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COMBINED SYSTEM FOR OFF-LINE OPTIMIZATION AND ADAPTIVE CUTTING FORCE CONTROL

The choice of manufacturing processes is based on cost, time and precision. A remaining drawback of modern CNC systems is that the machining parameters, such as feed-rate, cutting speed and depth of cut, are still 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 . Even if the machining parameters are optimised off-line by an optimisation algorithm they cannot be adjusted during the machining process. In this paper, a neural adaptive controller is developed and some simulations and experiments with the neural 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.

1. INTRODUCTION

The machining parameters are usually selected before machining according to a programmer's experience and machining handbooks. To prevent damage and to avoid machining failure the operating conditions are usually set conservatively. As a result, many CNC systems are inefficient and run under the operating conditions that are far from optimal. Even if the machining parameters are optimised off-line by an optimisation algorithm [9] 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 [6]. 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.

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The focus of this research is peak force regulation in 4-axis CNC machining through the use of off-line optimized feedrate and adaptive control.

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 Tlusty & Elbestawi [7]. Stute & Goetz [6] 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 Tomizuka [8]. These controllers were simulated and evaluated and physically implemented by Liu [5]. Both studies found all three parameter adaptive controllers to perform better than the fixed-gain PI controller. 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 on-line adaptive control in conjunction with off-line optimization. The optimization is performed employing an algorithm developed by Zuperl [10].

Much work has been done on the adaptive cutting force control for milling [1,2]. 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.

The paper is organised as follows. Section 2 briefly describes the overall cutting force control strategy. Section three covers the CNC milling simulator. Section five describes the experimental evaluation of combined adaptive control system. Finally, sections six and seven present experimental results, conclusions, and recommendations for future research.

2. COMBINED SYSTEM FOR OFF-LINE OPTIMIZATION AND ADAPTIVE CUTTING FORCE CONTROL

The basic idea of this approach is to merge the off-line cutting condition optimization algorithm and adaptive force control (Fig. 1). Based on this new combined control system, very complicated processes can be controlled more easily and accurately compared to standard approaches.

The objective of the developed combined control system 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 combined control system is automatically adjusted to the instant cutting conditions by adaptation of feedrate.

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 the cutting tool from damage and breakage.

When the system detects extreme forces, it automatically stops the machine to protect the cutting tool. This reduces the need for constant operator supervision. The sequence of steps for on-line optimization of the milling process is presented below.

1. The recommended cutting conditions are determined by ANfis (adaptive neuro-fuzzy inference system) models, which are basic elements of the software for selecting the recommended cutting conditions.
2. The pre-programmed feed rates determined by the off-line optimization algorithm are sent to the CNC controller of the milling machine
3. The measured cutting forces are sent to the neural control scheme,
4. The neural control scheme adjusts the optimal feedrates and sends data back to the machine,
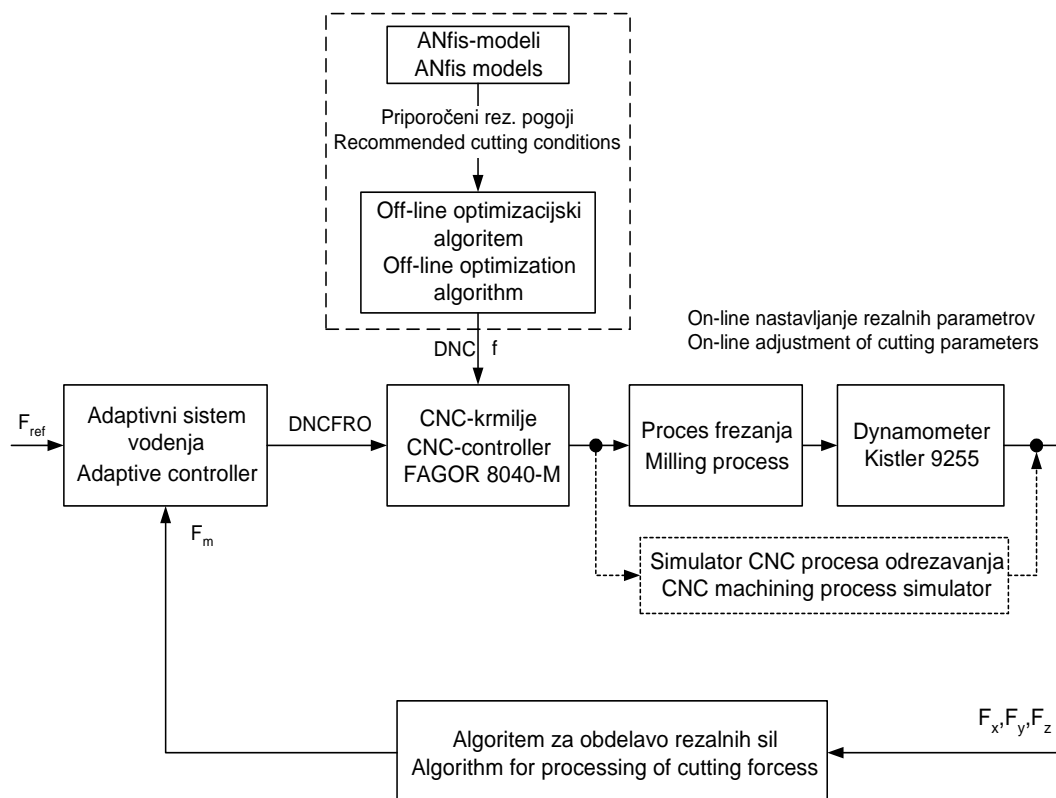5. Steps 1 to 3 are repeated until termination of machining.

