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Multi-Objective Optimization Using Genetic Algorithms of Multi-Pass Turning Process

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ABSTRACT

In this paper we present a multi-optimization technique based on genetic algorithms to search optimal cuttings parameters such as cutting depth, feed rate and cutting speed of multi-pass turning processes. Tow objective functions are simultaneously optimized under a set of practical of machining constraints, the first objective function is cutting cost and the second one is the used tool life time. The proposed model deals multi-pass turning processes where the cutting operations are divided into multi-pass rough machining and finish machining. Results obtained from Genetic Algorithms method are presented in Pareto frontier graphic; this technique helps us in decision making process. An example is presented to illustrate the procedure of this technique.

Keywords: Genetic Algorithms; Mutli-Objective Optimization; Turning Process; Machining

1. Introduction

Cutting parameters such as depth of cut, cutting speed and feed rate influence directly on machining time and cost, in addition these parameters have a great impact on product quality. The objective of process planning is to select appropriate cutting parameters which generate maximum profit rate to the company and reach costumer requirements in terms of product quality and lead time. Cutting parameters are: cutting speed (**V**), feed rate (**f**) and cutting depth (**d**), **Figure 1** illustrates these parameters. In the present paper we present a multi-objective optimization technique of multi-pass turning processes based on Genetic Algorithms. Indeed, tow objective functions are simultaneously optimized which are the cutting cost and the used tool life of cutting tool, subject to a set of practical constraints like cutting force, machine power and surface quality.

Several previous research have dealt with cutting conditions optimization by means of different techniques, fuzzy logics, neural networks, simulated annealing, genetic algorithms, colony optimization and practical swarm optimization, etc.

Tsai [1] studied the relationship between the multi-pass machining and single-pass machining. He presented the concept of a break-even point, *i.e.* there is always a point, a certain value of depth of cut, at which single-pass and double-pass machining are equally effective. When the depth of cut drops below the break-even point, the single-pass is more economical than the double-pass, and when the depth of cut rises above this break-even point, double-pass is better. Carbide tools are used to turn the carbon steel work material.

Chua [2] used a sequential quadratic programming technique for optimizing the cutting conditions for multi-pass turning operations. Shin and Joo [3] proposed a mathematical model for the multi-pass turning process, which was subsequently used by many researchers.

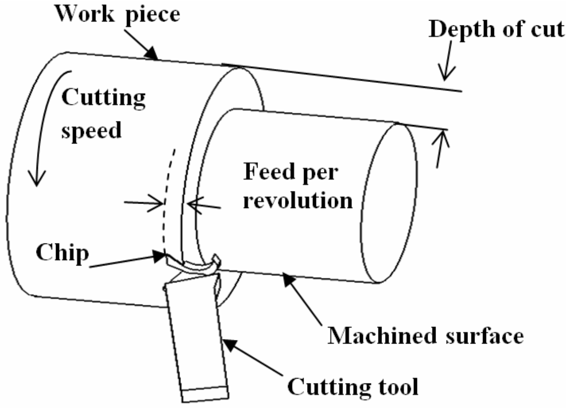

Figure 1. Cutting parameters of a turning operation.

Agapiou [4] formulated single-pass and multi-pass machining operations. Production cost and total time were taken as objectives and a weighting factor was assigned to prioritize, the two objectives in the objective function. He optimized the number of passes, depth of cut, cutting speed and feed rate in his model, through a multi-stage solution process called dynamic programming. Several physical constraints were considered and applied in his model. In his solution methodology, every cutting pass is independent of the previous pass; hence the optimality for each pass is not reached simultaneously.

A feed-forward neural network was used by Wang [5] for solving the multi-objective problem, which involved productivity, operation cost and cutting quality. Gupta [6] worked on the optimality of depth of cut of the multi-pass turning operation using an integer programming model. Chen and Tsai [7] applied the simulated annealing approach to solve the optimization problem for minimum unit production costs of the multi-pass turning process. Kee [8] outlined the optimization strategies for multi-pass rough turning on conventional and CNC lathes with practical constraints, such as force and power. Nian [9] carried out the optimization of turning operations based on the Taguchi method and considered various multiple performance characteristics, such as tool life, cutting force, and surface finish. Alberti and Perrone [10] used the genetic algorithm to solve a fuzzy probabilistic optimization model for determining the cutting parameters.

Arezoo [11] developed an expert system to select cutting tools and conditions of turning operations using Prolog. The system can select the tool holder, and the insert and cutting conditions, such as cutting speed, feed rate and depth of cut. Dynamic programming was used to optimize the cutting conditions. Dereli [12] developed an optimization system for cutting parameters of prismatic parts based on genetic algorithms. Onwubolu and Kumalo [13] used the mathematical model of Chen and Tsai [7] and applied the genetic algorithm to minimize the unit production cost. Al-Ahmari [14] presented a nonlinear programming model for the optimization of machining parameters and subdivisions of the depth of cut in multi-pass turning operations. Wang [15] used the genetic algorithm to select optimal cutting parameters and cutting tools in multi-pass turning operations with more focus on the tool wear and chip breakability aspects of the process.

Vijayakumar [16] used the ant colony optimization algorithm and attempted the same mathematical model as Chen and Tsai [7] and Onwubolu and Kumalo [13]. Franci and Joze [17] proposed a multi-objective optimization technique based on Genetic Algorithm where cutting cost, cutting time and surface quality are optimized simultaneously. Zuperl [18] proposed a hybrid optimization technique for complex optimization of cutting parameters; this optimization technique is based on the Artificial Neural Network ANN and OPTIS routine.

