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ORIGINAL ARTICLE

# Application of soft computing techniques in machining performance prediction and optimization: a literature review

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**Abstract** Machining is one of the most important and widely used manufacturing processes. Due to complexity and uncertainty of the machining processes, of late, soft computing techniques are being preferred to physics-based models for predicting the performance of the machining processes and optimizing them. Major soft computing tools applied for this purpose are neural networks, fuzzy sets, genetic algorithms, simulated annealing, ant colony optimization, and particle swarm optimization. The present paper reviews the application of these tools to four machining processes—turning, milling, drilling, and grinding. The paper highlights the progress made in this area and discusses the issues that need to be addressed.

**Keywords** Machining · Optimization · Process models · Soft computing

## 1 Introduction

Machining is one among the four popular manufacturing processes, the other three being forming, casting, and joining. Modeling of machining processes has attracted the attention of a number of researchers in view of its significant contribution to the overall cost of the product [1]. For the purpose of this paper, machining is defined as a process, in which the metal is removed in the form of chips by means of single or multiple wedge-shaped cutting tools. Thus, the scope of the present review paper on the application of soft computing techniques in machining performance prediction and optimization is limited to so called conventional machining processes and does not include the relatively newer machining processes such as water jet machining, electrodischarge machining, electrochemical machining, etc. Among the conventional machining processes, the attention has been paid to four commonly used processes—turning, milling, drilling, and grinding. Turning is used for producing axisymmetric components, milling for producing flat or curved surfaces and prismatic shapes, drilling for making holes, and grinding for improving the surface finish and/or for maintaining the tolerances. These processes are performed by conventional and computer numerically controlled (CNC) machine tools.

From the era of conventional machine tools to the present era of CNC machine tools, the prediction of cutting behavior of processes and optimization of machining parameters have been hot areas of research. In a review of metal cutting analyses in 1956, Finnie [2] pointed out—"Despite the large number of attempts, past and present, to analyze metal cutting, a basic relationship between the various variables is still lacking." This remark is valid till today, even after about a half century. Nevertheless, the efforts to model machining process are still going on, as the proper understanding of the machining process has a large bearing on the economics of machining. With the advent of capital intensive CNC machine tools, this need has strengthened. The prediction of surface roughness, cutting force, and tool life in machining is a challenging task, but is necessary for proper optimization of the process. Of late, with the development of computer technology, finite element and soft computing methods are being used for modeling and optimization of

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machining processes [3–7]. The soft computing differs from conventional (hard) computing in that it is tolerant of imprecision, uncertainty, partial truth and approximation, and metaheuristics may play an important role in soft computing [8].

This paper reviews research work on the application of soft computing methods in modeling and optimization of machining processes, spanning for approximately two decades. Section 2 provides a brief outline of the following soft computing techniques: neural network (NN), fuzzy set theory, genetic algorithm (GA), simulated annealing (SA), ant colony optimization (ACO), and particle swarm optimization (PSO). The application of these techniques to four common machining processes, viz., turning, milling, drilling, and grinding is presented in Section 3. Section 4 critically discusses the past research and provides some direction for future research. The conclusions are presented in Section 5.

## 2 An overview of soft computing techniques

Soft computing is an approach to computing which parallels the remarkable ability of the human mind to reason and learn in an environment of uncertainty and imprecision. In an attempt to find out reasonably useful solutions, soft computing-based methods [3, 4] acknowledge the presence of imprecision and uncertainty present in machining. Soft computing techniques such as fuzzy logic, NN, GA, SA, ACO, and PSO have received a lot of attention of researchers due to their potentials to deal with highly nonlinear, multidimensional, and ill-behaved complex engineering problems. A brief overview of various soft computing techniques is presented here.

### 2.1 Fuzzy set theory

In 1965, Lotfi Zadeh put forward the idea of fuzzy sets [9], in which the elements of the set can have partial membership in the set. Many linguistic terms can be converted into a fuzzy set. For example, the “low feed” can be represented by a fuzzy set in which the feed values more than an upper threshold value can be assigned a membership grade 1 and those lower than a lower threshold value can be assigned a membership grade 0. Between lower and upper threshold, the feed values can have a gradual variation of membership grades from 0 to 1. Once the linguistic variables have been converted into fuzzy sets, set theoretic operations on them can be carried out. Thus, the fuzzy set theory is a tool for “computing with language”. The fuzzy set-based techniques can be quite effective in converting subjective knowledge/opinion of the skilled operator into a mathematical framework [10].

In the literature, predominantly the fuzzy set theory has been used in three ways. In the first type of applications, fuzzy set theoretic operations help to arrive at certain decision. For example, if we know the membership grades of certain solutions in two conflicting objectives, then the optimum solution can be chosen as the one providing the highest membership grade in the intersection set of two objectives. The second type of application makes use of fuzzy arithmetic, which deals with fuzzy numbers. A fuzzy number is a generalization of an interval number, in which various intervals may have different membership grades. For example, the most likely estimate of friction may be assigned a membership grade 1 and the lower and upper estimate may be assigned a membership grade 0.5. With these three points, a triangle can be constructed to represent friction as a fuzzy number. Fuzzy arithmetic computations are useful when the input parameter values, for example friction and material properties, are not known precisely. In the third type of application, fuzzy logic is used for making inferences based on the input values. The fuzzy set-based prediction system takes input data and carries out “fuzzification”. In the fuzzification process, the input data undergo some translation in the form of linguistic terms such as “low feed”, “average cutting speed”, “high depth of cut”, “very high cutting force”, etc. The translated data are sent to an inference engine, which applies a set of predefined IF-THEN rules. The output of inference system in linguistic form will go through defuzzification process, which converts it to numerical data.

### 2.2 Neural networks

Neural networks are systems that can acquire, store, and utilize knowledge gained from experience. An artificial neural network (ANN) is capable of learning from an experimental data set to describe the nonlinear and interaction effects with great success. It consists of an input layer used to present data to the network, output layer to produce ANN’s response, and one or more hidden layers in between. The input and output layers are exposed to the environment and hidden layers do not have any contact with the environment. ANNs are characterized by their topology, weight vectors, and activation function that are used in hidden and output layers of the network. A neural network is trained with a number of data and tested with other set of data to arrive at an optimum topology and weights. Once trained, the neural networks can be used for prediction.

A multilayer perceptron (MLP) is a feedforward neural network with one or more hidden layers. A feedforward neural network has sequence of layers consisting of a number of neurons in each layer. The output of one layer becomes input to neurons in the succeeding layer. The radial basis function (RBF) neural network consists of three layers: an input layer, a single hidden layer with nonlinear processing neurons, and an output layer. During training process, the network adjusts its weights to minimize the errors between the predicted and desired outputs. Back-propagation algorithm is most common algorithm for adjusting the weights. A brief background of neural networks is provided in [3].

### 2.3 Genetic algorithm

GA mimics the process of natural evolution by incorporating the "survival of the fittest" philosophy [11]. In GA, a point in search space is represented by binary or decimal numbers, known as string or chromosome. Each chromosome is assigned a fitness value that indicates how closely it satisfies the desired objective. A set of chromosomes is called population. A population is operated by three fundamental operations, *viz*., reproduction (to replace the population with large number of good strings having high fitness values), crossover (for producing new chromosomes by combining the various pairs of chromosomes in the population), and mutation (for slight random modification of chromosomes). A sequence of these operations constitute one generation. The process repeats till the system converges to the required accuracy after many generations. The genetic algorithms have been found very powerful in finding out the global minima. Further, these algorithms do not require the derivatives of the objectives and constraints functions.

### 2.4 Simulated annealing

SA mimics the cooling process of metal during annealing to achieve the minimization of function values. The algorithm begins with an initial point, $x_1$, and a large number corresponding to a high temperature $T$. A second point $x_2$ is created near the first point using a Gaussian distribution with first point as a mean. The difference in the function values at these points is considered analogous to the difference in energy level ($\Delta E$). For a minimization process, if the second point has smaller function value, then it replaces the first point; otherwise, it replaces the first point with a probability $\exp(-\Delta E/T)$ [12]. The algorithm is terminated when a sufficiently small temperature is obtained or no significant improvement in the function value is observed.

