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INTELLIGENT ADAPTIVE CUTTING FORCE CONTROL IN END-MILLING

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Original scientific paper

In this article, an adaptive neural controller for the ball end-milling process is described. 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 article 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 the 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.

***Key words**: End-milling, adaptive force control, neural controller*

Inteligentna prilagodna kontrola sile rezanja u završnom glodanju

Izvorni znanstveni članak

U ovom je članku opisan prilagodljiv neuronski kontroler za proces glodanja kuglastim završetkom. Predložena je arhitektura s dvjema različitim vrstama neuronskih mreža, a korištena je za on-line optimalnu kontrolu procesa glodanja. BP neuronska mreža je korištena za identifikaciju stanja glodanja i za određivanje optimalnih reznih ulaza. Brzina posmaka je izabrana kao optimizirana varijabla, a stanje glodanja je procijenjeno pomoću izmjerene sile rezanja. Prilagodljivi kontroler je upravljan osobnim računalom, a podešene brzine posmaka se šalju do CNC-a. Svrha ovog članku je prikazati pouzdan, snažan neuronski kontroler koji je usmjeren na prilagodljivo podesivu brzinu posmaka radi sprječavanja pretjeranog trošenja alata, loma alata i održavanja visoke brzine uklanjanja čestica. Cilj je također dobiti poboljšanje produktivnosti procesa glodanja uporabom automatskog reguliranja sile rezanja. Brojne simulacije su vođene radi potvrđivanja učinkovitosti ove arhitekture. Predložena arhitektura za on-line određivanje optimalnih reznih uvjeta primijenjena je na glodanje s kuglastim završetkom u ovom radu, ali je očito da se sustav može proširiti na druge strojeve radi poboljšanja učinkovitosti rezanja.

***Ključne riječi:** završno glodanje, prilagodljiva kontrola sile, neuronski kontroler*

1 Introduction
Uvod

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 conservatively. 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 [4] 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 [1]. Adaptive control systems can be classified into: adaptive control with optimisation (ACO) [4] 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 [4, 5] 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 [4]. Three controllers have played important roles in machining process control. They are: CMAC controller [1], hierarchical neural controller [4], and multilayer neural controller [5].

2
Adaptive control with optimisation in end-milling
Prilagodljiva kontrola s optimizacijom u konačnom glodanju

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

- Neural network (NN) for optimisation determines the optimal feedrate and sends it to the milling machine and network for modelling,
- The measured output of the milling machine is used to train the NN for modelling,
- NN for optimisation 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.

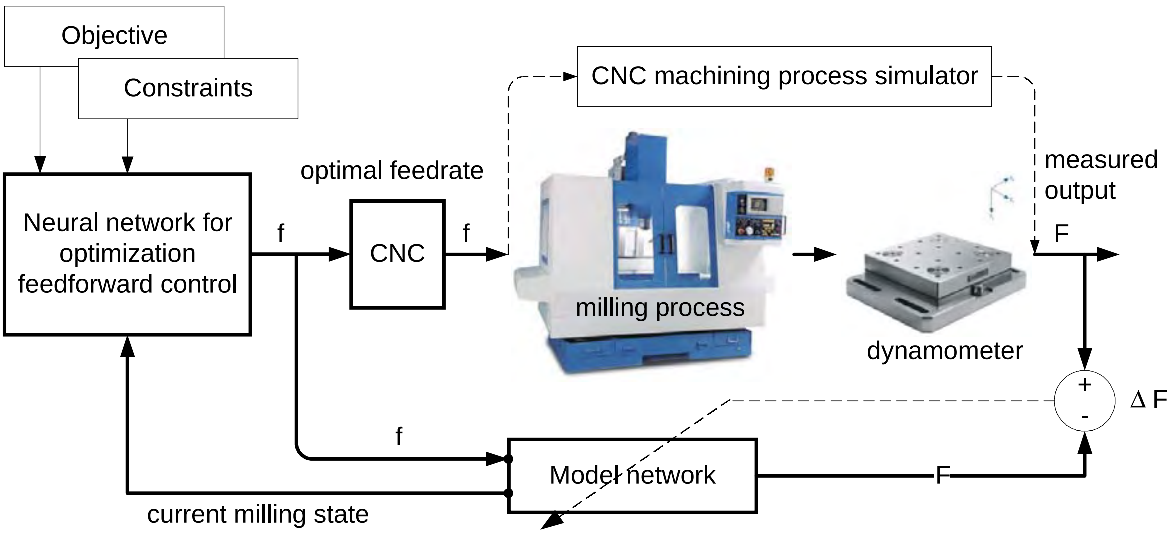

Figure 1. Scheme for adaptive control with optimisation in end-milling
Slika 1. Shema za prilagodljivu kontrolu s optimizacijom završnog glodanja

