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CONTROL STRATEGY FOR ASSURING CONSTANT SURFACE FINISH BY CONTROLLING CUTTING FORCES

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Summary

The objective of this paper is to present surface roughness control strategy aimed at controlling the cutting force and maintaining constant roughness of the surface being milled by digital adaptation of cutting parameters. The idea of this control structure is to merge the off-line cutting condition optimization and genetic programming (GP) model based surface roughness control. The off-line optimization integrates the neural network (NN) modelling of the objective function and particle swarm optimization (PSO) of cutting parameters. The GP method is conducted to find the correlation between surface roughness and the cutting force and to provide a functional relationship with controllable factors. Simulation setup and simulation results are presented to confirm the efficiency of the control model and its relevance to industry.

Key words: *End milling, surface quality control, PSO-NN optimization, GP, simulation.*

1. Introduction

Milling is a preferred manufacturing process for machining products of high quality at low cost. The machining cost on numerically controlled (CNC) machine tools is sensitive to the machining parameters. Therefore, the proper selection of machining parameters is an important step towards gaining a competitive advantage in the market [1]. In modern CNC systems, machining parameters are usually selected conservatively before machining according to the programmer's experience and machining handbooks. As a result, many CNC systems run under inefficient operating conditions. To improve the efficiency, a trend towards equipping the CNC milling machine with modern control systems was noticed [1]. Milling processes are interesting from a control perspective also due to difficulties such as system nonlinearities, tool wear [2] and surface quality. Most frequently that trend is materialized by measuring the cutting forces because they contain the information about the process and the tool condition. By analyzing the cutting force characteristics, it is possible to assess the changes in the quality of surface finish.

Due to the above mentioned facts, machine tool control systems which provide the on-line adjustment of operating parameters are being studied with interest. Since fixed-gain controllers cannot guarantee system performance and stability as the force process varies, a research effort has been invested in the development of adaptive force controllers. These adaptive systems can be classified into three types: a geometric adaptive compensation (GAC) system [3]; an adaptive control optimization (ACO) system [4]; and an adaptive control constraint (ACC) system [5,6]. Adaptive control system was introduced into the cutting process by Stute and Goetz [7]. The most frequently used systems are MRAC (Model Reference Adaptive Control) [8] and STR (Self Tuning Regulations) [9]. MRAC, developed from the adaptive control theory, is widely used because of its robustness and disturbance rejection capability. A purely adaptive model reference adaptive controller (MRAC) approach was originally investigated by Landers [10]. The application of the MRAC approach to milling operations was introduced by Tomizuka [11]. MRAC systems are easier to design and implement than other adaptive sytems. In recent years, soft controllers based on computational intelligence [12] have gained more attention. As regards fuzzy control systems, an introductory survey of pioneering activities is given by Tarng [13] and a more systematic view is presented in [14]. Cerebellar model articulation controller (CMAC) [15] and multilayered neural network controller [16, 17] have played important roles in research on the neural control of machining.

Unfortunately, adaptive control alone cannot effectively control surface finish. There is no controller that can respond quickly enough to sudden changes in the cut geometry to eliminate large spikes in surface roughness. Therefore, in this research, the off-line cutting condition optimization algorithm is merged with surface roughness control. The optimization is performed with the Particle Swarm-Neural Network method (PSO-NN) developed by Zuperl [18]. The GA method is used to obtain the relation between surface roughness and the cutting force. Then, the model control is developed based on this modelled relationship.

2. Surface roughness control

The idea of this control structure is to merge the off-line cutting condition optimization algorithm and the GP model based surface roughness control (Fig. 1). The objective of the proposed control is, therefore, to adjust the milling cutting parameters and maintain the cutting force constant to achieve the desired value of the surface finish. If the cutting force is maintained constant during the process of machining, then the surface finish also remains stable. The control system is automatically adjusted to the current cutting conditions by the adaptation of feed rate and spindle speed. The control system adjusts the feed rate and spindle speed by assigning an override percentage to the CNC controller on a 3.5-axis Heller, based on a measured resultant force. The actual feed rate is the product of the feed rate override percentage (DNCFRO) and the programmed feedrate. The actual spindle speed is the product of the spindle speed override percentage (DNCSPO) and the programmed spindle speed. If the software for the optimization of cutting conditions was perfect, the optimized feedrate would always result in the machining operations at the desired surface roughness. In this case the correct override percentage would be 100%.

In order for the controller to regulate surface roughness, the force information must be available to the control algorithm at every 20ms. Data acquisition software (LabVIEW) is used to provide this information. The cutting force resultant is obtained using a Kistler force dynamometer, which provides three orthogonal components of dynamic forces F_x, F_y, F_z. These measured cutting force signals are used in the model controller to regulate the cutting force.

Sequence of steps for surface roughness control strategy is presented below.

