Fabrício José Pontes
fpontes@embraer.com.br

Messias Borges Silva
messias@dequi.eel.usp.br
Faculdade de Engenharia de Guaratinguetá
UNESP – Universidade Estadual Paulista
Departamento de Mecânica
12516-410 Guaratinguetá, São Paulo, Brazil

João Roberto Ferreira
jorofe@iem.efei.br

Anderson Paulo de Paiva
andersonppaiva@unifei.com.br

Pedro Paulo Balestrassi
pedro@unifei.edu.br

Gustavo Bonnard Schönhorst
gustavobonnard@gmail.com
UNIFEI – Universidade Federal de Itajubá
Instituto de Eng. Produção e Gestão
Caixa Postal 50
37500-903 Itajubá, Minas Gerais, Brazil

A DOE Based Approach for the Design of RBF Artificial Neural Networks Applied to Prediction of Surface Roughness in AISI 52100 Hardened Steel Turning

The use of artificial neural networks for prediction in hard turning has received considerable attention in literature. An often quoted drawback of ANNs is the lack of a systematic way for the design of high performance networks. This study presents a DOE based approach for the design of ANNs of Radial Basis Function (RBF) architecture applied to surface roughness prediction in turning of AISI 52100 hardened steel. Experimental factors are the number of radial units on the hidden layer, the algorithm employed to calculate the spread factor of radial units and the algorithm employed to calculate radial function centers. DOE is employed to select levels of factors that benefit network prediction skills. Experiments with data sets of distinct sizes were conducted and network configurations leading to high performance were identified. ANN models obtained proved capable to predict roughness in accurate, precise and affordable way. Results pointed significant factors for network design and revealed that interaction effects between design parameters have significant influence on network performance for the task proposed. The work concludes that the DOE methodology constitutes a better approach to the design of RBF networks for roughness prediction than the most common trial and error approach.

Keywords: *surface roughness, design of experiments, radial basis function neural networks, hard turning, AISI 52100 hardened steel*

Introduction

Hard turning has become an important process in modern metal industry. It is defined as an operation in which materials in hardened state (50–70 HRC) are machined with single point cutting tools, and which was made possible due to the relatively recent development of new cutting tool materials, such as cubic boron nitride and ceramics (Singh and Rao, 2007). Its main goal is to remove work piece material in a single cut rather than in a lengthy grinding operation. Although presenting potential advantages over traditional machining processes in some applications, hard turning presents unique characteristics, such as segmented chip formation and micro-structural alterations at the machined surfaces, which are fundamentally different from conventional turning (Karpat and Özel, 2007). A better knowledge of this process could ultimately lead to the combination or elimination of one of the operations required, thus reducing product cycle time and increasing productivity, according to Singh and Rao (2007).

Many works on hard turning aim to develop models for surface quality. This is an essential consumer requirement in machining processes because of its impact on product performance (Ambrogio et al., 2008). Basheer et al. (2008) affirm that characteristics of surfaces machined have significant influence on the ability of the material to withstand stresses, temperature, friction and corrosion. A widely used surface quality indicator is surface roughness (Özel and Karpat, 2005). The formation of surface roughness is a complex process, affected by many factors as tool variables, work piece variables and cutting parameters (Singh and Rao, 2007).

Various authors have obtained good results employing artificial neural networks (ANNs) for surface roughness prediction. As pointed out by Coit, Jackson and Smith (1998), neurocomputing suits modeling of complex manufacturing operations due to its universal function approximation capability, resistance to the noise or missing data, accommodation of multiple non-linear variables for unknown interactions and good generalization capability. Some works, however, report drawbacks in using ANNs for prediction (Ambrogio et al., 2008; Bagci and Isik, 2006). An often reported problem with ANNs is the optimization of network parameters. Zhong, Khoo and Han (2006) affirm that there is no exact solution for the definition of the number of layers and neural nodes required for particular applications. This study proposes the application of the Design of Experiments (DOE) methodology for the design of neural networks of RBF (Radial Basis Function) architecture applied to the prediction of surface roughness (Ra) in the turning process of AISI 52100 hardened steel. The factors considered were the network parameters: number of radial units on the hidden layer, the algorithm employed to calculate the spread factor of radial units and the algorithm employed to calculate center location of the radial functions. The goals of the experimental planning are to identify levels of factors that benefits network prediction skills, to assess the relative importance of each design parameter on network performance and to investigate possible interactions between levels of design factors. Experiments with distinct sizes of training sets were conducted. This made it possible to evaluate the relative importance of each design factor on network performance and the accuracy attainable by RBFs as the amount of examples available for training and selection varies. Pairs of input-output data obtained from turning operations were used to generate examples for network training and for confirmation runs. Cutting speed (V), feed (f), and depth of cut (d) were employed as network inputs. The results pinpoint network configurations that presented the best results in prediction, for each size of training set.

