

## USING GENETIC ALGORITHMS FOR OPTIMIZATION OF TURNING MACHINING PROCESS

DUSAN PETKOVIC<sup>1\*</sup>, MIROSLAV RADOVANOVIC<sup>1</sup>

<sup>1</sup>*University of Nis, Faculty of Mechanical Engineering, A. Medvedeva 14, 18000 Nis, Serbia*

**Abstract:** Optimization methods of machining processes are tools for improving product quality and reducing cost and production time. Modern optimization methods, among which genetic algorithms (GA) have been, used a lot during last two decades. This paper describes the optimization of machining processes by using genetic algorithms. Optimal parameters of machining (cutting speed and feed) were determined. Also, minimal cost for the turning process was achieved.

**Key words:** machining process, turning, optimization, genetic algorithm

### 1. INTRODUCTION

Optimization of cutting parameters is one of the most investigated problems in machining processes. Many of the problems relate to turning as typical machining process. The cutting parameters are often selected based on the experience or by recommendations of cutting tools' manufacturers. Their selection influences on tool life, machining time and cost of manufacturing. Determination of optimal cutting parameters is a very important task in planning of machining process, such as turning operation. Minimization of the machining cost per part is often used criterion for determination the optimal cutting parameters.

Gilbert [1] did the study of machining costs. In this study, production rate and production cost were considered. Several optimization methods for selection of cutting parameters for turning using GA have been proposed. Wang et al. [2] used genetic algorithms for determining the optimum cutting parameters in multi-pass turning operations. Saravanan et al. [3] described various optimization methods for selection of cutting parameters for turning, using conventional and non-conventional techniques, such as genetic algorithms and simulated annealing. Onwubolu and Kumalo [4] proposed an optimization method based on GA for cutting parameters determination in multi-pass turning. Car, Barisic and Ikonc [5] used genetic algorithms in order to find optimal cutting parameters for CNC turning center. Objective functions were minimum machining time and minimum production cost [6].

In this paper, use of GA for cutting parameters' optimization for turning of mild steel is described. The key parameters are cutting speed and feed. By increasing both cutting speed and feed, the machining time and cutting tool life decrease, while cost of cutting tool and tool changing time become bigger. Appropriate selection of the cutting parameters can provide a minimum machining cost.

---

\* Corresponding author, email: [dulep@masfak.ni.ac.rs](mailto:dulep@masfak.ni.ac.rs)

## 2. GENETIC ALGORITHMS

Genetic algorithms (GA) were developed with the primary intention of imitating the processes that exist in nature. Basic principles of genetic algorithms were published in 1962 (Holland) and the mathematical framework for their development was published in 1975 by the same author. In the field of optimization, these algorithms were used to: optimize functions, process of images, solve trade man problem, identification systems and control and so on. In the area of machine learning, GA were used to implement simple “If-Then” rules in an arbitrary environment [7]. Figure 1 shows a typical pattern of a genetic algorithm [8].

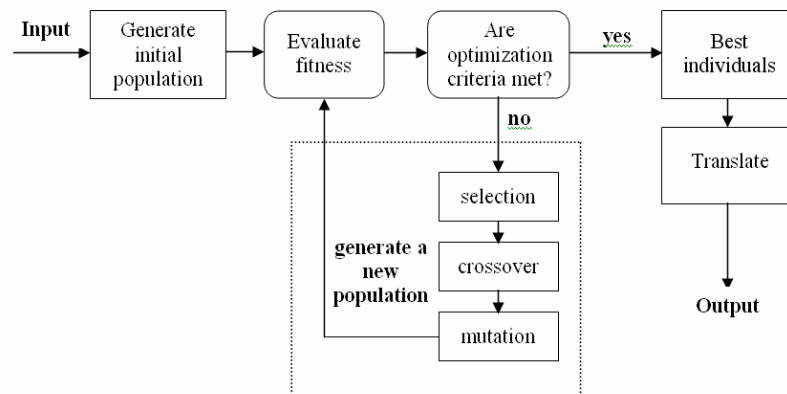


Fig. 1. Standard procedure of genetic algorithm.

