Grinding Forces Prediction Based Upon Experimental Design and Neural Network Models

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Abstract. The results presented are related to the prediction of the specific grinding force components. The main problems associated with the prediction capability of empirical models developed using the design of experiment (DOE) method are given. In this study an approach suggesting the combination of DOE method and artificial neural network (ANN) is developed. The inputs of the developed ANNs were selected among the factors and interaction between factors of the DOE depending on their significance at different confidence levels expressed by the value of α%. Results have shown particularly, the existence of a critical input set which improves the learning ability of the constructed ANNs. The built ANNs using these critical sets have shown low deviation from the training data and an acceptable deviation from the testing data. A high prediction accuracy of these ANNs was tested between models constructed using the developed approach and models developed by previous investigations.

1 Introduction

Because of the importance of the grinding forces regarding to the process outputs including wheel wear and surface integrity, many attempts were made to model its normal and tangential specific components. However, analyses of the obtained models have shown that the theoretical modeling [1] exhibits shortcomings from a quantitative aspect because the permanent changes on shapes and on density of the cutting edges cannot be clearly taken into account by these models. This suggests the use of simplifying hypotheses affecting the reliability of these models and limiting their employment to off-line prediction tasks. In contrast, empirical models, such as the regression analysis model [2, 3, 4], the fuzzy logic model [5, 6] and the neural network model [7-11] have, generally, shown satisfactory prediction accuracy, particularly useful for the on-line response evaluation and control. In many cases, data from design of experiment (DoE) were used to establish the regression models or to develop the fuzzy rule sets or to train the neural networks. Indeed, the DoE method offers the possibility to study the effects of several factors at one time and to investigate the inter-relationships between these factors, while conducting a relatively limited number of experiments [12].

Amamou R., Ben Fredj N. and Fnaiech F. (2005).
Grinding Forces Prediction Based Upon Experimental Design and Neural Network Models.
In *Proceedings of the 1st International Workshop on Artificial Neural Networks and Intelligent Information Processing*, pages 122-131
DOI: 10.5220/0001194101220131

However, this method has to be used with awareness, especially when it is applied for response minimization tasks. In fact, it was remarked that in many cases, the regression analysis models established by using the DoE were unable to predict an appropriate minimal response value [13].
This constitutes serious limitation of this method, particularly, for on-line process control, where the predicted optimal values have to be determined with high accuracy as they are continuously compared to targets to maintain the desired level of the outputs.
These inconveniences give rise to the need to develop improved methods with enhanced prediction capability. In this paper, feed forward neural networks using the Bayesian regularization were developed. The goal was to train ANNs to include the most important factors and interactions between factors affecting the surface roughness in order to make accurate and consistent predictions for new combinations of values for these factors. This was made by considering the extrapolation beyond the training data. The developed ANNs were trained using an experimental data set of a 48 runs factorial design and the best set of variables inputs, the number of neurons and the ANNs structures selection criteria were discussed. The performance of the developed ANNs on predicting the specific cutting force components F'_n and F'_t within the range of the factors levels fixed by the factorial design was compared to the statistical multiple regression models obtained directly using the design of experiment method. Here F'_n and F'_t are respectively the normal and the tangential specific components of the grinding force.

2 ANN approach

Even though several learning methods have been developed [7-11, 14-19], the back propagation method has been proven to be successful in applications related to surface integrity prediction [7, 8, 10, 18]. However, the effect of the neural network inputs selection was not elucidated sufficiently. Indeed, even though it is known that the selected inputs of the ANNs is an important parameter controlling the outputs prediction accuracy [8, 16 19], previous studies which have used the DoE data to train the ANNs, have also used the independent variables of the DoE as inputs of the developed ANNs. On the other hand the major problem encountered in the use of ANNs is over fitting [20]. A neural network can predict correctly the trained data set but it is unable to generalize for other input data. Consequently, the training error function E is modified to include not just the sum of square errors E_a but also the sum of squares of the network weights and biases E_w. This approach is called the weight decay regularization [20]. This modification forces the network to have smaller weights and biases and decrease the tendency of a model to over fit the training data. The modified error function to be minimized is:

$$E = \theta E_a + (1-\theta)\ E_w \qquad (1)$$

where θ is the weight decay parameter. The difficulty with regularization is in assigning an optimum value of θ. If the selected weight decay parameter is too large, so that overfitting may accrues. On the other hand if it is too small the network will not adequately fit the training data. Finding the optimum value for the weight decay

parameter that is appropriate for the training data is therefore an important task. In this investigation, the weight decay parameter was determined by the Bayesian framework. In this case all weight and biases of the network are assumed to be random variables with Gaussian distribution. The weight decay parameters are related to the unknown variances associated with these distributions.
In this study, a 48 runs DoE rotatable central composite design was developed. The data of this experimental design were utilized to train a one hidden layer back propagation neural network. In fact, previous investigations have proven that this architecture is enough for the majority of applications [7-11, 16-19].

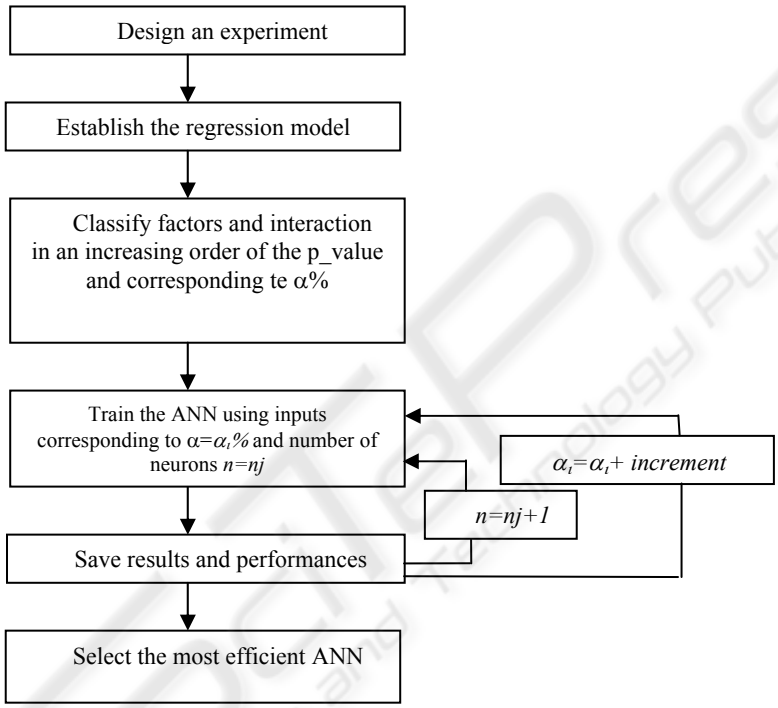

Fig. 1. Algorithm for ANN Training and selection

As for the inputs selection, it was discussed based on the statistical significance of the independent variables or interactions between these variables obtained from the quadratic regression models developed using the data of the 48 runs DoE according to the algorithm shown in figure 1. The point in this algorithm is that the ANN will be also trained for learning the factors interactions effects. In fact, the effects of interaction between factors can be in some cases, more significant than the effects of the factors. M. Thomas *et al* [3] have shown in their study related to the prediction of the surface roughness generated by the cutting process that the effect of the interaction between the feed rate *f* and the depth of cut (*a*) is more significant than the effect of the individual factors. On the other hand, as good generalization of the developed ANNs requires that their inputs contain sufficient information pertaining to the output, so that an accurate mathematical function relating the outputs to the inputs

can be established [21], using the interactions between factors as additional inputs for the ANNs improves this accuracy. Moreover, as the Multilayer perceptron (MLP) architectures are good at ignoring both redundant and irrelevant inputs [19], non-pertaining interactions, which are used as inputs for the developed ANNs will not be considered automatically. Nevertheless, as the training time of the developed ANNs is widely affected by the number of inputs, therefore, it is important to distinguish the significant interactions and to use them as additional inputs. This fact is well considered by the algorithm of figure 1.
The number of epochs was set to 200 and the ANN performances were evaluated by the training error MSE, training time (s), percentage of deviation from training data, percentage of deviation from testing data, and the values of the optimal outputs and the corresponding inputs combinations.

