

# Combined feedforward and feedback control of end milling system

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Received 18.01.2011; published in revised form 01.03.2011

## Manufacturing and processing

### ABSTRACT

**Purpose:** Purpose of this paper. An intelligent control system is presented that uses a combination of feedforward and feedback for cutting force control in end milling.

**Design/methodology/approach:** The network is trained by the feedback output that is minimized during training and most control action for disturbance rejection is finally performed by the rapid feedforward action of the network.

**Findings:** The feedback controller corrects for errors caused by external disturbances. The feedforward controller is an artificial neural network (ANN) which approximates the inverse dynamics of the machining process.

**Research limitations/implications:** The dynamic architecture of the neural controller is chosen, and the methods for delay time treatment and training network on line are investigated. The controller was designed and tested using a simulator model of the milling process that includes feed drive model and cutting dynamics simulator.

**Practical implications:** An application to cutting force control in end-milling is used to prove the effectiveness of the control scheme and the experiments shows that the dynamic performance of the cutting force control is greatly improved by this neural combined control system.

**Originality/value:** New combined feedforward and feedback control system of end milling system is developed and tested by many experiments. Also a comprehensive user-friendly software package has been developed to monitor the optimal cutting parameters during machining.

**Keywords:** Machining; Force control; Neural networks

#### Reference to this paper should be given in the following way:

F. Cus, U. Zuperl, J. Balic, Combined feedforward and feedback control of end milling system, Journal of Achievements in Materials and Manufacturing Engineering 45/1 (2011) 79-88.

## 1. Introduction

A great advantage of the CNC machining center is that it reduces the skill requirements of machine operators. However, a common drawback of CNC end milling is that its operating parameter such as spindle speed or feedrate is prescribed conservatively either by a part programmer or by a relatively static database in order to preserve the tool. As a result, many CNC systems run under inefficient operating conditions. For this

reason, CNC machine tool control systems, which provides on-line adjustment of the operating parameters, is being studied with interest. These systems can be classified into three types: a geometric adaptive compensation (GAC) system; an adaptive control optimization (ACO) system; and an adaptive control constraints (ACC) system. GAC systems enhance part precision by applying real time geometric error compensation for imprecision caused by varying machine temperature, imprecise machine geometry, tool wear and other factors [1]. However, due

to the difficulty in on-line measurement of tool wear and machine tool temperature, there are no commercial GAC systems available [2]. ACO systems and ACC systems enhance productivity by applying an adaptive control technique to vary then machining variables in real time [3]. ACO systems set up the most effective cutting condition for the present cutting environment. For this purpose, ACO systems require on-line measurement of tool wear. Due to this reason, few, if any, ACO systems are used in practice [4-6]. ACC systems increase productivity by maximizing one or many machining variables within a prescribed range bounded by process and system constraints [7]. The most commonly used constraints in ACC systems are the cutting force, spindle current and cutting torque. The operating parameters are usually feedrate and spindle speed. Unfortunately, adaptive control alone cannot effectively control cutting forces. There is no controller that can respond quickly enough to sudden changes in the cut geometry to eliminate large spikes in cutting forces.

Therefore, we implement feedforward control in conjunction with feedback control. In the industrial processes, the feedforward- feedback combined control system is often applied to achieve good control effect. When disturbances are measurable, the feedforward control is rapid, intellect, and sensitive, which can greatly improve the dynamic control performance of the process. Meanwhile, the uncertain disturbances and model mismatch can be compensated by feedback control.

However, lack of precision of the model makes it difficult to design the model- based controller for processes with time delays, strong interactions and non-linearities. Normally, it is necessary to adjust the dynamics parameters of the feedforward controller. However, a perfect and simple method to correct the parameters has still not been found up to now.

Artificial neural networks can be used to provide promising control solution to those very complicated systems. The dynamic relationship between the disturbances and feedforward actions can be learned by neural network, and the network can be used directly as the feedforward controller once the training is accomplished. In addition, the change in time- variable system can also be adapted by neural network. And fault tolerance is also provided since damage to a few links of the network would not significantly impair the overall performance of the network. Generally, using neural network to identify a nonlinear model of the plant requires a large number of input-output training pattern, the training procedure may be very long.

Current research [5, 8] in machining has shown that neural network controllers have important advantages over conventional controllers. The first advantage is that a neural network controller can efficiently utilise a much larger amount of sensory information in planning and executing a control action than an industrial controller can. The second advantage is that a neural network controller has the collective processing capability that enables it to respond quickly to complex sensory inputs while the executing speed of sophisticated control algorithms in a conventional controller is severely limited.

The most important advantage of neural controller is that good control can be achieved through learning [9]. Three controllers have played important roles in machining process control. They are: CMAC controller [10], hierarchical neural controller [11], and multilayer neural controller [11].

