DTD 5
ARTICLE IN PRESS

ELSEVIER

Journal of Materials Processing Technology xxx (2005) xxx–xxx

Journal of Materials Processing Technology

www.elsevier.com/locate/jmatprotec

Fuzzy control strategy for an adaptive force control in end-milling

U. Zuperl*, F. Cus, M. Milfelner

Faculty of Mechanical Engineering, University of Maribor, Smetanova 17, 2000 Maribor, Slovenia

Abstract

This paper discusses the application of fuzzy adaptive control strategy to the problem of cutting force control in high speed end-milling operations. The research is concerned with integrating adaptive control with a standard computer numerical controller (CNC) for optimising a metal-cutting process. It is designed to adaptively maximise the feed-rate subject to allowable cutting force on the tool, which is very beneficial for a time consuming complex shape machining. The purpose 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. Numerous simulations and experiments are conducted to confirm the efficiency of this architecture.

Keywords: End-milling; Adaptive force control; Fuzzy

1. Introduction

A remaining drawback of modern CNC systems is that the machining parameters, such as feed-rate, 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 [5] 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 (AC), which provides on-line adjustment of the operating conditions, is being studied with interest [3]. In our AC system, the feed-rate is adjusted on-line in order to maintain a constant cutting force in spite of variations in cutting conditions. In this paper, a simple fuzzy control strategy is developed in the intelligent system and some experimental simulations with the fuzzy control strategy are carried out. The results demonstrate the ability of the proposed system to effectively regulate peak forces for cutting conditions commonly encountered in end-milling operations.

Force control algorithms have been developed and evaluated by numerous researchers. Among the most common is the fixed gain proportional integral (PI) controller originally proposed for milling by [4]. Kim et al. [4] proposed an adjustable gain PI controller where the gain of the controller is adjusted in response to variations in cutting conditions. The purely adaptive model reference adaptive controller (MRAC) approach was originally investigated by Cus and Balic [2]. These controllers were simulated and evaluated and physically implemented by [1]. Both studies found all three-parameter adaptive controller to perform better than the fixed gain PI controller. As regards fuzzy control systems, an introductory survey of pioneering activities is given by Huang and Lin [3], and a more systematic view is presented by in [4]. Comparisons of fuzzy with proportional integral derivative (PID) control and stability analysis of fuzzy systems and supervisory fuzzy control are addressed in Ref. [3].

Much work has been done on the adaptive cutting force control for milling [2]. However, most of the previous work has simplified the problem of milling into one-dimensional motion. In this contribution, we will consider force control for three-dimensional milling.

* Corresponding author. Tel.: +386 2 220 7623; fax: +386 2 220 7990.
E-mail address: uros.zuperl@uni-mb.si (U. Zuperl).

0924-0136/$ – see front matter
doi:10.1016/j.jmatprotec.2005.02.143

The paper is organised as follows. Section 2 briefly describes the overall force control strategy. Section 3 covers the CNC machining process model. Section 5 describes the simulation/experiments and implementation method of proposed control scheme. Finally, Sections 6 and 7 present experimental results, conclusions, and recommendations for future research.

2. Adaptive fuzzy controller structure

A new on-line control scheme which is called adaptive fuzzy control (AFC) (Fig. 1) is developed by using the fuzzy set theory. The basic idea of this approach is to incorporate the experience of a human operator in design of the controller. The control strategies are formulated as a number of rules which are simple to carry out manually but difficult to implement by using conventional algorithm. Based on this new control strategy, very complicated process can be controlled more easily and accurately compared to standard approaches. The objective of fuzzy 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. Furthermore, the amount of computation task and time can be reduced as compared to classical or modern control theory. Schematic control rules are constructed by using real experimental data. Fuzzy adaptive control ensures continuous optimising feed rate 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 feed rates, resulting in considerable reductions in cycle times and production costs. When spindle loads are high the feed rates are lowered, safeguarding machine tools from damage from breakage. When system detects extreme forces, it automatically stops the machine to protect the cutting tool. It reduces the need for constant operator supervision. Sequence of steps for on-line optimisation of the milling process are presented below.