Wang and Jawahir [19] proposed a new GA-based methodology, whose research was focused on the selection of different cutting tools for different passes of turning operations and allocation of the depth of cut. Sardinas [20] used the micro-genetic algorithm for attempting the multi-objective optimization model and obtained the Pareto front result. Cus and Zuperl [21] proposed an optimization technique based on Artificial Neural Network to solve the same problem studied by Franci and Joze [17].

Abburi and Dixit [22] developed an optimization methodology, which was a combination of a real coded genetic algorithm and sequential quadratic programming, to obtain Pareto optimal solutions for minimizing the production cost. Yildiz [23] attempted the same mathematical model as Vijayakumar [16] using the hybrid Taguchi harmony search algorithm. Ojha [24] used a neural network fuzzy set and genetic algorithm-based soft computing methodology to optimize process parameters in multi-pass turning operations. Srinivas [25] used particle swarm intelligence for selecting the optimum machining parameters in multi-pass turning operations.

Deepak [26] used a geometric programming method to optimize the production time of turning process; in this technique, only cutting speed and feed rate are taken in consideration. venkata and kaliyankar [27] the parameter optimization of a multi-pass turning operation was carried out using an optimization algorithm, named, the teaching-learning-based optimization algorithm. For detailed literature review, see Aggarwal [28] and Deepak [29].

The above mentioned efforts show the interest of selecting optimal cutting parameters in turning process. Almost all research papers have dealt with multi-pass process turning; in our study we propose an optimization of multi-pass turning process where two objective functions are optimized simultaneously: cutting cost and used tool life of cutting tool.

2. Multi Pass Turning Process Model

The goal of this multi-optimization cutting model is to determine the optimal machining parameters "cutting speed, feed rate, and cutting depth" in order to minimize simultaneously the cutting cost and the used tool life of a multi pass turning process; In other words this turning process has multiple rough cut and a single finish cut. Therefore, this optimization model includes six machining parameters ($\mathbf{V}_r$, $\mathbf{f}_r$, $\mathbf{d}_r$, $\mathbf{V}_f$, $\mathbf{f}_f$, $\mathbf{d}_f$): the three first parameters for rough machining and the last three parameters are for finishing operation.

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2.1. Notation Used in the Cutting Model

C_m	cutting cost by actual time in cut ($/piece),
K_o	direct labor cost + overhead ($/min),
D, L	diameter and length of work-piece (mm),
n	number of rough cuts as integer
T, T_r, T_f	tool life, expected tool life for rough machining, and expected tool life, for finish machining (min),
T_p	tool life of weighted combination of T_f and T_r (min),
θ	a weight for T_p [0, 1],
T_U, T_L	upper and lower bounds for tool life (min),
d_t	depth of material to be removed (mm),
C_0, p, q, r	constants of the tool-life equation,
K_1, ν, μ	constants of cutting force equation,
K_2, τ, ϕ, δ	constants related to equation of chip-tool interface temperature,
R	Surface roughness
R_a	nose radius of cutting tool (mm),
SR_U	maximum allowable surface roughness (mm),
F_U	maximum allowable cutting force (kgf),
P_U	maximum allowable cutting power (kW), power efficiency,
Q_r, Q_f	chip-tool interface rough and finish machining temperatures(˚C),
Q_U	maximum allowable chip-tool interface temperature (˚C),
V_{rL}, V_{rU}	lower and upper bound of cutting speed in rough machining (m/min),
d_{rL}, d_{rU}	lower and upper bound of depth of cut in rough machining (mm),
f_{rL}, f_{rU}	lower and upper bound of feed rate in rough machining (mm/rev),
V_{fL}, V_{fU}	lower and upper bound of cutting speed in finish machining (m/min),
d_{fL}, d_{fU}	lower and upper bound of depth of cut in finish machining (mm),
f_{fL}, f_{fU}	Lower and upper boud of feed rate in finish machining (mm/rev),

2.2. Objective Functions

In this model, we adopt the same components considered in the previous works related to multi-pass turning process: [3,7,13].

2.2.1. Cutting Cost

According to [3], the unit production cost for the multi pass turning operations problem consists of four basic cost components:

- Cutting cost by actual time in cutting operation,
- Machine idle cost due to loading and unloading operations and idle tool motion,
- Cost for tool replacement,
- Tool cost.

In this work, we consider only the Cutting cost for multi-pass turning process, it is expressed as:

$$C_m = K_o \times t_m \tag{1}$$

where: t_m is the cutting time of the actual operation [3].

Since the operation is a multi-pass, t_m can be divided into two parts; therefore it is expressed as the sum of roughing and finishing operations times:

$$t_m = t_{mr} + t_{mf} \tag{2}$$

where:

$$t_{mr} = \frac{\pi DL}{1000 V_r f_r} \times n = \frac{\pi DL}{1000 V_r f_r}\left(\frac{d_t - d_f}{d_r}\right) \tag{3}$$

$$t_{mf} = \frac{\pi DL}{1000 V_f f_f} \tag{4}$$

Finally, based on the above equations, the cutting cost can be expressed as:

$$C_m = K_o \times \left[\frac{\pi DL}{1000 V_r f_r}\left(\frac{d_t - d_f}{d_r}\right) + \frac{\pi DL}{1000 V_f f_f}\right] \tag{5}$$

2.2.2. Used Tool Life

The second objective function is the used tool life ξ, it is considered as the part of the whole tool life which is consumed in the process:

$$\xi = \left(\frac{t_{mr}}{\theta T_r} + \frac{t_{mf}}{(1-\theta) T_f}\right) 100\% \tag{6}$$

where: T_r and T_f are the Taylor tool life of roughing and finishing operations, respectively [30].

$$\xi = \left(\frac{\frac{\pi DL}{1000 V_r f_r}\left(\frac{d_t - d_f}{d_r}\right)}{\theta T_r} + \frac{\frac{\pi DL}{1000 V_f f_f}}{(1-\theta) T_f}\right) 100\% \tag{7}$$

$$T_r = \frac{C_0}{V_r^p f_r^q d_r^r} \tag{8}$$

$$T_f = \frac{C_0}{V_f^p f_f^q d_f^r} \tag{9}$$

2.3. Machining Constraints

Several constraints are taken in consideration in this model; some of these limitations are the allowed values of cutting parameters (cutting speed **V**, feed rate **f** and cutting depth **d**), given by the tool maker, and limited by the bottom and top permissible limits.

