NEURAL NETWORK FOR CONSTANT FORCE CONTROL OF END MILLING

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Abstract. *In this paper, an adaptive neural controller with optimisation for the ball end-milling process is described. An architecture with two different kinds of neural networks is proposed, and is used for the on-line optimal control of the milling process. A BP neural network is used to identify the milling state and to determine the optimal cutting inputs. The feedrate is selected as the optimised variable, and the milling state is estimated by the measured cutting force. The adaptive controller is operated by a PC and the adjusted feedrates are sent to the CNC. The purpose of this contribution is to present a reliable, robust neural controller aimed at adaptively adjusting feed-rate to prevent excessive tool wear, tool breakage and maintain a high chip removal rate. The goal is also to obtain an improvement of the milling process productivity by use of an automatic regulation of the cutting force. Numerous simulations are conducted to confirm the efficiency of this architecture. The proposed architecture for on-line determining of optimal cutting conditions is applied to ball end-milling in this paper, but it is obvious that the system can be extended to other machines to improve cutting efficiency.*

Keywords*: end milling, adaptive force control, neural controller*

1. Introduction

A remaining drawback of modern CNC systems is that the machining parameters, such as feedrate, speed and depth of cut, are programmed off-line. The machining parameters are usually selected before machining according to programmer's experience and machining handbooks. To prevent damage and to avoid machining failure the operating conditions are usually set extremely conservative. As a result, many CNC systems are inefficient and run under the operating conditions that are far from optimal criteria. Even if the machining parameters are optimised off-line by an optimisation algorithm (Zuperl and Cus, 2003) they cannot be adjusted during the machining process. To ensure the quality of machining products, to reduce the machining costs and increase the machining efficiency, it is necessary to adjust the machining parameters in real-time, to satisfy the optimal machining criteria. For this reason, adaptive control, which provides on-line adjustment of the operating conditions, is being studied with interest (Balic, 2002; Deticek and Kiker, 2001). Adaptive control systems can be classified into: adaptive control with optimization- ACO (Liu and Wang, 1999) and adaptive control with constraints (ACC). In this paper an ACO system is presented, which adjusts the machining parameters to maximize the milling performance under given limitations. Current research (Tang *et al*.) 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 (Huang and Lin, 2002). 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 (Tandon and Mounayari, 2001). Three controllers have played important roles in machining control. They are: CMAC controller (Zhang, 1992), hierarchical neural controller (Kawato, 1990), and multilayer neural controller (Psaltis *et al*.).

2. Adaptive control with optimization in end milling

The proposed architecture for adaptive control of the machining process and on-line optimization of cutting parameters is shown in Fig. 1. Sequence of steps for on-line optimization of milling process is presented below:

- Neural network (NN) for optimization determines the optimal feedrate and sends it to the milling machine and network for modelling,
- The measured output of the milling machine are used to train the NN for modelling,
- NN for optimization uses the newly upgraded neural model to find the optimal feedrate and sends it to the machine and neural model,
- steps 2 and 3 are repeated until termination of machining.

