Optimization Technique For Surface Roughness Prediction in Turning Operation

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ABSTRACT

Surface roughness has a great influence on the functional properties of the product. Finding the rules that how process factors and environment factors affect the values of surface roughness will help to set the process parameters of the future and then improve production quality and efficiency. Since surface roughness is impacted by different machining parameters and the inherent uncertainties in the machining process, how to predict the surface roughness becomes a challengeable problem for the researchers and engineers. In this paper an attempt is made to review the literature on optimizing machining parameters in turning processes. Various conventional techniques employed for machining optimization include geometric programming, geometric plus linear programming, goal programming, sequential unconstrained minimization technique, dynamic programming etc. The latest techniques for optimization include fuzzy logic, scatter search technique, genetic algorithm, Taguchi technique and response surface methodology.

Keywords: *Machining optimization; Goal programming; Fuzzy logic; Genetic algorithms; Taguchi technique; response surface methodology*

1. INTRODUCTION

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 in process planning. Surface finish is the method of measuring the quality of a product and is an important parameter in machining process. It is one of the prime requirements of customers for machined parts. Productivity is also necessary to fulfill the customers demand. For this purpose quality of a product and productivity should be high. Even in the occurrence of chatter or vibrations of the machine tool, defects in the structure of the work material, wear of tool, or irregularities of chip formation contribute to the surface damage in practice during machining.

Turning is a material removal process, a subtractive form of machining which is used to create parts of circular or rotational form of desired geometry/shape by removing unwanted material. The essential elements of the turning process are machine or lathe, workpiece material which is a piece of a pre-shaped part, the fixture to which the material is attached. The

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fixture is secured to the turning machine and is then allowed to rotate for a wide range of speeds. The other end of the workpiece is hooked up with the tail stock to allow perfect rotation and avoid eccentric rotations.

Turning is usually opted as a secondary process; it is chosen in order to improve and refine the characteristics and features on parts made by using other processes. Turning is used to produce rotational, typically axi-symmetric, parts that have many features, such as holes, grooves, threads, tapers, various diameter steps, and even contoured surfaces. Parts completely made only on a turning machine are used as prototypes or parts with limited quantity, e.g. designed shafts and fasteners. The turning process offers very high tolerance and good surface roughness; hence, using it for improvements in the already existing part is recommended.

The accuracy of any process depends on involvement of operational variables. The operating parameters that contribute to the turning process are cutting feed (linear distance covered by the tool during one revolution of the workpiece), cutting speed (Speed of the workpiece surface relative to the edge of the cutting tool during a cut), spindle speed (the workpiece's revolution speed per minute), feed rate (linear velocity of the cutting tool with respect to the workpiece), depth of cut (depth of the tool tip with respect to the surface of the workpiece). Vibrations, tool wear, tool life, surface finish, and cutting forces, etc. are also in direct relation with values selected for process parameters. Hence, to improve the efficiency of the process and the quality of the product, it is necessary to control the process parameters.

So far in the industry the trend was such that the selection of the cutting parameters was carried out using previous records or experience. This may not be the most convenient way for the process to work efficiently as it may result in system failure, i.e. loss of tool life or insufficient surface roughness, which will add to the cost of production. Most researchers have shown a limited level of accuracy using either analytical or semi-empirical approaches. Even after considering the complicated nature of the process, researchers have been using a new technique, Artificial Neural Network (ANN) for simulation. In a short time this technique became the favorite since it offers simplicity, accuracy, and robustness.

The turning process is one of the oldest and most used processes in the industry. It has a wide range of applications. It is a material removal process. Once the process is complete there is no way that things can be reverted. The surface roughness of manufactured product is outcome of the turning process parameters, and an important characteristics that define product quality, aesthetics etc. Manufactured parts are often rejected, because of failure to comply with the surface quality requirements. Sometimes, if possible, rework or finishing cut can manage to reduce surface roughness and make part acceptable. There is not just one, but many factors responsible for resulting surface roughness e.g. feed, speed, depth of cut, cutting forces, tool geometry etc. As we know, the choice of cutting parameter values for turning process is mostly made on shop floor by the machinist from his previous experience or from material handbook. However, there is still possibility that the estimated outcome would not occur, as not all the factors can be manually controlled. Therefore, there is a need to use methodologies which will predict the outcomes for selection of corresponding cutting parameters. Optimum values of these cutting parameters is to be found out, so as to ensure the resultant surface roughness will be minimum.