For the selected tool the tool maker specifies the limitations of the cutting conditions. The limitation on the machine is the cutting power and the cutting force. Similarly, the machining characteristics of the work piece material are determined by physical properties. The consumption of the power [3] can be expressed as the function of the cutting force and cutting speed:

$$P = \frac{FV}{6120\eta} \tag{10}$$

where η is the mechanical efficiency of the machine and F is given by the following formula [3]:

$$F = K_1 f^{\mu} d^{\nu} \tag{11}$$

Other limitations that will be taken into account are: surface finish constraint [31] and chip-tool interface temperature constraint, [32].

$$Q = K_2 V^{\tau} f^{\phi} d^{\delta} \tag{12}$$

$$R = \frac{f^2}{8 \times R_a} \tag{13}$$

2.4. Final Cutting Model

Based on the previous equations, the optimization model for multi pass turning operation can be formulated as shown below:

$$\min\left(C_m = K_o\left[\frac{\pi DL}{1000V_r f_r}\left(\frac{d_t - d_f}{d_r}\right) + \frac{\pi DL}{1000V_f f_f}\right]\right) \tag{14}$$

$$\min\left(\xi = \left(\frac{\frac{\pi DL}{1000V_r f_r}\left(\frac{d_t - d_f}{d_r}\right)}{\theta T_r} + \frac{\frac{\pi DL}{1000V_f f_f}}{(1-\theta)T_f}\right)\times 100\%\right) \tag{15}$$

Subject to:

Roughing:

$$V_{rL} \le V_r \le V_{rU} \tag{16}$$

$$d_{rL} \le d_r \le d_{rU} \tag{17}$$

$$f_{rL} \le f_r \le f_{rU} \tag{18}$$

$$F_r \le F_U \tag{19}$$

$$P_r \le P_U \tag{20}$$

$$Q_r \le Q_U \tag{21}$$

Finishing:

$$V_{fL} \le V_f \le V_{fU} \tag{22}$$

$$d_{fL} \le d_f \le d_{fU} \tag{23}$$

$$f_{fL} \le f_f \le f_{fU} \quad (24)$$

$$F_f \le F_U \quad (24)$$

$$P_f \le P_U \tag{26}$$

$$Q_f \le Q_U \tag{27}$$

$$R_f \le SR_U \tag{28}$$

The cutting model formulated above is non-linear constrained programming (NCP) problem with multiple continuous variables referred to as the machining parameters. The machining parameters in roughing and finishing are dependent intrinsically, hence they are analyzed simultaneously. The proposed genetic algorithm optimization technique that is capable of solving the complex problem is described below.

3. Optimization Algorithm

3.1. Genetic Algorithms

Genetic Algorithms (GA) are search algorithms based on the mechanics of natural selection and natural genetics [33]. GA then iteratively creates new populations from the old by ranking the strings and interbreeding the fittest to create new, and conceivably better, populations of strings which are (hopefully) closer to the optimum solution to the problem at hand. So in each generation, the GA creates a set of strings from the bits and pieces of the previous strings, occasionally adding random new data to keep the population from stagnating. The end result is a search strategy that is tailored for vast, complex, multimodal search spaces. GA is a form of randomized search, in that the way in which strings are chosen and combined is a stochastic process; **Figure 2** shows a flow chart of

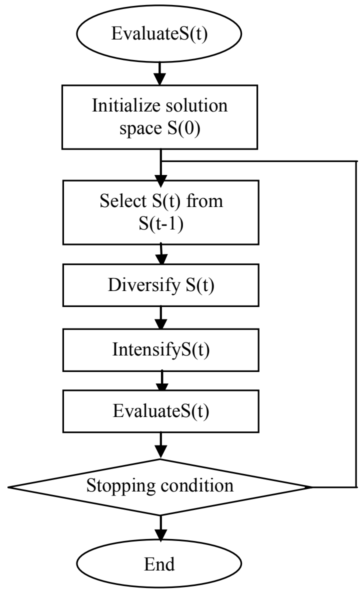

Figure 2. Flowchart of the basic genetic algorithm steps, [13].

geneticalgorithm method, [13].

3.2. Basic Genetic Algorithm Operations

There are three basic operators found in every genetic algorithm: initialization, evaluation, selection, diversification and intensification.

3.2.1. Initialization

The first step of GA is the generation of the individuals for the initial population. Randomly generated strings of Feed rate, speed and depth of cut form the solution space (popsize). These strings are generated between the limits:

- Feed rate: $[f_{rL}, f_{rU}]$ and $[f_{fL}, f_{fU}]$ for the roughing and finishing conditions respectively.
- Speed: $[V_{rL}, V_{rU}]$ and $[V_{fL}, V_{fU}]$ for the roughing and finishing conditions respectively.
- Depth of cut: $[d_{rL}, d_{rU}]$ and $[d_{fL}, d_{fU}]$ for the roughing and finishing conditions respectively.

3.2.2. Evaluation

This operation allows individual strings to be copied for possible inclusion in the next generation. The chance that a string will be copied is based on the string's fitness value, calculated from a fitness function. For each generation, the reproduction operator chooses strings that are placed into a mating pool, which is used as the basis for creating the next generation.

