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Simulation-based surface roughness modelling in end milling

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Abstract

The surface topography often is an important quality criterion for the manufacturing of milled workpieces as it often defines their functional behaviour. In machining both, the kinematics of the process and the stochastic influences deriving from the machine tool, workpiece and the surrounding environment affect the workpiece’s surface roughness. This paper presents a simulation-based method for flank milling, which considers kinematic and stochastic influences including run-out errors and tooth length variations. The simulation results are used in combination to predict the surface roughness depending on the chosen process parameters. Hence, also making in possible to choose appropriate process parameters to achieve a defined surface roughness.

Keywords: Simulation; Topography; Roughness; End milling

1. Introduction

The surface topography has a significant influence on the performance of a machined part within its life cycle. Functional properties such as resistance to wear and/or the fatigue life depend on the surface topography and subsurface properties such as hardness or residual stress. For this purpose, the designer specifies functional surfaces for a part, with the objective to meet set requirements regarding e. g. optics, sliding or sealing capacity. The specifications are generally set at the beginning of a product-development cycle and have a great impact on the resulting manufacturing costs. The surface topography in milling is determined by a number of factors including cutting tool and workpiece properties, machining parameters and cutting phenomena [1]. While the manufacturer cannot influence all of these factors, there remains the task of selecting appropriate process parameters, which is also referred to as the inverse problem in manufacturing [2]. This denotation describes the manufacturer specifying the target values for surface properties and then inversely deducing suitable values for the process parameters.

CAM systems are widely used to aid manufacturing companies in planning of complex machining processes. Although these systems use advanced geometric calculations for tool path calculation, they only consider the workpiece and a simplified cutting tool geometry while ignoring all physical restrictions and effects during the machining process. Thus, it remains a task for all manufactures to choose their own process parameters in order to meet requirements regarding part quality. During the first putting into operation of a machining process companies often rely on expert knowledge and trial-and-error strategies to choose appropriate process parameters. Here the most common strategy involves choosing conservative parameters, which however neither guarantee the desired surface quality nor maximize the material removal rate [1]. Given the increasing demand for customized products and small lot sizes, decreasing the time needed for putting a process into operation has become an increasingly relevant economic goal for manufacturers. In the scientific community, extensive research has been conducted regarding the modelling of surface roughness in various machining processes. However, manufacturing companies do not widely benefit from these results, as they are solemnly available within CAM systems [3]. Hence, the successful integration of models for parameter selection and tool path optimization within CAM would increase the practical applicability of these models and therefore increase their impact on the technological advances in manufacturing companies [4,5]. However, the availability of such models is often limited due to their specific scope of application. In this article, the authors strive to provide a model for end milling which can be parameterized using few

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empirical datasets. These datasets are to be easily obtainable for manufacturers with standard equipment also utilized for quality control purposes.

