Effect of Work Material, Tool Material on Surface Finish in Turning Operations

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Abstract— This project proposes a decision making model for the selection of an appropriate alternative to supply wood based raw material for paper and wood industries in India. A total of four major control criteria; benefits, opportunities, costs and risks (BOCR) are used to evaluate the procurement mechanism of the supply chain network. The Benefits, Opportunities, Costs and Risks associated with paper making factories and the region in the Indian scenario is critically examined. The decision-making is examined within the framework of BOCR and prioritized using the Analytic Hierarchy Process (AHP) ratings approach. To evaluate the control criteria of the system, a control hierarchy is also created and prioritized by applying the Analytic Network Process (ANP). Governmental purchase, Captive Plantation and Gate purchase are considered as the potential alternatives for Eucalyptus supply. The final outcome of the model gives a ranking among the various potential alternatives.

Keywords— Surface Finish, Turning Operations, Tool Material, PSO Technique.

I. INTRODUCTION

Optimization of machining operation is one of the greatest concerns in the manufacturing industry. The process of optimization may be based on various parameters like best possible surface finish, maximum production rate, minimum production cost etc. In machining operations this is possible by suitable representation of the parameters in terms of objective function and constraints. Different procedures have been used by researchers from time to time for the optimization process -e.g. Linear Programming, Quadratic programming, Langrangian multipliers etc. Heuristic methods belong to non – conventional methods of optimization which try to mimic natural processes and apply the principles to the problem at hand.

Heuristic techniques in general use a combination of randomness and heuristic “rules” to guide the search for global maxima or minima. Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Evolution Strategies (ES), Simulated Annealing (SA) etc. are some of the Heuristic Techniques developed for optimization process. The current work deals with the use of PSO, in the optimization of machining operations, in particular – turning. The experimental work as been conducted at HMT, Kalamaserry.

A. Research problem

The factors affecting the machining operations are numerous and include machine tool capacity, required workpiece geometry, cutting conditions such as speed, feed, and depth of cut, etc. Approximate determination of the cutting conditions not only increases the production cost, but also diminishes the product quality. In this work a new evolutionary computation technique, particle swarm optimization, is developed to optimize the machining process parameters of turning. The main objectives of the research work are mentioned below.

- To obtain optimum condition required for turning
- To use Taguchi’s method to find out the contribution of factors of turning
- To verify whether PSO technique can be used for turning
- To reduce time and cost for doing turning operation
- To verify whether Taguchi method can be used for turning
- To compare matrix inverse method and PSO technique

Hence research problem is defined as “To find the effect of cutting parameters on surface roughness and to obtain optimum condition for turning using Taguchi method and to compare it with PSO technique”.

II. LITERATURE REVIEW

Traditionally, the selection of cutting conditions for metal cutting is left to the machine operator. In such cases, the experience of the operator plays a major role, but even for a skilled operator it is very difficult to attain the optimum values each time. Machining parameters in metal turning are cutting speed, feed rate and depth of cut. The setting of these parameters determines the quality characteristics of turned parts. Following the pioneer work of Taylor (1907) and his famous tool life equation, different analytical and experimental approaches for the optimization of machining parameters have been investigated. Gilbert (1950) studied the optimization of machining parameters in turning with respect to maximum production rate and minimum production cost as criteria. Armarego & Brown (1969) investigated unconstrained machining-parameter optimization using differential calculus. Brewer & Rueda (1963) carried out simplified optimum analysis for non-ferrous materials.

For cast iron (CI) and steels, they employed the criterion of hardness. For cast iron (CI) and steels, they employed the criterion of hardness.
They pointed out that the more difficult-to-machine materials have a restricted range of parameters over which machining can be carried out and thus any attempt at optimizing their costs are artificial.

