Robotics and Computer Integrated Manufacturing 53 (2018) 215–227

Contents lists available at ScienceDirect

Robotics and Computer Integrated Manufacturing

journal homepage: www.elsevier.com/locate/rcim

Using artificial intelligence models for the prediction of surface wear based on surface isotropy levels

A. Bustillo[a,1], D.Yu. Pimenov[b,*,2], M. Matuszewski[c], T. Mikolajczyk[d]

[a] Department of Civil Engineering, University of Burgos, Avda Cantabria s/n, Burgos 09006, Spain
[b] Department of Automated Mechanical Engineering, South Ural State University, Lenin Prosp. 76, Chelyabinsk 454080, Russia
[c] Department of Vehicle Engineering, UTP University of Science and Technology, Al. prof. S. Kaliskiego 7, Bydgoszcz 85-796, Poland
[d] Department of Production Engineering, UTP University of Science and Technology, Al. prof. S. Kaliskiego 7, Bydgoszcz 85-796, Poland

ARTICLE INFO

Keywords:
Small size dataset
Ensembles
Wear
Isotropy level geometric structure of the surface
Roughness

ABSTRACT

Currently, a key industrial challenge in friction processes is the prediction of surface roughness and loss of mass under different machining processes, such as Electro-Discharge Machining (EDM), and turning and grinding processes. Under industrial conditions, only the sliding distance is easily evaluated in friction processes, while the acquisition of other variables usually implies expensive costs for production centres, such as the integration of sensors in functioning machine-tools. Besides, appropriate datasets are usually very small, because the testing of different friction conditions is also expensive. These two restrictions, small datasets and very few inputs, make it very difficult to use Artificial Intelligence (AI) techniques to model the industrial problem. So, the use of the isotropy level of the surface structure is proposed, as another input that is easily evaluated prior to the friction process. In this example, the friction processes of a cubic sample of 102Cr6 (40 HRC) steel and a further element made of X210Cr12 (60 HRC) steel are considered. Different artificial intelligence techniques, such as artificial regression trees, multilayer perceptrons (MLPs), radial basis networks (RBFs), and Random Forest, were tested considering the isotropy level as either a nominal or a numeric attribute, to evaluate improvements in the accuracy of surface roughness and loss-of-mass predictions. The results obtained with real datasets showed that RBFs and MLPs provided the most accurate models for loss of mass and surface roughness prediction, respectively. MLPs have slightly higher surface prediction accuracy than Random Forest, although MLP models are very sensitive to the tuning of their parameters (a small mismatch between the learning rate and the momentum in the MLP will drastically reduce the accuracy of the model). In contrast, Random Forest has no parameter to be tuned and its prediction is almost as good as MLPs for surface roughness, so Random Forest will be more suitable for industrial use where no expert in AI model tuning is available. Moreover, the inclusion of the isotropy level in the dataset, especially as a numeric attribute, greatly improved the accuracy of the models, in some cases, by up to 52% for MLPs, and by a smaller proportion of 16% in the Random Forest models in terms of Root Mean Square Error. Finally, Random Forest ensembles only trained with low and very high isotropy level experimental datasets generated reliable models for medium levels of isotropy, thereby offering a solution to reduce the size of training datasets.

1. Introduction

Today, the objective of using resource-saving technologies when working with machined surfaces is especially relevant. These surfaces include friction bearings, linear guide rails, friction joints for industrial robots, worm gear engagement, etc. Among other aspects, the working properties of the workpiece are affected by the roughness of the machined surface.

The surface wear of machined workpieces is mainly determined by the surface structure of the workpiece prior to the wear process and the friction distance, once the materials of the two friction surfaces are fixed. Therefore, the prediction of surface wear can be considered as an extension of the problem of predicting the surface roughness of a cutting process that includes the friction distance. To date, abundant research may be found on surface roughness that results from the main machining techniques: turning, grinding and Electro-Discharge

* Corresponding author.
E-mail addresses: abustillo@ubu.es (A. Bustillo), danil_u@rambler.ru (D.Y. Pimenov), matus@utp.edu.pl (M. Matuszewski), tami@utp.edu.pl (T. Mikolajczyk).
[1] Andres Bustillo: https://orcid.org/0000-0003-2855-7532.
[2] Danil Yu. Pimenov: https://orcid.org/0000-0002-5568-8928.

https://doi.org/10.1016/j.rcim.2018.03.011
Received 16 October 2017; Received in revised form 16 March 2018; Accepted 16 March 2018
0736-5845/

Nomenclature

L	Sliding distance (road friction)
Rq	Root mean square (RMS) profile
Rpk	Reduced peak height of profile
Ra	Arithmetic mean of the profile
V_c	Cutting speed for turning
V_s	Cutting speed for grinding (peripheral speed)
f	Feed rate
a_p	Grinding depth
I	Discharge current
Is	Isotropy level of the surface in percentage terms
t	Discharge time
τ	Break time
Δm	Loss of mass relative to the mass of the initial sample

Machining (EDM). Various authors have examined turning [1–5]. Benlahmidi et al. [1] demonstrated the influence of cutting modes and workpiece hardness on surface roughness, cutting pressure, and cutting power in the hard turning of hardened AISI H11 (X38CrMoV5-1) using CBN7020 tools. Debnath et al. [2] studied the influence of various cutting liquids and cutting modes for turning on surface roughness and tool wear. Li et al. [3] discussed the influence of surface isotropy on precision turning of the end surface. Chinchanikar and Choudhury [4] sought to show the influence of cutting parameters, tools and materials, various types of coating, and tool geometry on tool durability, and surface roughness, etc. Abbas et al. [5] obtained a Pareto frontier for surface roughness Ra and the minimum machining time of unit volume T_m of the finished turning workpiece from high-strength steel using the artificial neural network model that was later used to determine the optimum finishing cutting conditions. However, in none of the above articles is the relationship discussed between surface roughness and the isotropy level of the surface, depending on the surface processing method and the wear generated by surface friction.

