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Data-mining modeling for the prediction of wear on forming-taps in the threading of steel components

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Abstract

An experimental approach is presented for the measurement of wear that is common in the threading of cold-forged steel. In this work, the first objective is to measure wear on various types of roll taps manufactured to tapping holes in microalloyed HR45 steel. Different geometries and levels of wear are tested and measured. Taking their geometry as the critical factor, the types of forming tap with the least wear and the best performance are identified. Abrasive wear was observed on the forming lobes. A higher number of lobes in the chamber zone and around the nominal diameter meant a more uniform load distribution and a more gradual forming process. A second objective is to identify the most accurate data-mining technique for the prediction of form-tap wear. Different data-mining techniques are tested to select the most accurate one: from standard versions such as Multilayer Perceptrons, Support Vector Machines and Regression Trees to the most recent ones such as Rotation Forest ensembles and Iterated Bagging ensembles. The best results were obtained with ensembles of Rotation Forest with unpruned Regression Trees as base regressors that reduced the RMS error of the best-tested baseline technique for the lower length output by 33%, and Additive Regression with unpruned M5P as base regressors that reduced the RMS errors of the linear fit for the upper and total lengths by 25% and 39%, respectively. However, the lower length was statistically more difficult to model in Additive Regression than in Rotation Forest. Rotation Forest with unpruned Regression Trees as base regressors therefore appeared to be the most suitable regressor for the modeling of this industrial problem.

Keywords: Roll-tap wear; Roll taps; Threading; Forming taps; Ensembles; Rotation forest; Regression trees

1. Introduction

There are two basic technologies for manufacturing internal threads: form tapping (using roll/form taps) and cut tapping (using cut taps). The first process is chipless because the thread is formed by a cold-working process. Hence, stronger threads, particularly in materials susceptible to strain hardening, good thread calibration and a longer tool life are achieved. Form tapping is studied in the present work, applied in this case to a cold-forged piece, in which the holes were punched in a cold-forging process. In the case of form tapping, the thread is formed by deformation of the raw material in a cold-working process [1]. This process causes an imperfection at a minor diameter of the formed threads (thread peaks) referred to as a claw or a split crest, although these imperfections imply no reduction in strength [2,3]. Claw shapes depend on the hole diameter before threading [4]. Form tapping can be performed on ductile steels, non-ferrous alloys [5] and tempered steels [6].

Stéphan et al. [7] maintained an acceptable forming torque and deep enough threads to avoid stripping problems by optimization of the initial hole diameter. Fromentin et al. [8] studied the 3D plastic flow in form tapping, measuring material displacement and Stéphan et al. [9] developed a 3D finite element model for form tapping with the ABAQUS 6.5 software program.

The prediction of tap wear involves three degradation phenomena: adhesive, abrasive and erosive wear. Adhesive wear is caused by the transfer of material from one surface to the other. Abrasive wear is caused by material removal from a

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solid surface, due to the sliding effect of hard particles or roughness peaks against the other contact surface. Finally, erosive wear is material loss from a solid surface, due to the action of a fluid containing solid particles.

Simulations were focused on external thread manufacturing by deformation [10]. Domblesky [11] worked on the simulation of thread rolling with good accuracy and then on the optimization of process parameters [12]. The most direct approach involves a macroscopic description of worn surfaces and empirical modeling of the wear based on the process parameters [13].

