Abstract

It has long been recognized that conditions during cutting, such as feed rate, cutting speed and depth of cut, should be selected to optimize the economics of machining operations, as assessed by productivity, total manufacturing cost per component or some other suitable criterion. Taylor (1907) showed that an optimum or economic cutting speed exists which could maximize material removal rate. Manufacturing industries have long depended on the skill and experience of shop-floor machine-tool operators for optimal selection of cutting conditions and cutting tools. Further the performance equations have to be updated as new coatings; new work materials and new cutting tools are introduced. By using latest techniques for optimization of parameters one has to follow techniques which include fuzzy logic, scatter search technique, swarm optimization, Taguchi technique, response surface methodology, fem, Artificial neural network and other methods are shown in the form of equations and the drawbacks each technique were explained in this paper. In this research paper, a comparison has been made between different optimization techniques including their approaches. The proposed research can be very helpful for industries to determine the optimal cutting parameters and improve the process quality. The comparison will also be beneficial in minimizing the costs incurred and improving productivity of manufacturing firms.
1. Introduction

Turning and Milling process are the most fundamental and commonly encountered material removal operations in manufacturing process. The surface roughness is one of the important properties for evaluating the work piece quality during the end milling process. The surface roughness plays a great part in fatigue strength and corrosion resistance, surface friction, light reflection, ability of holding a lubricant, electrical and thermal contact resistance, appearance, cost, etc. High quality of the surface after end milling makes further machining of the surface not necessary, which brings about decreased power consumption and environment load. However, optimization of surface roughness is consistently challenged by its uncertainty of prediction model as well as various influencing parameters, which can be divided into controlled and non-controlled parameters. Main parameter of the first type includes spindle speed, feed rate, and depth of cut. And vibrations, tool wear, machine motion errors, and material non-homogeneity of both the tool and work piece, chip formation belong to the non-controlled parameters. The non-controlled cutting parameters are hard to reach and their interactions cannot be exactly determined. Surface roughness optimization is concerned with developing efficient prediction model to minimize order of deviation. Successful implementation of machining process optimization requires development of models for prediction of surface roughness. Process optimization means the resources which are utilizing the process should be used effectively and efficiently at minimum cost & maximum output. In optimization, we focus on different parameters which govern the process. In present scenario, it is a matter of great concern in industry to achieve a good quality product at minimum cost. This can be achieved by the different optimization techniques by considering various other factors as listed below:

I. Conventional Techniques [Optimal Solution]

Further classified into two parts:
(i) Design of Experiment
Further classified into three parts:
(a) Taguchi Method Based (b) Factorial Design Based
(c) Response Surface design Methodology (RSM) Based
(ii) Mathematical iterative Search
Further classified into three parts:
(a) Dynamic Programming based
(b) Nonlinear programming based
(c) Linear programming based

II. Non-Conventional Techniques [Near Optimal Solution(s)]

(i) Meta Heuristic Search
Further classified into three parts:
(a) Genetic Algorithm
(b) Simulated Annealing Algorithm
(c) Tabu Search

Machining Parameters
1) Process Kinematics 2) Cutting Fluid 3) Depth of Cut 4) Feed Rate 5) Step over 6) Tool Angle 7) Cutting Speed.

Cutting Phenomenon
1) Friction in the cutting zone 2) Cutting Force Variation 3) Accelerations 4) Chip Formation

Cutting Tool Properties
1) Tool Material 2) Tool Shape 3) Nose Radius 4) Run out Errors

The output parameters other than surface roughness are:
Material removal rate, Tool life, Productivity, Quality, Machining time, Machining cost
2. Optimization Techniques
The latest techniques for optimization include fuzzy logic, scatter search technique, Taguchi technique, response surface methodology, Finite Element Method, artificial neural network, ACO Optimization etc. In this paper each methodology merits and demerits given for implementing them.

2.1 Fuzzy Logic
Fuzzy logic has great capability to capture human commonsense reasoning, decision-making and other aspects of human cognition. Kosko (1997) shows that it overcomes the limitations of classic logical systems, which impose inherent restrictions on representation of imprecise concepts. Vagueness in the coefficients and constraints may be naturally modelled by fuzzy logic. Modelling by fuzzy logic opens up a new way to optimize cutting conditions and also tool selection.

- **Methodology:** As per Klir & Yuan (1998) fuzzy logic involves a fuzzy interference engine and a fuzzification-defuzzification module. Fuzzification expresses the input variables in the form of fuzzy membership values based on various membership functions. Governing rules in linguistic form, such as if cutting force is high and machining time is high, then tool wear is high, are formulated on the basis of experimental observations. Based on each rule, inference can be drawn on output grade and membership value. Inferences obtained from various rules are combined to arrive at a final decision. The membership values thus obtained are defuzzified using various techniques to obtain true value, say of flank wear.

