A review on the use of artificial neural networks for the prediction of surface roughness in machining processes

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Abstract. *The use of artificial neural networks for prediction of surface roughness in machining processes has been the subject of several research works in recent years. Even in such a specific niche of literature, considerable difference can be detected in terms of definition of network architectures, training algorithms, error measures, results validation, and others. Furthermore, the reading of individual papers does not provide a clear and panoramic view of the 'state-of-art' of the research. This work aims to review a number of studies dealing with the subject and to summarize the findings. The review included a set of comparison criteria as well as the observance of requirements regarding validation of conclusions obtained. Trends among the different works are identified and the main differences highlighted. The result of the evalution points out to under-explored issues for future research and reveals opportunities for improvement in the validation of the results obtained.*

Keywords*: Surface roughness, Artificial Neural Network, Prediction*

1. INTRODUCTION

Surface quality is an essential consumer requirement in machining processes because of its impact on product performance (Tamizharasan *et al.*, 2006; Ambrogio *et al.*, 2008). Basheer *et al.* (2008) affirm that characteristics of machined surfaces have significant influence on the ability of the material to withstand stresses, temperature, friction and corrosion. The need for the products with high quality surface finish keeps increasing rapidly because of new application in various fields like aerospace, automobile, die and mold manufacturing (Sharma *et al.*, 2008) and manufacturers are required to increase productivity while maintaining and improving surface quality in order to remain competitive (Karpat and Özel, 2008).

A widely used surface quality indicator is surface roughness (Özel and Karpat, 2005; Benardos and Vosniakos, 2003). High surface roughness values decrease the fatigue life of machined components (Benardos and Vosniakos, 2002). The formation of surface roughness is a complex process, affected by many factors like tool variables, workpiece material and cutting parameters (Tamizharasan *et al.*, 2006). According to Karpat and Özel (2008) the complex relationship among the parameters involved makes it difficult to generate explicit analytical models for hard turning processes.

As cited in Tamizharasan *et al.* (2006), even in hard turning most of process performance characteristics are predictable and, therefore, can be modeled. These models, obtained in different ways, may be used as objective functions in optimization, simulation, controlling and prediction algorithms. Al-Ahmari (2007) sustains that machinability models are important for a proper selection of process parameters in planning manufacturing operations. A better knowledge of the process could ultimately lead to the combination or elimination of one of the operations required in the process, thus reducing product cycle time and increasing productivity, as stated by Singh and Rao (2007).

Among the strategies employed for modeling surface roughness, methods based on expert systems are very often employed by researchers. Benardos and Vosniakos (2003), in a review about surface roughness prediction in machining processes, pointed that models built by means of artificial intelligence (AI) based approaches were more realistic and accurate in the comparison to those based on theoretical approaches. AI techniques, according to the authors, *"take into consideration particularities of the equipment used and the real machining phenomena"* and are able to include them into the model under construction. Several works make use of artificial neural networks (ANNs) for surface roughness prediction. It can be seen as a 'sensorless' approach for estimation of roughness (Sick, 2002), where networks are trained offline with historical or experimental process data and then employed to predict surface roughness. As pointed out by Coit *et al.* (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. For Balestrassi *et al.* (2009) *"the main reason for this increased popularity of ANNs is that these models have been shown to be able to approximate almost any nonlinear function arbitrarily close"*.

This article reviews a group of research works dealing with surface roughness prediction by means of artificial neural networks. It is an attempt to identify trends in literature, as well as to evaluate the compliance of the works to some requirements in the research involving artificial neural networks (Sick, 2002; Bishop, 2007; Haykin, 2008). The work is organized as follows: a brief introduction on surface roughness and neural networks is presented; selected papers are classified based on characteristics such as year of publication, network architectures employed, inputs and output utilized; a survey on model building strategies is conducted; finally, an evaluation on the methodology and a discussion on the results provided by the articles is performed. A direct comparison of the results is not conducted, since quite different approaches and experimental conditions are employed and different criteria for results evaluation are adopted. The goal is to provide useful information to the reader on the current status of the research, on commonly employed strategies and on opportunities of research quality in the field.

2. 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 maximum roughness exist in literature (Whitehouse, 1994; Krar, 2005). Those models, however, do not take into account any imperfections in the process, such as tool vibration or chip adhesion, as told by Sharma *et al.* (2008). In some cases, practical results diverge from theoretical predictions (Zhong *et al.*, 2006); Fredj and Amamou, 2006).

For Karpat and Özel (2008), 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) affirm that the formation of surface roughness is a complex process, affect by many factors as tool variables, workpiece material and cutting parameters. Cus and Zuperl (2006) suggested empirical models (linear and exponential) for surface roughness as a function of cutting speed, feed and depth of cut.

