the servo actuator receives the references defined by the treatment unit. At the CAID level, the treatment unit sends the results of its processes to the environment. It also receives information from the other units of the machine. It makes the appropriate decision from these data and those measured by the SSA and sends the references to the servo actuator.

The feed-drives and the spindle work simultaneously and interact during the cutting process since the work-piece held by the spindle is in contact with the cutting tool driven by the feed-drives. In the presented simulations, the models of the drives are supposed to be equipped with DC motors like many machine tools are.

The aim of keeping the accuracy of the machines constant in time guides the interest in monitoring their own state and the state of their main devices like axes and spindles. Indeed, the number and the effects of the sources of inaccuracy increase with time because of the wear of mechanical parts, the lubricating fluid pollution, the demagnetization of the motor magnets, and so on. The effects of these phenomena contribute to change the general behavior of the machines and seriously affect their accuracy. The dynamic of these phenomena is far slower than the cutting tool wear, which has direct effects onto the dimensions of the machined part. The monitoring of this last phenomenon is also important to ensure the quality of the work-pieces. This monitoring can be used to avoid or to predict tool breakage (Masory 1991), to adapt the cutting conditions (Carrillo & Rotella 1997), to correct tool trajectory...

### 3.2. Machine tool Monitoring

Works dealing with machine tool monitoring during manufacturing operation are quite seldom whereas machine tools can be considered as main work-piece sources of inaccuracy. The approach described in (Desforges & Habbadi 1998) is based on the estimation of physical parameters since this kind of parameters can easily be linked to feed-drive faults. Here, we consider one NC lathe equipped with DC motor feed-drives and spindle. The physical models of these drives is following:

$$u(t) - K_e \omega(t) = L \frac{di(t)}{dt} + R_e i(t) \quad (1)$$

$$K_t i(t) - T_{cf}(t) = J_t \frac{d\omega(t)}{dt} + v_t \omega(t) + T_{df} \text{sign}(\omega(t)) \quad (2)$$

with:

- $u$ : tension;
- $i$ : induced current;
- $\omega$ : motor shaft revolution velocity

that are the measured quantities used for the estimation of the following parameters:

- $T_{cf}$ : torque on the motor shaft induced by the cutting forces;
- $L$ : inductance;
- $R_e$ : resistance;

- $K$ : torque constant and counter electromotive force constant expressed in the same unit system;
- $J_t$ : total moment of inertia on the motor shaft;
- $v_t$ : total viscous friction coefficient on the motor shaft;
- $T_{df}$ : total dry friction torque on the motor shaft.

The relationships (1) and (2) can be written the following way:

$$y(k) = x(k).p \quad (3)$$

where  $k$  is the sample number ( $t=k.h$  with  $h$  the sampling period),  $p$  is the parameter vector,  $x(k)$  is the input vector and  $y(k)$  is the output.

The estimation method uses least squares estimator:

$$\hat{p} = \left[ \sum_{k=1}^n \vec{x}(k). \vec{x}(k)^T \right]^{-1} . \sum_{k=1}^n y(k). \vec{x}(k) \quad (4)$$

where  $p$  is the parameter vector,  $x$  the matrix of the variables measures and  $y$  is the vector of the derivative inputs are not measured by calculated by a zero forcing #1 operator (Söderstrom et al. 1997):

$$\frac{df(t)}{dt} \approx Df(t) = \frac{0,2047.f(t+h) + 0,886.f(t) - 1,386.f(t-h) + 0,2953.f(t-2h)}{h} \quad (5)$$

In this model, the velocity and current regulation loops are not modelled. If these loop were modelled this would mean that the regulators would be placed under monitoring. Here, this is not the case. Indeed, the features of the regulators do not change in time even if faults affect them.

This estimation method gives accurate and reliable results when a validation treatment correct possible faulty measures see (Habbadi et al. 1999). Table 1 presents the links between the parameters and faults (Desforges & Habbadi 1998).

We propose to estimate the physical parameters out of cutting periods. Indeed, if changes are observed in feed-drive physical parameter values during a cutting period, the changes can be due either to machine faults or changes in the cutting conditions or to tool state. The way to estimate the parameters in-operation but out of cutting periods consists in estimating them by using the high-speed motions of the feed-drive that occur for each tool exchange at least. The monitoring of the drives corresponds to an off-line monitoring for the following reason. Indeed, most of the faults that affect a feed-drive vary much slower than the faults affecting the cutting tool makes such a monitoring suitable. Therefore, the parameters of each feed-drive can be estimated after each



high-speed motion and during the starting up for the spindles. These parameters are then simply compared to thresholds in order to detect faults of the drives.

Let us note that only the relationship (1) changes for an AC motor.

An other ability of this monitoring consists in its possible integration to a proactive maintenance system by providing it the estimated parameters. The proactive maintenance system receives the estimated parameters regularly or on request in order to diagnose the origin of the degradation and to predict the delay remaining before failure through a trend analysis process (Léger and Morel 2001). The implementation of such a maintenance strategy aims at increasing the availability of the processes.

### 3.3. Optimization of the turning operation

Production research mainly deals with production optimization. In the case study, we develop the optimization concerns the turning operation. Many contributions aim at improving the efficiency of machining operations and they often deal with adaptive control.

Techniques have been developed for adaptive control of turning operation such as the one described in (Carrillo & Rotella 1997). It consists in keeping the tangential cutting force component  $F_t$  (see figure 7) constant for roughing out turning operation.

This force component should be kept at a constant value which maximize the electric power absorbed by the spindle motor for a given state of the spindle defined by the estimated values of its physical parameters. Indeed, most of electric power absorbed by these devices is used to overcome the tangential cutting force component whereas the feed-drives are designed to accelerate the heavy mass of tables. Therefore, the interest is to machine the work-piece at the highest velocity to make the spindles work at their maximum power. In order to minimize the machining time, the feed rate  $f$  can be increased until the maximum spindle electric power. This can only applied to roughing out because roughness specifications will be reached by finishing operations. Indeed, in mechanical manufacturing, obtaining the final surface of a work-piece with the required quality after only one machining operation is seldom and two cutting operations (roughing out and finishing) are at least necessary to obtain the expected surfaces. Of course, with the proposed adaptive control, gains are only obtained for roughing out operations.

In (Carrillo & Rotella 1997), the signals that are measured in order to realize this control correspond to the cutting force components. Their acquisition is done by means of a piezoelectric force sensor which is an expensive device and is difficult to implement onto machines of operational workshops. According to studies

that have been led to define the sensivity of the power absorbed by the drives to the cutting forces (Stein et al. 86, Stein & Shin 86, Altintas 1992), we here use the velocity and current measurements to estimated the cutting force components by using (2). This supposes that the parameters of (2) are previously identified.

