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Application of Statistical and Soft Computing techniques for the Prediction of Grinding Performance

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Abstract

Thermal load in manufacturing processes is of special interest as it is closely connected with the surface integrity and life-cycle of the finished product. Especially in grinding, heat affected zones are created due to excessive heat dissipated within the workpiece during the process. In these zones, defects are created that undermine the quality of the workpiece and as grinding is a precision finishing operation, may render it unsuccessful. Grinding forces and temperatures are usually studied in relation to the heat affected zones. However, their experimental estimation or analytical evaluation may prove laborious and costly. Thus, simulation and modeling techniques are commonly employed for the prediction of these parameters and through them the performance evaluation of the process is performed. In this paper, statistical methods and soft computing techniques, namely regression models completed with analysis of variance, and artificial neural networks respectively, are presented for the estimation of grinding forces and temperature. A brief description of the models and a comparative study is performed, based on experimental results. Both modeling tools prove to be quite successful, predicting with high accuracy forces and temperatures.

Keywords: Statistical regression analysis; Artificial neural networks; Grinding; Forces and temperatures; Analysis of variance.

Introduction

Grinding is a manufacturing process of great importance in contemporary industry. It is mainly used as a finishing operation, because of its ability to produce high workpiece surface quality. It is also used in bulk removal of material, maintaining at the same time its characteristic to perform precision processing and opening new areas of application in today's industrial practice. However, the energy per unit volume of material being removed from the workpiece during grinding is significant. Grinding forces are essential for calculating grinding energy, which in turn is almost entirely converted into heat, causing a rise of the workpiece temperature and, therefore, thermal damage. This heat input is responsible for a number of defects in the workpiece like metallurgical alterations, microcracks and residual stresses [1]. High surface temperatures are connected to these phenomena and may lead to grinding burn. The areas of the workpiece that are affected are described as heat affected zones.

The prediction of grinding forces and workpiece temperatures is considered useful for the assessment of the heat affected zones, for avoiding defects on finished products and the optimization of the manufacturing process. Nevertheless, grinding is characterized by complex relationships between process parameters, workpiece and cutting tools characteristics as well as quality features of the finished products. Furthermore, certain difficulties arise when experimentally measuring surface temperatures during grinding, mainly due to the set-up of the process. A lot of research pertaining to grinding is performed through modeling and simulation instead of experimental investigation [2]. Although most of the mentioned papers in the relevant literature pertain to Finite Element Method (FEM) models, other types of modeling methods have been reported, e.g. Artificial Neural Networks (ANNs) [3]. Furthermore, statistical and soft computing techniques have been employed for the prediction of the performance of manufacturing processes with success [4].

In the current study, statistical regression analysis models are employed to fit experimental data from grinding processes with various types of grinding wheels and workpiece materials, at various depths of cut. The accuracy of regression models is estimated and statistical analysis is employed to determine the validity of the regression model. Then, the results are compared to the results of a similar analysis conducted with Artificial Neural Networks models. Conclusions about the effectiveness of the application of regression models to grinding can be drawn, as well about its predictive accuracy compared to the accuracy of an artificial neural network.

Artificial Neural Networks and Regression models

In this section, a brief introduction to the artificial neural networks and statistical regression models is presented, with a view to clarify the basic aspects of these two methods.

Artificial Neural Networks

Artificial neural networks constitute one of the most widely used soft-computing methods in many scientific fields. Artificial neural networks have been extensively used to model machining processes and optimize their operating conditions [5-10]. Essentially, neural networks are statistical learning algorithms whose characteristics originate from biological neural networks e.g. the nervous system of animals. A system similar to the actual biological neural networks is created, consisting of various levels of interconnected neurons which are employed to approximate the behavior of a system whose function cannot be easily described with a suitable set of physical laws and equations or is generally unknown to the researcher, but a set of inputs and their related outputs is available. Each neuron constitutes essentially a node of the network and acts as a data processor receiving inputs, processing them and transforming them to appropriate outputs using a suitable function, called the activation function.

The simplest type of neural networks is the feed-forward neural network, as it can be seen in Figure 1.

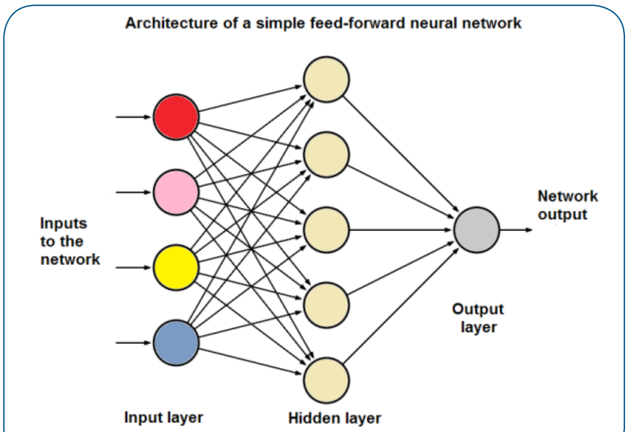

Figure 1: The structure of a feed-forward neural network

According to the interconnections between the various levels of neural networks, in such a network, the data is processed from the input layer to the output layer remaining only in one direction. Intermediate levels, called hidden layers, also exist and allow for the data to be further processed before it eventually reaches the output layer. The determination of the number of hidden layers and the number of neurons in each layer is usually a result of experimentation with various possible configurations with a view to find the network structure that leads to more accurate estimations of the desired results. Appropriate numerical values called weights are assigned to each connection between neurons. So, the output values for each neuron are obtained as follows: each input signal is multiplied by the relevant weight and these values are summed to form the total input. Then this value is transformed into output using the activation function of the neuron. Usually, this function is sigmoid and thus yields an output within the range 0-1. To the input signal a bias term, which represents a threshold value, is added.

