ANALYSIS AMONG THREE OPTIMIZATION TECHNIQUES TO SET CUTTING PARAMETERS IN TURNING OPERATIONS

Luiz C. A. Rodrigues, lcar@utfpr.edu.br
Mauricio I. Takano, takano@utfpr.edu.br
Rafael V. B. Wiecheteck, slackebr@gmail.com
Universidade Tecnológica Federal do Paraná, PPGEM. Av. Sete de Setembro, 3165.

Abstract. *Determination of the optimal turning parameters of lathes located in a Flexible Manufacturing System (FMS) (where production is made on small lots or even on individual lots) will impose the maximization of production rate at bottleneck resources and the minimization of production costs at non-bottleneck resources. Whenever production bottlenecks are identified, it is important to speedup the production of these bottleneck tasks as much as possible. But if a task is not on a production bottleneck, its production time should be revised on a struggle for tools and energy economy. Therefore, manufacturing industries should be able to revise turning parameters at lathes according to production mix. But this is clearly not the case at industries worldwide. From the literature, it can be observed that optimization of turning (or machining) parameters is a relevant problem. But there has only been a few articles using Operations Research approaches to solve this problem and most of this literature presents the use of heuristic methods. In this paper, an attempt to determine the optimal cutting parameters using Mathematical Programming commercial software is reported. A Mixed Integer Nonlinear Programming (MINLP) model is applied to the software GAMS/Baron to determine the optimal turning parameters. To optimize the cutting parameters in a FMS, minimization of production costs will be analyzed, taking into account the constraints of permissible surface roughness, cutting parameters range, and machine restrictions. Therefore, this work is focused on: i) presenting a thorough revision of the literature; ii) describing a nonlinear mathematical programming model to the problem taken from the literature; and iii) comparing the solution of a mathematical programming software to two other heuristic approaches (using simulated annealing and genetic algorithms) proposed in the literature. This paper presents the results of an ongoing research.*

Keywords*: Optimization, cutting parameters, FMS, mathematical programming, heuristic methods.*

1. INTRODUCTION

A Flexible Manufacturing System (FMS) is an automated production system which may be composed of several CNC machines. According to Xiaobo and Ohno (1999), a FMS is composed of workstations, a system for materials handling and a control system. Each workstation can contain input and output buffers, as well as CNC machines. The control system is responsible for commanding the FMS through a client-server control architecture.

An increasing investment in production automation is being observed in manufacturing industries, especially through the acquisition of CNC machines. Despite the fact that this investment can be expensive, the productivity accomplished using CNC machines can be questioned. The reasons for this inefficiency are twofold: *i*) lack of trained personnel to provide improvements; and *ii*) unawareness of the problem complexity. For instance, determination of the optimal turning parameters of lathes located in a Flexible Manufacturing System (FMS) (where production is made on small lots or even on individual lots) will impose the maximization of production rate at bottleneck resources and the minimization of production costs at non-bottleneck resources. It is important to notice that bottlenecks on a FMS are only identified after production scheduling or sequencing. On the other hand, consider the case of cellular manufacturing where, due to significant setup times, production is made on lots of hundreds or thousands of manufactured parts. At this situation, bottlenecks can be identified simply by an analysis of equipment loading. In both situations, whenever production bottlenecks are identified, it is important to speedup the production at bottleneck tasks as much as possible. But if a task is not on a production bottleneck, its production time should be revised on a struggle for tools and energy economy. What should be remarked from the above mentioned situations is that a task will or will not be on a bottleneck resource depending on the production mix and that industries may face significant production mix variations on their daily operations. Therefore, manufacturing industries should be able to revise turning parameters at lathes according to production mix.

From the literature, it can be observed that optimization of turning (or machining) parameters, as described previously is a relevant problem. According to Su and Chen (1999), cost, productivity, and quality of machined parts are significantly affected by its turning/machining parameters. But there has only been a few articles using Operations Research approaches to solve this problem and most recent literature presents the use of heuristic methods. The most used heuristic methods in the operations research literature are: simulated annealing (Aarts, 1989), tabu search (Glover and Laguna, 1997), genetic algorithms (Goldberg, 1989), and ant colonies (Dorigo *et al.*, 1996).

