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TRANSDUCTIVE NEUROFUZZY-BASED TORQUE CONTROL OF A MILLING PROCESS: RESULTS OF A CASE STUDY

Agustin Gajate[1], Andres Bustillo[2] and Rodolfo E. Haber[1]

[1]Centre for Automation and Robotics
Spanish Council for Scientific Research
Ctra. Campo Real Km. 0.200, 28500 Arganda del Rey (Madrid), Spain
{ agustin.gajate; rodolfo.haber }@car.upm-csic.es

[2]Department of Civil Engineering
University of Burgos
C/Francisco de Vitoria, s/n, 09001, Burgos, Spain
abustillo@ubu.es

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Abstract. *This paper presents the design and implementation of an intelligent control system based on local neurofuzzy models of the milling process relayed through an Ethernet-based application. Its purpose is to control the spindle torque of a milling process by using an internal model control paradigm to modify the feed rate in real time. The stabilization of cutting torque is especially necessary in milling processes such as high-speed roughing of steel moulds and dies that present minor geometric uncertainties. Thus, maintenance of the cutting torque increases the material removal rate and reduces the risk of damage due to excessive spindle vibration, a very sensitive and expensive component in all high-speed milling machines. Torque control is therefore an interesting challenge from an industrial point of view. Direct and inverse local neurofuzzy models used in the internal model control paradigm are obtained through an identification process which uses representative input-output data from the system under study. These local neurofuzzy models are dynamically created online (for each new datum to be processed). Once obtained, the models that describe the dynamic process form the basis of the networked control system. This methodology is successfully applied in a production environment, in order to demonstrate improvements in both performance and effectiveness. Two different industrial tasks are tested: roughing of slots and roughing of surfaces with sudden, unexpected height steps. In both cases the control system demonstrated its capability to avoid torque peaks that could lead to spindle damage while maintaining high productivity.*
Keywords: Neurofuzzy systems, Transductive inference, Milling process, Torque control, Ethernet

1. **Introduction.** Nowadays, increasing manufacturing process productivity is a fundamental industrial requirement for the survival of many companies. In the case of metal removal processes, improvements in productivity can only be achieved by modifying the cutting conditions of the process, such as cutting speed and feed per tooth [1]. However, any modifications to cutting conditions will, in many cases, increase tool wear and cutting vibrations, thereby reducing the quality of the machined part. Moreover, in certain critical cases these modifications may even damage the machine itself. It is therefore necessary to develop intelligent control systems capable of controlling these modifications, so that the new cutting conditions do not produce these undesirable effects [2].

High-speed Milling (HSM) is one of the most complex processes in the manufacturing industry, because it involves so many variables that determine productivity, such as surface quality and tool life [3]. If HSM processes are to expand in the industry, then optimization of the cutting conditions of the various subprocesses in the milling process of any industrial component is necessary, which will depend mainly on the spindle capabilities. The spindle is the machine part that provides power and torque to the cutting tool. The subprocesses that require less power and torque from the machine, such as finishing, are easily optimized, because neither the machine nor the milled work piece will be damaged if the programmed cutting conditions are too high. Trial and error methods are more commonly used for these subprocesses in the industry. On the contrary, it is not as easy to optimize the subprocesses that require the highest power or torque capabilities under industrial conditions. If the programmed cutting conditions are too high, damage could easily be produced to the spindle. Therefore, very conservative cutting conditions are often selected for these subprocesses.

Adaptive controls for cutting processes must therefore be developed to achieve the desired levels of autonomy, high productivity of milling machines that perform high torque operations, as well as their secure operation [4]. Such systems, used mainly to adjust and optimize the cutting conditions, have been an active area of research for many years [5,6]. However, very little research work has been developed under industrial conditions, unlike this investigation. The main reason is that developing adaptive controls for an industrial environment presents a major limitation: the impossibility of allocating the most suitable sensor in the most suitable position for the required task. When high productivity is sought, the best option appears to be motor power consumption [7]. When spindle safeguards are sought, accelerometers are often selected that measure close-to-tool-tip vibrations [8]. Nevertheless, the use of torque signal seems to be the best option for the case of High-Speed roughing of steel, because a balance needs to be struck between high productivity and spindle safeguard.

Artificial intelligence techniques are appropriate for these adaptive controls, due to the many uncertainties involved in metal removal processes, and milling processes in particular. In [9-11], various fuzzy controllers were designed to control the cutting torque (or cutting force) using the cutting torque itself or a motor current signal as an indirect sensor. In [12], the authors proposed hybrid models using neural networks, fuzzy logic and Particle Swarm Optimization to model the cutting torque (through cutting force). Then they applied a neural network to control through a Model Reference Adaptive Control system. However, their use of a force sensor means that possible industrial application is quite difficult.

This paper describes the synergy of combining two different artificial intelligent techniques: neural networks and fuzzy logic. The use of neural networks provides certain advantages, such as the capability of developing a model (and then a control system) without requiring physical process knowledge. Nevertheless, this black box approach has a drawback because the system's structure is unable to offer any physical meaning. The neurofuzzy systems emerged in the nineties to overcome this drawback, which combined an excellent ability to model any nonlinear function provided by the neural networks and the semantic transparency offered by fuzzy logic [13]. Moreover, this work uses transductive inference to model milling process from measured input/output (black box) data using engineering knowledge of the process variables, goals, and disturbances (white box) by applying recursive identification techniques (error backpropagation, least squares, singular value decomposition, etc.). The transductive neurofuzzy models are incorporated in an Internal Model Control paradigm (IMC).

Most neurofuzzy systems use inductive reasoning methods to identify a general model (function) drawn from the entire set of input/output data representing the whole system. In contrast, from a systems theory and system modelling perspective, transductive methods generate a model at a single point in the workspace. The closest examples are selected from among the known data for each new datum that has to be processed, so as to create a new local model that will dynamically approximate, as closely as possible, the process in its new state.

