A Review of the Surface Roughness Prediction Methods in Finishing Machining

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ABSTRACT

The desired Surface Roughness (SR) can be achieved via general machining methods by using a cutting tool to remove a material layer on the workpiece surface. Cutting Parameters (CP), cutting tool properties, and workpiece properties must be considered. The finishing machining methods that can be applied to produce the desired SR are turning, milling, grinding, boring, and polishing. The technological parameters must be tightly combined in the Machining Process (MP). The CP selection presents some issues regarding time, cost, and practical skill when considering different cutting methods, cutting tools, and workpiece materials. SR predicting methods of machined parts have the advantages of shortening the time of CP selection, reducing machining cost, and bringing the desired SR. This paper reviews the recent methods followed in predicting the SR of the MPs. The SR prediction methods will bring many benefits for MP, such as improved SR, reduced cost, improved cutting conditions, and enhanced quality.

Keywords-machining parameter; surface roughness; optimization; prediction; finishing machining

I. INTRODUCTION

Surface Roughness (SR) is one of the most important criteria of the metal cutting area. There are many vital applications of the machine parts with high Surface Quality (SQ) that are produced by using finishing machining methods, such as optimizing the Turning Process (TP) to get the required SR of the magnetic material for aerospace applications [1], introducing the grinding and polishing to enhance the SQ of the bladed rotor of aero engines [2], introducing a Fuzzy Logic (FL) model to predict the SR during the turning of carbon fiber reinforced polymer composites for automobile, aircraft, and sport applications [3], using techniques of grey relational techniques for order preferences by similarity to ideal solution (TOPSIS) method, and response surface analysis to optimize the SR during processing the magnesium alloy for aircraft engine, helicopter component, airframe, light truck, computer, and automotive parts [4], controlling the SR by using the Artificial Neural Networks (ANN) for milling wind turbine parts [5], using the integration method of grey and fuzzy methods to minimize the SR of AA6082/Sic/Gr material during TP on CNC [6], using the Taguchi Method (TM) to conduct experiments on the SR during the hard turning of EN24 steel [7], investigating the machining factors to improve surface roughness at turning titanium or its alloys [8, 9], milling SCM440 steel [10], milling 6061 Al alloy [11], turning Inconel 718 super alloy [12], and lowing the SR by using the TM for the mold surface application of 7075-T6 material [31]. The SR quality has been closely related to many mechanical properties of product like fatigue behavior, wear, and corrosion resistance. Many researches focus on methods and techniques to improve product SQ for its application such as deploying Response Surface Methodology (RSM) to minimize the SR for mold surface [14, 15], analyzing the SR [16], and utilizing ANN to improve the SR of steel [17].

The SR can be achieved via machining methods by using the cutting tools to remove a material layer on the product surface with many Cutting Parameters (CP), namely the machining parameters, cutting tool properties, workpiece properties, and coolant condition. The technological parameters must be tightly combined together in the Machining Process (MP). The CP selection has some issues regarding time, cost, and practical skill in accordance with the utilized cutting method, cutting material, and workpiece material. The selected CP in the MP are traditionally based on experiment, practical skill, and physicochemical phenomena occurring in the cutting process. To solve this problem, many researchers have performed experiments to acquire relationships between CP and the desired quality of product, such as using the predictive models [18], prediction tools [19, 20], vibration information [21-24], and evolutional programing methods [25] to predict the SR. Advanced technologies have been developed for improving the product quality purpose, enhancing the quality with CNC machine tools [26-29] and using Artificial Intelligence (AI) [30] in machining. Figure 1 shows the effect of these parameters on the SR. There are four basic groups of cutting conditions that effect SR including: (1) CP with feed rate, cutting speed, tool angle, step-over, process kinematics, and cooling fluid, (2) cutting tool with tool shape, tool material, nose radius, and runout errors, (3) cutting phenomena with acceleration, chip formation, vibration, cutting friction, cutting force, and (4) workpiece with diameter, length, and hardness.

