An Evaluation: Prediction of Surface Roughness in Machining

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Abstract— The general manufacturing problem can be described as the achievement of a predefined product quality with given equipment, cost and time constraints. Unfortunately, for some quality characteristics of a product such as surface roughness it is hard to ensure that these requirements will be met. This paper aims at presenting the various methodologies and practices that are being employed for the prediction of surface roughness. The resulting benefits allow for the manufacturing process to become more productive and competitive and at the same time to reduce any re-processing of the machined workpiece so as to satisfy the technical specifications. Each approach with its advantages and disadvantages is outlined and the present and future trends are discussed. The approaches are classified into those based on machining theory, experimental investigation, designed experiments and artificial intelligence (AI).

Key words: Surface Roughness; Surface Roughness Prediction; Machining

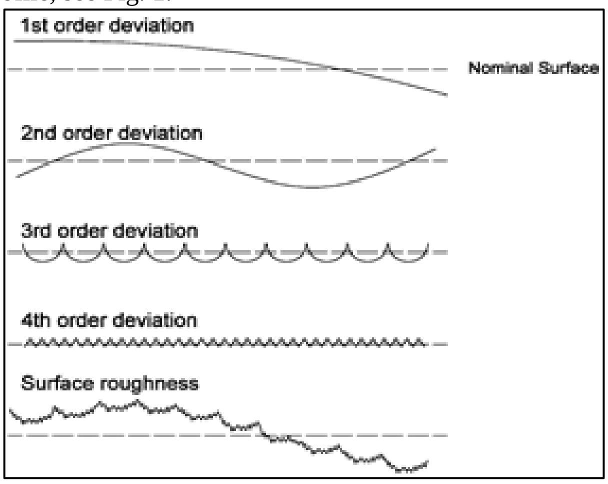
I. INTRODUCTION

There are two main practical problems that engineers face in a manufacturing process. The first is to determine the values of the process' parameters that will yield the desired product quality (meet technical specifications) and the second is to maximize manufacturing system performance using the available resources. The decisions made by manufacturing engineers are based not only on their experience and expertise but also on conventions regarding the phenomena that take place during processing. In the machining field, many of these phenomena are highly complex and interact with a large number of factors, thus preventing high process performance from being attained. To overcome these problems, the researchers propose models that try to simulate the conditions during machining and establish cause and effect relationships between various factors and desired pro-duct characteristics. Furthermore, the technological advances in the field, for instance the ever-growing use of computer controlled machine tools, have brought up new issues to deal with, which further emphasize the need for more precise predictive models.

Surface roughness is a widely used index of product quality and in most cases a technical requirement for mechanical products. Achieving the desired surface quality is of great importance for the functional behavior of a part. On the other hand, the process dependent nature of the surface roughness formation mechanism along with the numerous uncontrollable factors that influence pertinent phenomena, make almost impossible a straight-forward solution. The most common strategy involves the selection of conservative process parameters, which neither guarantees the achievement of the desired surface finish nor attains high metal removal rates.

The aim of this work is to present and discuss the various methodologies and strategies that are adopted by researchers in order to predict surface roughness. The presentation of each approach along with its advantages and disadvantages should help both the researchers and practitioners by providing compact yet adequate information so as to select the one that best suits their needs and specific requirements. The paper focuses on turning and milling since these are the most common cutting processes and the majority of the published work applies to them. Surprisingly enough a similar review was not found to be published before.

Surface roughness refers to deviation from the nominal surface of the third up to sixth order. Order of deviation is defined in international standards [1]. First- and second-order deviations refer to form, i.e. flatness, circularity, etc. and to waviness, respectively, and are due to machine tool errors, deformation of the workpiece, erroneous setups and clamping, vibration and workpiece material inhomogenities. Third- and fourth-order deviations refer to periodic grooves, and to cracks and dilapidations, which are connected to the shape and condition of the cutting edges, chip formation and process kinematics. Fifth- and sixth-order deviations refer to work-piece material structure, which is connected to physical– chemical mechanisms acting on a grain and lattice scale (slip, diffusion, oxidation, residual stress, etc.). Different order deviations are superimposed and form the surface roughness profile, see Fig. 1.



