Experimental investigation and regression modelling to improve machinability in CNC turning of CALMAX® tool steel rods

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Abstract. This paper studies the effect of cutting conditions (spindle speed - rpm; feed rate - mm/rev and depth of cut - mm) on main cutting force and surface roughness during CNC turning of the commercial tool steel CALMAX® by Uddeholm (Sweden). Experiments have been designed using the Central composite design (CCD) approach. The experimental design involved twenty base runs with eight cube points, four center points in the cube, six axial points and two center points in axial direction. Statistical analysis to examine the effect of cutting conditions on the responses of main cutting force and surface roughness included ANOVA under the scope of generating a full quadratic model for predicting the responses. Finally, a feed-forward back-propagation neural network was applied to predict the responses of cutting force and surface roughness. It was found that regression models corresponding to the responses as well as the neural network developed can efficiently explain much of the variation in terms of main cutting force and surface roughness and thereby they may be implemented to practical applications either for predicting actual machinability parameter values or for setting up objective functions to be evaluated by intelligent algorithms for process optimization.

1. Introduction
Machining processes of industrial products may affect directly production costs at almost 15 to 20% and is estimated that reach down to over 80% of their value. Thus, it is essential to study the process parameters, especially when it comes to difficult-to-machine materials. Machining productivity and surface quality may be significantly improved when appropriate selection of cutting tools and machining parameters is made.

The success of material removal operations lies heavily on several important technological aspects such as lubrication; [1-4], machining strategy selection; [5], cutting tools selection [6] and machining parameter selection [7]. Under this prism, noticeable contributions have examined the possibilities of modelling and optimizing discrete quality objectives by controlling parameters yielding strong influence on the objectives. It turns out that selecting proper cutting conditions, suitable cutting fluids as well as taking into consideration the properties of cutting tools, work materials and system stability, are of paramount importance. It is claimed in [8,9] that even small changes in any of the aspects
reported, may affect the results in terms of the produced part surface. A variety of research works have been proposed so far regarding modelling and optimization of discrete manufacturing criteria reflecting quality characteristics. Such quality characteristics are surface roughness, production cost, machining time, material removal rate, cutting forces, etc.

Musfirah et al. in [10] presented results concerning their work on tool wear and surface integrity during dry and cryogenic high-speed machining of Inconel 718. Cryogenic and dry cutting experiments were conducted with the utilization of a CNC milling machine capable of achieving a maximum speed of 8000 rpm. Devillez et al. [11] focused on the effect of dry machining on surface integrity of Inconel 718 alloy. Wet and dry turning tests were performed at various cutting speeds, with semi-finishing conditions using a coated carbide tool. For each cutting test, cutting force was measured, machined surface was observed, and residual stress profiles were determined. Xavior and Adithan in [12] investigated the effect of cutting fluids on tool wear and surface roughness during turning of AISI 304 with carbide tool. They also tried to identify the influence of coconut oil in reducing tool wear and surface roughness during turning. Lalwani et al. [13] examined the influence of cutting speed, feed rate and depth of cut on cutting force components; and surface roughness in finish hard turning of MDN250 steel which is equivalent to 18Ni (250) maraging steel, using coated ceramic tool. The machining experiments were conducted based on response surface methodology (RSM) and sequential approach using face centered central composite design. The results show that cutting forces and surface roughness do not vary much with experimental cutting speed in the range of 55–93 m/min. To predict optimal parameter sets satisfying productivity and quality demands, several artificial intelligence (AI) techniques for modelling and optimization have been employed so far. Most popular AI techniques involve the usage of genetic and evolutionary algorithms (GAs-EAs) and artificial neural networks (ANNs) [14-16], being supported by analyses of results obtained from experimental design.

2. Experimental

2.1. Design of experiments
In this work experiments have been conducted to investigate the effect of spindle speed, \( n \) (rpm); feed rate, \( f \) (mm/rev) and depth of cut, \( a \) (mm), on main cutting force, \( F_z \) (N) and surface roughness, \( R_a \) (\( \mu \)m). A rotatable central composite design (CCD) consisting of twenty experimental runs was established according to the number of cutting parameters and their experimental levels (see Table 1).

| Parameter     | Symbol | Level          | Unit        |
|---------------|--------|----------------|-------------|
| Spindle speed | \( n \) | 1500 1750 2000 | rpm         |
| Feed rate     | \( f \) | 0.050 0.125 0.200 | mm/rev     |
| Depth of cut  | \( a \) | 0.500 1.000 1.500 | mm         |

