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ORIGINAL ARTICLE

Artificial neural networks for machining processes surface roughness modeling

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Abstract In recent years, several papers on machining processes have focused on the use of artificial neural networks for modeling surface roughness. Even in such a specific niche of engineering literature, the papers differ considerably in terms of how they define network architectures and validate results, as well as in their training algorithms, error measures, and the like. Furthermore, a perusal of the individual papers leaves a researcher without a clear, sweeping view of what the field's cutting edge is. Hence, this work reviews a number of these papers, providing a summary and analysis of the findings. Based on recommendations made by scholars of neurocomputing and statistics, the review includes a set of comparison criteria as well as assesses how the research findings were validated. This work also identifies trends in the literature and highlights their main differences. Ultimately, this work points to underexplored issues for future research and shows ways to improve how the results are validated.

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Nomenclature

AFM	Abrasive flow machining
AISI	American Iron and Steel Institute
ANN	Artificial neural networks
ART	Adaptive resonance theory (a class of artificial network)
BP	Backpropagation algorithm
CNC	Computer numerical controlled
d	Depth of cut (mm)
DOE	Design of experiments
ECM	Electrochemical machining
EDM	Electrical discharge machining
f	Feed (mm/v)
F	Activation function in a multilayer perceptron
H	Total number of neurons in a layer of a multilayer perceptron
K	Number of radial units in a radial basis function network
LM	Levenberg–Marquadt algorithm
MAE	Mean average error
MLP	Multilayer perceptron
MSE	Mean square error
QN	Quasi-Newton algorithm
R_a	Average surface roughness (μm)
R_t	Peak-to-valley roughness (μm)
R_m	Maximum roughness (μm)
r	Tool nose radius (mm)
RBF	Radial basis function
RMSE	Root mean square error
RSM	Response surface methodology
R^2	Pearson coefficient
SOM	Self-organizing maps

SSE	Sum of square errors
u_h	Output of a neuron in a multilayer perceptron
v	Multilayer perceptron neuron output
V	Cutting speed (m/min)
w_0	Bias (or intercept) value in a multilayer perceptron
w	Synaptic weight
x	Input vector in a radial basis function network
ϕ	Activation function of radial unit in a radial basis function network
μ	Vector representing the hyper-center of a radial basis function
σ	Spread factor of a radial basis function

1 Introduction

Fierce competition and an increasingly demanding market signify today's manufacturing landscape. To remain competitive, according to Karpat and Özel [1], manufacturers must increase their productivity while maintaining, if not improving, product quality. Hitting this target is especially challenging in an industry where quality and productivity are typically conflicting objectives. An industry where such conflict is routine is modern machining. In the operation of turning, for example, Cus and Zuperl [2] note that production rate, cost, and product quality are three incompatible objectives. Moreover, as the machining industry welcomes the introduction of new materials and cutting tools, it finds itself undergoing a rapid development which is giving rise to processes of highly complex and nonlinear phenomena. Executing such processes, Singh and Rao [3] point out, constitutes an additional challenge for planning and optimization.

An important advantage in meeting this new challenge is being able to quickly acquire information on specific machining operations. When a key role in such operations is economy, Reddy and Rao [4] maintain that knowing the optimum machining parameters is vital. Researchers wanting to gather such knowledge have proposed using machinability models. For Paiva et al. [5], these models may be used as objective functions in optimization, simulation, control, and planning.

One area where machinability models have been extensively investigated is surface quality. Because of its impact on product performance [6, 7], surface quality in machining is an essential consumer requirement. Basheer et al. [8] affirm that characteristics of machined surfaces significantly influence its physical properties. According to Sharma et al. [9], new applications in various manufacturing fields like aerospace, automobile, and die and mold have fueled a rapid increase in the demand for products with high-quality finishes.

A surface quality indicator widely used is surface roughness [10, 11]. It plays a critical role, according to Öktem [12], in evaluating and measuring the quality of a machined product. For Öktem, the ability of a product to withstand stresses, temperature, friction, and corrosion is greatly affected by its roughness. In addition, roughness has an impact on properties like wear resistance, light reflection, and coating. Karayel [13] contends that the difficulty in controlling roughness is due to the intrinsic complexity of the phenomena that generates its formation. For these reasons, roughness modeling has become not just an especially defying business but an area of great interest for research.

Engineers involved with modeling of surface roughness have at their disposal a number of options. For a variety of reasons, one particular option has been largely investigated in the literature—the use of artificial neural networks (ANNs). ANNs, a paradigm of artificial intelligence, are claimed by El-Mounayri et al. [14] and Coit et al. [15] to have many attractive properties for modeling complex production systems. These include universal function approximation, resistance to noisy or missing data, accommodation of multiple nonlinear variables with unknown interactions, and good generalization capability. They are especially useful, according to Ezugwu et al. [16], for mapping complex relationships whose representation in analytical terms would otherwise be difficult. Among works on the subject, there are distinct strategies employed for data collection, model definition, model fitting, and validation of results obtained.

Applying ANNs for roughness prediction, however, is not without some reported shortfalls. In classifying quality prediction in high-speed milling processes, for example, Correa et al. [17] observed that Bayesian networks outperformed neural networks. In a study on waterjet machining, Çaydas and Hasçalik (2007) [18] found that a multiple regression model yielded slightly superior results for roughness prediction than did ANNs.

The present work tries to synthesize and analyze research efforts that utilize neural networks in off-line surface roughness modeling. The goal is to put forward a broad view of the strategies and problems that normally come up in the literature. The work provides a critical analysis of the current stage of research. Furthermore, by making use of recommendations from acknowledged scholars in neurocomputing science and statistics, the work discusses good practices.

The paper is structured as follows: Section 2 presents a review of surface roughness; Section 3 emphasizes historical aspects and main paradigms of ANNs; Section 4 reviews the conceptual framework around roughness

modeling via neural networks; Section 5 characterizes the analyzed papers and details the criteria adopted for the review; Section 6 reviews publications in terms of strategy and data collection techniques adopted; Section 7 analyzes the distinct model definition choices and the approaches used for finding suitable network configurations and for model fitting; Section 8 appraises how models are validated; finally, Section 9 presents the conclusions and points to directions for future research on the subject.

The authors hope that this bibliographic review is innovative in two ways: First, the means of modeling roughness are categorized, providing the reader a qualitative view of the distinct approaches adopted in each modeling phase; second, a guideline of good practices, based on recommendations from experts in the distinct research fields involved, is here assembled.

2 Surface roughness

Benardos and Vosniakos [11] define surface roughness as the superimposition of deviations from a nominal surface from the third to the sixth order where the orders of deviation are defined by international standards [19]. The concept is illustrated in Fig. 1. Deviations of first and second orders are related to form. Consisting of flatness, circularity, and waviness, these deviations are due to such things as machine tool errors, deformation of the workpiece, erroneous setups and clamping, and vibration and workpiece material inhomogenities. Deviations from third and fourth orders, which consist of periodic grooves, cracks, and dilapidations, are due to shape and condition of cutting edges, chip formation, and process kinematics. Deviations from fifth and sixth orders are linked to workpiece material structure and are related to physico-chemical mechanisms acting on a grain and lattice scale such as slip, diffusion, oxidation, and residual stress [11].

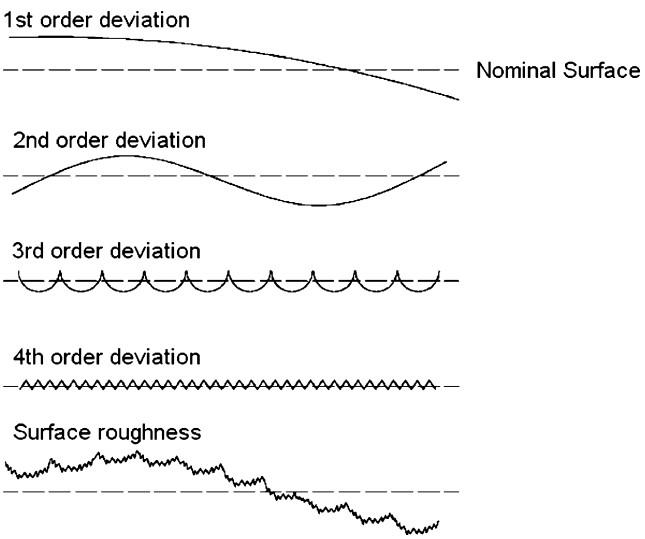

Fig. 1 Nominal surface deviations—adapted from DIN4760 [19]

Surface roughness, for Correa et al. [17], defines the functional behavior of a part. As pointed out by Oktem et al. [20] and by Chang and Lu [21], it plays an important role in determining the quality of a machined product. Roughness is thus an indicator, according to Pal and Chakraborty [22], of process performance and must be controlled within suitable limits for particular machining operations.

The factors leading to roughness formation are complex. Karayel [13] declares that surface roughness depends on many factors including machine tool structural parameters, cutting tool geometry, workpiece, and cutting tool materials. Erzurumlu and Oktem [23] assert that roughness is determined by the cutting parameters and by irregularities during machining operations such as tool wear, chatter, cutting tool deflections, presence of cutting fluid, and properties of the workpiece material. In traditional machining processes, Benardos and Vosniakos [24] maintain that the most influential factors on surface roughness are: mounting errors of the cutter in its arbor and of the cutter inserts in the cutter head, periodically varying rigidity of the workpiece cutting tool machine system wear on cutting tool, and formation during machining of built-up edge and non-uniformity of cutting conditions (depth of cut, cutting speed, and feed rate). The same authors claim that statistically significant in roughness formation are the absolute values of cutting parameters such as depth of cut, feed, and components of cutting force. Still, not only the enlisted factors are influential, according to Benardos and Vosniakos [24], but also the interaction among them can further deteriorate surface quality.

The process-dependent nature of roughness formation, as Benardos and Vosniakos [11] explain, along with the numerous uncontrollable factors that influence the phenomena make it difficult to predict surface roughness. The authors state that the most common practice is the selection of conservative process parameters. This route neither guarantees the desired surface finish nor attains high metal removal rates. According to Davim et al. [25], operators working on lathes use their own experience and machining guidelines in order to achieve the best possible surface finish.

Among the figures used to measure surface roughness, the most commonly used in the literature is roughness average (R_a). It is defined as the arithmetic mean value of the profile's departure from the mean line throughout a sample's length. Roughness average can be expressed as in Eq. 1 [26]:

$$R_a = \frac{1}{l_m} \int_0^{l_m} |y(x)| \mathrm{d}x \tag{1}$$

where R_a stands for roughness average value, typically measured in micrometers (μm), l_m stands for the sampling length of the profile, and $|y(x)|$ stands for the absolute measured values of the peak and valley in relation to the center line average (μm). According to the ISO:1302 4288:1996 [27] international standard, machining processes can achieve roughness values ranging from 0.006 to 50 μm,. For discrete measurement, surface roughness average can be defined as in Eq. 2 (ISO 4287/1, 1997) [26]:

$$R_a = \frac{1}{n}\sum_{i=1}^{n}|y_i| \tag{2}$$

where R_a is the roughness average, n stands for the number of samples in a given length, and $|yi|$ stands for the absolute measured values of the peak and valley in relation to the center line average. Correa et al. [17] point out that being an average value and thus not strongly correlated with defects on the surface, R_a is not suitable for defect detection. Yet they also proclaim that due to its strong correlation with physical properties of machined products, the average is of significant regard in manufacturing.

