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OPTIMIZATION OF MACHINING PROCESSES USING THE ABC METHOD AND GENETIC ALGORITHM

Abstract: *Optimization of machining processes is one of the most important elements in the planning of metal parts production. In this paper, we have applied ABC methods to determine the cost of all processes that are used in production of homocinetical sleeve joint. After that we have used multy-criterion optimization technique based on genetic algorithms, in order to optimize the basic parameters of all the processes: the speed and feed. The objective function is given in a form of specific cost for each processe, for which minimization it is need to consider the appropriate mechanical and manufacturing constraints. The proposed model uses a genetic algorithm, so that after a certain number of iterations optimal result is reached that will satisfy the objective function and all anticipated limitations. Obtained results shows that GA solves the optimization problem in an efficient and effective manner, so that the results can be integrated into an intelligent manufacturing system for solving complex optimization problems in machine production processes.*

Keywords: *Genetic algorithm, machine production processes, cost functions minimization*

1. Introduction

Optimization is the process of adjusting the input device characteristics, mathematical processes and experiments in order to find the minimum or maximum output or result (Haupt and Haupt, 2004). In recent years, new optimization methods are developed that are conceptually different from the classical methods of mathematical programming. These methods are called modern or metaheuristics optimization methods. Under metaheuristics optimization methods are considered direct search methods that converge to global optimum in a particular direction based on ideas of probability heuristics. Most of these methods are based on certain characteristics or behaviors of biological, molecular and neurobiological systems. These methods have become popular in recent years for the solution of complex engineering problems. One of the methods of optimization, which has experienced significant development, is the method of genetic algorithms (GA).

Genetic algorithms have been proposed by John H. Holland in the early seventies. Holand developed them, along with his students at the University of Michigan in the seventies and eighties. The book published by the Holand in 1975. "Adaptation of the neural and artificial systems" represends a

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genetic algorithm as an abstraction of biological evolution and provides a theoretical framework for the application of genetic algorithms. During more than two decades, and especially in the last few years have proven to be very powerful and at the same time general tool for solving a range of problems from engineering practice (Izadifar and Jahromi, 2007; Montazeri-Gh *et al.*, 2006).

In addition to the genetic algorithm, we have used one of the most widely used techniques for classification of different items. It is the ABC method which is based on Pareto analysis. This method is very easy for understanding and use. In classical ABC method, items are divided into three categories A, B, and C, according to one crisp criterion. Selection of the classification criterion depends on the kind of the problem being considered and in the first place it is based on estimation of the management. Typically items of group A represent 5 to10 percent in terms of quantity and 90 to 95 percent in terms of the value. Items of group B reperent 10 to 15 percent in terms of quantity and 85 to 90 percent in terms of the value. These items have average important for management. All other considered items belong to group C and they relatively unimportant.

The paper discusses the optimization of machining processes using genetic algorithms, and consequently in Chapter 2 presents a literature review of works relating to the application of genetic algorithms as a method to optimize the machining process. Chapter 3 presents the the application of ABC methods to manage costs, while Chapter 4 presents application of genetic algorithm for optimization of machining processes, while Chapter 5 concludes paper.

2. Literature review

In each optimizational procedure, a crucial aspect is to identify the key-outs, tj. key goals or criterias (Sardiñas *et al.*, 2006). In the manufacturing process, most commonly used optimization criterion is the specific cost, used by the majority of authors, from the beginning of research in this area to the most recent studies (Liang *et al.*, 2001; Wang *et al.*, 2002; Saravanan *et al.*, 2003; Cus and Balic, 2003; Amiolemhen and Ibhadode, 2004). Genetic algorithms as one of modern optimization methods give good results in terms of finding the optimal parameters of a number of processes including machining processes (Madic and Radovanovic, 2010). Optimization of machining cutting process is often a very demanding work (Kumar and Kumar, 2000), where the following aspects need: knowledge production, empirical equations related to the life cycle tools, power, strength, surface roughness, etc., to develop a real limitation, for the development of effective optimization criteria, and knowledge of the mathematical and numerical optimizations techniques (Sonmez *et al.*, 1999).

Onwubolu and Kumalo (2010) proposed a technique based on genetic algoritmimam to determine cutting parameters in multi-phase machine operations. The optimum processing parameters are determined by minimizing cost per unit of output with respect to all practical mechanical constraints. Venkata Rao and Kalyankar (2013) have carried out the optimization of the multipass turning process, with GA, were parameters that should be optimize were cutting speed, feed, depth of cut and number of passes. In this paper optimization problme was solved in two ways. The first way is the multi-target optimization with these already mentioned optimization parameters, while in the second case the problem is solved as a problem with one goal and 20 limiting factors. Many authors (Lee and Tarng, 2000; Zuperl and Cus, 2003; Cus and Balic, 2003), used a multi-objective optimization in wich decision-maker had combined multiple targets in one scalar function of cost. Abburi and Dixit (2007) in their paper used multi-objective optimization for process of multy pass-cutting with GA, but the algorithm is used to minimize production time. The results obtained were in terms of Pareto-optimal solutions, and then linear programming is used which provided the best solution of the proposed Pareto optimal solutions.