3
Neural network for optimisation
Neuronska mreža za optimizaciju

To realise 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 optimisation. This architecture that uses the Lagrange multiplier (ALM) method converges more quickly than other penalty methods. Detailed information about this type of network can be found in [4]. This method was first introduced by [4]. Combining both neural networks, an adaptive controller for the milling process is designed. The problem of the optimisation of cutting parameters in milling can be formulated as the following multi-objective optimisation problem: min T_p (f), min C_p (f), min R_a (f) subject to limitations L_1 - L_4. Where T_p, C_p and R_a are: production rate, operation cost and surface roughness [2]. 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. These factors originate usually from technical specifications.

The following limitations are taken into account:

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

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 behaviour is predicted by the measured cutting force.

4
Modelling of end-milling
Modeliranje završnog glodanja

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 (Figure 2) 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.

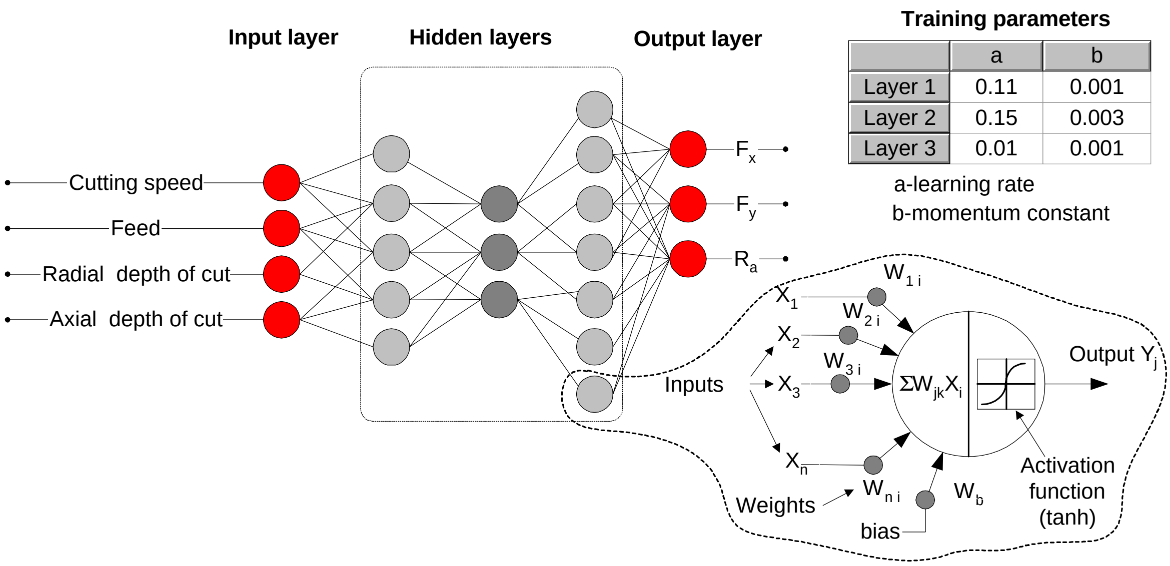

Figure 2. Predictive cutting force model topology
Slika 2. Topologija modela predviđanja sile rezanja

5 CNC machining process model simulator

Model simulator procesa CNC strojne obradbe

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 (Figure 2) and feed drive model. The neural model estimates cutting forces and surface roughness based on cutting conditions and cut geometry as described by Zuperl [6].

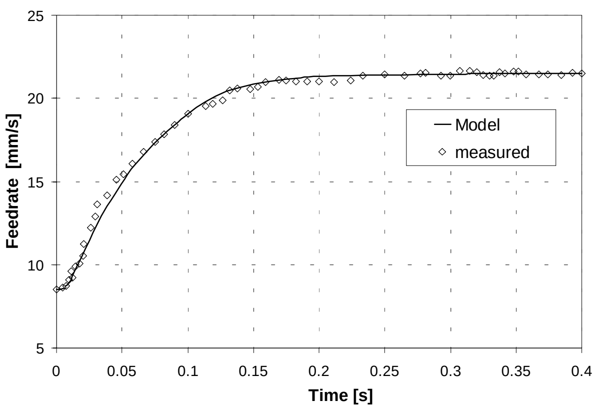

Figure 3. Comparison of actual and predicted feedrate
Slika 3. Usporedba stvarne i predviđene brzine ulaza

The feed drive model [6] simulates the machine response to changes in given feedrate. The feed drive model was determined experimentally by examining step changes in the given 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 mm/s to 22 mm/s is shown in Figure 3. The feed drive and neural force model are combined to form the CNC machining process model. Model input is the given feedrate and the output is the *X*, *Y* resultant cutting force.

