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Surface roughness prediction through internal kernel information and external accelerometers using artificial neural networks †

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Abstract

In this paper, the average surface roughness parameter (Ra) is predicted using artificial neural network (ANN) models and internal kernel information and external piezoelectric accelerometer data. Experiments were conducted to obtain data to develop ANN models to predict surface roughness. A total of 72 samples were used to develop two networks, one based on accelerometer inputs and the other on kernel inputs. The Matlab ANN Toolbox was used for the modeling. The two networks had similar characteristics. Feed-forward backpropagation, '*newff*', was the network structure selected, with a Levenberg-Marquardt backpropagation training function, 'trainlm', and a backpropagation weight and bias learning function, '*learngdm*'. Samples obtained at the experimental stage were randomly divided into three groups to train (70% of the samples), validate (15% of the samples) and test (15% of the samples) the neural networks with a 'dividerand' data division function. The input processing functions used were *'fixunknowns'*, *'removeconstantrows'* and *'mapminmax'*. The transfer function was *'tansig'* for hidden layers and *'purelin'* for the output layer. The output processing functions used were *'removeconstantrows'* and *'mapminmax'*. The inputs consisted of the process parameters of radial depth of cut (Ae), the axial depth of cut (Ap), the spindle speed (N), the feed rate (f), the feed per tooth (fz), the cutting speed (Vc), the tooth passing frequency (ft), the cutting section (Cs), the material removal rate (MRR) and the cutting tool characteristics of the cutter radius (R), the number of teeth (Z) and the tool shape. The main difference between the two neural networks consisted of data origin: one considered data obtained with accelerometers and the other data collected in the NC kernel. Results showing high correlation factors between outputs and targets confirm that data provided by both internal and external sources can be useful for Ra prediction. However, NC kernel data provide several advantages.

Keywords: Cutting parameters; Milling process; NC kernel; Surface roughness

1. Introduction

Surface topography is the result of a material removal process due to relative motion between the tool and the part, but the surface roughness generation process is not fully understood. The interactions and cause-effect relationships between the factors that influence surface roughness generation are complex. In 2003 Benardos and Vosniakos [1] published a review of the state of the art of surface roughness prediction in machining operations, and compiled the set of parameters that influence surface roughness generation in a fishbone diagram that considered machining parameters, cutting tool properties, workpiece characteristics and cutting phenomena, as shown in Fig. 1.

Surface properties have an enormous influence on features

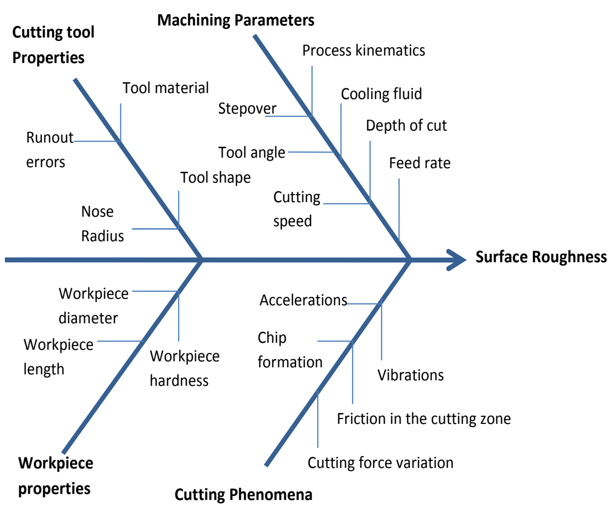

Fig. 1. Fishbone diagram with the parameters that affect surface roughness. Source: Ref. [1].

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such as dimensional accuracy, friction coefficient and wear, thermal and electric resistance, fatigue limit, corrosion, post-processing requirements, appearance and cost. Surface roughness is a widely used index of product quality and a technical requirement for mechanical products [2]. For this reason, a great deal of research has focused on understanding the complex process of surface generation and providing the knowledge necessary to ensure surface quality in manufacturing processes.

In Ref. [1], Benardos and Vosniakos provided an extensive study of the main research lines and classified the different approaches into four groups: machining theory [3, 4], experimental investigations [5, 6], designed experiments [7, 8] and approaches based on artificial intelligence [9-16].

