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A Survey on Artificial Intelligence Technologies in Modeling of High Speed End-Milling Processes

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***Abstract*— High Speed Machining centers (HSM) are considered as complicated industrial instruments. Finishing is a critical process in production procedure which is carried on by these machines. Among many types of cutters, ball-nose cutters are the preferred cutters to do these kinds of operations since they have extensive operating cutting edges and appropriate geometry. The main aim of the researches on cutting process is to understand its nature better and to use this knowledge to improve the quality of the product. To achieve this goal, it is necessary to have a descriptive reference model on the process using experiments' data. Increasing demands for better surface-finishing and concurrently the development of the available measurement instruments and modeling techniques make the methods and approaches to be novel. Present paper is a survey on the lack of literature on the state-of-the-art modeling paradigms of milling processes, mainly on ball-nose cutters for surface finishing.**

I. INTRODUCTION

Today, many High Speed Machining centers (HSM) are available to fulfill the overwhelming demands for the production of vital pieces for various industry fields. So, the throughput of the machining process is a critical parameter of industry's interest. Large throughput as well as product's quality is directly related to the change in the total production rate and the overall benefit on the production. Besides, in order to avoid some cost imposed by environmental protective rules, some of new approaches like dry machining against wet machining become considerable and it necessitates an extensive research in this area. In order to improve the performance and achieve the required quality and final mass production, many novel approaches are involved in the production process. Among all the manufacturing processes, surface-finishing is a crucial and yet challenging one. Since it is one of the last actions which are conducted on the piece, there is not much material removal. The objective is to achieve better surface-finish and to improve the quality of the final work-piece.

Three important factors are commonly used as indicators of the surface-finishing, R_a, X-Ray Diffraction (XRD) and Environmental Scanning Electron Microscopy (ESEM). Since XRD and ESEM are very expensive time-consuming experiments and hence not fulfilling the low cost production demands of industry, limited number of researches were conducted on their results [1].

Conversely, surface roughness measurement (R_a), is not so expensive and can be easily conducted in industrial environments [2]. It presents a rough indication of the product quality and surface-finish. However, it cannot be done repeatedly on the work-piece during production process. Hence there were many attempts to predict it from other associated signals. Therefore, many researches focus on the relationship among R_a, cutting parameters of the HSM centers, characteristics of the cutter and the intermediate signals like force, vibration and acoustic emission in three dimensions.

Each of these investigations uses a distinct method to develop a model for the process. Most of these methods are AI-based. This paper presents an overall survey on these information-extraction and modeling techniques in order to clarify the research gaps and illustrate the advances and achievements in this field. It also discusses the lack of the literature on some specific aspects of the investigation. Hence, it will be easier to choose the proper non-Artificial Intelligence (AI) or AI approaches for presentation of the experimental results and providing a good reference model. As the result, it will be easier to focus on the demanding research area. Hence, each of the next coming chapters will focus on one of these techniques. Section *II* will focus on non-AI-based analysis of the high speed cutting process while section *III* discusses mainly about the AI-based approaches. Then discussions on research gaps come in chapter *IV*.

II. EXPERIMENT SET-UPS

Most important part of the machining technology investigation is the experiment set-up. It is highly related to the industry needs or researcher's interest. Therefore many aspects of the process can be probed. For example, the geometry of the tool, the material which is used as a work-piece, the HSM center, dry/semi-dry/wet machining, the signals of interest, the correct choice for sensors and sampling period, the cutting parameters and the surface quality indicators are very well-known and general details of the experiment which are described in the experiment setup part of every paper.

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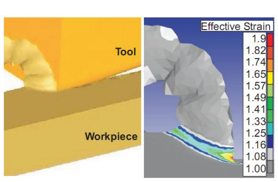
III. Non-AI-Based Analysis of the High Speed Cutting Process

One of the main considerations in qualified production of aerospace materials is to study the resulting surface-finish. Knowing more about the surface finishing and the influencing factors on it and the signals resulted from the cutting process facilitates the condition detection of the surface and cutter. Many papers only use the results of experiments or the pre-processed signals for better understanding of the nature of the process while others use information extraction techniques to determine the process' internal behavior. In the following subsections some of the commonly used non-AI methods in information extraction are briefed.

