APPLIED SOFT COMPUTING IN INTELLIGENT MACHINING: AN OVERVIEW

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Abstract. *In modern manufacturing systems, supervision and control activities for machine-tools with computer numerical control (CNC) call for a system to simultaneously monitor the machine, cutting tool and process, minimizing human interference and simplifying maintenance, training and operations. This fact imposes several requirements on the flexibility of monitoring system, as it should be able to: (a) integrate with any type of CNC; (b) be compatible with the machine numerical control interfaces; (c) allow the addition of different sensors; and (d) have appropriate monitoring strategies. Thus, the role of computational intelligence techniques (also known as soft computing) employed in order to ease such systems becomes crucial, since different learning algorithms can be used to develop a functional decision making systems concerning the machining process conditions based on acquired data sensor signals. This paper intend to present a brief review of the soft computing techniques most often applied in machining processes monitoring (artificial neural networks, fuzzy logic systems, genetic algorithms and hybrid systems), presenting their most relevant applications.*

Keywords*: soft computing, monitoring system, machining.*

1. INTRODUCTION

Machining is commonly used in manufacturing systems and includes cutting processes such as turning, drilling, milling and grinding. The trend toward automation in machining has been motivated by the need to maintain high quality products while improving production rates and the potential economic benefits of automation in cutting processes are significant. As illustrated in Fig. 1, a cutting process (e.g. turning) is carried out on a machine-tool (e.g. lathe) using a cutting tool for material removal on a workpiece to produce a part with desired geometry and exactness. A process reference (set using productivity and quality considerations) and the process state are fed to the controller, which adjusts the desired process variables. These references are input to the servo controllers, which drive the servo systems (e.g. slides and spindles) and produce the actual process variables (e.g. cutting force). Sensor measurements of the process are then filtered and input to the monitoring and control algorithms. Typically, this complex procedure must be carried out with high accuracy, high production rates, and low cost (Ulsoy, 2006).

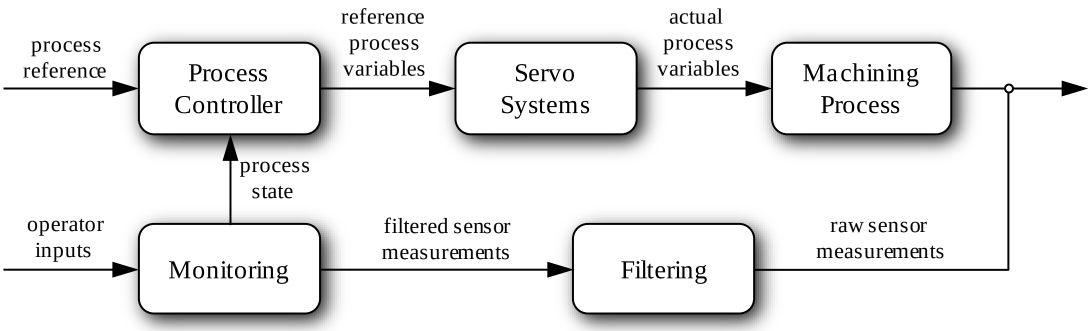


Figure 1. Schematic of monitoring and control of a machining process (adapted from Ulsoy, 2006)

Machining processes are naturally dynamic, complex, nonlinear, multivariate and often subjected to various unknown external disturbances. These processes are usually performed by a skilled human operator who uses his decision-making capabilities based on the intuition and know-how acquired gained from technical experiences. The development of intelligent functions for fully automated machining system, like those of expert human operators, is a very difficult assignment. A fully automated machining system requires capabilities for monitoring, diagnostics and control of cutting operations (Liang *et al*., 2004).

Intelligent machining system must be equipped with the knowledge of how to recognize failures, how to localize them and how to relate the faults and their effects to the operating state for machining processes and fault diagnostics monitoring. Furthermore, state classification and process involvement have to be completed in real-time to avoid additional damage when an abnormal state has been detected. There are various sensor signals (force, torque, temperature, vibration, acoustic emission, etc.) which correlate with the condition of the cutting process. The control and monitoring algorithms should be based on the simultaneous measurement and processing of different signals. The most common methods used to correlate a physical variable with machining process anomalies are presented in Tab. 1.

Table 1. Monitored conditions in machining processes (Tönshoff *et al.*, 1988)

	Time Critical	**Non-time Critical**
Machine	CNC control collision	accuracy thermal deformation
Tool	tool fracture tool approach	tool wear tool presence
Process	chatter force / torque / power chip forming	coolant
Tool condition	dressing	tool compensation
Workpiece	dimension in process shape in process roughness in process	raw stock dimension workpiece material surface integrity

Such a machining system can be compared with a human operator. Different sensors provide feedback to the system, in a way the sensory organs provide feedback to the operator. Like the human brain, an automated system is equipped with a computer for processing the feedback information from sensors in real-time and taking the appropriate decision to ensure optimal cutting conditions. For the decision making, an automated machining system must have a model of the cutting operations. This model must be based on the physics of cutting process. The physics of cutting process is understood by a researcher and converted in a mathematical model, usually in the form of differential equations. The differential equations of the process are solved by an appropriate technique such as the finite element method (FEM). In many instances, the physics of the cutting process is not known properly. However, if there is a sufficient amount of data describing the behavior of the machining operation, a model can be developed based on the data, which is called modeling based on the data (Deb and Dixit, 2008).