Tsai et al. [9] focused on the last group and presented an in-process system for surface recognition in end milling operations based on neural networks. They used an accelerometer to obtain vibration data from the machine tool and workpiece system, and a CNC vertical machining center to perform experimentation. The ANN model developed included the input parameters of the spindle speed, the feed rate, the depth of cut and the vibration. Ho et al. [10] proposed a method using an adaptive neuro-fuzzy inference system to predict surface roughness with the surface image features (obtained with a digital camera and a PC) and three cutting parameters: cutting speed, feed rate and depth of cut. Benardos and Vosniakos [11] used ANN modeling with experiments designed to predict surface roughness in face milling, which considered feed per tooth, axial and radial depths of cut, use of cutting fluid and the component of the cutting force along the feed direction. They showed that the use of ANNs can be extremely accurate. Brezocnik et al. [12, 13] proposed the use of a genetic algorithm to predict surface roughness in end milling. Ho et al. [8] proposed an adaptive network-based fuzzy inference system for surface roughness prediction in the end milling process, using a hybrid Taguchi-genetic learning algorithm. Zain et al. [14, 15] developed an application based on genetic algorithms to optimize cutting conditions and minimize surface roughness in end milling. They observed the effect of the radial rake angle of the tool, combined with the speed and the feed rate, on the surface roughness result. Later, in Ref. [16], the authors focused on surface roughness prediction with ANNs. Shie [17] focused on finding an optimal combination of cutting parameters using neural networks for the optimization of dry machining parameters for high-purity graphite in end milling processes. Suresh et al. [18] developed an approach using RSM. This model was then taken as an objective function and optimized with GA to obtain the machining conditions for a desired surface finish with minimum and maximum values. Correa et al. [2, 19] produced two models for roughness prediction in high-speed milling processes developed through a Bayesian networks (BN) approach. Quintana et al. [4] proposed an application for surface roughness monitoring based on an artificial neural network approach for vertical high-speed ball-end milling operations, using data captured from two unidirectional piezoelectric accelerometers that considered the vibrations occurring during the metal removal process. Brecher et al. [20] suggested using NC kernel data for surface roughness monitoring in milling operations and developed a human-machine interface implemented by means of global user data, to analyze data online with ANNs. Samanta et al. [21, 22] used soft computing and computational intelligence techniques to model surface roughness in end milling processes using multiple regression analyses, ANNs and adaptive neuro-fuzzy systems.

As surface roughness is usually measured post-process, it would be interesting to develop in-process solutions to control the surface generation process and avoid the need to scrap an unacceptable part once it is finished and time and energy have been spent on it. A monitoring approach detects quality shortfalls as soon as they occur and modifies the process parameters or stops the manufacturing process. However, a monitoring approach has to be developed based on indirect measures and evaluations.

In recent years, advances in computers and sensors have made it possible to monitor, measure and control the machining process, and to develop an intelligent machining approach. Several types of sensors and signal processing techniques have been used for direct or indirect diagnosis of factors such as chatter, tool wear or breakage and surface roughness. The principal advantage of surface roughness monitoring is that quality control can be carried out in-process instead of post-process, when the part is already finished and time and money have already been spent. However, the majority of existing applications require the use of external sensors that entail a longer set-up time and make the final solution more expensive.

In this paper, the use of internal kernel information is compared with external piezoelectric accelerometer data, in terms of surface roughness average parameter (Ra) prediction with ANN models in vertical milling operations. The use of piezoelectric accelerometer in-process data, for surface roughness prediction in machining operations has been widely used. However, the use of internal kernel information presents several advantages in comparison with accelerometers and has not been very studied as, in most of the cases, it can be quite complicated to extract information from internal kernels. Experiments were conducted to obtain data to develop the models, and in-process information was obtained from external and internal sensors. The approaches presented are based on ANNs as neural networks are especially suitable for modeling complex relationships between inputs and outputs. This paper shows that, as piezoelectric accelerometers data, internal kernel data for surface roughness prediction through artificial neural networks can be clearly reliable and provide good approaches.

2. Experimental set up

The machine tool used was a three-axis vertical EMCOMILL E900 with SIEMENS 840Dsl numeric control.

The tool's axes have a range of 900 mm in the X direction, 500 mm in the Y direction and 300 mm in the Z direction, and it is equipped with a 16kW motor spindle with a maximum rotational speed of 15000 rpm. The material used was steel C45 (AISI 1043), 50-55HRC.

The cutting tool used was a Sandvik Coromant R390-17 04 08M-PM 1030 with two inserts (z = 2) and the following parameters recommended by the tool manufacturer: feed per tooth (fz = 0.15 mm/z), spindle speed (n = 2018 rpm), cutting speed (vc =265 m/min) and axial depth of cut (Ap = 1 mm). The tool holder used was a Sandvik R216-16T08. First, the recommended parameters were programmed and radial depths of cut of 100%, 95%, 80% and 65% were tested. These measurements were then repeated with variations of up to +/-20% of the recommended values for each parameter. For each combination of process and technology parameter a raster path of 100 mm was machined.

