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Surface Roughness Prediction using Empirical Modelling Techniques: - A Review

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Abstract

Optimization of process parameters for minimum surface, along with its prediction and monitoring has long been studied, for it is one of the important indices of machining quality. This study continues to attract several researchers as development of newer work materials, tool materials, machining process, and quest for improved product quality because of increased market competition never cease to end. All the different approaches have a common aim of determining the relationships between the input- machining parameters and output-surface roughness.The empirical-AI based methods have been increasingly used for machining performance prediction due to their ability to acknowledge & address imprecision and uncertainty in the machining process, while learning from the experimental data. In this paper the different empirical AI based techniques are reviewed that employ surface roughness as a response variable for more conventional machining operations like turning, milling. The main purpose of this work is to review and re-evaluate machining process modelling literature related to surface roughness as modelling metal cutting process is highly dynamic in nature and highly interconnected to the technological developments.

Keywords: Artificial Intelligence, Machining Process, Surface Roughness Prediction.

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Introduction

The machined product quality is assessed by how closely it adheres to the geometry, dimensions and surface quality described in the drawing[1],[2],[3],[4],[6]. Metal cutting or machining is one of the most important secondary manufacturing operations amongst casting, forming, welding [1],[2]. In this review, the machining operations are defined as a metal removal operation where the metal is removed by relative motion between cutting tool and workpiece. This paper mainly focusses on turning and milling as the major machining operations that re studied by several researchers for surface roughness prediction. Any metal cutting operation is done with a sole aim to obtain the desired specifications and not only to remove the metal[3],[4]. Today most of the shop floor supervisors face two core issues while developing the process flow for any product [7],[8],[9]. Primary being meeting the specifications mentioned in the drawing, and meeting those with optimum use of resources of shop floor. These two can suitably be addressed by having a prediction model that is well integrated within the process plan [2][3][4].

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Modeling of machining operations has been receiving attention from several researchers and surface roughness as an important process output variable is no exception [1],[2],[3]. For most of the machined components, surface texture or roughness is one of the most important design requirements, when the components are subjected to fatigue, power transmission, precision fits, fastening, light reflection, glue adhesion, etc. [3],[6],[7],[8],[9],[10]. For components used in power transmission it is conspicuously specified in production drawing and a major indication of product quality. The roughness of machined component is an outcome of complex interaction of several parameters which is given by [2]. The factors affecting the generation of surface are classified into four categories related to machining process, cutting tool, workpiece and machine tool.

The factors affecting generation of surface in machining are grouped four broad categories viz. Machining parameters, cutting tool properties, cutting tool properties and workpiece properties and given in Figure 1 below.

Reference [2] defines surface roughness as deviations from the nominal surface of the third order up to sixth order. The deviations associated with first and second order are related to the form of the workpiece i.e., circularity, flatness arising due to machine tool error, inbuilt deformation of workpiece, misalignment due to improper setup, clamping, vibration and non-homogenous material [2]. Third order and fourth order deviation refers to periodic grooves, cracks because of chip formation, and kinematics of machining respectively. Lastly, the fifth and sixth order deviations arise out of workpiece structure, physical and chemical mechanisms like grain slip, diffusion and oxidation [13],[14]. When all of these are superimposed, a final surface is obtained as shown in Figure 2.

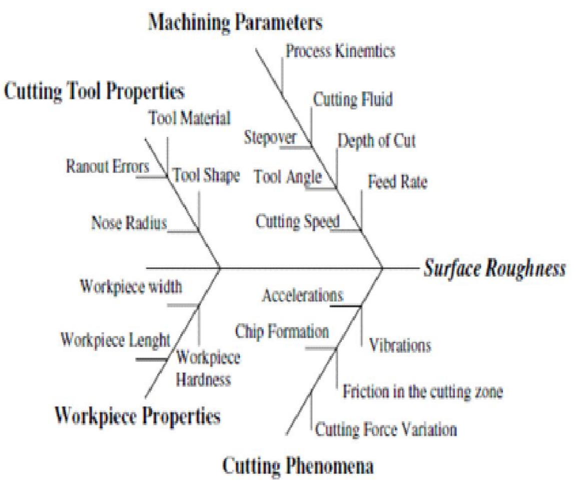

Figure 1: Dependency of parameters on the surface roughness [2].