Fig. 1. Structure of a combined system for off-line optimization and adaptive adjustment of cutting parameters

The neural adaptive force controller adjusts the feed-rate by assigning a feed-rate override percentage to the CNC controller on a 4-axis Heller, based on a measured peak force (Fig. 1).

The actual feed-rate is the product of the feed-rate 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 20 ms. Data acquisition software (LabVIEW) and the algorithm for processing the cutting forces are used to provide this information.

2.1. FEED-FORWARD NEURAL CONTROL SCHEME (UNKS)

The basic control principle is based on the control scheme (UNKS) consisting of three parts (Fig. 2). The first part is the loop known as external feedback (conventional control loop). The feedback control is based on the error between the measured (F_m) and desired (F_{ref}) cutting force. The primary feedback controller is a neural network (NM-R) which imitates the work of division controller.

The second part is the loop connected with neural network 1 (NM-1), which is internal model of process dynamics. It acts as the process dynamics identifier. This part represents an internal feedback loop which is much faster than the external feedback loop as the latter usually has sensory delays.
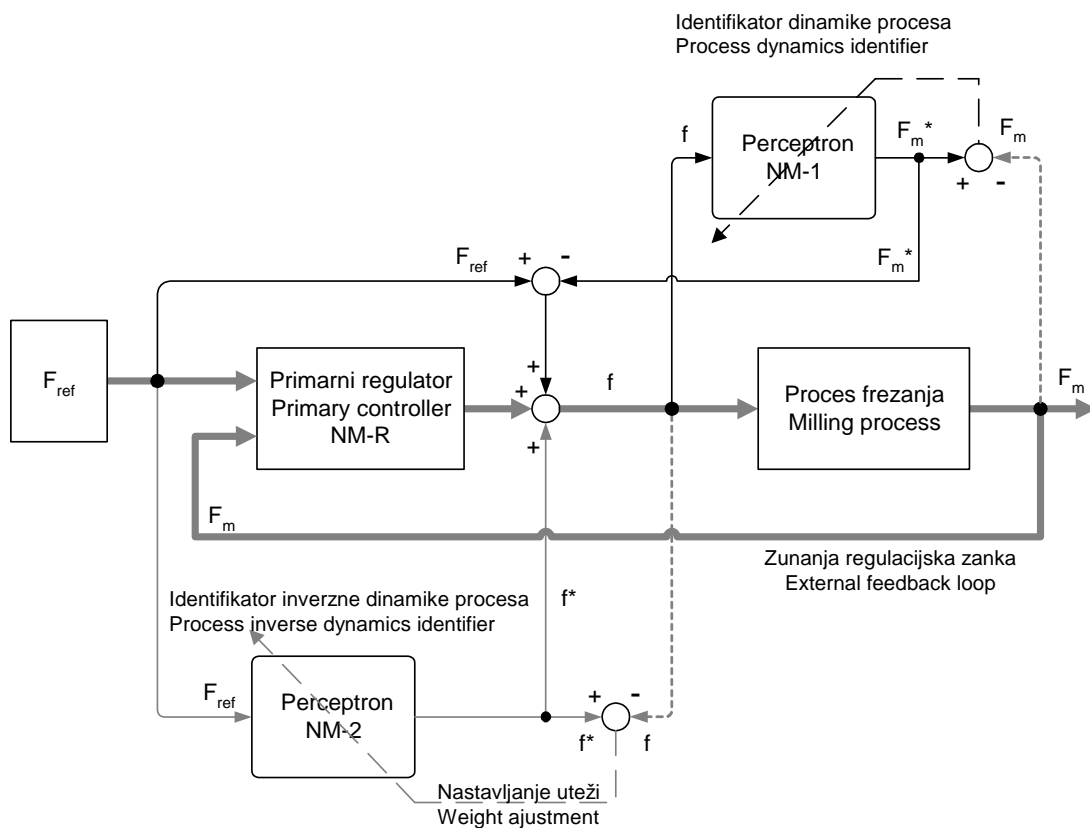