A score (objective) function is calculated, it represents the score for each strings of the solution space and the string that has the maximum score function value is determined. For an optimization problem where there is a function to be minimized, the competitiveness of the i^{th} solution $f^i(t)$ is obtained as follows:

$$f^i(t) = f^i_{\max} - g^i(t) \tag{29}$$

where $g^i(t)$ is the objective function of a string and $f_{\max}$ is the least objective function value in the current solution space. The corresponding selection probability $P(i)$ is equal to:

$$P(i) = \frac{f^i(t)}{\sum_{k=1}^{\text{popsize}} f^i(t)} \tag{30}$$

The most competitive solution strings are affected by a higher probability of sampling, for advancement to subsequent state.

There are six alternate selection schemes presented in [33] deterministic sampling, remainder stochastic sampling without replacement, remainder stochastic sampling with replacement, stochastic sampling without replacement, stochastic sampling with replacement, and stochastic tournament. The remainder stochastic sampling without replacement is superior to other five strategies [33] and is the one used in the work reported here. In this strategy, the expected count e_i is calculated as usual:

$$e_i = \frac{f^i(t)}{\sum_{k=1}^{\text{popsize}} f^i(t) / \text{popsize}} \tag{31}$$

The fractional parts of e_i are treated as probabilities. One by one, weighted coin tosses are performed using the fractional parts as success probabilities. The strings receive copies equal to the whole parts of e_i.

3.2.3. Crossover Operation

Crossover in biological terms refers to the blending of chromosomes from the parents to produce new chromosomes for the offspring. The analogy carries over to crossover in Gas. The GA selects two strings at random from the mating pool and then calculates whether crossover should take place using a parameter called the crossover probability (pcross). If the GA decides not to perform crossover, the two selected strings are simply copied to the new population. If crossover does take place, then a random splicing point is chosen in a string, the two strings are spliced and the spliced regions are mixed to create two (potentially) new strings. These child strings are then placed in the new population. As an example, we present a two-point crossover on a binary number. The following strings are selected for crossover:

String 1: 000000000000001^001^110.

String 2: 000000000000001^101^100.

where: "^" represents the cross positions.

After crossover operation, the newly created strings are:

New String 1: 000000000000001^101^110.

New String 2: 000000000000001^001^100.

3.2.4. Mutation

Mutation is a random modification of a randomly selected string. It guarantees the possibility of exploring the space of solutions for any initial solution space so as to permit a zone of local minimum to be abandoned. Mutation is done with a mutation probability (Pmutate). Two random integers r_1, and r_2 are selected from strings 1 and 2 respectively such that $1 \le r_1$; $r_2 \le n$ (block-size) and $r_1 \ne r_2$. The GA procedure then inverts (from 0 to 1, or 1 to 0) string bits designated by positions r_1 and r_2. For example, if $r_1 = 17$ and $r_2 = 18$, then the previous new strings 1 and 2 (mutated positions are underlined) become:

New String 1: 0000000000000001001110.

New String 2: 0000000000000001011100.

4. An Application Example

In this section an example is presented to illustrate the proposed multi-objective optimization. As presented in previous section two objective functions are optimized simultaneously and the optimal parameter conditions are to be found. Thereafter, we will present machining characteristics related to cutting tools, machine and characteristics of the part to be machined, etc. these machining characteristics are the same used previous studies, namely: [7,13].

4.1. Machining Parameters

- **Cutting tool:**
  $p = 5$, $q = 1.75$, $r = 0.75$, $\theta = 0.7$, $k_2 = 132$, $\phi = 0.2$, $\delta = 0.105$, $\tau = 0.4$, $Q_u = 1000^\circ C$, $C_0 = 6.10^{11}$.
- **Machine tool**
  $\eta = 0.85$, $P_u = 200$ kw, $k_1 = 108$, $\mu = 0.75$, $v = 0.95$, $F_u = 5.0$ kgf, $k_0 = 0.5$ \$/min.
- **Work piece**
  $D = 50$ mm, $L = 300$ mm, $d_t = 6$ mm, $S_r = 10$ μm, $R = 1.2$ mm.
- **Cutting parameters limitation**
  $V_{rL} = 50$ mm/min, $V_{rU} = 500$ mm/min, $f_{rL} = 0.1$ mm/rev, $f_{rL} = 0.9$ mm/rev
  $d_{rL} = 1.0$ mm, $d_{rU} = 3.0$ mm, $V_{fL} = 50$ mm/min, $V_{fU} = 500$ mm/min, $f_{fL} = 0.1$ mm/rev,
  $f_{fL} = 0.9$ mm/rev, $d_{fL} = 1.0$ mm, $d_{fU} = 3.0$ mm.

4.2. Genetic Algorithms Feature

The proposed optimization with genetic algorithms was written in Python 3.3.0 and the parameters used in this program are summarized in **table 1**.

4.3. Cutting Parameters Representation

The string-bit block encoding the machining information is structured as follows: the rough machining and finish machining parameters are variables that specify the values coded in six solution string-bit blocks. The cutting speeds (**V_r**, **V_f**), feed rates (**f_r**, **f_f**) and depths of cut (**d_r**, **d_f**) for both rough machining and finish machining conditions are real numbers. Each of these variables is converted to a binary string and allocated to a 22-bit block. The binary information is manipulated by the genetic operators and reconverted into real numbers.