After the architecture of the neural network is properly determined, the training of the network takes place. Essentially, the training stage of the algorithm consists of the determination of the value of each weight. Before the training process starts, the weights are initialized randomly. For the training, a proportion of the total available experimental results is used. Usually the backpropagation method is employed in order to train the network by propagating the error of the estimated results from the output level to the input level. The backpropagation process is implemented by various algorithms such as: Levenberg-Marquardt, BFGS quasi- Newton, conjugate gradient, secant method and others.

In the backpropagation process, the error in the output layer is first computed and then using the appropriate weight values, error calculations are performed to the previous layers until the input layer is reached. This error values are used for the calculation of the error derivative and the determination of the new weights. In the next step or epoch as is usually termed, the network is fed forward and this process carries on until the termination criteria are met. In order to test the validity and the generalization ability of the algorithm, other sets of experimental values are preserved to be used in the validation and test stages of the network before it can be employed as a predictive tool. Usually, the Mean Square Error (MSE) is calculated at each epoch and the simulation is terminated when the MSE value does no longer descent.

Statistical regression models

Statistical regression is a general process employed to determine the relationships of some input variables and their outputs in a studied system. Regression models are utilized generally to describe the relationship between one or more independent variables with the dependent variables by means of a function, called the regression function. Appropriate statistical methods are used to determine the variation of the measured dependent variable around the computed regression function and estimate its efficiency. Regression models are often employed as a predictive tool for a variety of systems.

Generally, the regression models can be divided into two categories according to the type of regression function employed in the analysis: linear and non-linear regression models. In linear regression models, the regression function is required to assume the dependent variables as a linear combination of the combination parameters, as it can be seen in equation (1):

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... \beta_p X_p + \varepsilon \quad (1)$$

where y is the dependent output variable, β_i is the i-th coefficient and β_0 is the constant term in the model, X is the independent input variable and ε is a general noise term. Nevertheless, the dependent variables can be a non-linear combination of the independent variable, as it can be seen in equation (2):

$$y = \beta_0 + \sum_{k=1}^{N} \beta_k f_k \left(X_1, X_2, \ldots, X_p\right) + \varepsilon \quad (2)$$

Where f is a scalar function of the input values, that can include non-linear terms but linearity in terms of coefficients β_k is not violated. The term simple linear regression is often employed in cases with a single independent variable, while the term multiple linear regression is used in cases involving more than one independent variables. The experimental results are fitted to the regression model using an appropriate minimization technique.

In the case of non-linear regression models, the regression function is essentially a non-linear combination of the regression parameters. Commonly, the non-linear models are employed in cases where the experimental results are assumed to vary according to a specific law e.g. power law, exponential law. Therefore, the regression function has a similar form so that along with the estimated parameters the model will yield more precise results. In several cases, these non-linear functions can be linearized and then processed in the same way as linear regression functions.

The fitness of the results to the regression function can be tested using appropriate measures such as: the multiple correlation coefficient R, the coefficient of determination R^2, the adjusted R^2 and the root mean squared error. The most widely used coefficient is the R^2, which indicates the fraction of the variability observed in the predicted results and can be observed in equation (3):

$$R^2 = 1 - \frac{\Sigma(y_i - f_i)^2}{\Sigma(y_i - \bar{y})^2} \quad (3)$$

where y_i are observed data with predicted value of f_i, $\bar{y}$ denotes the mean of the observed data and the nominator and denominator of the above fraction represent the residual sum of squares and total sum of squares, respectively. Although the use of some of these measures cannot be performed in non-linear regression, similar measures can assess the validity and precision of non-linear models. At last, the statistical analysis of variance (ANOVA) test can be conducted to assert the validity of the results and the regression model. In manufacturing, there are various cases where regression models have been employed to model machining processes and their parameters [11-15].

Methodology

The purpose of the current study is to test various linear regression models with a view to predict the tangential force and maximum temperature in grinding. In a previous study [16], a number of grinding experiments were conducted with different grinding wheels, workpiece materials and depths of cut. For the experiments, a surface grinding machine was employed, as it can be seen in Figure 2.

