MULTIOBJECTIVE OPTIMIZATION OF GROOVES MICROMILLING OF TI6AL4V ALLOY

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ABSTRACT

The increasing rise of micromachining processes, especially the micro-milling is motivated by the variety of parts of complex configuration that can be obtained, for medical (implants) and aeronautical (components) applications. This study is focused on the optimization of micro milling operation to achieve maximum productivity and the minimum surface roughness (R_a), finally with the results of the optimization process was created an intelligent system of decision making, which will improve the performance of the operation. Cutting speed, feed rate and axial depth of cut were the cutting parameters taken into account. Firstly, the cutting force was modeled by using a multiple linear regression and an adaptive neuro-fuzzy inference system (ANFIS); the proposed models correlate the cutting force with the cutting parameters mentioned above, also an ANFIS technique was used for modeling the surface roughness with the same input variables. Outcomes of the cutting force modeling showed that the neuro-fuzzy model has higher correlation than the corresponding regression-based-model. The optimization process is carried out by applying a modified multiobjective cross-entropy (MOCE+) method. Finally, the obtained outcomes were arranged in graphical form (Pareto's front) and analyzed to make the proper decision for different process preferences.

***Keywords**: Multiobjective optimization; micromilling; cross-entropy*

Introduction

For determining optimum process parameters of any micro-machining operations is usually a difficult work where the following aspects are required: knowledge of manufacturing process, empirical equations to develop realistic constraints, specification of machine tool capabilities, development of effective optimization criteria, and knowledge of mathematical and numerical optimization techniques(Pawar y Venkata Rao 2012).

However, very few studies concerning optimization of machining parameters in micro-milling were reported in the literature. Periyanan et al (Periyanan *et al.*, 2011) optimized material removal rate (MRR) considering the spindle speed, feed rate and depth of cut as the cutting parameters in micro-end milling using Taguchi method, also Kuram and Ozcelik (Kuram y Ozcelik, 2015) optimized tool wear, surface roughness and cutting forces in micro-milling operations of Ti6Al4V titanium alloy and Inconel 718 workpiece materials by employing Taguchi's signal-to-noise ratio. The surface roughness in micro milling of tungsten-cooper alloys was optimized by Beruvides et al.(Beruvides *et al.*, 2016) by applying a multiobjective genetic algorithm technique. The response surface methodology was employed by Natarajan et al.(Natarajan *et al.*, 2011) for maximizing material removal

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rate and minimize surface roughness in micro-milling of aluminum material, also Saedon et al.(Saedon *et al.*, 2012) used the same methodology in the optimization of tool life in micro milling AISI D2 (~62HRC) hardened steel. The effects of cutting speed, feed rate and depth of cut for higher MRR in micro milling of Al-6082 were investigated using ANOVA methodology by Kumar et al.(Kumar *et al.*, 2014). Another interesting method is presented by Surmann and Krebs (Surmann y Krebs, 2012) which is based on the geometric analysis of the various engagement conditions of the cutting edge and they optimized tool inclinations in a three- and five-axis micro milling processes.

An issue with multi-objective problems is that a complete ordering is not uniquely defined and instead of a single optimal solution there is a set of optimal solutions(Giagkiozis y Fleming, 2015). The interaction among different objectives gives rise to a set of compromised solutions, largely known as the trade-off, non-dominated, non-inferior or Pareto-optimal solutions. The consideration of many objectives in the design or planning stages provides three major improvements to the procedure that directly supports the decision-making process (Cohon *et al.*, 1988):

- A wider range of alternatives is usually identified when a multiobjective methodology is employed.
- Consideration of multiple objectives promotes more appropriate roles for the participants in the planning and decision-making processes, i.e. “analyst” or “modeler”– who generates alternative solutions, and “decision maker” - who uses the solutions generated by the analyst to make informed decisions.
- Models of a problem will be more realistic if many objectives are considered.

