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An economical approach to stop an experimental campaign with the aim of reducing cost

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Abstract

Nowadays, in a period of stagnation and economic crisis, the continuous improvement of the production technologies in order to optimize economic, energetic and productive resources is crucial. The increase in efficiency, measured in terms of cost reduction, is therefore a key problem that requires the attention of more and more companies and researchers. In particular, the productivity of a machining system and its related costs depend on the setup of the machining parameters. This choice plays a key role when the machining material is expensive, the production batch has a limited size and the tool to be used is new: typical examples are the aircraft and die/mold industries.
In order to optimally setup a machine, the study of the tool life according to the material and the machining parameters is critical. The expression of the tool life could be estimated using an appropriate experimental campaign, which should have a limited size in order to reduce the experimental costs. This approach becomes of primary importance when the production is not in series where the costs can be spread over a large number of pieces.
The aim of this paper is to propose a new methodology that stops the experimental campaign as soon as the expected gain in carrying on the experimentation does not justify the marginal cost of experimentation.
To prove our idea, a simple problem from the well-known turning cutting condition optimization is used and the optimization technique Response Surface Methodology is selected.

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Keywords: Economic stopping rules; Optimal cutting condition; Response surface methodology

1. Introduction

The selection of optimal operating parameters has been a challenging problem for manufacturing processes for nearly a century. It is well known that the cost of machining depends on the operating parameters, usually optimal values are determined before the beginning of the production. The reduction of production cost due to process optimization is a key competence in order to improve competitiveness and efficiency. We are focusing, specifically, in the optimization of a process where the material is expensive and the tool to be used is new. A typical example is the aircraft industry where very expensive alloys (such as titanium alloys) are used as machining material. Accordingly, the execution of experiments is expensive and its costs have to be taken into account in the optimization process.

Response Surface Methodology is a critical technology in optimizing a process performance when dealing with machine setup. It has been widely used both in literature and in real industrial cases because of its high performances and easy implementation.

In this paper the attention is focused on the available stopping rules determining when and how to stop the search. As a matter of fact, stopping the search too early implies that a good solution could be missed. Otherwise increasing the total number of experiments causes the experimentation cost to increase and this drawback is not justified by the application. The aim of this paper is to propose a new methodology that stops the experimental campaign as soon as the expected gain in carrying on the experimentation does not justify the incurred cost of experimentation.

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Nomenclature

B	batch size
$c_{exp,u}$	cost of single experiment (€/exp)
C	manufacturing cost per item (€/item)
C_{exp}	cost of experimentation (€)
C_m	machining cost (€/h)
C_p	production cost incurred at the *i*-th step (€). It is modeled as a normal random variable with mean μ_i and variance and variance σ_ε^2
C_{ut}	cutting tool cost (€/tool)
D_{in}	initial diameter of a mechanical piece (mm)
f	feed rate (mm/turn)
L	length of a mechanical part (mm)
n_{exp}	number of experiments
s	cutting speed (m/min)
T	tool life (min/tool)
t_{cu}	change tool time (min/tool)

The paper is organized as follows: Section 2 presents the problem definition; in Section 3 the optimization procedure and its details are described, the economic stopping rule is then formalized; in Section 4 the case study is introduced and in Section 5 the results are presented. The paper ends with recommendations and directions for further research.

2. The problem definition

Every time a new tool insert or a new material are used, the operator has to set the cutting parameters of the machine: the feed rate *f* and the cutting speed *s*. Once the machine is set, it starts to machine a batch of products of size B.

An opportune experimental campaign is performed to estimate the tool life equation of the new insert and consequently to define the optimal setup.

The parameter optimization has to consider that a large number of experiments may guarantee a decrease in the cost production. However, the consequence is an increase of the cost of experimentation, which is the product of the cost of the single experiment by the number of experiments. This drawback becomes of primary importance when the batch has a limited size and, therefore, the experimental cost cannot be spread over a large number of pieces.