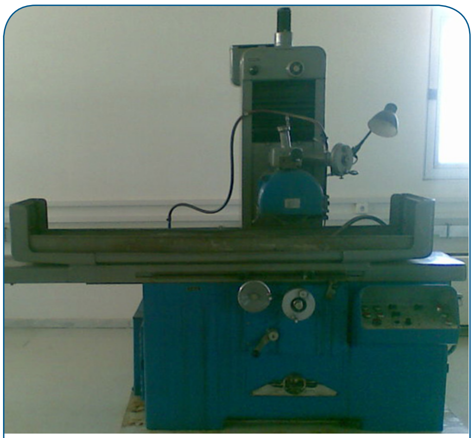

Figure 2: Surface grinding machine

Three different workpiece materials were used in the experiments, namely 100Cr6, C45 and X210Cr12 steels. The six aluminum oxide grinding wheels have a diameter of 250 mm, width of 20 mm and different bonding. The wheel speed was kept constant at 28 m/s and four different depths of cut were employed, namely 10, 20, 30 and 50 μm. The maximum temperature results were obtained from a FEM heat transfer simulation conducted using the Jaeger model [16]. In Jaeger's model the grinding wheel is represented by a heat source moving along the surface of the workpiece with a speed equal to the workspeed. The heat source is characterized by a physical quantity, the heat flux, q, that represents the heat entering the workpiece per unit time and area and it is considered to be of the same density along its length, taken equal to the geometrical contact length, l_c, as it is described in Figure 3.

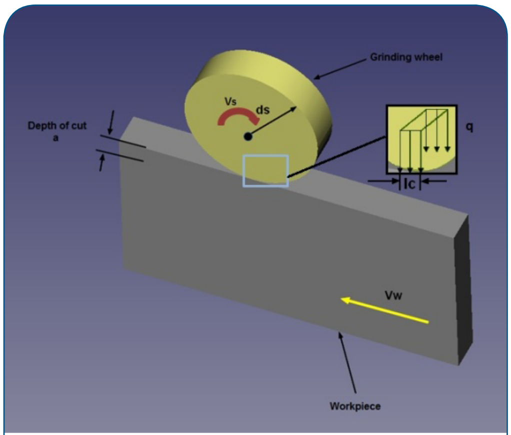

Figure 3: Jaeger's model in grinding

After the conduction of the experiments, a feed-forward neural network with three input neurons, one output neuron and one hidden layer with 5 neurons was proposed for the prediction of the tangential grinding force and maximum surface temperature. The input data was suitably normalized before they were fed to the network. The hyperbolic tangent sigmoid function was employed as activation function and the Levenberg-Marquardt algorithm as the learning algorithm [16]. In the current study, a regression analysis model is developed to study the tangential force produced in the grinding process and the maximum temperature on the workpiece. The input parameters, i.e. the independent variables, are chosen to be similar to the parameters chosen in [16], with a view to conduct a comparison between the two methods. Furthermore, variables are quantified based on the properties of the grinding wheel and the workpiece materials. More specifically, grinding wheel grain size and workpiece material hardness are used. For the determination of workpiece materials' hardness, appropriate tests are conducted. The corresponding values of hardness for each material designated in [16] as 1 to 3 are 250HV for 100Cr6, 210HV for C45 and 265HV for X210Cr12, respectively. The corresponding grain size for grinding wheels 1 to 6 are 180, 100, 90, 150, 120 and 80, respectively. However, in order to facilitate the comparison between regression models and ANN, the inputs are presented in the respective tables in the sense of encoded variables. Finally, in order to reduce undesired effects related to the magnitude of the values of each factor, normalization is performed to all input values before they are inserted in the regression model.

The type of regression chosen is linear regression. Although the choice of a linear regression model seems at first not appropriate to model a complicated problem, it is considered that it would be more suitable to use a less complicated model as there is no evidence of the type of relationship between the input parameters that dictates the use of a specific non-linear regression model. Thus, two different linear regression models are employed in this study, namely a first order model, and a second order model. After each model is fitted, an analysis of variance test is conducted. Furthermore, the results concerning these models and the comparison of the results to the ANN results are discussed. The set of results chosen for the comparison between regression models of first and second order and between regression models and ANN is the same in every case.

Results and discussion

Statistical regression analysis

In this subsection the results obtained from the linear regression models are presented and discussed. For both the regression analysis models created in this paper and the artificial neural networks created in reference work [16], the corresponding toolboxes of Matlab were used.

First order model

A simple first order model is assumed in each of the two aforementioned cases, namely for the prediction of tangential force and maximum temperature. The details about the model are summarized in Table 1, along with results obtained from the regression process. As it can be seen in Table 1, interaction terms between the various parameters are not taken into consideration. Furthermore, regression models were found to be statistically significant, as well as its coefficients, in both the tangential force and temperature models.

In Table 2, a comparison between experimental and predicted results is made. It is obvious that the performance of the model can be characterized as moderate. In the case of forces the discrepancies between experimental and predicted results are above 10% in the majority of examples. The results are worst in the case of temperatures; the discrepancies between FEM and regression analysis results quite higher. The first order model overestimates the maximum temperature, indicating an unsuccessful fitting.

