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# MULTI-OBJECTIVE OPTIMIZATION OF CUTTING PARAMETERS IN THE SAE 4340 STEEL TURNING PROCESS

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***Abstract.*** *In recent years, maximizing production efficiency in machining operations has been an important topic in the manufacturing industry. To achieve this goal, organizations usually increase the production rate, decrease the operational costs and improve the production quality. These activities can be affected by different factors such as machine tool conditions, cutting tool geometry, workpiece material and cutting parameters. Among these factors, the cutting parameters present important influence on the operation quality and are easily manipulated by the user. Therefore, the determination of optimal values for these parameters is important for planning an economically competitive process. In the light of these facts, this paper addresses the problem of multi-objective optimization of the SAE 4340 steel turning process. The objective functions seek a minimum cutting tool wear and a maximum material removal rate, subject to the constraints imposed by the cutting temperature and workpiece surface roughness. To solve this optimization problem, the generalized reduced gradient method and particle swarm optimization method were used. Despite the distinct nature of the techniques employed, both were able to converge to the optimal solution of the problem.*

***Keywords:*** *turning, optimization, cutting parameters, reduced gradient, particle swarm optimization.*

## 1. INTRODUCTION

The cutting parameters used in machining operations directly affects the process efficiency, the surface quality of the workpiece and the total cost of the operation. Therefore, the optimization of the values assigned to these parameters is a crucial task in order to obtain a commercially competitive manufacturing process (Sheng, 2015). According to Jafarian et al. (2013), among the parameters controlled by the user, the cutting speed, feed rate and depth of cut have an important influence on machining quality. Thus, a proper selection of these parameters is necessary to achieve optimal cutting conditions and consequently improve the productive efficiency.

Several solution approaches have been used to optimize turning operations, among which are the gradient-based methods, dynamic programming and the sequential unconstrained minimization technique (Yildiz, 2009). Despite the wide variety of methods available to optimize this type of problem, the evaluation of factors such as convergence speed and solution accuracy is of great importance to confirm the feasibility of the proposed technique.

So far, several researchers experimentally investigated machining operations to evaluate the effect of cutting parameters on process output variables. Xiaobin et al. (2013) studied the influence of the change in cutting speed values on the milling conditions of AISI H13 steel. The authors found an optimal cutting speed of 800 m/min, which results in longer tool life, lower cutting forces and better aspect of the produced chip when milling.

Despite the importance of experimental study of the machining operations, performing numerous test to determine the optimal cutting conditions is an expensive task and requires a great deal of time. Face with this scenario, some researchers have proposed computational approaches to solve this problem. Based on the mathematical modeling of the machining processes, the optimal cutting parameters are determined by optimization algorithms. This approach was successfully implemented by Saravanan et al. (2003) and Srikanth and Kamala (2008).

Vijayakumar et al. (2003) proposed a technique based on the ant colony algorithm to solve multi-pass turning optimization problems, considering the roughing and finishing stages. The objective function used by the authors was based on the minimization of the unit production cost, subject to various practical machining constraints. The authors concluded that the proposed methodology presented satisfactory results when compared to other techniques carried out by different researchers.

Umer et al. (2014) investigated the multi-objective optimization problem of oblique turning operations while machining AISI H13 tool steel, using finite element modeling and multi-objective genetic algorithm. The authors sought to optimize this process in terms of cutting force and temperature, adopting as constraints the required material removal rate and cutting power. The optimal parameters were validated with the developed finite element model and further experiments, which highlighted the efficacy of the methodology proposed by the authors to approach this type of problem.

Li et al. (2017) presented a multi-objective parameter optimization model for maximizing energy efficiency and minimizing production cost of multi-pass face milling operation. The proposed model was solved using a technique based on the particle swarm optimization algorithm. Subsequently, a case study was carried out to validate the proposed model and search for the trade-off solutions between maximum energy efficiency and minimum production cost. From the results of the case study, the authors found significant interaction effects between cutting parameters and number of passes. A satisfactory solution for the objective function was obtained by simultaneously optimizing the cutting parameters of each pass and the total number of passes, which highlights the importance in the balance between the objective functions of the problem.

