# MULTIOBJECTIVE OPTIMIZATION PARAMETERS OF TURNING PROCESS OF STEEL SCr445 USING GENETIC ALGORITHM

## TỐI ƯU HÓA ĐA MỤC TIÊU CÁC THAM SỐ QUÁ TRÌNH TIỆN THÉP SCr445 SỬ DỤNG THUẬT TOÁN DI TRUYỀN

**Dang Xuan Hiep*, Le Tien Duc**

**ABSTRACT**

Nowadays in manufacturing industry, there are always challenges in improving product quality, increasing productivity, reducing costs, reducing production costs ... Therefore, optimizing parameters of manufacturing process is necessary and urgent. The paper presents the multi-objective optimization of the SCr445 (45X) steel turning process with input parameters: cutting speed, feed rate and depth of cut. Two optimal targets are surface roughness (SR) and material removal rate (MRR). Based on the genetic algorithm (GA) optimizing multi-objective cutting parameters simultaneously combined with Pareto search solution and optimization solution, besides along with empirical research to select the optimal cutting parameters.

***Keywords:*** *Multi-objective optimization, optimizing turning process, genetic algorithm, Pareto optimal.*

**TÓM TẮT**

Ngày nay, trong sản xuất công nghiệp cơ khí luôn phải đối mặt với những thách thức trong việc nâng cao chất lượng sản phẩm, tăng năng suất, giảm giá thành, giảm chi phí sản xuất… Vì vậy, việc tối ưu hóa chế độ công nghệ là việc làm cần thiết và hết sức quan trọng. Bài báo trình bày việc tối ưu hóa đa mục tiêu quá trình tiện thép SCr445 (45X) với các thông số công nghệ: vận tốc cắt, lượng chạy dao, chiều sâu cắt. Hai mục tiêu được nghiên cứu là độ nhám bề mặt (SR) và tốc độ bóc tách vật liệu (MRR). Dựa trên thuật toán di truyền tối ưu hóa đa mục tiêu các thông số chế độ cắt đồng thời kết hợp với giải pháp tìm kiếm Pareto và giải pháp tối ưu thỏa hiệp, bên cạnh đó cùng với nghiên cứu thực nghiệm để lựa chọn chế độ cắt tối ưu.

***Từ khóa:*** *Tối ưu hóa đa mục tiêu, tối ưu hóa quá trình tiện, thuật toán di truyền, tối ưu Pareto.*

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## 1. INTRODUCTION

Optimizing the cutting process is an indispensable requirement in the manufacturing industry. The main problem of improving the efficiency of the mechanical processing is to determine the optimal cutting parameter for different tasks, adapting to specific production conditions.

Quality and productivity of manufacturing process are two important indicators in the manufacturing industry. One of the criteria to evaluate machining quality is surface roughness (SR) and to evaluate machining productivity through material removal rate (MRR). In previous documents, when studying the cutting process, it was studied independently or the effect of cutting parameters on surface roughness [1] or the effect of cutting parameters on MRR [2]. In fact, they are single-objective studies with many methods such as regression analysis method [3], differential method [4], geometric programming [5]...

However, in practice, manufacturers often encounter problems of optimizing multiple goals simultaneously. Thus, the goals are often contradictory and incompatible, or take a lot of time to conclude, resulting in increasing manufacturing cost. This is the multi-objective optimization problem.

There have been many different approaches to solving multi-objective problems such as using artificial neural network (ANN) [6], ant colony optimization (ACO) [7]., Taguchi method [8]… In Vietnam, there have been studies on the application of the above algorithms. However, they applied just in studies of prediction, identification and classification and researches in mechanical engineering are still limited.

This paper is based on the genetic algorithm for multi-objective optimization of turning process parameters of steel SCr445, and combined with the Pareto search solution [9], and experimental research to select the optimal cutting parameters. Steps are taken to solve the multi-objective optimization problem relatively accurately and quickly on a computer due to the fast processing speed, less computer resources, ensure optimization of cutting conditions in a short time.

## 2. METHOD OPTIMIZATION

### 2.1. Genetic algorithm

Genetic Algorithm (GA) [10] is a search algorithm, choosing the optimal solutions to solve different practical problems, based on the selection mechanism of nature: from the initial solution set, through many evolutionary steps, form a new set of solutions that are more appropriate, and eventually lead to a global optimal solution.