According to Lee and Tarng (2000), the economical analysis of machining processes was started in 1950. A Dynamic Programming approach to this problem was proposed by Agapiou (1992a; 1992b). Prasad *et al.* (1997) proposed a combination of Geometric and Linear Programming to solve a multi-stage turning problem, which was implemented within a PC-based Computer-Aided Process Planning (CAPP) system. Lee and Tarng (2000) constructed a machining model based on a polynomial network. Wang and Liu (2007) formulated a pair of two-level machining economics problems to calculate the upper and lower bounds of the unit production cost, which were transformed into one-level conventional geometric program, based on the duality theorem.

Su and Chen (1999) presented Simulated Annealing approaches to define turning parameters. Sankar *et al*. (2007) proposed the use of Genetic Algorithms to solve a multi-stage turning problem. Saravanan *et al.* (2003) attempted to compare the methods of Simulated Annealing and Genetic Algorithms.

The rest of this work has been organized as follows. Section 2 presents a nonlinear mathematical programming model to the problem. This work attempts to compare three different approaches: a proposed simulated annealing, a genetic algorithms proposed by Saravanan *et al.* (2003), and using GAMS/BARON/CPLEX which is a mathematical programming software. At section 3, the proposed simulated annealing approach is presented, as well as a brief description on how this problem is solved using mathematical programming. Results and conclusions are presented at section 4 and 5, respectively.

2. MATHEMATICAL MODEL

The turning process of a part is divided in two stages, the rough and the finish machining. The rough process consists in multiple tool passes removing as much material as possible, without compromising the tool, the machine or the machined part. The finish process, on the other hand, consists in a single tool pass bypassing the part after most of the material has been removed in the rough process. In the finish machining the most important is that the part ends up with the roughness and accuracy that was designed. According to Saravanan *et al.* (2003), Wang and Liu (2007), Su and Chen (1999), and Sankar *et al.* (2007) the parameters that must be optimized in the turning process are the cutting speed, the feed rate, and the depth of cut.

When it is required to use two or more machines inside a manufacturing cell to produce a certain lot of different parts, the optimal sequence of the manufacturing process is important, where one can seek after the lowest cost or the most productive sequence. This sequencing must consider some manufacturing bounds to each part in the lot, such as the loading level of the machines, time to machine the part, setup depending on the sequence, among others. In order to have a larger profit it is important that the time to manufacture a lot is as small as possible in the production bottleneck, so a greater quantity of parts is produced in the same amount of production time. Hence, the first step to optimize the production sequence (in a manufacturing cell, for example) is to define the minimum time to machine each part in each machine.

In a machining process, higher cutting speed, feed rate, and depth of cut guarantee more speed of material removal. However, the cutting tool consumption may become too high, causing more changes of tools, therefore reducing the global time to manufacture the parts. So, to calculate the minimum time to machine the parts (Eq. 1), it is considered the time whilst the tool is actually removing material, the setup time of a machine, and the time to load and unload the parts in the machine. Table 1 shows the notations of the mathematical expressions used in the bound modeling. According to Stemmer (2001), Eq. 1 shows the minimum machining time calculus and Eq. 2 indicates the calculus of machining costs.

Also, the physical limits of the machine and the cutting tool must be considered, such as the minimum and maximum cutting speed, maximum machine power and maximum temperature supported by the cutting tool and the machined part. The Eq. 3, 4, and 5 are the cutting parameters bounds (Saravanan et al., 2005). Equation 6 is the tool life calculus, which depends exclusively of the cutting speed (Stemmer, 2001). Equation 7 is associated to the calculus of setup times, that is considered the time to prepare the machine summed to the time used to change the cutting tools (Stemmer, 2001).

