# MINIMIZATION OF PRODUCTION TIME IN TURNING PROCESS CONSIDERING TOOL LIFE AND OTHER NON-LINEAR CONSTRAINTS USING PARETO TECHNIQUE

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*Increase of machining efficiency in turning processes requires optimization of cutting parameters with respect to different process performances. Over the past years a number of optimization methods and algorithms for solving different turning optimization problems have been proposed. This study promotes the use parameter free optimization approach for solving multi-objective turning optimization problems with several non-linear constraints. The proposed optimization approach was used for determining optimal turning regimes, in terms of cutting speed, feed rate and depth of cut, so as to simultaneously minimize production time and used tool life while considering process constraints such as cutting force and cutting power. The obtained optimization solutions were compared with those obtained by the previous researchers using different optimization approaches. Demonstration of effectiveness of the proposed optimization approach was also illustrated while solving the extended multi-objective turning optimization problem in which surface roughness constraint was included. Finally, considering the set of Pareto optimization solutions, data for cutting tool and costs related to cutting tool, labor and overhead, analysis of total cost was shown.*

**Keywords**: Turning, multi-objective optimization, non-linear constraints, Pareto front, production time, tool life.

## 1. Introduction

Turning is one of the oldest and most widespread materials machining technology based on material removal from the workpiece in the form of chips by using cutting tool with defined cutting geometry [1]. It represents a complex machining process in which different performances, such as quality, production time, productivity and production costs, are influenced in a varying amount of different turning parameters including cutting speed, feed rate, depth of cut, cutting tool properties, workpiece material properties, cutting fluid properties, etc. [2].

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In order to ensure machining effectiveness and manage to achieve appropriate balance between opposite performances, such as machining cost, production time and machining quality, optimization of turning parameters is of crucial importance. In most cases skilled machine operators select turning parameter and cutting tools based on the acquired knowledge and experience as well as considering cutting tool recommendations. Such approach is usually conservative and results in underutilization of the machine tool and cutting tool performances. Although such determined machining regimes are not even near optimal they are acceptable in most cases for machining of small series of parts or individual parts. However, in cases of machining of large series of parts and when there is a need to satisfy given quality characteristics, optimization of turning regimes is crucial for improving machining efficiency in terms of production time and cost. In such cases each performance would be taken as mathematical function of the set of turning parameters, but considering at the same time certain process constraints such as tool life, cutting forces, available machine tool power, cutting temperature etc. Establishing mathematical relationships between turning parameters and process performances, as well as turning parameters and process constraints, creates a basis for definition of different turning optimization problems for given turning operation.

The conventional approaches for solving turning optimization problems include analytical methods, differential calculus, application of Lagrange multipliers method, random searches, simplex search method, pattern search method, gradient methods and mathematical programming methods [3-10]. In recent years modern approaches are usually based on the application of meta-heuristic algorithms including genetic algorithm [11-13], simulated annealing [14], harmony search algorithm [15], cuckoo search algorithm [16], flower pollination algorithm [17], teaching-learning-based optimization algorithm [2], particle swarm optimization [18, 19], ant colony optimization [20], scatter search [21], artificial bee colony [22], firefly algorithm [23], etc.

An increasing number of applications of metaheuristics results from the fact that by applying them, the previous optimization solutions have been improved. One more reason is that conventional approaches usually have slow convergence speed and require much computing time [13], whereby the optimal solution convergence process depends on the chosen initial solution [24]. However, the application of metaheuristics is not without shortcomings. Among others, one of the biggest shortcomings is that the optimality of the determined optimization solution is impossible to prove [25]. As proved by Venkata Rao and Kalyankar [2], many of those meta-heuristic algorithms were not handled properly and their results were not valid (feasible). Moreover, since all these algorithms belong to the probabilistic algorithms, fine tuning of algorithm-specific control parameters may be of crucial importance to decrease computation time, escape from local minima and handle properly given optimization constraints [2, 26].

Considering above-mentioned this study proposes the use of parameter free optimization approach based the hybridization of exhaustive iterative search and the epsilon-constraint method. As it guaranties the optimality, in the given discrete optimization hyper-space all solutions, constraints can be easily verified making it very transparent and easy for practical use. In the present study, the multi-objective turning optimization model, proposed by Sardinas et al. [11], is adopted for determining of optimal turning parameter values for simultaneous minimization of production time and used tool life. The multi-objective turning optimization problem was formulated considering process constraints such as cutting force and cutting power. Demonstration of the effectiveness of the proposed optimization approach was illustrated while solving the extended multi-objective turning optimization problem in which surface roughness constraint was included. Finally, using the data for specific cutting tool and costs related to cutting tool, labor and overhead, a cost analysis complementing the Pareto front information, proposed by Sardinas et al. [11], for aiding the decision-making process was implemented.