Significance of Surface Roughness Studies

The surface finish desired for the component is specified in the drawing and accordingly different finishing and superfinishing operations are done for achieving it. The surface roughness in an important indicator of the stability of machining process, and often the deteriorating finish during a manufacturing process may indicate material homogeneity, progressive tool wear or even probable tool failure[4],[6],[8]. It also is important in determining machinability of materials [11],[15]. Apart from all of the above surface finish is the one of the critical performance parameters that has an appreciable effect on several mechanical properties of machined parts such as fatigue behavior, corrosion resistance and creep life [14].The parameters related to function of the part like friction, wear rate, light reflection, heat transmission, lubrication, electrical conductivity, ability to accept coating, production cost, productivity of machine tool, fatigue, corrosion resistance [11],[12],[13],[15],[16],[17] are also affected by surface roughness.

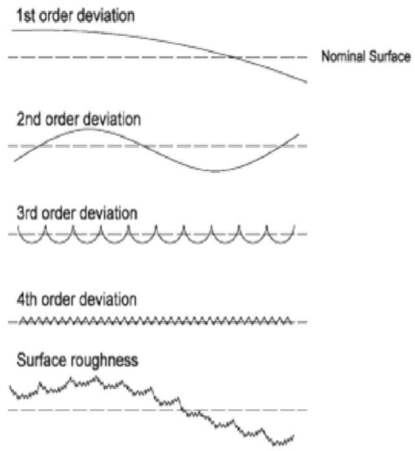

Figure 2: Surface Roughness form Deviations [11]

The table below lists down the important part attributes related to surface roughness [6].

Table-1: Part Attributes Related to Surface Roughness [6]

Functional Attributes	Mechanical Properties	Production Parameters
Friction	Fatigue Resistance	Stability of Manufacturing Process
Wear Rate	Corrosion Resistance	Production Cost
Light Reflection	Creep Life	Quality of Machined Product
Heat Transmission		Productivity of Machine Tool
Electrical Conductivity		
Lubricant holding ability		
Surface coating ability		

Although obtaining the desired level of surface roughness is important for functional specifications of the product, its formation is governed by lot of factors which are controllable and non-controllable [1]. Achieving the desired value of surface roughness is difficult because of two major reasons, while one being its process dependent nature and other is the associated complexity in machining operations because of large number of participating factors as already indicated in fig 1[2]. Till this date, most of the shop floor supervisors along with manufacturing engineers select the process parameters arbitrarily either by trial-and-error approach or out of experience which do not guarantee the desired output in terms of surface roughness, and optimum process parameters for achieving it[10]. The quest for improved shop floor productivity and intense market competition has led to development of newer work materials, tool materials, for engineering applications, and newer challenges for machining them. Hence modeling of machining operations has been attracting several researchers with surface roughness as the major factor.

SCOPE OF WORK

This study focuses of the different empirical and AI based techniques used for modeling of machining operations with surface roughness as an important process variable. As most of the machining processes are done on a CNC machine, the predictive models are more than ever needed. The combination of process simulation and predictive models can be integrated into process planning systems for productivity, and product quality improvement, thereby reducing the trial-and-error approaches of the shop floor supervisors for process development. Also, the utility of such work is to obtain a detained overview of the approaches adopted and assist in implementations of operational level predictions on shop floor.

LITERATURE REVIEW

The studies related to surface roughness can be classified in three major categories. The first being in process monitoring and control where the surface generated is monitored and corrective actions needed for cutting parameter modification are given in real time [1]. The second category is the prediction beforehand the machining process are either analytical-physics based, or numerical, or empirical-AI based models. These models are used in creating an input-output system in machining environment, where the output variables are determined as a function of input parameters. But most of these models require some preliminary data which is mostly in the form of experimentation. After the experimentation, the estimation is made on the data gathered. After the model construction, and validation, the input parameters either are maximized or minimized depending upon objective Reference [2] presented an exhaustive review of the literature available for surface roughness prediction. The total literature reviewed was classified into four approachesviz, i) Analytical or machining theory, ii) examining various factors and its effect on surface roughness, iii) design of experiments, iv) AI based. Each of these approach along with methodology adopted, advantages, disadvantages was discussed in detail. Integration of the surface roughness models as a general advisory system for the machine tool operator which can be useful and practical application was suggested in this review.