Many algorithms and mathematical models have been extensively studied with the aim to find the best solution for minimizing the SR of the machined parts. Some examples are: building SR modeling for turning 080A67 steel using Box-Behnken (BB) and Box-Cox (BC) transformations [31], enhancing SR modeling with BB & BC during the milling of 3×13 steel [32], using FL tool and regression analysis (RA) to predict the SR for face milling [33], applying the FL set for predicting the SR during milling process on the CNC [34], building a Genetic Algorithm (GA) model for SR minimization [35], using the GA for optimizing the SR of the hard TP [36], improving the SQ by using ANNs [37], studying the influence of CP to get effective SR prediction with Particle Swarm Optimization (PSO) [38], and developing a nested-ANN for predicting the SR [30]. CP optimization methods have been applied in the surface finishing machining of many materials, e.g. minimizing SR of titanium alloy via turning [9], finding the factors effecting on the SR for MDN350 steel by employing the Taguchi technique [39], improving the SR via implementing a Prediction Model (PM) with the LM algorithm for processing the SR of AL-7075 Al alloy [40], employing the Taguchi design technique to minimize the SR of C-103 Nb-alloy during machining with micro-end-milling [41], applying the machine learning technique to predict the SR of diamonds [42], predicting the SR of AISI H13 material after TP by using ANNs [43], introducing an orthogonal array and PSO for SR processing of AISI1045 steel during milling [44], and applying ANNs to predict the SR of Inconel 718 during the TP [45].

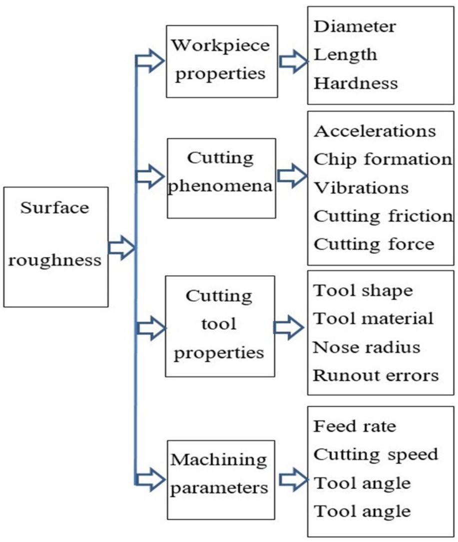

Fig. 1. Parameters affecting surface roughness.

Research groups have been focused on finding new solutions for enhancing SR, such as using minimal lubrication of carbon nanotube lubricant with multi-objective optimization for predicting the SR [46], SR modeling by developing an ANN and regression method [47], monitoring SR during TP on CNC by utilizing the wavelet packet transformation [48], developing an adaptive neuro fuzzy inference and a radial function neural network to predict the SR of milling [49], constructing an online monitoring method by employing the improved firework algorithm for SR enhancement of grinding [50], developing a numerical control kernel data model to monitor SR in the manufacturing process [51], building a high precision model of abrasive belt grinding for SR prediction during grinding of aero-engine blades [52], using ANNs to optimize the SR in TP [53], developing a soft computing model for predicting the SR during the milling of 606 Al [71], predicting SR by deploying a co-kriging model for the manufacturing process [54].

This paper reviews the most recent methods adopted in SR prediction of the MPs. SR prediction methods bring many positive characteristics on the manufacturing process, such as improved SR, reduced cost, and increased productivity quality of product.

II. CLASSIFICATION

The SR prediction models can be generally divided into four groups: (a) methods based on the cutting theory to create analytical models and numerical algorithms to solve the SR problem in machining, (b) the methods based on the effect of the technological factors acquired from machining practice and data analysis of the cutting process (experimental investigation), (c) the methods based on AI, and (d) the methods based on the experimental design.

III. METHODS BASED ON THE CUTTING THEORY

These methods focus on the machining theory to predict the SR of the machined parts. Parameters, such as the tool properties, process kinematics, and mechanism of chip formation are considered. PMs are acquired via computer tools, e.g. computer-aided design, computer-aided manufacturing, and computer-aided engineering to perform analysis and simulation of the cutting behavior for the purpose of assessing the SR of machined parts [55]. Mathematical models are built to explain the relationships between the parameters and the SR of the machined part and computer algorithms are constructed to solve the complicated calculations [56]. These methods have the advantage of solving problems considering huge amounts of data. On the machining theory, the chip thickness was used to predict the roughness of the machining part in the cutting process with the focus placed on the minimum of undeform thickness [57], showing the difference between the measured roughness value and the value of the theoretical model. The reason for this is that material adhesion occurs at the interface of the cutting tool and chip causing the minimum of chip thickness in deformation corresponding to the transformation from ploughing to another kind of micro-cutting. As a result, a predicting model was built to predict the SR of the machined surface. CP, tool geometry, and cutting motions have been considered in the model to improve the SR prediction.

