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A Review on Surface Roughness Prediction Optimization Techniques

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Abstract: Surface roughness has a amazing affect on the purposeful residences of the product. Finding the guidelines that how manner factors and surroundings factors affect the values of floor roughness will assist to set the technique parameters of the future and then improve production satisfactory and performance. Since ground roughness is impacted via considered one of a kind machining parameters and the inherent uncertainties within the machining manner, the manner to are awaiting the floor roughness becomes a challengeable problem for the researchers and engineers. In this paper an attempt is made to test the literature on optimizing machining parameters in turning methods. Various conventional strategies employed for machining optimization encompass geometric programming, geometric plus linear programming, cause programming, sequential unconstrained minimization approach, dynamic programming and so on. The modern-day techniques for optimization encompass fuzzy accurate judgment, scatter are seeking method, genetic set of regulations, Taguchi method and response floor technique.

Keywords-- Machining optimization; goal programming; fuzzy logic; genetic algorithms; Taguchi technique; response surface methodology.

1. Introduction

Turning Operation is one of the most crucial and typically encountered material removal operations in manufacturing way. The floor roughness is one of the essential residences for evaluating the workpiece pleasant sooner or later of the cease milling technique. The floor roughness plays a fantastic element in fatigue electricity and corrosion resistance, floor friction, light reflection, capability of maintaining a lubricant, electric and thermal touch resistance, look, price, and many others. High high-quality of the floor after cease milling makes similarly machining of the floor now not important, which brings about reduced power intake and surroundings load. However, optimization of floor roughness is continually challenged by way of the use of its uncertainty of prediction model similarly to diverse influencing parameters, which may be divided into managed and non-managed parameters. Main parameters of the first kind includes spindle pace, feed charge, and intensity of lessen. And vibrations, tool wear, tool movement errors, and cloth non-homogeneity of every the device and art work piece, chip formation belong to the non-controlled parameters. The non-controlled reducing parameters are tough to reach and their interactions cannot be precisely decided. Surface roughness optimization is worried with developing green prediction version to decrease order of deviation. Successful implementation of machining method optimization requires development of fashions for prediction of ground roughness. The contemporary severa methods for predicting floor roughness are based totally totally on experimental investigation, designed experiment, Artificial Neural Network (ANNs) and Neuro-Fuzzy Systems(NFS). The first magnificence includes processes that examine the consequences of different factors through the execution of experiments and the analysis of the consequences. Regression assessment is often used to assemble fashions primarily based mostly on the experimental facts. This technique is specifically applied in cases wherein there may be no analytical device some of the various factors. The second class includes the strategies based totally on Response Surface Method (RSM), Taguchi's Design of Experiments (DoE) and modern-day advanced Artificial Intelligence (AI) techniques to are expecting floor roughness. The fundamental advantages of the ANNs and NFS consist of the capability of approximating almost any characteristic with out requiring the knowledge of the system and the capability to deal with noisy records. Recently, AI-primarily based fashions have emerged as a desired fashion and are observed through most researchers to broaden models for near maximum quality situations in machining, because of its fault-tolerant, approximated, uncertain and meta-heuristic. Although the ANNs and NFS can collect a immoderate accuracy in the prediction of ground roughness, their universal performance is restricted via way of implicit models and unknown inner legal guidelines. Construct of express prediction version that can obviously screen the inherent regulation of machining device would surely make a contribution to the excessive excellent of surface roughness.

2. Review of Traditional Methods

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 pioneering 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 machine-parameter optimization using differential calculus. Brewer & Rueda (1963) carried out simplified optimum analysis for non-ferrous materials. 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 to selection of machining variables. Petropoulos (1973) investigated optimal selection of machining rate variables, viz. cutting speed and feed rate, by geometric programming. Sundaram (1978) applied a goal-programming technique in metal cutting for selecting levels of machining parameters in a fine turning operation on AISI 4140 steel using cemented tungsten carbide tools. Ermer & Kromodiharajo (1981) developed a multi-step mathematical model to solve a constrained multi-pass machining problem. 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. Tsai (1986) studied the relationship between the multi-pass machining and single-pass machining. He presented the concept of a break-even point. 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. Prasad *et al* (1997) reported the development of an optimization module for determining process parameters for turning operations as part of a PC-based generative CAPP system.