Modeling based on the physics of cutting process is accomplished by the conventional or *Hard Computing* methods. Nevertheless, modeling based on the data is accomplished by *Soft Computing* (SC) methods. SC techniques attempt to generate approximate solutions of the problem in the presence of uncertain or imprecise physics and/or the process variables. In effect, the role model for SC is the human mind. SC differs from hard computing in that, unlike conventional, permit the tolerance for imprecision, uncertainty, partial truth and approximation to achieve tractability, robustness and low solution cost (Kecman, 2001). At this moment, the principal constituents of SC are Fuzzy Logic (FL), Artificial Neural Network (ANN), Genetic Algorithm (GA), Machine Learning (ML) and Probabilistic Reasoning (PR), with the latter subsuming belief networks, chaos theory and parts of learning theory (Jin, 2011).

Human beings themselves adapt to changes in the environment. In the same way, an adaptive control system is a fundamental part of an intelligent machine-tool. An adaptively controlled machine-tool is capable to adjust to the dynamic disturbances of the system generated by the unpredictability of machining operations due to alterations in the cutting conditions such as work material hardness, tool failures, tool and/or workpiece deflections etc..

Figure 2 shows a scheme of an intelligent machining center. The design model of the component to be machined is provided to computer. Using proper software, the tool path is generated and the spindle speed and feed rate are determined. This data is fed to machine controller, which provides signals to drive motors. The adaptive controller adjusts the feed rate, spindle speed and tool path, according to changes in cutting conditions (Deb and Dixit, 2008).

An intelligent machining system should also have a memory, like an expert operator. The information available in machining data handbooks and that acquired from experience can be stored in the memory of the intelligent machining system. The system should have the capability to acquire data efficiently, store useful data by filtering out the noise and retrieve it efficiently. Simultaneously, it is desirable that the system is capable to communicate with humans in some way, such that its actions and decisions become obvious to the users concerned. This implies that the acquired or available information can be stored in the form of an expert system.

In this paper, the computational techniques and optimization methods that can be used to develop intelligent machining systems are briefly described. Section 2 presents the application of the artificial neural network (ANN) in modeling the machining processes. Section 3 shows the fuzzy logic (FL) based modeling. Section 4 describes the application of genetic algorithm (GA) for optimizing the machining processes. Section 5 presents the hybrid system composed by ANN, FL and GA, either in the form of the mixture or the compound. Finally, Section 6 discusses the challenges to be met for developing a truly intelligent machining system.

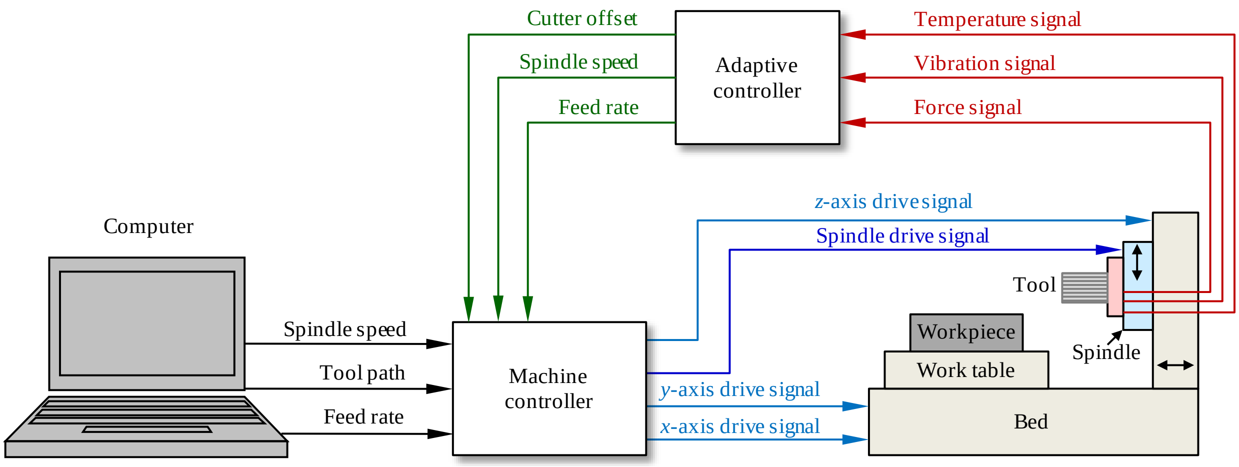
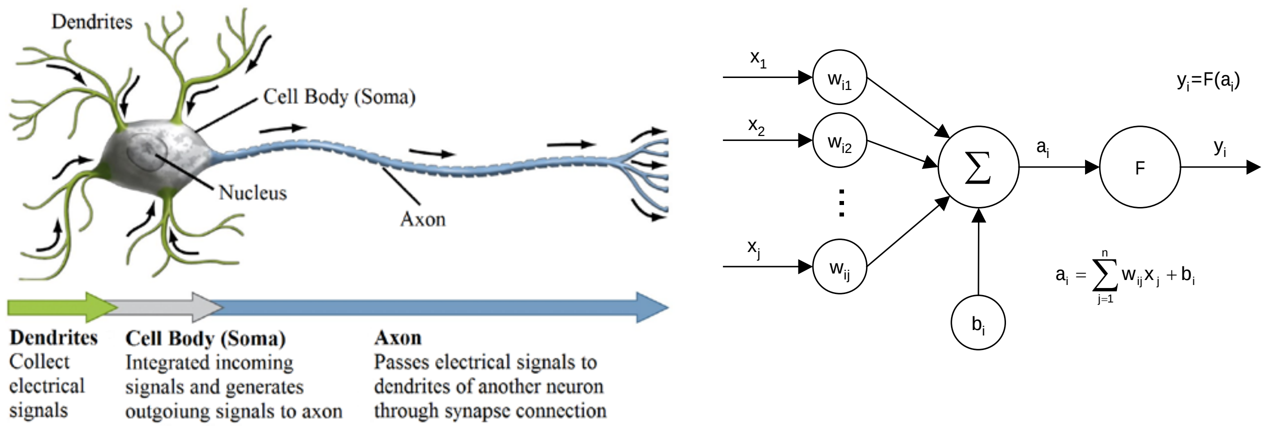