In this paper a titanium alloy (Ti6Al4V) micro milling process is modeled (i.e., a regression model and a neuro-adaptive fuzzy inference system) and optimized, considering two contradictory objectives: productivity (inverse of material removal rate) and surface roughness. The a posteriori approach is used and a multiobjective cross-entropy method is employed to find the Pareto-optimal solutions. The main contributions of this research are twofold: firstly, it applies the cross-entropy method for optimizing the micro milling process; secondly, this model-based cutting parameter optimization allows implementing an intelligent system of decision making.

The investigation is organized in five sections. After the introduction, the second section describes where the micro milling experiments were carried out, as well as, the tool, experimental design and measurement equipment used in the process. The third section explains the model fitting while the fourth one shows the formalization and execution of the optimization. Finally conclusions and future work are outlined in the last section.

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Experimental setup

The grooves cutting experiments by micro milling operation were carried out on a KERN Evo three-axis machining center (see Fig. 1a) with a maximum spindle speed of 50 000 rpm. The cutting forces in the feed (X), transverse (Y) and axial (Z) directions were measured during the experiments using the piezoelectric dynamometer Kistler Minidyn 9256 (see Fig. 1c); its mechanical parameters such as, the measuring range (*Fx, Fy, Fz*) from -250 N to 250 N, cross talk: ≤ ± 2 and natural frequencies: $fn(x) \approx 4.0\ kHz$, $fn(y) \approx 4.8kHz$ and $fn(z) \approx 4.6kHz$ were the best available and suits perfectly for the measurement of cutting forces in micro milling operation. The sensitivity of the dynamometer is 26 pC/N the X- and Y- directions and 13 pC/N in the Z-direction.

The data signals were fed into a NI PXI 6251 National Instruments data acquisition card (see Fig. 1e), with a sampling frequency of 50 kHz, and were processed in a National Instruments high-performance PXI-8187 embedded controller (see Fig. 1e). Also a Form Talysurf PGI was used for the surface roughness measurement tests. This equipment, specifically developed for the optics industry, operates with nanometric precision.

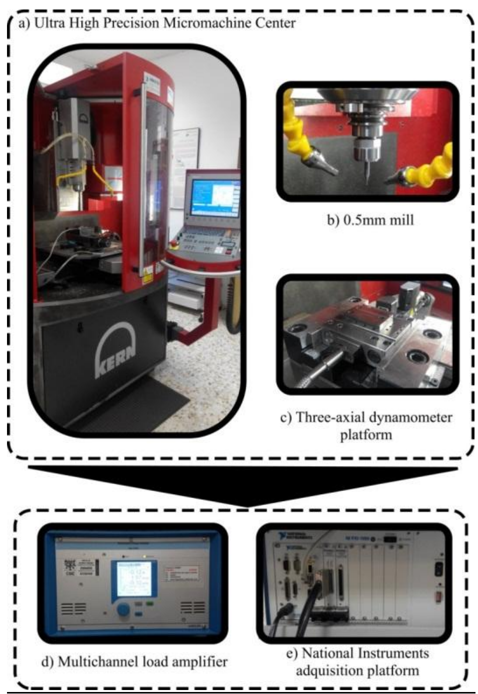

Figure 1. Equipment used in the experiments

The carbide milling cutter used in the experiments has two flute cutting edge and 30º helix angle. The cutting conditions are listed below in Table 1.

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A 0.5 mm-diameter mill (see Fig. 1 b) was used in the experimental study. For the workpiece material´s, three independent variables (cutting speed, V; feed rate, f_Z and axial depth of cut, a_P) were considered.

In order to obtain as much information as possible from the experimental study, a full-factorial design of experiments was selected. Three levels were chosen for the cutting speed while four levels, for the feed rate and the axial depth of cut (Table 1). Three replicates were carried out for each experimental point.

Table 1. Levels in the experimental design

<table>
<tr><th>Experimental factors</th><th colspan="12">Experimental levels</th></tr>
<tr><td>Cutting speed, V [m/min]</td><td colspan="4">32</td><td colspan="4">52</td><td colspan="4">72</td></tr>
<tr><td>Feed rate, f_z [μm/tooth]</td><td colspan="3">5</td><td colspan="3">10</td><td colspan="3">15</td><td colspan="3">20</td></tr>
<tr><td>Axial depth of cut, a_P [μm]</td><td colspan="3">13</td><td colspan="3">20</td><td colspan="3">27</td><td colspan="3">34</td></tr>
</table>

The components of the cutting forces were measured with a sampling frequency, f_S = 50 kHz. The resultant cutting force:

$$F_C = \sqrt{F_x^2 + F_y^2 + F_z^2}\ ; \tag{1}$$

was determined for each measured point. Then, the mean value of the force signal, corresponding to the cutting action of one tooth, was determined by superposing and averages all the samples (Fig. 2).

