International Journal of Systems Science
Vol. 39, No. 12, December 2008, 1181–1192

Taylor & Francis
Taylor & Francis Group

A Bayesian network model for surface roughness prediction in the machining process

M. Correa[a]*, C. Bielza[b], M. de J. Ramirez[c] and J.R. Alique[a]

[a]*Departamento de Informática Industrial, Instituto de Automática Industrial, Consejo Superior de Investigaciones Científicas (CSIC), Madrid, Spain;* [b]*Departamento de Inteligencia Artificial, Universidad Politécnica de Madrid, Madrid, Spain;* [c]*Departamento de Mecatrónica y Automatización, Instituto Tecnológico y de Estudios Superiores de Monterrey (ITESM), Monterrey, Mexico*

(*Received 19 April 2007; final version received 1 November 2007*)

The literature reports many scientific works on the use of artificial intelligence techniques such as neural networks or fuzzy logic to predict surface roughness. This article aims at introducing Bayesian network-based classifiers to predict surface roughness (*Ra*) in high-speed machining. These models are appropriate as prediction techniques because the non-linearity of the machining process demands robust and reliable algorithms to deal with all the invisible trends present when a work piece is machining. The experimental test obtained from a high-speed milling contouring process analysed the indicator of goodness using the Naïve Bayes and the Tree-Augmented Network algorithms. Up to 81.2% accuracy was achieved in the *Ra* classification results. Therefore, we envisage that Bayesian network-based classifiers may become a powerful and flexible tool in high-speed machining.

Keywords: Bayesian networks; supervised classification; probabilistic graphical models; surface roughness; high-speed milling

1. Introduction

Classification is an essential task for (defect) diagnosis, pattern recognition and prediction. Supervised classification is a task that assigns predefined class labels to items of data described by a set of characteristics or attributes (Duda, Hart, and Stork 2001).

Bayesian networks are a kind of probabilistic graphical model (directed acyclic graph) representing the conditional independencies embodied in a given joint probability distribution over a set of variables (network nodes) (Castillo, Gutiérrez, and Hadi 1997). Used as intelligent decision systems, inferences over the network generate probability charts that can provide sound support for particular decisions about a node. They also indicate the node's relationships with other variables. This information cannot always be detected by an expert's knowledge alone, and it provides an intuitive understanding of the model.

One of the major advantages of Bayesian networks is that they admit partial observations, i.e. not all the nodes have to be instantiated. Partial observations received in real-time can be immediately assimilated by the probabilistic network as evidence. This allows the real-time predictions to be updated as new observations are incorporated.

The article is organised as follows. Section 2 highlights the problems of predicting surface roughness and the models currently developed to tackle them. Section 3 defines Bayesian classifiers focussing on the structures used here, Naïve Bayes and Tree-Augmented Naïve Bayes (TAN) (Friedman, Geiger, and Goldszmit 1997), and briefly describes the learning methods for each of these structures. Section 4 shows our Bayesian network-based proposal and analyses the experimental results of classifying surface roughness in high-speed milling processes. Finally, Section 5 rounds the article off with some conclusions.

2. Surface roughness prediction

2.1. *Difficulties when measuring surface quality*

The main thrust of research in this area is to increase the use of high-speed machining in the automotive or aeronautical industries. These industries, as many others, require some pieces with high-quality surface properties and dimensional tolerances associated with their work to be performed, fixed by the standards that they are obliged to meet.

The surface quality of a piece is measured by the surface integrity that, apart from the surface topography, takes into account the mechanical and metallurgical properties. These properties are very important in fatigue, corrosion resistance or service life of the piece. The surface topology is identified by

*Corresponding author. Email: macorrea@iai.csic.es

ISSN 0020–7721 print/ISSN 1464–5319 online
© 2008 Taylor & Francis
DOI: 10.1080/00207720802344683
http://www.informaworld.com

its surface texture, where deviations in the pieces are measured and compared with the nominal surface. Surface roughness is the most representative parameter for describing the surface texture (Correa, de, Ramírez, Alique, and Rodríguez 2004).

Surface integrity implies assessing the sub-surface layers for their mechanical and metallurgical properties. This assessment is done using X-ray diffraction or other fundamentally laboratory techniques, which obviously take up time and effort. The techniques are destructive and, consequently, require specific testing profiles.

However, surface roughness is easy to measure. It is one of the most commonly used parameters in industry, and is what most current research has focussed on. Surface measurement instruments as surface (or stylus) profilometers are used together with post-process statistical control inspection methods to make roughness measurements since the profilometers cannot be used in-process.

The surface roughness term is quantified by surface characteristic parameters. The measurement most commonly used is the roughness average *Ra*. *Ra* is the arithmetic mean of the absolute ordinate values $f(x)$ within a sampling length (L), as shown in Equation (1).

$$Ra = \frac{1}{L}\int_0^L |f(x)|\mathrm{d}x \tag{1}$$

According to ISO 4288:1996, *Ra* values belong to [0.006 μm, 50 μm]. This parameter is primarily used to supervise the production process, where a gradual change may occur in the surface finish, mainly due to tool wear. As *Ra* is an arithmetical average, see Figure 1, the surface defects do not have much effect on its results. Therefore, *Ra* is not used to detect defects because it does not differentiate between peaks and troughs.

As mentioned above, profilometers cannot be used in-process and even using pre-process methods to assure the quality of the designed product based on the Taguchi method (Montgomery 1996), an intermediate stage needs to be added to guarantee surface quality *during* the machining process. Measuring *Ra* in-process is not an easy task given the problems of the sensors most commonly used in the workshop: they tend to be invasive hindering their use and they do not directly measure *Ra* but other variables related to surface quality. Thus, an accelerometer measures vibrations and a dynamometer measures forces. Therefore, it is necessary to develop virtual sensors based on predictive models. These models should be founded on machining (mechanistic) theory and supported by observed (empirical) data. The aim of this article is to propose one such model to predict *Ra* based on observed data but also taking into account the physics of the machining process.

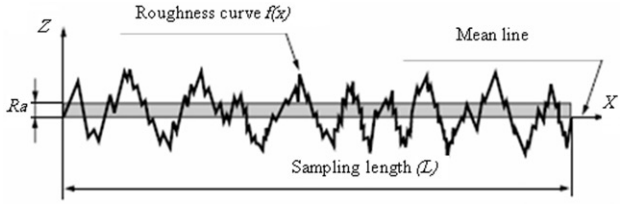

Figure 1. Average surface roughness graph or *Ra*.

2.2. *State-of-the-art*

On the one hand, the most commonly used artificial intelligence techniques within this context are artificial neural networks (ANN) with different training algorithms. Backpropagation is the usual and most tested algorithm. It provides very good results in the milling process, as investigated by one of the authors (Correa 2003).