Scientists have researched and built genetic algorithm based on natural selection and evolutionary laws. Each individual is characterized by a set of chromosomes, but for simplicity we consider the case of each individual cell has only one chromosome. The chromosomes are broken down into genes arranged in a linear sequence. Each individual chromosome represents a possible solution to the problem. An evolutionary process of browsing on a set of chromosomes is equivalent to finding a solution in the solution space of the problem.

In general, a GA has five basic components (figure 1):

- A genetic representation of potential solutions to the problem.
- A way to create a population (an initial set of potential solutions).
- An evaluation function rating solutions in terms of their fitness.
- Genetic operators that alter the genetic composition of offspring (selection, crossover, mutation, etc.).
- Parameter values that genetic algorithm uses (population size, probabilities of applying genetic operators, etc.).

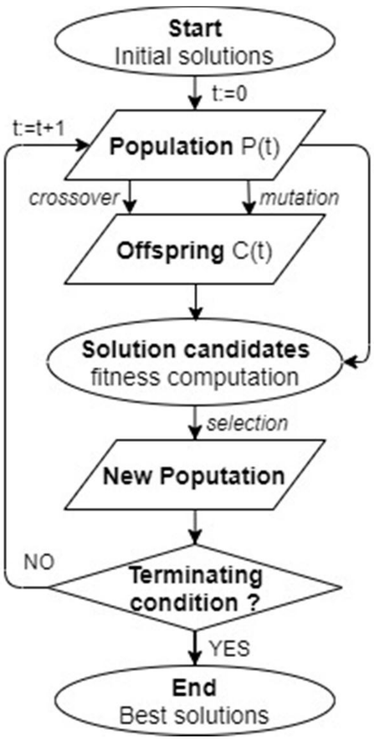


Figure 1. The general structure of GA

### 2.2. Multi-objective optimization

The general formulation of multi-objective optimization problems can be written in the following form:

Minimize (or maximize) $f_i(x) = \{f_1(x), f_2(x) \dots f_k(x)\}$

subject to $g_j(x) \le b_j$ for $j = 1, 2, \dots m$

and $h_j(x) \le b_j$ for $j = m+1, m+2, \dots m+p$

In this formulation: $f_i(x)$ denotes the $i^{th}$ objective function, $g_j(x)$ and $h_j(x)$ indicate inequality and equality type of constraints and the decision variables (machining parameters and tool geometry) are shown with the vector *x*, $x = (x_1, x_2, \dots x_n) \in R^N$. The ultimate goal is simultaneous minimization or maximization of given objective functions. As in most cases, some of the objective functions conflict with each other there is no exact solution but many alternative solutions. This family of potential solutions cannot improve all the objective functions simultaneously, called Pareto optimality [11].

There are numerous methods used to solve multiple objective optimization problems. The most common method is to combine all objectives into a single objective function through the use of "weights" or utility functions and solve for a single solution as reported by *Marler and Arora* [12]. Weighted-sum method is applied for multiparameter turning optimization using neural network modeling and particle swarm optimization in *Karpat and Özel* [13]. The combined objectives approach yields a unique solution that can be readily implemented, but this solution largely depends on numerical weights or utility functions that are often difficult to select, and are often somewhat selected arbitrarily. The Pareto optimal nondominated solution set avoids this problem and may provide numerous prospective solutions (sets of machining parameters and tool geometry) for the decision maker (manufacturer) during process planning for hard turning processes. In this study, the Pareto optimal solution set approach was applied to solve the problem of multi-objective optimization.

### 2.3. Multiobjective Optimization turning process of steel SCr445 using GA

Procedure of multi-objective optimization has four phases. First phase is mathematical modeling of machining performances related to process (tool life, cutting force, temperature,), quality (surface roughness,...), productivity (material removal rate, machining time,...), economy (cost,...) and ecology friendly (noise, pollution,...). Second phase is to define optimization problem. Third phase is selection of method for solution of optimization problem. Fourth phase is solution of optimization problem.

The proposed mathematical model of optimization, consists of two objectives (surface roughness and material removal rate), constraints and bounds.

