THE INFLUENCE OF CUTTING PARAMETERS ON THE SURFACE QUALITY OF ROUTED PAPER BIRCH AND SURFACE ROUGHNESS PREDICTION MODELING

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Abstract. The objective of this study was to characterize the routing process to better understand the machining conditions that affect surface finish. Experiments were designed to determine the impact of cutting depth, feed speed, and grain orientation of the workpiece on the surface quality of paper birch wood. Statistical analysis showed that the cutting depth did not influence surface finish. Roughness depended greatly on feed speed and grain orientation, increasing linearly as the feed speed increased. The roughest surfaces were obtained by routing against the grain between 120 and 135° grain orientation, depending on the feed speed. Two models able to predict the surface finish based on initial cutting parameters were developed and compared. Both the statistical regression and neural network models were subjected to a validation procedure in which their performance was confirmed using data that were not used for the learning process. Results indicated that the neural network system estimates the surface roughness with less error than the statistical regression model.

Keywords: Routing, surface roughness, paper birch, predictive modeling, neural network.

INTRODUCTION

Surface roughness of wooden elements determines not only the esthetic features of a final product, but in many situations it is an important quality parameter required for further processing (eg gluing, finishing). For a customer buying a final product, the surface quality can be considered one of the most important factors determining the cost of the product. Therefore, a numerical quantification of the surface roughness in the production plant plays a key role in determining prospective value of the product. In the wood industry, sanding is the most common process creating the final surface; however, among all the wood machining processes used in contoured furniture making, sanding is one of the most skill-based, time-consuming, and expensive operations (Taylor et al 1999). Therefore, it is essential to maintain high quality of the surface during operations preceding sanding such as routing or planing to improve productivity and lower the manufacturing cost. In this study, we attempted to develop surface roughness predictive models to help with the selection of machining parameters and thus with the improvement of the surface finish of paper birch.

The influence of machining parameters on the surface quality of routed soft maple was investigated by Mitchell and Lemaster (2002). The variables studied were: feed per tooth, spindle speed, cutting direction, and tool condition. After machining, three individuals visually graded the surface quality. Although they routed end grain, flat side grain, and curved side grain surfaces, they did not investigate cutting against

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the grain, limiting their research to routing following the grain. Comparable research on modeling of the surface roughness of wood in abrasive machining using nonlinear regressions and fuzzy knowledge-based approaches was conducted by Carrano et al (2004). A statistical model performed better than a fuzzy knowledge-based model, especially when the data set was large. A similar conclusion of superiority of statistical regression toward fuzzy regression in terms of predictive capability was drawn by Kim et al (1996). In metal turning, attempts of developing empirical models to predict surface finish (Feng and Wang 2002) and comparison of empirical and neural network predictive modeling (Feng and Wang 2003) have been undertaken. Such studies proved that the nonlinear regression and the artificial neural network models can reliably estimate the surface roughness using certain turning parameters as inputs. Also, the radial basis function neural networks were successfully used to predict the surface profile of machined surfaces in metal cutting (Lu 2008). Cutting speed, cutting depth, and feed rate were used to actually reproduce an entire profile of a turned surface.

The objective of this research was to examine surface roughness obtained by routing paper birch wood (*Betula papyrifera* Marsh.) under different cutting conditions. The influence of cutting parameters such as grain orientation, feed speed, and depth of cut on surface roughness were investigated. The grain orientations tested included routing following and against the grain. Based on the experimental data, an attempt to develop a neural network system and empirical model able to predict surface finish was undertaken. The predictive capabilities of these models were verified using a validation procedure.

EXPERIMENTAL PROCEDURE

Test Specimens

Workpieces of paper birch were cut from three boards taken from three different logs. The boards were previously kiln-dried and stored in a conditioning chamber at 20°C and 40% RH to establish an 8% EMC. Each board was then planed to 19 mm thickness, and six defect-free, 100 × 200 mm samples were cut. The samples were manipulated in such a way that each had different grain orientations assuring a wide range of cutting directions of 90 – 0, 90 – 45, 90 – 90, 90 – 120, 90 – 135, and 90 – 150. The cutting directions indicated as 90 – 0 to 90 – 90 implied cutting following the grain, whereas those above 90 – 90 (perpendicular) were cut against the grain.