Fig. 2. Feed-forward neural control scheme (UNKS)

The third part of the system is neural network 2 (NM-2). The NM-2 learns the process inverse dynamics. The UNKS operates according to the following procedure. The sensory feedback is effective mainly in the learning stage. This loop provides a conventional feedback signal to control the process. During the learning stage, NM-2 learns the inverse dynamics.

As learning proceeds, the internal feedback gradually takes over the role of the external feedback and primary controller. Then, as learning proceeds further, the inverse

dynamics part will replace the external feedback control. The final result is that the plant is controlled mainly by NM-1 and NM-2 since the process output error is nearly zero.

This is an adaptive control system controlling the cutting force and maintaining constant roughness of the surface being milled by digital adaptation of cutting parameters. In this way it compensates all disturbances during the cutting process: tool wear, non-homogeneity of the workpiece material, vibrations, chatter etc.

A CNC milling simulator is used to evaluate the controller design before conducting experimental tests. The CNC milling simulator tests the system stability and tunes the control scheme parameters. The simulator consists of a neural force model, a feed drive model and model of elasticity (Fig. 3). The neural model predicts cutting forces based on cutting conditions and cut geometry as described by Zuperl [11]. The feed drive model simulates the machine response to changes in desired feedrate.
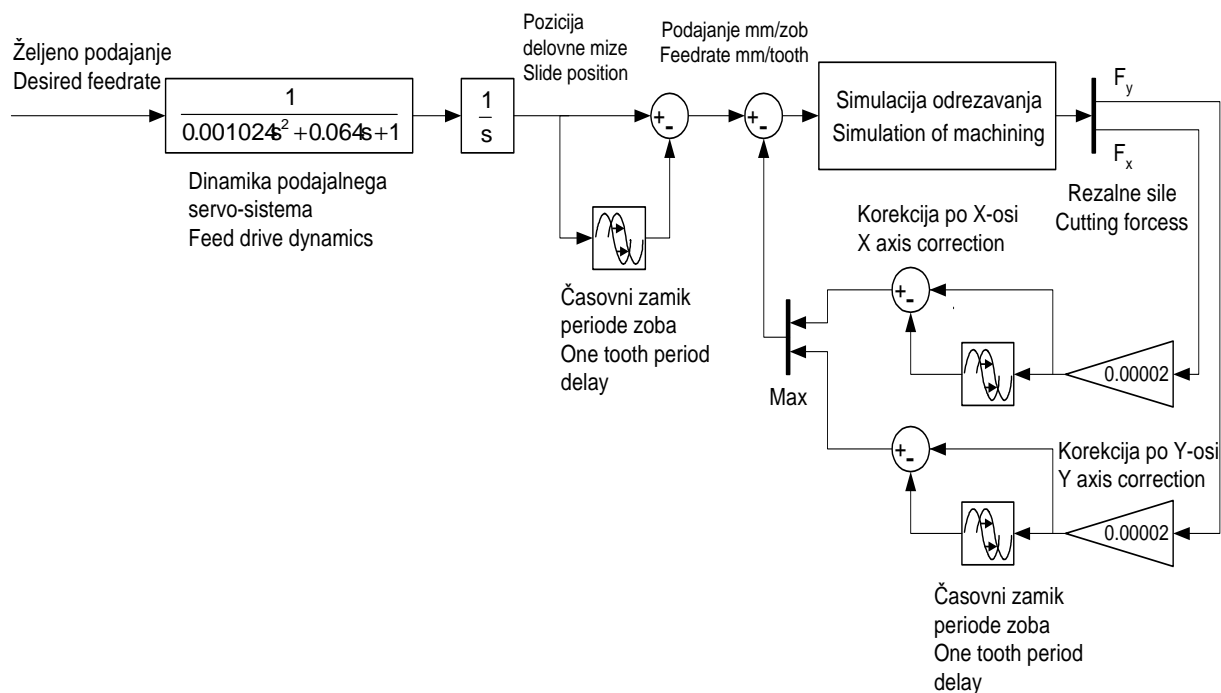

