Stochastic optimization of AISI 52100 hard turning with six sigma capability constraint

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The authors thank Fapemig, CNPq and CAPES for supporting this research.

ABSTRACT Hard turning optimization problems are usually approached using Response Surface Methodology. By running designed experiments, researchers build analytical models to represent the outputs under interest. However, most studies focus on the expected values of the outputs, and only a few consider the variances of the models, even though there are several stochastic programming (SP) techniques available in the literature. Such variances may have a significant impact on the problem solution. This paper aims to optimize the AISI 52100 hardened steel turning process using SP. Decision variables are cutting speed, feed rate and depth of cut, outputs are cost per part and material removal rate, and average surface roughness six sigma capability is modeled as a stochastic constraint. The SP method is also compared to the conventional one, which did not include the variances into the problem. Results show that taking the variability of the models into account is necessary to obtain a satisfactory process capability and to analyze different scenarios. Finally, this study shows that competitive results can be achieved by simplifying the problem formulation.


I. INTRODUCTION

Hard turning has been of interest to both industry and academy due its particular characteristics and several advantages compared to conventional turning [1]. Such advantages include cost reduction, productivity increase, cycle time reduction, quality and material properties improvement, lower energy consumption and pollution reduction, as it eliminates coolant [2].

There are already a great number of recently published papers on hardened steel turning analysis and optimization. Some studies focus on the effects of process parameters (such as cutting speed, feed rate and depth of cut) on performance characteristics (i.e.: tool wear, surface roughness and material removal rate etc.) on AISI 52100 [3]–[6]. Others investigate the effects of inserts characteristics [7], [8]. Taguchi method is usually used for effects analysis. But for hard turning modeling and optimization, response surface methodology (RSM) is one of the most common techniques [9]. The optimization of industrial processes often includes two or more outputs [10], some of which may be strongly correlated. In this case, RSM has been combined with other methods such as multi criteria decision making [11], principal component analysis (PCA) [12], or artificial neural networks (ANN) [13]–[15]. In particular, multivariate statistics are used when outputs are correlated [16]. This is an alternative to keep all the responses included in the problem. Many of the aforementioned papers include a lot of correlated outputs in their optimization problem. However, multiobjective optimization problems may be simplified by selecting only a few key outputs instead of including all of the correlated outputs. Such approach may be suitable for industrial purposes, since what companies usually aim is to minimize costs, maximize productivity as long as quality requirements are achieved.

In order to use process capability, the variance of the outputs must be modeled along with their expected value. The coefficients of the response surface models are commonly estimated by ordinary least squares (OLS). These analytical models are stochastic, because their coefficients are normally distributed and represent a linear combination of the observations [11]. Nevertheless, most of the available studies on hard turning only use the expected values of the RSM model coefficients. The gap is to verify if the stochastic
nature of the models’ coefficients is significant to the problem solution.

Within this context, this paper aims to optimize the AISI 52100 hardened steel turning process using stochastic programming. The main goals are: a) to formulate an optimization problem which is more related to industrial purposes; b) to quantify the impact of the variance of the output models on the results. In this study, the problem is to minimize cost per piece and maximize material removal rate, submitted to a six sigma average surface roughness capability. In addition, results of the present work are compared to the results of a previous study on hard turning optimization.

The paper is structured as follows: chapter II presents the method, which involved multiobjective optimization programming (MOP), stochastic programming coupled with MOP and process capability modeled as a stochastic constraint, chapter III details the experimental procedure and materials used, chapter IV presents the results, discussions are in chapter V and conclusions are in chapter VI.

II. METHOD

The analysis and optimization of the AISI 52100 hardened steel turning started with the definition of a central composite design array and the experimental runs. After measuring the outputs under interest, analytical models were built using response surface methodology (RSM) to represent the expected values of the outputs under interest. In this work, two objective functions (cost and productivity) were defined and joined in a global function by Weighted Sums (WS) method using the formulation described in section A. Then, a stochastic constraint which defines a minimal process capability is established. Section B presents the general aspects of the stochastic programming technique and section C describes a specific formulation of a stochastic constraint of the process capability which includes the experimental data and the response surface models. Finally, the problem is solved using the general reduced gradient (GRG) method described in section D.