Benardos and Vosniakos [11], in a review on the subject, grouped the efforts to model surface roughness into four main groups: (1) methods based on machining theory, aimed at the development of analytical models; (2) investigations on the effect of various factors on roughness formation through the execution of experiments; (3) design of experiment (DOE)-based approaches; and (4) methods based on artificial intelligence techniques.

Equation 3 [28] offers an example of a theoretical model where R_a stands for roughness average (in μm), f stands for feed (in mm/rev), and r stands for tool nose radius (in mm).

$$R_a \approx \frac{0.032 \times f^2}{r}. \tag{3}$$

Such models, Sharma et al. [9] tell us, take no account of imperfections in the process, such as tool vibration or chip adhesion. In some cases, according to authors like Zhong et al. [29], Özel and Karpat [10], and others [29, 30], results differ from predictions.

Singh and Rao [3] describe experimental attempts to investigate the process of roughness formation. Using finish hard turning of bearing steel (AISI 52100), the authors study the effects of cutting conditions and tool geometry on surface roughness.

Empirical models are also employed for modeling surface roughness, generally as a result of experimental approaches involving multiple regression analysis or experiments planned according to DOE techniques. An example of this strategy can be found in Sharma et al. [9]. Cus and Zuperl [2] and Fang and Safi-Jahanshaki [31] proposed empirical models (linear and exponential) for surface roughness as a function of cutting conditions, as shown in Eq. 4:

$$R_a = c_o\left(V^{c1} f^{c2} d^{c3}\right). \tag{4}$$

In Eq. 4, R_a stands for roughness average. V, f, and d stand for cutting speed (m/min), feed (mm/rev), and depth of cut (mm), respectively. $c0$, $c1$, $c2$, and $c3$ are constants that must be experimentally determined and are specific for a given combination of tool, machine, and workpiece material. Fredj and Amamou [30] point to the fact that in many cases, regression analysis models established using DOE techniques failed to correctly predict minimal roughness values.

3 Neural networks

According to Haykin [32], ANNs are massive parallel distributed processors made up of simple processing units or neurons. These neurons have a natural propensity for storing and making available for use experiential knowledge. ANNs acquire knowledge from an environment through a learning process. They create a representation of this knowledge in the form of interneuron connection strengths, known as synaptic weights. Neural network processing, or neurocomputing, can be seen as a non-algorithmic form of computation; it constitutes one of the main branches of the learning machines field of research [32, 33].

ANNs have their roots in the initial forays into artificial intelligence. McCulloch and Pitts [34] outlined the first mathematical model of the neuron. Hebb [35] introduced the concept that learning is a process of adjusting synaptic weights. Among the first practical implementations were simple networks capable of performing some logical operations and classifying simple patterns—the perceptron [36] and the adaline [37]. These achievements introduced important concepts like network training and the delta rule for error minimization. Minsky and Papert [38] proved that perceptrons were incapable of solving linearly inseparable problems, a serious limitation that curbed scientific activity in the matter. Interest in neural networks was revived by the works of Hopfield [39] and Kohonen [40]. In 1986, the limitations revealed by Minsky were overcome by an algorithm introduced by Rumelhart et al. [41]—the back-propagation (BP) training algorithm. Since then, new ANN architectures and training algorithms have been investigated deeply, leading to huge developments in neurocomputing. In addition to that, neural networks have been successfully applied to solve a wide range of practical and complex problems in several distinct fields. These include pattern recognition, signal processing, chemical and biomedical

industrial processes, and in manufacturing operations like welding, molding, machining, and many others.

According to several authors [14, 15, 32, 42], there are two main motivations for solving problems using ANNs—to learn through example and to generalize learned information. What exactly does "to learn" mean? It is to adapt a neural network's parameters by training the stimuli embedded in the network's environment. "To generalize" is to produce coherent outputs of patterns unseen during learning [32].

There are two main paradigms of learning: supervised and unsupervised. For each of them, distinct training algorithms can be found. In supervised learning, a network is presented a set of patterns containing input values and the corresponding expected outputs; parameters are adjusted based on an error figure. In contrast, unsupervised learning networks are given no output values, only input. The network, by identifying statistic regularities of input data, forms internal representations; this process gives way to encoding features of inputs that allow its mapping of outputs [32]. As a result of learning, a neural network acquires knowledge of the underlying relationships between independent and dependent variables of a process.

Figure 2 shows the most commonly employed ANN architecture: a multi-layer perceptron (MLP) network. The ANN has three types of layers: the input, output, and the hidden layers. Each neuron on the input layer is assigned to an attribute in data and produces an output which is equal to the scaled value of the corresponding attribute. The hidden layers, usually numbering one or two, are intermediate between the input and output layers. Neurons on the hidden layer perform the scalar product of the neuron's input vector by the vector of weights associated to its inputs. The result of the scalar product is compared to a threshold limit. In case the limit is exceeded, the scalar product is used as an independent variable to an activation function whose output will be the neuron's output. Sigmoid functions are largely employed as activation functions,

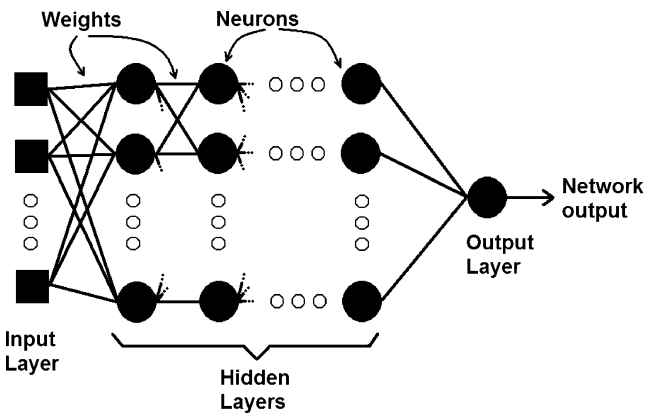

Fig. 2 Multilayer feedforward ANN structure

although linear Gaussian and hyperbolic functions are also utilized. The output layer sums up the resulting vector from the hidden layer, thus providing the network's overall outputs. Each layer consists of neurons, those in adjacent layers being fully connected with respective weights, while those in the same layer are not. Equation 5 shows a type of activation function found commonly in the literature.

$$f(z) = \frac{2}{(1+e^{-z})} - 1. \tag{5}$$

For each neuron in the hidden or output layer, the input–output transformation employed is defined as in Eq. 6:

$$v = F\left(\sum_{h=1}^{H} w_h u_h + w_0\right) \tag{6}$$

where v is the output of the neuron, 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), and F is the nonlinear activation function. Neurons on the output layer perform a weighted sum over the outcomes of the hidden layer to generate network outputs.

Another well-known architecture, proposed by Broomhead and Lowe [43], is the radial basis function network (RBF). In RBFs, the activation function is a radial basis function, a class of functions whose value increases or decreases with the distance to a central point. The argument of such a function is basically a Euclidean norm (a distance) between vectors. One such function commonly employed in RBFs is the Gaussian function shown in Eq. 7 [44]:

$$\phi_i(\mu) = -\exp\left(\frac{\|x-\mu_i\|^2}{2\sigma^2}\right) \tag{7}$$

where x corresponds to an input vector, μ_i is a vector corresponding to the hyper-center of function ϕ_i, and σ is a spread factor for that function. In a RBF network having K radial units in the intermediate layer and one output, this is given by Eq. 8 [44]:

$$y = \sum_{i=1}^{K} w_i \phi\left(\|x-\mu\|^2\right) + w_0 \tag{8}$$

where x and μ are defined as in Eq. 7, ϕ represents the activation function of the radial units, as the Gaussian function represented by Eq. 7, 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. According to Bishop [33], RBFs are suitable for performing a series of tasks, among which is the approximation of functions. The training of RBF networks, which include both supervised and unsupervised learning, is hybrid.

4 Surface roughness modeling with ANNs

The use of ANNs in machining applications, according to Sick [45], can be grouped into online and off-line approaches. Online approaches, in order to collect modeling data, fit sensing devices to the machine. Networks are trained in real time using process parameters measured by sensors and results are employed in time-critical tasks. In the off-line approach, experimental data, historical data, or previously collected sensor data are used to train the network in order to build models for use in process planning or optimization purposes.

The potential of ANNs for use in machining processes was perceived during the 1990s. In order to predict tool life in turning gray cast iron with cutting tools of mixed oxide ceramic type, Ezugwu et al. [46] used results from experiments involving distinct cutting speed and feed values to train an MLP. Chao and Hwang [47] performed a similar study. Early works on surface roughness modeling can be found in Chien and Chou [48] where, in the process of turning of a 304 stainless steel, networks predict surface roughness, cutting force, and tool life. Tsai and Wang [49] compared distinct ANN structures for prediction of surface roughness in electrical discharge machining (EDM). Using data obtained from experiments conducted on a computer numerically controlled (CNC) milling machine and planned according to DOE techniques, Benardos and Vosniakos [24] trained a neural network to predict surface roughness.

The notion of using ANNs in machining processes has yielded a considerable number of papers. In many of them, researchers argue for their use. Davim et al. [25] maintain that neural networks are able to capture the characteristic nonlinearity of turning. Karpat and Özel [1] speak of the difficulty of generating, in hard turning, explicit analytical models of the complex relationship among the parameters involved. Neural networks, according to the authors, pose a suitable and practical option for modeling. Results obtained by Özel et al. [50] show that neural network models are able to predict, for a range of cutting conditions, tool wear and surface roughness patterns; moreover, for hard turning, they can be utilized in intelligent process planning. Oktem et al. [20], using data obtained experimentally, trained an MLP according to the BP algorithm for roughness prediction. The authors reported that results were excellent.

More examples can be found in the work of Assarzadeh and Ghoreishi [51], aimed at optimizing the surface roughness in EDM using neural networks. The authors declared the effectiveness of using the MLPs for the prediction of material removal rate and R_a. In Hossain et al. [52], an ANN model was developed for the investigation and prediction of the relationship between cutting parameters and surface roughness during high-speed end milling of nickel-based Inconel 718 alloy. A very good predicting performance of the neural network was observed. Other approaches include the work of Panda and Mahapatra [53] in which principal components were used for modeling of drill wear. The principal components of drilling parameters were calculated and networks were trained to predict them. Networks were able to classify low wear and high wear within an accuracy of 90% and to predict the drill flank wear within ±6.5% error.

The use of ANNs in online control of machining operations is the subject in Gao et al. [54] where they are applied for mapping relations between tool condition and features extracted from distinct sensor signals by using experimental data. Huang et al. [55] applied ANNs for the adaptive surface roughness control in end milling operations. For those authors, off-line, manual techniques to assess surface roughness and part quality are costly and time-consuming, which favors the use of neural networks. The same conclusion can be found in Nalbant et al. [56] who sustain that ANNs are a good alternative to conventional empirical modeling based on linear regressions for surface roughness modeling.