3. NEURAL NETWORKS

According to Haykin (2008), an artificial neural network (ANN) is a distributed parallel systems composed by simple processing units called nodes or neurons, which perform specific mathematic functions (generally non-linear), thus corresponding to a non-algorithmic form of computation. In its most basic format, an artificial neuron is an information processing unit composed of: a set of synapses, each one characterized by a weight value; an adder, responsible by summing the input signals properly multiplied by the weight values in the synapses; and an activation function. In an artificial neural network, the knowledge about a given problem is stored in the values of the weights of the synapses that interconnect neurons in the layers of the network. An activation function defines the output of a network node in terms of the level of activity in its inputs (Haykin, 2008).

The ability to learn by means of examples and to generalize learned information is, doubtless, the main attractive in the solution of problems using artificial neural networks, according to Braga *et al.* (2007). It is a main task of a neural network to learn a model from from its surrounding environment and to keep such a model sufficiently consistent to the real world so as to reach the goals specified for the application it is intended to perform. The use of neural networks in solving a given problem involves determining the design parameters of the network, a learning phase and a test phase, during which the performance of the network is assessed (Haykin, 2008). Figure 1 shows, as an example, a multilayer perceptron (MLP) network.

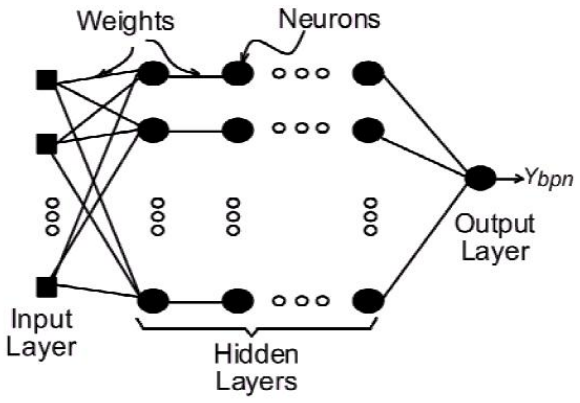

Figure 1: Multilayer Perceptron ANN structure

The ANN has three types of layers, namely, the input layer, the output layer and one or more hidden layers, located between the input and output layers. The number of hidden layers is usually one or two. Each layer consists of neurons, and the neurons in two adjacent layers are fully connected, while the neurons within the same layer are not connected. In this example, the output layer has just a single neuron. Each neuron in the input layer is designated to an attribute in input data, and produces an output which is equal to the (scaled) value of the corresponding attribute. For each neuron in the hidden or output layer, the following input–output transformation is employed:

$$v = f\left(\sum_{h=1}^{H} w_h u_h + w_{o)}\right) \tag{1}$$

In Eq. 1 v is the output, H is the total number of neurons in the previous layer, u_h is the output of the hth neuron in the previous layer, w_h is the corresponding connection weight, w_0 is the bias (or intercept). f is the nonlinear transformation function (or activation function) employed to process data.

4. CHARACTERIZATION OF THE WORKS REVIEWED

Many authors argue in favor of neural networks for prediction tasks in machining. For Quiza *et al.* (2008) traditional regression methods present severe limitations for hard turning applications, due to the extreme non-linearity that characterizes the process and to the use of modern tool materials. Some works, however, report drawbacks in using ANNs for prediction. Ambrogio *et al.* (2008) points the need for large amount of data points for training and validation as a limiter for the application of neural networks in machining processes. Bagci and Işik (2006) declare that ANNs models require greater computational effort when compared to RSM models. Comparisons between neural network based models and models obtained by other techniques present mixed results.

In order to form a synthetic picture of the current status of the research in the field, a series of papers dealing on the subject were collected and reviewed. The following criteria were adopted for selecting reviewed articles:

- Papers aiming to develop models to predict surface roughness in machining processes;
- Papers using neural networks to develop a roughness model;
- Papers employing historical or experimental data collected from the process to train and test networks;

Based on these criteria, 45 research works, compliant with the enounced requirements, were selected and reviewed. The year of publication of the reviewed works is depicted in Fig. 2.