1. The optimized cutting conditions are determined by the PSO-NN method,
2. The pre-programed cutting conditions determined by PSO-NN are sent to the machine tool CNC controller,
3. The desired value R_a is initiated,
4. Based on the desired R_a, the reference force F is predicted according to the GP model M1
5. When the force F is known, the command values f_c and n_c are determined,
6. The measured cutting forces are compared with the reference value and sent to the control system,
7. Control system adjusts the optimal feed rates and spindle speeds and sends it back to the machine tool,
8. Steps 5 to 7 are repeated until the termination of machining

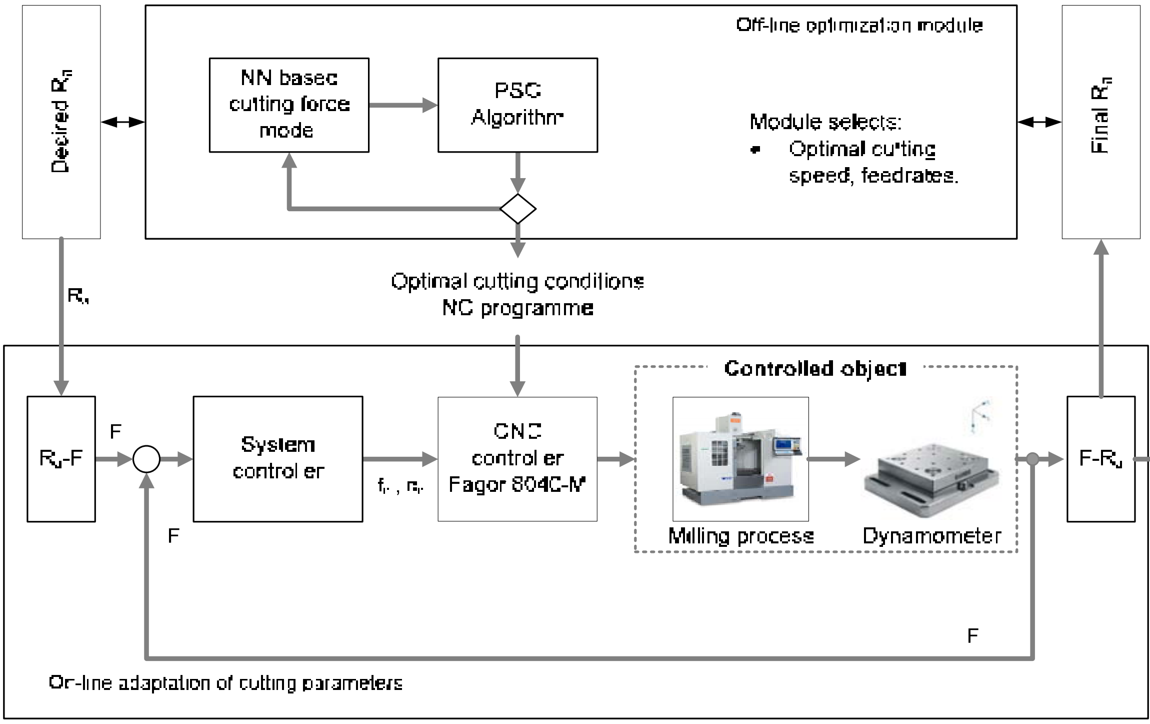

Fig. 1 Structure of surface roughness control strategy

2.1 PSO-NN optimization of cutting conditions

The basic idea of this optimization approach is to merge the PSO algorithm and neural network model of cutting forces. Based on this new combined optimization system, milling process can be optimized more easily and accurately compared to standard approaches.

PSO is a relatively new technique, first presented by Shi & Eberhart [19]. Swarm behavior can be modelled with a few simple rules. Even if the behaviour rules of each individual (particle) are simple, the behaviour of the swarm can be very complex. The behaviour of each agent inside the swarm can be modelled with simple vectors [18]. The architecture of the system, developed by Zuperl [18], is shown in Fig. 2.