Table 1: Results concerning the fitting of the first-order model in the two cases

Model type = $b_0 + b_1 x_1 + b_2 x_2 + b_3 x_3$		**Output = tangential force**		
Estimated coefficients				
	Estimate	SE	t-value	p-value
Intercept (b_0)	-1.1311	0.11369	-9.9486	6.7414e-15
b_1	-0.11407	0.052223	-2.1843	0.032388
b_2	1.4418	0.11631	12.396	4.0942e-19
b_3	0.52905	0.034445	15.359	8.5e-24
Number of observations : 72		Error DOF : 68		
RMS error : 0.0865		R-squared : 0.853		
Adjusted R- squared : 0.846		p – value : 3.06e-28		
Model type = $b_0 + b_1 x_1 + b_2 x_2 + b_3 x_3$		**Output: maximum temperature**		
Estimated coefficients				
	Estimate	SE	t-value	p-value
Intercept (b_0)	-1.4125	0.12996	-10.868	1.6295e-16
b_1	-0.15096	0.059698	-2.5287	0.013775
b_2	1.9971	0.13296	15.02	2.7564e-23
b_3	0.34012	0.039375	8.6379	1.5247e-12
Number of observations:72		Error DOF: 68		
RMS error : 0.0988		R-squared: 0.818		
Adjusted R- squared : 0.81		p-value:3.84 e-25		

Table 2: Comparison of predicted results with experimental results in both cases

Output variable: tangential force (N/mm)					
Process parameters			Results		
Grinding Wheel	Workpiece material	Depth of cut (μm)	Experimental result	Predicted value	Difference (%)
3	1	50	10.66	12.5581	17.81
6	1	30	7.23	8.8815	22.84
3	3	50	16.09	14.0198	12.87
6	3	30	11.05	10.3432	6.40
Output variable: maximum temperature (^oC)					
Process parameters			Results		
Grinding Wheel	Workpiece material	Depth of cut (μm)	Computed result (FEM)	Predicted value	Difference (%)
1	1	50	688.6	779.0447	13.13
3	1	50	748.0	868.0333	16.05
6	1	30	631	850.8015	34.83
2	3	30	1074	831.0262	22.62

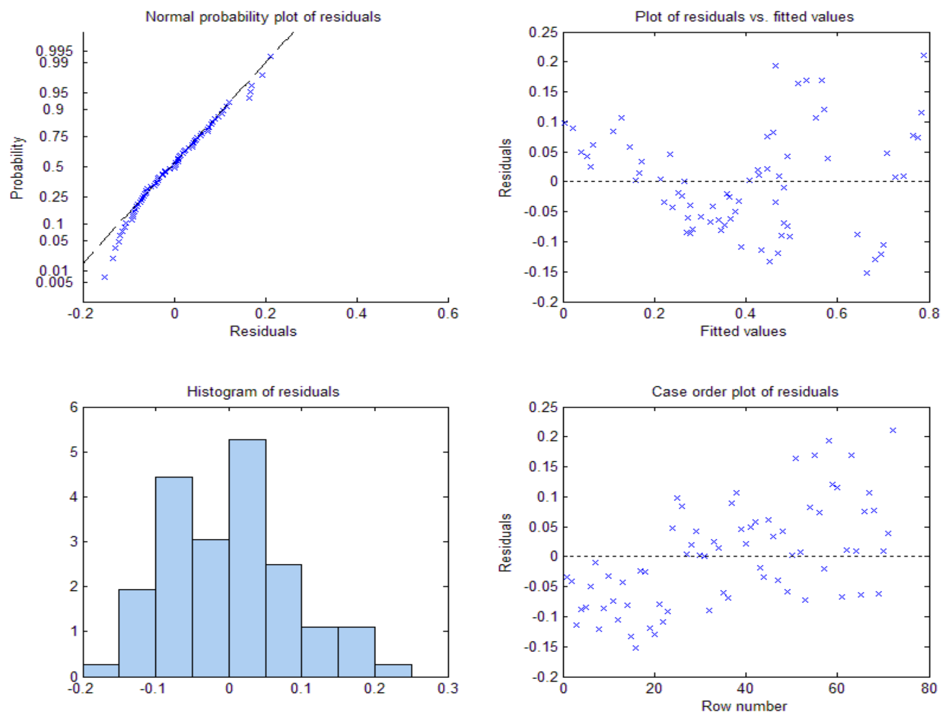

Figure 4: Residuals plot in the case of first order model for tangential force

Moreover, in order to assess the validity of the first order model, plots of the regression residuals are constructed and observations are conducted. Plots depicted in Figure 4 and Figure 5 are considered as useful diagnostic tools for the analysis of regression models' results. In case of regression models it is required that the error terms are independent and no correlation exists between them; in the opposite case that would mean that the error terms contain predictive information for which the regression model could not adequately account. In Figure 4 the residual plots for the tangential force model are presented. The normal probability plot is useful in order to determine if the error terms are normally distributed. If these terms follow a normal distribution, the relationship between the theoretical percentiles of the normal distribution and the observed sample percentiles should be linear. At first, it can be observed that there are clearly some deviations from the linear curve in this case. A modified Shapiro-Wilk statistical test was then conducted, in order to determine the normality of error terms distribution. The null hypothesis in this statistical test states that a population is normally distributed. The results of the test indicate that the null hypothesis for this case is accepted, as a p-value of 0.1408 for alpha level 0.05 was obtained and the value of W-statistic was 0.9740;