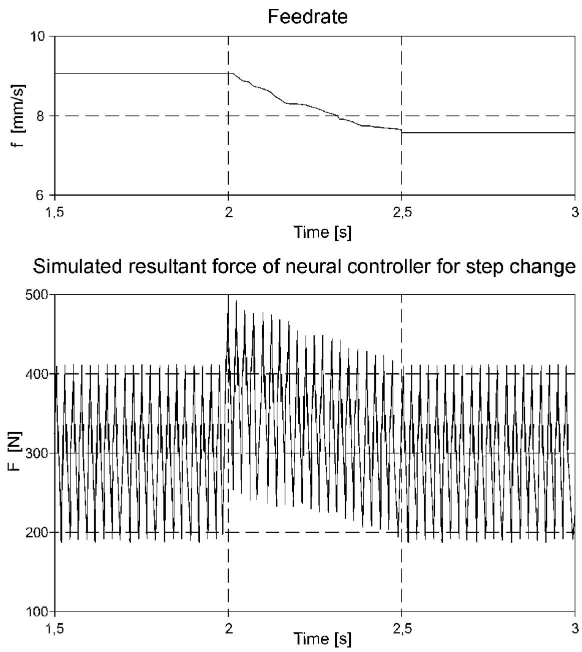

Figure 4. Simulated neural control response to a step change in axial depth of cut
Slika 4. Simulirana reakcija neuronske kontrole na promjenu koraka u aksijalnoj dubini reza

In simulations the real end milling process was replaced with trained neural model (Figure 1). The simulator is verified by comparison of experimental and model simulation results. A variety of cuts with feedrate changes were made for validation. Simulated control response to a step change in axial depth is presented in Figure 4. 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 s.

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.

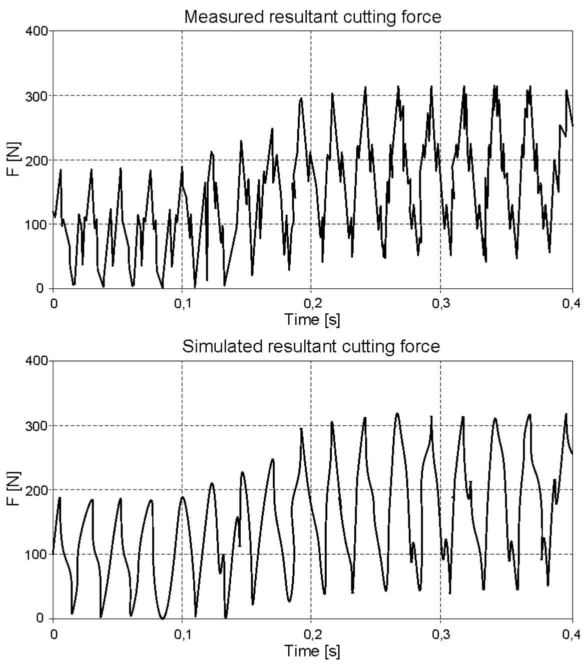

Figure 5. Comparison of simulated and measured cutting force
Slika 5. Usporedba simulirane i izmjerene sile rezanja

The measured and simulation resultant force for a step change in feedrate from 0,05 mm/tooth to 2 mm/tooth is presented in Figure 5.

The experimental results correlate well with model results in terms of average and peak force. The obvious discrepancy may be due to inaccuracies in the neural force model [3], and unmodeled system dynamics.

6
Data acquisition system and experimental equipment
Sustav prikupljanja podataka i mjerna oprema

The data acquisition equipment used in this acquisition system consists of dynamometer, fixture, hardware and software module as shown in Figure 6. 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 workpiece. 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 (Kistler 5019A). In the 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 are then converted into forces in X, Y and Z directions using the LabVIEW program.