1. The pre-programmed feed rates are sent to CNC controller of the milling machine.
2. The measured cutting forces are sent to the fuzzy controller.
3. Fuzzy controller uses the entered rules to find (adjust) the optimal feed-rates and sends it back to the machine.
4. Steps 1 and 3 are repeated until termination of machining.

The adaptive force controller adjusts the feed-rate by assigning a feed-rate override percentage to the CNC controller on a four-axis Heller, based on a measured peak force. The actual feed-rate is the product of the feed-rate override percentage and the programmed feed-rate. If the feed-rate optimisation models were perfect, the optimised feed-rate 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 controller sample time. A data acquisition software (Labview) is used to provide this information.

2.1. Structure of a fuzzy controller

In fuzzy process control, expertise is encapsulated into a system in terms of linguistic descriptions of knowledge about human operating criteria, and knowledge about the input ± output relationships. The algorithm is based on the operator's knowledge, but it also includes control theory, through the error derivative, taking into consideration the dynamics of the process. Thus, the controller has as its inputs, the cutting force error ΔF and its first difference $\Delta^2 F$, and as outputs, the variation in feed rate Δf. The fuzzy control variables fuzzification (see Fig. 2) as well as the creation of the rules base were taken from the expert operator. The cutting force error and first difference of the error are calculated, at each sampling instant k, as: $\Delta F(k) = F_{\text{ref}} - F(k)$ and $\Delta^2 F(k) = \Delta F(k) - \Delta F(k-1)$, where F is measured cutting force and F_{ref} is force set point.

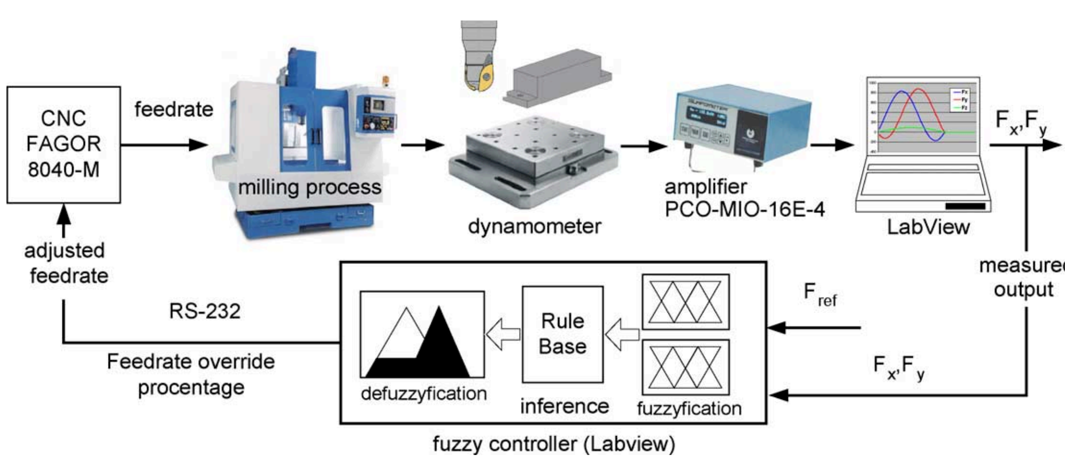

Fig. 1. Comparison of actual and model feed-rate.