Brewer (1966) suggested the use of Lagrangian multipliers for optimization of the constrained problem of unit cost, with cutting power as the main constraint. Bhattacharya et al (1970) optimized the unit cost for turning, subject to the constraints of surface roughness and cutting power by the use of Lagrange’s method. Walvekar & Lambert (1970) discussed the use of geometric programming for the selection of machining variables. They optimized cutting speed and feed rate to yield minimum production cost. Petropoulos (1973) investigated optimal selection of machining variables, viz. cutting speed and feed rate, by geometric programming. Ermer & Kromodiharajo (1981) developed a multi-step mathematical model called Optimization of machining techniques to solve a constrained multi-pass machining problem. They concluded that in some cases with certain constant total depths of cut, multi-pass machining was more economical than single-pass machining, if depth of cut for each pass was properly allocated. They used high speed steel (HSS) cutting tools to machine carbon steel. Hinduja et al (1985) described a procedure to calculate the optimum cutting conditions for turning operations with minimum cost or maximum production rate as the objective function.

For a given combination of tool and work material, the search for the optimum was confined to a feed rate versus depth-of-cut plane defined by the chip-breaking constraint. Some of the other constraints considered include power available, work holding, surface finish and dimensional accuracy.

Tsai (1986) studied the relationship between the multi-pass machining and single-pass machining. He presented the concept of a break-even point, that, there is always a point to ascertain value of depth of cut, at which single-pass and double-pass machining are equally effective. When the depth of cut in below the break-even point, the single-pass is more economical than the double-pass, and when the depth of cut is more than this break-even point, double-pass is economical. Carbide tools are used to turn the carbon steel work material. Gopalakrishnan & Khayyal (1991) described the design and development of an analytical tool for the selection of machine parameters in turning.

Agapiou (1992) formulated single-pass and multi-pass machining operations. Production cost and total time were taken as objectives and a weighting factor was assigned to prioritize the two objectives in the objective function. He optimized the number of passes, depth of cut, cutting speed and feed rate in his model, through a multi-stage solution process called dynamic programming. Several physical constraints were considered and applied in his model. In his solution methodology, every cutting pass is independent of the previous pass, hence the optimality for each pass is not reached simultaneously. Prasad et al (1997) reported the development of an optimization model for determining process parameters for turning operations of HSS and carbide tool materials. The minimization of production time is taken as the basis for formulating the objective function. The constraints considered in this study include power, surface finish, tolerance, and work piece rigidity, range of cutting speed, maximum and minimum depths of cut and total depth of cut.

### Latest techniques

The latest development in the area of optimization techniques for machining are mentioned below.

#### A. Fuzzy logic

Fuzzy logic has great capability to capture human commonsense reasoning, decision-making and other aspects of human cognition. Kosko (1997) showed 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. Models by fuzzy logic open up a new way to optimize cutting conditions and also tool selection.

#### B. Genetic algorithm (GA)

These are the algorithms based on mechanics of natural selection and natural genetics, which are more robust and more likely to locate global optimum. It is because of this feature that GA goes through solution space, starting from a group of points and not from a single point. The cutting conditions are encoded as genes by binary encoding to apply GA in optimization of machining parameters. A set of genes is combined together to form chromosomes, used to perform the basic mechanisms in GA, such as crossover and mutation. Crossover is the operation to exchange some part of two chromosomes to generate new offspring, which is important when exploring the whole search space rapidly. Mutation is applied after crossover to provide a small randomness to the new chromosomes.

To evaluate each individual or chromosome, the encoded cutting conditions are decoded from the chromosomes and are used to predict machining performance measures. Fitness or objective function is a function needed in the optimization process and selection of next generation in genetic algorithm. Optimum results of cutting conditions are obtained by comparison of values of objective functions among all individuals after a number of iterations. Besides weighting factors and constraints, suitable parameters of GA are required to operate efficiently. GA optimization methodology is based on machining performance predictions models developed from a comprehensive system of theoretical analysis, experimental database and numerical methods. The GA
parameters along with relevant objective functions and set of machining performance constraints are imposed on GA optimization methodology to provide optimum cutting conditions.

**Implementation of GA:** First of all, the variables are encoded as n-bit binary numbers assigned in a row as chromosome strings. To implement constraints in GA, penalties are given to individuals out of constraint. If an individual is out of constraint, its fitness will be assigned as zero. Because individuals are selected to mate according to fitness value, zero fitness individuals will not become parents. Thus most individuals in the next generation are ensured in feasible regions bounded by constraints. The GA is initialized by randomly selecting individuals in the full range of variables. Individuals are selected to be parents of the next generation according to their fitness value. The larger the fitness value, the greater their possibility of being selected as parents. Wang & Jawahir (2004) have used this technique for optimization of milling machine parameters. Kuo & Yen (2002) have used a genetic algorithm based parameter tuning algorithm for multi dimensional motion control of a computer numerical control machine tool.