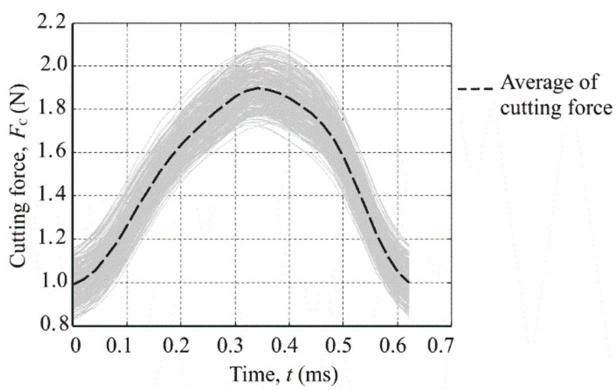

Figure 2. Cutting force signal processing

After completing the signal processing, 144 values were obtained for resultant cutting force, matching with the three replicates of the 48 experimental points. Also, 144 surface roughness values after the corresponding measurements.

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Modelling

Regression-based modelling

For establishing the mathematical relationship between the studied variables (cutting force and surface roughness) with the experimental factor (cutting speed, feed and axial depth of cut), the first choice is the statistical regression (Multiple Linear Regression, MLR) because it is simple and have a solid mathematical foundation.

By applying the multiple regression technique, the following models were obtained for the resultant cutting force and the surface roughness:

$$F_{\mathrm{c}} = 0.1145 a_{\mathrm{p}}^{0.5184} f_{\mathrm{z}}^{0.4785}; \quad (2)$$

$$R_{\mathrm{a}} = \frac{e^{1.77} \cdot f_{\mathrm{z}}^{0.21} \cdot a_{\mathrm{p}}^{0.17}}{v_{\mathrm{c}}^{0.29}}; \quad (3)$$

with a correlation coefficient, R^2, of 0.82 and 0.86 respectively, which means that the first fitted model explains only an 82% of the variability of the dependent variable; the second fitted model explains more than 85% of the variability in the dependent variable. The ANOVA (Table 2 and Table 3 respectively) show that in Eq. 1 there is statistically significant relationship between the resultant cutting force and the two included independent variables and also exist the same relationship in the surface roughness regression at a confidence level of 95%. The cutting velocity was removed from the model of the cutting force (Eq. 1) because the *t*-Student test showed that this term was not significant at the 90% or higher confidence level.

The Standard Error of the Estimations (SEE) and the average value of the residual described by the Mean Absolute Error (MAE) were other parameters calculated associated with the quality of the regression model; a SEE of 0.8546 and a MAE of 0.6123. The principal reason to calculate these errors (SSE, MAE) is to give the maximum possible information on the accuracy of the obtained model.

Table 2. ANOVA for the statistical model of the cutting force

Source	Sum of squares	Degrees of freedom	Mean square	F-ratio	p-value
Model	4.646	2	2.323	100	0,000
Residual	1.045	141	0.023		
Total	5.691	143			

Table 3. ANOVA for the statistical model of the surface roughness

Source	Sum of squares	Degrees of freedom	Mean square	F-ratio	p-value
Model	3.653	3	1.218	304.7	0,000

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Residual	0.560	140	0.004
Total	4.213	143	

ANFIS-based modeling

One of the most recently used neuro-fuzzy approach is the adaptive neuro-fuzzy inference system (ANFIS), which is a multilayer feed-forward network using learning algorithms and fuzzy reasoning to map the relationship between the input and output variables. This technique was selected due to its computational simplicity and suitability for real-time applications [11]. ANFIS implements the Takagi–Sugeno model for the structure of the fuzzy system if-then rules. The neuro-fuzzy model's architecture has five layers, as shown in Fig. 3.

