OPTIMIZATION OF PARAMETERS FOR MATERIAL REMOVAL RATE USING QUALITY ENGINEERING TECHNIQUES

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Abstract: One of the major problems in industries is to cut down the manufacturing cost without sacrificing the quality of the components. As a consequence of this, modern sophisticated machine tools need optimization procedure for the selection of operating parameters such as the cutting speed, feed rate, depth of cut, and nose radius. In the present study Aluminum Alloy 6351- T6 Material is used and various parameters are analyzed for maximum value of material removal rate.

***IndexTerms* – Quality Engineering Techniques, MRR, Aluminum Alloy**

I. INTRODUCTION

Proper selection of the cutting tools, parameters, and conditions for the maximum MRR requires a more methodical approach by using the experimental methods and mathematical and statistical models. Not only does this require a considerable knowledge and the experience to design experiments and analyze the data but also traditional techniques require a large number of samples to be produced. Therefore, a more efficient method is needed to effectively optimize the cutting parameters.

Process modeling and the optimization are the two important issues in manufacturing products. The manufacturing processes are characterized by a multiplicity of dynamically interacting process variables. The predictive modeling of machining operations requires detailed prediction of the boundary conditions for stable machining. Optimizations of the machining parameters not only increase the utility for machining economics but also the product quality increases to a great extent. Tool wear and MRR in turning has been found to be influenced in varying amounts by a number of factors such as the 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.

Box, G. E. P. et al [1951] work is the result of a study extending over the past few years by a chemist and a statistician. Development has come about mainly in answer to problems of determining optimum conditions in chemical investigations, but we believe that the methods will be of value in other fields where experimentation is sequential and the error fairly small.

Derringer et al [1980] described the problem faced by the product development community. The problem was the selection of a set of conditions which will result in a product with a desirable combination of properties. This essentially was a problem involving the simultaneous optimization of several response variables (the desirable combination of properties) which depend upon a number of independent variables or sets of conditions. Harrington, among others, has addressed this problem and has presented a desirability function approach. This study modified this approach and illustrated how several response variables can be transformed into a desirability function, which could be optimized by univariate techniques. Its usage illustrated in the development of a rubber compound for tire treads

Yang et al [1998] In this study, the Taguchi method, a powerful tool to design optimization for quality, is used to find the optimal cutting parameters for turning operations. An orthogonal array, the signal-to-noise (S/N) ratio, and the analysis of variance (ANOVA) are employed to investigate the cutting characteristics of S45C steel bars using tungsten carbide cutting tools. Through this study, not only can the optimal cutting parameters for turning operations be obtained, but also the main cutting parameters that affect the cutting performance in turning operations can be found. Experimental results are provided to confirm the effectiveness of this approach.

Azouzi, R et al [1998] presented a feedback neuro control scheme that used an inverse turning process model to synthesize optimal process inputs. The inverse process neuro controller was implemented in a multilayer feed forward neural network. On-line adjustments of feed rate and cutting speed parameters were carried out based on a cost/quality performance index, estimated from force and vibration sensor measurements. Both non-adaptive and adaptive neurocontrol schemes were considered. The simulations and experimental investigations presented herein demonstrated the effectiveness of neural networks for controlling and optimizing turning operations. Applied to single point turning of a typical finishing cut, the final dimensions and surface finishes were found to be better by 40 and 80 percent respectively, while productivity was increased by 40 percent over the conditions proposed in machining data handbooks. This approach is also applicable to several other manufacturing processes.

Liao et al [1998] showed that a manufacturing process can be modeled (learned) using Multi-Layer Perceptron (MLP) neural network and then optimized directly using the learned network. This research extended the previous work by examining several different MLP training algorithms for manufacturing process modeling and three methods for process optimization. The transformation method was used to convert a constrained objective function into an unconstrained one, which was then used as the error function in the process optimization stage. The simulation results indicated that: (i) the conjugate gradient algorithms with backtracking line search outperform the standard BP algorithm in convergence speed; (ii) the neural network approaches could yield more accurate process models than the regression method; (iii) the BP with simulated annealing method is the most reliable optimization method to generate the best optimal solution, and (iv) process optimization directly performed on the neural network is possible but cannot be especially automated totally, especially when the process concerned is a mixed integer problem.