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Nomenclature

ANN	*= Artificial Neural Networks*
CCD	*= Central Composite Design*
CNC	*= Computer Numerical Controlled*
d	*= Depth of Cut, mm*
DOE	*= Design of Experiments*
f	*= Feed, mm/revolution*
ISO1	*= Isotropic Algorithm, scale factor equal to 1*
ISO10	*= Isotropic Algorithm, scale factor equal to 10*
KM	*= K-Means Algorithm*
KN5	*= K-Nearest Algorithm, K factor equal to 5*
KN10	*= K-Nearest Algorithm, K factor equal to 10*
MAE(%)	*= Mean Absolute Error, percentage*
MLP	*= Multi Layer Perceptron*
Ra	*= Average Surface Roughness, µm*
RBF	*= Radial Basis Function*
SOFM	*= Self Organized Feature Maps*
SS	*= Sub-Sampling algorithm*
V	*= Cutting Speed, m/min*
VBmax	*= Maximum Flank Wear, mm*
yexpt	*= Measured roughness experimental value, µm*
ypred	*= ANN roughness prediction value, µm*
X1	*= Algorithm for calculation of the radial spread factor*
X2	*= Number of radial units present on the hidden layer of the network*
X3	*= Algorithm for calculation of the center location of radial functions*

Surface Roughness

Surface roughness refers to deviations from nominal surface from third to sixth order (Benardos and Vosniakos, 2003). Deviations from distinct order are superimposed to form the roughness profile (Benardos and Vosniakos, 2002). Theoretical models for the maximum roughness in a turning process exist in literature (Whitehouse, 1994; Krar, 1990). Those models, however, do not take into account any imperfections in the process, such as tool vibration or chip adhesion, according to Sharma et al. (2008). In some cases, practical results diverge from theoretical predictions (Zhong, Khoo and Han, 2006; Fredj and Amamou, 2006).

For Karpat and Özel (2007), the complex relationship among the parameters involved makes it difficult to generate explicit analytical models for hard turning processes. The authors sustain that surface roughness is mainly a result of process parameters such as tool geometry and cutting conditions. Singh and Rao (2007) sustain that the formation of surface roughness is a complex process, affected by many factors as tool variables, workpiece variables and cutting parameters. Cus and Zuperl (2006) suggested empirical models (linear and exponential) for surface roughness as a function of cutting speed (V), feed (f) and depth of cut (d).

Roughness measurement criterion adopted in this study is Roughness Average (Ra). This is defined as arithmetic average value of the departure of the profile from the centre line throughout the sampling length. For discrete measurement, average surface roughness can be defined as in Eq. (1) (ISO, 2005):

$$R_a = \frac{1}{n}\sum_{i=1}^{n}\left|y_i\right| \tag{1}$$

where Ra is the roughness average, n stands for the number of samples in a given length and yi stands for the absolute values of the peak and valley (measured) in relation to the centre line average. Ra is the most popular parameter related to roughness measurement in literature (Oktem, Erzurumlu and Erzincanli, 2006).

RBF – Radial Basis Function Networks

Radial basis functions represent a class of functions whose value increases or decreases as a function of distance to a central point. They are employed for tasks of interpolation of sets of points in multidimensional spaces. Such a problem is characterized by mapping a vectorial space $\boldsymbol{x}$ of multiple dimensions in a uni-dimensional vectorial space $\boldsymbol{t}$. The data set consists of N input vectors $\boldsymbol{x}^n$, and its corresponding values of $\boldsymbol{t}^n$. The goal is to find a function $\boldsymbol{h(x)}$, as in Eq. (2) (Bishop, 1995):

$$\mathrm{h}(\mathbf{x})=\mathrm{t}, \quad n = 1,\ldots, N. \tag{2}$$

The use of radial basis functions has proved to be appropriate for the task of interpolation, with the use of sets of N basis functions, one for each point, being the functions of the form given in Eq. (3) (Bishop, 1995):

$$\rho\left(\left\|x - x^n\right\|\right) \tag{3}$$

where ϕ is some kind of non-linear function. The argument of function ϕ is basically a Euclidean norm (a distance) between two vectors. A kind of radial basis function widely employed is the Gaussian function given in Eq. (4) (Bishop, 1995):

$$\phi_j(\mu) = -\exp\left(\frac{\|\mathbf{x}-\boldsymbol{\mu}_j\|^2}{2\sigma^2}\right) \tag{4}$$

where $\mathbf{x}$ corresponds to one of the input vectors $\mathbf{x}^n$, having elements x_i, $\boldsymbol{\mu_j}$ is a vector that specifies the hyper-center for function ϕ_j, having elements μ_{ij}, and σ represents a parameter that defines the spread of the function. RBF networks were proposed by the work of Broomhead and Lowe (1988), and comprise a class of multi-layer neural networks in which the activation function of each neuron in the intermediate layer is a radial basis function. The concept of an RBF network is illustrated in Fig. 1.