II. CLASSIFICATION OF APPROACHES

The classification of the selected papers was not easy due to two main reasons. First, there are many papers that do not strictly follow a certain methodology in its entirety, they rather select some of its basic principles and combine them into a 'new' approach. Secondly, there are many cases where researchers blend different strategies into a single approach and therefore no single classification would be entirely accurate.

Taking into account the above, four major categories were created to classify the selected papers. These are:

1) Approaches that are based on machining theory to develop analytical models and/or computer algorithms to represent the machined surface;
2) approaches that examine the effects of various factors through the execution of experiments and the analysis of the results;
3) Approaches that use designed experiments; and
4) artificial intelligence (AI) approaches.

III. Machining Theory Based Approach

This category includes approaches that place emphasis on certain aspects from the theory of machining such as process kinematics, cutting tool properties, chip formation mechanism etc. Computer-aided design (CAD) methods and tools are utilized so as to achieve the goal of building a model that will be able to simulate the creation of the machined surface profile, thus visualizing surface topography and assessing surface roughness.

In general, geometric model development forms the basis of the approach through rigorous mathematical equations. This model is then implemented by a computer algorithm in order to handle the complex calculations. Also, there are some theoretical models that relate surface roughness to cutting conditions such as the feed rate [2]. These models are generally not accurate so their improvement with the introduction of additional parameters is examined by researchers.

In any case, experiments are conducted in order to compare the predicted with the actual results. It must be noted that despite the strong background of the afore-mentioned theories, the phenomena that lead to the formation of surface roughness are very complex and inter-acting in nature so a comprehensive solution has not yet been found.

The theoretical background used by the research efforts in this category is considered a prerequisite for anyone who is involved in machining studies and there-fore no analytical description is presented in this paper. However, work by Kaczmarek [3] can be used for reference purposes.

A. *Machining theory studies*

Grzesik [4] used the minimum unreformed chip thickness to predict surface roughness in turning. The molecular–mechanical theory of friction (Kragelskii's theory) and the Hencky– Ilyushin theory of plasticity were used to mathematically model the tribological effects at the chip–cutting tool interface. The approach was based on the assumption that the difference between the theoretical and measured surface roughness values is due to adhesion at the chip– cutting tool interface and that the minimum unreformed chip thickness corresponds to the transition from ploughing to micro cutting. Consequently, an existing model for predicting the roughness of a turned surface was improved and the difference between the measurements and predicted results was markedly reduced.

In Ref. [5], a surface topography simulation model was established to simulate the surface finish profile generated after a turning operation with known vibration characteristics. The model incorporated the effects of tool geometry, cutting parameters and the relative motion between the cutting tool and the workpiece on the surface finish profile, which was 'decomposed' into three directions, namely, the radial, tangential and axial direction. The vibration frequency ratio (FR), which was defined as the ratio of vibration frequency (in Hz) over spindle rotational speed (in rps), was thought to influence the period of the surface waviness along the axial direction. It was also found that the effects of the radial direction vibrations on the surface roughness measures were much more significant than those of either the tangential direction vibrations or the axial direction vibrations as would be expected.

The study of Baek et al. [6] presented a surface roughness model for face-milling operations considering the profile and the run out error of each insert in the cutter body. It was stated that because of manufacturing errors in making the cutters, axial (affecting the depth of cut) and radial (affecting the surface roughness) run out errors exist. The feed rate was also taken into account so as to formulate a geometric model. After the model validation with experimental cutting data, the material removal rate was maximized through optimization of the feed rate with the surface roughness as a constraint by means of a bisection optimization algorithm.

The computer modeling technique developed in Ref.