***Decision variables***

In the turning process, the optimization of the cutting parameters plays a particularly important role. While the cutting parameters can be easily controlled to suit each machining process, it is very difficult to change other parameters about machine, knife or material. To ensure efficiency, turning is usually done only on automated machining machines with high rigidity and precision with pre-fabricated cutting tools that are expensive and do not sharpen.

Therefore, the variables considered during the optimization of the cutting process are three parameters: the cutting speed *v* (m/min), the feed rate *f* (mm/rev) and the depth of cut *t* (mm).

***Objective functions***

The most important objective of the machining process is the quality of the machining surface characterized by surface roughness. From the experiments, many authors also pointed out that mathematically, the relationship between the cutting mode and the surface roughness SR according to the formula: $SR = Cv^{\alpha}f^{\beta}t^{\gamma}$ [1] (C is constant and *α, β, γ* are determined experimentally).

Besides, production speed is also an important consideration, production speed is calculated in the whole time to process a product (Tp). It is the dependency function and material removal rate (MRR) and tool life (T), in this paper we are interested in the material removal rate and calculated by the formula: $MRR = 1000vft$ [2].

Therefore, the objective of the problem is to optimize two opposing objectives: maximizing material removal rate and minimizing surface roughness.

***Constraints***

The binding parameters affecting the determination of the optimum cutting mode are the limits of the cutting parameters. The upper and lower limit values of cutting parameters are determined based on the instrument manufacturer's recommendations and results from screening experiments [14]: $v_{min} \le v \le v_{max}$; $s_{min} \le s \le s_{max}$; $t_{min} \le t \le t_{max}$.

In addition, in some studies, there are also some parameters related to the characteristics of the machine such as cutting force (limited by machine capacity), knife stiffness.. However, because this is a processing process. Therefore, these parameters usually do not exceed the permissible limits, so there is no need to include constraints.

## 3. EXPERIMENTAL AND OPTIMIZATION RESULTS

### 3.1. Experimental details


Figure 2. DMG MORI CLX 450-CNC machine

The turning experiments on steel SCr445 rods were conducted in cutting conditions on DMG MORI CLX 450-CNC lathe machine (figure 2) with TNMG 160404E-M GRADE T9325 insert (figure 3).

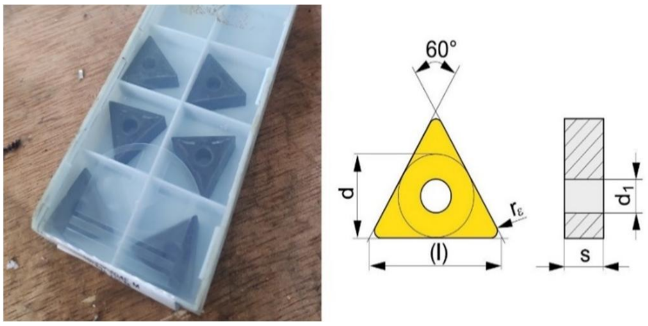


Figure 3. TNMG 160404E-M GRADE T9325 Insert

l = 16.5mm; d = 9.525mm; s = 4.76mm, $d_1$ = 3.81mm, $r_\varepsilon$ = 0.8

Workpieces: steel SCr445, dimensions: Φ30, cutting length L = 30 mm (figure 4).

Constraints: 100m/min ≤ *v* ≤ 200m/min; 0.1mm/rev ≤ *f* ≤ 0.2mm/rev; 0.1mm ≤ *t* ≤ 0.2mm.


Figure 4. Machined workpieces

Using the Hommel-Tester T1000 roughness meter to measure each detail three times in three different locations, according to the DOE matrix and experimental results of turning process are shown in table 1.