Reference [3]classified the machining parameters into six major categories that affect the surface roughness as shown in the figure below. Turning and Milling are the two major machining processes that were identified for such study.

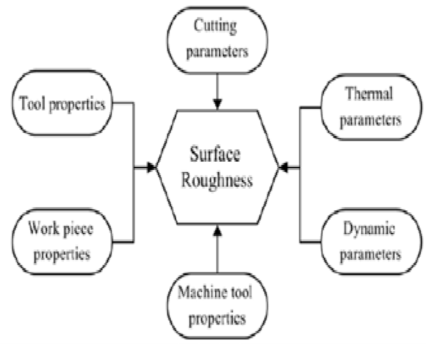

Figure 3: Six Major Categories that effect the surface roughness [3]

The literature available was reviewed and classified under each of these categories and illustrated in tabular format. However, parameters like machine tool power, tool shape, work piece length, work piece thickness, work piece clamping, feed direction, cutting zone temperature, are left out which needs to be investigated and analyzed further.

Regression and Response Surface Method

Regression analysis is a popular statistical method that gives a functional relationship between the dependent and the independent variables of a process [5]. This relationship is expressed in the form of equation, which may be linear or nonlinear in nature. The function that describes the relationship and coefficients of the equation are the outcomes of the regression problem [5]. The coefficients of linear and nonlinear regression are determined by least squares method. The regression analysis is an iterative process which can be best described by the figure below.

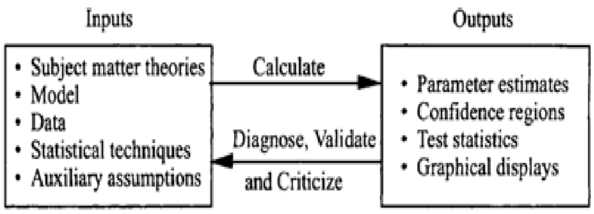

Figure 4: Iterative nature of Regression Process [5]

The response surface methodologyis a collection of mathematical and statistical techniquesthat are useful for modeling and analyzing problems in which response of interest is influenced by several variables, and the objective is to optimize the response [5]. The function that determines the relationship between the variables is represented as a surface in a 3D plane called as response surface.

In [6] the author developed an empirical model using work piece hardness, feed rate, cutting point angle, spindle speed and cutting time as the input parameters and multiple regression technique for predicting surface roughness in turning operation. The statistical tests conducted demonstrate that model predicts the values of surface roughness with good accuracy.

In [7] an attempt was made to determine the relation between tool life, cutting force, surface roughness in turning of AISI302 material. The regression analysis, response surface method and neural networks were the main tools used. The cutting parameters (cutting speed, feed rate and depth of cut) along with nose radius was used for predicting surface roughness. The data from 28 experiments was collected to mode a second order polynomial expression for cutting force, tool life,and roughness. A two-layer neural network was also developed for predicting the value the above response variables. Out of the total three methods employed for empirical models it was observed that neural networks have the least possible relative error in terms of prediction.

In [8] it was demonstrated that power consumed in turning operation can be modeled as a function of cutting speed, feed rate, depth of cut and nose radius of the tool. Compared to the first order model, the second order model demonstrated better fit with the experimental data.

Reference [9] employedresponse surface methodology for studying the effects of milling parameters like spindle speed, feed rate, depth of cut on surface roughness. The Box-Behenken design was employed along with ANNOVA for testing the adequacy of the data.Surface roughness was found to be most influenced by cutting speed along with feed rate as against depth of cut. during experimentation.

In the end milling operation of composite material to predict surface roughness the effect of spindle speed, feed rate, and depth of cut and percentage of silicon carbide as tool material on surface roughness was studied [10]. Weight percent of silicon carbide material was found to have highest influence on surface roughness as compared with spindle speed and feed rate, whereas depth of cut was observed to have the least. The empirical model developed by RSM has good prediction ability.