Accordingly, the objective function to be minimized in respect to the cutting parameters is the manufacturing cost per item produced in a batch of B pieces:

$$C(s,f) = C_p(s,f) + C_{exp}/B \quad (1)$$

where:

- C_p is the random variable production cost and it is defined as follows:

$$C_p(s,f) = \frac{\alpha}{Z}\left(1 + \frac{\gamma}{T(s,f)}\right) \quad (2)$$

where α is a constant that depends on the piece of material to be machined and on the machine used; Z is the material removal rate; T(*s*, *f*) is the random variable tool life, and γ is a constant that depends on the machine and the tool insert used.

- C_{exp} is the production cost (€) and it is:

$$C_{exp} = c_{exp,u} \cdot n_{exp} \quad (3)$$

where $c_{exp,u}$ is the cost of single experiment (€/exp) and n_{exp} is an unknown random variable that characterizes the number of experiments.

3. The optimization methodology

In order to set the machine, an optimization routine is required. The Response Surface Methodology (RSM) is an experimental method used in the industrial world to optimize a process. In this section, the RSM is briefly introduced, for a detailed description the readers may consult [1], [3], [7].

The RSM is an iterative routine characterized by a sequence of experiments. In this paper, after performing each experiment, the tool life T(*s*, *f*) of the insert is measured and the corresponding production cost is calculated.

Usually, a standard RSM consists in two phases. In the first phase the objective function is locally approximated by a first-order polynomial.

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \varepsilon \quad (4)$$

where y is the production cost, $x_1,\dots,x_k$ are the coded input variable (speed and feed), β_0 and β_i are respectively the constant and the linear coefficient that are estimated from the experimental data.

When the first order model is adequate a line search algorithm is applied to find a new region of interest. The line search is ended when there is no further improvement in the response along the line using a stopping rule. At that point, a new experiment is performed and a first-order model is fitted and a new line search phase is started. The procedure is repeated until the first-order polynomial model is not adequate (i.e. if a significant lack-of-fit is present). At that time the RSM moves to the second phase and additional experiments are conducted to obtain a more precise estimate of the response function. In this phase the objective function is approximated by a second-order polynomial (5) and a canonical analysis is used to find the optimum point, if it exists.

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \sum_{i=1}^{k} \sum_{j>i} \beta_{ij} x_i x_j + \varepsilon \quad (5)$$

Although there are many designs to choose from, a two-level factorial design augmented by three center points is used to reduce the number of experiments. Moreover, this design is orthogonal, gives unbiased estimators of the regression coefficients of a first-order model and it was easily augmented to derive a second-order design (a CCD - Central Composite

Design) in the second phase.

In order to overcome the steepest descent well-known problems (i.e. the scale dependency and the arbitrary choice of the step size along its path), the step size and the line search direction are determined using the technique proposed by Kleijnen [4].

Usually the cutting parameters have bounds (e.g. a maximum cutting speed is allowed), a constrained approach is used according to [7, section 5.5].

3.1. State of the art of the stopping rules

Different heuristic stopping rules have been proposed in literature. The ‘’classical’’ rule stops the algorithm when an observed value of the objective function is higher than the preceding observation. But a rise in the response may be due to ‘’noise’’, not to a real increase of the mean response. As a consequence, the 2-in-a-row rule (i.e. 2 consecutive response rises) and the 3-in-a-row one (i.e. 3 consecutive response rises) have been proposed and widely used. Del Castillo [2] demonstrated that the ``classical'' rule and its improvements perform very poorly, stopping far before the optimum, especially when the noise level is high and the optimum is far away from the starting point. Thus, three formal sequential stopping rules have also been proposed in the frequentist literature. Firstly, Myers and Khuri [6] proposed a rule that involves a sequential hypothesis test to check if the response is still decreasing whenever a rise in the response is observed. However this rule requires a preliminary guess of the step number required to reach the optimum and, as expected, the procedure is rather sensitive to this parameter. Secondly, del Castillo [2] proposed the Recursive Parabolic Rule (RPR). This rule fits a second order model in the direction of steepest descent. The search is stopped when there is enough evidence to reject the hypothesis that the first derivative is strictly positive, since this assures that the average response is starting to increase. Lastly, Mirò and del Castillo [5] proposed the Enhanced Recursive Parabolic Rule (ERPR), as an improvement of the previous one. In fact, the RPR becomes sensitive to non-quadratic behavior.