The Eq. 8, 9, 15, and 16 are the bounds of maximum machine power, maximum cutting temperature supported by the cutting tool and by the part, dimensional constraint, and the maximum roughness allowed in the part after the finish machining (Saravanan et al., 2005). Equations 10, 12, 13, and 14 are the time to remove material of the part in straight machining, where there is only diameter reduction, linear machining, face machining, and circular machining, as proposed by Su and Chen (1999). Equation 11 shows the calculus used to set the angles θ used in Eq. 12, 13, and 14 (Su and Chen, 1999). Equations 17, 18, 19, and 20 are relations between the cutting parameters in rough and finish turning (Sankar et al., 2007).

The Eq. 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, and 14 are used for both rough and finish machining and all equations will be used directly for mathematical programming, at simulated annealing, and at the genetic algorithm. It is important to notice that this section presents the equations that are most popular in the literature concerning cutting parameters definition.

$$T_t = m * t_p + t_{setup} + m * T_s = m * t_p + t_{setup} + CONSTANT \quad (1)$$

Table 1. Notation used in the mathematical expressions.

Nomenclature	
T_t	Total time of the production cycle [min.]
T_s	Secondary time is the part's loading/unloading time which is a constant
t_{setup}	Sum of the times used to change the cutting tools and the machine's setup time [min.]
t_p	Sum of the rough and finish machining times [min.]
t_r, t_s	Time of the rough and finish machining, sum of straight, linear, face and circular turning times [min.]
t_{sr},t_{ss}	Time of straight turning in rough and finish machining [min.]
t_{lr}, t_{ls}	Time of linear turning between any two points in rough and finish machining [min.]
t_{fr}, t_{fs}	Time of face turning in rough and finish machining [min.]
t_{cr}, t_{cs}	Time of circular turning between any two points in rough and finish machining [min.]
m	Quantity of parts to be produced
K	Total costs of the production cycle [$]
K_c	Constant costs for each produced part, such as raw material [$/Part]
K_p	Machining time cost [$]
K_t	Tool cost [$/Toll]
T_{vr}, T_{vs}	Tool life in rough and finish machining [min.]
C_t, n	Constants of tool life equation
t_{tf}	Changing tool time [min.]
v_{cr}, v_{cs}	Cutting speed in rough and finish machining [m/min.]
v_{crL}, v_{crU}	Lower and upper bound of cutting speed in rough machining [m/min.]
v_{csL}, v_{csL}	Lower and upper bound of cutting speed in finish machining [m/min.]
f_r,f_s	Feed rate in rough and finish machining [mm/rev.]
f_{rL}, f_{rU}	Lower and upper bound of feed rate in rough machining [mm/rev.]
f_{sL}, f_{sU}	Lower and upper bound of feed rate in finish machining [mm/rev.]
a_{pr},a_{ps}	Depth of material to be removed in rough and finish machining [mm]
a_{prL}, a_{prU}	Lower and upper bound of depth of cut in rough machining [mm]
a_{psL}, a_{psU}	Lower and upper bound of depth of cut in finish machining [mm]
b_r,b_s	Chip width in rough and finish machining [mm]
h_r, h_s	Chip thickness in rough and finish machining [mm]
$K_{c1.1}$	Specific cutting pressure that gives a chip with bxh = 1x1 [N/mm^2]
mc	Constant of cutting force equation
P_r, P_s	Cutting power during rough and finish machining [kW]
P_{rU}, P_{sU}	Maximum cutting power allowed during rough and finish machining [kW]
Q_r, Q_s	Temperature during rough and finish machining [ºC]
Q_{rU}, Q_{sU}	Maximum temperature allowed during rough and finish machining [ºC]
K_g, T,Φ, δ	Constants related to machining temperature
d, l	Diameter and length of straight turning operation [mm]
r	Nose radius of the cutting tool [mm]
x_1, x_2	Radius of the initial and final points in linear, face or circular turning [mm]
x_c	Equivalent radius of the position of the center of the circular turning [mm]
Δ	Length between the final and initial points in linear or circular turning [mm]
ra	Radius of the circular turning [mm]
θ	Angle used in the calculus of linear and circular turning [rad.]
R_{max}	Maximum allowable surface roughness [mm]
n_c	Number of rough cuts [an integer]
k_1, k_2, k_3	Constants for rough and finish parameters relations