The paper is organised as follows. The following section briefly describes a background of the typical neural network

applications to force control in machining. Section 3 describes the overall cutting force control strategy. Section four covers the CNC milling simulator. Section five describes the experimental equipment of combined control system. Finally, sections 6 and 7 present experimental results, conclusions, and recommendations for future research.

## 2. Survey of neural network applications in machining

As an emergent technology, neural networks appear to have a great deal to offer machining research. Two distinct directions of research appear to be the application of neural networks to control systems and to sensory integration. The introduction of Back Propagation has helped rejuvenate the neural network field. The new cutting force control research covers several fields:

- Single Input/ Single Output controllers
- Adaptive Controllers based on System Identification
- Model Based Dynamic Controllers
- Inverse Kinematics
- Neuromorphic Controllers
- Vision and Sensor Systems.

These areas will be described in brief to give the reader a background of the typical neural network applications to force control in machining. The final discussion will also briefly cover the main neural network paradigms.

### 2.1. Neural network applications to SISO control

Single Input/ Single Output controllers (Figure 1) have been the mainstay of classic linear control theory. Even though these controllers may be very dependable, their performance is greatly degraded when exposed to the non-linear nature of the robotics problem. These controllers do have some interesting benefits, as shown by [4]. They discuss a controller that learns its control rules by observing a human teacher.

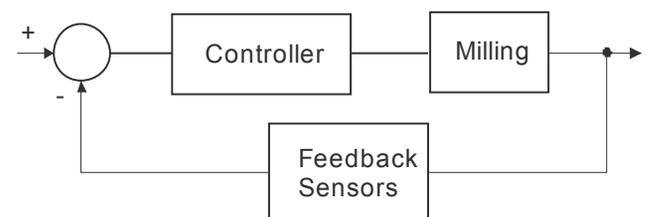


Fig. 1. A Single Input/ Single Output Controller

Norgaard [12] proposed a feedback controller for force control in milling that uses a dynamometer system for a feedback of force. He discussed adaptive control strategies for force control of the milling process, based upon a controller to replace a 'normal controller', like a PID controller. He also performed fault tolerance

tests and found that the networks were able to continue operation and overcome failures with neurons removed.

The flaw with the SISO methods is that a linearized model of the process must be assumed. Milling is rarely linear and as a result the method is subject to potential failure.

### 2.2. System identification with neural networks

Adaptive controllers allow compensation for non-linearities in systems. Even though these controllers are more complicated, they have inspired some interesting papers. The approaches which have been found, have been done with system identification. System Identification involves using the current state of the system to estimate controller parameters (Figure 2). This is a good method for dealing with non-linear systems. Stute [4] proposed a neural network system which identifies the state of a process and estimates the control parameters that should be used in the feedback controller. Cus [6] also describes a self tuning controller scheme using system identification to select system parameters. Chen [8] give a rather rigorous approach to system identification and modelling. Their work was quite successful, and produced excellent control of a manipulator with neural networks.

An alternative to self tuning controllers are model based controllers, these typically require good models of machining processes.

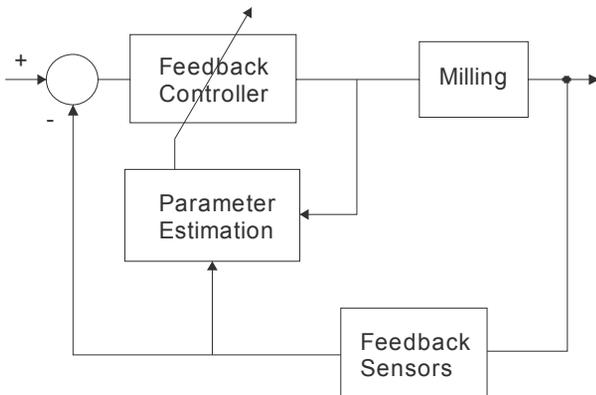


Fig. 2. A Self Tuning Controller

### 2.3. Non-linear control with neural networks

The basic control functions of the milling process may be modelled. The state of the process will be used as inputs to the neural network and the model outputs are estimated. These models may then be used in more sophisticated controllers.

A simple example of a model may be seen in the work by [12] who discuss the use of neural networks to control the thrust cutting force in end milling. This controller uses one input to produce the recommended thrust force.

Researchers have applied the non-linear neural network controllers to force control problems. Zhang [13] discuss using Kohonen networks to remember the force output for ball end-mill.

Their work has identified some problems inherent in the feature detection networks with associative memory paradigms, they have “choppy” control signals. He also uses a novel learning paradigm that allows them to learn the inverse dynamics in real time for force control in turning.