A binary string is used as solution string to represent real values of a variable x. The length of the string depends on the required precision, which in the turning operations; we used six places after the decimal point. The domain of the variable x has length = 4, so that the precision requirement implies that the range [−2; −1; 1; 2] should be divided into at least 4.10^6 equal size ranges. This symmetric range was chosen to accommodate the roughing and finishing machining conditions. This means that 22 bits are required as a binary string (solution string):

$$2097152 = 2^{21} \le 4000000 \le 2^{22} = 4194304$$

The mapping from a real number x from the range into a binary string $\{b_{21}; b_{20}; \cdots; b_0\}$ is completed in two steps:

Step 1. Find a corresponding real number x:

$$x = -2.0 + x' \times \frac{4}{\left(2^{22}-1\right)} \quad (32)$$

where 2.0 is the left boundary of the domain and 4 is the length of the domain.

Step 2. Convert the binary string from the base 2 to base 10 as follows:

$$\left(\{b_{21}, b_{20}, \cdots, b_0\}\right)_2 = \left(\sum_{i=0}^{21} b_i \times 2^i\right)_{10} = x' \quad (33)$$

For example, a solution-string block for a feed rate of 0.729 mm/rev is obtained by inserting this value into Step 1 above as x and solving for x'. The x' is then transformed into a binary string in Step 2 as follows:

$$0.729 = -2.0 + x' \times \frac{4}{\left(2^{22}-1\right)}$$

$$x' = \left(0.729+2\right) \times \frac{\left(2^{22}-1\right)}{4} = 2861560.5 = \left(2861561\right)_{10}$$

In binary form, $x' = \left(1010111010100111111001\right)_2$.

Operationally, the six machining parameters generated randomly are in base 10 as real numbers, for each string of the solution space. Internally, the information is converted into binary numbers and operated upon by the genetic operators. These are stored in temporary solution space and reconverted into real number again, using the binary mapping technique.

5. Results and Discussion

The results obtained from GA are discussed in this section. **Table 2** shows the obtained Paretian points after evolutionary process. Used tool life (ξ) and cutting cost (\$) are reported in the second and the third column, respectively. Cutting parameters (for roughing and finishing operations) related to each point are also presented in the same table. These points were plotted on **Figure 3**. From this graph, some decisions could be made.

Indeed, from C_m = 2.128\$ to C_m = 3.774\$, the used tool life decreases 6 times while the cutting cost increases by 77%. But, from C_m = 3.774\$ to C_m = 9.013\$,

Table 1. The proposed genetic algorithms parameters.

Parameter	value
Solution space size (*popsize*)	200
Maximum number of iterations	100
Crossover probability (*Pcoss*)	70%
Mutation probability (*Pmutate*)	5%

Table 2. Pareto front points generated by the proposed optimization technique.

N°	C_m ($)	ζ (%)	f_r (mm/rev)	d_r (mm)	V_r (m/min)	f_f (mm/rev)	d_f (mm)	V_f (m/min)
1	2.128	27.780	0.258	1.231	212.127	0.193	1.303	250.777
2	2.251	22.064	0.258	1.231	212.128	0.193	1.428	186.777
3	2.546	13.081	0.116	2.289	208.381	0.240	1.309	177.725
4	2.951	8.887	0.115	2.287	176.138	0.241	1.309	173.600
5	3.303	6.758	0.163	1.749	157.624	0.297	1.030	113.811
6	3.619	5.006	0.106	2.468	165.480	0.139	1.962	119.811
7	3.774	3.963	0.115	2.373	144.219	0.166	1.634	121.162
8	5.003	1.684	0.142	1.994	101.711	0.120	2.197	103.352
9	5.543	1.214	0.114	2.376	94.075	0.131	2.056	94.648
10	6.242	0.899	0.133	2.135	82.057	0.118	2.106	86.302
11	7.044	0.530	0.103	2.628	75.415	0.231	1.371	60.907
12	8.056	0.435	0.207	1.486	60.565	0.177	1.566	54.171
13	9.013	0.274	0.127	2.205	55.618	0.226	1.332	52.609

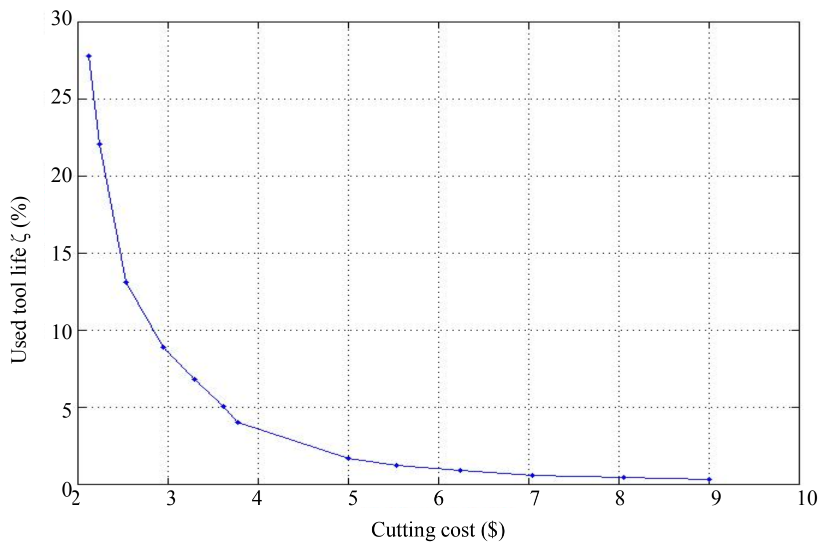

Figure 3. Pareto Front.

the used tool life decreases drastically, however the cutting cost increases by 140%. For a normal state, it is clear that the point (C_m = 3.774$ and ξ = 4%) is to be selected point 7 in **Table 2**.

After this point: cutting cost increases but the other hand we do not gain great reduction of used tool life; before this value (3.774$ and ξ = 4%), cutting cost is reduced but used tool life is more and more greater which could increases strongly the total cutting cost.