The central composite design sampling method is widely used in response surface applications. By selecting corner, axial, and center points, it is an ideal solution for fitting a second-order response surface model [17]. However, as it requires a relatively large number of sample points, the CCD method should only be chosen in a later stage of the RSM application when the total number of important variables is reduced to an acceptable figure. In this work the three cutting parameters produce only few experiments. The rotatable central composite design is the most widely used experimental design for modelling a second-order response surface. A design is called rotatable when the variance of the predicted response at any point depends only on the distance of the point from the center point of design. The rotatable design provides the uniformity of prediction error and it is...
achieved by proper choice of $\alpha$. In rotatable designs, all points at the same radial distance \( r \) from the center point have the same magnitude of prediction error. For a given number of variables, the $\alpha$ required to achieve rotatability is computed as $\alpha = n_f^{1/4}$, where $n_f$ is the number of points in the $2^k$ factorial design. A rotatable CCD consists of $2^k$ fractional factorial points, augmented by two $k$ axial points $[(\pm \alpha, 0, \ldots, 0), (0, \pm \alpha, \ldots, 0), (0, 0, \ldots, \pm \alpha)]$ and $n_c$ center points $(0, 0, 0, \ldots, 0)$. Here also, the center points vary from three to six. With proper choice of $n_c$ the CCD can be made orthogonal or it can be made uniform precision design. It means that the variance of response at origin is equal to the variance of response at a unit distance from the origin. Considering uniform precision for three-factor experimentation, eight $(2^3)$ factorial points, six axial points and six center runs, a total of 20 runs are considered whilst the value of \( \alpha \) is $(8)^{1/4} = 1.682$.

2.2. Materials and equipment

The material under investigation was the ‘‘CALMAX®’’ tool steel by Uddeholm (Sweden) with the chemical composition given in Table 2. The steel has been used in its soft-annealed condition, having a hardness of 220 HV.

| Table 2. General properties of CALMAX® tool steel of Uddeholm-Sweden. |
|---------------------------------------------------------------|
| **Chemical composition**                                      |
| **Element** | **Content amount (%)** |
| C           | 0.60                  |
| Si          | 0.35                  |
| Mn          | 0.80                  |
| Cr          | 4.50                  |
| Mo          | 0.50                  |
| V           | 0.20                  |

| **Properties** | **Value** |
|----------------|-----------|
| Modulus of elasticity (at 20°C) | 194000 MPa |
| Hardness (Rockwell C)          | 56 HRC    |

Machining experiments were conducted using two Ø30x300mm pre-machined bars comprising ten discrete zones per bar for facilitating chip removal among the cuts. Machining experiments were conducted using a HAAS® TL-1 CNC turning center equipped with a typical HAAS CNC control unit. The cutting insert used was a SECO® TNMG 160404-MF2 TP200 with the suitable insert holder. Figure 1 illustrates the two CALMAX bars; one before preparation and one after preparation. Figure 2 depicts the HAAS TL-1 CNC turning center used for conducting the experiments.

![Figure 1. Ø30x300mm CALMAX® bars for CNC turning experiments.](image_url)
The CNC turning center was integrated with a computer-assisted apparatus based on a Labview® module capable of taking performing online measurements for the three cutting force components, $F_x$, $F_y$ and $F_z$ (Nt). A typical and commercially available three-component dynamometer of Kistler® was selected to measure the main cutting force. Figure 3 depicts the trend for online measurements for the main cutting force $F_z$, obtained during the experiments.

Figure 3. Trend for online measurements for main cutting force, $F_z$ (Nt).

These measurements provided the raw data for further processing on the context of computing the final output for cutting forces. From the trend depicted in figure 3, the average value from the regions where large cutting forces exhibited, was computed to formulate the first response. Mean arithmetic
surface roughness $Ra (\mu m)$ was treated as the second response. Surface roughness was measured using a TESA® Rugorsurf® 10G portable roughness tester along with its respective software, according to ISO-4287 standard. Figure 4 depicts the results obtained from measuring the 6$^{\text{th}}$ cutting zone of the first tool steel bar. For each cutting zone three roughness measurements were taken by rotating the workpiece at an angle of 120°. As a final output for surface roughness corresponding to a cutting zone, the average value from the three measurements was computed.

Figure 4. Indicative results from measurements taken on the 6$^{\text{th}}$ cutting zone (1$^{\text{st}}$ tool steel bar).