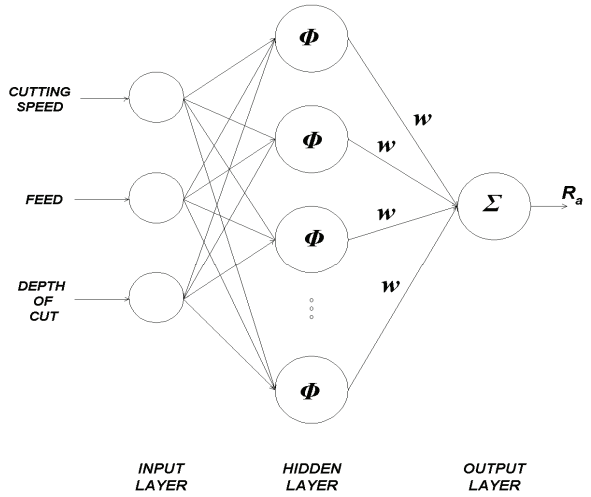

Figure 1. Schematic diagram of a RBF network.

The figure shows a typical RBF composed of three layers: an input layer composed of three radial units, a hidden layer where non-linear processing (represented by function ϕ) is carried out, and an output layer, containing a single unit. Each input unit is connected to all radial units on the hidden layer and each radial units on the hidden layer is connected by weighted synapses (represented

by w) to the output layer. The synaptic weights are modified during training phase in order to teach the networks the non-linear relationship that exists between inputs and output.

The radial function in use is usually a Gaussian function, of the kind shown in Eq. (4), in which vector x corresponds to the input vector of the radial unit and μ_j represents the center of the radial function. The output layer usually contains neurons that calculate the scalar product of its inputs. In a RBF network having k radial units in the intermediate layer and one output, this is given by Eq. (5) (Bishop, 1995):

$$y = \sum_{i=1}^{k} w_i \, \phi(\| \mathbf{x} - \boldsymbol{\mu} \|^2) + w_o \qquad (5)$$

where $\mathbf{x}$ and $\boldsymbol{\mu}$ are defined as in Eq. (4), ϕ represents the activation function of the radial units, as, for instance, the Gaussian function represented by Eq. (4), w_i represents the weight values by which the output of a radial unit is multiplied in the output layer and w_0 is a constant factor.

RBF networks are able to perform a series of tasks, among which approximation of functions. They can act as universal approximators, being one hidden layer enough to approximate any continuous function (Haykin, 2008).

The traditional approach to train RBF networks involves two phases. In the first, the parameters of the radial basis function (the centers and the spread factor) are determined. In the second phase, weights of neurons in the output layer shall be adjusted, by means of linear optimization method, thus implying in simple processing (Haykin, 2008). The two methods usually employed for calculation of the centers are sub-sampling and the K-Means algorithm (Bishop, 1995), both corresponding to methods of unsupervised learning. In the sub-sampling method, input patterns randomly chosen are copied as the center of radial units. In the K-Means algorithm, an effort is made to select an optimal set of input patterns to be set as the centroids of the training set. After calculation of the centers, the spread factor for the activation function shall be determined. The most commonly employed algorithms for this operation are the Isotropic and the K-Nearest algorithm. In the Isotropic method, the value for the spread factor is chosen heuristically starting from a scale factor in order to reflect the number of centers and the volume of the hyperspace occupied by them. In the K-Nearest algorithm, the value for the spread factor is calculated individually as the average distance to the K closest radial units. Values of parameter K should be defined by the designer. After this phase, the next step corresponds to the optimization of the output layer, what can be performed by employing a standard technique for linear optimization, as the pseudo-inverse method (Haykin, 2008).

RBF's applied to surface roughness prediction

Neural network models have been widely applied to prediction tasks in hard turning processes. Networks of MLP (multi-layer perceptron) architecture are employed in most of them. Works comparing the performance of ANN models to that presented by DOE based models are not rare, with mixed results. In Erzurumlu and Oktem (2007), a response surface model RSM and an ANN are developed for prediction of surface roughness in mold surfaces. According to the authors, the neural network model presented slightly better performance, though at a much higher computational cost. In Çaydas and Hasçalik (2008), an ANN and a regression model were developed to predict surface roughness in abrasive waterjet machining process. In this case, the regression model was slightly superior. Palanisamy, Rajendran and Shanmugasundaram (2008) compared the performance of regression and ANN models for predicting tool wear in ending milling operation, with ANNs presenting better results. Karnik, Gaitonde and Davim (2007) applied neural networks and RSM models to predict the burr size for a drilling process. The authors concluded that ANN performance was clearly superior to that obtained by the polynomial model. Bagci and Işik (2006) developed an ANN and a response surface model to predict surface roughness on the turned part surface in turning unidirectional glass fiber reinforced composites. Both models were deemed as satisfactory. The use of neural networks in conjunction with other methods is yet another strategy adopted by some authors (Karpat and Özel, 2007). Only a few studies make use of RBF networks for prediction in machining processes. Shie (2008) combined a trained RBF network and a sequential quadratic programming method in order to find an optimal parameter setting for an injection molding process. In Dubey (2009), they are employed in conjunction with desirability function and genetic algorithms in a hybrid approach for multi-performance optimization in electro-chemical honing process. Sonar, Dixit and Ohja (2006) made use of RBFs for prediction of surface roughness in the turning process of mild steel with carbide tools. In that work, RBFs were outperformed by MLPs. Nevertheless, the authors emphasized that RBF definition was simple and its training fast. Cus and Zuperl (2006) performed a comparison between the performance of MLP and RBF networks applied to predict surface roughness in turning operations. Although MLP have outperformed the RBF, that work evidences that RBF is stable and converges much faster than MLPs. El-Mounayri, Kishawy and Briceno (2005) employed RBF networks to prediction of cutting forces in CNC ball end milling operations. Results of that work reveal that RBF's achieved a high level of accuracy in the proposed task. Once more, authors stressed the easy definition and fast convergence of the network.