3.2. Economic stopping rule

A stopping rule that ensures a reduction of both the production cost and the experiment cost is necessary. The stopping rules proposed in literature do not satisfy this requirement, thus an economic stopping rule is proposed in this paper.

The production cost $C_{p,i}$ at the *i*-th step of the optimization is modeled as a random variable normally distributed with mean μ_i and variance σ_ε^2 that is unknown but constant. The *economic rule* stops the optimization routine when the difference in economic gain $(\mu_{i-1}-\mu_i)B$ is less than the cost of experimentation C_{exp} incurred to pass from the (*i-1*)-th step to the *i*-th one. Consequently, the hypothesis test is:

$$H_0:\ \mu_{i-1}-\mu_i \le c_0 \qquad H_1:\ \mu_{i-1}-\mu_i > c_0 \tag{6}$$

where $c_o = C_{exp}/B$. The search is stopped when there is enough evidence to reject the null hypothesis, hence the expected economic gain is not enough to carry on the experimentation. Then the appropriate test statistic is:

$$t_0 = \frac{\overline{C}_{p,i-1}-\overline{C}_{p,i}-c_0}{\sqrt{\frac{S_{i-1}^2+S_i^2}{n}}} \tag{7}$$

where:

$\overline{C}_{p,i-1}$, $\overline{C}_{p,i}$ are the sample production cost mean respectively at step (*i-1*) and at step *i*;

S_{i-1}^2, S_i^2 are the sample variances and *n* is the size of samples.

If $t_0 > t_\alpha(2n-2)$ the null hypothesis is rejected and the experimentation carries on, otherwise the search stops and the optimal setup is defined.

Moreover, the standard RSM is changed. Firstly, according to [8], the use of the economic stopping rule is extended also to the second phase. The standard approach end the optimization at the first optimal point found. Instead, the economic stopping rule stops the routine only if it is not profitable to carry on the experimentation. Secondly, before performing an experiment, a prevision interval is calculated according to the latest model found. Then, the experiment is performed and the economic rule is checked; if it is satisfied (in first phase or in the second one), the reliability of the model is checked: if the production cost of the experiment does not belong to the prevision interval, the model is not more adequate. Thus, a new first order model needs to be fitted at that point.

4. Case Study

The well-known problem of optimization of the turning cutting parameters (feed and speed) minimizing the manufacturing cost of a mechanical piece is used to compare the economic stopping rule and a standard stopping rule. Hence, the parameters in (2) can be better characterized according to the turning operation:

- $Z = s \cdot f$ (8)
- $\alpha = \dfrac{C_m L \pi D_{in}}{60 \cdot 10^3}$ (9)

where L is the length of the mechanical part (mm), D_{in} is the initial diameter of a mechanical piece (mm), C_m is the machine cost (€/h);

- $\gamma = t_{cu} + \dfrac{60 C_{ut}}{C_m}$ (10)

where C_{ut} is cutting tool cost (€/tool) and t_{cu} is the time to change the tool (min/tool).

In order to select the optimal turning cutting parameters, as previously stated, the RSM is used as optimizer. Then, a simulator of the machine is built and a Monte Carlo procedure is used to evaluate the production cost. The paper [9] is used as a reference to simulate the tool life. For carrying out experiments, they used a NH-26 lathe. The work piece used for the experiments was cut from rolled steel bars of diameter ranging from 30 to 50 mm and lengths ranging from 110 to 130 mm. Dry turning tests were conducted for predicting the tool life and the cutting tool used were a TiN coated tungsten carbide triangular inserts. The ranges of process parameters were cutting speed 135–270 m/min, feed 0.04–0.32 mm/rev and depth of cut 0.3–1.2 mm.