Cutting Conditions

The experiments were conducted on a Fulltech Centek 5121-A, 3-axis CNC machine (Fulltech Mechtronics Co Ltd, Taichung, Taiwan) equipped with a 10/110 Osai controller (OSAI S.p.a., Torino, Italy). Routing was carried out with a 30 mm dia cutter provided with two tungsten carbide (K-10) insert knives with rake and clearance angles of 20 and 15°, respectively. Up-milling was performed during all tests at five feed speeds. The rotation speed of the spindle was constant and set at 24,000 rpm. A face routing was performed with a cutting width of 19 mm (thickness of the workpiece) and cutting depths of 1, 2, and 3 mm. The factors controlled in this study are summarized in Table 1.

Surface Roughness Measurement

The roughness of the machined surfaces was measured with a profilometer Hommel Tester T1000 (Hommel-Etamic GmbH, Schwenningen, Germany) equipped with an inductive pick-up diamond stylus tip with a radius of 5 μm and cone of 90°. The Gaussian filter with a cutoff wavelength of 2.5 mm was used to process the data. The measurements were conducted following the feed direction, across the

Table 1. *Values of the cutting variables tested.*

Factor	Values
Depth of cut (mm)	1, 2, 3
Feed speed (m/min)	1, 5, 10, 15, 20
Grain orientation angle (deg)	0, 45, 90, 120, 135, 150
Samples (repetitions)	3 for each grain angle

knife marks, with a traverse speed of 1 mm/s. After several preliminary tests, the arithmetic average of the absolute deviations from the mean surface level, R_a parameter, was chosen as the indicator of surface roughness. Six measurements were performed for each sample and each set of cutting conditions, for two consecutive traverse lengths of 20 mm each to ensure repeatability, and the results were averaged.

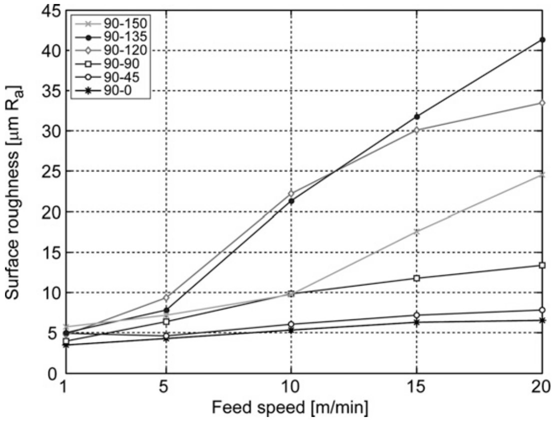

Figure 1. Surface roughness as a function of feed speed for the six cutting directions studied.

RESULTS AND DISCUSSION

Surface Roughness Results

The effects of feed speed and grain orientation on surface roughness are summarized in Figs 1 and 2. Surface roughness increased linearly as feed speed increased, but this effect depends on grain orientation (Fig 1). In contrast, the effect of grain orientation on surface roughness is nonlinear (Fig 2). Thus, R_a increases slightly when the cutting direction changes from 90 – 0 to 90 – 90 (cutting following the grain) and then rises sharply reaching its maximum at either 90 – 120 or 90 – 135 (machining against the grain). The surface smoothens when the grain orientation angle is higher than 135°. Similar results were obtained for Japanese beech wood in a previous study (Iskra and Tanaka 2005). The interaction effect of the grain angle and feed speed on the R_a can also be noticed. The shape of the curves indicating the influence of the grain orientation on the surface roughness changes with the feed speed (Fig 2).

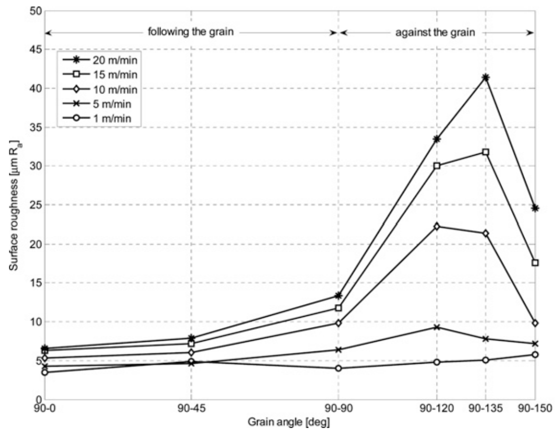

Figure 2. Surface roughness as a function of the grain orientation angle for the five feed rates examined.