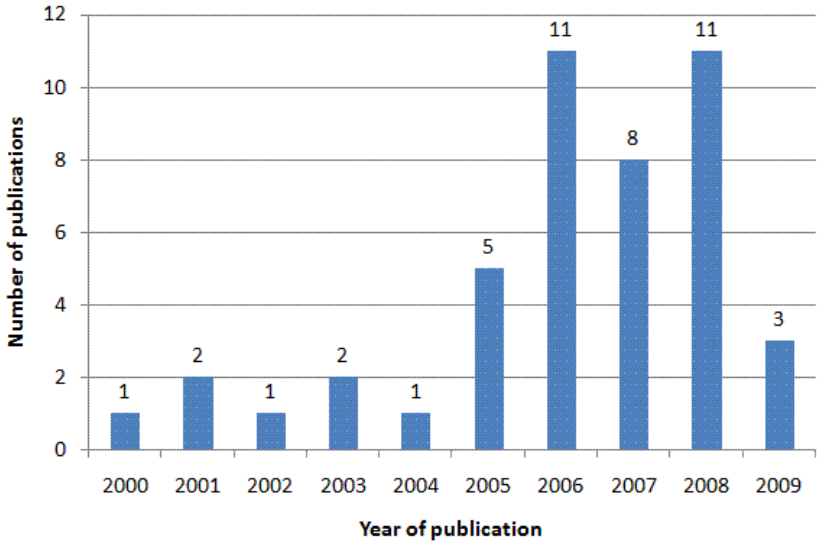

Figure 2. Yearly distribution of publications reviewed

The machining process under scrutiny in the publications reviewed is displayed in Fig. 3. In that figure AFM stands for abrasive flow machining, EDM stands for electrical discharge machining, ECM stands for electrochemical machining. It can be seen that turning accounts for about 42% of the total. The reasons for this prevalence might lie in the fact that it is a "process less complex than other processes with defined cutting edges (such as drilling or milling) because only one cutting edge is involved", as stated by Sick (2002).

As seen in Fig. 4, networks of MLP architecture are by far the most employed ones. They can be found in 39 works (roughly 87% of the total). RBF is adopted in eight publications (around 18% of the publications). Performance comparisons between those architectures are conducted in Tsai and Wang (2001), Cus and Zuperl (2006), for example.

In Sarma and Dixit (2007) they are used in conjunction. Networks of unsupervised learning paradigms are hardly employed along the reviewed works. While MLP and RBF (examples of supervised and hybrid learning paradigms, respectively) are employed in the vast majority of the papers, only in three publications the use of unsupervised learning networks is verified. In Balic (2004), Self Organizing Maps (SOM) are employed as part of a bigger network array to generate part-programs for milling and drilling on machining centers. The use of polynomial networks for roughness modeling is proposed by Chang and Lu (2006) for side milling operations, and by Ali-Tavoli *et al.* (2006), for use in AFM. Unsupervised networks are recommended by Neurocomputing theory for pattern recognition and data clustering in situations where classes are unknown. The applicability of unsupervised network paradigms, in special architectures such as SOM or ART (Adaptive Resonance Theory) for roughness classification remains an underexplored branch of literature.

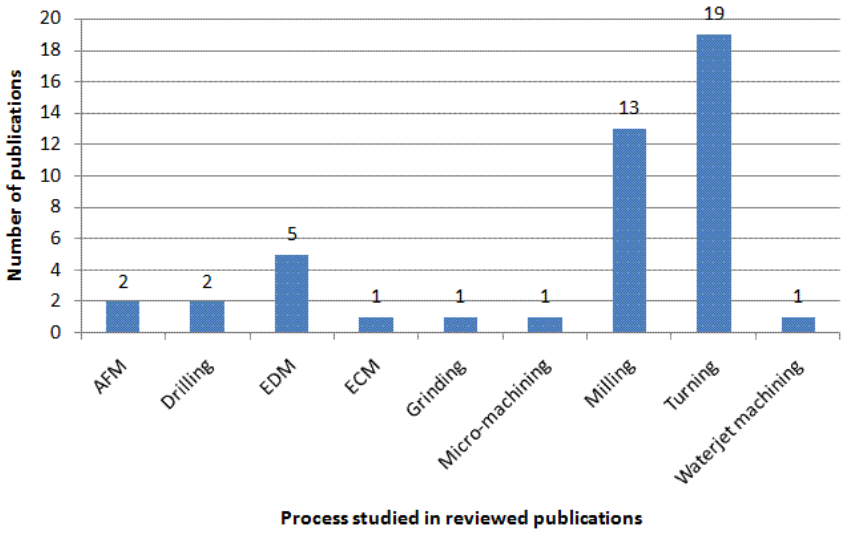

Figure 3. Number of publications dealing with specific processes along publications reviewed