Figure 2. An intelligent horizontal machining center (adapted from Deb and Dixit, 2008)

2. ARTIFICIAL NEURAL NETWORKS (ANN)

The human brain contains a neural net consisting of a number of interconnected information-processing units called neurons, Fig. 3a. Each neuron consists of a cell body called soma, a number of fibers denominated dendrites and a single long fiber with some terminals so-called axon. Dendrites receive electrical signals from the axons of other neurons. Axon transmits the electrical signal from one to other neurons via dendrites. The connection between axon and dendrite is called synapse. Electrical signals at the synapses are modulated by different amounts. Synapses release chemical substances that cause changes in electrical potential of soma. When the potential reaches its threshold, an electrical pulse called action potential is sent down through the axon; in other words, a biological neuron generates an output signal only when the total strength of the input signals exceeds a certain threshold. Nevertheless, artificial neural network (ANN) is a simple attempt to simulate a biological neural net by a computational model. Fig. 3.b shows a scheme of an artificial neuron receiving input signals (x_j) from different neurons and transmitting output signals (y_i) to others distinct neurons. The signals are in the form of numerical values. The action of synapses is simulated by multiplying each input value (x_j) by a suitable weight (w_{ij}). The action potential is modeled in an artificial neuron by calculating the weighted sum of the inputs to represent the total strength of the input signals (a_i), and applying a suitable activation function (F) to the sum to determine its output function y_i = F (a_i). Bias (b_i) is used to modify the activation function in order to increase sensitivity in the neuron; this ensures that two neurons that receive the same F are not necessarily equals (Deb and Dixit, 2008; Haykin, 2008).

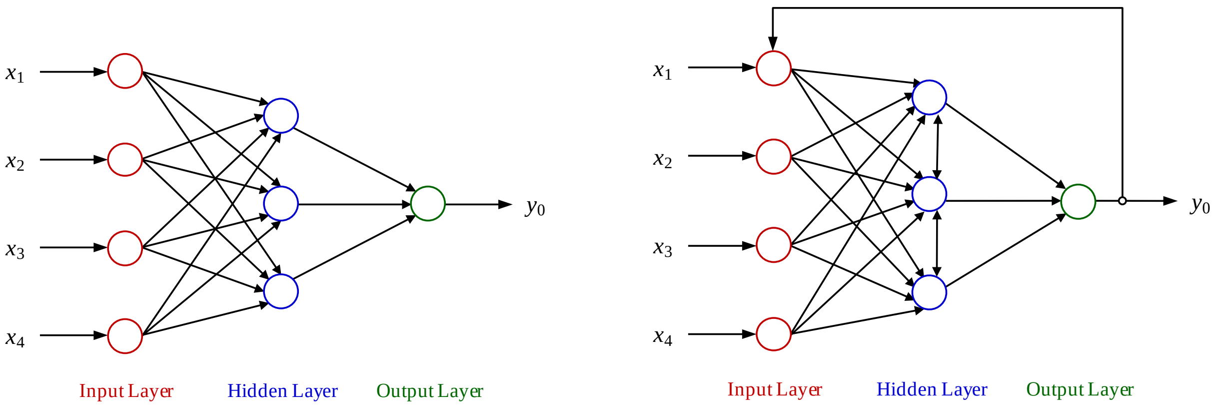


(a) (b)

Figure 3. A scheme of a neuron: (a) information flow through biological neuron (adapted from www.uic.edu/classes/bios/bios100/summer2006/lect18.htm); (b) artificial neuron (adapted from Haykin, 2008)

Artificial neural networks can be classified based on their topology and the method of training.

The most common neural network topologies are illustrated in Fig. 4: feedforward neural network (FFNN); and recurrent or feedback neural network (RNN).



(a) (b)

Figure 4. Typical neural networks topologies: (a) feedforward (adapted from Risbood *et al.*, 2003);
(b) recurrent or feedback (adapted from Deb and Dixit, 2008)

FFNN are the most popular and widely used ones. There are two neural network models in this category: multi-layer perceptron (MLP) and radial basis function (RBF). A typical FFNN topology consists of three layers. Each layer contains a defined number of neurons. Each layer has full interconnection to the next layer but no connection within a layer. The first layer of the network is known as the input layer whose neurons employ values corresponding different variables that symbolize the input pattern. The second layer is known as a hidden layer because its outputs are used internally and not used as the final output of the NN. The end layer of network is known as the output layer. The values of the neurons of the output layer constitute the response of the neural network to an input pattern presented at the input layer. The general rule is just to design an ANN which uses fewer parameters (weights and biases).

In RNNs, the outputs of some neurons are also fed back to some neurons in layers before them. Thus, signals can flow in both forward and backward directions. A recurrent network is said to have a dynamic memory. The output of such networks at a given instant reflects the current input as well as the previous inputs and outputs.