Along the same lines, other researchers [6–13] have presented studies on surface textures resulting from grinding. Jain and Jain [6] described the processing profiles of the finished surface and the workpiece material, their analysis, modelling, and subsequent machining by means of abrasive grain grinding. Niemczewska-Wójcik [7] studied the surface texture of titanium alloy TiAlSiZr samples after precision grinding. Chen et al. [8] discussed the influence of surface roughness and precision turning on friction and wear for cutting diamonds. Chi et al. [9] suggested a simulation model of the workpiece surface in external cylindrical grinding. Vainer et al. [10] studied the microgeometry of end surfaces in bidirectional grinding. Yali et al. [11] evaluated surface topographical characteristics in correlation with the random process of machining. Stout et al. [12] used 3D characterization to study the topography of the grinding process. Cao et al. [13] established a new analysis and a simulation model for surface topography of the grinding process, taking account of vibration between the grinding wheel and the machined workpiece. Finally, the determination of roughness in EDM was described by Wu et al. [14] and Markopoulos et al. [15], considering the main process parameters such as polarity, discharge current, pulse duration time, open circuit potential, gap voltage, and surfactant concentration. However, the articles do not show the relationship between the surface roughness structure and the surface isotropy level, depending on the method of obtaining the surface.

Petropoulos et al. [16] presented the isotropy of machined surfaces and methods for surface typology. Krolczyk et al. [17] analysed high-strength steel surfaces using an optical 3D measurement system to investigate the surface morphology and the parameters of surface topography in turning, grinding, planning and abrasive blasting. Krolczyk et al. [18] studied the surface texture of machine parts produced by turning. In Bulaha [19], the topography of the given samples was taken in order to obtain and to compare the roughness parameters and for the purpose of setting a relation between the cutting regime and the roughness parameters, and for determining the mathematical model of cylindrically ground samples, which allow us to estimate service properties. In their scientific investigation of surfaces with irregular roughness, Bulaha and Rudzitis [20] set out to check the compliance of the surface roughness model with the theoretical parameters and to evaluate roughness anisotropy, using 3D and 2D surface roughness parameters. Sedlaček et al. [21,22] investigated the possibility of designing contact surfaces with reduced friction using surface roughness and topography analysis. However, the above methods for surface machining are limited by the number of experiments and will not allow us to predict the roughness of random surface isotropy. Matuszewski et al. [23] discussed the influence of the geometric structure of the machined surface and the parameters of turning, grinding, and EDM on the progressive wear of frictional pairs. Nieslony et al. [24] revealed that the surface topography, alongside the 3D functional parameters, and PSD influences the performance of the machined surface.

Due to the interaction of friction pairs with the interaction of their surfaces, the geometric structure of the surface has a significant effect on the tribological properties and characteristics [25–30]. The metrological measurements of surface topography should as far as possible reflect the actual structural configuration, which will in turn allow a proper assessment of the useful features of friction pairs.

A detailed analysis of the theoretical aspects of the impact of surface topography on friction can be found in [31–37]. A large number of these works prove that topological analysis in the tribological aspect has a wide field of application. However, the wide variety of research conditions and the assumptions used to describe change to Geometric Surface Structure (GSS) parameters greatly hinder the formulation of generalizations. There is no general information on the effect of the isotropy level on the operating conditions of the friction node - oil film formation, motion resistance. At present, it is always advisable to use a set of appropriately selected parameters [38,39], which is often a complex problem. In the work by Wieczorowski [39], it is suggested that, in addition to the parameters to be selected for the assessment, the method of treatment is also provided.

Alongside both the analytical and the experimental models for the previously presented cutting processes, there are different Artificial Intelligence (AI) techniques that have been tested to model the prediction of surface roughness after a cutting process, which many reviews have described as a very extensive area of research [40–43]. In-process neural network-based systems for surface roughness prediction are proposed in [15,44–47] using cutting forces in electrical-discharge machining, turning, CNC turning, end-milling, and face milling, respectively. Similar neural-network based systems in [48–50] focus on face-milling operations. Abburi and Dixit [51] proposed a method based on a neural network and fuzzy set theory to predict surface roughness during turning processes. Zhang and Chen [52] proposed an end-milling in-process adaptive control system, based on multiple-regression algorithms, including machine-cutting parameters such as feed rate, spindle speed, cutting depth, and cutting-force signals detected by a dynamometer sensor for surface-roughness control. Related to wear prediction, Alauddin et al. [53] predicted tool life in end milling with a response surface methodology, Mikołajczyk et al. [54] described a set up for the automatic prediction of tool life in turning operations, and Martins et al. [55] used neural networks for this task in grinding operations. Finally, ensemble methods [56] used several prediction models at the same time. Each model provides its prediction and all the predictions are joined. Ensembles have demonstrated their high accuracy at predicting different manufacturing processes: Bustillo et al. [57]