**C. Scatter search technique (SS)**

Scatter search 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 on-line quality control strategy for optimizing machining parameters based on signals from sensors. Chen & Chen (2003) have done extensive work on this technique.

**D. Taguchi technique**

Genichi Taguchi is a Japanese engineer who has been active in the improvement of Japan’s industrial products and processes since the late 1940s. He has developed both the philosophy and methodology for process or product quality improvement that depends heavily on statistical concepts and tools, especially statistically designed experiments. Sullivan (1987) reported that the term “Taguchi methods” (TM) refers to the parameter design, tolerance design, quality loss function, on-line quality control, design of experiments using orthogonal arrays, and methodology applied to evaluate measuring systems. Taguchi’s ideas can be distilled into the following fundamental concepts.

- Quality losses must be defined as deviations from targets, not conformance to arbitrary specifications (Benton 1991).
- Achieving high system-quality levels economically requires quality to be designed into the product. Quality is designed, not manufactured; into the product (Daetz 1987; Taguchi1989). Lin et al (1990) stated that Taguchi methods represent a new philosophy. Quality is measured by the deviation of a functional characteristic from its target value. Noises (uncontrolled variables) can cause such deviations resulting in loss of quality. Taguchi methods seek to remove the effect of noises.

Taguchi (1989) described that quality engineering encompasses all stages of product/process development: system design, parameter design, and tolerance design. Byrne & Taguchi (1987), however, pointed out that the key element for achieving high quality and low cost is parameter design. Through parameter design, levels of product and process factors are determined, such that the product’s functional characteristics are optimized and the effect of noise factors is minimized. Singh & Kumar (2003, 2004, 2005) have applied Taguchi’s technique for optimizing surface finish, tool wear, cutting force and power consumed in turning operations for machining En24 steel with titanium carbide-coated tungsten carbide inserts.

**E. Latest works related with optimization of turning parameters**

T. Srikanth, and Dr V. Kamala, 2008 developed a (Real Coded Genetic Algorithm (RCGA) approach for optimization of cutting parameters in turning. This RCGA approach is quite advantageous in order to have the minimum surface roughness values, and their corresponding optimum cutting parameters, for certain constraints.

Their work shows that in constrained optimization problem, RCGA approach is good to get the optimum solutions faster. This would be helpful for a manufacturing engineer to choose the machining conditions for desired machining performance of a product. With the known boundaries of surface roughness and machining conditions, machining could be performed with a relatively high rate of success, with selected machining conditions. Integration of the proposed approach with an intelligent manufacturing system will lead to reduction in production cost and production time, flexibility in machining parameters, selection and overall improvement of the product quality.

Dr. S.S.Mahaputra Amar Patnaik Prabina Ku. Patnaik, (2006) has made an attempt to generate a surface roughness prediction model and optimize the process parameters Genetic algorithms (GA). F. Cus, J. Balic, U. Zuperl,(2009) proposed a new hybrid multi-objective optimization technique, based on ant colony optimization algorithm (ACO), to optimize the machining parameters in turning processes. It uses adaptive neuro-fuzzy inference system (ANFIS) system to represent the
manufacturer objective function and an ant colony optimization algorithm (ACO) to obtain the optimal objective value. ACO algorithm is completely generalized and problem independent so that it can be easily modified to optimize turning operation under various economic criteria. It can obtain a near-optimal solution in an extremely large solution space within a reasonable computation time. Adeel H. Suhail, N. Ismail, S.V. Wong and N.A. Abdul Jalil,(2010) conducted experimental study to optimize the cutting parameters using two performance measures, work piece surface temperature and surface roughness. Optimal cutting parameters for each performance measure were obtained by employing Taguchi techniques. The orthogonal array, signal to noise ratio and analysis of variance were employed to study the performance characteristics in turning operation. The experimental results showed that the work piece surface temperature can be sensed and used effectively as an indicator to control the cutting performance and improves the optimization process.