1.1 Surface roughness modelling in machining

Available models to predict the surface topography can be categorized into physical, empirical and semi-empirical models. In milling, physical models describe the shape of the cutting tool and/or the trajectory of the individual cutting edges and solve these problems by means of either analytical or numerical approaches. Arizmendi et al. present an example for a physical model, where the surface topography generated by ball-end milling is described using equations for the cutting edge trajectories and converging them into 3D surfaces of the machined workpiece. By this, the authors were able to simulate the geometric shape of the surface topography while also considering the effect of tool run-out. Visually comparing measured and simulated surfaces, validated the model to predict the topography reasonably well [6]. Baek et al. presented a surface roughness model for face milling operations considering the run-out of individual inserts and the feedrate as input parameters. With the presented geometric model, it was possible to predict the trajectory for each individual cutting edge and determine the resulting surface profile as well as the corresponding value for Ra. The model was then used to heuristically maximize the feedrate while not exceeding a set roughness value [7]. Empirical models use data, generated from an experimental set up where some factors are systematically varied while the change of value in specified responses is measured. Regression analysis is often employed in order to derive models from the data collected. Routara et al. used the response surface method (RSM) to evaluate the effect variation in process parameters, viz spindle speed, depth of cut and feedrate, and workpiece material had on the surface roughness in end milling. The accuracy of the prediction is confirmed to be also dependent on the actual roughness parameter observed; leading the authors to the hypothesis that adapting the modelling techniques according to the particular roughness parameter of concern might yield the best modelling results [8]. Semi-empirical models are a combination of the two approaches described above. The aim when combining the two approaches is to create a physical model, which is then modified using empirical data to describe the observed phenomenon with greater accuracy. For a ball-end milling process Denkena et al. combined the result of a material removal simulation with empirical measurements to depict the surface geometry and corresponding roughness parameters more accurately [9]. All of the above-mentioned models have their field of application. In order to choose the appropriate modelling technique, the user has to define clearly the purpose of the model. Depending on the resolution and complexity of the necessary calculation, physical approaches can require large amounts of computation power and simulation time. Which can hence applicability of these models for optimization scenarios, where multiple simulation runs are necessary to find an acceptable solution. On the other hand, the empirical approach often yields an accurate and easy to use model for the observed case, but has limited validity beyond the experimental scope [10].

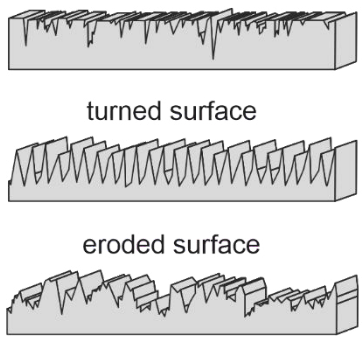

Fig. 1. Roughness parameters for machined surfaces [11]

Experimental models are generally adopted when the problem cannot be (easily) expressed analytically [1]. The combination of both modelling types into semi-empirical models is one possibility to merge the strength of both approaches into one: Maintaining a physical explicability while modifying the results to fit the empirically observed. This also potentially limits the amount of empirical data required to refine the model, as the majority of the effect should be explicable through the physical part of the model. Moreover, the combinations of these two modelling types yields a surface profile rather than only predicting values for certain roughness values. The profile itself is of interest as the roughness parameters only give an indication as to whether or not the surface topography is suitable to fulfil the functional requirement. Identical surface roughness values may be used to describe vastly different topographies as depicted in Fig. 1. While it is not possible to deduce a surface topography from given roughness parameters, it is possible to calculate any given roughness parameter from a simulated topography. Hence, making this approach more flexible while also allowing for a visual feedback regarding the geometric constitution of the surface.

Although all model-types can potentially be integrated within a CAM-System, choosing semi-empirical models, which use the empirical data only to refine the roughness prediction, could allow these models to be adjusted by the user to fit their specific use-case. Therefore, a semi-empirical model is pursuit for surface roughness prediction within this paper.

1.2 Surface generation in end milling

In end milling, the influence of the feed per tooth f_z on surface roughness can be described analytically. The movement of the cutting edge's tip during one revolution of the cutter follows a cycloidal trajectory. This kinematic leads to the fact that the material is not completely removed to the nominal dimension, but a residue remains. Leftover residual material is called kinematic or theoretical roughness and is shown in Fig. 2. The feed per tooth f_z or respectively the feed velocity v_f in combination with the rotations per minute n determine the theoretical roughness. The rotational speed n does not have any impact on the theoretical roughness, as it only determines how fast the tool is removing the workpiece material, but not on which path.