On the other hand, statistical models use regression analysis, offer more information and give a better view of the process than the ANN models, since the functional relationships can be determined between variables (Correa et al. 2004). However, when the data are sparse and/or generated by experimental designs, regression analysis is unable to produce a better model than ANN (Feng and Wang 2003). In these cases, both models have a statistically satisfactory behaviour from the point of view of model validation and model construction. There is no significant difference between the linear regression model and the ANN model from the point of view of the results (errors), although the ANN model tends to better generalise than the regression model. The main papers that use ANN and/or regression models are briefly detailed in what follows.

In the last 10 years, Iowa State University has conducted detailed research on topics like prediction and control in machining targeting tool state and surface roughness. The group led by J. Chen has published several works on this topic for turning and milling tasks (Lou and Chen 1997; Lou and Chen 1999; Lou, Chen, and Li 1999).

(Tsai et al. 1999) present a surface roughness prediction system for the milling process, where they innovate and include spindle vibration and rotation – VAPR (vibration average per revolution) – in the roughness recognition system. Their work includes a review of the techniques used for measuring roughness, where they list the sensors used in the process. Most sensors were developed for turning. To find the predicted R_a value, two statistical models were

developed with multiple regression, and one model with ANN based on an off-line trained backpropagation. The three models were tested in an end-milling operation with 6061 aluminium, and just four-flutes tools. The criterion used to judge the model efficiency and capacity at predicting average roughness values was the roughness deviation percentage, established as:

$$\Delta = \frac{|\text{predicted}R_a - \text{actual}R_a|}{\text{actual}R_a} \times 100$$

After comparing the models, it was concluded that the results obtained with the ANN model were much nearer to the real *Ra* values than using the multiple regression model.

In the late 1990s, a design of experiments (DoE) was used to select the manufacturing process parameters that could give good-quality products. Yang and Chen (2004) proposed a system for identifying optimum surface roughness in an end-milling operation applying the technique known as Taguchi parameter design (Montgomery 1996) based on off-line quality control techniques with activities done during the product plan or process and its development stages. They performed an analysis of the results of experiments using high-speed four-flutes tools in an end-milling operation on 6061 aluminium blocks and determined the optimum cutting conditions to obtain the minimum surface roughness. This work was only tested with one material type and a particular combination of cutting conditions.

In 2003, Huang and Chen (2003) proposed an in-process surface roughness prediction system associating a neural network with sensoring technology applied to a decision-making system for a wide range of machining processes in an end-milling process. This system was based on works by Ismail, Elbestawi, Du, and Urbasik (1993); Lou et al. (1999); Tsai et al. (1999), where surface roughness is related to cutting force and speed. Huang and Chen considered the forces applied to all the cutting planes (*Fx* and *Fy*) irrespective of the normal force to the cutting plane (*Fz*), and found that the cutting forces have a high correlation with the surface roughness. The experimental data were obtained taking only 6061 aluminium cutting pieces with maximum turning speed levels of 2250 rpm.

In the same year, Samson and Chen (2003) also used neural networks and proposed a surface roughness recognition system in turning operations. Taking, up Tsai et al.'s (1999) idea, they used VAPR to compare a statistical model with a neural network. Taking the same input variables as in the previous works, but changing the forces (dynamometer) for vibration (accelerometer), a common feature in these processes, they obtained a network with a 4-7-7-1 architecture, the same as in Huang and Chen (2003) with fairly similar results.

Yang et al. (2006) proposed an adaptive surface roughness control system for end-milling operations. This system was based on the neuro-fuzzy training scheme proposed by Chen (2000). The fuzzy regions were defined for each parameter: cutting speed, feed rate, resulting force on the cutting plane (*Fxy*), normal force to the cutting plane (*Fz*), *Ra* deviation (*DRa*) and feed rate deviation (*Df*). The system had two subsystems, one for predicting in-process *Ra* and another to control the feed rate (*Df*) that is adapted based on the predicted *Ra*.

Kirby, Zhang, and Chen (2004) published the development of a surface roughness prediction system using accelerometers in a turning operation with multiple regression techniques. In 2006, the same authors (Kirby, Chen, and Zhang 2006) published the development of an adaptive control system that uses the same technique proposed by Chen (2000) and developed for milling by Yang et al. (2006).

Evolutionary computation methods have also been recently used for the *Ra* prediction (Suresh, Venkateswara Rao, and Deshmukh 2002; Brezocnik et al. 2004). Suresh et al. (2003) proposed a genetic algorithm to optimise a surface roughness (*Ra*) model based on surface response methodology and obtained process parameters (cutting speed, feed rate, depth of cut and tool nose radius) attaining the required surface quality. Brezocnik et al. (2003) presented a *Ra* predictor integrating genetic programming and genetic algorithms starting from spindle speed, feed rate, depth of cut and vibrations, where one of the main conclusions was to establish that the surface roughness is most influenced by the feed rate, and the vibrations increased the prediction accuracy.

Therefore, the main tools used in the most recent significant works for predicting surface roughness are linear or multiple regression and ANN, and they often do not bear in mind the mechanical analysis of the cutting process or the expert's (operator, production engineer or mechanical engineer) process experience. This was a fundamental point for us when choosing the tool to develop an optimum *Ra* predictor.

In short, there is no agreement on the general prediction concept and on the models to be used, since the research done to date has not yet satisfied industry's real needs. Also, there is no reliable device on the market to measure on-line surface roughness. The use of off-line surface roughness measurement instruments means that production line efficiency is affected due to the lack of real-time control. This is especially evident in the time required for post-process inspection and in the waste of material and production time on manufacturing faulty pieces.

3. Bayesian network-based classifiers

Bayesian networks have important practical applications and are very competitive with other artificial intelligence methods like ANN or decision trees. A Bayesian classifier is a Bayesian network applied to classification tasks, where each training sample changes the estimated probability that a hypothesis is correct and prior knowledge can be used to determine the probability of a hypothesis. A Bayesian network can classify new instances by combining different hypotheses probabilistically.

The aim of supervised classification is to classify instances given by certain characteristics $\boldsymbol{x_i} = (x_{i1}, x_{i2}, \ldots, x_{in})$ into r class labels, c_i, $i = 1, \ldots, r$. The main principle of a Bayesian classifier is the application of Bayes' theorem (James, 1985). Bayes' theorem, Equation (2), calculates the *posterior* probability $P(c_j|\boldsymbol{x_i})$ from the conditional probabilities $P(\boldsymbol{x_i}|c_k)$ and the prior probabilities $P(c_k)$ as

$$P(c_j|\boldsymbol{x_i}) = \frac{P(\boldsymbol{x_i}|c_j)P(c_j)}{\sum_k P(\boldsymbol{x_i}|c_k)P(c_k)}. \tag{2}$$

The posterior probability $P(c_j|\boldsymbol{x_i})$ is the probability that a sample with characteristics $\boldsymbol{x_i}$ belongs to class c_j. The prior probability $P(c_j)$ is the probability that a sample belongs to class c_j given no information on its characteristic values. The probabilities of Equation (2) can be estimated from the expert or from a training set required for building the classifier, where each instance i is given by $(\boldsymbol{x_i}, c_i)$.