3. Modern Techniques

The latest techniques for optimization include fuzzy logic, genetic algorithm, Taguchi technique and response surface methodology.

3.1 Artificial Neural Network

Considering the needs of a fast growing manufacturing industry, researchers came up with a new alternative to avoid deviation in prediction, a technique which operates far differently from traditional simulation techniques. This technique is Artificial Neural Network (ANN). It is a relatively new technology. It operates on a philosophy similar to that of biological nervous systems. This technique became famous quickly and has been applied throughout the industry for real world problem solving. It is one of the most popular nonlinear mapping systems in A.I. This technique is mainly used for two applications, classification and prediction. The neural network determines the pattern between input and output data by training. The ability of neural networks to solve complex and nonlinear problems makes them more suitable for simulation of the manufacturing process.

Lee and Chen (2003) highlighted on artificial neural networks using a sensing technique to monitor the effect of vibration produced by the motions of the cutting tool and work piece during the cutting process developed an on-line surface recognition system. Choudhury and Bartarya (2003) focused on design of experiments and the neural network for prediction of tool wear. The input parameters were cutting speed, feed and depth of cut; flank wear, surface finish and cutting zone temperature were selected as outputs. Chien and Tsai (2003) developed a model for the prediction of tool flank wear followed by an optimization model for the determination of optimal cutting conditions in machining 17-4PH stainless steel. The back-propagation neural network (BPN) was used to construct the predictive model.

Ozel and Karpat (2005) studied for prediction of surface roughness and tool flank wear by utilizing the neural network model in comparison with regression model.

Kohli and Dixit (2005) proposed a neural-network-based methodology with the acceleration of the radial vibration of the tool holder as feedback. For the surface roughness prediction in turning process the back-propagation algorithm was used for training the network model.

Pal and Chakraborty (2005) studied on development of a back propagation neural network model for prediction of surface roughness in turning operation and used mild steel work-pieces with high speed steel as the cutting tool for performing a large number of experiments.

Ozel and Karpat (2005) developed models based on feed forward neural networks in predicting accurately both surface roughness and tool flank wear in finish dry hard turning.

Abburi and Dixit (2006) developed a knowledge-based system for the prediction of surface roughness in turning process. Fuzzy set theory and neural networks were utilized for this purpose.

Zhong et al. (2006) predicted the surface roughness of turned surfaces using networks with seven inputs namely tool insert grade, work piece material, tool nose radius, rake angle, depth of cut, spindle rate, and feed rate.

Reddy et al. (2008) adopted multiple regression model and artificial neural network to deal with surface roughness prediction model for machining of aluminium alloys by CNC turning. For judging the efficiency and ability of the model in surface roughness prediction the authors used the percentage deviation and average percentage deviation.

Wang et al. (2008) studied on Hybrid Neural Network-based modeling approach integrated with an analytical tool wear model and an artificial neural network that was used to predict CBN tool flank wear in turning of hardened 52100 bearing steel.

Basheer et al. (2008) presented an experimental work on the analysis of machined surface quality on Al/SiCp composites leading to an artificial neural network-based (ANN) model to predict the surface roughness. The predicted roughness of machined surfaces based on the ANN model was found to be in very good agreement with the unexposed experimental data set.

3.2 *Neuro Fuzzy logic*

Fuzzy logic has great capability to capture human commonsense reasoning, decision-making and other aspects of human cognition. In the field of artificial intelligence, neuro-fuzzy refers to combinations of artificial neural networks and fuzzy logic. Neuro-fuzzy was proposed by J. S. R. Jang. Neuro-fuzzy hybridization results in a hybrid intelligent system that synergizes these two techniques by combining the human-like reasoning style of fuzzy systems with the learning and connectionist structure of neural networks.

The strength of neuro-fuzzy systems involves two contradictory requirements in fuzzy modeling: interpretability versus accuracy. In practice, one of the two properties prevails. Kosko (1997) shows that fuzzy logic 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. Modelling by fuzzy logic opens up a new way to optimize cutting conditions and also tool selection.