2.2 Finite Element Method
Fundamentally, metal cutting process can be considered as a deformation process where deformation is highly concentrated in a small zone. Thus, chip formation in milling process can also be simulated using Finite Element Method (FEM) techniques developed for deformation processes [2a]. The main advantage of using such an approach is to be able to predict chip flow, cutting forces, and especially a distribution of tool temperatures and stresses for various cutting conditions. In this section, simulation of the micro-milling process is presented. FEM-based commercially available software, DEFORM-2D, was used for the process simulations. An FEM model is designed as used for rigid-perfectly plastic deformation analysis. In the FEM model, a constant friction factor of 0.65 at the chip-tool-work piece contacts is used. The finite element modeling of micro-milling based on rigid-plastic deformations is also conducted to predict chip formation, forces, and strain, strain-rate and temperature fields without considering process dynamics.

2.3 Scatter search technique (SS)
This technique originates from strategies for combining decision rules and surrogate constraints. SS is completely generalized and problem-independent since it has no restrictive assumptions about objective function, parameter set and constraint set. It can be easily modified to optimize machining operation under various economic criteria and numerous practical constraints. It can obtain near-optimal solutions within reasonable execution time on PC. Potentially, it can be extended as an online quality control strategy for optimizing machining parameters based on signals from sensors. Chen & Chen (2003) have done extensive work on this technique.

- **Methodology:** First of all, machining models are required to determine the optimum Machining parameters including cutting speed, feed rate and depth of cut, in order to minimize unit production cost. Unit production cost can be divided into four basic cost elements.
  - Cutting cost by actual cut in time
  - Machine idle cost due to loading and unloading operation and idling tool motion cost
• Tool replacement cost
• Tool cost

For the optimization of unit production cost, practical constraints which present the state of machining processes need to be considered. The constraints imposed during machining operations are:
• Parameter constraint – Ranges of cutting speed, feed rate and depth of cut
• Tool life constraint – Allowable values of flank wear width and crater wear depth
• Operating constraint – Maximum allowable cutting force, power available on machine tool and surface finish requirement.

An optimization model for multi-pass turning operation can be formulated. The multipass turning model is a constrained nonlinear programming problem with multiple variables (machining variables). The initial solution for SS is picked in a random way. The user-specified parameters have to be given. The experimentation can be run on a PC with Pentium800Mhz processor. The computational results validate the advantage of SS in terms of solution quality and computational requirement.

2.4 Taguchi Method

Taguchi’s philosophy, developed by Dr. Genichi Taguchi, is an efficient tool for the design of high quality manufacturing system. It is a method based on Orthogonal Array (OA) experiments, which provides much-reduced variance for the experiment resulting optimum setting of process control parameters. Orthogonal Array provides a set of well-balanced experimental settings (with less number of experimental runs), and Taguchi’s Signal-to-Noise ratios (S/N), which are logarithmic functions of desired output; serve as objective functions in the optimization process. This technique helps in data analysis and prediction of optimum results. In order to evaluate optimal parameter settings, Taguchi method uses a statistical measure of performance called signal-to-noise ratio. The S/N ratio takes both the mean and the variability into account. The S/N ratio is the ratio of the mean (Signal) to the standard deviation (Noise). The ratio depends on the quality characteristics of the product/process to be optimized. The standard S/N ratios generally used are as follows: - Nominal-is-Best (NB), Lower-the-Better (LB) and Higher-the-Better (HB). The optimal setting is the parameter combination, which has the highest S/N ratio, [Mahapatra and Chaturvedi (2009), Moshat et al. (2010)]

• Methodology
  a. Signal to noise ratio(S/N), which measures quality with emphasis on variation and
  b. Orthogonal arrays, which accommodate many design factors simultaneously

When a critical quality characteristics deviates from the target value it causes a loss. Continuously pursuing variable reduction from the target value in critical quality characteristics is the key to achieve high quality and reduce cost. In Taguchi method, signal to noise (S/N) is used to represent a response or quality characteristic and the largest S/N ratio is required. There are usually three types of quality characteristics, i.e. target-the-best, larger-the-better and smaller-the better.

i. Target-the-best: S/N = 10 log a/b²y
ii. Larger-the-better: S/N = -10 log 1/n[Σ /c²]
iii. Smaller-the-better: S/N = -10 log 1/n [Σc²]