Thus, the main contribution of this investigation is the design and application of a Transductive NeuroFuzzy Inference System (TNFIS) to control a complex milling operation process. A novel aspect is the synergy between TNFIS and the IMC paradigm to achieve good closed-loop dynamic behaviour (i.e., transient response and steady state error), in addition to robust control system performance in the presence of non-modelled dynamics and disturbances. The main results show an increased lifespan of both spindle and tool, because cutting torque control reduces severe vibration levels, and in some cases leads to increased productivity. The demonstration of the good performance of this control under industrial conditions assures the industrial viability and robustness of this control.

Therefore, the main advantage of this approach over others in the literature is that it increases productivity and is a safeguard against spindle damage, by using only the cutting torque signal. This advantage is due to the use of local control models that are able to detect strong system nonlinearities.

2. **The High-speed Milling Process.** Milling is one of the most common processes of the manufacturing industry and, at the same time, one of the most complex. Over the last two decades, conventional milling at medium cutting speeds has given way to High-speed Milling, in which the transfer of generated heat from chip to tool is negligible [14]. These cutting conditions are only made possible by a significant increase in the feed rate and the rotation speed of the tool. Thus, the guidance systems of the machine and the milling head that provide the rotation force to the cutting tool must be redesigned. Friction guides and mechanical-transmission heads are respectively replaced by rolling guides and milled heads equipped with High-Speed spindles [15]. But these changes entail a significant decrease in the rigidity of the machine and its capabilities for cutting operations that require high cutting forces. HSM machines are therefore mainly used in industry for milling soft materials such as aluminium or for finishing steel components [16]; processes now known as high-speed manufacturing.

High-Speed manufacturing of a high-value industrial components such as moulds or dies implies different sequential subprocesses to achieve the final surface and geometrical specifications. First of all, milling operations are completed (Figure 1). Then drilling and Electrical Discharge Machining (EDM) operations are performed. The first milling operation, known as roughing, should eliminate all the waste material in the main extensive areas of the mould or die. This material presents strong variations, of up to 1 mm, in its geometry, due to uncertainties in the casting process. The milling machine should therefore cut under slow feed rates, because any sudden increase in cutting height would risk damaging not only the tool but worse still, the spindle bearings. The process engineer usually selects a very conservative feed rate for this first task and no on-line optimization is done. The following task, known as semi-roughing, gets rid of waste material in corners that are inaccessible to the high-diameter roughing tool and achieves close-to-final geometry of the whole mould or die surface. The last milling operation, known as finishing, performs a soft cut to improve surface quality and achieve the final geometry. This last task does not require a high torque cut, because there is limited waste material that is less than 0.1 mm in height, and its geometry is already well-defined. The programmed cutting conditions can therefore be very high. In the simplest cases, trial and error methods may

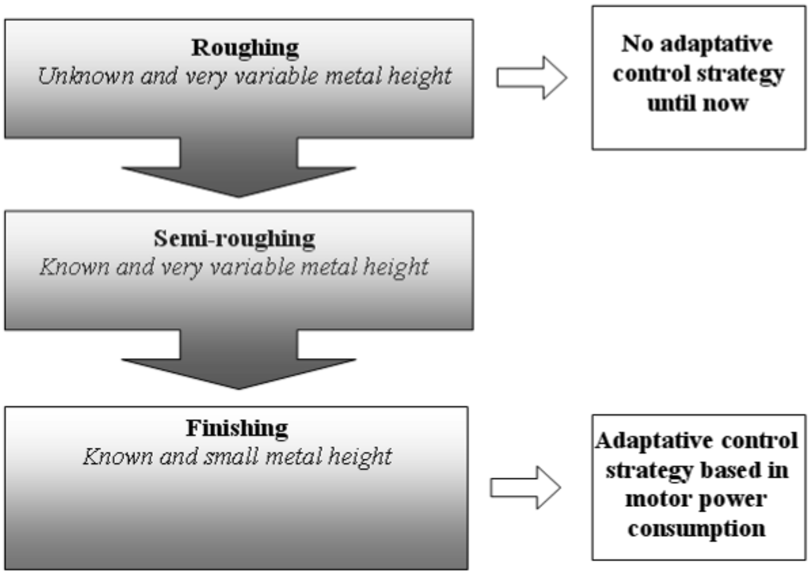

Figure 1. Milling subprocesses and possible control strategies for the manufacturing of a mould or die

be used to optimize this process, and in the most complex ones, the power consumption of the feed motors or spindle is controlled.

The most critical of the above-mentioned subprocess is roughing, the first stage of the machining process. Throughout this operation, the highest cutting forces (and therefore the highest cutting torque) of the whole process takes place. Moreover, torque control through feed rate manipulation can produce significant economic benefits for machining processes by reducing cycle time, avoiding spindle damage and, at times, by avoiding tool breakage [10]. Although, in some cases, torque requirements for the cutting process may be calculated [17], the result is only an estimation. This is mainly because the chip formation process is still not well known, hence the cutting forces can only be roughly estimated [18].

In contrast, real-time control requires precise modelling of the milling process, which is complicated due to changes in the dynamic process that the model has to capture (tool wear and breakage, vibrations, etc.). Indeed, the main challenge in designing a control system for milling is that the dynamics can not be accurately modelled in mathematical terms. Model parameters such as gains and time constants depend on the work piece material, and the cutting and tool conditions. Therefore, the model coefficients are time-varying functions of tool characteristics and conditions, work piece hardness, etc. If a linear model is available, the design of a linear controller is straightforward. However, it is at times impossible to identify the process dynamics and modelling on an experimental basis, due to technical or cost constraints (e.g., on-line experimental measurements constraints, production process limitations, etc.). In other situations, the validity of available models is very limited, as pointed out above. It is, therefore, rather difficult to design and implement classical and adaptive control schemes. However, neurofuzzy control schemes provide a feasible option for the design of a real-time control system.