For large scale of production, machine parameters (cutting speed, step and depth of cut) have a significant impact on the performance of the machines when it comes to productivity (time Cikls production), reliability (lifecycle tools) and product quality (surface roughness). In addition, production parameters (size and quantity ordered materials) are critical when it comes to high-volume production, because it directly affects the fulfillment of the demanded order. On these assumptions (Al-Aomar and Al-Okaily, 2006) in their paper developed a simple genetic algorithm and applied it on a CNC lathe to determine the optimal value and the mechanical and manufacturing process parameters in order to minimize the cost per order.

Examples of the application of genetic algorithms could be found in machining and milling process. In paper, which focuses on the development of an effective methodology for determining the optimal cutting conditions that lead to the reduction of surface roughness in machining processes milling, (Oktema *et al.*, 2005) used a genetic algorithm as optimization method. Optimization parameters that thaz used were the cutting conditions: feed, cutting speed, axial depth of cut, radial depth of cut and machining tolerances. Also, Mohd in their work related to the optimization of cutting parametars with GA in milling machining process as the most important influencing factor specify radial angle of milling tool, combined with speed and pitch tools, in order to come to a minimization of surface roughness. Based on case studies of machining, thay have developed regression model. The best regression model has represented the objective function for the GA. After analysis of the study, they found that the GA technique is able to estimate the optimal cutting conditions that yield the minimum value of surface roughness with respect to mechanical constraints.

For high-speed machining process milling (Wang *et al.*, 2005) in their paper used genetic algorithm in combination with another method of optimization, simulated annealing (SA). By combining these two methods thay have overcomed the weaknesses of both methods. The optimization objective in this paper was to reduce the production time.

Multi-objective optimization with genetic algorithm could be used to optimize the electroerosion processing. Mandal *et al.* (2007) used a GA with a non-dominated sorting to optimize this process and as a result thay got a set of Pareto optimal solutions.

The main difficulty that arises in the optimization of machining processes is the knowledge about the process. Before setting up optimization models it is needed to define: functions of the process, the objective function, functions and limitations of optimization criteria. Functions of the machining process are in most cases: force (resistance) cutting, cutting force, cutting temperature, tool wear, tool life and surface finishing. The objective function is usually: processing time, processing costs, accuracy of production, productivity, cost, profit, etc. Functions of limitations are related to restrictions on the features: machine, tool and workpiece. Optimization criteria usually include: minimization of time and processing costs or maximization of productivity and profit, but may be some other, such as the realization of a given surface finishing. But optimization is not an easy task because many factors of process are interconnected and change of each factor affects the others. Machining processes, as already mentioned, are usually carried out in several passages, with the final finish, and with the prevoius passes marked as roughing. When processing in multiple passes, cutting speed, step and depth of cut in each pass are the primary variables.

3. The application of ABC methods to manage costs

ABC method was founded in the late 80s of the last century for the purpose of calculating the cost as support to the management decision-making. This method monitors and distributes the cost to the activities, by assigns the costs to the each performance (Jadransic, 2003). So, it is necessary to identify activities and their costs.

In this paper, the method was applied to the fabrication of the sleeve homocinetical joint, in order to determine the bigest costs that belong to A category, that were afterwards optimized with GA. Activities that occur in process of making a single piece of homocinetical joint sleeve are shown in the table below (Table 1).

Table 1. Activities in technological procedure of maiking a homocinetical sleeve

10	Alignment of one and drilling of the other side of metal piece	120	Marking labels and year series mark
20	External turning	130	Induction hardening of the inner surface
30	Copying of the inner sphere and alignment	140	Induction hardening the outer surface
40	Rolling process of teeth making	150	Low relaxation
50	Cutting through channels for fuse	160	Control of the existence of cracks
60	Previous drilling to diameter d = 81,3	170	Grinding of thread M 20x1,5
70	Washing in the emulsion and exhaust with air	180	Grinding of diameter d = 48 i čela
80	Digging in six reliefs in the inner part with the purpose of facilitating the exit cutters	190	Grinding of diameter d = 81
90	Preliminary and final milling of six lanes for balls	200	Grinding of sphere d = 59,69
100	Chamfering the forehead of the six balls paths	210	Grinding of the six paths for balls
110	Washing in the emulsion and exhaust with air	220	Control of the existence of cracks

After the analysis of price determination cost of each activity individually was obtained and the distribution of all costs is shown in Figure 1.

