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An intelligent system for monitoring and optimization of ball-end milling process

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Abstract

The paper presents an intelligent system for on-line monitoring and optimization of the cutting process on the model of the ball-end milling. An intelligent system for monitoring and optimization in ball-end milling is developed both in hardware and software. It is based on a PC, which is connected to the CNC main processor module through a serial-port so that control and communication can be realised. The monitoring system is based on LabVIEW software, the data acquisition system and the measuring devices (sensors) for the cutting force measuring. The system collects the variables of the cutting process by means of sensors. The measured values are delivered to the computer program through the data acquisition system for data processing and analysis. The optimization technique is based on genetic algorithms for the determination of the cutting conditions in machining operations. In metal cutting processes, cutting conditions have an influence on reducing the production cost and time and deciding the quality of a final product. Experimental results show that the proposed genetic algorithm-based procedure for solving the optimization problem is effective and efficient, and can be integrated into a real-time intelligent manufacturing system for solving complex machining optimization problems.

Keywords: Ball-end milling; Cutting forces; Monitoring; Optimization; Genetic algorithm

1. Introduction

The purpose of this paper is to present an intelligent system for on-line monitoring and optimization of cutting conditions in ball-end milling. The force generated during machining process is an important parameter, which reflects the machining conditions. The most frequent approach taken to ball-end milling process monitoring is to attach sensors to the machine, and then monitor the signals obtained from these sensors. With a cutting force acquisition system, the cutting process can be monitored easily.

In this paper, an intelligent system is developed with the on-line monitoring equipment (hardware) and real-time data analysis and optimization software. The monitoring system frequently commences with experiments using a table force dynamometer, which quantifies the actual force exerted on the milling tool during the cutting process. The monitoring system is connected with the PC (data processing and analysis, optimization), which is connected to the CNC main processor through a serial-port, so that the communication with the tool machine (optimal cutting conditions) can be realised (Fig. 1).

To ensure the quality of machining products, and to reduce the machining costs and increase the machining effectiveness, it is very important to select the optimal machining parameters. The genetic algorithms (GA), based on the principles of natural biological evolution, will be used for the optimization of the cutting conditions in ball-end milling. Compared to traditional optimization methods, a GA is robust, global and may be applied generally without recourse to domain-specific heuristics. It can be used not only for general optimization problems but also in indifferent optimization problems and unconventional optimization problems, etc. [1,2]. So GA's are widely used for machine learning, function optimizing and system modelling etc. Although GA is an effective optimization algorithm, it usually takes a long time to optimize machining parameters because of its slow

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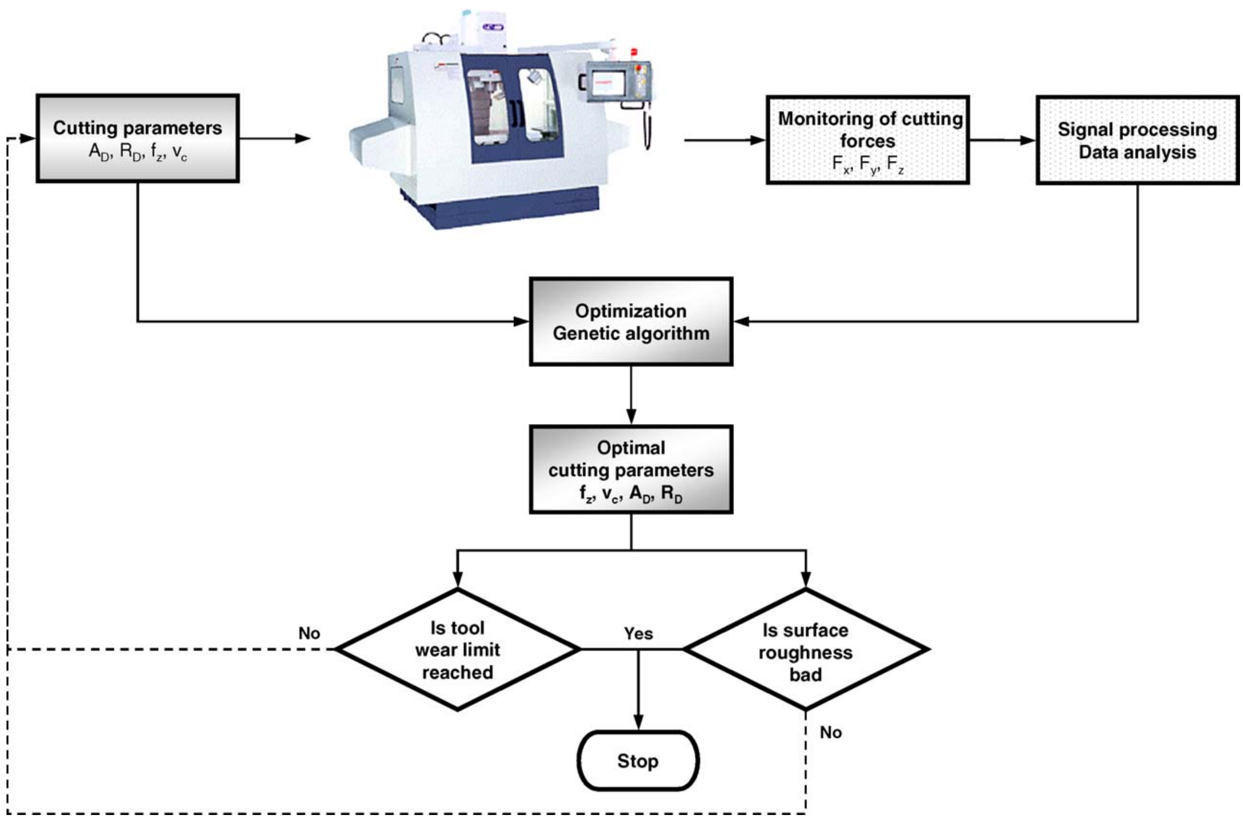

