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ADAPTIVE SELF-LEARNING CONTROLLER DESIGN FOR FEEDRATE MAXIMIZATION OF MACHINING PROCESS

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Abstract:
An adaptive control system is built which controlling the cutting force and maintaining constant roughness of the surface being milled by digital adaptation of cutting parameters. The paper discusses the use of combining the methods of neural networks, fuzzy logic and PSO evolutionary strategy (Particle Swarm Optimization) in modeling and adaptively controlling the process of end milling. An overall approach of hybrid modeling of cutting process (ANfis-system), used for working out the CNC milling simulator has been prepared. The basic control design is based on the control scheme (UNKS) consisting of two neural identificators of the process dynamics and primary regulator. Experiments have confirmed efficiency of the adaptive control system, which is reflected in improved surface quality and decreased tool wear.

Key Words: Modeling, Artificial Intelligence, End-milling, Adaptive force Control, Optimisation.

1. INTRODUCTION

The use of computer numerical control (CNC) machining centers has expanded rapidly through the years. 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 system, 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 on-line adaptive control in conjunction with off-line optimization.

The optimization is performed with algorithm developed by Zuperl [8]. In our AC system, the feedrate is adjusted on-line in order to maintain a constant cutting force in spite of variations in cutting conditions.

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

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

The overall force control strategy consists of optimizing the feedrates off-line, and then applying on-line adaptive control during the machining process. The basic idea of this design 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. Combined control system is automatically adjusted to 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 cutting tool from damage and breakage.

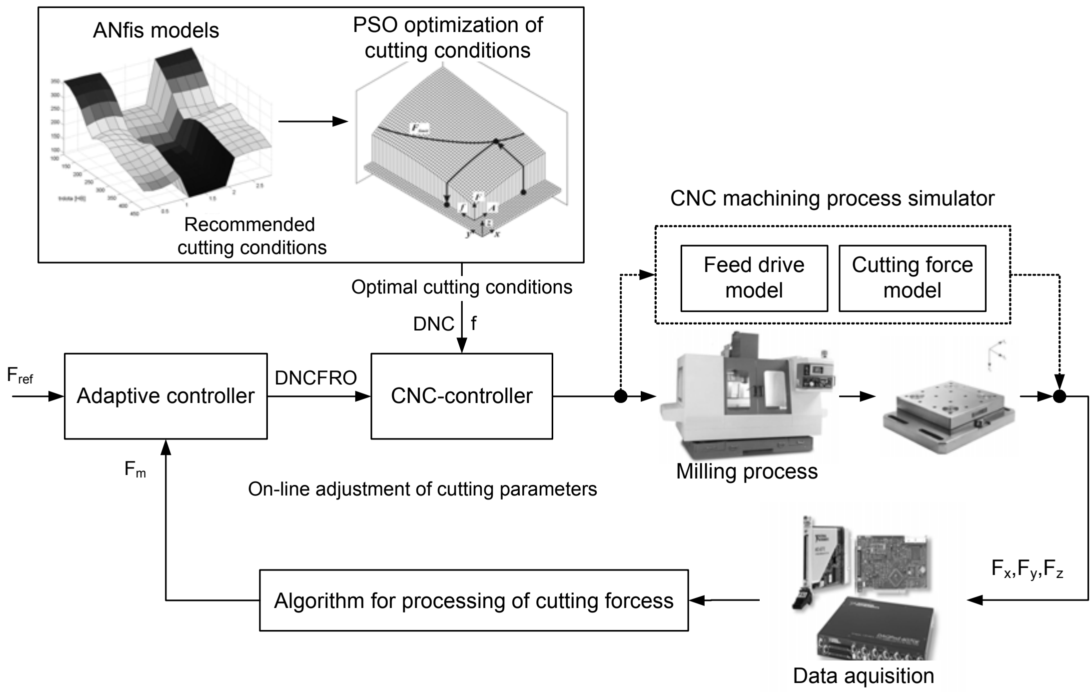


Figure 1: Feedrate Override Percentage in Closed Loop System

Sequence of steps for on-line optimization of the milling process is presented below.