A. MULTIOBJECTIVE OPTIMIZATION

Multiobjective Optimization Programming (MOP) can be defined as the formulation of problems whose objective is to optimize at least two results, which can be represented by analytical models $f(x)$, where $x = [x_1, ..., x_n]$ is a vector composed by the decision variables [17]. There are many strategies for MOP available in literature, among which there is the weighted sums (WS). For instance, Eq. (1) presents the general formulation for WS including two objective functions, where $\bar{f}_1(x)$ and $\bar{f}_2(x)$ are the standardized objective functions based on its utopian and Nadir values, where $w$ is the weight of function 1 and $g_j(x)$ refers to the problem constraints.

$$\text{Min } F(x) = w\bar{f}_1(x) + (1-w)\bar{f}_2(x)$$

s.t.: $g_j(x) \leq 0$

$$0 \leq w \leq 1$$

Eq. (2) presents the formula of a standardized model $\bar{f}_i(x)$. In this case, each model $\bar{f}_i(x)$ is staggered based on its utopic value $f_i^U(x)$ and its Nadir value $f_i^N(x)$. The utopic value is found by optimizing $\bar{f}_i(x)$ alone, Nadir is the worst value of $\bar{f}_i(x)$ among the other individual optimizations and $f_i(x)$ is the current value of function $i$.

$$\bar{f}_i(x) = \frac{f_i(x) - f_i^U(x)}{f_i^N(x) - f_i^U(x)} \quad (2)$$

A payoff matrix $P$ of two objective functions is presented in Eq. (3).

$$P = \begin{bmatrix} f_1^U(x) & f_1^N(x) \\ f_2^U(x) & f_2^N(x) \end{bmatrix} \quad (3)$$

B. STOCHASTIC PROGRAMMING IN MOP

Stochastic programming (SP) consists of a strategy to build objective functions and constraints whose coefficients or decision variables are modeled as stochastic variables. The purpose of SP is to transform a stochastic problem into a deterministic one. The transformation depends intrinsically on the probability distributions used to represent the stochastic variables.

There are already different modeling strategies for stochastic programming (SP) proposed in the literature, including the E-model, V-model, P-model, minimax-methods [18] and stochastic DEA model [19]. Since in most MOP approaches the analytical models $f_i(x)$ are usually obtained through Response Surface Methodology (RSM) [9], the SP method selected in the present study is specific for RSM.

After executing experiments according to a Central Composite Design array (CCD), results can be approximated to a second order polynomial model, as shown in Eq. (4).

$$Y \sim f(x) = \beta_0 + \sum_{i=1}^{K} \beta_i x_i + \sum_{i=1}^{K} \bar{\beta}_i x_i^2 + \sum_{i<j}^{K} \beta_{ij}x_i x_j + \epsilon = Z^T \bar{\beta} + \epsilon \quad (4)$$

In Eq. (4), $Y$ is the real response, $Z$ is the vector composed by the terms (constant 1, linear, quadratic and interactions), $\beta$ is a vector composed by the coefficients of each term and $\epsilon$ is the model error.

Coefficients in $\beta$ are considered normally distributed $\beta \sim N(\bar{\beta}, \Sigma)$, so it is reasonable to investigate if the variance and covariance matrix $\Sigma$ causes a significant impact in the variance of $f(x)$.

