Bootstrapping Neural Network Regression Model for Milling Process Optimization in Industrial Environment

Fabio Henrique Pereira¹, Daniel Benedito Rosa², Ademir Oliveira¹, Elesandro Antonio Baptista¹ and Nivaldo Lemos Coppini¹

¹Industrial Engineering Post Grad. Program, Nove de Julho University - UNINOVE, São Paulo, SP, Brazil
²Faculty of Mechanical Engineering of State University of Campinas – UNICAMP, Campinas, SP, Brazil.

fabiohp@uninove.br, daniel.b.r@uol.com.br, ademir.oliveira@uninove.edu.br, elesandro@uninove.br, ncoppini@uninove.br

Abstract
This work proposes an optimization procedure based on a data interpolation approach using a bootstrapped neural network. The bootstrapped neural network is used to generate designed data sets in order to improve the value of statistical information and to estimate a mapping from input to output space in an intrinsic experiment applied to the manufactory process. The optimization procedure is aimed to minimize the cost and/or to increase the production in the milling process of forging tools currently used. The designed data set is statistically analyzed and it is used to determine the Taylor’s equation coefficients in the manufactory environment, allowing the determination of the Maximum Efficiency Interval. The results shown that the proposed approach can improve the value of statistical information for some cases, presenting at least similar results to those obtained from a fractional factorial design of the small original data set.

Keywords: High speed milling. Cutting process optimization. Bootstrapped neural network. Cutting tool life

1. Introduction
The emphasis in continuous improvement, prioritized by the organizations, has motivated the development of this intrinsic experiment applied to the manufactory process optimization, which involving the cutting parameters in shop floor and verifying advantages and disadvantages of the procedure used. Four variables had been used: Material’s hardness of the parts and the cutting parameters of the milling process in high speed machine of hardened steel (cutting speed, feed per tooth and cutting depth).

From the operating conditions, cutting depth and the feet per tooth are the most easily optimized: we can have values so closer to the best value, just pondering the machine power, the over metal dimension to be removed, the chip shape and quality of the final piece required for the specific target of the operation optimization [1]. Unlike, the cutting speed optimization is not a trivial task. It is a problem because the cutting speed has more significant influence on tool life, when compared with depth of cut and feed, and also it exercises larger influence on the costs and production [2]. Although the Maximum Efficiency Interval approach to be known as one of the most convenient way to find the optimized cutting speed, the use of the values of (x) and (K), constants in the Taylor equation, obtained from the literature or other sources from testing laboratory under ideal conditions, has making difficult the task of optimizing the cutting speed, because are different from the reality, causing distortions in the optimization process results. So, it seems that the best option is to use the Taylor equation constants from its determination in a factory floor. In this case there will be greater confidence in selecting the optimum cutting speed, because the procedure will be performed in real time with the occurrence of the process, with data obtained from the own machine-tool-part, targets of the optimization.

Unfortunately, the determination of constant values from experimental procedure in factory floor has many limitations. In such cases the initial collected data set is most of the time very small, the magnitude of variable effects is sometimes ambiguous and data gathering costs are high. An alternative to overcome these problems is to use a resampling approach as, for example, the bootstrap method which is based on an imitation of the probabilistic process using the information provided by a given small set of random observations. Many works has shown the feasible of the bootstrapping technique for estimating objectives out of sample by redrawing small subsets [3]-[5], but the use of that approach in a machining process optimization is practically nonexistent. As the quality of empirical research depends in part on the quality and suitability of available data, making the search for new approaches to deriving better statistical estimators from constrained data sets is of continuing importance [5].

On the other hand, the use of artificial neural network for the control, modeling and optimization of machining process is widespread [7]-[9]. However, the use of neural networks also is limited by the size of data set [10]. This work proposes an optimization procedure based on a data interpolation approach using a Bootstrapped Neural Network to generate designed data sets in order to improve the value of statistical information and to estimate a
mapping from input to output space. The optimization procedure is aimed to minimize the cost and/or to increase the production in the milling process of forging tools currently used. The designed data set generated by Bootstrapped Neural Network will be statistically analyzed and it will be used, in one second stage, to determine the Taylor’s equation coefficients in manufactory environment, allowing the determination of the Maximum Efficiency Interval.