For the spindle, the torque on the motor shaft directly depends on  $F_t$ :

$$T_{c/S}(t) = \frac{d \cdot G_S}{2} F_t(t) \quad (6)$$

where  $G_S$  is the gear box reduction ratio.

For the feed-drives, all force components act on the table. Considering a longitudinal turning operation, only  $F_t$  is directly acts on the Z axis drive. Although the other ones also acts on the drive by the bias of friction terms, they can be considered as negligible because of the low velocity of the feed-rates and the low dry friction coefficients. In this case, one can consider that only  $F_t$  acts on the motor shaft of an Z axis feed-drive  $F_r$  acts on the X axis one. This gives:

$$T_{c/Z}(t) = G_Z \cdot F_t \text{ and } T_{c/X}(t) = G_X \cdot F_r \quad (7)$$

where  $G_X$  and  $G_Z$  are respectively the reduction ratios of the gear boxes and ball screws of the X axis and Z axis.

The cutting velocity  $V_c$  is defined for each tool matter couple. Knowing this and the final diameter of the machined part both given by the Numerical Controller (NC) unit from the work-piece program, the reference velocity of the spindle is calculated from:

$$\omega = \frac{V_c}{\pi \cdot d \cdot G_S} \quad (8)$$

which will be kept constant. The power maximization will therefore consist in maximizing the current. This means by calculating the value of  $F_t$  for which the current is the maximum current that can pass through the motor by taking into account the physical parameters of the spindle estimated during its start up.

The value of the depth of cut  $a$  is supposed to be defined in the work-piece program and is sent to the SSA.

Then, in order to define the feed rate  $f$ , the empirical models of turning process proposed in (Koren et al. 1991, Ravindar et al. 1993) can be used. The structure of these models is the following one:

$$F_j = K_{wj}(t) \cdot V_c^{pj} \cdot f^{qj} \cdot a^{rj} \quad \text{with } j=l,r,t \quad (9)$$

where  $K_{wj}(t)$  is a coefficient that increases with tool wear and  $pj$ ,  $qj$  and  $rj$  are empirical coefficients that are transmitted to the SSA as well as the value of  $K_{wj}(0)$  for a sharp tool. We then suppose, in order to simplify the simulations, that the empirical coefficients are not functions of the tool wear  $V_B(t)$ .

The value of  $f$  estimated by the spindle SSA from (9) with  $K_{wj}(0)$  considered for a sharp tool and  $j=t$  is then sent to the Z axis SSA. For the simulations, we assume that:

$$K_{wj}(t) = K_{wj}(0) + vj \cdot V_B(t) \quad (10)$$

Of course, the NC unit also transmits the values of  $K_{wj}(0)$  and  $vj$  to the relevant SSA before the machining operation. Then, the spindle SSA and the Z and X axis SSA estimate their corresponding  $F_j$  from (2) and compare it to the one estimated with (9). If there is a difference between the two estimations, they compute again the  $K_{wj}(t)$  and the spindle SSA also recompute  $f$  in order to keep  $F_t$  constant and transmit this new value to the Z axis SSA.

This description of the control of the cutting process and the machine monitoring enable to define the control framework.

The computation and the transmission of  $K_{wj}(t)$  can be used for monitoring of the tool state and also to prognose the delay remaining before replacing it.

#### 4. Control framework

The aim of the cooperation between the agents is to machine work-pieces close to the maximum of the machine ability. The maximum ability is reached when one of the three drives works under its maximum current or maximum power boundaries and the two other drives work within their maximum current and power limits.

According to the organization of a machine in three levels defined in section 2 in order to increase the autonomy of the lowest decision level and the control scheme presented in section 3, four agents with decision ability are involved in the control of a lathe. The NC unit and the treatment units of the SSA behave like distributed agents. These four agents exchange messages to control the lathe. Figure 8 illustrates this data exchange between the agents and the equipment of the process level.

Each component of this diagram can be considered as an object. Indeed, the object-oriented approach used in (Filali et al. 1994, Luttenbacher et al. 1996) is a major trend in the specification of smart sensors and actuators as well as in the specification of control achieved by distributed objects.

In this framework eight objects are involved in the control of a lathe. The process objects just behave like their process models. The spindle and axis processes belong to the same class and consists in DC motor servo drives models (1) and (2) controlled with overlapped speed and current PID regulators. In order to simplify the simulated models, the depth of cut and the final diameter of the work-piece are supposed to be constant. The machining process is described by (9) and (10). This process also generates the wear considered as the

disturbance. In the simulations that are presented in the next section,  $v_l$  and  $v_r$  are supposed to be zero. This assumption means that  $F_l$  and  $F_r$  do not depend on wear.

The "machining process" object is the only one of its class. The axis and spindle belongs to the same class because they estimate their physical parameters and test them by comparing them to fixed boundaries in order to send or not to send a fault message. Although these objects have this same property, they do not belong to the same subclass as shown in figure 9.

Indeed, the axis agents calculate their torques by using (2) and from (7) compute the radial force (for X axis agent) and longitudinal force (for Z axis agent). They compare this value to the one obtained with (9) and compute the new values of  $K_{wj}(t)$  (assuming that  $v_l$  and  $v_r$  are nil, this last operation is never done). Then, they estimate the force from (9) with the new feed-rate, and verify, by using (2) and (7) that the maximum induced current will not be reached. If it is reached, they send a "reduce feed" message to the spindle otherwise they send the reference velocity to the axis process. Of course, they emit a "max power" message only if feed reduction is no more possible. They also check that the feed received from the spindle is higher than the one required by the minimum allowance and calculate the reference velocity for the drive which is defined from a ratio that takes

into account the feed in both axis ( $f = \sqrt{f_x^2 + f_z^2}$ ).

The spindle agent object verifies the reference velocity which is then sent to the spindle process. If it is too high, it sends a message to the NC unit. From the physical parameters and (2), it calculates the maximum torque that can be applied to the spindle. Then it uses this torque and the cutting conditions to define the initial feed-rate that is sent to the axis agents. During the cutting operation, it calculates the tangential by using (6) and (2) before recomputing  $K_{wt}(t)$  from (9). It also verifies that the maximum torque is not reached. From the new value of  $K_{wt}(t)$  and  $F_t$ , it computes a new feed that will be send to the axis agent. If this feed is too high, it decreases it by a gain factor.