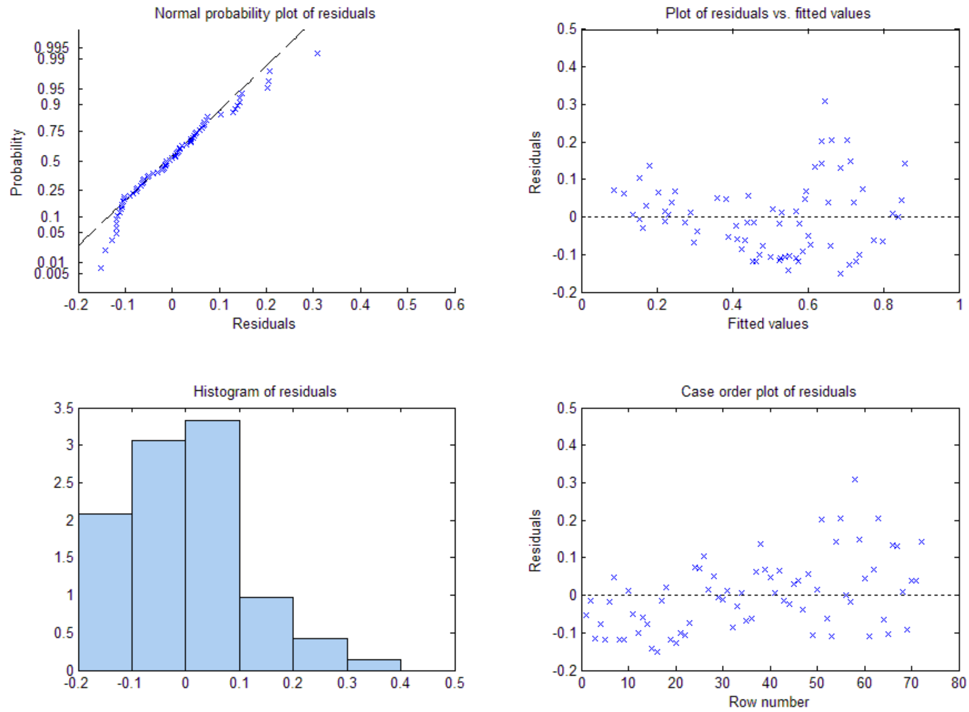

Figure 5: Residuals plot in the case of first order model for maximum temperature

thus, the error terms are normally distributed. Additionally, the residuals versus case order plot allows for the determination of the independence of error terms. More specifically, this plot is used in order to detect correlation between error terms and the values of the residuals should vary randomly around zero. As it can be observed in Figure4, there exists a certain trend in the residuals; although the values seem to fluctuate, their values seem to increase in an almost constant rate. This is another indication that a non-random pattern is likely to exist in the residuals and thus a part of explanatory information is essentially captured in the residuals. In that case, and regarding the analysis of the normal probability plot, there are possibilities that a missing variable, a missing higher-order term or a missing interaction between terms in the model exists.

Similar conclusions can be drawn in the case of maximum temperature model. In this case, the null hypothesis for the Shapiro-Wilk test is rejected with a p-value of 0.0112 and a W-statistic value of 0.9532 thus indicating that there is no normality in the distribution of residuals, something that can also be seen in the residuals' histogram. Additionally, the observations concerning the other residual plots are similar to those for the tangential force model and, consequently, the inadequacy of the model to represent accurately the experimental data is noted, as it was also indicated by the relatively high error percentage in predictions in Table 2. Thus, a second order model is proposed.

Second order model

Accordingly to the previous sub-section, a second-order model is assumed in both studied cases with a view to fit the experimental results more successfully. The details about the second-order model are presented in Table 3. The R^2 values of the models are 0.918 and 0.889 for forces and temperatures, respectively, which are very close to 1; the model can be characterized as effective. R^2 coefficient measures the good fit of the data to the model, with value 1 for perfect fit. Furthermore, the R^2 is in reasonable agreement with adjusted R^2, for both cases. In Table 4, for the same data used in the first order model, the comparison between some experimental and predicted results is presented. It is quite clear that second order models provide better results both for tangential forces and temperatures. Differences in values are below 10%, with an exception of only one example. As in the case of the first-order model the calculated p-values indicate that both models are statistically significant. Moreover, it is found that in both cases, the parameters b_1 and b_4, which are related to the grinding wheel, are not statistically significant, as it was indicated to a certain degree from the first-order model in which p-values for parameter b_1 were greater from those related to the other parameters but their value was slightly under 0.05. Furthermore, in the case of the tangential force model, the p-value corresponding to the x_3^2 term indicates that this quadratic term can also be neglected.

Table 3: Results concerning the fitting of the second-order model in the two cases

Model type = $b_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 + b_4 x_1^2 + b_5 x_2^2 + b_6 x_3^2$			**Output** = tangential force	
Estimated coefficients				
	Estimate	SE	t-value	p-value
Intercept (b_0)	9.8018	1.5763	6.2183	4.0647e-08
b_1	-0.28546	0.38644	-0.73869	0.46275
b_2	-23.358	3.5606	-6.5601	1.031e-08
b_3	0.74995	0.13745	5.456	8.1327e-07
b_4	0.1189	0.26666	0.44589	0.65716
b_5	13.926	1.9988	6.9672	1.9821e-09
b_6	-0.17981	0.10981	-1.6374	0.10637
Number of observations : 72	Error DOF : 65			
RMS error : 0.0661	R-squared : 0.918			
Adjusted R- squared : 0.91	p –value : 2.56e-33			
Model type = $b_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 + b_4 x_1^2 + b_5 x_2^2 + b_6 x_3^2$			**Output**: maximum temperature	
Estimated coefficients				
	Estimate	SE	t-value	p-value
Intercept (b_0)	8.3459	1.8844	4.4289	3.7115e-05
b_1	-0.25856	0.46198	-0.55968	0.57762
b_2	-20.384	4.2567	-4.7887	1.0088e-05
b_3	0.93772	0.16433	5.7065	3.0747e-07
b_4	0.074653	0.31879	0.23418	0.81558
b_5	12.568	2.3896	5.2595	1.7278e-06
b_6	-0.48642	0.13128	-3.7053	0.00043824
Number of observations: 72	Error DOF: 65			
RMS error : 0.079	R-squared: 0.889			
Adjusted R- squared : 0.879	p-value: 4.13e-29			