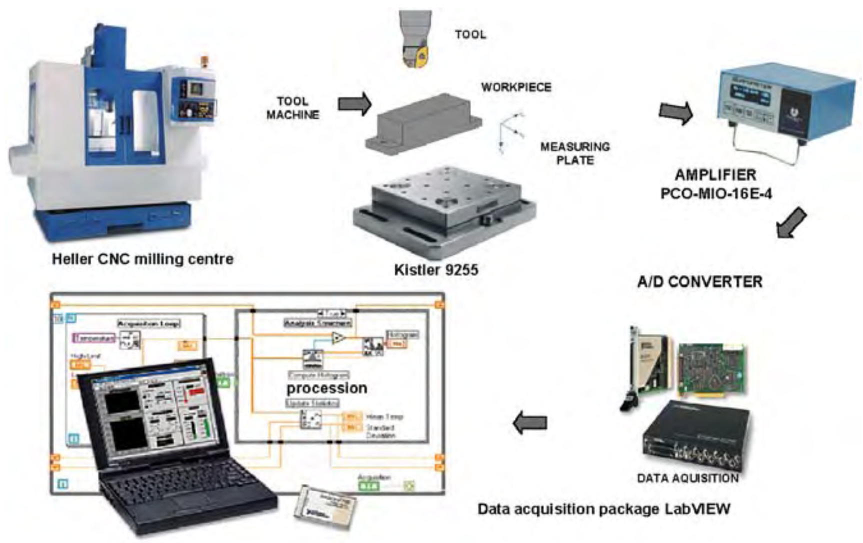

Figure 6. The experimental set-up
Slika 6. Mjerna instrumentarija i mjerni postupak

With this program, the three axis force components can be obtained simultaneously, and can be displayed on the screen for further analysis. 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 P10-20 coated with TiC/TiN, designated GC 1025. Communication between the control system and the CNC machine controller is accomplished over RS-232 protocol. The feedrate override percentage variable DNCFRO is available to the control system at a frequency of 1 kHz.

7
Testing of adaptive control system
Provjera prilagodljivog kontrolnog sustava

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 (prismatic profile, see Figure 7).

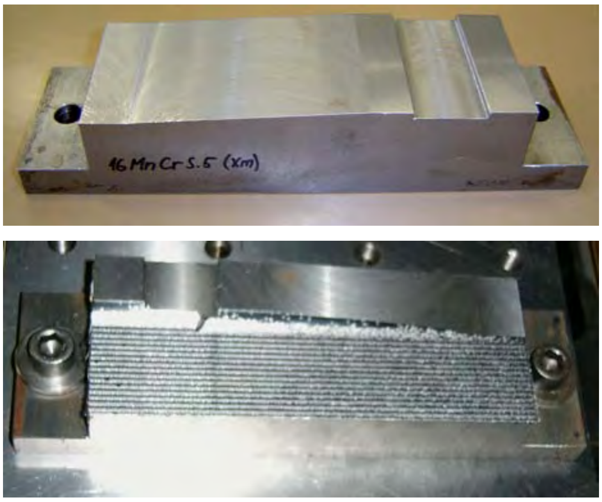

Figure 7. Workpiece profile
Slika 7. Profil radnog komada

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 R_d=3 mm, milling depth A_d=2 mm and cutting speed v_c=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 in Figure 1 and to optimise the feedrate, the desired cutting force is F_{ref}]=280 N, pre-programmed feed is 0,08 mm/teeth and its allowable adjusting rate is [0 to 150 %]. The objective of neural control is to keep the metal removal rate (MRR) as high as possible and to maintain 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 18 tests were carried out. To optimise the feedrate, the constraints are F = 240 N, pre-programmed feed is 0,08 mm/teeth and its allowable adjusting rate is from 0 to 150 %.

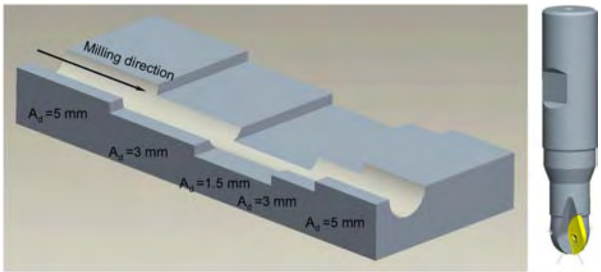

Figure 8. Experiment-2; Irregular workpiece profile
Slika 8. Pokus-2; neregularni profil radnog komada

The second group of experiments deals with the machining of irregular workpiece (Figure 8) consisting of five straight cuts with different axial and radial depths of cut. This experiment demonstrates the ability of adaptive system to maintain the constant cutting force during machining. The desired cutting force is 650 N. A sample time is 20 ms and scanning rate is 28,8 kHz. The results of the second experiment using neural network control are presented in Figure 10.