## 2. Multi-objective turning optimization problem formulation

The proposed optimization approach for solving multi-objective turning optimization problems with non-linear constraints was demonstrated considering the initial multi-objective turning optimization model given by Sardinas et al. [11] and the obtained optimization results were discussed and compared with results obtained by previous researchers. Moreover, the initial multi-objective turning optimization model was expanded by including the additional constraint, i.e. constraint on surface finish since it is inevitable part in each part drawing.

Sardinas et al. [11] applied genetic algorithm for selection of cutting parameters, i.e. cutting speed, feed rate and depth of cut, so as to minimize two mutually conflicting objectives, production time and used tool life. Production time which counts for entire time required for cutting is given by:

$$\tau(\min) = \tau_s + \frac{V}{M}\left(1 + \frac{\tau_{TC}}{T}\right) + \tau_0 \tag{1}$$

where $\tau_s$ is the set-up time, $\tau_{TC}$ is the tool changing time, $\tau_0$ is the tool idle time, $V$ is the volume of the removed material, $T$ is the tool life and $M$ is the material removal rate.

As the second objective, Sardinas et al. [11] considered used tool life, i.e. the part of the entire tool life which is being consumed during the actual machining process. The model for used tool life is given as:

$$\varepsilon(\%) = \frac{V}{M \cdot T} 100\% \tag{2}$$

Taylor's tool life equation, relating the cutting parameters and tool life is given by the following power model:

$$T(\min) = C_T \cdot v^{\alpha} \cdot f^{\beta} \cdot a_p^{\gamma} \tag{3}$$

where $v$ is the cutting speed, $f$ is the feed rate, $a_p$ is the depth of cut, and $\alpha$, $\beta$, $\gamma$ and $C_T$ are empirical constants.

For estimation of production time and used tool life Sardinas et al. [11] used the following model for calculation of the material removal rate:

$$M(\text{mm}^3/\text{min}) = 1000 \cdot v \cdot f \cdot a_p \tag{4}$$

The optimization problem formulation by Sardinas et al. [11] involved two important process constraints related to a given machine tool, i.e. cutting force and cutting power constraints. The cutting force must not be greater than a certain maximum value ($F_{max}$) which, besides the selected cutting regime, depends on the strength and stability of the given machine tool and cutting tool characteristics. The cutting force can be computed from empirical model in the following form:

$$F_c(\text{N}) = C_F \cdot v^{\alpha'} \cdot f^{\beta'} \cdot a_p^{\gamma'} \tag{5}$$

where $\alpha'$, $\beta'$, $\gamma'$ and $C_F$ are empirical constants.

During turning process the cutting power must not exceed the machine tool motor power ($P_m$) considering transmission efficiency ($\eta$). Cutting power can be calculated taking into account cutting speed and cutting force by the following model:

$$P(\text{kW}) = \frac{v \cdot F_c}{60000} \le \frac{P_m \cdot \eta}{100} \tag{6}$$

Due to the techno-technological limitations of the machine tool, cutting tool features as well as due to the machining safety, the main cutting parameter values are limited by the bottom and upper allowable limit:

$$\begin{aligned} v_{\min} &\le v(\text{m/min}) \le v_{\max} \\ f_{\min} &\le f(\text{mm/rev}) \le f_{\max} \\ a_{p_{\min}} &\le a_p(\text{mm}) \le a_{p_{\max}} \end{aligned} \tag{7}$$

The upper and lower limits of the main turning parameters such as cutting speed, feed rate and depth of cut, empirical constants for the cutting force and tool life mathematical models, which were obtained after an experimental investigation by Sardinas et al. [11], as well as other necessary optimization data are summarized in Table 1. Beside these data, the data that were included in the extended multi-objective optimization model were provided. These data are related to tool nose radius ($r_E$), maximal surface roughness ($R_{amax}$), cost for each tool edge ($z_t$), labor cost ($z_L$) and overhead cost ($z_O$). One has to note that labor cost is calculated assuming labor expenses of 50 EUR for eight working hours.

