Turning Process Parameters Optimization of Mild Steel Using Advanced Optimization Techniques

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Abstract- *The rapid advancement in production technologies needs development of manufacturing processes which initiates by optimization to scrutinize feasibility of modifications. Turning process is widely used for material removal because it has higher production rate. The process parameters and geometrical parameters of the tool are influences the production rate. Optimization plays vital role nowadays to get optimized parameters which help the manufacturers without going for trial and error process. Therefore in the present study advanced optimization techniques viz: teaching learning based optimization, particle swarm optimization, an artificial bee colony and simulated annealing are used to optimize turning process parameters of ASTM A48 grey cast iron cylindrical bar of 30mm diameter. The turning process parameters considered are speed, feed and depth of cut for aresponse parameter material removal rate which is significant as it influences the rate of production. The results were compared with Taguchi method and it shows that the advanced techniques are more effective.*

Keywords*:* Turning process, Material removal rate, Advance optimization techniques.

I. INTRODUCTION

Now-a-days manufacturing processes developing drastically because of tremendous competition and customers demand. This development era started from 'Industrial Revolution' which has been taken placed in England during the 18th century and ultimately stretched in the neighboring countries such as Germany, France etc. Finally, now this revolution came across the world. The development era necessitates further and drastic changes in manufacturing processes in the aspect of economic manufacturing and enhances the performance of components. Conventionally this enhancement carried through trial and error methods which lead the costing of manufacturing and it's much hectic to the manufacturer. Hence, the trial and error methods are replaced by advanced optimization techniques like Teaching Learning Based Optimization (TLBO), Artificial Bee Colony (ABC), Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Simulated Annealing (SA), Response Surface Methodology (RSM), Jaya Algorithm etc.

Turning is one of the most important methods in industries for removal of material in order to acquire the desired shape. The economy and properties of product highly influenced by process parameters viz. speed, feed, depth of cut and rate of production is affected by material removal rate. As customer demand increasing day by day, production rate must be high enough. Hence, to decide feasible input parameters in the aspect of optimum material removal rate for higher production rate is an important task. Hence, optimization techniques viz. TLBO, PSO, ABC, and SA are used for selection of best parameters which satisfies customers as well as manufacturers demands.

Artificial bee colony is used to solve the multi-objective Reactive Power Optimization (RPO)[1]. Artificial bee colony has three different approaches in parallelization and to obtain better results by using a large number of location approaches[2].Performance of basic artificial bee colony, harmony search, and bees algorithm are compared on unimodal and multimodal on well-known benchmark problems for better optimization problems[3].A comprehensive survey of the artificial bee colony are focused on algorithms and application aspects[4].Artificial bee colony also useful on the differential evolution and evolutionary algorithm for multidimensional and multimodal numeric problems[5].

An efficient optimization method TLBO proposed for the optimization of mechanical design problems which works on teacher-learner philosophy. TLBO is more effective and efficient than the other optimization methods [6]. TLBO techniques applied for non-linear large scale problems and compared the results with those obtained by other techniques such as GA, particle swarm optimization (PSO) and artificial bee colony (ABC) techniques and obtained the best results[7]. TLBO algorithm applied for optimization of advanced manufacturing processes namely ECM and ECDM. In their journal they optimized these process parameters and compared results with ABC algorithm and proved that TLBO algorithm is superior over the other optimization tools [8]. TLBO algorithm applied to the multi-pass turning process. Optimization of process and response parameters done and compared with genetic algorithm solution [9]. Modified TLBO algorithm applied for optimizing process parameters of grinding operation and compared between the results and proved the superiority of the new algorithm in the aspect of better results and computational time [10].