Results of the analysis of variance (ANOVA) confirm that the grain angle, feed speed, and their interaction have statistically significant effects on the R_a variation (Table 2). Any other two-way and three-way interactions appear to be nonsignificant. In contrast, changes in cutting depth did not affect R_a variation regardless of the grain angle and feed speed. This may be explained by considering the fact that in up-milling, the part of the knife path that remains visible on the surface is the initial portion where chip thickness is minimal. Furthermore, the entrance angle at which the knife penetrates the wood is not influenced by changes in cutting depth. As a result, the mechanism of the new surface formation remains unaffected.

It is hence apparent that cutting following the grain (ie, from 90 – 0 up to 90 – 90), including routing perpendicular to the grain (90 – 90), occurs in fairly mild conditions (Fig 1). As expected, the surface quality worsens significantly when cutting against the grain. The roughest surfaces were observed for the grain angles of either 120 or 135° depending on the feed speed considered (Fig 2). The maximum roughness was obtained at 120° grain angle for feed speeds lower than about 12 m/min (Fig 1). At higher feed speeds, the worst surface was

Table 2. *Results of the analysis of variance for the significance of variables.*

Source of variation	Numerator df	Denominator df	F value	P > F
Grain angle	5	178	341.09	<0.0001
Feed speed	4	178	504.63	<0.0001
Grain angle*feed speed	20	178	26.27	<0.0001
Depth of cut	2	178	1.82	0.1654
Grain angle*depth of cut	10	178	0.60	0.8097
Feed speed*depth of cut	8	178	0.81	0.5979
Grain angle*feed speed*depth of cut	40	178	0.21	1.0000

obtained at 135° grain angle. This behavior could be explained by considering the effects of both the feed speed on chip thickness as well as on the progression of the resultant cutting force occurring during a single incision. The path of the knife edge during the cut is produced by the joint action of the rotation and feed speeds. At a constant rotation speed, chip thickness increases as feed speed rises. The forces required for cutting a single chip are also increased. In fact, the magnitude and direction of the resultant cutting force will depend on the instantaneous position of the tool edge on the workpiece. This is because, in up-milling, the instantaneous chip thickness is constantly changing from a minute value at the knife entrance to a maximum value near the point that the knife exits the workpiece. Furthermore, the knife edge continually changes its cutting direction with respect to the grain until it emerges at the wood surface. The present results would indicate that the variation in cutting forces from changes in chip thickness appears influenced by grain direction; samples with 135° grain angle could be more sensitive to changes in chip thickness than samples with 120° grain angle. Figure 2 confirms that variation in roughness was higher for 135° grain angle than for the others. This implies that the maximum roughness, measured at 120° at 10 m/min feed speed and 135° at 15 m/min feed speed, could have been produced under the maximum resultant cutting forces attainable for these particular feed speeds. However, more research needs to be done to validate this hypothesis. Thus, the effect of chip thickness on cutting forces at different levels of grain orientation should be assessed.

According to Stewart (1969), the low surface quality obtained when cutting against the grain is the result of the fact that the tool edge indents and deflects the fibers before they are cut. Chip formation will therefore be a cyclical phenomenon under these conditions of cutting. This is confirmed by the results of Costes et al (2004), who observed a spiky (force peaks) behavior of the orthogonal cutting forces within the range of 100 and 145° grain angle. The cutting forces became more stable beyond this range of grain values. As noted by Stewart (1969), the maximum deflection of the fibers in orthogonal cutting of white ash occurred between 120 and 145° grain angle. This maximum fiber deflection varied between 130 and 145° grain angle for three other wood species (Stewart 1983). However, the cutting action generating wood surfaces is more complex for peripheral up-milling than for orthogonal cutting as explained previously.

