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CONTRIBUTION TO THE ASSESSMENT OF ECONOMIC VIABILITY OF HARD MILLING PROCESS

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Original scientific paper
Hard milling is milling of the parts with hardness of above 45 HRc. As a technology in the development, hard milling has a potential to replace the procedure which includes milling and finishing operations like grinding or electrical-discharge machining. The process parameters and machining performance considered in this work deal with the real experimental data in the down and up milling as well as down and up hard milling process. Based on the optimal parameters of observed processes, the estimation of economical and quality sustainability of hard milling process, regarding the conventional milling process of hardened steel, has been carried out. Genetic algorithms are used to estimate optimal values of cutting parameters that lead to a minimum unit machining time and a minimum unit production costs. Optimal values, obtained by means of genetic algorithms, have been compared with the results obtained by using simulated annealing optimization. The results of this study showed that down hard milling costs are 14 % higher than the costs of down milling while the costs of up hard milling are 4,48 % higher than the costs of up milling. This is a source data for a detailed comparison of standard procedure of machining parts increased hardness and hard milling procedure.

Keywords: *flank wear, genetic algorithms, hard milling, regression analysis, simulated annealing*

Doprinos procjeni ekonomske održivosti tvrdog glodanja

Izvorni znanstveni članak
Tvrdo glodanje je postupak obrade materijala tvrdoće iznad 45 HRc. Kao tehnologija u razvoju, tvrdo glodanje predstavlja alternativu postupku obrade koji uključuje glodanje i završne operacije kao što su brušenje ili elektroerozijska obrada. U radu se na temelju eksperimentalnih podataka analizira istosmjerno i protusmjerno glodanje te istosmjerno i protusmjerno tvrdo glodanje. Na osnovi optimalnih parametara promatranih procesa, provedena je procjena ekonomske i kvalitativne održivosti tvrdog glodanja u odnosu na uobičajeni postupak obrade otvrdnutog čelika. Za procjenu optimalnih vrijednosti parametara obrade, kojima će se osigurati minimalno vrijeme obrade i minimalni troškovi obrade, korišteni su genetski algoritmi. Optimalne vrijednosti dobivene genetskim algoritmima, uspoređene su s vrijednostima dobivenim metodom simuliranog žarenja. Rezultati istraživanja pokazuju da su troškovi istosmjernog tvrdog glodanja 14 % viši od troškova istosmjernog glodanja, a troškovi protusmjernog tvrdog glodanja za 4,48 % viši nego troškovi protusmjernog glodanja. Ovo predstavlja polazni podatak u detaljnoj usporedbi standardne obrade tvrdih materijala i postupka tvrdog glodanja.

Ključne riječi: *genetski algoritmi, regresijska analiza, simulirano žarenje, trošenje alata, tvrdo glodanje*

1 Introduction

Developments of machine tools and new production tool materials technologies have a great impact on the development of new methods of machining. An example of this is hard machining as a relatively recent technology that can be defined as a machining operation using tools with geometrically defined cutting edges. The values of workpiece hardness are in the 45 HRc ÷ 70 HRc range. Hard machining presents the challenge of selecting a cutting tool insert that facilitates high-precision machining of the component [1]. There are several advantages over traditional methodology based on finish grinding operations after heat treatment of workpieces. These advantages are reported as: greater part geometry flexibility, increased procedure effectiveness due to shorter cycle time, machining ability in only one fixture and using only one machine tool and the possibility of cutting fluid elimination [2]. The main disadvantage is exceedingly high amount of heat generated in hard machining process, as compared to that in conventional machining, which causes rapid tool wear. Most papers in this area deal with researching the influence of machining parameters on the quality of the machined surface [3 ÷ 5], the occurrence of white layers [6, 7], cutting force models and optimization of processing parameters [8]. Quite a many research papers can be found explaining different techniques for estimation of tool wear for different forms of machining processes.