The majority of studies on milling control and optimization acknowledge that cutting force is the most important variable in machining operation [19]. The problem is that a solution that uses this variable would not be applicable in certain production environments. However, the use of other variables such as torque, power consumption and spindle currents provide new technological alternatives for control systems.

In this case, we focus on neurofuzzy based torque control of high-speed face milling of steel components. Two of the main applications of this technology in this material are the roughing of deep cavities in moulds and dies and the machining of slots in machine-tool tables. These kinds of work pieces are very often unique pieces coming from casting processes without a precise geometry. Therefore, the large HSM machines that mill these work pieces do not perform repeatable work and cutting depths may vary greatly, especially during the first roughing operation, owing to imprecise geometric casting of the work piece.

3. **Transductive Neurofuzzy System.** Neurofuzzy inference techniques combine the paradigms of fuzzy logic and neural networks in order to take advantage of both techniques, achieving the simplicity of modelling (neural networks), while providing knowledge explicitly expressed in a set of "if-then" rules. In terms of learning procedures, most evolutionary neurofuzzy strategies apply inductive reasoning systems. The key issue in inductive reasoning is to find a general model (function) drawn from the entire set of input/output data that represent the whole system. The model is then used for designing the required control system. In contrast, there are transductive reasoning methods that generate a model at a single point in the workspace. The dynamic generation of local models represents the knowledge as the set of known data, which facilitates an incremental expansion on-line learning. In addition, these strategies are capable of functioning correctly with a small training set.

The Transductive NeuroFuzzy Inference System is a relatively new transductive reasoning system that consists of a dynamic neurofuzzy inference system with local generalization [20]. TNFIS, inspired by Song and Kasabov's approach [21], involves the creation of unique local models for each subspace of the problem, using the Euclidean distance. Gaussian membership functions and Mamdani-type systems are also used in TNFIS. Figure 2 shows the relevant steps for modelling on the basis of this approach. Some details are given as follows.

The system's inputs can be treated in different kinds of physics units, although normalization is recommended. In this paper, each input data (x'_j) is normalized according to (1):

$$x_j = \frac{x'_j - \mu_j}{\sigma_j} \tag{1}$$

where μ_j is the mean and σ_j is the standard deviation of the set of known data, i.e., the training set.

After normalization (x_j), the personalized local model is then created using data from the training set that are the closest to each new input datum. The Euclidean distance is used for selecting this data subset (2). The size of this subset (N_q) is an input parameter for the algorithm.

$$\left\|\bar{x} - \bar{k}\right\| = \left[\frac{1}{P}\sum_{j=1}^{P} |x_j - k_j|^2\right]^{\frac{1}{2}} \tag{2}$$

$$v_i = 1 - (d_i - \min(\bar{d})) \tag{3}$$

where P is the number of elements in the input data vector, $\bar{x}$ is the input data vector, $\bar{k}$ is each vector or datum in the training set, $\min(\bar{d})$ is the minimum element in the distance vector $\bar{d} = \left[d_1, d_2, \ldots, d_{N_q}\right]$, and N_q is the index representing the number of nearest neighbours.

The Evolving Clustering Method (ECM) [22] is used to create membership functions and fuzzy rules. It basically consists of a single-iteration algorithm for the dynamic on-line

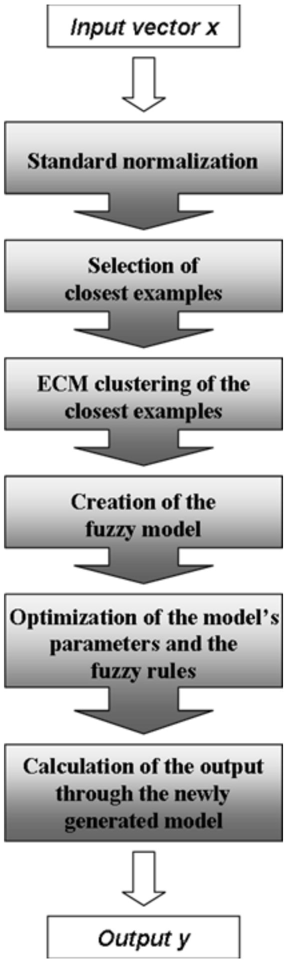

FIGURE 2. Block diagram of the TNFIS algorithm

clustering of a data set and begins with an initial set for the first datum. On the basis of Euclidean distances and the clustering threshold value (D_{thr}), the algorithm either adds each datum to an existing set (updating the center and the radius of the set) or creates a new set for all subsequent data. The resulting clusters are circular and are used to create the Gaussian membership functions. For that purpose, the center of the set is taken as the center of the Gaussian function, and the radius is taken as the width. A single-input/single-output theoretical example of ECM is depicted in Figure 3.

Considering P inputs, one output and M fuzzy rules initially defined by the clustering algorithm, the lth rule has the form:

$$R_l: \text{ If } x_l \text{ is } \Phi_{l1} \text{ and } x_2 \text{ is } \Phi_{l2} \text{ and } \ldots x_P \text{ is } \Phi_{lP}, \text{ then } y \text{ is } \Gamma_l. \text{ (Cluster } l) \tag{4}$$

$$\Phi_{lj} = \alpha_{lj} \exp\left[-\frac{(x_{ij} - m_{lj})^2}{2a_{lj}^2}\right] \tag{5}$$

$$\Gamma_l = \exp\left[-\frac{(y - n_l)^2}{2\delta_l^2}\right] \tag{6}$$

where m and n are the centres of the Gaussian functions for the inputs and outputs, a and δ are the widths, $i = 1, 2, \ldots, N_q$ is the index representing the number of closest neighbours (N_q), $j = 1, 2, \ldots, P$ represents the number of input variables, and $l = 1, 2, \ldots, M$ represents the number of fuzzy rules.