Artificial neural network need to be trained so that produces an output suitable reaction from a known input vector. The training procedure is an iterative process that adjusts the parameters (weights and biases) of the hidden layer until the network is capable to produce the desired output from a set of inputs. The network training methods are generally classified into supervised and unsupervised learning. A number of training algorithms based on the supervised learning are available of which the most common is the backpropagation (BP) algorithm. The BP algorithm provides the ANN with a sequence of input and output patterns, which jointly constitute the training pairs. As an input pattern is presented to the ANN, the output "target" response is calculated on a feedforward through the network (Haykin, 2008).

2.1. ANN Applications in Machining

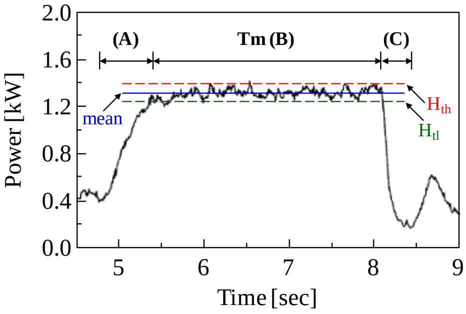
Artificial neural networks (ANNs) are excellent tools for complex manufacturing processes that have many variables and complex interactions. Neural networks have provided a means of successfully controlling complex processes. Other applications of neural networks include bearing fault classification, turning, tapping, and welding comparisons, acoustic emission for tool condition monitoring, temperature control in a continuous-stirred-tank reactor, and monitoring of chip production and cutting-tool wear (Stich *et al.*, 2000).

Dimla *et al.* (1997) showed a review of tool condition monitoring system, developed or implemented through application of neural networks, included a critical analysis of ANN methods and the trend in obtained results. Sick (2002) presented a "state of the art" review in the area of indirect on-line tool wear monitoring in turning with ANNs. Many of the conclusions and recommendations are valid for other machining processes using tools with defined cutting edges (e.g. milling or drilling) or even for other material removing processes (e.g. grinding) as well.

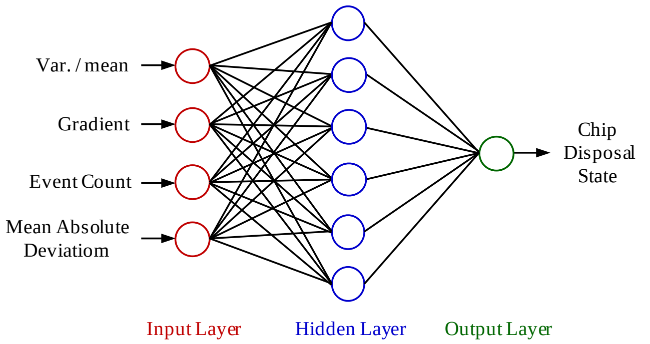
In Kim and Ahn (2002), a sensor monitoring method, based on spindle motor power sensing and NN processing, was evaluated for chip disposal state detection in drilling. Fig. 5a shows the typical behavior of spindle motor power during drilling and Fig. 5b illustrates the structure of the neural network used for chip disposal state monitoring.

Risbood *et al.* (2003) fitted a MLP for the prediction of surface roughness in a turning process. The input neurons correspond to feed (f), cutting speed (v), depth of cut (d) and acceleration of radial vibrations (a) of the high-speed steel turning tool, and the output neuron corresponds to the surface roughness R_a of steel. Ghasempoor *et al.* (1999) proposed a tool wear classification and continuous monitoring system for turning by employing RNN design.

Teti *et al.* (2006) describe a collaborative work involved the following main round robin activities: (a) generation, detection, storage and exchange of cutting force sensor signals obtained at three different laboratories (Italy, USA and Poland) during sensor-based monitoring of machining processes with variable cutting conditions yielding diverse chip forms, and (b) cutting force signal characterization and feature extraction through ANNs and wavelet decomposition, both aimed at comparing chip form monitoring results achieved on the basis of innovative analysis paradigms.



(a)



(b)

Figure 5. Chip disposal state monitoring in drilling (adapted from Kim and Ahn, 2002): (a) spindle motor power and threshold method; (b) structure of the neural network

The use of probabilistic neural network (PNN) for automated classification of broaching tool conditions utilizing cutting force data is described in Axinte (2006).

2.2. Sensor Fusion Technology

Usually, the signal from only one sensor is typically insufficient to give enough information concerning the machining process and tool-state. Therefore, using a number of sensors at different places simultaneously has been proposed for knowledge acquisition. Signals from different sources are integrated to provide the maximum information needed for monitoring and control tasks in machining automation. A schematic diagram of Fig. 6 shows the use of multiple sensors in unmanned condition monitoring systems.

