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Research Article

Multi Pass Optimization of Cutting Conditions by Using the Genetic Algorithms

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Abstract: Production of high-quality products with lower cost and shorter time is an important challenge to face of increasing global competition. Determination of optimal cutting parameters is one of the most important elements in any planning process of metal parts. In this study we present a multi-optimization technique based on genetic algorithms and dynamic programming, to search for optimal cuttings parameters such as cutting depth, feed rate and cutting speed of multi-pass turning processes. Two conflicting objectives, the production cost and operation time are simultaneously optimize under a set of practical of machining constraints. The proposed model deals with multi-pass turning processes in which the cutting operations are divided into multi-pass rough machining and finish machining. Results obtained from Genetic algorithms method are used to define the optimum number of machining passes by dynamic programming; such technique helps us in the decision making process. An example is presented to develop the procedure of this technique.

Keywords: Cutting parameters, dynamic programming, genetic algorithms, mathematical programming, optimization

INTRODUCTION

In previous works (Assas and Djenane, 2001, 2003a), we have proposed an optimization method based on a combined criterion, by solving an optimization problem with a Bi- criteria objective function for a unique pass manufacturing in the case of turning. In this study, the previous approach is applied but for the optimization of conditions in multiple passes manufacturing.

In turning operations, a cutting process can possibly be completed with a single pass or by multiple passes. Multi-pass turning is preferable over single pass turning in the industry for economic reasons (Wang, 2007). The optimization problem of machining parameters in multi-pass turnings becomes very complicated when plenty of practical constraints have to be considered (Shutong and Yinbiao, 2011).

Abuelnaga and El-Dardiry (1984) discussed a number of traditional optimization methods and highlighted the relative advantages and disadvantages of the methods for solving the problems of machining economics. These objectives can be represented in terms of the machining parameters such as cutting speed, feed, depth of cut and the number of passes.

During selection of the parameters, care must be taken to ensure that the essential constraints are satisfied. Cutting force, power, surface finish and tool life are some of the commonly considered constraints (Ermer, 1971; Shin and Joo, 1992; Al-Ahmari, 2001; Sankar *et al.*, 2007). Initial research in machining process optimization focused on single pass operations (Taylor, 1906; Gilbert, 1950; Petropoulos, 1973; Abuelnaga and El-Dardiry, 1984). The mathematical programming techniques like linear programming (Ermer and Patel, 1974), graphical methods (Kiliç *et al.*, 1993) and geometric programming (Ermer, 1971; Petropoulos, 1973) had been used to solve optimization problems of machining parameters in multi-pass turnings. But, these methods of optimization do not fare well over a broad spectrum of problem domains.

Jawahir and Wang (2007) have summarized the recent contributions to the field of machining process modeling and optimization. They have also presented a machining process optimization method in which many process performances such as surface roughness, cutting force, tool life and material removal rate have been combined into a single objective using weight factors.

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In this study, we use the method developed by Agapiou (1992a), based on the dynamic programming to which we have introduced modifications and developed a program for that purpose. The optimal value of passes, the speed, the advance and the cutting depth for each pass represent the decision variables. It is a four -variable problem in which the pass number and the cutting depth for each pass are determined by the dynamic programming procedure. The speed of optimal cutting as well the optimal advance for each pass is determined by using the combined criterion method.

Cutting process model: The concept of dynamic programming is very useful for the treatment of multi-pass problem.

The total cutting depth is divided into N sections equal to *d:* $d = \frac{D}{N}$.

The decision variable which is the cutting depth, d_c , to be removed by pass *i* is represented by *d* (*i, j*) and the variable of state which is the part diameter of the pass *i* is represented by D_i . The *d* (*i, j*) means that the cutting depth begins at diameter D_i and includes *j* sections of dimensions *d*.

Consequently, the total cutting depth D_C is divided into *N* equal sections which are the *N* discrete decision states for the dynamic programming.