2. Materials and Methods
The experimental procedure was performed at the XZY Industry.

The milling tests were performed in horizontal machining center CNC, model MC 98 – A40, manufactured by Makino Inc., in 2000, projected to machining molds and matrices with power in the axis tree of 15 Kw, torque 32 N. m, programmable rotation of 200 to 15000 rpm, course of the axes x=915 mm, y=810 mm and z=750 mm, feed speed programmable of 1 to 24000 mm/min, equipped with numeric command Fanuc 16M.

The carries tools type used was HSK 100-A. Its fixing system is by thermal interference, known as Shrink Fit System, which demands a special device for fixation; it allows a maximum radial deviation of the mill cutter of 0.003 mm in high-speed centrifuges.

The cutting tools used in the tests are from the company Hanita Cutting Tools, and are recommended for use in milling, both for roughing and finishing of hardened steel. Its specification is HN44105522022S HN series of 7151, which corresponds to a mill cutter to top-edge of spherical solid carbide (micro grains). Its nominal diameter is 6 mm. Cutting tool with two edges, coating of TiNAl and angle of de helices of 15°. Its total length of 50 mm allows for sure work with the free length (balance of the tool in the process) of 27 mm. These values were determined measuring the depth of the cavity to be cut. It was possible to maintain that condition for all tests. Only new tolls were applied to each test.

The raw materials for testing, consisted of blocks of DIN 1.2367 steel, vacuum treated, with hardness from 49 to 53 HRc, supplied by Villares Metals Company. Its average chemical composition is described in Table 1 and their mechanical properties in Table 2, the data was also supplied by Villares Metals Company.

Table 1: Chemical Composition of Steel DIN 1.2367.

<table>
<thead>
<tr>
<th>%C</th>
<th>%Si</th>
<th>%Cr</th>
<th>%Mo</th>
<th>%V</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.36</td>
<td>0.30</td>
<td>3.80</td>
<td>2.50</td>
<td>0.50</td>
</tr>
</tbody>
</table>

Table 2: Mechanical Properties of Steel DIN 1.2367.

<table>
<thead>
<tr>
<th>MATERIAL</th>
<th>MECHANICAL PROPERTIES</th>
</tr>
</thead>
<tbody>
<tr>
<td>VHSUPER (1.2367)</td>
<td>Sut (MPa)</td>
</tr>
<tr>
<td></td>
<td>Tensile strength</td>
</tr>
<tr>
<td></td>
<td>1200</td>
</tr>
</tbody>
</table>

All machining programs were to cut a cavity of a die forging used produce an automotive connecting rod.

This cavity, specified by the customer, has volume of 55,287.93 mm³, which was completely removed by each of the different sets of cutting parameters used in the tests. The cutting parameters selection was made considering several factors: tool maker catalogs [11], Makino’s training manuals, from other industries and ThyssenKrupp experiences. So it was adopted the following data: cutting speed Vc = 155 m/min; feed per tooth fz = 0.1 mm; depth of cut ap = 0.3 mm; width of cut ae = 2.4. The CNC programs were always the same. Only was changed the different values of (Vc), (fz) and (ap), selected to be tested. Each program includes the machining of only one cavity.

All programs were generated with the same level of safety of 10 mm (distance of approach of the tool part in the fast forward), 5 mm as value of the plan of retreat in case of change of trajectory and 1 mm for retroaction (change of levels of machining in Z coordinate). Besides, the same attack strategy was used (the initial approach of the tool part towards coordinated Z). This strategy foresaw a propeller with a diameter twice the nominal diameter of the cutting tool and angle of entry of 2°. The movement starts from the outside of the cavity to its interior and remains all the time towards in concordance with the cutting direction movement.

It was prepared a enough number of sheets for data collection to be used by the operators. In these sheets all the details of the experiment as well the CNC program to be executed was informed.

The operator performed this program as many times as necessary until the end of tool life. Then, he wrote down the following data: cutting time for one piece, tool life in minutes to cut pieces until the failure tool (T) and quantity of...
pieces that had been completed. Besides, the tool wear, volume of chip removal (V) and cost per piece were written down also.

Cutting tool wear was evaluated only at the end of each program, as to say, for the last piece cut after the tool failed. It was adopted as criterion of end of life, 0.03 mm of flank wear (VB). This value was determined by the experience of operators. Normally when the wear reaches VB > 0.03 mm, the tool is nearly to break. The wear was measured by a pre-set laser system which enables a measurement of the wear into a reliable standard of accuracy.