Genetic algorithms are robust and adaptive methods, successfully used for solving optimization problems. They are powerful tools for the optimization of functions that can more easily locate the global optimum. The reason lies in the fact that GA seeks an optimal solution in the space of solutions, starting from groups of points, rather than a starting point. GA use only the objective function to search optimal solutions (derivatives or other additional information on the function are not necessary). The basic building block in the GA is a population of individuals, which is usually between 10 and 200. Each individual represents a possible solution of the problem. The data processed by GA are represented by an array of strings (or chromosomes) with finite length, where each bit is called allele or gene. A value of the fitness function is attached to each individual, in order to evaluate its quality. A collection of strings is called population, and the population at a certain point of time is referred as generation. The generation of the initial population of strings is done in a random way.

The basic operators on the genes in the chromosome are crossover and mutation. Reproduction of some selected chromosomes is a process in which certain binary strings are transformed and passed to the next generation. Selection is usually implemented through the so called process roulette wheel. The crossover is the main operator, which generates new strings, eventually with better fitness values. After crossover, mutation is performed to ensure some randomness in the new chromosomes. In fact, even though crossover generally leads to better results, this does not bring new quality of information on the level of bits. As a source of different quality, the mutation of bits is usually performed. Mutations can lead to degenerative solutions (which probably will be soon eliminated by the process), or to a completely new solution. These basic operators, as well as many other operators which can be applied depending on the problem, generate a new population, starting from the initial population and passing through an iterative process. This process creates a new population, which is estimated according to predefined criteria. The procedure repeats until the stopping criterion is satisfied. The Genetic algorithm has to provide a way to permanently improve, from generation to generation, the absolute fitness for each individual in the population and the average adaptability of the whole population. This is achieved by successive application of genetic operators of selection, crossing and mutation, thus getting better and better solutions to the problems under consideration [7].

Since a genetic algorithm is a stochastic search method, it is difficult to specify some convergence criteria. Fitness of the whole population may remain unchanged through generations, while superior individuals appear. Because of that, the termination of the algorithm in the classical way (conditions satisfying) becomes problematic. Most often, in practice, genetic algorithm is stopped after a certain number of generations or after a certain time interval, after which the quality of the best individuals is tested. If the result is not acceptable, we can start again to search for new (better) solutions [8].

### 3. MATHEMATICAL MODELING OF MACHINING COST

Machining optimization provides optimal or near-optimal solutions in actual metal cutting process. The optimization procedure has two phases. First phase is mathematical modeling of the machining process (cutting performances) where an objective multivariable function should be defined. In that phase, all constraints and bounds of the variables, by using equalities and (or) inequalities should be defined too. Second phase is searching for a global minimum of objective function, under all defined limitations.

The mathematical model of optimization consists of the objective function and constraints, as follows:

- Objective function:

$$\min_x f(x) \quad (1)$$

- Constraint functions:

$$A \cdot x \leq b \quad (\text{linear inequalities}) \quad (2)$$

$$A_{eq} \cdot x = b_{eq} \quad (\text{linear equalities}) \quad (3)$$

$$C_i(x) \leq 0, i = 1, \dots, m \quad (\text{nonlinear inequalities}) \quad (4)$$

$$C_{eqi}(x) = 0, i = m + 1, \dots, m + t \quad (\text{nonlinear equalities}) \quad (5)$$

$$L_b \leq x \leq U_b \quad (\text{bounds of variables}) \quad (6)$$

The objective function of the optimization model, when optimizing the turning process, is usually the cost of machining. In this case, the objective function is the minimal cost of machining. Cost of machining is directly related to machining time which is dependent on cutting speed and feed, and is defined [9] by the equation:

$$C = C_r t_L + C_r t_m + \frac{t_m}{T} (C_r t_d + C_a) \quad (7)$$

where:  $C$  (EUR) – cost of machining,  $C_r$  (EUR) – labor plus overhead cost,  $t_L$  (min) – nonproductive time,  $t_m$  (min) – machining time,  $T$  (min) – tool life,  $t_d$  (min) – tool changing time,  $C_a$  (EUR) – tool cost per cutting edge. Machining time, in turning process, can be expressed as:

$$t_m = \frac{\pi D L}{1000 v_c f} \quad (8)$$

where:  $D$  (mm) – workpiece diameter,  $L$  (mm) – length of turning,  $v_c$  (m/min) – cutting speed,  $f$  (mm/rev) – feed. The tool life is a critical parameter for the objective function and one of the machining parameters. For a given machine tool and cutting tool-workpiece combination, the relationship between the tool life and cutting speed, feed and depth of cut is:

$$T = \frac{C_T}{v_c^p \cdot f^q \cdot a_p^r} \quad (9)$$

where:  $T$  (min) – tool life,  $a_p$  (mm) – depth of cut,  $C_T$ ,  $p$ ,  $q$  and  $r$  – empirical constants. Cost of machining for turning, according to (7), (8) and (9) can be expressed by the following equation:

$$C = C_1 + C_2 v_c^{-1} f^{-1} + C_3 v_c^{p-1} f^{q-1} \quad (10)$$

where:  $C_1 = C_r t_L$ ,  $C_2 = \frac{\pi D L C_r}{1000}$  and  $C_3 = \frac{\pi D L a_p^r (C_r t_d + C_a)}{1000 \cdot C_T}$

For the elected combination of workpiece material, cutting tool, and machine tool, the cutting process becomes optimal when the cost of machining is minimal or near minimal, respecting the constraints on the operation variables  $v_c$  and  $f$ .

Constraint functions are:

- a) Constraint on the cutting tool ability:

$$v_c f^y \leq \frac{C_v k_v}{T^m a_p^x} \quad (11)$$

- b) Machine tool power force constraint:

$$v_c f^{y_1} \leq \frac{6120 \cdot P_M \cdot \eta}{C_{k1} \cdot k_F \cdot a_p^{x_1}} \quad (12)$$

- c) Strength tool constraint:

$$f^{y_1} \leq \frac{R_{sd}}{C_{k1} \cdot C_o \cdot k_F \cdot a_p^{x_1}} \quad (13)$$

- d) Stiffness workpiece constraint:

$$f^{y_1} \leq \frac{\delta_2 \cdot E \cdot I}{0.8 \cdot \mu \cdot C_{k1} \cdot l_1^3 \cdot k_F \cdot a_p^{x_1}} \quad (14)$$

- e) Constraint on the minimal spindle speed:

$$v_c \geq \frac{\pi \cdot D \cdot n_{\min}}{1000} \quad (15)$$

- f) Constraint on the maximal spindle speed:

$$v_c \leq \frac{\pi \cdot D \cdot n_{\max}}{1000} \quad (16)$$

- g) Constraint on the minimal feed:

$$f \geq f_{\min} \quad (17)$$

- h) Constraint on the maximal feed:

$$f \leq f_{\max} \quad (18)$$

In what follows, an example of optimization for single-pass external longitudinal turning is presented. The workpiece is a bar 80 mm in diameter and 165 mm in length, made from mild steel C45E (EN). Machine tool is the universal lathe powered by an electric motor of 11 kW and efficiency of  $\eta=0.8$ . Cutting tool is holder PTG NR 2020K-16 with insert TNMM 160408 made of carbide GC 135 (P35), Sandvik Coromant.

It is necessary to determine the optimal values of cutting speed and feed for the following data: starting outside diameter  $D=80$  mm, final outside diameter  $D_f=68$  mm (depth of cut  $a_p=6$  mm) and length  $l=120$  mm. Minimal spindle speed 20 rev/min, and maximal 2000 rev/min. Minimal feed is 0.04 mm/rev, and maximal feed 9 mm/rev. Maximal depth of cut is  $a_p=14$  mm. Economical tool life is  $T=15$  min. Other cutting process data [8] are:  $C_r=0.15$  EUR/min,  $C_a=0.50$  EUR,  $t_L=2.00$  min,  $t_d=1.00$  min,  $L=122$  mm  $C_1=5.13 \cdot 10^{12}$ ,  $p=5.55$ ,  $q=1.67$ ,  $r=0.83$ ,  $C_v=292$ ,  $k_v=0.668$ ,  $x=0.15$ ,  $y=0.30$ ,  $m=0.18$ ,  $C_{k1}=300$  kN/mm<sup>2</sup>,  $x_1=1.0$ ,  $y_1=0.75$ ,  $k_F=0.4$ ,  $C_o=0.03$ ,  $R_{sd}=140$  kN/mm<sup>2</sup>,  $E=2.2 \cdot 10^5$  N/mm<sup>2</sup>,  $I=88408$  mm<sup>4</sup>,  $\mu=1/3$ ,  $\ell_1=130$  mm, dry cutting.