3 Experimental Set-up and design

All the grinding tests were realized in down cut plunge surface grinding mode using a Teknoscuola RT600 grinding machine. Grinding wheels were dressed using a single point diamond dresser with a constant gross feed (0.2 mm/rev). The workpieces dimension was $100^{L}x30^{H}x15^{W}$ mm. The grinding force components were measured using a piezo-electric transducer based type dynamometer (kistler 9257A). Three workpiece materials having different structures and mechanical properties were selected, 42CrMo4, 90MnCrV8 and X160CrMoV12. Chemical composition and hardness of these materials are given in table 1. The selection was made based on the wide industrial application of these materials.

Table 1. Chemical composition of the used material

material	C	Si	Mn	Cr	Mo	P	S	Hardness HR_C
42CrMo4	0.41	0.28	0.77	1.02	0.25	0.02	0.03	36
90MnCrV8	0.9	_	2.0	0.4	0.7	_	_	60
X160CrMoV12	1.55	_	_	12.0	0.7	_	_	63

Concerning the grinding parameters, table speed (v_w), depth of cut (a), grinding wheel grain mesh size (#), dressing depth (a_d) and the number of passes (N_p) were selected. The selected values of the process parameters, given in table 2, cover conditions related to both coarse and fine grinding. For experiments a 48 runs DoE rotatable central composite design was selected and experiments were conducted in a random order. Three factorial experimental designs using the L_{27} [3^5] standard table were used for testing the prediction performances of the regression models and the different ANN structures selected in this study. Here, the material was not considered as an independent factor and the 27 testing experiments were repeated for each material type.

Table 2. Process parameters and values

Factor	Level		
	1	2	3
Material	42CrMo4	90MnCrV8	X160CrMoV12
v_w (m/min)	1	5.5	10
a (mm)	0.050	0.100	0.150
N_p	2	11	20
a_d (mm)	0.010	0.020	0.030
#	46	60	80

4 Results and discussions

4.1 Statistical results

Table 3 summarizes the statistical performances of the regression models developed for F'_n and F'_t. This table shows, particularly, an important average percentage of deviation from the testing data calculated for the three kinds of materials. Moreover, negative optimal values of F'_n and F'_t are calculated. It can be notice that the regression model of F'_n and F'_t established using the DoE presents low capability to predict the optimal output value rather than the corresponding factors level. Indeed, the combinations corresponding to the optimal values for F'_n and F'_t are in good correlation with the results of previous studies [22,23]. This constitutes a serious limitation of the prediction performances of the regression models established in this study.

Table 3. Summary of the statistical performances of the DoE multiple regression models.

Results	Model for F'_n						Model for F'_t					
Percentage deviation of the training data	51,58%						44,95%					
Percentage deviation of the testing data: • 42CrMo4 • 90MnCrV8 • X160CrMo V12	24,1% 28,01% 28,032%						23,31% 37,05% 35,62%					
Grinding conditions for the minimal value: • 42CrMo4 • 90MnCrV8 • X160CrMo V12	V_w	a	N_p	a_d	#	$F'_{n\,min}$	V_w	a	N_p	a_d	#	$F'_{t\,min}$
	1	50	2	30	46	-1,273	1	50	2	30	46	-0,744
	1	50	2	28	46	-1,341	1	50	2	30	46	-0,558
	1	50	2	30	46	-0,045	1	50	2	10	46	0,068

4.2 ANN results

4.2.1 6-n-1 structure

At first, the common method for establishing ANN's architecture was used. This was realized by selecting the same inputs for the developed ANN as those selected for the DoE. Hence, a *6-n-1* structure was constructed; with *n* is the number of neurons in the hidden layer. The value of *n* was varied from 2 to 40 and the average $\overline{MSE}$ error of the 39 constructed artificial neural networks was 0.023 in the case of F'_n and 0.0037 in the case of F'_t. When considering the structure 6-5-1 for which the lowest training error *MSE* (*MSE=1.04e-03*) and deviations from testing data were computed, the calculated deviations from the training data were 0.84% for F'_n and 0.47% for F'_t. However, the percentages of deviations from the testing data for F'_n were 26.82% for 42CrMo4, 22.71% for 90MnCrV8 and 23.17% for X160CrMoV12. Concerning the specific tangential force F'_t, the calculated deviations from the testing data were 19.42% for 42CrMo4, 20.87 for 90MnCrV8 and 23.34% for X160CrMoV12. These high deviations express poor generalization capability of the ANN structures with 6 inputs. Therefore, more training data are needed to improve the prediction efficiency of this neural network architecture when extrapolation beyond the training data is considered.