### 2.5 Ant colony optimization

The ACO algorithm is a kind of natural algorithm inspired by foraging behavior of real ants. Researchers are fascinated by seeing the ability of near-blind ants in establishing the shortest route from their nest to the food source and back. These ants secrete a substance, called pheromone, and use its trails as medium of communicating information [13]. The probability of the trail being followed by other ants is enhanced by further deposition of pheromone by other ants moving on that path. This cooperative behavior of ants inspired the new computational paradigm for optimizing real life systems, which is suited for solving large scale problems [14].

There are different variants of ant colony optimization algorithm. In essence, these algorithms carry out three operations: (1) ant-based solution construction, (2) pheromone update, and (3) daemon actions. In ant-based solution construction, solutions representing artificial ants are constructed. Solutions are chosen probabilistically based on pheromone level. Thus, this operation forces the algorithm to search in the area of better solutions. The aim of pheromone update is to increase the pheromone values associated with good or promising solutions and decrease those that are associated with bad ones. Usually this is achieved by increasing the pheromone levels associated with chosen good solutions and by decreasing the pheromone values through pheromone evaporation, which basically reduces the pheromone level. Daemon actions are used to implement centralized actions which cannot be performed by a single ant. For example, the global information can be collected to decide whether it is useful or not to deposit additional pheromone.

Initially, the ant colony optimization was used for combinatorial problems. Nowadays, it is also being used for solving continuous optimization problems.

### 2.6 Particle swarm optimization

Particle swarm optimization is a population-based stochastic optimization technique developed by Kennedy and Eberhart in 1995 and is inspired by the social behavior of bird flocking or fish schooling [15]. In PSO, each solution in search space is analogous to a bird and generally called "particle". The system is initialized with population of random particles (called swarm) and search for optima continues by updating generations. The fitness value of each particle is evaluated by objective function to be optimized. Each particle remembers the coordinates of the best solution (pbest) achieved so far. The coordinates of current global best (gbest) are also stored. The coordinates of the particle are updated according to the following relation:

$$\begin{aligned} \text{new\_coordinates} = \text{coordinates} &+ c_1\, r\,(\text{pbest} - \text{coordinates}) \\ &+ c_2\, r\,(\text{gbest} - \text{coordinates}) \end{aligned} \quad (1)$$

where $c_1$, $c_2$ are learning factors and $r$ is a random number between 0 and 1.

PSO is simple to implement and needs less parameters to adjust. In many cases, it has been reported to be more efficient than GA.

## 3 Application of soft computing to various machining processes

In this section, application of major soft computing tools to various machining processes is discussed. Soft computing tools can be used for prediction of the performance parameters of machining as well as for the optimization of the process. Figure 1a, b schematically depict the application of soft computing techniques for these tasks.

### 3.1 Turning process

In turning processes, a single point cutting tool moves along the axis of a rotating work piece. The peripheral speed of the work piece called cutting speed, movement of the tool along the axis of job for one revolution of job called feed, and radial depth of cut of the tool are the process parameters. These parameters may be optimized for obtaining the minimum cost of machining and minimum production time. However, for optimization, performance of the process has to be predicted. Soft computing for machining performance prediction is discussed in Sections 3.1.1–3.1.3. Section 3.1.4 reviews the soft computing applications in turning process optimization.

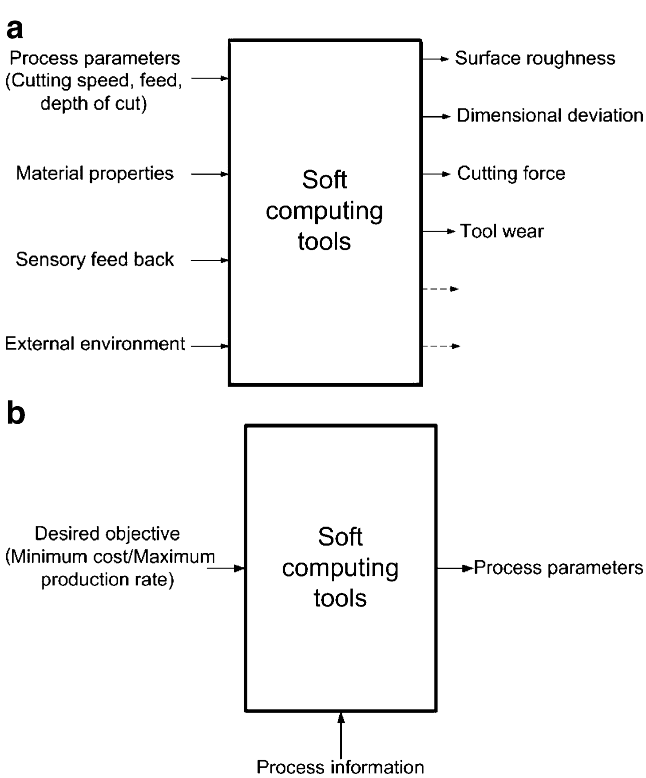


**Fig. 1** Two applications of soft computing in machining: **a** performance prediction and **b** optimization

#### *3.1.1 Surface finish and dimensional deviation*

Two main attributes of quality of turned job are surface finish and dimensional deviation. Surface finish is defined as the degree of smoothness of a part's surface after it has been manufactured. Surface finish is the result of the surface roughness, waviness, and flaws remaining on the part. Dimensional deviation is defined as the radial difference between the set depth of cut and the obtained depth of cut. Researchers studied the effect of number of factors such as feed rate, cutting speed, depth of cut, work material characteristics, unstable built up edge, tool nose radius, tool angles, stability of material, tool and work piece setup, use of cutting fluids, radial vibration, tool material, etc. on surface finish. For modeling of machining processes, researchers used four main methods, viz., multiple regression, mathematical modeling based on physics of process, fuzzy set theory, and neural network. The review in this paper will focus on last two techniques.

An early work for the prediction of machining performance using neural networks is by Rangwala and Dornfeld [16]. The authors utilized a feedforward network model to predict the cutting performance in turning process. The network is trained using a number of patterns of input variables, viz., cutting speed, feed rate, and depth of cut, and the output variables, viz., cutting force, power, temperature, and surface finish. Rangwala and Dornfeld [16] and many later researchers used MLP neural network for machining performance prediction. An MLP neural network consists of input layer, output layer, and one or more hidden layers. Each layer consists of a number of neurons. Neurons in the hidden and output layers get input from the neurons of the preceding layers. Neurons in the input and hidden layers emit the output to be received by the neurons of the succeeding layer.

Azouzi and Guillot [17] proposed neural network model to predict surface finish and dimensional deviation of the job based on the feedback from various sensors. They developed several network models to find out the influence of feedbacks from a number of sensors. The author observed that feed, depth of cut, radial force, and feed force provide the best combination to build a model for online prediction of surface roughness and dimensional deviation.

Several researchers have compared the effectiveness of the neural network model with statistical regression models. Chryssolouris and Guillot [18] observed the superiority of neural network model compared to regression model. On the other hand, Feng and Wang [19] found multiple regression analysis and neural networks equally effective in predicting surface roughness for a finish turning process.

Risbood et al. [20] predicted the surface roughness for the dry and wet turning of mild steels using carbide and high-speed steel tools. For each tool–job combination and cutting condition (dry or wet), different networks were used. The acceleration of radial vibration was taken as an input for online prediction of surface roughness. The authors also developed a neural network model for predicting the dimensional deviation of the job. For this purpose, the radial cutting force, the radial acceleration of vibration, cutting speed, feed, depth of cut, length-to-diameter ratio of the job, and position of the tool was taken as input parameter. Pal and Chakraborty [21] predicted surface roughness by taking main cutting force, feed force, cutting speed, feed, and depth of cut as input parameters of the network. Ozel and Karpat [22] predicted surface roughness by developing two different network models. One model was offline with process parameters, tool and job information as input, while the other was an online model with cutting forces as an additional input. It was observed that the model with cutting forces as additional input yielded better results.

The major limitation to the use of neural networks is that it requires a large set of experimental data. Considering this limitation, Kohli and Dixit [23] proposed a MLP neural network-based methodology to predict surface roughness in turning process that uses small-sized training and testing data sets. Their model predicts lower, most likely, and upper estimate of the surface roughness for a cutting condition based on the algorithm developed by Ishbuchi and Tanaka [24].