Kwon and Fisher [9] in their work have developed tool wear index (TWI) and the tool life model, analysing the wear surface areas and material loss from the tool. With relation to surface roughness, TWI measures minimum risk for in-process tool failure and is integrated in an optimal control strategy according to productivity improvement and reduction of manufacturing cost. In the analysis of static and dynamic process of hard milling, the influence of the axial depth of cut (10 mm < a_p < 20 mm), in down and up milling of workpiece made of steel 40CrMoV5, has been investigated [8]. Cutting force component in a perpendicular direction to the feed, designated as F_y, is the most sensitive to tool wear, regardless of whether it is about down or up milling. Cutting parameters have the greatest impact on this cutting force component.

The traditional nonlinear optimization techniques are usually gradient methods and they have many limitations in the application of today's complex design. They cannot use integer and discrete variables. Integer variables must be approximated by continuous variables. A simple rounding procedure is usually unreliable. A proper choice of initial conditions is also needed. Further, it is very likely to obtain a local optimum. As machining has become much more complex, process models have been discontinued, non-derivable or non-explicit. These optimization problems are difficult to solve with gradient optimization techniques. In practice, there is often a simultaneous optimization of several functions, which are mutually contradictory. For example, increasing the cutting speed leads to an increase in productivity, but also increases production costs due to wear of tools and deterioration of machined surface. Optimization of the milling process is a multi-objective optimization problem with constraints in the form of equations and inequalities, and several conflicting objective functions, such as: increase productivity, reduce costs, improve quality of machining, etc.

Many researchers have presented non-traditional optimization techniques for optimization of machining operation. The theoretical foundations of genetic algorithms (GA), and applications mimicking the natural evolutionary process were set in the early seventies last century [10]. This method belongs to the stochastic search methods of the allowable area, and to obtain new and better solutions uses information and knowledge from previous phases. Regarding to the ability factors of GA for the optimization of machining process, an effort is taken to estimate the best combination of cutting parameters for the minimizing surface roughness in end milling process [11]. Čuš et al. [12] have used intelligent system for on-line monitoring and optimization of the cutting conditions in ball-end milling. Tool geometry, workpiece material and cutting conditions have been considered in their genetic algorithm optimization approach. Wang et al. [13] presented a new hybrid approach, named genetic simulated annealing (GSA) and parallel genetic simulated annealing (PGSA), based on genetic algorithm and simulated annealing to find optimal machining parameters in milling operations. They pointed out that the obtained results were found to be better than those of genetic algorithm and geometric programming. Čuš and Zuperl [14] have proposed a neural network based approach to multi-objective optimization of cutting parameters taking into consideration the technological, economical and organizational limitations. Baskar et al. [15] investigated a specific case in milling operation and solved the same by using three different non-traditional optimization techniques comprising a genetic algorithm, local hill climbing and memetic algorithm. To find the optimal process parameters which minimize the surface roughness and formation of the burs in micro-end milling of Ti-6Al-4V titanium alloy, Thepsonti and Özel [16] have performed modelling and multi-objective optimization by using experimental, statistically based modelling and particle swarm optimization method.

The main objective of this study is to perform an analysis of the milling and hard milling which could contribute in making decision about the economic viability of the hard milling process. In the designing of high loaded machine elements (moulds and dies, shafts, bearings, gears, etc.) there are indispensable requirements for improving the geometrical characteristics, surface quality and extension of their life time. The above requirements could be provided by using hard steel in construction of these components. Thanks to new technological developments in cutting tool materials, hard milling is used for the machining of hardened steel parts.

2 Experimental work

The goal of experimental work was to obtain the results of measurements that will determine allowable range of input variables and development of mathematical models for the tool life in the process of milling and hard milling. Below are described the elements of the used machining system consisting of machine tool, tool and workpiece, and measurement equipment.

The end milling experiments were conducted on CNC vertical machining centre, Spinner VC560, equipped with a 12 000 rpm electrospindle and the SK 40 tool holder. Workpiece material, steel 42CrMo4, was prepared for milling operations in the form of 250 × 110 × 110 mm blocks and adapted to the experiment needs. For the hard milling operations the same material was used but thermally treated. Workpiece hardness after heat treatment was 48 HRc.

The cutting tool was end mill CoroMill R390-02A20-11M produced by Sandvik. Inserts with highly resistant coating made of TiN, which was in a thickness of 6 µm in the physical vapour deposition (PVD) process applied to the hard metal, have been used for conventional milling. Inserts with multi-layered coating of TiAlN were used for hard milling. Tool wear was measured by means of toolmaker's microscope with 100× magnification and USB camera. For surface roughness measuring the profilometer Mitutoyo Surftest 301 was used. Three orthogonal components of cutting force were measured by means of dynamometer Kistler 9257A.