3. Theoretical Bases

The proposed optimization procedure in this paper was divided in three steps. First of all, the original small data set was used to create bootstrapped data sets for training feed forward neural networks, which were used to generate new designed data sets. So, the designed data sets generated by bootstrapped Neural Network were statistically analyzed and used, in the third step, to determine the Taylor’s equation coefficients in manufactory environment, allowing the determination of the Maximum Efficiency Interval. These steps are described in the next sections and they are illustrated in Fig. 1. Each arrow in Fig. 1 represents a procedure.

![Figure 1: The three steps proposed optimization approach](image)

3.1. The Bootstrapped Neural Network

The original small data set, obtained from a fractionated $2^4$ factorial design and 0 Midpoint (8 rounds), was used to generate thirty bootstrapped data set for training feed forward neural networks. This bootstrap method is based on an imitation of the probabilistic process using the information provided by a given small set of random observations.

In this phase it was used a three layers neural network with 13 nodes in hidden layer and bootstrapped training sets with 12 samples with replacement. The numbers of nodes in hidden layer and the size of the bootstrapped samples are chosen experimentally.

The training process was accomplished separately for each one of the response variables presented in table 3 (cutting tool life, chip removed volume and cost per units). So, considering the four input variables in the experiment, the neural network was created with 4 and 1 nodes in input and output layers, respectively. Also, it was used tangent sigmoid as transfer function, gradient descent with momentum back-propagation training with 0.3 of learning rate [12].

After the training, the neural networks were used to generate new data sets that were used to improve the original set. This second step allows determining all the output values for life, volume and cost as if a complete factorial experiment had been accomplished. The mean value of life, chip volume and cost from the 30 neural network output was used in this case to create the full factorial designed data set presented in table 4.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
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<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>255</td>
<td>0.2</td>
<td>0.48</td>
<td>49</td>
<td>39.2</td>
<td>221152</td>
<td>70.021</td>
</tr>
<tr>
<td>1</td>
<td>155</td>
<td>0.1</td>
<td>0.48</td>
<td>49</td>
<td>309.1</td>
<td>608167</td>
<td>63.641</td>
</tr>
<tr>
<td>1</td>
<td>255</td>
<td>0.2</td>
<td>0.6</td>
<td>53</td>
<td>15.6</td>
<td>110577</td>
<td>80.048</td>
</tr>
</tbody>
</table>

Table 3: Parameters tested X obtained Answer (Cost expressed in Brazilian Real – R$)
Table 4: Designed Neural Network Data Set (Cost expressed in Brazilian Real – R$)

<table>
<thead>
<tr>
<th>Blocks</th>
<th>Vc [m/min]</th>
<th>fz [mm/tooth]</th>
<th>ap [mm]</th>
<th>Material hardness [HRc]</th>
<th>Life [min]</th>
<th>Chip volume [mm3]</th>
<th>Cost/Piece [R$]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>255</td>
<td>0,1</td>
<td>0,6</td>
<td>49</td>
<td>75</td>
<td>276440</td>
<td>68,016</td>
</tr>
<tr>
<td>1</td>
<td>155</td>
<td>0,1</td>
<td>0,6</td>
<td>53</td>
<td>136,8</td>
<td>331728</td>
<td>66,679</td>
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<tr>
<td>1</td>
<td>155</td>
<td>0,2</td>
<td>0,6</td>
<td>49</td>
<td>150</td>
<td>663455</td>
<td>63,337</td>
</tr>
<tr>
<td>1</td>
<td>155</td>
<td>0,2</td>
<td>0,48</td>
<td>53</td>
<td>31,2</td>
<td>110576</td>
<td>80,048</td>
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<tr>
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<td>255</td>
<td>0,1</td>
<td>0,48</td>
<td>53</td>
<td>57,6</td>
<td>165864</td>
<td>73,363</td>
</tr>
</tbody>
</table>

3.2. The Statistical Analysis

The designed new data set was evaluated using the Analyze Factorial Design tool in Minitab 15 Statistical Software allowing an analysis of full factorial effect. This software provides tools that allow graphical analysis of the effect of factorial design, and even showing the full factorial statistical accuracy. Pareto Charts to identify the factors of greatest influence on the statistics of response variables also were used. Another tool used was the "Response Optimizer." This tool allows identifying which combination of imputed variables induces the desired responses [13].

The objective of this phase was to identify the variables of greatest influence (effect) on the cutting tool life, on the chip removed volume and the cost/piece. The use of statistical techniques, added up to methodology of inquiry, provides, when they resulted with elevated levels of reliability and costs reduction, analyze very efficiently all the influence factors involved in the process [14].