The figure shows that the largest cost associated with 5 operations (operations that belong to part A), which account for 22% of total operations. Consequently the operations that are located in areas B and C, i.e. number of these operations is significantly higher, but the cost of their performance is considerably smaller. Five operations on which to apply the optimization method for genetic algorithms, operations, belonging to the A, are:

1) 40 - Rolling process of teeth making
2) 90 - Preliminary and final milling of six lanes for balls
3) 20 - External turning
4) 100 - Chamfering the forehead of the six balls paths (milling)
5) 30 - Copying of the inner sphere and alignment (rubbing)

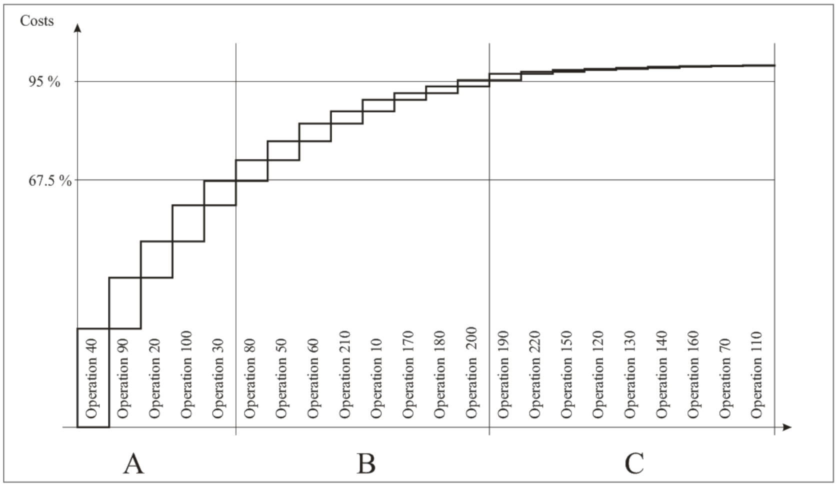

Figure 1. Cost-sharing by operations

On this five operations we have used GA to optimize costs regarding all constraints.

4. Application of genetic algorithm for optimization of machining processes

After completion of ABC method it was established that optimization should be performed on the operations of rolling, two milling processes and two turning processes.

Rolling process is usually applied to large-volume production; production of gear teeth with rolling consists of imprinting profile tool (which is often in the form of gear) in the workpiece material, while workpiece and tool simultaneous rotate.

Turning and milling processes are widely used in practice as basic manufacturing processes in a wide range of products. Economy of mechanical turning and milling operations play a key role in a competitive market (Ganesan *et al.*, 2011).

The processes of rolling, turning and milling of machine workpiece are shown respectively on Figures 2, 3 and 4. Parameters whose optimization was performed in the process of rolling, milling and turning are speed V_c and feed f of tools. When the quantity of material that has be removed, exceeds the maximum value of the depth of processing, multiple-pass processing is used, ie. certain number of rough passes and finishing as a fine passe. So in that case it is necessary to use multiple passes with a fixed or variable depth.

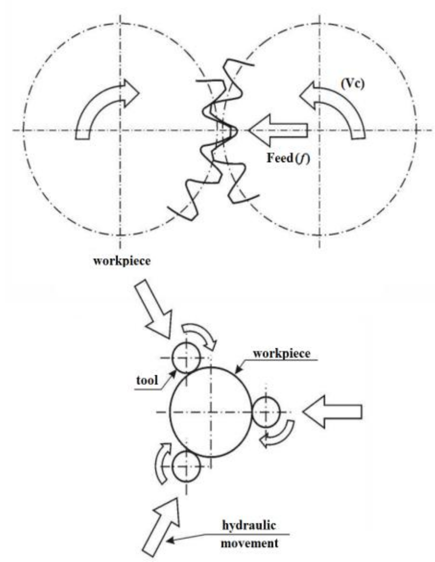

Figure 2. Parameters influencing the gear rolling

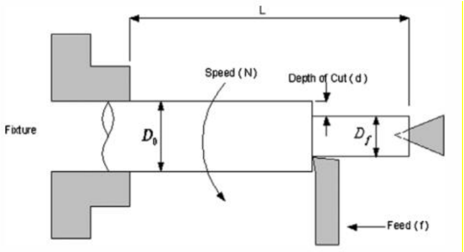

Figure 3. A basic turning process (Al-Aomar and Al-Okaily, 2006)

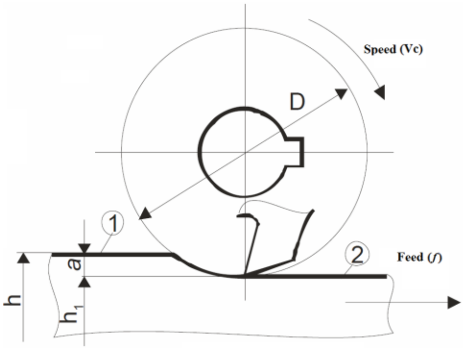

Figure 4. A basic milling process (Nedic and Lazic, 2007)