4.2.2 x-n-1 structure

For improving the prediction capability of the ANNs, the number of inputs was varied. Therefore, instead of selecting the same inputs as the DoE, the factors and the second order interactions between factors were selected as inputs. Figure 2, show the relation between the averages $\overline{MSE}$ error for the 39 artificial neural networks structures constructed using the significant factors and interactions at different confidence levels for F'_n et F'_t. A clear improvement of the learning capability of the constructed artificial neural networks can be seen from this figure as an important reduction of the average $\overline{MSE}$ error could be realized. Moreover, these figures put in evidence the existence of a threshold value of α% for which no significant learning improvement can be realized by increasing the number of inputs. Here a threshold value about *50%* was observed for F'_n and F'_t.

On the other hand, as in this work we are particularly interested on the grinding force minimization, extrapolation beyond the training data have to be considered. Hence, calculation of a global error (E_g) expressing the deviation of the predicted values using the developed neural networks from the testing data sets is required to valid the results of this investigation.

This error is composed of two terms: the *bias* which measures the extent to which the average predicted output, over all testing data sets, of the network function differs from the experimental values and the *variance* which measures the extent to which the network function is sensitive to particular choice of data set [18]. As in this investigation 27 testing experiments were conducted for each material (*n=81*) and 39 different networks (*m=39*) were trained for each input set, the expressions of the *bias* and the *variance* can be written in the following forms [20]:

$$E_g = \overline{(bias)^2} + \overline{\text{var}\,iance} \quad (2)$$

$$\overline{F}_{predicted}(X) = \frac{1}{m}\sum_{i=1}^{m} F_{i\,predicted}(X) \quad (3)$$

$$\overline{(bias)^2} = \frac{1}{n}\left[\sum_{k=1}^{n}\left\{\overline{F}_{predicted}(X_k) - F_{\exp erimental}(X_k)\right\}^2\right] \quad (4)$$

$$\overline{\text{var}\,iance} = \frac{1}{n}\left[\sum_{k=1}^{n}\frac{1}{m}\sum_{i=1}^{m}\left\{(F_{i\,predicted}(X_k) - \overline{F}_{predicted}(X_k)\right\}^2\right] \quad (5)$$

Here F represents F'_n or F'_t depending on the considered output and X and X_k are the input sets.

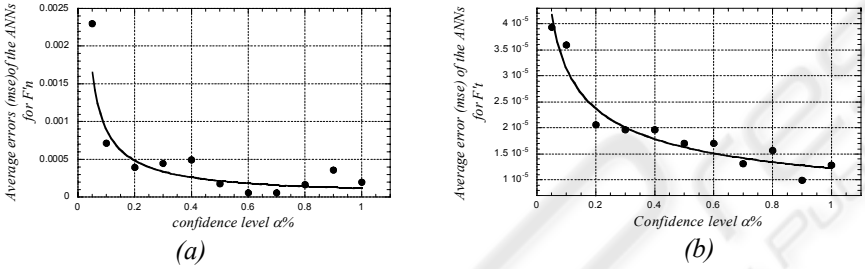

Fig. 2. Relation between the average $\overline{MSE}$ errors of the 39 ANN structures and α%: *(a)* F'_n and *(b)* F'_t

Figure 3 gives the relation between the average error E_g for F'_n and F'_t respectively at different confidence levels. It can be seen from these figures that for the testing data sets selected in this investigation, the minimum average error E_g occurs at α around *50%* for the specific normal component F'_n and *40%* for F'_t. However, the input set which have to be selected for the developed ANNs is the set that offers, simultaneously, high leaning performance of the training data characterised by low $\overline{MSE}$ and good generalisation characterized by low value of E_g. Therefore, inputs sets corresponding to α=*50%* have to be retained for the ANNs related to F'_n and F'_t.
Therefore, the corresponding inputs are used to train the artificial neural networks and the best structure offering the lowest deviation from the training and testing data were 16-18-1 for F'_n and 19-11-1 for F'_t. The full performances of these structures are given in table 4. This table shows particularly positive values for the predicted minimal cutting force parameters F'_n and F'_t. Here 0% and 0.028% deviations from the training data were calculated respectively for F'_n and F'_t. The percentages of deviations from the testing data for F'_n were 7.6% for 42CrMo4, 8.55% for 90MnCrV8 and 7.46% for X160CrMoV12. These deviations are clearly lower than those calculated using the 6-5-1 structure. Concerning the specific tangential force F'_t, the calculated deviations from the testing data were 7.32% for 42CrMo4, 8.58% for 90MnCrV8 and 7.11% for X160CrMoV12.According to these findings, it can be concluded that a factor or an interaction between factors, which is statically not significant in the case of the DoE, can be a significant input for the ANN.