The aforementioned researchers have essentially employed MLP neural networks and differ in terms of the network training methodology and input parameters. Of late, there have been some applications of RBF neural network as a substitute for MLP neural networks. Compared to MLP neural networks, RBF neural networks can be trained faster although requiring more training data. Sonar et al. [25] studied the performance of RBF network for predicting lower, most likely, and upper estimates of surface roughness in turning process. They observed that the performance of RBF neural network was slightly inferior to MLP neural networks. Basak et al. [26] used RBF models to predict surface roughness in finish hard turning process of AISI D2 cold rolled steel with mixed ceramic tools. For better modeling of an RBF network, assistance of multiple-linear regression was taken. Authors observed that in RBF neural network training, the spread parameter, which is essentially the zone of influence of a neuron, plays a significant role. Authors have proposed a strategy for the optimal selection of this parameter. Sarma and Dixit [27] employed the MLP and RBF sequentially for predicting surface roughness of cast iron work piece with a ceramic tool. First, an MLP network was trained with limited training data. Afterward, the trained MLP network was used to generate a large training data set for the RBF network. The experimental data set were used for testing of the RBF network. Considering that data may be noisy, authors have proposed a strategy to slightly perturb the data for better prediction.

Apart from neural networks, fuzzy set theory has been used for turning performance prediction in general and surface roughness in particular. A fuzzy-based methodology has been proposed by Fang and Jawahir [28] to assess total machining performance encompassing surface finish, tool-wear rate, dimensional accuracy, cutting power, and chip breakability. The authors quantified the effect of major influencing factors on total machining performance by fuzzy set method and developed a series of fuzzy set models to give quantitative assessments for the given set of input conditions.

Abburi and Dixit [29] developed a knowledge base system with the help of neural network and fuzzy set theory to predict surface roughness in turning process. The neural network is trained with experimental data. The trained network generates a huge data set that is fed to a fuzzy set-based rule generation module. A large number of IF-THEN rules are generated that are reduced by using Boolean operations. This rule base module is used for predicting surface roughness for given process variables as well as for the inverse prediction of process variables for a given surface roughness. The performance of the developed knowledge based system was found satisfactory based on the validation with shop floor data.

A number of authors have used the combination of two or more soft computing tools as an effective strategy for the prediction of surface roughness. Jiao et al. [30] used a neurofuzzy approach for the prediction of dimensional deviation. The developed fuzzy adaptive neural networks are capable of providing both learning ability of a neural network and tolerance of imprecision, uncertainty, and vagueness in the machining process. First, an approximate model representing the influence of machining parameters on dimensional deviation is established. This model is then improved by learning with the given training data. The authors showed the superiority of their model over a classical regression model. Nandi and Pratihar [31] employed a fuzzy basis function network for predicting the surface roughness in ultraprecision turning. The parameters of the network were optimized with a genetic algorithm code.

### *3.1.2 Tool life and tool wear*

Tool life and tool wear play a major role in the economic aspects of metal cutting operations. Most of the time, tool life is considered as a time lapse between two successive regrinds of tool when operating under specified cutting conditions. In an early work on tool wear estimation using neural networks, Ezugwu et al. [32] predicted tool life and failure mode in machining of gray cast iron with ceramic cutting tools. The tool failure based on average and maximum flank wear, crater depth, notch depth, surface roughness, and catastrophic failure of the tool have been considered. The experimental data have been used to train the MLP neural network using backpropagation algorithm. However, the authors had limitation of having just 25 data. With these data, they could predict the correct tool life (within 20%) in 58.3% cases and tool failure mode in 87.5% cases. Dutta et al. [33] studied the application of neural network with different learning schemes for faster processing of data which is a major criterion in online tool condition monitoring. Speed, feed, depth of cut, and three components of cutting forces were inputs of the neural networks and flank wear was output of the network. The authors found that the modified backpropagation algorithm converge faster than standard backpropagation algorithm.

Tool life in hot machining of high magnesium steel has been modeled by Tosun and Ozler [34] using an MLP neural network. The turning was carried out at four temperatures—room temperature, 200°C, 400°C, and 600°C. The neural network model predicted the tool life with better accuracy as compared to a regression model.

Ojha and Dixit [35] proposed an economic and quicker method of tool life estimation and predicted low, most likely, and higher estimates of tool life using neural networks. In their approach, the tool life is estimated by fitting a best-fit line for the data falling in steady wear zone and finding the time till tool fails by extrapolation. For predicting the lower and upper estimates of the tool life, they used the backpropagation (BP) algorithm of Ishbuchi and Tanaka [24], as was earlier done by Kohli and Dixit [23]. The neural network model was found superior to the multiple regressions model. Quiza et al. [36] carried out an experimental investigation on tool wear prediction on ceramic cutting tools used for turning hardened cold rolled tool steel. They predicted tool wear with the help of neural network and regression models. The neural network model was found superior to the regression model.

Soft computing optimization techniques, viz., genetic algorithm, particle swarm optimization, and simulated annealing, were used for optimizing neural network model parameters. For tool life estimation, Natarajan et al. [37] employed a neural network model that was optimized by PSO. The use of PSO resulted in reduction of training time by 50%.

Tool wear monitoring has been other widely investigated research topic. Tool wear monitoring is of two types: direct and indirect. Direct methods measure the actual values of size of wear parameters with optical instruments, while indirect methods measure parameters such as cutting forces or vibrations that are correlated with tool wear. A number of tool wear monitoring schemes have been proposed that employ vibrations, ultrasonic, torque, power, velocity, and temperature sensors and sensor fusion. Sick [38] has reviewed a number of research papers dealing with online and indirect tool wear monitoring in turning using artificial neural networks. Mainly, vibrations, acoustic emission (AE), torque, power, velocity, and temperature sensors were employed for obtaining the feedback for indirect estimation of tool wear. Some of the representative work is as follows: Das et al. [39] developed a backpropagation neural network model for the reliable online tool condition monitoring based on cutting force measurement. The ratio of cutting force components have been found as a better indicator of the tool wear. Silva et al. [40] developed neural network based online tool condition monitoring for turning process using signals from five sensors. They used two types of neural network learning algorithms—adaptive resonance theory (ART) and self-organizing map (SOM) to classify statistical and frequency domain features of the sensor signals. The ART2 creates and classifies tool wear with less number of sampled data and has the ability to respond immediately. The SOM is a method of mapping a high-dimensional input space on to a one- or two-dimensional output space by using an unsupervised neural model. The authors found that the NN with the SOM perform better than the ART2 in classifying unseen sampled data. Nadgir and Ozel [41] employed a neural network to model tool condition monitoring system. Online cutting forces were measured by a piezoelectric tool dynamometer and used as inputs to the network. Data obtained from several machining test with use of different cutting speed, feed, and a constant depth of cut were used to train the network. Chungchoo and Saini [42] proposed an online fuzzy neural network to predict tool wear. Cutting forces, acoustic emission signals, skew and kurtosis of force bands, and total energy of forces were taken as input parameters of the neural network.

*3.1.3 Cutting force*

Cutting force is one of the important characteristic variables to be monitored during machining process. Tool breakage, tool wear, and work piece deflection are mainly due to abnormal cutting force developed during machining process. To predict and monitor cutting forces, various models were proposed using soft computing techniques.

Khanchustambham and Zhang [43] used neural network to predict cutting force as well as surface finish during machining of ceramic material. Feed, depth of cut, and spindle speed are used as input parameters for the network. The network is trained by cutting force signal and measured surface finish for online monitoring of turning process. Lee et al. [44] used feedforward neural network to predict cutting force components. The network is trained using undeformed chip thickness, chip width, cutting speed, and tool rake angle as input parameters. The authors found the predicted results are in good agreement with experimental data. Luong and Spedding [45] developed neural network model to find cutting conditions for a given work material and required depth of cut to predict the cutting forces, surface roughness, and tool life. They trained the network using data from Machining Data Handbook and have shown that the neural network establishes a correlation from empirical data. Szecsi [46] used neural network model for cutting force estimation in turning process. Process parameters, tool geometry, work piece material, and flank wear were taken as input parameters of the network. The author used 3,200 training and 1,500 testing data to train the network and found very good prediction accuracy. However, there is no discussion about the statistical variation of the cutting forces. Lin et al. [47] used radial basis function neural network and multiple regression analysis to predict machining forces–tool wear relationship in machining of aluminum metal matrix composites. Besides process parameters, feed and cutting forces were used to estimate tool wear. The authors obtain better correlation of tool wear with feed force data than with cutting force.

