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"MULTI OBJECTIVE OPTIMIZATION OF END MILLING PROCESS PARAMETER USING AI TECHNIQUES:A REVIEW"

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Abstract-*Multi Objective Optimization of cutting parameters is very important in terms of high precision and efficient machining.. Due to complexity and uncertainty of the End milling processes, AI techniques are being preferred to optimization the performance of the machining processes. AI Techniques applied for this purpose like neural networks, fuzzy sets, genetic algorithms, simulated annealing, ant colony optimization, and particle swarm optimization. In this paper reviews the application of AI to End milling processes.*

Keywords *End milling. Multi Objective Optimization . AI Techniques.*

I. INTRODUCTION

End Milling is one of the most vital and common metal cutting operations used for machining parts. It is widely used in most of the manufacturing industries due to its capability of producing complex geometric. 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. End Milling for producing flat or curved surfaces for improving the surface finish and/or for maintaining the tolerances.

II. An overview of AI techniques

AI Techniques 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. AI 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 AI techniques is presented here.

2.1 Fuzzy set theory

Lotfi Zadeh put forward the idea of fuzzy sets [2], in which the elements of the set can have partial membership in the set. The fuzzy logic and fuzzy inference system (FIS) is an effective technique for the identification and control of complex non-linear systems. For prediction, fuzzy logic is used. The theory of fuzzy logics, initiated by Zadeh professor of computer science at the University of California in Berkeley, is useful for dealing with uncertain and vague information. Fuzzy logic is particularly attractive due to its ability to solve problems in the absence of accurate mathematical models. Fuzzy Logic (FL) is a multi valued logic that allows intermediate values to be defined between conventional evaluations like true/false, yes/no, high/low, etc. Notions like rather tall or very fast can be formulated mathematically and processed by computers, in order to apply a more human like way of thinking in the programming of computers. [1] The fuzzy set-based prediction system takes input data and carries ou "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. Backpropagation algorithm is most common algorithm for adjusting the weights. A brief background of neural networks is provided in [2].

2.3 Genetic algorithm

GA mimics the process of natural evolution by incorporating the "survival of the fittest" philosophy. 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. [3]

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, 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 $\exp(-\Delta E/T)$[4]. 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 [5]. 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 [6]. 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 [7]. 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. In many cases, it has been reported to be more efficient than GA.

III. AI Techniques for milling processes

Parameters for milling process like Speed, Feed and Depth of cut may be optimized for obtaining the minimum cost of machining and minimum production time. To predict performance of process and optimization, AI techniques have been applied.

P.Palanisamy et al.[8] used genetic algorithm for Optimization of machining parameters for end milling process. cutting speed, feed rate and depth of cut were considered as input parameters. The machining time is considered as the objective function and constraints are tool life, surface roughness, cutting force and amplitude of vibrations while maintaining a constant material removal rate. Experimental end milling tests have been performed on mild steel to measure surface roughness. From the estimated surface roughness value of 0.71 µm, the optimal cutting parameters that have given a maximum material removal rate of 6.0×103 mm3/min with less amplitude of vibration at the work piece support 1.66 µm maximum displacement.

K.D. Bouzakis et al. [9] used genetic algorithms for multi-objective optimization to obtain the optimum cutting parameters like cutting depth, feed rate and cutting speed in milling. The Objectives like machining cost and machining time and several technological constrains are simultaneously taking into consideration. A Pareto ranking approach is used to determine the optimum cutting parameters.

Reddy and Rao [10] developed an empirical surface roughness model for end milling of medium carbon steel, whose parameters were optimized using GA. Oktem et al. [11] 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 [12] 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. [13] 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.

F. Cus, U. Zuperl[14] used neural network modeling and Particle swarm optimization for optimization of high speed end-milling. A neural network model was used to predict cutting forces during machining and PSO algorithm was used to obtain optimum cutting speed and feed rate. The MRR is improved by 28%. Machining time reductions of up to 20% are observed.

K. Bharathi et al. [15] used Genetic algorithm coupled with neural network for find best cutting parameters leading to minimum surface roughness and maximum Material Removal Rate in machining Cast Iron on Machining Centre. A feed forward neural network model is developed exploiting experimental values.

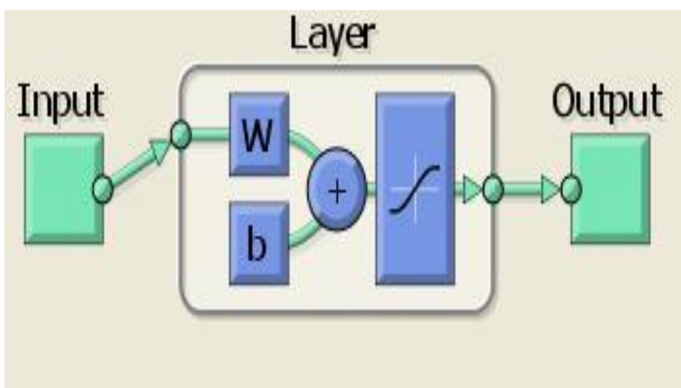

Fig-1. Neural Network Model

Abraham Gilbert et al. [16] used Genetic Algorithm for minimize the surface roughness and cutting force simultaneously for making the milling operation more economic and productive. The experiments were designed using Taguchi's orthogonal array consisting of 9 experimental runs. This work focussed on minimizing the surface roughness and cutting forces simultaneously by determining the optimal parameters likes Spindle Speed, Feed Rate, Depth of Cut under bounded constraints. The experimental output were analyzed using ANOVA to determine the most significant parameter that affects the surface roughness and cutting force. Then using Regression analysis, a mathematical model of the milling operation is formulated to predict the performance measures of surface roughness and cutting force.