Bali J et al [2002] showed how with the help of Artificial Neural Network (ANN), the prediction of milling tool-path strategy could be made in order to establish which milling path strategy or their sequence will show the best results (will be the most appropriate) at free surface machining, according to set technological aim. In our case the best possible surface quality of machined surface was taken as the primary technological aim. Configuration of used Neural Network (NN) was presented, and the whole procedure is shown on an example of mould, for producing light switches. The verification of machined surface quality, according to average mean roughness, R_a, was also being done, and compared with the NN predicted results

Balic J[2006] contributed to more intelligent systems in production environment and used genetic based methods to solve problems

JozeBalic et al (2006) introduced an Intelligent Programming of CNC turning operations using genetic algorithm. CAD/CAM systems are nowadays tightly connected to ensure that CAD data can be used for optimal tool path determination and generation of CNC programs for machine tools. The aim of our research is the design of a computer-aided, intelligent and genetic algorithm (GA) based programming system for CNC cutting tools selection, tool sequences planning and optimization of cutting conditions. The first step is geometrical feature recognition and classification. On the basis of recognized features the module for GA-based determination of technological data determine cutting tools, cutting parameters (according to work piece material and cutting tool material) and detailed tool sequence planning. Material, which will be removed, is split into several cuts, each consisting of a number of basic tool movements. In the next step, GA operations such as reproduction, crossover and mutation are applied. The process of GA-based optimization runs in cycles in which new generations of individuals are created with increased average fitness of a population. During the evaluation of calculated results (generated NC programme)several rules and constraints like rapid and cutting tool movement, collision, clamping and minimum machining time, which represent the fitness function, were taken into account.

A case study was made for the turning operation of a rotational part. The results show that the GA-based programming has a higher efficiency. The total machining time was reduced by 16%. The demand for a high skilled worker on CAD/CAM systems and CNC machine tools was also reduced.

Escamilla et al (2008) presented a Development and application of an Intelligent System to predict and optimize the surface roughness of Aluminum 6061 and Aluminum 6351 T10. The aim of this research is to present a new methodology for predicting and optimizing the surface roughness during machining of 1018 and 4140 Steel.

There is particular interest in finding the best machining value parameters that should be used to achieve good surface roughness. These parameter values can be found by this neural intelligent approach. This methodology analyzes and identifies the parameters involved in the machining process; with this information the model is able to predict the surface roughness value in different conditions and then optimize the results with different intelligent euristics. The experimental results show that we may conclude that this intelligent system is a suitable methodology for predicting and optimizing surface roughness during the machining of Aluminum 6061 and Aluminum 6351 T10.

Radhakrishnan Ramanujam et al (2011) developed an Optimization of Cutting Parameters for Turning Al-SiC(10p) MMC Using ANOVA and Grey Relational Analysis.

This paper presents the detailed experimental investigation on turning Aluminum Silicon Carbide particulate Metal Matrix Composite (Al-SiC –MMC) using polycrystalline diamond (PCD) 1600 grade insert. Experiments were carried out on medium duty lathe. A plan of experiments, based on the techniques of Taguchi, was performed. Analysis of variance (ANOVA) is used to investigate the machining characteristics of MMC (A356/10/SiCP). The objective was to establish a correlation between cutting speed, feed and depth of cut to the specific power and surface finish on the work piece. The optimum machining parameters were obtained by Grey relational analysis. Finally, confirmation test was performed to make a comparison between the experimental results and developed model and also tool wear analysis is studied.

Akdemir et al (2012) carried out the study with the aims to identify the function of different cutting parameters affecting machinability of austempered ductile iron and to quantify its effects. Turning was performed to test machinability according to the ISO3685-1993 (E) standard. The cutting force signals along three directions were measured in real time, whereas flank wear and surface roughness were measured offline. For the cutting parameters, the cutting speed and depth of cut were varied, but the feed rate was kept constant. In the flank wear tests, machining length was corresponded to tool life. In addition, in order to find out the effect of cutting parameters on surface roughness (Ra), tangential force (Ft), and flank wear (VB) during turning, RSM was utilized by using experimental data. The effect of the depth of cut on the surface roughness was negligible but considerable in the cutting forces. The increased cutting speed produced a positive effect on surface roughness. It is found that the cutting speed was the dominant factor on the surface roughness, tangential force, and flank wear.