Klir & Yuan (1998) shows that fuzzy logic involves a fuzzy interference engine and a fuzzification-defuzzification module. Fuzzification expresses the input variables in the form of fuzzy membership values based on various membership functions. Governing rules in linguistic form, such as if cutting force is high and machining time is high, then tool wear is high, are formulated on the basis of experimental observations.

Palanikumar (2008) used fuzzy logic for modeling machining parameters in machining glass fiber reinforced plastics by polycrystalline diamond tool. An L27 orthogonal array was used to investigate the machining process with selected cutting parameters: cutting speed, feed, and depth of cut. The output responses considered for the investigation were surface roughness parameters such as arithmetic average height (Ra) and maximum height of the profile (Rt).

Singh et al. (2009) reported experimental work conducted using 8 Facet Solid Carbide drills based on L27 orthogonal array. The process parameters investigated were spindle speed, feed rate and drill diameter.

3.3 *Genetic algorithm (GA)*

Kumanan et al. [30] proposed the methodology for prediction of machining forces using multi-layered perceptron trained by genetic algorithm (GA). The optimal ANN weights were obtained using GA search. This function-replacing hybrid made of GA and ANN was found computationally efficient as well as accurate to predict the machining forces for the input machining conditions.

M. Brezocnik et al. (2004) proposed the genetic programming approach to predict surface roughness based on cutting parameters (spindle speed, feed rate and depth of cute) and on vibrations between cutting tool and workpiece. From their research, they conclude that the models that involve three cutting parameters and also vibrating, give the most accurate predictions of surface roughness by using genetic programming. In addition, feed rate has the greatest influence on surface roughness.

3.4 *Taguchi technique*

Genichi Taguchi is a Japanese engineer who has been lively inside the development of Japan’s commercial merchandise and strategies because the overdue 1940s. He has developed both the philosophy and technique for procedure or product excellent development that relies upon closely on statistical standards and equipment, particularly statistically designed experiments. Wu (1982) has mentioned that thousands of engineers have performed tens of thousands of experiments based on his teachings. Sullivan (1987) reviews that Taguchi has acquired a number of Japan’s most prestigious awards for great fulfillment, which includes the Deming prize.

Sing and Kumar (2006) studied on optimization of feed force through placing of most efficient value of system parameters namely pace, feed and intensity of cut in turning of EN24 metal

with TiC lined tungsten carbide inserts. The authors used Taguchi’s parameter layout method and concluded that the impact of intensity of reduce and feed in version of feed force were affected extra as examine to speed.

Thamizhmanii et al. (2007) applied Taguchi technique for finding out the top-rated price of floor roughness below most beneficial cutting situation in turning SCM 440 alloy metallic. The work concluded that intensity of cut become the most effective enormous thing which contributed to the surface roughness.

Wang and Lan (2008) used Orthogonal Array of Taguchi approach coupled with grey relational analysis thinking about 4 parameters viz. Velocity, slicing depth, feed price, tool nose run off and so forth. For optimizing 3 responses: surface roughness, device put on and cloth removal charge in precision turning on an ECOCA-3807 CNC Lathe.

Sahoo et al. (2007) studied for optimization of machining parameters mixtures emphasizing on fractal characteristics of surface profile generated in CNC turning operation. The authors used L27 Taguchi Orthogonal Array layout with machining parameters: speed, feed and depth of cut on three one-of-a-kind paintings piece substances viz. Aluminum, mild steel and brass. It become concluded that feed rate was greater sizeable influencing surface end in all 3 materials

Tsao and Hocheng (2008) highlighted the prediction and evaluation of thrust pressure and surface roughness in drilling of composite cloth the use of candle stick drill. The technique became based totally on Taguchi technique and the artificial neural network. A correlation was mounted among the feed rate, spindle speed and drill diameter with the caused thrust force and surface roughness in drilling composite laminate.

Mohan et al. (2005) outlined the Taguchi optimization technique, implemented to optimize slicing parameters in drilling of glass fiber strengthened composite material. The drilling parameters and specimen parameters evaluated have been speed, feed price, and drill length and specimen thickness.