A cooperative simulated annealing (CoSA) approach for the process planning problem to minimize total manufacturing cost [11]. Five level factorial techniques to predict four critical dimensions of bead geometry as it plays a significant role in the performance of weld. Optimization of GMAW method's process and response parameters by SA. [12]. Conducted experimental work to optimize various input process parameters of GMAW to get optimum dilution in stainless steel cladding of low carbon structural steel. Use of regression method for mathematical modeling and finally optimization of the percentage of dilution of stainless steel cladding done by SA and Artificial Neural Network[13]. The significance of surface roughness as response factor in CNC machine tool. Experimental work for measurement of roughness by POCKET SURF EMD-1500 tester. Prepared mathematical model by observing results and optimize the turning process parameters by SA algorithm and claimed as SA is very precise and superior method for optimization and may be used for high precision work [14].

The greater significance of surface finish of product in the aspect of quality control and optimization of end milling process parameters is done. Use of regression method for mathematical modeling and applied PSO algorithm for various types of tools and compares the results with GA solution [15]. PSO algorithm for optimization of MIG welding process and avoided the problems of PSO techniques by implementing with back propagation algorithm. The performances are found to be better than that of the other two [16]. Multi-objective optimization of milling process by Neural Network Modeling and Particle swarm optimization and used an Artificial Neural Network (ANN) for building a mathematical model and PSO algorithm is used to optimization[17]. Depicts the PSO is used to produce metamodel for highly non-linear problems with multi-parameter but validating the results of finite element simulations[18]**.**Particle swarm optimization of tungsten arc welding of stainless steel grade 202 in order to minimize angular distortion and claimed that optimized process parameters are feasible are feasible for minimum angular distortion by experimental work[19].

These optimization techniques work on certain philosophies like teaching learning, the behavior of swarm birds, continuous temperature decrement, and bees philosophy. In this study, the advanced techniques viz. Teaching Learning Based Optimization (TLBO), Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC) and Simulated Annealing(SA) were used to optimize turning process parameters namely speed, feed and depth of cut to have optimum material removal rate. The mathematical module built by Taguchi method are used for optimization and final results compared with Taguchi methods optimized parameters[20].

II. IMPLIMANTATION OF ADVANCE OPTIMIZATION TECHNIQUES

A. Artificial Bee Colony Algorithm

The artificial bee colony (ABC) algorithm is an evolutionary computational technique, it was initially published by Karaboga in 2005 as a scientific report for numerical optimization problems. Its development was motivated by simulating the intelligent foraging behavior of honey bees in their colony and its performance was initially measured using benchmark optimization function. In the ABC algorithm, the colony of artificial bees is the makeup of three groups of bees: employed bees, onlooker bees, and scout bees. The first part of the colony consists of employed bees and the second part is consists of onlooker bees. An onlooker bee is the one waiting in the dance area for making the outcome of choosing a food source. Each food source is signified by an employed bee. Once a food source is finished, the employee and onlooker bees become scout bees.

The algorithm consists of three steps are as below

i) Sending the employed bees into the food sources and measuring their nectar amounts
ii) Selection of food source by the onlooker bees after distributing the information of the employed bees
iii) Selection of scout bees and sending them into possible food sources

The main components of model are as below

i. Food sources: In order to select a food source, a forager bee evaluates several properties related to the food source such as its closeness to the hive, the richness of the energy, taste of its nectar, and the ease or difficulty of extracting this energy. For the simplicity, the quality of a food source can be represented by only one quantity although it depends on various parameters.
ii. Employed foragers**:** An employed forager carries information about her specific source and shares it with other bees waiting in the hive. The information includes the distance, the direction and the profitability of the food source.
iii. Unemployed foragers: A forager bee that looks for a food source to exploit is called unemployed. It can be either a scout who searches the environment randomly or an

onlooker who tries to find a food source by means of the information given by the employed bee.

Pseudo Code of Artificial Bee Colony (ABC) Algorithm

- Initialize the population of solutions x ijk (i =1, 2, . . . , SN; j = 1, 2, . . . , D; k = 1, 2, . . . , V).
- Evaluate the population.
- Cycle = 1.
- Repeat.
- Produce new solutions V_{ijk} for the employed bees and evaluate them.
- Apply the greedy selection process.
- Calculate the probability values for the solutions x_{ijk}.
- Produce the new solutions V_{ijk} for the onlookers from the solutions x_{ijk}selected depending on probability values and evaluate them.
- Apply the greedy selection process.
- Determine the abandoned solution for the scout, if exists, and replace it with a new randomly produced solution x_{ijk}.
- Memorize the best solution achieved so far.
- Cycle = cycle + 1.
- Until cycle = MCN.