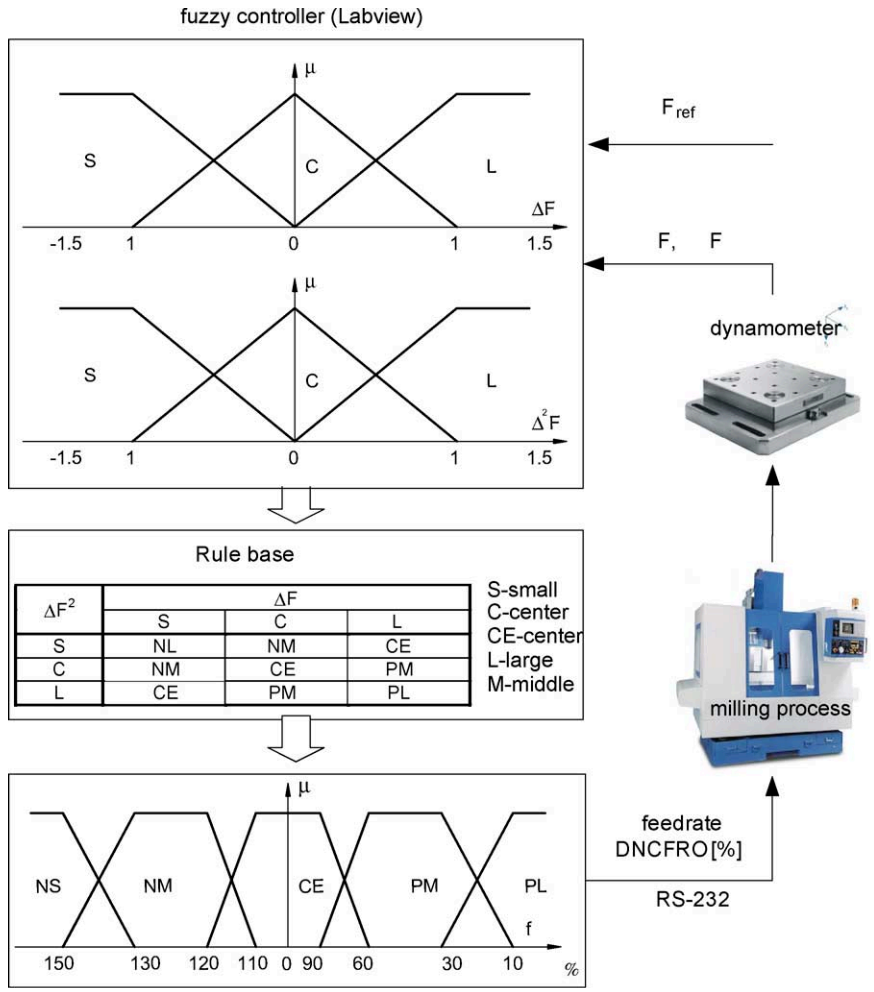

Fig. 2. Structure of a fuzzy controller.

3. CNC machining process model

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. The neural model estimates cutting forces based on cutting conditions and cut geometry as described by Zuperl [1]. The feed drive model simulates the machine response to changes in commanded feed-rate. 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 s. Comparison of experimental and simulation results of a velocity step change from 7 to 22 mm/s is shown on Fig. 3.

The feed drive and neural force model are combined to form the CNC machining process model. Model input is the commanded feed-rate and the output is the X, Y resultant cutting force. The cut geometry is defined in the neural force model. The simulator is verified by comparison of experimental and model simulation results. A variety of cuts with feed-rate changes were made for validation.

The experimental and simulation resultant force for a step change in feed-rate from 0.05 to 2 mm/tooth is presented in Fig. 4. The experimental results correlate well with model results in terms of average and peak force. The experimental

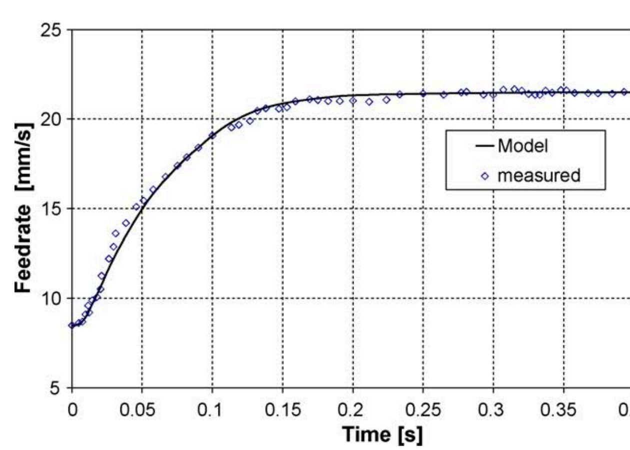

Fig. 3. Comparison of actual and model federate.