Fig. 1. Intelligent system for on-line monitoring and optimization in ball-end milling.

convergence speed. The operating domain is defined and changed to be around the optimal point in its evolutionary processes so that the convergence speed and accuracy are improved.

2. On-line monitoring system

This paper presents our research progress on practical methods for the optimization of cutting conditions during CNC machining. The on-line monitoring system for the cutting force monitoring presents the data acquisition system, LabVIEW software, and the results measured cutting forces. The data acquisition system used in this experimental model consists of dynamometer, fixture module, hardware and software module as shown in Fig. 2.

A significant amount of research has been based around the monitoring of cutting forces [3–8]. Force monitoring is commonly taken using a table-mounted dynamometer during machining. These dynamometers measure the cutting force in three mutually perpendicular directions notationally the *X*, *Y* and *Z* axis. The dynamometer is clamped between the workpiece and the table or pallet.

The dynamometer system is composed of a dynamometer (Kister Model 9259A), a multi-channel charge amplifier (Kister Model 5001) and their connecting cable. 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. The LabVIEW data acquisition module is based on a PC computer, and is a general-purpose programming system with an extensive library of functions and subroutines for any programming task. It also contains an application specific library for data acquisition, serial instrument control, data processing, analysis presentation and storage.

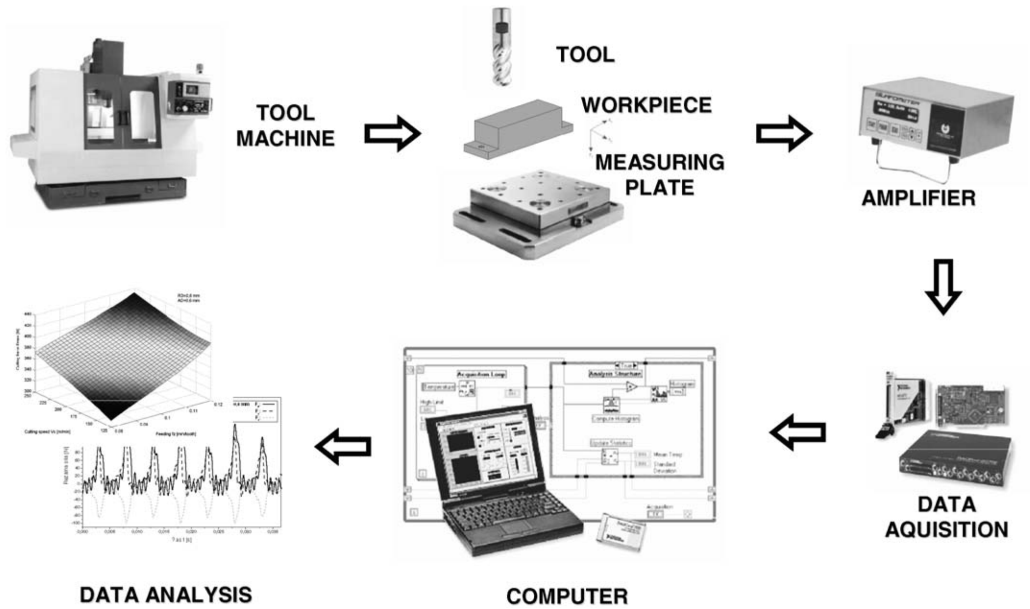

Fig. 2. On-line monitoring system.