After setting the values from Table 1 and normalizing constraints the final formulation of the multi-objective turning optimization problem can be reduced to:

$$\text{Minimize: } \tau(\text{min})=0.2+\frac{219.912}{v\cdot f\cdot a_p}\left(1+\frac{0.2}{T}\right) \text{ and } \varepsilon(\%)=\frac{219.912}{v\cdot f\cdot a_p\cdot T}100\%$$

$$\text{Subject to: } g_1(\text{N})=\frac{6.56\cdot f^{0.917}\cdot a_p^{1.1}}{v^{0.286}}\le 5000 \text{ (cutting force constraint)} \tag{8}$$

$$g_2(\text{kW})=\frac{v\cdot F_c}{60000}\le 7.5 \text{ (cutting power constraint)}$$

*Table 1*

**Multi-objective optimization model data**

| Parameter | Value | Parameter | Value |
|---|---|---|---|
| $v_{min}$ | 250 m/min | $P_m$ | 10 kW |
| $v_{max}$ | 400 m/min | $\eta$ | 75% |
| $f_{min}$ | 0.15 mm/rev | $F_{max}$ | 5000 N |
| $f_{max}$ | 0.55 mm/rev | $\tau_s$ | 0.15 min |
| $a_{pmin}$ | 0.5 mm | $\tau_{TC}$ | 0.2 min |
| $a_{pmax}$ | 6 mm | $\tau_0$ | 0.05 min |
| $R_{amax}$ | 3.2 μm | $r_E$ | 1.2 mm |
| $\alpha$ | -3.46 | $z_t$ | 5 EUR |
| $\beta$ | -0.696 | $z_l$ | 0.104 EUR/min |
| $\gamma$ | -0.46 | $z_o$ | 0.1 EUR/min |
| $\alpha'$ | -0.286 | $C_T$ | $5.48\cdot10^9$ |
| $\beta'$ | 0.917 | $C_F$ | $6.56\cdot10^3$ |
| $\gamma'$ | 1.1 | $V$ | 219912 mm$^3$ |

As in other machining operations the turned part must meet certain quality characteristics. In that sense it is common that surface roughness must be smaller than the specified maximal value ($R_{tmax}$). The two most important parameters which affect surface roughness are tool nose radius ($r_E$) and feed rate ($f$). Their effects are usually combined into a theoretical surface roughness mathematical model in the form:

$$R_a(\mu\text{m})=\frac{125f^2}{r_E}\le R_{a\max} \tag{9}$$

After setting the values from Table 1 and including the surface roughness constraint one obtains the extended multi-objective turning optimization problem which is now formulated as:

$$\begin{aligned}&\text{Minimize: } \tau(\text{min})=0.2+\frac{219.912}{v\cdot f\cdot a_p}\left(1+\frac{0.2}{T}\right) \text{ and } \varepsilon(\%)=\frac{219.912}{v\cdot f\cdot a_p\cdot T}100\% \\ &\text{Subject to: } g_1(\text{N})=\frac{6.56\cdot f^{0.917}\cdot a_p^{1.1}}{v^{0.286}}\leq 5000 \text{ (cutting force constraint)} \\ &g_2(\text{kW})=\frac{v\cdot F_c}{60000}\leq 7.5 \text{ (cutting power constraint)} \\ &g_3(\mu\text{m})=104.17\cdot f^2\leq 3.2 \text{ (surface roughness constraint)}\end{aligned} \qquad (10)$$

Formulations in Equations 8 and 10 represent nonlinearly constrained multi-objective turning optimization problems with three continuous independent variables.

### 3. Applied optimization approach

To handle optimization problems, as given in Equations 8 and 10, in this study an optimization approach based on the hybridization of exhaustive iterative search and the epsilon-constraint method was proposed. Its effective implementation was realized in the specialized software tool “BRUTOMIZER” [27]. This approach was attempted as it represents a parameter free optimization approach which guaranties the optimality of the determined solutions at the cost of performing a large number of computations that are, however, executed very fast.

When solving an optimization problem exhaustive iterative search systematically searches all possible solutions without the use of any heuristic only by optimization problem’s formulation. It is one of the simplest optimization algorithms for implementation that always finds the solution if one exists [28]. The algorithm can tackle a wide variety of problems, however is inefficient, i.e. takes a lot of computational time for its solving. Thus its application is justified for solving small/medium scale optimization problems where the number of possible solutions is limited. The greatest advantage is that it guaranties the optimality of the determined solution. In such way it is often used as a baseline method when benchmarking other optimization algorithms or metaheuristics.