Could represent the spectrum of components of surface topography ranging over shape, waviness and roughness in a way suitable for generating macro- and micro-level finishing position commands. In order to do this, a three-dimensional (3D) filter was created in four steps. First, surface shape filtering was used to 'remove' the surface shape from inspection data resulting in a native surface shape. Surface topography analysis by 3D motif filter method was used in the next step to obtain surface roughness and waviness motif elements. Surface shape error could then be calculated as the deviation of the neutral surface shape and the design surface shape within each surface waviness element. Then the sculptured surface shape was added back to obtain the regenerated surface roughness, surface waviness and surface shape error. Finally, a surface roughness model was obtained by using B-spline curve fitting of the regenerated roughness data within each roughness element, and similarly the surface waviness model and surface shape error model could be obtained by the B-spline fitting of the regenerated waviness data and regenerated surface shape error data within each waviness motif element. The entire model was based on the 3D motif elements and the necessary combination rules that were created.

Ehmann and Hong [8] introduced a new method to represent the surface generation process, which they called 'surface-shaping system'. Their system basically consisted of two parts, one that modeled the machine tool kinematics and another that modeled the cutting tool geometry. For the latter, specific interest was given in the area of the cutting edge that was described as the intersection of the tool's face and flank surfaces along with the respective angles. In general, the surface-shaping system could account for spindle run out and machine vibrations while additional research for the estimation of cutting forces was still underway. In the work the system was applied for the simulation of the 3D topography of a peripherally milled surface.

B. Remarks

The conclusion that can be drawn is that these, theoretical for the most part, studies simulate the cutting process in terms of kinematics and cutting tool properties. Additional parameters such as vibrations are factors that contribute to the roughness formation mechanism are not considered, for example wear and deflection of the cutting tool or certain thermal phenomena.

IV. EXPERIMENTAL INVESTIGATION APPROACH

The experimental approach may be thought of as the most 'obvious' method: experiments with the factors that are considered to be the most important are conducted and the obtained results are used to investigate the effect of each factor as well as the influencing mechanism on the observed quality characteristic. Regression analysis is often employed in order to build models based on the experimental data. The researcher's intuition and insight play a great role in this approach but a high understand-ing of the examined phenomenon is also necessary for the experiment to yield any meaningful results. The experimental approach is mainly adopted in cases where there can be no analytical formulation of the cause and effect relationships between the various factors.

A. Experimental studies

The relationship between tool life, surface roughness and vibration was examined in Ref. [11]. The variables that were considered included the cutting speed, feed rate, depth of cut, tool nose radius, tool overhang, approach angle, workpiece length and workpiece diameter and the accelerations in both radial and feed directions. The acceleration signals were fed to an FFT analyzer that produced ASCII fi les. The experimental data were analyzed to produce regression analysis models.

Ghani and Choudhury [12] followed a similar approach in which the vibration signals were used to monitor tool wear and to verify the correlation between tool wear progression and surface roughness during turn-ing. The experiments were conducted on nodular cast iron with ceramic tool, something that lead to very short tool life (approximately 1.5 min).

Jang et al. [13] focused on the development of an on-line roughness measuring technique by studying the effects of cutting vibration during hard turning. It was assumed that the average surface roughness is the result of the superposition of a theoretical profile (process kinematics) and an oscillatory profile (process dynamics). An inductance type displacement sensor was used to measure the relative movement between cutting tool and workpiece. The results showed that surface roughness along the workpiece had specific frequency components that were determined by feed marks, in the lower frequency range, and that were closely related to included in an attempt to more accurately depict the phenomenon and the obtained results can be characterized as fairly good. The drawback of the approach is that a lot of the natural frequencies of spindle–workpiece system, in the high frequency range.

Acoustic emission analysis was employed in Ref. [14] to predict surface quality. Acoustic emission (AE) is defined as the class of phenomena whereby transient elastic waves are generated by the rapid release of energy from localized sources within a material. In the case of turning such sources can be found in the primary (due to chip formation), secondary (due to friction between cutting tool and chip) and tertiary (due to friction between cutting tool flank and workpiece) cutting zones. Instead of using the RMS value of the AE measured signals, a new quantity called AE_{RMS20} was introduced in the paper and correlated with surface roughness.