Network Topology Definition

Distinct approaches can be found in literature for the definition of the network topologies employed for roughness prediction. In a review of several publications dealing with surface roughness modeling in machining processes by means of artificial neural networks, Pontes et al. (2010) pointed to the fact that trial and error still remain as the most frequent technique for ANN topology definition, as in Erzurumlu and Oktem (2007).

In some studies, heuristics are used to define the parameters (Kohli and Dixit, 2005). In other cases, a 'one-factor-at-a-time' technique is used in the search for a suitable configuration (Fredj and Amamou 2006; Kohli and Dixit, 2005).

The use of DOE techniques for optimization is scarcely found. One rare example is the work of Quiza, Figueira and Davim (2008), where an experimental design is employed to configure a neural network of MLP architecture intended to predict tool flank wear in hard machining of D2 AISI steel. The following factors are employed in the experimental design: learning rate, moment constant, training epochs and number of neurons in hidden layer. In Balestrassi et al. (2009) the Taguchi methodology was employed for the optimization of MLP networks applied to time series prediction. The authors sustain that traditional methods of studying one-factor-at-a-time may lead to unreliable and misleading results while error can lead to sub-optimal solutions.

In the comparison with previous works, the present paper could be innovative in the following points:

- The use of full factorial technique for the design of RBF networks in surface roughness prediction, considering a large database;
- The study of the relative importance of the design factors on network performance;

- The assessment of the attainable accuracy in surface roughness prediction for turning of AISI 52100 steel for distinct amounts of examples available for training the networks;
- The investigation of existence and significance of interactions among design factors on network performance.

Experimental Procedures

The experimental procedure consisted in the following steps:

- Cutting operations intended to build a database to train and select the ANNs;
- Generation of training and testing data sets;
- Simulation experiments, planned according to DOE techniques, intended to identify best network topologies;
- Confirmatory experiments intended to validate the network topologies identified during planned experiments.

The workpieces employed were made with dimensions of ϕ49 x 50 mm. All of them were quenched and tempered. A total of 60 workpieces of AISI 52100 steel bars of the same lot were employed during the experiments (chemical composition shown on Table 1). They were machined using a Romi S40 machine tool. After this heat treatment, their hardness was between 53 and 55 HRC, up to a depth of 3 mm below the surface. Hardness profile was measured at six points in each workpiece and no significant differences in hardness profile were detected.

Table 1. Chemical composition of the AISI 52100 steel (weight percentage).

C	Si	Mn	Cr	Mo	Ni	S	P
1.03	0.23	0.35	1.40	0.04	0.11	0.001	0.01

The machine tool used was a CNC lathe with power of 5.5 KW in the spindle motor, with conventional roller bearings. The mixed ceramic (AL_2O_3 + TiC) inserts used were coated with a very thin layer of titanium nitride (TiN) presenting a chamfer on the edges. The tools employed in the study were produced by Sandvik Coromant, class GC6050, CNGA 120408 S01525. The tool holder presented negative geometry with ISO code DCLNL 1616H12 and entering angle $\chi r = 95°$.

In this study, cutting speed (V), feed (f), and depth of cut (d) were employed as controlling variables. Those cutting conditions varied as follows: 200 m/min ≤ V ≤ 240 m/min, 0.05 mm/r ≤ f ≤ 0.10 mm/r and 0.15 mm ≤ d ≤ 0.30 mm. The adopted values correspond to the operational limits enlisted by the toolmaker on its catalogue (Sandvik Coromant, 2009). The cutting experiments used to train and test the ANN followed a RSM design as detailed in Paiva et al. (2005). This original CCD design is formed by three distinct groups of experimental points: (i) a full factorial design with 23 runs, (ii) six axial points and (iii) four center points, resulting in 18 runs. Using three replicates for each run and augmenting the experimental design with 6 face centered runs, the entire design was built with 60 runs, as can be seen in Fig. 2. Then, 60 workpieces of AISI 52100 hardened steel were turned with 60 different configurations. In each of 60 workpieces, twelve surface roughness measurements were done, resulting in a data set for training and testing sets for the ANN with 720 cases.

A Taylor Hobson rugosimeter, model Surtronic 3+ was employed for roughness measurements, as well as a Mitutoyo micrometer. The twelve roughness measures were collected from each workpiece as follows: four measurements at each extremity (chuck and live centre) and four at the middle point. The horizontal displacement between each sample was 25 mm. The four measurements at the extremities and at the middle point were collected with angular displacements of 90º. All measures were taken after the end of tool life. The criteria adopted for determining the end of tool life was tool flank wear VBmax equal or greater than 0.3 mm.