Eqs (5) and (6) present the formulas for $\bar{\beta}$ and $\Sigma$ respectively, where $X$ is a matrix whose lines are composed by the values of $Z^T$ in all the experimental runs. Proof of Eq.
had already been presented in Rocha et al. [11], while Eq.
(6) is found in Diaz-Garcia et al. [18].
\[
\hat{\beta} = (X^T X)^{-1} (X^T Y) \quad \Sigma = \sigma^2 (X^T X)^{-1} \tag{5}
\]
Finally, Eq. (7) presents the general formula to calculate the
variance of the second order polynomial model as in Eq. (3)
[16].
\[
Var[f(x)] = Z^T \Sigma Z \tag{7}
\]
C. PROCESS CAPABILITY AS A STOCHASTIC CONSTRAINT
There are several ways to formulate an MOP problem
including stochastic programming (SP). For instance, if a
result has only an Upper Specification Limit (USL), which is
the case for average surface roughness, its capability
\(C_{pU}\) can be calculated by Eq. (8) [20].
\[
C_{pU} = \frac{USL - \mu}{3\sigma} \tag{8}
\]
Based on Eq. (7), it is possible to formulate a constraint for
a minimal process capability required in a process and add it
to the MOP problem, as shows Eq. (9), where \(C_{p0}\) is the
minimal capability required for the process.
\[
\left[ \frac{USL - [Z^T \beta]}{3[\sqrt{Z^T \Sigma Z}]} \right] \leq C_{p0} \tag{9}
\]
D. GENERALIZED REDUCED GRADIENT ALGORITHM
The optimum values can be obtained by finding the
stationary point of the fitted surface. The goal is to find the
settings of \(x\)’s that optimize the objective function subject to
the constraints. There are already several algorithms available in literature to solve such nonlinear optimization
problems, including the generalized reduced gradient (GRG)
[11], sequential quadratic programming (SQP), genetic
algorithms (GA), simulated annealing, particle swarm
and ant colony. The GRG is considered one of the most efficient
and robust methods of constrained nonlinear optimization.
The method is called “reduced gradient” because the
algorithm works by substituting the constraints on the
objective function and thus reducing the number of variables.
Therefore, the number of gradients reduces [17].
The GRG method starts by classifying the original variables
into basics \((Z)\) (dependents) and nonbasics \((Y)\)
(independents). Then, one can write \(F(x) = F(Z, Y)\) and
\(h(x) = h(Z, Y)\). It is necessary that \(dh_j(x) = 0\) in order to
meet the condition of optimality. So, if we define \(A =
\nabla_Z h_j(x)\) and \(B = \nabla_Y h_j(x)\), then we have \(dY = -B^{-1} AdZ\).
Hence, the GRG is defined as:
\[
G_R = \frac{d}{dZ} F(x) = \nabla_Z F(x) - [B^{-1} A]^T \nabla_Y F(x)^T \tag{10}
\]
The Searching direction is \(S_c = [-G_\beta dY]^T\) and we can use
\(x^{k+1} = x^k + \alpha S^{k+1}\) to compute the interactions and to verify if
\(x^{k+1}\) is adequate and \(h(x^{k+1}) = 0\) at each step. The last
step of the method is the solution of \(F(x)\) as a function of \(\alpha\),
using a one-dimensional algorithm of search, as the Newton
method for instance.
III. APPLICATION: HARD TURNING PROCESS
In this chapter, the design of experiments is described
(section A), followed by the experimental procedure (section
B) and, finally, the multiobjective optimization problem
proposed in this research.
A. DESIGN OF EXPERIMENTS
Decision variables were cutting seed \((S)\), feed rate \((f)\)
and depth of cut \((d)\). Experiments were carried out according to
a central composite design (CCD): eight factorial points, six
axial points and five center points, leading to a total of 19
runs. Eq. (11) was used to calculate the axial points distance
to the center point \((\rho)\) for \(k\) number of factorial levels and \(n\)
decision variables. The levels are shown in Table 1.
\[
\rho = \frac{\sqrt{k^3}}{4} = \frac{\sqrt{2^3}}{4} = 1.682 \tag{11}
\]
\begin{table}[h]
  \caption{Levels and values of the decision variables}
  \begin{tabular}{|c|c|c|c|}
    \hline
    Level & \(S\) (m/min) & \(f\) (mm/v) & \(d\) (mm) \\
    \hline
    -1.682 & 186.4 & 0.13 & 0.10 \\
    -1 & 200.0 & 0.20 & 0.15 \\
    0 & 220.0 & 0.30 & 0.22 \\
    1 & 240.0 & 0.40 & 0.30 \\
    1.682 & 253.6 & 0.47 & 0.35 \\
    \hline
  \end{tabular}
  \label{tab:1}
\end{table}
SOURCE: [21]