In [11] turning operation of AISI1019 steel was carried out using response surface methodology and Box-Cox transformation for prediction of surface roughness. Initially a quadratic model was developed with depth of cut, nose radius and feed as primary input parameters. Subsequent to which the model was improved by enhancing the normality, linearity, and homogeneity of the data using Box-Cox transformation and lastly, the confirmation experiments are done for ascertaining the predictive ability of the Box-Cox transformation for empirical models.

$42CrMo_4$ alloy steel was turned and surface roughness was predicted using cutting parameters and tool vibrations [12].The study of combined effect of cutting parameters and tool vibrations was accomplished using ANNOVA. The optimum values of cutting parameters and tool vibrations for minimum surface were determined using response optimization technique along with composite desirability function. The most affecting variable was the feed rate along with cutting vibrations being the least.

Reference [19],[20] developed a second order mathematical model for turning of Al7075-T6 alloy, with nose radius, and cutting parameters.The optimization of cutting parameters for minimum surface roughness was accompanied by using Genetic Algorithm (GA).

Life of machine tool was evaluated in [21]in addition of prediction of surface roughness in turning of stainless steel. The Influence of cutting parameters was analyzed using ANNOVA and using RSM a second order model was developed, with central composite method and Taguchi used for experimentation design. The significant factor was feed rate followed by cutting speed and depth. In order to carry out economical machining of difficult-to-cut materials the optimum tool life was determined using cutting parameters.

Fuzzy Logic

In 1965 LoftiZadeh [25],proposed fuzzy logic, where conventional computer logic was not capable of manipulating data representing subjective or unclear human ideas. The model is obtained by using the descriptive language from statements. The figure below represents the architecture of fuzzy logic [25]

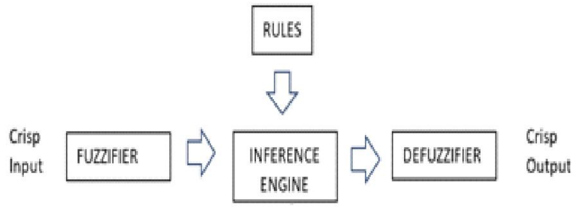

Figure 5: Working of Fuzzy Logic [25]

The subjective knowledge/ opinion from the operator or foreman regarding any machining process are formulated as "if-then statements", which later is used for controlling the decision-making process [26]. The crisp (numerical) inputs which can often be the results of numerical evaluation are the process inputs which are sent to the fuzzifier [26]. The crisp input can be sensory data which is converted into fuzzy sets by fuzzy linguistic terms, fuzzy linguistic variables and membership functions. This operation is called fuzzification [25]. The degree of match between the fuzzy input and rules is determined by inference engine. Based on the degree of match, it differentiates, which rule is applied to which field. The corrective control action is taken based on applied rules. The defuzzification action performs the fuzzy sets again into a crisp output value [25].

Reference [26] developed a fuzzy parametric deduction scheme for optimizing the material removal rate in turning operation. There are 27 fuzzy control rules generated using 4 input process parameters and a trapezoidal function. The optimal process parameters are determined using Taguchi for obtaining maximized material removal rate.

Reference [27] developed a surface roughness prediction model for turning process using triangular membership function. The inputs were cutting parameters along with vibrations in X and Y axis. The prediction accuracy was found close to 95 %.

[28] predicted the thrust force, main cutting force and feed force in turning operations using Mamdani Fuzzy Inference model and validated it using extensive set of runs.

[29] predicted the tool flank wear using a co-active neurofuzzy inference system (CANFIS). However, ANN was found to outperform CANFIS in terms of prediction accuracy.

As mentioned in [30] flank wear was estimated in addition to surface roughness on the cryogenically treated AISI-M2 HSS tool using ANFIS model. Cutting parameters along with cutting time, soaking time, temperature were the input process parameters. Additional experiments were performed for framing the fuzzy rules.

[31] predicted the cutting speed and feed rate for the end milling process for the given hardness of material, depth of cut and diameter of the tool.

[35] carried out end milling operation using Adaptive neuro fuzzy interface (ANFIS) method to predict surface roughness with cutting parameters as the input.