Figure 10 presents the activity charts and the state charts that specify the spindle and axis agents. The activity charts is a kind of data flow diagram where:

- the boxes are the activities,
- the boxes with round corners are the controls of the activities (described by the state charts),
- the boxes with dotted lines are the context objects,
- the boxes with dotted lines and full lines are the data storages,
- the full arrows are the data flows,

- the dotted arrows are the control flows.

The figure 10 only presents the Z axis agent diagrams. The X axis agent one are directly obtained from the Z axis ones by replacing Z by X and  $l$  by  $r$ .

The state charts describe dynamic behavior of the objects. They are state-transition diagrams where the round corner boxes are the state and the arrows are the transitions ("sp!" for stopping an activity and "st!" for starting an activity).

The role of the NC unit agent is to send to the spindle and axis agents, control data as well as the value of constants of the cutting models, the depth of cut, the cutting speed, the feed ratios calculated from the work-piece program and the position of X and Z drives. It also make decisions according to the data flows it receives.

## 5. Simulations and results

The experiments using the presented control framework are obtained by the means of an integration platform that simulates the system behavior during a cutting process. The message exchange between the agents is implemented with CORBA protocol. Here, we present two cases for a same profile of wear presented in figure 11. In order to simplify the simulated models, we assume that the tool wear does not affect  $F_l$  and  $F_r$ . This means that  $v_l$  and  $v_r$  are zero. The initial maximum value of  $T_{max}$  is calculated in order to work at 80% of the maximum current that can pass through induced circuit of the spindle motor. When  $T_{max}$  generates a current that is 20% greater than this maximum value, the  $T_{lim}$  message is sent to the NC unit agent that stops the process.

In both cases, the values of the physical parameters enable to start the cutting process. Thus, no fault message is sent to the NC unit agent. The cutting operation is a turning operation at with constant final diameter  $d$  and depth of cut  $a$ . In such an operation only the Z axis is moving. The X axis does not generate any table motion but, here, the ball screw systems of both axes are considered as reversible and the force that is applied onto the feed-drives is greater than the friction terms and X axis motor is consuming electric energy even if it is not moving the table. Aiming at showing the interest of the cooperation between agents, the first case simulates a control without any cooperation between the CAID level agents whereas the second one considers the cooperation mode presented in the previous section for the same conditions.

### 5.1. Scenario 1 (no cooperation)

In this scenario, no message is exchanged at the CAID level. References are given to the process objects and the measures delivered by these same objects are acquired. When the NC unit agent receives the  $T_{lim}$  due to the

increasing tool wear, it asks the CAID level agent to stop the process by sending the "end" and "eocut" controls. The effect of these controls is to stop abruptly the cutting process. We show in figure 12 (where *Zone 3* consists in the values of  $F_t$  that make the spindle agent send  $T_{lim}$ ) the evolution of the efforts estimated by the CAID level agents over time when there is no cooperation between these agents.

We observe that from time  $t_0$  the effort on the spindle increases following the tool wear introduced in the simulation. The machining process goes on until time  $t=45$  when  $F_t$  enters in *Zone 3* and the spindle agent sends the  $T_{lim}$  message that stops the machining process. This configuration of agents does not efficiently answer to the reactivity objective by its lack of corrective and cooperative actions.

## 5.2. Scenario 2 (cooperation)

In this second scenario, we choose to make CAID level agents cooperate in order to enable to continue the machining process as long as possible.

The aim of the spindle agent is to keep the torque due to the tangential cutting force  $F_t$  constant and at value for which the current in the induced circuit of the spindle motor is 80% of its maximum value. The aim of the axis agents is to verify that the feed-rate asked by the spindle is not under the minimum allowance in order to avoid tool chattering and, therefore to warranty the specified roughness of the machined surface. From these goals, three situations can be encountered:

- the tool wear does not vary (*Zone 1*) until  $t_0$ , in this zone no change of feed-rate is required,
- the tool wear generates increasing cutting forces (*Zone 2*), an adaptation (which a reduction) of the feed-rate to  $F_t$  is then operated until the minimum allowance is reached,
- the minimum allowance is reached and there is no more adaptation and the feed rate corresponds to the minimum allowance, the tool wear still generates increasing cutting forces and when  $F_t$  corresponds to the maximum torque for which the current of the spindle motor is 20% greater than the maximum one (*Zone 3*) the machining process stops.

One can observe in figure 13 the evolutions of the cutting forces estimated by the CAID level agents over time. The cooperation between agents enable the machining process to last longer than in the first scenario. The cooperation between agents therefore improves the reactivity of the system and corrects the drifts induced by the environment: the tool wear in this case.

## 6. Conclusion

The natural convergence between the increasing flexibility of manufacturing systems and the need of reactivity of these systems leads to link the operative sub-system which interface is made of sensors and actuators and the decisional sub-system that enable, through autonomization a better reactivity.

The study of an integration architecture of these two aspects leads to the definition of a decisional level called CAID which represents the link between operational and decisional systems. This CAID level enriches the smart sensors and actuators with a decisional possibilities. The decision may be local or generated by a cooperation between several entities of the CAID level. The first results obtained with the integration platform show the interest of a cooperative approach for the control of a machining process according to the context. The information provided by the CAID level agents can become useful for condition maintenance actions scheduling in a productive system entirely integrated.

These first experiments permit to consider the implementation of complex decision making (fuzzy inference for instance) in a unified framework. The integration platform is quite flexible because it enables to reconsider the physical processes and the control structure. Further works will deal with the ability of fieldbuses to transfer the different kinds of data flows exchanged between the distributed agents and with the respect of real time constraints linked to the machining operation control in order to improve machine tools performances. Further developments of the control framework will deal with the position control adapted to the states of feed-drives and to the feed velocity.

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| <b>Faults</b>   | <b>Sensitive parameters</b>  |
|---|--|
| bearings and/or slide-ways wear                       | total dry friction torque $T_{df}$<br>total viscous friction coefficient $v_t$ |
| lack of lubricating oil and/or lubricating oil ageing | total dry friction torque $T_{df}$<br>total viscous friction coefficient $v_t$ |
| no work-piece and/or work-piece holder                | moment of inertia $J_t$  |
| brush wear  | resistance $R$   |
| motor heating   | resistance $R$ , inductance $L$ ,<br>torque coefficient $K$                    |
| demagnetization                                       | inductance $L$ ,<br>torque coefficient $K$                                     |
| ...   | ...  |

Table 1. Links between parameters and faults.