It must be stated, however, that there is no consensus on the experience with neural networks for surface roughness modeling. Authors like Dhokia et al. [57] point to the lack of systematic design methods for neural networks as a disadvantage. For Cervellera et al. [58] and for Karnik et al. [59], finding a good ANN architecture requires several modeling attempts, making it a time-consuming activity. Ambrogio et al. [7] testify of the need for large amounts of data for training and validation; such a need limits the practical application of neural networks in machining processes. More computational effort is required, according to Bagci and Işik [60], to build an artificial neural network model than other methods.

In fact, the effective design of ANNs is a defying problem even in neurocomputing domain, as stated in Zanchettin et al. [61]. The authors proposed a DOE-based scheme for the identification of the most influential factor on the performance of a neuro-fuzzy inference system. Examples of optimization attempts can be found in the work of Mohana Rao et al. [62] aimed at modeling surface roughness of die sinking EDM using neural networks. Genetic algorithms were used in their research to optimize the weight factors of the network. Ortiz-Rodrigues et al. [63] proposed the use of the Taguchi methods (a DOE technique) for robust design of MLPs trained by back-propagation algorithm and develops a systematic and experimental strategy which emphasizes simultaneous optimization artificial neural network's parameter optimization under various noise conditions.

An analysis of the literature reveals that most of the studies follow common steps like problem delimitation, definition of an experimental strategy, data collection,

choice of a network architecture and topology, network fitting by means of training, data analysis, network selection, and some kind of validation of results. This sequence closely resembles, as seen in Fig. 3 [64], the forecasting and modeling conceptual activities enlisted by Montgomery et al. [64] and Montgomery and Runger [65] for multiple regression analysis and time series forecasting models.

For those authors, the development of models for forecasting must follow a well-defined set of steps. The first step, as seen in Fig. 3, is the problem definition which comprises the specification of what will be forecasted, the independent variables to be used as predictors, and also the definition of how users expect to use the resulting model. The following step is the data collection which includes the techniques employed to collect valid and representative data from the process. Data analysis refers to the treatment applied to collected data in order to convert it in useful information. As the behavior of a model is defined by its free parameters, it is necessary to perform model selection and fitting. Model fitting corresponds to the adjustments made on model parameters to ensure maximum accuracy and precision and to the techniques applied in the search for optimal parameters. Model selection is related to the rules employed to decide in favor of a given parameter configuration. The final step in this framework is model validation where a model shall be applied to forecast new cases, not included in selection and fitting, to provide an independent measure of the model quality. For every aforementioned step, the mentioned authors strongly recommend the use of statistical techniques to ensure the development of useful and reliable models.

In fact, the result obtained when ANNs are employed to model surface roughness is a semi-parametric model [66], that is, a model where roughness is represented not only in machining terms but also in terms of the network architecture selected, network configuration parameters (such as the number of hidden layers, the number of neurons, and the activation functions employed), and of the training strategy adopted. As with any other kind of model, an ANN model is required to have a well-defined accuracy, precision, and associated confidence levels. Those characteristics are essential in order to ensure model quality and to grant model acceptance in production floor environments. In order to achieve such desirable characteristics, some good practices have to be observed during model elaboration and validation activities. These practices are related to the observance of neurocomputing and statistical principles. It is under this conceptual framework that the research works this study focuses on are reviewed.

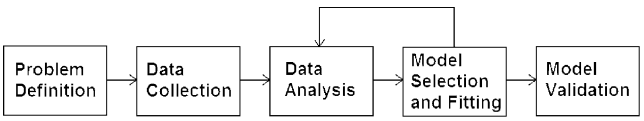

Fig. 3 Forecasting process—adapted from Montgomery et al. [64]

The review begins by specifying the criteria employed for the selection of papers. A characterization will be done in terms of date of publication and specific machining process dealt with by the publications. In the sequence, the studies will be classified and analyzed in regard to the following modeling aspects, derived from Montgomery's [64] conceptual framework:

- Problem definition and data collection
- Model selection and fitting
- Model validation

Together with the qualitative classifications, comments are included in order to highlight good practices or to identify opportunities for improvement in research. As a way of giving insight into possibilities for future research, modeling ideas from other domains are also introduced when applicable.

5 Characterization of reviewed works

The search for papers was conducted using scientific resource bases, such as Elsevier, Springer, Taylor and Francis, Emerald, and others. Publications were chosen for evaluation if they matched the following requirements:

- focused on surface roughness prediction in machining processes
- made use of neural networks as modeling technique
- adopted an off-line approach to fit network models

Based on these criteria, 45 publications were selected and reviewed. Figure 4 depicts their chronological distribution. The figure shows that off-line roughness prediction in machining by means of ANNs has attracted a sustained interest from researchers. In fact, from 2005 to 2008, there was an increase in the number of papers published on the subject (the survey was conducted during the first quarter of 2009).

Table 1 synthesizes distinct options taken by authors along reviewed papers. The table shows specific network architectures adopted in each paper as well as the number of inputs and outputs of the networks. The first column contains the number of the reference as seen in the "References" section. The use of cutting speed, feed, and depth of cut as inputs for prediction is also detailed. In addition to that, the table specifies the roughness measurement figures employed. Information is provided on the

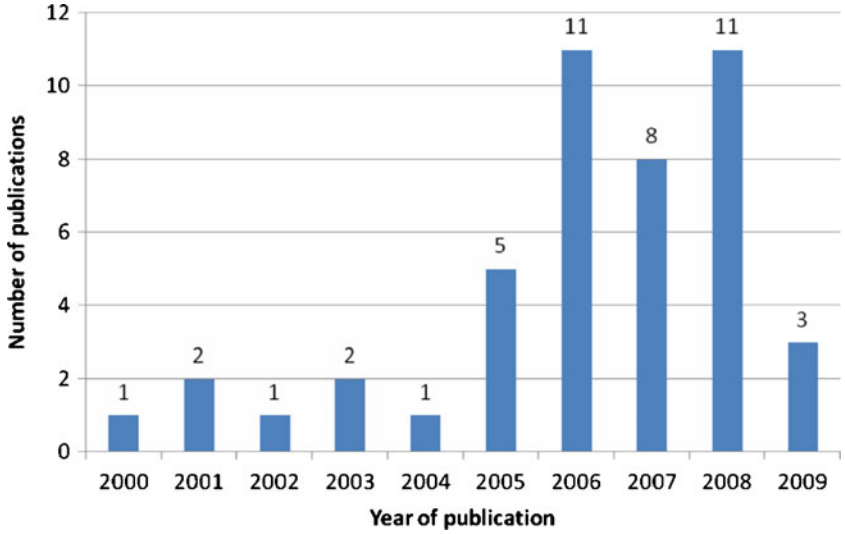

Fig. 4 Yearly distribution of reviewed publications

training algorithm used (for works using MLPs), on the use of distinct sets for training and selection, on the use of a third validation set, and on the figure adopted to measure network accuracy in each study.

Figure 5 displays the specific machining processes investigated along selected publications. Thirty-six out of the 45 works deal with conventional machining processes, including turning [2, 8–10, 13, 16, 22, 25, 29, 42, 48, 50, 60, 67–72], milling [12, 17, 20, 21, 23, 24, 57, 73–78], drilling [79, 80], and grinding [30]. The remaining papers are focused on EDM [49, 81–84], abrasive flow machining (AFM) [85, 91], electrochemical machining (ECM) [86], micro-end milling [87], and waterjet machining [18].

Accounting for about 42% of the total works reviewed, turning was the process most studied. The same was observed by Sick [45] in his review about tool condition monitoring. Among selected publications dealing with turning is the work of Karayel [13] where a neural network model is proposed for the prediction and control of surface roughness in a CNC lathe. Davim et al. [25] developed surface roughness prediction models using networks of MLP architecture to investigate the effects of cutting conditions, using cemented carbide tools, in the turning of free machining steel, 9SMnPb28k(DIN). In Basheer et al. [8], an artificial neural network model is employed to predict the surface roughness on Al/SiCp composites.

There are also applications in hard turning. This process became possible due to new cutting tool materials, such as cubic boron nitride and ceramics [3]. Hard turning behaves differently from ordinary turning [1]. Quiza et al. [88] maintain that traditional regression methods present severe limitations for hard turning applications due to the extreme nonlinearity that characterizes the process and to the use of modern tool materials. This seems to favor the use of ANN in such a process. An example can be found in Özel et al. [50] in which neural networks were used to investigate the influence of cutting parameters on tool flank wear and surface quality in hard turning of AISI D2 steel (60 HRC) using ceramic inserts with wiper (multipoint radius) nose geometry.

Accounting for another 28% of the publications reviewed is milling process. Öktem [12] conducted a study on surface roughness to model and optimize the cutting parameters in end milling process of AISI 1040 steel material with TiAlN solid carbide tools under wet conditions. The work of Bruni et al. [75] aimed at building predictive models for surface roughness in the finish face milling process of AISI 420 B stainless steel. Examples of applications involving other conventional material removal processes can be found in Tsao and Hocheng [80] who made use of networks to predict the thrust force and surface roughness of candlestick drill in drilling of composite materials and in Fredj and Amamou [30] who proposed the use of ANNs for roughness prediction in grinding processes.

Other reviewed applications include machining of non-metallic materials. Dhokia et al. [57] focused on the machining of soft materials, as polypropylene. Their work was directed to create a model and to find optimal cutting conditions for roughness minimization. In Bagci and Işik [60], an ANN is employed for the estimation of surface roughness in the process of turning unidirectional glass fiber-reinforced plastic composites.