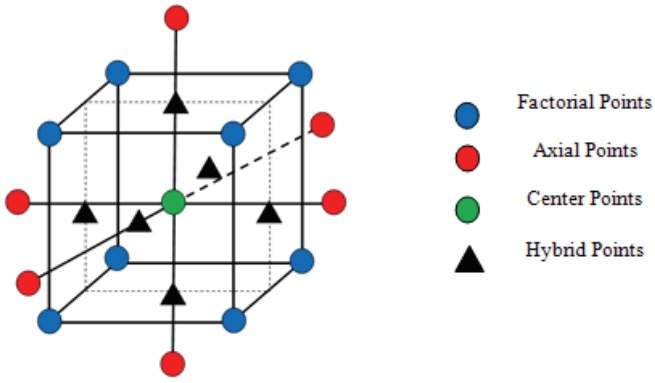

Figure 2. Central Composite Design (CCD) augmented with hybrid points.

Experimental Design for selection of ANN parameters

The problem to be addressed by the designed experiment was to identify the best topology for roughness prediction. The experimental factors considered were the design parameters of the RBF networks: the algorithm for calculation of the radial spread factor (X1), with four levels; the number of radial units present on the hidden layer of the network (X2), also with four levels, and the algorithm for calculation of the center location of radial functions (X3), with two levels. The criterion employed for network selection was the minimization of Mean Absolute Error (expressed in percentage) in prediction. To achieve the established goals for the study, distinct experiments were conducted for different sizes of data sets. Twelve data sets of different sizes were formed, containing 18, 24, 36, 45, 72, 90, 180, 240, 360, 450, 500 and 600 examples. The first data set contained the first 18 examples (V, f, d, Ra); the second training set contained the first 24 examples (V, f, d, Ra), and so on, up to the last training set, containing 600 examples. Two thirds of the examples contained in each data set were used as training set for networks and one third was employed as a selection set. The remaining 120 examples did not take part in any network training activity and were spared to be used as test cases during confirmation runs.

Two experimental cycles were conducted. The first one was an exploratory experimental cycle involving full factorials of mixed levels (Coleman and Montgomery, 1993). Regarding the algorithm for calculation of the radial spread factor, two distinct algorithms were tested: the Isotropic and the K-Nearest algorithms (Haykin, 2008). For the Isotropic algorithm two levels of its scaling factor were investigated, based on results of preliminary experiments. For the K-Nearest algorithm, the influence of its defining factor K was investigated. Once more, two different values of the factor were selected for testing, based on results of preliminary experiments.

Regarding the number of radial units, the levels of the factor were defined as proportions between that number of radial units and the number of training examples, as suggested by Haykin (2008). The proportions established as levels of the factor were 25%, 50%, 75% and 100% of the number of examples available for training in each experiment.

Two distinct algorithms for calculation of the center location of radial functions were tested: the Sub-Sampling algorithm and K-Means algorithm (Moody and Darken, 1989). Each algorithm was established as a level of the experimental factor.

The second cycle involved 12 full factorial experiments (Coleman and Montgomery, 1993), one for each size of training set. Levels that led to minimum error in predictions during the first cycle were kept for the second one. Best network configurations obtained during the second cycle were pinpointed and subjected to confirmation runs. The selected levels for each factor in the experiments of the second cycle are shown in Table 2. Actual treatments were not the same in all experiments, for they were selected based on the best results obtained from the previous exploratory experimental cycle, which varied depending on the size of the training set. The results obtained in this cycle were statistically analyzed and employed to select the best network topologies and to form the conclusions of this study.

Table 2. ANN factors and levels used in the training and test phase.

Training Examples	Algorithm of Spread Factor (X1)	Number of Radial Units (X2)	Algorithm of Center Location (X3)
18	ISO10 KN10	6 9	SS KM
24	ISO10 KN10	8 12	SS KM
36	ISO10 KN10	12 18	SS KM
45	ISO10 KN10	15 23	SS KM
72	ISO10 KN10	24 36	SS KM
90	ISO10 *KN5*	30 *45*	SS KM
180	ISO1 ISO10	30 60	SS KM
240	ISO10 KN10	38 75	SS KM
360	ISO10 KN5	60 120	SS KM
450	ISO10 KN10	75 150	SS KM
500	ISO1 ISO10	100 200	SS KM
600	ISO10 KN10	125 250	SS KM

In Table 2, ISO1 stands for Isotropic Algorithm with scale factor equal to 1; ISO10 stands for Isotropic Algorithm with scale factor equal to 10; KN5 stands for K-Nearest Algorithm with K factor equal to 5; KN10 stands for K-Nearest Algorithm with K factor equal to 10; SS stands for Sub-Sampling, and KM stands for K-Means algorithm. Each cutting condition (V, f, d) was assigned to a network input. The choice is usual in literature (Bagci and Işik, 2006). Networks of single output were employed, being the output defined as the network prediction for surface roughness (Ra).

