# Optimization of MRR and surface roughness for turning of AA6061 using Taguchi method and PSO

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***Abstract** - In the era of mass manufacturing, Material Removal Rate (MRR) and Surface roughness ($R_a$) are of primary concern even in manufacturing using contemporary computer numerical controlled (CNC) machines. In this paper Taguchi method has been employed with L9 Orthogonal Array for three process parameters namely Speed, Feed and Depth of cut. For each of these parameters three different levels have been identified and used to perform the turning operation on CNC lathe for maximization of material removal rate and minimization of Surface roughness. The material selected for machining was AA 6061 with carbide cutting tool. The MRR and surface roughness are considered as objectives to develop the combination of optimum cutting parameters. This paper proposes an optimization approach using Particle Swarm optimization (PSO) for the maximized MRR and minimized Surface roughness. This study also produced a predictive equation for determining MRR and surface roughness with a given set of parameters in CNC turning. Thus with the proposed optimal parameters it is possible to increase the efficiency of machining process and decrease production cost in an automated manufacturing industry.*

***Key words***: CNC Lathe; Carbide tool; AA6061; MRR, Surface roughness Taguchi method; Particle Swarm Optimization (PSO),

## 1.INTRODUCTION

Now a day's focus is made on the accuracy and precision of a manufactured component in machining industry. As conventional machining is incapable of producing such a high accuracy and precision, the CNC machining has grown to be an indispensible part of machining industry. Out of various objectives of machining the MRR and surface roughness are considered to be most important.
In the present work, the turning operation was made on AA6061 using carbide tool on CNC lathe. The focus is made on investigating the combination of process parameters viz cutting speed, feed rate and depth of cut that results in maximum MRR and minimum surface roughness by using Taguchi method and PSO.
In order to find the optimized set of input parameters and also to identify the effect of each towards a particular output, researchers have been trying for years together. Meng [1] tried to calculate optimum cutting condition for turning operation using a machining theory. Researchers [2-7] have tried to optimize the machining parameters using various methods like Genetic Algorithm, simulated annealing method, Multi-Objective Evolutionary Algorithm etc.Bharathi and Baskar reviewed the researches made on optimization techniques for machining using various mathematical models. Chen [8] tried for optimization of machining conditions for turning cylindrical stocks into continuous finished profiles and Negrete et.al. [9] tried to optimize the cutting parameters for minimizing cutting power where as Cayda [10] tried to vary the cutting tool to evaluate the machinability of AISI 4340 steel. The Taguchi method emphasizes over the selection of the most optimal solution (i.e. MRR) over the set of given inputs (i.e. cutting speed, feed rate and depth of cut) with a reduced cost and increased quality. The optimal solution so obtained is least affected by any outside disturbances like the noise or any other environmental conditions [11]. Thus, the modern day approach to find the optimal output over a set of given input can be easily carried out by the use of Taguchi method rather than using any other conventional methods.

## 2.EXPERIMENTAL WORK

2.1 Design of experiment using Taguchi method:

The experiments for this work are planned using Taguchi's design of experiments (DoE).Taguchi's approach to parameter design provides the design engineer with a systematic and efficient method for determining near optimum design parameters for performance and cost . This method can dramatically reduce the number of experiments required to gather necessary data. In this study, the experimental plan has tool cutting speed, feed rate, and depth of cut as the controllable variables. On the basis of preliminary experiments conducted by using one variable at a time approach, the feasible range for the machining parameters is selected.
The experiments are performed on CNC lathe selected. The tool and material selected were carbide and AL6061 respectively. Three process parameters, as already stated above, Cutting speed (A), Feed rate (B) and Depth of cut (C) were considered in the study. Equally spaced three levels within the operating range of the input parameters were

selected for each of the process parameters. Based on Taguchi method, an L9 orthogonal array (OA) which has 9 different experiments at three levels was developed. Table 1 shows the design factors along with their levels.

**Table - 1:** Parameters, codes, and level values used for orthogonal array

| S.NO | CODE | PARAMETERS | LEVEL 1 | LEVEL 2 | LEVEL 3 |
|---|---|---|---|---|---|
| 1 | A | SPEED | 1000 | 1500 | 2000 |
| 2 | B | FEED RATE | 0.1 | 0.15 | 0.2 |
| 3 | C | DEPTH OF CUT | 0.3 | 0.2 | 0.1 |

### 2.1 Determination of MRR and $R_a$:

Taguchi technique is a powerful tool for identification of affect of various process parameters based on orthogonal array (OA) experiments which provides much reduced variance for the experiments with an optimum setting of process control parameters. As referred earlier, in this work L9 orthogonal array was used to carry out the experiments and the experimental results (Table 2) were analyzed using PSO.