K. Palanikumar, L. Karunamoorthy, R. Karthikeyan, and B. Latha , 2006 discussed the application of the Taguchi method with fuzzy logic to optimize the machining parameters for machining of GFRP composites with multiple characteristics. A multi-response performance index (MRPI) was used for optimization. The machining parameters viz., work piece (fiber orientation), cutting speed, feed rate, depth of cut and machining time were optimized with consideration of multiple performance characteristics viz., metal removal rate, tool wear, and surface roughness.

III. EXPERIMENTAL WORK DONE

A. Working procedure

The following experiment has been conducted at HMT tool room Kalamaserry to get the following results. The materials used for the experiment is MS and we provide a tool with specifications HSS. A work piece of 100mm length and 32mm diameter taken and two conditions with five independent factors like cutting speed, feed rate, depth of cut, nose radius, hardness.

STEP 1

For each condition an orthogonal array is obtained comprising five factors. We get a roughness value for each trail no by using perthometer. From the above anova table has been created. The following method has been used to create the anova table.

1. Independent factors fixed
2. Degree of freedom can be found
3. Sum of the squares found by using equations
   \[(Ra_1+Ra_2+Ra_3+Ra_4)-(Ra_5+Ra_6+Ra_7+Ra_8)\]
4. Mean square value of each factors is found by using equation
   \[\frac{\text{Sum of square}}{\text{Degree of freedom}}\]
5. To find the percentage of contribution by using equation
   \[\frac{\text{Mean square value}}{\text{Total mean square value}} \times 100\]
6. Finally pie diagram has been drawn

STEP 2

Fifteen sets of reading have been taken for surface roughness. By using matrix inverse method the actual value of perthometer reading is compared. For getting the Ra value we use the following equations \[Ra = K \cdot v^x \cdot f^y \cdot d^z \cdot H^p \cdot r^q\] from T. Srikanth and Dr V. kamala “A Real Coded Genetic Algorithm for Optimization of Cutting Parameters in Turning” IJCSNS International Journal of Computer Science and Network Security, VOL.8 No.6, June 2008 pp 189 – 193. After solving 5005 combination x y z p and q are obtained. From these values the lowest one is taken. In order to find the mean square error value of the Ra values and from these set of reading the values with minimum mean square error values is takes for final solution. For solving the above equation we used mat lab and the program is given in the appendix

STEP 3

PSO is a heuristic technique inspired by the collective intelligence of swarms of biological populations. It is an evolutionary computation technique developed by Eberhart and Kennedy in 1995 inspired by the social behaviour of bird flocking or fish schooling. It is a very simple concept and can be implemented in a few lines of computer code. Using PSO codes we have created in a program in mat lab and direct solution is obtained. Which is compared with matrix inverse method and finally result is obtained.

B. Process parameters [J S Senthilkumar et al.]

1. cutting speed (v) m-m-1
2. \[\min \leq v \leq \max\]
3. feed (f) mm – rev-1
4. \[\min \leq f \leq \max\]
5. depth of cut (d) mm
6. \[\min \leq d \leq \max\]
7. nose radius (mm)
8. \[\min \leq r \leq \max\]
9. Hardness (160BHN to 170BHN)

C. Contraints [R Saravanan et al]

1. Surface roughness constraint (Ra)
   It indicates the quality of machined surface (used surface text equipment to measure surface roughness).
2. Cutting force constraint(F)
High cutting force creates rapid tool failure, poor surface finish and chatter in machine, so minimum cutting force is required. (tool dynamometer to measure cutting force)

D. Work piece material

The work piece material used in the study was MS. They were in the form of cylindrical bar of diameter 32mm and length 100mm.

E. Cutting tool material

HSS (10% T) ½ inch Sq x 4 inch length

F. Taguchi method

The quality of design can be improved by improving the quality and productivity. Robust design is an engineering methodology for obtaining product and process condition, which are minimally sensitive to the various causes of variation, and which produce high-quality products with low development and manufacturing costs. Taguchi’s parameter design offers a simple, systematic approach and can reduce number experiment to optimize design for performance, quality and cost. Surface roughness has received serious attention for many years. It has formulated an important design feature in many situations such as parts subject to fatigue loads, precision fits, fastener holes, and aesthetic requirements. In addition to tolerances, surface roughness imposes one of the most critical constraints for the selection of machines and cutting parameters. A considerable number of studies have investigated the general effects of the speed, feed, and depth of cut on surface roughness. Process modeling and optimization are the two important factors required to predict machining performances of any machining operations.