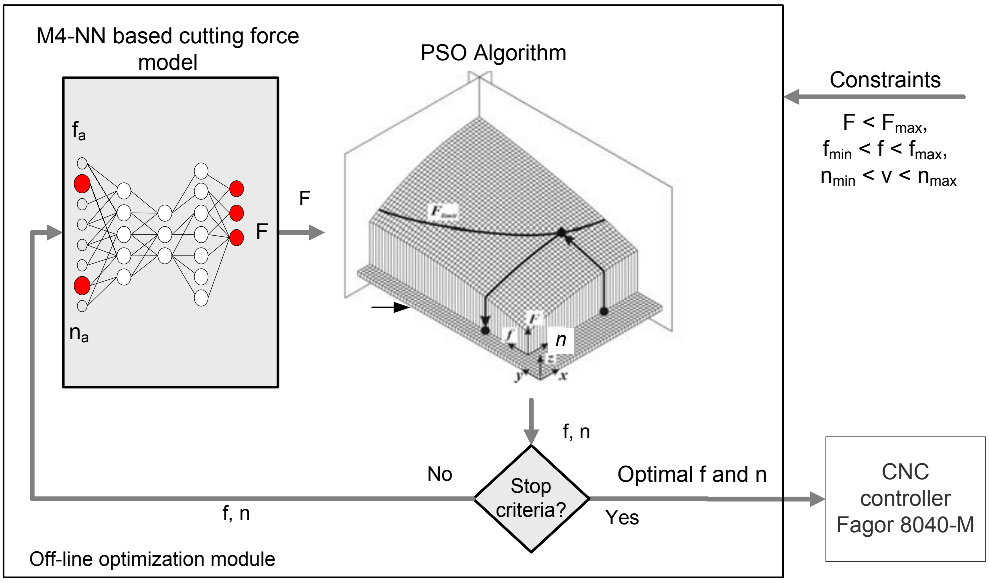

Fig. 2 Structure of an off-line optimization module

The optimization process is executed in two stages. In the first stage, the neural prediction model generates a 3D surface of the cutting force, which represents the feasible solution space for the PSO algorithm. The output of neural network cutting force model is fed into the multi-objective particle swarm optimizer where the constraints are defined. The cutting force surface is limited with planes which represent the constraints of cutting process. Seven constraints, which arise from technological specifications, are listed in [18]. The PSO algorithm generates a swarm of particles (optimum solution candidates) on the cutting force surface during the second phase. The swarm of particles flies over the cutting force surface and searches for maximal cutting force. The coordinates of the particle which has found the maximal (but still allowable) cutting force represent the optimal cutting conditions.

2.2 Controller of CNC machine feed drive

The system is tested by simulations. In simulations, a model of a Heller CNC milling machine bea 01 is used. This is a 3.5-axis machine tool which allows 3 translations along the X, Y, and Z- axis and the rotation of machine table in the horizontal plane. It is fitted with FAGOR 8040-M CNC controls. The block diagram and numerical values of constants of the feed drive servo system, provided by Heller, are presented in [20].

By introducing the technical constants of the system to transfer function stating the relation between the feed rate command signal change (f_c) and the change of the actual feed rate (f_a), the following form is obtained:

$$F(S) = \frac{f_a(s)}{f_c(s)} = \frac{1}{0.001024 \cdot s^2 + 0.064 \cdot s + 1} \tag{1}$$

where, t = 0.04 s: time delay, f_c: feed rate velocity command [mm/min], f_a: actual feed rate velocity [mm/min].

This simplified transfer function is used for the feed drive system. The time required for the controller to respond to the controller command signal is called the time of the delay. For the comparison purposes, the feed drive model was determined also 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.

2.3 Algorithms of models for prediction of milling quantities

The predicting modes of machining parameters developed in this study are based on experimental results performed in research [20]. The genetic programming (GP) method is used to provide a functional relationship with the most important controllable parameters: feed rate, spindle speed, surface roughness, and cutting force.

In the case of GP modelling, the result is a mathematical equation consisting of a series of prescribed operations. In simulation, the GP models are used because, in the simulation package Simulink, they can be more easily transformed into the block recording. Two hundred items of experimental data are used to develop each genetic model. An experimental item of data contains the value of the predicted (modelled) quantity and the appurtenant influencing parameters (cutting parameters). The models M1, M2, M3, M4, M5 = M6 are generated on the basis of the input and experimental data and a selected series of calculations. A series of the following basic calculations $\mathcal{F}$ = {+, -, *, u^v, ln. e^v} and arguments $\mathcal{P}$ = {2, 2, 3, 2} is selected. The set of terminals ($\mathcal{F}$) is given besides the block diagram of the individual model. The size of the population of organisms M = 1500 and the number of generations G = 100 have been selected for the determination of the model of cutting process (K4). For other models M = 850 and G = 100. The standard genetic operations of reproductions, crossover, and mutation have been used. The reproduction probability p_r = 0.17, the crossover probability p_c = 0.7, and the mutation probability p_m = 0.2 have been selected. The development of the model is stopped when the prescribed number of generations has been reached or when fitness of the organism is more than 98 %.

Before machining, the required quality of the surface finish (R_a) is always prescribed.

Equation (2) determines the cutting force (F) which is necessary to reach and maintain the desired surface roughness. For the parameter F(M1), the following equation has been derived according to the GP method:

$$F = 69.306 \cdot R_a^{\,3} - 270.18 \cdot R_a^{\,2} + 398.82 \cdot R_a + 14.875 \tag{2}$$

The set of terminals: $\mathcal{T}$ = {R_a, F, $\mathcal{R}$}is used. $\mathcal{R}$- real number at the interval from -1000 to 1000.

The following two GP models are used to determine the optimal cutting parameters.

$$f_c = 10^{05} \cdot F^4 - 0{,}01 \cdot F^3 + 2{,}7568 \cdot F^2 - 333{,}75 \cdot F + 15348 \tag{3}$$

$$n_c = 7641.3 \cdot e^{-0{,}004F} \tag{4}$$

where, n_c: spindle speed command [min^{-1}], f_c: feed rate command [mm/min].