Table -2: Experimental results.

| EXP NO | Cutting speed (m/s) (A) | Feed Rate (mm/rev) (B) | Depth of Cut (mm) (C) | MRR (mm/min) | $R_a$ |
|---|---|---|---|---|---|
| 1 | 1 | 1 | 1 | 2213.7 | 1.1528 |
| 2 | 1 | 2 | 2 | 2213.7 | 1.3330 |
| 3 | 1 | 3 | 3 | 1475.8 | 1.9166 |
| 4 | 2 | 1 | 2 | 2213.7 | 1.0232 |
| 5 | 2 | 2 | 3 | 1660.27 | 1.3674 |
| 6 | 2 | 3 | 1 | 6641.1 | 1.9094 |
| 7 | 3 | 1 | 3 | 1475.8 | 0.9002 |
| 8 | 3 | 2 | 1 | 6641.1 | 1.3492 |
| 9 | 3 | 3 | 2 | 5909.2 | 1.9424 |

## 3. Optimization process parameters using PSO:

A basic variant of the PSO algorithm works by having a population (called a swarm) of candidate solutions (called particles). These particles are moved around in the search-space according to a few simple formulae. The movements of the particles are guided by their own best known position in the search-space as well as the entire swarm's best known position. When improved positions are being discovered these will then come to guide the movements of the swarm. The process is repeated and by doing so it is hoped, but not guaranteed, that a satisfactory solution will eventually be discovered.

In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particles. Each particle keeps track of its coordinates in the problem space which are associated with the best solution (fitness) it has achieved so far. (The fitness value is also stored.) This value is called p best. Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the neighbors of the particle. This location is called 'l' best. When a particle takes all the population as its topological neighbors, the best value is a global best and is called 'g 'best.

The particle swarm optimization concept consists of, at each time step, changing the velocity of (accelerating) each particle toward its 'p' best and 'l' best locations (local version of PSO). Acceleration is weighted by a random term, with separate random numbers being generated for acceleration toward 'p' best and 'l' best locations.

In past several years, PSO has been successfully applied in many research and application areas. It is demonstrated that PSO gets better results in a faster, cheaper way compared with other methods.

### 3.1 PSO ALGORITHM:

Particle, X (t):

It is a candidate solution represented by an m-dimensional vector, where m is the number of optimized parameters. At time t, jth particle $X_j(t)$ can be described as $X_j(t)=[x_{j,1}(t),.....,x_{j,m}(t)]$, where $x^s$ are the optimized parameters and $x_{j,k}(t)$ is the position of the jth particle with respect to the kth dimension , i.e. The value of the kth optimized parameter in the jth candidate solution.

Population, pop(t):

It is the set of n particles at time t, i.e. pop (t) $=[X_1(t)...X_n(t)]^T$.

Swarm:

It is an apparently disorganised population of the moving particles that tend to cluster together while each particle seems to be moving in a random direction.

Particle velocity, V(t):

It is the velocity of the moving particles represented by an m-dimensional vector. At the time t, the jth particle velocity

$V_j(t)$ can be described as $V(t)=[v_{j,1}(t), \ldots v_{j,m}(t)]$, where $v_{j,k}(t)$ is the velocity component of the jth particle with respect to the $k^{th}$ dimension.

Inertia weight, w (t):

It is a control parameter that is used to control the previous velocities on the current velocity. Hence it influences the trade of between global and local exploration abilities of the particles.

For initial stages the search process , large inertia weight to enhance global exploration is recommend while for last stages the inertia weight is reduced for better local exploration.

Individual best $X^*(t)$:

As the particle moves through the search space, it compares its fitness value at the current position to the fitness value it has ever attained at any time up to the current time. The best position that is associated with the best fitness encountered so far is called the individual best, $X^*(t)$. For each particle in the swarm, $X^*(t)$ can be determined and updated during the search. In a minimization problem with objective function J, the individual best of the $j^{th}$ particle $X_j^*(t)$ is determined such that

$J(X^{**}(t)) \leq J(X_j(t))$, j=1.....n, For simplicity assume that $J^{**}=J(X^{**}(t))$

Stopping criteria: These conditions are under which the search process will terminate if one of the following criteria is satisfied:

(a) Iterations > pre specified number
(b) Iterations reaches maximum allowable number

In PSO algorithm, the population has n particles and each particle is an m-dimensional vector, where m, is the number of optimized parameters.