Bayes' rule is used to predict the class and classify each unseen instance: a new instance or example only characterised with the values of the predictor variables is given a class label according to the class that has the maximum posterior probability. A useful property of the Bayesian classifier is that it is optimum in the sense that the expected rate of misclassifications is reduced to a minimum (Ripley 1996).

Of the different Bayesian classifiers, we will focus on two specific structures: Naïve Bayes and TAN. The first paradigm (Minsky 1961) is the simplest model. It is defined by the conjunction between the conditional independence hypothesis of the predictor variables given the class, yielding the following factorisation to be substituted in Equation (2):

$$P(\boldsymbol{x_i}|c_j) = P(x_{i1}|c_j) \cdots P(x_{in}|c_j)$$

Although this assumption is violated on numerous occasions in real domains, the paradigm still performs well in many situations (Domingos and Pazzani 1997; Hand and You 2001). The TAN classifier (Friedman et al. 1997) extends the Naïve Bayes model with a tree-like structure across the predictor variables. This tree is obtained by adapting the algorithm proposed by Chow and Liu (1968) and calculating the conditional mutual information for each pair of variables given the class.

4. Classifying *Ra* using bayesian networks

As mentioned above, what we are looking for here is an efficient *Ra* classifier learnt via a Bayesian network to try to convey the physical relationships of the machining process and other not so obvious (perhaps stochastic) relationships among the variables, not generally analysed in depth in other *Ra*-predicted models based on artificial intelligence. The final aim is to develop a virtual sensor to predict *Ra* on-line, while the machining process is taking place.

4.1. *Predictor variables*

The main relationships between cutting data in a milling process are explained by the following formulas:

$$\begin{aligned} V_c &= \frac{\text{Ø} \times \pi \times rpm}{1000} \\ \text{feed rate} &= fz \times \text{flutes} \times rpm \\ V &= a_p \times a_e \times \text{feed rate} \end{aligned} \tag{3}$$

where:

V_c = cutting speed ($\mathrm{m\,min^{-1}}$)
rpm = spindle speed ($\mathrm{min^{-1}}$)
feed rate = machine feed ($\mathrm{mm\,min^{-1}}$)
fz = feed per tooth ($\mathrm{mm\,tooth^{-1}}$)
Ø = tool diameter (mm)
flutes = total number of teeth
a_p = axial depth of cut (mm)
a_e = radial depth of cut (mm)
V = material removal rate ($\mathrm{mm^3\,min^{-1}}$)

The classifier was developed using the 'Elvira' programme (Elvira 2002). Elvira is the result of a research project funded by the Ministry of Science and Technology in which several Spanish universities and researchers from other Spanish and Latin American centres are participating. This programme, developed in Java, is available on the Internet. It is designed to edit and make inferences with Bayesian networks and influence diagrams, and also to generate Bayesian networks from a data file, as in our case.

Seven variables measured inside and outside the milling process were taken to construct the network structure. The average surface roughness, `Ra`, was chosen as the *class* variable, and it was the only variable measured post-process. The cutting force (`FT`) was measured during the cutting process, once the following cutting parameters had been set: cutting

depth (a_p), feed rate and spindle speed (rpm). Finally, two tool variables were included: number of teeth (flutes) and tool diameter (Ø).

Since Bayesian network algorithms require all the variables to be discrete, we chose the K-means algorithm (MacQueen 1967) to discretise feed rate and Ra, and Fuzzy K-means algorithm (Duda et al. 2001) to discretise rpm and FT, all with K=4. The other variables were already discrete. The K-means algorithm, Equation (4), is an algorithm for clustering objects into K partitions based on attributes. It is a variant of the expectation-maximisation algorithm whose goal is to determine the K-means of data generated from Gaussian distributions. It assumes that the object attributes form a vector space. The objective is to minimise total intra-cluster variance or the squared error function:

$$J = \sum_{i=1}^{K} \sum_{x_j \in S_i} \|x_j - \mu_i\|^2 \quad (4)$$

where there are K clusters S_i, $i = 1, 2, \ldots, K$ and μ_i is the centroid or mean point of all the points $x_j \in S_i$.

The algorithm starts by partitioning the input points into K initial sets, either at random or using some heuristic data. It then calculates the mean point, or centroid, of each set. It constructs a new partition by associating each point with the closest centroid. Then the centroids are recalculated for the new clusters, and the algorithm is repeated by alternate application of these two steps to convergence. Convergence is when the points no longer switch clusters (or, alternatively, centroids are no longer changed).

In the fuzzy K-means algorithm, given a set of r classes, $c_1, c_2, \ldots, c_r$, and a set $x_1, x_2, \ldots, x_n$ of N samples, it is considered from a fuzzy perspective that a sample x_j can belong to more than one class. This membership is measured by what is known as the *membership degree*, $P(c_i|x_j)$, indicating how much sample x_j belongs to class c_i. The classes are characterised by a vector called class centre, $m_1, m_2, \ldots, m_r$. The fuzzy K-means algorithm looks for a minimum of the following global heuristic function cost defined in Duda et al. (2001):

$$J_D = \sum_{i=1}^{r} \sum_{j=1}^{N} [P(c_i|x_j)]^b \|x_j - m_i\|^2$$

where b is a free parameter, chosen to adjust the overlapping or different class mix. If b is 0, J_D is a simple sum of squares error criterion with each pattern assigned to one class; if $b > 1$, each pattern can belong to more than one class.

These algorithms were chosen because of the nature of the process, which, together with the expert's knowledge, makes it possible to define *prior* intervals for clustering the sample data according to the variable to be treated. This was helpful in the choice of the discretisation algorithm that is closer to this clustering (Table 1).

The Ra class labels (Table 1) were assigned in accordance with the average roughness value (μm) established according to ISO 1302:2002 standard. They are as follows: Mirror 0.10, Polished 0.20, Ground 0.40, Smooth 0.80, Fine 1.60, Semi-fine 3.20, Medium 6.30, Semi-rough 12.50, Rough 25 and Clean 50. In our case we took the range from Smooth to Medium because of the operation (groved) and type of material (steel) used in the experiment.

4.2. *Data and experimental setup*

To obtain data, tests were carried out in a Kondia HS1000 machining centre equipped with a Siemens 840D open-architecture CNC. The blank material used for the tests was a 180 mm profile of F114 steel cutting with Karnash end-mill tools model 30.6472 with two flutes and model 30.6455 with six flutes. For the test, each tool (Ø 6, 8, 10 and 12 mm separated by families according to the flute numbers, 2 and 6) mechanised each slot with constant values of spindle speed and depth of cut, with increments of 25, 50 and 75% of the initial feed rate. Then other slots were mechanised increasing the value of the spindle speed (under the same pattern of 25, 50 and 75%) maintaining constant values of feed rate and depth of cut. For all the tests, new tools and combinations of parameters free of chatter were always used. A data set of 250 records

Table 1. Grouping for each variable after applying the corresponding discretisation algorithms.