Artificial Neural Networks

Artificial Neural Network is one of the popular machine learning algorithm which can be trained and apply the knowledge gained. Neural networks trained using experimentation data and are best in describing the relationship between the process variables. ANN are most suitable for modeling various manufacturing functions due to their ability to learn complex non-linear and multivariable relationships between process parameters[36]. ANN gives explicit relationship between input and output variables for a process [37]. The fundamental entity of a neural network is a neuron which takes a single input and produces multiple outputs [38] The structure of a typical neuron is shown in the figure below.

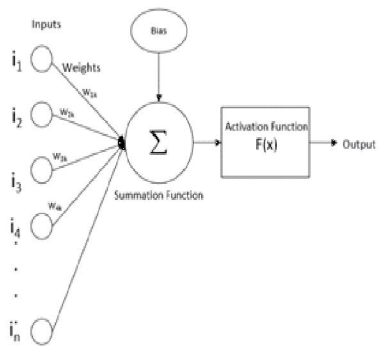

Figure 2: Structure of a singular neuron used in ANN [36]

The network comprises of several neurons interconnected across layers. There is a weight associated with each input that determines its intensity. A typical network comprises of input hidden and output layer. The information related to the process variables is collected in the input layer. As shown in figure 1, in case of multiple input vectors it is in the form of an input vector (i_1, i_2, i_3……i_n). This information is transmitted to the summation function by multiplying the strength through weights (w_1, w_2, w_3…. w_n). Each neuron is composed of the summation function and the activation function. The summation function is multiplied by bias b_j, whereas the activation function coverts the weighted input to output using different linear, nonlinear algebraic functions. Every neural network has a target value which is to be achieved.

In [40] a Non dominated Sorting Genetic Algorithm (NSGA-II) coupled with ANN and desirability function (DF) based regression models were employed for improving the prediction of cutting force, surface roughness and optimizing the process parameters. ANN coupled with NSGA was found to predict the response variables better compared to regression. [41] predicted the surface roughness using alternative variables like Tool stiffness ratio, cutting depth, tool overhang length, tool geometry, insert hardness work hardness. The variable selection method was based on ANN. It was found that surface roughness was most affected by cutting depth, tool overhang, spindle speed, work piece diameter. [42] optimized the cutting parameters in keyway milling operation for C40 material.

The comparison of surface roughness models developed using ANN-GA and RSM-PSO was done, in addition to determining optimum cutting conditions. It was found that RSM coupled with PSO predicted the values better. [43] predicted surface roughness in milling of Ti-6Al-4V alloy using RSM and ANN.

After an initial formulation of model using RSM, the ANN model was also used for predicting the value of surface roughness. [44] developed a hybrid Adaptive Neuro Fuzzy Inference System (ANFIS) for prediction of surface roughness in turning of H13 tool steel. The cutting was done with minimal application of cutting oil. The effect of different input parameters like cutting force, temperature and vibration on the surface roughness was analyzed and it was found that the ANFIS model predicted the value of surface roughness with very close to the actual value. [45] predicted surface roughness in turning using high pressure coolant using ANN.[46] proposed a dynamic surface monitoring system based on ANN for milling process. The inputs used were cutting parameters, material and coolant type, cutting force components and vibration data. The proposed model indicated accuracy of 99.7 and 99.8 % in testing and recalls procedures respectively.

Support Vector Machines

SVMs are a promising classification technique based on the framework of statistical learning theory or VC theory [49]. Concisely, the VC theory highlights the properties of learning machines, that help them to generalize and test the given data. The principle of this technique is to separate the classes with a hyper plane surface that maximizes the margin between them [49].

The vectors that are close enough to the hyper plane, called as support vectors, constrain the margin of the optimal hyperplane. This technique is an approximate representation of the SRM induction principle. As this principle aims at minimizing the bound on the generalization error of the model, rather than minimizing the mean square error over the dataset, training an SVM to obtain the maximum margin classifier requires a different objective function.

[38] proposed an in-process prediction of surface roughness based on least square support vector machines for turning operations, while the cutting parameters, tool properties used as an input. The most strongly corelated signals related to surface roughness were extracted using single spectrum analysis. There was a good agreement between experimental values and theoretical values.

[23] applied three different types of support vector machines (SVM) for estimating surface roughness in turning of stainless steel. Spider SVM, least square (LS-SVM), and SVM-KM were used in conjunction with ANN to predict the surface roughness.