All experiments were conducted without cutting fluid and every experiment was performed with new inserts.

2.1 Cutting parameters

Preliminary tests which determine threshold values of cutting parameters and tool wear criterion, have been performed. Tests were conducted for the following machining procedures: up and down milling as well as up and down hard milling. To determine the range of input variables, three series of experiments were performed, for all four procedures, in which the milling force components were measured in the condition of different cutting parameters.

Milling force components, F_x, F_y and F_z, are the sum of projections of the tangential, radial and axial forces acting on the cutting edges during milling. Milling force components present the mean value of the maximum cutting force on each insert.

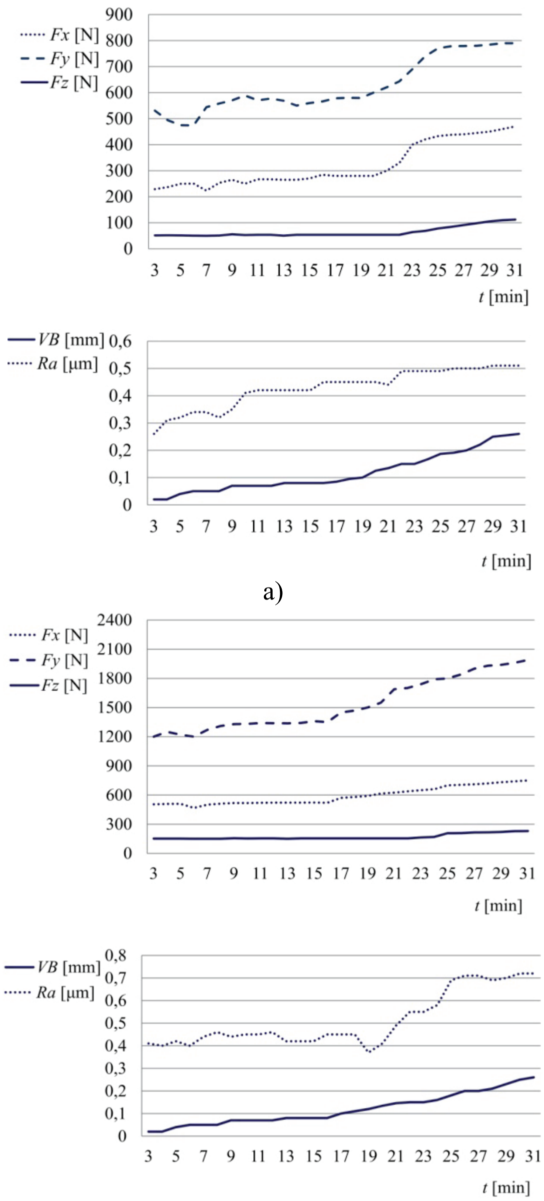
Cutting speed, v_c, values are selected based on the recommendations of the tool manufacturer and workpiece hardnees. The radial depth of cut, a_e, and feed per tooth, f_t, will be determined after the tests, depending on the measured cutting forces because the machine tool overload occurs when the cutting force component, in the feed direction, F_x, exceeds a value of 1000 N. The cutting parameters range is selected after performing and analyzing previous tests and this is presented in Tab. 1.

Tool wear depends on many factors such as properties of workpiece and tool materials, geometric characteristics of the cutting tools, machine tool characteristics and working conditions. As a result of all factors in the machining process, different types of wear occur. Flank wear has been used in production practices as a primary indicator of tool wear. Direct consequences of this type of wear are increasing on both the cutting force and the surface roughness. Recommendations for the criterion of the flank wear *VB*c are numerous, but because of the large number of impact factors, not unambiguous. For that reason, in this work the experimental determination was performed to determine the tool wear criterion. Measurements of cutting force components, surface roughness and flank wear are performed so that all of the measured values correspond to the same point of insert engagement time.

A series of three experiments was performed, with new inserts for each method. Fig. 1 shows a part of the measurement results of the cutting force components, surface roughness and flank wear.

