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Optimization of Surface Roughness Using Quality Engineering Techniques

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Abstract: Predicting surface roughness value before machining parts on a CNC lathe is very important. Improving quality and reducing cost, is possible by choosing optimum cutting parameters, using predictive models not by trial and error method. Surface roughness is an important measure of product quality since it greatly influences the performance of the mechanical parts as well as the production cost optimization of machining parameters not only increases the utility for machining economics, but also the product quality increases to a great extent. The study is focused on applicability of CNC turning machine to perform operation on Aluminum Alloy 6351- T6 Material, which is having various advantages and applications. The study has resulted in arriving at factor level combinations corresponding to minimum value of surface roughness and maximum value of material removal rate.
***Keywords*: surface roughness, ANOVA, material removal rate, depth of cut, nose radius**.

I. INTRODUCTION

Turning is a machining process in which a cutting tool, typically a non-rotary tool bit, describes a helical tool path by moving more or less linearly while the work piece rotates. The tool's axes of movement may be literally a straight line, or they may be along some set of curves or angles, but they are essentially linear (in the nonmathematical sense). Usually the term "turning" is reserved for the generation of *external* surfaces by this cutting action, whereas this same essential cutting action when applied to *internal* surfaces (that is, holes, of one kind or another) is called "boring". Thus the phrase "turning and boring" categorizes the larger family of (essentially similar) processes. The cutting of faces on the work piece (that is, surfaces perpendicular to its rotating axis), whether with a turning or boring tool, is called "facing", and may be lumped into either category as a subset. Surface roughness is used to determine and evaluate the quality of a product, is one of the major quality attributes of an end-milled product. In order to obtain better surface roughness, the proper setting of cutting parameters is crucial before the process take place. This good-quality milled surface significantly improves fatigue strength, corrosion resistance, or creep life. Thus, it is necessary to know how to control the machining parameters to produce a fine surface quality for these parts. The control factors for the machining parameters are spindle speed, feed rate and depth of cut and the uncontrollable factors such as tool diameter, tool chip and tool wear. Wu (2004) also employed PCA and GRA to optimize multi-response process, but it was assumed that starting conditions of a process are known, which is unsuitable for designing new processes. Liao (2006) used weighted PCA on SNR data to include all principal components, by which he improved the application of PCA to multi-response problems. Wang and Tong (2005) used PCA and the grey relational analysis (GRA) to 123J Intell Manuf transforms several responses into a single measure in dynamic multi-response problem. Sivarao et al. (2007) optimized the surface roughness by CNC turning process by considering spindle speed, depth of cut, and feed rate as parameters, with three levels at each. The material used was Aluminum rod on which turning operation was performed, by using a carbide tool. The ANOVA method and Taguchi’s robust design method was used for determining most significant parameters on surface roughness and material removal rate (MRR), with the optimum level range. S. Thamizhmanii et al. (2007) optimized the surface roughness SCM 440 alloy steel. The purpose of this research paper was focused on the analysis of optimum cutting conditions to get lowest surface roughness in turning SCM 440 alloy steel by Taguchi method. Experiment was designed using Taguchi method and 18 experiments were designed by this process and experiments conducted. The results are analyzed using analysis of variance (ANOVA) method. Taguchi method has shown that the depth of cut has significant role to play in producing lower surface roughness followed by feed. The Cutting speed has lesser role on surface roughness from the tests. The vibrations of the machine tool, tool chattering are the other factors which may contribute poor surface roughness to the results and such factors ignored for analyses. The results obtained by this method will be useful to other researches for similar type of study and may be eye opening for further research on tool vibrations, cutting forces etc P. Venkateswara Rao et al. (2007) optimized the surface roughness of aluminum alloys by using CNC turning. An experimental investigation was conducted to determine the effects of cutting conditions and tool geometry on the surface roughness in the finish hard turning of the aluminum 6351. Mixed ceramic inserts made up of aluminum oxide and titanium carbo nitride (SNGA), having different nose radius and different effective rake angles, were used as the cutting tools. This study shows that the feed is the dominant factor determining the surface finish followed by nose radius and cutting velocity. Though, the effect of the effective rake angle on the surface finish is less, the interaction effects of nose radius and effective rake angle are considerably significant. Mathematical models for the surface roughness were developed by using the response surface methodology. D. R. Salgado et al. (2007) optimized the surface roughness of aluminium by CNC turning process.In this work, an in-process surface roughness estimation procedure, based on least-squares support vector machines, is proposed for turning processes. The cutting conditions (feed rate, cutting speed, and depth of cut), parameters of tool geometry (nose radius and nose angle), and features extracted from the vibration signals constitute the input information to the system. Experimental results show that the proposed system can predict surface roughness with high accuracy in a fast and reliable way. 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 heuristics. 