In terms of cost, the cost selected tool edge is 14.17$, which means that the tool cost of this operation is 0.5$ and cutting cost is 4$. After this point cutting tool cost is reduced to 0.25$ but which means that we gain 0.25$ but in the other hand cutting cost increase by 1$, **Figure 4**.

The total cost of cutting operation is the sum of cutting cost and the tool cost. **Figure 4** presents the sum of these two entities of each points of **Table 2**. From this graph it is clear that: points from 4 to 7 are optimal values of cutting cost and used cutting tool.

Figure 5 presents objective functions (Used tool life and cutting cost) in function of feed rate and cutting speed. From these figures it is clear that:

- Used tool life increases with cutting speed,
- Cutting cost decreases with cutting speed.

Minimum cutting cost is achieved for maximal values of cutting speed, however for minimal used tool life, lit-

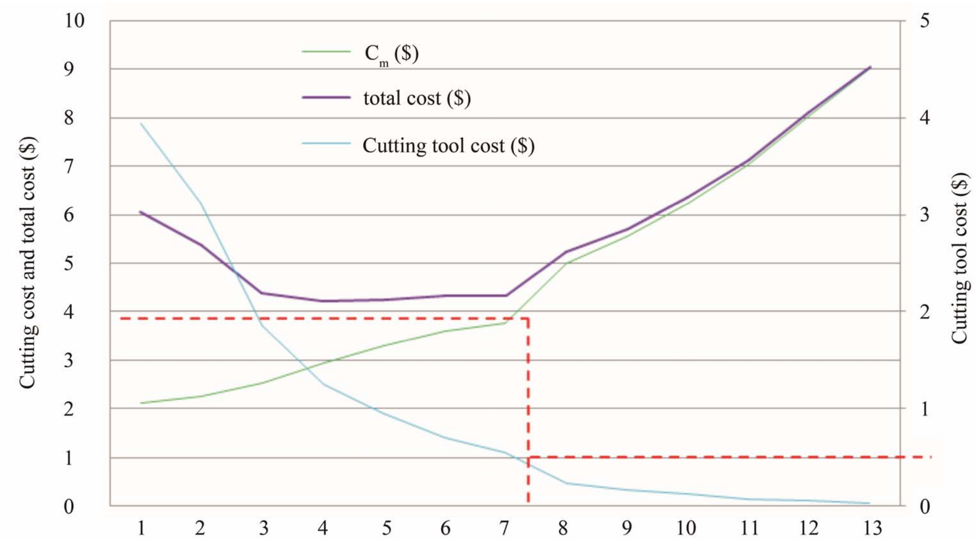

Figure 4. Cutting tool, cutting cost and total cutting cost.

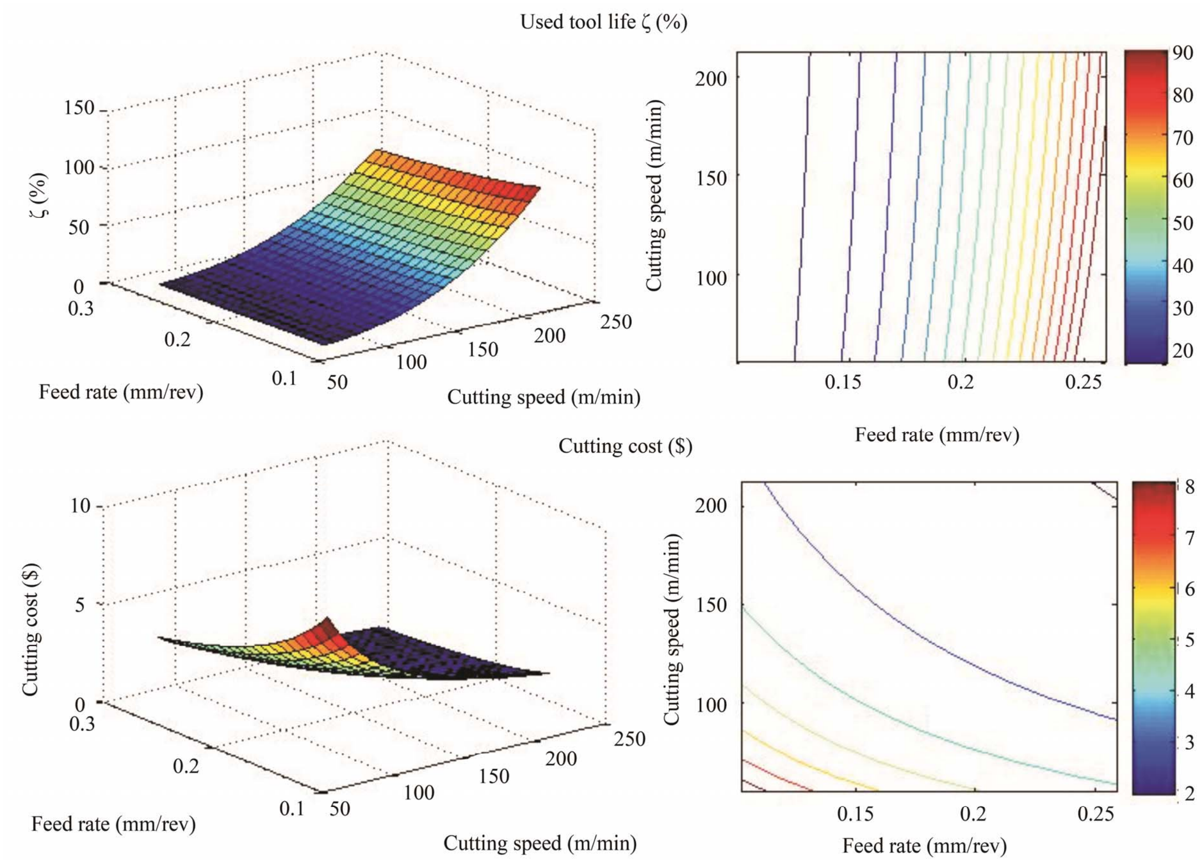

Figure 5. Cutting cost and used tool life with optimal cutting conditions.

tle values must be selected. And it is the same for feed rate.