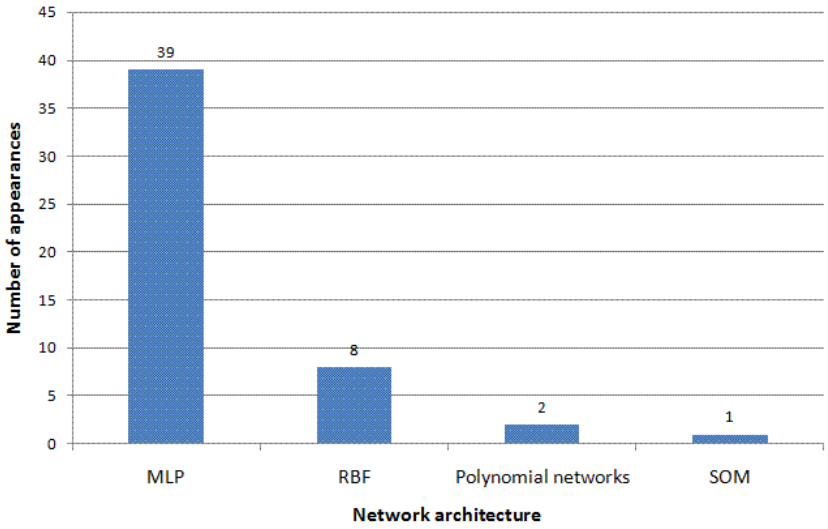

Figure 4. Network architectures employed by publications reviewed

In the studies that employ networks of MLP architecture approximately 56% make use of the back-propagation training algorithm (Rumelhart *et al.*, 1986). The applicability of other network paradigms or algorithms for roughness prediction has not been fully explored in literature. It is also worth noting that in those studies employing networks of MLP architecture, 13 make use of the hyperbolic tangent sigmoid activation function. In 8 works, the log-sigmoid activation function is chosen and in 19 publications, the choice of activation function is unclear.

5. MODELING STRATEGIES

It can be observed that roughness average (R_a) is by far the most employed figure to measure surface roughness, appearing in approximately 91% of the total. R_a is defined as arithmetic average value of the departure of the profile

from the centre line throughout the sampling length. Although the main goal of the reviewed papers is to model roughness, some of them also employ ANNs to predict other parameters of interest. The neural network outputs employed are summarized in Fig. 5. In 29 out of 45 studies, networks of single outputs are employed. In the remaining ones, networks having two, three or more outputs are found. The effects of using networks of one or more outputs over final model accuracy were not investigated along the papers reviewed.

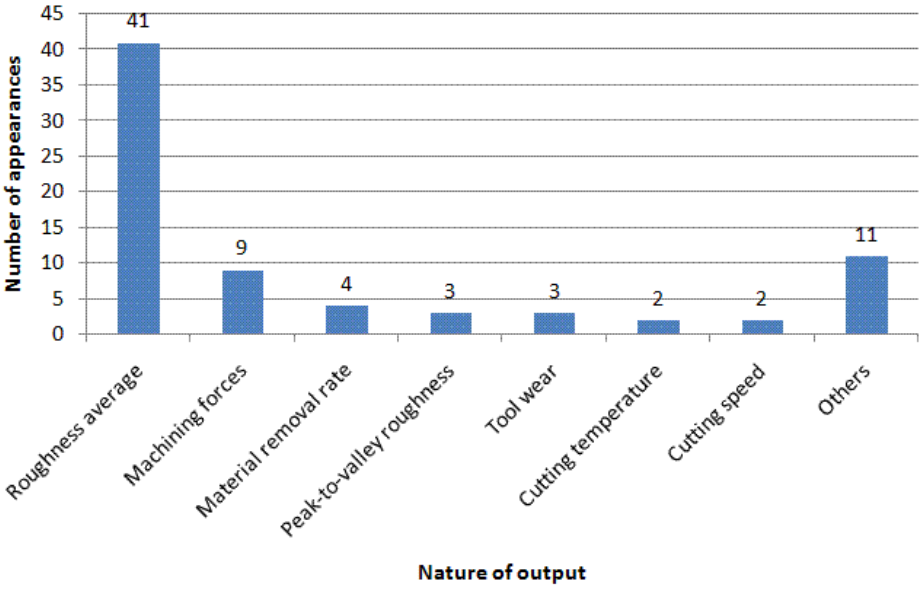

Figure 5. Predicted outputs in publications reviewed

All publications studied made use of more than one input to predict roughness. The number of parameters employed for building surface roughness models can be seen in Fig. 6. Virtually all works (43 out of 45) define clearly inputs employed. In only two cases actual inputs cannot be defined, although the text suggests they are based on cutting parameters. The modeling strategy consists in collecting data covering the experimental space in order to build a roughness model. In one study (Shie, 2008), the nature of inputs itself is varied, in the search for the most suitable input set.