Vibrations during the experiments were collected using two unidirectional piezoelectric accelerometers placed in line with the machine tool X and Y axis directions, one on the spindle and the other on the machine tool table. The sampling frequency was 10 kHz. A data acquisition platform was developed using Labview™ to obtain the vibrations that occurred. After the experiments, the vibration signals captured were analyzed and cut in order to distinguish between the rapid traverses along the Y axis, where acceleration is maximum, and the traverses during the effective cut, when the tool is definitely removing material and generating roughness.

Modern machine tool controls include software that records digital drive data. The main purpose of such trace tools is to control parameter optimization. However, this function can also be used to identify machine tool behavior regarding friction and acceleration [23], and to carry out tasks such as collision monitoring [24] and tool condition diagnosis [25]. The numeric control available is a Sinumerik 840Dsl that provides a server software application – the so-called Trace Server (TS). This server offers access to the control data and drive signals to several numeric controller kernels at the same time. It has been applied to the data acquisition of position signals, torque producing current signals of the feed drives, and the rotational speed and mechanical power of the main spindle. Moreover, the first and second deviations of these drive signals have been calculated.

The control configuration that was applied worked with a sample time of 2 ms (500 Hz), and the location of the signal sources was fixed as well. Either the linear position encoder or the rotational encoder can be used. The current signal is measured directly at the drives. For control purposes, the transformation into the torque producing component and the field controlling current component is already carried out by the power converter. In addition, the control applies several filter and preprocessing algorithms to the drive signals, so that they can directly monitor or diagnosis applications.

Finally, the rugometer used to measure the surface roughness Ra parameter, once the experiments had been performed,

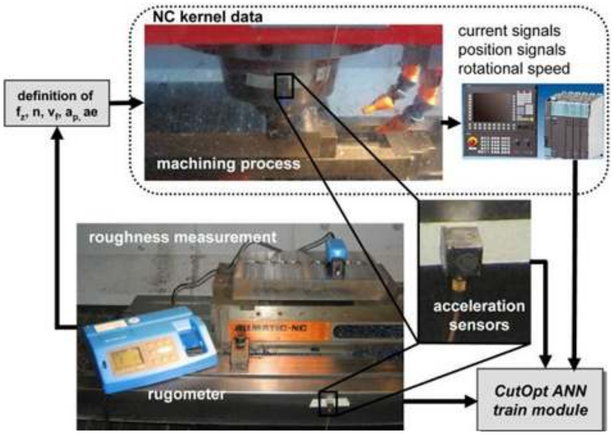

Fig. 2. Experimental set-up.

was a Hommel Tester T1000 with a 2 µm nominal stylus tip. The evaluation length was 4.8 mm, composed of six basic lengths of 0.8 mm, and the speed was 0.50 m/s with a 0.75 mN static stylus force. Fig. 2 shows the schematically the experimental setup.

The average roughness (Ra) parameter was measured three times along the tool path and the mean value was taken. The results obtained are shown in Table 1.

3. Average surface roughness approaches

ANNs are mathematical models made up of an interconnected group of artificial neurons that simulate the structure of biological neurons. Neural networks are composed of neurons arranged in different layers and linked through variable weights. These weights are calculated by an iterative method during the training process when the network is fed with training data, input and output pairs that represent the pattern to be modeled [26]. Once the weights have been set, the model is able to produce answers for input values which were not included in the training data. Any real-world system which has measurable inputs and outputs may be modeled by training a neural network to predict the outputs, given the inputs. In order to build an adequate neural network model it is necessary to consider factors such as the network algorithm, the transfer function, the training function, the learning function, the network structure, the number of training data, the number of testing data and the normalization of data input.

Once the experiments were over, the data from accelerometers and the NC kernel had been captured and analyzed and surface roughness measured, all the data required to build and train an ANN were ready to be modeled. Two networks were built with a total of 72 samples obtained with the experiments. Both networks took into consideration in the input layer, elements composed of the following process parameters: radial depth of cut (Ae); axial depth of cut (Ap); spindle speed (N); feed rate (f); feed per tooth (fz); cutting speed (Vc); tooth passing frequency (ft); cutting section (Cs); material removal

Table 1. Experimental parameters and results obtained.