$$K = m * K_c + m * K_t * \left(\frac{t_r}{T_{vr}} + \frac{t_s}{T_{vs}} \right) + K_p * T_t \tag{2}$$

$$v_{crL} \le v_{cr} \le v_{crU} \tag{3}$$

$$f_{rL} \le f_r \le f_{rU} \tag{4}$$

$$a_{p_{rL}} \leq a_{p_r} \leq a_{p_{rU}} \tag{5}$$

$$T_{v_r} = \left(\frac{C_t}{v_{c_r}} \right)^{\frac{1}{n}} \tag{6}$$

$$t_{setup} = m * \frac{t_r}{T_{v_r}} * t_{tf} + m * \frac{t_s}{T_{v_s}} * t_{tf} + SETUP \tag{7}$$

$$P_r = \frac{k_f * f_r^{\mu} * a_{pr}^{\upsilon} * v_{c_r}}{60000} \leq P_{rU} \tag{8}$$

$$Q_r = K_q * v_{c_r}^{\tau} * f_r^{\varphi} * a_{p_r}^{\upsilon} \leq Q_{rU} \tag{9}$$

$$t_{sr} = \frac{\pi * d * l}{1000 * v_{c_r} * f_r} \tag{10}$$

$$\theta_{fi} = \tan^{-1} \frac{x_f - x_i}{\Delta_{fi}} \tag{11}$$

$$t_{lr} = \frac{\pi}{1000 * v_{c_r} * f_r} * \left| \frac{x_2^2 - x_1^2}{\sin \theta_{21}} \right| \tag{12}$$

$$t_{fr} = \frac{\pi}{1000 * v_{c_r} * f_r} * \left| x_2^2 - x_1^2 \right| \tag{13}$$

$$t_{cr} = \frac{\pi * r_a}{500 * v_{c_r} * f_r} * \left| x_c * (\theta_{c2} - \theta_{c1}) - r_a * (\cos\theta_{c2} - \cos\theta_{c1}) \right| \tag{14}$$

$$\delta_1 = 100.66 * v_{cr}^{-0.2848} * f_r^{0.9709} * a_{pr}^{0.4905} \tag{15}$$

$$\frac{f_s^2}{8r} \leq R_{\max}. \tag{16}$$

$$a_{p_r} = \frac{d - a_{p_s}}{n_c} \tag{17}$$

$$a_{p_r} \geq k_1 * a_{p_s} \tag{18}$$

$$v_{c_s} \geq k_2 * v_{c_r} \tag{19}$$

$$f_r \geq k_3 * f_s \tag{20}$$

3. SOLUTION METHODOLOGY

To optimize the cutting parameters in a FMS, minimization of production costs is analyzed, taking into account the constraints of permissible surface roughness, cutting parameters range, and machine restrictions. This paper analyzes three optimization techniques to set cutting parameters in turning operations, which are simulated annealing, genetic algorithm, and mathematical programming. The genetic algorithm approach used in this paper was proposed by Saravanan *et al.* (2003) and the reader should refer to this paper for details concerning this approach.

3.1. Mathematical Programming

A branch of research in mathematical programming is the so called Global Optimization which seeks to solve mixed integer nonlinear problems (MINLP) to optimality. At nonlinear problems a significant number of local optimal solutions can be found. The greatest challenge on such problems is on how to separate a concave surface into a collection of several convex hulls (where each convex hull will possess a single optimal solution). Therefore global optimization approaches attempt to form a collection of convex subproblems. A way to obtain convex subproblems is by using an Outer Approximation approach (Horst and Tuy,1992), which make use of cutting planes to transform a nonlinear problem into several linear subproblems. Each linear subproblem (whose solution is found within pseudo-polynomial time) becomes a relaxed convex hull which contains one or more local optimal solutions of the nonlinear problem within it. These linear subproblems can be submitted to a Branch-and-Bound search (Horst and Tuy, 1992) or to a Disjunctive Programming approach (Tawarmalani and Sahinidis, 2002) which identifies the most promising subproblem. The most promising subproblem receives additional cutting planes to prune it. The goal of Global Optimization is only to identify a local optimal solution if it is promising candidate to become a global optimal solution. Notice that if Branch-and-Bound (or Disjunctive Programming) is solved until its end, the global optimal solution will be identified due to its combination of mixed integer linear programming (MILP) and nonlinear programming (NLP) search approaches. For instance, readers interested in the subject can refer to the books by Horst and Tuy (1992) and Tawarmalani and Sahinidis (2002).