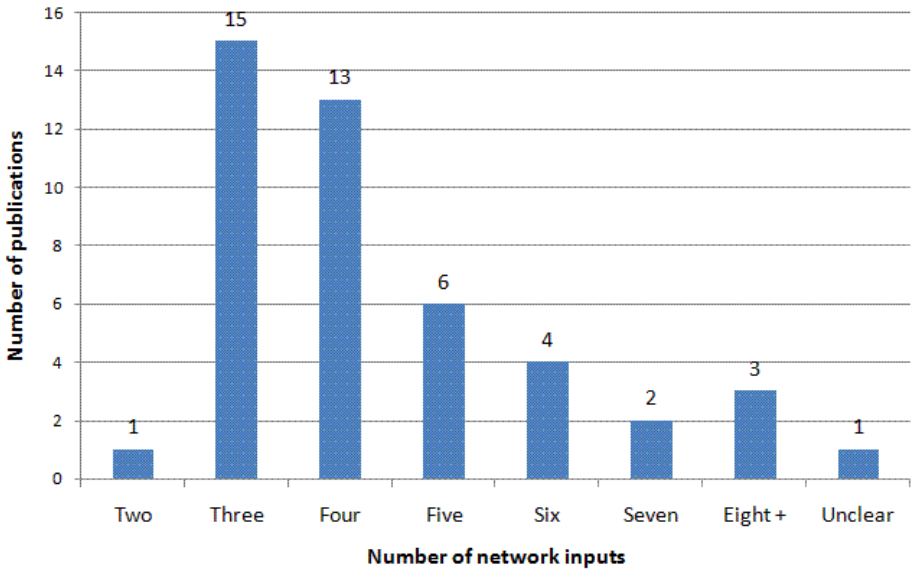

Figure 6. Number of predictors employed in publications reviewed

Twenty seven works present some kind of justification for the choice of the inputs of the network. In Oktem *et al.* (2006) for instance, cutting parameters are defined into the limits fixed by the tool manufacturer. In some works, inputs are selected based on previous machining studies, while in others, no justification is presented at all. Figure 7 details the nature of inputs employed by the publications reviewed. Cutting speed, feed and depth of cut (axial or radial) are by far

the most employed ones. Inputs appearing only once along the papers were grouped together under the label 'Others'. Examples of those inputs include drill diameter, feed force, cutting force, lubrication cooling condition, among others. A question that could be further explored is: what is the best set of inputs in terms of roughness prediction for a given process? Would there be any significant change in model accuracy when a given input is added or removed?

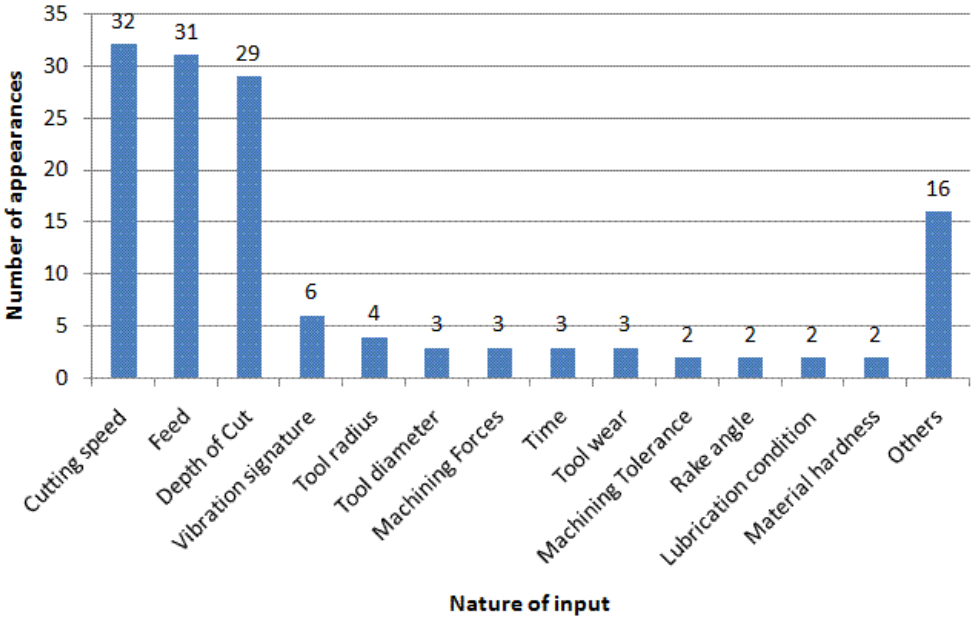

Figure 7. Nature of input parameters employed for model building.