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. Al-Refaie and Al-Tahat (2009) proposed a procedure for solving multi response problems by using benevolent formulation in data envelopment analysis (DEA), but they assumed that responses are uncorrelated ChinnasamyNatarajan et al. (2010) optimized the surface roughness of aluminum by CNC turning process. Surface roughness, an indicator of surface quality is one of the most-specified customer requirements in a machining process. For efficient use of machine tools, optimum cutting parameters (speed, feed, and depth of cut)are required. So it is necessary to find a suitable optimization method which can find optimum values of cutting parameters for minimizing surface roughness. The turning process parameter optimization is highly constrained and non-linear. In this work, machining process has been carried out on brass C26000 material in dry cutting condition in a CNC turning machine and surface roughness has been measured using surface roughness tester. To predict the surface roughness, an artificial neural network (ANN) model has been designed through feed forward back-propagation network using Mat lab (2009a) software for the data obtained. Comparison of the experimental data and ANN results show that there is no significant difference and ANN has been used confidently. The results obtained conclude that ANN is reliable and accurate for predicting the values. The actual Ra value has been obtained as 1.1999 µm and the corresponding predicted surface roughness value is 1.1859 µm, which implies greater accuracy. M. Seeman et al (2010) developed a Study on surface roughness optimization in machining of particulate aluminum metal matrix composite-response surface methodology approach. Metal matrixes composites (MMC) have become a leading material among composite materials, and in particular, particle reinforced aluminum MMCs have received considerable attention due to their excellent engineering properties. These materials are known as the difficult-to-machine materials because of the hardness and abrasive nature of reinforcement element-like silicon carbide particles (SiCp). In this study, an attempt has been made to model the mach inability evaluation through there response surface methodology in machining of homogenized20% SiC_p LM25 Al MMC manufactured through stir cast route. The combined effects of four machining parameters including cutting speed (s), feed rate (f), depth of cut (d), and machining time (t) on the basis of two performance characteristics of flank wear (VB_{max}) and surface roughness (Ra) were investigated. The contour plots were generated to study the effect of process parameters as well as their interactions. The process parameters are optimized using desirability-based approach response surface methodology. Tatjana V. Sibalija et al (2010) presented an integrated approach to optimize parameter design of multi-response processes based on Taguchi method and artificial intelligence. The Taguchi robust parameter design has been widely used over the past decade to solve many single response process parameter designs. However, the Taguchi method is unable to deal with multi-response problems that are of main interest today, owing to increasing complexity of manufacturing processes and products. Several recent studies have been conducted in order to solve this problem. But, they did not effectively treat situations where responses are correlated and situations in which control factors have continuous values. This study proposed an integrated model for experimental design of processes with multiple correlated responses, composed of three stages which use expert system, designed for selecting an inner and an outer orthogonal array, to design an actual experiment, use Taguchi's quality loss function to present relative significance of responses, and multivariate statistical methods to uncorrelated and synthesize responses into a single performance measure, use neural networks to construct the response function model and genetic algorithms to optimize parameter design. The effectiveness of the proposed model is illustrated with three examples. Results of analysis showed that the proposed approach could yield a better solution in terms of the optimal parameters setting that result in a higher process performance measure than the traditional experimental design. HarnusAkkus et al. (2011) optimized the surface roughness of aluminum alloy by CNC turning process. In this study, the average surface roughness values obtained when turning AISI 4140 grade tempered steel with a hardness of 51 HRC, were modeled using fuzzy logic, artificial neural networks (ANN) and multi-regression equations. Input variables consisted of cutting speed (V), feed rate (f) and depth of cut (a) while output variable was surface roughness (Ra). Fuzzy logic and ANN models were developed using Mat lab Toolbox. Variance analysis was conducted using MINITAB. The predicted values of mean squared errors (MSE) were employed to compare the three models. Results showed that the optimum predictive model is the fuzzy logic model. With small errors (e.g. MSE = 0.0173166), the model was considered sufficiently accurate. Rituparna Datta and Anima Majumder (2012) did a work on Optimization of Turning Process Parameters using Multi-objective Evolutionary algorithm. Machining parameters optimization is very crucial in any machining process. This research focuses on Multi objective Evolutionary Algorithm based optimization technique, to determine optimal cutting parameters (cutting speed, feed, and depth of cut) in turning operation. Two conflicting objectives (operation time and tool life) with three constraints, which depend on the turning parameters, are optimized using Genetic algorithm (GAs). The Pareto-optimal front of the bi-objective problem is obtained using non dominated Sorting Genetic Algorithm (NSGA-II). The extreme and intermediate points of Pareto optimal front is verified using real coded Genetic Algorithm (RGA) as well as ε–constraint method. The performance of NSGA-II is found to be more effective and efficient as compared to micro-GA. Innovization study carried out to correlate cutting parameters with the aforementioned objective functions. The effect of cutting speed is found more as compared to feed rate and depth of cut.