3. Experimental results and analysis

3.1. Results
The results obtained from the experiments are presented in Table 3. Analysis of variance (ANOVA) for the results was performed to evaluate the importance of machining parameters and estimate the experimental error. ANOVA for the results of main cutting force – $F_z$ and arithmetic surface roughness average – $Ra$ are given in table 4.
Table 3. Experimental results for main cutting force ($F_z$) and arithmetic surface roughness average ($R_a$).

| No. | n (rpm) | s (mm/rev) | a (mm) | $F_z$ (N) | $R_a$ (μm) |
|-----|---------|------------|--------|----------|------------|
| 1   | 1500.00 | 0.050      | 0.500  | 128.476  | 1.011      |
| 2   | 2000.00 | 0.050      | 0.500  | 104.210  | 0.981      |
| 3   | 1500.00 | 0.200      | 0.500  | 208.923  | 3.999      |
| 4   | 2000.00 | 0.200      | 0.500  | 179.380  | 1.045      |
| 5   | 1500.00 | 0.050      | 1.500  | 181.104  | 1.473      |
| 6   | 2000.00 | 0.050      | 1.500  | 157.742  | 3.760      |
| 7   | 1500.00 | 0.200      | 1.500  | 381.403  | 1.696      |
| 8   | 2000.00 | 0.200      | 1.500  | 369.989  | 3.760      |
| 9   | 1750.00 | 0.125      | 1.000  | 241.514  | 2.069      |
| 10  | 1750.00 | 0.125      | 1.000  | 236.655  | 1.971      |
| 11  | 1750.00 | 0.125      | 1.000  | 346.399  | 1.696      |
| 12  | 1750.00 | 0.200      | 1.500  | 327.378  | 1.332      |
| 13  | 1342.00 | 0.125      | 1.000  | 285.807  | 1.294      |
| 14  | 1750.00 | 0.125      | 1.000  | 308.746  | 1.566      |
| 15  | 1750.00 | 0.250      | 1.000  | 404.271  | 8.946      |
| 16  | 1750.00 | 0.250      | 1.000  | 404.271  | 8.946      |
| 17  | 1750.00 | 0.125      | 1.000  | 212.287  | 1.717      |
| 18  | 1750.00 | 0.125      | 1.800  | 266.242  | 1.896      |
| 19  | 1750.00 | 0.125      | 1.000  | 236.270  | 1.870      |
| 20  | 1750.00 | 0.125      | 1.000  | 241.126  | 1.763      |

Table 4. ANOVA results for main cutting force ($F_z$) and mean arithmetic surface roughness ($R_a$).

| Source of variation | Seq SS | Adj SS | Adj MS | % contribution |
|---------------------|--------|--------|--------|----------------|
| Model               | 194669 | 194669 | 19466.9| 92.10          |
| Linear              | 147807 | 147807 | 49269.0| 69.93          |
| Square              | 38449  | 38449  | 12816.3| 18.19          |
| Interactions        | 8302   | 8302   | 2767.5 | 3.93           |
| Residual error      | 16706  | 16706  | 1856.2 | 7.90           |
| Pure error          | 149669 | 149669 | 18466.9| 2.10           |
| Lack-of-fit (p-value)|        |        |        | 0.729          |

| Source of variation | Seq SS | Adj SS | Adj MS | % contribution |
|---------------------|--------|--------|--------|----------------|
| Model               | 617461 | 617461 | 6.8607 | 93.64          |
| Linear              | 439142 | 439142 | 14.6381| 66.60          |
| Square              | 177683 | 177683 | 5.9228 | 26.95          |
| Interactions        | 0.0637 | 0.0637 | 0.0212 | 0.10           |
| Residual error      | 4.1930 | 4.1930 | 0.4193 | 6.36           |
| Pure error          | 0.3375 | 0.3375 | 0.0675 | 0.51           |
| Lack-of-fit (p-value)|        |        |        | 0.770          |
Analysis of the experimental data obtained from the central composite design was carried out on MINITAB® R17 software using the full quadratic response surface model as given by equation 1.

\[ y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \sum_{j>i}^{k} \beta_{ij} x_i x_j \]  

(1)