In high speed turning, the correlations between various cutting parameters play an important role while model building. Ezugwu et al. [48] used an ANN approach to model the correlation between five process parameters, viz., speed, feed rate, depth of cut, cutting time, and coolant pressure, with seven performance parameters, viz., tangential force, feed force, spindle motor power consumption, surface roughness, average flank wear, maximum flank wear, and nose wear. The developed model agrees well with experimental data and can be used to analyze and predict the relationship between process and performance parameters.

Hao et al. [49] proposed multilayer perceptron neural network model for predicting cutting force in self-propelled rotary tool in turning. Cutting speed, feed rate, depth of cut, and tool inclination angle were input parameters and thrust force, radial force, and main cutting force are output parameters of the network. The authors applied hybrid of GA and BP algorithm to improve performance of neural network model.

Lin et al. [50] predicted surface roughness and cutting force using abductive neural network during turning of high carbon steel with carbide inserts. Abductive networks are composed of a number of polynomial functional nodes organized into several layers. Unlike general neural network, abductive neural network generate optimal network architecture automatically and take less iterations in training. The network is trained with cutting speed, feed, and depth of cut as input parameters. Predicted results are found more accurate compared to regression analysis. Li et al. [51] used neurofuzzy techniques to estimate feed cutting force by measuring motor current using current sensor in CNC turning center. Motor current and feed rate were used as input parameters. The authors found that the estimated force was within an error of 5%.

### 3.1.4 Process optimization

The machining optimization problem is highly nonlinear and possesses multiple solutions. In multi-objective optimization, cutting parameters is of great concern in manufacturing environment. Researchers considered various input (cutting) parameters like cutting speed, feed rate, depth of cut, cutting time, coolant pressure, etc. and output (process) parameters like tangential force, axial force, radial force, feed force, spindle power consumption, surface roughness, tool life, average and maximum flank wear, and nose wear, etc. for modeling. Optimization of single-pass turning has been attempted in early works. However, in general, a turning operation involves a number of rough cuts and a final finish cut. In manufacturing industries, multipass turning is widely used than single-pass turning. The highest possible metal removal is aimed in rough passes, where surface finish is not an important consideration. However, in finish turning process, surface finish is the most important consideration. Researchers have used soft computing optimization techniques, viz., fuzzy logic, neural network, simulated annealing, genetic algorithm, ant colony optimization, and particle swarm optimization to optimize both single and multipass turning problem.

Karpat and Ozel [52] developed a multi-objective optimization model for single pass turning to model surface roughness and tool wear. They used PSO-based neural network optimization scheme to optimize finish hard turning processes using cubic boron nitride tools. NN model predicts surface roughness and tool wear during machining and PSO is used to obtain optimum cutting speed, feed rate, and tool geometry. The authors found that PSO takes less number of iterations to reach optimal conditions.

Neural network used in fuzzy decision environment have been reported in literature. Wang [53] uses feedforward neural network using manufacturer's fuzzy preferences to determine the optimum cutting parameters by solving the multi-objective problem with the help of a neural network model. The objectives considered were productivity, operation cost, and cutting quality. Lee et al. [54] presented fuzzy nonlinear programming model to optimize cutting conditions for a turning process. Subsequently, a neural network model is trained based on the results of the optimization model. The trained neural network is able to predict the cutting speed accurately. The readers may note that these authors have used the term "machinability" for "material removal rate". Hashmi et al. [55] developed a fuzzy logic model for selection of cutting conditions for machining

GAs are very suitable for solving multi-objective problems. Based on representation of design variables, they are of two types: binary-coded genetic algorithm and real-coded genetic algorithm (RGA). In machining optimization, RGAs are more precise, more consistent, and lead to faster convergence. Abburi and Dixit [56] developed an optimization methodology which is a combination of a RGA and sequential quadratic programming (SQP) to obtain Pareto-optimal solutions to minimize production cost. The major advantage of the methodology is that various Pareto-optimal solutions are generated without the knowledge of the cost data. The optimization is carried out with equal depths of cut for roughing passes and the authors found that RGA combined with SQP is very efficient in reaching up to global optima. Kim et al. [57] also explored the applicability of RGA in machining optimization. In their work, RGA has been compared to SA, continuous SA, GA, and generalized reduced gradient method.

Chen and Tasi [58] followed by many researchers applied SA approach to solve the optimization problem for minimum unit production cost of multipass turning process. Baykasoglu and Dereli [59] have used SA to optimize cutting conditions in their heuristic model. However, they did not take surface finish into consideration. Onwubolu and Kumalo [60] applied GA to minimize unit production cost and concluded that GA significantly performs better than SA. However, Chen and Chen [61] have shown that Onwubolu and Kumalo have incorrectly handled the machining model and showed that the GA provides no better solution than SA.

The distribution of total depth of stock among different rough cuts and final finish pass is an important task in multipass turning optimization. Wang and Jawahir [62] proposed GA-based methodology for the allocation of total depth of cut in multipass turning. A novel feature of this work is the consideration of tool wear in the optimization procedure.

In recent literature, newer optimization techniques such as ACO and PSO are used to optimize multipass machining. Srinivas et al. [63] optimized multipass turning process to minimize total production cost using PSO in their mathematical model. They used six cutting constraints, viz., variable bounds, tool life, cutting force, power, stable cutting region, and chip–tool interface temperature. It is found that PSO provides optimal feasible solutions within a reasonable computational time. Vijayakumar et al. [64] used ACO to minimize unit production cost subjected to various practical constraints and found that the approach performs better than SA and GA. However, it has been contradicted by Wang [65].

Ojha et al. [66] used neural network-, fuzzy set-, and genetic algorithm-based soft computing methodology to optimize process parameters in multipass turning operation. Neural network has been used for prediction of surface finish and tool life. In view of uncertainty, surface roughness is quantified by using fuzzy number. An equal depth of cut for roughing passes along with a single finish pass strategy, similar to earlier work of Yeo [67] has been considered in optimization model. The optimization model has been applied for determining the optimum cutting parameters for two cases, viz., minimization of production cost and maximization of production rate.

## 3.2 Milling process

Milling is a multipoint tool cutting process in which the cutter rotates at some speed while the work feeds past the cutter. The peripheral speed of the cutter called cutting speed, movement of the work piece under the cutter per unit time called feed rate or table feed, depth of cut in the direction along the cutter axis called axial depth of cut, depth of cut normal to the cutter axis called radial depth of cut, and number of passes are process parameters. These parameters may be optimized for obtaining the minimum cost of machining and minimum production time. To predict performance of process and optimization, soft computing techniques have been applied. Sections 3.2.1–3.2.3 discuss machining performance prediction. Section 3.2.4 reviews the soft computing applications in milling process optimization.

### *3.2.1 Surface roughness*

Surface roughness has been an important factor in predicting the performance measure of any machining process. In milling, it is influenced by machining parameters such as speed, feed, and depth of cut, tool diameter, radial rake angle, nose radius, work piece material, tool material, machine vibration, etc. Researchers have attempted to predict surface roughness using an adaptive neurofuzzy inference system (ANFIS), genetic programming (GP), and fuzzy logic, mostly on end milling operation. GA and PSO were used as optimization techniques.

Lo [68] used ANFIS to predict the surface roughness in end milling process. Spindle speed, feed rate, and depth of cut were considered as input parameters. The ANFIS was modeled using triangular and trapezoidal membership functions. The average error of prediction of surface roughness for triangular membership function was found lower, around 4%. Ho et al. [69] also proposed ANFIS to predict surface roughness on aluminum alloy work piece milled with HSS tool. They used a hybrid Taguchi genetic learning algorithm in the ANFIS to determine the most suitable membership functions and simultaneously find optimal parameters by directly minimizing surface roughness error. The result shows that their approach using Gaussian membership function outperforms the ANFIS method given in the MATLAB® tool box and other reported work.

Brezocnik et al. [70] proposed a GP approach to predict surface roughness in end milling process. The genetic programming is an evolutionary computation method that was first introduced by Koza [71] in the year 1992. It aims to find out computer programs (called as chromosomes) whose size and structure dynamically changes during simulated evolution that best solve the problem. Cutting parameters, viz., spindle speed, feed, and depth of cut as well as vibration between tool and work piece, were used to predict the surface roughness and the authors found that the model that involves all these variables accurately predict the surface roughness.