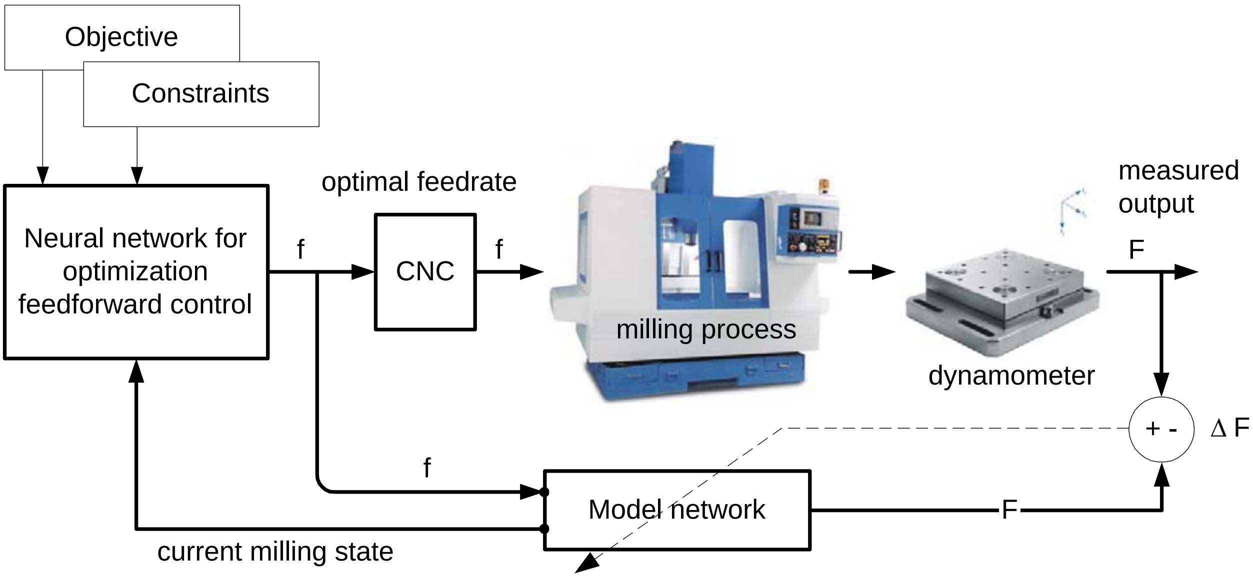

Figure 1. Scheme for adaptive control with optimization in end milling

2.1. Neural network for optimization

To realize real-time optimal control of the machining process, an ALM neural network is proposed. It is used to determine the optimal inputs (feedrate), so we shall refer to it as a NN for optimization. This architecture that uses the Lagrange multiplier (ALM) method converges more quickly than other penalty methods. Detail information about this type of network can be found in (Albus, 1999). Combining both neural networks, an adaptive controller for the milling process is designed. The problem of the optimization of cutting parameters in milling can be formulated as the following multi-objective optimization problem: min Tp (f), min Cp (f), min Ra (f) subject to limitations L1- L4 (Equation 1). Where Tp, Cp, Ra are: production rate, operation cost and surface roughens (Cus and Balic, 2003). All the above mentioned objectives are represented as a function of the cutting speed, feed rate and depth of cutting. These are two conflicting objectives, therefore a compromise must be reached. There are several factors limiting the milling parameters. Those factors originate usually from technical specifications. The following limitations are taken into account:

$$L_1(f) = f - f_{max} \leq 0\,;\; L_2(f) = f_{min} - f \leq 0\,;\; L_3(f) = F(f) - F_{max} \leq 0\,;\; L_4(f) = R_a - R_{a,allowable} \leq 0\,; \qquad (1)$$

where f_{max} and f_{min} are the maximum and minimum feedrate, F(f) is the output of the BP NN, and F_{max} is maximum cutting force. In our research the feedrate is selected as the optimised variable, and the milling behavior is predicted by the measured cutting force.

2.2. 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 consist of a neural force model and feed drive model. The neural model estimates cutting forces based on cutting conditions and cut geometry as described by (Fourie, 2002). 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 0.4sec. Comparison of experimental and simulation results of a velocity step change from 7mm/sec to 22mm/sec is shown on Fig. 2. 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. To realise the on-line modelling of cutting forces, a standard BP NN is proposed based on the popular back propagation learning rule. During preliminary experiments it proved to be sufficiently capable of extracting the force and surface roughness model directly from experimental machining data. It is used to describe the cutting process. The NN for modelling (Fig. 3) needs four input neurons for milling federate (f), cutting speed (v_c), axial depth of cut (A_d) and radial depth of cut (R_d). The output from the NN are cutting force components and surface roughness, therefore three output neurons are necessary.