In view of the above, this work investigates the problem of multi-objective optimization for the turning operation, where it is sought to minimize the cutting tool wear and maximize the material removal rate, subject to the constraints established by the temperature imposed to the cutting tool and the surface roughness of the workpiece. The cutting parameters considered as optimization variables were the cutting speed, feed rate and depth of cut. The optimum combination of values for these three input parameters was defined for the SAE 4340 single pass turning operation using a tungsten carbide tool.

## 2. MATHEMATICAL DEFINITION

### 2.1 Proposed model

The mathematical model presented by Yang and Natarajan (2010) was adopted in this work in order to describe the optimization problem of minimizing the tool wear and maximizing the material removal rate when turning SAE 4340 with tungsten carbide tools. The objective functions presented by these authors for tool wear ($T_w$) and material removal rate ($M_r$) are:

$$T_w = 0.33349 v^{0.1480} f^{0.4912} d^{0.2898}\ [mm] \tag{1}$$

$$M_r = 1000 v f d\ [mm^3/min] \tag{2}$$

Being ($v$) the cutting speed, ($f$) the feed rate and ($d$) the depth of cut.

The temperature ($T$) at the tool-workpiece interface is defined by:

$$T = 88.5168 v^{0.3156} f^{0.2856} d^{0.2250}\ [°C] \tag{3}$$

The temperature constraint is defined by the maximum value allowed for the workpiece-tool combination. For tungsten carbide tools and SAE 4340 steel workpiece, this relation can be expressed as $T \leq 500°C$.

The surface roughness ($R_a$) is expressed by:

$$R_a = 18.5167 v^{-0.0757} f^{0.7592} d^{0.1912}\ [\mu m] \tag{4}$$

Considering the roughness limit value for a surface finishing operation, the arithmetical mean deviation parameter shall not exceed 1.5 to 2 µm. Therefore, the adopted limit is $R_a \leq 2\mu m$.

The available range for cutting speed ($v$) and feed rate ($f$) are defined by the couple of tool/workpiece materials, as also by the machine tool operational characteristics. The range of depth of cut is considered to lie in-between 0.5 to 2.5 mm to compensate both finish and rough machining. Thus, the cutting parameters (optimization variables) range are:

$$42 \leq v \leq 201\ [m/min] \tag{5}$$

$$0.05 \leq f \leq 0.33\ [mm/rev] \tag{6}$$

$$0.5 \leq d \leq 2.5\ [mm] \quad (7)$$

### 2.2 Problem formulation with constraints

The problem presented by Yang and Natarajan (2010) for the turning operation is classified as a multi-objective optimization problem. For this reason, the method of objective weighting is used to combine the two objective functions. Thus, the weighted objective can be defined by $wT_w + (1 - w)M_r$. A weighting value ($w$) of 0.5 is considered for the problem. The new objective function is also normalized with the use of a constant multiplier ($\lambda$), defined by:

$$\lambda = M_{r\,max}/T_{w\,max} \quad (8)$$

The maximum material removal rate ($M_{r\,max}$) is obtained by replacing the maximum allowed values for the cutting parameters in Eq. (2), given that the temperature and roughness restrictions are not violated. The maximum flank wear ($T_{w\,max}$) allowed for the cutting tool is assumed to be 0.5 mm. Thus, the combined objective function ($C.O.F.$) is expressed by:

$$C.O.F. = w\lambda T_w - (1 - w)M_r \quad (9)$$

Finally, the turning optimization problem can be mathematically expressed by:

$$Minimize\ C.O.F. = w\lambda T_w - (1 - w)M_r \quad (10)$$

Subject to the constraints:

$$88.5168v^{0.3156}f^{0.2856}d^{0.2250} \leq 500 \quad (11)$$

$$18.5167v^{-0.0757}f^{0.7592}d^{0.1912} \leq 2 \quad (12)$$

Given the following variation interval for the cutting parameters:

$$42 \leq v \leq 201 \quad (13)$$

$$0.05 \leq f \leq 0.33 \quad (14)$$

$$0.5 \leq d \leq 2.5 \quad (15)$$

## 3. METHODOLOGY

In order to solve the multi-objective optimization problem, two different approaches were used: the generalized reduced gradient method (GRG) and the particle swarm optimization (PSO). These methods were employed with the purpose to compare their respective search mechanisms, convergence speed and accuracy. The methodology applied in each of these approaches is briefly described below.

