A Pre-process Model for Surface Finish Prediction in High Speed Milling Based on Softcomputing

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Performance of Predicting Surface Quality Model Using Softcomputing, a Comparative Study of Results

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Abstract. This paper describes a comparative study of performance of two models predicting surface quality in high-speed milling (HSM) processes using two different machining centers. The models were created with experimental data obtained from two machine-tools with different characteristics, but using the same experimental model. In both cases, work pieces (probes) of the same material were machined (steel and aluminum probes) with cutting parameters and characteristics proper of production processes in industries such as aeronautics and automotive. The main objective of this study was to compare surface quality prediction models created in two machining centers to establish differences in outcomes and the possible causes of these differences. In addition, this paper deals with the validation of each model concerning surface quality obtained, along with comparing the quality of the models with other predictive surface quality models based on similar techniques.

Keywords: High-speed machining · High-speed milling · Softcomputing · Bayesian networks · Predictive models

1 Introduction

High-speed milling (HSM) is a technique used for producing industrial pieces using materials such as plastic or metal alloys. One of the reasons for using HSM is the high-quality surface finishing possible to get [13]. Currently, HSM is one of the processes producing the greatest economic impact on the metal making industry owing to the surface finishing influencing the functional behavior of a resulting piece, which is subjected to demanding friction conditions, sudden temperature changes, etc. [2,4].

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The surface quality obtained with material removal techniques such as HSM greatly depends on experimental design (DOE) [18]. This must include several factors such as properties of the material to be milled, characteristics of the machining center, and the tool used. In the field of surface quality, there is a trend to use data management techniques such as Soft computing to obtain data for improving HSM quality outcomes using a given DOE. Soft computing techniques help identify factors influencing HSM and their most convenient values to achieve the best surface quality (Ra), minimizing associated costs such as instrument calibration, experimentation, intermediate or final quality measures, etc. [7].

Surface quality is frequently associated with texture or surface roughness; this can be calculated from several parameters [18]. In practice, Ra is the parameter most used for estimating the quality of a piece and may be quite easily measured [9] using, for example, profilometers. According to ISO standard 4288:1996, Ra values may be calculated with a equation, in [5] this procedure is described.

In addition, Ra has a great influence on other interesting factors for making metal pieces such as friction, electric and thermal resistance, and the appearance of a finished piece. In the same context, Ra is important because it contributes with ideas about the behavior of a surface in contact with others or dimensional warping [12]. In this way, the DOE and Ra are importants, since that the costs, machining time can be reduced [9,22]. Recently, studies as one presented in [1] introduce Artificial Intelligence techniques on DOE and pre-process designs, adding variables as power-consumption or results of previous experiences (learning) in order to achieve a automatic cutting parameters configuration.

1.1 Bayesian Models

A Bayesian network is a directed acyclical graph with nodes representing predictive variables and the class and arcs representing their relational conditions. Nodes may represent variables such as cutting parameters in a HSM process. So, given two variables X1, X2, an arc between X1 and X2 represents the conditional relation between X1 and X2 [10]. The acyclical graph contains the probabilistic distributions of the influences among variables P(X1, X2, ..., Xi, ..., Xn). This can be written as the product of local distributions of each node as follows [11]:

$$P(X_1, X_2, \ldots, X_n) = \prod_{k=1}^{k=n} X_1, X_2, \ldots X_n \tag{1}$$

The distribution of the conditional probability P(Xi) in Eq. 2 is determined by the set of parameters Parents(Xi). The Bayesian classifier selects the most probable classification P(Xi), given distribution values X1, X2, ...Xi, ..., Xn. The Bayesian classifier results from the Bayes theorem application (Friedman et al. 2005), which calculates the a posteriori probability P(Cj|Xi) from conditional probabilities P(Xi|Ck) and a priori probability P(Ck) as:

$$P(Xi) = \frac{P(Cj|Xi)}{\sum_{k=1}^{n} P(Ck)} \tag{2}$$

where: P(Cj|Xi) represents the a posteriori probability of Xi giving the class Cj. That is: giving the class Cj in the presence of the value Xi, the probability that sample Xi (with given characteristics) belong to a given class Cj. P(Cj) represents the a priori probability. This is the initial probability for a sample Xi to belong to a given class Cj, without Xi characteristic information.