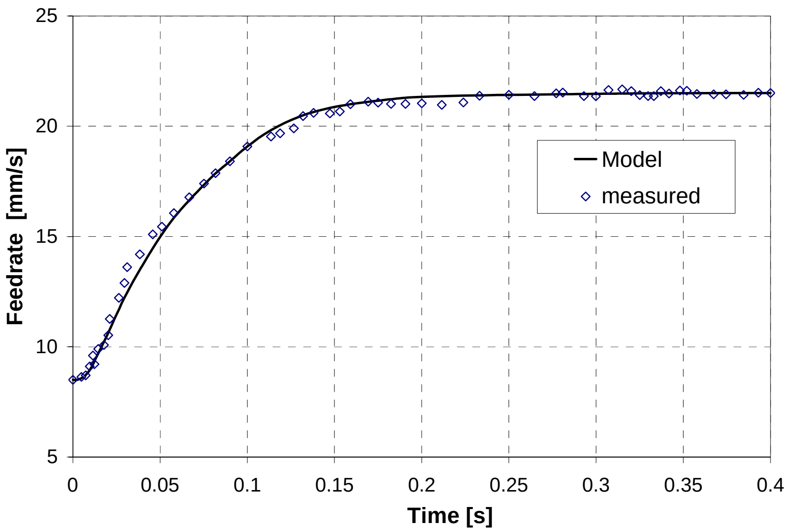

Figure 2. Comparison of actual and model feedrate

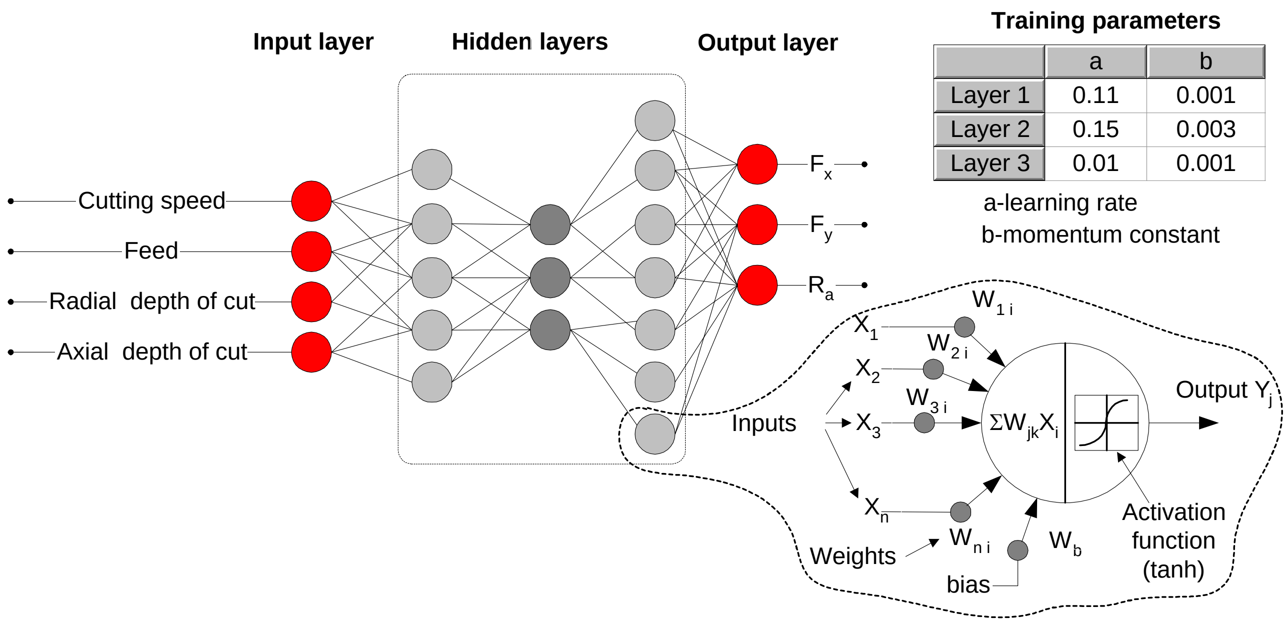

Figure 3. Predictive cutting force model topology

3. Data acquisition system and experimental equipment

The data acquisition equipment used in this acquisition system consists of dynamometer, fixture, hardware and software module as shown in Fig. 4. The cutting forces were measured with a piezoelectric dynamometer (Kistler 9255) mounted between the workpiece and the machining table. When the tool is cutting the workpiece, the force will be applied to the dynamometer through the tool. The ball-end milling cutter with interchangeable cutting inserts of type R216-16B20-040 with two cutting edges, of 16 mm diameter and 10° helix angle was selected for machining.