Data-mining represents a collection of computational techniques, which analyze very complex phenomena. The most common data-mining techniques applied to manufacturing problems include Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), k-Nearest Neighbors Regressors, and Regression Trees. A combination of two or more models, known as an ensemble, sums the predictions capabilities of the combined models. Ensembles have demonstrated their superiority over single models in many applications. For instance, Yü [14] used ensembles to identify out-of-control signals in multivariate processes. Liao et al. [15] and Bustillo and Rodriguez [16] used ensembles for grinding wheel and multitooth tool condition monitoring, respectively, while Cho [17] and Bisaeid [18] used ensembles for end-milling condition monitoring and simultaneous detection of transient and gradual abnormalities in end milling. Ensembles have the advantage of circumventing the fine tuning of other artificial intelligence models such as ANNs [19]. The most common types of ensemble techniques are Bagging, Boosting and Random Subspaces. Finally, a recent ensemble technique, Rotation Forest [20], has demonstrated a capability to model different industrial problems [21]. All these techniques will be presented in detail in Section 3. To the best of the authors' knowledge, there are no other investigations that have modeled form tapping process outputs with data-mining techniques. One novel robust approach for root-cause identification in machining process using a hybrid learning algorithm and engineering-driven rules was developed by Shichang et al. [22]. In contrast, Mazahery [23] proposed the use of ANN for tribological behavior modeling of composites, adjusting the weights and biases in the network during the training stage to minimize modeling error. In relation to aluminum nanocomposite processing, Mazahery [24] proposed the use of genetic algorithms to predict the mechanical properties and to optimize the process conditions and Shabani [25] used adaptive neuro-fuzzy inference systems combined with the particle swarm optimization method for process optimization.

The novelty of this paper resides in its combination of an experimental analysis and a data-mining model to extract as much information as possible on tool wear in form tapping processes, an industrial process in high demand. The Multilayer Perceptron, the most widely used standard artificial intelligence technique mentioned in the literature, was used to identify the baseline improvements of this new approach [19]. This paper is structured as follows: at the end of this introduction, Section 2 presents the fundamentals of form tapping and the experimental set-up realized to obtain real data for this industrial process; Section 3 introduces the data-mining techniques that will be used to model these industrial data; Section 4 presents and discusses the experimental results of the measurements and of the modeling using the data-mining techniques; finally, Section 5 sums up the main conclusions obtained from this research and future lines of work.

2. Form tapping fundamentals and experimental procedure

2.1. Form tapping

Tap geometry is the most important parameter for a reliable process. The standard tap characteristics are chamfer length, the number of pitches in the chamfer, tap diameter and the number of lobes around a tap section. Fig. 1 shows the geometry and features of a typical forming tap. All pictures showing taps are oriented with the tap tip to the left. As shown in Fig. 1, each rounded corner of a tap section is referred to as a lobe, where deformation or friction occurs against the inner surface of the previous hole. Hence, the tap section is defined by a curved side polygon that may typically have three, five, or six corners, which are referred to as lobes.

Three type of lobes are distinguished in each tap: i) incremental forming lobes situated in the chamfer area; ii) calibration forming lobes around the nominal diameter; and, finally, iii) guiding lobes leading up to the tap shank. The

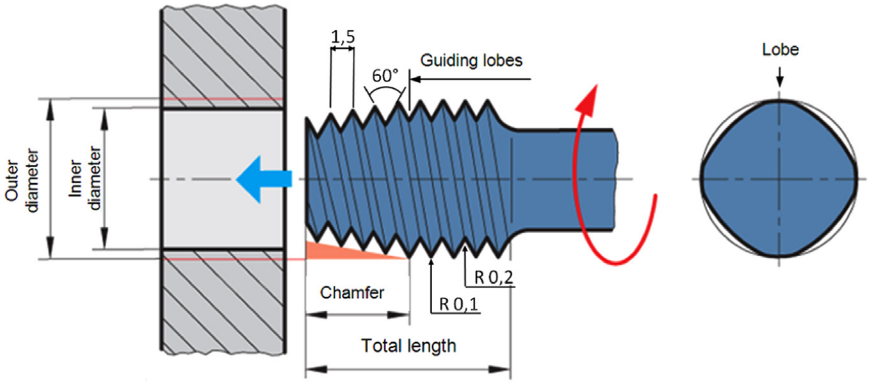

Fig. 1. Terminology and geometry of roll taps [13].