2. LITERATURE SURVEY

There are various studies aimed at determining the relationship between surface roughness and cutting conditions. Wang has studied the effect of special cutting conditions for micro cutters on the formation of surface roughness by using a miniature bench and composing a mathematical model of these effects. Davim has studied the difference between processing conditions of turn bench and surface roughness formation of glass-fiber-reinforced and non-reinforced PA66 polyamide materials. In some studies, the processing of rough metals, such as cobalt alloy, and change in their cutting parameters are analyzed or optimized by using techniques such as the Taguchi method on the experimental results of Bagci, E et al. & Aykut, S et al. [1, 2]. The observation of surface roughness values by using optimization methods and predictions based on artificial mind techniques can be made. The Statistical Modeling of Surface Roughness in High-Speed Flat End Milling have designed a model based on the predictability of surface roughness value with statistical method [3]. While most formulas are developed by studying the relationship between the controlled cutting conditions that are created and surface roughness, in some conditions the shape of chip waste formed during treatment is observed as well as Effect of Coolant Strategy on Tool Performance, Chip Morphology and Surface Quality during High-Speed Machining of A356 Aluminum Alloy [4]. Generally in the metal cutting processes, cutting conditions, cutting tool geometry, cutting tool type, the usage or non-usage of coolant, the rigidity of work bench used, the cutting method used and the material type used all have effects on average surface roughness. Cutting parameters, i.e. feed rate, depth of cut, cutting speed, cutting edge and the number of cutting tool, also have effects on cutting under varying cutting conditions [5, 6]. Several modeling techniques of input–output and in-process parameter relationship using ANN sets offer a distribution-free alternative and have attracted the attention of manufacturing practitioners and researchers alike when they run into difficulties in building empirical models in metal cutting process control. These techniques can offer a cost effective alternative in the field of machine tool design and manufacturing approaches, and have thus received wide attention in recent years on optimization techniques in metal cutting processes, computers & industrial engineering [7].

A few applications of ANN-based input-output relationship modeling for metal cutting processes are reported in literature. The literature is rich with relevant investigations on choosing the best machining parameters for low surface roughness during different machining processes. Modeling and Optimization of Drilling Process used abductive network modeling for the drilling process to predict surface roughness [8]. Chien, W. T., Chou, C. Y., 2001. presented an ANN approach to predict the surface roughness of AISI 304 stainless steel, the cutting forces and the tool life [9]. Then the genetic algorithm was introduced to find the optimum cutting conditions for the maximum material removal rate under the constraints of the expected surface roughness. Risbood, K. A., et al. utilized a neural network to predict surface roughness and dimensional deviation based on the cutting forces and vibrations in turning of rolled steel bars containing about 0.35% carbon[10,11,12]. Topal, EY et al. discovered the role of the step-over ratio in surface roughness prediction studies in flat-end milling operations. Machining experiments were performed under various cutting conditions by using sample specimens. The surface roughness of these specimens was measured [13,14].

3. OBJECTIVE AND SCOPE OF THE PRESENT WORK

Several factors directly or indirectly influence output responses in turning. The objective of this research was to investigate the effects of major input parameters on the output in dry turning and to optimize the input parameters. Again from the literature review it is evident that though some research work was under taken into study the influence of machining input parameters on various output responses in machining of mild steel, still there exits some disparities which need to be studied with more detail. In multi-response optimization, it is very difficult to select the optimal setting which can achieve all quality requirements simultaneously. Otherwise optimizing one quality feature may lead severe quality loss to other quality characteristics which may not be accepted by the customers. In order to tackle such a multi-response optimization problem, the present study applied Taguchi method through a case study.

The objective of the present work is

1. To study the influence of cutting velocity, depth of cut, feed rate and surface roughness for a constant duration of machining for each run.
2. ANN (artificial neural network) approach to develop a prediction model prior to the implementation of the actual machining.

4. BRIEF OUTLINE ABOUT ANN

Artificial neural networks (ANNs) are one of the most powerful computer modeling techniques, currently being used in many fields of engineering for modeling complex relationships which are difficult to describe with physical models. ANN is one of the most widely used technique in the forecasting field. It has proven to be effective in modeling virtually any nonlinear function to an arbitrary degree of accuracy. The main advantage of this approach over traditional methods is that it does not require the complex nature of the underlying process under consideration to be explicitly described in mathematical form. This makes ANN an attractive tool for modeling. It is a Non linear predictive models that learn through training and resemble biological neural networks in structure [15,16,17]. ANNs were first developed in the 1940s when they were originally designed to mimic the functioning of the brain [18,19]. However, it has only been the last 20 or so years, since the development of new calibration techniques and the increase in computational power, that their popularity in various fields as predication tools has blossomed [20]. ANNs are mathematical models composed of a number of highly interconnected processing units called “nodes” or “neurons”, which, individually, carry out rather simple and limited computations. However, collectively as a network, complicated computations can be performed due to the connectively betweens the nodes and the way in which information is passed through and processed with in the network [17].

4.1 *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. Wu (1982) has reported that thousands of engineers have performed tens of thousands of experiments based on his teachings. Sullivan (1987) reports that Taguchi has received some of Japan’s most prestigious awards for quality achievement, including the Deming prize.

Sing and Kumar (2006) studied on optimization of feed force through setting of optimal value of process parameters namely speed, feed and depth of cut in turning of EN24 steel with TiC coated tungsten carbide inserts. The authors used Taguchi’s parameter design approach and concluded that the effect of depth of cut and feed in variation of feed force were affected more as compare to speed[21].

Thamizhmanii et al. (2007) applied Taguchi method for finding out the optimal value of surface roughness under optimum cutting condition in turning SCM 440 alloy steel. The work concluded that depth of cut was the only significant factor which contributed to the surface roughness[22].