These two models determine the optimal spindle speed and feed rate required to obtain the controllable cutting force. The following GP equation (model parameter M4) is used for the cutting process simulation.

$$F = 265.11 \cdot \left(1 - 2.0 \cdot 10^{-12} \cdot n^3 - \frac{31.32}{f} \cdot \ln\left(0.039 \cdot f\right)\right) \tag{5}$$

Based on the values of 3500 items of experimental data, the cutting force was calculated according to derived equation 2. The calculated cutting forces were then compared to the predictions of the artificial neural network force model developed by Zuperl [20]. The predictive and the generalising capability of using the GP and neural network approaches are compared using statistics, which showed that the neural network predictions for cutting dynamics were by 4% closer to the experimental measurements, compared to 6% obtained by using the GP method.

Therefore, a neural network cutting dynamics model is used in the simulation model instead, due to better prediction accuracy.

To realise the modelling of cutting process, a popular, multi-layer architecture of feedforward neural network (NN) is used based on the popular back propagation learning rule. An NN needs eight input neurons for modelling: federate (f), spindle speed (n), 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. Tool geometry is represented by cutting insert geometry optimisation model developed by Tamizharasan [21]. The NN registers the input data only in the numerical form. Therefore, the information about the tool, cutting geometry, and material must be transformed into a numerical code. The output from the NN are cutting force components, therefore, three output neurons are necessary. For the simplification of the milling simulator, the NN is adapted in the way that, during prediction, it overlooks all input parameters except the feed rate and spindle speed. Therefore, all other input vector parameters do not change during simulation. The detailed topology of the used neural network with optimal training parameters is shown in Fig.3. Signals passed through the neurons in the hidden and output layers are transformed on the basis of an ArcTangent (nonlinear) activation function. The data is automatically normalized in order to make the training process faster. This was done by mapping each term to a value between 0 and 1 using the Max Min method.

To evaluate the individual effects of network topology and training parameters on the performance of neural network, 40 different networks were trained, tested, and analyzed. From the results [20], the following conclusions can be drawn:

- Learning rates below 0.2 give acceptable prediction errors. The learning rates must be between 0.03 and 0.1 to minimize the (training speed) number of training cycles and to obtain low prediction errors. In training, the training speed is very important. However, at too high learning rates, the network may converge to a local minimum instead of the global minimum in the error space.
- To minimize the estimation errors, momentum rates between 0.008 and 0.01 are good. However, the momentum rate should not exceed 0.004 if the number of training cycles is also to be minimized;
- It is found that there is an optimum number of hidden nodes beyond this number there is no significant change in the error prediction. In this instance, the number of hidden nodes was found to be 15. The optimum number of hidden layer nodes is 15. Networks with 9 -17 hidden layer nodes, other than with 15, also performed fairly well but resulted in higher training cycles;
- Networks trained with the “tanh” transfer function in all their processing elements give the least prediction error, while those employing the sigmoid and sine functions give the highest and the next highest prediction error, respectively;
- 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;

Verification experiments are conducted to evaluate the feed forward and Radial Basis networks. It is found that the feed forward network is superior. The radial basis neural networks require more neurons than the standard feed forward neural networks with the Back Propagation (BPN) Learning Rule, but the conceiving of radial basis neural networks takes much less time than the training of the feed forward network.

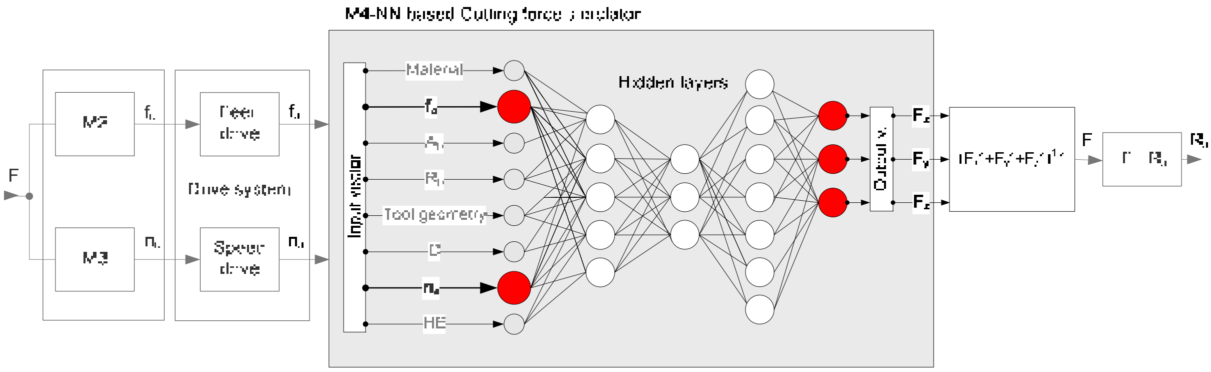

Fig. 3 Neural network-based cutting force simulator

The produced surface roughness is calculated according to the GP-derived equation:

$$R_a = 0.0001 \cdot \mathrm{F}^2 - 0.0341 \cdot \mathrm{F} + 3.018 \tag{6}$$

where: R_a: surface roughness [μm], F: cutting force [N].