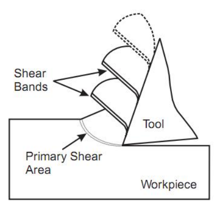
A. Mathematical Modeling and Numerical Difference Equation Solution Methods

Mathematical modeling of a process is an abstract way to model it. In some papers the thermo-dynamical behavior of cutting tool and the work-piece are studied [3]–[5]. The thermo-mechanical equations are represented and coupled. At the beginning, the mathematical dynamics and static equations of the system are presented. Then, two distinct analysis approaches are usually followed. First approach is to solve the nonlinear partial differential equations according to specified boundary conditions [6]. Since most of the pertaining equations do not have analytical solutions, some of the papers proceed to solve those equations using numerical methods.

Therefore, solving the thermo-mechanical coupled equations by numerical methods is another choice. Solving the equations numerically, usually the continuous partial differential equations are changed to the form of finite-element equations [3]–[5]. In this kind of solution, the differential equations are usually broken into proper number of discretized difference equations and the parameters of interest, like temperature and membrane surface height are considered as the states of the system. Afterwards, the changes in the shape of the surface, the formation of the chips, the heat profile on the tool and work-piece and surface changes are studied using computer simulations, Fig.1(a) and Fig.1(b).



(a) Result with modeling of thermal softening, [4].



(b) Shear bands in segmented chip formation, [4].

Fig. 1. Some result on mathematical finite-element studies of the cutting process.

This approach is not practical because of many imperfections in the industrial processes and modeling difficulties and cost inefficiencies of the simulation of every individual process. Another weakness of this approach is that it cannot be extended to the real-time analysis. Therefore, these studies are not common in industrial environments while experimental studies and sensor-based system's condition detection are more common.

B. Statistical and Experimental Evaluation

In some non-AI approaches statistical properties of the surface measurement are deliberated. To compare the experimental results, some basic computations are performed on them and some frequency domain pre-processing techniques are used to illustrate the differences of each individual experiment to the reader. This method is used in [7] where the Inconel 718 end-milling process is investigated. Inconel 718 is a chemical composition of 53% Ni, 19% Cr, 18% Fe, 5% Nb, 3% Mo, 0.9% Ti, 0.5% Al and C balance and it is considered as one of the difficult to cut materials. One of the challenging issues of cutting this kind of super-alloys is the generated heat in the cutting point which makes the tool to be welded. Hence, cutting direction and alignment of the work-piece against tool as well as the coating material of the tool are studied as a vital factor in the process. The cutter is chosen to be 2-flute solid carbide ball-nose. It is PVD-coated with CrN and $TiAlN$. The horizontal-downward cutting direction is demonstrated as the best working direction for the tool and consequently results in longer tool life [7].

The same method is used in [8] for representation of the experimental results. Tool-wear is represented versus cutting time by the experimental results. As an informative features of the force signal, it is mentioned that peak of force signal varies in each successive cut or equivalently with the cutting distance, Fig.2(a). The tool-wear also depicted versus cutting distance Fig.2(c), and from the results it can be seen that an interesting similarity exist between the nonlinear nature of the flank wear and resulting surface roughness.

Therefore there were many attempts in order to model these nonlinearities to be used for controlling of the resulting surface-finish.

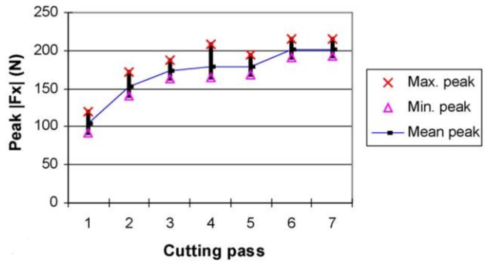
C. Multiple Regression

Multiple regression method is one of the most used ways to model the nonlinear behavior of the cutting process among the methods based on statistical and experimental representations. It used to be the preferred method for modeling the resulting experiment data and to provide a very simple model for the process.

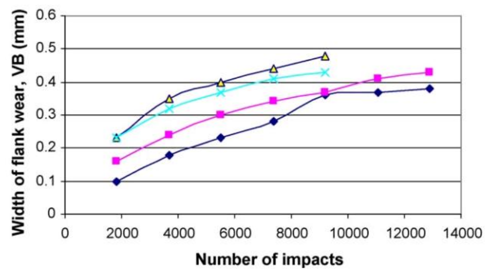
Basically, in this method the result of the cutting process, R_a, is considered as linear combination of the cutting parameters or their natural logarithm [1], [9]. It makes the modeling very simple and hence inaccurate. It also indicates that it is useful to benefit from some methods that have the ability of expressing the nonlinear processes. Some comparisons between this approach and neural network based methods shows the superiority of intelligent methods against these simple modeling approaches [10].