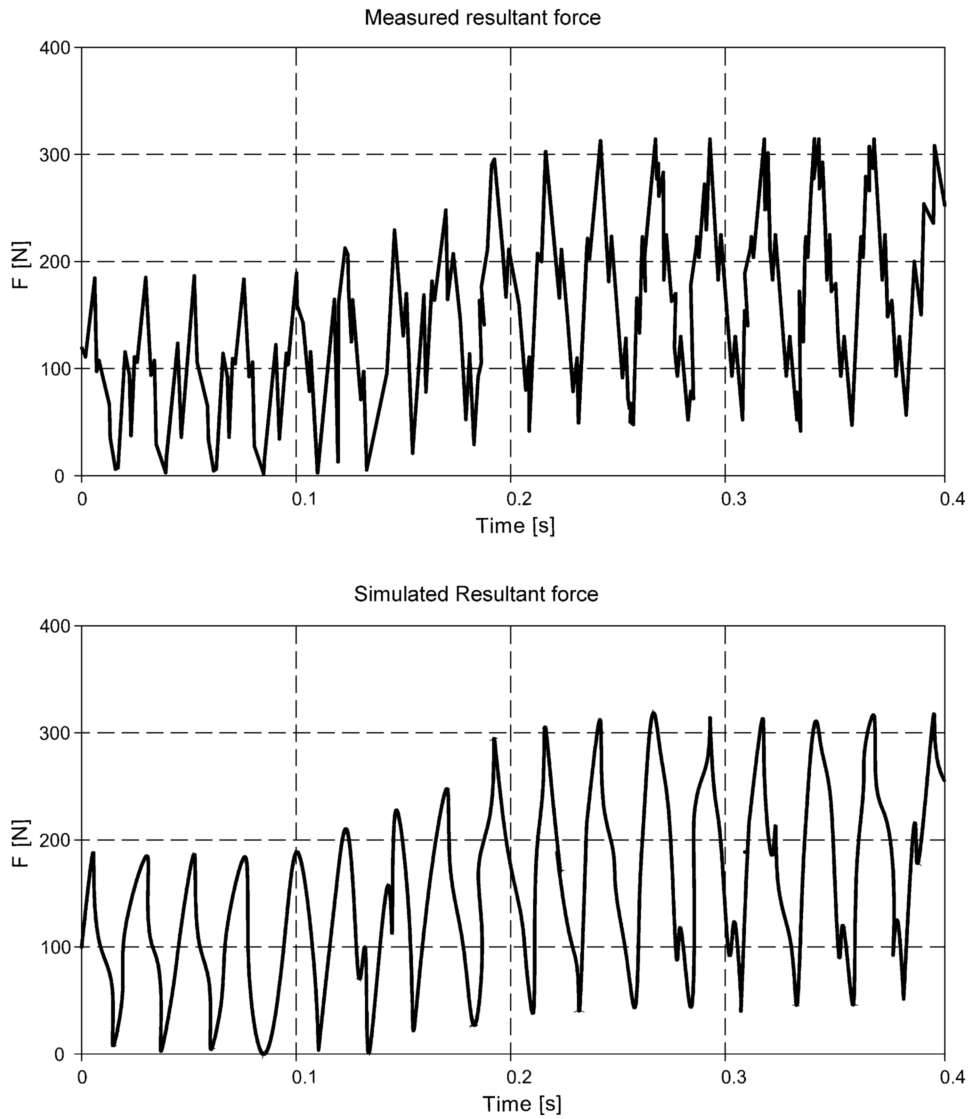

Fig. 4. Structure of a fuzzy controller.

results correlate well with model results in terms of average and peak force.