A typical Pareto multi-objective optimization problem considers a number of objective functions which are to be maximized or minimized. In the epsilon-constraint method the idea is to optimize one of the objective functions using the other objective functions as constraints incorporating them in the constraint part of the multi-objective problem formulation [29]. Thus, the mathematical formulation can be expressed as:

$$\begin{aligned} &\text{Maximize}: f_1(\mathrm{x}) \\ &\text{Subject to}: f_2(\mathrm{x}) \le \varepsilon_2, \\ &\qquad f_3(\mathrm{x}) \le \varepsilon_3, \\ &\qquad \ldots \\ &\qquad f_m(\mathrm{x}) \le \varepsilon_m,\ \mathrm{x} \in \mathrm{X} \end{aligned} \tag{11}$$

where $\mathbf{x}=(x_1, x_2, ..., x_n)$ is the $n$-dimensional vector of decision variables, $f_1(\boldsymbol{x})$, $f_2(\boldsymbol{x})$, ..., $f_m(\boldsymbol{x})$ are $m$ objective functions and $\mathbf{X}$ is the feasible region.

Dimensional representation of the epsilon-constraint method in the case of two objective functions which are to be minimized is given in Fig. 1.

The set of solutions laying on the curve between points A and B represents the set of non-inferior solutions, i.e. Pareto optimal solutions, since an improvement in one objective function requires a degradation in the other objective function. A specific convenience of the epsilon-constraint method is that it is possible to control the number of the generated non-inferior (efficient) solutions by properly adjusting the number of grid points in each one of the objective function ranges [29]. Moreover, in comparison to widely applied weighted sum method, the epsilon-constraint method can identify a number non-inferior solutions on a non-convex boundary.

Finally, as noted by Mavrotas [29], effective application of the epsilon-constraint method requires the calculation of the range of the objective functions over the non-inferior set and the guarantee of efficiency of the obtained solution. In order to tackle these issues in this study, for the generation of the sets of non-inferior solutions, the epsilon-constraint method was hybridized with exhaustive iterative search ensuring at the same time optimality of the determined solutions.

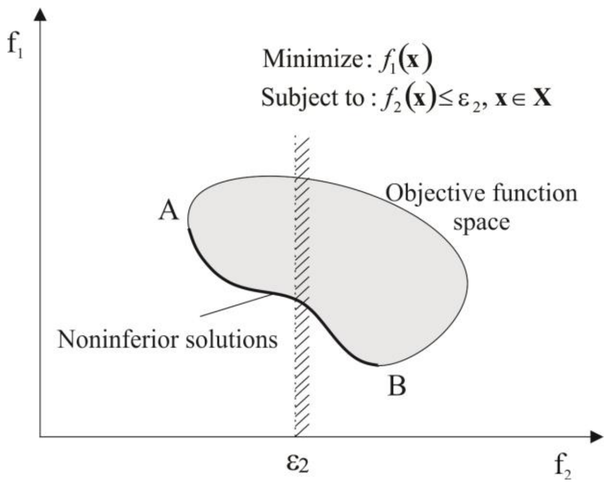


Fig. 1. Geometrical representation of the $\varepsilon$-constraint method in the case of two objective functions

## 4. Results and discussion

In order to minimize both objectives (production time and used tool life) Sardinas et al. [11], applied genetic algorithm for determination of a set of Pareto set consisting of 14 combinations of optimal values of cutting parameter values. However, as proved by Venkata Rao and Kalyankar [2], only six optimization solutions are feasible, whereas the other eight violate cutting power constraint. The Pareto front generated with the optimization solutions determined by the proposed optimization approach and the feasible optimization solutions by Sardinas et al. [11] are given in Figure 2.

From Figure 2 it is clear that the proposed optimization approach made a considerable improvement in optimization results. The optimization solutions, obtained using the proposed optimization approach, are not dominated by any other solution obtained by GA. Moreover, improvement in the distribution of optimization solutions can be easily perceived. It could be observed that production time is decreased from 0.91 min to 0.855 min, however at the same time the used tool life is increased from 4.02% to 9.5%. On the other hand, on the far right side of the Pareto front, the used tool life can be decreased to about 2.13 % at the cost of increasing production time to 1.12 min. It has to be noted that, in general, all solutions in the Pareto fronts are optimal solutions depending upon the requirement of decision maker (Table 2).