ANNs have been employed for roughness prediction in non-conventional machining processes as well. Markopoulos et al. [82], Mandal et al. [84], and Sarkar

Table 1 Summary of network usage decisions taken along reviewed works

Reference	ANN	Input	Cutting speed	Feed	Depth of cut	Outputs	Figure	Algorithm	Distinct sets	Validation set	Error
2	MLP/RBF	3	X	X	X	3	R_a	BP	Yes	No	None
8	MLP	5		X	X	1	R_a	LM	Yes	No	MAE(%)
9	MLP	4	X	X	X	4	R_a	BP	Yes	Yes	MSE
10	MLP	7	X	X		1	R_a	LM	Yes	No	RMSE
12	MLP	4	X	X	X	1	R_a	BP	Yes	No	RMSE
13	MLP	3	X	X	X	1	R_a/R_{max}	BP	Yes	Yes	MAE(%)
16	MLP	4	X	X	X	1	R_a	LM	Yes	Yes	Correlation
17	MLP	6		X	X	1	R_a	BP	Yes	No	Proportion
18	MLP	5				1	R_a	BP	No	No	MAE(%)
20	MLP	5	X	X	X	1	R_a	Unclear	Yes	No	MAE(%)
21	Other	6	X	X	X	1	R_a	NA	Yes	No	MAE(%)
22	MLP	5	X	X	X	1	R_a	BP	Yes	No	MSE
23	MLP	5	X	X	X	1	R_a	Unclear	Yes	No	MAE(%)
24	MLP	8+	X	X	X	1	R_a	LM	Yes	Yes	MSE
25	MLP	3	X	X	X	2	R_a/R_t	BP	Yes	No	MAE(%)
29	MLP	7		X	X	2	R_a/R_t	BP	Yes	Yes	MAE(%)
30	MLP	8+	X		X	1	R_a	BP	Yes	No	unclear
42	MLP	4	X	X	X	3	R_a	BP	No	No	MAE(%)
48	MLP	3	X	X	X	Unclear	R_a	BP	Yes	No	MAE(%)
49	MLP/RBF	Unclear				1	R_a	BP	Unclear	No	MAE(%)
50	MLP	6	X	X		1	R_a/R_t	LM	Yes	No	None
57	MLP/RBF	3	X	X	X	1	R_a	LM	Yes	Yes	MAE(%)
60	MLP	3	X	X	X	1	R_a	BP	Yes	No	MAE(%)
67	MLP	3	X	X	X	4	R_a	BP	Yes	No	None
68	MLP	4	X	X	X	1	R_a	BP	Yes	Yes	MAE(%)
69	RBF	4	X	X	X	1	R_a	NA	Yes	Unclear	MAE(%)
70	MLP/RBF	3	X	X	X	Unclear	R_a	Unclear	Yes	No	None
71	MLP	3	X	X	X	1	R_a	New	Yes	No	MAE(%)
72	MLP	3				1	R_a	BP	Yes	No	MAE(%)
73	RBF	4	X	X	X	1	Unclear	NA	Yes	No	None
74	MLP	3				3	Unclear	BP	Yes	No	None
75	MLP	8+	X			1	R_a	BP	No	No	Unclear
76	MLP	5	X	X	X	1	Fractal Para	LM	Yes	Yes	R2
77	MLP	4	X	X	X	1	Binary clas	QN	No	No	None
78	MLP	4	X	X	X	1	R_a	New	Unclear	No	MAE(%)
79	MLP	3	X	X		1	R_a	BP	No	No	None
80	RBF	4	X	X	X	2	R_a	NA	Yes	No	MAE(%)
81	MLP	3				2	R_a	LM	Yes	No	MAE(%)
82	MLP	3				1	R_a	BP	Yes	Yes	None
83	MLP	6				3	R_a	BP	Yes	No	MAE(%)
84	MLP	3				3	R_a	BP	Yes	No	MAE(%)
85	RBF	4				2	R_a	NA	Yes	No	MAE(%)
86	MLP	4				2	R_a	Unclear	Yes	No	MAE(%)
87	MLP	4	X	X	X	1	R_a	BP	Yes	No	MAE(%)
91	Other	2				2	R_a	NA	Yes	No	None

et al. [83] proposed neural models for the prediction of surface roughness in EDM. Being an already established technology in the tools and dies industry, EDM is still one of the expertise-demanding processes in the manufacturing industry [82]. Another example is the work of Mollah and Pratihar [85] which employed RBF networks for modeling input–output relationships in abrasive flow machining processes.

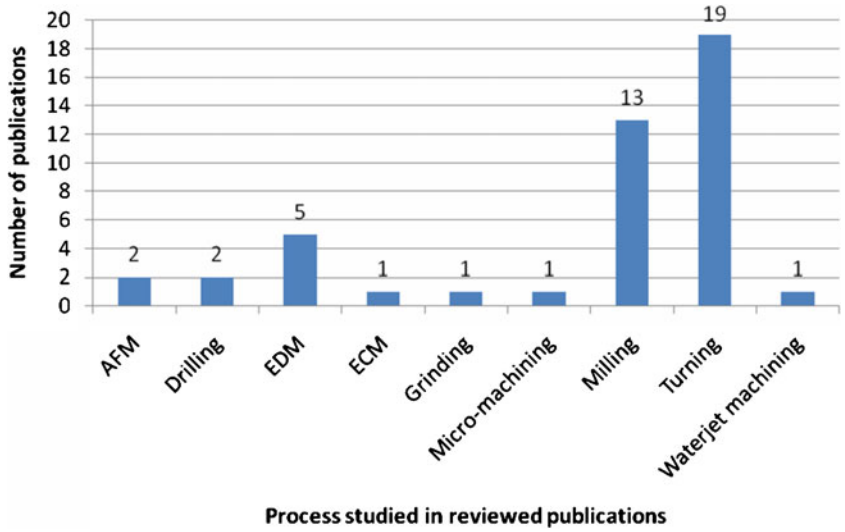

Fig. 5 Machining processes studied in reviewed publications

6 Problem definition and data collection

The initial steps for model elaboration, as set out by Montgomery et al. [64], are problem definition and data collection. Problem definition comprises the specification of what is to be modeled, the strategy to be employed, and the understanding of how users expect to employ the resulting model. Data collection includes the selection of predictor variables and the techniques used to obtain relevant data to be used in building the model.

The problem in question along the reviewed papers is the use of ANNs as a modeling tool for the estimation or classification of surface roughness prediction in machining. Process parameters are typically used as independent variables. The usual expectation is to obtain models presenting smaller errors in prediction than from other methods. Davim et al. [25] sustain that RSM-based models are restricted to a small range of input parameters and hence not suitable for highly complex and nonlinear processes.

Applications of ANN models in conjunction with other tools are common. The motivation for the use of hybrid approaches is to obtain results superior to those obtained separately by any of the techniques involved. This is observed in Öktem [12] where a genetic algorithm was employed to explore the ANN roughness model in a search for combinations of cutting parameters able to deliver the smallest surface roughness. The same approach is observed in Tansel et al. [87]. Other examples of such a strategy are the works of Mollah and Pratihar [85], Oktem et al. [20], and also Gao et al. [89] where an artificial neural network and a genetic algorithm are used together for the optimization of an EDM process.

Eighteen papers compare models obtained from ANNs to those elaborated using other techniques, such as multiple regression analysis or response surface methodology. Out of this number, network models, in ten publications, are considered to be superior. Examples can be found in Tsao and Hocheng [80], Asokan et al. [86], and Çaydas and Hasçalik [18]. Al-Ahmari [42] conducted statistical tests to establish the difference in performance between distinct models. The author concluded that the neural network was superior. The performance of ANN models, in six works, is deemed as equal. In two articles, the alternative method outperformed the neural model. This was the conclusion obtained by Correa et al. [17] where neural networks were compared to Bayesian networks (a machine learning classification method) for the prediction of surface roughness in high-speed machining.

Comparisons between distinct types of networks are performed in six publications [2, 48, 49, 57, 69, 86]. In Dhokia et al. [57], the authors compared the performance of two distinct network architectures, MLPs and RBFs. Their conclusion, based on hypothesis tests, is that RBF networks outperformed MLPs. Sonar et al. [69] made the same comparison. In that study, the MLPs were superior to the RBFs. Tsai and Wang [49] compare six network configurations including MLPs and RBFs trained by distinct algorithms. Error in validation and the Pearson coefficient (R^2) were used to express the results. Although a lot of data are presented, the article points to no clear winner. It must be pointed out that both MLPs and RBFs possess properties of universal function approximation [90]. As a consequence, there will always be a topology of one type capable of emulating the performance of a network of another type. Hence, instead of focusing on architecture comparison, research efforts should be concentrated in other directions, such as network optimization.

Less usual approaches can be found as well. El-Sonbaty et al. [76] developed ANN models for the analysis and

prediction of the relationship between the cutting conditions and the corresponding fractal parameters of machined surfaces in face milling operations. In the work of Balic [74], roughness is actually an input of an MLP network trained to predict optimal cutting conditions as outputs for process planning purposes.

The next step, after defining the problem to be treated and adopting the research strategy, is collecting data to be used to train and test the network. One must initially define the number and nature of the independent variables (or predictors) to be employed. This is an important issue in ANN modeling. The set of inputs shall ideally include all variables of significance for roughness prediction. At the same time, though, neurocomputing authors like Haykin [32] recommend the use of a minimal set of uncorrelated inputs for best modeling. Figure 6 displays the number of predictors among the 45 reviewed papers.

There is a range of inputs. The minimum observed is two [91]. In three papers [24, 30, 75], more than eight are employed. A useful example, taken from the area of tool life prediction, is the work of Chao and Wang [47]; by analyzing and removing correlated or irrelevant inputs, they proposed a method of reducing the dimensionality of inputs for predicting cutting tool life in turning.

Virtually all works reviewed (43 out of 45) clearly define the nature of predictors employed. In only two cases, actual inputs cannot be identified, although the texts suggest they were based on cutting parameters. Figure 7 shows the number of times a given input appeared among the 36 papers dealing with conventional machining processes. It can be observed that cutting conditions (cutting speed, feed, and depth of cut) are by far the most employed roughness predictors, as for instance in Karayel [13], Öktem [12], Dhokia et al. [57], and Bagci and Işik [60]. Although less frequently, other process parameters are also employed as model inputs. Tool radius, for example, is one of the factors investigated by Al-Ahmari [42]. Sanjay and Jyothi [79] utilize drill diameter along with cutting conditions in drilling as a predictors. Rake angle is adopted as an input by Zhong et al. [29]. Worth mentioning also is that in only three publications is tool wear information employed as an input; this is in spite of many authors considering it an influential parameter in roughness formation [1, 21, 92].

Inputs appearing only once among the papers were grouped under the label "Others." Those inputs include size and volume of tool reinforcements, dressing depth, number of passes, tool insert grades, workpiece material, coolant pressure, cutting edge geometry, lubrication condition, and cutting length.

Papers dealing with non-conventional machining processes make use of process-specific information for modeling. Markopoulos et al. [82] employed pulse current, pulse duration, and kind of processed material for the prediction of roughness in EDM. Five steel grades were tested and the remaining factors varied over a wide range, from roughing to near-finished conditions. The model for EDM proposed by Sarkar et al. [83] employed pulse time on, pulse time off, peak current, wire tension, dielectric flow rate, and servo reference tension as inputs. In Asokan et al. [86], current, electrical tension, flow rate, and gap are considered as inputs for roughness prediction in electrochemical machining.