Table 1 Type of milling and cutting parameters range

Type of milling	Input factor					
	v_c / m/min		f_t / mm		a_e / mm	
	min	max	min	max	min	max
milling	100	150	0,05	0,11	1	2
up milling	100	150	0,02	0,07	1	2
down hard milling	70	120	0,05	0,11	1	2
up hard milling	70	120	0,02	0,07	1	2



a)

b)

Figure 1 Components of cutting force, surface roughness and tool wear:
a) down milling; v_c= 100 m/min, f_t = 0,05 mm, a_e = 1,5 mm,
b) down milling; v_c= 150 m/min, f_t = 0,11 mm, a_e = 1,5 mm

After the measurement and analysis of the results for all cutting procedures, flank wear criterion VBc = 0,15 mm has been adopted. When the flank wear reaches the value of 0,15 mm, the process becomes unstable. The instability is reflected in the increasing of cutting force components as well surface roughness.

2.2 Design of experiments

Experimental design predicts all influencing factors and actions that will, through a rational examination, lead to the new insights. It is necessary to manage experiment with the statistical multifactor method due to stochastic characteristic of a machining process [17]. The tool life equation can be displayed in the form:

$$T = C v_c^{a_1} f_t^{a_2} a_e^{a_3}, \tag{1}$$

where C, a_1, a_2, a_3 are unknown coefficients.

To obtain the regression model for prediction of the tool life value, mathematical model given in Eq. (1) is linearized by performing a logarithmic transformation as follows:

$$\ln T = \ln C + a_1 \ln v_c + a_2 \ln f_t + a_3 \ln a_e. \tag{2}$$

Eq. (2) can be written in this form:

$$y = b_0 + a_1 b_1 + a_2 b_2 + a_3 b_3, \tag{3}$$

where y=ln$T$, b_0=ln$C$, b_1=lnv_c, b_2=lnf_t, b_3=lna_e.

To define linear model, the first order design of experiment is applied; in particular, a full factorial design of experiments. The minimal number for the level of factor variation is two and the required number of runs is $N = 2^k = 2^3 = 8$.

By means of multiple linear regression, the coefficient of multiple regressions R, R^2, adjusted R^2, standard deviation and regression coefficients that define the mathematical model are determined. This mathematical model can be adopted after testing the significance of the model coefficient, as well as verification of the model adequacy.

2.3 Experimental results and tool life models

Experimental results for the design of experiments, presented in Tab. 2, were indirectly obtained. The wear profiles were created based on the measurement of flank wear in sufficient small size of the measurement intervals. Through applying the previously established criteria of flank wear, the tool life was graphically determined and this value has been used as a response variable, Fig. 2.

By applying regression analysis on the experimentally determined data, the regression coefficients were obtained and thereby the regression equation for the tool life as well:

$$T = \mathrm{e}^{5,0114} v_c^{-0,4565} f_t^{-0,1293} a_e^{-0,1507} \tag{4}$$

Using the same methodology on up milling, down hard milling and up hard milling the following models have been obtained:

Up milling:

$$T = \mathrm{e}^{5,00503} v_{\mathrm{c}}^{-0,4617} f_{\mathrm{t}}^{-0,0555} a_{\mathrm{e}}^{-0,0097}. \tag{5}$$

Down hard milling:

$$T = \mathrm{e}^{3,9087} v_{\mathrm{c}}^{-0,3064} f_{\mathrm{t}}^{-0,2705} a_{\mathrm{e}}^{-0,2002}. \tag{6}$$

Up hard milling:

$$T = \mathrm{e}^{4,571} v_{\mathrm{c}}^{-0,3972} f_{\mathrm{t}}^{-0,0614} a_{\mathrm{e}}^{0,2316}. \tag{7}$$

Table 2 Physical values of input variables, design of experiment with response values in down milling process

Physical parameters				
v_{c} / m/min	f_{t} / mm	a_{e} / mm		
100	0,05	1		
150	0,11	2		
No.	v_{c} / m/min	f_{t} / mm	a_{e} / mm	T / min
1	100	0,05	1	27,5
2	150	0,05	1	22,0
3	100	0,11	1	24,8
4	150	0,11	1	20,0
5	100	0,05	2	23,5
6	150	0,05	2	21,0
7	100	0,11	2	21,5
8	150	0,11	2	18,2