### 2.4. Model based neural network controllers

Modelling the machining system will allow compensation for the non-linearities. These models are generally based on the dynamics. The models are useful for developing Feedforward Controllers and Model Reference Adaptive Controllers (MRAC-Figure 3).

The neural network models allow much faster calculation of the model, and thus make these controllers practical. Non-Neural Network MRAC controllers may not always be suitable to real time control because they require an explicit model, and a lot of computation. Advanced model based controllers have also been developed by Gomi [14]. He investigates an approximation of the control scheme.

This control scheme actually involves modelling inverse dynamics for a feed forward controller, with a proportional feedback controller. Other works have also been seen to involve modelling of the inverse dynamics. The Hebbian Neural Network paradigm was used to model the inverse dynamics of a plant in the work of [15].

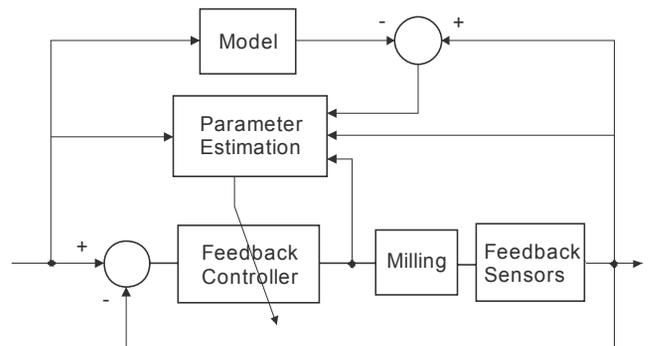


Fig. 3. A Model Reference Adaptive Controller

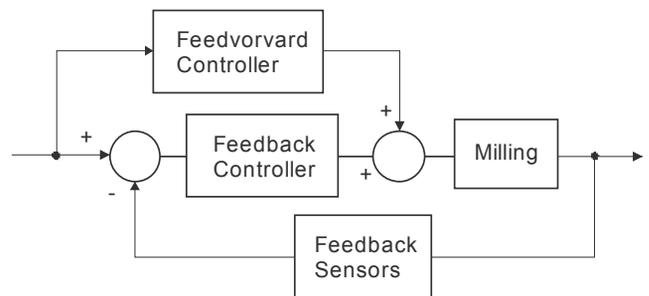


Fig. 4. A Feed Forward Controller

They incorporate the inverse dynamics model into a feedforward controller then add a second neural network adaptive error feedback controller. Albus [10] uses the CMAC ("Cerebral Model Articulated Control") paradigm to learn the inverse dynamics of a process, and the models are used in a feed-forward control scheme (Figure 4). This scheme is very fast and could update in real time. The method successfully learns control of a milling process, with dynamical considerations. The controller uses a combination of feed-forward, and proportional feed-back control, based on a simple neural network based model. The neural network is trained in real time, and adjusts weights in the massively parallel CMAC network.

## 2.5. Neuromorphic controllers

The approach, which is used often, is to pretrain a neural network for control. Sometimes it is advantageous to have the neural network learn as the process is occurring. This requires a neuromorphic approach. Neuromorphic controllers (Figure 5) may be devised which can learn on-line, when supplied with a measure of control success. These methods require that some objective be established for the system, and that an appropriate learning rule be used. Cus [6] describes a neuromorphic controller that maps the system state to a control signal. This controller is updated with a payoff feedback function. Ha also uses a similar approach in which the control model is adapted by an error function feedback. Psaltis [11] discusses using architectures of controllers that will learn the inverse control model of a process, on-line. A similar structure has been proposed by [16], to control the non-linear manipulator.

They used a feedback of a reinforcement signal to control learning of a neural network. These approaches all seemed to have good success.

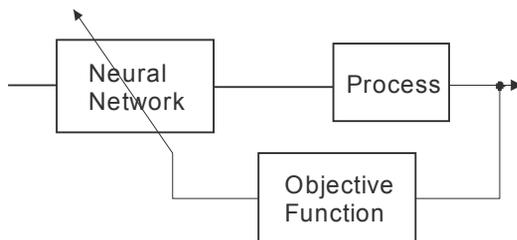


Fig. 5. An example of a neuromorphic controller

## 3. Combined feedforward and feedback control system in milling

Figure 6 shows the block diagram of the feedforward and feedback controller system which is used in milling to achieve an automatic on-line adjustment of feedrate with a constant milling force  $F_{ref}$ . The milling force will increase when the depth of cut increases in the milling process.

The control system immediately decreases feedrates to avoid tool breakage. When the depth of cut decreases the system generates a larger feedrate to maintain high cutting efficiency.

The developed system controls the peak milling force  $F$  in a tooth period. When spindle loads are low, the system increases feeds above and beyond pre-programmed values, resulting in considerable reductions in machining time and production costs. When spindle loads are high the feed rates are lowered, safeguarding cutting tool from damage and breakage. The combined control system adjusts the feedrate by assigning a feedrate override percentage to the CNC controller on a 4-axis Heller, based on a measured peak force (see Figure 6).