B. Teaching Learning Based Optimization Algorithm

The TLBO method works on the teaching-learning phenomenon. Teacher knowledge has a high impact on the learners study and outcome of this process. Teacher knowledge level also differentiates understanding of concepts amongst students. As teacher convey his knowledge as best as possible, even though the grasping level of students may different. Hence, firstly best teacher will convey the concept to a student, then students try to get that concept as per capability. Finally, students clear all those doubts regarding concept by mutual interaction amongst them which results inbetter outcome. Similarly, the optimization takes place in two phases namely teacher phase and learner phase. The optimization technique further elaborated by following the pseudo code.

Pseudo Code of Teaching Learning Based Optimization

- Set k=1;
- Objective function f (X), X = $(x_1, x_2, \ldots, xd)^T$
  d=no. of design variables
- Generate initial students of the classroom randomly X^i, i=1, 2,.., n   n=no. of students
- Calculate objective function f (X) for whole students of the classroom
- While (The termination conditions are not met)
  {Teacher Phase}
- Calculate the mean of each design variable Mean X
- Identify the best solution (teacher)
  For i=1→n
- Calculate teaching factor T_F^i = round [1+ rand (0,1){2-1}]
- Modify solution based on best solution (teacher)
  $X^i_{new} = X^i$ + rand (0,1) $[X_{teacher} – (T_F^i * X_{mean})]$
- Calculate objective function for new mapped student $f(X^i_{new})$
- If X^i_{new} is better than X^i, i.e. $f(X^i_{new}) < f(X^i)$
- $X^i = X^i_{new}$
  End if {End of Teacher Phase}
  {Student Phase}
  Randomly select another learner X^j, such that j ≠i
- If X^i is better than X^i, i.e. f $(X^i) < f$ (X^j)
- $X^i_{new} = X^i$ +rand (0,1)$(X^i – X^j)$
  Else
- $X^i_{new} = X^i$ +rand (0,1)$(X^i – X^j)$
  End if
- If X^i is better than X^i, i.e. f $(X^i) < f$ (X^j)
- $X^i = X^i_{new}$
  End
- If {End of Student Phase}
  End For
- Set k = k + 1
  End while
- Post process results and visualization

C. Simulated Annealing Algorithm

Simulated annealing (SA) is a generic probabilistic technique for approximating the global optimum of a given function. Simulated annealing works on the principle of annealing process in metallurgy which is one of the most important heat treatment carried on materials to enhance properties. In annealing heating of material takes place and followed by controlled cooling i.e. slower cooling. Simulated annealing concerned with continuous temperature decrement similarly the probability of accepting worst solutions decreases. This process of lowering probability explores the solution space. Simulated annealing is widely used for a large-scale problem which requires a long timeto other techniques.

Pseudo code of Simulated Annealing (SA) Algorithm

- Generate initial Solutions
- Input and Access initial Solution
- Estimate Initial Temperature
- While (termination criteria is not met)
  {
    Generate new solution;
    Assess new solution;

If (accept new solution)
{
Update storage.
Adjust Temperature;
}

D. Particle Swarm Optimization Algorithm

It is a robust stochastic optimization technique based on the movement and intelligence of swarms. It is the population-based approach for solving continuous and discrete problems. The advantage of PSO is its robustness in controlling parameters and its high computational efficiency The PSO simulates the behavior of individuals in a group to maximize survival of species and uses a number of particles which constitutes a movement of swarms around search space for examining best solution. In this principle, each swarm tracks its own coordinate in solution space as personal best. The best position found among all particles in the swarm is called global best. Then all particles that fly over N-dimensional solution space are accelerated towards its personal best and global best locations, with random weighted accelerations for new positions, until the global position is found.