In practice, the selection of cutting parameters is from the specification machine manual, which is based on experience, to satisfy the required accuracy of the final product. Variations in the selection of machine parameters affect machine productivity, reliability and quality. Influence of these parameters, which can be expressed through the price, is increased with the volume of production. For example, when using the no appropriate feed, the amount of scrap material (surface roughness exceeds a certain required threshold) will be large for large scale of production. The case is similar when analyzing the economic impact of of cutting conditions on tool life and production time. Because of the multiple and interconnection of costs of production significant parameters of tools can reduce the cost of production in one place and increase costs elsewhere. For example, while high-speed processing results in a shorter production time, they shorten the tools life cycle and increase the cost of tool changes. For this reason it is necessary to optimize the effective parameters in process (Sardinas *et al.*, 2005).

To optimize with GA we have used the optimization tool method in Matlab environment. With genetic algorithm in Matlab optimization could be done in two ways: first by using the syntax in the main Command Window and another using an optimization tool Optimisation Tool. For this example we used the Optimization Tool software in Matlab package. Optimization problem in Matlab can be represented in the form of a mathematical model:

Objective function is:

min F(x)

Limitation functions are:

A - x <b (linear inequality)
Aeq - x = beq (linear equations)
Ci (x) <0, i = 1,..., m (nonlinear inequality)
Ceqi (x) = 0, i = 1, ..., m + t (nonlinear equations)
Lb <x <K (set of variable).

The general form of the objective function optimization problem in the case of the five processes in the A category is to minimize the cost of processing. Processing costs can represent with relation:

$$C = n(t_g + t_p + t_{pz} + t_d)\sum_{i=1}^{r} k_{1i} + \sum_{i=1}^{n}[(nk_1t_1 + k_2t_2 + \frac{Ca}{i+1})\cdot\left(\frac{t_g}{T}\right)] +$$
$$+ \frac{C_m \cdot P}{F \cdot \eta \cdot 60 \cdot 100}(t_g + t_p + t_{pz} + t_d) + \frac{Q_{shp} + C_{shp}}{60}(t_g + t_p + t_{pz} + t_d)$$
(1)

C (EUR) - the processing costs, n - coefficient whose size depends on the number of machines on which an employee works at the same time and the number of machines serviced by a professional worker (1,1 - 1.3), k_1 - gross salary of workers (EUR/min) t_g - effective cutting time (min), t_p - extra time that, during processing, is spent on setting up the workpiece in the machining system, t_{pz} - preliminary final time that refers to the time of the preparation of the machining system (machines, tools, equipment, etc.) for processing of one series with z units (workpieces) and clearing away the working system after completion of the processing of all pieces, t_d - additional time in production process that is spent on short breaks of workers during the construction of a series of z items, C_a - tools costs (EUR), i - the number of possible tool sharpenings, t_1 - tool changing time (min), t_2 - tool sharpening time (min), k_2 - personal income of workers who performs sharpening of tool in the gross amount (EUR/ min) , T - tool life, Cm - price of the machinery which is affected by the amortization rate (EUR), P - machinery amortization rates (%), η - time-efficiency machines, Q_{shp} - the amount spent SHP-a (l / h), C_{shp} - price of SHP-a (EUR/l), q - the quantity (number of units) of the i-th pieces (workpiece) produced during one year on the machine.

Mechanical time in all the operations is:

$$t_g = \frac{\pi DL}{1000 v_c f} \tag{3}$$

where: D (mm) - diameter of the workpiece, L (mm) - the length of processing v_c (m / min) - speed, f (mm / rev) – feed.

A critical parameter the in objective function is a resistance tool (T), this value represents the time of constant cutting between two sharpening or replacement of tools. It is expressed in time units.

Tool resistance depends on many parameters: cutting regime, tool geometry, workpiece and the tool material, tool type, type of manufacturing operations, treatment process, types of cutting (intermittent or continuous), dynamic phenomena in the process and so on. At optimum tool geometry and constant processing conditions main parameters influencing on tool resistance are the feed of tools, speed and depth of cut. Based on these parameters follows the relation:

$$T = \frac{C_T}{v_c^p f^q a_p^r} \tag{4}$$

where a_p (mm) – is depth of cut, C_T, p, q and r – are empirical constants.