Twenty-seven works justify their choice and range of inputs. In some works, inputs are selected based on previous machining studies, while in others, no justification at all is presented. In [20] for instance, the range for cutting parameters is defined by the limits fixed by the tool manufacturer. In four studies [10, 24, 30, 67], distinct sets of predictors are used in the search of the best set to build the model. An example of such a strategy can be seen in

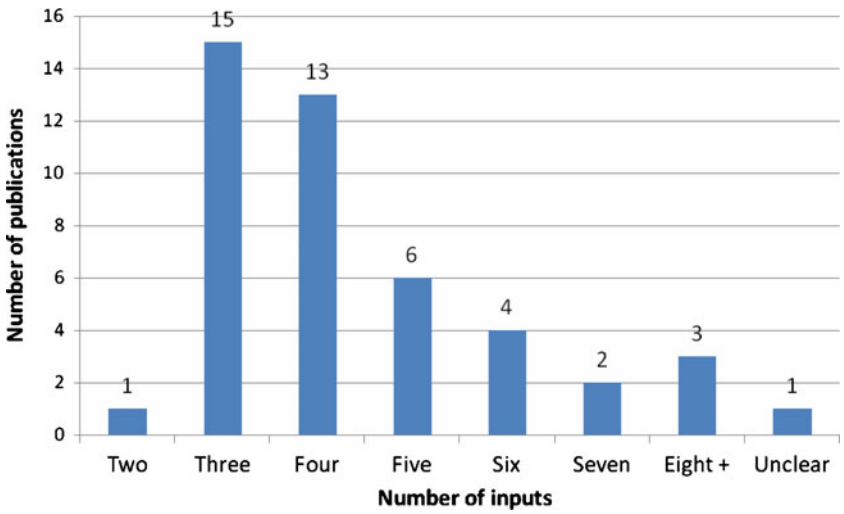

Fig. 6 Number of predictors employed as network inputs

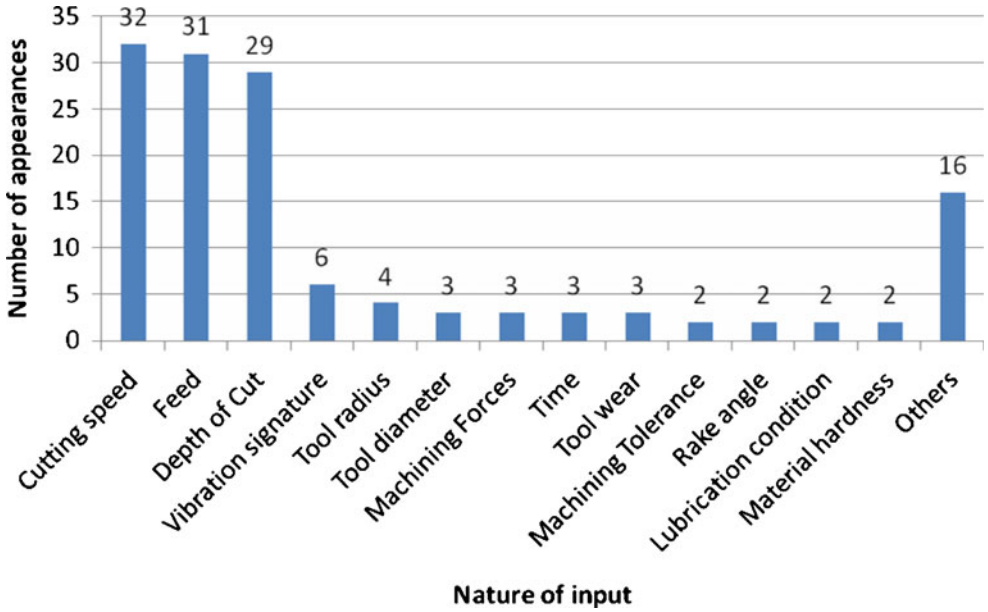

Fig. 7 Nature of predictors employed in model building

Benardos and Vosniakos [24] who employed a Taguchi arrangement (a DOE technique) to select the inputs for roughness prediction in the CNC face milling process.

Another issue in data collection is the technique adopted for collecting training data. Five distinct approaches can be found among the works reviewed, as seen in Fig. 8.

In over a third of the publications (17), the training set is built from results of experiments planned and executed according to DOE techniques. Examples are found in Öktem [12] who uses results from a full factorial experimental arrangement. Çaydas and Hasçalik [18] employed the results of a Taguchi arrangement. About a fourth of the papers (11) employ arrangements resembling those of experimental designs. No explicit mention, however, is made of this methodology nor indication given, as for instance in [13], that DOE principles were followed in the execution of the experiments. In some works, the actual arrangement is only suggested, not shown explicitly. For instance, [20] uses a remarkable set of 243 examples collected from cutting experiments. Close to a third of the publications (13) formed the training set with data obtained from non-DOE techniques. Chien and Chou [48] employed experimental results obtained from 96 test points randomly selected between cutting condition limits established. In two papers, training examples were generated by simulations, and in two others, textbook equations were employed. DOE is prevalent in data collection mainly because many papers compare neural and multiple regression models obtained as a result of DOE techniques. Then, in an attempt to provide a common base for comparison between the two approaches, the same data are employed for training networks.

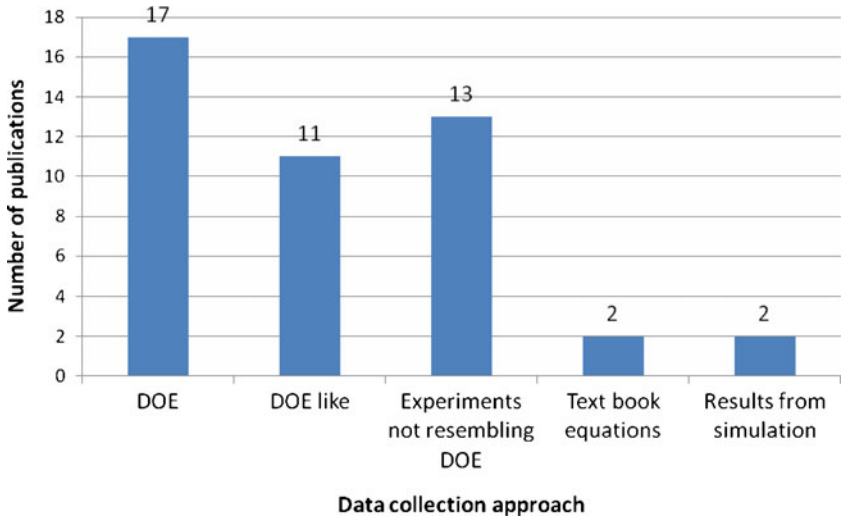

Fig. 8 Approach adopted to build neural network training sets

Whether or not it is convenient to use DOE techniques to form training sets is an open question. None of the papers reviewed assess the influence of data collection techniques on the performance of models. Would another approach lead to better results, or to the same results with a smaller number of experimental runs? Yet another point not sufficiently explored is how efficiently the data from ANNs is used compared to other approaches. Only Kohli and Dixit [68] investigate the number of cases required to produce an accurate model for a given machine–tool–workpiece combination. Their work proposes a method of establishing the minimum number of training cases required, in roughness modeling, for a good performance of networks. Two issues that could receive more attention in future research are the number of cases required to build a model of certain precision and the influence of the technique adopted to collect data.

Another classification can be made in regard to the nature and number of model outputs. Figure 9 shows the number of network outputs employed among reviewed publications. For the most part, networks of only one output are employed.

Figure 10 summarizes the nature of neural network outputs in use. Roughness average is employed to measure surface roughness in 41 works, accounting for about 90% of the total. In addition to roughness average, neural networks are commonly applied to predict some other parameters of interest. An example can be found in Davim et al. [25] who developed ANN models to predict peak-to-valley roughness (R_t). As a measure of the process performance, Mandal et al. [84] consider material removal rate, tool wear, and surface roughness. Sarkar et al. [83] proposed a model for the EDM process that adopted as model outputs cutting speed, surface roughness, and wire offset.

Outputs appearing only once were grouped together under the label "Others." Those outputs include maximum roughness, ten point average roughness, depth of cut, wire offset (in EDM process), fractal parameters, production rate, cost, power consumption, tool wear rate, and machining time.

7 Model selection and fitting

Model selection and fitting consist of choosing one or more forecasting techniques and estimating model parameters in order to fit it to data [64]. After data are collected, it is necessary to select, or specify, the neural network to be used. Network designers choose the learning paradigm to be employed as well as the network architecture and the neuron activation function to be used. The concept of fitting, for its turn, when applied to ANNs, corresponds to the definition of a suitable network topology, to the training it will be submitted to learn the relationship between inputs and outputs, and to the data analysis conducted to establish model fitness.

Researchers have at their disposal several options for model selection. The first step is the definition of the learning scheme and of the architecture to be used. Figure 11 shows the number of times a given ANN type appears among publications reviewed. Because some papers employ more than one type of network in order to compare their performances, the total number of appearances exceeds 45.

Figure 11 reveals that networks of MLP architecture, found in 39 works, are used in the vast majority (87%) of the papers. RBFs are adopted in eight publications (around 18%). It is remarkable that among papers reviewed, networks of unsupervised learning paradigms are scarcely

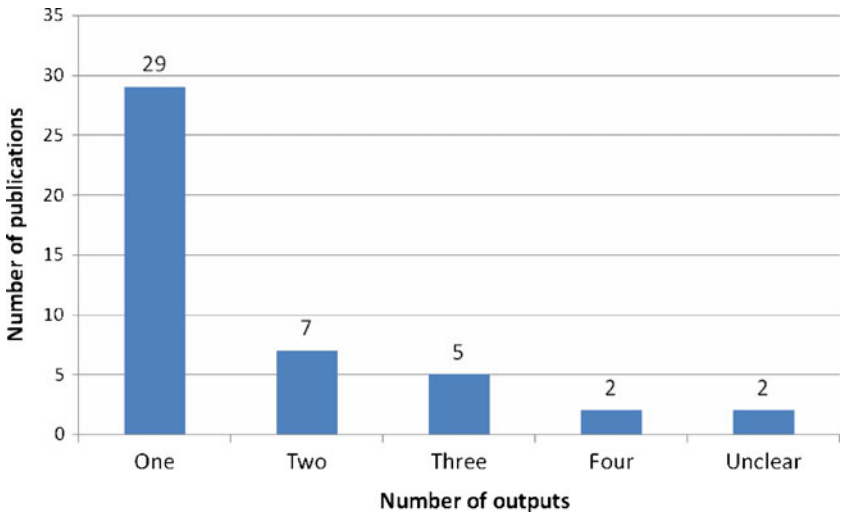

Fig. 9 Number of network outputs along reviewed publications

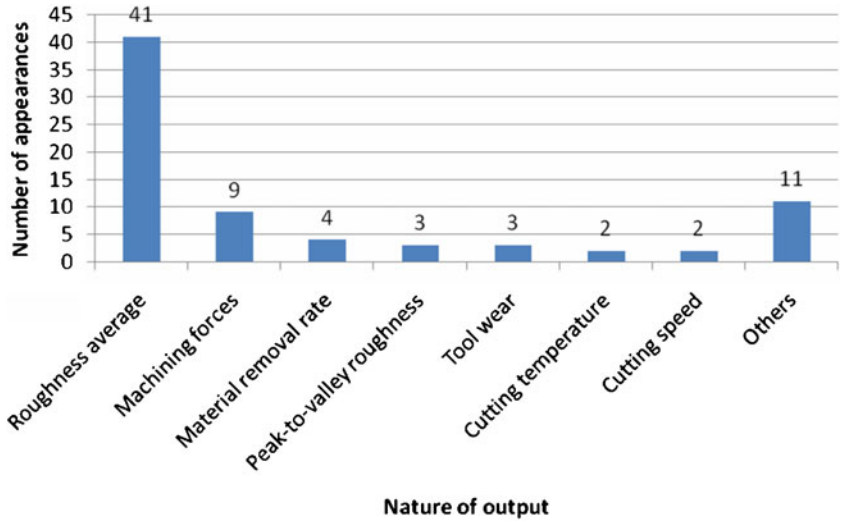

Fig. 10 Nature of network model outputs along reviewed publications

employed. While the use of MLPs and RBFs (examples of supervised and hybrid learning paradigms, respectively) is widespread, only three publications employ unsupervised learning networks. An example can be found in Balic [74] where self-organizing maps (SOM) [40, 93] are employed as part of a bigger network array to generate part programs for milling and drilling on machining centers. Polynomial networks [94], another type of unsupervised learning network, are proposed for roughness modeling by Chang and Lu [21] and Ali-Tavoli et al. [91]. For data clustering in situations where classes are unknown, neurocomputing theory recommends unsupervised networks. Remaining an underexplored branch of the literature is the applicability of unsupervised network paradigms, for roughness classification, in special architectures such as SOM or ART (adaptive resonance theory networks) [95, 96].