B. Remarks

This is the most conventional approach adopted. The experiment– observation– conclusion strategy is the cornerstone of every scientific research activity. Its advantage lies in the fact that it is not difficult to implement and that, depending on the level of understanding of the participating phenomena, it can produce very good results. On the other hand, the obtained conclusions have little or no general applicability. It must be pointed out that it is very easy for an experiment not to produce the expected results because there are too many factors to be considered regarding not only the examined phenomenon but also the equipment that is used.

V. DESIGNED EXPERIMENTS APPROACH

The reason why designed experiments were classified under a different category from the previous approaches is because they constitute a systematic method concerning the planning of experiments, collection and analysis of data with near-optimum use of available resources.

The response surface methodology (RSM) and Taguchi techniques for design of experiments (DoE) seem to where an ultrasonic system was developed for in-process monitoring and control of surface roughness. An ultra-sonic sensor connected to a PC, produced a pulse which was reflected by the surface of the workpiece and measured the amplitude of the returned signal. The system once calibrated with data from a stylus profilometer could produce the actual roughness values. The main advantage was that it was not affected by cutting fluids and chips as is the case of other in-process schemes. Additionally, a control scheme that aims at maintaining constant surface roughness throughout tool degradation was demonstrated.

The argument presented in Ref. [20] stated that the length of cut, number of teeth, cutting forces and the engagement of the cutting tool's tooth with the work-piece are all affected by the relative position of the cut-ting tool and workpiece and consequently tool life, tool wear and surface roughness are influenced by it.

The relation between vibrations and surface generation was investigated in Ref. [21] for slab milling operations. Since the periodical microgroove structure that is generated by sequential engagement of the cutter teeth is the primary parameter of surface roughness, it was suggested that in a dynamic process, the different surface profiles would depend on the amplitude, frequency and phase of the relative motion between the workpiece and the cutting tool. The separate contribution of each of the cutter's teeth to the resulting surface profile was verified by conducting experiments with known vibration characteristics.

A. Remarks

Although the common goal of the techniques investigated is to organize the experimental procedure and the necessary data processing, each follows a different path. The RSM is mainly a model formulation procedure to investigate how important factors affect the response of an experiment and leads to the development of first- and second-order polynomial models that include the parameters under consideration and their statistical significance. These models are used to create contour plots that can be more practically utilized to draw conclusions compared to using a polynomial function. On the other hand, the Taguchi DoE is more of a factor-screening procedure to determine the significance of each factor, that is, it identifies the most influential parameters and the values that produce the desired output without formulating any kind of model. Nevertheless, it must be pointed out that because of their generality and strong statistical background, certain tasks of these methodologies can be isolated and applied to a wide range of engineering problems where the size of the search space must be reduced.

VI. ARTIFICIAL INTELLIGENCE APPROACH

AI is implemented in engineering problems through the development of artificial neural network (ANN) models, genetic algorithms (GAs), fuzzy logic and expert systems. Simulating the way in which human beings process information and make decisions, in the developed for end milling of 190 BHN steel and inconel 718 First- and second-order models were constructed along with contour plots that more easily enable the selection of the proper combination of cutting speed and feed to increase the metal removal rate without sacrificing surface quality.

The purpose of the work carried out in Ref. [33] was to study the influence of tool geometry and cutting conditions on the machined surface quality and to build a model that would be able to predict it. Investigation of the above factors in relation to the residual stresses was also carried out. The innovation of the work was that RSM and Taguchi's method were combined to develop the model.

RSM was also successfully applied for surface roughness modeling of difficult to machine materials as the EN32 (a semi-free cutting carbon casehardening steel) [34]. A first-order model covering the speed range 30–m/min and a second-order model covering the speed range 24– 38 m/min were built in terms of cutting speed, feed rate and axial depth of cut under dry cutting conditions.