Variable	Label	Lower limit	Upper limit
FT (N)	<35	6.687	35.02
	<56	>35.02	56.17
	<73	>56.17	73.33
	<142	>73.33	142.31
rpm	Slow	5520	7964
	Medium	>7964	10,758
	Semi-quick	>10,758	14,813
	Quick	>14,813	19,400
feed rate	<1000	300	1000
	<2050	>1000	2050
	<2775	>2050	2775
	<3850	>2775	3850
Ra	Smooth	0.7	1.1
	Fine	>1.1	2.1
	Semi-fine	>2.1	5.1
	Medium	>5.1	8.5

was obtained. Each record includes the information on the seven variables defined in Section 4.1.

All machined profiles were measured with the stylus profilometer Karl Zeiss Handysurf model E-35A to evaluate the changes of the *Ra* (μm) value due to the increment of feed rate and spindle speed that also varied the cutting forces. To measure these forces, a multi-component dynamometer with an upper plate was used. *Ra* was measured along the feed-rate direction.

4.3. *Case 1: learning a Naïve Bayes classifier*

The first network was obtained with the Naïve Bayes classifier structure. Laplace correction was applied to the probabilities estimates. This is a good option because our training data do not have representatives from all the possible combinations of variables. Laplace correction ensures that a proportion of participation is assigned even to examples that are not present at the time of training but that can appear in the future.

The network generated using the Elvira inference mode is shown in Figure 2. Each node shows the prior probability (i.e. without introducing any evidence) of its associated variable. Thus, initially the probability that the tool has six flutes is 0.26 and 0.74 is the probability that the tool has two flutes. With Elvira it is also possible to detect the causal effect between nodes, shown as different kind of arcs. The network learnt in Figure 2 only indicates a positive relationship between `Ra` and the `flutes` node (dotted arc). This means that higher values of `Ra` make high values of `flutes` more probable. However, the relationship between `Ra` and the rest of the variables: `feed rate`, `rpm`, `FT`, axial depth of cut (a_p) and diameter (Ø) was found to be neither positive nor negative, i.e. indefinite (solid arcs).

Assuming that the aim of a classification model is to correctly classify new cases, it should not be validated on the same data used to create the classifier. Accordingly, the K-fold cross-validation method was chosen (Stone 1974). The original sample is partitioned into K disjoint subsamples. Of the K subsamples, a single subsample is retained as the validation data for testing the model, and the remaining K − 1 subsamples are used as training data. The cross-validation process is then repeated K times (the folds), with each of the K subsamples used exactly once, like the validation data. Then the K results from the folds can be averaged (or otherwise combined) to produce a single estimate.

A confusion matrix was generated after validation. This is a contingency table crossing the variable derived from the classification output by the model with the variable that has the true classification. The results are shown in Table 2.

The Naïve Bayes classifier accuracy was 76%. This is the honest estimate of the true error rate, i.e. an indicator of how good the classifier is or the

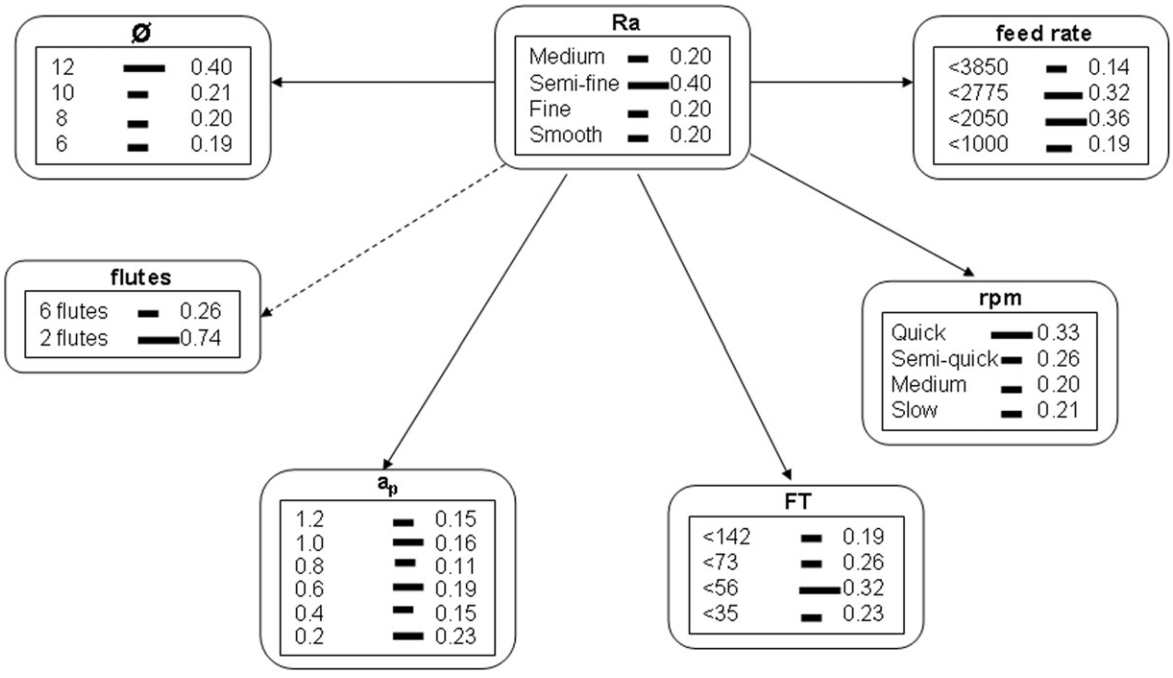

Figure 2. Bayesian network using Naïve Bayes in inference mode. Prior probabilities of each variable are shown at each node.

probability of it classifying new cases correctly. Analysing the confusion matrix, it was found that accuracy was better for Smooth class (98% of the cases were properly classified), Semi-fine (85% correctly classified) and Medium classes (62%). However, there was greater confusion with Fine class. In this case, 50% were correctly classified, whereas 28% Fine were classified as Semi-fine and 22% as Smooth.

4.4. *Case 2: learning a TAN classifier*

The second network was obtained with the TAN structure. Figure 3 shows the marginal probabilities of each of the variables involved. The TAN network shows the relationship and type of causal effect existing between its nodes. This provides more information on the relationship of each variable with the class, because all the links in the Naïve Bayes structure have the same weight and there is no influence between the predictor variables.

For this structure, the relationships we have obtained match the knowledge of the machining process. For instance, the relationship between the tool characteristics (flutes and diameter) with the cutting axial depth is unusual and it is not present in other kind of models based on other predictive techniques. This relationship is not evident from (4), see Section 4.1, but after consulting the expert, it was confirmed that there is an intuitive relationship between these nodes. This relationship links tool geometry characteristics and workpiece material properties with the axial depth.

Table 3 shows the results. The confusion matrix shows an accuracy of 81.2%, higher than in Case 1. Analysing this matrix the results generally improve, although the percentage of correct classifications for some classes decreases slightly. The percentage of

Table 2. Confusion matrix using Naïve Bayes.