In order to solve the proposed problem using mathematical programming, a software for mixed integer nonlinear programming (MINLP) problems was used. The chosen software was GAMS/BARON/CPLEX, where GAMS is a modeling platform for mathematical programming problems, CPLEX is a MILP solver which is controlled by BARON, that is a MINLP solver developed by Tawarmalani and Sahinidis (2002). Since there is a paradigm that heuristic methods are the best choice to solve MINLP problems (due to its complexity), the authors have decided to test GAMS/BARON/CPLEX at the proposed problem. In order to use this software to solve the proposed problem, equations presented in section 2 have been modeled in GAMS. GAMS was set to use BARON as its solver, demanding no addition actions to solve the proposed problem.

3.2. Simulated Annealing

Unlike the GA (proposed by Saravanan *et al.* (2003)) and the mathematical programming approaches (which only required the modeling within GAMS), a simulated annealing (SA) algorithm is proposed in this work to be compared to the two other approaches. The simulated annealing is a probabilistic local search technique based in an analogy with the change of the state of the material when simulating its cooling after being heated to its liquid state (Aarts, 1989). The analogy between the optimization technique and the change of the state of the material is very direct, where the objective function is associated to the evaluation on the amount of internal energy. The several states of the material are the possible solutions. The meta-stable states of the material are the local optima and the crystalline structure is the possible local optimum (considering a crystal being cooled). The initial value of the temperature – which will have no physical meaning at optimization problems – and its decrement expression are important factors to the good performance of SA.

This work intends to compare different optimization approaches. Therefore, this paper tests different SA approaches, which are compared to the SA approach proposed by Saravanan *et al.* (2003; 2005). In order to enable an easier comparison to the approach proposed by Saravanan *et al.* (2003; 2005), all the tested SA approaches use the same initial temperature, equal to 475 (which was proposed by Saravanan *et al.*, 2005).

Notice that Saravanan *et al.* (2003; 2005) have presented several heuristic approaches to solve this problem but they do not present or compare different parameters for each heuristic. Due to this, SA approaches at this paper are tested for different cooling factors $\boldsymbol{\alpha}$ – which assumed the values 0.9 and 0.99 – and with the use or not of re-heating. Re-heating is used to re-start the SA using the last solution – which is expected to be close to or at a local optimum – as the initial solution. Whenever used, re-heating is performed 10 times. The SA proposed by Saravanan *et al.* (2005) only used a cooling factor equal to 0.9 and did not use re-heating. The steps to perform the simulated annealing – which are different from those of previous papers – are as follows. The goal is to test the influence of these parameters to SA. The steps to perform the simulated annealing are as follows. The variable s* represents the best solution found during the execution of the algorithm. Minimum temperature was set to 30, as a limit when SA behaves as a "Hill-Climbing" approach; that is, SA starts performing a local search. C_i is used to count the amount of iterations within local search that have been performed. C_f indicates the maximum number of iterations within local search. K indicates the cost of a solution.

Step 1 SET $C_i = 0$, C_f, T_0, initial solution (s).
Step 2 Randomly generate a neighbor solution (s').
Step 3 IF K(s') ≤ K(s), THEN:
s = s'
IF K(s') ≤ K(s*), THEN: s* = s'
ENDIF
ELSEIF K(s') > K(s), THEN:
Δ = K(s') - K(s)
IF R ≤ EXP(Δ /T), THEN: s = s'
ENDIF
ENDIF.
Step 4 SET T = αT
IF T < 30, THEN:
$C_i = C_i + 1$
IF $C_i > C_f$, THEN:
$C_i = 0$
$T = T_0$
COUNT RE-HEATING
ENDIF
ENDIF
Step 5 IF RE-HEATING ≤ STOP_CRIT, THEN: GOTO STEP 2
Step 6 Present best solution found (s*)

4. RESULTS

There was an effort to use only data extracted from Saravanan *et al.* (2005) in order to compare their results with all three results from our optimization techniques, but some bounds and considerations were not presented by them. Then, data used in this paper were extracted from Saravanan *et al.* (2005), Sankar *et al.* (2007), and Stemmer (2001) and are described in Tab. 3.