Neural Network Modeling

Artificial neural networks (ANN) feature a number of interesting properties for modeling a complex system or process. They are more forgiving with noisy or missing data, have the unique capability to approximate any function, and can operate using multiple nonlinear variables for unknown interactions. One motivation for the development of neural network process models is that they do not depend on simplified assumptions such as linear behavior or production heuristics (Coit et al 1998). Neural networks provide models of data relationships through highly interconnected, simulated neurons that accept inputs, apply weighting coefficients, and feed their output to another layer of neurons. This process is continued through the subsequent layers throughout the entire network to the output. Neural networks offer a good alternative for modeling a manufacturing process in which no satisfactory analytic models exist or when low-order polynomial models are inappropriate (Feng and Wang 2003). Another advantage of ANN is that they can accept a large number of input–output data, whereas multiple regression analysis can deliver only one output. Training of the neural networks takes place by searching over controllable variables for the combination of settings that yield the best performance of the output function. A properly designed and well-trained neural network can represent the process being modeled with fidelity, but special care must be taken to properly select a range of learning data. The output from the neural network can be unpredictable if the input vector is outside of the range of learning data used to train the network.

Among a number of different learning algorithms available, back propagation is most commonly used because it is the best general purpose model. It is a supervised learning method in which the learning data set has both predictor (independent) variables and a target (dependent) variable whose value is to be estimated. By using the learning algorithm, the network is trained (by adjusting the weighting coefficients) to model the value of the target variable based on the given input variables. In the present work, feed-forward back-propagation that uses the Levenberg-Marquardt optimization and the gradient descent with momentum weight/bias learning function was implemented. This algorithm appears to be the fastest method for training moderate-sized feed-forward neural networks (Demuth et al 2007).

Using the average value of three replications of surface roughness measurements for each possible factor combination (Table 1), and averaging the results for cutting depth (because the cutting depth was already proven to be nonsignificant), a total of 30 learning vectors along with adequate targets were paired to be used as a learning data set. After a number of trials, it was determined that a neural network with two hidden layers consisting of four and two neurons, respectively, and one output was sufficient to give a satisfactory approximation of the model (Fig 3). Generally, the higher number of learning vectors and fewer neurons that are used in the hidden layer, the better. It is understood that a neural network with a number of inputs and one output with no neurons in the hidden

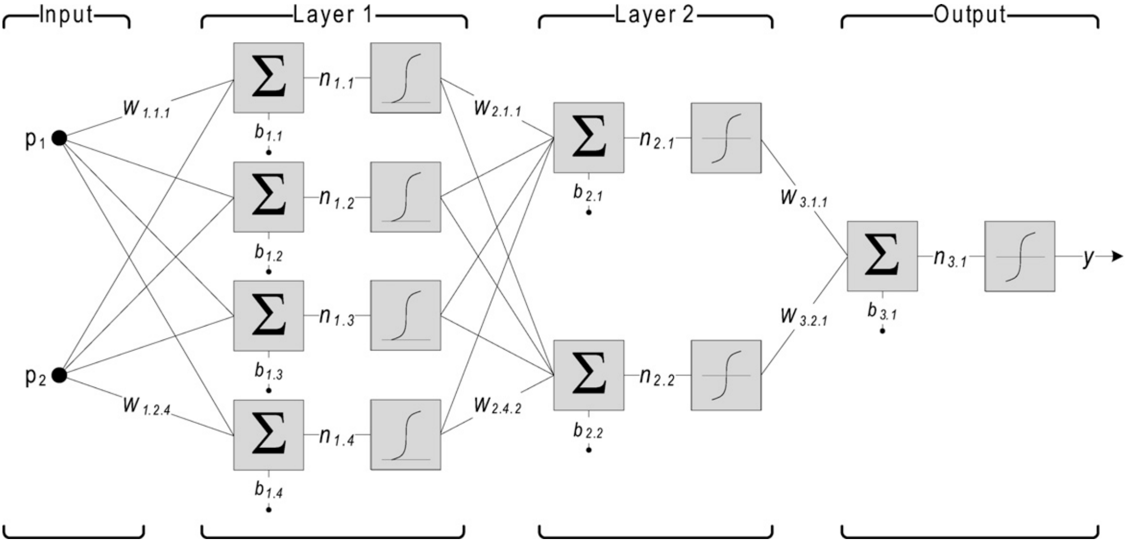

Figure 3. The neural network architecture.

layer can approximate only a linear function with no interactions between inputs. To approximate functions with higher order, one needs to use a number of hidden layers and several neurons in each layer depending on the function complexity. The network in this study had two input neurons, p_1 and p_2, that represent the grain orientation angle (deg) and feed speed (m/min), whereas the output is R_a (μm). This parameter represents the arithmetic average of the absolute value of the heights of roughness irregularities from the mean value. The number of required learning vectors for a given network architecture is suggested by the following relationship (Lawrence and Fredrickson 1998):

$$\begin{cases} \min = & 2\times(i+n+o) \\ \max = & 10\times(i+n+o) \end{cases} \tag{1}$$

where i is the number of inputs, n is the number of neurons in the hidden layer, and o is the number of outputs. The 30 training vectors gathered during the experiments satisfy this requirement.