Figure 1. Structure of a smart sensor.

Figure 2. Example of structure of a smart actuator.

Figure 3. Control structure of a NC machine tool.

Figure 4. New organization for the machine.

Figure 5. Distributed control architecture.

Figure 6. Feed-drive control (Z-axis).

Figure 7. Cutting force components in turning.

Figure 8. Data exchange for distributed control of a lathe.

Figure 9. UML class and object diagrams.

Figure 10. Activity charts and state charts of the spindle and Z axis agents.

Figure 11. Tool flank wear profile.

Figure 12. Cutting forces without cooperation between agents.

Figure 13. Cutting forces with cooperation between CAID level agents.

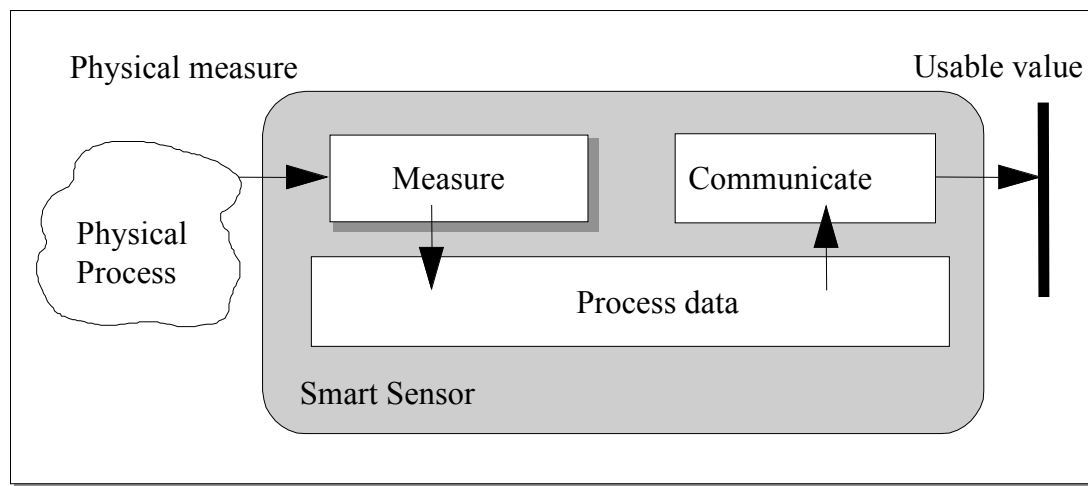


Figure 1.

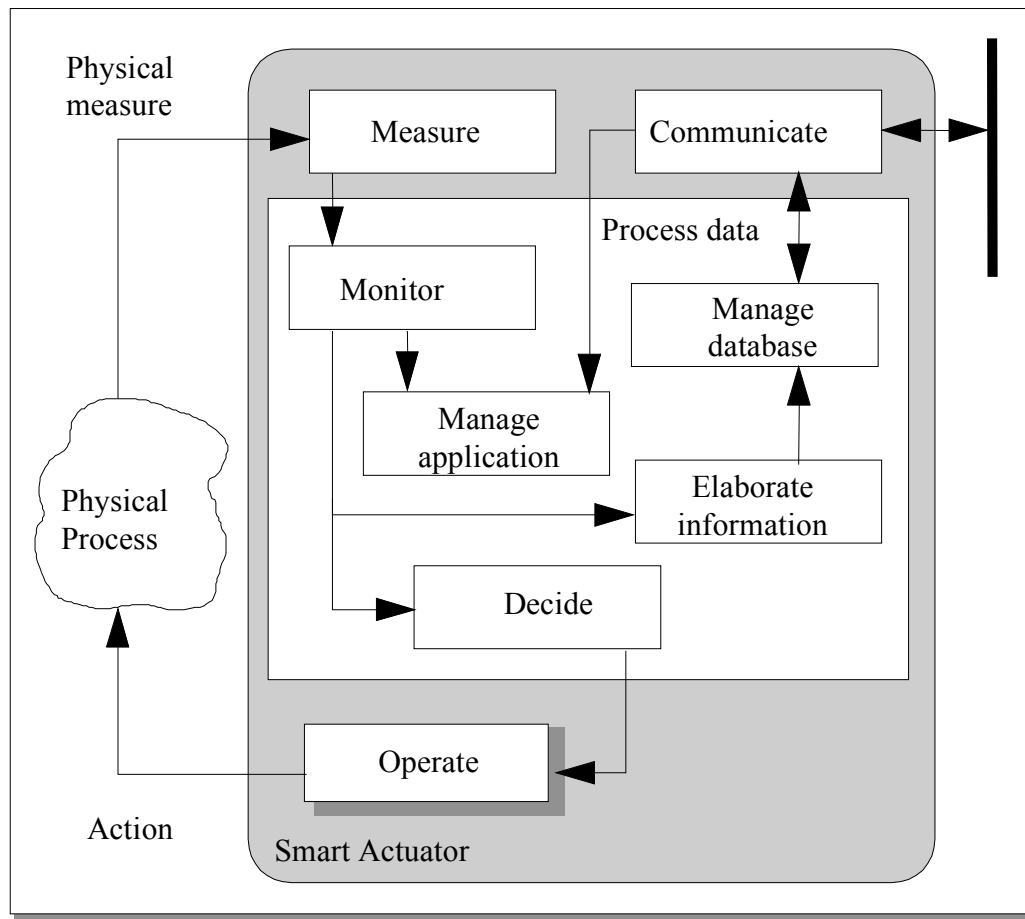


Figure 2.