3. Cutting force model

Products with 3D sculptured surfaces are widely used in the modern tool, die and turbine industries. These complex-shaped premium products are usually machined using the ball-end milling process. The objective of this work is to develop an accurate and practical cutting force model for ball-end milling in the three-axis finishing machining of 3D sculptured surfaces. This requires the model to be able to characterize the cutting mechanics of non-horizontal and cross-feed cutter movements that are typical in 3D ball-end milling. Cutting forces are modelled since they directly affect the product quality and process efficiency in 3D finishing ball-end milling. It is important that the cutting forces are maintained close to the optimal values. Excessive cutting forces result in low product quality while small cutting forces often indicate low machining efficiency.

The geometry and the cutting forces on the ball-end milling cutter are shown in Fig. 3. The cutting edge of the milling cutter lies on the hemisphere surface and is determined with the constant helix angle. The cutting edges have the helix angle λ_b at the transition from the hemispherical part of the milling cutter into the cylindrical part. With respect to reduction of the milling cutter radius in X–Y plane towards the milling cutter tip in Z direction, the helix angle—the local helix angle changes.

The z-coordinate of the point located on the cutting edge of the milling cutter is [9]:

$$z = R_b \frac{\beta}{\tan \lambda_b} \tag{1}$$

where R_b is the radius of the hemispherical part of the milling cutter, β the angle between the cutting edge tip in case of $z = 0$

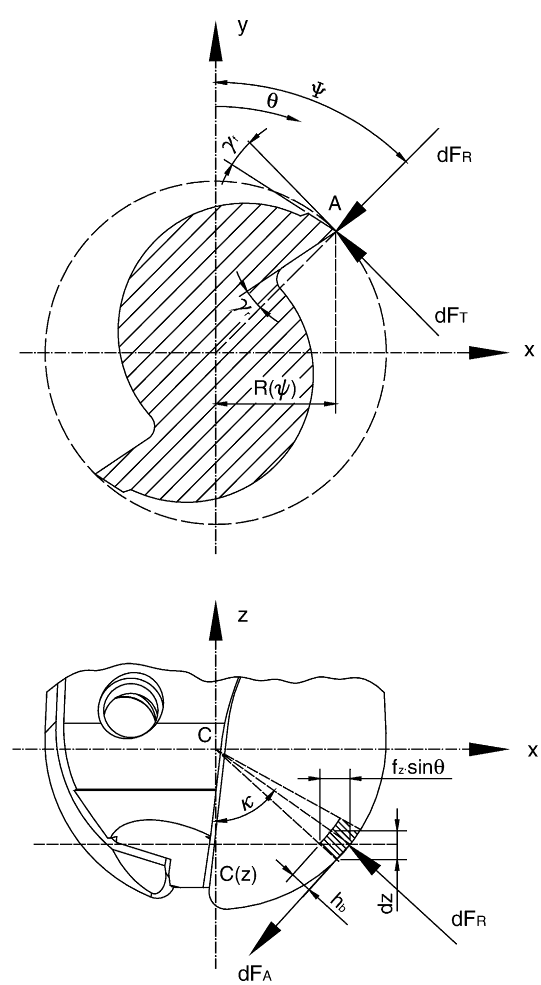

Fig. 3. Cutting forces in ball-end milling.

and the axial position Z, and λ_b is the helix angle of the cutting edge of the milling cutter.

For the milling cutters of constant length the local helix angle changes with respect to the milling cutter radius and it is calculated according to the equation [9]:

$$\tan\lambda_b(\beta) = \frac{R(\beta)}{R_b}\tan\lambda_b \tag{2}$$

where $R(\beta)$ is the tool radius in X–Y plane with respect to angle η

$$\eta = \arcsin\frac{R(\beta)}{R_b} \tag{3}$$

where η is the angular position in the direction of Z axis from the center of the hemispherical part to the point on the cutting edge.

The radius of the cutting edge in the X–Y plane, which touches the point on the helical and spherical cutting edge with angle β is determined as follows:

$$R(\beta) = \sqrt{1-(\beta\cot\lambda_b - 1)^2}\,R_b \tag{4}$$

Angular spacing between the cutting edge on the milling cutter [9]:

$$\phi_{\mathrm{P}} = \frac{360^\circ}{N_f} \tag{5}$$

where N_f is the number of cutting edges.

Angular position of cutting edge:

$$\theta(j) = j\left(\frac{\phi_{\mathrm{P}}}{N_\theta}\right), \quad j = 1, 2, \ldots, N_\theta \tag{6}$$

where N_θ is the number of angular positions, $\theta(j)$ the angular position of cutting edges and ϕ_{P} is the angular spacing between cutting edges.