Execution of experiments and confirmation runs

Execution of each experimental arrangement consisted in configuring the network as specified by the factorial design and training the ANN. The Neural Networks suite of the statistical software package Statistica® release 7.1 was employed. Sixty replications were performed for each network configuration, meaning that a network configuration under test was independently initialized and trained for sixty times, in order to mitigate risks associated to the random initialization of synaptical weights (Haykin, 2008). Examples were presented in a random sequence to the network during training.

Regarding pre and post processing, data was normalized to the interval (0, 1) to be applied to network inputs and re-scaled to the original dominium at the output. Results were stored under the format of files produced by the software package, containing the prediction of the networks for test cases. The results were compiled to identify factor levels favoring network performance in prediction, to investigate relative importance of each factor and the existence of interactions.

The best network configurations for each data set were kept and subjected to confirmation runs. Those consisted in applying the networks to predict surface roughness for the 120 examples spared from training, in order to assess network generalization capability. The output variable chosen as performance measure in confirmation runs was the mean absolute error, in percentage, given by Eq. (6).

$$MAE(\%) = \left| \frac{y_{expt} - y_{pred}}{y_{expt}} \right| \times 100 \tag{6}$$

In Eq. (6), y_{expt} stands for the measured experimental value and y_{pred} stands for the ANN predicted value of the response.

Results and Discussion

The ANOVA results allowed the determination of factors and interactions significant to the performance of the network in the prediction task. Individual effect analysis and interaction effect analysis were conducted, for each of the 12 experiments conducted. Standardized residuals were analyzed by means of Anderson-Darling test, at the level of significance of 0.05. Figures 3 and 4 show the individual and interaction effects obtained from the experiment involving a data set composed of 72 examples. The results shown in Fig. 3 and Fig. 4 correspond to network predictions for cases of the selection set, which is composed, as mentioned, of 1/3 of the total number of training cases. So in the example depicted (72 examples), the graphs are a measure of the effects of network design on the prediction accuracy obtained in 24 cases included in selection set.

In Fig. 3 the individual effects of each experimental factor on the network error in prediction (on the vertical axis) are plotted against factor level (on the horizontal axis).

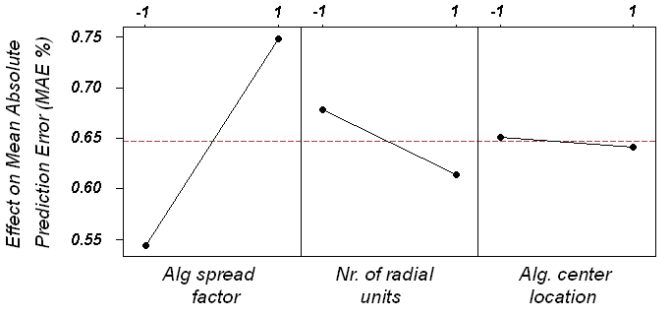

Figure 3. Individual effects for the experiment involving 72 training examples.

It is clear that the algorithm employed for calculation of the radial spread factor has a strong influence, indicated by the strong difference in network errors observed varying the level of that factor. As the desired output for the network is the smallest prediction error, it is clear that level -1 (Isotropic algorithm with a scaling factor set to 10) is the setting that leads to the best accuracy. In regard to the number of radial units, level 1 (corresponding to 50% of the number of training examples, i.e., 36 units in the experiment with 72 examples) is the best setting. The figure shows also that influence of the algorithm employed to calculate center location has negligible influence on network accuracy.

Figure 4 refers to the interaction effects between experimental factors on network error in prediction (on the vertical axis). The figure shows a pronounced influence of the interaction between the algorithm for calculation of the radial spread factor and the number of radial units.

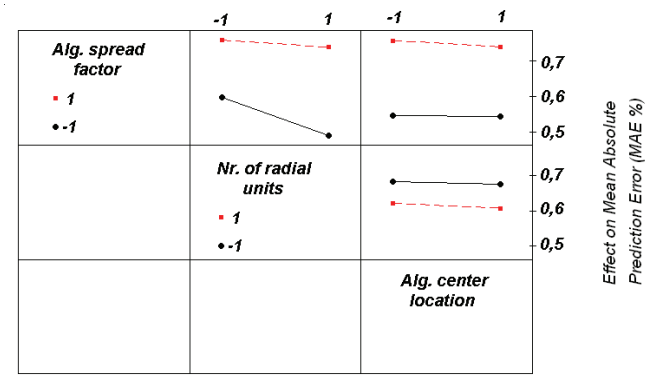

Figure 4. Interaction effects for the experiment involving 72 training examples.

Results of ANOVA for individual significance of the effects for the experiment involving 72 examples are shown in Table 3.

Table 3. ANOVA results for 72 training examples.