Real	Medium	Semi-fine	Fine	Smooth
Assigned				
Medium	31	0	0	0
Semi-fine	19	85	14	0
Fine	0	6	25	1
Smooth	0	9	11	49

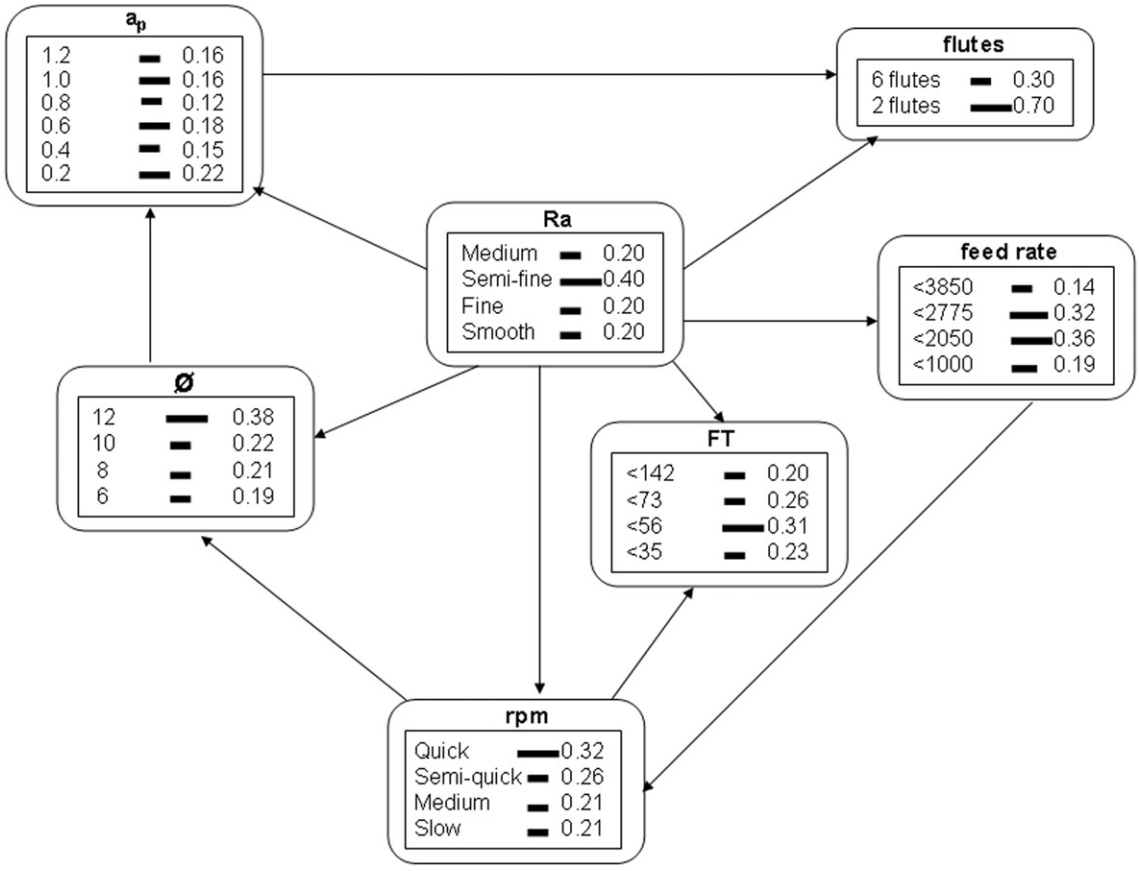

Figure 3. Bayesian network using TAN in inference mode. Prior probabilities of each variable are shown at each node.

correctly classified cases for the Fine class increases considerably from 50 to 80%. For the Smooth class, the percentage of correct classifications decreases from 98 to 90%, for the Semi-fine class from 85 to 83%, and for the Medium class, there is an increase from 62 to 70%.

4.5. *Response to the evidence input*

Now we can take advantage of the different queries we can make to the network. First, the model can infer what the (prior) probabilities (shown as dark bars) of each Ra value are without introducing any evidence. Second, we introduce some evidence at the rpm, feed rate and FT (shaded) nodes, and the network computes the posterior probabilities of each Ra value given that evidence (light grey bars). All the results are summarised in Table 4.

The second column of Table 4 summarises the marginal probabilities assigned to each Ra class without introducing any evidence (prior probabilities). The mode is located in the Semi-fine class, with a probability 0.4. Columns 3 and 4 of Table 4 show the posterior probabilities after incorporating evidence on feed rate ('<3850') and on rpm ('Quick'), respectively. Each time a node is instantiated, it is shaded in the respective figure.

According to the model output, when the feed rate is increased to '<3850', there is a 0.65 probability of Ra being achieved in the Semi-fine range (Figure 4).

Table 3. Confusion matrix using TAN.

Real	Medium	Semi-fine	Fine	Smooth
Assigned				
Medium	35	0	0	0
Semi-fine	12	83	5	1
Fine	3	14	40	4
Smooth	0	3	5	45

Similarly, the Ra value is affected when the spindle speed (rpm) is increased to the 'Quick' range, since the probability of Ra belonging to the Semi-fine class changes from 0.40 to 0.46, whereas it moves from 0.20 to 0.26 in the Smooth class (Figure 5).

Given that with the rpm effect, the highest probability (0.47) was that the feed rate variable was in the range '<2775' and that the FT variable was in the range '<56' (with a probability of 0.29), these three variables were then simultaneously so instantiated (column 5 of Table 4). The quality (*Ra*) moved up into the Smooth range with a probability of 0.78 (Figure 6).

Now, to verify that the model complies with the physics of the process, let us ask the network what happens when the flutes variable is firstly instantiated at 6. Physically speaking, the rpm and feed rate should increase, with respect to the prior probabilities shown in Figure 3, the probability of being at their quickest ranges of values, as the model actually outputs: the rpm moves up to 'Quick' (probability 0.40) or 'Semi-quick' (probability 0.33), the feed rate achieves '<3850' (probability 0.19), while Ra is in 'Fine' (0.18) or 'Smooth' (0.08). Secondly, when flutes is instantiated at 2, rpm is in 'Medium' (0.29) or 'Semi-quick' (0.25), feed rate is '<1000' (0.35), while Ra is in 'Fine' (0.21) or 'Smooth' (0.25). In both cases the other nodes (cutting force, axial depth of cut and tool diameter) also change their probability values influenced by the instantiated variable. Another test aimed to show that rpm increases if feed rate is instantiated and its values are increased, since these variables have a direct physical relationship, as was shown in Section 4.

Working in a reverse order, this model can also be used to output the cutting parameter and tool variable values. This is done by instantiating Ra at the target level. For example, if we want Ra to be in the 'Fine' class, the model recommends $a_p = 1.0$ (probability 0.43), rpm = Medium (probability 0.43), feed rate < 1000 (probability 0.46) and tool of diameter 10 mm (probability 0.47) with two flutes (probability 0.73), as you could actually prove in the laboratory.