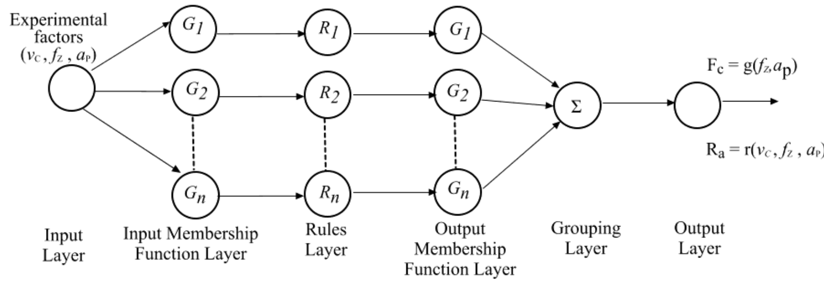

Figure 3. Architecture of ANFIS-based modeling

This second model based on ANFIS was used for estimating the cutting force and the surface roughness too. The neuro-adaptive fuzzy inference system was created by using the MATLAB Fuzzy Logic Toolbox (version 2.2.17).

The cutting force fuzzy model obtained has an *r*-squared (R^2) of 0.92, also were calculated the SEE (0.7243) and the MAE (0.4567), the cutting speed was removed of this model because the *t*-Student test showed that this term was not significant at the 95% confidence level. The ANFIS model of the R_a has a correlation coefficient, of 0.96, the standard error of the estimations calculated is 0.0091 and the mean absolute error of the model is 0.0184. This outcome reflects that an ANFIS has unlimited approximation power for matching any nonlinear function arbitrarily well on a compact set [12].

Optimization

Problem definition

The purpose for applying the optimization procedure is to obtain the best set of cutting parameters in the micro-milling process. The decision variables involved in the optimization process were the same experimental factors: cutting speed, V; feed rate, f_Z and axial depth of cut, a_P.

The optimizations targets are the unit machining time (inverse of the material removal rate, MRR), T_0 [min/mm^3] and the surface roughness, Ra [mm], which are given by the expressions:

$$T_0 = \frac{1}{MRR} = \frac{1}{f_\mathrm{z} \cdot a_\mathrm{p} \cdot n \cdot a_\mathrm{e} \cdot z}; \tag{4}$$

where n [rev/min] is the spindle speed, a_e [mm] is the radial depth of cut and z is the teeth number of the mill, in all cases, a mill with two-toothed cutting tool was used; and:

$$R_a = \psi_{ANFIS}(V, f_\mathrm{z}, a_\mathrm{p}); \tag{5}$$

$$F_\mathrm{c} = \psi_{ANFIS}(f_\mathrm{z}, a_\mathrm{p}); \tag{6}$$

where ψ is the neuro-adaptive fuzzy inference system function obtained in the previous section. Both fitness functions must be minimized.

Besides those indicating the intervals of the decision variables (Eqs. 8a, 8b and 8c), the considered constraints include the maximum stress caused by the cutting force, which can be expresses as:

$$\tau_\mathrm{eq} = \frac{F_\mathrm{C}\sqrt{L^2 + D^2}}{(\pi/16)D^3} \leq \frac{\tau_\mathrm{U}}{\eta}; \tag{7}$$

where τ_eq is the equivalent stress in the more loaded section; L, the flute length of the cutting tool; D, the cutting tool diameter; τ_U, the ultimate strength of the cutting tool material; and η, the security coefficient.

For the used tool, L = 1.5 mm and D = 0.5 mm. The tool material was tungsten carbide with τ_U = 700 MPa. Due to the dynamics characteristics of the micromilling process, a high value was selected for the security factor, η = 5.0.