Reddy and Rao [72] developed an empirical surface roughness model for end milling of medium carbon steel, whose parameters were optimized using GA. Oktem et al. [73] determined the optimum cutting conditions for minimum surface roughness in milling of mold surfaces. The surface roughness was modeled by response surface method and GA was used for optimizing the cutting conditions. Reddy and Rao [74] used genetic algorithm to optimize tool geometry, viz., radial rake angle and nose radius and cutting conditions, viz., cutting speed and feed rate to obtain desired surface quality in dry end milling process.

Prakasvudhisarn et al. [75] proposed an approach to determine optimal cutting condition for desired surface roughness in end milling. The approach consists of two parts: machine learning technique called support vector machine to predict surface roughness and particle swarm optimization technique for parameters optimization. The authors found that PSO shows consistent near-optimal solution with little effort.

Chen and Savage [76] used fuzzy net-based model to predict surface roughness under different tool and work piece combination for end milling process. Speed, feed and depth of cut, vibration, tool diameter, tool material, and work piece material are used as input variables for fuzzy system. The authors found that the predicted surface roughness is within an error of 10%. Iqbal et al. [77] developed a fuzzy expert system for parameter optimization that includes prediction of tool life and surface finish in hard-milling (high speed milling of steel having 45 HRC hardness) process.

### 3.2.2 *Tool wear and tool condition monitoring*

During milling process, cutter wear reduces surface finish of the work piece and increases cutting forces, power consumption, etc. Unfortunately, there is no direct way of online measuring of tool wear. In indirect method of estimation, sensors are used to extract features from cutting zone and tool wear is estimated. Neural network, fuzzy logic, and genetic algorithm are used to predict wear and monitoring tool condition online in face and end milling processes. Ghosh et al. [78] developed a neural network-based sensor fusion model to estimate tool wear during CNC milling process. Signals in the form of cutting forces, spindle motor current, and sound pressure level were used as inputs for neural network. The authors have proposed newer methods such as feature space filtering, prediction space filtering, etc. to improve prediction accuracy and found that the prediction is satisfactory in a real-time error-prone environment.

Chen and Black [79] proposed a fuzzy nets tool-breakage detection system for monitoring tool breakage in end milling operations. The developed system has self learning capability and generates fuzzy rule base based on experimental data. However, for the generation of fuzzy rules from given input–output data pairs, they have used large data sets compared to that used by Kohli and Dixit [23] in fitting neural networks for predicting surface roughness in turning process. The proposed system has ability to detect tool breakage online, approaching real time basis. Dutta et al. [80] also proposed a fuzzy controlled backpropagation neural network (BPNN) model for predicting the tool wear in face milling process. The convergence speed, prediction accuracy, and total time of system development make this approach an attractive technique suitable for online tool condition monitoring. Fuzzy logic-based in-process tool wear monitoring system has been proposed by Susanto and Chen [81]. Cutting parameters, viz., feed and depth of cut, and maximum resultant cutting force, were used as variables to predict flank wear of the cutter. The authors found that the system effectively monitors the wear condition on the tool during cutting process with an average error of 8.7%. Tansel et al. [82] proposed tool monitoring system using genetic algorithm to monitor micro-end milling operations that is able to estimate wear and local damages of the cutting edges of a tool. Dutta et al. [83] predicted the wear of the tungsten carbide inserts using neural network during face milling of steel. They proposed a new approach called modified backpropagation neural network with delta bar delta (MBPNND) learning to enhance the convergence speed and prediction accuracy of the network. The authors found that MBPNND is efficient compared to three other approaches, viz., backpropagation neural network, fuzzy backpropagation neural network, and modified backpropagation neural network.

Ching-kao and Lu [84] used gray-fuzzy logic approach to predict optimal cutting conditions for improved tool life and metal removal rate during side milling of SUS304 stainless steel. Gray-fuzzy logic that combines gray-relational analysis and a fuzzy logic is useful to deal poor, incomplete, and uncertain information. The approach converts multiresponse variable into single response gray-fuzzy reasoning grade and simplifies optimization procedure. The result shows improved performance on side milling process with heavy cutting.

*3.2.3 Cutting force*

The performance of milling process is monitored through measurable output parameters mainly by cutting forces and controlling input cutting parameters to suit particular cutting conditions. Neural networks were used to predict cutting forces during machining. Tandon and El-Mounayari [85] employed multilayer perceptron network for modeling the cutting forces in end milling process. The model was limited to one tool–work material combination (high speed steel tool and aluminum work piece) and the authors used 96 data for training and testing the network. However, the model does not take into account the tool wear. Zuperl et al. [86] proposed feedforwarded neural network model with ten input neurons to estimate cutting forces in ball-end milling operation. Cutting speed, feed rate, axial and radial depth of cut, cutter diameter, work material type and its hardness, type of insert, tool wear, and cutting fluid are used as input parameter of the neural network to predict three cutting force components.

Radhakrishnan and Nandan [87] predicted cutting force model using regression and neural networks. A regression model is used to filter out abnormal data points and the filtered data were used in neural network for better prediction.

Briceno et al. [88] compared a multilayer perceptron neural network with radial basis function network (RBFN) for prediction of machining forces in milling. The radial basis function neural network was found to be superior to multilayer perceptron neural network. Considering the statistical variation, the neural networks were used for predicting minimum, maximum, mean, and standard deviation of the cutting forces. Zuperl et al. [89] also found the radial basis function neural networks superior to the multilayer perceptron in modeling of machining forces in ball-end milling. Aykut et al. [90] used artificial neural network to predict cutting forces and studied machinability in face milling process**.** Cutting speed, feed rate, and depth of cut were used as input parameters of the network to predict three cutting forces and they found the estimated force within an error of 10%.

*3.2.4 Process optimization*

Most of the work in machining optimization has been focused on turning problems. In milling, the process is modeled with input parameters like cutting speed, feed rate, radial depth of cut, axial depth of cut, number of passes, cutter diameter, helix angle of the cutter, work piece hardness, milling orientation, cutting time, etc. and performance parameters like tangential force, axial force, radial force, feed force, spindle power consumption, arbor defection, surface roughness, tool life, average and maximum flank wear, and nose wear, etc. Soft computing optimization techniques such as neural network, genetic algorithm, and simulated annealing are mostly employed to optimize both single and multipass milling problem.

Tandon et al. [91] used an artificial neural network to predict the cutting forces which in turn was used to optimize both feed and speed using particle swarm optimization algorithm for NC pocket milling process. They observed that the approach reduces machining time up to 35%.

Shunmugam et al. [92] used genetic algorithm to optimize minimum production cost in face milling operation. The machining parameters, viz., number of passes, depth of cut in each pass, speed, and feed, are obtained. The authors found that the proposed optimization method yields better results to those reported in literatures. Cus et al. [93] proposed an online monitoring and optimization of cutting process to optimize production cost and time for a desired surface finish in ball-end milling process. The cutting forces measured by sensors were analyzed and optimum cutting parameters was obtained by using genetic algorithm. The results show that the method is effective and can be integrated into real-time manufacturing environment. Sreeram et al. [94] also proposed genetic algorithm to optimize cutting parameters for maximum tool life as well as minimum production cost in micro-end milling process. Depth of cut along with other cutting parameters (cutting speed and feed rate) has been considered as decision variables. The authors found improved results compared to tool supplier's data.

Genetic–simulated annealing (GSA) algorithm, which is a hybrid of GA and SA, is used by Wang et al. [95] to determine optimal machining parameters for plain milling process. GSA being hybrid algorithm exploits the strength of SA and GA and overcome their weakness in optimizing feed rate and speed for an objective of minimum total production time. Number of constraints such as allowable cutting speed, feed rate, horse power, arbor strength, and arbor deflection are considered. The results show that GSA is more efficient than GA and geometric programming.

Apart from economic objective of optimization, soft computing techniques have also been used for tool path planning in milling complex part geometry. Suh and Shin [96] used neural network model for generation of tool path during rough cutting of pocket milling. The algorithm is validated through computer simulation as well as real machining.