The obvious discrepancy may be due to inaccuracies in the neural model, and unmodeled system dynamics.

3.1. Cutting force modeling

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

The NN for modelling 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, therefore two output neurons are necessary. The detailed topology of the used NN with optimal training parameters and mathematical principle of the neuron is also shown in Fig. 5. Best NN configuration contains 5, 3 and 7 hidden neurons in hidden layers.

3.2. Topology of neural network and its adaptation to modeling problem

The effect of topology is also studied by considering different cases. The topologies are varied by varying the number of neurons in hidden layers. To evaluate the individual effects of training parameters on the performance of neural network 40 different networks were trained, tested and analysed. The network performances were evaluated using four different criteria [5]: ETstMax, ETst, ETrn, and ETrnMax and the number of training cycles. The number of neurons in the input and output layers are determined by the number of input and output parameters. From the results the following conclusions can be drawn.

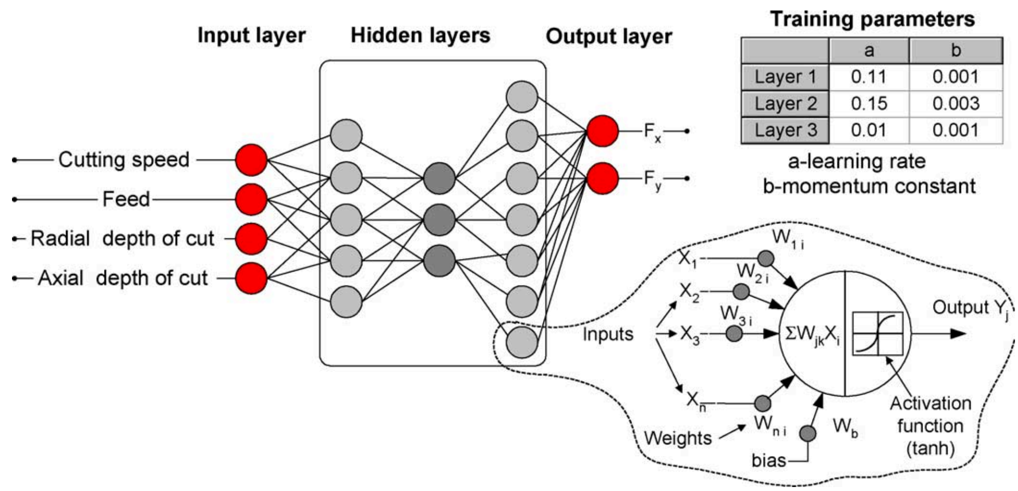

Fig. 5. Structure of a fuzzy controller.

- Learning rates below 0.3 give acceptable prediction errors while learning rates must be between 0.01 and 0.2 to minimise the number of training cycles.
- To minimise the estimation errors, momentum rates between 0.001 and 0.005 are good. However, the momentum rate should not exceed 0.004 if the number of training cycles is also to be minimised.
- The optimum number of hidden layer nodes is 3 or 6. Networks with between 2 and 12 hidden layer nodes, other than 3 or 6, also performed fairly well but resulted in higher training cycles.
- Networks that employ the sine function require the lowest number of training cycles followed by the ArcTangent, while those that employ the hyperbolic tangent require the highest number of training cycles.