- 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.

- Optimization of recommended cutting conditions by PSO optimization.
- The pre-programmed feed rates determined by off-line optimization algorithm are sent to CNC controller of the milling machine.
- The measured cutting forces are sent to neural control scheme.
- Neural control scheme adjusts the optimal feedrates and sends it back to the machine.
- Steps 1 to 3 are repeated until termination of machining.

The adaptive force controller 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 Fig.1). 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 0,001s. The combined control system returns the cutting force value to the desired value level within four or less iteration at the latest.

3. SELF- LEARNING CONTROL SCHEME

The fundamental control principle is based on the Feed-forward neural 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.

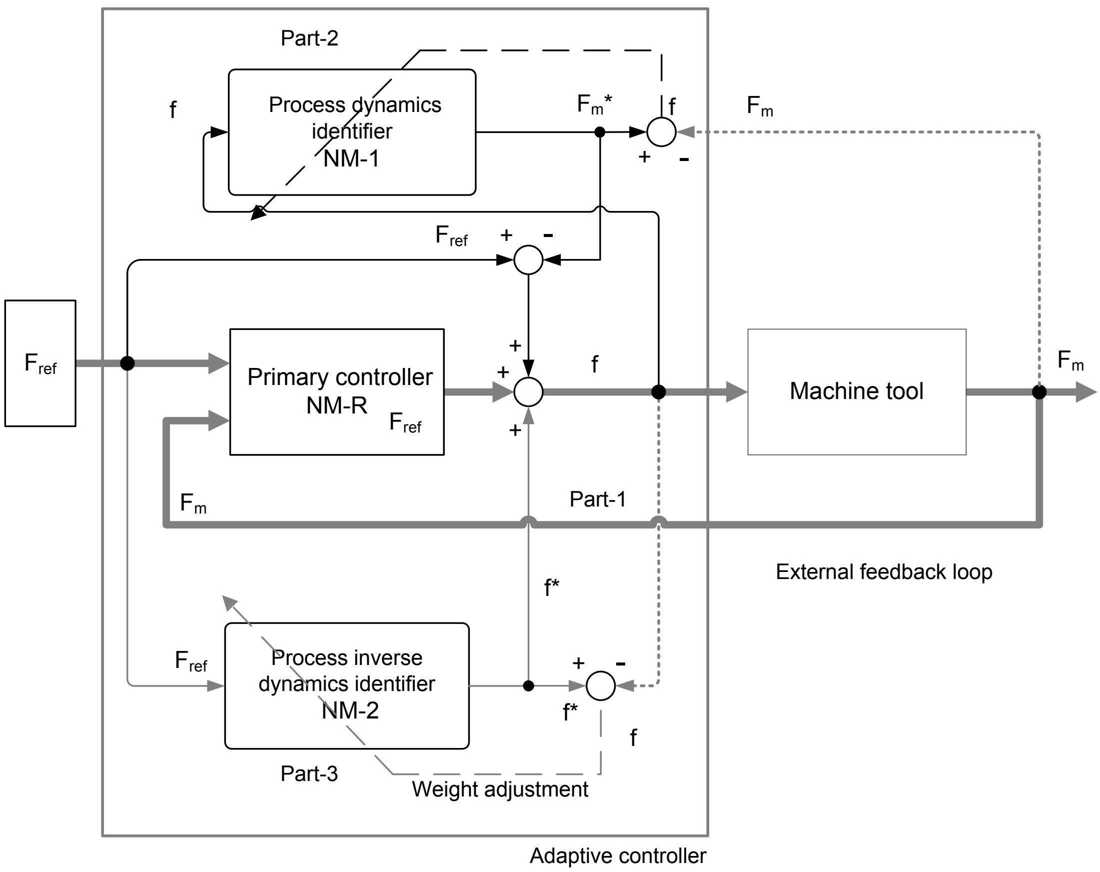


Figure 2: Feed-Forward Neural Control Scheme (UNKS)

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.