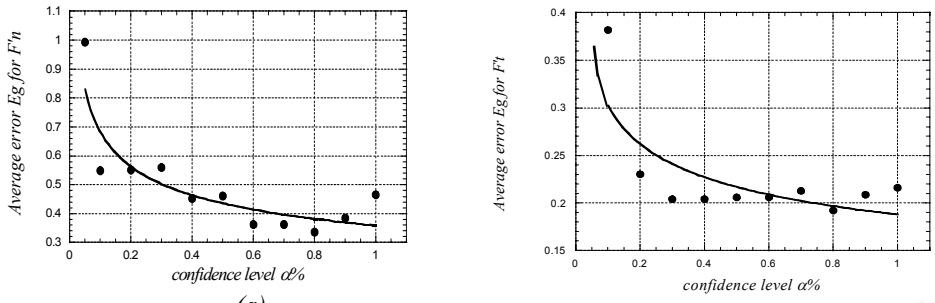

Fig. 3. *(a)* Relation between the confidence level α% and the average error E_g : *(a)* F'_n and *(b)* F'_t

Table 4. Summary of the selected ANN performances

Results	*Model for F'_n (16-18-1)*						*Model for F'_t (19-11-1)*					
Number of inputs	16						19					
Hidden nodes	18						11					
Mean Square Error	1.956e-05						5.58e-12					
Sum Square Error	8.804e-04						2.51e-10					
Running time* (s)	18						34					
Training cycles	200						200					
Percentage deviation of the training data	0%						0.028%					
Percentage deviation of the testing data for:												
• 42CrMo4	7.6%						7.32%					
• 90MnCrV8	8.55%						8.58%					
• X160CrMoV12	7.46%						7.11%					
Grinding conditions for the minimal value	V_w	a	N_p	a_d	#	$F'_{n\,mini}$	V_w	a	N_p	a_d	#	$F'_{t\,mini}$
• 42CrMo4	1	50	2	30	46	0,0757	1	50	2	30	46	0,0551
• 90MnCrV8	1	50	2	30	46	0,1371	1	50	2	20	46	0,0753
• X160CrMoV12	1	50	6	10	46	0,3956	1	50	2	10	46	0,0889

5 Conclusions

In this paper an approach combining the application of the design of experiment (DoE) and the neural network methods was developed to establish accurate models for specific grinding forces prediction. This approach uses data of the DoE to train artificial neural network for which the input set is composed of significant factors and interaction between the factors of the DoE. The significance was evaluated based on

the Fisher test at different values of the confidence levels α%. When this level increases, the number of significant factors and interactions increased, and thus the number of inputs of the ANN increases. Average learning $\overline{MSE}$ which express the average error between the training data and the corresponding predicted values and the generalization error $\overline{Eg}$ which express the deviation from the testing data have shown the existence of a critical set of inputs offering the highest prediction capability of the developed ANNs. By using this approach, substantial improvements of the prediction capability of the ANNs could be realized comparatively with the prediction ability of the quadratic models developed using the DoE. On the other hand the developed ANNs have shown better capability comparatively with the commonly used structures, which use the DoE factors as inputs.

It was also remarked that the developed ANNs present higher sensibility to the input variations than the DOE as they can distinguish between particular phenomena occurring at low and high work speeds. At last, problems related to the minimal negative predicted value, calculated by using models established with DOE method could be solved as ANNs respects the output sign.