In case of availability of data on consumption of coolants and lubricants for operations Qshp in liters, SHP counts in the form:

$$SHP = Q_{shp} \cdot C_{shp} \tag{5}$$

The cost of operations of rolling, milling and turning, on the basis of (2), (3), (4) and (5) can be represented by equations for:

- the development of teeth by rolling; preliminary and finish milling, for chamfering and for external turning:

$$C = n\frac{\pi DL}{1000 v_c f} k_l + \frac{Ca_1}{1} \cdot \left(\frac{\pi DL v_c^{p-1} f^{q-1} a_p^r}{1000 C_T} \right) + \frac{C_m \cdot P}{F \cdot \eta \cdot 60 \cdot 100} \cdot \frac{\pi DL}{1000 v_c f} + SHP \tag{6}$$

- Copying of the inner sphere and alignment:

$$C = n\frac{\pi DL}{1000 v_c f} k_l + (\frac{Ca_1}{1} + \frac{Ca_2}{1}) \cdot \left(\frac{\pi DL v_c^{p-1} f^{q-1} a_p^r}{1000 C_T} \right) + \frac{C_m \cdot P}{F \cdot \eta \cdot 60 \cdot 100} \cdot \frac{\pi DL}{1000 v_c f} + SHP \tag{7}$$

Function of limitations for machining processes are:

a) Limits of tools cutting ability:

$$v_c f^y < \frac{C_v k_v}{T^m a_p^x} \tag{8}$$

b) the limits on use of machine power:

$$v_c f^{y_1} < \frac{6120 P_m \eta}{C_{k1} k_f a_p^{x_1}} \tag{9}$$

c) limitation with respect to the resistance of the tools:

$$f^{y_1} < \frac{R_{sd}}{C_{k1} C_0 k_f a_p^{x_1}} \tag{10}$$

d) limits on the rigidity of the workpiece:

$$f^{y_1} < \frac{\delta_2 EI}{0.8 \mu C_{k1} l_1^3 k_f a_p^{x_1}} \tag{11}$$

e) cutting speed limit due to the minimum spindle number of revolutions:

$$v_c > \frac{\pi D n_{\min}}{1000} \tag{12}$$

e) cutting speed limit due to the maximum spindle number of revolutions:

$$v_c < \frac{\pi D n_{\max}}{1000} \tag{13}$$

g) limitation of feed with respect to the minimum feed:

$$k > k_{\min} \tag{14}$$

h) limitation of feed with respect to the maximum feed:

$$k < k_{\max} \tag{15}$$

The table below contains information that we take into the equations (6 - 15) to determine the optimal processing speed and feed to create the homokinetic sleeve:

Table 2. The parameters of the technological procedure for creating the sleeve

	Operation 40	Operation 90	Operation 20	Operation 100	Operation 30
D [mm]	50	65	90	60	80
D_1 [mm]	42	60	80	58	80
L_p [mm]	55	32	160	28	140
L_1 [mm]	50	28	140	27	135
P [kW]	15	7	4	6	20
η [%]	0,7	0,85	0,78	0,88	0,9
n_{min} [o/min]	20	20	20	20	20
n_{max} [o/min]	2000	200	100	400	3000
a_p [mm]	0,5	0,5	0,5	0,5	0,5/0,5
T_e [min]	15	15	15	15	15
n [-]	1,13	1,14	1,14	1,13	1,14
k_1 [EUR/min]	0,034	0,04	0,04	0,034	0,04
Ca_1 [EUR]	60	15	15	15	4,15
Ca_2 [EUR]	/	/	/	/	10
Cm [EUR]	15 000	3000	1000	2500	20 000
Pa [%]	1	1	1,2	1	1
F [h]	3000	3000	3000	3000	2000
SHP [EUR]	0,0916	0,096	0,0916	0,083	0,083
L [mm]	52	30	142	27	137
C_T [-]	$5{,}13*10^{12}$	$5{,}13*10^{12}$	$5{,}13*10^{12}$	$5{,}13*10^{12}$	$5{,}13*10^{12}$
p [-]	5,55	5,55	5,55	5,55	5,55
q [-]	1,67	1,67	1,67	1,67	1,67
r [-]	0,83	0,83	0,83	0,83	0,83
C_v [-]	292	292	292	292	292
k_v [-]	0,688	0,688	0,688	0,688	0,688
x [-]	0,15	0,15	0,15	0,15	0,15
y [-]	0,3	0,3	0,3	0,3	0,3
m [-]	0,18	0,18	0,18	0,18	0,18
C_{k1} [kN/mm^2]	300	300	300	300	300
x_1 [-]	1,0	1,0	1,0	1,0	1,0
y_1 [-]	0,75	0,75	0,75	0,75	0,75
k_f [-]	0,4	0,4	0,4	0,4	0,4
Co [-]	0,03	0,03	0,03	0,03	0,03
R_{sd} [kN/mm^2]	140	140	140	140	140
δ_2 [mm]	1,2	1,2	1,2	1,2	1,2
E [N/mm^2]	2,2*105	2,2*105	2,2*105	2,2*105	2,2*105
I [mm^4]	88408	88408	88408	88408	88408
μ [-]	1/3	1/3	1/3	1/3	1/3
l_1 [mm]	130	130	130	130	130