Table 3. Cutting model data.

Parameter/ Constraint	Values	Parameter / Constraint	Values	Parameter / Constraint	Values
v_{crU}	550 m/min.	v_{crL}	50 m/min.	f_{rU}	1.0 mm/rev.
f_{rL}	0.2 mm/rev.	a_{prU}	3.0 mm	a_{prL}	1.0 mm
v_{csU}	550 m/min.	v_{csL}	50 m/min.	f_{sU}	1.0 mm/rev.
f_{sL}	0.2 mm/rev.	a_{psU}	3.0 mm	a_{psL}	1.0 mm
C_t	300	n	0.2	k_f	108
μ	0.75	υ	0.95	P_{rU}	200 kW
K_q	132	T	0.4	Φ	0.2
Q_{rU}	1000 °C	Q_{sU}	1000 °C	δ_1	20
r	1.2 mm	$R_{max.}$	10.0 µm	k_1	1.0
k_2	1.0	k_3	1.0	t_{tf}	3.0 min.
m	1.0	K_t	15 $/Tool	K_p	2.0 $/min.

Maintenance times and fixed costs to each produced part were considered as constants and ignored for the calculus of Eq. 1 and 2, because they do not influence in the choice of the value of the cutting parameters. The software used to solve non-linear programming was GAMS/BARON/CPLEX. All equations were included in the mathematical model (including rough and finish turning bounds) calculation of production time and the objective function which in this model is to reduce costs.

A part/component extracted from Saravanan et al. (2005) was used to analyze the three optimization techniques and to compare the results. The time to machine this part was calculated using Eq. 10, 11, 12, 13, and 14. Figure 1 shows the component used for the tests.

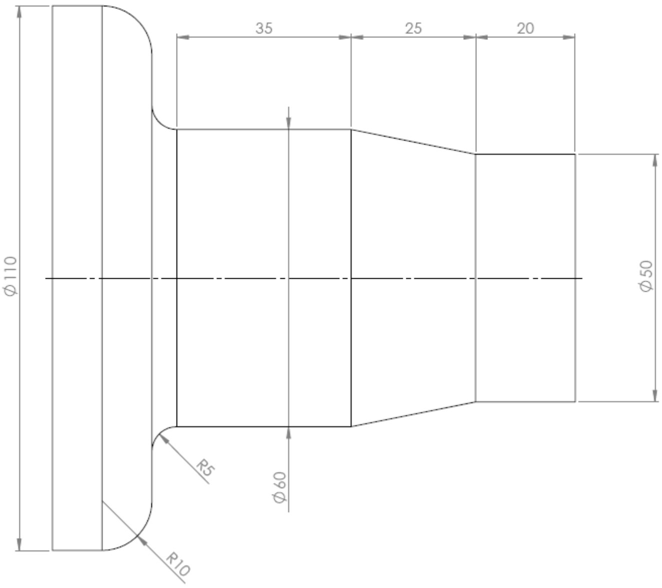

Figure 1. Component used to test the three optimization techniques (Saravanan *et al.*, 2005)

Using a Pentium IV PC with 2.4 GHz and 2 GB of RAM memory, GAMS/BARON/CPLEX software took 0.31 seconds to solve the non-linear mathematical programming, while SA was performed within 2 seconds and GA was solved within 87 seconds. The results obtained using simulated annealing, genetic algorithms, and mathematical programming are in Tab. 4. Firstly, it is possible to identify that SA was outperformed by the two other approaches, both in the best solution found, average cost (when mathematical programming seems to have always converged to the optimal solution), and computational time. This is an indication that there are so-called "global optimization software" (Neumaier, 2009) which are able to deal with non-linear mathematical programming problems.