OPTIMIZATION OF THE NUMBER OF PASSES BY DYNAMIC PROGRAMMING

In general when the pass begins from the section *i* and ends at the section *q* the objective function is expressed by:

$$U(i, j) = W_1 C_u(i, j) + W_2 T_u (i, j) \quad (1)$$

With $j = i - q$, *j* is the number of size sections *d*.
The cost of production by pass is expressed by:

$$Cu(i,j) = C_0 A V^{-1}(i,j) f^{-1}(i,j) + A V^{(\frac{1}{a_3}-1)}(i,j) f^{(\frac{1}{a_3}-1)}(i,j) d^{(\frac{a_2}{a_3})}(i,j) k^{(\frac{-1}{a_3})}(C_0 t_{cs} + C_t) + C_0 t_r \quad (2)$$

The duration of production is expressed by:

$$Tu(i,j) = C_0 A V^{-1}(i,j) f^{-1}(i,j) + A V^{(\frac{1}{a_3}-1)}(i,j) f^{(\frac{1}{a_3}-1)}(i,j) d^{(\frac{a_2}{a_3})}(i,j) k^{(\frac{-1}{a_3})}(t_{cs} + C_t) \quad (3)$$

with: $A = \frac{\pi D_i L(i,j)}{1000}$ and $d(i, j) = dc = j.d$

The cutting length is always constant for all manufacturing passes:

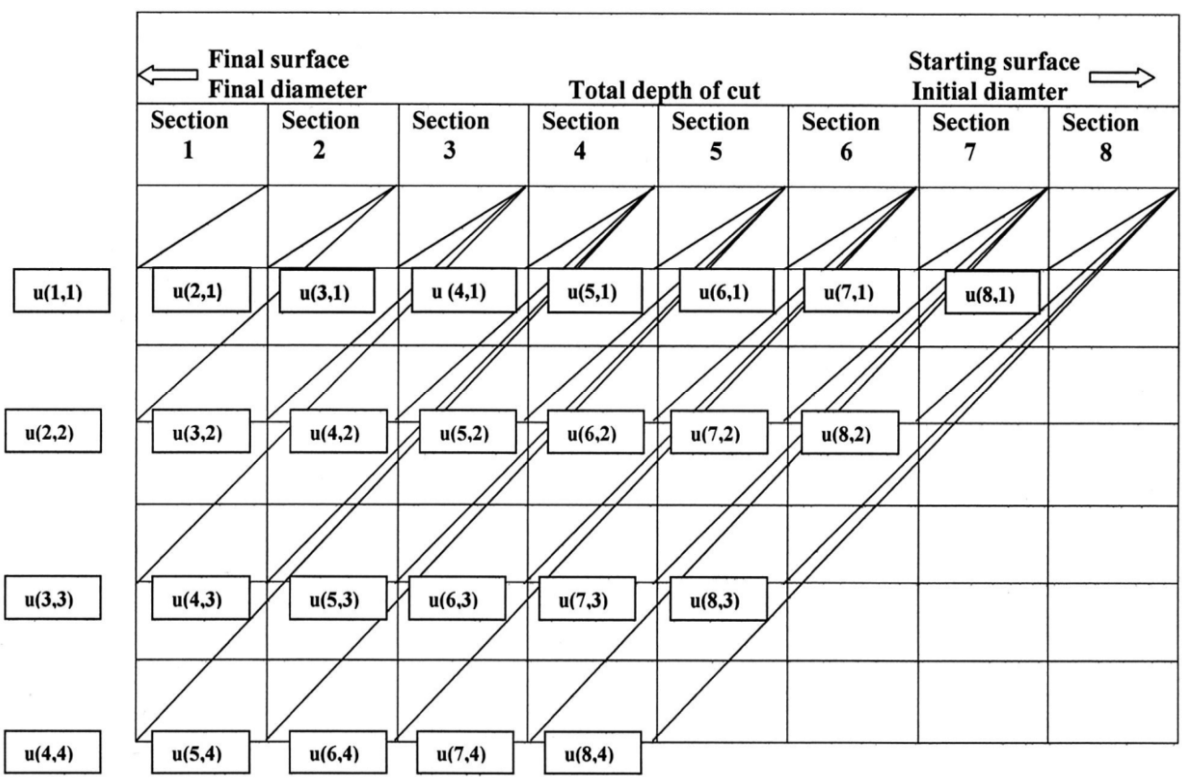

Fig. 1: Schema for the decomposition of the total cutting depth in 8 sections for the dynamic programming

$L(i, j) = L$

$$C_u = \sum_{k=1}^{M}\left[C_0\left(t_m(i,j)_k + t_r\right) + \frac{t_m(i,j)_k}{T(i,j)_k}(C_0 t_{cs} + C_t)\right] + C_0 t_h \quad (5)$$

The diameter for each pass is expressed by:

$$D_i = D - 2(N + j - i)d = D_0 + 2q.d$$
$$\text{and } D_{i-1} = D_i - j.d \quad (4)$$

For the multi-passes manufacturing where *M* passes are necessary to achieve the turning operation the total production cost and total production duration are expressed by:

$$T_u = \sum_{k=1}^{M}\left[t_m(i,j)_k + t_r + \frac{t_m(i,j)_k}{T(i,j)_k}t_{cs}\right] + t_h \quad (6)$$

k is the index which indicates the number of any pass. The timing machine for each pass is:

$$t_m(i,j) = \frac{\pi (D_i)_k L(i,j)_k}{1000 V(i,j)_k f(i,j)_k} \quad (7)$$

The steps of dynamic iterations are represented by an inferior triangular matrix with $N \times N$ dimension. The elements (i, j) of the matrix respectively represent the diameter of starting section and the number of manufactured sections for any kind of pass.

The schematic representation of the dynamic programming process is expressed by the diagram of Fig. 1, where D_c is divided into eight equal sections:

$N = 8$

It is known that below a certain depth cutting value *DMOP*, for a specific couple tool-matter, the simple pass manufacturing is optimal.

The maximum value of the cutting depth *DMAXP* is also known.

The inferior triangular matrix for the example in Fig. 1, is expressed as following by:

$$U(i,j) = \begin{bmatrix} X & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & X & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & X & 0 & 0 & 0 & 0 & 0 \\ X & X & X & X & 0 & 0 & 0 & 0 \\ X & X & X & X & 0 & 0 & 0 & 0 \\ X & X & X & X & 0 & 0 & 0 & 0 \\ X & X & X & X & 0 & 0 & 0 & 0 \\ X & X & X & X & 0 & 0 & 0 & 0 \end{bmatrix}$$

where *X* represents the values of objective function, the diagonal elements represent the possible simple passes. The elements: 21, 31 and 32 are nil because the cutting depth for one given pass d_c is inferior to *DMOP* and the elements: 55, 65, 75, 77, 86, 87 and 88 are nil because the cutting depth for one donated pass *dc* is superior to *DMAXP*.

In the same procedure, the cutting speeds and the advances are also arranged in two inferior separated triangular matrixes

We introduce the following notations:

$U(1, 1) = UOP(1), U(2, 2)$
$= UOP(2), U(3,3) = UOP(3)$

Using the strategy of dynamic programming, supposing that the optimum is obtained from the $i^{ème}$ section, $(1<i<N)$ until the final diameter (Intern) of the 1st section, the steps of dynamic programming are the followings:

Step 1: For a cutting depth inferior to *DMOP* such as: $d(i,\ j)\ =\ i.\ d \leq DMOP$, we calculate the objectives ''functions'' corresponding *UOP*(*i*) to one pass finishing operations and we continue with the following steps.

Step 2: For the depths of pass $DMOP<i.d \leq DMAX$: we calculate the 'objectives' functions corresponding *u(i, j)* to one finishing pass operation.