The mathematical model of the optimization is represented as:

- Objective function:

$$\min \quad C = 0.30 + \frac{4.60}{v_c f} + 1.72 \cdot 10^{-11} v_c^{4.55} f^{0.67} \quad (19)$$

- Constraint functions:

$$(a) \quad v_c f^{0.30} \leq 91.57 \quad (20)$$

$$(b) \quad v_c f^{0.75} \leq 74.80 \quad (21)$$

$$(c) \quad f^{0.75} \leq 6.48 \quad (22)$$

$$(d) \quad f^{0.75} \leq 55.33 \quad (23)$$

$$(e) \quad v_c \geq 5.03 \quad (24)$$

$$(f) \quad v_c \leq 502.65 \quad (25)$$

$$(g) \quad f \geq 0.04 \quad (26)$$

$$(h) \quad f \leq 9 \quad (27)$$

The cost function, as the objective function, presents - in coordinate system  $0v_c f C$  - the profile surface in the first octant. Graphical representation of the cost of machining versus cutting speed and feed in turning process, based on the equation (19), is shown in Figure 2. The same figure allows us to conclude that the minimum of the function  $C = \phi(v_c, f)$  exists.

#### 4. USING GENETIC ALGORITHMS TO OPTIMIZE MACHINING COST OF TURNING PROCESS

As we mentioned in previous paragraph, the second phase is solving of mathematical model to find a global minimum of the objective function. In this case, the objective function (machining cost  $C=\phi(v_c, f)$ ) was minimized by using GA toolbox in Matlab. The definition of the machining cost in Matlab environment is as follows:

```
function C = turning_cost(x)
C = 0.3+4.6/(x(1)*x(2))+1.72*10^-11*x(1)^4.55*x(2)^0.67;
end
```

Now we need to define the nonlinear constraints, based on inequalities (20), (21) and (22). The inequality (23) was not considered, because it has been incorporated in the inequality (22). Nonlinear constraints were defined as:

```
function [c, ceq] = nonlinear_constraints(x)
c = [x(1)*x(2)^0.3-91.57;
x(1)*x(2)^0.75-74.8;
x(2)^0.75-6.48];
ceq = [];
end
```

All data should be typed in the appropriate fields (Figure 3).

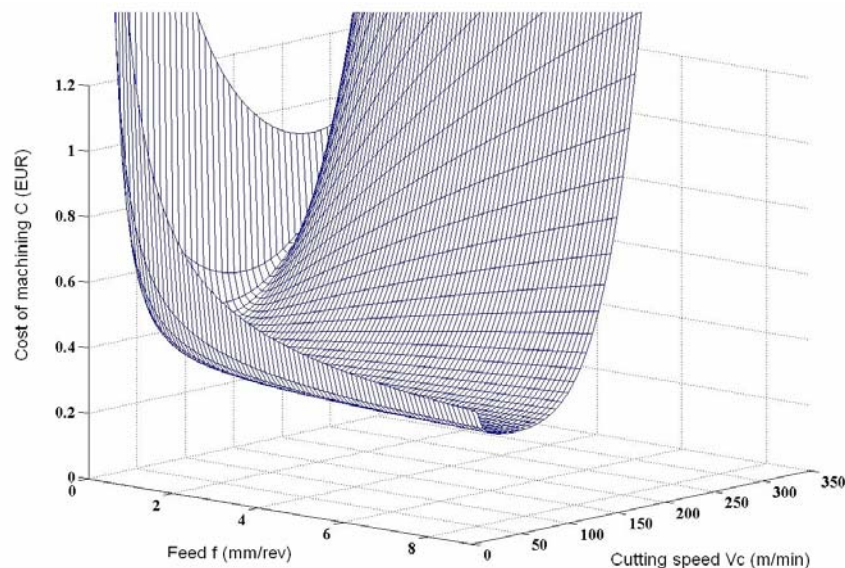


Fig. 2. Graphical representation of cost of machining versus cutting speed and feed in turning process.