\( Y \) is the response -main cutting force \( F_z (Nt) \) and surface roughness \( Ra (\mu m) \) - and \( x_i \) is the \( i \)th parameter. Probability of \( F \)-value greater than calculated \( F \)-value due to noise is indicated by \( p \)-value. If \( p \)-value < 0.05, significance of corresponding term is established. For lack of fit, \( p \)-value > 0.05. An insignificant lack of fit is desirable because it indicates that any term excluded by the model is insignificant and that the developed model fits well. Anderson–Darling normality test is used to verify the suitability of the models corresponding to the main cutting force and surface roughness, for practical applications. If \( p \)-value for the Anderson–Darling test is lower than the chosen significance level, i.e. 0.05, it is concluded that the data do not follow a normal distribution. In this work, ANOVA indicates that both quadratic models are suitable for predicting the main cutting force \( F_z (Nt) \) and surface roughness \( Ra (\mu m) \) with high contributions, i.e. 92.10\% and 93.64\% and \( p \)-value for lack-of-fit far beyond 0.05 (\( p \)-value > 0.25) - see figure 5a and figure 5b.

**Figure 5.** Probability plots for regression models: (a) main cutting force, \( F_z \); (b) surface roughness, \( Ra \).
3.2. Statistical analysis

Based on p-value, it has been concluded that the main cutting force $F_z$ (Nt) and surface roughness $Ra$ ($\mu$m) are mainly influenced by the linear terms and square terms followed by interaction terms. The individual significance of each term is calculated by t-test at 95% confidence level, thus; terms having p-value less than 0.05 are significant. The coefficient of determination ($R^2$) which indicates the percentage of total variation in the response explained by the terms in the model has been found equal to 92.10% and 93.64% for main cutting force $F_z$ (Nt) and surface roughness $Ra$ ($\mu$m) respectively.

Specifically the linear terms in the case of main cutting force $F_z$, have a 69.93% contribution whereas square terms reach 18.19% as a contribution percentage. Interaction terms contribute to main cutting force as much as 3.93%. In the case of surface roughness $Ra$, linear terms have a 66.60% contribution whereas square terms reach 26.95% as a contribution percentage. Interaction terms contribute to surface roughness as much as 0.10%.

![Figure 6. Plots for the main effects: (a) main cutting force, $F_z$; (b) surface roughness, $Ra$.](image)

From figure 6a it is evident that feed rate $f$ (mm/rev) and depth of cut $a$ (mm) have the largest effect on the response of main cutting force $F_z$ (Nt). Main cutting force gradually increases with the increase of feed rate. Main cutting force reaches its highest mean under the feed rate value equal to 0.25 mm/rev. A noticeable increase in main cutting force is observed for the three first levels of depth of cut whilst the two higher levels equal to 1.50 mm and 1.82 mm do not seem to further increase main cutting force. Spindle speed reduces the mean of main cutting force in general, however its highest level tends to increase it. From figure 6b it is evident that feed rate $f$ (mm/rev) and spindle speed $n$ (rpm) have the largest effect on the response of surface roughness $Ra$ ($\mu$m). Surface roughness gradually increases with the increase of feed rate whilst it reaches its highest mean under the feed rate value equal to 0.25 mm/rev. Spindle speed comes as the second variable to affect surface roughness. Its lower level maintains low surface roughness, however surface roughness increases when moving towards the second level for spindle speed. The next spindle speed levels gradually reduce surface roughness where the lowest result is observed for spindle speed equal to 2158 rpm. Depth of cut is the third parameter to affect surface roughness and based to its rank, it can be advocated that it does not significantly affect surface roughness. Nevertheless, lowest and highest levels for depth of cut seem to be advantageous for surface roughness, whereas intermediate level deteriorate it. Contour plots allow to depict a three-dimensional surface on a two-dimensional plane. They graph two predictors-variables on $X$ and $Y$ axes whereas the response variable is appeared in $Z$ axis as a contour. Corresponding contour plots for the responses of main cutting force and surface roughness were generated to show how their values change as functions of different pairs of independent variables. Figure 7 shows the resulting changes in main cutting force when altering spindle speed, feed rate and depth of cut, as a function of two inputs, i.e. $F_z = f(n, f)$, $F_z = f(n, a)$, $F_z = f(f, a)$ whereas figure 8 shows the resulting changes in surface roughness when altering spindle speed, feed rate and depth of cut, as a function of two inputs, i.e. $Ra = f(n, f)$, $Ra = f(n, a)$, $Ra = f(f, a)$. 
Contour plots for $F_z$: (a) $F_z = f(n, f)$, (b) $F_z = f(n, a)$, (c) $F_z = f(f, a)$.