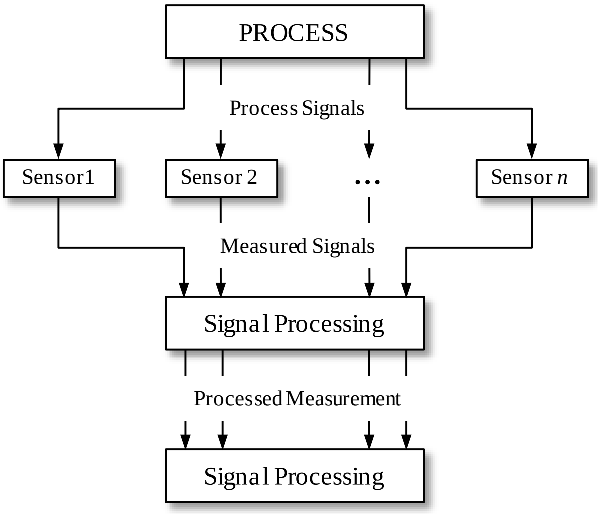


Figure 6. Multiple sensors in monitoring (adapted from Elbestawi *et al.*, 2006)

Considering the variety of sensors and its applications in the machining processes, the machine-tools require a large number of sensors (Tab. 2). Integrated sensor systems can accomplish several tasks and cooperate to insure process optimization. Cutting performance commonly requires reduction in-process and non-productive times, verification and maintenance of cutting operations, while reducing direct costs and ensuring environmentally-friendly production.

Sensor fusion generally covers all the issues of connecting sensors of different types together in one basic system architecture. The strategy of integrating the information from various sensors enlarges the accuracy and resolves ambiguities in the knowledge about the environment. The most important aspects are its enhanced data for feature extraction and decision-making strategy, and its ability to self-adjust due to changes in the operating characteristics of the individual sensors caused by calibration, drift, failure etc. The type and the number of sensors used for unmanned machining process monitoring are chosen according to type of supervision and control tasks (Elbestawi *et al.*, 2006).

Perhaps the best review of some of the individual sensing and automation machining systems, application potential and limitations as well as identification, decision making and fusion methodologies can be found in Byrne *et al.* (1995), Byrne *et al.* (2003) and Teti *et al.* (2010).

Table 2. Sensors used for tool condition monitoring (Tlusty and Andrews, 1983)

Sensor	**Dimensional**		**Cutting Force**		**Feed Force**	**Spindle Motor**	**Acoustic Emission**
Task	Touch Trigger	Non Contact	Dynamo-meters	Process		Torque; Power	
Dimensional check of the blank, machined surface, or thermal drifts	★★★					★	
Tool Wear	★		★★★	★★★		★★★	★
Tool Breakage							
in drilling	★	★★			★★		
in turning	★		★★★	★			★★★
in milling	★		★★	★		★★	★★
Preload in rolling bearings				★★★			
Friction in guideways resistance to feed						★★★	
Adaptive Control			★★★	★★		★★	

The NN pattern recognition of the reconfigurable multi-sensor monitoring system proved able to effectively realize the concept of sensor fusion for a wide range of cutting process monitoring applications, producing satisfactory results also under adverse situations by combining the knowledge extracted from different data sources (Sick, 2002).

In Souza (2004), a development on intelligent monitor system in turning using force, vibration and acoustic emission sensor fusion signals to recognize the tool failure patterns (wear estimation and fracture detection) and make an on-line tool-state diagnosis is provided. After that, the monitor system carries out a tool-life prognostication (time-to-end estimation) using the previous tool-state diagnosis in order to determine the best moment for tool replacement.

In order to perform an on-line tool wear condition monitoring for different cutting conditions in drilling and milling machining process, a sensor integration strategy was proposed by Kandilli *et al.* (2007). The cutting force signals were used as the input data of ANNs. The outputs were assumed as zero for workable condition and one for dull (worn) condition. The used system was capable of precise tool wear monitoring in around 97% accuracy

A chatter detection system in milling via multiple sensors and suitable for application in industrial conditions was investigated by Kuljanic *et al.* (2009) using artificial intelligence classification system based on ANNs and wavelet decomposition (Fig. 7).

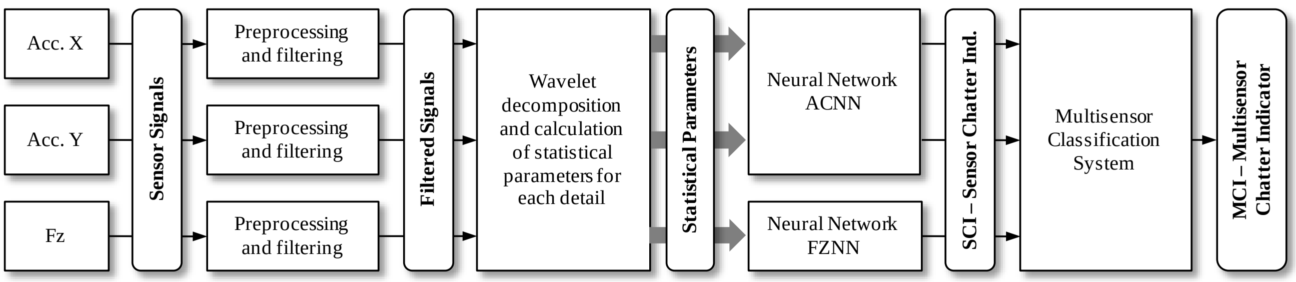


Figure 7. General outline of the multisensory chatter detection system (adapted from Kuljanic *et al.*, 2009)

In different papers cited by Teti *et al.* (2010), the system was applied to process condition and machinability evaluation during cutting of difficult-to-machine materials such as Ti and Ni-Ti alloys, using cutting force and vibration through both single signal and sensor fusion data analysis. Furthermore, sensor monitoring during cutting of plastic-matrix-fiber-reinforce composites was performed for consistent and reliable identification of tool-state.

3. FUZZY LOGIC (FL)

In the conventional crisp set theory, an element is either a member of the set or a non-member of the set. With each member, we can associate a number 1 or 0, depending on whether it is a member or non-member of the particular set.