Where, y is the measured data a is the average of measured data, b²y is the variance of c and n is the number of samples. For each type of the characteristics, with the above S/N ratio transformation, the higher the S/N ratio the better is the result.
The drawbacks of this are as follows: i. Taguchi proposed a short term, one-time improvement technique to reduce the number and cost of experimentations, which may eventually lead to sub-optimal solutions. ii. Taguchi’s method refers to optimization without intrinsic empirical or mechanistic modeling during experimentation. This type of technique closes the possibility for greater in-depth knowledge of the process. iii. Alternative methods, claimed to be efficient for simultaneous optimization of multiple responses (such as data transformation and using dual-response surface technique).

2.5 ACO Optimization

Ant-colony optimization (ACO) algorithms evolve not in their genetics but in their social behavior. ACO was developed by Dorigo et al. based on the fact that ants are able to find the shortest route between their nest and a source of food. This is done using pheromone trails, which ants deposit whenever they travel, as a form of indirect communication. When ants leave their nest to search for a food source, they randomly rotate around an obstacle, and initially the pheromone deposits will be the same for the right and left directions. When the ants in the shorter direction find a food source, they carry the food and start returning back, following their pheromone trails, and still depositing more pheromone. An ant will most likely choose the shortest path when returning back to the nest with food as this path will have the most deposited pheromone. For the same reason, new ants that later starts out from the nest to find food will also choose the shortest path. Over time, this positive feedback (autocatalytic) process prompts all ants to choose the shorter path. There are some advantages of ACO optimization technique. K.Vijayakumar et al: (i) ACO algorithm can obtain a near optimal solution in an extremely large solution space within reasonable computation time, and (ii) ACO is made an effective global optimization procedure by introducing a bi-level search procedure, termed a local and global search. Adil Baykasoglu et al: (i) it is based on the behavior of natural ants that succeeding finding the shortest paths from their nest to food sources by communicating via a collective memory that consists of pheromone trails, and (ii) due to ant’s weak global perception of its environment, an ant moves essentially at random when no pheromone is available.

There are some disadvantages of ACO optimization technique. Adil Baykasoglu et al: (i) it tends to follow a path with a high pheromone level when many ants move in a common area, which leads to an autocatalytic process, and (ii) the ant does not choose its direction based on the level of pheromone exclusively, but also takes the proximity of the nest and of the food source, respectively, into account; this is allows the discovery of new and potentially shorter paths.

2.6 Response Surface Method

Response surface method (RSM) adopts both mathematical and statistical techniques which are useful for the modeling and analysis of problems in which a response of interest is influenced by several variables and the objective is to optimize the response. In most of the RSM problems, the form of the relationship between the response and the independent variables is unknown. Thus the first step in RSM is to find a suitable approximation for the true functional relationship between response of interest ‘y’ and a set of controllable variables \{x_1, x_2, \ldots, x_n\}. Usually when the response function is not known or non-linear, a second-order model is utilized in the form

\[
y = b_0 + \sum_{i=1}^{n} b_i x_i + \sum_{i=1}^{n} b_{ii} x_i^2 + \sum_{i<j} b_{ij} x_i x_j + \varepsilon
\]
Where, $\varepsilon$ represents the noise or error observed in the response $y$ such that the expected response is $(y - \varepsilon)$ and $b$’s are the regression coefficients to be estimated. The least square technique is being used to fit a model equation containing the input variables by minimizing the residual error measured by the sum of square deviations between the actual and estimated responses. The calculated coefficients or the model equations however, need to be tested for statistical significance.

### 2.7. Swarm Optimization

Kennedy & Eberhart (1995) proposed the bio-inspired PSO approach, which can be seen as a population-based algorithm that performs a parallel search on a space of solutions. In the optimization context, several solutions of a given problem constitute a population (the swarm). Each solution is seen as a social organism, also called particle. The method attempts to imitate the behavior of real creatures making the particles “fly” over a solution space. These particles search the problem’s solution space balancing the intensification and the diversification efforts. Each particle has a value associated with it. In general, particles are evaluated with the objective function of the considered optimization problem. A velocity is also assigned to each particle in order to direct the “flight” through the problem’s solution space. The artificial creatures have a tendency to follow the best ones among them. At each iteration step, a new velocity value is calculated for each particle. This velocity value is used to update the particle’s position. The process iterates until reaching a stopping condition. Particle swarm optimization (PSO) is a population based stochastic optimization technique, inspired by social behavior of bird flocking or fish schooling. If a problem is given, and there is some way to find a solution to it in the form of a fitness function, then this method can be used. A population of individuals defined as random guesses of the problem solution is initialized. These individuals are also known as the particles, hence the name particle swarm. Value of the objective function for these individuals represents their positions. An iterative process to improve these positions is then started. The particles iteratively evaluate the positions and remember the location where they had their best success. The individual's best solution is called the particle best or the local best. Each particle makes this information available to their neighbors. They are also able to see where their neighbors have had success. The best solution among all the neighbors is called global best. Movements through the search space are guided by these successes, with the population usually converging, by the end of a trial, on a problem solution better than that of non-swarm approach using the same methods as this algorithm uses the global best and local bests.