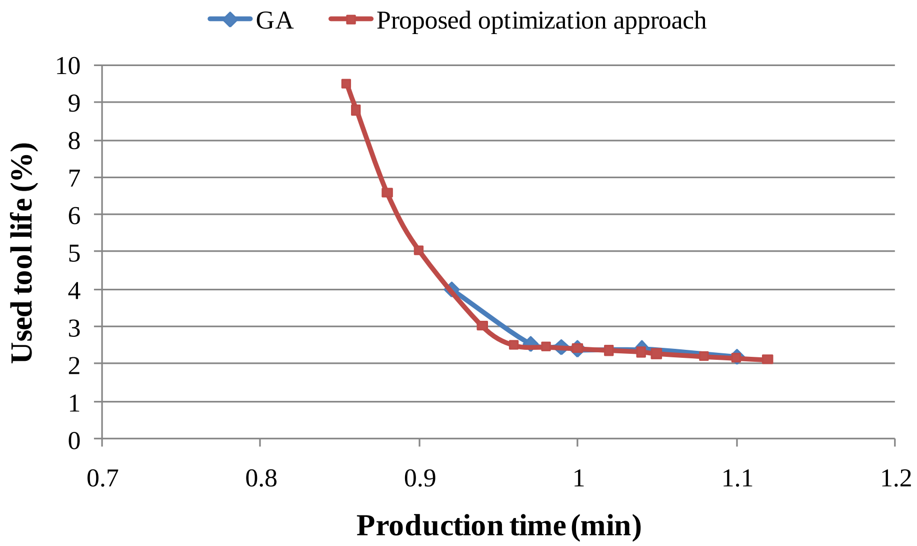


Fig. 2. Comparison of Pareto fronts obtained by Sardinas et al. [11] and the proposed optimization approach

*Table 2*

**Pareto optimal solutions determined using the proposed optimization approach**

| Pareto solution | Production time $\tau$ (min) | Used tool life $\varepsilon$ (%) | $v$ (m/min) | $f$ (mm/rev) | $a_p$ (mm) |
|---|---|---|---|---|---|
| 1 | 0.85445 | 9.489256 | 400 | 0.55 | 1.573 |
| 2 | 0.86 | 8.78 | 389 | 0.55 | 1.6 |
| 3 | 0.88 | 6.58 | 300 | 0.55 | 1.71 |
| 4 | 0.9 | 5.03 | 319 | 0.55 | 1.82 |
| 5 | 0.94 | 3.02 | 266 | 0.55 | 2.05 |
| 6 | 0.96 | 2.52 | 250 | 0.53 | 2.2 |
| 7 | 0.98 | 2.47 | 250 | 0.46 | 2.47 |
| 8 | 1 | 2.41 | 250 | 0.39 | 2.84 |
| 9 | 1.02 | 2.36 | 250 | 0.34 | 3.18 |
| 10 | 1.04 | 2.32 | 250 | 0.3 | 3.53 |
| 11 | 1.05 | 2.27 | 250 | 0.26 | 3.98 |
| 12 | 1.08 | 2.22 | 250 | 0.22 | 4.58 |
| 13 | 1.1 | 2.17 | 250 | 0.19 | 5.17 |
| 14 | 1.12 | 2.13 | 250 | 0.17 | 5.68 |

The results from Table 2 were compared with the optimization solution of Venkata Rao and Kalyankar [2] and Deb abd Datta [30], who applied the TLBO algorithm and multi-objective genetic algorithm (NSGA-II), respectively. It can be shown that the proposed optimization approach as the TLBO and NSGA-II algorithm determined the same solution, i.e. solution 1 (Table 2). Therefore, considering the obtained optimization results, one can argue that the proposed optimization approach proved its effectiveness for solving constrained multi-objective turning optimization problem.

Now the extended nonlinearly constrained multi-objective turning optimization problem (Equation 10) was solved using the proposed optimization approach. The set of optimization solutions upon which the Pareto front may be generated is given in Table 3. When comparing the obtained results (Table 3) and the results obtained without inclusion of surface roughness constraint (Table 2) it could be observed that because feed rate above 0.17 mm/rev is not allowable, minimal production time is increased to 1 min. This, relatively small increase, was obtained because somewhat smaller cutting speed is used (368 m/min instead of 400 m/min), however tripled depth of cut value is used (4.42 mm instead of 1.573 mm).