The actual feedrate is the product of the feedrate override percentage (DNCFRO) and the programmed feedrate. If the software for optimization of cutting conditions was perfect, the optimized feedrate would always be equal to the reference peak force. In this case the correct override percentage would be 100%. In order for the controller to regulate peak force, force information must be available to the control algorithm at every 20ms. Data acquisition software (LabVIEW) and the algorithm for processing the cutting forces are used to provide this information. The optimization time by the use of off-line optimization algorithm based on feedforward neural network, is equal to 0.001 s. The combined control system returns the cutting force value to the desired value level within four or less iteration at the latest. A combination of feedforward and feedback control has the best results, and is the preferred control method in several force control system designs [12] including the one presented in this paper. The feedforward controller is typically an inverse-dynamic model of the controlled system. Since an actual inverse-dynamic model is usually not available, data collected from the system itself are used to train an artificial neural network (ANN) to behave like the inverse-dynamic model.

An ANN that includes time-delayed inputs can approximate any dynamic system based solely on the knowledge of inputs and outputs. In order to train the network to represent the inverse dynamics of the system, inputs and outputs are recorded from the system and used as the outputs and inputs, respectively, of the ANN. We have used the actual inverse-dynamic model of the system to train the ANN in the feedforward component of our controller. Optimization was used to ensure uniqueness of the solution. The inverse-dynamic model itself was used as a feedforward controller, but a relatively simple model had to be designed so that it was fast enough to run in real-time. An ANN, however, is a system of simple processing elements, connected into a network by a set of weights, so it is computationally light. Off-line training of the ANN according to the inverse-dynamic model allows us to include all the complexities of the milling process in a real-time controller. We have created a neuro-PID controller for the feedback loop, which combines the attractive features of PID control (robustness and ease of implementation) with the nonlinear nature of ANN. The goal of the ANN is to model the nonlinear relationships, allowing the linear PID controller to deal solely with the dynamic response. For the feedback part of the controller, the feasibility of PID controllers for use in force control applications has been examined [17]. However, the performance of these controllers has been limited. As discussed in [17], PID controllers are linear and have been incapable of providing good control over nonlinear milling.