Each node of the network has an activation function also called a transfer function. The sum of each input (p_i in Fig 3) multiplied by their respective weights ($w_{l,s,n}$) and the bias ($b_{l,n}$) are fed into the transfer function, and the resulting value is the node's output. The transfer function simulates the threshold potential of a biological neuron, ie allows the output of a node to be passed on to the next layer. After a number of trials, we concluded that the best results are obtained when log-sigmoid and tan-sigmoid activation functions are being used in the hidden and the output layers, respectively (Fig 3). Such a constructed network has been then trained using the learning data set in which 80% of the data was used for actual training and the remaining 20% for testing. The goodness of fit expressed by the mean squared error after 100 training epochs was 0.096 (μm^2 R_a). The measured values of surface roughness as well as those predicted by the ANN are compared with show performance of the network (Fig 4). This figure shows that values predicted by the network closely approximate those of the observed measurements with a maximum absolute error of 0.66 (μm R_a). Also, the relative percentage error ($e_{\%}$) between the fitted value and the observed measurements was calculated based on the following equation:

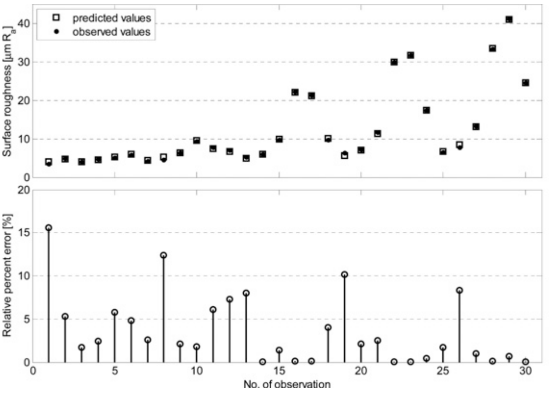

Figure 4. Observed and predicted values of surface roughness using the artificial neural network model (above) and relative percentage error between the predicted and measured surface roughness values (below).

$$e_{\%} = \frac{P_t - A_t}{P_t} \times 100 \tag{2}$$

where P_t is the predicted value of surface roughness and A_t is the actual measured surface finish (Fig 4). The relative percentage error reaches up to 16%, but the majority of the error observed falls below 10%. The analysis of variance shows that the values of both predicted and measured values are highly comparable as indicated by a high p value of 0.998 (Table 3). Such good approximation of the target was expected given that the same data set was used to train the network. Therefore, an independent procedure using a different data set is required to validate the performance of the model (as discussed subsequently).

Statistical Regression Modeling

A multiple statistical regression (SR) model was also developed with the data obtained from the experiments. A log transformation of the dependent variable (surface roughness) was required to meet the assumptions of normality and homogeneity of data. Because linear and quadratic equations were not satisfactory enough to model the relationship, a cubic equation regression was derived by performing the mixed procedure that fits a variety of mixed linear models to data (Table 4). Akaike's and Bayes' information criterions of the fit as well as the partial F-test of each coefficient were performed to assure the goodness of the approximation. All of the selected variables were statistically significant at the confidence level of 0.05. This approach, after the reverse logarithmic transformation, produced the following prediction equation:

$$R_a = \exp(-0.01882g + 0.000392g^2 - 1.76e^{-6}g^3 + \\ + 0.006087f^2 - 0.00026f^3 + \\ + 0.000536gf + 1.3821) \quad (3)$$

where R_a is the estimated surface roughness parameter (μm), g is the grain orientation angle (deg), and f is the feed speed (m/min).

To evaluate the performance of the SR approach, the same input data that was used to construct Eq 3 was used to calculate the output (Fig 5). It can be observed that the model (3) approximates the actual results with some margins of error. The model estimates lesser values of R_a rather well, whereas prediction of higher values is problematic. Although the highest absolute error reaches a significant value of 9.6 (μm R_a), the correlation coefficient calculated for observed and estimated values is relatively high (0.95) indicating a good fit. The percentage relative error reaches up to 40% (Fig 5), which is more than twice the error observed for the ANN model. ANOVA analysis (Table 5) confirms that the predicted and observed values are alike, but the p value is not as high as it was in the case of the ANN model.