Thickness of axial differential elements on the cutting edge of the milling cutter:

$$\mathrm{d}z(i) = i\left(\frac{A_{\mathrm{D}}}{N_z}\right), \quad i = 1, 2, \ldots, N_z \tag{7}$$

where A_{D} is the axial depth, R_{D} the radial depth and N_z is the number of axial differential elements on the cutting edge of the milling cutter.

Angular position of the cutting edge during cutting $B(i, j, k)$:

$$B(i, j, k) = \theta(j) + \phi_{\mathrm{P}}(k-1) - \frac{z}{R_b}\tan\lambda_b \tag{8}$$

The chip thickness h_b in the function of the radial and axial angle:

$$h_b = f_{z_b}\,\sin B\,\sin\eta \tag{9}$$

where f_{z_b} is the feeding per tooth, B the angular position of cutting edge during cutting in the direction of rotation of the milling cutter and η is the angular position in the direction of Z axis from the center of the hemispherical part to the point on the cutting edge.

The generalized equation for the chip thickness is as follows:

$$h_b(i, j, k) = f_{z_b}\,\sin[B(i, j, k)]\,\sin[\eta(i)] \tag{10}$$

where dz is the thickness of axial differential elements.

Geometry of the ball-end milling cutter and orientation of the cutting edge are used in the equation for determination of cutting forces.

The equation for the tangential cutting force, radial cutting force and axial cutting force is:

$$\mathrm{d}F_{\mathrm{T,R,A}} = K_{\mathrm{T,R,A}}h_b\mathrm{d}b = K_{\mathrm{T,R,A}}f_{z_b}\,\sin B\,\sin\eta\,\mathrm{d}b \tag{11}$$

where K_{T} is the tangential coefficient of material, K_{R} the radial coefficient of material, K_{A} the axial coefficient of material, dz the differential length of axial differential elements and db is the differential length of cutting edge.

If instead of db, we enter [9]:

$$\mathrm{d}b = \frac{\mathrm{d}z}{\sin\eta} \tag{12}$$

we obtain:

$$\mathrm{d}F_{\mathrm{T,R,A}} = K_{\mathrm{T,R,A}}f_{z_b}\,\sin B\,\mathrm{d}z \tag{13}$$

The generalized equation for the tangential, radial and axial cutting force is:

$$\mathrm{d}F_{\mathrm{T,R,A}}(i, j, k) = K_{\mathrm{T,R,A}}f_{z_b}\,\sin[B(i, j, k)]\mathrm{d}z \tag{14}$$

The forces expressed in the Cartesian coordinate system are obtained if the transformation matrix $[T]$ is inserted [9]:

$$\{\mathrm{d}F_{X,Y,Z}\} = [T]\{\mathrm{d}F_{\mathrm{R,T,A}}\} \tag{15}$$

$$[T] = \begin{bmatrix} -\sin\eta\,\sin B & -\cos B & -\cos\eta\,\sin B \\ -\sin\eta\cos B & \sin B & -\cos\eta\,\cos B \\ \cos\eta & 0 & -\sin\eta \end{bmatrix} \tag{16}$$

$$[\mathrm{d}F_{X,Y,Z}(i, j)] = \sum_{k=1}^{N_f}[T][K_{\mathrm{R,T,A}}]f_{z_b}\,\sin[B]\,\mathrm{d}z \tag{17}$$

The total force on the cutting edge in case of jth position:

$$[\mathrm{d}F_{X,Y,Z}(j)] = \sum_{i=1}^{N_z}\sum_{k=1}^{N_f}[T][K_{\mathrm{R,T,A}}]f_{z_b}\,\sin[B]\,\mathrm{d}z \tag{18}$$

The average cutting force is:

$$[\bar{F}_{X,Y,Z}] = \frac{\left\{\sum_{i=1}^{N_z}\sum_{j=1}^{N_\theta}\sum_{k=1}^{N_f}[T][K_{\mathrm{R,T,A}}]f_{z_b}\,\sin[B]\,\mathrm{d}z\right\}}{N_\theta} \tag{19}$$

4. Genetic algorithms

Genetic algorithms are a family of computational models inspired by evolution. These algorithms encode a potential solution to a specific problem on a simple chromosome-like data structure and apply recombination operators to these structures so as to preserve critical information. In a broader usage of the term, a genetic algorithm is any population-based model that uses selection and recombination operators to generate new sample points in a search space. Researchers largely working from an experimental perspective have introduced many genetic algorithm models. Many of these researchers are application oriented and are typically interested in genetic algorithms as optimization tools. Modelling, machining, selection of cutting conditions and monitoring often have to deal with the problem of optimization.