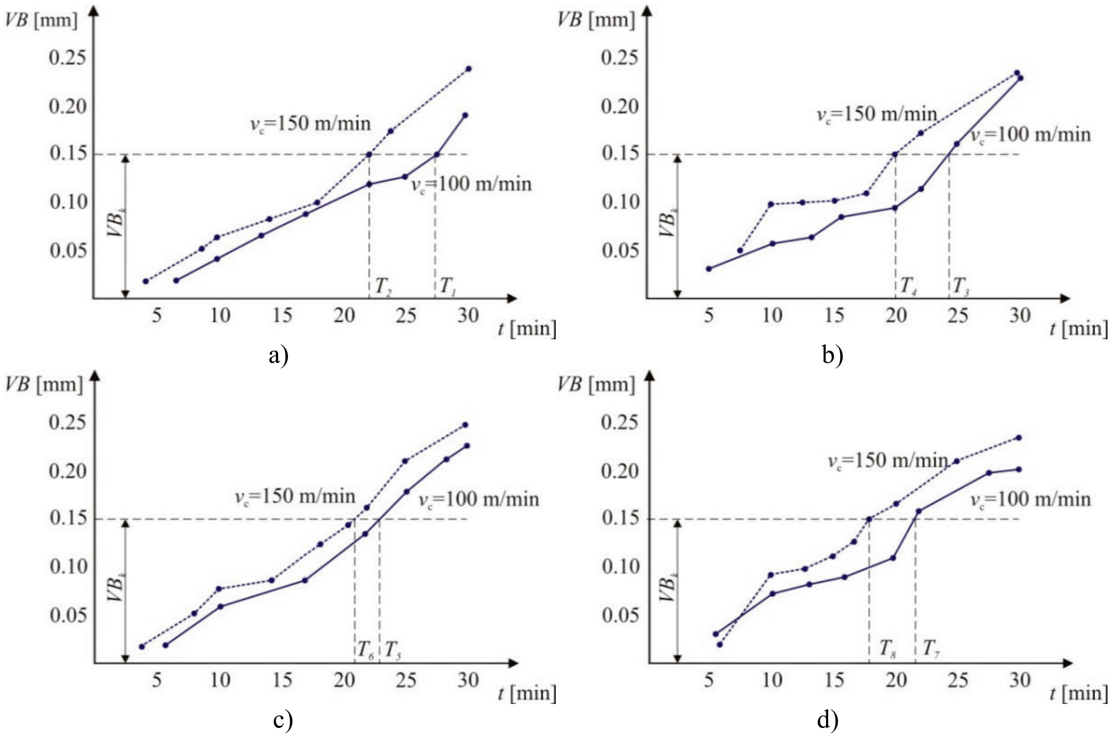


Figure 2 Wear profiles– down milling:
a) f_{t} = 0,05 mm, a_{e} = 1 mm, (exp. 1 and 2), b) f_{t} = 0,11 mm, a_{e} = 1 mm, (exp. 3 and 4),
c) f_{t} = 0,05 mm, a_{e} = 2 mm, (exp. 5 and 6), d) f_{t} = 0,11 mm, a_{e} = 2 mm, (exp. 7 and 8)

3 Optimization

The machining process optimization can be defined as a constrained, nonlinear programming problem. The general machining process optimization is presented as:

Optimize (minimize or maximize):

$$f(X), X \in F_{\mathrm{s}} \quad X = \{x_1, x_2, x_3, \ldots x_n\}. \tag{8}$$

Subject to constraints:

- physical constraints, the boundaries of independent variables $x_{i\min} \le x_i \le x_{i\max}$
- constraints expressed as inequality and equality:

$$g_j(X) \ge 0, \qquad j = 1, 2, \ldots, k$$
$$h_j(X) = 0, \; j = 1, 2, \ldots, m,$$

where $f(X)$ is objective function for the design problem, X is n-dimensional design vector, the subject of optimization, and F_{s} is a space of satisfactory solutions.