The cutting inserts R216-16 03 M-M with 12° rake angle were selected. The cutting insert material is P30-50 coated with TiC/TiN, designated GC 4040.

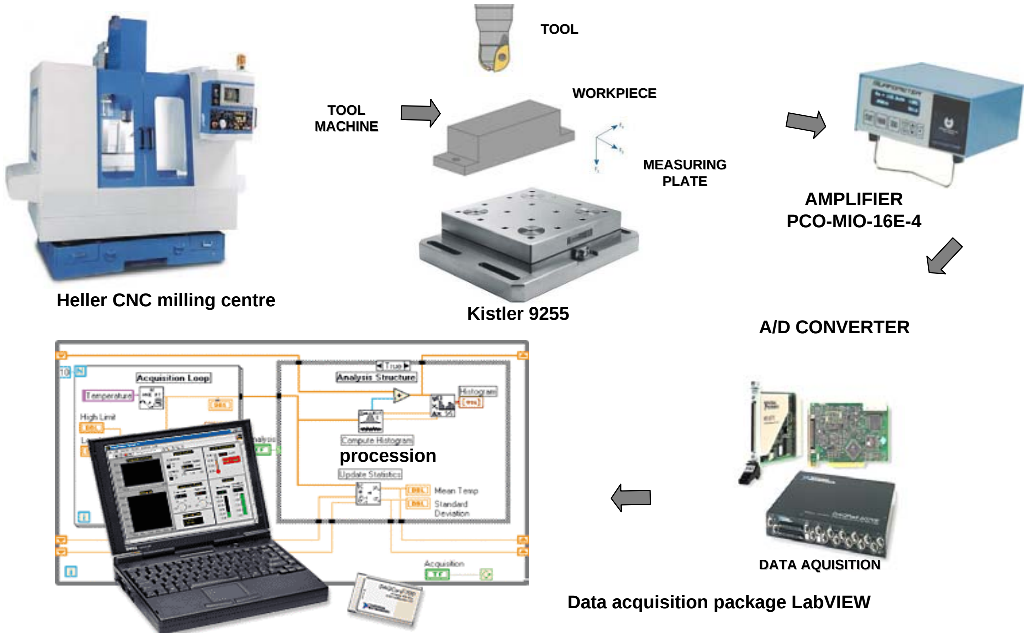

Figure 4. The experimental set-up

4. Testing of adaptive control system

To examine the stability and robustness of the adaptive neural control strategy, the system is first examined by simulation using Simulink and Labview neural Toolset. Then the system is verified by various experiments on a CNC milling machine (type HELLER BEA1) for Ck 45 and 16MnCr5(Xm) steel workpiece with variation of cutting depth (irregular profile, see Fig. 5).