Figure 7.

Contour plots for $Ra$: (a) $Ra = f(n, f)$, (b) $Ra = f(n, a)$, (c) $Ra = f(f, a)$.

Figure 8.
4. Experimental results and analysis
To investigate whether the prediction for the responses can be improved an artificial neural network (ANN) with back propagation algorithm was adapted to model the CNC turning process. For this analysis, the three independent variables spindle speed $n$, feed rate $f$ and depth of cut $a$ were considered as the input parameters for the ANN. Each of these parameters has been characterized by one neuron, thus, the input layer in the ANN structure had three neurons. The database has been built considering the series of CNC turning experiments at the limit ranges of each independent variable. Experimental results for main cutting force and surface roughness were used to train the ANN to understand the input–output correlations. The database was then divided into two categories, namely the training category which has been exclusively used to adjust the network weights and the test category, which corresponds to the set that validates the results of the training protocol. Factorial runs were used for training, whilst the rest of experimental runs were used for testing. Experimental runs corresponding to center points have the same factor level values, hence mean of main cutting force and surface roughness were used as representative values related to these experiments. Neural network training involved updating the weights of the connections in such a manner that the error between the network’s outputs and the actual output is minimized. To determine the number of neurons in the single hidden layer selected, different network structures with varying number of neurons in the hidden layer were tested. After training, the topology 3-10-2 was finally selected as the optimum. The activation level of neurons was determined by tan–sigmoid transfer function except for output layer neurons for which linear output transfer function was used so that output is not limited to small values. Figure 9 gives the schematic representation of ANN used in present work. The ANN was simulated in MATLAB® 2014b. To evaluate the competence of this trained network, the training data set was presented to the trained network.

![Figure 9. ANN architecture with three inputs, one hidden layer (10 neurons) and two outputs.](image)

Mean squared error (MSE) in ANNs is the average squared difference between network output values and target values. For the network implemented in the study, best validation performance was equal to 185.4179 at epoch 11; see figure 10.
Figure 10. Best validation performance for the ANN implemented.

Figure 11 shows the regression analysis results between the network response and the corresponding targets. High correlation coefficient $R^2$ between predicted results (outputs) and targets validated the performance of the ANN implemented. Regression values measure the correlation between output values and targets. The results acquired for this study shown a good correlation among output values and targets during training ($R=0.981$), validation ($R=0.998$), and testing ($R=0.97956$).

Figure 11. Regression plots for ANN performance verification.
The values predicted by ANN and regression models for main cutting force and surface roughness are depicted in figure 12. Figure 12a shows the comparison among experimental, predicted and ANN result whereas figure 12b shows the same comparison referring to the results obtained for surface roughness. In both figures, it can be observed that the trend corresponding to the results variation for the ANN matches more accurately the one corresponding to the experimental results. Based on these outputs it is proven that the ANN is better for modelling the non-linearity presented in the experimental domain.

![Graph](image)

**Figure 12.** Comparisons among results obtained: (a) main cutting force \( F_z (N_t) \), (b) surface roughness \( Ra (\mu m) \).

5. Conclusions
In this work, the effect of cutting parameters (spindle speed-\( n \), feed rate-\( s \) and depth of cut –\( a \)) on the main cutting force -\( F_z \), and arithmetic surface roughness average -\( Ra \) were studied. Experimental results were obtained through the utilization of response surface methodology by establishing a central composite design. The analysis and interpretation of the respective results was carried out by performing analysis of variance using the full quadratic model and sequential SS for tests. Signal-to-noise and interaction plots were also exploited to study the effects of parameters on the responses. The experimental outputs were further used for the training, testing and validation of a feed forward back propagation artificial neural network model. It was shown that the regression models and the ANN can predict experimental results when CNC turning the commercially available CALMAX\textsuperscript{®} tool steel, in terms of main cutting force and surface roughness with good correlation. To depict variations of quality objectives studied, contour plots were generated considering the different values (levels) of cutting parameters. As a future work authors plan to implement different evolutionary algorithms and optimize the CNC turning operation of CALMAX\textsuperscript{®} tool steel by formulating a multi-objective optimization problem and having the regression models under the role of objective functions.

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Acknowledgements
This work was funded by the “Research & Management committee – E.L.K.E. ASPETE” under the auspices of the Research program “Parametric Analysis & Machining Parameters Optimization of Special Purposes Steels” for the project “Research strength in ASPETE 2018-2020”-Ref.No.: 80156.