References

1. H.K. Tönshoff, J. Peters, I. Inasaki, T. Paul, Modelling and Simulation of Grinding Process, Annals of the CIRP vol. 41, 2, (1992) 677-688.
2. Y. S. Lio, J. T. Huang, H.C. Su, A study on the machining-parameters optimization of wire electrical discharge machining, J. Mater. Proc. Technol. 71 (1997) 487-493.
3. M. Thomas, Y. Beauchamp, Youssef, A. Youssef, An experimental design for surface roughness and built-up edge formation in lathe dry turning, Int. J. of Quality Science, Vol. 2 (3), (1997) 167-180.
4. Y. A. Youssef, Comparison of a full factorial experiment to fractional and Taguchi design in a lathe dry turning operation, Computers in ind. Engng., Vol. 27 (1-4), (1994) 59-62.
5. J. L. Lin, K.S. Wang, B.H. Yan, Y. S. Tarng, Optimization of the electrical discharge machining process based on the Taguchi method with fuzzy logics, J. Mater. Proc. Technol., 102 (2000) 48-55.
6. Y. Ali, L.C. Zhang, Estimation of Residual Stress Induced by Grinding Using a Fuzzy Logic Approach, J. Mater. Proc. Technol. 63 (1997) 875-880.
7. Y.-H. Tsai, J. C. Chen, S.-J. Lou, An in-process surface recognition system based on neural networks in end milling cutting operations, Int. J. Mach. Tools Manufact., Vol. 39, (1999) 583-605.
8. R. Azouzi, M. Guillot, On-line prediction of surface finish and dimensional deviation in turning using neural network based sensor fusion, Int. J. Mach. Tools Manufact., Vol. 37 (9), (1997) 1201-1217.
9. T. Warren, L.J. Chen, A neural network approach for grinding process: Modeling and optimization, Int. J. Mach. Tools Manufact., Vol. 34 (7), (1994) 919-937.
10. N. Zouaghi, Y. Ichida, N. Ben Fredj, N. Kimura, Grinding mode identification of silicon carbide by using neural network, in: Proceeding of the third international conference on progress of cutting and grinding Vol. III (JSPE, Osaka, 1996) 342-347.
11. K. M. Tsai, P. J. Wang, Predictions on surface finish in electrical discharge machining based upon neural network models, Int. J. Mach. Tools Manufact., Vol. 41, (2001) 1385-1403.

12. Douglas C. Montgomery, Design and Analysis of Experiments 3rd edition, (Jhon Wiley & son 1991).
13. Nabil Ben Fredj, Ridha Amamou, Ground Surface Roughness Prediction Based Upon Experimental Design and Neural Network Models, accepted for publication in Int. J. advanced Manufacturing Technology.
14. D. H. kim, D. J. Kim, B. Kim, The application of neural networks and statistical methods to process design in metal forming, Int. J. Adv. Manuf. Technol., Vol.15, (1999) 886-894.
15. D.-C. Ko, D.-H. Kim, B.-M Kim, Application of artificial neural network and Taguchi method to perform design in metal forming considering workability, Int. J. Mach. Tools Manufact., Vol. 39, (1999) 771-785.
16. E. Mainsah, D.T. Ndumu, Neural network in surface topography, Int. J. Mach. Tools Manufact., Vol. 38 (5-6), (1998) 591-598.
17. S.-T Chiang, D.-I Liu, A.-C. Lee, W.-H. Chieng, Adaptive control optimization in end milling using neural network, Int. J. Mach. Tools Manufact., Vol. 34 (5), (1995) 637-660.
18. T. S. Spedding, Z. Q. Wang, Study on modelling of wire EDM process, J. Mater. Proc. Technol. 69 (1997) 18-28.
19. S. Haykin, Neural Networks a comprehensive foundation, (Macmillan College Publishing Company 1994).
20. C. M. Bishop, Neural Networks for Pattern Recognition, Oxford University Press, 1995.
21. M. Sakakura, I. Inasaki, A neural network approach to the decision-making process for grinding operation, Annals of the CIRP Vol. 41 (1), (1991) 353-356.
22. S. Malkin, Y. Koren, Off-line Grinding Optimisation with a Micro-Computer, Annals of the CIRP, Vol. 29 (1), (1980) 213-215.
23. S.Malkin, Grinding Technology theory and applications of machining with abrasives, (Ellis Horwood Ltd. 1989).