Julie Z.Zhang et al. (2006) decided top of the line reducing parameters for face milling via the Taguchi parameter design approach. From the test results showed that the consequences of spindle speed and feed rate on surface roughness have been large than intensity of reduce for milling operations. In addition, one of the noise elements, device put on turned into discovered to be statistically significant.

3.5 *Response surface methodology (RSM)*

Experimentation and making inferences are the dual features of popular clinical methodology. Statistics as a scientific discipline is in particular designed to achieve these targets. Planning of experiments is in particular very beneficial in deriving clear and accurate conclusions from the experimental observations, on the idea of which inferences can be made in the nice feasible way. The technique for making inferences has three essential components. First, it establishes strategies for drawing inferences from observations while those are not actual but subject to variant, because inferences aren't genuine but probabilistic in nature. Second, it specifies methods for collection of statistics correctly, so that assumptions for the application of suitable statistical strategies to them are satisfied. Lastly, techniques for proper interpretation of outcomes are devised.

Suresh et al. (2002) focused on machining slight metal by Tin-coated tungsten carbide (CNMG) reducing equipment for growing a surface roughness prediction model by using Response Surface Methodology (RSM).

Doniavi et al. (2009) used response surface method (RSM) so as to expand empirical model for the prediction of surface roughness by determining the top of the line cutting condition in turning. The analysis of variance became implemented which showed that the have an impact on of feed and pace have been greater in surface roughness than intensity of reduce.

Al-Ahmari (2007) developed empirical models for device lifestyles, surface roughness and slicing pressure for turning operation. The system parameters used in the look at had been speed, feed, intensity of reduce and nostril radius to broaden the machinability model. The techniques used for developing aforesaid models were Response Surface Methodology (RSM) and neural networks (NN).

Mata et al. (2010) applied reaction surface methodology to are expecting the slicing forces in turning operations the usage of TiN-covered reducing gear below dry situations wherein the machining parameters were reducing velocity tiers, feed fee, and depth of reduce.

W. Wang et al. (2005) studied on the surface roughness of brass machined by using micro-cease-milling miniaturized gadget device. The cutting parameters considered were spindle velocity, feed rate, intensity of reduce and tool diameter. They implemented statistical strategies, along with ANOVA and RSM to analyze the test facts.

Babur Ozcelik and Mahmut Bayra moglu (2005) evolved a statistical version through reaction surface methodology for predicting floor roughness in high-velocity flat quit milling manner below moist reducing situations by way of the use of machining variables which include spindle speed, feed fee, intensity of cut and step over. They determined that, the order of significance of the primary variables is as overall machining time, of reduce, step over, spindle velocity and feed rate, respectively.

Hussain et al. (2010) evolved a surface roughness prediction version for the machining of GFRP pipes the use of reaction floor technique (RSM). The reducing parameters considered have been slicing velocity, feed, intensity of cut, and paintings piece (fiber orientation). A 2nd order mathematical model in terms of cutting parameters became developed the usage of RSM.

4. Conclusions

A overview of literature indicates that diverse conventional machining optimization strategies like Lagrange's technique, geometric programming, dynamic programming etc. Had been effectively applied inside the beyond for optimizing the diverse turning procedure variables. Fuzzy logic, genetic algorithm, Taguchi method and reaction floor methodology are the ultra-modern optimization strategies that are being applied effectively in commercial applications for superior selection of procedure variables inside the place of machining. A evaluation of literature on optimization strategies has revealed that there are, in particular, a hit industrial packages of design of experiment-primarily based tactics for greatest settings of system variables. Taguchi techniques and response surface technique are strong layout techniques broadly used in industries for making the product/procedure insensitive to any uncontrollable elements which includes environmental variables.

Based at the literature evaluate, the maximum parameters that broadly taken into consideration when investigating the most reliable floor roughness are feed charge, spindle pace and intensity of reduce. Most of the researches didn't recall the uncontrolled parameters, along with device geometry, device put on, chip masses, and chip formations, or the fabric residences of each tool and paintings-piece. However inside the gift paintings other than the above parameters, axial intensity of reduce, radial intensity of reduce and inclination attitude have also been taken into consideration.

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