A. Artificial neural networks overview

An ANN is an information processing system that displays similar behavior to that of its biological analog. It is essentially a mathematical model that mimics the human reasoning and neurobiology and that is based on the following assumptions [35]:

- Information processing occurs in a number of simple elements called neurons.
- Signals are transmitted between neurons over connection links.
- Each connection link has an associated weight that multiplies the signal transmitted.
- Each neuron applies an activation function to the incoming signal to determine its output sig

B. Artificial intelligence studies

A sensor fusion technique was presented in Ref. [38] to evaluate the surface roughness and dimensional deviation during turning. The systematic method for the selection of the candidate sensors determined the aver-age effect of each in the performance of the measuring system. The sensors that affected it the most were fused using ANN modeling. The results showed that the models created with the above technique were more accurate than regression analysis models that were developed for comparison purposes.

Sensor fusion incorporating ANNs is also described in Ref. [39]. Capacitive, inductive and fiber optic sensors were used so as to cover an as wide as possible range of application by detecting features that cannot be sensed by a single sensor type. The RMS value of the three sensors along with the type of manufacturing process (face turning, milling, electro-discharge machining and grinding), all of which were coded in binary format, were used to train a 17 × 20 × 15 ANN and the results obtained could be characterized as fairly good.

The work of Chien and Chou [40] can be divided in two parts. The first part deals with the building of three predictive models, using multilayer functional-link net-works, for surface roughness, cutting force and tool life, respectively. The second part focused on finding the optimum cutting conditions by combining surface roughness and tool life network with a genetic algorithm. In that way, the cutting conditions that maximized the metal removal rate were obtained, under the constraints of surface roughness and cutting tool life.

Suresh et al. [41] also adopted a two stage approach towards optimizing for surface roughness. First, experimental results were used to build two mathematical models for surface roughness by a regression method according to RSM. Secondly, the second-order mathematical model was taken as an objective function and was optimized with a GA to obtain the machining conditions for a desired surface finish.

Polynomial networks were considered in Ref. [42] to construct the relationships between the cutting parameters (cutting speed, feed rate, depth of cut) and cutting performance (tool life, surface roughness and cutting force). In that way, a machining database could be constructed for turning operations. It was stated that a comparison between polynomial networks and back propagation networks has shown that the former have higher prediction accuracy and fewer internal connections. Additionally, the best network structure was determined by using an algorithm for synthesis of polynomial net-works (ASPN). The principle of the ASPN criterion is to select a network as accurate as required but as less complex as possible, too.

Li et al. [43] developed a hybrid machining model that integrated analytical models and neural network

Models for predicting all of the machining characteristic factors. The analytical component was based on the predictive machining theory proposed by Oxley [44] and served as a predictor for the cutting forces, temperature in the cutting region and chip geometry. It also served as a pre-processor of the neural network model that predicted the tool wear, surface roughness and chip break-ability, which could not be dealt with in a completely analytical manner.

Another approach that used a criterion for determining a network's architecture automatically can be found in Ref. [45]. The aim was to develop a prediction model prior to the implementation of the actual machining process to determine certain cutting conditions (cutting speed, feed rate and depth of cut) in order to obtain a desired surface roughness value and cutting force value. Furthermore, using the obtained cutting force, the cutting power and optimal metal removal rate could be calculated next. The abductive networks that were created using the predicted square error (PSE) criterion performed more accurately than the respective regression analysis models.

C. Remarks

In spite of the fact that these methodologies were developed decades ago, recent advances in the field, the ANN training algorithms for example, as well as the rapid increase of available computing power have brought revived interest among researchers. It is obvious that the approaches that have been described in this section can produce very good results and simultaneously offer the possibility for on-line monitoring and/or control of the process.