A three-level full factorial experiment design experiment was conducted to determine the experimental values for surface roughness. These values were compared with predicted values and SVM methods seemed to outperform ANN. The computational time required by ANN was more as compared with SVM. [50] also adopted a LS-SVM approach for surface roughness prediction. Two materials AISI4340 and ASISID2 steels of average surface hardness 50,55 and 60 HRC were used for turning. With cutting conditions as input a neural network model with RBF was employed for optimizing surface roughness. The NN model was trained using datasets obtained during experimentation and it was observed that LS-SVM model demonstrated better predicting ability as compared with neural network.

[33] utilized SVM, along with RSM and ANN in modelling and optimization of surface roughness in boring operation AISI316 stainless steel material. 18 experiments were done with cutting conditions and nose radius as the input parameters, using a PVD coated tool. The vibration of the workpiece was measured using a laser dopplervibrometer. After transforming the signals using suitable method, RSM, ANN and SVM were used to build the roughness model using RMS values of workpiece vibration as the input. The optimization of cutting parameters for minimum surface roughness were done using multi response optimization technique.

[51] formulated an effective hybrid method employing ABC-SVM technique for surface roughness prediction in turning of AISI1045 steel. Artificial Bee Colony (ABC) algorithm was employed to reduce the parameter adjustment time required in SVM. Using four evolutionary swarm-based algorithms like Differential Evolution (DE), Genetic Algorithm (GA), Particle Swarm Based Algorithm (PSO), and Artificial Bee Colony (ABC) the prediction performance of SVM was optimized. It was found that ABC-SVM combination exhibits better prediction accuracy as compared with all other contemporary techniques like DE, GA and PSO algorithms, in terms of aspects like less number of control parameters, stronger ability to search, and convergence speed.

Discussion and Conclusions

CNC controlled Conventional machining process still dominate all the other manufacturing process. Robust models for prediction enable better control of the machining process and assist in making decisions like section of optimal cutting conditions, coolant/ lubricant type and mode (Flooded, or Mist), selection of cutting tools, so that the product meets its functional requirement. Out of the several approaches adopted for modelling of machining operations, the growing popularity of AI based methods can be attributed to inability of pure analytical physics-based models to be applied for machining due to complex nature, and ability of AI based models to tolerate imprecision, uncertainty, partial truth and approximation in machining.

The evolutionary methods like regression, ANN, fuzzy logic and SVM are reviewed for prediction of surface roughness as a significant machining process output variable limited to machining operations such as turning and milling. Since these operations form the bulk of machining operations.

Majority of the studies indicate that out of the cutting parameters, speed and feed are the most dominating parameters affecting the surface roughness in machining. However, factors like material hardness, use of cutting fluids, composition of cutting fluids, mode of lubrication and cooling, needs to be investigated in further detail. All most all of the empirical methods employ a common method, where after identification of input parameters like cutting speed, feed and depth of cut followed by design of experiments, identification of most affecting variable using analysis of variance and regression analysis for determining the response variable using experimental data.Most of the regression models employed for prediction have linear or quadratic function. However, these models applied along with adequacy tests like ANNOVA have significant number of statistical assumptions which cannot be overlooked. The most important being the presence of independent and normally distributed errors with zero mean, constant variance, and another being the very strong requirement of assumption of initial linear or nonlinear model structure. RSM, regression coupled with other approaches has been widely adopted by [7] to [21]The model assumption and statistical assumption result in uncertainty in the predictive ability of the model. Mamdami Fuzzy models along with ANFIS are the most routine FL models employed for surface roughness prediction. Fuzzy models coupled with ANN and RSM for surface roughness prediction are proposed by [23]. The ANN models for surface roughness make use of Multiple Layer Perceptron (MLP) and Radial Basis Network (RBF) employed for turning and milling process. MLP network has ability to work on limited datasets but require considerable effort and skills in training, in turn the RBF requires humongous amount of data for the training which can be resource constrained. The least square-SVM was the most used method employed for surface roughness prediction[47], [48], [49], [50]. There are other machining process output variables like cutting force, tool wear/life, cutting temperature needs to bethoroughly investigated by applying similar approaches.

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