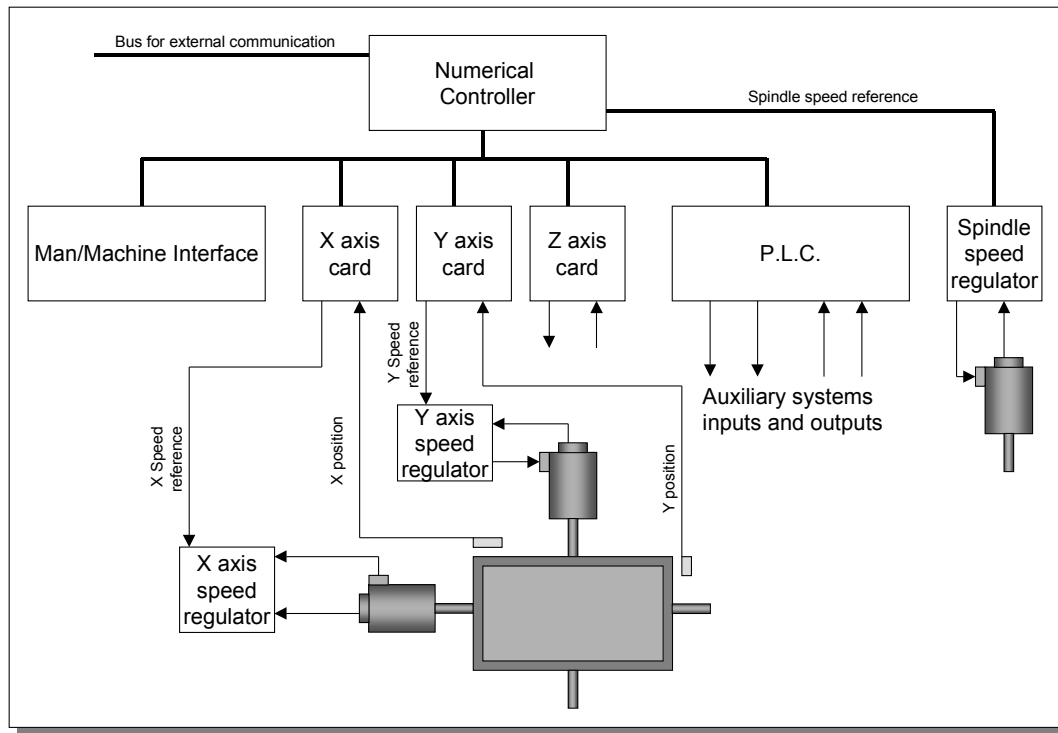


Figure 3.

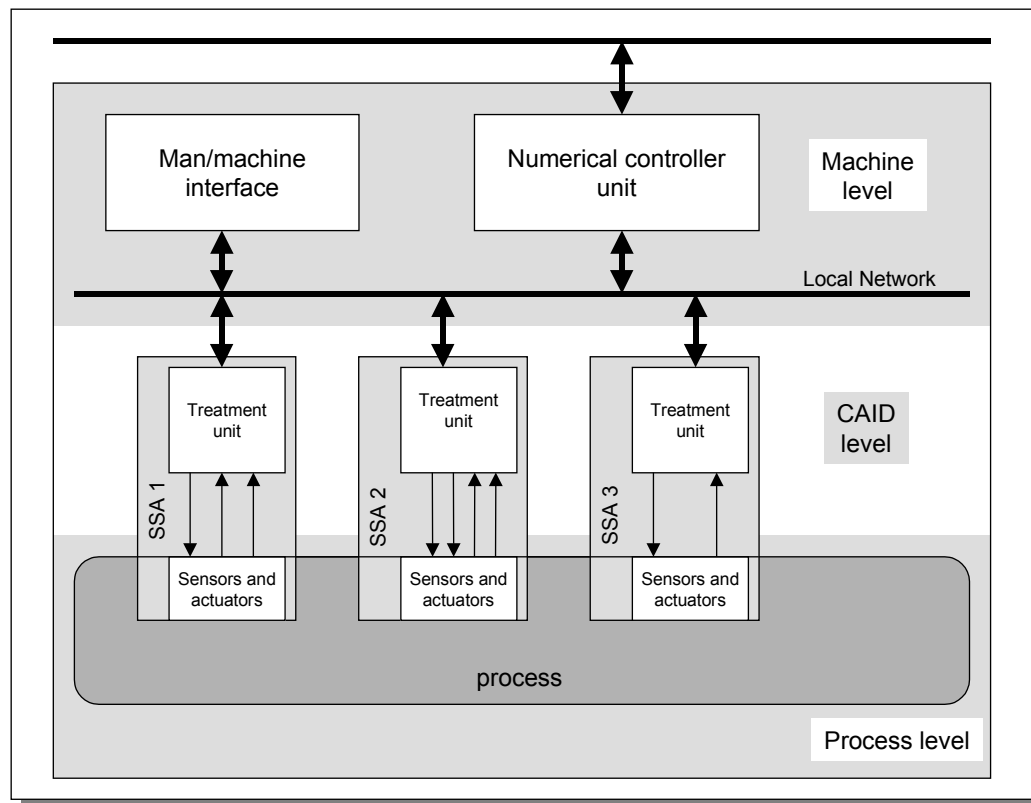


Figure 4.

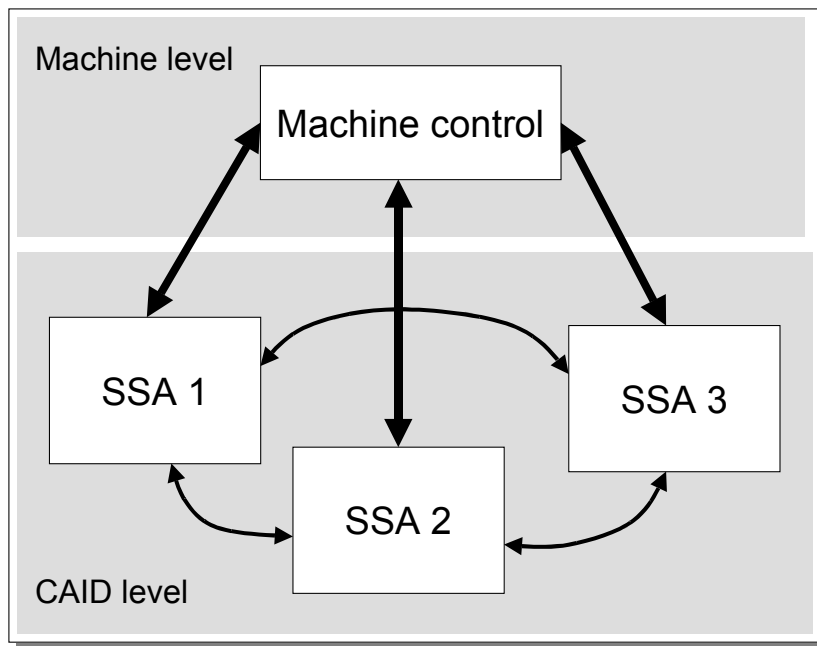


Figure 5.