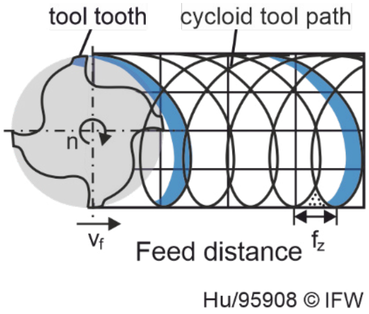

Fig. 2. Surface generation in end milling [12]

The theoretical surface that can also be described mathematically using the cutting edges trajectory, which refer to the outermost point of the cutting edge. However, empirical studies show that the roughness actually measured is higher than the theoretical roughness [9,13]. In addition to the process kinematics, there are other factors that influence the surface roughness, some of which are deterministic and some stochastic. Additional deterministic influences are e. g. run-out errors or deviations of the cutting edge's length of the milling cutter from the nominal geometry. Stochastic influences include inhomogeneity in the workpiece material, vibrations occurring in the process or the chipping of the cutting edge. In [9] it was shown that a superposition of the kinematic and stochastic influences in ball-nose milling leads to an increased roughness prediction quality, so that a higher agreement between measured and simulated roughness was achieved. A similar approach is adopted in this paper to model the surface roughness for end milling.

2. Approach

The objective of the presented approach is to predict the surface topography for an end milling process for varying the cutting speed v_c and the feed per tooth f_z using a semi-empirical model.

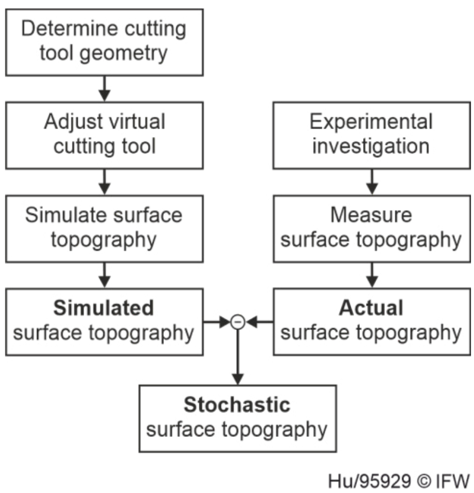

Fig. 3. Steps for determination of stochastic surface roughness model

This model consists of two components: A physical model predicting the kinematic topography taking into consideration the cutting tool geometry, tooth length variation and run-out errors and an empirical model predicting the stochastic deviations from the simulated profile.

The steps to attaining the stochastic roughness model are shown in Fig. 3. First, the real tool geometry is optically measured determining the deviation in length of each cutting edge from the nominal diameter of the tool. This information is applied to adapt a virtual tool model. Using the adapted model, a material removal simulation is performed to create the kinematic surface topography. Apart from that, the real tool is also used to perform an experimental investigation varying the process parameters f_z and v_c systematically. The resulting surface topographies are evaluated and profiles are extracted. These profiles are then compared to the kinematic profile. When aggregating the differences between the real and the kinematic topography a mathematical distribution, which models the stochastic deviations, is obtained. The definition of both model parts are explained in more detail within the next two chapters.

2.1 Physical model definition

Within the physical model, three effects are considered: the tool geometry, the run-out error and the variation in tooth length.