### 3.1 Generalized reduced gradient method (GRG)

As its name suggests, the GRG method relies on the objective function gradient information to find a local optimal solution. Thus, given an arbitrary initial value, the algorithm will always seek within the search space in the direction of the lowest gradient of the objective function until the optimal solution is found.

The major disadvantage in using this method is its dependence on the initial value used to start the solution search. Hence, to obtain the global optimum, the searching must start from an initial point that belongs to the same region that contains this solution. To cope with this issue, 120 initial points, randomly defined within the space of viable solutions, were used to perform the search. At the end of the process, all the minimums found were compared to each other by the algorithm and the smallest of them is presented as result.

### 3.2 Particle swarm optimization (PSO)

Particle swarm optimization is an evolutionary metaheuristic. In this method, a population called "swarm" of viable candidates or "particles" move through the search space obeying certain relatively simple rules. The movement of each particle is guided by its respective best position known in the search space and by the value of the best position known by the whole swarm. When better positions are discovered along the algorithm iterations, they will guide the movement of the swarm, directing it to a solution that is satisfactorily close to the global optimum of the objective function.

In order to simplify the space of solutions for the application of the PSO algorithm, some principles of the Lagrangian relaxation were used on the constraints (11) and (12), making the problem constrained only to the decision variables domain. Hence, the Eq. (10) becomes:

$$Minimize\ C.O.F. = w\lambda T_w - (1-w)M_r - u_1(500 - 88.5168v^{0.3156}f^{0.2856}d^{0.2250}) - u_2(2 - 18.5167v^{-0.0757}f^{0.7592}d^{0.1912}) \tag{16}$$

By simplifying the solving method of the Eq. (16), is intended to penalize the objective function only when the constraints (11) and (12), now relaxed, are violated.

Another simplification carried out concerns the multipliers $u_1$ and $u_2$, which are transformed into a sufficiently large constant $\theta$, capable of penalizing the objective function if the relaxed constraints are violated. Thus, the new objective function is:

$$Minimize\ C.O.F. = w\lambda T_w - (1-w)M_r - \theta \cdot \min(0; 500 - 88.5168v^{0.3156}f^{0.2856}d^{0.2250}) - \theta \cdot \min(0;\ 2 - 18.5167v^{-0.0757}f^{0.7592}d^{0.1912}) \tag{17}$$

Subject to the domain presented in Eq. (13), (14) and (15).

Finally, as previously mentioned, the PSO metaheuristic was applied to solve the adapted problem. Both methods proposed in this work were performed on a computer with an Intel i3 processor and 8 GB of standard DDR3 RAM.

## 4. RESULTS AND DISCUSSION

Table 1 shows the results obtained with the GRG and PSO methods and the optimal solutions presented by Yang and Natarajan (2010). These authors proposed the use of multi-objective differential evolution (MODE) and non-dominated sorting genetic algorithm (NSGA-II) methods to solve the multi-objective optimization problem. Both methods converged to the same optimal solution, as can be seen in Tab. 1. In addition to the optimal cutting parameters, tool wear ($T_w$), material removal rate ($M_r$) and the values of the combined objective function ($COF$) are also shown in Tab. 1.

Table 1. Results obtained from the GRG and PSO in comparison to those proposed by Yang and Natarajan (2010).

| Parameters | MODE (Yang and Natarajan, 2010) | NSGA-II (Yang and Natarajan, 2010) | GRG | PSO |
|---|---|---|---|---|
| $v$ (m/min) | 200.980 | 200.980 | 201.0 | 201.0 |
| $f$ (mm/rev) | 0.071 | 0.071 | 0.07186 | 0.07186 |
| $d$ (mm) | 2.489 | 2.489 | 2.50 | 2.49985 |
| $T_w$ (mm) | 0.261 | 0.261 | 0.26157 | 0.26157 |
| $M_r$ (mm$^3$/min) | 35979.300 | 35979.300 | 36109.814 | 36108.166 |
| $COF$ (mm$^3$/min) | -8564.990 | -8564.990 | -8609.664 | -8608.840 |

From Tab. 1, it is possible to see that the results achieved by the methods proposed in this work are close to the optimal solutions obtained by Yang and Natarajan (2010), presenting an insignificant difference when compared to the cutting parameters employed in industrial turning operations. Observing the values of the combined objective function, one can notice that the algorithms proposed in this work were able to find better solutions for the problem, converging to values lower than those obtained by Yang and Natarajan (2010).