When the optimization process was terminated, the minimal value of the objective function (19), satisfying the constraints from (20) to (27), was found to be cost of machining  $C_{\min}=0.335519$  EUR, for cutting speed  $v_c=14.395$  m/min and feed  $f=9.0$  mm/rev. This result was obtained with initial population [15 9] in the 8<sup>th</sup> iteration and the necessary time for solving was approximately 60 seconds. Then, population size, generations and initial population have been changed, but the same or very closed results have been obtained in all cases. GA parameters of the case, illustrated in Figure 3, are listed below.

Options:

- Population type: double vector
- Pop init. range: 2x1 double
- Population size: 100
- Elite count: 2
- Crossover fraction: 0.8
- Pareto fraction: []
- Migration direction: forward
- Migration interval: 20
- Migration fraction: 0.2
- Generations: 100
- Time limit: Inf
- Fitness limit: -Inf
- Stall gen limit: 50
- Stall time limit: Inf
- Tol fun: 1.0000e-015
- Tol con: 1.0000e-015

Initial population: [15 9]  
 Initial scores: []  
 Initial penalty: 10  
 Penalty factor: 100  
 Plot interval: 1  
 Creation fcn: @gacreationuniform  
 Fitness scaling fcn: @fitscalingrank  
 Selection fcn: @selectionstochunif  
 Crossover fcn: @crossoverscattered  
 Mutation fcn: [1x1 function\_handle] [1] [1]  
 Distance measure fcn: []  
 Hybrid fcn: []  
 Display: diagnose  
 Plot fcn: @gaplotbestf @gaplotbestindiv  
 Output fcn: [] @gatooloutput  
 Vectorized: off  
 Use parallel: never  
 Diagnostic information:  
   Fitness function = @ turning\_cost  
   Number of variables = 2  
   Nonlinear constraint function = @ nonlinear\_constraints  
   0 Inequality constraints  
   0 Equality constraints  
   0 Total numbers of linear constraints