The found empirical tool life model is:

$$\ln T = -329 + 127{,}8 \ln s + 0{,}08 \ln f - 12{,}36 \ln^2 s - 0{,}077 \ln^2 f \text{ -}0{,}320 \ln s \ln f + err \quad (11)$$

where $err \sim N(0, \sigma_T^2)$ and the error variance is estimated using the mean square error $\hat{\sigma}_T^2 = 0.48055$.

5. Results

In this Section the performance of the economic stopping rule and a standard stopping rule are compared. Easily to compare these rules, we could select just two specific conditions and based on that we could draw the conclusions. In order to increase the reliability of the analysis, other parameters that could affect the manufacturing cost are taken into account. In particular, the batch size could be a critical parameter, in fact if the batch size is large, the economic stopping rule should suggest to carry on the experimentation as the experiment cost is spread on a large number of worked pieces. The cost of the single experiment could be a crucial parameter, as a matter of fact a high cost causes the search to be ended sooner than a situation characterized by low cost of single experiment. Moreover the use of mechanical pieces with different sizes or the use of different tools could affect the manufacturing cost.

As a consequence, the parameters of the optimization campaign are:

- $\gamma \in \{2.5; 5.5\}$ these levels are selected considering different combinations among $t_{cu} \in$ {1min; 2.5min} and $C_{ut} \in$ {10€; 20€};
- $c_{exp,u} \in$ {1€; 10€ }, it supposed to be independent from the cutting parameters used;
- $B \in \{200; 600; 1000\}$;
- Economic stopping rules ∈ {economic rule (Rule 1); RPR [2] (Rule 2)}.

We suppose to perform all the experiments with the same machine, thus the machining cost C_m is fixed and equal to 400€, the D_{in} is fixed at 40 mm averaging the diameters of the bars used to define the tool life equation (11) and L is fixed equal to 120 mm as average of the bar lengths. Consequently, the α value in (5) is fixed at 100.

Hence 24 experimental conditions are tested. Each condition is started from 50 different initial point randomly picked in the feed-speed space, these points are considered as replications of each condition. The boundaries of the feed rate are 0.04-0.32 mm/rev, instead the boundaries of the speed are 135-270 m/min.

The optimization is ended when the stopping rule occurs and the optimal setup found is used to estimate the manufacturing cost (8).

Figure 1 presents the boxplot of the manufacturing cost. The graph reveals that the costs corresponding to the condition γ=5.5 appear greater than the costs of γ low level. This result does not surprise us because it is coherent with (2), a cutting tool that costs more has a greater impact on the manufacturing cost, the same conclusion is drawn if the time to change the insert tool increases. Then, the economic stopping rule seems to perform better than the RPR. Furthermore, the batch size seems to influence the manufacturing cost. As the batch size increases, the manufacturing cost decreases because the experiment cost can be spread over a larger number of pieces produced. Moreover the cost of the single experiment appears relevant. The manufacturing cost increases according to the cost of the single experiment, and this is again coherent with (3).

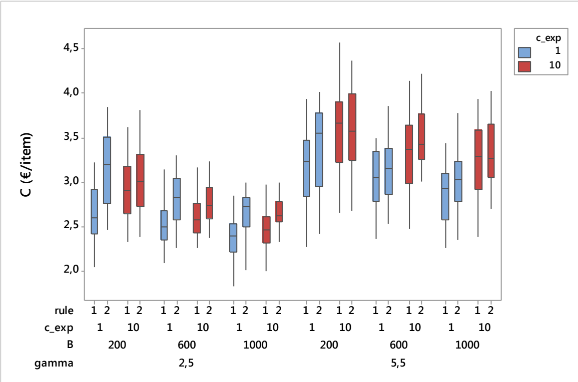

Fig. 1. The boxplot of the manufacturing cost. Rule 1 is the economic stopping rule in the modified RSM and Rule 2 is the RPR in the classic RSM.

Table 1. The Analysis of the Variance of the manufacturing cost.