A genetic algorithm was applied to the simulation model to determine the process parameter values that would result in the simulated cutting forces in ball-end milling. Most of the researchers have used traditional simulation techniques for solving machining problems [10]. The traditional methods of simulation and search do not fare well over a broad spectrum of problem domains. Traditional techniques are not efficient when practical search space is too large. These algorithms are not robust. Numerous constraints and number of passes make the machining simulation problem more complicated. Traditional techniques such as geometric programming, dynamic programming, branch and bound techniques and quadratic programming found it hard to solve these problems. And they are inclined to obtain a local optimal solution. GA comes under the class of the non-traditional search and simulation techniques.

Genetic algorithms are search algorithms for simulation and optimization, based on the mechanics of natural selection and genetics [10]. The power of these algorithms is derived from a very simple heuristic assumption that the best solution will be found in the regions of solution space containing high proposition of good solution, and that these regions can be identified by judicious and robust sampling of the solution space. The mechanics of genetic algorithms is simple, involving copying of binary strings and the swapping of the binary strings. The simplicity of operation and computational efficiency are the two main attractions of the genetic algorithm approach. The computations are carried out in three stages to get a result in one generation or iteration. The three stages are reproduction, crossover and mutation.

4.1. Reproduction

This is the first of the genetic operators. It is a process in which copies of the strings are copied into a separate string called the ‘mating pool’, in proportion to their fitness values. This implies that strings with higher fitness values will have a higher probability of contributing more strings as the search progresses.

4.2. Crossover

This operator, second among the genetic operators, is mostly responsible for the progress of the search. It swaps the parent strings partially, causing offspring to be generated. In this, a crossover site along the length of the string is selected randomly, and the portions of the strings beyond the crossover site are swapped.

4.3. Mutation

It is one of last GA operators, this is the occasional random alteration (with a small probability) of the value of a string position. In binary strings, this simply means changing 1 to 0 or vice versa.

5. Optimization of cutting conditions with GA

Process modelling and optimization are two important issues in manufacturing. The manufacturing processes are characterized by a multiplicity of dynamically interacting process variables. Cutting forces have been important factors to predict machining performances of any machining operation. The predictive modelling of machining operations requires detailed prediction of the boundary conditions for stable machining.

In a traditional CNC system, machining parameters are usually selected at the start according to handbooks or people’s experiences, and the selected machining parameters are usually conservative so as to avoid machining failure. Even if the machining parameters are optimized off-line by an optimization algorithm, they cannot be adjusted in the machining process, but the machining process is variable owing to tool wear, heat change and other disturbances. To ensure the quality of the machined products, to reduce the machining costs and to increase the machining efficiency, it is necessary to optimize and control the machining process on-line when the machine tools, are used for CNC machining. The machining parameters must be adjusted in real-time so as to satisfy some optimal machining criteria.

Intelligent manufacturing achieves substantial savings in terms of money and time if it integrates an efficient automated process-planning module with other automated systems such as production, transportation, assembly, etc. Process planning involves determination of appropriate machines, tools for machining parts, cutting fluid to reduce the average temperature within the cutting zone and machining parameters under certain cutting conditions for each operation of a given machined part. The machining economics problem consists in determining the process parameter, usually cutting speed, feed rate and depth of cut, in order to optimize an objective function. A number of objective functions by which to measure the optimality of machining conditions include: minimum unit production cost, maximum production rate, maximum profit rate and weighted combination of several objective functions. Several cutting constraints that should be considered in machining economics include: tool-life constraint, cutting force constraint, power, stable cutting region constraint, chip–tool interface temperature constraint, surface finish constraint, and roughing and finishing parameter relations.

The main objective of the present paper is to determine the optimal machining parameters that minimize the unit production cost without violating any imposed cutting constraints.

5.1. Optimal working condition selection

In ball-end milling operations, it is important to select the tool optimal cutting conditions. Because the small tools are very easily broken, the conservative selections of the tool working conditions would cost longer machining time, otherwise the unsuitable selections of the tool cutting conditions would make change the tools frequently that waste the machining time too. It is very difficult for operators to select the optimal working conditions in so many different types of tools, workpieces and different machining tasks.

In the paper, the tool cutting conditions were optimized based on the minimum machining time that is to find the maximum feed rate that is able to meet the tool life requirement in the specific machining task. It is known how many cutting millimeters are required in the specific machining task. Approximated tool life can be estimated depended on how many tools will be used in the task. Referred to tool life estimation the maximum feed rate can be determined with the other possible working conditions (for example, maximum spindle speed of the machine tool) by the analytical cutting force model.