A neural network is selected based on the value of error figures obtained during training phase. Networks presenting minimum error are selected and then submitted to validation tests, when their accuracy, precision and generalization capabilities shall be tested using data not previously presented to the network. Distinct figures are used along the papers reviewed for network selection and to express the resulting model accuracy, as can be seen in Fig. 8. MSE stands for mean square error, RMSE stands for Root mean square error and SSE stands for sum of square errors. Even though figures involving square error are prevalent for selection of network architectures, mean error is used in 25 publications (approximately 56% of the total) in order to express the final results of the neural network models or to compare the performance of neural networks models to that of models obtained by other methods. In addition to that, Basheer *et al.* (2008), Çaydas and Hasçalik (2008) and Tsai and Wang (2001) use R^2 (a Pearson coefficient) as the statistical index employed to measure the adequacy of the neural network model.

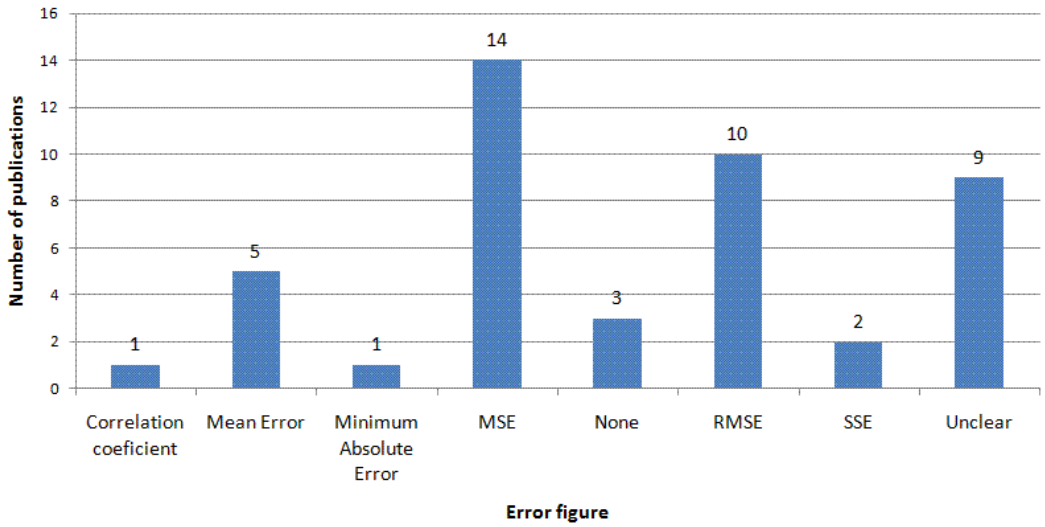

Figure 8. Error figures employed for network selection

The approach adopted to build the training set varies along the works reviewed, as seen in Fig. 9. In 38% of the cases, the training set is build explicitly from results obtained experiments planned and executed according to DOE

(Design of Experiments) techniques. In 24% of the cases, arrangements resembling those of DOE are employed, although there is no explicit mention to the methodology, and no indication that DOE principles were followed during experiments. In some of these works the actual experimental arrangement is only suggested, and not shown explicitly, as in Oktem *et al.* (2006), where a remarkable set of 243 examples collected from cutting experiments is used. In two papers, cases are generated by simulation over DOE built models and in the remaining works, they are collected from experimentation techniques not resembling DOE. The number of cases required to train the network is explored in only one publication Kohli and Dixit (2005). In that work a method is proposed to establish the minimum number of training cases required for good performance of the networks.

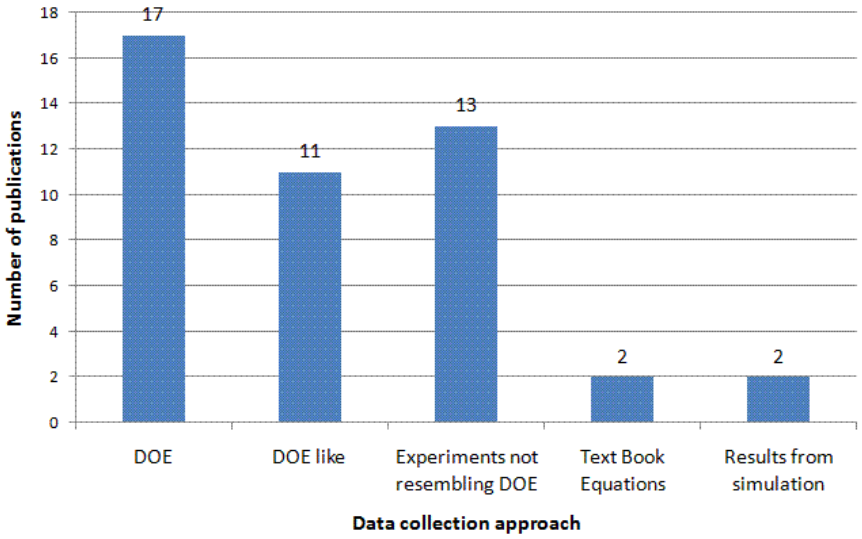

Figure 9. Approaches adopted by publications to build neural network training sets

The previous discussion leaves an open question: is a DOE generated data set the most efficient way to collect training cases? Would another approach lead to better results, or to the same results with a smaller number of training cases? Another issue that has not been sufficiently investigated is: for a given experimental ensemble piece material-tool-machine, is there a minimum number of training cases that cause ANNs to be superior to other approaches?