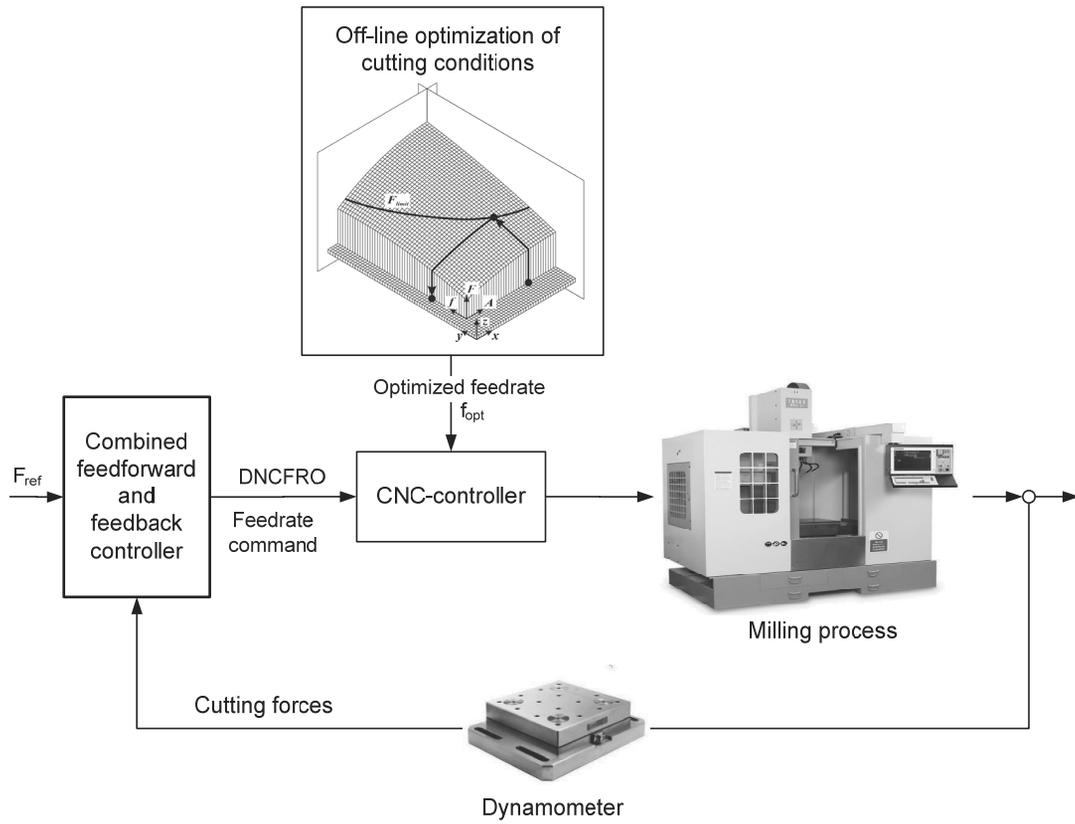


Fig. 6. Scheme of cutting force control strategy

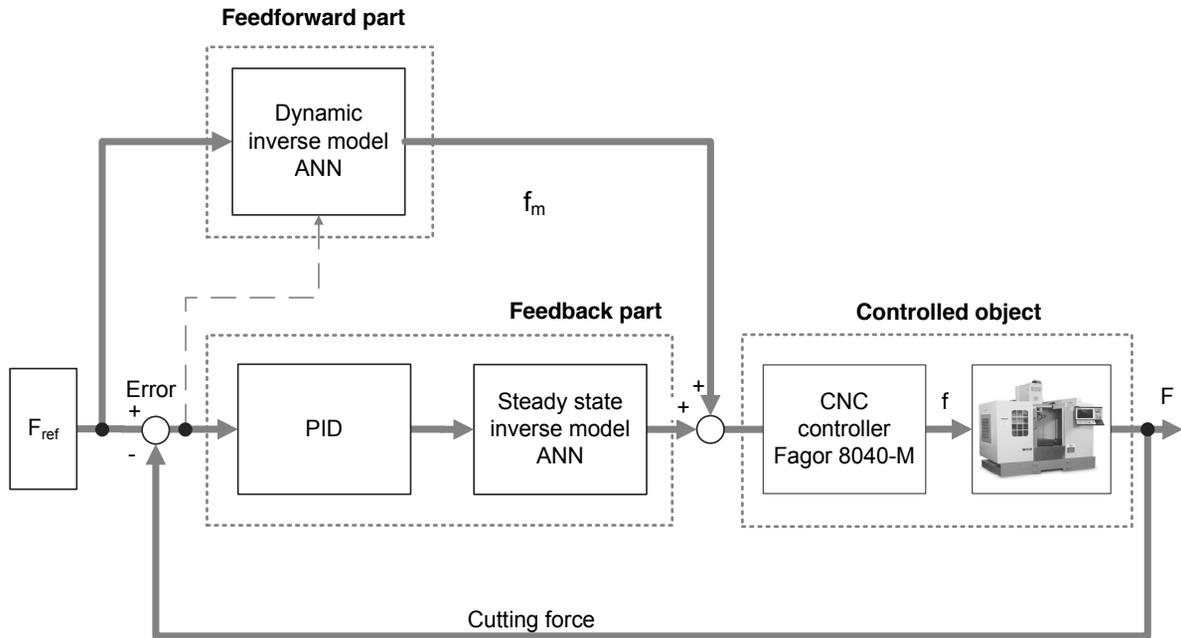


Fig. 7. The combined feedforward and feedback controller scheme

### 3.1. The controller

The controller consists of a feedforward and a feedback part (Figure 7). The feedforward part is an ANN trained to behave like the inverse-dynamic model of the milling process, so that it can generate the feedrate command, based on knowledge of system dynamics.

This ANN is a two-layer network with a sigmoidal transfer function in the hidden layer, and a linear transfer function in the output layer. This ANN is a two-layer network with a sigmoidal transfer function in the hidden layer, and a linear transfer function in the output layer. The input is desired cutting force. The output is feedrate command.

Training of this ANN was done using data from inverse-dynamic simulations using the model.

In order to improve learning, Gaussian white noise with mean zero and standard deviation equal to 5% of the maximum reference force was added to the input data.

The ability of the network to approximate the inverse-dynamic model was quantified using the root mean squared error between the original model-based activations (i.e., the outputs of the inverse-dynamic simulations) and ANN-predicted feedrate commands (i.e., the output of the ANN that approximates the inverse-dynamic model).

Networks with different numbers of neurons in the hidden layer were trained, and it was found that the network with 15

neurons had the smallest testing RMS error: 0.07 (no units, this is normalized feedrate command ranging from 0 to 1). Consequently, this ANN was chosen as the feedforward part of the controller.