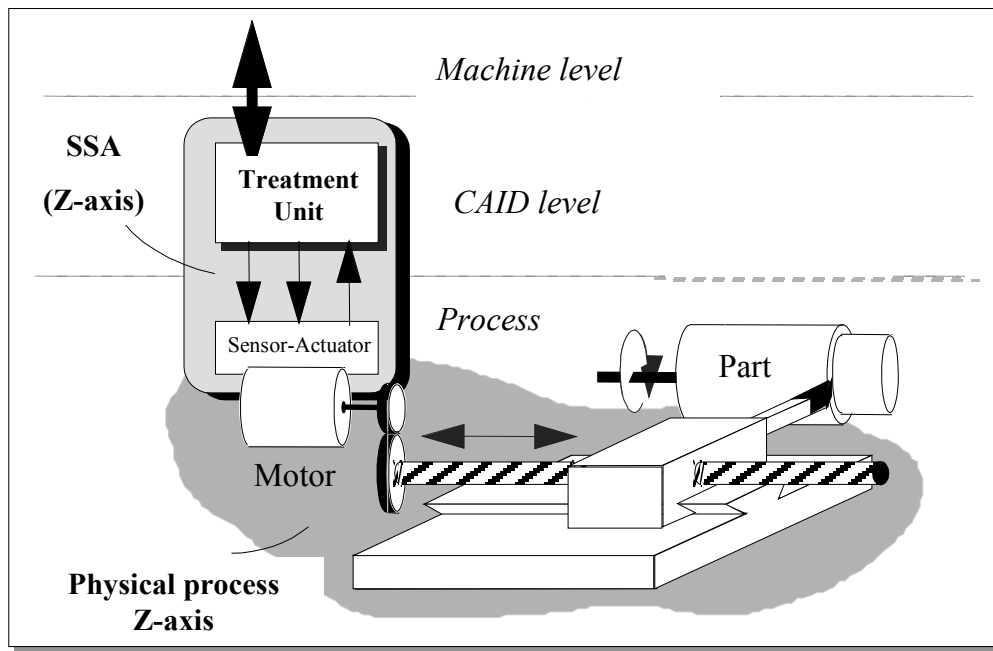


Figure 6.

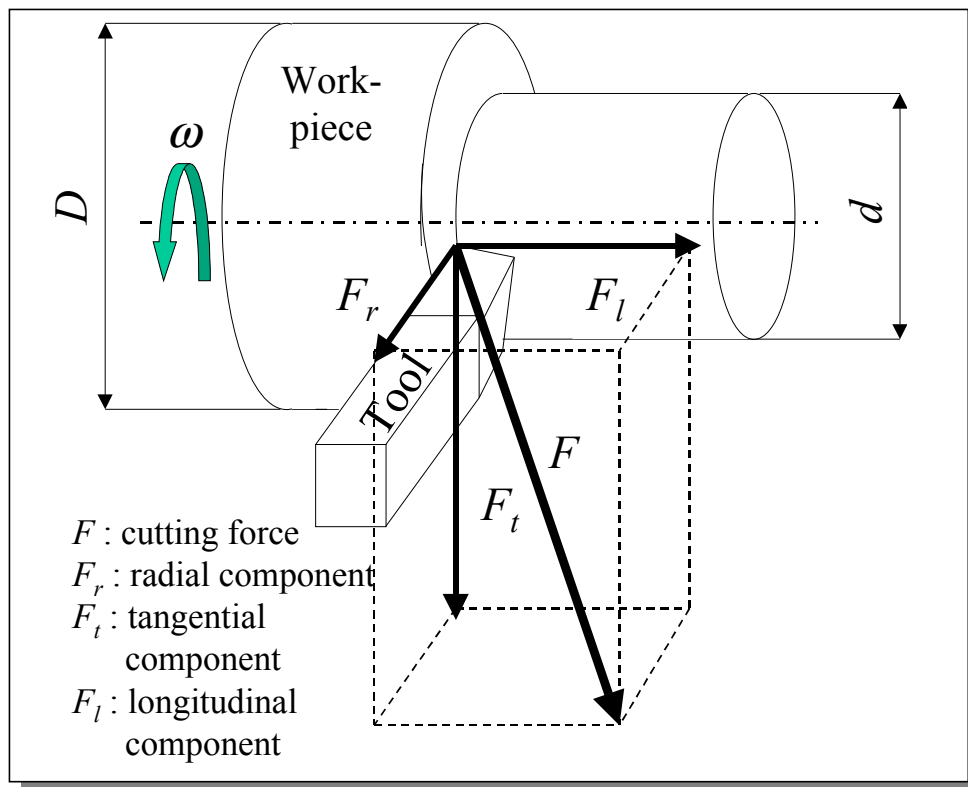


Figure 7.

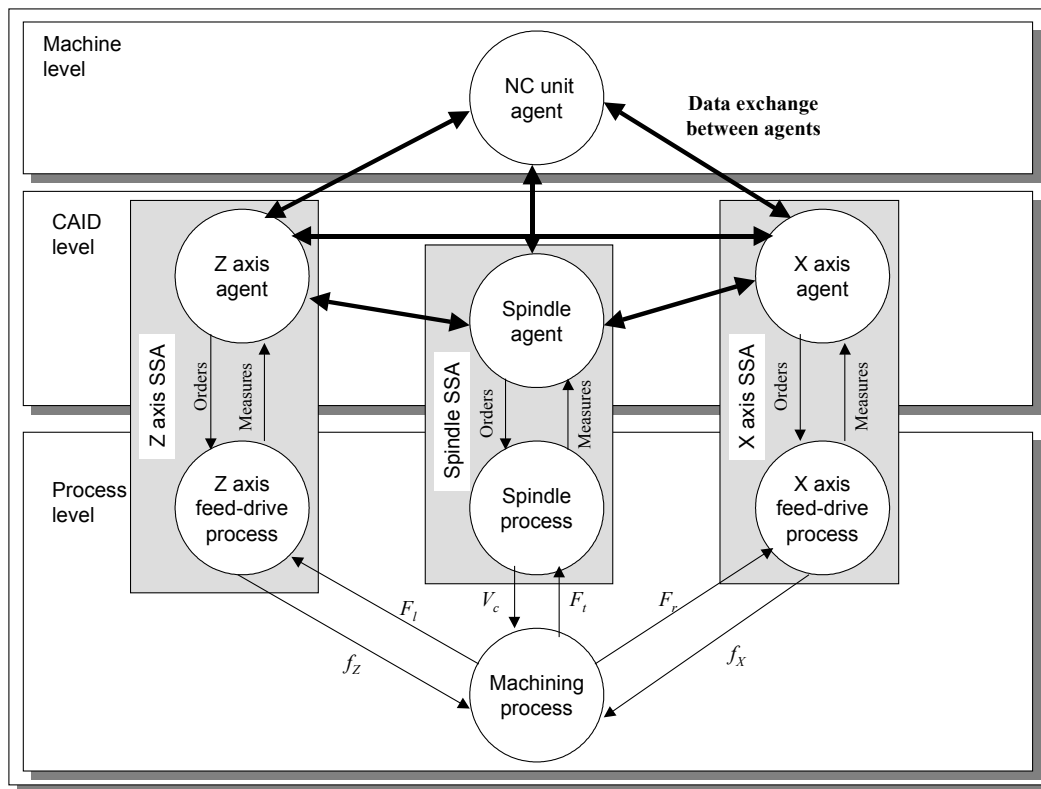


Figure 8.