D. Feature Extraction and Pre-processing Methods

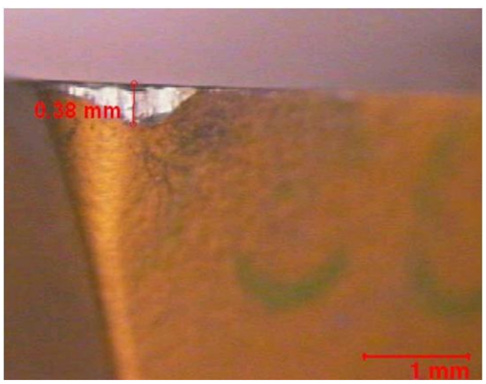
One benefiting approach for better usage of the experiment's data is to extract the most informative features of



(a) Cutting force is increasing linearly with cutting distance, [8].

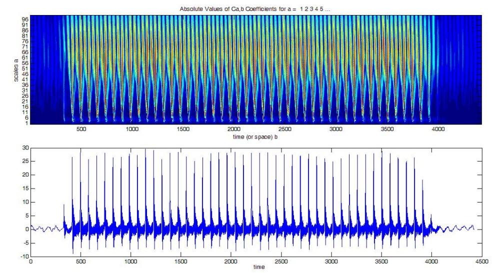


(b) Development of flank wear under 900 rpm [8].

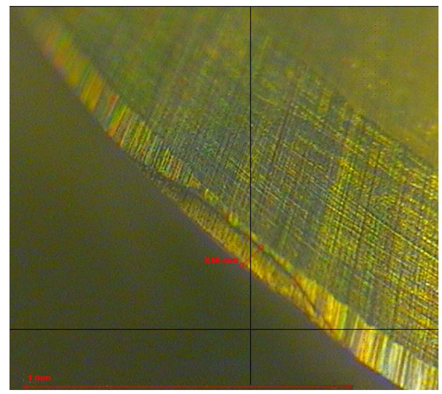


(c) Flank wear of the insert after the seventh pass of down milling under 900 rpm [8].

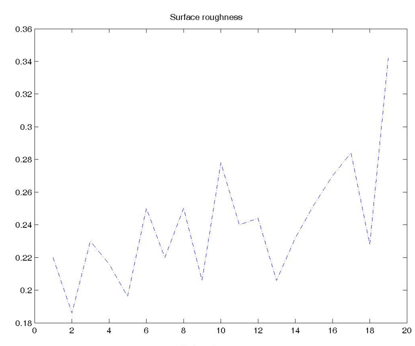
Fig. 2. Statistical approach is used for representation of experimental results in [8].



(a) Wavelet analysis which is done by the author on a one cut signal for detecting the start points of each individual revolution.



(b) Development of tool-wear in our studies on Inconel material.



(c) Surface roughness versus cutting distance. A Titanium work-piece and ball-nose two flute cutter.

Fig. 3. Some analysis on the results of Ball nose end-milling process.

the data to be used as the inputs of the reference model. It is usually done to move from continuous multi-dimensional complex signals to a very neat well-organized model. In case of cutting parameters it is obvious that their exact value can be used as an input and feature extraction is not necessary. Comparing to the continuous signals collected form the process, these signals usually represented by their distinguishing features rather than the raw shape of time series. Some of the most applicable features of these signals are the maximum and minimum peaks, RMS values, average values, etc.

Besides, in some papers instead of using the time series of the collected signals from the process, it is preferred to use pre-processed signal as a modeling data. Wavelet transform, Fig.3(a), Fourier transform and noise filtering are the most common data processing methods which are used for denoising raw signals and extracting their features in this field [7], [11].

IV. AI-based Analysis of the High Speed Cutting Process

Commonly, one of the goals of the experiments in the high speed machining field is to represent a good descriptive model for the cutting process. These models are usually used for predicting the tool-condition and monitoring of the cutting process in non-intrusive manner. From the previous section we understood that cutting process has a nonlinear multi-variable nature and the resulting signals which were collected from the process can be used to roughly determine the state of the process. To model this nonlinear process, many techniques are applied. These techniques should have two characteristics. Firstly, they must be able to describe the inherence of the experiment well. Secondly, they should be applicable for improvement of the resulting quality of the surface. Some of the AI techniques are commonly used for feature extraction and providing model reference in this field. They are presented in the following parts.