Table 4. *Ra* probabilities calculated from the starting data without instantiations (second column) and after introducing evidence on feed rate, rpm, and FT variables (columns 3–5).

Ra classes	Prior probabilities	Example 1 Instantiating feed rate at '<3850'	Example 2 Instantiating rpm at 'Quick'	Example 3 Instantiating FT at '<56', feed rate at '<2775' and rpm at 'Quick'
Medium	0.20	0.27	0.15	0.01
Semi-fine	0.40	0.65	0.46	0.20
Fine	0.20	0.05	0.13	0.01
Smooth	0.20	0.03	0.26	0.78

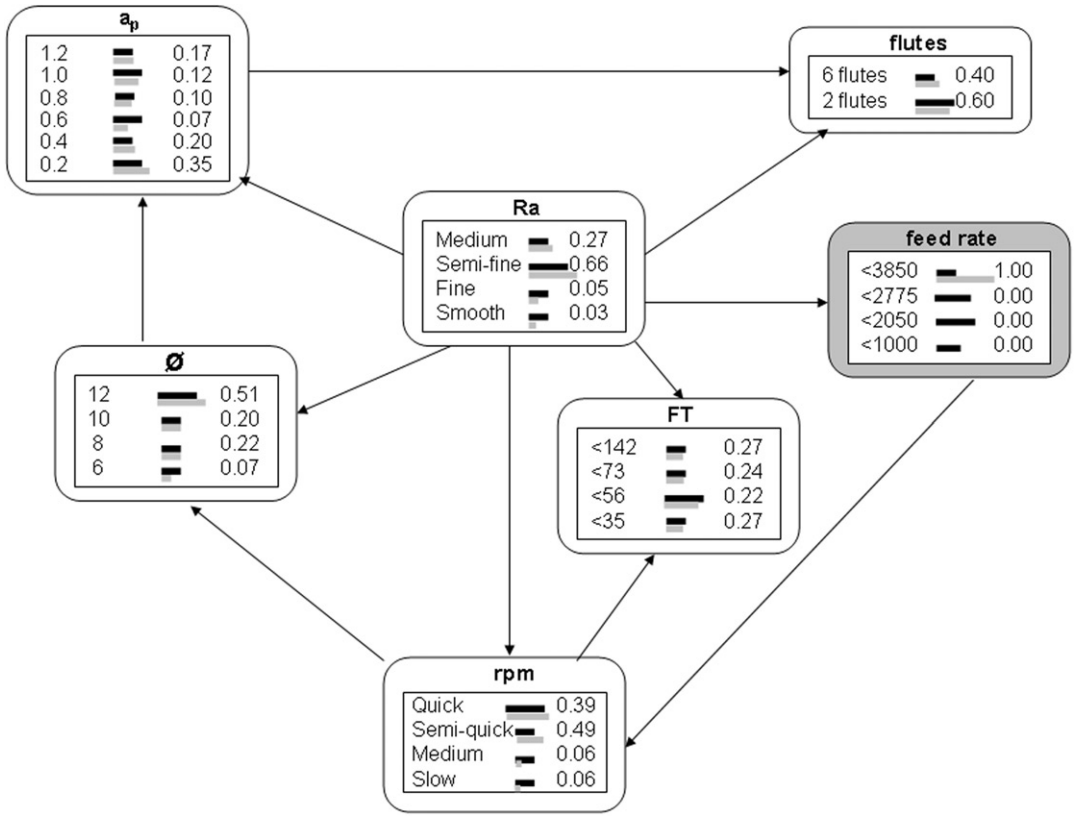

Figure 4. Tree-Augmented Naïve Bayes classifier instantiating the `feed rate` at '<3850'. Posterior probabilities of each variable, given this evidence, are shown at each node in grey.

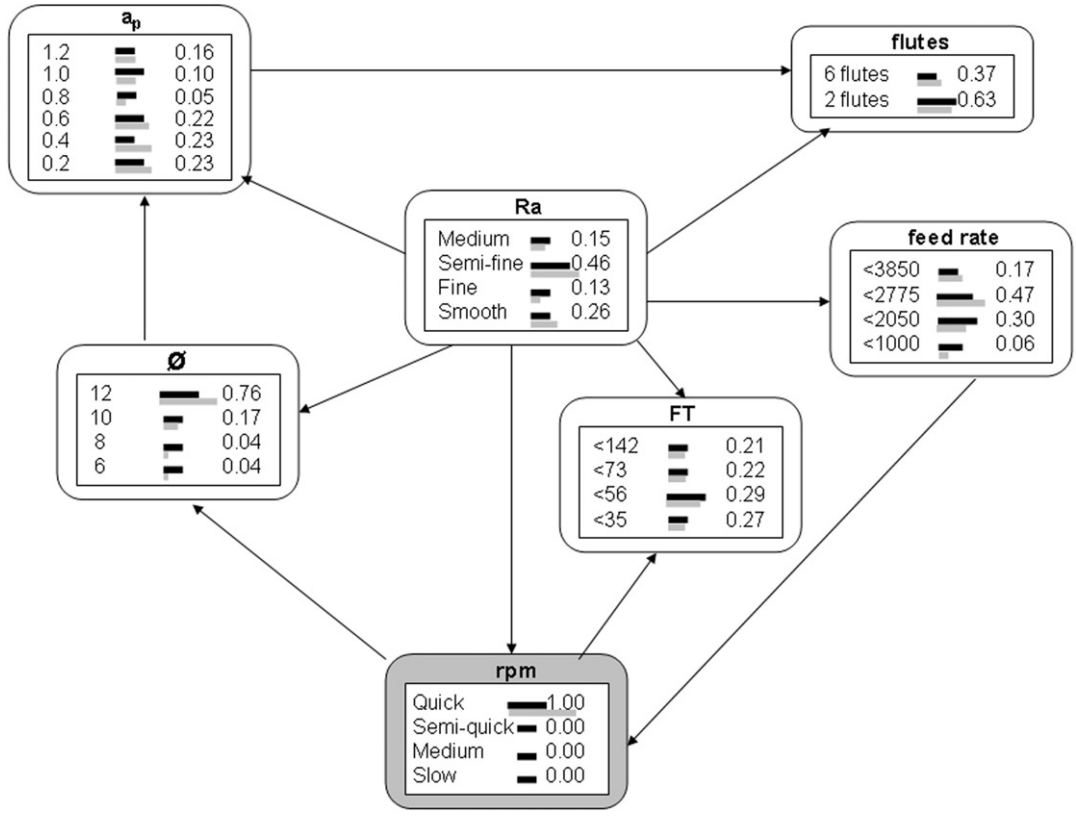

Figure 5. Tree-Augmented Naïve Bayes classifier instantiating the `rpm` node at 'Quick'. Posterior probabilities of each variable, given this evidence, are shown at each node in grey.