The Bayesian classifier can be used to predict class or classify new or unknown instances of a class. In addition, the probabilities of Eq. (2) can be estimated from expert knowledge or training data, using predictive variables and class in the latter case [15]. There are several Bayesian classifiers for creating predictive models from data. This study uses the Tree Augmented Nave Bayes model (TAN), which is a variant of Nave Bayes model. TAN allows calculating conditional mutual data for each pair of predictive variables for a given class [6].

1.2 Related Studies

The use of Soft computing techniques to generate Ra predictive models has increased in the last few years. One of the reasons for this is the quality and accuracy of the estimation of a parameter such as Ra done with Soft computing techniques [3,14]. For example, in [8] a technique based on Artificial Neural Networks is proposed to optimize the selection of parameters participating in the process of mechanical cutting using steel Inconel 718. Other studies propose the use of Artificial Neural Networks to study the surface roughness on-line [22].

The Artificial Neuronal Networks are used also on [19] to studied the variables influence on final Ra where a milling process on aluminum alloys, variables as feed rate, milling deep or speed milling are been studied here. Other methods to Ra estimated based on Neuronal Artificial Networks are described on [17] using AISA1054 alloys or [7] that describe a Soft Computing experience to generate a Ra predictive model using neuro-fuzzy and artificial neuronal networks. To make this work, variables as milling speed or milling deep had been used.

2 Models Description

In this study, Bayesian networks were used to create probabilistic Ra prediction models in HSM by milling metal alloys. The models were created using data from two different machining centers, but only one experimental design (details in [6,9]). Two HSM geometries kinds had made here: slots and girth. Slots were made in the first essay and various geometries were conducted in the second one.

Essays were first conducted in a Kondia HS1000 machining center with 3 degrees of freedom equipped with a CNC Siemens 840D, maximum engine power of 17.5 KW, and maximum spindle speed of 24000 rpm. In the second essay, a machining center made by Nicolás Correa S.A., Versa model (variant 675004) with 5 degrees of freedom (hereinafter M-Versa) was used. This machining center is equipped with a CNC Heidenhain TNCi530, with maximum engine power of 50 KW and maximum spindle speed of 15000 rpm.

A Kistler dynamometric platform was used for collecting power data in axes x y, and z and a Kistler 5070 amplifier to improve signals. The signals collected were later registered with a data acquisition software (designed with Labview software tool) and installed in an industrial computer. The models were created with software Weka (http://www.cs.waikato.ac.nz/~ml/weka/index.html. Weka is a software licensed by GNU. It is implemented with Bayesian algorithms necessary to do this study).

2.1 Description of Experimention with Slots

To mill slots, $180 \times 100 \times 25$-mm F114 steel probes were used and 2–6 teeth Karnash tools (models 30.6455 and 30.6465) were used for milling the probes. Tools with different diameters were used in the experiments: 6, 8, 10, and 12 mm for each number of teeth. Slots were milled at different depths, varying the progress and spindle speed with the same tool to render several combinations of experiments (with increases of 25%, 50%, and 75%). Then, the essays were repeated for each tool. Table 1 shows values of variables in the essays.

To calculate Ra values, post-process measures were taken with a Karl Zeiss Handysurf profilometer, model E-35A. In the case of the Kondia machining center, experimentation rendered 625000 measures which were grouped in 250 cases from averaging roughness values, according to the experimentation objectives described in [6]. In the case of experimentation, the result was 1475 cases obtained in the same way.

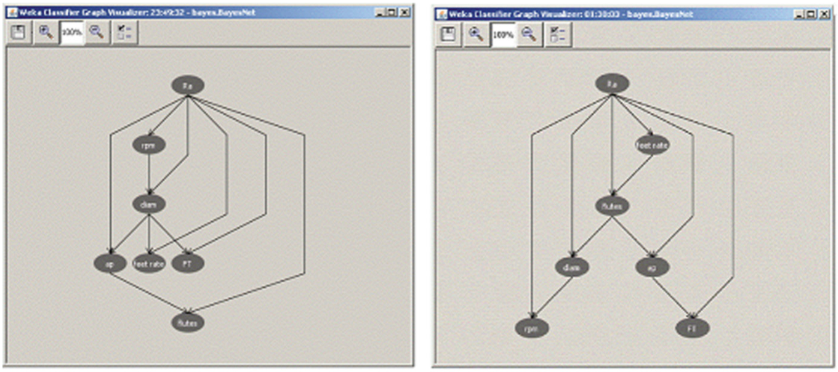
To create the Ra predictive model with slots, a Bayesian model with 7 variables (6 predictive variables plus class Ra) were used. The variables associated with cutting conditions are: axial depth of cut (ap), feed rate (F), and spindle rotation speed (n). The variables associated with the tool are: number of teeth (z) and diameter (diam). Variable FT corresponds to the force resulting from measures in axes x, y, and z.