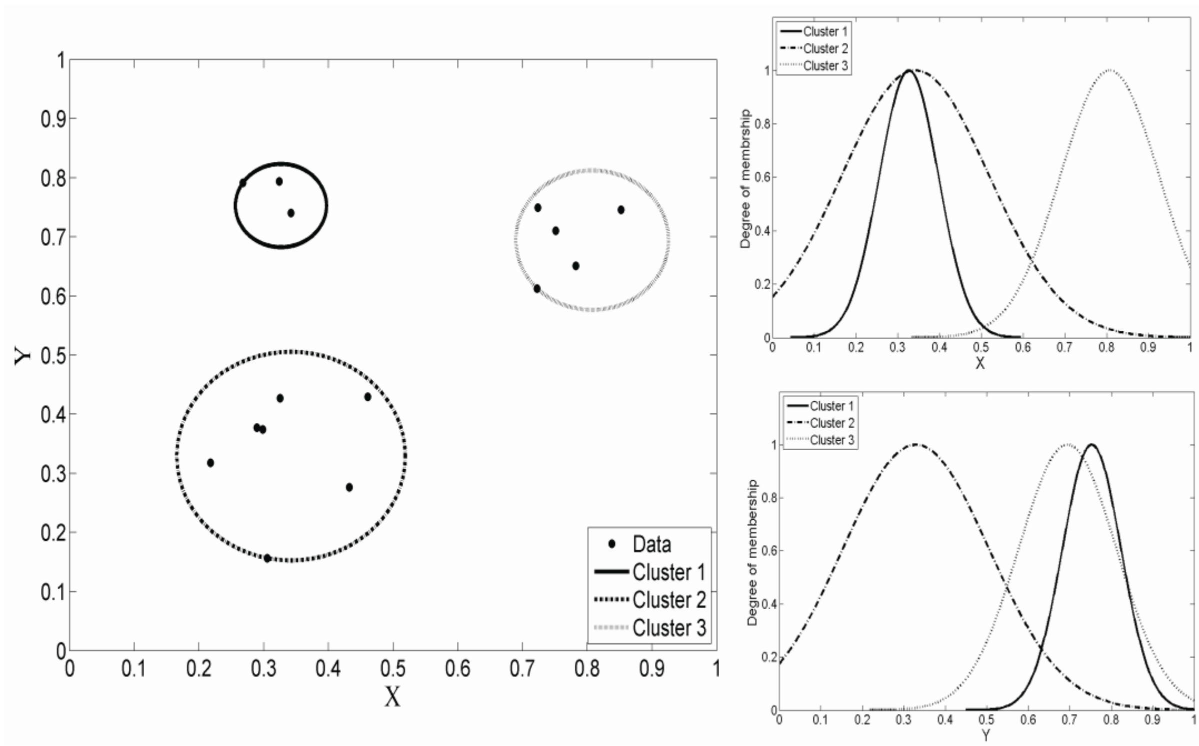

FIGURE 3. Example of the ECM algorithm for two inputs and the corresponding membership function that is generated

The centres m and n and the widths a and δ are obtained from the ECM algorithm, while the parameter α_{lj} is chosen by design ($\alpha_{lj} = 1$) and represents the weight of each input membership function. These parameters are adjusted with the back-propagation algorithm described in [23].

Using the center of area defuzzification method, the output of the TNFIS for an input vector $\bar{x}$ is calculated as follows:

$$O(\bar{x}_i) = \frac{\sum_{l=1}^{M} \frac{n_l}{\delta_l^2} \prod_{j=1}^{P} \alpha_{lj} \exp\left[-\frac{(x_{ij} - m_{lj})^2}{2a_{lj}^2}\right]}{\sum_{l=1}^{M} \frac{1}{\delta_l^2} \prod_{j=1}^{P} \alpha_{lj} \exp\left[-\frac{(x_{ij} - m_{lj})^2}{2a_{lj}^2}\right]} \quad (7)$$

The system uses input/output data of the closest training data $[\bar{x}_i, Y_i]$ and the goal is to minimize the following target function:

$$E = \frac{1}{2} v_i [O(\bar{x}_i) - Y_i]^2 \quad (8)$$

where v_i, with $i = 1,2,\ldots,N_q$, indicates the distance weight (the proximity of each target to the expected outputs) calculated in the first step, $O(\bar{x}_i)$ is the defuzzification function that yields the output of the TNFIS, and Y_i is the desired output.

4. **Internal Model Control.** Internal model control is an widely used, well-established technique for designing intelligent controllers [24]. This closed-loop control scheme explicitly uses a model (G_M) of the dynamics of the plant to be controlled situated in parallel with the plant (G_P). Furthermore, it also contains another model of the inverse of the plant's dynamics (G'_M) situated in series with the process and acting as a controller.

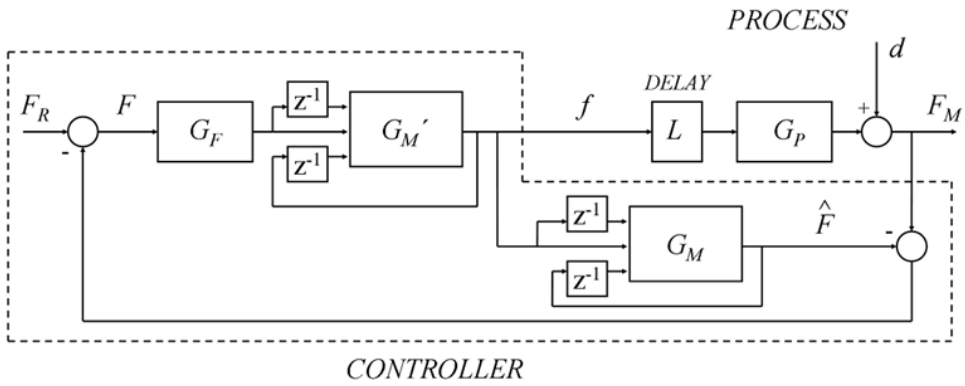

Figure 4. Internal model control scheme

One of the advantages of this control scheme is that dynamic analysis and robustness properties can be easily checked. However, the inversion of a nonlinear model is no easy task, and there may be no analytical solutions. Another associated problem is that inverting the process model can lead to unstable controllers when the system is a non-minimum phase system [25].