The results were compared with Taylor equation coefficients determination.

For the experiments the following conditions were adopted:

- cutting fluid: dry; width ae = 40% of the cutting tool diameter; part of cutting tool balanced equal to 27mm, CNC program;
- variable response limited to wear (VB = 0.03 mm);
- chip removed volume (cm$^3$): obtained by multiplying the number of pieces machined by the chip removal volume of one piece;
- tool life measure in time [min];
- Cost per piece (RS) obtained through Equations 1, 2 and 3. To implement these equations were given the values of Table 5.

$$K_p = K_u + K_m + K_f$$ (1)
\[ K_{uf} = \frac{K_{ft}}{Z_{t}} \]  

\[ K_{ft} = \frac{V_{si}}{N_{fp}} + \frac{K_{pi}}{N_{s}} \]

In which:

\( K_{p} \) = production per piece cost [R$];  
\( K_{us} \) = machining labor cost [R$];  
\( K_{uf} \) = tool cost (depreciation, exchange, grind, etc.) [R$];  
\( K_{um} \) = machine cost (depreciation, maintenance, etc.) [R$];  
\( K_{ft} \) = cutting tool life cost [R$];  
\( Z_{t} \) = number of pieces machined per cutting tool life;  
\( V_{si} \) = tool holder cost [R$];  
\( N_{fp} \) = average tool holder life, in quantities of cutting edges;  
\( K_{pi} \) = acquisition cost / per cutting edge [R$];  
\( N_{s} \) = number of cutting edges/ per insert;

Table 5: Data used for calculations and its origin

<table>
<thead>
<tr>
<th>Nomenclature</th>
<th>Values</th>
<th>Origination</th>
</tr>
</thead>
<tbody>
<tr>
<td>( K_{us} )</td>
<td>R$ 17,09</td>
<td>Database Manufactures X</td>
</tr>
<tr>
<td>( K_{um} )</td>
<td>R$ 42,90</td>
<td>Database Manufactures X</td>
</tr>
<tr>
<td>( N_{fp} )</td>
<td>5000 min</td>
<td>Database Manufactures X</td>
</tr>
<tr>
<td>( V_{si} )</td>
<td>R$ 530,00</td>
<td>Database Manufactures X</td>
</tr>
<tr>
<td>( N_{s} )</td>
<td>R$ 1,00</td>
<td>Database Manufactures X</td>
</tr>
<tr>
<td>( K_{pi} )</td>
<td>R$ 40,00</td>
<td>Database Manufactures X</td>
</tr>
<tr>
<td>( Z_{t} )</td>
<td>As each test</td>
<td></td>
</tr>
</tbody>
</table>

- Factors and levels of input parameters: Cutting speed (155 and 255 m/min), feed rate per edge (0.1 and 0.2 mm/edge), depth of cut (8 and 10% diameter of the cutting tool), hardness of the material (49 and 53 HRC).

3.3. Determination of Maximum Efficiency Interval

Finally, the best possible result obtained using the Minitab Response Optimizer tool, aiming to maximize cutting tool life and chip removed volume and to minimize the cost per units, was used for determination of Maximum Efficiency Interval, based on Taylor equation coefficients. Based in the results obtained in the first two steps some data were followed, as [15], [16]:

- best machining conditions determinate (cutting speed, feed rate per edge, and depth of cut): obtained when was searching for the cutting conditions to maximize the chip removed volume, cutting tool life and minimize the cost per piece;
- as the first cutting speed \( V_{c1} \) was choose 155 m/min and its tool life \( T_{1} \), according the results from DOE;
- the second cutting speed \( V_{c2} \) was calculated as 20% bigger than \( V_{c1} \) and keeping the same values for all others cutting condition and the same tool life criterion, tests were done to determinate tool life \( T_{2} \);
- with these data, the constant \( K \) and the coefficient \( x \) of Taylor tool life equation were calculated in accordance with the equations 4 and 5 [1].

\[
\log \left( \frac{T_{1}}{T_{2}} \right) = \frac{1}{x} \log \left( \frac{V_{c2}}{V_{c1}} \right)
\]

\[ K = T_{1}V_{c1}^{x} \]

Where:

\( T_{1} \) = cutting edge life for \( V_{c1} \) [min];  
\( T_{2} \) = cutting edge life \( V_{c2} \) [min];  
\( V_{c1} \) = First cutting speed [m / min];  
\( V_{c2} \) = Second cutting speed [m / min];
Obtained the coefficients of Taylor equation, was possible to calculate the cutting speeds of minimum cost \(V_{co}\) and maximum production \(V_{cmxp}\) through equations 6 and 7 as shown below [1], [2].

\[
V_{co} = \left( \frac{K(S_h + S_m)}{60(x-1)^{1/2}} \right)^{2} 
\]

\[
V_{cmxp} = \frac{k}{(x-1)^{3/2}} 
\]

Where:

\(t_0 = \text{cutting edge change time [min]; } S_h = \text{man (operator) cost [R$/h]; } S_m = \text{cost time / machine [R$/h];}

4. Results and Discussions

The bootstrapped neural network designed data sets presented in Table 4 were statistically analyzed using the Analyze Factorial Design and Response Optimizer tools from Minitab. For convenience, it was used the following notation for the factors:

<table>
<thead>
<tr>
<th>Term</th>
<th>Standardized Effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>A Vc (cutting speed)</td>
<td></td>
</tr>
<tr>
<td>B Fz (feed rate per tooth)</td>
<td></td>
</tr>
<tr>
<td>C Ap (depth of cut)</td>
<td></td>
</tr>
<tr>
<td>D Material Hardness</td>
<td></td>
</tr>
</tbody>
</table>

Considering the response variable tool Life, it is clear the greater influence of factor D (Hardness), followed by factor A (Vc) and then factor B (fz). It can be seen also an important influence of the interaction between factors A and D. This enhances the influence of hardness on tool life. These results are illustrated by the Pareto chart and the Normal plot effects presented in Fig. 2.

Also, the normal probability plot of the residuals for Life in Fig. 3 shown that the plot has tails that do not fall exactly along a straight line passing through the center of the plot, indicating some potential problems with the normality assumption, but the deviation from normality does not appear severe. The graph of residuals versus fitted values does not reveal any unusual or diagnostic pattern [17].

It is important to highlight that this result are very similar those obtained from a fractional factorial design when only the small original data set is considered (table 3). However, the proposed approach increased the statistical accuracy from 96.13% to 96.57%. Although small, this increase demonstrates the feasibility of the proposed approach for this problem.

Similar results were obtained to other two response variables. The material hardness is the factor of greatest influence in relation to the chip remove volume, followed closely by the cutting speed as shown in Fig. 4. The D and A factors interaction effect is also very significant, with a statistical accuracy of 97.45% (against 99.17% from the fractional factorial design). The residual distribution assumptions for this case are shown in Fig. 5.

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Figure 2: Pareto chart and the Normal plot effects for Life
Finally, the analysis of response about cost per piece shows that the material hardness is the factor of greatest influence followed by the cutting speed and feed rate as shown in Fig. 6. The graphical residual analysis is shown in Fig. 7. The statistical accuracy here is 96.25% against 94.59% from the original data set.

4.1. Evaluating Best Answers
The influence of hardness in the responses is a factor that should be considered. As the tolerance to material hardness is from 49 to 53 HC (tolerance of project) only the higher value was considered in the optimization procedure, as a factor of safety about the conditions to be recommended for use as optimization results. According the results from the Response Optimizer shown in Fig. 8, the global solution aiming to maximize cutting tool life and chip removed volume and to minimize the cost per units is as follow: Vc = 155 m/min; Fz = 0.1 mm/edge; Ap = 10% of the diameter of the tool (0.6 mm)
4.2. Maximum Efficiency Interval Determination

For determination of x and K was used the best cutting conditions found by the method of design of experiment, as already mentioned in last sections. As shown, the best conditions are: cutting speed = 155 m/min, depth of cut= 0.6 mm and feed per tooth = 0.1 mm/rot. So these values will be used as the initials data for the Maximum Efficiency Interval determination, as proposed above. So: \( Vc_1 = 155 \text{ m/min}; \ T_1 = 136.8 \text{ min} \)

Again, following the proposed procedure to Maximum Efficiency Interval, another test was done for the second cutting speed \( Vc_2 = 1.2 \times Vc_1 \). The test showed \( T_2 = 77.2 \text{ m/min} \). Thus, we have \( Vc_2 = 186 \text{ m/min}; \ T_2 = 77.2 \text{ min} \)

Replacing these values in equations 4 and 5 it is possible to find the following values of \( x = 3.1 \) and \( K = 10.2 \times 10^7 \), which are used to determine the maximum production cutting speed \( V_{cmxp} \) through the equation 6. Here is considered that the change tool time (tft) is 15 min. This value was obtained in the real working environment, timing the activity during its accomplishment. \( V_{cmxp} = 246 \text{ m/min} \)

As this value is outside of the cutting speed interval used for the coefficients determination [155,186], the maximum cutting speed must be considered or another test using a new cutting speed interval, for instance [186,223], or to consider a maximum value of 10% about the largest cutting speed (186 m/min) as an extrapolation to adopt the cutting speed of maximum production in an approximate way as 205 m/min.