Ae (mm)	f (mm/min)	S (rpm)	fz (mm/z)	Vc (m/min)	Ra (μm)
40	632	2108	0.150	265	0.694
38	632	2108	0.150	265	0.702
32	632	2108	0.150	265	0.595
26	632	2108	0.150	265	0.560
40	632	2108	0.150	265	0.695
38	632	2108	0.150	265	0.645
32	632	2108	0.150	265	0.719
26	632	2108	0.150	265	0.514
40	632	2108	0.150	265	0.688
38	632	2108	0.150	265	0.718
32	632	2108	0.150	265	0.765
26	632	2108	0.150	265	0.640
40	1054	2108	0.250	265	0.927
38	1054	2108	0.250	265	0.970
32	1054	2108	0.250	265	0.772
26	1054	2108	0.250	265	0.734
40	422	2108	0.100	265	0.588
38	422	2108	0.100	265	0.564
32	422	2108	0.100	265	0.325
26	422	2108	0.100	265	0.575
40	632	2108	0.150	265	0.785
38	632	2108	0.150	265	0.732
32	632	2108	0.150	265	0.685
26	632	2108	0.150	265	0.774
40	632	2108	0.150	265	0.836
38	632	2108	0.150	265	0.836
32	632	2108	0.150	265	0.865
26	632	2108	0.150	265	0.836
40	758	2108	0.180	265	0.868
38	758	2108	0.180	265	0.786
32	758	2108	0.180	265	0.939
26	758	2108	0.180	265	0.702
40	506	2108	0.120	265	0.717
38	506	2108	0.120	265	0.676
32	506	2108	0.120	265	0.676
26	506	2108	0.120	265	0.623
40	569	2108	0.135	265	0.751
38	569	2108	0.135	265	0.798
32	569	2108	0.135	265	0.819
26	569	2108	0.135	265	0.698
40	632	2029	0.156	255	1.085
38	632	2029	0.156	255	1.286
32	632	2029	0.156	255	1.051
26	632	2029	0.156	255	0.898
40	695	2029	0.171	255	1.147
38	695	2130	0.163	268	1.214
32	695	2130	0.163	268	0.926
26	695	2130	0.163	268	1.052
40	569	2108	0.135	265	0.813
38	569	2108	0.135	265	0.753
32	569	2108	0.135	265	0.820
26	569	2108	0.135	265	0.521
40	569	1897	0.150	238	0.714
38	569	1897	0.150	238	0.887
32	569	1897	0.150	238	0.863
26	569	1897	0.150	238	0.814
40	696	2319	0.150	291	1.313
38	696	2319	0.150	291	1.310
32	696	2319	0.150	291	1.312
26	696	2319	0.150	291	1.082
40	506	1686	0.150	212	1.160
38	506	1686	0.150	212	1.050
32	506	1686	0.150	212	1.320
26	506	1686	0.150	212	0.894
40	759	2530	0.150	318	1.350
38	759	2530	0.150	318	1.358
32	759	2530	0.150	318	1.279
26	759	2530	0.150	318	1.117
40	569	2149	0.132	270	0.847
38	569	2149	0.132	270	0.723
32	569	2149	0.132	270	0.969
26	569	2149	0.132	270	0.974

rate (MRR); the cutting tool characteristics of cutter radius (R); number of teeth (Z); and tool shape, flat or ball-end mill, as presented in Ref. [6]. The selection of the inputs was carried out with the aim of introducing a realistic point view of the cutting process into the ANN input layer considering process parameters, deterministic process parameters and cutting tool characteristics as in Ref. [4]. So that, the ANN had the same input elements than an operator in order to predict surface roughness. Of course, some of these elements are interrelated and not independent, for example f and fz but, introducing them into the input layer permits to enlighten this relation. In other way, the ANN would not have evidence of the influence of these parameters on surface roughness. The main difference between the two neural networks lies in the in-process data origin. One network considers data obtained with the accelerometers and the other the data collected in the NC kernel.

Vibration signals captured with the piezoelectric accelerometers were analyzed to separate the data between the rapid traverses where acceleration is maximum, and during the effective cut when the tool removes material. Only those vibrations occurred when the tool was immersed in the workpiece were taken into account for the datasets. Different vibration variables were taken into consideration: low, medium and high frequency vibration amplitudes, temporal domain vibration amplitude and tooth passing frequency amplitude all of them both in X and Y axes. Low frequencies were considered those lower than 500 Hz that capture, if they occur, vibrations due to machine-tool structure modes, habitually around 200 Hz. Medium frequencies were considered those between 500 Hz and 2500 Hz as the spindle, the tool-holder and the cutting tool modes are typically around 2000 Hz. High frequencies were considered those between 2500 Hz and 5000 Hz.