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.

4. CNC MILLING SIMULATOR

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 [9] and Cus [10]. The feed drive model simulates the machine response to changes in desired feedrate. The elasticity model [11] represents the deflection between the tool and the workpiece. Model is adapted from [12]. The system elasticity is modeled as static deflection of the cutter [13].

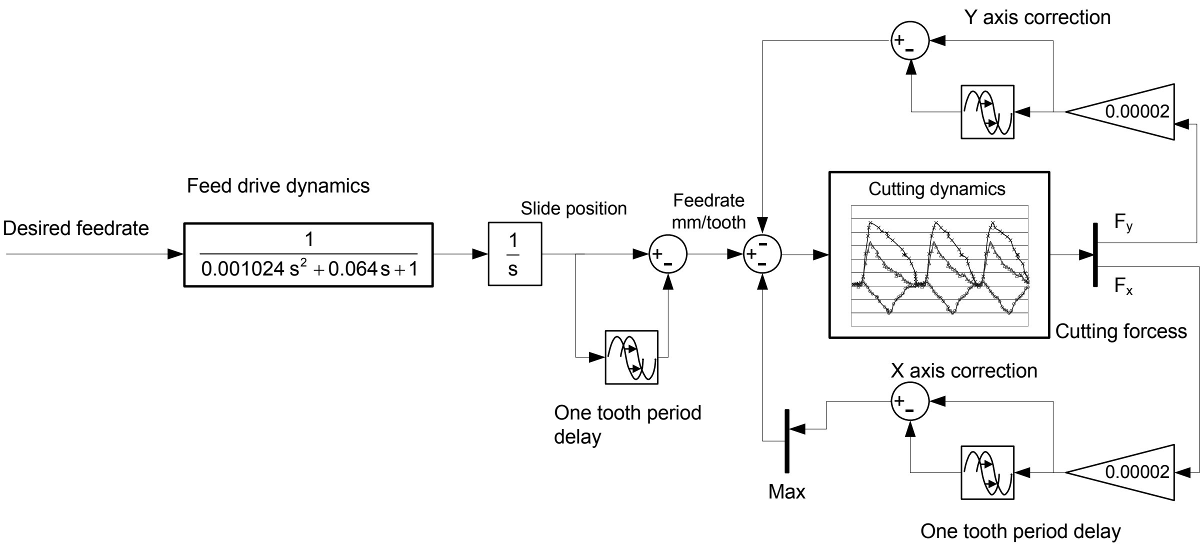


Figure 3: CNC Milling Simulator

4.1 The Feed Drive Model

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 0.4sec. Comparison of experimental and simulation results of a velocity step change from 7mm/sec to 22mm/sec is shown on Fig. 4.