Source	Coefficient	T	**P-Value**
Alg. Spread Factor	.103	93.19	0.000
No. of Radial Units	-0.032	-29.34	0.000
Alg. Center Location	-0.005	-4.74	0.000
Alg. Spread Factor X No. of Radial Units	0.022	19.93	0.000
Alg. Spread Factor X Alg. Center Location	-0.004	-3.28	0.002
No. of Radial Units X Alg. Center Location	-0.002	-1.63	0.108
Alg. Spread Factor X No. of Radial Units X Alg. Center Location	0.001	0.60	0.550

The results reveal the effects that a significant influence has on network performance. A factor is considered as significant if its p-value is inferior to the level of significance adopted, which is 0.05 in this case. Individual effects of the three experimental factors are significant. Two interaction effects are significant as well: the interaction between the algorithm for calculation of the spread and the number of radial units, and the interaction between the algorithm for algorithm for calculation of the spread and the algorithm for calculation of center locations. The remaining effects are not significant for this size of data set.

Analysis of the absolute values of the effects made it possible to determine the configurations that yielded the best result in the prediction task among the configurations tested, for each size of the data set. Isotropic algorithm employed with a scale factor of 10 presented the best results in all experiments conducted. The best settings for all factors are shown in Table 4.

Table 4. Best ANN configurations for each data set size.

Training examples	Algorithm for calculation of the spread factor	Number of radial units	Algorithm for calculation of radial centers
18	Isotropic, Scale factor = 10	9	Sub-Sampling
24	Isotropic, Scale factor = 10	12	Sub-Sampling
36	Isotropic, Scale factor = 10	12	Sub-Sampling
45	Isotropic, Scale factor = 10	23	Sub-Sampling
72	Isotropic, Scale factor = 10	36	K-Means
90	Isotropic, Scale factor = 10	45	K-Means
180	Isotropic, Scale factor = 10	60	Sub-Sampling
240	Isotropic, Scale factor = 10	75	K-Means
360	Isotropic, Scale factor = 10	120	K-Means
450	Isotropic, Scale factor = 10	150	Sub-Sampling
500	Isotropic, Scale factor = 10	200	Sub-Sampling
600	Isotropic, Scale factor = 10	250	Sub-Sampling

Regarding the number of radial units on the network hidden layer, the best results were achieved using proportions of 75% between the number of units and the number of training examples available, in the experiments involving 18, 24, 45, 72 and 90 examples. In the remaining experiments, the number of radial units that led the network to the best performance equaled the proportion of 50% between number of units and number of examples.

In regard to relative importance of factor on network performance, it was observed that factor X1 (the algorithm for calculation of the spread factor) was pointed by ANOVA as the most significant in 10 experiments. The exceptions were the experiments involving the smallest number of examples (18 and 24). The effect of algorithm employed to calculate the spread became dominant in experiments involving 36 examples and more. The significance of this factor becomes overwhelming as the number of examples available for training increases.

Factor X2 (the number of radial units), was pointed as significant in all experiments, although its relative weight in network performance is inferior to that of algorithm for calculation of the spread factor in experiments with 36 examples or more. This factor was the most significant one in the experiment involving 24 examples.

Factor X3 (the algorithm for calculation of the center location of radial functions) was the less influential of the factors under investigation. The effect of that factor was pointed by the ANOVA as insignificant or only marginally significant in the experiments conducted. Figure 5 shows an example of the Pareto chart for the standardized effects obtained with 72 examples.

In the Pareto diagram, the dashed line indicates the threshold for factor significance, for an adopted level of significance of 5%. The chart reveals the relative impact of each factor on network accuracy. The diagram clearly displays the prevalence of algorithm for calculation of the spread factor on network performance, followed by the effect of the number of radial units and by the effect of the interaction between the two factors.

In respect to the existence of interactions, all twelve experiments presented at least one interaction pointed as significant to the performance of the network, according to ANOVA results. In some experiments interaction effects of 3rd order were pointed as significant. The existing interaction between factors algorithm for calculation of the radial spread factor and number of radial units was pointed as significant in eleven out of twelve experiments. The effect of this interaction is particularly pronounced. It rivals, and in some cases overcomes, the individual effect of varying the number of radial units on the hidden layer.

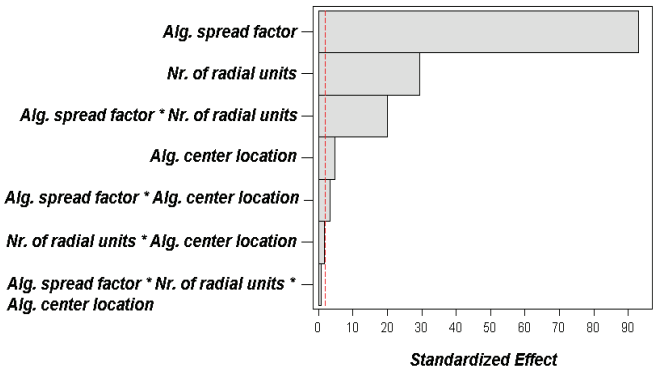

Figure 5. Pareto chart of the standardized effects for 72 training examples (α = 0.05).