Model Validation and Comparison

For validation purposes of the developed models, an independent set of cutting experiments was performed with quite different machining parameters than those used for model building. The cutting conditions were not extended beyond the parameters range of initial data used for model construction. If the model successfully passes the validation procedure, it can be applied to predict the surface roughness within the relatively wide range of cutting parameters presented in Table 1. Results show that

Table 3. *Analysis of variance for observed and predicted measures (artificial neural network model).*

Source of variation	Sum square	df	Mean square	F value	P > F
Columns	6.16e-4	1	0.001	5.73e-6	0.998
Error	6232.52	58	107.5		
Total	6232.52	59			

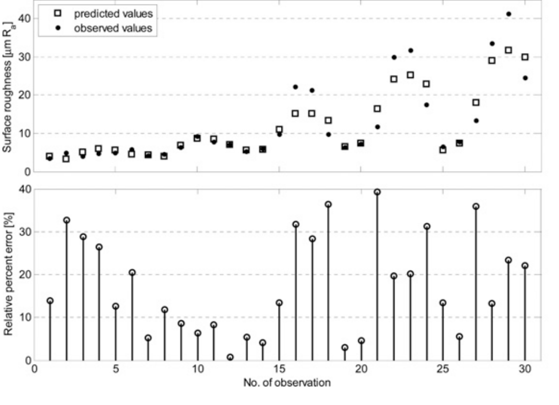

Figure 5. Surface roughness observed and predicted values using the statistical regression model (above) and relative percentage error between the measured and predicted values (below).

Table 4. *Results of the multiple regression analysis with fixed effects.*

Source of variation	Estimate	Standard error	df	t value	P > |t|
Intercept	1.382100	0.154400	0	8.95	—
Grain	−0.018820	0.007245	23	−2.60	0.0161
Grain^2	0.000392	0.000118	23	3.32	0.0030
Grain^3	−1.76e-6	0	23	−Infty	<0.0001
Grain*feed	0.000536	0.000120	23	4.48	0.0002
Feed^2	0.006087	0.002217	23	2.75	0.0115
Feed^3	−0.000260	0.000098	23	−2.64	0.0145

Table 5. *Analysis of variance for observed and predicted measures (statistical regression model).*

Source of variation	Sum square	df	Mean square	F value	P > F
Columns	6.37	1	6.37	0.07	0.792
Error	5248.37	58	90.49		
Total	5254.74	59			

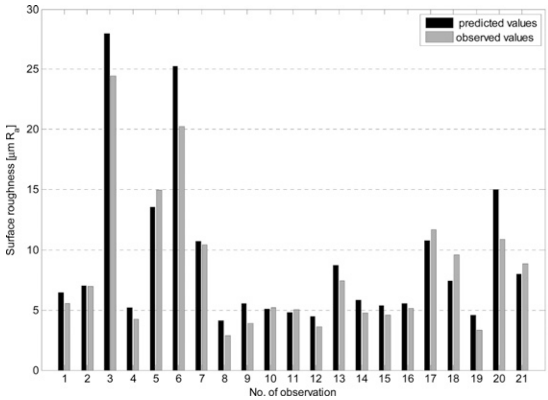

Figure 6. Observed and predicted values of the surface roughness for validation data (artificial neural network model).

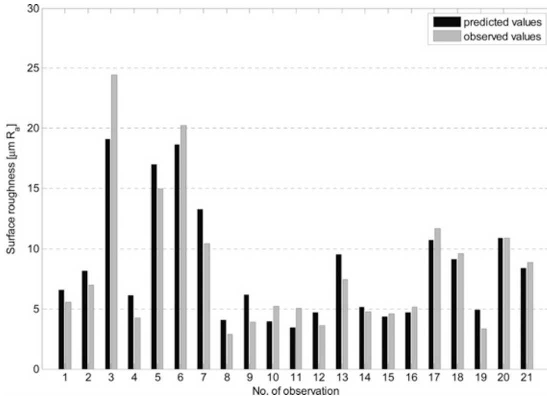

Figure 7. Observed and predicted values of the surface roughness for validation data (statistical regression model).