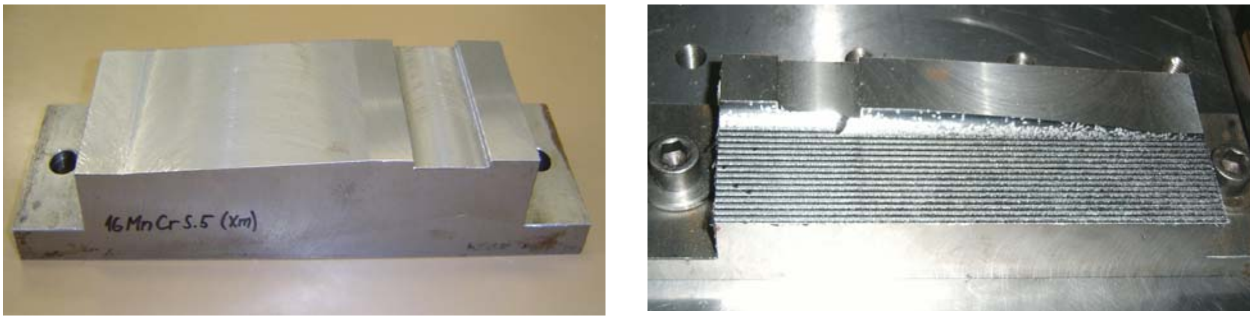

Figure 5. Workpiece profile

The ball-end milling cutter (R216-16B20-040) with two cutting edges, of 16 mm diameter and 10° helix angle was selected for experiments. Cutting conditions are: milling width Rd=3 mm, milling depth Ad=2 mm and cutting speed vc=80 m/min. The parameters for neural control are the same as for the experiments for the traditional system performance. To use the neural control structure on Fig. 1 and to optimise the feedrate, the desired cutting force is [Fref]=280 N, pre-programed feed is 0.08 mm/teeth and its allowable adjusting rate is [0 to 150%]. The objective of neural control is keeping the metal removal rate (MRR) as high as possible and maintaining cutting force as close as possible to a given reference value. The adaptive controller is operated on PC and the adjusted feedrates are sent to CNC. For this purpose we carry out 18 tests. To optimise the feedrate, the constraints are [F]=240 N, pre-programed feed is 0.08 mm/teeth and its allowable adjusting rate is from 0 to 150%. In simulations the real end milling process was replaced with trained neural model (Fig. 3). Simulated control response to a step change in axial depth is presented in Fig. 6. The simulation represents a 16 mm, two flute cutter, at 2000 RPM, encountering a step change in axial depth from 3 mm to 4.2 mm. The step change occurs at 2 sec and the controller returns the peak forces to the reference peak force within 0.5 sec. In this research the stability of neural controller is first evaluated by simulation. Test simulations with small and large step changes in process gain are run to ensure system stability over a range of cutting conditions. Small process gain changes are simulated with an axial depth change from 3 mm to 4.2 mm at a spindle speed of 2000

RPM. Large gain changes are simulated with an axial depth change from 3 mm to 6 mm at 2000 RPM. The system remains stable in all simulation tests, with little degradation in performance.

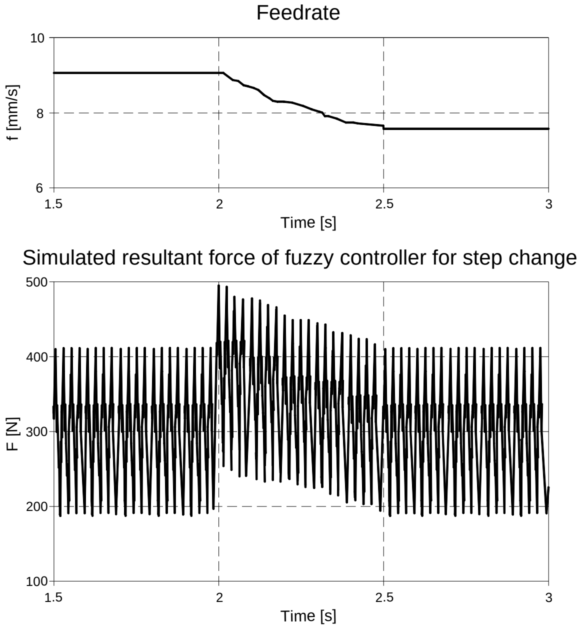

Figure 6. Simulated neural control response to a step change in axial depth

5. Results and discussion

Figure 7 is the response of the cutting force and the feedrate when the cutting depth is changed.