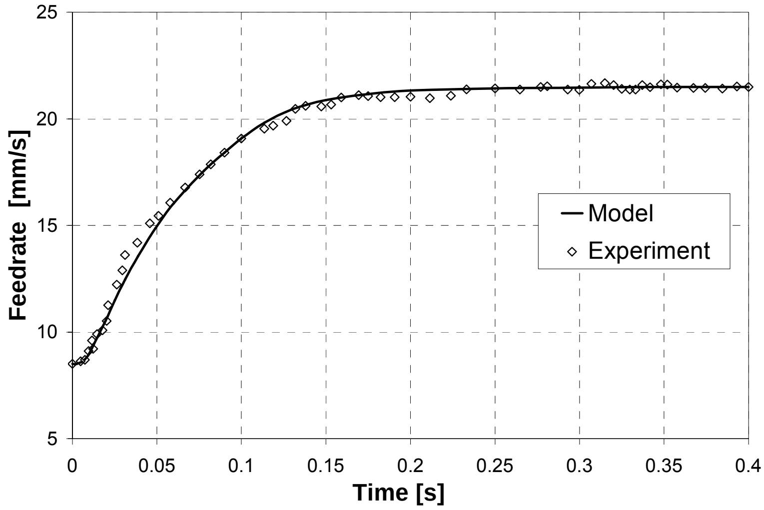


Figure 4: Comparison of Actual and Simulated Federate

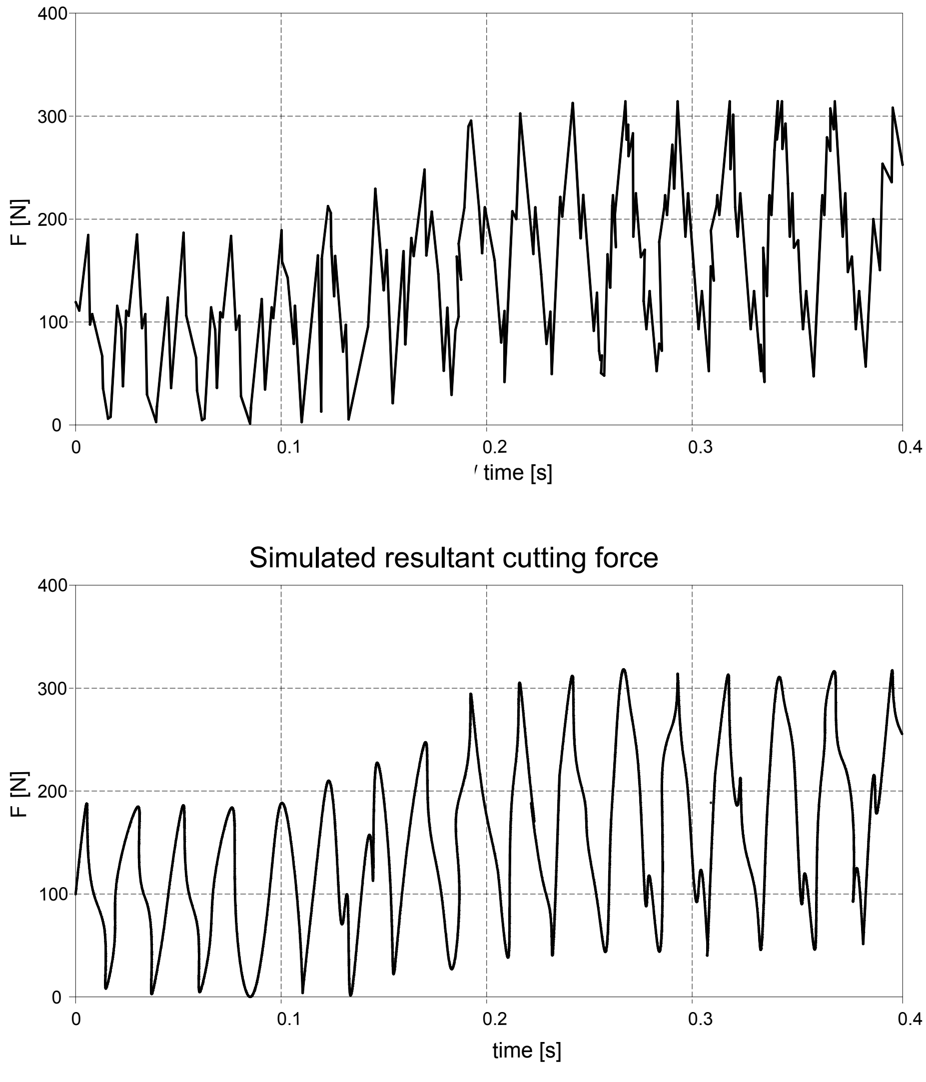


Figure 5: Comparison of simulated and experimental resultant force

The feed drive model, neural force model and elasticity model are combined to form the CNC milling simulator. 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 step change in feedrate from 0.05mm/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.