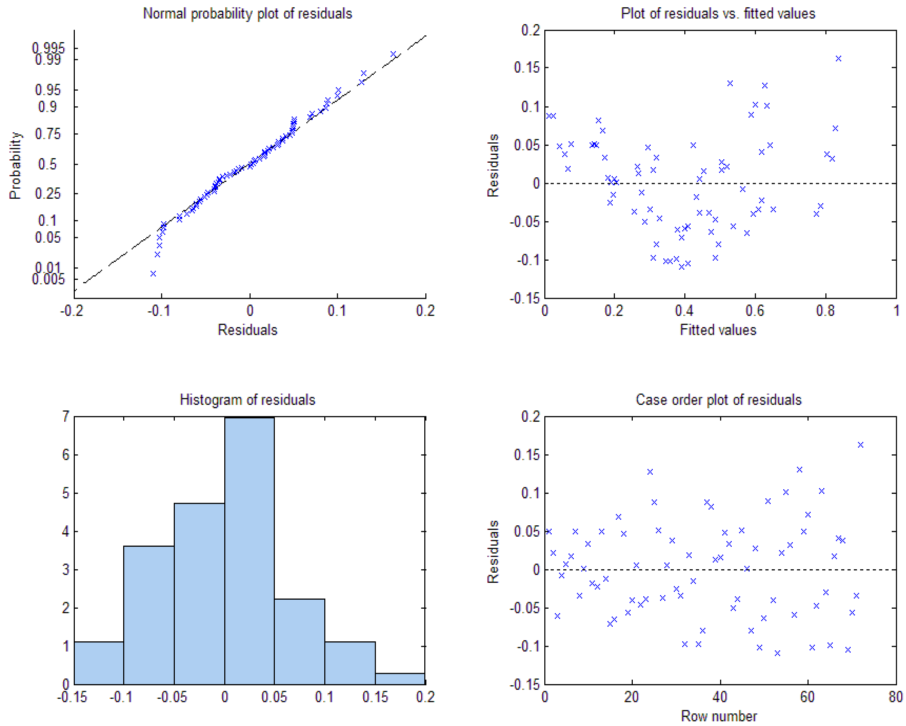

Figure 6: Residuals plot in the case of second order model for tangential force

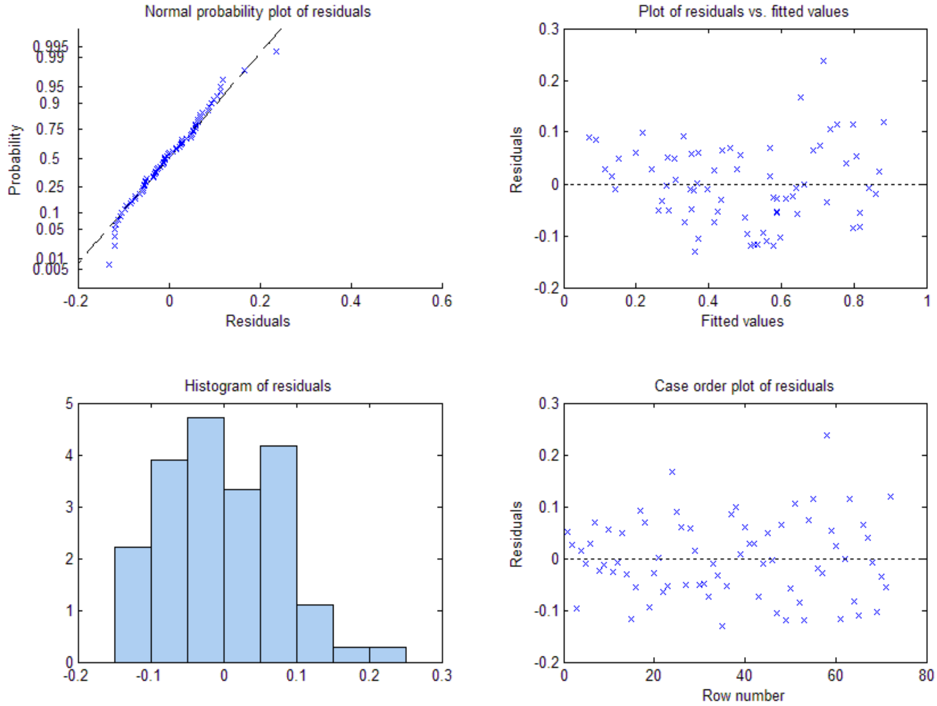

Figure 7: Residuals plot in the case of second order model for maximum temperature

As in the case of the first order regression model, residuals plots are created and they are presented in Figure 6 and Figure 7. In the case of the normal probability plot, it is observed that most of the residual terms lie on the linear curve. The Shapiro-Wilk test results prove that, in this case, the null hypothesis can be accepted with a p-value of 0.1867 and a W-statistic value of 0.9761; so, normality of error terms distribution is guaranteed. Similarly, the case order plot of residuals indicates that no certain pattern exists in the error terms and so they can be considered as randomly varying around zero.