Step 3: Next we evaluate the calculations of objective 'functions' for multi- pass operations such as:

$$UOP(i) = UOP(i - r) + u(i, r) \text{ for } i = 1,2,\dots,p \quad (8)$$

With:

$$p = min\{ i\text{-}1, DMAXP/d\} \quad (9)$$

UOP (i-r) is the minimum objective function starting from the section *(i-r)* until the first section, *u(i, r)* is the objective function of one pass from the section (*i*) to the section *(i - r)* with a cutting depth $d_c = r.d$.

Step 4: We continue this process for $i = DMOP/d, \dots, N$.

The approach based on the dynamic programming is described by the algorithm of Fig. 2.

The mathematic formulation of these functions is as following:

The optimum in section 1 to 3 is obtained with one pass, since it is supposed that: $d(i,\ i) \leq DMOP$, the sections $i = 1, 2, 3$ form a single branch.

In the 4th section for i = 1, 2, 3 the results are formulated in four branches:

$$UOP(2) + u(4, 2) > UOP(4) > UOP(1) + u(4, 3) > UOP(3) + u(4, 1) \quad (10)$$

The optimum is obtained by the equation:

$$UOP(4) = UOP(3) + u(4, 1) \quad (11)$$

$u(4, 3)$ represent the branch of the 4th section connected to the 1st section and $UOP(1)$ corresponds to the branch of the 1st section which is connected to final diameter D_0.

We repeat the process in each iteration, we obtain the following results:

$$UOP(5) = UOP(2) + u(5, 3) \quad (12)$$

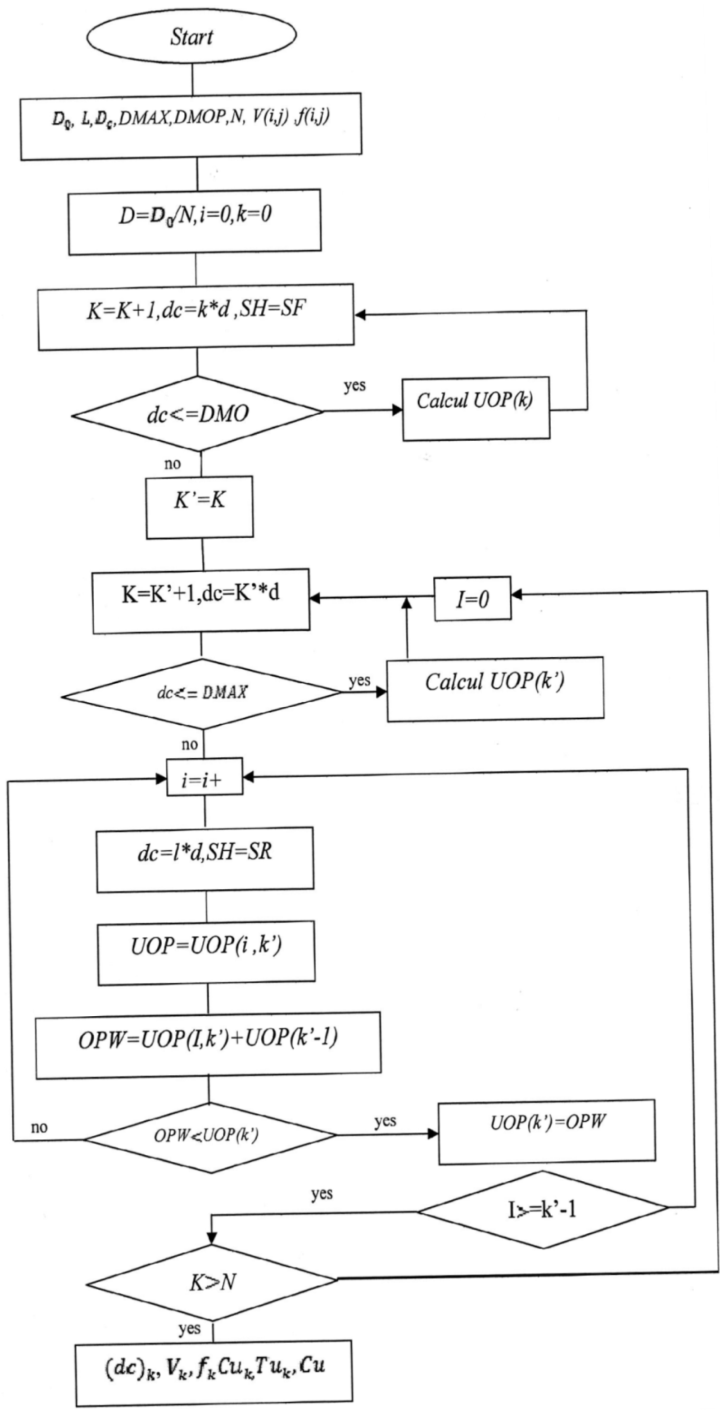

Fig. 2: Organization chart of the dynamic programming for multi-pass machining

$UOP(6) = UOP(4)+u(6, 2)$ (13)

$UOP(7) = UOP(5)+u(7, 2)$ (14)

$UOP(8) = UOP(4)+u(8, 4)$ (15)

The 6th section is not connected to D_O because $d(6, 6)$ is much bigger than *DMAXP*.

The same, the 7th and the 8th sections are not connected to the 1st section and to D_0

Because $d(7, 6)$, $d(7, 7)$, $d(8, 8)$, $d(8, 7)$ et $d(8, 6)$ are bigger than *DMAXP*.

By substituting (11) in (15) we obtain:

$UOP(8) = u(8, 4) + u(4, 3) + UOP(1)$ (16)

The Eq. (16) gives the number of optimum passes $M = 3$, two passes for the draft operations and one pass for the finishing with the cutting depths respectively: $d(8, 4) = 4d$, $d(4,3) = 3d$, $d(1, 1) = d$, with the total cutting depth:

$$Dc = 4d+3d+d = 8d$$

OPTIMIZATION BY GENETIC ALGORITHM

The GA are exploration algorithms based on the mechanisms of natural selection and genetics. They use at a time the survival principles of the best adopted structures. In each generation, a new set of artificial creatures (chains of characters) is created using parts of the best elements of the previous generation. Although using the hazard, the GA is not purely random. They effectively exploit information obtained previously to speculate on the position of new points to be explored, hoping to improve the performance (Assas and Djenane, 2003b; Djari *et al*., 2007; Sardiñas *et al*., 2006; Rao and Pawar, 2010).

General function of Ga: Stages of GA (Assas and Djenane, 2003b; Djari *et al*., 2007).
The steps of an AG are as follow (Fig. 3):

- Creation of the initial population.
- Evaluation of each chromosome of the initial population.
- Selection and regrouping of the chromosomes per pairs.
- Application of crossover and the mutation operators.
- Evaluation of new chromosomes and insertion in the following population.
- If the stopping criterion is reached, the genetic algorithm stops; otherwise the algorithm returns back at the stage 3.

From generation to generation, the size of population remains constant.

At a generation, the terminology used is that of genetics.

- For each variable x_i we associate a gene
- The chromosome is a set of genes; the chromosomes are the elements from which the solutions are elaborated
- The reproduction is the step of chromosomes combination. The genetic mutation and the crossing are reproduction methods.