In the classical PSO algorithm, each particle
- has a position and a velocity
- knows its own position and the value associated with it
- knows the best position it has ever achieved, and the value associated with it
- knows its neighbors, their best positions and their values

The best position a given particle has ever achieved is called $p_{best}$. In some versions of particle swarm algorithms the particles also track the best position achieved so far by any particle of the swarm. This position is called $g_{best}$. By changing their velocities with individualistic moves or toward $p_{best}$ and $g_{best}$, the particles change their positions. The move of a particle is a composite of three possible choices (Onwubolu & Clerc, 2004):
- To follow its own way
- To go back to its best previous position
- To go towards its best neighbor’s previous or present position
The neighborhood may be physical or social. Physical neighborhoods take distances into account, thus a distance metric has to be established. This approach tends to be time-consuming, since each iteration distances must be computed. In general, social neighborhoods are based upon “relationships” defined at the very beginning of the algorithm.

There are some advantages of PSO optimization technique. Bilal Alatas et al [9] stated that PSO: (i) a simple stochastic search method and requires little memory, (ii) it has also fast converging characteristics and more global searching ability at the beginning of the run and a local searching near the end of the run, and (iii) can solve discontinuous, multimodal, and non-convex problems. Yinggan Tang and Xinping Guan [10]: (i) it has been proved to be powerful tool for solving system optimization problem, especially with non-smooth objective function, (ii) PSO does not need the derivative information about the objective function, (iii) PSO adopts velocity position model other than complex genetic operators, (iv) PSO can be easily implemented and converges quickly, and (v) PSO is very suitable to deal with most of real engineering application problems. R.E. Perez and K. Behdinan [11]: (i) it easiness of implementation makes it more attractive as it does not required specific domain knowledge information, internal transformation of variables or other manipulations to handle constraints and (ii) it is a population-based algorithm, so it can be efficiently parallelized to reduce the total computational effort. There are some disadvantages of PSO optimization technique. Bilal Alatas et al [9] stated that PSO: (i) different numbers of iterations may also be required to reach the same optimal values. Suganthan PN [12]: (i) sometimes it has a slow fine-tuning ability of the solution quality.

2.8. Artificial Neural Network (ANN)

Modeling techniques of ANN have attracted attention of practitioners and researchers alike in manufacturing when faced with difficulties in building empirical models in metal cutting process control. These techniques offer a cost effective alternative in the field of machine tool design and manufacturing approaches, receiving wide attention in recent year. ANN may handle complex input and in-process parameter relationship of machining control problems. There are certain assumptions, constraints, and limitations inherent in these approaches, which may be worth mentioning. ANN techniques are attempted only when regression techniques fail to provide an adequate model. Several applications of ANN-based input-output relationship modeling for metal cutting processes are reported in the literature. Grzesik and Bro92 showed the usefulness of ANN modeling for controlling surface finish characteristics in multistage machining processes. Back propagation neural network, proposed by Rumelhart, Hilton, and Williams30 have been successfully applied by Sathyarayanan, Lin, and Chen31 for modeling a typical creep feed super alloy-grinding, prediction of material removal rate and surface finish parameter of a typical abrasive flow machining, and a honing operation of engine cylinder liners.

The drawbacks of ANN techniques are: i. it is dependent on voluminous data set, as sparse data relative to number of input and output variables may result in over fitting or terminate training before network error reaches optimal or near-optimal point, ii. Model parameters may be uninterpretable for nonlinear relationship, and iii. Identification of influential observations, outliers, and significance of various predictors may not be possible by this technique. There is always an uncertainty in finite convergence of algorithms used in ANN based modeling technique, and generally convergence criteria are set based on prior experiences gained from earlier applications. No universal rules exist regarding choice of a particular ANN technique for any typical metal cutting process problem.
3. Methodology Of Optimization Techniques And Their Parameters

Step-1 Define the cutting process optimization problem highlighting its criticality in terms of the selected criteria and also the objective function which has to be optimized.