II. OBJECTIVES

A. Objectives

1) Studying the various effects of various CNC turning parameters on the surface roughness and MRR.
2) Performing Taguchi's method and ANOVA on multiple responses to determine the optimum parameters and most influencing parameters.
3) Development of a mathematical model and predicting the responses.

III. METHODOLOGY

A. Methodology to carry out the Present Work

The methodology adopted for the proposed work is as follows

1) Initial study to determine various controllable and uncontrollable parameters.
2) Selection of work material based on literature.
3) Selection of parameters, responses and their levels.
4) Selection of experimental layout using Taguchi' method.
5) Conduction of experiment.
6) Measurements of responses using standard equipments.
7) Analysis of data using statistical tool.

IV. RESULTS AND DISCUSSION

A. For Surface Roughness (R_a)

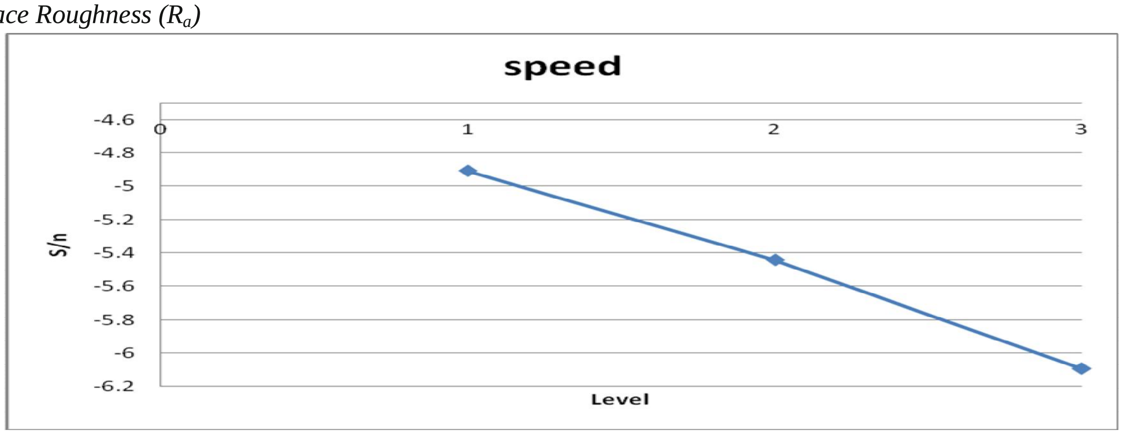

Fig 4.1

Fig 4.2

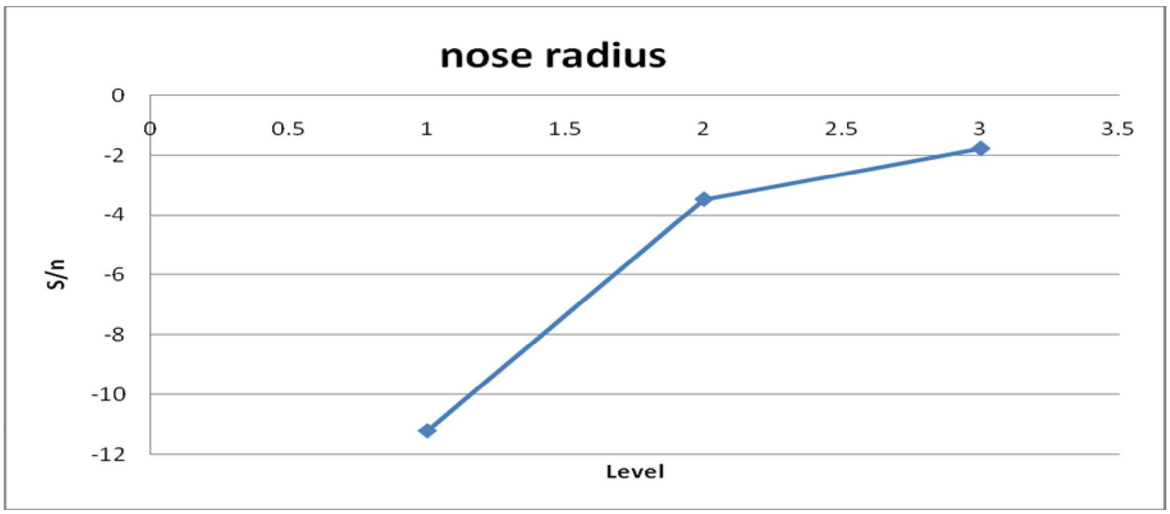

Fig 4.3

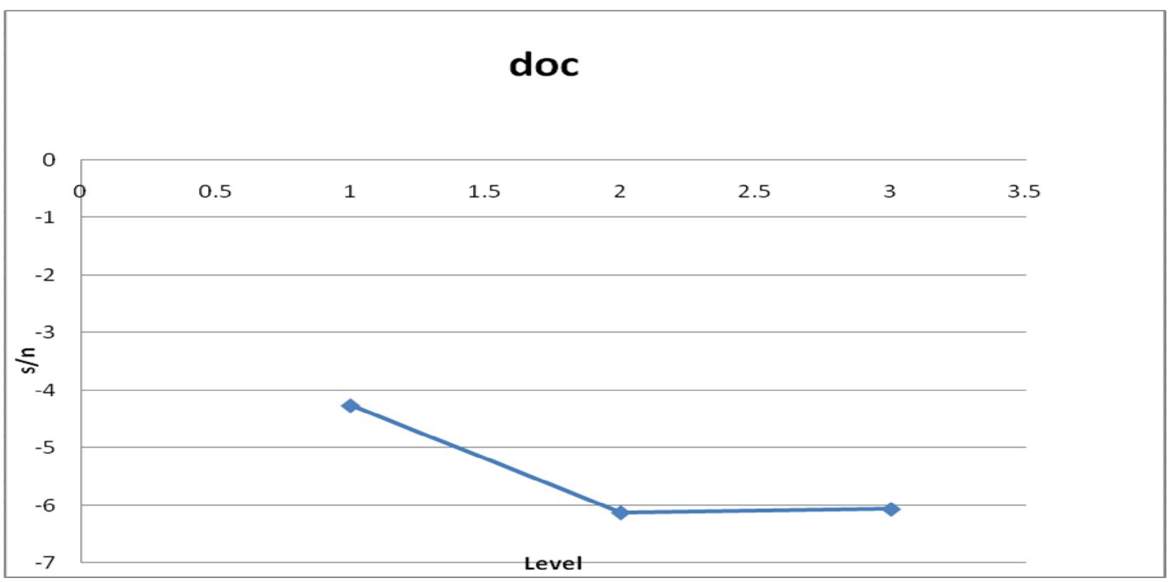

Fig 4.4

Result plots 4.1 to 4.4 are developed with the help of a software package Microsoft Excel. These results are analyzed using ANOVA for the purpose of identifying the significant parameters, which affects the surface roughness.

V. CONCLUSION

A. Based on experimental results, following conclusions are reached

1) From initial investigation for L9 array experiment, by ANOVA it is found that the Nose radius is the most significant parameter on surface roughness and then it is followed by feed rate and depth of cut.