Optimization of machining parameters not only increases the utility for machining economics, but also increases the product quality to a great extent. In this context, an effort has been made to estimate the surface roughness using experimental data. Since turning is the primary operation in most of the production processes in the industry, surface finish of turned components has greater influence on the quality of the product. Surface finish in turning has been found to be influenced in varying amounts by a number of factors such as feed rate, work material characteristics, work hardness, unstable built-up edge, cutting speed, depth of cut, cutting time, tool nose radius and tool cutting edge angles, stability of machine tool and work piece setup, chatter, and use of cutting fluids. Taguchi method consist of a plan of experiments with the objective of acquiring data in a controlled way, executing these experiments and analyzing this data, in order to obtain information about the behaviour of a given process. It uses orthogonal arrays to define the experimental plans and the treatment of the experimental results is based on the analysis of variance (ANOVA).

IV. DESIGN OF EXPERIMENT AND EXPERIMENTAL DETAILS

The experiments were carried out with five independent factors and two interaction factors at two levels each, as shown in Table 1. Here we use a standard L8 orthogonal array. The machining trials were carried out on the lathe machine.

<table>
<thead>
<tr>
<th>SLNO</th>
<th>Factors</th>
<th>1</th>
<th>2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Cutting speed (m/min)</td>
<td>30.144</td>
<td>25.12</td>
</tr>
<tr>
<td>2</td>
<td>Feed rate (mm/rev)</td>
<td>0.275</td>
<td>0.110</td>
</tr>
<tr>
<td>3</td>
<td>Depth of cut (mm)</td>
<td>1</td>
<td>0.8</td>
</tr>
<tr>
<td>4</td>
<td>Nose radius (mm)</td>
<td>0.4</td>
<td>0.8</td>
</tr>
<tr>
<td>5</td>
<td>Hardness</td>
<td>160</td>
<td>170</td>
</tr>
</tbody>
</table>

Table 1 Two level tables with five factors

<table>
<thead>
<tr>
<th>Trial no</th>
<th>1 (d)</th>
<th>2 (r)</th>
<th>3 (v)</th>
<th>4 (f)</th>
<th>5 (H)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>2</td>
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<td>2</td>
<td>1</td>
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<td>5</td>
<td>2</td>
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<td>6</td>
<td>2</td>
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<td>7</td>
<td>2</td>
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<td>1</td>
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<td>1</td>
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<tr>
<td>8</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>2</td>
<td>2</td>
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</tbody>
</table>

Table 2 Standard orthogonal array (L8)

<table>
<thead>
<tr>
<th>Trial no</th>
<th>Surface roughness (μm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.52</td>
</tr>
<tr>
<td>2</td>
<td>1.25</td>
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<tr>
<td>3</td>
<td>1.40</td>
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<tr>
<td>4</td>
<td>1.60</td>
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<td>5</td>
<td>1.82</td>
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<td>6</td>
<td>1.50</td>
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<tr>
<td>7</td>
<td>1.05</td>
</tr>
<tr>
<td>8</td>
<td>1.45</td>
</tr>
</tbody>
</table>

Table 3 The values of objective function (surface roughness)