Objective functions are used to evaluate a design solution within the optimization context. The number of objective functions, their nature and whether they are separable determines the complexity of the optimization task. In real life most of the optimization problems are multi-objective, ie. they are often composed of several partial objectives that individually do not have a common optimum at the same point. Unified criterion of excellence solutions and integrated objective function is formed by combining the partial set of criteria. In this paper the optimization is performed by using the sum of "weighted" criteria with weights w_i that show the relative importance of each criterion in the overall excellence:

$$f(x) = \sum w_i f_i(x), \quad \sum w_i = 1, \quad w_i > 0. \tag{9}$$

The goal of optimization in this work is to determine the optimum cutting parameters to achieve the minimum unit machining time and the minimum unit production costs. According to Eq. (9), the problem is mathematically formulated as follows:

Minimize:

$$f(x) = w\frac{t_1}{t_1^*} + (1-w)\frac{C_1}{C_1^*}, \tag{10}$$

where w is weighted factor, $0 \leq w \leq 1$, t_1^* is target numerical value, unit machining time, C_1^* is target numerical value, unit production costs.

Constraints of cutting parameters were determined with respect to type of milling, workpiece and tool material. Target numerical values, t_1^* and C_1^* were obtained by minimizing the actual function presented below.

3.1 Machining time per piece

Machining time per piece t_1 for end milling is calculated as:

$$t_1 = t_\mathrm{m} + t_\mathrm{a} = t_\mathrm{m} + t_\mathrm{s} + i_\mathrm{p} t_\mathrm{m} + t_\mathrm{t} \tag{11}$$

where t_m is the main machining time, t_a is auxiliary machining time, t_s is tool setup time, i_p is number of passes, t_wr is workpiece return time, t_t is proportion of tool change time for one workpiece. After substituting the formulas for calculating these times and rearranging them, the final equation form was obtained:

$$t_1 = t_\mathrm{s} + \left[\frac{L}{v_\mathrm{wr}} + \frac{\pi D_\mathrm{c} L}{v_\mathrm{c} f_\mathrm{t} N 1000}\left(1 + \frac{t_\mathrm{tc}}{T} K_\mathrm{tl}\right)\right] i_\mathrm{p}\ , \tag{12}$$

where L is the total path length of the workpiece relative to the milling cutter, v_wr is workpiece return rate, D_c is mill diameter, N is number of inserts (tooth), t_tc is tool change time, T is tool life, K_tl *i*s the factor which takes into account time of inserts engagement related to one mill revolution and is calculated as:

$$K_\mathrm{tl} = \frac{\arccos(1 - 2a_\mathrm{e}/D_\mathrm{c})}{2\pi}\ . \tag{13}$$

3.2 Production costs per piece

Production costs per piece C_1 in end milling operation are calculated as:

$$C_1 = C_\mathrm{f} + C_\mathrm{m} + C_\mathrm{t} \tag{14}$$

where C_f is fixed costs of machinery and personnel, C_m is machining costs, C_t is tool costs. After substituting the formulas for calculating these costs and rearranging it, the final equation form was obtained:

$$C_1 = C_\mathrm{f} + \frac{\pi D_\mathrm{c} L}{v_\mathrm{c} f_\mathrm{t} N \cdot 1000}\left[(G_0 + O_\mathrm{w}) + \left(\frac{N C_\mathrm{ci}}{N_\mathrm{ce}} + \frac{C_\mathrm{c}}{N_\mathrm{cf}}\right)\frac{K_\mathrm{tl}}{T} + \right.$$
$$\left. + \frac{(G_0 + O_\mathrm{w}) t_\mathrm{tc}}{T}\right] \tag{15}$$

where G_0 is gross income of operators in the workplace, O_w is other general costs in the workplace, C_ci is price of the insert, N_ce is number of cutting edges on the insert, C_c is price of the mill and N_cf is number of inserts fastening that can withstand the milling cutter.

Based on the specified goals of machining, the optimization algorithm will generate the optimal machining parameters.

3.3 Optimization methods

In this work, two optimization schemes have been employed to minimize unit machining time and unit machining costs: genetic algorithms (GA) and simulated annealing (SA). The main advantages of these two methods are: their search procedure being stochastic, they do not impose pre-conditions, such as differentiability, continuity and convexity on the objective functions form, they perform global search and thus are more likely to arrive at or near the global optimum.