We may call this number the membership grade of the element in the set. In crisp set theory, the membership grades of the elements contained in the set are 1 and the membership grades of the elements not contained in the set are 0. A fuzzy set theory is a set without a crisp, clearly defined boundary. It can contain elements with only a partial degree of membership. A fuzzy set defines a mapping between elements in the input space (sometimes referred to as the universe of discourse) and values in the interval [0, 1]. A membership grade 1 indicates full membership and 0 indicates full non-membership in the set. Any other membership grade between 0 and 1 indicates partial membership of the element in the set (Kecman, 2001; Deb and Dixit, 2008).

A membership function is a curve that defines how each point in the input space is mapped to a membership value (degree of membership or truth degree) between 0 and 1. The membership function can be any arbitrary curve, the shape of which can be defined as a function suitable from the point of view of simplicity, convenience, efficiency and speed. Membership function shapes typically employed are triangular, rectangular, trapezoidal, gaussian, sigmoid etc.

FL is a multivalued logic that has important application in control systems and pattern recognition. It is based on the observation that people can make good decisions on the basis of non-numerical information. Fuzzy models are mathematical means of representing vagueness and imprecise information (hence the term “fuzzy”). These models have the capability to recognize, manipulate, interpret, and use data and information that are vague or that lack in precision with fuzzy-logic methods including reasoning and decision making at a level higher than ANNs. Typical concepts used in fuzzy logic are: few, more or less, small, medium, extreme, and almost all (Youssef and El-Hofi, 2008)

Linguistic rules describing the control system consist of two parts; an *antecedent* block (between the IF and THEN) and a *consequent* block (following THEN). Depending on the system, it may not be necessary to evaluate every possible input combination, since some may rarely or never occur. By making this type of evaluation, usually done by an experienced operator, fewer rules can be evaluated, thus simplifying the processing logic and perhaps even improving the fuzzy logic system performance. The inputs are combined logically using the AND operator to produce output response values for all expected inputs. The active conclusions are then combined into a logical sum for each membership function. A firing strength for each output membership function is computed. All that remains is to combine these logical sums in a *defuzzification* process to produce the crisp output (Hellmann, 2001). A fuzzy inference system (FIS) essentially defines a nonlinear mapping of the input data vector into a scalar output, using fuzzy rules. The mapping process involves input/output membership functions, FL operators, fuzzy IF–THEN rules, aggregation of output sets, and defuzzification. An FIS with multiple outputs can be considered as a collection of independent multiinput, single-output systems. A general model of FIS is shown in Fig. 8 (Kulkarni, 2001).

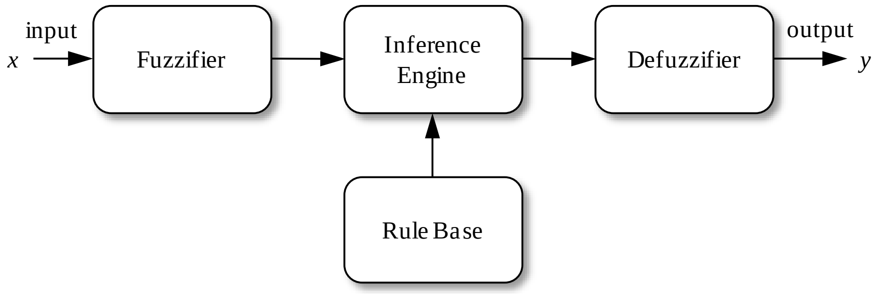


Figure 8. Block diagram of a fuzzy inference system (adapted from Kulkarni, 2001)

3.1. FL Applications in Machining

FL technologies and devices have been developed and successfully applied in areas such as intelligent robotics, motion control, image processing and machine vision, machine learning, and design of intelligent systems. Some applications of fuzzy logic include automatic transmissions of Lexus cars, automatic washing machines, and helicopters that obey vocal commands (Kalpakjian and Schmid, 2010).

In D’Errico (2001), practical approaches were developed and focused on real time problems related to machining systems. Applications of FL systems to monitoring and control of metal working processes, and to problems of related interest were reviewed.

Sokolowski (2004) discusses some aspects of FL applications in machine monitoring and diagnostics in order to analyze the applicability of the considered methods. The cutting tool wear monitoring, the thermal deformation monitoring and the burr height modeling were shortly analyzed.

Jee and Koren (2004) developed an adaptive FL controller on a 3-axis milling machine to achieve good contouring accuracy in the presence of disturbances, such as cutting forces or friction in the feed drives. The proposed controller as well as a conventional FL controller and a PID controller were simulated and implemented in contour milling.

Membership functions of drill wear states (initial, normal, acceptable, severe and failure) based on experimental data and the observed system behavior were set for output indices of the fuzzy neural network (Fig. 9). According to respective authors (Li *et al*., 2000), the reason for choosing a trapezoid shape is that it is difficult to quantify what exact percentage of the tool condition corresponds to a certain linguistic variable.