<table>
<thead>
<tr>
<th>Factor</th>
<th>D.O.F</th>
<th>Sum Of Squares</th>
<th>Mean Squares</th>
<th>Percentage Contribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>D</td>
<td>1</td>
<td>0.0218</td>
<td>0.0218</td>
<td>3.96</td>
</tr>
<tr>
<td>R</td>
<td>1</td>
<td>0.0996</td>
<td>0.0996</td>
<td>18.13</td>
</tr>
<tr>
<td>V</td>
<td>1</td>
<td>0.1750</td>
<td>0.1750</td>
<td>31.85</td>
</tr>
<tr>
<td>Vxd</td>
<td>1</td>
<td>0.0122</td>
<td>0.0122</td>
<td>2.22</td>
</tr>
<tr>
<td>Dxf</td>
<td>1</td>
<td>0.0004</td>
<td>0.0004</td>
<td>0.07</td>
</tr>
<tr>
<td>F</td>
<td>1</td>
<td>0.1987</td>
<td>0.1987</td>
<td>36.17</td>
</tr>
<tr>
<td>H</td>
<td>1</td>
<td>0.0416</td>
<td>0.0416</td>
<td>7.5</td>
</tr>
<tr>
<td>Total</td>
<td>5</td>
<td>0.5493</td>
<td>0.5493</td>
<td>100</td>
</tr>
</tbody>
</table>
Sum of the squares = 
=(Ra₁+Ra₂+Ra₃+Ra₄)−(Ra₁+Ra₄+Ra₇+Ra₈)
Sum of squares =
=(1.522+1.252+1.402+1.602)−(1.822+1.502+1.052+1.452)
= 0.0218
Mean squares = \( \frac{\text{Sum of squares}}{\text{D.O.F}} \)
= \( \frac{0.5493}{1} \)
Percentage of Contribution = \( \frac{\text{Mean square value}}{\text{Total mean square value}} \times 100 \)
= \( \frac{0.0218}{5493} \times 100 \) = 0.5493

A. Pie chart

Analyzing the pie diagram it can be observed that cutting velocity, federate, nose radius has great influence on surface roughness. Compared to above influence of the other factors observed negligible.

B. Linear programming

Linear programming is a mathematical technique to optimize performance of an organization controlled by a set of constraints. Performance involves profit or cost. Constraints are machine hours, man-hours, money, materials. etc. Linear Programming normally consists of :-
1. Objective function
2. Set of constraints
3. Non-negative restrictions

Objective function is an expression representing total profit or cost of a set of activities carried out at different levels. The objective function will be either a maximization type or minimization type. The benefit-related objective function will come under maximization type while the cost-related function will come under the minimization type. A set of constraints is a kind of restriction on the total amount of a particular resource required to carry out the activities at various levels. Each and every decision variable in the linear programming problem is a non-negative variable. Each of these three components consists of one or of the following:
- 1. Decision variable
- 2. Objective function coefficients
- 3. Technological coefficients
- 4. Availability of resources

A decision variable is used to represent the level of achievement of a particular course of action. Objective function coefficient is a constant representing a profit per unit or cost per unit of an activity. Technological coefficient is the amount of resource required for the activity. Resource availability is the amount of resource available during the planning period. One method of solving linear programming problems is by using matrix inversion.

C. Observed Readings

<table>
<thead>
<tr>
<th>Cutting speed (m/min)</th>
<th>Feed (mm/rev)</th>
<th>Depth of cut (mm)</th>
<th>Nose radius (mm)</th>
<th>Hardness (BHN)</th>
<th>Roughness (µm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>30.144</td>
<td>0.275</td>
<td>1.2</td>
<td>0.4</td>
<td>160</td>
<td>1.52</td>
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<tr>
<td>28.165</td>
<td>0.161</td>
<td>1.2</td>
<td>0.4</td>
<td>160</td>
<td>1.82</td>
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<tr>
<td>25.716</td>
<td>0.121</td>
<td>1.2</td>
<td>0.6</td>
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<tr>
<td>25.12</td>
<td>0.110</td>
<td>1.2</td>
<td>0.7</td>
<td>170</td>
<td>0.95</td>
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<tr>
<td>21.838</td>
<td>0.107</td>
<td>1.2</td>
<td>1</td>
<td>170</td>
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<td>28.574</td>
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<td>160</td>
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<td>25.12</td>
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<td>0.6</td>
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<td>22.451</td>
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<td>170</td>
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<td>28.982</td>
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</tr>
<tr>
<td>27.349</td>
<td>0.121</td>
<td>0.8</td>
<td>0.8</td>
<td>170</td>
<td>1.54</td>
</tr>
<tr>
<td>25.716</td>
<td>0.112</td>
<td>0.8</td>
<td>1</td>
<td>160</td>
<td>1.68</td>
</tr>
<tr>
<td>23.879</td>
<td>0.112</td>
<td>0.8</td>
<td>0.8</td>
<td>160</td>
<td>1.70</td>
</tr>
</tbody>
</table>

Table 5 Observation

Fifteen values of surface roughness for H.S.S were measured by using perthometer and plotted in Table 4.5. By using matrix inversion method the equation, 

\[ R_a = K \times v \times f \times d \times H \times r \]

is solved.