The inverse model G'_M (9) and the direct model G_M (10) are output error (OE) models to achieve a better approximation of the TNFIS algorithm training set.

$$f(k) = G'_M(T_q(k), T_q(k-1), f(k-1)) \tag{9}$$

$$\hat{T}_q(k) = G_M(f(k), f(k-1), \hat{T}_q(k-1)) \tag{10}$$

where $\hat{T}_q(k)$ is the torque estimated by the direct model, and $f(k)$ is the feed rate calculated by the inverse model.

Once the models have been obtained, a low-pass filter (G_F) is included in the control scheme. The filter is incorporated in the control system to enhance its robustness and to reduce high-frequency gain. It also works to soften fast, brusque signal changes, thus improving the controllers' response.

Figure 4 shows the internal model control scheme for networked control. The filter G_F and the process represented by G_P are shown in the control scheme. The scheme also includes the delay (network-induced delay plus dead-time process) through block L. The issues related with delay L and the architecture of the networked control system are explained in following section.

In this paper, the TNFIS algorithm is used to create the models (both direct and inverse) on line. Both models are calculated with each new input into the control scheme. Using this neurofuzzy inference technique, the creation of the inverse model proves to be simpler and always offers a solution.

The direct model must be trained to learn the dynamics of the process. A TNFIS system is used with a training set made up of input/output data, where the input is the feed rate, while the torque is used as the output variable. In order to calculate the inverse model, instead of inverting the direct model found analytically, another TNFIS system is used, the training set for which contains data with torque values as its input and feed rate values as its output. Thus, the system can successfully learn the inverse dynamics of the high-performance milling process.

The training data for both the direct model and the inverse model were obtained from real milling operations with test pieces made of steel F114 material (ASTM) under actual cutting conditions. Nevertheless, the training data set does not have to be very extensive, because it is enough to have representative values of each operating region.

The accuracy of the models depends on the choice of certain parameters of the TNFIS algorithm, such as the number of closest neighbours, the maximum number of iterations and the learning rate of the back-propagation algorithm, and the set-clustering threshold value (parameter of the clustering algorithm in use). When choosing these parameters, the goal is to find a trade-off between accuracy and the quality of the dynamic response of the local models.

5. **Networked Industrial Platform.** A software platform for network-based applications of manufacturing processes was previously introduced in [26]. This platform provides a standard interface for machining processes that ensures the transparency and portability of the software that is developed for process supervision and control. Figure 5 shows a schematic diagram of the system with two network levels. A first level is implemented in a real-time local area network (Profibus) and the second one, is run over a wide area network (Ethernet or even Internet).

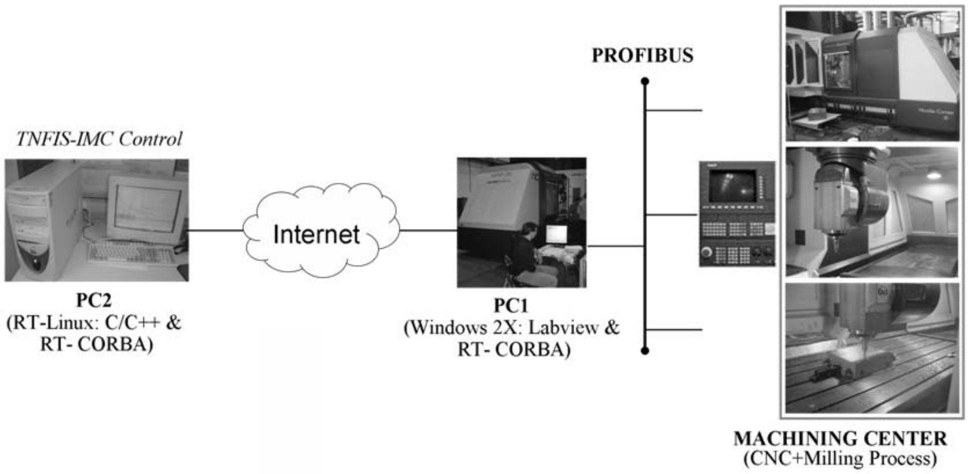

FIGURE 5. Networked industrial platform

Two personal computers (PC) perform the control and supervision tasks at two levels. One PC is located in the manufacturing company and it is connected to the open Computerized Numerical Control (CNC) through a Profibus network. This local PC performs three different tasks. The first, torque measurement, is done directly from PC1 that reads the spindle motor current consumption of the CNC. The second task is to receive the control signal computed by PC2, and enable data interface and synchronization tasks performed by commercial software (Labview, NC-DDE application) over Internet. PC2 cannot be connected directly to the CNC due to proprietary CNC software constraints. The third task is to link up the second personal computer, PC2, via Internet with standard object-oriented middleware. The second computer implements the TNFIS-IMC control strategy and it communicates with the first level through Internet using CORBA middleware.

The control loop consists of the transductive neurofuzzy controller (with the direct and inverse neurofuzzy models) and the HSM machine tool. The control system acquires torque values through Profibus for each sampling instant. The TNFIS-IMC controller calculates the control action and sends it to the open CNC via Profibus. The sampling time is set according the spindle speed of the corresponding HSM operation (revolutions per minute). The setpoint, the process output (i.e., spindle torque) and the control action (i.e. feed rate modification) are sent from the first to the second level via Internet, in order to perform networked neurofuzzy control of the system. Networked control at a lower level network (i.e., Profibus) requires data transmission in real time. The communication technology is therefore a critical issue to satisfy this constraint. Fieldbus technologies guarantee a deterministic behaviour which makes them suitable for industrial automation. A Profibus-based proprietary industrial network, Siemens MultiPoint Interface (MPI), performs the communication between the controller PC and the open CNC. The maximum network induced delay is experimentally estimated and used in the design of the controllers [26].