When the processing parameters are entered into the objective function they look like this:

$$C_1 = 0{,}313 / v_c f + 5{,}34*10^{-11} v_c^{p-1} f^{g-1} + 2{,}5 + 0{,}0916$$

$$C_2 = 0{,}279 / v_c f + 1*10^{-11} v_c^{p-1} f^{g-1} + 0{,}5 + 0{,}0916$$

$$C_3 = 1{,}829 / v_c f + 6{,}57*10^{-11} v_c^{p-1} f^{g-1} + 0{,}5 + 0{,}0916$$

$$C_4 = 0{,}195 / v_c f + 8{,}33*10^{-12} v_c^{p-1} f^{g-1} + 0{,}41 + 0{,}083$$

$$C_5 = 1{,}569 / v_c f + 5{,}31*10^{-11} v_c^{p-1} f^{g-1} + 0{,}3 + 0{,}083$$

While the limitations of the tool have the following forms for each of the the operations listed in the table below:

Table 3. Limitations of operations for technological procedures of creating the sleeve

	Operation 40	Operation 90	Operation 20	Operation 100	Operation 30
$v_c f^{0,3} <$	239,6	239,6	239,6	239,6	239,6
$v_c f^{0.75} <$	594,17	336,69	176,55	298,78	1018,58
$f^{0,75} <$	43,14	43,14	43,14	43,14	43,14
$f^{0,75} <$	670.67	670.67	670.67	670.67	670.67
$v_c >$	3.14	4.82	5.652	3.768	5.024
$v_c <$	314	40.82	28.26	75.36	753.6
$f >$	0.5	0.5	0.5	0.5	0.5
$f <$	15	9	17	14	12

To solve the optimization task with GA in Matlab it is necessary to define the function that we want to minimize (in this case, the function depends on two variables), and we did it this way for each of the operations, in this paper it is given as an example of the objective function for the operation 40:

```
function C = rolling_cost (x)
C=0.313/(x(1)*x(2))+5.34*10^-
11*x(1)^4.55*x(2)^0.67+2.5916;
End
```

After defining the objective function we have defined non-linear constraints, shown in the Table 3, in Matlab:

```
function [c, ceq] = nelog(x)
c = [x(1)*x(2)^0.3*-239.6;
x(1)*x(2)^0.75-594.17;
x(2)^0.75-43.14];
ceq = [];
end
```

After defining all the necessesry informations, in order to start the genetic algorithm, thay have to be entered into the fileds provided for it in the toolbox (Figure 5) as follows: Fitness function: @ troskovi_valjanja, Number of variables: 2, Bounds: Lower: [3:14 0.5] Upper [314 9] and Nonlinear constraint function: @nelog.

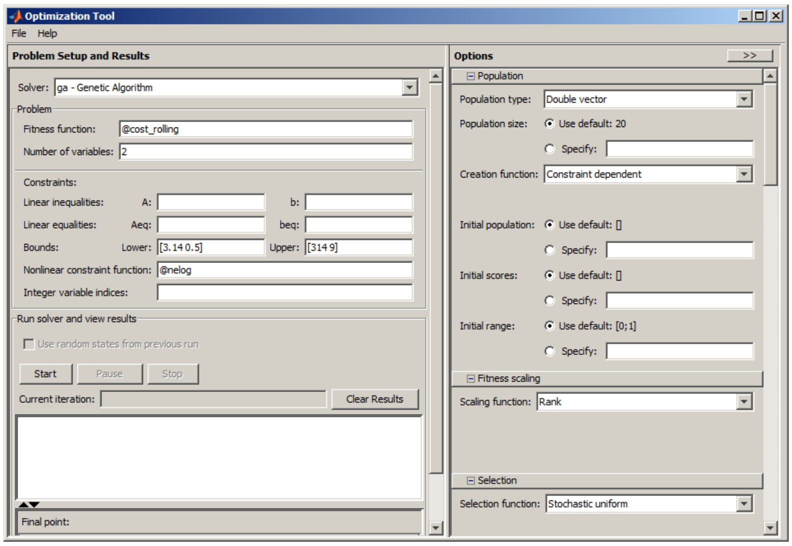

Figure 5. Appearance of GA toolbox in Matlab

Program is than started with previously set parameters necessary for the GA, which are: population size, initial population, the data related to the selection, hybridization, mutation, reproduction and migration, stopping criteria, presentation of results, etc.. When the stopping criterion is reached, the program terminates iteration and provides the required results, which are shown in Figure 6 and Table 4. In Figure 6, it can be seen a price reduction after the optimization with respect to real cost of processing, while in Table 4 it can be seen separated rates with suitably optimized process parameters.