4. Data acquisition system and experimental equipment

The data acquisition equipment used in this acquisition system consists of dynamometer, fixture module, hardware and software module as shown in Fig. 1. 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 piezoelectric quartz in the dynamometer will be strained and an electric charge will be generated. The electric charge is then transmitted to the multi-channel charge amplifier through the connecting cable. The charge is then amplified using the multi-channel charge amplifier. In the multi-channel charge amplifier, different parameters can be adjusted so that the required resolution can be achieved. Essentially, at the output of the amplifier, the voltage will correspond to the force depending on the parameters set in the charge amplifier. The interface hardware module consists of a connecting plan block, analogue signal conditioning modules and a 16 channel A/D interface board (PC-MIO-16E-4). In the A/D board, the analogue signal will be transformed into a digital signal so that the LabVIEW software is able to read and receive the data. The voltages will then be converted into forces in X, Y and Z directions using the LabVIEW program. With this program, the three axis force components can be obtained simultaneously, and can be displayed on the screen for analysing force changes. 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 R216-1603 M-M with 12° rake angle were selected. The cutting insert material is P30-50 coated with TiC/TiN, designated GC 4040 in P10-P20 coated with TiC/TiN, designated GC 1025. The coolant RENUS FFM was used for cooling. The fuzzy control is operated by the intelligent controller module (Labview) and the modified feed-rates are send to the CNC. Communication between the force control software and the NC machine controller is enabled through memory sharing. The feed-rate override percentage variable DNCFRO is available to the force control software for assignment at a rate of 1 kHz.

5. Simulations and fuzzy control milling experiment

To examine the stability and robustness of the adaptive fuzzy control strategy, the system is first examined by simulation using Simulink and Labview fuzzy Toolset. Then the system is verified by various experiments on a CNC milling machine (type HELLER BEA1) for Ck 45 and Ck 45 (XM) steel workpiece with variation of cutting depth (Fig. 6).

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

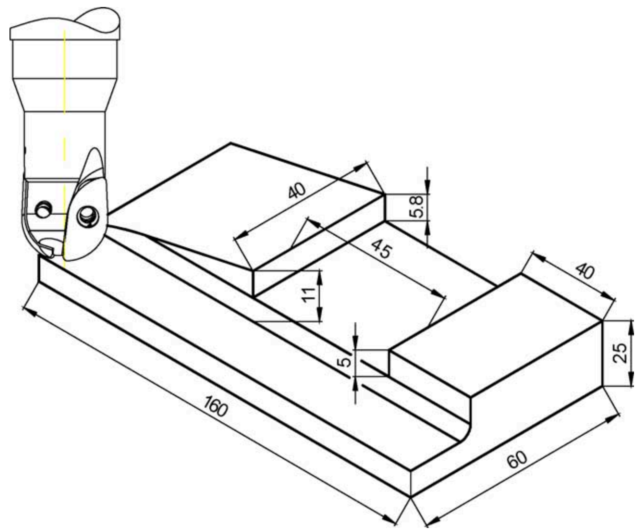

Fig. 6. Workpiece profile.

width R_D = 3 mm, milling depth A_D = 2 mm and cutting speed $v_c = 80\,\mathrm{m/min}$.

The parameters for fuzzy control are the same as for the experiments for the traditional system performance.

To use the fuzzy control structure on Fig. 1 and to optimise the feed-rate, the desired cutting force is [F_{ref}] = 280 N, pre-programmed feed is 0.08 mm/teeth and its allowable adjusting rate is [0–150%].

Fig. 7 is the response of the cutting force and the feed-rate when the cutting depth is changed. It shows the experimental result where the feed-rate is adjusted on-line to maintain the cutting force at the maximum desired value.

Simulated control response to a step change in axial depth is presented in Fig. 8. The simulation represents a 16 mm, two-flute cutter, at 2000 rpm, encountering a step change in axial depth from 3 to 4.2 mm. The step change occurs at 2 s and the controller returns the peak forces to the reference peak force within 0.5 s. In this research the stability of fuzzy controller is 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 to 4.2 mm at a spindle speed of 2000 rpm. Large gain changes are simulated with an axial depth change from 3 to 6 mm at 2000 rpm. The system remains stable in all simulation tests, with little degradation in performance.