Fig. 3. CNC milling simulator

The elasticity model represents the deflection between the tool and the workpiece (Figure 3). Model is adapted from Cus [3]. The system elasticity is modelled as static deflection of the cutter. The elasticity equation for X direction of tool travel is:

$$X_m(t) = (-F_x(t)) + F_x(t - T_{tp})) \cdot G_x \qquad (1)$$

Where X_m is the tool elastic deflection affecting the chip thickness, F is the cutting force G_x is the compliance, t is time and T_{tp} is tool passing period.

3. CNC MILLING SIMULATOR

The feed drive model was determined experimentally by examining responses of the system to step changes in the desired feed 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 on Fig. 4.
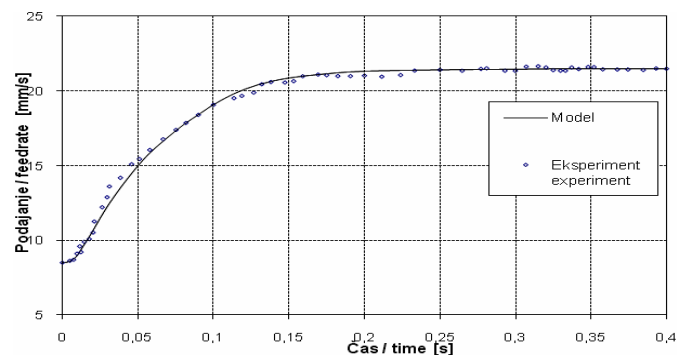
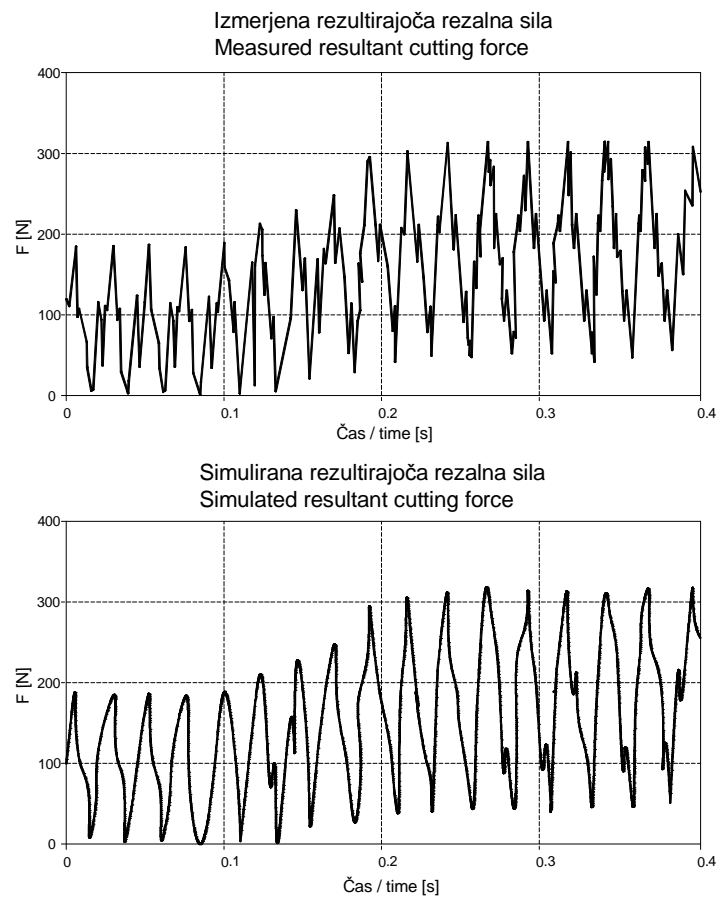Fig. 4. Comparison of actual and simulated federate

Fig. 5. Comparison of simulated and measured cutting force

The feed drive model, neural force model and elasticity model are combined to form the CNC milling simulator. The simulator input is the desired feedrate 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 feedrate changes were made for validation. The measured and simulation resultant force for a step change in feedrate from 0.05 mm/tooth to 2 mm/tooth is presented in Fig. 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, and unmodeled system dynamics.