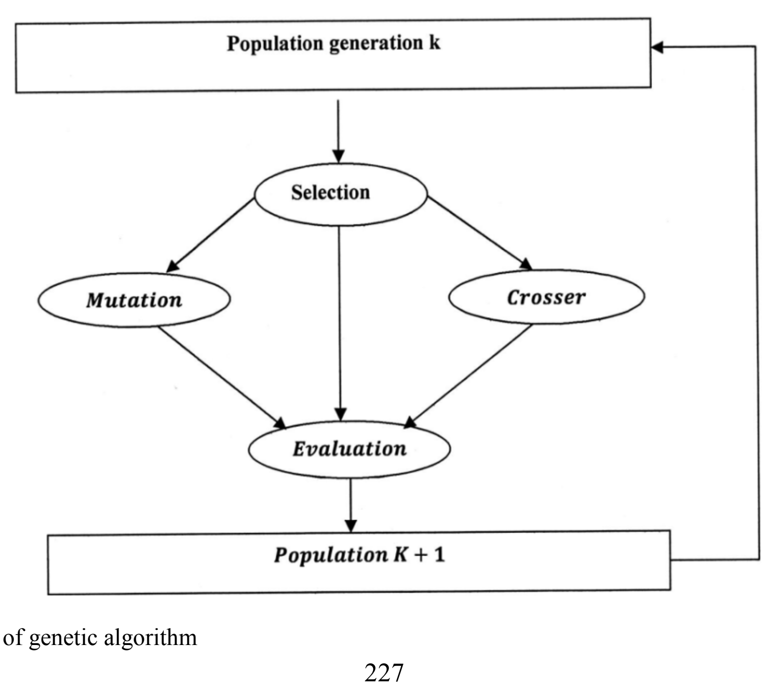

Fig. 3: General principle of genetic algorithm

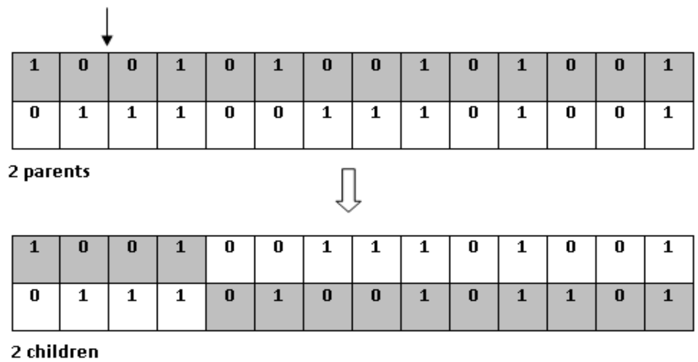

Fig. 4: Representation of crossover in 1 point

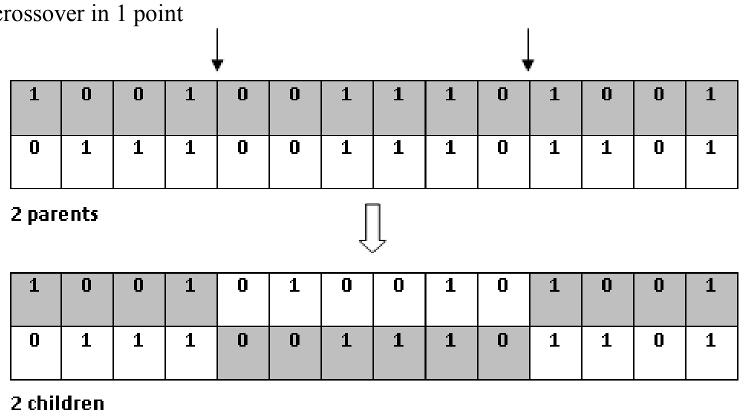

Fig. 5: Representation of crossover in 2 points

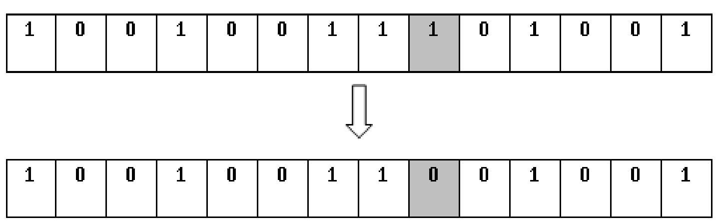

Fig. 6: Mutation representation. Muli-passes

ELITISM SRATEGY

The strategy called Elitism consists in recopying the best chromosome of the current population on the population of the next generation. This latter is completed by other chromosomes, generated with a traditional manner until getting the needed number of individuals. So, it becomes impossible for the e best chromosome of the next generation to be inferior to that of the former generations.