Genetic algorithms use the "survival of the fittest" principle of natural evolution with the genetic propagation of characteristics, to arrive at a robust search and optimization technique. In the GA procedure, the search for an optimal solution vector, begins from a randomly initialized population of probable solutions. The solutions, usually coded in the form of binary strings (chromosomes), are then tested to measure their fitness in fulfilling the optimization objective. Subsequently, the main loop comprising the following operations is performed: selection of better parent chromosomes, production of an offspring solution population by crossing over the genetic material between pairs of the fitter parent chromosomes, and mutation of the offspring strings. Implementation of this loop generates a new population of candidate solutions, which as compared to the previous population, usually fares better at fulfilling the optimization objective. The best string that evolves after repeating the above described loop till convergence forms the solution to the optimization problem.

Results obtained by GA method will be compared with the results obtained by using SA optimization. SA is based on imitation of the metallurgical annealing process. Annealing is a metallurgical process in which controlled heating and cooling returns metal to a steady state whether the phases (ferrite, perlite) or mechanical properties. Heat affects the atoms so that it distances them from their starting positions, allowing them to freely move through the higher energy levels. Slow cooling of atoms provides a greater probability to find a state with lower energy than the initial. By analogy with the mentioned physical process, each step of the SA algorithm replaces the current solution to one close to it, a randomly selected solution. Goal is to achieve low-energy configurations. The probability of selecting a replacement solution depends on the difference between the power level candidate solution and current solution. In the SA algorithm, the objective function represents the equivalent of energy and the base point in the problem domain is equivalent to the state of a material [18]. SA optimization is performed using the same mathematical model, constraints and weighted factor, as well as the GA optimization.

The process of planning and optimization is important in order to establish the economic and quality viability of hard milling process. Hard milling process presents a potential replacement for the conventional milling of the parts with increased hardness. For this purpose, the optimization of these processes will be carried out at a concrete example. Volume of the material that has to be removed is $L \times B \times S$ (mm^3). Axial depth of cut a_p equals 5 mm. Other values of parameters used in optimization are listed in Tab. 3.

GA method has been used with 100 generations, population size in the amount of 200, with the probability of crossing – 0,75, mutation probability – 0,01, two–point crossover and tournament selection size – 5. For the SA method, the initial temperature was 100 °C, with 100 iterations, the function of annealing – Bolzmann's annealing, the function of the temperature change – change in the exponential function. Minimization of the fitness function, Eq. (10), is subjected to the boundaries of cutting condition values determined in preliminary testing, Tab. 1. Optimal cutting parameters are given in Tab. 4.

Table 3 Weight factor and parameters values used in GA optimization

	Down milling	Up milling
w - weight factor	0,5	0,5
t_1^* / min/pc	32	44
C_1^* / €/pc	40	61
$t_{1\ h}^*$ / min/pc	38	53
$C_{1\ h}^*$ / €/pc	52	77

Simbol	Value	Simbol	Value
a_p / mm	5	G_0 / €/pc	0,50*
D_c / mm	20	O_w / €/pc	0,50*
L / mm	250	C_{ci} / €/pc	10,88
S / mm	40	C_{cih} / €/pc	11,32
B / mm	16	N_{ce}	2
t_{tc} / min	0,022		

* Adopted values; H refers to the values considering the hard milling process

Table 4 Optimal cutting parameters

	down milling	up milling	down hard milling	up hard milling
GA				
v_c / m/min	150	150	119,99	120
f_t / mm	0,11	0,07	0,1099	0,07
a_e / mm	2	2	1,999	2
Objective function	0,9998	1,0001	1,0044	1,0013
SA				
v_c / m/min	149,96	149,99	119,99	119,94
f_t / mm	0,11	0,069	0,11	0,07
a_e / mm	1,998	1,999	1,998	2
Objective function	1,0009	1,0002	0,9974	1,0152

Deviation from optimal results, which are obtained by different optimization methods, GA and SA, is a maximum of 0,88 %, which could mean that optimal results obtained by GA are the global minimum of the objective function, or are very close to the global minimum.