During the machining process, we collect cutting force data, which can then be compared to model predicted force [11]. Model parameters can then be refined to more accurately optimize the cutting conditions. In this way, the models can be calibrated "on-line" for the specific workpiece material–cutting tool combination.

The experimental data was utilized to build the analytical and genetic force model and empirical tool wear by genetic programming method. This analytical force model was taken as objective function and was optimized using a genetic algorithmic approach to obtain the optimal machining parameters for the required task. A new local search optimization based on genetic algorithm approach is developed to solve the machining optimization model (Fig. 4).

The PC, which is connected to the CNC main processor through a serial-port, sends the optimal cutting conditions to the tool machine. The tool wear, breakage or chatter is recognised by a PC supervisory control software that monitors the process. Therefore, one of the critical phases of production automation is to monitor the cutting tool on-line and ensure timely replacement of the cutting tool if necessary.

The genetic algorithm was used to optimize the tool cutting conditions with the analytical cutting force model. The maximum cutting forces of the cutting force profiles, which were got from the analytical model and estimation, were used for the optimal objective function and conditions as the following.

Objective function:

$$\min(E) = \frac{1}{3}\left(\left|F_{X_{\max}}^{\text{model}} - F_{X_{\max}}^{\text{allowed}}\right| + \left|F_{Y_{\max}}^{\text{model}} - F_{Y_{\max}}^{\text{allowed}}\right| + \left|F_{Z_{\max}}^{\text{model}} - F_{Z_{\max}}^{\text{allowed}}\right|\right) \tag{20}$$

or

$$\min(E) = \left|F_{\max}^{\text{model}} - F_{\max}^{\text{allowed}}\right| \tag{21}$$

Conditions:

$$F_{X_{\max}}^{\text{model}} \le F_{X_{\max}}^{\text{allowed}},\ F_{Y_{\max}}^{\text{model}} \le F_{Y_{\max}}^{\text{allowed}},\ F_{Z_{\max}}^{\text{model}} \le F_{Z_{\max}}^{\text{allowed}},\ F_{\max}^{\text{model}} \le F_{\max}^{\text{allowed}} \tag{22}$$

where E is the absolute error; $F_{X_{\max}}^{\text{allowed}}$, $F_{Y_{\max}}^{\text{allowed}}$, $F_{Z_{\max}}^{\text{allowed}}$, $F_{\max}^{\text{allowed}}$ the allowable maximum cutting forces determined by the tool life estimation and $F_{X\max}^{\text{model}}$, $F_{Y\max}^{\text{model}}$, $F_{Z\max}^{\text{model}}$, $F_{\max}^{\text{model}}$ are the estimated maximum cutting forces calculated by the analytical cutting force model.

The tool working condition optimization program was made in Matlab. In the program, the tool cutting conditions can be selected automatically according to the required tool.

5.2. An illustrative example

Many experiments were conducted to evaluate the validity of the optimization model in various cutting modes and conditions (Fig. 5). The instantaneous cutting force signals in three orthogonal directions were measured by a table-mounted piezoelectric dynamometer (Kistler Model 9259A). These signals were amplified (Kistler Model 5001), digitized (PC-MIO-16E-4) and stored in computer. The measured data was processed with the computer program made by LabVIEW. The experiments were run on the NC milling machine (MORI SEIKI FRONTIER-M) and performed on material Ck 45 and Ck 45 (XM) with improved machining properties. The solid ball-end milling cutter type R216.44-10030-040-AL10G—GC 1010 with four cutting edges, of 10 mm diameter and 30° helix angle was used for machining of the material.

For the determination of optimal cutting conditions the optimization of two variables (feeding f_z and cutting speed V_c) was used. The evolutionary parameters for the genetic algorithm were: population size 500, number of generations 30 and number of genes of each chromosome 10. The genetic operations crossover and mutation were used. Probability of crossover was $p_c = 0.65$ and mutation $p_c = 0.1$.

Optimal cutting conditions were found in 13 generation with average error 0.28% (Fig. 6).

With the optimal cutting conditions the machining time was reduced for 16.4%.