*Table 3*

**Pareto optimal solutions while solving the extended multi-objective problem**

| Pareto solution | Production time, $\tau$ (min) | Used tool life, $\varepsilon$ (%) | $v$ (m/min) | $f$ (mm/rev) | $a_p$ (mm) |
|---|---|---|---|---|---|
| 1 | 1 | 6.32 | 368 | 0.17 | 4.42 |
| 2 | 1.03 | 4.98 | 338 | 0.17 | 4.67 |
| 3 | 1.05 | 4.09 | 315 | 0.17 | 4.88 |
| 4 | 1.07 | 3.33 | 293 | 0.17 | 5.12 |
| 5 | 1.09 | 2.73 | 273 | 0.17 | 5.36 |

| | | | | | |
|---|---|---|---|---|---|
| 6 | 1.11 | 2.28 | 256 | 0.17 | 5.59 |
| 7 | 1.13 | 2.11 | 250 | 0.17 | 5.97 |
| 8 | 1.13 | 2.12 | 250 | 0.16 | 5.93 |
| 9 | 1.15 | 2.15 | 250 | 0.16 | 5.81 |

Finally, one can calculate the total production cost which consists of tool cost, labour cost and overhead cost. It is clear that the tool cost is directly related to the used tool life, whereas the production time affects both labour and overhead cost. Therefore the total production cost models is as:

$$Z_{total}(\text{EUR}) = \varepsilon \cdot z_t + \tau \cdot z_l + \tau \cdot z_o \quad (12)$$

Considering the obtained set of optimization solutions (Table 3) and by using the given optimization data (Table 1) one can generate Pareto front of total cost with respect to labour and overhead cost separately (Figure 3). One can observe a continuous increase in labour and overhead cost. However, in the case of tool cost, for the first 7 Pareto solutions there is a decrease in tool cost and afterwards tool cost tends to increase. Hence, the Pareto solution 7 has the smallest total production cost of 0.336 EUR and this solution corresponds to the minimal used tool life of 2.11% which can be beneficial for the workshops with small and discontinuous productions. However, as noted by Sardinas et al. [11] in special conditions production time may be far more important with respect to tool life and/or total production cost. Consequently, in some circumstances, selection of the Pareto solution 1 is justified.

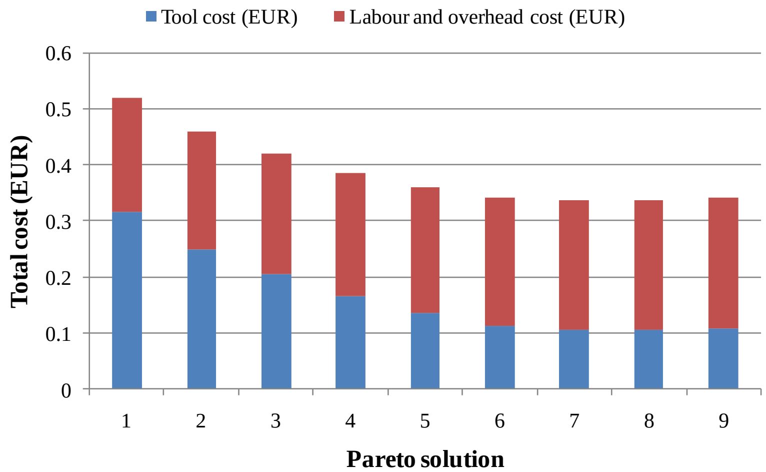


Fig. 3. Pareto front of total cost

## 5. Conclusions

This study proposed the use of optimization approach based on the hybridization of exhaustive iterative search and the epsilon-constraint method for solving turning multi-objective optimization problems with several non-linear constraints. The multi-objective optimization problem for simultaneous minimization of production time and used tool life was considered for demonstration of the effectiveness of the proposed approach as well as to compare the optimization results with those previously obtained using different optimization approaches. It has been observed that the proposed approach is able to solve complex turning multi-objective optimization problems, handle non-linear constraints and provide feasible set of well distributed Pareto optimization solutions within reasonable computational time. The proposed optimization approach allows the user to specify the number of sub-segments and thus the number of Pareto optimization solutions as well as to include specific machine tool limitations regarding the allowable values of cutting parameters making it more convenient approach for determination of turning regimes. Finally, it has to be noted that the optimality of Pareto optimization solutions is guaranteed.

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