8
Results and discussion
Rezultati i diskusija

Figure 9 shows the response of the cutting force and the feedrate when the cutting depth is changed. 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-Figure 9a) the MRR reaches its proper value only in the last step. However, in the second test (Figure 9b), machining the same piece but using adaptive neural control, the average MRR achieved is much more close to the optimal MRR. Comparing the Figure 9a to Figure 9b, the cutting force for the neural control milling system is maintained at about 240 N, 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 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 modelling-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.

The second group of experiments (Figure 10) with small and large step changes is run to test system stability over a range of cutting conditions. The system remains stable in all experiments, with little degradation in performance. In the second experiment, the UNKS increases the feedrates to obtain peak forces close to 650 N. The slower response of the neural control scheme is noticeable at the beginning of cut one and three.

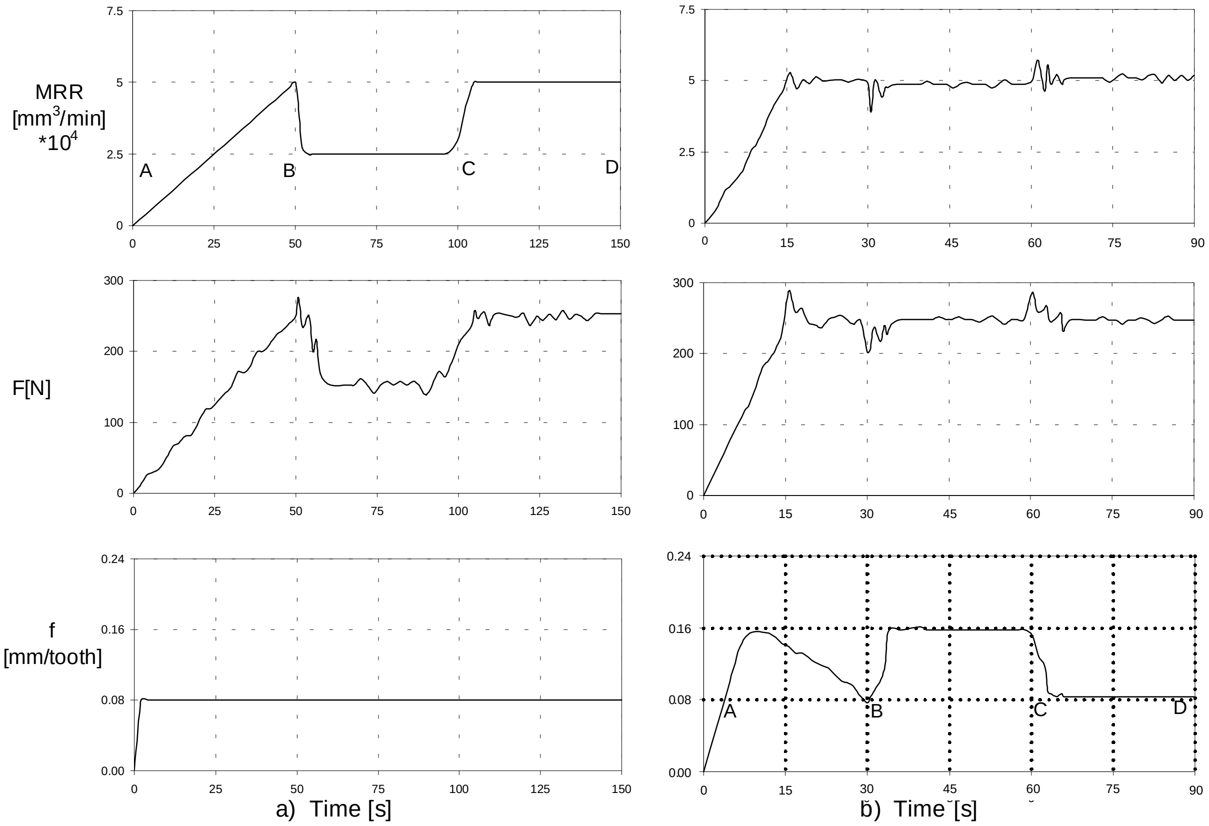

Figure 9. Experimental results. Response of MRR, resulting cutting force, feedrate.
a) Conventional milling. b) Milling with adaptive NN control system.
Slika 9. Eksperimentalni rezultati. Odziv MRR, rezultirajuća sila rezanja, brzina ulaza.
a) Konvencionalno glodanje. b) Glodanje s prilagodljivim NN kontrolnim sustavom.