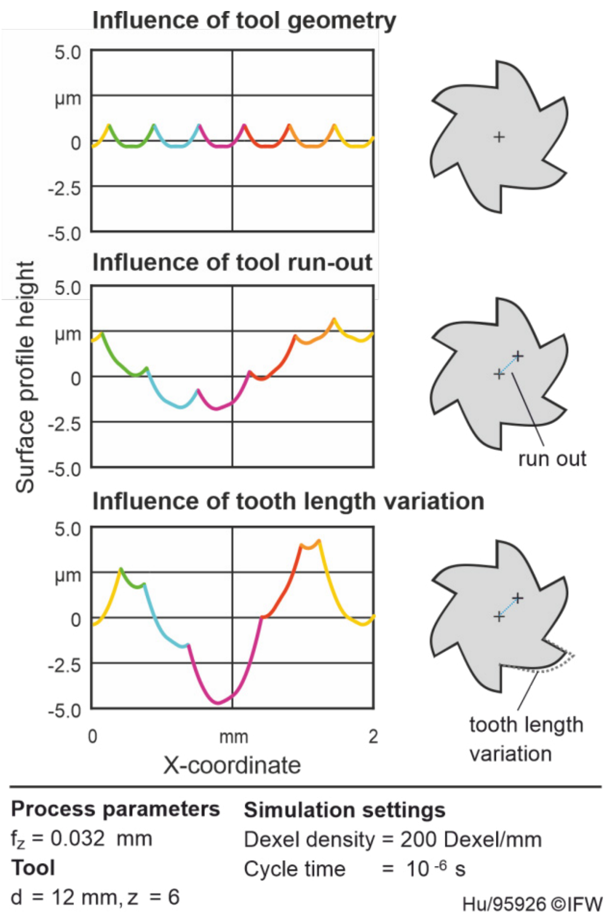

Fig. 4. Influence of tool run-out and tooth length variation on surface topography

The tool geometry itself is responsible for the theoretical surface roughness. If no other factors were influencing the surface generation, this would be the surface obtained after end milling. However, cutting tools often have a run-out error, which results from the combined run-out errors of the tool itself, its holder and the machine's spindle. Another influence is a variation in tooth length that can occur within a multi-toothed end mill because each individual tooth has a specific depth of cut. The effects and the resulting surface profiles were simulated using the material removal software IFW CutS [14]. The results for the influence of the different effects are shown in Fig. 4. Here, for visualization purposes the surface generated by each tooth is coloured differently, thus marking the finale surface generated by each tooth. It is noteworthy that with a tool run-out or a variation in length of the cutting tools' teeth, the length of a single tooth's' engagement and its depth of cut varies. This can also result in a surface profile, which is generated by only a few of the cutters' teeth. In such a case, the surface generated from a tooth with a smaller depth of cut is undercut from the subsequent tooth. These phenomenon's therefore cause irregularities in the surface profile.

With the goal of integrating the above-mentioned effects, a 3D CAD model of the tool is modified. For this purpose, the tips of the tools' teeth are isolated, making them freely positionable as individual CAD objects. The real positions of the tools cutting edges were then measured using a Zoller Venturion pre-setting and measuring machine. The teeth were shifted by a distance Δd in- or outwards along the radius of the tool. The process is visualized in Fig. 5. With this method the run-out of the tool-holder, tool and the variation of tooth length is measured as a superposed effect.

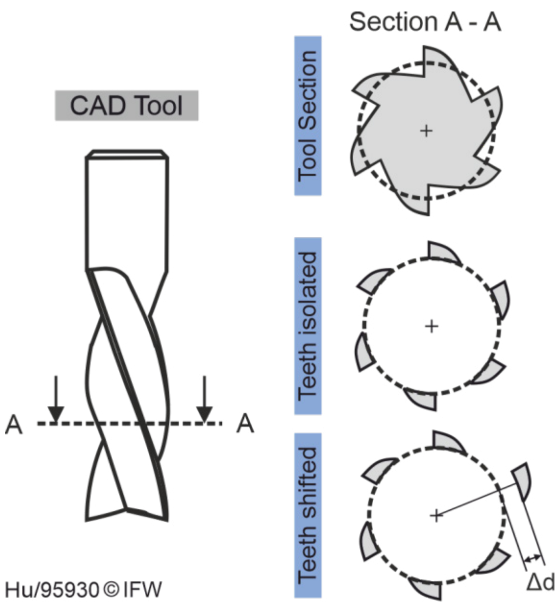

Fig. 5. Isolation and repositioning of cutting tool teeth

2.2 Empirical model definition

To obtain a statistical distribution, which describes the deviation between the kinematic and the actual topography, milling experiments according to the process parameters in Table 1 were conducted. The workpiece material 42CrMo4 (1.7225, EN 10083-3) was used in the investigations. The experiments where performed on a DMG HSC 55 linear machine tool with a Heidenhain iTNC 530 control unit. A cemented carbide end mill with a diameter of 12 mm and z= 6 teeth (Walter H3021138-12) was applied. The resulting surface topography was measured in feed direction with the optical surface measuring system TOOLinspect from Confovis, which can be utilized to digitize surfaces through focus variation. The digitized surface was then used to extract 10 profiles for each parameter combination. These profiles are the empirical database from with the statistical distribution is derived.