4 Results and discussion

Multi-objective optimizations have been performed by using GA and SA methods to determine the optimal combination of cutting parameters which presents trade-off between minimum machining time per unit and the minimum unit costs of machining. Optimal cutting parameters and comparison of economic parameters are presented in Tab. 5. Machining costs per unit time of down hard milling are higher in the amount of 14,05 % than the costs of conventional down milling process while by up hard milling costs are higher in amount of 4,88 % than the costs of conventional up milling. This could be the source data for a detailed comparison of hard milling and conventional ways of the machining parts with increased hardness.

After machining, in the process of exploitation, the workpiece must meet several functionalities. The functionality of the workpiece made of hardened steel is directly related to the finishing as the last step in the production chain. Finishing can be performed as hard milling, grinding or any of the electrical erosion processes. The requirements to be met by the production process correspond to global trends, such as: economic viability, environmental aspects, reduced production time and satisfactory product quality. Economic efficiency of the process is associated with the properties of the workpiece and cannot be analyzed separately. Increasing the material removal rate or tool wear has an effect on the surface finish, and consequently on the properties of the workpiece and its functionality. Great flexibility and ability to produce parts of complex geometry in only one fixture is the greatest benefit of hard milling in relation to the conventional operation based on milling and grinding. Surface finish quality obtained with hard milling is comparable to that obtained by grinding. The overall options assessment is very complex because for the detailed process capabilities assessment basic research is necessary.

An analysis of the milling and hard milling can contribute to making good decisions about the economic viability of the hard milling process. Optimal cutting conditions of milling and hard milling have been obtained by multi-objective optimization. Machining costs per unit of time is lower in down milling than in up milling for several reasons coming from the differences in these two methods. Observed from the viewpoint of tool life, down milling is favorable compared to the up milling. In the up milling, cutting edge gradually enters into the workpiece material and slides over the surface of workpiece material.

Before the removing, the workpiece material is compressed and the first cracks occur as well. As a result, the temperature in the cutting zone is increased and this leads to intensify all forms of tool wear, and there are also new wear forms, such as diffusion wear. The chip formation in down milling is opposite to the chip formation in up milling. The cutter edge begins to mill the full chip thickness. Then the chip thickness gradually decreases. Since there is no sliding or upsetting of workpiece material, the treated surface is smooth and has better quality, and there are no negative impacts on the tool wear, i.e. flank wear. In the presented case, the material removal rate in down milling should be greater than in up milling. The cutting force in feed direction has a considerably lower value in down milling and because of that it is possible to apply the higher value of feed rates. All of the above contributes that the down milling process performed on CNC machine center is more effective than the up milling.

Table 5 Comparison of economic indicators

Type of milling	Optimal cutting parameters			Machining time per piece / min/pc	Machining costs per piece / €/pc	Machining cost per unit of time / €/s
	v_c / m/min	f_t / mm	a_e / mm			
up	150	0,11	2	32,12	39,54	1,24
down	119,99	0,1099	1,999	37,38	52,99	1,42
up hard	150	0,07	2	44,15	61,65	1,40
down hard	120	0,07	2	52,67	77,15	1,46

5 Conclusions

In this study multi-objective optimization, which is based on technological and economic indicators of machining, has been carried out. Experiments have been performed on the steel 42CrMo4 in normalised and hardened state. Four series of experiments have been performed: down and up milling, as well down and up hard milling. Tool life equations which are later used in optimization algorithm have+ been obtained by means of regression analysis of experimental results.

Two optimization criteria are based on the weighting coefficients that indicate the priority of two objective functions: the minimal machining unit time and the minimal machining unit costs. If the same priority of the functions is taken, two criteria optimization showed that the costs of the down hard milling are 14 % higher than the costs of down milling and the costs of up hard milling are 4,48 % higher than the costs of up milling. It is well known that the costs resulting from finishing operation performed in a new workpiece set-up should be added to the costs of conventional milling. Costs of heat treatment are neutral in this comparison. Optimization procedures were carried out using GA, and optimization results were verified by SA. The deviations amount to a maximum of 0,88 %, which means that the optimal values obtained by GA are the global optimum of the objective function, or are very close to the global optimum.

This research has shown that hard machining allows increased productivity compared with the conventional procedure of machining of hard materials.

6 References

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