B. EXPERIMENTAL PROCEDURE
A CNC Nardini Logic 175 lathe was used with a maximum
rotation speed of 4000 rpm and a cutting power of 5.5 kW.
The composition of the pieces of AISI 52100 used in the
experiments was: 1.03% C, 0.23% Si, 0.35% Mn, 1.40% Cr,
0.04% Mo, 0.11% Ni, 0.001% S, 0.01%. After quenched and
tempered, the pieces’ hardness got between 49 and 52 HRC,
up to a depth of 3 mm below surface. Wiper mixed ceramic
inserts were used, coated with a thin layer of titanium nitride
(TiN). The tool holder had a negative geometry with ISO
code DCLNL 1616H12 and entering angle \(\gamma_r = 95^\circ\). More
details of the materials and methods are found in [22]. Figure
1 shows the turning process of this study.
To measure tool life \((T)\), the wiper inserts were worn until
their flank wear (VBC) indicator on the tool tip to reach 0.30
mm. This was the adopted criterion for the end of tool life
and it was measured by an optical microscope. Cutting time
\((C_t)\) was calculated by Eq. (12) for each experiment,
according to the values of \(f\) and \(S\). The pieces had a diameter
\(d = 49\) mm and a length \(l_f = 50\) mm. Total cycle time \((T_i)\)
was calculated by Eq. (13),
\[
\frac{d}{dZ} F(x) = \nabla_Z F(x) - [B^{-1} A]^T \nabla_Y F(x)^T \tag{10}
\]
where $t_1 = t_x + t_a + \frac{t_p-t_s}{Z}$ is the inproductive time and $t_2 = \frac{C_t}{T}$ is the tool changing time. After obtaining $t_1$, $t_2$, $C_t$, measuring tool life ($T$) and using other data presented in Table 2, Eq. (14) can be used to calculate the total process cost per piece ($K_p$).

Finally, material removal rate (MRR) was calculated by multiplying the decision variables $S$, $f$ and $d$. Table 3 shows the experimental data.

Instead of the six outputs, only three of them were initially considered in this study: total process cost per piece ($K_p$), material removal rate (MRR) and average surface roughness ($R_a$). The response surface model in Eq. (4) was used to model tool life ($T$) and average surface roughness ($R_a$). Vectors $\beta$ were obtained using Eq. (5) and are shown in Table 4 along with the adjusted $R^2$ for the models. $K_p$ and MRR were directly calculated by formulas and thus did not require regression models.

C. PROPOSED OPTIMIZATION PROBLEM (MOP 1)

The analytical models of $K_p$ and MRR were standardized using Eq. (2) and agglutinated by Eq. (1). To do so, their utopic and Nadir values were required. Hence, each $f_i(x)$ was individually optimized. The only restriction was related to the experimental space, as shows Eq. (15).

$$g(x) = \sqrt{S^2 + f^2 + d^2} \leq \sqrt{k^2} = 1.682$$

Table 5 presents results in a payoff matrix. The numbers in blue are utopic values and the red ones are Nadir values.