Cross-entropy-based optimization

The algorithm called MOCE+ (modified Multi-Objective Cross-Entropy) is focused on solving a multi-objective optimization problem (see Fig. 4). It starts by creating an empty elite population Q*= {ø}; then a loop of N iterations is performed, where the values of the means and standard deviations (μ_i, σ_i) for each decision variable is computed. Then a nested loop takes place until it reaches some stopping conditions, this loop starts by creating the working population (which can be done in two different ways). On the other hand, the working population is created from de elite population. In the next step the elite population is increased by adding all the solutions with a lower Pareto dominance than some threshold value, also the means and standard deviation of each variable are updated from de values of the elite population λ_t. Finally, three stopping conditions are evaluated: the convergence

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limit (ε_{max}); the maximum evaluation number (S_{max}) and the maximum elite population size (Z_{max}).

```
Begin MOCE+
   Create Q*={ø}
   FOR t = 1 to N
      Initialize randomly μi , σi
      S = 0
      DO
         IF ((Q*={ø}) OR (t = 1))
            Create randomly Qt
         ELSE
            Create Qt from Qt-1 by using μi, σi
         END IF
         Evaluate Qt
         Update Q* from Qt by using λt
         Update μi, σi from Q*
         Compute εi from σi
         Compute S = S+Z
    UNTIL ((max(εi) ≤ εmax) OR (S ≥ Smax))
     Filter Q*
    Update λt = (1-k) λt-1
END MOCE+
```

Figure 4. Pseudo code of the MOCE+

The decision variables mentioned above were considered with their respective experimental intervals:

$$32 \text{ m/min} \leq V \leq 72 \text{ m/min}; \tag{8a}$$

$$5 \text{ μm/tooth} \leq f_Z \leq 20 \text{ μm/tooth}; \tag{8b}$$

$$13 \text{ μm} \leq a_P \leq 34 \text{ μm}; \tag{8c}$$

The algorithm was implemented with a maximum convergence limit of 0.001, and a maximum number of epochs equal to 100. The size of the elitist population was set at 15 and the maximum evaluation number of 1000 was applied.

With the optimization process finished the non-dominated solutions can be graphically represented in the so called Pareto front and in the Pareto set (see Fig. 5). The most convenient cutting parameters can be selected depending on the specific conditions of the productions. While the point 1 represents the highest surface roughness and the lowest unit machining time; point 2 includes the highest unit machining time and the lowest surface roughness. All the other points are intermediate combinations.

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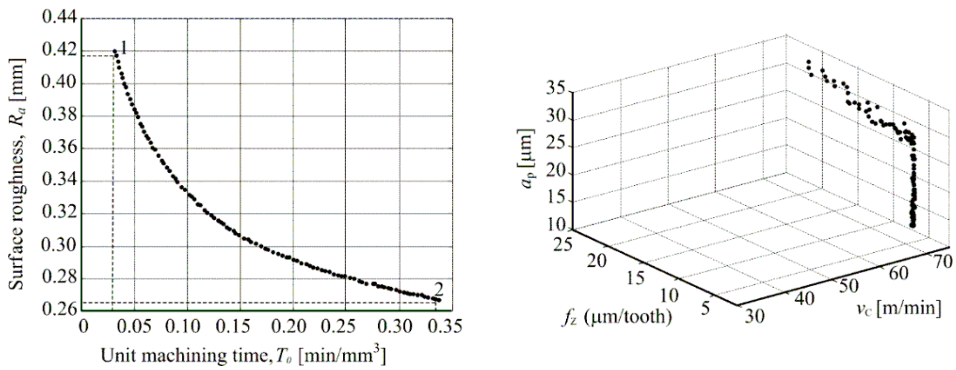

Figure 5. Unit machining time vs. surface roughness multiobjective optimization

Conclusions

The *a posteriori* multiobjective optimization has shown to be a suitable option on selecting the most convenient cutting parameters in micromilling processes. Furthermore this technique offers a greater piece of information and it allows carrying out a more flexible decision-making process.

In comparing the obtained neuro-adaptive fuzzy inference system with the statistical multiple regression, it has been shown that the fuzzy model allows obtaining more accurate predictions for the cutting force.

The modified cross-entropy method used was capable to obtain a set of solution, which are uniformly distributed, in order to arrange the Pareto's front, at a reasonably low computational cost. By means of Pareto frontier graphics, several different situations may be considered, facilitating the choice of right parameters for any condition.

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