2.2 Slots Models Validation

Figure 1a and b illustrate the TAN structure learned from experimentation with slots in the Kondia HS1000 and M-Versa machining centers. Figure 1 also shows the causal arcs between predictive variables and the class.

The causal arcs in Fig. 1 represent the influence of physical relations between predictive variables and the class. The causal structure on Fig. 1a show the influence of variable rpm over diam, and the influence of variable diam on the rest of predictive variables. The rpm causal influence can be wear-machine attributed, losing all influence in M-Versa model. The networks in Fig. 1a show the influence of variable diam on the rest of the predictive variables in Kondia model, losing influence in M-Versa model.

The clear influence of variable F (feed rate) on the rest of the predictive variables is observed in the model of M-Versa machining center, while this influence



(a) (b)

Fig. 1. TAN structure learned from slot experimentation.

does not exist in the model of the Kondia machining center. The causal structure on Fig. 1b show the influence of variable feed rate on the rest of predictive variables, while this influence does not exist in the model of the Kondia.

Differences in the conditional relationships obtained may correspond to the physical influence as vibrations of machines or other factors such power equipment, where the classification results are analyzed, they show interesting finds respect to Bayes classifier blessing [20]. Tables 3 and 4 shows these results. The Table 3 shows that 76.80% of cases are correctly classified instances (CCI) for Kondia, while 72.74% are CCI for M-Versa (Table 4). The variation between Kondia classification and M-Versa classification can be explained by the DOE and Bayesian model were designed for Kondia.

2.3 Description of Experimentation with Islands and Pockets

To create cases with geometries (islands and pockets), aluminum pieces of 65–70 Brinell hardness and $170 \times 100 \times 25$ mm were milled. Milling was done with Sanvik tools of 2 teeth and 8, 10, 12, 16, and 20-mm diameter at a maximum of 10-mm depth of cut. Millings consisted of two types: pockets and islands. Pockets were milled on 35-mm and 55-mm diameter circumferences, respectively, reaching 10-mm depth.

Two types of geometries were designed for pockets: the first ones were designed with 60-mm diameter pockets (pocket ++), milling the material at a 0.5-mm axial depth of cut and a 10-mm radial depth of cut. The second ones were designed with 35-mm diameter pockets (pocket +), milling the material at a 1-mm axial depth of cut and a 5-mm radial depth of cut. To create the Ra predictive model, an 8-variable Bayesian model (7 predictive variables and class Ra) was used. The variables are feed rate (fz), tool diameter (diam), radial depth of cut (ae), material hardness in Brinell (HB), geometry (geom) resulting from

Table 1. Stratification and confusion matrix for Kondia milling center with slots cutting

=== Stratified cross-validation ===
=== Summary ===
Correctly Classified Instances 192 76.80 %
Incorrectly Classified Instances 58 23.2%
Kappa statistic 0.6708
Mean absolute error 0.1392
Root mean squared error 0.2754
Relative absolute error 38.6323%
Root relative squared error 64.9107%
Total Number of Instances 250
=== Confusion Matrix ===
a, b, c, d, <– classified as
29 17 4 0 | a = Smooth
1 90 8 1 | b = Fine
0 11 33 6 | c = Semi-fine
0 1 9 40 | d = Medium

Table 2. Stratification and confusion matrix for Kondia milling center with slots cutting

=== Stratified cross-validation ===
=== Summary ===
Correctly Classified Instances 1073 72.74 %
Incorrectly Classified Instances 402 27.25%
Kappa statistic 0.465
Mean absolute error 0.1552
Root mean squared error 0.2827
Relative absolute error 59.8084%
Root relative squared error 78.5208%
Total Number of Instances 1475
=== Confusion Matrix ===
a, b, c, d, <– classified as
524 195 0 0 | a = Smooth
179 549 0 0 | b = Fine
27 1 0 0 | c = Semi-fine
0 0 0 0 | d = Medium

the combination of the characteristics of cut radio and curve, spindle rotation speed (n), and the resulting cutting force on the plane (Fxy) (Table 2).