IV. EXPERIMENTAL INVESTIGATING METHOD

In the experimental method, experiments are conducted considering the factors and their effect on the quality or the working mechanism of the system [58]. Designers often use RA to construct the desired models from the experimental values. In this case/study, the designer should be equipped with skills and experience and be able to understand the experimental area and to analyze the experimental data. For example, the researches of the relationship of the tool life, vibration, and SR were done by utilizing the variables of feed rate, cutting speed, depth of cut, tool overhang, workpiece geometry, approach angle, and tool-nose radius. This work employed an FFT analyzer and accelerometer to measure the vibration and process the experimental data with Matlab from ASCII format converted by a binary file [59].

V. THE ARTIFICIAL INTELLIGENCE (AI) METHOD

AI exhibits satisfactory characteristics at solving engineering problems, such as monitoring the MP, controlling technological parameters in manufacturing, computing technical solutions, simulating the act of systems, and predicting SR in cutting process [60-63]. AI uses complicated algorithms, like ANNs [64-66], FL models [67-69], GA solution [70, 71], and expert systems [72] to solve the roughness-related cutting problems. Some AI tools that have been successfully applied to predict the SR are GL [73, 75], ANNs [74, 76, 76]. ANNs are effective at noise management. The GL has the positive attribute of simple operation and high efficiency in solving optimization issues [25, 63, 78, 79]. Figure 2 portrays an ANN as an information processing system.

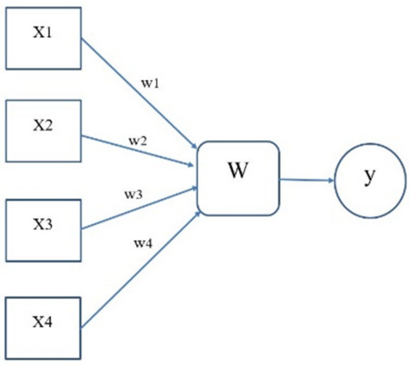

Fig. 2. An artificial neutral network for roughness surface prediction.

This model manifests efficiency in predicting the SR of the machined parts [80, 81]. The general mathematical model can be expressed by:

$$y = f(W\chi) \quad (1)$$

The x1, x2, x3, and x4 variables represent the survey parameters, in this case the machining parameters. The w1, w2, w3, and w4 represent weights.

VI. THE METHOD OF EXPERIMENT DESIGN

A. *Design of Experiment (DoE) with the Taguchi Method*

DoE constructs a range of experiments to perform a machining duty using many CP in the cutting process [82] and the MP [83-85]. The purpose is to reduce the number of experiments to get the optimal SR via CP selection. The TM have been successfully applied in predicting the SR of manufacturing processes. Some examples are analyzing the SR during the turning of 7075-T6 Al alloy [86], minimizing the SR for turning the hardened AISI 4140 steel on the CNC [87], optimizing the turning parameters by utilizing TM for improving the SR [88], minimizing the SR of Al alloy on the CNC machine tool [89], investigating the optimal cutting parameters by using TM and ANOVA analysis when machining Al 6082 on CNC lathe [90], and enhancing the SR by employing the TM during milling [91]. Figure 3 depicts the diagram of the DoE following TM. This method has three main stages, including the planning stage, the execution stage, and the analysis stage. In the first stage, researchers need to complete the problem statement, set objectives for experimentation, quality requirement, measurement methods, select related factors, set levels for these factors, set orthogonal arrays or fractional matrices, set the interactions for quality requirements, and set the factor for the orthogonal and interactions. In the second stage, the researchers carry out the set experiments following the orthogonal arrays. In the third stage, the researchers analyze the results from the experiment data, and finish with the conformation of the experiments. In the first and second stages, the orthogonal arrays can be the minimum values/ parameters that respond to the problem. In the third stage, a large number of experiments can be conducted to get high resolution. The range of resolution is from one to four, indicating the effect of the factors and the evaluation of their interaction in the experiments. Columns of the orthogonal arrays arrange the factors and take proper mathematical properties into account. A next column of factor will be automatically created after one is finished. The column patterns are the interaction columns of the orthogonal arrays and are used in the analysis with linear graphs and tables. Taguchi-based SR predictions tend to build prediction and optimization models from CP to support technological engineers' beneficial choices on the manufacturing field [96].