Class Diagram

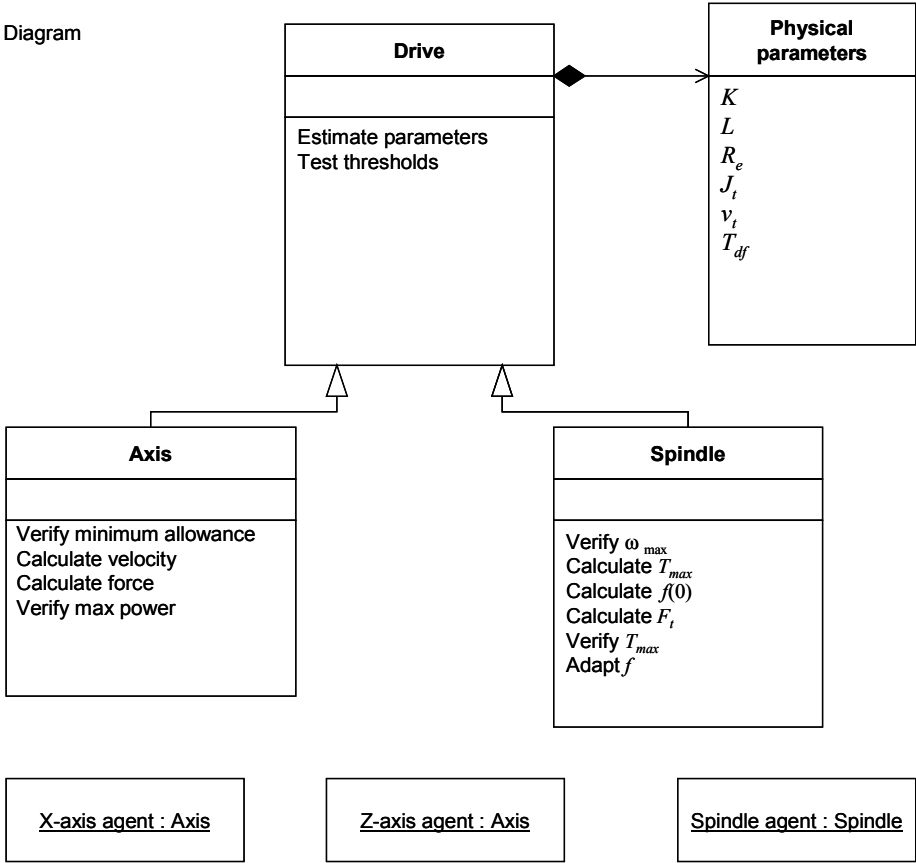


Figure 9.

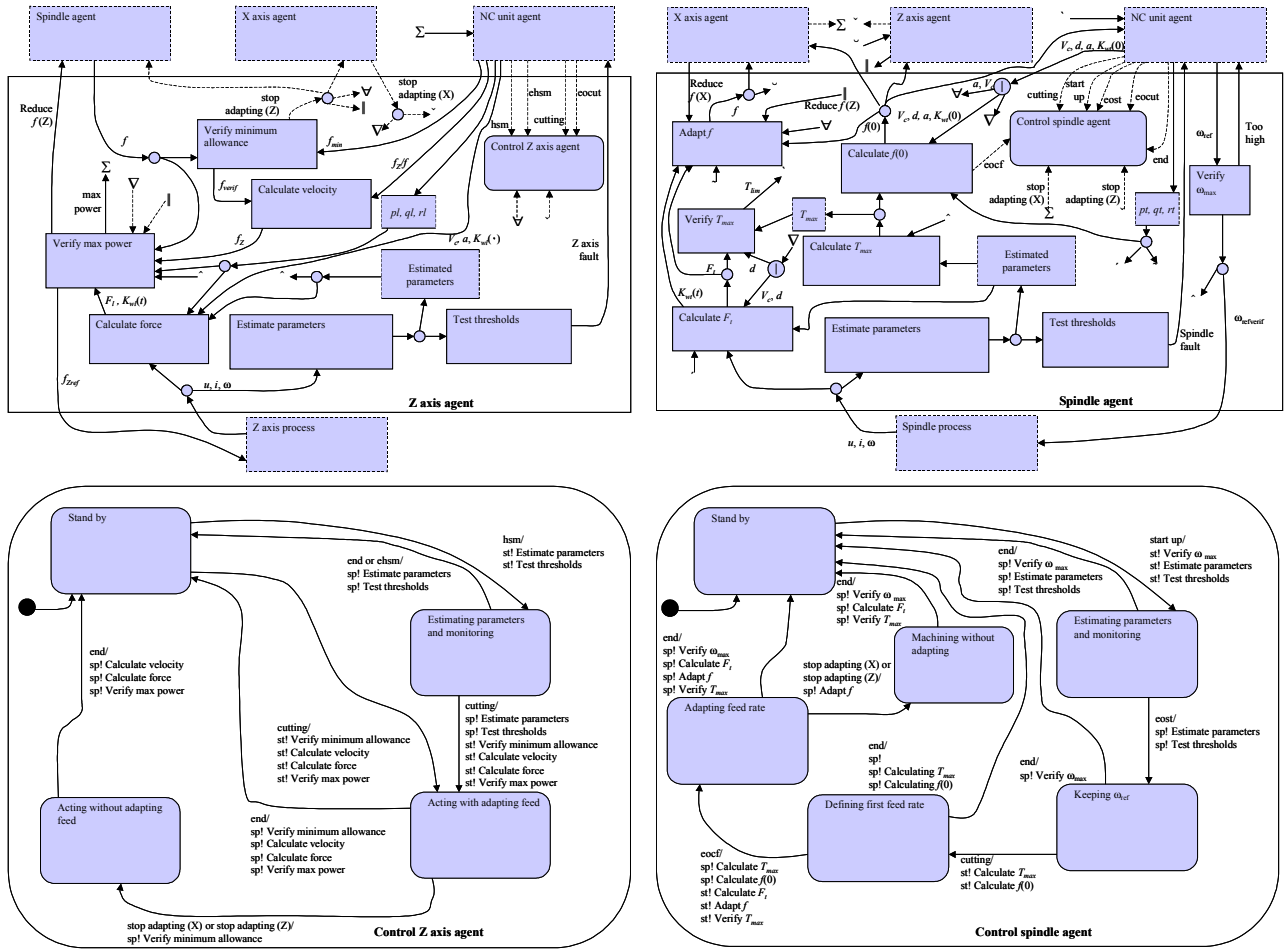


Figure 10.