The results using mathematical programming and GA indicate that it is not possible to select the best approach. Many works in the literature try to point to the "best" approach without a statistical background, as in (Saravanan *et al.*, 2003) and in Saravanan *et al*. (2005). Analysis of Variance (ANOVA) was used to check the hypothesis that there is no significant difference among the average of all treatments (or approaches) (Montgomery, 1991). With the use of ANOVA and repeating each treatment 20 times, it was not possible to refuse this hypothesis. That is, due to the variance (or standard deviation) of the results, there will be a superposition of the normal curves for all these two approaches.

Table 4. Results obtained using simulated annealing, genetic algorithms and mathematical programming.

Optimization Technique	Minimum Cost *K* [$]	Average Cost *K* [$]	v_{cr} [m/min.]	v_{cs} [m/min.]	f_r [mm/min.]	f_s [mm/min.]	a_{pr} [mm]	a_{ps} [mm]	T_t [min.]
SA (α=0.9 and no re-heating)	16.53	55.54 ± 36.6	140.0	140.0	0.90	0.56	1.0	1.0	7.22
SA (α=0.9 and with re-heating)	22.59	38.39 ± 6.85	164.0	206.2	0.76	0.72	1.0	1.0	7.3
SA (α=0.99 and no re-heating)	18,65	40.38 ± 9.68	146.0	152.61	0.79	0.51	1.0	1.0	7.68
SA (α=0.99 and with re-heating)	16.53	38.16 ± 6.08	140.0	140.0	0.90	0.56	1.0	1.0	7.22
GA	12.62	13.97 ± 2.19	148.7	157.8	1.0	0.84	1.0	1.0	5.1
Mathematical Programming	12.62	12.62 ± 0	148.7	157.8	1.0	0.84	1.0	1.0	5.1

5. CONCLUSION AND DISCUSSIONS

This paper is part of two ongoing M.Sc. degree works which studies the optimization of cutting parameters at turning operations. Three different approaches have been tested – mathematical programming, simulated annealing

(SA), and genetic algorithms (GA). The goal was to analyze the behavior of SA and GA (originally presented by Saravanan et al. (2003; 2005)), comparing their results to a mathematical programming approach. As part of an ongoing research, SA has been tested with different cooling factors and with the possibility of performing re-heating. There was an effort to use only data extracted from Saravanan *et al.* (2005) in order to compare results, but there was not enough data to repeat their work. Therefore, data has been collected from different sources. The results indicate that SA was outperformed by mathematical programming and GA. But the standard deviation on SA and GA indicate that there is room for improvements on both heuristic approaches.

As another future work, the fact that Saravanan *et al.* (2003; 2005) used minimization of production costs as their objective function suggests that this work can be extended to the maximization of production on flexible manufacturing cells (FMC). In order to accomplish this, it is necessary to use minimization of production times as the objective function. With the minimum time to manufacture each part in each machine it is possible to optimize the sequence of the lot production, looking to reduce the time of idle machines, reducing, thereby, the global time of the production cycle. Using the GANTT diagram it is possible to find where the times of idle machines are.

Cutting out completely the machine idleness is ideal to reduce the production time of the lot. However, this is very difficult to happen in practice. The idleness in manufacturing can be “filled” by increasing the production time of the parts at the idle times of the machines. That is, if it is not possible to eliminate idleness, it is possible to seek production cost reduction at idle machines. At idle times of machines, the reduction on cutting speed, feed rate, and depth of cut will increase the time to remove material, but the cutting tool consumption will also be reduced and, consequently, the manufacturing costs will tend to become smaller. Therefore whenever there is machine idleness it will be important to seek costs reduction. Optimization of FMC operation is also proposed as a future work.

6. ACKNOWLEDGEMENTS

This paper has been partially supported by CAPES (Maurício I. Takano).

7. REFERENCES

Aarts, Emile H.L. and Korst, J., 1989, “Simulated Annealing and Boltzmann Machines : A Stochastic Approach to Combinatorial Optimization and Neural Computing”, Ed. Wiley, Chichester, New York, 272 p.