GP-derived equation results are consistent with the results of the model developed by Chaari [22].

2.4 Block diagram of control system simulator

The block diagram of the proposed control system is constructed from basic prediction models of machining quantities which are described in the previous chapter. The block diagram is shown in Fig. 4. It enables a closed loop control of cutting force and thus produces a desired surface roughness.

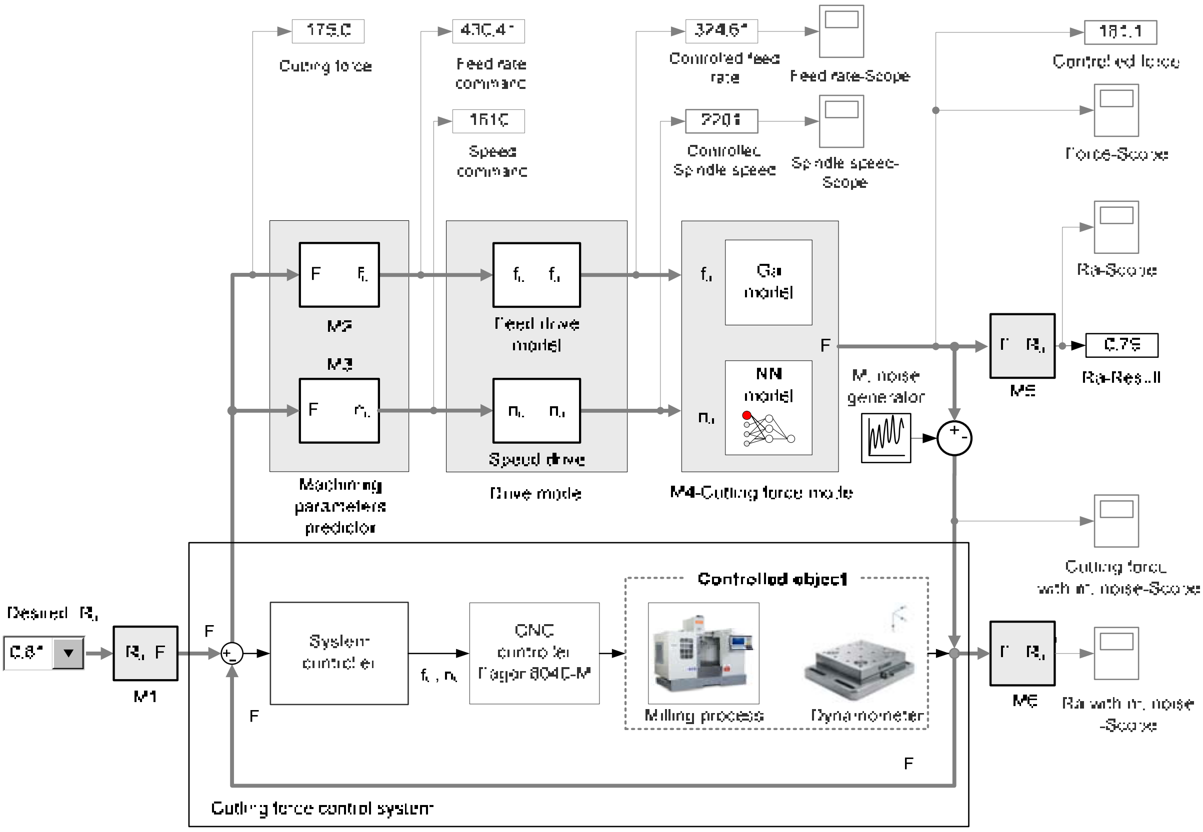

Fig. 4 Block diagram of the control system developed in Matlab

Simulator input is the desired surface roughness and the output is the actual surface quality. The simulator block diagram consists of 6 main models (transfer functions) which describe the dynamics of individual control model simulator elements. These models are: simulation model of cutting dynamics, feed drive model, spindle speed model, surface roughness inspection model, command signal prediction models.

The drive models simulate the machine response to changes in the desired feed rate and spindle speed. The objective of the drive system is to minimize the error and provide the appropriate and actual feed rate and spindle speed for a specific machining situation.

GP model M2 represents the transfer function for force-feed rate command which is derived according to equation 3. $\mathcal{T} = \{F, f_c, \mathcal{R}\}$. GP model is then inserted as a building block in the programme package Matlab.

The transfer function of GP model defining the dependence of the desired surface roughness and the appurtenant cutting force F is labelled as M1.