### 3.3 Grinding process

Grinding is a finishing process, widely used in manufacturing of components requiring fine tolerances and good surface finish. In basic cylindrical grinding process, the peripheral speed of the grinding wheel called wheel speed, the peripheral speed of the work against wheel rotation called work speed, the table traverse speed per second called work feed rate, and radial depth of cut of the work are the process parameters. The parameters slightly vary for surface grinding and other grinding process. These parameters may be optimized for obtaining the minimum cost of machining and minimum production time. However, for optimization, performance of the process has to be predicted. Soft computing has been applied for machining performance prediction as discussed in the three Sections 3.3.1–3.3.3. Section 3.3.4 reviews the soft computing applications in grinding process optimization.

#### 3.3.1 Surface finish

In grinding process, surface roughness is one of the important factors in assessing the quality of the ground component. Operating parameters such as wheel speed, work speed, feed, and depth of cut, work material properties, grinding wheel composition, coolant application, machine vibration, etc. are the variables that affect the surface roughness in the grinding process. Many of these variables are nonlinear, interdependent, and difficult to quantify. In recent decades, due to complexity of the grinding process, soft computing techniques were used to estimate surface roughness that takes many variables into account and covers a wide range of cutting conditions.

Ali and Zhang [97] proposed a fuzzy logic model for surface roughness estimation of work piece produced by surface grinding operation. They used 16 variables which are influential for surface roughness and found that the method is simple, effective, and superior in modeling nonlinearity. Nandi and Pratihar [98] developed a genetic fuzzy system for prediction of surface finish as well as power required in grinding process. They used GA to optimize fuzzy knowledge base offline and compared the predicted results with experimental data.

Kim [99] developed a neurofuzzy model to optimize cycle time in plunge grinding process. He used grinding power, peak value of power spectrum, and time constant as inputs for neural network to estimate work piece surface roughness. From the results obtained, he found that the model is more reliable than regression model. Samhouri and Surgenor [100] proposed an ANFIS to predict surface roughness in grinding process. The power spectral density parameters of piezoelectric accelerometer were used as inputs to ANFIS and the authors found prediction accuracy as 91%.

In 1992, Wang and Mandel [101] first introduced fuzzy basis function which has the capability of combining both numerical data and linguistic information. Thereafter, many researchers used fuzzy basis function network employing single or multiple variables. Nandi and Banerjee [102] used fuzzy basis function neural network to predict surface roughness and corresponding power requirement in cylindrical plunge grinding process. Wheel speed, work speed, and feed rate were considered as input variables and, power requirement and surface roughness as output variables of the network architecture. The fuzzy rule base was designed automatically using a genetic algorithm and from the results, it was concluded that the model predicts better than mathematical models.

#### 3.3.2 Wheel wear and grinding burn

Estimation of life of grinding wheel is important in grinding process. Generally, surface roughness, chatter marks, and burn marks, etc., on work piece surface are considered as an indication for wheel life limit in grinding process. Deivanathan et al. [103] used neural network to predict wheel life in cylindrical plunge grinding process. The occurrence of burn marks on the work piece surface was adopted as criterion for wheel life. Work speed, work diameter, infeed, and power were taken as inputs of feedforward neural network to estimate “time to burn” as output parameter. Wang et al. [104] proposed a radial basis function neural network approach to detect grinding burn on work piece from AE signals. The neural network is trained with two sets of data, one being mean and standard of frequency of band power, the kurtosis, and skew of AE signals, and other being autoregressive coefficients. The authors found good prediction in both the cases. Ali and Zhang [105] developed a fuzzy rule-based model for predicting burns in surface grinding of steel. They used 37 absolute and eight relative rules to predict the grinding conditions. The method was found suitable for many types of steels and grinding condition. Liu et al. [106] used fuzzy pattern recognition technique to predict grinding burn. They used acoustic signals which were obtained by wavelet pocket transform and optimized by fuzzy clustering.

Lezanski [107] used neural network and fuzzy logic to monitor the grinding wheel condition using multiple sensors. Two grinding parameters, viz., grinding engagement and coolant volume rate and 14 sensory signal feature related to vibration, grinding forces, vibration-power spectrum, acoustic emission root mean square (RMS), and acoustic emission-power spectrum RMS, were used as inputs to the neural network. The author found that neurofuzzy system performs lower than neural network approach.

#### *3.3.3 Grinding force and vibrations*

Grinding forces influence the efficiency and productivity of the process since it affects the mechanism of metal removal, wheel wear, etc. Neural network approach is used to estimate grinding force in various grinding processes. Fuh and Wang [108] used backpropagation neural network to model grinding force in creep feed grinding process. Work speed, wheel speed, wheel diameter, depth of cut, and grinding manner (up or down) are used as input parameters of the neural network to estimate vertical force and horizontal force.

Kawak and Ha [109] proposed a neural network approach to predict chatter vibration and grinding burn. Data from AE sensor and power meter, viz., RMS peak, fast Fourier transform peak, static power, and dynamic power, were used as input parameters to predict status of grinding condition as normal, burning, or chatter vibration. The authors found that the learned neural network with power and AE parameter provides the diagnosis of the grinding process better.

#### *3.3.4 Process optimization*

The optimization of grinding process is an important task due to accurate and economical means of shaping the parts into final product with required surface finish and high dimensional accuracy. Problems are formulated to maximize production rate and minimize production cost subject to constraints such as burns, wheel wear, and machine stiffness and so on.

Liao and Chen [110] used BPNN model to optimize creep feed grinding process and found better result than the regression method. The model considers five input variables, viz., bond type, mesh size, concentration of abrasive particles, work speed, and depth of cut, and three output parameters, viz., surface finish, normal grinding force per unit width, and grinding power per unit width. Govindasamy et al. [111] developed a dynamic neural network model-based control strategy to minimize defects in grinding of aluminum disks. They found that the approach reduces thickness defects of the component by 50%.

Brinksmeier et al. [112] proposed NN and fuzzy set-based model to optimize the grinding processes. They evaluated the grinding process in terms of geometric quantities (such as dimension, shape, waviness, and surface integrity) and product quality, i.e., surface roughness. Lee and Shin [113] proposed fuzzy basis function neural networks for modeling of grinding processes to find optimal process conditions. The model was applied for two grinding optimization problems, viz., creep feed grinding and surface grinding process, and it was found that the NN-based algorithm outperforms traditional optimization techniques in surface grinding process.

Saravanan and Sachithanandam [114] proposed GA-based optimization procedure to optimize cutting conditions, viz., wheel speed, work speed, lead of dressing, and depth of dressing in multi-objective surface grinding problem. They found that GA performs better than traditional quadratic programming. Gopal and Rao [115] developed a GA-based optimization procedure to optimize grinding conditions, viz., depth of cut, work speed, grit size, density, using a multi-objective function model. From the results obtained, they found that the material removal rate and cost of grinding are influenced more by surface roughness constraint than by that of surface damage. Baskar et al. [116] also considered multi-objective surface grinding problem to optimize cutting conditions. They used ACO-based optimization and found that it outperforms quadratic programming technique and GA.

### 3.4 Drilling process

Drilling is the process of making a cylindrical hole in a solid work piece using a cutting tool called drill. The peripheral speed of the drill called cutting speed, movement of the drill along the axis of the hole for one revolution called feed, and radius of the drill called as depth of cut are the process parameters. The special feature of drilling is that the cutting speed varies along the cutting edge, from almost zero near the center of the drill to the circumferential speed of the drill at its outer radius. These parameters may be optimized for obtaining the minimum cost of machining and minimum production time. However, for optimization, performance of the drilling process has to be predicted. Soft computing has been applied for machining performance prediction as discussed in the three Sections 3.4.1–3.4.3. Subsection 3.4.4 reviews the soft computing applications in drilling process optimization.

#### *3.4.1 Surface finish and dimensional deviation*

In industrial modern precision assembly system, “hole quality” in term of surface roughness and roundness is an important factor and is achieved by reaming process. The reaming is the process of accurately sizing and finishing the previously produced hole. Mathews and Shunmugam [117] used ANN approach for predicting hole quality in reaming process. Acoustic emission, cutting force, and vibration sensor data were used as input parameters and surface finish, roundness error, and residual stress as output parameters of the neural network. The result shows that ANN predictions using multisensor data were much closer to the experimental values and this approach is found to be an effective approach.