Table 1. Process matrix for the experiments

	Feed/tooth f_z [mm]	Cutting speed v_c [m/min]
Range of variations	0.24 – 0.4	80 – 220
Number of variations	3	4
Process parameters		
Depth of cut [mm]	20	
Width of cut [mm]	0.3	

To compare the simulated and measured surface profiles they are first aligned in x- and z-direction, where x is the feed direction and z is the profile height, employing the method of least squares. An example for the simulated and measured profile before and after alignment is shown in Fig. 6. The tool used for the experiments had a run-out error of 10 µm, which is also visible in measured profile.

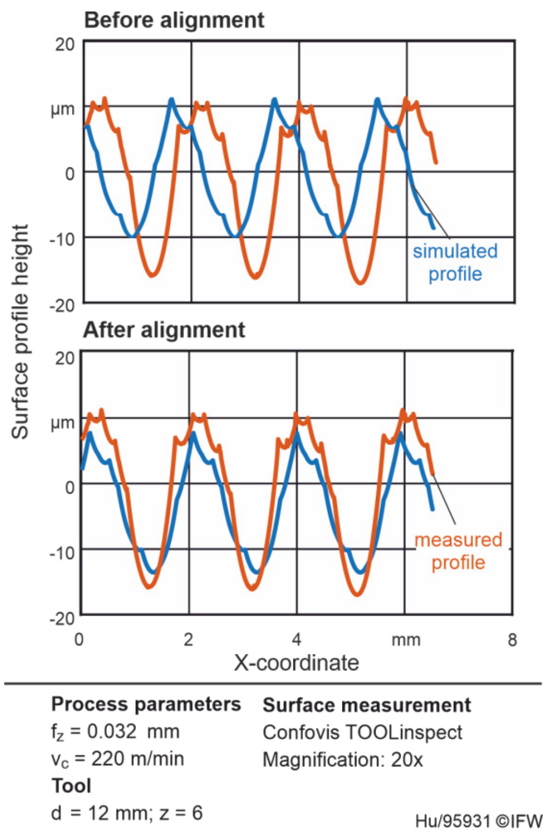

Fig. 6. Simulated and measured profile before and after alignment

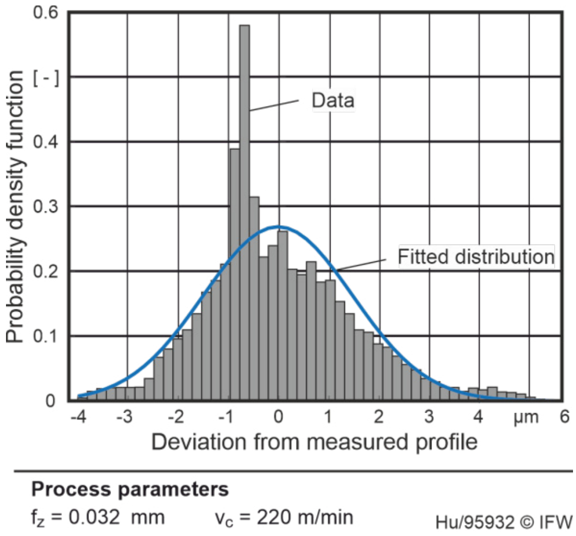

Fig. 7. Data distribution for stochastical surface roughness

The differences in z-direction between the measured and simulated profile are then extracted point-by-point using the simulated profile as an origin. For each point in the simulated profile, the corresponding point with the same x-coordinate in the measured profile is found. If there is no point with the exact coordinate, linear interpolation between the two closest neighbouring points is used to determine the z-coordinate.

This method is performed for all 10 profiles measured for each parameter combination. Afterwards the data is plotted in a probability density plot showing how often which deviation between simulated and measured profile occurs. Further the data is fitted with a gauss distribution as shown in Fig. 7.