Pseudo-Code of the Particle Swarm Optimization (PSO) algorithm

- void particle swarm optimization ()
  {
- Initialize ();
- Evaluate ();
- Update Particle Memories ();
- for (int i=0; i<num Iterations; I + +) {
- update Velocities ();
- update Positions ();
- evaluate ();
- update Particle Memories ();
  }

III. EXPERIMENTAL DATA AND MATHEMATICAL MODEL

The experiment is conducted for Dry turning operation (without cutting fluid) of using cast iron as work material and high speed steel as tool material on a conventional lathe machine. The tests are carried for a 67 mm length work material. The process parameters used as spindle speed (rpm), feed (mm/rev), depth of cut (mm). The response variable is material removal rate and the experimental results are recorded in Table.

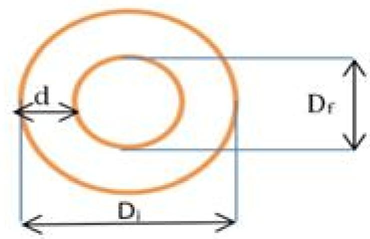
The material removal rate is calculated by the following aformula.

Let,

D_i = Initial diameter of the metal bar,
D_f = Final diameter of the metal bar,
L =Cutting length of work piece,
t =time
π =3.1416(Constant value)

Now,

Volume= $(\pi/4)\ LD_i^2 - (\pi/4)LD_f^2$
$= \pi/4L\ (D_i^2 – D_f^2)$
$= (\pi/4)\ L\ (D_i + D_f)\ (D_i – D_f)$
$= \pi\ L\ \{(D_i + D_f)/2\}\ \{(D_i – D_f)/2\}$
=πL(Average diameter) (Depth of cut)



From Fig,

$D_i - D_f = 2d$ [Where, d = Depth of cut]
$d = (D_i - D_f)/2$ And,
$(D_i + D_f)/2$= Average diameter of the cutting section $= D_{avg}$

So, Experimental formula for MRR

M.R.R=$\pi \times L \times d \times D_{avg}/t$ (mm^3/sec)

From the linear regression analysis (running a program in Minitab 17) the following equation has derived:

MRR= (-1.92)+0.0134*(Spindle speed) +1.67*(Feed rate)
+14.60*(Depth of cut)

The constraints for the process parameters are as follows

112 < Spindle Speed (rpm) < 280
0.125 < Feed Rate (mm/rev) < 0.153
0.25 < Depth of Cut (mm) < 0.35

IV. RESULTS & DISCUSSION

The results of respective techniques were compared with Taguchi method and it shows that advanced techniques viz. TLBO, PSO, ABC, SA etc. are superior thanTaguchi. Also concluded that PSO gives extremely optimized parameters than others namely TLBO, ABC and SA with same iteration number and span of optimization.

Method	Spindle Speed (rpm)	Feed Rate (mm/min)	Depth of Cut (mm)	MRR (mm^3/min)
TLBO	279.29	0.143	0.347	7.1313
SA	279.2415	0.153	0.35	7.1873
PSO	279.153	0.15	0.35	7.1975
ABC	279.4565	0.1376	0.3455	7.0994
Taguchi Algorithm	280	0.153	0.35	7.09

V. CONCLUSION

The present work analyzed the various manufacturing processes with their process and response parameters. The multi-objectivedecision-making methods are versatile in nature. These optimization algorithms are more accurate and effective than other conventional methods of mathematics. The optimization span i.e. running the span of the optimization process is tremendously smaller as compared to other tools of optimization.

The MODM methods used viz. PSO, ABC, SA, and TLBO are very much adaptable and easy to apply for any optimization problem like constrained and unconstrained, single objective and multiple objectives etc. These methods are derived from the natural phenomena of particle movement, honey bee structure, infinitely temperature decrement and teacher-learner philosophy hence very easy to understand.

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