The feedback part of the controller was designed as a traditional PID controller in series with a static ANN. The PID controller is described by:

$$u_i(t) = K_{P_i} e_i(t) + K_{D_i} \cdot \frac{de_i(t)}{dt} + K_{I_i} \int e_i(t); \quad i = 1, 2 \quad (1)$$

where  $K_{P_i}$ ,  $K_{D_i}$  and  $K_{I_i}$  are the proportional, derivative and integral gains. The outputs of the PID controller ( $u_1$  and  $u_2$ ) then serve as the inputs to the static ANN. The PID controller gains were tuned using the Ziegler–Nichols step response method, which correlates the controller parameters to features of the step response, with additional manual fine-tuning. The values found after tuning were:  $K_P = 1.6$ ,  $K_I = 0.3$  and  $K_D = 1$ . The feedback ANN has the same architecture as the feedforward ANN (two layers, sigmoidal and linear transfer function in the hidden and output layer, respectively). However, this ANN is static, since it uses only the present force values (and no past values) as inputs. The feedforward–feedback cutting force controller presented in this paper was designed and tested in simulation. Model-based evaluations were used to explore various control strategies before implementing invasive, expensive control systems.

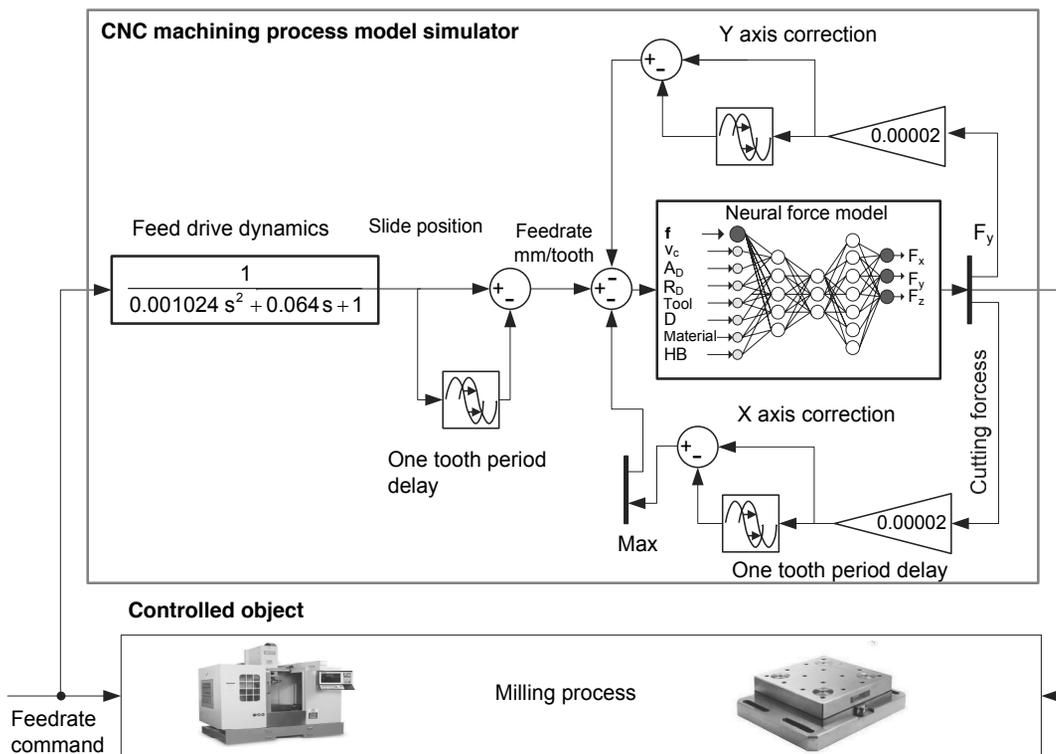


Fig. 8. CNC machining process model simulator

## 4. CNC machining process model simulator

A CNC machining process model simulator is used to evaluate the controller design before conducting experimental tests.

The process model consists of a neural force model and feed drive model (Figure 8). The neural model estimates cutting forces based on cutting conditions and cut geometry as described by [18].

### 4.1. The feed drive model

The feed drive model simulates the machine response to changes in commanded feedrate. The feed drive model was determined experimentally by examining step changes in the commanded velocity. The best model fit was found to be a second-order system with a natural frequency of 3 Hz and a settling time of 0.4 sec. Comparison of experimental and simulation results of a velocity step change from 7 mm/sec to 22 mm/sec is shown in Figure 9. The feed drive and neural force model are combined to form the CNC machining process model. Model input is the commanded feedrate and the output is the X, Y resultant cutting force.

### 4.2. Neural force model

To realise the on-line modelling of cutting process, a standard BP neural network is used based on the popular back propagation learning rule. During preliminary experiments it proved to be sufficiently capable of extracting the force dynamics model directly from experimental machining data.