The performances of genetic algorithm are largely ameliorated.

GA operators:

Crossing operator: This operator combines the chromosomes of two individuals to get two new. A crossing in one point consists of exchanging a fragment of two chromosomes. The couple being created, the process happens in two steps:

Random choice of an identical cut-off point on both chromosomes.

Cutting of the two chromosomes (Fig. 4) and exchanging the two fragments located on the right.

The crossing"1 point" is the simplest and most classical for coding using a binary encoding.

An immediate generalization of this operator consists of multiplying the cut-off points on each genotype. The crossing "1 point" and "2 points" (Fig. 5) are frequently practiced for their simplicity and good efficiency.

Mutation operator: We define a mutation as being the inversion of a bit in a chromosome (Fig. 6). Classically, the mutation operator modifies randomly the symbols of genotype with a weak probability, equal to the rate of mutation. On the other hand, the mutation ensures a random local research around each individual.

Following this order of idea, the mutation can considerably improve the quality of solutions discovered.

APPLICATION AND RESULTS OF OPTIMIZATION

To find the number of optimal passes, we have developed a program in Fortran language (Fig. 2).

In order to test the influence of sections number on the optimal value of pass number, we have divided the total cutting depth Dc = 10.16 mm successively into 4, 8, 10 and12 sections equals for the piece length L = 203 mm and one diameter D = 152 mm. The parameters of machining are mentioned in Table 1.

Table 2 represents the values of advance speed and cutting speed corresponding to different depths of cutting calculated by a genetic algorithm for draft operations SR_{max} = 8 µm and finishing SF_{max} = 2 µm.

The limitations on the constraints (Agapiou, 1992b) are the followings:

- Limitations on the advance speed:

$f \geq f_{min}$, $f \leq f_{max}$

Table 1: Machining parameters

Paramètre	Valeur	Paramètre	Valeur
L	203 mm	t_r	0.13 min/pass
D	152 mm	t_h	1.5 min/pièce
V_{min}	30/min	θ_{max}	500°C
V_{max}	200 m/min	a_1	0.29
f_{min}	0.254 mm/ tour	a_2	0.35
f_{max}	0.762 mm/tour	a_3	0.25
SF_{max}	2 µm	K	193.3
SR_{max}	8 µm	t_{cs}	0.5 min/arrêt
HP_{max}	5KW	C_o	0.1 s/min
F_{max}	1100N	C_t	0.5 s/arrête
C_t	0.5 s/arrête	W_1	0.6
	W_2	0.4	

Table 2: The optimal value of speed and the cut advance obtained by the genetic algorithms method

	SF_{max} = 2 μm		SR_{max} = 8 μm	
d_c *mm*	*F mm/t*	*V m/min*	*f mm/tour*	*V m/min*
0.85	0.437	197.55	0.761	149.93
1.02	0.409	195.00	0.761	142.59
1.27	0.377	191.00	0.760	134.82
1.69	0.339	187.16	0.738	126.34
2.03	0.317	184.56	0.695	123.96
2.54	0.291	181.00	0.641	122.48
3.05	0.333	178.93	0.598	120.30
3.38	0.262	177.15	0.576	119.58
3.81	0.251	174.00	0.552	118.62
4.06	0.245	174.16	0.531	116.74
4.23	0.242	174.16	0.521	116.16
5.08	0.226	170.71	0.461	109.94