Criteria adopted for stop training in the publications dealing with MLPs is distributed as follows: in 4 studies, time is the criteria selected; number of epochs is employed by 7 studies. The achievement of a pre-specified error limit is adopted in 5 publications while a compromise solution between training time and error level is adopted by 2 others. Finally, in fourteen publications the criteria adopted to stop training is unclear.

In six works, as for instance in Tsai and Wang (2001) and Pal and Chakraborty (2005) network paradigms are compared. In Tsai and Wang (2001), six network configurations comprising MLP and RBF trained by different algorithms are compared. Average checking error (i. e. error in validation) and Pearson coefficient R^2 are the figures compared. Although a lot of data is presented, the article points to no clear winner. In Sonar *et al.* (2006), performances of MLP and RBF networks are compared. The MLPs outperformed RBF in that study. Even though, those comparisons could be considered to be definitive, since a systematic effort to optimize network being compared cannot be detected in those works.

In 18 publications, models obtained by means of neural networks are compared to models obtained by other approaches, such as multiple regression analysis or response surface methodology. Out of this number, network models are considered to be superior in 10 publications. Neural models performance is deemed as equal to other approaches in 6 out of 18 works. In 2 articles the neural model is outperformed by the alternative model.

6. EVALUATION OF THE NEURAL NETWORKS EXPERIMENTS

In this section, the compliance of the reviewed papers with requirements regarding validation of results obtained is evaluated. The criteria adopted follow recommendations from Neurocomputing theory authors like Bishop (2007) and Haykin (2008). Another useful set of criteria adopted is the one proposed by Sick (2002) in his prolific review about the use of ANNs for tool wear monitoring in turning operations.

An often reported problem with ANNs is the optimization of network parameters. Zhong *et al.* (2006) affirm that there is no exact solution for the definition of the number of layers and neural nodes required for particular applications. Regarding network optimization, in 42% of the papers reviewed a trial and error approach is adopted. In some cases, like in Zhong *et al.* (2006), Kohli and Dixit (2005), Sonar *et al.* (2006) and Pal and Chakraborty (2005), even though the best network architecture is determined by trial and error, the authors affirm it is an 'optimal network'. In 18% of the

cases, not even the best configuration is detailed, thus preventing paper results to be reproduced. The review also shows that in 16% of the cases only the best network is presented. In 11% of the publications optimization is dealt with in a strategy of varying network features one at a time. A clear disadvantage of this approach is that it is not able to detect interaction among factors involved. In 11% of the papers reviewed a new method for optimization is proposed. Finally, in 7% of the papers, network optimization is only mentioned, and the best resulting configuration presented. In those works, configuration parameters such as number of hidden layers, number of neurons in hidden layers or training algorithms are fixed with no investigation.

One of the primary recommendations for the use of neural networks in modeling is the use of distinct sets of data for training and testing Haykin (2008). In 84% works reviewed the use of distinct set is clearly established. In 11% the same sets are used to train and to test the networks and in 5% the distinction is unclear.

In addition to the distinction between training and test sets, the use of a third dataset as a validation set is recommended (Sick, 2002; Haykin, 2008). This recommendation is hardly followed in the publications reviewed, being found in only 17% of the papers reviewed.