The present model provides excellent optimization of the cutting conditions. It accurately predicts fine details of the

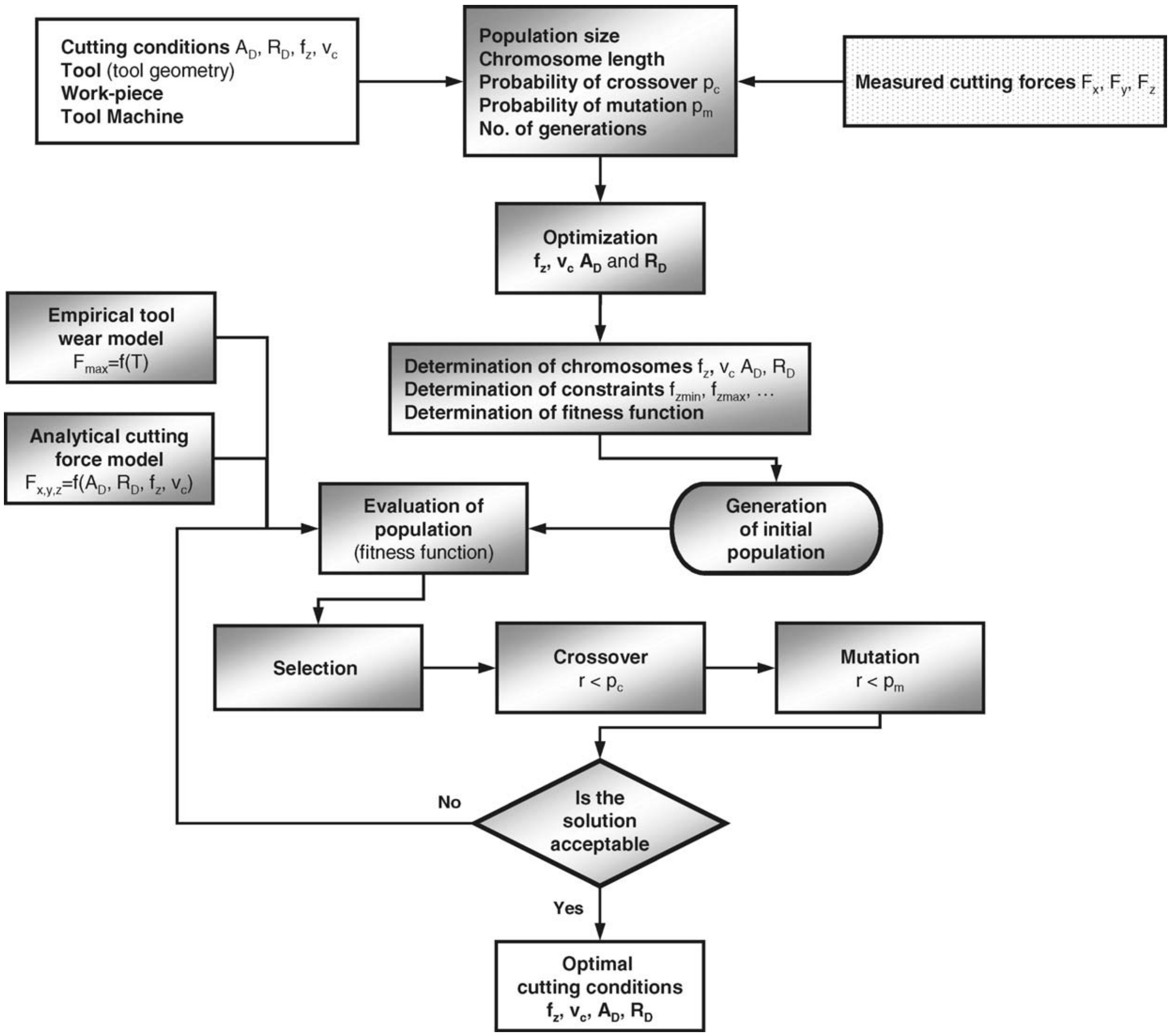

Fig. 4. Flowchart of the GA solution.