3.1. SIMULATOR OF CUTTING DYNAMICS

To realise the on-line modelling of cutting process, a standard BP neural network (UNM) 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.
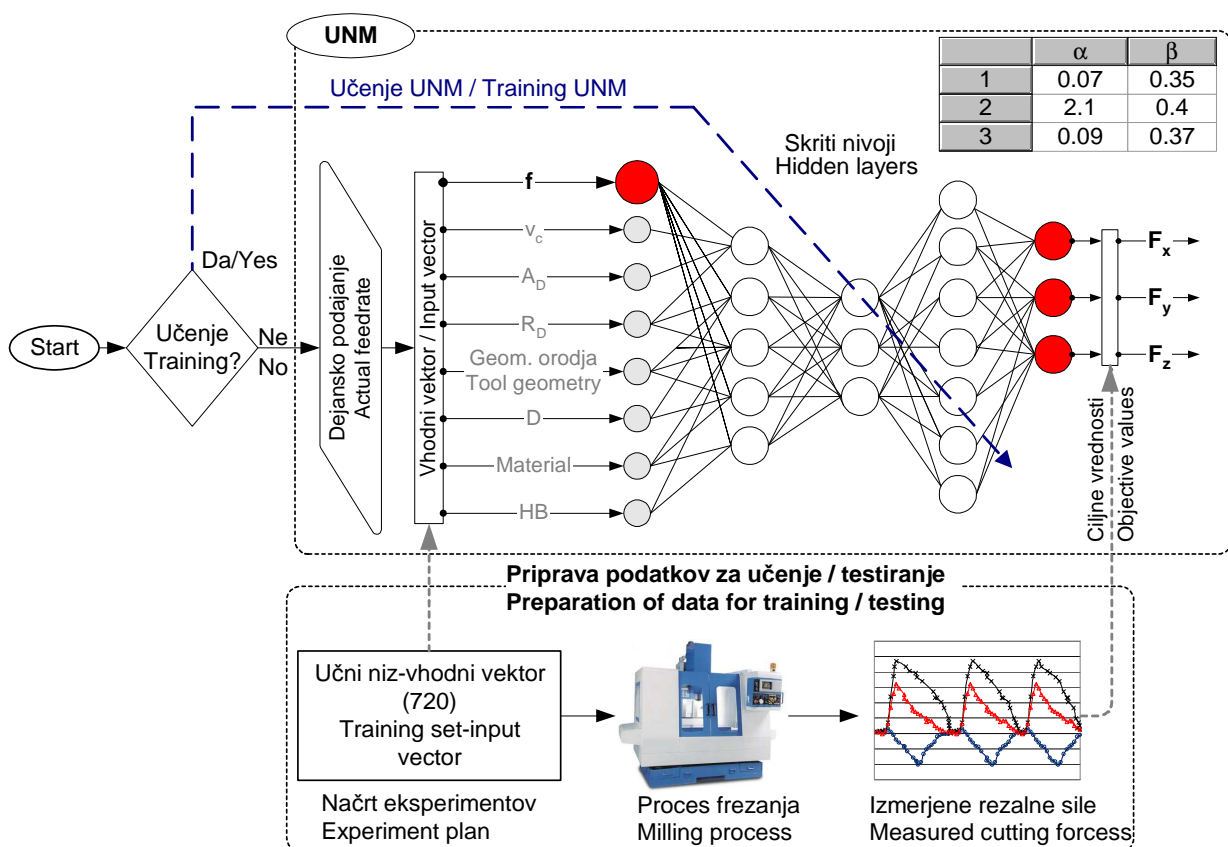

Fig. 6. Predictive cutting force model topology

4. DATA ACQUISITION SYSTEM AND EXPERIMENTAL EQUIPMENT

The data acquisition equipment consists of dynamometer, fixture and software module as shown in Fig. 7. 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 is applied to the dynamometer through the workpiece. The piezoelectric quartz in the dynamometer is strained and an electric charge is generated. The electric charge is then transmitted to the multi-channel charge amplifier through the connecting cable.