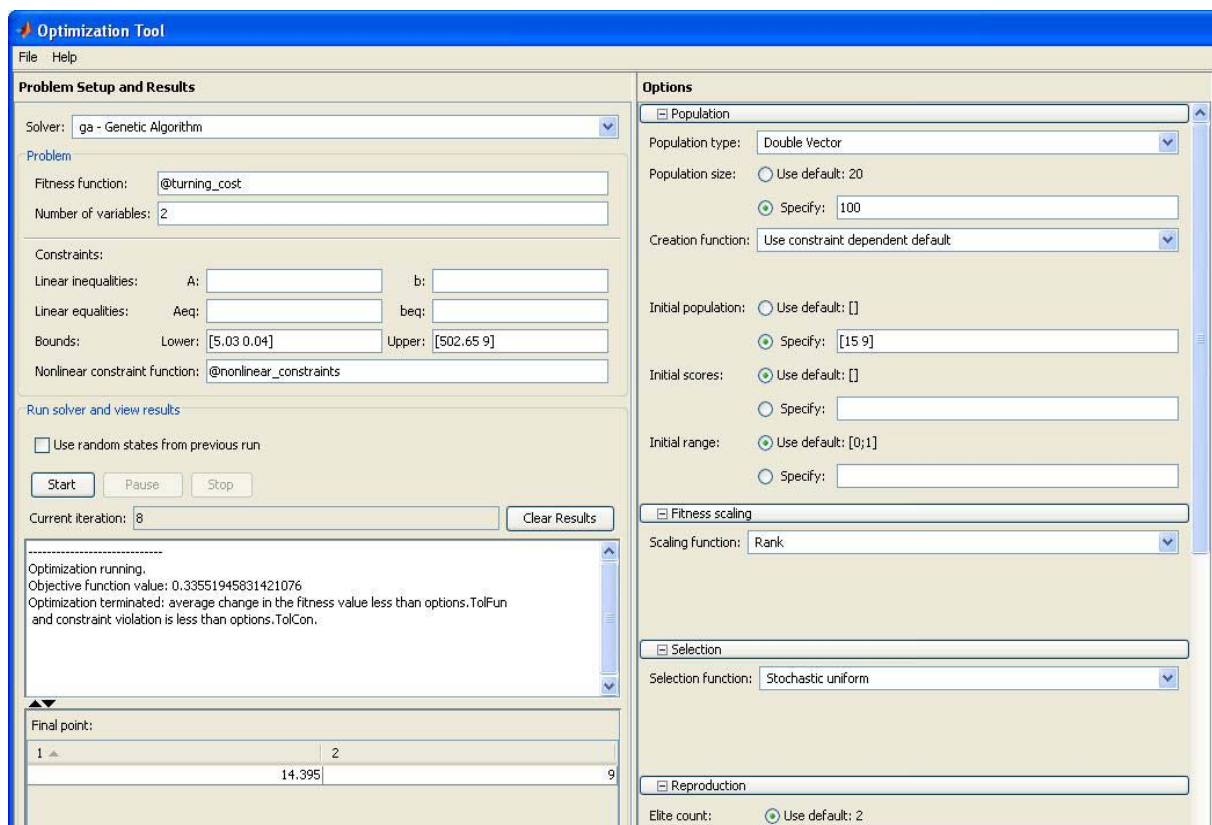


Fig. 3. GA Toolbox in Matlab environment.

## 5. RESULTS CHEKING BY USING SEQUENTIAL QUADRATIC PROGRAMMING ALGORITHM

Sequential quadratic programming algorithm (SQP) was applied to check the result obtained through the use of GA (described in previous paragraphs). The data to be introduced in SQP are the same as in the GA (fitness function: @ turning\_cost; bounds: lower [5.03 0.04] and upper [502.65 9]; and nonlinear constraint function: @nonlinear\_constraints). When the optimization process was terminated, the minimal value of the objective function (19), satisfying the constraints from (20) to (27) was found to be  $C_{\min}=0.335519$  EUR, for cutting speed  $v_c=14.395$  m/min and feed  $f=9.0$  mm/rev. This result was obtained in the 19<sup>th</sup> iteration and corresponded with values of cost of machining, cutting speed and feed obtained through the use of GA. Appearance of SQP Toolbox in Matlab environment is shown in Figure 4.