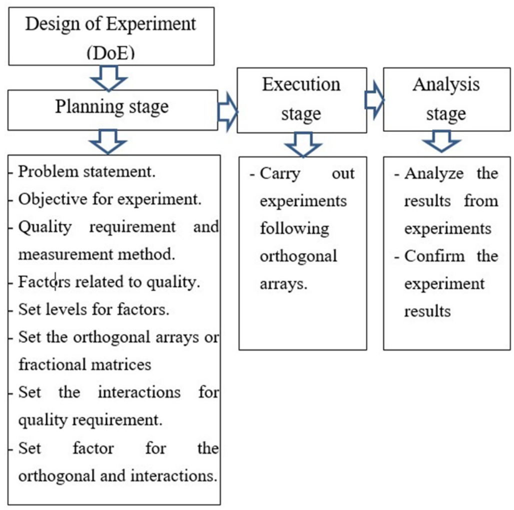

Fig. 3. The diagram of the experiment design following the Taguchi method with three basic stages.

B. *Response Surface Methodology (RSM)*

RSM uses factors to construct a polynomial equation with the independent variable as the experimental response. The experiments must be considered and designed to get the minimum value of response. In that, the response surface gradient goes along with an algorithm with the sharpest slope [94]. The two basic models of this method are shown in Figure 4. The series of steps in RSM allows the designer to study the process by deploying the advanced experiment distribution. With RSM, the number of experiments can be proposed, the optimization position can be acquired, and the approximately mathematical expression can be achieved [95].

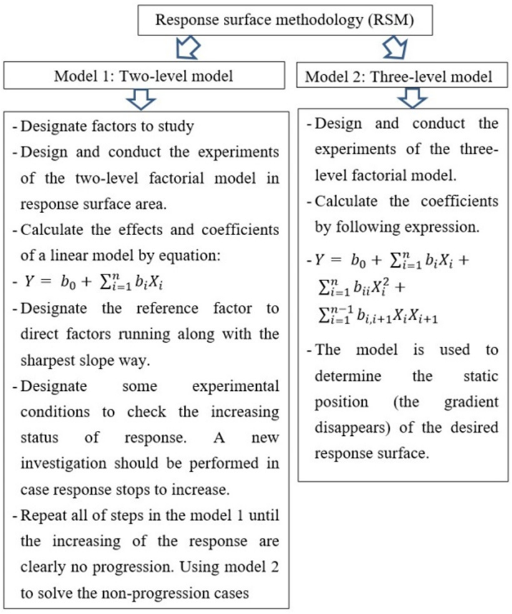

Fig. 4. The response surface methodology.

Results show the effectiveness of the predictive models that use RSM to predict the SR of MPs in turning [95, 97-99].

VII. HYBRID METHODS (HMS)

HMs have been applied to solve technological problems in manufacturing processes and to meet the criteria of SR optimization and prediction. Some examples are the use of an HM of ANNs, GA, and PSO in predicting the SR and to increase computation speed and efficiency [73], combining FL and TOPSIS to minimize the SR during the machining of pure titanium with quantitative and qualitative benefits [100], using combinations of grey relational analysis, the TOPSIS, and the response surface analysis to optimize the SR of TP [101] and milling Ti-6Al-4V alloy [102], coupling TM and fuzzy multi decision making to optimize SR during TP of stainless steel [103], utilizing RSM and ANNs for predicting the SR during TP of Al 7075 ceramic and Al 7075 hybrid composite [104], combining TM and ANOVA for SR during turning [90], predicting the SR of MPs of milling, grinding, and turning [105], using a combination of Taguchi and RSM methods for improving the SR of the facing process on CNC [106], optimizing the SR of the machined part by employing TM, ANOVA, GA in coupling with RSM to optimize the cutting condition when machining a mold cavity [15], constructing a combination of TA and grey analysis for Al6063A-T6 turning to optimize the cutting factors with the purpose of minimizing SR [92], and RA during turning EN-45 steel on CNC [93].

VIII. CONCLUSION

The current paper demonstrates a review of recent SR prediction methods in machining. The prediction methods are really important in the selection of CP to acquire the desired SR during the cutting process. Recent approaches tend to deploy complex multi-parameter systems to get the best SR utilizing advanced techniques of online cutting-process monitoring, such as AI, DoE based on TM, RSM, and HMs of ANNs, GA, and FL. The recent methods also focus on using the ability of large data storage and high speed processing of modern computers to process big data volumes to receive a PM of SR with more accuracy. The results are a useful reference for designers and engineers who want to find ways to predict SR or build PMs of SR and optimize machining conditions.

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