A. Bayesian Network

A Bayesian Network (BN) is a probabilistic graphical model which represents a set of random variables and their probabilistic independencies. It is one of the famous decision making methods based on statistical behavior of the process [12] [13]. Hence, it is used to find hidden probabilistic relations between variables in a process. It is one of the AI techniques that are used for correlating random variables which are resulted from the cutting process and their mutual influence. Using the famous Bayes rule for conditional probability, an extended form of this rule for joint distribution of variables and their parent variables are represented in (1). It facilitates making a belief network to provide the probability of successive phenomena by using the presence of its parents.

$$P(X) = \prod_{i=1}^{n} P\left(X_i | parents(X_i)\right), x_i \in X \tag{1}$$

A Bayesian network is used in [14] to present the surface-finishing results of a cutting process. "Elvira" software [15] is one of the softwares that capable of making a graphical model of the process parameters using Bayesian network. The model represents the correlation between cutting conditions, e.g. spindle speed, feed-per-tooth, depth-of-cut and the resulting surface roughness, R_a. The process was end-milling of steel with two-flute and six-flute tools. Naive and TAN classifiers were used as the learning paradigm. After validation and comparing the resulting confusion matrices, it is shown that in many cases TAN-trained Bayesian network can predict the surface roughness well [14].

Also in [13] Bayesian network was used on acoustic emission and spindle power metrics. Face-milling and drilling processes were investigated and some comparisons were made for the applicability of BN on prediction of their surface-finishing results, Fig.4.

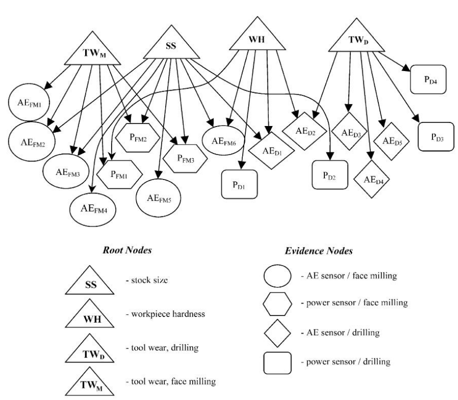


Fig. 4. Structure of Bayesian belief network for root cause diagnosis, [13].

B. Fuzzy-Logic and Neural Network Based Methods

Fuzzy-logic, neural-network and their combinations like Fuzzy-Nets (FN) are widely used in modeling the High Speed Machining (HSM) process. They showed their capability not only in end-milling but also in other kinds of machining processes in providing a well performance and approximation of the resulting surface-finish [16]–[22].

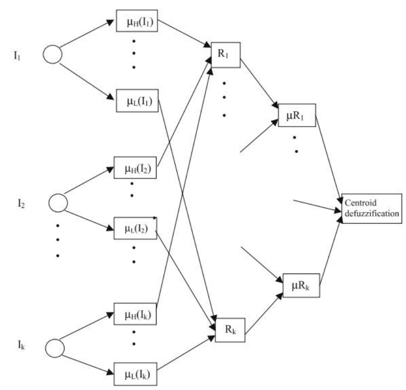


Fig. 5. An example Fuzzy-Nets which is used in [18].

Hybrid Taguchi-Genetic Learning Algorithm (HTGLA) is used in [16] to fit a nonlinear model on the R_a values resulted by certain experiments with distinct spindle-speed, feed-rate and depth-of-cut. The learning data is identical to what has been used in [23]. Therefore the performance of the method can be easily compared. The aim is to compare the results of different choices for membership functions which are used in fuzzy layer of the ANFIS. It is shown that Gaussian membership functions are suitable choices for fuzzy layer of the network for predicting the surface-roughness. The steel 4-flute end-milling cutter was used to machine a 6061 aluminum alloy work-piece.

FN Adaptive Surface Roughness Control (FN-ASRC) is used in [21] instead, Fig.5. The FN-ASRC is divided into two distinct parts. One is the FN in-process surface roughness recognition (FN-IPSRR) which contributes the prediction of the surface roughness. The other one is FN adaptive feed-rate control (FN-ASRC).