Figure 6 shows surface quality variation as it is expressed by Equation (13). For the optimal point previously selected ($\mathbf{f_f}$ = 0.166), surface roughness is equal to: 2.78 µm.

6. Conclusions

This paper presents a posteriori multi-objective optimization of turning process. Multi-pass turning operation is considered in this study and the objective was to select cutting parameters of turning operation (cutting speed,

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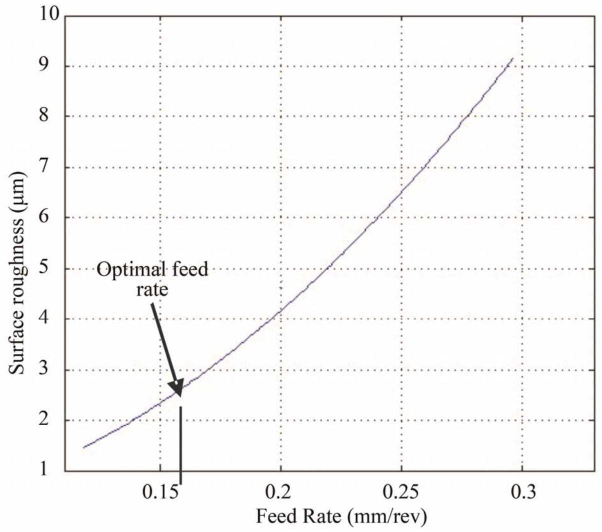

Figure 6. Surface roughnesses.

feed rate and depth of cut) which minimizes simultaneously cutting cost and used tool life subject to practical constraints.

To search these optimal parameters Genetic Algorithms method was used and results are presented in a Pereto frontier graphic. This technique allowed us to select optimal cutting parameters of a normal stat; other cutting parameters can be selected for different situation.

Further study is to compare these results with other optimization techniques such as simulated annealing, artificial neuron networks, etc.

REFERENCES

[1] P. Tsai, "An Optimization Algorithm and Economic Analysis for a Constrained Machining Model," Ph.D. Thesis, West Virginia University, Morgantown, 1986.

[2] M. S. Chua, H. T. Loh, Y. S. Wong and M. Rahman, "Optimization of Cutting Conditions for Multi-Pass Turning Operations Using Sequential Quadratic Programming," *Journal of Material Processing Technology*, Vol. 28, No. 1-2, 1991, pp. 253-262. doi:10.1016/0924-0136(91)90224-3

[3] Y. C. Shin and Y. S. Joo, "Optimization of Machining Conditions with Practical Constraints," *International Journal of Production Research*, Vol. 30, No. 12, 1992, pp. 2907-2919. doi:10.1080/00207549208948198

[4] J. S. Agapiou, "The Optimization of Machining Operations Based on a Combined Criterion, Part 1: The Use of Combined Objectives in Single-Pass Operations, Part 2: Multi-Pass Operations," *ASME Journal of Engineering for Industry*, Vol. 114, 1992, pp. 500-513.

[5] J. A. Wang, "Neural Network Approach to Multiple-Objective Cutting Parameter Optimization Based on Fuzzy Preference Information," *Computer Industrial Engineering*, Vol. 25, No. 1-4, 1993, pp. 389-392. doi:10.1016/0360-8352(93)90303-F

[6] R. Gupta, I. L. Baaa and G. K. Lal, "Determination of Optimal Subdivision of Depth of Cut in Multi-Pass Turning with Constrains," *International Journal Production Research*, Vol. 33, No. 9, 1995, pp. 2555-2565. doi:10.1080/00207549508904831

[7] M. C. Chen and D. M. Tsai, "A Simulated Annealing Approach for Optimization of Multi-Pass Turning Operations," *International Journal Production Research*, Vol. 34, No. 10, 1996, pp. 2803-2825. doi:10.1080/00207549608905060

[8] P. K. Kee, "Development of Constrained Optimization Analyses and Strategies for Multi-Pass Rough Turning Operations," *International Journal of Machine Tools Manufacturing*, Vol. 36, No. 1, 1996, pp. 115-127. doi:10.1016/0890-6955(95)00009-M

[9] C. Y. Nian, W. H. Yang and Y. S. Tarng, "Optimization of Turning Operations with Multiple Performance Characteristics," *Journal of Materials Processing Technology*, Vol. 95, No. 1-3, 1999, pp. 90-96. doi:10.1016/S0924-0136(99)00271-X

[10] N. Alberti and G. Perrone, "Multi-Pass Machining Optimization by Using Fuzzy Possibilistic Programming and Genetic Algorithms," *Journal of Engineering Manufacture*, Vol. 213, No. 3, 1999, pp. 261-273. doi:10.1243/0954405991516741

[11] B. Arezzo, K. Ridgway and A. M. A. Al-Ahmari, "Selection of Cutting Tools and Conditions of Machining Operations Using an Expert System," *Computers Industry*, Vol. 42, No. 1, 2000, pp. 43-58. doi:10.1016/S0166-3615(99)00051-2

[12] T. Dereii, I. H. Filiz and A. Baykasoglu, "Optimizing Cutting Parameters in Process Planning of Prismatic Parts by Using Genetic Algorithms," *International Journal Production Research*, Vol. 39, No. 15, 2001, pp. 3303-3328. doi:10.1080/00207540110057891

[13] G. C. Onwubolu and T. Kumalo, "Optimization of Multi-Pass Turning Operations with Genetic Algorithm," *International Journal Production Research*, Vol. 39, No. 16, 2001, pp. 3727-3745.