Process capability of $R_a$ was modeled as a stochastic constraint using Eq. (9). In this case, the upper specification limit (USL) was established as 0.25 $\mu$m and the minimal capability required ($C_{p0}$) of 1.67. This value is usually defined for experiments because additional variability sources appear in the real systems, so $C_p$ may be around 1 in practice [23]. Eq. (16) shows the proposed MOP problem.

$$Min F(x) = wE[K_p] + (1 - w) E[MRR]$$
$$s.t.:$$
$$g_j(x) \leq 0$$
$$\left[0.25 - E[R_a]\right] \geq 1.67$$
$$0 \leq w \leq 1$$

IV. RESULTS

In order to obtain the Pareto boundary, Eq. (16) was solved using the generalized reduced gradient (GRG) algorithm in Excel® Solver, with $w$ varying from 0.05 to 0.95, in a 0.05 scale. Figure 2 presents the Pareto boundary for $E[K_p]$ and $E[MRR]$ using MOP 1. Along with the average curve, and considering a 95% confidence interval, two other ones were plotted: the best and worst scenarios. The best scenario uses the lower limit for $K_p$ and upper limit for MRR, which means high productivity and low cost, respectively. The worst scenario is the opposite: upper limit for $K_p$ and lower limit for MRR.
A. CONVENTIONAL OPTIMIZATION (MOP 2)

The proposed method was compared to modeling the results of interests by only their expected values $E[f(x)]$. Eq. (17) shows the proposed MOP problem and Fig. 3 presents the Pareto frontier for $E[K_p]$ and $s[K_p]$ for MOP 2.

$$Min \ F(x) = wE[K_p] + (1 - w) E[MRR]$$

$$s.t.: \ g_f(x) \leq 0$$

$$E[R_a] \leq 0.25$$

$$0 \leq w \leq 1$$

V. DISCUSSION

At first, results seemed better in MOP 2. Fig. 3 shows material removal rates (MRR) between 14.5 and 16.5 and costs per parts ($K_p$) from 0.74 to 0.8. Meanwhile, Fig. 2 lower MRRs (from 12.5 to 14.5). As an example, let’s consider the solution where $w = 0.5$, which means cost and productivity have the same importance. Results of MOP 1 and 2 are presented in Table 6.

Nevertheless, the variances of the models were not considered in MOP 2. For that reason, the capability results for $R_a$ were null, because the expected value for $R_a$ was always equal to its upper specification limit (USL). It happened due the fact that the capability constraint was always active. But even if the decision makers set a minimal capability $C_{PK_0}$ lower than the USL, they cannot be certain about the capability. The only way to guarantee that the capability is reasonable is by considering the models’ variances like in MOP 1, where all solutions presented $C_{PK} = 1.67$. 

### Table 3

<table>
<thead>
<tr>
<th>Run</th>
<th>Decision variables</th>
<th>Process outputs</th>
</tr>
</thead>
<tbody>
<tr>
<td>S</td>
<td>f</td>
<td>d</td>
</tr>
<tr>
<td>1</td>
<td>200</td>
<td>0.20</td>
</tr>
<tr>
<td>2</td>
<td>240</td>
<td>0.20</td>
</tr>
<tr>
<td>3</td>
<td>200</td>
<td>0.40</td>
</tr>
<tr>
<td>4</td>
<td>240</td>
<td>0.40</td>
</tr>
<tr>
<td>5</td>
<td>200</td>
<td>0.20</td>
</tr>
<tr>
<td>6</td>
<td>240</td>
<td>0.20</td>
</tr>
<tr>
<td>7</td>
<td>200</td>
<td>0.40</td>
</tr>
<tr>
<td>8</td>
<td>240</td>
<td>0.40</td>
</tr>
<tr>
<td>9</td>
<td>186</td>
<td>0.30</td>
</tr>
<tr>
<td>10</td>
<td>254</td>
<td>0.30</td>
</tr>
<tr>
<td>11</td>
<td>220</td>
<td>0.13</td>
</tr>
<tr>
<td>12</td>
<td>220</td>
<td>0.47</td>
</tr>
<tr>
<td>13</td>
<td>220</td>
<td>0.30</td>
</tr>
<tr>
<td>14</td>
<td>220</td>
<td>0.30</td>
</tr>
<tr>
<td>15</td>
<td>220</td>
<td>0.30</td>
</tr>
<tr>
<td>16</td>
<td>220</td>
<td>0.30</td>
</tr>
<tr>
<td>17</td>
<td>220</td>
<td>0.30</td>
</tr>
<tr>
<td>18</td>
<td>220</td>
<td>0.30</td>
</tr>
<tr>
<td>19</td>
<td>220</td>
<td>0.30</td>
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</tbody>
</table>