After solving, 5005 combination values of x, y, z, p, q, K are obtained. From these values the lowest values are taken. To find the mean square error value of the Ra values and from these set of readings the values with minimum mean square error values is taken as the final solution.

\[ Ra = \text{Surface roughness value (} \mu \text{m)} \]
\[ v = \text{Cutting speed (m/minus)} \]
\[ f = \text{Feed rate (mm/rev)} \]
\[ d = \text{Depth of cut (mm)} \]
\[ r = \text{Nose radius (mm)} \]
\[ H = \text{Hardness (BHN)} \]
\[ K, x, y, z, x, y = \text{Constants} \]
V. RESEARCH METHODOLOGY

A. PSO algorithm

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 pbest. 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 lbest. When a particle takes all the population as its topological neighbors, the best value is a global best and is called gbest. The PSO [Wen –Jye Shyr] concept consists of, at each step, changing the velocity of (accelerating) each particle towards its pbest and lbest locations (local versions of PSO). Acceleration is weighted by a random term, with separate random numbers being generated for acceleration towards pbest and lbest locations. The steps involved in PSO are outlined as follows which is taken from reference [LIU Yi-jian et al].

Phase I - Initialization

1. The particle positions are randomly generated in solution space. This provides a set of values to begin the iteration.
   \[ x_i^k = x_{min} + [x_{max} - x_{min}] \times \text{rand}( ) \]  
   ...(1) 
2. The velocity vectors are randomly generated for each particle in solution space.
   \[ v_i^k = \left( x_{min} + [x_{max} - x_{min}] \times \text{rand}( ) \right) / \Delta t \]  
   ...(2)

For each swarm movement (iteration), each particle (agent) matches the velocity of its nearest neighbor. Random changes in velocities are added in each iteration to provide variation in motion and “life-like” appearance.

Phase II

1. The fitness of the particle is evaluated.
2. In every iteration, each particle is updated by following two "best" values.
   a) Best solution (fitness) it has achieved so far (pbest).
   b) The best value, obtained so far by any particle in the population (gbest). When a particle takes part of the population as its topological neighbors, the best value is a local best (lbest).

3. After finding the two best values, the particle updates it’s velocity and positions.
   \[ v_{i+1} = w \times v_i + c_1 \times \text{rand}( ) \times ( p_i - x_i ) + c_2 \times \text{rand}( ) \times ( g_i - x_i ) \]  
   ...(3)
   \[ x_{i+1} = x_i + v_{i+1} \times \Delta t \]  
   ...(4)

Fig 2 Updating particle positions

RESULTS

From the above experiment conduct, it is evident that feed rate and cutting velocity have maximum effect on surface finish. The other factors have negligible effect on surface finish. We have compared the results by using matrix inverse method and PSO technique for getting optimum result. Future study can be conducted by using different material and different cutting tools. This can be very helpful by cutting costly material like titanium, zirconium etc.

<table>
<thead>
<tr>
<th>x</th>
<th>y</th>
<th>z</th>
<th>p</th>
<th>q</th>
</tr>
</thead>
<tbody>
<tr>
<td>5231909.37</td>
<td>0.15271</td>
<td>0.45881</td>
<td>0.01584</td>
<td>3.22129</td>
</tr>
</tbody>
</table>

The mse value obtained is 0.067
2. Flow chart

Initialize population with random particles (\(X\)) and Velocity Vector (\(V\))

For each particle

Evaluate fitness of the particles

If fitness (\(X\)) > fitness (gbest) \(X\)= gbest

If fitness (\(X\)) > fitness (pbest ) \(X\)=pbest

Check for termination criteria

Parameters of the best solution= gbest

Update each particle using Eqn.(4)

Update velocity vector using Eqn. (3)