Step-2 All relevant decision variables and operating levels and ranges need to be identified at this stage. If an optimization problem is subjected to some operating constraints, then, the constraints should also be expressed in terms of decision variables.

Step-3 The pertinent and reliable data related to input conditions, in-process parameters, and response variable(s) are to be collected through discussion with the concerned personnel, reference to the relevant documents, standards and performance statistics, and inputs from the feedback sessions for the cutting process. The whole exercise may be planned in an open and interactive mode.

Step-4 In this step, an empirical model is to be developed to express the complex relationship between input(s), in process parameter(s) and output(s) based on prevailing constraints and assumptions need to be applied. Then, the value of the objective function is found out by the developed model.

Step-5 The designed process model is tested, and validated in a number of dissimilar situations and circumstances. Validation evaluates the relevance of the testing methods determines if the developed model is a representation of real world. Then, graphs and charts are plotted to analyze the results of the model pictorially. It shows the variation of the objective function with change in the values of the decision variables and the optimal range of values of the decision variables

The above methodology can be followed for the below parameters for turning operation [14]

The multi-objective optimization problem formulation is adopted from [15, 16]. The decision variables are x = (v, f, a), where v is the cutting speed, f is the feed rate and a is the depth of cut. The objectives are as follows:

- **Operation time**: The operation time is measured as the total time required manufacturing a product Tp(x) and is to be minimized:
  \[ Tp(x) = Ts + V \left( 1 + Tc/T(x) \right)/MRR(x) + Ti. \]
  It is function of metal removal rate MRR(x) and tool life T(x). The term Ts is toolset- up time, Tc is tool-change time, Ti is idle time between two consecutive cuts, and V is volume of material removed. For particular machining operations, Ts, Tc, Ti, and V are constant so that Tp(x) is function of MRR(x) and T(x) only.

- **Metal removal rate**: MRR(x) can be expressed as the product of cutting speed, feed, and depth of cut and is to be maximized for a better machining operation:
  \[ MRR(x) = 1000vfda. \]  

- **Tool life**: The tool life T(x) is measured as the average time between the tool changes or tool sharpening, which is to be maximized. The relation between the tool life and the parameters is expressed with the well-known Taylor’s formula:
  \[ T(x) = KT / (v_1f_2a_3), \]
  where kT, a1, a2, and a3, are positive constants.

- **Operation cost**: The operation cost can be expressed as the cost per product, as follows:
  \[ Cp(x) = Tp(x)(Ct/T(x) + Cl + Co), \]
  where Ct is tool cost, Cl is labor cost, and Co is the overhead cost. For a specific machining operation, the Ct, Cl, and Co are constant.

- **Cutting quality**: The most important criterion for the determination of the surface quality is roughness and is given as follows:
Ra(x) = kv1f2a3 , (5)
where γ1, γ2, γ3, and k are constants relevant to a specific tool-work piece combination
• Limitations: There are several factors that limit the cutting parameters. Permissible range of cutting conditions are as follows:
  ➢ speed minimum to maximum
  ➢ feed minimum to maximum
  ➢ Depth of cut minimum to maximum

• Cutting power P and force F: Consumption of power can be expressed as a function of the cutting force and cutting speed, as follows:
P(x) =VF(x)6122.45η, (9)
where η is the mechanical efficiency of the machine, and F is given by .F(x) = KF f2a_3 . (10)
The limitations of the power and cutting force are given as follows:
P(x) <_ Pmax, 11
F(x) _<Fmax. (12)

4. Conclusions
A review of literature shows that various optimization techniques like Fuzzy logic, FEM, scatter search, Taguchi technique, ACO Optimization, response surface methodology, Swarm Optimization are the latest optimization techniques that are being applied successfully in industrial applications for optimal selection of process variables in the area of machining. In this optimization techniques has revealed they are part in industries, in particular products for successful development of designing of experiment. Taguchi methods and response surface methodology are robust design techniques widely used in industries for making the product/process insensitive to uncontrollable factors such as environmental variables .The first category includes approaches that examine the effects of various factors through the execution of experiments and the analysis of the results. Regression analysis is often used to build models based on the experimental data. The main advantages of the ANNs include the capability of approximating almost any function without requiring the knowledge of the process and the ability to handle noisy data. PSO can be easily implemented and converges quickly, and is very suitable to deal with most of real engineering application problems. The main advantage of using such as FEM approach is to be able to predict chip flow, cutting forces, and especially a distribution of tool temperatures and stresses for various cutting conditions.

5. References
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