By incorporating the above modifications, the PSO technique can be described in following steps:

STEP-I (Initialization): Set the time counter t=0 and generate randomly n particles, $\{X_j(0), j=1.....n\}$, where $X_j(0)= [x_{j,1}(0), \ldots\ldots x_{j,k}(0)$ is generated is randomly selected with a value with uniform probability.

Similarly generate randomly initial velocities of all possible $\{V_j(0), j=1,\ldots n\}$, where $V_j(0) = [v_{j,1}(0), \ldots, v_{j,m}(0)]$.

STEP-II (Time Updating): Update the time counter t=t+1

STEP- III (Weight Updating): Update the inertia weight $w(t)=\alpha\, w(t-1)$

STEP-IV: (Velocity Updating): Using the global best and individual best of each particle, the $j^{th}$ particle velocity in $k^{th}$ dimension is updated according to the following equation:

$V_{j,k}(t)=w(t)v_{j,k}(t-1)+(t-1)+c_1\ r_1(x^*_{j,k}(t-1) - x_{j,k}(t-1))+c_2r_2(x_{j,k}^{**}(t-1))$

Where

$c_1, c_2$ are positive constants

$p^1, p^2$ are distributed random numbers in [0,1].

STEP-V (Position Updating): Based on updated velocities, each particle changes its position according to the following equation: $x_{j,k}(t)=v_{j,k}(t)+x_{j,k}(t-1)$

If a particle violates the position limits in any dimension, set its position at the proper limit.

STEP VI(Individual Updating): Each particle is evaluated according to its updated position. If $J_i<J^*_j$, j=1 ...n, then the updated individual best as $X_j^*(t)=X_j(t)$ and $J^*_j= J_j$.

STEP –VII(Global Best Updating): Search the minimum value $J_{min}$among $j^*_j$, where min is the particle with minimum objective function, i.e. mine{ j;j=1,....n}. If $J_{min}<J^{**}$, then update the global best as $X^{**}(t)=X_{min}(t)$ and $J^{**}=J_{min}$.

STEP- VIII(Stopping Criteria): If one of the stopping criteria is satisfied then stop; else go to step 2..

## 3.2 INPLEMENTATION OF PSO ALGORITHM USING MAT LAM:

Simplifying PSO was originally suggested by Kennedy and has been studied more extensively, where it appeared that optimization performance was improved, and the parameters were easier to tune and they performed more consistently across different optimization problems.

Another argument in favor of simplifying PSO is that met heuristics can only have their efficacy demonstrated empirically by doing computational experiments on a finite number of optimization problems. This means a met heuristic such as PSO cannot be proven correct and this increases the risk of making errors in its description and implementation.

A good example of this presented a promising variant of a genetic algorithm (another popular met heuristic) but it was later found to be defective as it was strongly biased in its optimization search towards similar values for different dimensions in the search space, which happened to be the optimum of the benchmark problems considered. This bias was because of a programming error, and has now been fixed.

Initialization of velocities may require extra inputs. A simpler variant is the accelerated particle swarm optimization (APSO), which does not need to use velocity at all and can speed up the convergence in many applications. A simple demo code of APSO is available

After giving the programming to this particular problem by using the PSO technique in MAT Lab . The optimum values of the different control parameters such as speed, feed, depth of cut has been obtained according to the optimum output results as metal removal rate and surface roughness are as follows.

| S.NO | PROCESS PARAMETERS | OPTIMUM VALUE |
|---|---|---|
| 1 | Optimum speed (N) | 1932.2 rpm |
| 2 | Optimum feed rate (f) | 0.1835 mm/min |
| 3 | Optimum depth of cut(d) | 0.2791 mm |
| 4 | Optimum metal removal rate (Q) | 6907.2 $mm^3$/min |
| 5 | Optimum surface roughness(Ra) | 0.2312 microns |

## 3. CONCLUSIONS

In this paper, a study had been carried out to optimize the process parameters viz. Cutting Speed, Feed and Depth of Cut maximizing material removal rate (MRR) and minimizing Surface Roughness ($R_a$) of AA 6061 using PSO.Taguchi method has been employed with an orthogonal array L9 was used to conduct the experiments.

The study shows that PSO technique can be applied for different predicted *Ra* values that are modeled by using different conventional approaches (such as DP, and RSM) and non-conventional approaches (such as ANN, and PSO itself). In other word, PSO technique does not strictly state particular modeling approaches in order to be coupled with it in finding the optimal *Ra* and *MRR* value. It is important for researchers to provide many alternatives by using various matching approaches between modeling and optimizing approaches to give the best result of *Ra and MRR* value in an optimization problem.

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