Although being a method normally used for local optimization problems, the GRG was able to find the global optimum solution of the problem, which evidences the importance of using several random initial points in the search for the optimal solution. Despite the success obtained by this method, the advantages of using metaheuristics in this type of problem are clear, since this kind of approach is able to converge to a solution sufficiently close to the optimal values faster than gradient-based methods. To solve the SAE 4340 turning problem, the GRG took approximately 12 seconds to find the optimal solution, while the PSO algorithm spent only 3 seconds to converge to the optimal solution.

The efficiency of evolutionary methods in obtaining global optimum solutions was proven by the employment of the PSO algorithm, which presented a much faster convergence when compared to the GRG method. Another important characteristic that justifies the use of metaheuristics is the fact that they do not present great dependence on the problem in question, being able to be applied in several different models without the necessity of great adjustments on the optimization algorithm. Figure 1 shows the convergence graph of the implemented PSO, where the values of the combined objective function were plotted as a function of the number of generations for six different runs of the algorithm.

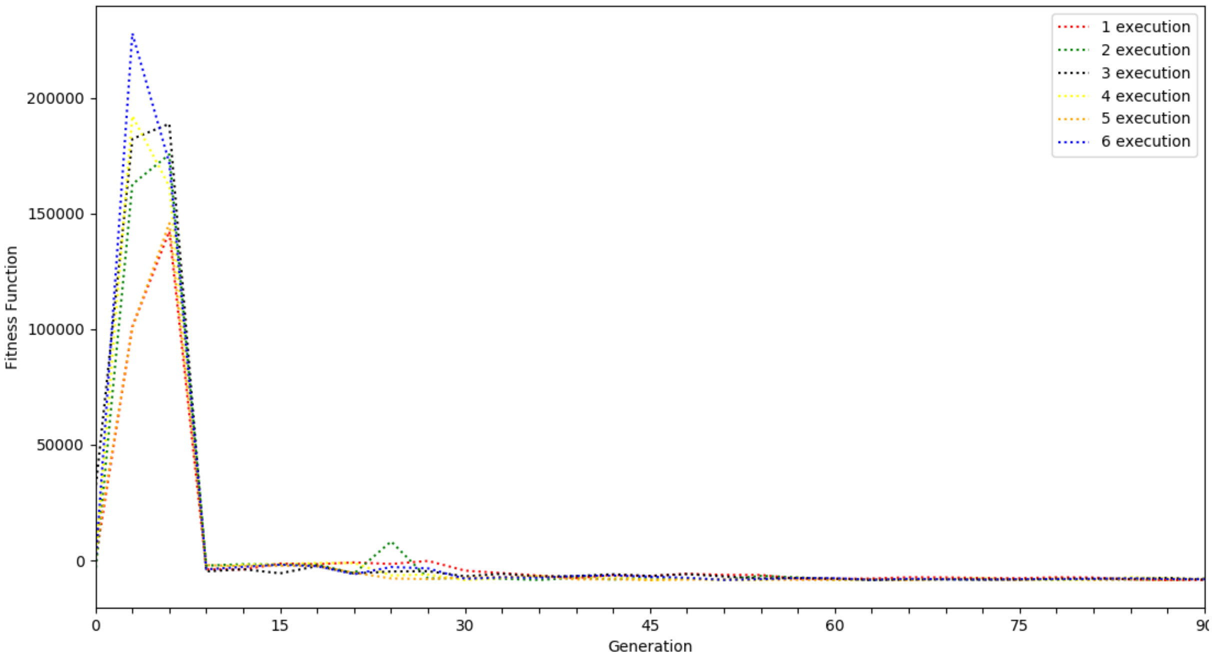


Figure 1. Convergence of the PSO algorithm through generations.