Table 1. Experimental results

| No. | V (m/min) | T (mm) | F (mm/rev) | SR (µm) | Ln (SR) | MRR ($mm^3$/min) | Ln (MRR) |
|---|---|---|---|---|---|---|---|
| 1 | 100 | 0.1 | 0.1 | 2.647 | 0.973 | 1000 | 6.908 |
| 2 | 200 | 0.1 | 0.1 | 0.478 | -0.737 | 2000 | 7.601 |
| 3 | 100 | 0.2 | 0.1 | 2.367 | 0.862 | 2000 | 7.601 |
| 4 | 200 | 0.2 | 0.1 | 0.397 | -0.925 | 4000 | 8.294 |
| 5 | 100 | 0.1 | 0.2 | 2.566 | 0.942 | 2000 | 7.601 |
| 6 | 200 | 0.1 | 0.2 | 1.346 | 0.297 | 4000 | 8.294 |
| 7 | 100 | 0.2 | 0.2 | 1.862 | 0.622 | 4000 | 8.294 |
| 8 | 200 | 0.2 | 0.2 | 1.261 | 0.232 | 8000 | 8.987 |
| 9 | 150 | 0.15 | 0.15 | 1.199 | 0.182 | 3375 | 8.124 |
| 10 | 150 | 0.15 | 0.15 | 1.143 | 0.133 | 3375 | 8.124 |
| 11 | 150 | 0.15 | 0.15 | 1.129 | 0.121 | 3375 | 8.124 |

According to the experimental results, the regression matrix is constructed as in table 2.

Table 2. Regression matrix

| No. | $X_0$ | $X_1$ | $X_2$ | $X_3$ | $X_{12}$ | $X_{13}$ | $X_{23}$ | $Y_1$ | $Y_2$ |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | -1 | -1 | -1 | 1 | 1 | 1 | 0.973 | 6.908 |
| 2 | 1 | 1 | -1 | -1 | -1 | -1 | 1 | -0.737 | 7.601 |
| 3 | 1 | -1 | 1 | -1 | -1 | 1 | -1 | 0.862 | 7.601 |
| 4 | 1 | 1 | 1 | -1 | 1 | -1 | -1 | -0.925 | 8.294 |
| 5 | 1 | -1 | -1 | 1 | 1 | -1 | -1 | 0.942 | 7.601 |
| 6 | 1 | 1 | -1 | 1 | -1 | 1 | -1 | 0.297 | 8.294 |
| 7 | 1 | -1 | 1 | 1 | -1 | -1 | 1 | 0.622 | 8.294 |
| 8 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0.232 | 8.987 |
| 9 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.182 | 8.124 |
| 10 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.133 | 8.124 |
| 11 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.121 | 8.124 |

By the method of regression analysis [15], we determine the objective function of the form:

$$SR = e^{-15.571} v^{3.378} f^{-0.248} s^{2.562 \ln v - 11.993}$$

and $MRR = 1000vft$

Therefore, the optimal problem will be taken as follows:

Minimize $F(x) = \{f_1, f_2\}$

$$f_1 = e^{-15.571} x_1^{3.378} x_2^{-0.248} x_3^{2.562 \ln x_1 - 11.993},$$

$$f_2 = (1000 x_1 x_2 x_3)^{-1},$$

where $100 \le x_1 \le 200$; $0.1 \le x_2 \le 0.2$; $0.1 \le x_3 \le 0.2$.

### 3.2. Optimization results

Parameters of the Matlab Multi-objective Genetic Algorithm Solver are presented in table 3.

Table 3. Parameters of the multi-objective genetic algorithm

| | |
|---|---|
| **Population type** | Double vector |
| **Population size** | 50 |
| **Selection function** | Tournament, Tournament size: 2 |
| **Crossover fraction** | Intermediate, Ratio: 1.0 |
| **Mutation function** | Constraint dependent |
| **Multiobjective problem settings** | Pareto front population fraction: 0.35 |
| **Stopping criteria** | Generations: 100*number of variables=300<br>Function tolerance: e-4 |

The Pareto-optimal solutions (along with corresponding performance measure values) are reported in table 4.