4.2 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. The UNM for modelling needs eight input neurons: for federate (f), cutting speed (vc), 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 UNM 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. During simulation most input vector parameters do not change (e.g. cutter diameter and geometry, material etc.). The detailed topology of the used NN with optimal training parameters is shown in Fig. 6. Optimal UNM configuration contains 5, 3 and 7 neurons in hidden layers.

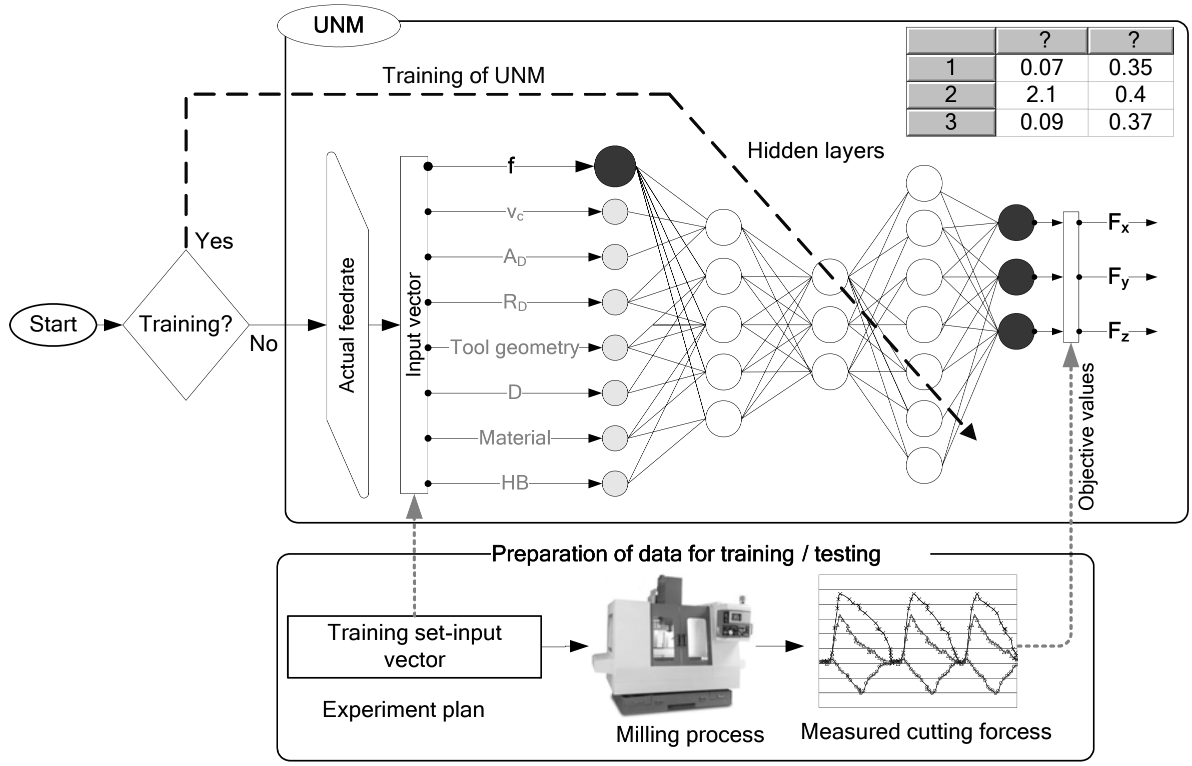


Figure 6: Comparison of Simulated and Experimental Resultant Force

5. EXPERIMENTAL EQUIPMENT AND DATA ACQUISITION SYSTEM

The data acquisition equipment consists of dynamometer, fixture and software module. The cutting forces were measured with a piezoelectric dynamometer (Kistler 9255) mounted between the workpiece and the machining table. 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. With this program, the three axis force components can be obtained simultaneously, and can be displayed on the screen for further analysis. The feedrate override percentage variable DNCFRO is available to the control system at a frequency of 1 kHz Communication between the control system and the CNC machine controller is accomplished over RS-232 protocol.