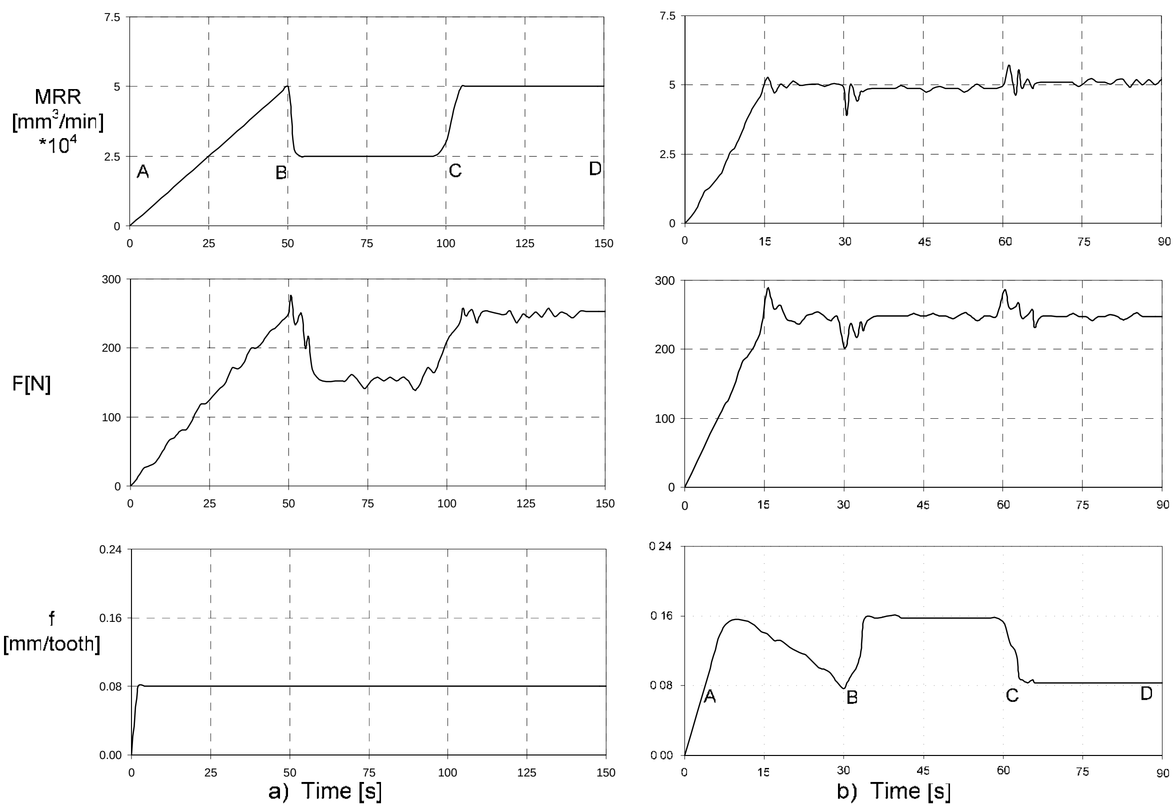

Figure 7. Experimental results. Response of MRR, rezulting cutting force, feedrate. a) Conventional milling. b) Milling with adaptive NN control system.

It shows the experimental result where the feedrate is adjusted on-line to maintain the cutting force at the max. desired value. In the first experiment using constant feed rates (conventional cutting-Fig. 7a) the MRR reaches its proper value only in the last step.

However, in second test (Fig. 7b), machining the same piece but using adaptive neural control, the average MRR achieved is much more close to the optimal MRR. Comparing the Fig. 7a to Fig. 7b, the cutting force for the neural control milling system is maintained at about 240N, and the feedrate of the adaptive milling system is close to that of the traditional CNC milling system from point C to point D. From point A to point C the feedrate of the adaptive milling system is higher than for the classical CNC system, so the milling efficiency of the adaptive milling system is improved.

The experimental results show that the milling process with the designed neural controller has a high robustness, stability, and also higher machining efficiency than standard controllers. The experimental results show that the MRR can be improved by up to 27%. As compared to most of the existing end milling control systems, the proposed neural control system has the following advantages: 1. multi-parameter adjustment; 2. insensitive to changes in workpiece geometry, cutter geometry, and workpiece material; 3. cost-efficient and easy to implement; and 4. mathematically modeling-free.

Neural network adaptive control ensures continuous optimising feedrate control that is automatically adjusted to each particular cutting situation.

When spindle loads are low, the system increases cutting feeds above and beyond pre-programmed feedrates, resulting in considerable reductions in cycle times and production costs. When spindle loads are high the feedrates are lowered, safeguarding machine tools and workpieces from damage and tool breakage.

The proposed system is still in experimental phase but it can be easily extended with minimal costs to real industrial use. It reduces the need for constant operator supervision

6. Conclusion

The purpose of this contribution is to present a reliable, robust neural force controller aimed at adaptively adjusting feedrate to prevent excessive tool wear, tool breakage and maintain a high chip removal rate. The approach was successfully applied to an experimental milling centre Heller BEA 01.

The results of the intelligent milling experiments with adaptive control strategy show that the developed system has high robustness and global stability.

The proposed architecture for on-line determining of optimal cutting conditions is applied to ball-end milling in this paper, but it is obvious that the system can be extended to other machines to improve cutting efficiency.

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