The relation between the cutting force F and the command signal n_c is expressed by the GP model (M3) representing the transfer function derived according to equation 4. M3 model is used to continuously generate the command signal of the spindle speed n_c. $\mathcal{T} = \{F, n_c, \mathcal{R}\}$.

The cutting dynamics model (GP model M4) predicts cutting forces based on the cutting conditions described in the previous section. $\mathcal{T} = \{n_a, f_a, F, \mathcal{R}\}$.

During preliminary tests the neural network model of cutting dynamics proved to be more efficient and accurate than the GP model; therefore, the neural model is chosen for use in the simulator.

Model M5 and M6 test if the simulated R_a corresponds with the desired R_a.

$\mathcal{T} = \{F, R_a, \mathcal{R}\}$.

During the machining process, undesirable vibrations and disturbances occur. They are caused by: nonhomogeneity of the base material, tool wear, tool damages, defects in guides and bearings of the machine, etc. Stability and robustness of the proposed control system is tested by introducing the random disturbances (machine noise) into the simulation.

3. Testing of control strategy performance

The control model efficiency is tested by numerous simulations. This chapter presents the simulation example where the GP model-based control was applied to demonstrate its performance.

To use the proposed control system and to adjust the feed rate/spindle speed, the desired surface roughness is 0.81 μm, pre-programmed (optimized) feed is 430.41 mm/min and its allowable adjusting rate is [0 – 250%].

The simulation is initiated by the selection of the reference value R_a and then the starting cutting force F is predicted according to the GP model M1. The data of simulation example is marked as No. 5 and is presented in Table 1. The starting optimum cutting parameters are determined by the PSO algorithm [18]. They are given in Table 1.

When the force F is known, the command values f_c and n_c are predicted according to the GP models M2 and M3. The initial value f_c is 430.41 mm/min.

The transfer functions of drive systems simultaneously control the command signals f_c and n_c, and thus generate the actual feed rate (f_a) and speed (n_a) so that the cutting force, predicted according to the cutting dynamics model M4, is constant. The system is changing the initial value f_c, until the optimum controlled feed rate of 324.61 mm/min has been reached. The optimum final spindle speed is 2201 min^{-1}. Dynamic adjustment of feeding and the spindle speed is a prerequisite for maintaining a constant maximum cutting force of 181.1 N. The simulated R_a is determined by the GP model M5. The simulation result is the roughness of 0.79 μm which is acceptable if compared with the desired value of 0.81 μm (Fig. 4).

The simulation outputs are shown in Fig. 5 and Fig. 6. It can be seen that the cutting force is maintained constant by continuously adjusting the cutting parameters so that the desired surface roughness can be attained.