The effect of drilling a hole on specialized materials like composites has been addressed by few researchers. In drilling of fiber-reinforced composites delamination and surface finish are two major concerns. Taso and Hocheng [118] used RBF neural network with three drilling factors, viz., spindle speed, feed rate, and drill diameter to predict thrust force and surface finish of candlestick drill in drilling of composite materials. The predicted results show that the errors in thrust force and surface finish prediction are below 2% and 4%, respectively, and the procedure is more accurate compared to regression analysis.

Nandi and Davim [119] used fuzzy logic rules to predict the performance of drilling process with minimum quantity lubricant in aluminum alloy work piece. The comparison of model prediction with experimental results shows that the fuzzy rule base model with Takagi–Sugeno–Kang type of fuzzy rules provides better prediction of surface roughness, cutting power, and specific cutting force.

### 3.4.2 Tool Life and tool wear

The useful life of drill and its operating conditions largely control the economics of the machining operations. Cutting parameters such as speed, feed, cutting force, etc. influences flank wear of the drill. Fuzzy logic and neural network were used to estimate the drill life, drill wear, and monitor the drill condition.

Biglari and Fang [120] used real-time fuzzy logic control for maximizing drill life in a small-hole drilling (3 mm diameter) process. Experiments were conducted under five different drill wear conditions—initial, normal wear, acceptable wear, severe wear, and drill failure to record thrust force, torque, and radial force, which developed 53 fuzzy rules. The methodology based on online monitoring of drill wear is used for controlling drill feed rate for maximum tool life.

Lin and Ting [121] predicted drill wear using neural network and regression models. Average thrust force and torque, spindle speed, feed rate, and drill diameter were used as input parameters and average flank wear was the only output parameter of the neural network. The authors found that the neural networks with two hidden layers learn faster and can more accurately estimate tool wear than the networks with one hidden layer.

Liu et al. [122] used polynomial network for in-process prediction of corner wear on the drill. The polynomial network is composed of a number of functional nodes having self-organizing feature with an ability to construct the relationship between input and output variables. It has greater prediction accuracy and have fewer internal network connections, compared to backpropagation network. Thrust force or torque, cutting speed, feed rate, and drill diameter were used as input parameters. The authors found that the use of thrust force in the model provides predictions within an error of 10%. Abu-Mahfouz [123] compared several architectures of feedforward BPNN for tool condition monitoring of twist drill wear. The network is trained using vibration data and five drill wear conditions, viz., chisel wear, crater wear, flank wear, edge fracture, and corner wear, which were artificially introduced in the network for prediction of drill wear. Fully connected networks were found to be better than grouped network and the vibration signals are promising data for tool condition monitoring.

Sanjay et al. [124] proposed BPNN to detect drill wear on 8 mm HSS drill while machining mild steel. The network is trained using spindle speed, feed, drill size, machining time, torque, and thrust force as input parameters. The authors found that the three layered network with the hidden layer having two and ten neurons is the best layered network and predicted values are accurate compared to regression analysis for all the combination of cutting speed and feed. Panda et al. [125] also used BPNN for predicting flank wear on HSS twist drill while drilling mild steel work piece. The network is trained with spindle speed, feed rate, drill diameter, thrust force, torque, and chip thickness as input parameters. The authors found that the inclusion of chip thickness reduces mean square training error and takes less number of iteration. Patra et al. [126] have considered spindle motor current signal (RMS current) in addition to process parameters, used as input parameters for predicting drill wear using BPNN. They found that the predicted values provide better accuracy compared to a regression model. Garg et al. [127] compared BPNN with RBFN for prediction of flank wear in drilling process. Chip thickness was used as additional parameter to train the networks. From the results, the authors found that RBFN requires large number of training patterns and large network architecture to achieve same level of desired accuracy as the BPNN in machining copper and mild steel work piece with HSS drill bits.

Choi et al. [128] used neural network to predict incipient stage of drill failure so as to prevent any damage in the drilling process. Time and frequency domains of feed motor current were taken as input parameters and drill wear state, viz., 0.1 mm for normal state and 0.9 mm for drill failure state, as output parameters of the neural network. The authors found that the proposed algorithm predicted the drill breakage accurately for different cutting conditions and machine tool types.

Khajavi and Komanduri [129] used BPNN to predict drill wear employing multiple sensors. The signals from four sensors, viz., thrust, torque, and strain in two directions, were used. It is found that the change in area under power spectral density plots shows good correlation with corner drill wear. The authors concluded that one sensor signal would be adequate for drill wear estimation.

Liu et al. [130] developed a BPNN model for online detection of drill wear for drilling stainless steel work piece with HSS drills. They trained the network with drill size, feed rate, spindle speed, and eight features of thrust and torque signals, viz., average thrust, average torque, peak thrust, peak torque, RMS thrust, RMS torque, area under thrust vs time curve, and area under torque vs time curve as input parameters and two stage drill wear state—useable and failed as output parameters of the network. The authors found that the developed system shows high robustness and usefulness for complex production environments like flexible manufacturing system. Li and Tso [131] proposed fuzzy logic model for online drill wear state monitoring using spindle motor and feed motor current signals. They classified drill wear into three categories, viz., small (0.2 mm), normal (0.5 mm), and severe (0.8 mm), to ensure tool replacement at the proper time and found that flank wear can be accurately predicted by using feed motor current.

### *3.4.3 Drilling force*

In drilling process, thrust force and its control is a major concern. The thrust force and torque are influenced mainly by work piece hardness, drill point angle, drill diameter, and feed rate. The various soft computing techniques were used to estimate the thrust force and control the drilling process particularly in drilling of composite laminates where occurrence of delamination at exit and entrance planes is the main problem.

Stone and Krishnamurthy [132] used neural network to model the relationship between feed rate and the thrust force during drilling of fiber-reinforced composite materials using diamond-tipped drill. They developed a neural network-based controller that minimizes the problem of delamination or crack growth during the drilling process. The authors compared the proposed method with experimental results and found that thrust force controlled drilling process is advantageous over conventional constant feed drilling process. The similar problem of delamination during drilling is modeled by Chung and Tomizuka [133] using fuzzy logic. They proposed drill thrust force control strategy by adjusting drill feed rate to reduce occurrences of delamination in drilling composite materials.

Karri [134] used RBF neural network to predict thrust and torque during process. Tool geometry and operating conditions, viz., spindle speed, feed, and drill diameter, were used as input parameters of the network. The author tested network over a range of process variable and found the predicted values within an error of 10%.

Sheng and Tomizuka [135] developed an intelligent control system using neural network and fuzzy logic to control thrust force in drilling process. Drill head position information is included in neural network model and fuzzy logic is used to deal with gain variation due to drill wear. The proposed model was compared with simulation and experimental results. It was found that the method worked well over a wide operating range.

### *3.4.4 Process optimization*

In conventional drilling process, actual cutting takes very less time compared to other nonproductivity time. Therefore, the process optimization to minimize cutting time is of less concern among the researchers compared to other metal cutting process. Few researchers have attempted to determine correlation among cutting parameters.

Lee et al. [136] developed an abductive neural network model for predicting drill life, metal removal rate, thrust force, and torque. Cutting speed, feed rate, and drill diameter were taken as input parameters of the network and simulated annealing algorithm is used to optimize the process parameters considering tool cost and productivity.

Hashmi et al. [137] developed fuzzy logic model for selection of cutting speed to drill three different work materials, viz., medium carbon steel, low carbon alloy steel, and medium carbon-free machining steel. The predicted drilling speeds for different work material hardness shows good corelation with Machining Data Handbook.

Ghaiebi and Solimanpur [138] used an ant algorithm to minimize tool air-time and tool switching time in a multiple hole making process employing several tools. The authors found that the proposed method is effective and efficient compared to traditional dynamic programming. Zhu and Zhang [139] proposed a PSO algorithm for solving the problem of drilling path optimization in holes-machining in CNC machining center. The proposed algorithm obtains the global optimization solution with reduced computational time.

## 4 Discussion and future directions

From the description in Section 3, it is clear that soft computing techniques have been applied for prediction of surface roughness, dimensional deviation, tool life, tool wear, and cutting forces. A number of soft computing techniques have been used for the optimization of machining processes. The main objectives in the optimization of turning, milling, and grinding have been minimization of cost of machining and maximization of production rate. Multi-objective problems also have been solved. In drilling process, maximization of drill life and optimization of drill path have been the main objectives.