9 Conclusions
Zaključci

The purpose of this paper 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.

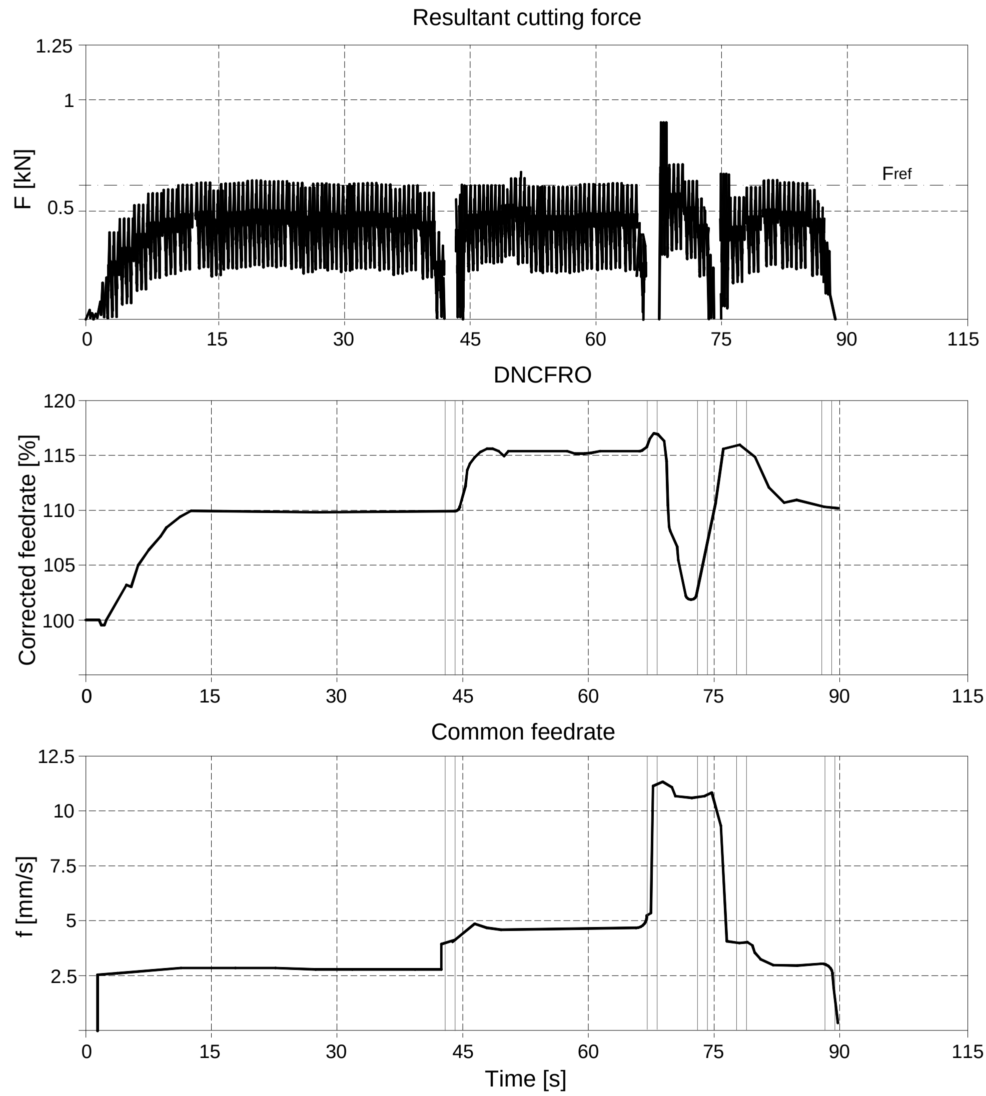

Figure 10. Machining of irregular profile by intelligent adaptive cutting force control; 2. group of experiments
Slika 10. Strojna obradba regularnog profila pomoću inteligentne prilagodljive kontrole sile rezanja; 2. grupa eksperimenata

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