Agapiou, J. S., 1992, “The optimisation of machining operations based on a combined criterion, Part-1: the use of combined objectives in single pass operations”, ASME Journal of Engineering for Industry, Vol. 114, pp. 500–507.

Agapiou, J. S. , 1992, “The optimization of machining operations based on a combined criterion, Part 2: multi pass operations”, ASME Journal of Engineering for Industry, Vol. 114, pp. 508–513.

Dorigo, M., Maniezzo, V. and Colorni, A.., 1996, “Ant System: Optimization by a Colony of Cooperating Agents”, IEEE Transactions on Systems, Man, and Cybernetics - Part B, Vol.26, pp. 29-41.

Glover, F. and Laguna, M., 1997, “Tabu Search”, Ed. Kluwer Academic, Norwell, Massachusetts, 382 p.

Goldberg, D.E., 1989, “Genetic Algorithms in Search, Optimization and Machine Learning”, Ed. Addison-Wesley, Boston, Massachusetts, 372 p.

Horst, R., Tuy, H., 1992, “Global Optimization: Deterministic Approaches”, Ed. Springer-Verlag, Heidelberg, Germany, 698 p.

Lee, B.Y. and Tarng, Y.S., 2000, “Cutting-Parameter Selection for Maximizing Production Rate or Minimizing Production Cost in Multistage Turning Operations”, J. of Materials Processing Technology, Vol.105, pp. 61-66.

Montgomery, D. C., 1991, “Design and analysis of experiments. 3rd ed.”, J. Wiley, New York, USA, 649p.

Neumaier, A., 2009, “Global Optimization Website”, 29 May 2009, http://www.mat.univie.ac.at/~neum/glopt.html

Prasad, A.V.S.R.K., *Rao*, *P.N.*, *Rao*, *U.R.K.*, 1997, “Optimal selection of process parameters for turning operations in a CAPP system”, International Journal of Production Research, Vol. 35, 1495–1522.

Sankar, R.S., Asokan, P., Saravanan, R., Kumanan, S. and Prabhaharan, G., 2007, “Selection of machining parameters for constrained machining problem using evolutionary computation”, Int. J. Adv. Manuf. Technol., Vol.32, pp. 892-901.

Saravanan, R., Asokan, P. and Vijayakumar, K., 2003, “Machining Parameters Optimisation for Turning Cylindrical Stock into a Continuous Finished Profile Using Genetic Algorithm (GA) and Simulated Annealing (SA)”, Int. J. Adv. Manuf. Technol., Vol.21, pp. 1-9.

Saravanan, R., Sankar, R.S., Asokan, P., Vijayakumar, K. and Prabhaharan, G., 2005, “Optimization of Cutting Conditions During Continuous Finished Profile Machining Using Non-Traditional Techniques”, Int. J. Adv. Manuf. Technol., Vol.26, pp. 30-40.

Stemmer, C.E.,2001, “Ferramentas de Corte I”, Ed. UFSC, Vol.1, Florianópolis, Brazil, 249 p.

Su, Chao-Ton and Chen, Mu-Chen, 1999, “Computer-Aided Optimization of Multi-Pass Turning Operations for Continuous Forms on Cnc Lathes”, IIE Transactions, Vol.31, pp. 583-596.

Tawarmalani, M., Sahinidis, N. V., 2002, "Convexification and Global Optimization in Continuous and Mixed-Integer Nonlinear Programming: Theory, Algorithms, Software, and Applications", Ed. Springer, Dordrecht, The Netherlands, 504 p.

Wang, Rong-Tsu and Liu, Shiang-Tai, 2007, "An Economic Machining Process Model With Interval Parameters", Int. J. Adv. Manuf. Technol., Vol.33, pp. 900-910.

Xiaobo, Z. and Ohno, K., 1999, "Modeling for Flexible Manufacturing Systems With an FMS Blocking Mechanism and a BDSM Job Routing", IIE Transactions, Vol.31, pp. 957-963.

8. RESPONSIBILITY NOTICE

The authors are the only responsible for the printed material included in this paper.