Moreover, Internet assists with network control by enabling connections between the distributed software components. The suggested tuning law suggests that this communication link does not require strict real time. In addition, the proposed communication method makes the supervision system immune to the influence of delays on deteriorating control performance. All information is sent through a tunnelling mechanism that uses an encrypted connection over an untrusted network, in order to guarantee security and safety over the Internet.

6. **Results of Industrial Test.** Experimental milling test was conducted at the Nicolas Correa factory in Burgos (Spain). The personal computer that performed the transductive neurofuzzy control strategy (PC2) was located 250 kms away from the manufacturing plant in Burgos at the Universidad Autonoma of Madrid where the TNFIS control system was implemented. TNFIS-IMC was written in C++ and deployed on PC2, with an RT-Linux operating system and RT-CORBA middleware. PC2 operates as a server, processing the torque signal from the PC1 located in the factory in Burgos and sent back the control action (feed rate) to run on the open-architecture CNC (connected with PC1).

A *Rapid-30* HSM Machine, equipped with a Sinumerik 840D open CNC was used. The cutting tool was an insert mill with 2 round 20 mm diameter inserts specially designed for steel HSM roughing. This tool is especially suitable for high-speed roughing of moulds and dies under high productivity conditions.

The work piece material was F114-quality steel and the profile dimensions were 410 mm $\times$ 410 mm. The nominal cutting conditions obtained from the cutting tool handbook were $s_0 = 3500$ rpm (spindle speed) and $f_0 = 3500$ mm/min (feed rate). The feed rate override range was 90-120%, which represents the range that the machine operator can change directly from the machine's keyboard, because the other cutting parameters are completely fixed by the CAM Program designed by the process engineer. Therefore if severe vibrations occur during the cutting process, the operator only needs to change the feed rate in this interval to solve the problem. The sampling time of the acquisition and control signals was 18 ms, according to the rotation speed of the spindle.

The torque setpoint was selected according to the corresponding cutting conditions and spindle power constraints. The setpoint was then set to 5.5% of the maximum. Due to the noise of the torque signal, a low pass filter (second order Butterworth filter) with a cut-off frequency 11.14 Hz was used.

The TNFIS algorithm parameters chosen were the same for the direct model and the inverse model (with the exception of the training sets, which represent different dynamics although they contain the same data). The chosen number of closest neighbours (N_q) was 5, and the number of iterations of the back-propagation algorithm was 20, with a learning rate of 0.001. The whole number of input and output membership functions is directly related with the number of closest neighbours (N_q), and therefore the maximum number of membership functions is 5 but changes dynamically according each new datum and the ECM algorithm. The threshold value selected for set generation in the ECM algorithm is $D_{thr} = 1$. According to these parameters and models (9) and (10), the mean elapsed time between data input and control signal computation by NFI-IMC was 2.3

ms, calculated with an Intel Core 2 CPU (CPU 6400, 2.13 GHz, 0.98 GB RAM) and a Linux operating system. When choosing these parameters, the goal is to find a trade-off between the accuracy and the quality of the dynamic response of the local models.

Two experiments were performed to test the performance of the new controller. The first experiment simulated industrial roughing of slots of machine-tool tables. The second simulated HSM roughing of casting of moulds and dies the geometry of which was not well-known. This second experiment is also useful to check the robustness of the controller.

The first experiment was a slot milling operation on the cubic steel work piece. The objective of the TNFIS-IMC system was to obtain a good transient response without overshoot, using the cutting parameters given by the tool manufacturer for this tool and work piece material combination. The response of the system is shown in Figure 6.