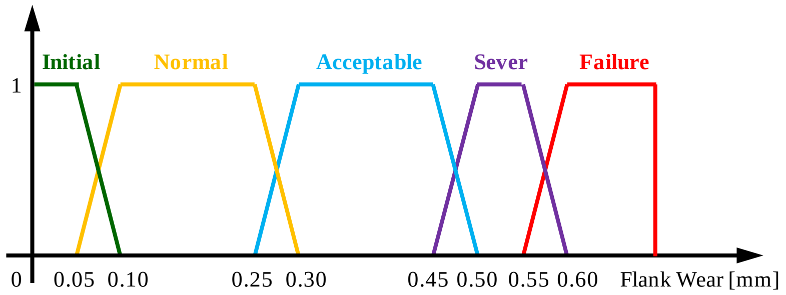


Figure 9. Fuzzy membership function of drilling conditions (adapted from Li *et al*., 2000)

Wavelet transforms and fuzzy techniques are used by Li and Tso (2000) to monitor drill breakage and drill wear conditions in real time according to the measured spindle and feed motor currents in machine-tool, respectively. In paper of Nandi and Davim (2009), a study on the prediction of machining performances with minimum quantity of lubricant in drilling using two different types of fuzzy logic rules and two different membership function shapes was used. The FL models were applied in order to predict surface roughness, cutting power and specific force requirement in drilling of aluminum AA1050. The prediction capabilities of these models are verified by comparing their results with the experimental values.

4. GENETIC ALGORITHMS (GA)

Genetic algorithms (GA) belong to a subdivision of computer science called *evolutionary computation* where programmers, inspired by phenomena in the biological world, create models of these systems on a computer. This technique can solve complex problems by imitating Darwinian theories of evolution on a computer. The first step in the use of a GA is building a computer model to represent a given problem. Interacting variables in the problem are first combined and encoded into a series of binary strings (rows of 1 and 0) to form numerical *chromosomes*. The computer randomly generates an entire *population* of these chromosomes and ranks them based on a *fitness function* which determines how well they solve the problem. Those strings which are deemed the *fittest* are allowed to *survive* and to *reproduce* with other chromosome strings, through genetic operators such as *crossover* and *mutation*, to create *offspring* chromosomes. This population of strings evolves by continuously cycling the genetic operators (Mitchell, 1996).

A powerful search engine is thus available which inherently preserves the balance between *exploitation* (take advantage of information already obtained) and *exploration* (search new areas). The result is then decoded back to its original value to make known the solution. Although simplistic from a biologist's viewpoint, GA is sufficiently complex to provide robust and powerful search mechanisms.

After the application of three GA operators in succession, a new generation is formed and the iteration is said to be complete. The iterations are carried out until the average fitness in successive generations more or less becomes constant. The entire methodology is illustrated by a flowchart in Fig. 10.

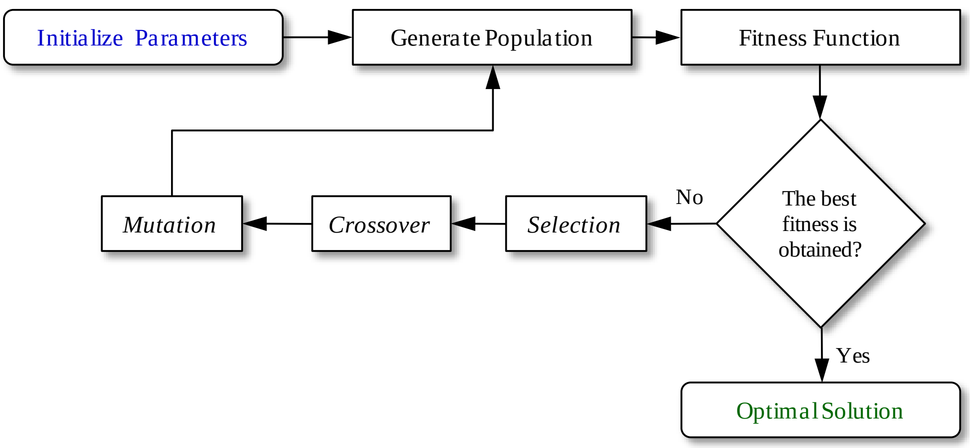


Figure 10. A flow chart illustrating the methodology of genetic algorithm (adapted from Zain *et al*., 2010)

4.1. GA Applications in Machining Optimization

Machining parameters are typically adjusted according to the instructions in the tools catalogues and/or handbooks without regard to the roughness requirements and geometrical tolerances of the surface to be machined. Incorrect adjustment of the end-milling parameters (feed rate and depth of cut) lead to tool deflection and consequently reduced surface quality. With increasing feed rate and depth of cut, the tool deflection is increased.

Thus, the optimization of cutting processes is one of the most widely investigated problems in machining. The objective functions in the cutting operation problems are: (a) minimization of production cost, (b) maximization of production rate, and (c) maximization of profit rate. A weighted combination of these objectives may be taken, or the problem can be solved as a multi-objective optimization problem. In the machining optimization problem, there are constraints on tool life, surface finish, cutting force, power consumption etc. Usually, the machining processes are performed in a number of passes; the last pass being the finishing pass and other passes being the rough passes. In a multipass machining process, the cutting speed, feed rate and depth of cut in each pass are the primary variables (Deb and Dixit, 2008). According to Brezocnik *et al.* (2004) and Saffar *et al.* (2009), the optimization of machining parameters using GA tends to minimize machining errors and so it is valuable in terms of providing high precision and efficient cutting. The application of GA to machining process optimization has been carried out by different researchers.

Cus and Balic (2003) present an optimization technique based on GA for the determination of the cutting parameters in turning operations. It performs the following: the modification of recommended cutting conditions obtained from a machining data, learning of obtained cutting conditions using NNs and the substitution of better cutting conditions for those learned previously by a proposed GA.