Source	Adj SS	Adj MS	F	p-value
B	25.854	12.927	109.16	0.000
$c_{exp,u}$	9.233	9.233	77.97	0.000
γ	91.494	91.494	772.63	0.000
rule	10.762	10.762	90.88	0.000
$c_{exp,u}$ * γ	4.664	4.664	39.39	0.000
$c_{exp,u}$ * rule	1.926	1.926	16.26	0.000
rule * γ	1.121	1.121	9.47	0.002
B * $c_{exp,u}$ * rule	1.264	0.632	5.34	0.005
Error	140.801	0.1184		
LOF	1.345	0.103	0.87	0.582
Pure Error	139.455	0.118		
Total	287.119			

In order to support the conclusions drawn from the graphical analysis, a statistical analysis is performed. The

ANOVA table of the reduced model is shown in Table 1. The analysis confirms that the batch size, the cost of the single experiment and the values of γ influence the manufacturing cost. Moreover the economic stopping rule performs always better than the RPR in the classic RSM, this means that an economical approach helps to define a better setup of the machine and allow the manufacturing cost to decrease. The interaction rule*$c_{exp,u}$ is significant and supports the idea that as the cost of the single experiment increases the economic stopping rule stops the search earlier than the RPR rule, in fact the RPR rule does not notice the increasing in the experimental cost and thus it is not able to stop the search when the expected gain is lower than the experimental cost.

Let us focus the attention on the performance of the economic stopping rule. The use of a larger batch size causes the manufacturing cost to diminish, in fact the number of experiments performed are greater and this guarantee to find out a better cutting parameters. Moreover, as the cost of single experiment increases, the performance gets worse; in fact the stopping rule ends the optimization before than a situation in which the cost of single experiment is lower.

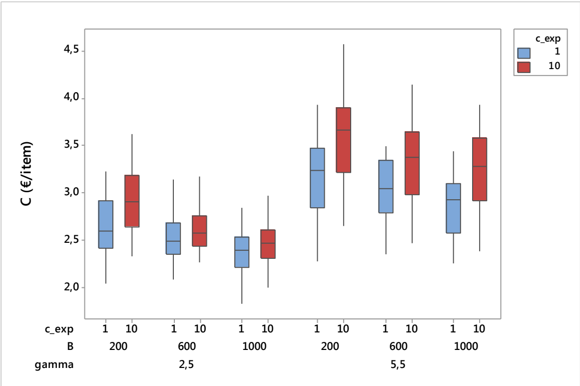

Fig. 2. The boxplot of the manufacturing cost considering only the economic stopping rule.

6. Conclusions and further research

The efficiency and the competitiveness of a machining system depend on the setup of the machining parameters. The choice of the best machine setup plays a key role when the machining material is expensive, the production batch has a limited size and the tool to be used is new.

The study of the tool life of the insert is of primary importance in order to optimize the cutting parameters. The tool life equation needs to be estimated thanks to an experimental campaign. A deep experimental campaign allows the experimenter to find out better cutting parameters that guarantee a lower production cost. However, in a situation characterized by small batch of product, the number of experiments should have a limited size in order to decrease the experimental cost.

In this paper an approach that considers both the production cost and the experimental cost is proposed. In particular, an economic stopping rule able to stop the optimization when the incurred cost of experimentation is greater than the expected gain (that is the decrease of production cost) is proposed and formalized.

The Response Surface Methodology is used as optimizer because of its outperformance in the process optimization in the industrial world. The well-known turning cutting condition optimization problem is used as case study to show the performance of the proposed approach.

Specifically, the economic stopping rule is compared with another rule taken from the classical literature. The results show that the economic rule performs always better and it is able to find out cutting parameters that reduce more the manufacturing cost. In particular, the economic rule stops the optimization search earlier when the batch has a small size or when the cost of the single experiment is large. Otherwise, if the batch size has a large size, the experimental cost can be spread over a larger number of pieces, thus the optimization is carried on for a greater number of step and better cutting parameters are find out.

Future researches may move towards the use of different stopping rules. In this paper, the attention is focused on a frequentist approach; we think that an economic Bayesian approach could improve the optimization routine.

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