Figure 1 evidences the high efficiency presented by the PSO in converging to the optimal solution of the problem addressed in this work, obtaining this value before the 40th generation. The accuracy of the proposed method is also perceived, since the output values remains unchanged throughout all the generations following the convergence.

The swarm behavior can be seen even more clearly in Fig. 2, where the evolution of the population is presented along the first generations of the algorithm. Figure 2 shows that the particles cluster rapidly, confirming the algorithm efficiency in relation to the convergence of the solution set, which is initially scattered by the search space.

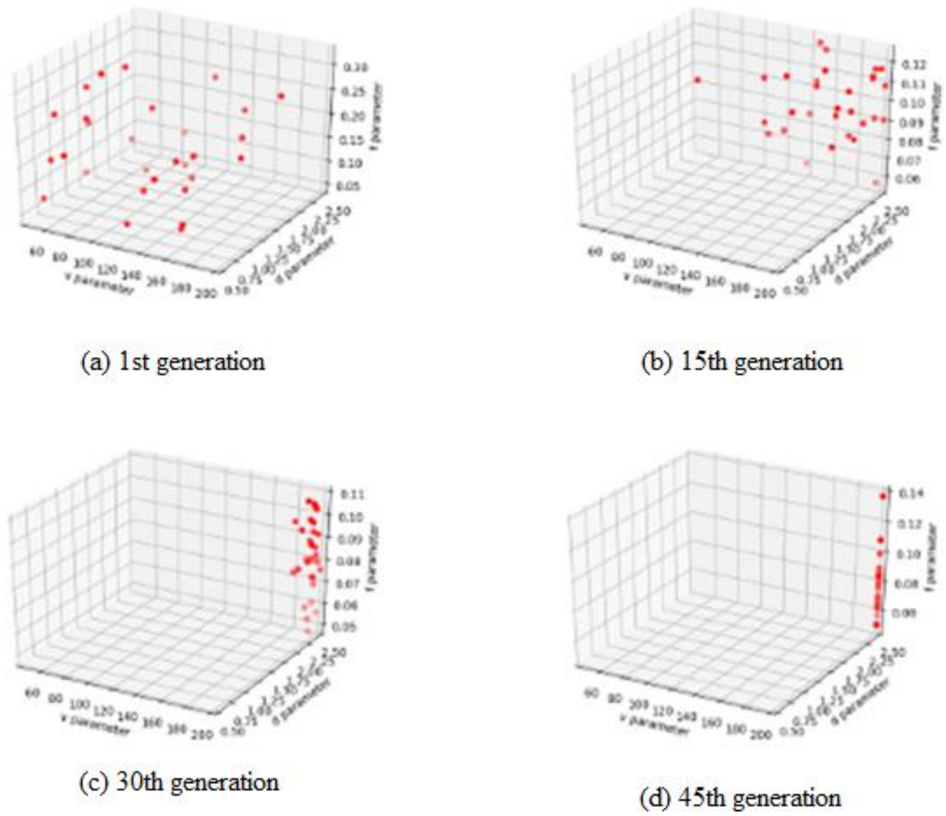


Figure 2. Swarm behavior throughout first generations.

## 5. CONCLUSIONS

In this work, the SAE 4340 steel turning optimization problem was studied for two distinct and inversely proportional objectives, these being the minimization of tool wear and the maximization of material removal rate. Two different approaches were presented to solve this problem, aiming to compare the results obtained. The generalized reduced gradient method (GRG) and the metaheuristic called "particle swarm optimization" (PSO) were used to optimize the problem.

A satisfactory outcome was achieved from the experiments performed in this work, considering that both methods were able to converge to the solution considered optimal for the SAE 4340 turning problem. However, it is worth to point out the existence of the risk in obtaining a local optimum solution using gradient-based methods in this type of problem. Thus, the use of metaheuristics is advantageous due to the robustness presented by this mode of approach, in addition to a greater potential for solving problems that are mathematically more complex.

## 6. ACKNOWLEDGMENTS

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