Regarding the activation function in use with networks of MLP architecture, 11 publications make exclusive use of the hyperbolic tangent sigmoid function. Seven papers choose to use the logistic sigmoid function. Two papers compare their effect on network accuracy and 19 publications make no mention of the activation function in use. Although there is no evidence of difference in performance linked to the activation function employed in MLPs, Haykin [32] affirms that the hyperbolic tangent function, due to its symmetrical shape, can lead to a faster convergence in training. Publications working with RBF architecture make explicit use of Gaussian function, as seen in [49, 69, 80, 85] or do not specify the activation function employed.

After the neural network model is selected, its parameters must be fitted. Once again, many options are available

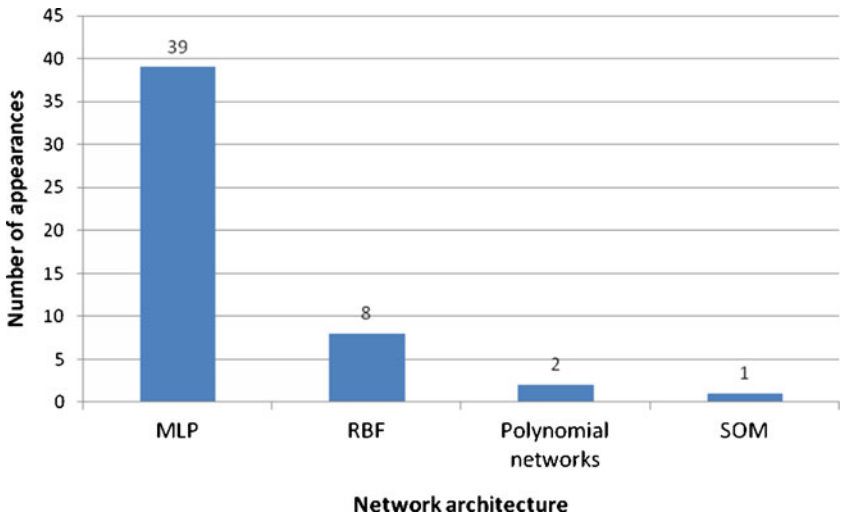

Fig. 11 Number of appearances of distinct network architectures along reviewed publications

in terms of topology definition, learning algorithms, training strategies, and fitness evaluation.

Topology definition is the most frequently reported problem. Authors involved with roughness prediction with ANNs repeatedly cite a disadvantage being the lack of systematic procedures to efficiently design networks. Correa et al. [17] declare, "There are no principled methods of choosing the network parameters (number of hidden layers, number of nodes in the hidden layers, form of activation functions)." Similar observations are found in Dhokia et al. [57] and Zhong et al. [29]. The choice of suitable design parameters is essential to a well-performing network. It is therefore important to analyze how the issue is dealt with. The treatments given to network topology definition along the reviewed publications are summarized in Fig. 12.

As seen in Fig. 12, six distinct approaches can be found. Trial and error, the most common approach, shows cause for complaints about the lack of systematic design procedures. It is employed in 19 papers (about 42% of the total), as for instance in [13], for MLPs, and in [69] and [80] for RBFs.

Authors propose their own methods for topology definition in four publications. In Jesuthanam et al. [78], a genetic algorithm was used for choosing optimized initial weights to be given as inputs to a particle swarm optimization algorithm, which was in turn used for searching optimal synaptic weights. The weights were applied to the neural network and the average error compared to the expected result. The cycle was repeated until a best fit was observed. Tansel et al. [87] applied genetic algorithms in the search for optimized network topologies for predicting machining parameters (roughness included) in micro-machining operations. Sharma et al. [9] offers a rather odd approach where the subject of optimization is the number of training epochs itself. It resulted in poor results of roughness prediction.

Four studies attempt to optimize network parameter using a "one-at-a-time" strategy in which factors are varied individually: Mollah and Pratihar [85], who employed RBF networks for modeling in AFM, Mandal et al. [84], Fredj and Amamou [30], and Kohli and Dixit [68].

In three other papers, optimization is only mentioned, but actual optimization procedures are not detailed. Seven papers present only the "best" topology; configuration parameters such as number of hidden layers, number of neurons in hidden layers, or training algorithms are fixed with no justification. Finally, in eight publications, not even the best topology is presented.

Some observations can be made about this topic. Given the impact of network topology on the overall model performance, the fact that networks are designed by trial and error in almost half of the publications suggests that roughness models obtained in those studies can be far from optimal. The same can be said about models presented with no objective evidence of optimization. "One-at-a-time" strategies are not ideal for network design either; they can lead to suboptimal solutions and are unable to detect interactions among design factors involved [65]. The worst situation, however, happens in those cases where not even the best topology is presented. This absence thwarts any possibility of reproducing the results and renders useless the conclusions obtained.

In order to take advantage of the full potential of ANNs for modeling, more effort should be spent on efficient network design. A deeper understanding of neurocomput-

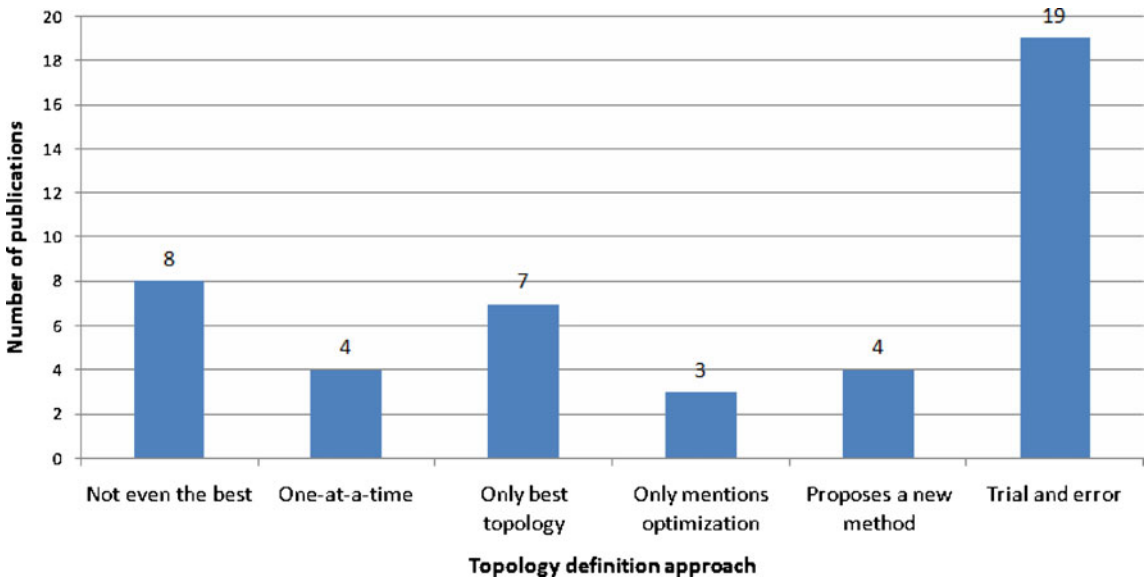

Fig. 12 Topology definition approaches adopted along reviewed publications

ing principles is required for this task. One interesting example on the subject, from another field of research, are the works of Balestrassi et al. [97] and Queiroz et al. [98] who successfully employed the DOE methodology in the design of MLP networks for time series forecasting in applications related to the electric energy sector. In Guimarães et al. [99] and Guimarães and Silva [100], neural networks were employed to model the discoloration of acid orange 52 dye in the presence of H_2O_2 by photo-oxidation. The authors proposed the use of the Garson partition method [101] to quantify the influence of independent variables associated to each input neuron on the outcome of the process.

After defining topology, it is necessary to define how training will be performed. In only two publications, [22] and [85], could mention be found of the training mode in use for MLPs. In these, two batches training mode was used. The training algorithms in use for MLP networks are displayed in Fig. 13. Twenty-four papers make use of the standard backpropagation algorithm [41] (indicated as BP in the figure). An example can be found in Karayel [13]. BP is the foremost training algorithm for MLPs, being used as the didactical example in most neurocomputing text-books. It is simple and stable, but very slow and prone to get trapped in local minima.

Many other algorithms were proposed for MLP training in order to increase speed of convergence and accuracy, as were, for instance, the Levenberg–Marquadt [102] and Newton-based methods [103]. The use of alternative algorithms for MLP training should be encouraged among researchers. Among the reviewed works, the Levenberg–Marquadt (quoted as LM in Fig. 3) algorithm is employed in eight papers, as in Basheer et al. [8] and Ezugwu et al. [16], always with good results. In one paper [77], a Newton algorithm is adopted. Three papers propose new approaches for training [13, 71, 78], and in three others, the choice of training algorithm is unclear.

The training of an MLP should ideally reduce the network error on the training set and stop when the point of minimum on error surface is reached. The criteria adopted for interruption of the training phase for multilayer perceptrons are distributed among the papers as shown in Fig. 14.

Four publications made use of the early stopping technique [16, 24, 57, 82]. It is widely used, according to Haykin [32], and consists of periodically checking the network error against a validation set during training. Training is interrupted when minimum error is achieved. The criteria adopted to finish training among the remaining works were unable to guarantee minimum error. In five works, training was stopped after a prespecified error in estimation set was reached. Seven studies interrupted training after a certain number of training epochs. Four others established a fixed time limit for training. In five publications, a trade-off criterion was adopted, and 14 works made no mention of the policy adopted to interrupt training.

In addition to previous recommendations, neurocomputing authors suggest the use of techniques to optimize the use of training sets, such as K-fold cross-validation [32, 104]. The use of such a technique could be observed only in Correa et al. [17].