[14] A. M. A. Al-Ahmari, "Mathematical Model for Determining Machining Parameters in Multi-Pass Turning Operations with Constraints," *International Journal Production Research*, Vol. 39, No. 15, 2001, pp. 3367-3376. doi:10.1080/00207540110052562

[15] X. Wang, Z. J. Da, A. K. Balaji and I. S. Jawahir, "Performance-Based Optimal Selection of Cutting Conditions and Cutting Tools in Multi-Pass Turning Operations Using Genetic Algorithms," *International Journal Production Research*, Vol. 40, No. 9, 2002, pp. 2053-2065. doi:10.1080/00207540210128279

[16] K. Vijayakumar, G. Prabhaharan, P. Asokan and R. Saravanan, "Optimization of Multi-Pass Turning Operations Using Ant Colony System," *International Journal of Machine Tools Manufacture*, Vol. 43 No. 15, 2003, pp. 1633-1639. doi:10.1016/S0890-6955(03)00081-6

[17] C. Franci and B. Joze "Optimization of Cutting Process by GA Approach," *Robotics and Computer Integrated Manufacturing*, Vol. 19, 2003, pp. 113-121. doi:10.1016/S0736-5845(02)00068-6

Copyright © 2013 SciRes.

[18] U. Zuperl, F. Cus, B. Mursecb and T. Ploj, "A Hybrid Analytical-Neural Network Approach to the Determination of Optimal Cutting Conditions," *Journal of Materials Processing Technology*, Vol. 157-158, 2004, pp. 82-90. doi:10.1016/j.jmatprotec.2004.09.019

[19] X. Wang and I. S. Jawahir, "Optimization of Multi-Pass Turning Operations Using Genetic Algorithms for the Selection of Cutting Conditions and Cutting Tools with Tool-Wear Effect," *International Journal Production Research*, Vol. 43, No. 17, 2005, pp. 3543-3559. doi:10.1080/13629390500124465

[20] R. Q. Sardinas, M. R. Santana and E. A. Brindis, "Genetic Algorithm-Based Multi-Objective Optimization of Cutting Parameters in Turning Processes," *Engineering Applications of Artificial Intelligence*, Vol. 19, No. 2, 2006, pp. 127-133. doi:10.1016/j.engappai.2005.06.007

[21] F. Cus and U. Zuperl "Approach to Optimization of Cutting Conditions by Using Artificial Neural Networks," *Journal of Materials Processing Technology*, Vol. 173, No. 3, 2006, pp. 281-290. doi:10.1016/j.jmatprotec.2005.04.123

[22] N. R. Abburi and U. S. Dixit, "Multi-Objective Optimiza-Tion of Multi-Pass Turning Processes," *International Journal of Advanced Manufacturing Technology*, Vol. 32, No. 9-19, 2007, pp. 902-910. doi:10.1007/s00170-006-0425-6

[23] A. R. Yildiz, "Hybrid Taguchi-Harmony Search Algorithm for Solving Engineering Optimization Problems," *International Journal of Industrial Engineering*, Vol. 15, No. 3, 2008, pp. 286-293.

[24] D. K. Ojha, U. S. Dixit and J. P. Davim, "A Soft Computing Based Optimization of Multi-Pass Turning Processes," *International Journal Material Production Technology*, Vol. 35, No. 1-2, 2009, pp. 145-166. doi:10.1504/IJMPT.2009.025224

[25] J. Srinivas, R. Giri and S. H. Yang, "Optimization of Multi-Pass Turning Using Particle Swarm Intelligence," *International Journal of Advanced Manufacturing Technology*, Vol. 40, 2009, pp. 56-66.

[26] K. Deepak "Cutting Speed and Feed Rate Optimization for Minimizing Production Time of Turning Process," *International Journal of Modern Engineering Research*, Vol.2, No. 5, 2012, pp. 3398-3401.

[27] R. Venkata and V. Kalyankar "Multi-Pass Turning Process Parameter Optimization Using Teaching-Learning-Based Optimization Algorithm," *Transactions D: Computer Science & Engineering and Electrical Engineering*, 2013 (in press).

[28] A. Aggarwal and H. Singh, "Optimization of Machining Techniques—A Retrospective and Literature Review," *Sadhana*, Vol. 30, No. 6, 2005, pp. 699-711. doi:10.1007/BF02716704

[29] K. Deepak "Applications of Different Optimization Methods for Metal Cutting Operation—A Review," *Research Journal of Engineering Sciences*, Vol. 1 No. 3, 2012, pp. 52-58.

[30] E. J. A. Armarego and R. H. Brown, "The Machining of Metal," Prentice-Hall, Englewood Cliffs, 1969.

[31] S. K. Hati and S. S. Rao, "Determination of Optimum Machining Conditions Deterministic and Probabilistic Approaches," *Journal of Engineering for Industry*, Vol. 98, No. 1, 1976, pp. 354-359.

[32] R. V. Narang and G. W. Fischer, "Development of a Frame Work to Automate Process Planning Functions and Determine Machining Parameters," *International Journal of Production Research*, Vol. 31, No. 8, 1993, pp. 1921-1942. doi:10.1080/00207549308956832

[33] D. Goldberg "Genetic Algorithms in Search, Optimization, and Machine Learning," *Machine Learning*, Vol. 3, No. 2-3, 1988, pp. 95-99. doi:10.1023/A:1022602019183

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