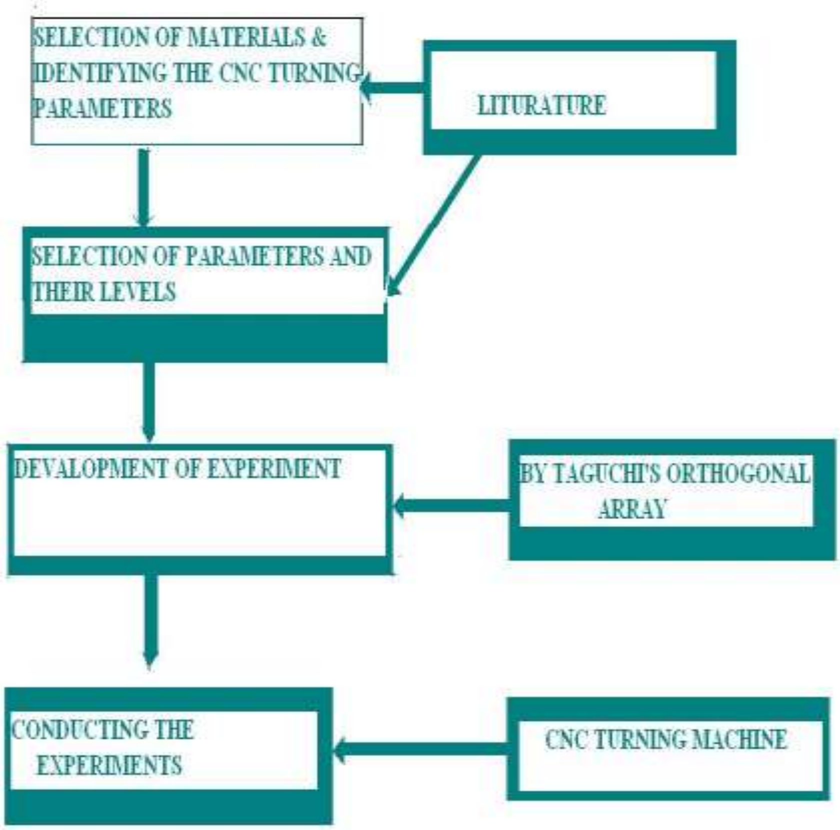
II. OBJECTIVES

The Objectives are as follows

1. Analyzing the different effects of parameters on the material removal rate
2. Using Taguchi's approach and ANOVA to determine the optimum parameters and most influencing parameters.
3. Mathematical Model development