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. 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.
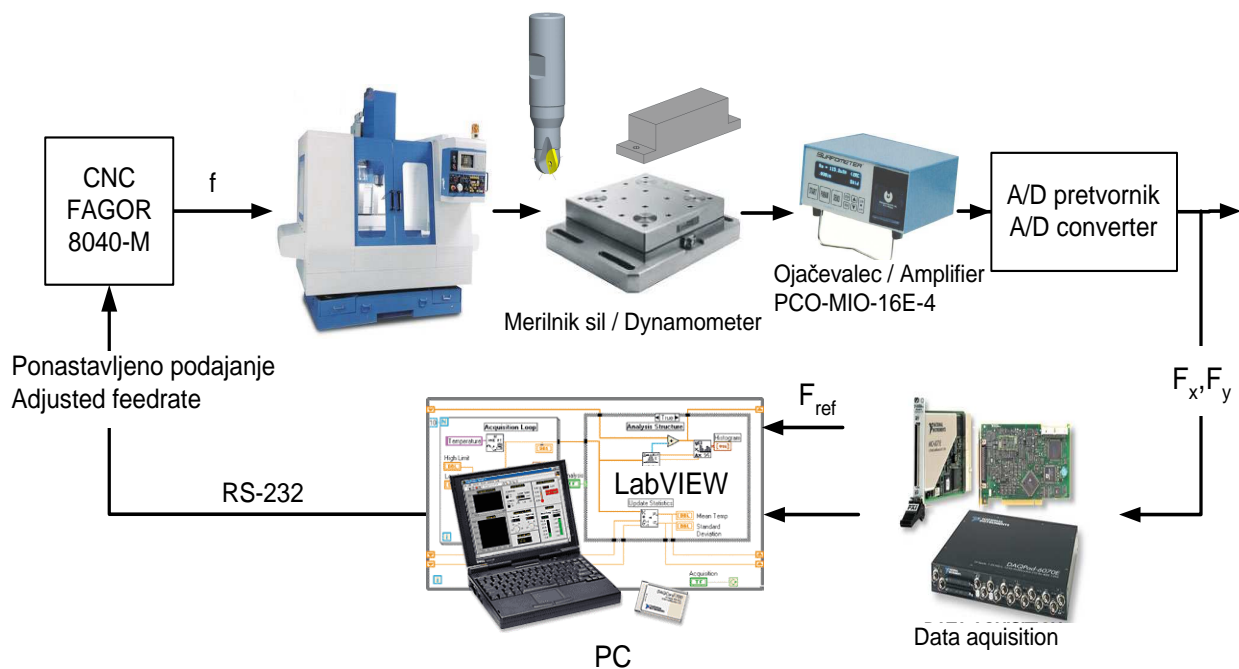

Fig. 7. The experimental equipment

5. EXPERIMENTAL TESTING OF COMBINED ADAPTIVE CONTROL SYSTEM

To examine the stability and robustness of the proposed control strategy, the system is first analysed by simulations using LabVIEW's simulation package Simulink. Then the system is verified by two experiments on a CNC milling machine (type HELLER BEA1) for Ck 45 and 16MnCrSi5 XM steel workpieces with variation of cutting depth. Feedrates for each cut are first optimized off-line, and then machining runs are made with controller action.

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 v_c=80 m/min. The parameters for adaptive control are the same as for the experiments in the conventional milling. To use the structure of combined system on Figure 1 and to optimise the feedrate, the desired cutting force is [F_{re}f]=280 N, pre-programmed feed is 0.08 mm/teeth and its allowable adjustment rate is [0 – 150 %].

6. RESULTS AND DISCUSSION

In the first experiment using constant feed rates (conventional cutting) the MRR reaches its proper value only in the last section. However, in second test (Fig. 8), machining the same piece but using adaptive control, the average MRR achieved is much closer to the maximal MRR.

Comparing, it is seen that the cutting force for the neural control milling system is maintained at about 650 N, and the feedrate of the adaptive milling system is close to that of conventional milling 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 adaptive milling is improved. The experimental results show that the MRR can be improved by 27 %.