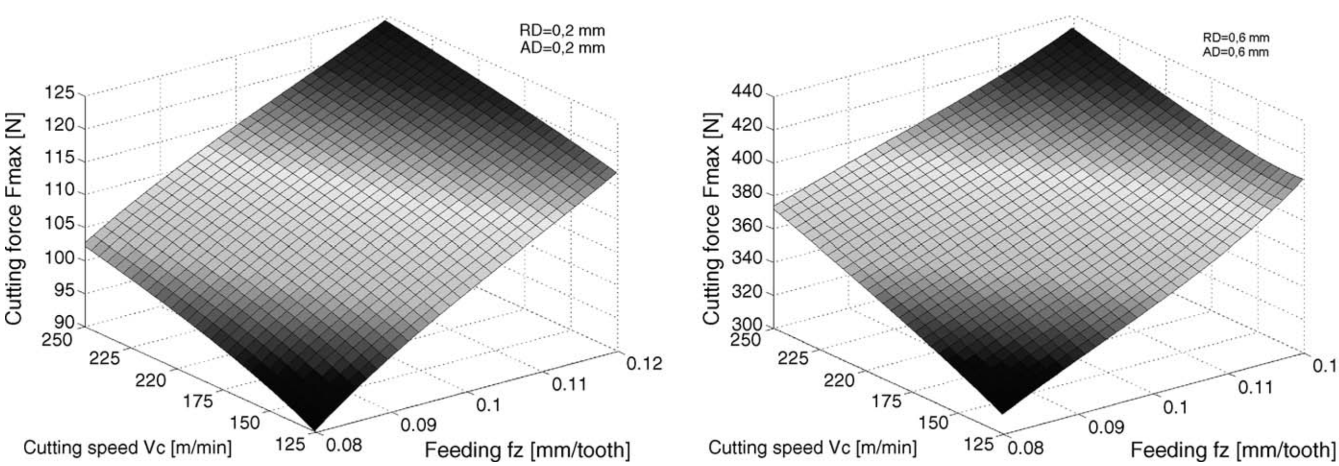

Fig. 5. Measured cutting forces in ball-end milling.

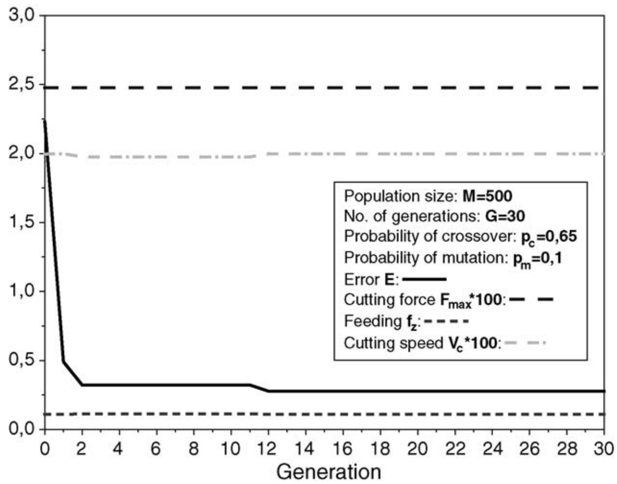

Fig. 6. Evolution of the GA.

measured force signals. The present model has proven to provide reliable optimization of the cutting process for 3D ball-end milling. This model has great potential to be used to develop optimization technologies for sculptured surface machining with ball-end mills.

Experimental results show that the proposed genetic algorithm-based procedure for solving the optimization problem is effective and efficient, and can be integrated on-line into an intelligent manufacturing system for solving complex machining optimization problems.

6. Discussion of results

For the optimization of the cutting conditions, the genetic algorithm was used. The genetic algorithm gives accurate results and it is very fast. Precision of results is very reliable. Table 1 shows the selected optimum cutting conditions predicted by genetic algorithm. Clearly, the genetic algorithm-based optimization approach provides a sufficiently approximation to the true optimal solution.

Advantages of the developed algorithm:

- simple complementing of the model by new input parameters without modifying the existing model structure;
- automatic searching for the non-linear connection between the inputs and outputs;

Table 1
Optimized cutting conditions

Cutting conditions	Start parameters	Optimized cutting conditions
F_{max} (N)	247.6	247.61
R_D (mm)	0.4	0.4
A_D (mm)	0.4	0.4
f_z (mm/tooth)	0.1	0.11
V_c (m/min)	188.5	199.5
l_m (mm)	100	100
T_c (s)	2.5	2.1
Difference (%)		16.4

- fast and simple optimizing.

Disadvantages:

- time-consuming determination of optimal cutting conditions;
- experience is necessary for conceiving of the algorithm;
- repeatability of training is not assured.

Due to the changes of the cutting conditions, it is predictable that the life of the cutting tool will be prolonged. We assume that the life of the cutting tool can be increased by 1.2–1.5 times.

7. Conclusion

The paper presents the development and use of the intelligent system for on-line monitoring and optimization of the cutting conditions in ball-end milling. The system is based on computer programme, acquisition system, and theoretic knowledge of technological processes, machines and tests performed. All influencing factors: tool geometry, workpiece material, and cutting conditions were considered. The on-line monitoring system provides a practical way for obtaining cutting forces in the ball-end milling process. Genetic algorithm optimization approach was used for solving the machining operations problem with ball-end milling. The results obtained from the proposed genetic algorithm optimization approach prove its effectiveness. The implication of the encouraging results obtained from the present approach is that such approach can be integrated on-line, with an intelligent manufacturing system for automated process planning. Since the genetic algorithm-based approach can obtain near-optimal solution, it can be used for machining parameter selection of complex machined parts that require many machining constraints. Integration of the proposed approach with an intelligent manufacturing system will lead to reduction in production cost and production time, flexibility in machining parameter selection, and improvement of product quality. This research definitely indicates some directions for future work.

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