Brezocnik *et al.* (2004) proposed the GA approach to predict surface roughness in end-milling operations based on cutting parameters (spindle speed, feed rate, and depth of cut) and on vibrations between cutting tool and workpiece. It was established that the surface roughness is most influenced by the feed rate, whereas the vibrations increase the prediction accuracy. In Shunmugam *et al.* (2000), the face-milling parameters such as number of passes, depth of cut in each pass, speed and feed were obtained using a GA, to yield minimum total production cost while considering technological constraints such as allowable speed and feed, dimensional accuracy, surface finish, tool wear and machine-tool capabilities.

Saffar *et al.* (2009) developed a computer algorithm based on GA to optimize the cutting parameters to minimize tool deflection and increase tool life and surface roughness for a constant material removal rate in end-milling operations. Zain *et al*. (2010) applied the GA technique to estimate the optimal solutions of the radial rake angle of the tool in the end milling machining process of titanium alloy that lead to the minimum surface roughness value.

Saravanan *et al.* (2002) describe a GA based optimization procedure to optimize grinding conditions, i.e., wheel speed, workpiece speed, depth of dressing, and lead of dressing, using a multi-objective function model with a weighted approach for surface grinding. Jain *et al.* (2007) describes the optimization of process parameters of four mechanical type advanced (or unconventional) machining processes (ultrasonic, abrasive jet, water jet, and abrasive-water jet) using GAs giving the details of formulation of optimization models, solution methodology used, and optimization results.

5. HYBRID SYSTEMS APPLICATIONS

With the increasing need for effective and robust automated machining process and condition monitoring, a significant amount of research work has been performed to find decision-making strategies. The principal constituents of soft computation include fuzzy logic for imprecision in the acquired data and artificial neural networks for learning. Often, it is convenient to apply both these techniques together (fuzzy neural networks). There are two ways in which both these techniques can join hands. One way is to have two separate modules for the ANN and FL, and use these modules in the main task appropriately (Elbestawi *et al.*, 2006; Deb and Dixit, 2008).

For example, for predicting the surface roughness in a turning process, Abburi and Dixit (2006) trained an ANN by using shop floor data. The trained network was used to generate a large number of predicted datasets. These datasets were used to feed a FL based rule generation module. The generated rules were in the form of IF–THEN rules, providing transparency to a user. The developed rule base was used for predicting the surface roughness by using a FL inference system. The second way is to have an entirely different technique which uses the features of both the FL and ANN, but can be classified into neither category. One such technique is the adaptive neuro-fuzzy inference system (ANFIS) cited by Jang *et al.* (1997), which can be considered a newborn of ANN and FL. In Sokolowski (2004), the results achieved with the feed forward back propagation NN were presented to generalize the assessment of performance of the FL systems designed.

In Achichea *et al.* (2002), GA are utilized to automatically construct a FL knowledge base (KB) from a set of experimental data on tool-wear monitoring during unmanned turning. The performance of FL-GA system is compared with the performance of classical FL and ANN systems for application to tool wear estimation. The construction of a FL KB necessitates skills and expertise. The operator has to analyze the dependence of cutting force (F_c) on flank wear (VB) so that the experimental results have to be presented in a conveniently understandable form. This makes FL systems rather difficult for practical implementation in their human manual form. This problem can be solved using a

GA to automatically construct the FL KB. The operator no longer needs to analyze the experimental data. He only needs to select the maximum level of complexity he wants to consider. The learning time of the GA method was the shortest among the considered methods, making it very convenient for shop floor use. Moreover, one can specify the maximum complexity level together with how much emphasis the GA must place on accuracy increase versus complexity reduction. There are definite advantages for practical applications since the GA provides more generality to the KB. Nandi and Pratihar (2004) propose an approach for automatic design of FL controller using a GA and its performance was compared to a previous approach based on GA-fuzzy combination for making predictions of power requirement and surface finish in grinding.

6. CONCLUSIONS

In comparison between the intelligent system of a machine-tool and a skilled human being, the performance of a trained operator is dependent to a great extent on its sensory organs and brain. Hence, to develop a smart system that is able to function like an experienced worker, it is necessary to develop high-quality sensors and efficient computing (hardware and software) tools. Luckily, modern sensor systems are becoming increasingly available and low-priced and the signal processing capabilities of advanced algorithms and decision making strategies are also rapidly progressing. A lot of research needs to be done to develop effective, compact and low-cost sensors.

At the same time, soft computing methods need to be further improved. The computational model-based methods on the available data need to be more robust. They should be able to eliminate noise from the data and make the best output of the available information. There should be simultaneous efforts to understand the physics of the process and use that knowledge to complement the data processing task. The proper formulation of optimization problems for different processes and selecting of an efficient algorithm is another area that needs to be explored further.

The future enhancement of machining systems and their operation performance will vitally depend upon the development and implementation of innovative sensor monitoring systems. These novel systems will need to be robust, reconfigurable, reliable, intelligent and inexpensive in order to meet the demands of advanced machining technology. One of the main challenges in future machining process automation and monitoring systems is the development of algorithms and paradigms really autonomous from machine-tool operators, who are not required to know about methods like wavelet transform, fuzzy neural networks, genetic algorithms etc., with signal feature extraction and decision making performed without intervention of the operator, who should provide only very simple input and information.

Finally, the intelligent system must exploit the developments in Internet technologies, which requires research in the Internet-based machining area.

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