Table 4. Pareto-optimal solutions

| No. | V (m/min) | T (mm) | S (mm/rev) | SR (μm) | MRR ($mm^3$/min) |
|---|---|---|---|---|---|
| 1 | 199.953 | 0.199 | 0.100 | 0.403 | 3980.050 |
| 2 | 199.953 | 0.199 | 0.100 | 0.403 | 3980.050 |
| 3 | 199.997 | 0.199 | 0.199 | 1.188 | 7889.924 |
| 4 | 199.971 | 0.193 | 0.124 | 0.567 | 4795.954 |
| 5 | 199.953 | 0.196 | 0.131 | 0.617 | 5147.173 |
| 6 | 199.970 | 0.197 | 0.157 | 0.820 | 6170.963 |
| 7 | 199.954 | 0.199 | 0.134 | 0.635 | 5333.856 |
| 8 | 199.956 | 0.198 | 0.149 | 0.754 | 5907.705 |
| 9 | 199.994 | 0.198 | 0.168 | 0.916 | 6675.478 |
| 10 | 199.970 | 0.198 | 0.106 | 0.439 | 4196.538 |
| 11 | 199.942 | 0.198 | 0.119 | 0.528 | 4691.523 |
| 12 | 199.987 | 0.198 | 0.194 | 1.143 | 7684.623 |
| 13 | 199.966 | 0.198 | 0.113 | 0.490 | 4484.094 |
| 14 | 199.961 | 0.199 | 0.126 | 0.579 | 5017.774 |
| 15 | 199.983 | 0.195 | 0.155 | 0.807 | 6030.669 |
| 16 | 199.976 | 0.198 | 0.171 | 0.940 | 6786.878 |
| 17 | 199.960 | 0.197 | 0.184 | 1.057 | 7274.432 |
| 18 | 199.981 | 0.198 | 0.138 | 0.667 | 5471.094 |

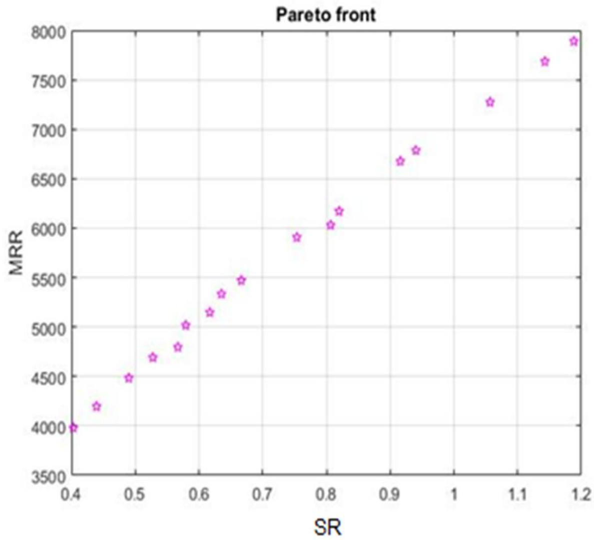


Figure 5. Pareto-optimal front

Figure 5 shows the formation of Pareto-optimal front that consist of the final set of solutions. The shape of the Pareto optimal front is a consequence of the continuous nature of the optimization problem posed. The results reported in table 4 clearly show that in 18 Pareto optimal solutions, the whole given range of input parameters is reflected and no bias towards higher side or lower side of the parameters is seen. This may be attributed to the controlled MOGA that forcible allows the solutions from all non-dominated fronts to co exist in the population. Since the performance measures are conflicting in nature, surface roughness value increases as MRR increases and the same behavior of performance measures is observed in the solutions obtained. Since none of the solutions in the Pareto optimal set is absolutely better than any other, any one of them is an acceptable solution. The choice of one solution over the other depends on the requirement of the process engineer. It should be noted that all the solutions are equally good and any set of input parameters can be taken to achieve the corresponding response values depending upon manufacturer's requirement.

Hence, based on the actual situation we select the appropriate machining parameters. For example, when required to achieve a small surface roughness should choose points 1, 2 corresponding to the cutting speed v = 199.953m/min, depth of cut t = 0.199mm, feed rate s = 0.1mm/rev, material removal rate here is MRR = 3980.050mm$^3$/min, surface roughness is SR = 0.403µm....; when need a high MRR should choose points 3 corresponding to the cutting speed v = 199.997m/min, depth of cut t = 0.199mm, feed rate s = 0.199mm/rev, material removal rate here is MRR = 7889.924mm$^3$/min, surface roughness is SR = 1.188µm ...

## 4. CONCLUSION

This paper presented a machining parameters-based optimization for the turning of steel SCr445 in order to increase the effectiveness and quality of turning process by two objectives - the surface roughness and increases the material removal rate. It has been observed that there are always conflicting relations between the objective functions of turning processes, the solutions that minimize each objective are almost impossible. Fortunately, the genetic algorithm can find the Pareto optimal solutions by global search procedure without combining all the objectives into a single objective by weight coefficients, and designer can find the optimal solutions from the Pareto optimal front with their preferences. The methodology shown in this paper provides the designer with more short analysis cycle time and more accurate design results than traditional optimization methods.

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