III. METHODOLOGY

The following flowchart shows the complete methodology



IV. RESULTS AND DISCUSSION

For Material Removal Rate

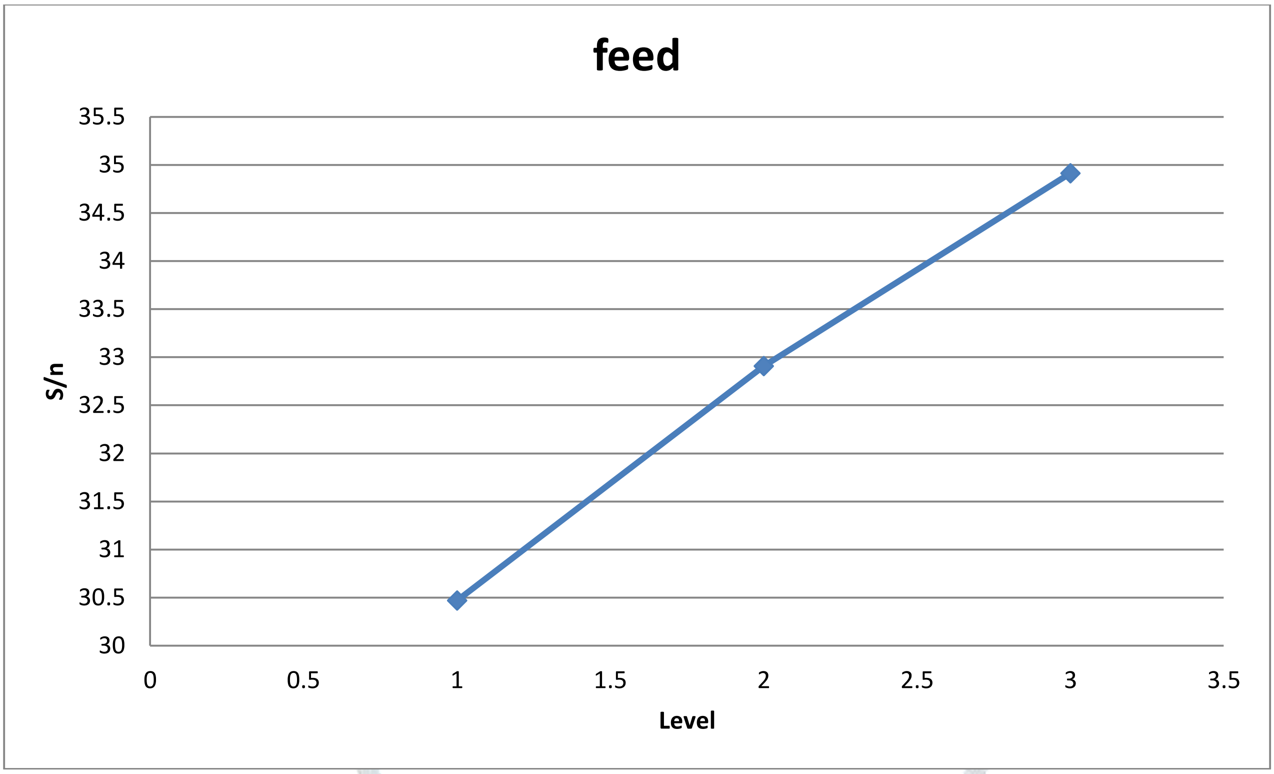

feed
35.5
35
34.5
34
33.5
33
32.5
32
31.5
31
30.5
30
S/n
0
0.5
1
1.5
2
2.5
3
3.5
Level