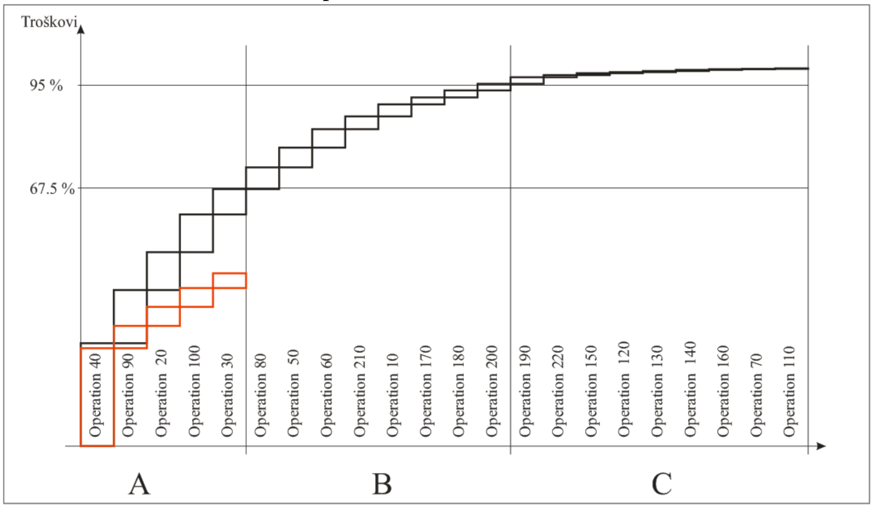

Figure 8. Comparison of costs of experimental data and the costs obtained after optimization

Table 4. Extracted comparison of the optimization results with experimental data

	Optimized			Experimental data		
Operation	V_c	*f*	Cost	V_c	*f*	Cost
40	22.61	2.9	2.59	5.87	4.6	2.72
90	29.95	8.7	0.59	7.29	2.5	1.40
20	28.26	9.2	0.50	6.64	14	1.01
100	19.16	8.9	0.49	28.63	11	0.99
30	30.26	8.8	0.39	332.94	8	0.67
		Total Price	4.57		Total Price	6.80

By comparing the optimized parameters with the parameters used in the real experiment it can be observed that a small change of parameters may get a big change in the cost of the machining process.

5. Conclusion

Based on the literature review it can be concluded that modern optimization methods give very good results when it comes to machining processes, as they allow easy selection of influential parameters. The development of modern methods is motivated by the fact that some complex problems could not be solved by classical methods of optimization.

In this paper, we have used ABC method to determine what the biggest costs are and than we have used a genetic algorithm as an optimization method to optimize the case of machining process of homokinetical sleeve. Genetic algorithm showed good results, because the initial cost of the most expencive operations was reduced for nearly 20 percents. Genetic algorithms should be used because, as in contrast to traditional methods wich observe function from a single point, it observes function from different points simultaneously.

If compared with the weak local methods (eg, gradient descent method) which use deterministic rules, genetic algorithm uses probabilistic rules of selection. For this reason, the genetic algorithm has the advantage so that does not remain "trapped" in the sub-local minimum of the cost function. It uses informations from many different regions of the field of definition of cost function and in that way it easely moves from local minima if population finds a better solution in some other region domain.

Since the genetic algorithm can provide so coled near-optimal solutions it can be used to select the parameters of mechanical processing of complex mechanical parts, which have a number of limitations. The integration of the proposed approach with inteligenitnim production systems will lead to a reduction in production costs, production time and improve of product quality.

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References:

Abburi, N. R., & Dixit, U. S. (2007). Multi-objective optimization of multipass turning processes. *International Journal of Advanced Manufacturing Technology, 32*, 902-910.

Al-Aomar, R., & Al-Okaily, A. (2006). A GA-based parameter design for single machine turning process with high-volume production. *Computers & Industrial Engineering, 50*, 317-337. doi: 10.1016/j.cie.2006.02.003

Amiolemhen, E., & Ibhadode, A. O. A. (2004). Application of genetic algorithms—determination of the optimal machining parameters in the conversion of a cylindrical bar stock into a continuous finished profile. *International Journal of Machine Tools and Manufacture*, *44*(12-13), 1403-1412.

Cus, F., & Balic, J. (2003). Optimization of cutting process by GA approach. *Robotics and Computer Integrated Manufacturing*, *19*, 113-121.

Ganesan, H., Mohankumar, G., Ganesan, K., & Kumar, K. R. (2011). Optimization of machining parameters in turning process using genetic algorithm and particle swarm optimization with experimental verification. *International Journal of Engineering Science and Technology, 3*(2), 1091-1102.