6. EXPERIMENTAL TESTING OF 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 [14].

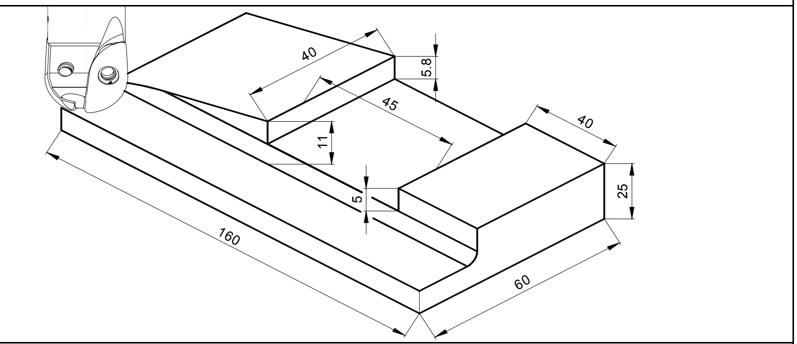
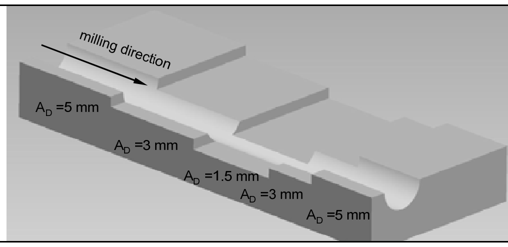
a)	
Experiment 1: Prismatic Workpiece	
Test_A Constant feedrate	Cutting conditions: Feedrate: 0.08mm/zob, Cutting speed: v=80m/min, Pre-programmed axial depth of cut A_D=2 mm, Radial depth of cut R_D =4mm, F_{ref}=280N, Result: Fig.: 8a
Test_B Proposed adaptive control system	Starting feedrate: 0.08mm/zob, Allowable adjusting rate: 00.8 - 0.20 mm/zob, Cutting speed: v=80m/min, Axial depth of cut A_D=2-11mm, Radial depth of cut: R_D =4mm, F_{ref}=280N, Result: Fig.: 8b
b)	
Experiment 2: Irregular workpiece profile	
Test_A Constant feedrate	Cutting conditions: Feedrate: 3mm/s, Spindle speed: 2400min^{-1}, Axial depth of cut A_D=2 -5mm, Radial depth of cut: R_D =16mm, F_{ref}=650N
Test_B Proposed adaptive control system	Starting Feedrate: 2.5mm/s, Allowable adjusting rate of federate: 2.5-11mm/s, Spindle speed: 2400min^{-1}, Axial depth of cut A_D=2 -5mm, Radial depth of cut: R_D =16mm, F_{ref}=650N, Result: Fig.: 9

Figure 7: Plan of Experiments; a) Cutting Conditions for Prismatic Workpiece.
b) Cutting Conditions for Irregular Workpiece Profile

