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Review of Techniques used to Optimize the Test cases

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ABSTRACT

Thorough literature review of various modern machining processes is presented in this paper. The main focus is kept on the optimization aspects of various parameters of the modern machining processes and hence only such research works are included in this work in which the use of advanced optimization techniques were involved. The review period considered is from the year 2006 to 2012. Various modern machining processes considered in this work are electric dis-charge machining abrasive jet machining, ultrasonic machining, electrochemical machining, laser beam machining, micro-machining, nano-finishing and various hybrid and modified versions of these processes. The review work on such a large scale was not attempted earlier by considering many processes at a time, and hence, this review work may become the ready information at one place and it may be very useful to the subsequent researchers to decide their direction of research.

Introduction:

The modern machining processes are now replacing the conventional machining processes rapidly for many applications due to their significant advantages which are proving beneficial to a greater extent to the present industrial scenario. The requirements of industrial products have started increasing and new materials are getting introduced which are very hard in nature and difficult to cut by conventional machining processes. Successful machining of such materials by the modern machining processes have added significant lifeline to the industrial growth and given new dimensions to the quality of components. The various modern machining processes getting widely used in the industries are: electric discharge machining (EDM), abrasive jet machining (AJM), ultrasonic machining (USM), electrochemical machining (ECM) and laser beam machining (LBM) including various modified versions of these processes. These processes work on a particular principle by making use of certain properties of materials which makes them most suitable for some applications and at the same time put some limitations on their use. These processes involve large number of respective process variables (also called as process parameters) and selection of exact parameter setting is very crucial for these highly advanced machining processes which may affect the performance of any process considerably. Due to involvement of large number of process parameters, random selection of these process parameters within the range will not serve the purpose. The situation becomes more severe in case if more number of objectives is involved in the process. Such situations can be tackled conveniently by making use of optimization techniques for the parameters optimization of these processes.

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, electro discharge machining, electro-chemical 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.

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.

In this paper, efforts are made to identify all such works in which the use of various advanced optimization techniques are involved during years 2006–2012 for the parameters optimization of modern machining processes. In the next section, importance of each process is described separately including the important input and output parameters involved. It is then followed by the thorough literature review based on parameters optimization of respective processes.

Review of modern machining processes:

The modern machining processes considered in this work are categorized in the following subsections separately as EDM, AJM, USM, ECM, LBM, micro-machining and nano- finishing processes, respectively.

Review of electric discharge machining process parameters optimization:

The concept of EDM process was found long back to100 years but its real practical use was implemented for industries during 1950s and since then it is slowly progressing. However, in the 1980s, it was coupled with the computer numerical control approach and that brought significant developments in EDM process and made it suitable for machining of complex shapes and hard to cut materials. Presently, the modern industries started using the EDM process for machining of various materials such as alumina particle reinforced material, high-speed tool steel, titanium aluminizes alloy, nickel-based super alloy, various metal matrix composites (MMC) and ceramics, etc. which cannot be machined easily by the conventional machining processes. In recent years, some modifications took place in the basic EDM process and various versions of EDM process were developed such as WEDM, powder-mixed EDM, micro-EDM, die- sinking EDM, etc. in order to make the process more efficient.

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- edge 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.

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].

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.

Review of micro-machining process parameters optimization:

Micro-machining processes are also finding their use in large number of applications, especially in high quality requirements during the production of micro-sized parts. The major application areas include products related to medical fields and aerospace components. In such cases, the MRR will be comparatively less but more consideration will be given to surface roughness and dimensional accuracy. Two important micro-machining processes which are getting widely used in industries are micro-drilling and micro-milling. Some re- search work was observed in the literature related to parameters optimization of these processes and the same is summarized below for each process.

Micro-drilling process:

Sen and Shan [35] used the hybrid approach of ANN, desirability function and GA for modeling and optimizing the micro-drilling operation performed by electro jet drilling process on the nickel base super alloy and attempts were made to optimize the MRR and roundness error. Yoon et al. [36] used Taguchi methods and RSM to analyze the performance of micro drill-bits during drilling on printed circuit boards. Guu et al. [37] used the Taguchi-based experimental design coupled with FEM for determining the machining parameters in order to optimize the stress concentration during the micro-drilling of titanium alloy. Chen et al. [38] optimized the tool life and surface roughness, during micro-drilling of polymethyl methacrylate polymer, using Taguchi method. The important process parameters considered were: coated deposition, spindle speed and feed rate and the work had shown that the least tool wear and best holes quality was obtained by using TiAlN-coating drills. It is observed that comparatively less work was carried out in the past for the micro-drilling process parameters optimization and most of them were based on the Taguchi method. Hence, attempt can be made in future to carry out research on micro-drilling process.

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.

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, x1, and a large number corresponding to a high temperature T. A second point x2 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 (ΔE). 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.