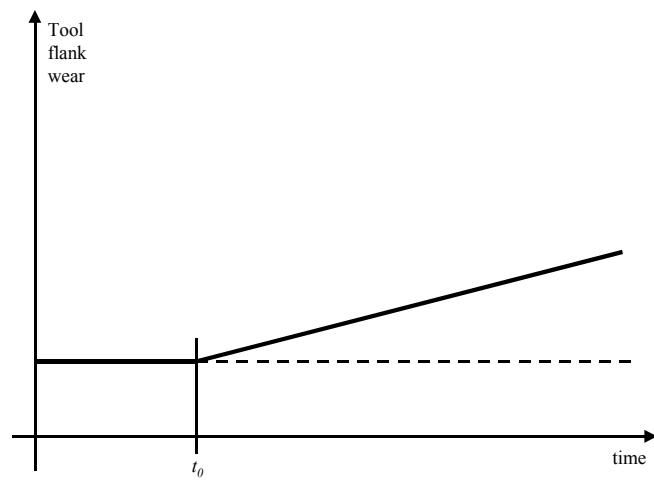


Figure 11.

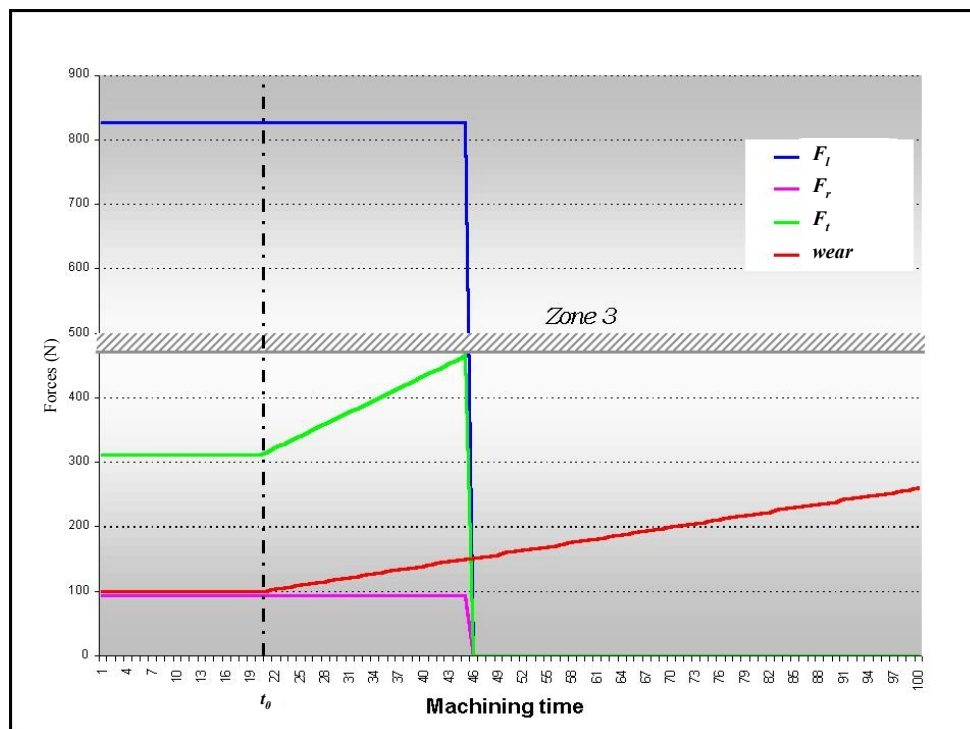


Figure 12.

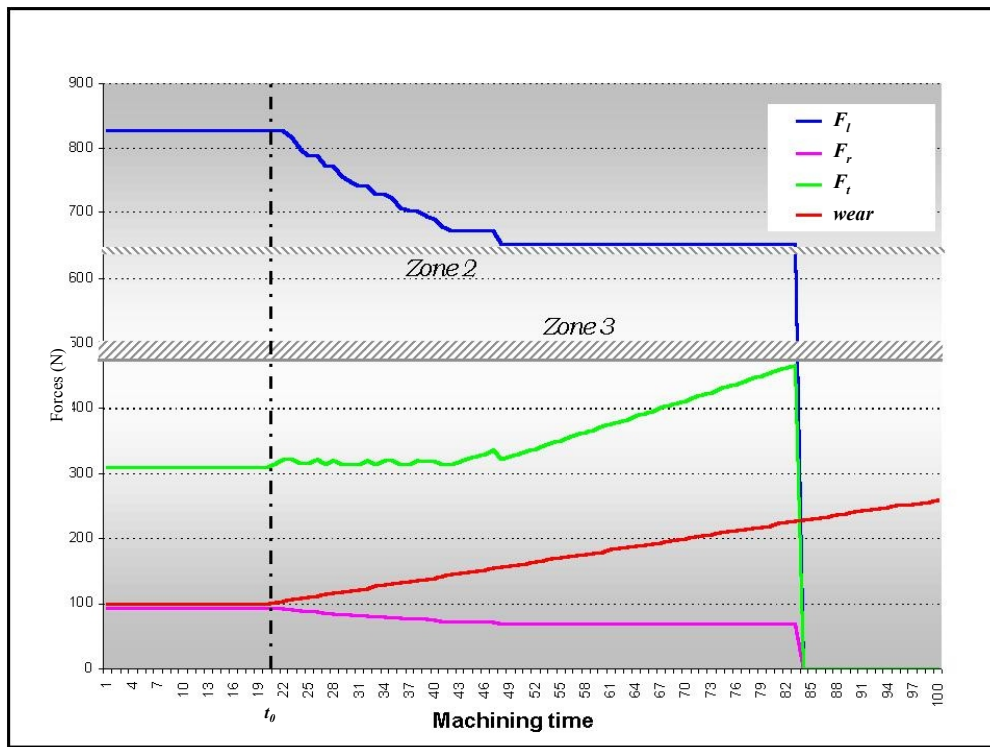


Figure 13.