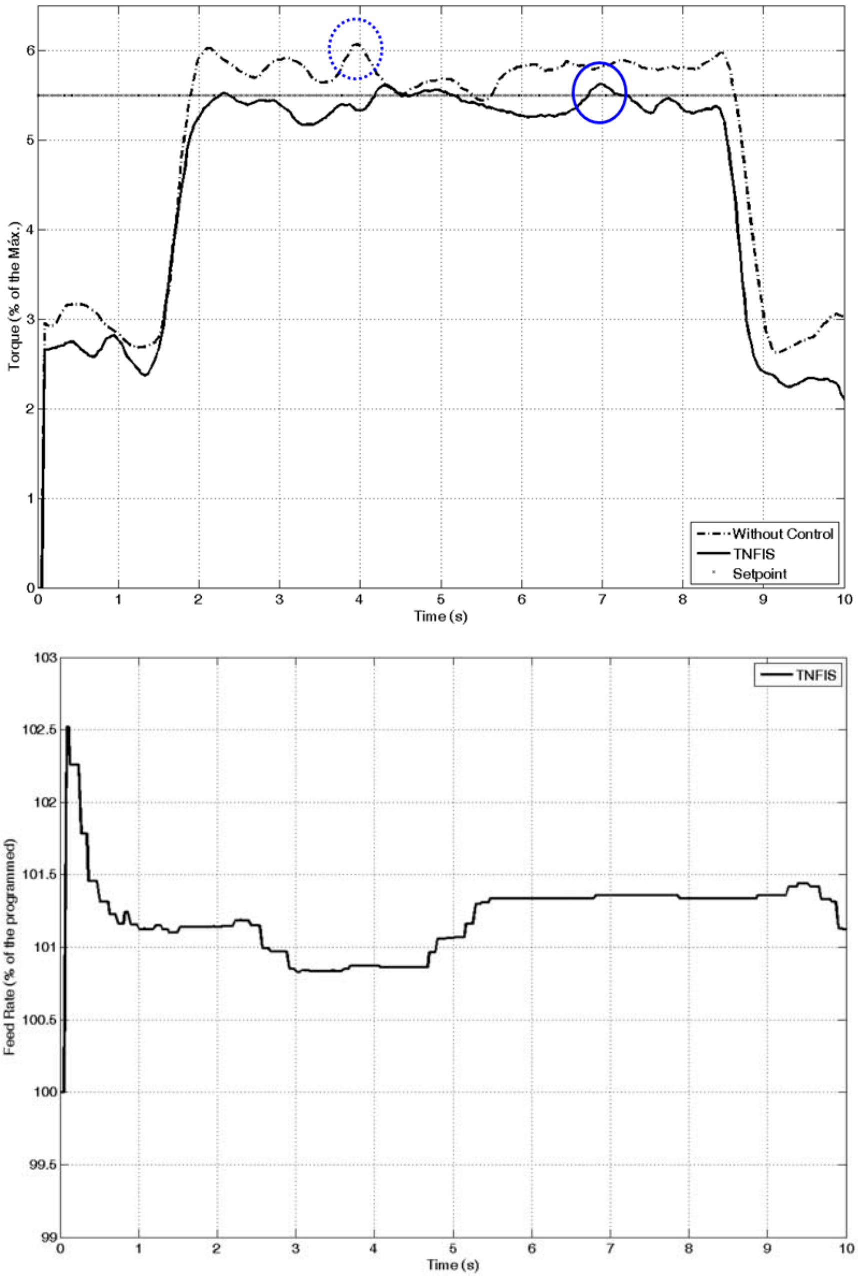

Figure 6. Real system response and control signal in the first experiment

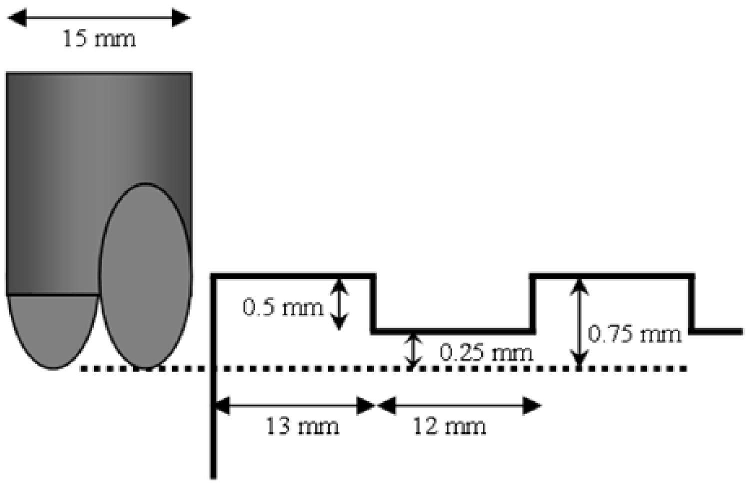

FIGURE 7. Work piece profile for the second experiment

It may be concluded from Figure 6 that the new system can increase the feed rate by an average of 1.2% above the programmed value, and that it also increases machining productivity by the same percentage. At the same time, the system decreases the cutting torque by an average of around 8% under the programmed value with regard to non-controlled milling and, more importantly, avoids torque peaks (Figure 6, moment 2.2 s or 3.9 s) that could cause spindle damage. In this case, without torque control, the maximum torque peak during the experiment (blue circle in Figure 6) is 0.5 (11%) higher than the programmed torque. With active torque control, this maximum is only 0.15 (less than 3%) higher than the programmed torque.

The second experiment consisted in the HSM of a sixteen step-shaped profiles to emulate abrupt variations in cutting depth. Figure 7 shows the profile of the work piece with a depth of cut that varies between 0.25-0.75 mm. The top stair width is 13 mm and the down stair width is 12 mm, in both cases shorter than the tool diameter of 15 mm. The relation between tool diameter and stair width is not considered conducive to stable cutting, because, the tool is neither completely immersed in the material, nor is it completely out of contact with the material under these conditions. That is the worse condition that could occur in the real roughing of a mould's surface. In this abnormal situation, it is expected that the TNFIS-IMC system will become unstable. The setpoint is fixed at 5.5% of the spindle's maximum torque. Figure 8 shows the behaviour of the system during the second experiment.

Figure 8 shows a strong smooth variation of cutting torque throughout the whole experiment in both the controlled and the non-controlled experiment. This first result was expected because the tool's immersion in the work piece was continuously changing due to the experiment design. Although the control system fails to maintain the setpoint at all times, the control system does not become unstable, which could be especially serious for the industrial application of the control. The new control is able to decrease the cutting torque by an average of 6.48 to 4.95 (% of the maximum spindle capability): as the programmed value is 5.5%, this means a reduction of 28%. The productivity can not be increased at the same time, but its reduction is relatively small with an average feed rate of 99.2% for the programmed value of the whole work piece. Cutting torque modulations decrease with the new control in comparison with non-controlled machining: the standard deviation of the cutting torque throughout the whole cutting profile decreased from 1.37 in the non-controlled experiment to 1.17 in the TNFIS experiment. As happened in the first experiment, the maximum peaks decrease strongly with the new control: without torque