The main advantages that ANNs have in contrast to classic programming is that they can manage noisy or incomplete data with ease, there is no need to explicitly formulate the problem, the solution algorithm or to write code and that the process of information is distributed over the neurons which operate in parallel, therefore resulting in increased computational power in contrast to the sequential operation of today's computers. The most obvious drawback of the ANNs is that there is no guarantee for their resulting performance in an application.

The simplicity of operation and efficiency with multi-criterion optimization problems are the two main attractions of the GA approach. Since there is ready-for-use GAs available, it is not necessary to write code for a selected application from scratch

A new technique, an in-process surface recognition system that used the fuzzy-nets and a sensor-testing sys-

VII. CONCLUSIONS AND DISCUSSION

The current work presented a review of the different approaches that are used for predicting the surface roughness and certain remarks concerning each approach can be found in the respective sections. As is evident from the referenced papers, in recent years there has been a great deal of research activity in the field and the results that have been produced are good. The trend that is formed encourages more automated systems building for on-line monitoring, measuring or control and is mainly driven by the fact that the processes themselves have been automated to a great extent. All the methodologies that are presented here can exhibit advantages and disadvantages when compared to one another, but given this trend the most promising seem to be the theoretical and the AI approaches.

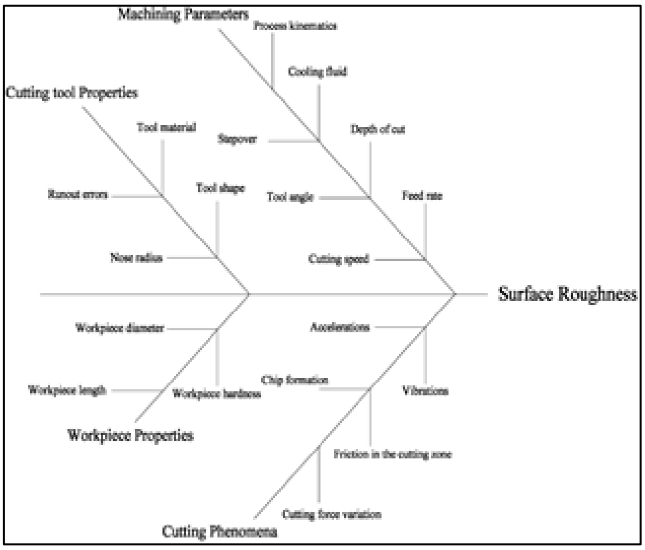
A comparison of these two approaches reveals that AI models take into consideration the particularities of the equipment used and the real machining phenomena, information that is stored in the experimental data used to develop the models. On the other hand, the theoretical approach is based on conventions and idealizations, which are responsible for errors and limitations. Surprisingly enough, a combined effort that would involve both AI and analytical modeling so as to validate, refine or correct the theoretical models was not found in the literature.

Other advantages of the AI approach are that the models created seem to be the most realistic and accurate, they probably exhibit the highest level of integration with computers and that this approach can be used in conjunction with other more conventional techniques. With these facts taken into consideration, it can be concluded that there are not so many efforts as would have been expected. The same applies to the existing number of hybrid AI research approaches, such as the neuro-fuzzy systems. The advantages that they offer (knowledge representation in the form of if-then rules, ANN assisted parameter determination) should be more than enough to encourage researchers to adopt these techniques, yet this has not been the case.

Optimization of cutting conditions for a certain surface roughness is another field that has not received too much attention. GAs and other optimization algorithms could be ideally used in conjunction with the developed models for the prediction of surface roughness but as is evident from the above, very few similar approaches have been found.

It must also be noted that despite the fact that accurate models have been developed there are still issues to be dealt with. Certain cases like high accuracy machining, where surface roughness is of great importance, are still under investigation and factors such as the cutting tool's deflection or the thermal conditions must be introduced to future models for a more realistic depiction of surface roughness creation. The integration of the existing models to a more general advisory system, which could be used by a machine tool operator for example, could be another very useful and practical application.

Finally, the set of parameters that are thought to influence surface roughness and thus have been investigated by the researchers, is diagrammatically displayed.



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