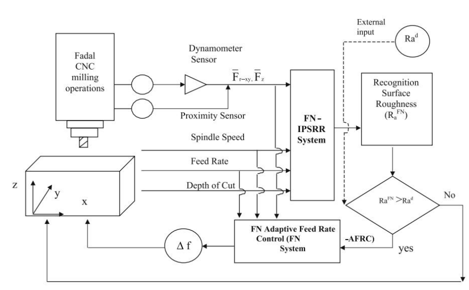


Fig. 6. Fuzzy-Nets system proposed by [21] to adaptively control the surface roughness according the predicted values for surface-finish.

Therefore, the distinguishing idea is to predict the surface roughness by using some artificial-intelligence-based systems and to do the necessary actions to correct the cutting conditions so that the resulting surface-finish fits the required set point, Fig.6.

In order to develop the whole system, two 5-layer fuzzy nets were used. The layers are the input layer, feature-extraction level, relations layer, combination layer and de-fuzzification layer. The fuzzy rules for identification and control are defined for the two parts and the rules with conflicting outputs are moved out from the rule-base. Then a combined fuzzy rule-base is properly defined and is followed by the determination of the output mapping based on the fuzzy rule-base. Three-dimensional force sensors and proximity sensor for rotation counting are used for the study and Aluminum 6061 is used as the work-piece. The cutting process is done half-way to have the FN-IPSRP predict the surface-roughness for the rest of the path. In order to achieve a better surface roughness results, Some corrections in cutting conditions, here feed rate, will be suggested by FN-ASRC which is highly depends on the predicted results of the FN-IPSRP. Then the remaining half is cut according to the change of the feed-rate, Fig.7.

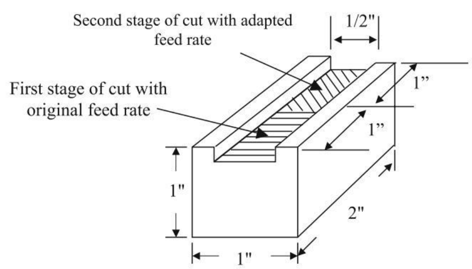


Fig. 7. Fuzzy-Nets controlled surface-finish [21].

C. Discrete-Event-Based Intelligent Methods

Although the cutting conditions and signals that are collected in the high speed machining process have continuous nature, but the changes in the system can be interpreted as incoming events and thus it can be modeled as Discrete EVent System (DEVS). Hence, using these kinds of representations, some studies focus on providing a model for high speed machining process.

Among the studies on DEVS modeling, Kasirolvalad and Hanna managed to present an Adaptive Fuzzy Petri Net (AFPN) model for the high speed machining process [17], [19]. Petri Net (PN) is a modeling structure which considers the states of the system and the input events in a graphical model. It has been widely used to model the production lines, queues, serving networks, and many manufacturing issues. Like other discrete-event modeling systems, PN is generally a n-tuple machine with some nodes representing the states of the system. Just like other DEVS paradigms, it uses some arrows and circles which represent the incoming events and internal relationship and the states of the machine, respectively [24]. After the definition of fuzzy automata, Fuzzy Petri Nets (FPN) were also introduced [25]. Like in the case of fuzzy automata, FPN has membership values for states and transitions. So, in [17] for all the cutting conditions, collected signals and resulting surface roughness, some membership functions are defined. Then each membership function is related to an individual node. Using some fuzzy rules and the relations between the cutting conditions, Kasirolvalad suggests a PN and weighted transitions so that the dynamic behavior of the process in conjunction with its resulting surface roughness can be represented [17].

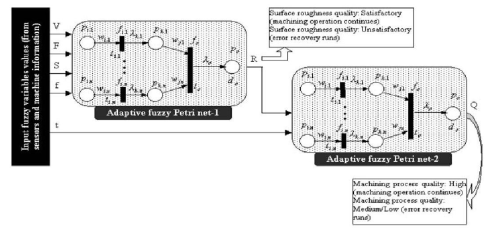


Fig. 8. A technique based on AFPNs for modeling and control of product and machining process quality [17].

By defining two separate AFPNs for prediction and error reporting algorithm it tries to avoid unsatisfactory surface finishing by reporting an error in cutting parameters or tool's status, Fig.8.