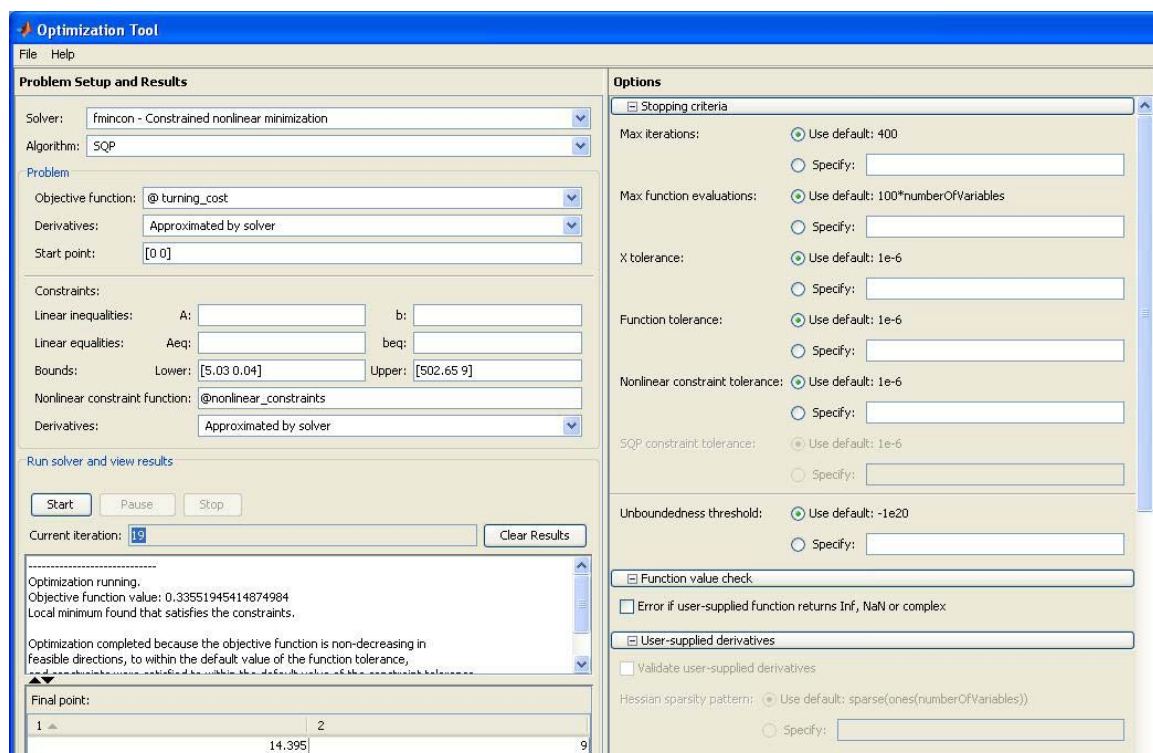


Fig. 4. SQP Toolbox in Matlab environment.

## 6. CONCLUSION

Modern methods of optimization are powerful and popular tools for solving complex engineering optimization problems. This paper shows the possibilities of using genetic algorithms for solving such problems. Cost of machining in turning process, depending on cutting speed and feed was minimized under some nonlinear constraints. The possibility of finding the minimum of the function (under linear and nonlinear constraints) and the fact that derivatives or other additional information on the function are not necessary are basic advantages of GA. The results obtained through the use of GA were checked by SQP (Sequential Quadratic Programming) algorithm and proved to be the same with the values of machining cost, cutting speed and feed found with the GA. In this case was shown the GA method is better than SQP in terms of execution time and number of iterations. We can conclude that GA is a modern optimization method for finding the optimal values of functions with many variables, such as those modeling the turning process.

## ACKNOWLEDGEMENT

The paper is a result of the technological project TR35034 which is supported by the Ministry of Science and Technological Development of the Republic of Serbia.



**REFERENCES**

- [1] Gilbert, W., Economics of machining - Machining Theory and Practice, American Society for Metals, 1950, p. 465-485.
- [2] Wang, D., Zuo, M., Qi, K., Liang, M., On-line tool adjustment with adaptive tool wear function identification, International Journal of Production Research, vol. 34, no. 9, 1996, p. 2499-2515.
- [3] Saravanan, R., Ashokan, P., Sachithanandam, M., Comparative analysis of conventional and non-conventional optimization technique for CNC-turning process, International Journal of Advanced Manufacturing Technology, vol. 17, 2001, p. 471-476.
- [4] Onwubolu, G., Kumalo, T., Optimization of multi pass turning operations with genetic algorithms, International Journal of Production Research, vol. 39, no. 16, 2001, p. 3727-3745.
- [5] Car, Z., Barisic, B., Ikonic, M., GA based CNC turning center exploitation process parameters optimization, Metalurgija, vol. 48, no. 1, 2009, p. 47-50.
- [6] Neelesh, K. J., Jain, V.K., Kalyanmoy, D., Optimization of process parameters of mechanical type advanced machining processes using genetic algorithms, International Journal of Machine Tools and Manufacture, vol. 47, no. 6, 2007, p. 900-919.
- [7] Cao, Y., Wu, Q., Teaching genetic algorithm using Matlab, International Journal of Electrical Engineering Education, vol. 36, 1999, p. 139-153.
- [8] Chipperfield, A., Fleming, P., Pohlheim, H., Fonseca, C., Genetic algorithm toolbox for use with Matlab, 1994, [www.citeseer.ist.psu.edu/502345.html](http://www.citeseer.ist.psu.edu/502345.html).
- [9] Radovanovic, M., Marinkovic, V., Graphical-Analytical Method for Determining the Optimal Cutting Parameters, Proceeding of the International Conference Mechanical Engineering in XXI Century, University of Nis, Faculty of Mechanical Engineering, Nis, Serbia, 2010, p. 171-174.