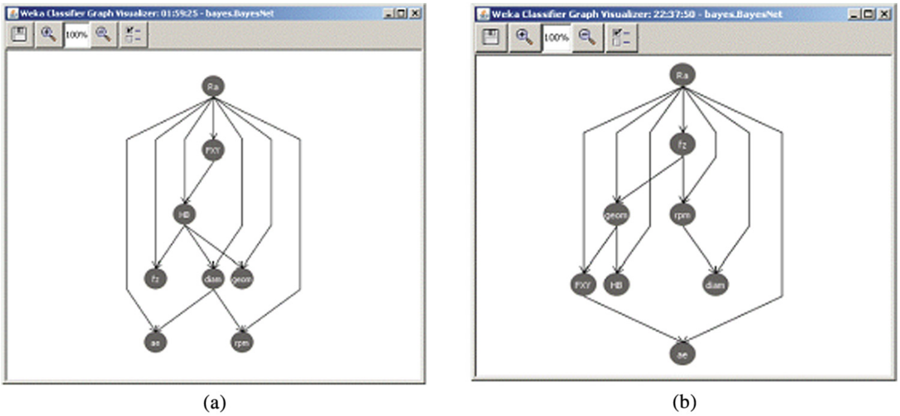


Fig. 2. TAN structure learned from islands and pockets experimentation.

2.4 Islands and Pockets Models Validation

Figures 2a and b illustrate the TAN structures learned from experimentation with islands and pockets. In the TAN network of the Konia model (Fig. 2a) the influence of variable Fxy on the other predictive variables can be observed; on the contrary, in the model obtained for the M-Versa center (Fig. 2b), the variable Fxy loses importance. In the two models, variable geom and variable hardness (HB) has reverse influences each other. This can indicates that the cutting geometry and material hardness relation of the workpiece to be machined must be taken into account in this type of milling.

In addition, the variations in conditional relations observed may correspond to the physical influence of the machining centers, although there are not enough data to interpret the phenomenon. It is sensed in this case being M-Versa a machining center stronger and better anchor (less vibration occurs), in add, on this case the relationship can be given by the type of material being cut.

Tables 3 and 4 summarize the classifications obtained. In the case of M-Versa, 96.09% cases were correctly classified, while in the case of Kondia, classification is quite significant (94.05%). The classification closest to this value is the one generated with the essays conducted in the Kondia machining center, thus supporting the good selection of predictive variables with respect to the class for this machine-tool.

Table 3. Stratification and confusion matrix for Kondia milling center with islands and pockets cutting

=== Stratified cross-validation ===
=== Summary ===
Correctly Classified Instances 1187 94.0571%
Incorrectly Classified Instances 75 5.9429%
Kappa statistic 0.9105
Mean absolute error 0.0381
Root mean squared error 0.1359
Relative absolute error 11.4089%
Root relative squared error 33.2712%
Total Number of Instances 1262
=== Confusion Matrix ===
a, b, c, d, <– classified as
492 15 0 3 | a = Smooth
50 324 0 0 | b = Fine
0 0 17 1 | c = Semi-fine
6 0 0 354 | d = Medium

Table 4. Stratification and confusion matrix for M-Versa milling center with islands and pockets cutting

=== Stratified cross-validation ===
=== Summary ===
Correctly Classified Instances 1575 96.0952%
Incorrectly Classified Instances 64 3.9048%
Kappa statistic 0.8454
Mean absolute error 0.0444
Root mean squared error 0.1781
Relative absolute error 18.2638%
Root relative squared error 51.0883%
Total Number of Instances 1639
=== Confusion Matrix ===
a, b, c, d, <– classified as
1364 43 0 0 | a = Smooth
21 211 0 0 | b = Fine
0 0 0 0 | c = Semi-fine
0 0 0 0 | d = Medium

3 Conclusion

The contribution of this study is mainly associated with the validation of an experimental design ad hoc for a machining center (Kondia) in another machine-tool with different characteristics. This validation is rather unusual in the domain of this industry because experimentation is rather costly. The models performance had been found during tests and analysis made on classifiers results.

This study proved that this experimental design can be applied in other machining centers with similar characteristics to Kondia center. That is the case of M-Versa, in which classification outcomes show accuracy higher than 70% correctly classified for slots cases and higher than 96% correctly classified for islands and pockets cases.

This allows to believe that the DOE and model designs are good quality for Ra estimation when machining center characteristics has been given. Another important contribution is that the models were created without considering the forces during milling as part of predictive variables, unlike previous studies. This makes the models rather independent of possible classification distortions, which may be caused by the different millings in the machining centers (e.g., spindle wear).

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