Haupt, R. L., & Haupt, S. E. (2004). *Practical Genetic Algorithms*. New Jersey: John Wiley & Sons.

Izadifar, M., & Jahromi, M. Z. (2007). Application of genetic algorithm for optimization of vegetable oil hydrogenation process. *Journal of Food Engineering,78*(1), 1-8.

Jadranšić, K. (2003). *Troškovi Kvalitete i ABC Metoda*, Zbornik radova 5. Simpozija o kvaliteti Suvremena stremljenja u upravljanju kvalitetom. Hrvatsko društvo menadžera kvalitetom i Oskar, Zagreb, Trogir, 191-195.

Kumar, R., & Kumar, V. (2000). Optimum selection of machining conditions in abrasive flow machining using neural networks. *Journal of Material Processing Technology, 108*, 62-67.

Lee, B. Y., & Tarng, Y. S. (2000). Cutting-parameter selection for maximizing production rate or minimizing production cost in multistage turning operations. *Journal of Materials Processing Technology, 105*(1-2), 61-66.

Liang, M., Mgwatu, M., & Zuo, M. (2001). Integration of cutting parameter selection and tool adjustment decisions for multipass turning. *International Journal of Advanced Manufacturing Technology¸ 17*, 861-869.

Madic, M., & Radovanovic, M. (2010). Savremene metode optimizacije obradnih procesa. *IMK-14 Istraživanje i razvoj, 37*(4), 19-24.

Mandal, D., Pal, S. K., & Saha, P. (2007). Modeling of electrical discharge machining process using back propagation neural network and multi-objective optimization using non-dominating sorting genetic algorithm-II. *Journal of Materials Processing Technology, 168*, 154-162. doi: 10.1016/j.jmatprotec.2006.12.030

Montazeri-Gh, M., Poursamad, A., & Ghalichi, B. (2006). Application of genetic algorithm for optimization of control strategy in parallel hybrid electric vehicles. *Journal of the Franklin Institute*, *343*, 420-435. doi: 10.1016/j.jfranklin.2006.02.015

Nedić, B., & Lazić, M. (2007). *Proizvodne Tehnologije Obrada Metala Rezanjem*. Mašinski Fakultet – Kragujevac.

Oktema, H., Erzurumlu, T., & Kurtaran, H. (2005). Application of response surface methodology in the optimization of cutting conditions for surface roughness. *Journal of Materials Processing Technology, 170*, 11-16. doi:10.1016/j.jmatprotec.2005.04.096

Onwubolu, G. C., & Kumalo, T. (2010). Optimization of multipass turning operations with genetic algorithms. *International Journal of Production Research*, *39*(16), 3727-3745. DOI: 10.1080/00207540110056153

Saravanan, R., Asokan, P., & Vijayakumar, K. (2003). Machining parameters optimisation for turning cylindrical stock into a continuous finished profile using genetic algorithm (GA) and simulated annealing (SA). *International Journal of Advanced Manufacturing Technology*, *21*, 1-9.

Sardinas, R. Q., Santana, M. R., & Brindis E. A. (2005). Genetic algorithm-based multi-objective optimization of cutting parameters in turning processes. *Engineering Applications of Artificial Intelligence*, *19*, 127-133. doi: 10.1016/j.engappai.2005.06.007

Sardiñas, R., Q., Santana, M. R., & Brindis, E. A. (2006). Genetic algorithm-based multi-objective optimization of cutting parameters in turning processes. *Engineering Applications of Artificial Intelligence, 19*, 127-133.

Sonmez, A. I., Baykasoglu, A., Dereli, T., & Filiz, I. H., (1999). Dynamic optimization of multipass milling operation via geometric programming. *International Journal of Machine Tools & Manufacturing, 39*, 297-320.

Venkata Rao, R., & Kalyankar, V. D. (2013). Multi-pass turning process parameter optimization using teaching–learning-based optimization algorithm. *Computer Science & Engineering and Electrical Engineering*, 1-8. doi:10.1016/j.scient.2013.01.002

Wang, J., Kuriyagawa, T., Wei, X. P., & Gou, G. M. (2002). Optimization of cutting conditions using a deterministic approach. *International Journal of Machine Tools & Manufacture*, *42*, 1023-1033.

Wang, Z. G., Rahman M., Wong, Y. S., & Sun, J. (2005). Optimization of multi-pass milling using parallel genetic algorithm and parallel genetic simulated annealing. *International Journal of Machine Tools & Manufacture*, *45*, 1726-1734.

Zuperl, U., & Cus, F. (2003). Optimization of cutting conditions during cutting by using neural networks. *Robotics and Computer Integrated Manufacturing, 19*, 189-199.

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