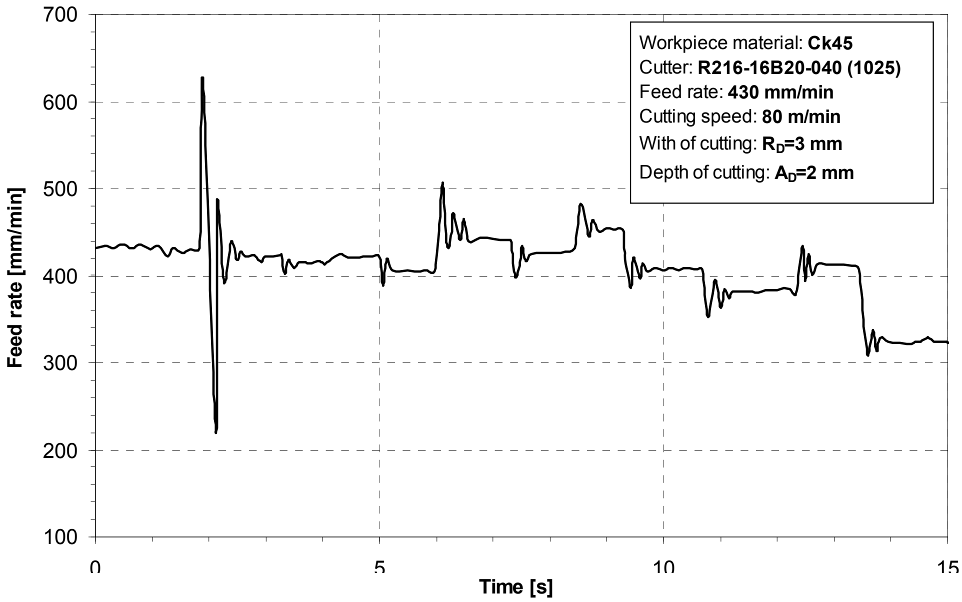

Fig. 5 Simulation control signal of feed rate

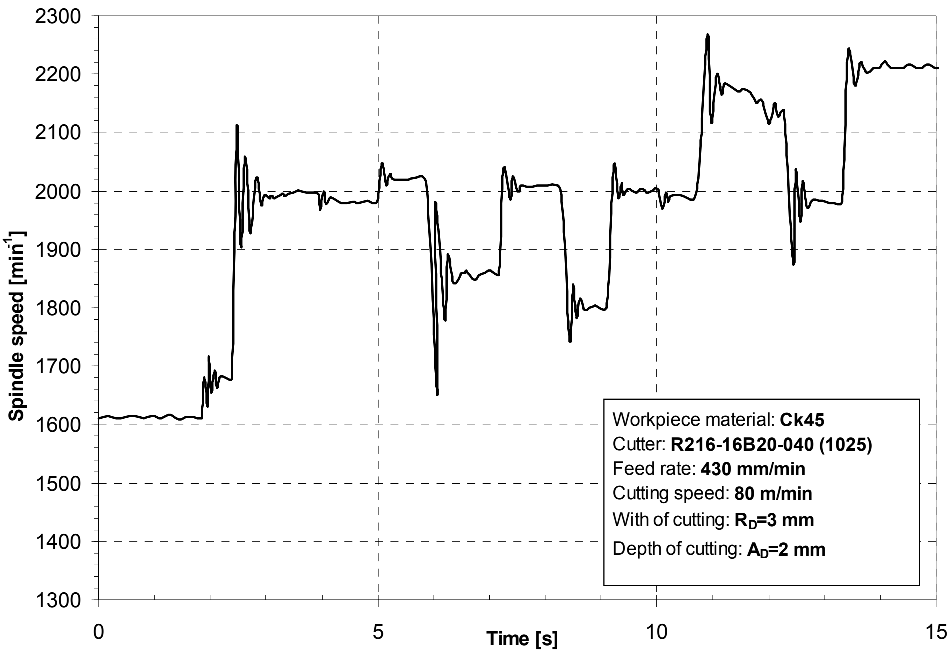

Fig. 6 Simulation control signal of spindle speed

4. Simulation results

The efficiency and stability of the control model with different requirements of the surface quality are tested by simulations. The criterion for the efficiency of the control system is the difference between the desired and the simulated R_a. The starting cutting conditions and the desired R_a are the input data. Table 1 presents the requirements and the results of simulations.

Table 1 The simulation results

Sim No.:	Desired surface roughness R_a [μm]	Initial cutting conditions before simulation			Results after control model simulation			Produced surface finish R_a [μm]
		F [N]	f_c [mm/min]	n_c [min^{-1}]	F [N]	f_a [mm/min]	n_a [min^{-1}]	
1	0.40	164.5	362.85	2000	157.5	264.92	2350	0.44
2	0.55	168.91	401.92	1900	168.0	287.32	2310	0.57
3	0.66	172.1	416.02	1712	175.6	301.88	2298	0.68
4	0.74	174,4	445.1	1630	177	309.43	2250	0.76
5	**0.81**	**175,0**	**430.41**	**1610**	**181.1**	**324.61**	**2201**	**0.79**
6	0.86	180.1	469.30	1501	183.8	329.95	2160	0.80
7	1.05	185.4	491.93	1400	184.8	352.52	2007	0.97
8	1.11	188.1	507.75	1290	188.1	355.60	1921	0.99

The results confirm that the proposed control model is efficient at gaining the desired surface roughness. It is efficient in fine machining; this is particularly favourable since the model is intended for the operations of end milling with shank end mills, where the requirements for the quality of machining are strict. Fig. 7 shows the random trend of the surface roughness where there is no feed rate and spindle speed adjustment. In the case of no control feedback, the cutting force has also a random trend.

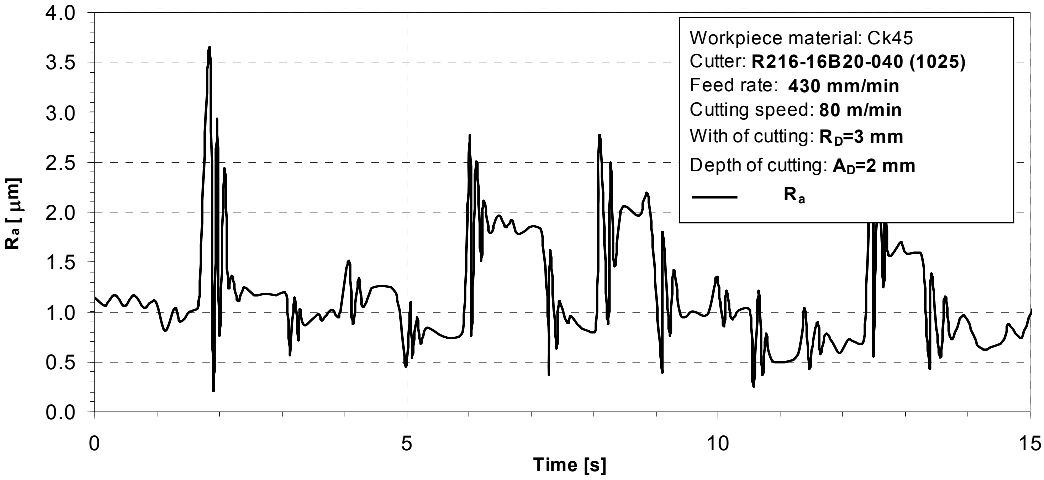

Fig. 7 Random surface roughness signal before the control model simulation

The dynamic component of the cutting force is simulated by the machine noise model which is shown in Fig. 4.