It is good remembering that this work has the objective to optimize the process and reduce costs, so the maximum production cutting speed is presented only to give consistence to the proposed procedure of x and K determination. In this paper only the minimum cost cutting speed will be considered. This is because the actual target is the cost and not the question of a machine bottleneck analyze.

4.3. Determination of Minimum Cost Cutting Speed (Vco)

Before determining the minimum cost cutting speed is necessary to know the tool cost for cutting tool life (Kft), which is obtained by replacing in equations 3 the values presented in table 6. After the calculation was found that the (Kft) value is: \( Kft = R$ 40,11 \)

Others required information to Vco calculation are presented in table 7. Replacing these values in the equation 7 we have: \( Vco = 162 \text{ m/min} \)

The Vco value was found to be in the interval [155,186] used to its determination with data from the shop floor. So, it is a very reliable value.
Figure 8: Results from the Response Optimizer tool

Table 6: Data to be used for Vco calculation

<table>
<thead>
<tr>
<th>Nomenclature</th>
<th>Values</th>
<th>Origination</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nfp</td>
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<td>Database</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Manufactures X</td>
</tr>
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<td>Vsi</td>
<td>R$ 530,00</td>
<td>Database</td>
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<td></td>
<td></td>
<td>Manufactures X</td>
</tr>
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<td>Manufactures X</td>
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Table 7: Data to be used for Vco calculation

<table>
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<tr>
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<td>3,137975334</td>
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</tr>
<tr>
<td>K</td>
<td>1021628361</td>
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</table>

From data in table 8 is possible to compare the cut parameters found during these experiences with previously used to cut this piece.

It is possible to see that the cutting speed (155 m/min) and depth of cut (0.3) were respectively inferior to the minimum cost speed found during Taylor tests (162 m/min), and inferior to depth of cut (0.6) found during the tests. It is possible to see as well, that the feed of rate per tooth was found to be the same, as to say, the smallest values between the tests used in the experiences.

The consequence of the adoption of these new cut conditions is that an increase of 64 % observed on the efficiency of the process. This occurred because costs were reduced and productivity was increased with the new cutting condition.

Table 8: Cutting conditions before and after the experiences

<table>
<thead>
<tr>
<th>Cutting Conditions Before the Experiences</th>
<th>Cutting Conditions After the Experiences</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cutting Speed [m/min]</td>
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<tr>
<td></td>
<td>162</td>
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<tr>
<td>Depth of Cut [mm]</td>
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<td></td>
<td>0.6</td>
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<td>Feed Rate per Tooth [mm/rot]</td>
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</tr>
</tbody>
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It is important to stand out that the new optimized cut conditions are in use by the industries at this moment.
5. Conclusions

The use of the proposed optimization procedure, based on a data interpolation approach using a bootstrapped neural network to generate designed data sets, allows determining the best factor values in order to minimize the cost and/or to increase the production in the milling process of forging tools currently used. These best values were used to determine the Taylor’s equation coefficients in the manufactory environment, allowing the determination of the Maximum Efficiency Interval.

The results using the designed data set are very similar those obtained from a fractional factorial design when only the small original data set is considered. However, the proposed approach increased the statistical accuracy from 96.13% to 96.57% for tool Life and from 94.59% to 96.25% for the response variable Cost. Although small, this increase demonstrates the feasibility of the proposed approach.

It is important to point out that the work does not suggest that two proceedings must be always used. In fact, the work adds his contribution trying to show that the proposed approach could be useful for problems in which the initial collected data set is very small, the magnitude of variable effects is ambiguous and data gathering costs are high. Also, the show that the cutting process optimization based on Taylor’s equations determination was ratified by the design of experiments of bootstrapped neural network data sets.

Finally, the application of the optimized cutting conditions brings to the industry an increase of 64% in process efficiency.

References