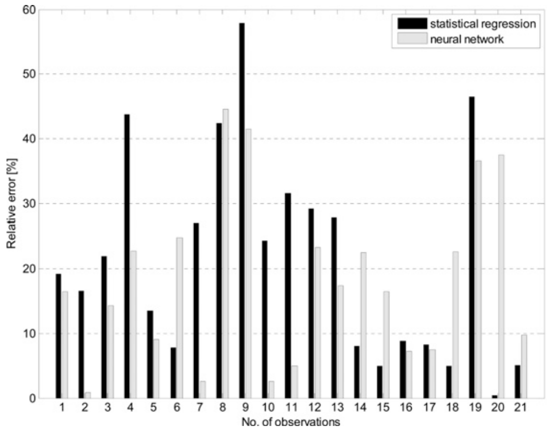

Figure 8. Relative percentage error between the measured and predicted values for artificial neural network and statistical regression models.

surface roughness predicted with the ANN model approximates the measured data quite well (Fig 6). The SR model was also able to predict the surface finish of paper birch wood fairly well (Fig 7). The ANN model has the tendency to overestimate the target, whereas the SR model underestimates the validation data, especially for higher values of R_a. The two models were compared in terms of the percentage of relative error (Fig 8). During the validation procedure, the SR model showed higher error than the ANN. For the total of 21 observations, error generated by the SR model suppresses the error of the ANN in 14 cases.

For further analysis of the two models, various error statistics were calculated and summarized in Table 6. Mean absolute percentage error (MAPE) measures the accuracy of fitted series and is described by the following equation:

$$\mathrm{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\frac{|P_t - A_t|}{A_t} \times 100\% \tag{4}$$

where P_t is the predicted value, A_t the observed measurement, and n is the number of observations. Root mean square error (RMSE) is a measure of the residuals (differences) between the modeled values and the observed data.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(A_t - P_t)^2} \tag{5}$$

The calculated statistics determined for the ANN model appear to be generally slightly better than those obtained for the SR model. Under these terms, the ANN model should be preferred over the SR model. However, although the SR

Table 6. *Error comparison for the models' validation process.*

Model	Maximum absolute error (μm R_a)	Maximum percentage error (%)	RMSE[a] (μm R_a)	MAPE[b]	R[c]
Artificial neural network	5.00	44.6	1.88	18.3	0.970
Statistical regression mixed	5.35	57.9	1.82	21.4	0.951

[a] Root mean square error.
[b] Mean absolute percentage error.
[c] Correlation coefficient.

model may have generated higher errors, it is an explicit construct that is transparent and comprehensible in its representation. The regression model along with its associated statistics (Table 2) provides much better process insight and much clearer information than the ANN model (Feng and Wang 2003). The ANN is often called a "black box," ie, we know generally how the learning process takes place but it is not clear why given weights are assigned to certain values. Moreover, every time a neural network is initialized and trained using the same learning data set, the weights, the performance, and the outcomes may be slightly different if the initial weights are chosen randomly (which is a common practice). Nevertheless, when the experimental data are not obtained from a structured design of an experiment or when data are sparse, SR may not be able to give satisfactory results and in such cases these can be considerably outperformed by the neural networks.

CONCLUSIONS

The surface roughness of paper birch wood after routing at different machining conditions was examined. Results showed that the surface quality decreases linearly as the feed speed rises. In contrast, a nonlinear behavior was observed between the surface roughness and the grain orientation. The worst surface was obtained when cutting against the grain, between 120 and 135° grain angle, depending on the feed speed considered. There was not a statistically significant relationship proven between surface roughness and cutting depth. Moreover, two different predictive models of surface finish were presented. The artificial neural network and the statistical regression approach were used to construct models that were able to forecast the final surface roughness. Validation procedures performed with additional experimental data and selected error statistics were calculated and compared. The neural network model appeared to slightly outperform the statistical regression model. It was suggested, however, that traditional statistical modeling is more reliable and predictable because it is more explicit. Moreover, the error analyses of the validation procedure results show comparable values. Nevertheless, there are circumstances in which the data collected would not be able to satisfy a statistical regression approach. In such cases, the neural network modeling would be a valid solution. The models developed in this study can aid simulation, prediction, and optimization of the surface roughness during routing and can be helpful in the selection of cutting parameters.

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