Data collected from the NC kernel included: X, Y and Z axes current; spindle current; X, Y, Z axes velocity (obtained with the first derivative of the position with respect to time); spindle rotational speed; X, Y, Z axes acceleration, calculated as the second derivative of the position with respect to time; spindle rotational acceleration; X, Y, Z axes and spindle current variation velocity, calculated as the first derivative of the current with respect to time); X, Y, Z axes and spindle current variation acceleration calculated with the second derivative of the current with respect to time. NCK signals were also trig-

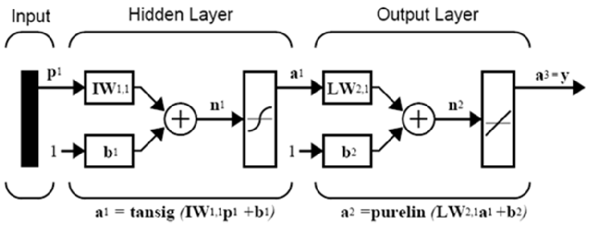

Fig. 3. Two-layer tansig/purelin network developed with MATLAB.

gered in order to extract the effective cutting data and eliminate the information captured when the tool was in the air or in the process of entering or leaving the workpiece.

The main structure of the two networks was kept very similar to facilitate comparison of the data source usefulness. The Matlab ANN Toolbox was used for the modeling. Feedforward backpropagation, 'newff', is the network structure with a Levenberg-Marquardt backpropagation training function, '*trainlm*', and a backpropagation weight and bias learning function, '*learngdm*'. A two-layer feed-forward network was used as it can approximate any function with a finite number of discontinuities given sufficient neurons in the hidden layer. Samples obtained at the experimental stage were randomly divided into three groups to train (70% of the samples), validate (15% of the samples) and test (15% of the samples) the neural networks with a *'dividerand'* data division function. Training samples were introduced during the training and the network was adjusted according to the error. Validation samples were used to measure network generalization and stop the training when the generalization stopped improving. Testing samples have no effect on training and so provide an independent measure of a network's performance. The Levenberg-Marquardt backpropagation algorithm automatically stops training when generalization ceases to improve, as an increase in the mean square error of the validation samples indicates. Input processing functions used were *'fixunknowns'*, *'removeconstantrows'* and *'mapminmax'*. tansig/purelin was the transfer function of the i^{th} layer: 'tansig' for the hidden layer and *'purelin'* for the output layer. The output processing functions used were *'removeconstantrows'* and *'mapminmax'*. An example of this neural network architecture is shown in Fig. 3.

3.1 External sensor data approach

A total of 5000 ANNs were built, trained and tested with the samples containing data from the accelerometers. Fifty network iterations were evaluated from 1 to 100 neurons. The best network was composed of three neurons in the hidden layer and had a correlation value of R = 0.94353.

Correlation factors of the ANN developed are shown in Fig. 4, while Fig. 5 shows network performance for the training validation and testing samples. The plot shows the mean squared error of the network decreasing while it is learning. Training continues as long as it reduces the network's error in respect of the validation samples, but ceases when the validation error increases for six iterations.

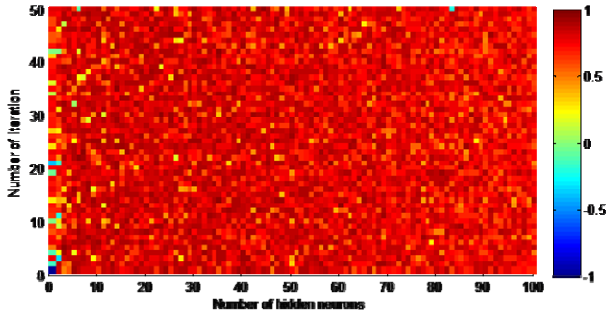

Fig. 4. Correlation factors (R) of the 5000 neural networks tested using external sensor data.

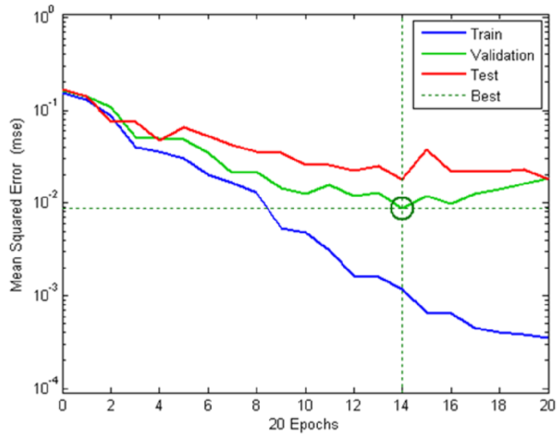

Fig. 5. Best validation performance using external sensor.