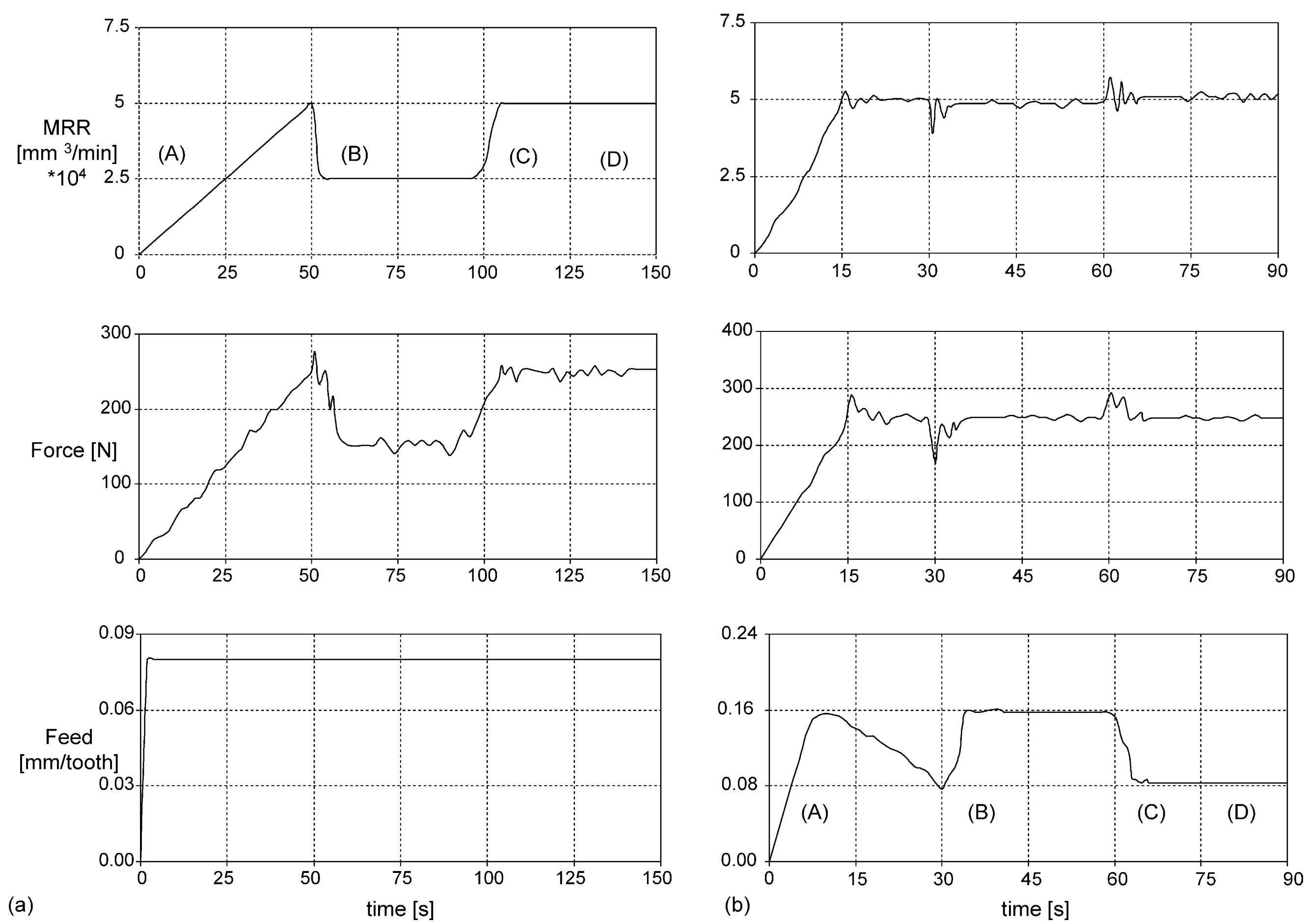

Fig. 7. Experimental results with variable cutting depth. Response of MRR, resulting cutting force, feed-rate. (a) Conventional milling and (b) milling with adaptive fuzzy control.