Accordingly, in the case of the temperature model, the normality of the error terms distribution is again confirmed, as the p-value of the Shapiro-Wilk test is 0.3000 and the W-statistic value is 0.9798, thus indicating that the null hypothesis can be accepted. This statement is further confirmed by observing the histogram of residuals which has a shape similar to normal distribution shape, as in the case of tangential force model, in spite of the existence of a two outliers. Finally, the case order plot indicates that no observable pattern in the sequence of error terms exists.

Concerning the comparison between the two models, based on the previous analysis for each model, the second order model is clearly more preferable than the first-order model. The value of the adjusted R^2 coefficient which can indicate the goodness of fit regardless the number of predictors is greater in the case of the second order model, thus suggesting a clear improvement in the adequacy of the regression model. Accordingly the RMS error values are significantly lower in the case of the second order model and so the observations are lying closer to the regression model outputs, providing a strong indication of the improvement of the precision of the model.

Finally, the second order model was able to predict the actual experimental results with a significantly lower error value, as it can be seen by comparing the results from Table 2 and 4. Thus, taking account of all aforementioned points, it can be concluded that the second order model is more preferable than the first order model.

Analysis of variance test

Before comparing the second-order linear regression model results with the results obtained from artificial neural networks, analysis of variance test is conducted for the second-order model. In Tables 5 and 6, the results of the analysis of variance for the tangential force and temperature, respectively, are tabulated. The developed models are tested at 95% confidence level, as P-value is lower than 0.05. The high F-values imply that the model is significant and quadratic terms are also significant, except for the term x_1^2 in both models and the term x_3^2 in the tangential force model, as it was also deduced from the analysis of the regression model results in previous subsections.

Artificial Neural Networks

The experimental data from Reference [16] were treated in order to become suitable for input to the program. All the data were normalized; i.e., all input and output data were suitably transformed so that their mean value be equal to zero and the standard deviation equal to one. Normalization is a method used in neural networks so that all the data present a logical correlation. Otherwise, the neural network could suppose that a value is more significant than the others because its arithmetic value is greater. This could damage the generalization ability of the network and lead to overfitting. After normalization all inputs are equally important in the training of the network. Then, the number of hidden layers, the number of neurons, the activation function and the learning algorithm which are most suitable for the problem were determined. As activation function the hyperbolic tangent sigmoid transfer function was used because the connection between the input and the output values is not linear and such a function can provide good results. For the learning algorithm the back propagation one is very commonly used. However, the Levenberg-Marquardt algorithm which is network training function that updates weight values according to Levenberg-Marquardt optimization was used [16]. Furthermore, various combinations of hidden layers and neurons were worked out in order for the best possible model to be found. Each model was trained both with back propagation and Levenberg-Marquardt algorithm and was trained five times in order to clearly determine whether a model truly converges to a low value or it is a false value due to a local minimum.

Table 4: Comparison of predicted results with experimental results in both cases

Output variable: tangential force (N/mm)					
Process parameters			**Results**		
Grinding Wheel	Workpiece material	Depth of cut (μm)	Experimental result	Predicted value	Difference (%)
3	1	50	10.66	11.0614	3.77
6	1	30	7.23	7.9220	9.57
3	3	50	16.09	14.8189	7.90
6	3	30	11.05	11.6795	5.70
Output variable: maximum temperature (°C)					
Process parameters			**Results**		
Grinding Wheel	Workpiece material	Depth of cut (μm)	Computed result (FEM)	Predicted value	Difference (%)
1	1	50	688.6	670.5679	2.62
3	1	50	748.0	756.9794	1.20
6	1	30	631.0	694.1024	10.00
2	3	30	1074.0	939.6809	8.23

Table 5: Analysis of variance test for the second-order model for the prediction of tangential force

Term	Sum of squares	Degrees of freedom	Mean squares	F-value	p-value
X_1	0.035664	1	0.035664	8.169	0.0057195
X_2	1.1486	1	1.1486	263.1	1.5479e-24
X_3	1.7633	1	1.7633	403.89	1.3644e-29
X_1^2	0.00086798	1	0.00086798	0.19881	0.65716
X_2^2	0.21192	1	0.21192	48.542	1.9821e-09
X_3^2	0.011705	1	0.011705	2.6812	0.10637
error	0.28378	65	0.0043658		

Table 6: Analysis of variance test for the second-order model for the prediction of maximum temperature

Term	Sum of squares	Degrees of freedom	Mean squares	F-value	p-value
X_1	0.062455	1	0.062455	10.009	0.0023688
X_2	2.2037	1	2.2037	353.17	5.6873e-28
X_3	0.72878	1	0.72878	116.8	3.71e-16
X_1^2	0.00034218	1	0.00034218	0.05484	0.81558
X_2^2	0.1726	1	0.1726	27.663	1.7278e-06
X_3^2	0.085664	1	0.085664	13.729	0.00043824
error	0.40558	65	0.0062396		

It is very important for the model to be able to generalize and use the function that emerges from the analysis with data that were not inserted during its training. For this reason the experimental data were divided into three groups. The first and bigger one was used for training, the second one was used for validation and the third one was used for testing. The validation group determines when the training stops. The MSE of the results is calculated and when its value does not decent anymore the training ends. The MSE is also calculated for the test group values and thus it is shown whether the model can successfully predict the output. This is the so-called early stopping technique.