It is used to simulate the dynamics of cutting process. The for modelling needs eight input neurons: for federate ( $f$ ), cutting speed ( $v_c$ ), radial and axial depth of cut ( $A_D / R_D$ ), type of machined material, hardness of the machined material, cutting tool diameter ( $D$ ), and tool geometry. The ANN registers the input data only in the numerical form therefore the information about the tool, cutting geometry and material must be transformed into numerical code. The geometry of the cutter is indicated with an 8-digit systematization code containing the data on the cutting edge shape, rake angle, free angle, tip radius, base material, cutting coating and length of the cutting edge. The output from the ANN are cutting force components, therefore three output neurons are necessary. For simplification of the milling simulator the neural network is so adapted that during prediction overlooks all input parameters except feeding.

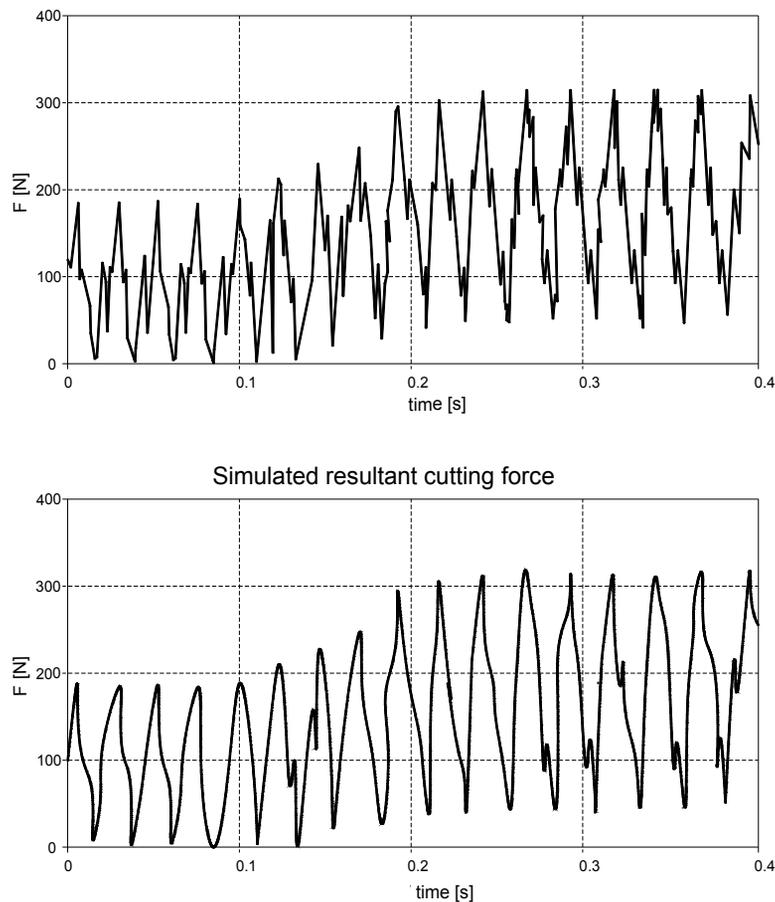


Fig. 9. Comparison of simulated and experimental resultant force

During simulation most input vector parameters do not change (e.g. cutter diameter and geometry, material etc.). Optimal ANN configuration contains 5, 3 and 7 neurons in hidden layers. Signals passed through the neurons in the hidden and output layers are transformed on the basis of an ArcTangent (nonlinear) function which allows the identification of the nonlinear system. The data is automatically normalized in order to make the training process faster. This was done by mapping each term to a value between 0 and 1 using the Max Min method.

## 5. Experimental equipment

In the experiments, a ball-end milling cutter (R216-16B20-040) with two cutting edges was mounted on a Heller Bea 01.

CNC machining center equipped with a Fagor CNC controller. The cutting inserts R216-16 03 M-M with  $12^\circ$  rake angle were selected [19, 20]. Cutting conditions are [21]: milling width  $R_D=16$  mm, milling depth  $A_D=4$  mm and cutting speed  $v=95$  m/min. The milling force signal was measured by using a table type dynamometer (Kistler 9255B) mounted between the workpiece and the machining table and recorded on a PC-386 workstation through a data acquisition board (PC-MIO-16E-4). To use the developed system on Figure 6 and to adjust the feedrate, the desired cutting force is  $[F_{ref}] = 280$  N and pre-programmed feed is 0.11 mm/tooth.

The developed adaptive control algorithm could not be directly implemented on Fagor controller. Feedrate override panel provided by the CNC controller was connected to the PC workstation. Communication between the control system and the CNC machine controller is accomplished over RS-232 protocol.

The adaptive learning control algorithm was then installed on the PC to adjust the feedrate command. Figure 10 shows basic cutting geometry features of a workpiece. Test workpiece contains changes of the axial depths of cut.