2) Also it is found that the depth of cut is most significant parameter for Material Removal rate

3) Finally it is concluded that, the minimum Nose radius, depth of cut and feed rate with higher spindle speed will provide optimum surface quality and minimum depth of cut and higher feed rate and spindle speed leads to higher productivity.

VI. ACKNOWLEDGMENT

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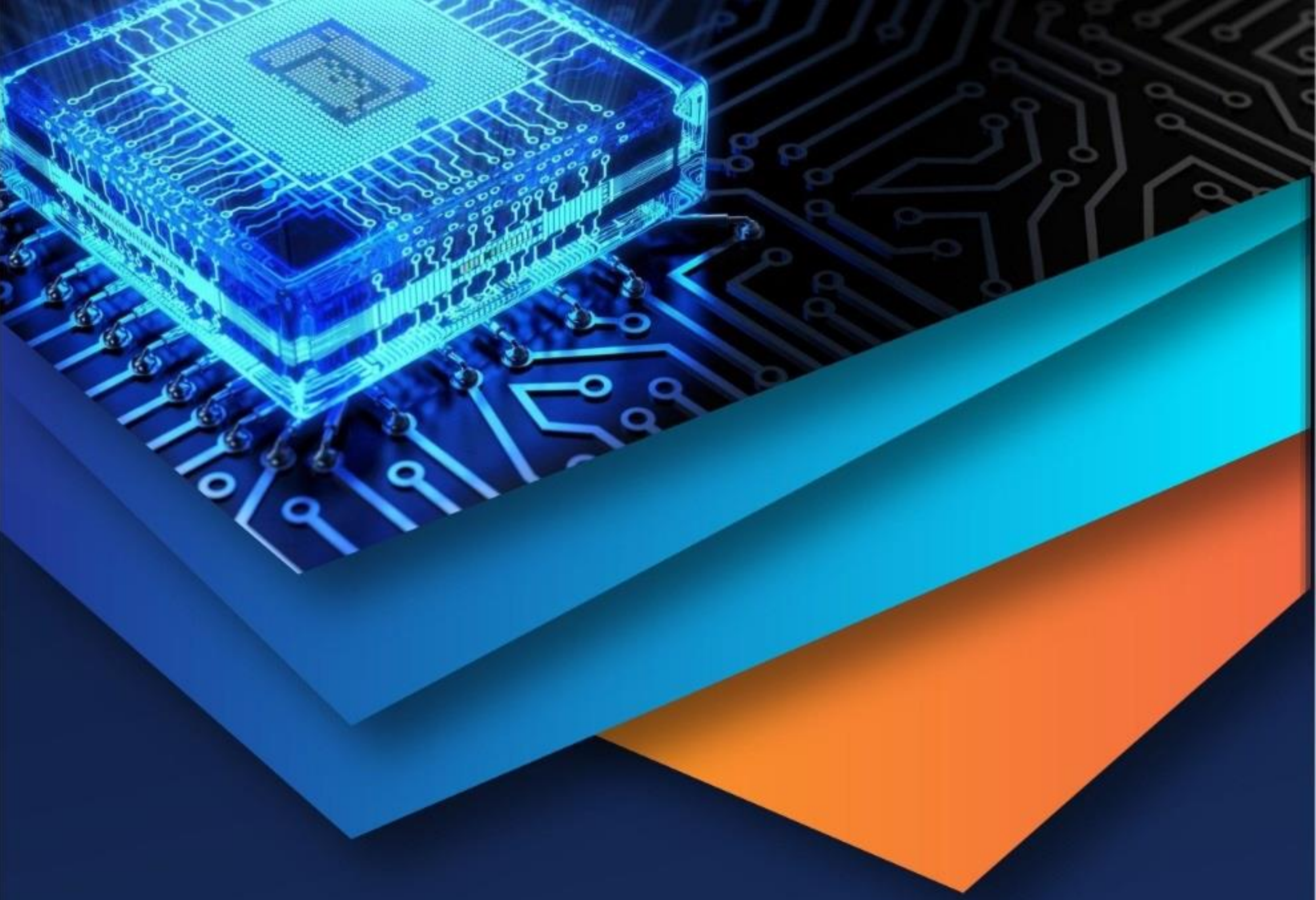

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