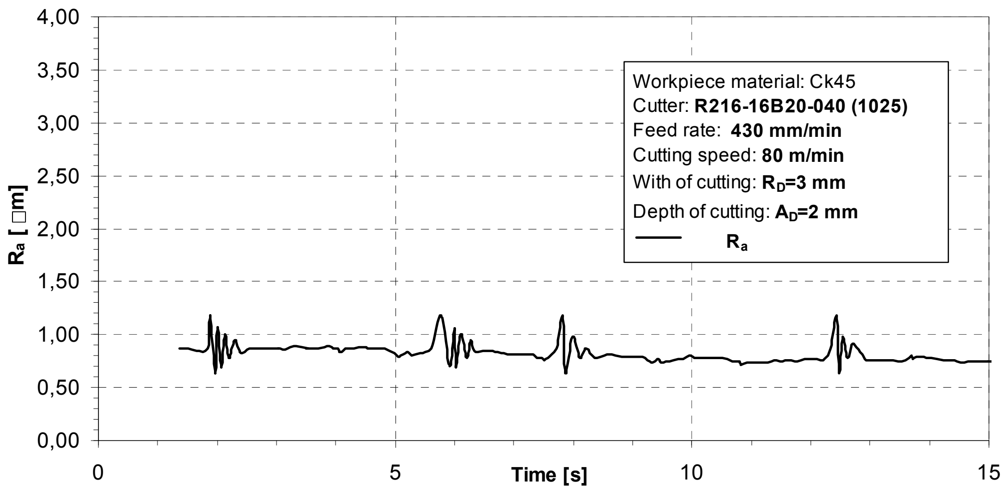

Fig. 8 Surface roughness signal after control model action

The cutting force signals and the quality of surface are interrelated and have identical trends. The control model assures constant roughness throughout machining (Fig. 8).

The control system responds to the increase in the cutting force by immediate reduction of feeding; as a result, the cutting force decreases to the reference value level (Fig. 9). Constant cutting forces lead to a better quality of surface.

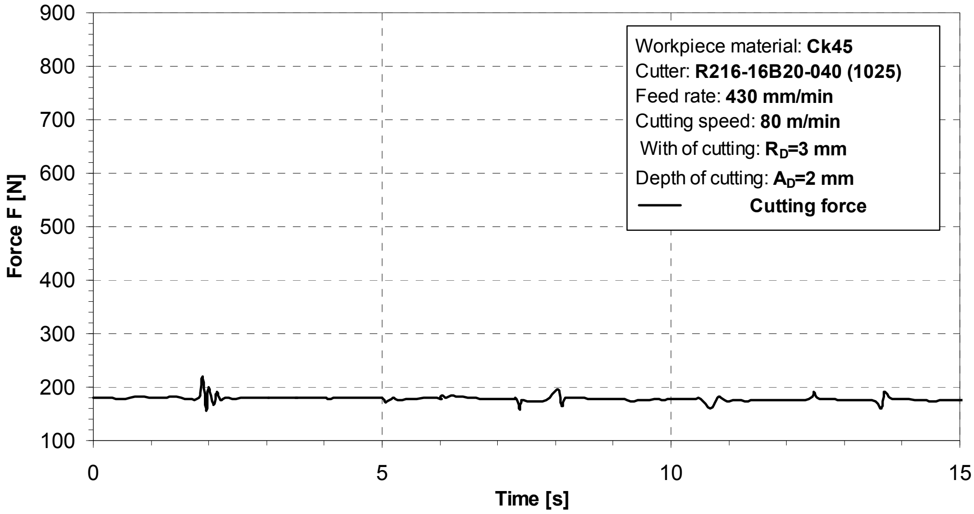

Fig. 9 Cutting force signal after the control model simulation

5. Conclusion

The purpose of this contribution is to present a control strategy aimed at controlling the cutting force and maintaining constant roughness of the surface being milled by digital adjusting of cutting parameters. To find the connection between the surface roughness and the cutting force, genetic programming models were developed. The GP and NN method is also conducted to provide a functional relationship with the controllable factors such as: spindle speed, surface roughness, and cutting force. The developed GP based models are basic elements of model-based control simulation, which is capable of controlling a desired surface roughness. Simulations have also confirmed the efficiency of control system, which is reflected in improved surface quality. The simulation results indicated that maintaining constant cutting force leads to a better (constant) quality of surface and prevents undesirable vibrations and deflections of the cutting tool. The proposed strategy is applied to 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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