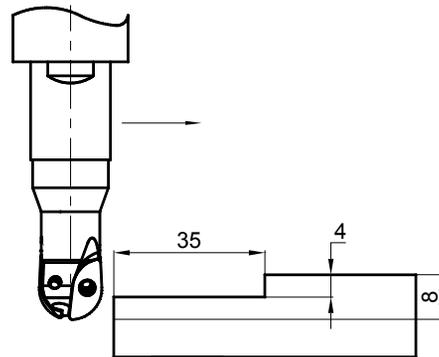


Fig. 10. Configuration and dimensions of a milled sample

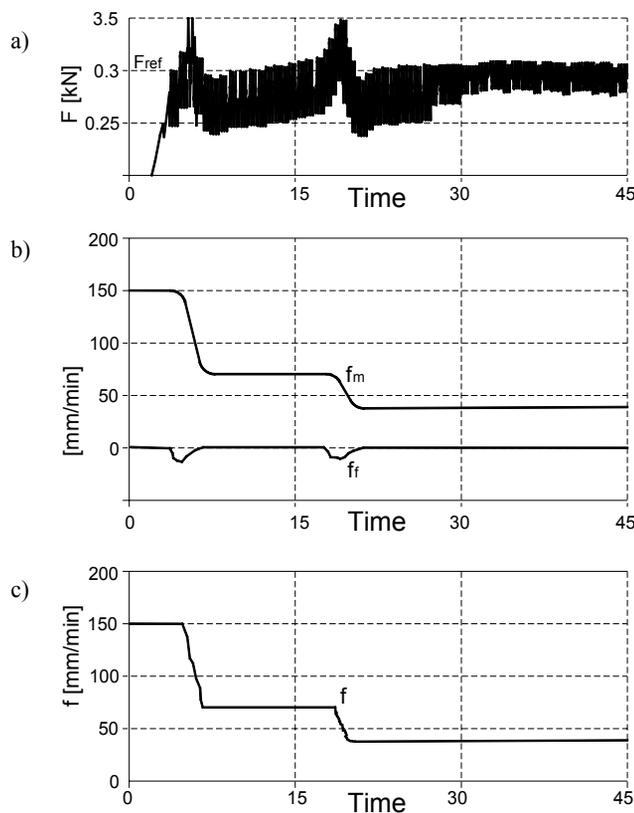


Fig. 11. Experimental results with the change of axial depths of cut: cutting force response, feedrate response, response of the process inverse-dynamics identifier ( $f_m$ ) and response of the feedback ( $f_f$ )

## 6. Experimental results and discussion

Figure 11 shows the cutting test results using the full immersion of cut with varying axial depths of cut corresponding to Figure 10. The output of the inverse-dynamics model  $f_m$ , and the steady state inverse model  $f_r$  in the cutting process are shown in Figure 11b. The summation of these output signals is actual feedrate  $f$  which is sent to the CNC controller (Figure 11c).

The experiment demonstrate that when the end mill starts to cut the workpiece with a step increase of axial depth of cut (4 mm), the cutting force immediately increases and even exceeds the reference cutting force, 300 N (Figure 11a). Then the Steady state inverse model ANN  $f_r$  modifies the connection weights of the neural network. As a result, the output signal of the inverse-dynamics model  $f_m$  decreases immediately and so does the feedrate  $f$ . Once the milling force is adjusted to the nominal value (Figure 11a) the end mill proceeds at a constant feedrate again. The same cutting phenomenon is also shown in the change of axial depth of cut from 4 to 8 mm.

The experiments with small and large step changes are run to test the proposed system stability over a range of cutting conditions and to compare its performance with "conventional" ACC systems.

As compared to most of the existing ACC end milling control systems, the proposed system has the following advantages:

1. The computational complexity of neural control system does not increase much with the complexity of process;
2. The learning ability of neural identifiers is more powerful than that of conventional adaptive controller;
3. System has a generalisation capability;
4. Insensitive to changes in workpiece geometry, cutter geometry, and workpiece material;
5. Cost-efficient and easy to implement;
6. Mathematically modelling-free.

By proposed control system time saving of 4% was reached in comparison with conventional ACC system. The MRR was improved by 6%. The main advantage of proposed system is that there is no need to analyze and model the controlled plant including the servo-loops and the milling process dynamics.

## 7. Conclusions

A feedforward-feedback control of milling operations in order to improve productivity is presented. The proposed control system consists of two parts. The feedforward part is an ANN trained to behave like the inverse-dynamic model of the milling process, so that it can generate the feedrate command, based on knowledge of system dynamics. The feedback part of the controller was designed as a traditional PID controller in series with a static ANN. The milling force is continuously regulated by the combined controller due to the varying axial depths of cut. By the use of proposed control system the machining time is reduced for 21%. The experiments have demonstrated that the combined controller has the intelligence to maintain a constant milling force under varying cutting conditions. Further research will be needed to determine the stability of the developed control system.

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