Table 3: Optimal manufacturing conditions for the different section

N	d_c *mm*	*f mm/tour*	*V m/min*	C_u *\$*	T_u *min*
4	5.08	0.461	109.9	0.599	2.285
	2.54	0.641	122.4	0.341	1.438
	2.54	0.291	181	0.767	2.264
				1.858	7.486
8	5.08	0.461	109.9	0.599	2.285
	3.81	0.552	118.6	0.477	1.740
	1.27	0.377	191	0.406	1.546
				1.632	7.071
10	5.08	0.457	109.9	0.599	2.285
	4.06	0.531	116.7	0.495	1.818
	1.02	0.409	195	0.336	1.380
				1.581	6.982
12	5.08	0.461	109.9	0.599	2.285
	4.23	0.521	116.1	0.511	1.859
	0.85	0.437	197.5	0.288	1.263
				1.548	6.901

- Limitations on the cutting speed:

$V \geq V_{min}$, $V \leq V_{max}$

- Limitations on the cutting depth:

$dc \geq dc_{min}$, $dc \leq dc_{max}$

- Limitations on the maximum power allowed by the machine:

$0.0373\ V^{0.91} f^{0.78} d^{0.75} \leq HP_{max}$

- Limitations on the cutting effort:

$V^{-0.1013} f^{0.725} d^{0.75} \leq F_{max}$

- Limitations on the surface state:

$14.75 V^{-1.52} f^{1.004} d^{0.25} \leq SR_{max}$

- Limitations on the temperature of cutting:
$74.96 V^{0.4} f^{0.2} d^{0.105} - 17.8 \leq \theta_{max}$

The conditions of optimal manufacturing for the different numbers of sections 4, 8, 10, 12 are mentioned in Table 3.

The influence of the sections number ***N*** used by the technique of dynamic programming is observed by comparing the results of Table 3 for N = 4, 8, 10, 12.

By increasing the number of sections N from 4 to 8the timing cost of total production decreases from 12.16% and 5.54%, similarly the increase in the number of sections from 8 to 10 causes a reduction of cost and time of total production at about 3.125% and 1.25%, whereas if we increase the number of sections from 10 to 12 we obtain a slight diminution of total cost and time.

Finally we notice that the number of optimum passes and the corresponding manufacturing conditions respecting all the limitations of constraints for a total cutting depth equal to 10.16 mm is obtained with the number of sections N equals to 12.

CONCLUSION

In the current study we propose an approach which uses jointly the Genetic Algorithms and the dynamic programming for the multi-criteria optimization of machining conditions.

The optimization of manufacturing process to several passes was resolved in an efficient manner through the use of dynamic programming. Such procedure allowed determining the number of optimal passes for a given total depth of cut. The optimization of each phase was accomplished through the Genetic Algorithms (AG) method, which provides independently the optimum speed and advance for each pass. We have presented the procedure of determination for the number of optimal sections and the number of optimal passes.

NOMENCLATURE

$a_1; a_2; a_3$	:	Constants
C_o	:	Machine cost $/min
C_t	:	Cutting edge cost $
Cu	:	Production cost $/min
D	:	Depth of cut mm
d_c	:	Depth of cut for a pass mm
D	:	Initial diameter of work piece mm
f	:	Feed rate mm/tr
F	:	Cutting force N
HP	:	Power of the machine KW
L	:	Cutting length of work piece mm
SF	:	Surface finish roughness µm
SR	:	Surface roughness µm
t_{cs}	:	Time of tool replacement min
t_h	:	Auxiliary time min
t_m	:	Machining time min
t_r	:	Return time min/pass
T	:	Tool life min
V	:	Cutting speed m/min
u,U	:	Objective functions
$W_1; W_2$	:	Weight coefficients
θ	:	Medium temperature of cutting °C
D_c	:	Total depth of cut mm
D_0	:	Final diameter of part mm
$DMOP$	:	Optimal depth of cut mm
$DMAXP$	:	Maximum depth of cut mm
UOP	:	Optimal objective function
i	:	Index of boot section
j	:	Index of number of section

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