Vishwajit D. Patil et al. [17] developed a Expert system for determine the best cutting parameters leading to minimum surface roughness and maximum material removal rate. Cutting speed, feed rate and depth of cut were considered as input parameters for Machining of Aluminium Alloy (Al2024-T4). These techniques that are being applied successfully in industrial applications for optimal selection of process parameters with economic production cost in the area of machining.

Muataz Hazza F. Al Hazza et al. [18] used Simulated Annealing Algorithm for Multi objective Optimization for High Speed End Milling. The mathematical models have been generated using Response surface Methodology (RSM) for optimum cutting parameters like cutting speed, feed rate and depth of cut to achieve the minimum values of surface roughness and minimum flank wear length. The results show that the cutting speed in the range of 200 m/min, feed rate of 0.05 mm/tooth and depth of cut of 0.1mm gave the minimum arithmetic mean roughness (Ra) for 164 nm and minimum flank wear for 0.0379 mm in the boundary design of the experiment after 8000 iteration.

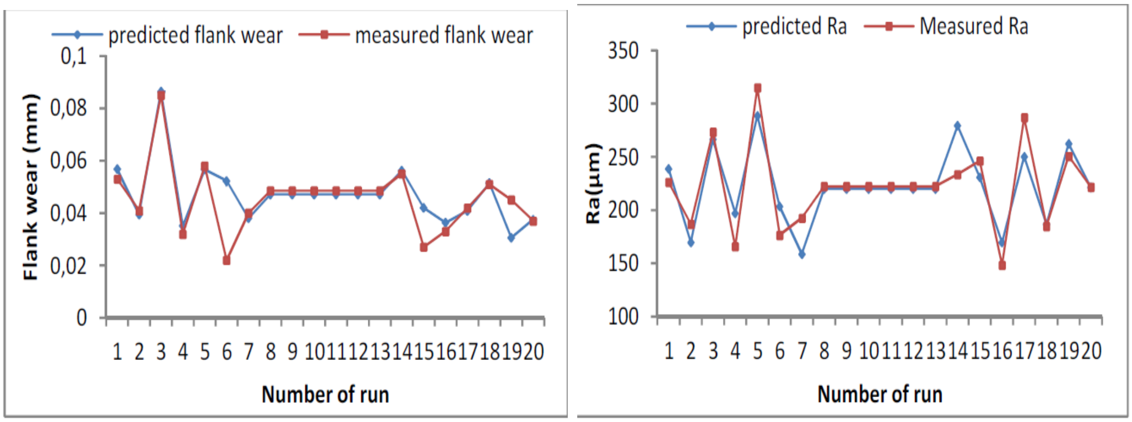

Fig-2.Comparison of Predicted and Measured Values

Amir Mahyar Khorasani et al. [19] developed ANN model for Prediction of tool life in milling operations. Cutting speed, feed rate and depth of cut were considered as input parameters. It was found that (ANN) prediction correlates very well with the experimental results. Finally the correlation for training and test was obtained 0.96966 and 0.94966 respectively and mean square error was calculated 3.1908% for test data. Kurapati venkatesh et al.[20] developed ANN structures for designed and investigated to estimate the tool wear accurately. Cutting velocity, feed, cutting force and machining time are given as inputs parameter.

Abdel Badie Sharkawy et al. [21] developed a intelligent systems for prediction of surface roughness in end milling process. The machining parameters, namely, the spindle speed, feed rate and depth of cut have been used as inputs to model the work piece surface roughness. Procedure is illustrated using experimental data of end-milling 6,061 aluminum alloy. Here three types of intelligent networks used like RBFN, ANFIS and G-FIS. RBFN has been found to be the most successful technique to perform surface roughness prediction with RMSE of 2.95 %.

Milling U. Zuperl et al. [22] applied ANFIS to predict the effect of cutting parameters like spindle speed, feed rate and axial/radial depth of cut and cutting force signals on surface roughness. The prediction error of the values predicted by ANFIS with the triangular member ship function is 3%. The accuracy is 97%. When the trapezoidal member ship function is used the average error is 5.3%, with an accuracy of 94.7%.

IV. Conclusions

In this paper, a review of application of AI techniques for multi objective optimization of Milling process. Following are the major observations from the literature:

1. Multi-objective problems have been solved by AI Techniques.
2. AI Techniques have been effectively employed for optimization.
3. ANN 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.
4. Fuzzy sets and neural networks have been used for predicting the surface roughness in milling.
5. AI 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.

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