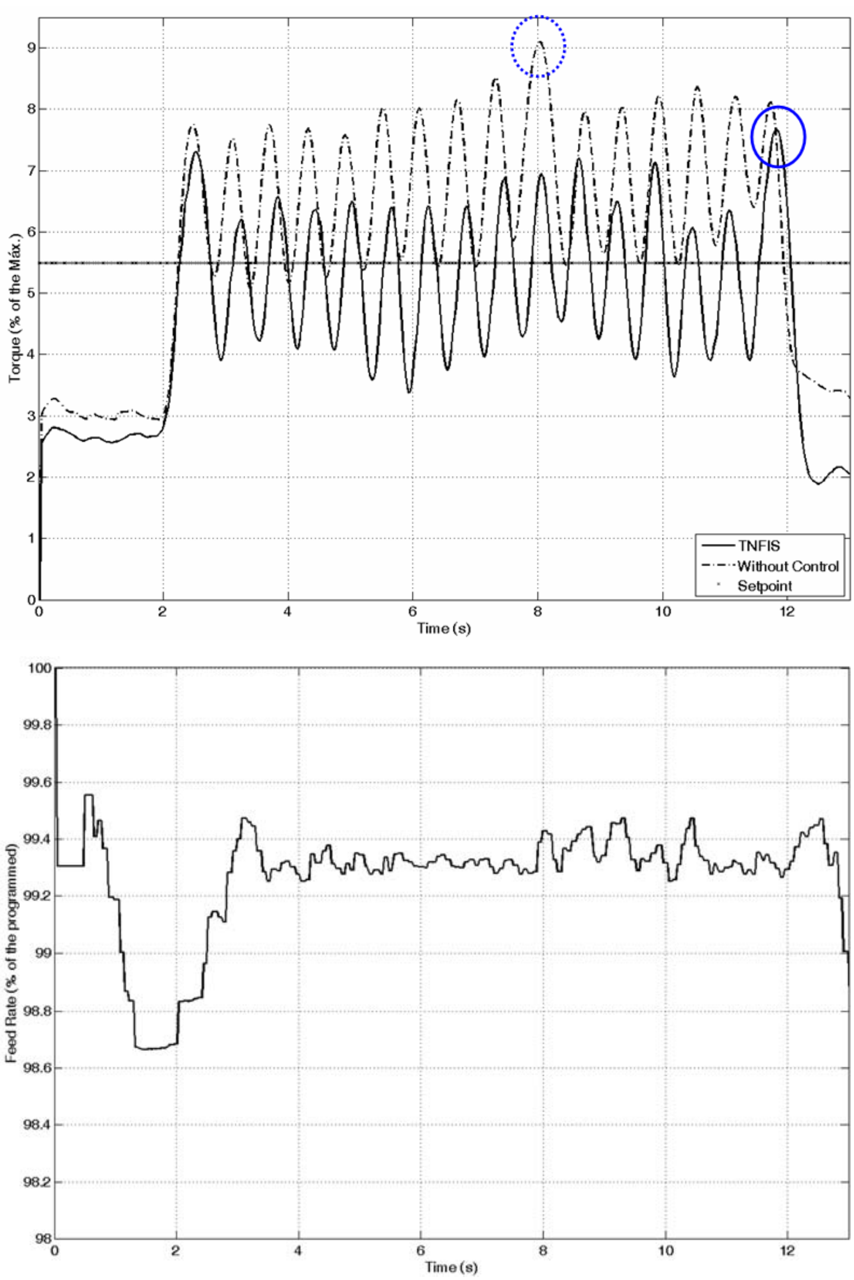

FIGURE 8. Real system response and control signal in the second experiment

control, the maximum torque peak (blue circle in Figure 8) during the experiment is 4.6 higher than the programmed torque, which is to say 83.5% higher. With active torque control, this maximum is only 2.2 times higher than the programmed torque, which is only 40% higher.

Table 1 summarizes differences between performance, using the new control for both experiments, compared with no-control performance.

7. **Conclusions.** The on-line optimization of HSM roughing operations is an industrial requirement that can not be performed using traditional controllers. This paper has described the novel application of an intelligent control system based on local neurofuzzy models that are applied to this industrial task. The novel approach includes the control of the spindle torque instead of the motor current consumption, the most often approach

Table 1. Cutting performance with the new control compared with no control for both experiments

Experiment	Application	Productivity	Torque average from programmed value	Torque peaks from programmed value	Standard deviation
1- Slot milling	Machine tools table manufacture	+1.2%	−8%	−8%	Not significant
2- Step-shaped profile milling	Mould and dies roughing	−0.8%	−28%	−43.5%	−17%

that is not suitable to avoid spindle damage in HSM roughing. The control modifies the feed rate in real time using an internal model control paradigm. This new control is especially suitable for HSM roughing of steel components that present small geometrical uncertainties such as the castings of moulds and dies.

The TNFIS system is capable of generating sufficiently accurate local models with good dynamic behaviour. A control strategy based on the transductive neurofuzzy system and the internal model control paradigm was proposed and applied in an industrial environment. Introducing the local direct and inverse neurofuzzy models into an IMC scheme enabled networked cutting-torque control to be performed under different conditions.

The proposed transductive neurofuzzy controller yields a suitable system regardless of disturbances and nonlinearities, making it a good choice for coping with disturbances such as work piece hardness and changes in milling depth. The transductive neurofuzzy inference system was also shown to be a simple, fast, precise, and computationally viable tool for controlling such complex processes as HSM.

Moreover, this work has also presented an industrial demonstration of the possibilities of the new control system under two different conditions: 1) roughing of slots and 2) roughing of surfaces with sudden and unexpected height steps. In both cases the control shows that it can avoid torque peaks that could lead to spindle damage and can, at the same time, keep high productivity. In the first experiment the new control increases productivity by 1.2% and reduces the torque peaks and the average torque value by around 8% compared with no-control milling. In the second experiment, the new control loses a 0.8% of productivity in the most critical situation that a spindle could suffer under continuous cutting, but reduces the torque peaks and the average torque value by around 43% and 28% respectively compared with no-control operation.

Future work will focus on the application of this controller to High-Speed Drilling of multi-layer components such as aeroplane skins with Titanium and carbon fibre layers. This control may be improved if the neurofuzzy system was self-learning and self-developing. Similarly, it intends to introduce a parameter in the algorithm that relates to the sensitivity of the user to decide in certain cases to prioritize productivity over conservation.

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