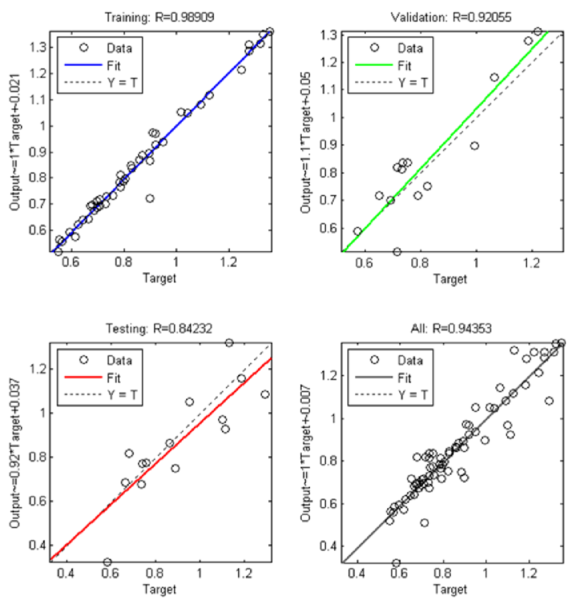

Fig. 6. Regression plot and correlation value (R) for training, validation, testing and all samples.

Fig. 6 shows the results from the ANN selected. Outputs given by the network are plotted against the targets collected

Table 2. Validate and testing samples targets and outputs.

Validate targets (μm)	Validate outputs (μm)	Test targets (μm)	Test outputs (μm)
0.702	0.693	0.927	1.112
0.514	0.714	0.970	1.100
0.718	0.652	0.772	0.742
0.588	0.573	0.325	0.581
0.836	0.735	0.685	0.664
0.836	0.754	0.774	0.755
0.717	0.791	0.676	0.735
0.819	0.717	0.751	0.887
0.898	0.996	1.085	1.293
1.147	1.065	1.051	0.951
0.753	0.825	0.820	0.679
0.814	0.734	0.863	0.862
1.312	1.222	1.160	1.185
1.279	1.190	1.320	1.131

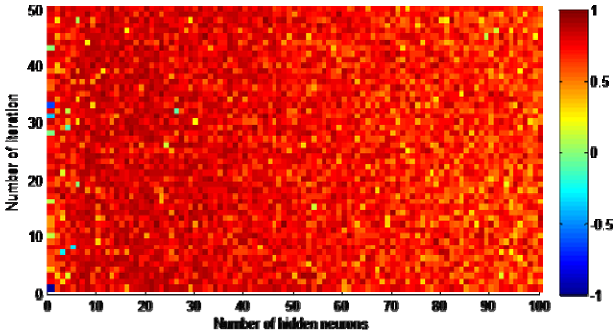

Fig. 7. Correlation factors (R) of the 5000 neural networks tested using NC kernel data.

during the experiments. The points on the chart are composed of target-and-output pairs and represented by empty circles. Regression (R) values measure the correlation between outputs and targets. The figure shows the correlation value for the training samples (R = 0.98909), validating samples (R = 0.92055), testing samples (R = 0.84232) and the fitting correlation of the entire surface roughness prediction model (R = 0.94353). Table 2 shows in more detail results obtained for validation and testing samples, the targets and the outputs provided by the ANN.

3.2 NC kernel data approach

In the case of the neural networks developed using NC kernel data, the same method was used as in the previous subsection. A total of 5000 ANNs (50 iterations of networks from 1 to 100 neurons) were built, trained and tested in around 10 hours of computation. The best network was composed of three neurons in the hidden layer and had a correlation value of R = 0.95947, a value slightly better than the correlation factor obtained for the network that considered accelerometer data. Fig. 7 shows the correlation factors, colored in accordance with the colorbar values on the right-hand side of the figure, of the 5000 neural networks generated.