V. Discussion

The AI-based methods which were already presented are most commonly used methods in the field of machining. Some of the results are depicted in this section. Aliustaoglu and Ertunc showed some methods which could be used in determining the tool status, [22], [26]. Hidden Markov Models (HMM), fuzzy inferencing and sensor fusion are well used to detect the tool-condition and resulting surface-finish while fuzzy-nets [18] are used to determine the state of the system. Other methods like Bayesian networks [13], [14] and Petri nets [17] are applied for tool status and surface-finish prediction. All the methods seem to be successful to determine the internal state of the process. Obviously, one of the conclusions is that the predictions resulted from the AI-based approaches are more accurate than the non-AI ones and It is clear that each of the state-of-the-art modeling, inferencing and decision making methods are able to predict the surface roughness and tool wear in a non-intrusive manner. As such, advances in these approaches result into more informative models. However, from the industry point of view any suggested approach must be easy to be implemented. The learning speed and flexibility of the AI structure to deal with the changes of the system are the challenges to the new approaches.

Firstly, one challenging area is to take better and descriptive features out of the collected signals and using a suitable signal processing schemes. Frequency drift of the signals and the change of the shape of the signal during the life time of the tool have not been extensively investigated. The lacks of the proper investigation on the data pre-processing methods are also obvious in the field of machining. For example, wavelet analysis has not been used widely to the resulting signals form the cutting process but it seems to be a proper tool for extraction the different properties of the signal.

Secondly, there is a lack of the investigation in usage of the clustering and grouping methods in this field. One of the reasons may be the usage of the discrete parameters of cutting conditions and the features of the signal instead of the real signal data. In the literature there is very limited number of papers who paid attention to the changes in the shape of the signal due to tool degradation and aging and the tool wear. These methods do not quantitively investigate the changes. Mostly, they are limited to the usage of the frequency and time domain features and not the cross-correlation of the signals with a meaningful signal data-base.

Finally, many researches only provide a solution for their own experiment and the results cannot easily been generalized to other issues and conditions. As a result, many experiments are needed for a new set-up of the work-piece, machine and the material. The ability of the models to remain descriptive and useful in different scenarios is a critical issue of interest. Besides, the resulting reference model should be used by many model based controllers to adjust the cutting parameters according to the end user needs. It can improve the AI-based modeling approaches to result in newer models for new circumstances.

As such, these lacks of the investigation are the challenging parts of the future research in this field. Advances in AI and clustering methods as well as data pre-processing schemes should be considered to affect the future of the investigations and provide better solutions for the industry, such as better quality and more productivity.

VI. Conclusion

This paper investigates among some commonly used methods for modeling the surface-finish quality of the high speed machining processes. These methods can be divided into two main categories, non-AI technology based approaches and the AI-based ones. Usually the non-AI researches are for presenting the behavior of the process while AI-based methods are for modeling and predictive control. Based on these two categories, we presented those famous ones which are commonly used for both modeling and control. Since the nature of the process is multi-variable and nonlinear, most of these modeling structures must be able to model such systems. So, Bayesian networks, fuzzy petri-nets, hidden Markov models and dynamic fuzzy-neural networks seem to be most suitable which are already under investigation.

References

[1] Pinaki Chakraborty, Shihab Asfour, Sohyung Cho, Arzu Onar, and Matthew Lynn. Modeling tool wear progression by using mixed effects modeling technique when end-milling AISI 4340 steel. *Journal of Materials Processing Technology*, 205(1-3):190–202, August 2008.

[2] ASME. Y14.36m - 1996 surface texture symbols, 1996. [online] `http://catalog.asme.org/Codes/PrintBook/Y1436M_1996_Surface_Texture.cfm`.

[3] marusich. Modelling and simulation of High-Speed Machining. *International journal for numerical methods in engineering*, 38:3675–3694, 1995.

[4] J.C. Aurich and H. Bil. 3D finite element modelling of segmented chip formation. *CIRP Annals - Manufacturing Technology*, 55(1):47–50, 2006.

[5] Jun Yan and John S. Strenkowski. A finite element analysis of orthogonal rubber cutting. *Journal of Materials Processing Technology*, 174(1-3):102–108, May 2006.

[6] Ying Tang and Hongsheng Guo. HSM strategy study for hardened die and mold steels manufacturing based on the mechanical and thermal load reduction strategy. *Journal of University of Science and Technology Beijing, Mineral, Metallurgy, Material*, 15(6):723–728, December 2008.