For the prediction of performance parameters, MLP neural networks with single hidden layer have been widely used. Some authors [121] have found that MLP neural networks with two hidden layers are superior to those with single hidden layer. However, there is no general agreement for it. Neural network training algorithms require some adjustable parameters. Some skill is needed in choosing the proper value of the parameter for faster training and better accuracy. Some authors [80, 83] have modified the standard backpropagation algorithm for improving the training. There are few papers that paid attention to develop a systematic procedure for deciding the size of training and testing data sets and for improving the quality of the data [23, 78]. A number of authors have used radial basis function networks and observed their superiority in terms of network training [25, 26, 118, 134].

Compared to neural networks, there is lesser number of applications of fuzzy sets for the prediction of machining performance. Neural network models have been found superior to fuzzy set-based model in learning. However, the knowledge captured by them is not transparent. On the other hand, fuzzy set-based models provide a rule base that can be interpreted. To take the advantages of both, Abburi and Dixit [29] developed a knowledge base system, in which the neural network was used for learning and fuzzy set theory was used for rule generation and inference. There have been some applications of neurofuzzy systems [31, 42, 51, 68, 76, 99, 100]. For optimization, GA and SA have been applied by a number of researchers [56–62, 66, 73, 92, 95, 114]. There have been a few application of neural networks [53, 91, 110–112], fuzzy sets [54, 55, 137], PSO [63, 139], and ACO [64, 138] in optimization.

MLP neural networks, RBF neural networks, and fuzzy sets have been used mostly for performance prediction of machining processes. The applicability of a particular soft computing technique is not dependent on the type of machining process, but is dependent on the amount of data/information available, training time required, and the transparency in prediction needed. Table 1 shows the relative merits and demerits of these three techniques based on the information available in the literature and the experience of the last author of the present paper. These techniques do not provide a unique solution and their performance is dependent on the skill of model-developer, at least to some extent. However, Table 1 fairly summarizes the general observation. Considering the relative merits and demerits, it is natural that many authors are prompted to use the techniques that are combinations of these techniques. In the opinion of present authors, the best strategy can be to first develop a neural network-based model and use it to build a fuzzy set-based model to attain transparency and improved performance as was done in [29]. If enough training data are available, then RBF neural network should be given preference to MLP neural network. In absence of enough data, a strategy suggested in [27] may be adopted, where first an MLP neural network is trained with limited data, which is used to generate a huge amount of data for training an RBF neural network with real data reserved for testing.

Soft computing-based optimization techniques like GA, SA, ACO, and PSO are suitable for optimization. The best strategy is to use neural networks and fuzzy set theory for performance prediction and GA/SA/ACO/PSO for optimization. The optimization techniques can be used for adjusting the internal parameters of predictive systems, for example, for adjusting the weights in neural networks and membership functions in fuzzy sets. Among the four optimization techniques mentioned in this paper, GA has been widely used and has matured as a robust technique of metal cutting optimization. The real parameter GA that does not require the decision variables to be converted as binary numbers is very effective for solving multi-objective optimization problem. ACO and PSO have been applied for machining optimization recently. Due to simplicity in its execution, the PSO may emerge out to be a viable alternative to GA.

Following issues have not received enough attention and need to be addressed:

1. *Data filtration*: The prediction accuracy is dependent on the accuracy of the experimental data. The data may invariably contain noise. Therefore, it is necessary to filter it for removing the outliers. Only a few researchers have paid attention to this aspect [23, 87].
2. *Coping with statistical variation*: In machining, the performance variables possess statistical variation. A reliable model building requires a number of replicate experiments. The built model should be able to predict the probability distribution of the performance parameters. There have been very few attempts in this direction. Some authors have developed neural network models that can predict the confidence intervals [140, 141] of the prediction. However, it has not been applied to machining. In [23, 25], the most likely upper and lower estimates of the performance variables are predicted.
3. *Hybrid computing*: The combination of hard (physics-based) and soft computing has not been provided proper attention in metal cutting arena. Such attempts have been successfully employed in other areas of manufacturing, for example in [142]. Finite element analysis can be combined with soft computing tools to obtain more accuracy and have less dependency on experimental data.
4. *Incorporating the time as a variable in prediction and optimization*: Most of the researchers have predicted surface roughness and cutting force as a function of cutting process parameters only. The performance of the machining process gets changed with time due to tool wear. Therefore, there is a need to model these parameters with time as a variable. Similarly, in optimization also, the time effect has to be considered. For example, the effect of tool wear has been considered to optimize multipass turning operations in [62].

**Table 1** Comparison of MLP neural network, RBF neural network, and fuzzy sets for performance prediction in machining

| Technique | Merits | Demerits |
|---|---|---|
| MLP neural network | Can learn from limited dataset | Training process requires skill and is time consuming |
| | Provide enough accuracy if trained properly | Very poor in extrapolation |
| RBF neural network | Training is easier and faster | Requires more training data than MLP |
| | | Accuracy slightly inferior to MLP |
| Fuzzy sets | Can easily incorporate expert knowledge | Need huge amount of data for automatic rule generation |
| | Transparent compared to neural networks | Some skill is needed for assigning membership grades to subjective information |
| | Reasonable performance in extrapolation | |

5. *Research on hardware side*: Effectiveness of soft computing tools for online prediction is dependent on the use of proper sensors. In many cases, combination of many sensors called sensor fusion is helpful. The development of proper sensors should go side by side with the development of software tools. At the same time, efficient techniques for data acquisition, data filtration, and feature extraction should be developed.
6. *Optimization with online learning*: In optimizing machining process, the knowledge of tool life as a function of cutting parameters is an essential requirement. It is not economical to conduct tool life test for different work piece–tool combinations. Also, the neural network or fuzzy-based systems need a number of data for training. The experiments consume a lot of time and may not be sufficient for online optimization. A scheme can be developed that can carry out the optimization with online learning. The approach may be helpful for predicting optimized process parameters in real time machining environment economically.

## 5 Conclusions

In this paper, a review of application of soft computing techniques in machining performance prediction and optimization has been presented. It has been decided to present the review of major machining process at one place so as to provide a complete picture to reader. Following are the major observations from the literature:

1. Neural network models have been effectively employed for predicting the surface roughness of machined components in turning and drilling. However, most of the models do not predict the surface roughness as a function of time, concentrating on the time zone when surface finish changes only slightly with time.
2. Most of the authors have used MLP neural networks. Some authors have employed RBF neural networks due to their ability of getting trained much faster. RBF neural networks require more training data and provide slightly inferior accuracy. However, it is only an experimental observation and in the context of machining, no mathematical proof has been provided to support this observation.
3. Fuzzy sets and combination of fuzzy sets and neural networks have been used for predicting the surface roughness in turning, milling, and grinding. Fuzzy set-based methods are especially advantageous when the expert knowledge is available.
4. Neural networks have also been used for surface finish prediction in reaming and drilling of composite materials.
5. Soft computing tools have been used for estimating the tool wear and tool life. However, the results are not as impressive as in the case of surface roughness prediction. This is due to highly statistical nature of tool life and tool wear and difficulty in identifying a measurable parameter with which the tool wear can be well-correlated. Most of the authors have used cutting force components as input parameters in their soft computing-based models. Several other signals such as acoustic emission, vibrations, and temperatures have also been tried. It is observed that instead of raw data from sensors, features extracted from the signals are more effective in modeling the tool wear and tool life.
6. Whereas surface roughness and tool wear are the major indicators of machining performance, modeling of cutting force gains importance for its use in estimating the tool condition, particularly the tool breakage detection. Modeling of cutting force may also be used for estimating the power in machining. However, minimization of cutting power is not as significant objective as the minimization of machining cost and time.
7. Soft computing optimization methods like GA have been used in machining area for two purposes—(a) for optimizing the internal parameters of neural networks, fuzzy sets, and neurofuzzy systems and (b) for machining optimization. Application of GA for ma-

chining has attained maturity. PSO, a relatively newer technique, may emerge as a better alternative to GA.

The best strategy is to use a combination of fuzzy and neural network for performance prediction and soft computing optimization tool like GA or PSO for optimization. However, some important issues need urgent attention. These are (a) acquisition of data in an economical and efficient way, (b) filtering of noisy data, and (c) extracting the statistical feature of the data. If these issues are addressed, the industrial application of these techniques will become an easy and fruitful task.

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