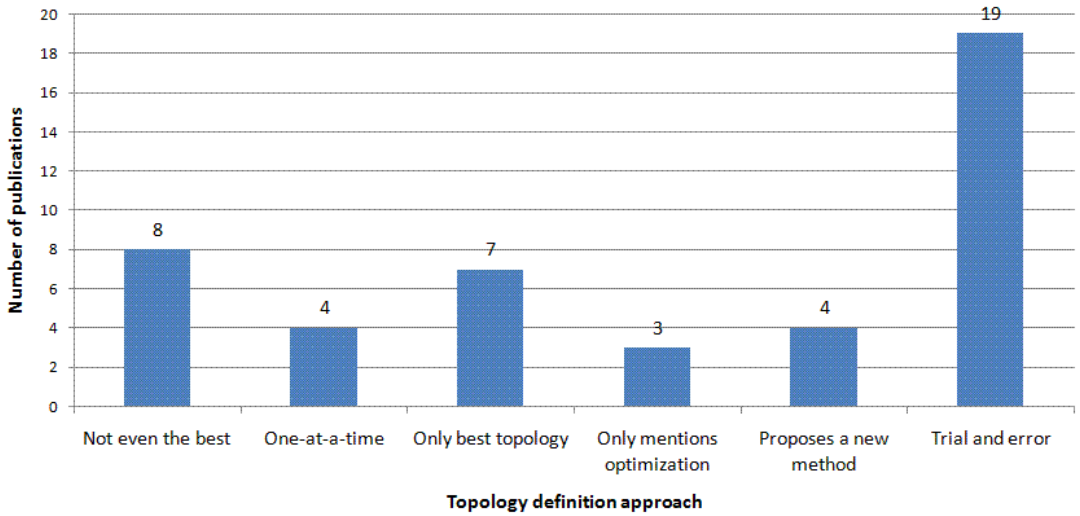

Figure 10. Topology definition approaches adopted by publications reviewed

Sick (2002) strongly recommends the repetition of experiments in order to avoid random influences due to weight initialization and the computation of mean and variance for certain performance measures, such as the average error for an independent set of patterns. In only eight publications repetitions of experiments are performed for each network topology employed.

The use of statistical to objectively ensure model accuracy or to compare networks with different structures, inputs or learning parameters is essential to sustain conclusions obtained in research with neural networks, according to Sick (2002). In only 10 publications, or 22% of the total, could any statistical test be detected at all. Examples of the use of such approach can be found in Sonar *et al.* (2006) and Kohli and Dixit (2005). Moreover, in a 53% of the publications reviewed results are expressed only in graphical format, what makes it difficult to evaluate model accuracy.

Some papers lack basic information necessary to the reproduction of results. In some works, training and test cases are not provided. In Basheer *et al.* (2008), for instance, it is not even clear how many cases were employed as training and test cases. A mention on the subject of training mode employed was found in a single work dealing with MLP networks (Pal and Chakraborty, 2005), where batch mode is used. Finally, little attention is paid to the possibility of occurrence of the overfitting phenomena (Haykin, 2008), and almost no paper reports explicit tests to verify the absence of that condition. Techniques like pruning or regularization are hardly discussed.

Neural networks constitute a powerful and flexible tool for function mapping. The review of the literature, however, allows no objective conclusion regarding the superiority or efficiency of network when applied to the task of surface roughness prediction. In the opinion of these authors, publications more firmly established on the neurocomputing and statistical grounds are critical to clarify the issue.

7. CONCLUSIONS

A review of several publications on the subject of surface roughness in machining processes by means of artificial neural networks (ANNs) was conducted. They were compared based on architecture, configuration and training of networks employed and also on the observance of criteria for validation of conclusions obtained. The review shows that most of the work in the area aims to predict average surface roughness (R_a). Cutting conditions are employed as network inputs in virtually all publications. Networks of single outputs are the most commonly found.

Most of training cases employed are the results of experiments planned according to DOE methodology, or at least results of experimental arrangements resembling those from DOE. Efforts to establish the minimum number of training cases necessary to make neural models to outperform models obtained by other approaches were not found. In the opinion of the author, investigations on efficient data collection techniques are research issues that could be further explored in literature.

Most of the papers employ networks of MLP architecture trained by the back-propagation algorithm. The use of unsupervised network paradigms is extremely rare. The adequacy of such network paradigms and other training algorithms to the prediction task constitutes yet another possibility to be investigated.

In many studies, only the 'best' network configuration is presented, and optimization efforts are hardly mentioned. In those who attempt to find suitable configurations, trial and error is still the most frequent technique. The use of pruning techniques could not be found. A comparison between network optimization approaches was not mentioned.

Most publications observe the principle of using distinct sets of data to train and the networks. The use of a third data set for validation, recommended by some authors as an independent measure of the generalization ability of the networks can be found in only a sixth of works. Techniques to avoid overfitting are not employed in many articles.

Another important requirement, the repetition of network simulation experiments was found in less of 20% of the works. The use of statistical evaluation and comparison of trained networks, or to compare networks of different paradigms, could be found in only about a quarter of the works reviewed. There is also a lack of statistical evaluation in the comparison between ANN based models and those models obtained by other methodologies.

All the aforementioned issues reveal an opportunity for improvement in research on the field. More attention, however, should be paid to the basic theory of connectionism, to statistical treatment required to validate results and to the inclusion of data necessary to reproduce them. Authors should fulfill those requirements in future research in order to establish their conclusions on more firm grounds and to explore the full potential of neural network on roughness modeling.

3. ACKNOWLEDGEMENTS

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