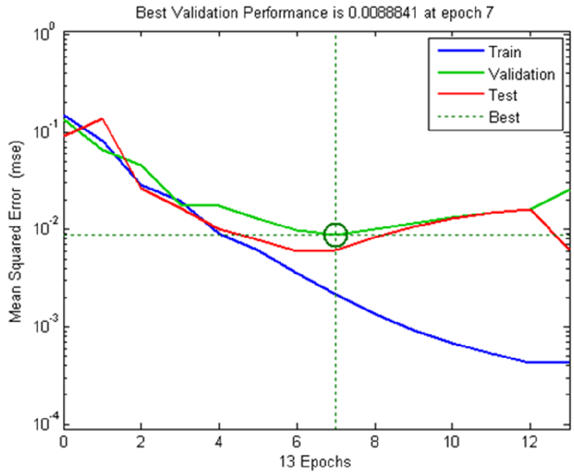

Fig. 8. Best validation performance using kernel data.

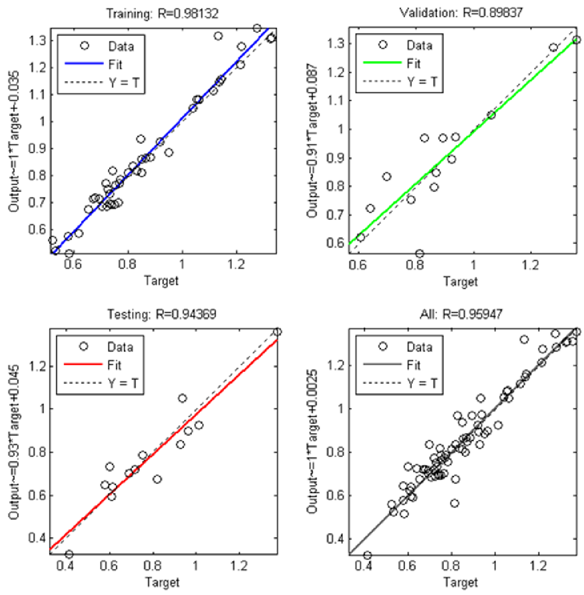

Fig. 9. Regression plot and correlation value (R) for training, validation, testing and all the samples.

A plot of the training, validation and testing errors is shown in Fig. 8. The mean squared error of the network decreases while the neural network is learning. Training continues as long as network error is reduced in the validation samples, and automatically stops when the validation error increases for six iterations.

Fig. 9 shows the correlation value for the training samples (R = 0.98132), validation samples (R = 0.89837), testing samples (R = 0.94369) and the fitting correlation of the developed surface roughness prediction model (R = 0.95947).

Table 3 shows in more detail results obtained for validation and testing samples, the targets and the outputs provided by the ANN.

Table 4 summarizes the steps followed in the process of

Table 3. Validate and testing samples targets and outputs.

Validate targets (μm)	Validate outputs (μm)	Test targets (μm)	Test outputs (μm)
0.970	0.892	0.702	0.691
0.564	0.813	0.595	0.611
0.836	0.697	0.645	0.576
0.623	0.607	0.719	0.718
0.798	0.864	0.640	0.612
1.286	1.280	0.325	0.410
0.753	0.783	0.785	0.751
1.313	1.358	0.732	0.599
1.050	1.064	0.836	0.928
0.894	0.924	0.676	0.818
0.847	0.869	1.051	0.935
0.723	0.640	0.898	0.965
0.969	0.828	0.926	1.013
0.974	0.938	1.358	1.373

Table 4. Method applied to external sensor and kernel data acquisition.

	External sensor	Kernel data
Data acquisition	Vibrations in xy-axis	torque generating current (xyz-axis, main spindle) actual position x,y,z rotational speed (main spindle)
Signal preprocessing	High-pass filter (>2500Hz) Low-pass filter (<500Hz) Band-pass (500Hz÷2500Hz)	1st, 2nd deviation of measured signals
Training of ANN	Network structure: 'newff': Feedforward backpropagation network Training function: 'trainlm': Levenberg-Marquardt backpropagation algorithm Learning function: 'learngdm': Backpropagation weight/bias Input processing functions: 'fixunknowns' 'removeconstantrows' 'mapminmax' Data divison function: 'dividerand': Training samples (70%) Validation samples (15%) Testing samples (15%) Transfer function of ith layer: 'tansig' for hidden layers 'purelin' for output layer. Output processing functions. 'removeconstantrows', 'mapminmax' Number of iterations: 5000	Network structure: 'newff': Feedforward backpropagation network Training function: 'trainlm': Levenberg-Marquardt backpropagation algorithm Learning function: 'learngdm': Backpropagation weight/bias Input processing functions: 'fixunknowns' 'removeconstantrows' 'mapminmax' Data divison function: 'dividerand': Training samples (70%) Validation samples (15%) Testing samples (15%) Transfer function of ith layer: 'tansig' for hidden layers 'purelin' for output layer. Output processing functions. 'removeconstantrows', 'mapminmax' Number of iterations: 5000
Results	Ra	Ra
Training samples	0.98909	0. 98132
Validation samples	0.92055	0. 89837
Testing samples	0.84232	0. 94369
ANN model	0.94353	0. 95947

obtaining, processing and analyzing the data to develop an optimal ANN based on external sensor information and NC kernel information.