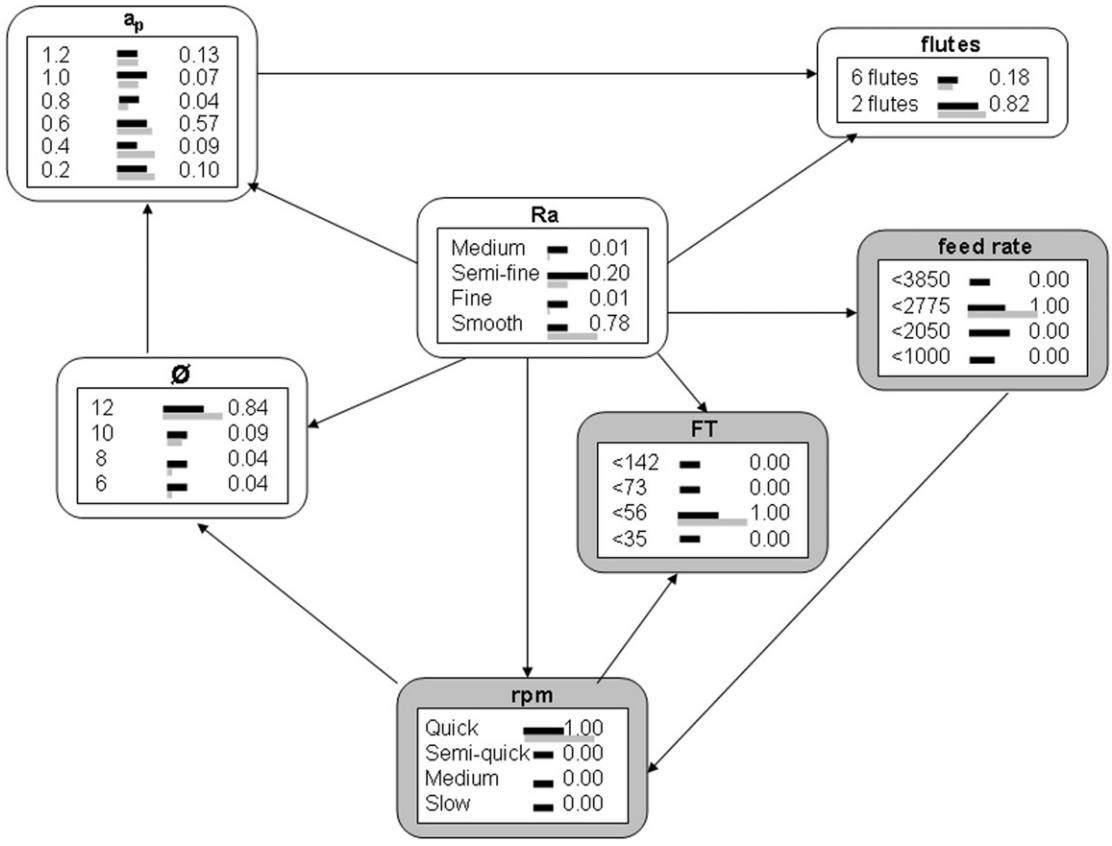

Figure 6. Tree-Augmented Naïve Bayes classifier instantiating the `rpm` node at 'Quick', `FT` at '<56' and `feed rate` at '<2775'. Posterior probabilities of each variable, given this evidence, are shown at each node in grey.

5. Conclusions

The use of Bayesian classifiers for modelling surface roughness in a milling process is an important advance towards achieving optimum machining. The method presented in this article is an analysis of the use of Bayesian networks with the Naïve Bayes and TAN structures to develop empirical models that estimate the surface finish, specifically *Ra*, in machining processes, using data obtained in the cutting process.

The variables defined for each node are the same irrespective of the method used to obtain the network. The significant differences lie in the relationships among the network nodes in the learnt structures and, consequently, in their inferred probabilities.

Bayesian networks have proved to be a very useful tool for providing knowledge to develop an *Ra* predictor, since interesting relationships between nodes were found. According to the expert's knowledge, some such relationships are evident in the process, even though they do not have any mathematical relationship in the formulas that define the metal cutting process.

The processing time for each classifier handling a file of 250 records was 150 ms for Naïve Bayes and 78 ms for TAN. From the point of view of performance, the TAN classifier is better because it generates a more complete network than Naïve Bayes and processing time is lower. The results of the two structures were compared using experimental data. Both models provided a statistically satisfactory prediction.

With other artificial intelligence techniques used to predict *Ra*, the error rates range from 2 to 25%. Despite being at an initial phase of the study, our model reports an average classification accuracy of 81.2%, the Smooth class having the best accuracy of 90%. Also, we can make different queries to the network and infer the *Ra* distribution given some evidence or knowledge on the rest of variables. Furthermore, the model may be used to recommend the values of each variable that yield, with certain probability, a desired *Ra* level. Our model definitely contributes towards a better knowledge of the process with variables not taken into account in previous studies.

Other process characteristics could be added to the network to improve model performance, including the type of material to be machined and the geometry of the pieces, etc. The relationship between these variables, and between these variables and the *Ra* value, has not yet been investigated. This would be

a significant milestone. The research group is now focussing on these new variables.

Acknowledgements

We are grateful to the referees for their useful comments. This work was partially supported by the AFAVE Project under Grant DPI2003-07798-C04-01 and by the Spanish Ministry of Education and Science under Grant TIN2004-21428-E.

Notes on contributors

Maritza Correa received a BSE degree in Industrial Engineering from Universidad Autónoma de Occidente (UAO), Cali, Colombia, in 2000. She received a MSc degree in Information technology in manufacturing from Technical University of Madrid (UPM), Spain, in 2003. In 2002, she joined the Computer Science Department of the Industrial Automation Institute (IAI), part of the Spanish Council for Scientific Research (CSIC). Currently, she is a PhD candidate at the Technical University of Madrid in the Artificial Intelligence Department. Her research interests are focused on artificial intelligence techniques, classification models, sensors and signal processing, and monitoring of manufacturing processes.

Concha Bielza received her MS degree in Mathematics in 1989 from Complutense University (UCM), Madrid, and PhD in Computer Science in 1996 from Technical University of Madrid, Madrid. She is currently an Associate Professor of Statistics and Operation Research in the School of Computer Science at Technical University of Madrid. Her research interests are primarily in the areas of probabilistic graphical models, decision analysis, metaheuristics for optimization, data mining, classification models and real applications. Her research has appeared in journals like Management Science, Computers and Operations Research, Statistics and Computing, Naval Research Logistics, Journal of the Operational Research Society, Medical Decision Making, Briefings in Bioinformatics and as chapters of many books.