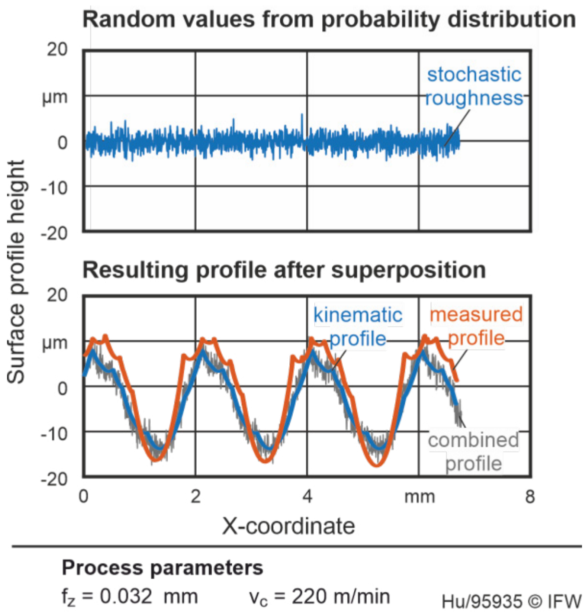

Fig. 8. Stochastical profile derived from probability distribution and resulting profile after combining kinematic and stochastic profile

Having derived a probability distribution P for the stochastical surface deviations, it can be used to superpose the kinematic surface profile. In order to perform the superposition a random value X is generated for every data point in the kinematic profile using P. X is then added to the corresponding point in the kinematic profile forming the resulting profile of the combined model. The process is shown in Fig. 8. The resulting profile can then be visually compared to the measured profile and the desired surface roughness values can be calculated.

3. Results and discussion

A single superpositioning of values from the probability distribution with the kinematic profile yields only one possible surface profile. Every repetition results in a slightly different surface profile due to the fact that the numbers from P are chosen randomly. This also causes the roughness values calculated using the superposed profile to scatter. One possibility to counter this problem, is to perform multiple superpositions until the change in the average roughness value $\Delta\bar{R}$ is below a threshold.

$$\Delta\overline{Ra} = \sum_{i=1}^{n} Ra_i \cdot \frac{1}{n} - \sum_{i=1}^{n+1} Ra_i \cdot \frac{1}{n+1} \tag{1}$$

Equation (1) shows the calculation for $\Delta\bar{R}$ exemplary using Ra and Fig. 9 shows the change in $\Delta\overline{Ra}$ and $\Delta\overline{Rz}$ depending on the number of iterations performed. In conclusion about 100 iterations are required to reach a steady state for Ra and Rz where $\Delta\bar{R}$ is below 0.01µm. However, the scattering causes a standard deviation of 2% for Ra and 6-8% for Rz. Rz scatters significantly more than Ra, because it is calculated using the minima and maxima of a profile, which are more prone to change between subsequent superpositionings.

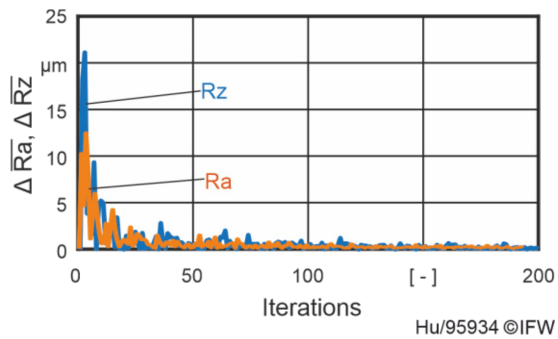

Fig. 9. Change in average roughness values Ra and Rz for multiple superpositions of kinematic and stochastic surface profiles.

In order to evaluate the accuracy of the developed semi-empirical model the ratio between the simulated and measured Ra and Rz values is considered for the investigated process parameters v_c and f_z. Further, the accuracy of only the kinematic model compared to the accuracy of the combined model. Accuracy is understood as a measure of how close the simulated and measured roughness values coincide, a ratio of 1 between the simulated and measured values describes a perfect match. The results for the models' accuracy are shown in Fig. 10. A general observation for the results is that the kinematic roughness is always lower than the roughness values predicted from the combined model and also always below 1. This coincides with the ambition to model as many effects as possible using the kinematic model and bridging the gap to the measured profile by modelling the stochastic influences. It can

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be observed that v_c has only a slight influence on Ra and Rz.