Finally, Table 5 provides a comparison between the performance of the NCkernel data approach and the standard alternative technique that consists on using a rugometer for measuring surface roughness. Principal advantages and drawbacks of both techniques are contrasted. The possibility of being able to evaluate surface roughness while the part is being machined is the most relevant advantage of the use of the

Table 5. Rugometer measurement method vs. Kernel data acquisition.

	Rugometer measurement	Kernel data
Data acquisition	Direct measurement Out-of-process External device Extra investment Quality measurement	Indirect evaluation In-process Fully integrated No extra investment Quality assurance
Signal preprocessing	Automatically performed by the rugometer No experimentation required	Programmed Experimentation required
Results	Rugometer's accuracy and repeatability Calibration and maintenance	High correlation factor but certain uncertainty

NC kernel data for surface roughness prediction and makes this methodology very interesting.

4. Conclusions

The use of the data obtained directly from the NC kernel is very interesting as it allows external sensors, which require extra investment and therefore increase the final cost of the solution, to be eliminated. Moreover, there is a higher correlation factor in the case of data obtained from the NC kernel, R = 0.95947, than in the case of the neural network using accelerometer data, where there is a correlation factor of R = 0.94353. A further factor is that accelerometers must be installed in a fixed place that cannot be changed on the machine tool, and the information provided can be affected by several levels of noise or dissipation due to the varying distance between the point of origin of the vibration (i.e. the contact zone between tool and material) and the point where vibration is captured (i.e. the accelerometer), or by the influence of vibrations coming from other machines. Accelerometers also increase the final cost of the solution.

A similar characteristic has to be taken into account with regard to NC kernel data. The transfer behavior between the signal source and the process is defined by the mechanical components of the machine tool that can be modeled as a low-pass characteristic. However, the numeric control and the power transformer already preprocess the signals by means of several filters and transformations, thereby markedly reducing the influence of noise and dissipation. The evaluation can be provided with further information by a defined correlation to the actual process situation, i.e. NC data, the path left until the next tool change. Similarly, information about the applied tool is available from the tool data base. Hence, this data base can be expanded by the specifically trained ANN and applied when a tool change takes place.

One of the drawbacks of this method is that experiments have to be carried out. This drawback is not to do with the source of the data, (NC kernel or accelerometers) as experiments are necessary in both cases. Experiments are expensive and are required for each combination of machine tool, cutting tool, tool holder and work piece material. The use of NC kernel data provides an excellent initial situation for automation. Aside from the roughness measurement, all essential information is available from the numeric control: the applied tool data, i.e. diameter and number of cutting edges, the position and current signals as well as their deviations. Furthermore, the signal sources are always located at the same point, which increases the portability of trained algorithms between machine tools of the same type. However, it has to be mentioned that the usefulness of digital drive signals is limited. For tools with small diameters and therefore smaller process forces, the effects might be absorbed by the machine's components.

Results show that data provided by accelerometers and data provided by an NC kernel can be useful to predict average surface roughness. This is confirmed by high correlation factors between outputs and targets provided by the ANNs developed. The principal advantage of the methodology proposed is that quality control, in terms of surface roughness requirements assurance, can be carried out in-process, when the part is being machined and the surface roughness is being generated. In comparison with the traditional or conventional method where surface roughness is measured at the end of the machining process with a rugometer this becomes an important advantage as permits to reduce times and lack of quality costs through indirect evaluations of surface roughness average parameter, Ra, a very common parameter for surface quality measurement.

This research has used the ANN technique for developing a model to predict the surface roughness average parameter (Ra) in vertical milling operations. However, ANNs have several drawbacks. For instance, experiments are indispensable for creating and training a realistic network. These can be costly and time consuming, and the repeatability of training for a new model is not assured. In further research it would be interesting to study the possibilities of other artificial intelligence approaches such as genetic algorithm (GA), simulated annealing (SA), ant colony algorithm (ACO) and particle swarm optimization (PSO). Clarity of all figures is extremely important. If the final version is not prepared in two column format or does not include author(s)' biographies, the publication process will be delayed. The DOI number will be assigned by the journal office. The manuscript received, revised and accepted dates will be checked and corrected by the journal office.

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