As compared to most of the existing end milling control systems, the proposed combined system has the following advantages: 1. the computational complexity of UNKS does not increase much with the complexity of the process; 2. the learning ability of UNKS is more powerful than that of a conventional adaptive controller; 3. UNKS has a generalisation capability; 4. The system is insensitive to changes in workpiece geometry, cutter geometry, and workpiece material; 5. It is cost-efficient and easy to implement; and 6. It is mathematical modelling-free.

The experimental results show that the milling process with the designed adaptive controller has a high robustness, stability, and also higher machining efficiency than standard controllers. Current research has shown that neural control scheme has important advantages over conventional controllers.

The first advantage is that it can efficiently utilize 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 control scheme responds quickly to complex sensory

inputs while the execution speed of sophisticated control algorithms in a conventional controller is severely limited.
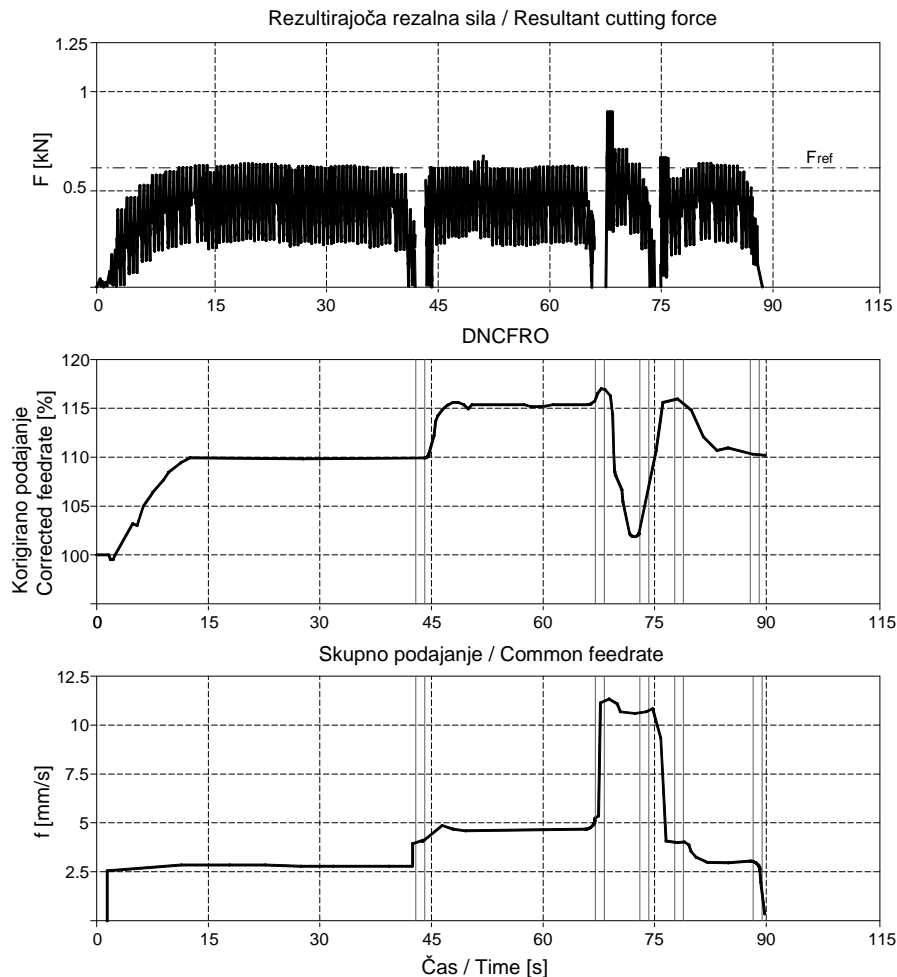

Fig. 8. Experiment-2; Machining of irregular profile by off-line optimizing of cutting conditions and adaptive adjusting of feedrate

7. CONCLUSION

A combined system for off-line optimization and adaptive adjustment of cutting parameters is developed on the basis of the cutting process modelling, off-line optimization and feed-forward neural control scheme (*UNKS*). This is an adaptive control system controlling the cutting force and maintaining constant roughness of the surface being milled by digital adaptation of cutting parameters.

Applicability of the methodology of adaptive adjustment of cutting parameters is experimentally demonstrated and tested on a Heller 4-axis *CNC* milling machine. The results of the intelligent milling experiments with adaptive control strategy show that the developed system has high robustness and global stability.

Experiments have confirmed efficiency of the adaptive control system, which is reflected in improved surface quality and decreased tool wear. 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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