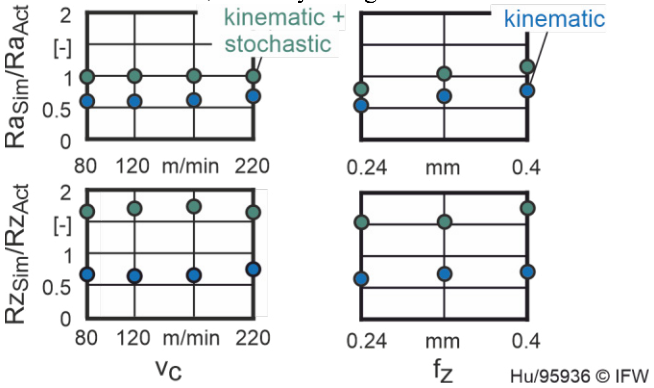

Fig. 10. Model accuracy for investigated process parameters

Regarding the kinematic simulation results lower v_c yield a lower accuracy for both Ra and Rz. The process parameter v_c has no influence on the kinematics of the process, however with higher v_c the measured roughness decreases, hence increasing the accuracy of the kinematic model for higher v_c. Therefore, this effect would have to be modelled in the empiric part of the model. For Ra the accuracy is very close to 1 for the combined model. For Rz the combined model yields results that are around 1.7, while the kinematic model alone results in a 0.7 accuracy value. Further, the influence of f_z is investigated, showing a higher influence on both roughness parameters than v_c. For Ra the accuracy is increasing with an increase in f_z. One explanation is that with a higher f_z more of the surface roughness can be contributed for by the kinematic roughness alone, making other factors secondary. The accuracy for the kinematic model is between 0.5 and 0.8 and between 0.8 and 1.2 for the combined model. However, for Rz the accuracy for only the kinematic model is between 0.6 and 0.75 while the accuracy of the combined model is between 1.6 and 1.9. In total, the combined model does prove to predict Ra values reasonably well while delivering much higher than expected values for Rz. A like cause is the higher sensibility of Rz to outliers which are likely created by the empiric model. Further investigations have to be made to adapt the kinematic model in order to better predict a sensitive parameter such as Rz. One field worth investigating in this regard is the strategy, which is applied in choosing numbers from the probability distribution. Neighbouring points in a measured profile are not independent from one another and large differences in consecutive profile points are unlikely. With the current superpositioning strategy it is possible to have values from opposing ends of the probability distribution added to consecutive points. This can lead to large height differences which in turn impact Rz. Including a maximal allowed height difference in two consecutive points might yield a better empirical model to predict Rz, as this could limit the number of peaks created in a profile. Further it seems plausible to assume this would limit the high frequency noise which the stochastic roughness adds to the kinematic profile and hence also result in a better fit.

4. Conclusion and Outlook

This paper presents a semi-empirical model for the prediction of surface topographies and surface roughness values in end milling. The kinematic model uses a material removal simulation to consider the kinematic characteristics of the milling process. The empirical part models the stochastic influences on the surface topography. By applying multiple superpositions of the kinematic and stochastic topography a steady state for the roughness values can be reached. Overall the prediction accuracy for the combined model is good for Ra. For Rz the combined model however does consistently values which are 60 to 90% higher than desired. The kinematic model alone provides more accurate results for Rz. While refining the model is still future work, it was shown that it is possible to create an empirical model with a relatively small number of experiments. Thus, also making it more feasible for CAD/CAM providers to integrate these models at lower costs due to the small database required. Hence increasing the availability of technological knowledge regarding the choice of appropriate surface parameters for manufacturers.

5. Acknowledgements

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