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Wang and Lan (2008) used Orthogonal Array of Taguchi method coupled with grey relational analysis considering four parameters viz. speed, cutting depth, feed rate, tool nose run off etc. for optimizing three responses: surface roughness, tool wear and material removal rate in precision turning on an ECOCA-3807 CNC Lathe [23].

Sahoo et al. (2011) studied for optimization of machining parameters combinations emphasizing on fractal characteristics of surface profile generated in CNC turning operation. The authors used L27 Taguchi Orthogonal Array design with machining parameters: speed, feed and depth of cut on three different work piece materials viz. aluminum, mild steel and brass. It was concluded that feed rate was more significant influencing surface finish in all three materials[24].

Tsao and Hocheng (2008) highlighted the prediction and evaluation of thrust force and surface roughness in drilling of composite material using candle stick drill. The approach was based on Taguchi method and the artificial neural network. A correlation was established between the feed rate, spindle speed and drill diameter with the induced thrust force and surface roughness in drilling composite laminate.

Mohan et al. (2005) outlined the Taguchi optimization methodology, applied to optimize cutting parameters in drilling of glass fiber reinforced composite material. The drilling parameters and specimen parameters evaluated were speed, feed rate, and drill size and specimen thickness[25].

Julie Z.Zhang et al. (2006) determined optimum cutting parameters for face milling through the Taguchi parameter design method. From the experiment results showed that the effects of spindle speed and feed rate on surface roughness were larger than depth of cut for milling operations. In addition, one of the noise factors, tool wear was found to be statistically significant[26].

4.2 *Response surface methodology (RSM)*

Experimentation and making inferences are the twin features of general scientific methodology. Statistics as a scientific discipline is mainly designed to achieve these objectives. Planning of experiments is particularly very useful in deriving clear and accurate conclusions from the experimental observations, on the basis of which inferences can be made in the best possible manner. The methodology for making inferences has three main aspects. First, it establishes methods for drawing inferences from observations when these are not exact but subject to variation, because inferences are not exact but probabilistic in nature. Second, it specifies methods for collection of data appropriately, so that assumptions for the application of appropriate statistical methods to them are satisfied. Lastly, techniques for proper interpretation of results are devised.

Suresh et al. (2002) focused on machining mild steel by Tin-coated tungsten carbide (CNMG) cutting tools for developing a surface roughness prediction model by using Response Surface Methodology (RSM) [27].

Doniavi et al. (2009) used response surface methodology (RSM) in order to develop empirical model for the prediction of surface roughness by deciding the optimum cutting condition in turning. The analysis of variance was applied which showed that the influence of feed and speed were more in surface roughness than depth of cut [28].

Al-Ahmari (2007) developed empirical models for tool life, surface roughness and cutting force for turning operation. The process parameters used in the study were speed, feed, depth of cut and nose radius to develop the machinability model. The methods used for developing aforesaid models were Response Surface Methodology (RSM) and neural networks (NN) [29].

Mata et al. (2010) applied response surface methodology to predict the cutting forces in turning operations using TiN-coated cutting tools under dry conditions where the machining parameters were cutting speed ranges, feed rate, and depth of cut [30].

W. Wang et al. (2005) studied on the surface roughness of brass machined by micro-end-milling miniaturized machine tool. The cutting parameters considered were spindle speed, feed rate, depth of cut and tool diameter. They applied statistical methods, such as ANOVA and RSM to analyze the experiment data [31].

Babur Ozcelik and Mahmut Bayra moglu (2005) developed a statistical model by response surface methodology for predicting surface roughness in high-speed flat end milling process under wet cutting conditions by using machining variables such as spindle speed, feed rate, depth of cut and step over. They observed that, the order of significance of the main variables is as total machining time, of cut, step over, spindle speed and feed rate, respectively [32].

Hussain et al. (2010) developed a surface roughness prediction model for the machining of GFRP pipes using response surface methodology (RSM). The cutting parameters considered were cutting speed, feed, depth of cut, and work piece (fiber orientation). A second order mathematical model in terms of cutting parameters was developed using RSM [33].

5. CONCLUSIONS

A review of literature shows that various traditional machining optimization techniques like Lagrange's method, geometric programming, dynamic programming etc. have been successfully applied in the past for optimizing the various turning process variables. Fuzzy logic, genetic algorithm, Taguchi technique and response surface methodology are the latest optimization techniques that are being applied successfully in industrial applications for optimal selection of process variables in the area of machining. A review of literature on optimization techniques has revealed that there are, in particular, successful industrial applications of design of experiment-based approaches for optimal settings of process variables. Taguchi methods and response surface methodology are robust design techniques widely used in industries for making the product/process insensitive to any uncontrollable factors such as environmental variables.

Based on the literature review, the most parameters that widely considered when investigating the optimal surface roughness are feed rate, spindle speed and depth of cut. Most of the researches didn't consider the uncontrolled parameters, such as tool geometry, tool wear, chip loads, and chip formations, or the material properties of both tool and work-piece. However in the present work apart from the above parameters, axial depth of cut, radial depth of cut and inclination angle have also been considered.

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