For the evaluation of the generalization ability of the trained neural networks a linear fit between the output of the model and the experimental data was performed. The graph of the linear fit is presented in Figure 8 for tangential force and Figure 9 for temperature; note that T represents the experimental results and A the output values of the model. For tangential force, the best linear fit function is calculated as being: A=0.951T+0.263, while the correlation coefficient R is equal to 0.974, with R=1 meaning that the best linear fit is achieved and the A=T curve match perfectly. For temperature, the best linear fit function is calculated as being: A=0.933T+30.9, while the correlation

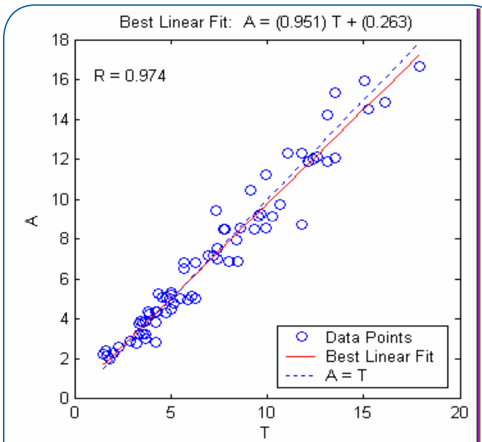

Figure 8: Correlation between experimental data and neural network output for tangential force

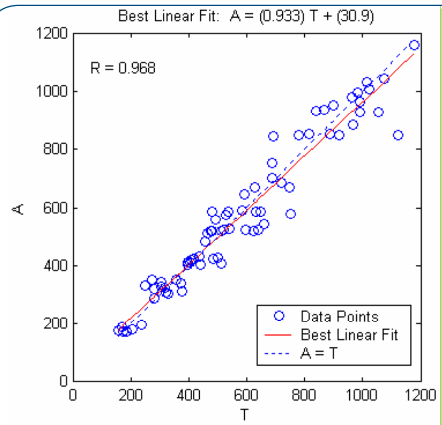

Figure 9: Correlation between experimental data and neural network output for temperature

Table 7: Comparison of second-order linear regression model and artificial neural networks model concerning the tangential force prediction

ANN	Second-order model	Experimental value	Difference (ANN) %	Difference (2nd order) %
9.77	11.0614	10.66	8.35	3.77
7.15	7.9220	7.23	1.10	9.57
14.89	14.8189	16.09	7.46	7.90
12.31	11.6795	11.05	11.41	5.70

Table 8: Comparison of second-order linear regression model and artificial neural networks model concerning the maximum temperature prediction

ANN	Second-order model	Computed value (FEM)	Difference (ANN) %	Difference (2nd order) %
702.8	670.5679	688.6	2.06	2.62
669.9	756.9794	748	10.44	1.20
585.8	694.1024	631	7.16	10.00
1043	939.6809	1074	2.83	8.23

coefficient R is equal to 0.968. It can be concluded from the results that the predicted values are very close to experimental ones, thus indicating that the model can successfully predict grinding forces and temperatures. Tables 7 and 8 compare the second order regression models with neural networks, for forces and temperatures. It is often argued in the relevant literature that for complicated problems, neural networks perform better than regression models [17-20]. It can be concluded from the analysis that both methods can provide reliable results.

Conclusions

In this paper, regression analysis and artificial neural networks models are employed for the prediction of grinding forces and temperatures in grinding. These parameters are important for this manufacturing process as they are connected to the quality of the final product. Knowing these parameters before the actual process takes place, its performance is evaluated and optimized. It was decided to use statistical and soft computing methods for the estimation of forces and temperatures in grinding.

First, linear regression models were constructed. A first order model was proven to provide poor results, given to the complexity of the addressed problem. Next, second order models were constructed. These models exhibited better results, able to adequately predict the performance of grinding. Analysis of variance was also used for the evaluation of the models and the significance of the terms, for the calculation of forces and temperatures.

Soft computing techniques have been widely used in manufacturing technology. Artificial neural networks were constructed for the prediction of grinding forces and maximum temperature. The models' architecture and parameters were determined by testing different models and comparing their results. The Levenberg-Marquardt algorithm was used for the training of the program and the results of the model show very good convergence with experimental data. This way the grinding forces and temperatures are successfully predicted and can be used for the optimization of the process. The training time of each model is relatively small, owing to the selected training algorithm that converges in only a few epochs and the early stopping technique which was applied to the models. A comparison between the results of the two different modeling approaches used, indicates that both of them can produce reliable results in a quick and computationally undemanding manner. Especially, the regression models are proven to be particularly useful for the establishment of empirical relationships between various machining process parameters as the form of these models is actually a mathematical formula which can be easily manipulated and employed for further investigations e.g. optimization of process parameters and reduction of cost.

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