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].

Abrasive flow machining process:

Mali and Manna [39] had given the review of research related to application of AFM processes. A combination of ANN and GA was used by Tavoli et al. [50] for modeling and optimizing the parameters of AFM process. Walia et al. [41] used the hybrid version of AFM process referred as centrifugal- gal force assisted abrasive flow machining (CFAAFM) for machining of brass material and attempted to optimize MRR and scatter of surface roughness using Taguchi method where- as the input parameters considered in their work were: rotational speed of rectangular rod, extrusion pressure, and grit size. In another work, Walia et al. [32] extend their work to carry out multi-objective optimization of the process by optimizing MRR, % improvement of surface finish and scatter of surface roughness simultaneously using the combined approach of utility theorem and Taguchi method.

Singh et al. [33] studied the effect of various input parameters of AFM process, including the effect of magnetic field, on the surface roughness using Taguchi method. A surface roughness model was developed by Jain et al. [34] for the AFM process and used GA for the parameters optimization of the process. Reddy et al. [35] used RSM for developing the relationship between the input parameters of CFAAFM process in terms of MRR and % improvement in surface finish during machining of cast aluminum alloy components. Sankar et al. [36] carried out the experimental investigation on AISI 1040 and AISI 4340 materials using the hybrid process referred as drill bit-guided abrasive flow finishing process and compared the results with abrasive flow finishing process. Pawar et al. [47] used the PSO and SA algorithms for the parameters optimization of AFM process. Mali and Manna [38] investigated the finishing of Al/15 wt% SiCp-MMC work piece using AFM process and used Taguchi method for developing mathematical models and optimization of MRR and surface finish.

Magnetic abrasive finishing process:

Jain et al. [34] used GA for optimizing the surface roughness model of a MAF process. The input parameters involved in their work were: mean diameter of the magnetic abrasive particles, relative velocity between magnetic abrasive particles work piece, volume ratio of ferromagnetic material in the magnetic abrasive powder, input current and finishing time whereas the aim of the work includes the difference between initial and final surface roughness values. Taweel [39] carried out the research on 6061 Al/Al2O3 composite using the hybrid process by combining the electrochemical turning process and MAF process. The modeling and analysis of MRR and surface roughness was carried out using RSM and the input process parameters considered were: magnetic flux density, applied voltage, tool feed rate and work piece rotational speed.

Yang et al. [40] carried out the research on AISI304 stainless steel using MAF process in order to optimize surface roughness and material removal weight. Mulik and Pandey [41] used RSM and Taguchi method for optimizing the surface roughness and MRR during machining of AISI 52100 hardened steel using ultrasonic-assisted MAF process. The authors had shown that the MRR was significantly affected by weight of the abrasives whereas the surface roughness was influenced by the abrasive mesh number.

Magneto rheological abrasive flow of finishing process:

Jung et al. [32] used the concept of penalized multi-response Taguchi method to optimize the parameters of a wheel-type magneto rheological finishing process used for machining of Al2O3–TiC made hard-disk slider surface. Two objectives were involved in their work related to MRR and surface roughness and the response weights and constraint conditions were considered while attempting the multi-objective task by including the weighting loss factor and the severity factor in the Taguchi method. RSM was used by Das et al. [33] to study the effects of process parameters of MRAFF process on its finishing performance such as surface finish and % improvement in the MRR. Das et al. [34] extended their work to investigate the out-of-roundness of the internal surface of the tube using RSM. In another work, Das et al. [35] attempted the similar work for nano-finishing of flat work piece by considering four important process parameters as: hydraulic extrusion pressure, number of finishing cycles, rotational speed of the magnet and volume ratio of CIP/SiC and considered RSM for the process parameters optimization.

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:

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.

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 [32] 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.

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 discusses machining performance prediction. Section 3.2.4 reviews the soft computing applications in milling process optimization.

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 neuro fuzzy inference system (ANFIS), genetic programming (GP), and fuzzy logic, mostly on end milling operation. GA and PSO were used as optimization techniques.

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. [38] 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 [39] 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. [40] also proposed a fuzzy controlled back propagation 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 [40]. 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. [40] 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. [33] predicted the wear of the tungsten carbide inserts using neural network during face milling of steel. They proposed a new approach called modified back propagation 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., back propagation neural network, fuzzy back propagation neural network, and modified back propagation neural network.

Conclusion:

In this work, the optimization aspects of the widely used modern machining processes such as EDM, AJM, USM, ECM, LBM, micro-machining processes, nano-finishing processes and the allied versions are considered. The thorough literature review related to parameters optimization of these processes from year 2006 to 2012 is made and summarized. The work materials used by several researchers are also highlighted including the various input and output parameters. A critical remark on various research works is also presented and following observations are made based on this review work.

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