Miguel J. Ramírez received the BSE degree in Industrial Electronics Engineering from Veracruz Institute of Technology in 1992, the MSc degree in Electronics Systems from Monterrey Institute of Technology (ITESM) in 1998. Since 2000, he has been a Professor at the Department of Automation and Mechatronics of ITESM where teaches and coordinates Manufacture Systems Automation and Mechatronics Design areas. He is a Certified Manufacturing Technologist (CMfgT) by the Society of Manufacturing Engineers (SME) and belongs to 4.4 IFAC International Technical Committee in Cost Oriented Automation. Currently, he is a PhD Candidate in Mechatronics Systems from ITESM with research stays in Loughborough University, UK, and Industrial Automation Institute (IAI), Spain. His research interests are in the areas of Machining Process Automation and Modelling, Intelligents Manufacturing Systems and Mechatronics Systems Design.

José Ramón Alique received his MSc degree and PhD in physics sciences from Philips International Institute, Eindhoven- Holland in 1970, and University of Basque Country in 1973. From 1968 to 1972, he was Assistant Professor of physics and automation (switching theory) at UCM. He has been working in automation since 1972 in the National Council for Scientific Research (CSIC). From 1991 to 1996, he was the Director of the Technology Transfer Office in the CSIC. From 1996 to 2001, he was the Subdirector General of R&D in the Ministry of Science and Technology. He is currently Research Scientist at Industrial Automation Institute (CSIC) and Head of the Computer Science Department. He is currently the main researcher of several projects funded by National Plan of R&D and Spanish machine-tool industries. His present interests include automation of high speed machining and mechanical micromachining, intelligent machining sensors, embedded intelligent control, intelligent modelling and control and soft-computing.

References

Brezocnik, M., and Kovacic, M. (2003), 'Integrated genetic programming and genetic algorithm approach to predict surface roughness,' *Materials and Manufacturing Processes*, 18(3), 475–491.

Castillo, E., Gutiérrez, E., and Hadi, A.S. (1997), *Expert Systems and Probabilistic Network Models*, NY: Springer.

Chen, J.C. (2000), 'An effective fuzzy-nets training scheme for monitoring tool breakage,' *Journal of Intelligent Manufacturing*, 11, 85–101.

Chow, C.K., and Liu, C.N. (1968), 'Approximating discrete probability distributions,' *IEEE Transactions on Information Theory*, 14, 462–467.

Correa, M. (2003), 'A survey of artificial intelligence techniques applied to the modelling of milling process,' Master thesis, Madrid: Universidad Politécnica de Madrid (in Spanish).

Correa, M., Ramírez, de M., J., Alique, J.R., and Rodríguez, C., (2004), 'Factors affecting the surface roughness in the machining processes: Analysis techniques and models', in *25th Conference on Automation*, pp. 8–10 (in Spanish).

Domingos, P., and Pazzani, M. (1997), 'On the optimality of the simple Bayesian classifier under zero-one loss,' *Machine Learning*, 29, 103–130.

Duda, R.O., Hart, P.E., and Stork, D.G. (2001), *Pattern Classification*, NY: Wiley.

Feng, C.X., and Wang, X.F. (2003), 'Surface roughness predictive modelling: Neural networks versus regression,' *IIE Transactions*, 35, 11–27.

Friedman, N., Geiger, D., and Goldszmit, M. (1997), 'Bayesian network classifiers,' *Machine Learning*, 29, 131–161.

Hand, D., and You, K. (2001), 'Idiot's Bayes – not so stupid after all?,' *International Statistical Review*, 69, 385–398.

Huang, B., and Chen, J.C. (2003), 'An in-process neural network-based surface roughness prediction (INN-SRP) system using a dynamometer in end milling operations,' *International Journal of Advanced Manufacturing Technology*, 21, 339–347.

Ismail, F., Elbestawi, M.A., Du, R., and Urbasik, K. (1993), 'Generation of milled surface including tool dynamics and wear,' *Journal of Engineering for Industry*, 115, 245–252.

ISO 1302:2002, Geometrical Product Specifications (GPS) – Indication of surface texture in technical product documentation. International Organization for Standardization. 01/02/2002. 46 pages.

James, M. (1985), *Classification Algorithms*, London: Collins.

Kirby, D., Chen, J.C., and Zhang, Z. (2006), 'Development of a fuzzy-nets-based in-process surface roughness adaptive control system in turning operations,' *Expert Systems with Applications*, 30(4), 592–604.

Kirby, D., Zhang, Z., and Chen, J.C. (2004), 'Development of an accelerometer-based surface roughness prediction system in turning operations using multiple regression techniques,' *Journal of Industrial Technology*, 20(4), 1–8.

Lou, J., and Chen, J.C. (1997), 'In-process surface recognition of a CNC milling machine using the fuzzy nets method,' *Computers and Industrial Engineering*, 33(1–2), 401–404.

Lou, J., and Chen, J.C. (1999), 'In-process surface roughness recognition (ISRR) system in end-milling operations,' *International Journal of Advanced Manufacturing Technology*, 15(3), 200–209.

Lou, J., Chen, J.C., and Li, C.M. (1999), 'Surface roughness prediction technique for CNC end-milling,' *Journal of Industrial Technology*, 15(1), 1–6.

MacQueen, J.B. (1967), 'Some methods for classification and analysis of multivariate observations,' in *5th Berkeley Symposium on Mathematical Statistics and Probability* (Vol. 1), pp. 281–297.

Minsky, M. (1961), 'Steps toward artificial intelligence,' *Transactions on Institute of Radio Engineers*, 49, 8–30.

Montgomery, D.C. (1996), *Introduction to statistical quality control*, US: John Wiley and Sons.

Ripley, B.D. (1996), *Pattern Recognition and Neural Networks*, Cambridge, UK: Cambridge University Press.

Samson, S.L., and Chen, J.C. (2003), 'On-line surface roughness recognition system using artificial networks system in turning operations,' *International Journal of Advanced Manufacturing Technology*, 22, 498–509.

Stone, M. (1974), 'Cross-validatory choice and assessment of statistical predictions,' *Journal of the Royal Statistical Society B*, 36, 211–147.

Suresh, P.V.S., Venkateswara Rao, P., and Deshmukh, S.G. (2002), 'A genetic algorithmic approach of surface roughness prediction model,' *International Journal of Machine Tools and Manufacture*, 42, 675–680.

The Elvira Consortium, (2002), 'Elvira: An environment for creating and using probabilistic graphical models', in *1st European Workshop on Probabilistic Graphical Models (PGM'02)*, pp. 1–11.

Tsai, Y.H., Chen, J.C., and Lou, S.J. (1999), 'An in-process surface recognition system based on neural networks in end-milling cutting operations,' *International Journal of Machine Tools and Manufacture*, 39(4), 583–605.

Yang, J.L., and Chen, J.C. (2004), 'A systematic approach for identifying optimum surface roughness performance in end-milling operations,' *Journal of Industrial Technology*, 17(2), 1–8.

Yang, L., Chen, J.C., Chow, H., and Lin, C. (2006), 'Fuzzy-nets-based in-process surface roughness adaptive control system in end-milling operations,' *International Journal of Advanced Manufacturing Technology*, 28(3–4), 236–248.