[7] E.-G. Ng, D.W. Lee, R.C. Dewes, and D.K. Aspinwall. Experimental evaluation of cutter orientation when ball nose end milling inconel 718(TM). *Journal of Manufacturing Processes*, 2(2):108–115, 2000.

[8] H.Z. Li, H. Zeng, and X.Q. Chen. An experimental study of tool wear and cutting force variation in the end milling of inconel 718 with coated carbide inserts. *Journal of Materials Processing Technology*, 180(1-3):296–304, December 2006.

[9] Caleb M. Li Mike S. Lou, Joseph C. Chen. Surface roughness prediction technique for cnc end-milling. *Journal of Industrial technology*, 15(1):1–6, November 1998.

[10] Hasan Gokkaya Muammer Nalbant and I.hsan Toktas. Comparison of regression and artificial neural network models for surface roughness prediction with the cutting parameters in cnc turning. *Modelling and Simulation in Engineering*, 15(1), November 2007.

[11] A.M. Bassiuny and Xiaoli Li. Flute breakage detection during end milling using Hilbert-Huang transform and smoothed nonlinear energy operator. *International Journal of Machine Tools and Manufacture*, 47(6):1011–1020, May 2007.

[12] Todd A. Stephenson. An introduction to bayesian networks theory and usage, February 2000. [online] `ftp://ftp.idiap.ch/pub/reports/2000/rr00-03.pdf`.

[13] S. Dey and J. A. Stori. A bayesian network approach to root cause diagnosis of process variations. *International Journal of Machine Tools and Manufacture*, 45(1):75–91, 2005.

[14] M. Correa, C. Bielza, M.D.J. Ramirez, and J.R. Alique. A bayesian network model for surface roughness prediction in the machining process. *International Journal of Systems Science*, 39(12):1181–1192, 2008.

[15] CICYT. ELVIRA software, 2005. [online] `http://www.ia.uned.es/~elvira/index-en.html`.

[16] Wen-Hsien Ho, Jinn-Tsong Tsai, Bor-Tsuen Lin, and Jyh-Horng Chou. Adaptive network-based fuzzy inference system for prediction of surface roughness in end milling process using hybrid taguchi-genetic learning algorithm. *Expert Systems with Applications*, 36(2, Part 2):3216–3222, March 2009.

[17] Z. Kasirolvalad, M.R.J. Motlagh, and M.A. Shadmani. An intelligent modeling system to improve the machining process quality in CNC machine tools using adaptive fuzzy petri nets. *International Journal of Advanced Manufacturing Technology*, 29(9-10):1050–1061, 2006.

[18] E. Daniel Kirby, Joseph C. Chen, and Julie Z. Zhang. Development of a fuzzy-nets-based in-process surface roughness adaptive control system in turning operations. *Expert Systems with Applications*, 30(4):592–604, May 2006.

[19] M.M. Hanna, A. Buck, and R. Smith. Fuzzy petri nets with neural networks to model products quality from a CNC-milling machining centre. *IEEE Transactions on Systems, Man, and Cybernetics Part A:Systems and Humans.*, 26(5):638–645, 1996.

[20] F. Dweiri, M. Al-Jarrah, and H. Al-Wedyan. Fuzzy surface roughness modeling of CNC down milling of alumic-79. *Journal of Materials Processing Technology*, 133(3):266–275, February 2003.

[21] L.-D. Yang, J.C. Chen, H.-M. Chow, and C.-T. Lin. 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, 2006.

[22] Cuneyt Aliustaoglu, H. Metin Ertunc, and Hasan Ocak. Tool wear condition monitoring using a sensor fusion model based on fuzzy inference system. *Mechanical Systems and Signal Processing*, 23(2):539–546, February 2009.

[23] Ship-Peng Lo. An adaptive-network based fuzzy inference system for prediction of workpiece surface roughness in end milling. *Journal of Materials Processing Technology*, 142(3):665–675, December 2003.

[24] Ren David and Hassane Alla. Petri nets for modeling of dynamic systems : A survey. *Automatica*, 30(2):175–202, February 1994.

[25] Heloisa (Eds.) Cardoso, Janette; Camargo. *Fuzziness in Petri Nets*. Springer, 1999.

[26] Huseyin Metin Ertunc and Cuneyt Oysu. Drill wear monitoring using cutting force signals. *Mechatronics*, 14(5):533–548, June 2004.