The interaction between the algorithm for calculation of the radial spread factor and the algorithm for calculation of center location was pointed as significant in seven experiments, although with much smaller impact. The remaining interaction effects were pointed by the analysis as insignificant or minimally significant.

ANN model accuracy

During confirmation runs, the best network for each size of training set were employed to predict surface roughness for the 120 examples spared from network training and selection. The results agreed to those obtained during the planned experiments. Results are summarized in Table 5. It shows the values for mean absolute error, standard deviation of the error and maximum error, for the network configurations described in Table 4.

Table 5. Accuracy of the Best ANN Prediction Models in confirmation runs.

Training examples	Error in prediction (MAE %)	Standard Deviation of the error (%)	Maximum error (%)
18	7.88	5.34	18.97
24	1.07	0.46	2.82
36	0.39	0.16	0.96
45	0.23	0.03	0.31
72	0.04	0.02	0.17
90	0.02	0.00	0.03
180	0.01	0.00	0.01
240	0.01	0.00	0.01
360	0.00	0.00	0.00
450	0.00	0.00	0.00
500	0.00	0.00	0.00
600	0.00	0.00	0.00

Error in prediction falls steadily and becomes negligible as the number of examples available for training increases, as predicted in literature. It is important, however, to emphasize that a mean absolute error of 0.388% was obtained using only 36 examples. This suggests the feasibility of identifying RBF network configurations able to predict accurately using a relatively small number of training cases, with the aid of the DOE methodology. Results show also that dispersion in prediction falls as training sets become larger.

An example of the resulting ANN models for surface roughness prediction is shown in Fig. 6. The best identified network configuration for prediction using 72 examples was applied to predict surface roughness for a fixed depth of cut of 0.25 mm and for several values of cutting speed and feed between the limits employed in experimentation.

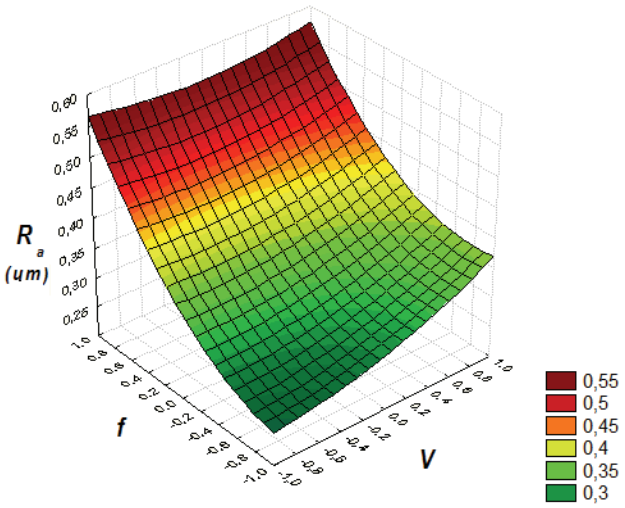

Figure 6. Response surface of the best ANN model for 72 examples. Hold value: d = 0.25 mm.

In Fig. 6, independent variables V (cutting speed), in m/min, and f (feed), in mm/r, are displayed on the horizontal axes. The plotted response surface corresponds to a fixed value of 0.25 mm for variable d (depth of cut). Values of predicted roughness average (Ra), in μm, are shown on the vertical axis.

Conclusions

The use of DOE methodology proved to be an efficient tool for the design of neural networks of RBF architecture for surface roughness prediction in the turning of AISI 52100 hardened steel. The methodology made it possible to identify network configurations presenting high degree of accuracy and reduced variability in the proposed task. Results obtained show that RBF ANNs trained with only 36 examples can present mean absolute errors equal to 0.388%. This fact suggests that RBF networks designed with the use of DOE methodology can be an effective, efficient and affordable alternative for surface roughness prediction in hard turning.

The algorithm for calculation of the radial spread factor was the most influential among the three factors under investigation. The influence of that factor becomes dominant as the number of examples available for training increases. The second most influential factor was the number of radial units on the network hidden layer. The less influential factor was found to be the algorithm for calculation of center locations. The influence of this factor was negligible in almost all experiments. The conclusion is that the option for any of the algorithms tested implied in no pronounced difference in network performances. Such finding can further simplify the design of the ANN to be used for roughness prediction in AISI 52100 hard turning. Interaction effects between levels of factors involved were pointed as significant to the performance of RBF networks. In each of the experiments conducted at least one interaction effect was pointed as significant. In some cases, interaction effects were more significant to network performance than individual factor effects. This means that not only the straightforward configuration parameters should be considered when designing networks for surface roughness prediction, but also the amount and the nature of the interaction among them.

It must be emphasized that conclusions obtained in this work cannot be extrapolated to other neural network architectures, other kind of machining operations, other materials or tools. The approach can, nonetheless, be recommended to different network

architectures. A study on tool surface roughness can also be elaborated using the same method employed here, replacing the machining process under study. Further investigation is required in order to evaluate the nature and the impact of the interactions among design factors on the network performance, and also on reduction of computational costs associated with extensive experimentation required by network optimization.

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