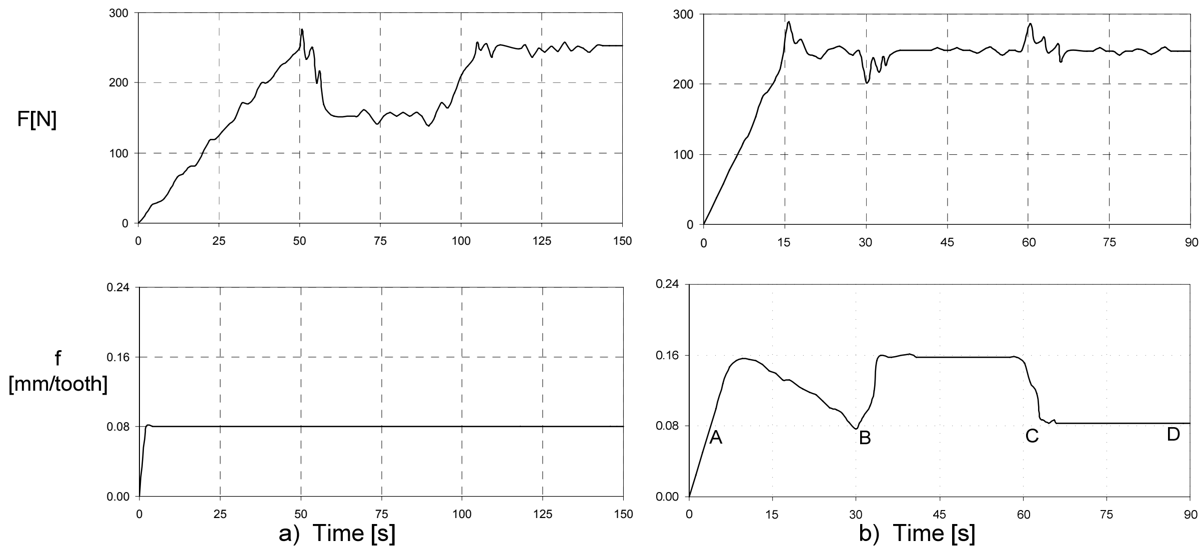


Figure 8: Experiment-2; Machining of Irregular Profile by Off-Line Optimizing of Cutting Conditions and Adaptive Adjusting of Federate