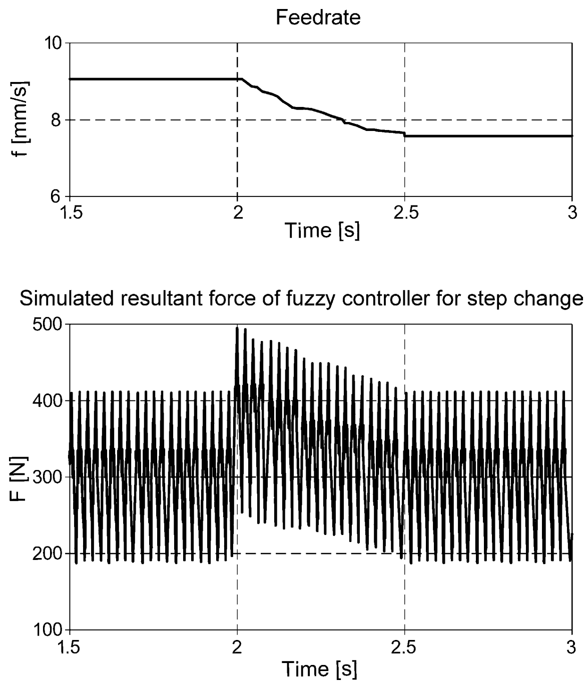

Fig. 8. Simulated fuzzy control response to a step change in axial depth.

6. Results and discussion

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 fuzzy control, the average MRR achieved is much more close to the proper MRR.

Comparing Fig. 7a and b, the cutting force for the neural control milling system is maintained at about 240 N, and the feed-rate 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 feed-rate 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 MRR can be improved by up to 27%. As compared to most of the existing end-milling control systems, the proposed fuzzy control system has the following advantages [3]: 1. multi-parameter adjustment; 2. insensitive to changes in workpiece geometry, cutter geometry, and workpiece material; 3. cost-efficient and easy to implement; 4. mathematically modeling-free. The simulation results show that the milling process with the designed fuzzy controller has a high robustness, stability, and also higher machining efficiency than standard controllers.

Experiment has shown that fuzzy controllers have important advantages over conventional controllers. The main advantage is that a fuzzy controller responds quickly to complex sensory inputs while the executing speed of sophisticated control algorithms in a conventional controller is severely limited.

Current research has shown that fuzzy controller has important advantages over conventional controllers. The first advantage is that a fuzzy 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 fuzzy controller responds quickly to complex sensory inputs while the executing speed of sophisticated control algorithms in a conventional controller is severely limited.

7. Conclusion

The purpose of this contribution is to present a reliable, robust fuzzy force controller aimed at adaptively adjusting feed-rate to prevent excessive tool wear, tool breakage and maintain a high chip removal rate.

The results of the intelligent milling experiments with adaptive control strategy show that the fuzzy controller has high robustness and global stability. The approach was successfully applied to an experimental milling centre Heller.

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.

References

[1] J. Balic, A new NC machine tool controller for step-by-step milling, Int. J. Adv. Manuf. Technol. 8 (2000) 399–403.

[2] F. Cus, J. Balic, Optimization of cutting process by GA approach, Robot. Comput. Integr. Manuf. 19 (2003) 113–121.

[3] S.J. Huang, C.C. Lin, A self-organising fuzzy logic controller for a coordinate machine, Int. J. Adv. Manuf. Technol. 19 (2002) 736–742.

[4] M.K. Kim, M.W. Cho, K. Kim, Application of the fuzzy control strategy to adaptive force control of non-minimum phase end milling operations, Int. J. Machine Tools Adv. Manuf. Technol. 15 (1999) 791–795.

[5] U. Zuperl, F. Cus, Optimization of cutting conditions during cutting by using neural networks, Robot. Comput. Integr. Manuf. 19 (2003) 189–199.