Fig 4.1

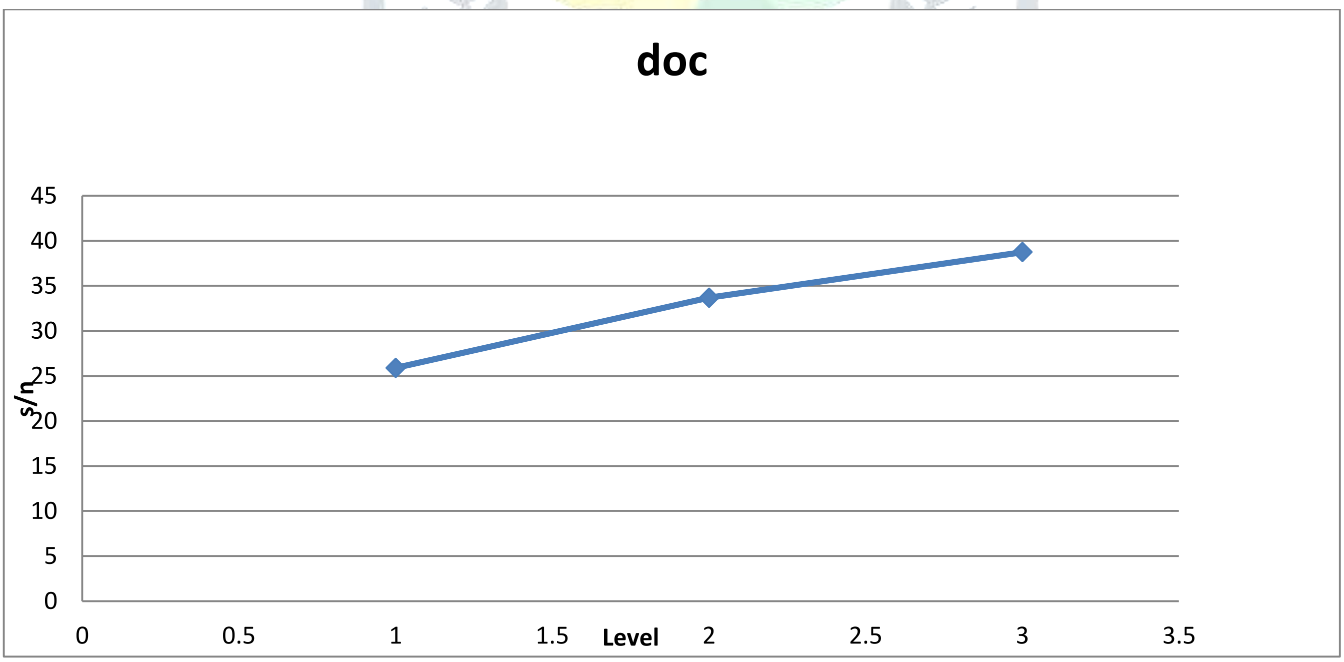

doc
45
40
35
30
25
20
15
10
5
0
s/n
0
0.5
1
1.5
Level
2
2.5
3
3.5

Fig 4.2

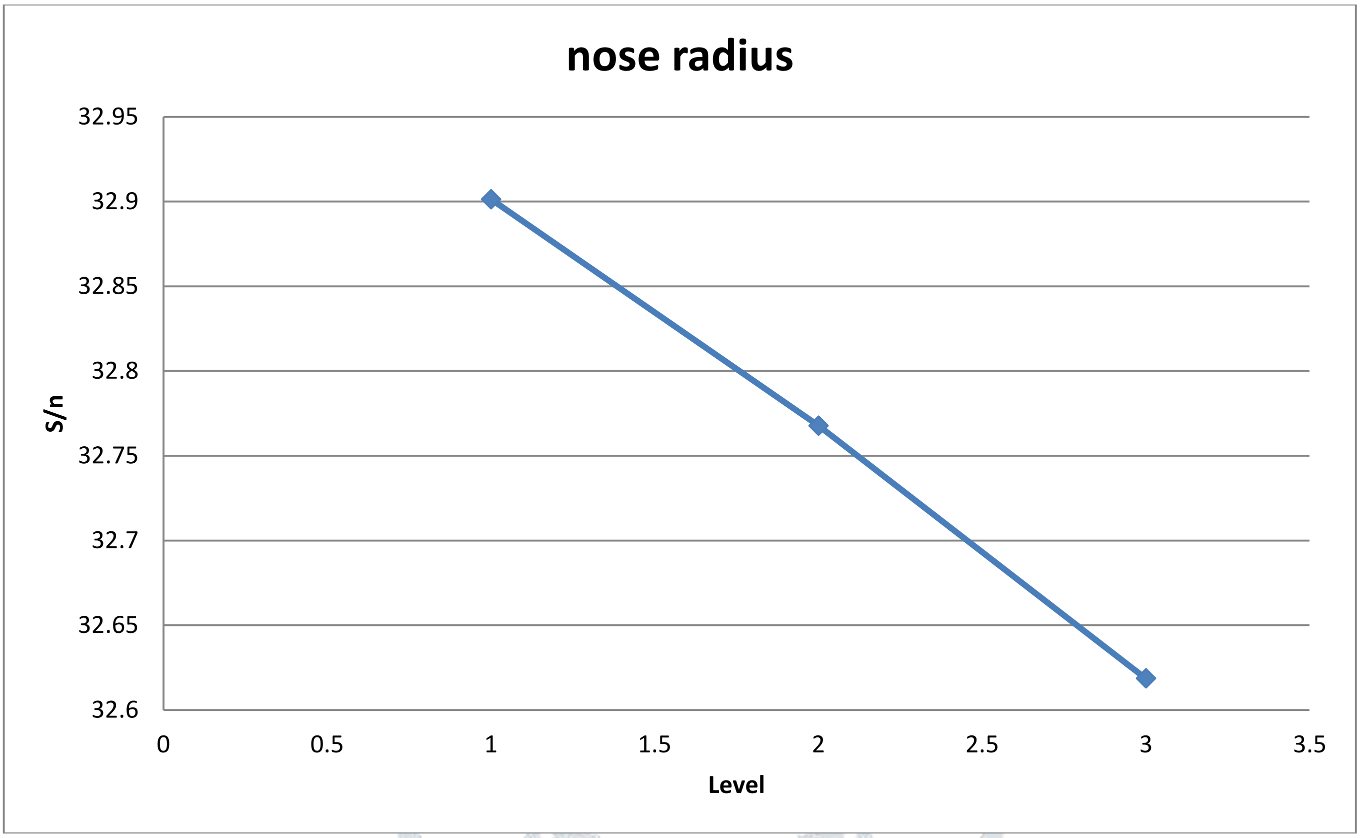

nose radius
S/n
32.95
32.9
32.85
32.8
32.75
32.7
32.65
32.6
0
0.5
1
1.5
2
2.5
3
3.5
Level

Fig 4.3


speed
S/n
35.5
35
34.5
34
33.5
33
32.5
32
31.5
31
30.5
30
0
1
2
3
Level

Fig 4.4

Using Microsoft Excel software package Result plots 4.1 to 4.4 are developed. To find the effective parameters affecting the material removal rate the above results are analyzed using ANOVA.
Based on ANOVA table, the optimal machining parameters for Al 6351- T6 for Material Removal Rate are: (based on study of graph)-

a) Cutting Speed at level 3 – 750 rpm

b) Feed at level 3 – 0.25 mm/min

c) Depth of Cut at level 1 – 0.2 mm

d) Nose Radius at level 3 – 1.2 mm

V. CONCLUSION

Based on experimental results, following conclusions are reached:

1. For material removal rate Depth of cut, Feed and Spindle Speed are significant parameters
2. Also it is found that the depth of cut is most significant parameter for Material Removal rate
3. Depth of Cut (80.90%), followed by Feed (9.58%) and Spindle Speed (9.48%) is contributing to Material Removal Rate.

VI. ACKNOWLEDGMENT

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