Following the aforementioned steps, it is necessary to select a network model. The selection of a network is based on the analysis of error figures obtained from the end of training phase. Networks presenting minimum error in training are selected and then submitted to validation tests. Here, their accuracy, precision, and generalization capabil-

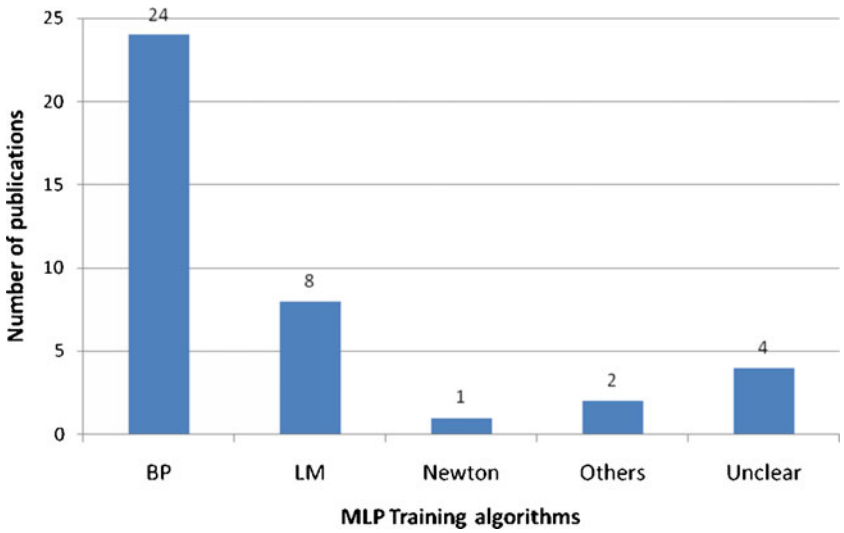

Fig. 13 Algorithms employed to train MLP networks

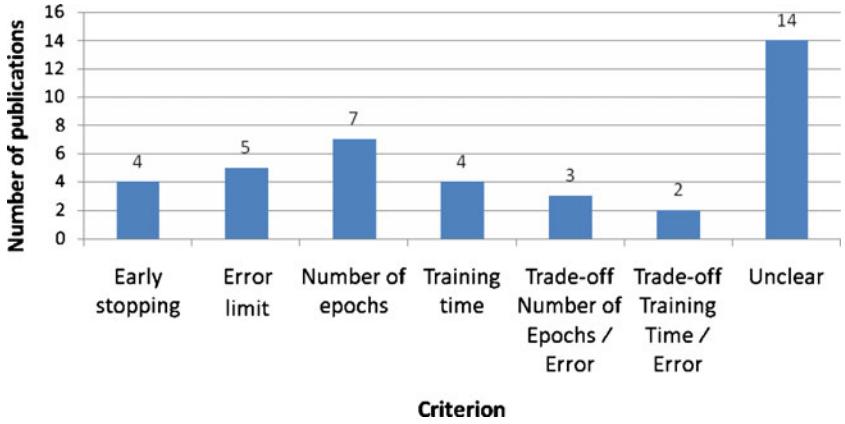

Fig. 14 Criteria adopted to stop training in publications using MLP networks

ities will be estimated using data not presented to the network heretofore. Distinct figures are used among the papers reviewed for network selection and to express the accuracy of the final model, as can be seen in Figs. 15 and 16.

In Figs. 15 and 16, MSE stands for mean square error, RMSE stands for root mean square error, and SSE stands for sum of square errors. In those figures, papers that express accuracy using absolute mean error or mean error in percentage were grouped together under the label "Mean error." Error figures involving square errors are seen to be prevalent for the selection of network architectures. This is due to the fact that error functions employed in training algorithms are mostly quadratic. On the other hand, mean error figures are prevalent in the reviewed works as the estimate for model accuracy or to compare the performance of neural network models to that of models obtained by other methods. Such figures are adopted in 25 publications (about 56% of the total).

8 Model validation

The ultimate goal of a model is to provide accurate and reliable forecasts about variables of interest. The utilization of a model in practical situations, therefore, requires the evaluation of the extent to which the model represents the underlying phenomena. This is accomplished by means of model validation. As defined by Montgomery et al. [64], validation consists of assessing model performance in the intended application. It implies, according to the authors, having objective estimates of the amount of error expected when the model forecasts fresh data. In addition, a model should lend itself to peer validation and reuse.

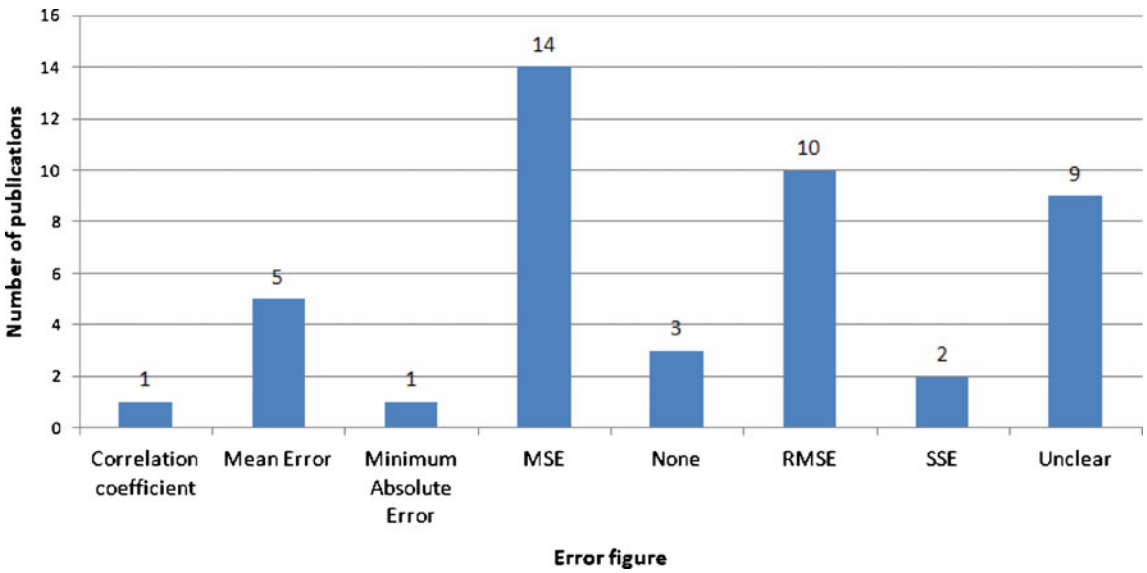

Fig. 15 Error figures adopted for network selection

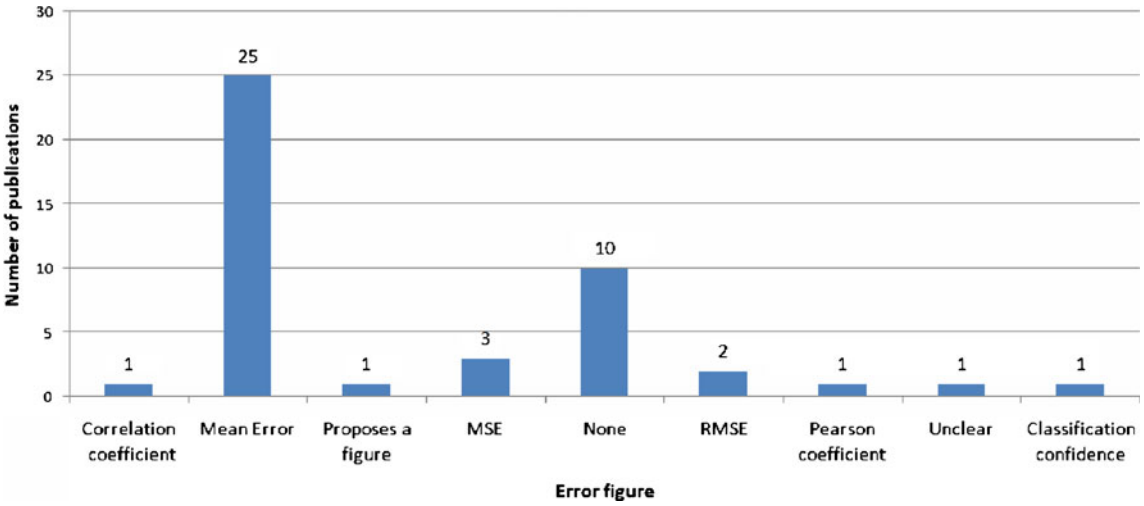

Fig. 16 Error figures adopted for model validation

Assessing the reliability associated with a model requires two things: (1) independent validation tests after training and (2) statistical treatment of test results. The reusability of a model can be achieved by including in the paper information on how to reconstruct the model as well as data and experimental conditions employed to train and test the networks.

A basic technique in modeling, according to Montgomery et al. [64], is the use of distinct data sets for model fitting and validation (data splitting). It is necessary in assessing the performance of a model when exposed to new data and in comparing distinct models. The concept, when applied to ANNs, corresponds to splitting available data into training and test sets. The concept also constitutes one of the elementary practices in neurocomputing. Figure 17 shows how the issue is dealt with among the reviewed publications. In approximately 84% of the works reviewed, the use of distinct sets is clearly established. In five works (or 11% of the total), the same data set is wrongly applied to train and to test the networks, and in two studies, that distinction is unclear.

A problem to avoid in the work with ANNs is the onset of overfitting. It is a phenomenon that leads to a reduction in the generalization capability of a network. It can arise as the result of overtraining or as a consequence of the adoption of an excessive complex topology. Some strategies are available to deal with the problem. The most common, according to Haykin [32, 41], is the use of a basic form of cross-validation [104] which consists of splitting data in three subsets: estimation, validation, and test. The estimation subset is used for network training. Periodically, training is interrupted and the network is tested against the validation subset until the validation error reaches a minimum and starts to increase. The network configuration at the point of minimum is restored, the training phase interrupted, and the network is then submitted to predict the test set. It corresponds, in practice, to the already mentioned early stopping technique. The use of such a scheme among the reviewed papers is displayed in Fig. 18.

The figure shows that only 20% of the papers make use of a third data set. An example can be found in Sharma et al. [9]. In that work, 30 examples are used for training, four

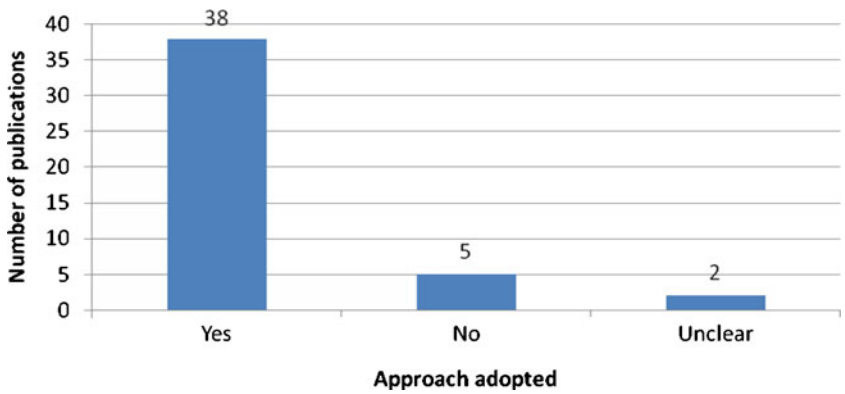

Fig. 17 Use of distinct data sets for network training and test

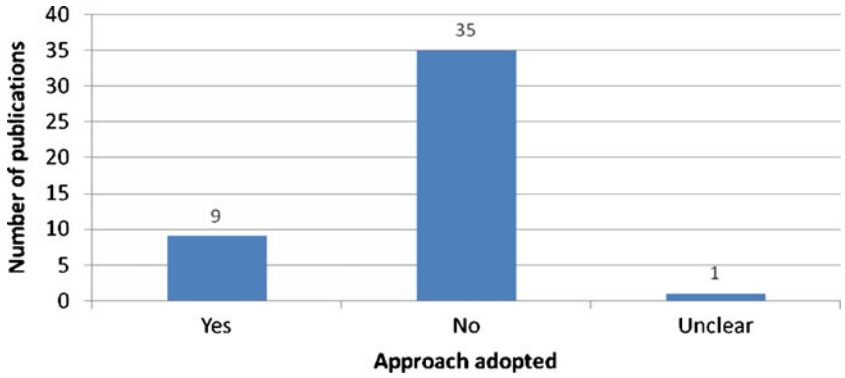

Fig. 18 Use of a third validation set for network selection

for validation, and 17 are reserved to be used as an independent test set. Note that among the publications, other techniques for preventing overfitting are hardly discussed. Bayesian regularization techniques [105] were employed in only five cases [8, 10, 16, 30, 50]. The use of pruning techniques [106] was not observed.