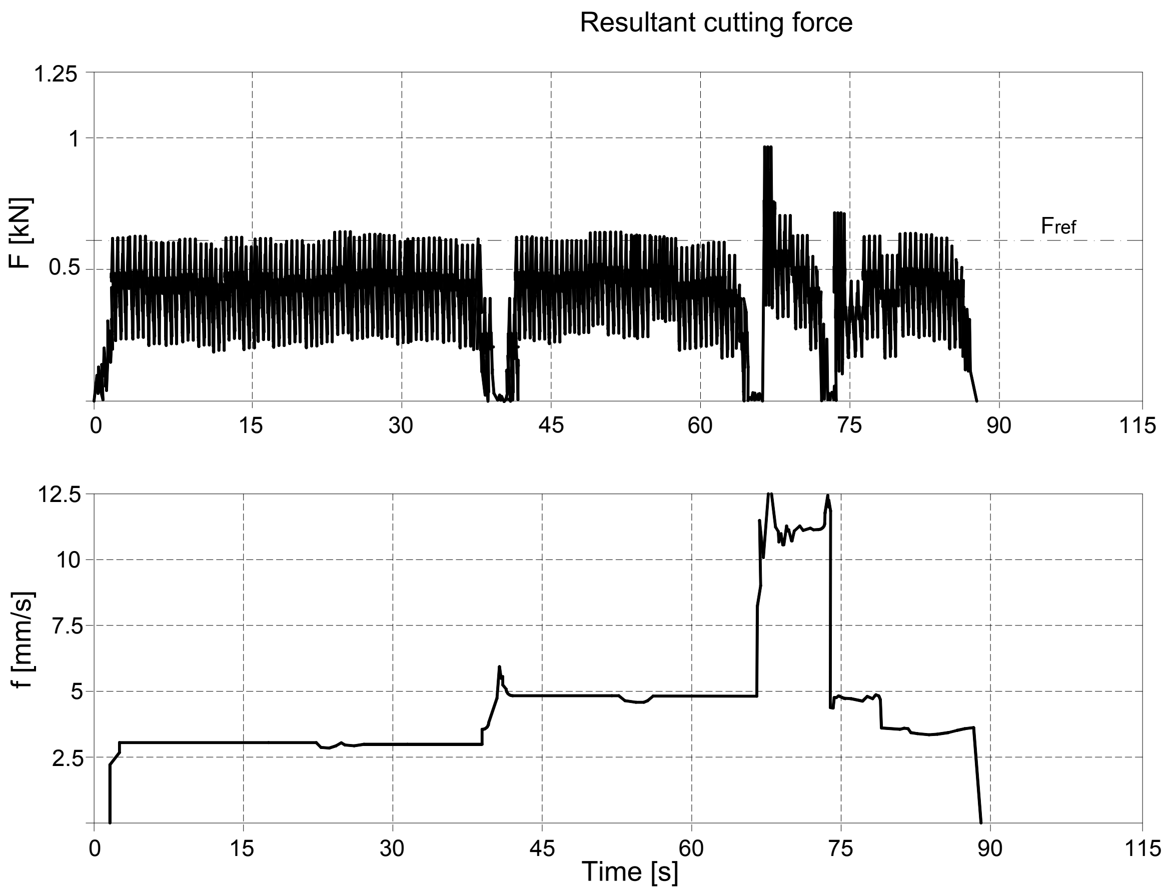


Figure 9: Experiment-2; Machining of Irregular Profile by Off-Line Optimizing of Cutting Conditions and Adaptive Adjusting of Federate

Then the system is verified by two experiments on a CNC milling machine for Ck 45 and 16MnCrSi5 XM steel workpieces with variation of axial cutting depth (Experiment 1- prismatic workpiece; experiment 2- workpiece with irregular profile, see Fig. 7).

Details of the experimental conditions and the dimensions of the workpiece are shown in Fig. 7. Feedrates for each cut are first optimized off-line, and then machining runs are made with controller action. The first test is conventional cutting with the constant feedrate (Test_A). In the second test, the proposed combined system was applied in milling to demonstrate its performance (Test_B).

The parameters for adaptive control are the same as for the experiments in the conventional milling. Fig. 8 is the response of the cutting force and the feedrate when the cutting depth is changed (experiment-1). It shows the experimental result where the feedrate is adjusted on-line to maintain the maximal cutting force at the desired value. The second experiment is machining of irregular workpiece consisting of five straight cuts with different axial and radial depths of cut. The results of the second experiment using optimized feedrates and UNKS are presented in Fig. 9.

7. RESULTS AND DISCUSSION

Comparing the Fig. 8a to Fig. 8b, the cutting force for the neural control milling system is maintained at about 250N, and the feedrate of the adaptive milling system is close to that of the 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 the adaptive milling is improved. The time analysis for conventional and adaptive control system has been curried out.

By adaptive control system of time saving of 40% with one cut was reached. The complete machining requires 15 cuts; thus machining of a simple workpiece is shortened for 155 seconds. The second experiment 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 adaptive controller increases the feedrates to obtain peak forces close to 650N.

The slower response of the neural control scheme is noticeable at the beginning of cut one and three. The results reached are in accordance with the objectives of researches, according to which the controlled cutting force must not deviate from the desired value for more than 10%.

As compared to most of the existing end milling control systems [15,16], the proposed adaptive system has the following advantages:

- The computational complexity of UNKS does not increase much with the complexity of process;
- The learning ability of UNKS is more powerful than that of conventional adaptive controller;
- UNKS has a generalisation capability [17];
- Insensitive to changes in workpiece geometry, cutter geometry, and workpiece material;
- Cost-efficient and easy to implement;
- Mathematically modeling-free.

8. CONCLUSION

In this paper, a hybrid adaptive control algorithm that controls feedrate is proposed to regulate the cutting force.

On the basis of the cutting process modeling, off-line optimization and feed-forward neural control scheme (UNKS) the combined system for off-line optimization and adaptive adjustment of cutting parameters is built. 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 order to check the applicability of the adaptive control algorithm, cutting experiments were carried out under various cutting conditions, different tool diameters and different work materials. The results show that the developed adaptive control algorithm has good stability as well as excellent applicability behavior.

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