VI. PSEUDO CODE FOR THE ALGORITHM

For each particle

{ Initialize particle
  } END
Do
{ For each particle
  Calculate fitness value (If the fitness value is better than the best fitness value (pBest) in history set current value as the new pBest)
  } END
(Choose the particle with the best fitness value of all the particles as the gBest)
For each particle

{ Update particle position & velocity
  } END
(While maximum iterations or minimum error criteria is attained)

1. Optimization Of Machining Operations

The independent variables for optimal cutting parameters have been identified as the following.
1. Tool diameter and length
2. Number of passes
3. Depth of cut (radial & axial) for each pass
4. Spindle speed and
5. Feed (per tooth, per revolution or per unit time)

Most studies state one of three objectives:-
1. Minimum manufacturing cost.
2. Maximum production rate.
3. A variant of maximum productivity

It has also been realized that a combination of the minimum production cost and minimum production time is the most effective objective since neglecting either requirement alone does not do justice to the problem at hand.

A comprehensive list of constraints:-
1. Available feed and speeds (machine tool related), power, arbor rigidity, and arbor deflection.
2. Maximum available machine power and maximum permitted cutting edge load for roughing, and allowed maximum tool deflection for finishing.
3. Tool normal and tangential deflection limits.
4. Machine tool limiting power, spindle torque, maximum feed force, spindle speed boundaries, and feed per tooth boundaries.
5. Avoid excess cutting force and chatter vibration.

2. Programming in MATLAB

Whilst there exist many good public-domain genetic algorithm packages, such as GENESYS and GENITOR, none of these provide an environment that is immediately compatible with existing tools in the control domain. The MATLAB Genetic Algorithm Toolbox aims to make GAs accessible to the control engineering. This allows the retention of existing modelling and simulation tools for building objective functions and allows the user to make direct comparisons between genetic methods and traditional procedures.

- **Simple Genetic Algorithm**

{ Initialize population;
  Evaluate population;
  While Termination Criteria Not Satisfied
  { Select parents for reproduction;
    Perform recombination and mutation;
    Evaluate population;
  }
}

Using PSO codes we have created in a program in matlab and direct solution is obtained. the program shown in the appendix
• Results obtained
Value of $K = 191122550$
$X = 0.432456$
$Y = -0.149431$
$Z = -0.194431$
$p = -0.009520$
$q = -4$
Mean square error value = 0.056927

Empirical model, $R = K \times v \times f \times d \times H \times r$
Empirical model by GA =
$191122550 \times 0.432456 \times (-0.149431) \times (-0.009520) \times (-4)$

Checking. Selecting, $V = 30.615\text{m/min}$, $f = 0.117\text{mm/rev}$,$d=1.2\text{mm}$, nose radius $=0.6\text{mm}$,$H=160$
Value from genetic algorithm model = 1.58\text{μm}$
Actual experiment = 0.875\text{μm}$

<table>
<thead>
<tr>
<th>PSO</th>
<th>Matrix inverse method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean square error value = 0.056927</td>
<td>Mean square error value = 0.067</td>
</tr>
</tbody>
</table>

Table 6 for comparison of mean square error value

We have found out mean square value using matrix inverse method and compared with mean square value found out by PSO method. It clearly shows that there is no significance difference between the values.

VII. CONCLUSION
For solving machining optimization problems, various conventional techniques had been used so far, but they are not robust and have problems when applied to the turning process, which involves a number of variables and constraints. To overcome the above problems, particle swarm optimization is used in this work. Particle swarm optimization converges to the global optimal solution faster. The PSO technique was found to converge to optimum in a faster rate. PSO is a generalized technique and can be easily modified. The method requires only primitive mathematical operators, so is computationally inexpensive in terms of both memory requirements and speed. Taguchi's parameter design offers a systematic approach and can reduce number experiment to optimize design for performance, quality and cost. From the taguchi experiment it is evident that the feed rate (36.17%) and cutting velocity (31.85%) have maximum effect on the surface finish.

By Taguchi method, one can observe that the cutting velocity, feed rate &nose radius have great influence on surface roughness. The interactions of depth of cut/feed rate and cutting velocity/depth of cut have negligible influence. But the factor depths of cut and Hardness have present less significant contribution on the surface roughness. The constants obtained by solving the equations by PSO method differ but almost the same MSE is obtained.

REFERENCES