An important contribution to ANN modeling in machining processes was given by Sick [45] in his prolific review about the use of ANNs for tool wear monitoring in turning operations. In addition to the two issues discussed earlier, Sick enlisted some important practical requirements for model validation. The author recommended the repetition of experiments with a given network topology in order to reduce stochastic influences linked, for example, to randomly initialized weights, to random sequences of training patterns, or to random partitions of data. Those factors modify the initial point and the trajectory described by a network over error surfaces along training, as seen in Haykin [90], thus introducing a random component to the fitting process. It is necessary to acquire statistically significant samples of a network in order to assess its modeling properties. The repetition of experiments can be clearly detected in only eight publications, including Kohli and Dixit [68] who conducted ten repetitions for each topology being tested.

Another requirement for model validation is the estimation of the accuracy and dispersion of the ANN model and their expression in terms of statistical figures. Authors recommend models to be delivered with estimates such as mean error, variance, confidence intervals, or prediction intervals [33, 45]. This practice is almost never followed. Rare examples are found in Sonar et al. [69] and Kohli and Dixit [68]. An additional point to remember is the fact that not only network errors but also the amount of error in data collection impacts the overall model accuracy. Estimates of error in data collection should be presented along with those of networks. Among the 45 publications reviewed, not one adopted this approach.

The application of statistical tests to compare networks with distinct structures, input features, or training algorithms is yet another condition to sustain conclusions obtained in research with neural networks. As mentioned by Sick [45], "a decision in favour of or against a certain number of hidden neurons should be based on an appropriate number of repetitions of the experiments and on a comparison of the results of these repetitions by means of a statistical test." The practice is also recommended by the author for comparisons between ANN models and models obtained by other methods. The lack of objective evidence on model accuracy can raise doubts about the validity of conclusions obtained in a study. In only ten publications, or about 22% of the total, the application of any statistical test was observed. A good approach is found in the work of Al-Ahmari [42]. To compare errors in roughness prediction of models obtained by regression analysis, response surface methodology, and neural networks, in hard turning of austenitic AISI 302 steel, he employed paired t tests and F tests. The same author compared the dispersion of each model by means of Levene tests.

There is one problem found regularly in the publications proposing to compare distinct networks or to compare networks to other models. This problem is that in most of them, no systematic effort is made in order to optimize the ANN model. Such an effort could dramatically change the results obtained. One is left to wonder whether the result of a comparison is just the outcome of a poor choice of network topology. This is yet another issue that may lead to mistaken conclusions in regard to algorithms, architectures, or to the very use of networks as an option for roughness modeling.

In addition to issues related to the validation process, also evaluated were aspects regarding the reproducibility of a model. Reproducibility of results is implied by results being included in papers. Though this seems obvious, it is not always the case in works dealing with this subject. As a matter of fact, in 53% of the publications reviewed, network results in training and tests are expressed only in graphical format, making reproduction impracticable.

Another common problem is the lack of the data sets used for training and testing the networks. In some papers, it is not even clear how many examples were employed as training cases or as testing cases.

The reproduction of a study comprises also the ability to reconstruct the ANN model proposed. Unlike models obtained by methods such as multiple regression analysis, neural networks require more information to be rebuilt. The reconstruction of an ANN involves the knowledge of the architecture employed, the number of neurons in each layer, the nature of every input and output, the input and output modulation schemes, the activation function employed in each neuron, and the values of all synapses across the network. A text should clearly provide all this information. In case the final values of weights are not given, which is usually the case, it becomes necessary to provide the initial distribution of weights, the algorithm and training mode applied, the criteria adopted to interrupt training, and the regularization techniques, if any, employed.

Other basic neurocomputing practices are often overlooked among works reviewed. The initialization of weights is an important issue for network convergence, as mentioned by Haykin [90]. The author recommends weights to be uniformly distributed inside a small range. Only five publications mention the approach adopted to initialize weights. In [24, 76, 84] Nguyen–Widrow [104] rule is employed, in agreement with recommended practices. In [80], initial weights are all set to the same value, and in [78], a genetic algorithm is employed to define initial weights. In addition to initialization, authors recommend the order of presentation of training examples to be randomized during training cycles. No clear mention of such a practice could be found.

On the other hand, some misconceptions can be found. In one paper, authors add more neurons to the hidden layers, assuming that more neurons will necessarily imply fewer errors. In another one, in an example of a wrong conception of the generalization capability, validation tests using cases located outside the trained domain were applied, obviously leading to poor results.

The analysis of each categorization carried out from Figs. 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, and 17 clearly provides some insights. In Fig. 4, the average number of reviewed works dating from 2000 to 2004 is 1.4 and jumps to 7.6 when the period of 2005 to 2009 is considered. Figure 5 shows the overwhelming prevalence of works dealing with turning and milling. The two processes together account for 71% of all works found on the subject. Figure 6 demonstrates the dominance of networks having three to five inputs which account for 75% of the applications. In Fig. 7, the conclusion to be drawn is that cutting speed, feed, and depth of cut constitute the bulk of the predictors employed for modeling roughness. Together, they account for 67% of all inputs employed for prediction, while the other inputs are scattered in 26 distinct categories. Results from DOE or experiments resembling DOE are employed in 62%, as shown in Fig. 8, mainly because researches want to take advantage of previously obtained experimental results to train and select networks and then carry out comparisons between least square-based methods and ANN predictors. On account of Fig. 9, it is clear that single output networks are preferred in practice (64% of the total). Roughness average (R_a) is the preferred figure to express roughness, as shown by Fig. 10, appearing in 54% of the works studied. The dominance of MLP networks, which appear in 86% of the reviewed papers (as seen in Fig. 11), has already been mentioned. A striking finding, as observed in Fig. 12, is that 42% of the networks are designed by trial and error and that systematic optimization efforts can be clearly established in only 7% of the papers. Another result is the preference given to BP algorithm for the training of MLPs shown in Fig. 13, employed in more than half (53%) of the papers using the referred ANN architecture. The analysis of Fig. 14 indicates that the approach used to stop MLP training greatly varies. The techniques used are scattered in seven categories, with no individual approach reaching more than 18% of the works involving that kind of network. It is remarkable that the technique used is not mentioned in 36% of MLP-based studies. Figure 15 reveals how prevalent the use of square error figures to network selection is. MSE, RMSE, and SSE hold 57% of the total. Mean error-based figures are the preferred choice to express final ANN model accuracy, as observed in Fig. 16. Those figures are adopted in 55% of the investigated works. A final finding can be drawn from Fig. 17 which shows that the use of distinct sets for training and selection is explicitly adopted in the vast majority (84%) of the research works, in agreement with neurocomputing theory.

The construction of good ANN models is a complex and demanding task when compared to other modeling techniques. This is the trade-off for the superior computing capability of an artificial neural network. The present analysis suggests that great improvement could be made on works produced on the subject, if basic requirements in neurocomputing were observed, and possibilities offered by the technique were better explored. It shows that in many works, inadequate treatment is given to model validation. Moreover, confidence in the use of ANN models could be substantially improved where data and information required to reproduce results and networks are provided by the papers.

9 Conclusions

A review of several publications dealing with surface roughness modeling in machining processes by means of

artificial neural networks was conducted. The objective was to identify common approaches adopted by authors and to evaluate the adherence to requirements concerning model elaboration, fitting, and validation. As references, concepts and practices recommended by authors from both neurocomputing and statistic fields were adopted.

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. Most of training cases originate from results of experiments planned according to DOE methodology or at least results from experimental arrangements resembling those from DOE. The use of other approaches for data collection is uncommon. Little attention is paid to efficient use of training sets. Practices like cross-validation are not common. Efforts to determine the minimum number of training cases necessary to make neural models outperform other modeling approaches for machining processes are extremely rare. Those are issues that could be further investigated by researchers.

A vast majority of the publications make use of supervised learning networks of MLP architecture, trained by the backpropagation algorithm. Networks of RBF architecture are a distant second. Only a few papers use networks of the unsupervised learning paradigm. There is an open field for studies aiming to investigate the applicability and efficiency of unsupervised learning, distinct network architectures, and training algorithms for the task of roughness prediction.

In roughness modeling with ANNs, researchers point to the main problem being the definition of optimal network topologies. Trial and error follows as the most frequent approach for topology definition. Optimization efforts can be detected in a small number of publications, and in many works, only the "best" network configuration is presented. Comparisons between topology definition approaches could not be found. Given the particular characteristics of neurocomputing and the scant attention paid to network optimization in the articles reviewed, it seems probable that there are suboptimal results among the articles reviewed.

In regard to model validation, most of the publications clearly observe the principle of using distinct sets of data to train and test the network to measure its generalization capability, that distinction being neglected or unclear in some works. On the other hand, the use of a third data set for validation, recommended by some authors as a way to prevent overfitting, can be found in only a few studies. The use of regularization techniques is rare and the practice of pruning was not observed.

An important requirement concerning validation, the repetition of experiments with a given network topology, was found in a small fraction of reviewed works. The use of statistical evaluation to compare trained networks, or to compare networks of different paradigms, could be found in only about a fifth of the works reviewed. There is also a lack of statistical evaluation in comparisons between ANN-based models and models obtained by other methods. The estimation of accuracy and precision of ANN models are other points requiring further attention. In only a reduced group of papers were tests conducted and error estimates presented. Additional problems were detected in regard to model reusability. In some works, prediction results are presented only in a graphical way. It was also observed that many papers lack basic information that would allow reproduction of results obtained. Papers should include training and test sets employed, results obtained in numerical format, and the specifications of the resulting network models.

The failure to meet such requirements can compromise the validity and sustainability of conclusions obtained. It does not allow the assessment of how efficient neural networks can be in the task of roughness prediction in machining processes and how they compare to other modeling approaches.

Accurate and reliable models are becoming more and more necessary to quickly acquire knowledge of operations involving new tools and materials. Neural networks are a suitable tool for the task. Their use, however, depends on the objective assessment of their potential and on the identification of systematic and efficient ways to deliver neural models of high performance. The conclusion of this review is that while many works have been produced on the subject, there is still a great need for methodology improvement. Future works should be more deeply rooted in neurocomputing concepts, devote more effort to network optimization; they should be validated on firmer statistical grounds, and, finally, be more careful about presentation of results obtained. Those characteristics will be essential to obtaining models possessing the qualities expected by manufacturers and to establish confidence in the use of ANN modeling by the machining industry.

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