### Table 4

<table>
<thead>
<tr>
<th>Coefficients</th>
<th>RS models</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_0$</td>
<td>4.963</td>
</tr>
<tr>
<td>$\beta_1$</td>
<td>-0.861</td>
</tr>
<tr>
<td>$\beta_2$</td>
<td>-3.055</td>
</tr>
<tr>
<td>$\beta_3$</td>
<td>-1.440</td>
</tr>
<tr>
<td>$\beta_{11}$</td>
<td>1.115</td>
</tr>
<tr>
<td>$\beta_{22}$</td>
<td>1.456</td>
</tr>
<tr>
<td>$\beta_{23}$</td>
<td>0.756</td>
</tr>
<tr>
<td>$\beta_{12}$</td>
<td>1.060</td>
</tr>
<tr>
<td>$\beta_{13}$</td>
<td>0.918</td>
</tr>
<tr>
<td>$\beta_{23}$</td>
<td>1.435</td>
</tr>
<tr>
<td>$R^2$ (adj)</td>
<td>99.74%</td>
</tr>
</tbody>
</table>

### Table 5

<table>
<thead>
<tr>
<th>Payoff matrix for $K_p$ and MRR</th>
</tr>
</thead>
<tbody>
<tr>
<td>$K_p$</td>
</tr>
<tr>
<td>0.700</td>
</tr>
<tr>
<td>14.85</td>
</tr>
</tbody>
</table>
The problem was also modeled using normal boundary intersection (NBI) method. However, the Pareto boundary was twisted and did not present equally spaced solutions. It happened because the stochastic constraint of $R_a$ capability was always active, so the solutions found by the algorithm got twisted from each other. On the other hand, when the stochastic constraint was changed until it was no longer active, the Pareto boundary were equally spaced and no longer twisted. Although, when the process capability is no longer a concern, then using an MOP with stochastic programming would not be relevant in the first place.

Finally, results between this study and the addressed one are compared. Competitive results were achieved in the current paper by modeling the problem in a simpler manner and in a closer perspective to industrial reality.

### VI. CONCLUSIONS

The present study optimized the AISI 52100 hardened steel turning process using stochastic programming. The input variables were cutting speed, feed rate and depth of cut, the objective functions were cost per part and material removal rate and the capability of the average surface roughness was modeled as a stochastic constraint.

The proposed method (MOP 1) was applied and then compared to the traditional approach (MOP 2), where the variance is not modeled. Results showed that, differently from MOP 2, MOP 1 could guarantee a minimal process capability. Best and worst scenarios were also plotted in the Pareto boundary, for a 95% confidence interval. In this specific case, normal boundary intersection (NBI) presented some difficulties in providing a satisfactory Pareto boundary. Finally, results between this study and the addressed one were compared. Competitive results were achieved in the current paper by modeling the problem in a simpler manner and in a closer perspective to industrial reality.
Future research may consider the stochastic nature of many other input variables that are related to the cost per part. Another possibility is to optimize not only the expected values of the models, but also minimize their variances, and use multivariate statistics such as PCA in case of highly correlated responses.

ACKNOWLEDGEMENT
The authors gratefully acknowledge CAPES, CNPq PQ 303586/2015-0 and Fapemig for supporting this research.

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