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Design of experiments and focused grid search for neural network parameter optimization

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ABSTRACT

The present work offers some contributions to the area of surface roughness modeling by Artificial Neural Networks (ANNs) in machining processes. It proposes a method for an optimized project of a Multi-Layer Perceptron (MLP) network architecture applied for the prediction of Average Surface Roughness (R_a). The tuning method is expressed in the format of an algorithm employing two techniques from Design of Experiments (DOE) methodology: Full factorials and Evolutionary Operations (EVOP). Datasets retrieved from literature are employed to form training and test data sets for the ANN. The proposed tuning method leads to significant reduction of roughness prediction errors in machining operations in comparison to techniques currently used. It constitutes an effective option for the systematic design models based on ANN for prediction of surface roughness, filling the gap reported in the literature on this subject.

1. Introduction

As newcomers to the use of Artificial Neural Networks (ANN), researchers on the field of manufacturing started to explore ways to apply networks to control or to foresee critical product quality features, and to optimize multiple objective production processes. The growing number of papers published during the past decade testifies this interest.

Machining processes, for example, generates surfaces or parts through removal of material. Production rate, cost, and product quality are conflicting objectives in this kind of process, posing additional challenges to its planning and optimization [1,2]. One feature particularly difficult to control in machined products is the surface roughness, a widely used index of product quality and a technical requirement for machined parts [3]. It affects properties such as fatigue behavior, corrosion resistance, friction, wear, light reflection, heat transmission, lubrication, electrical conductivity and coating [4,5].

The ability to accurately control surface quality can reduce machining costs by lessening the rework activities. It means that this is not just a defying issue, but also an area of research interest. The surface roughness cannot be controlled as accurately [6] because it is influenced by many variables like steel properties, tool material and geometry, vibration of cutting tool, cutting speed, feed, depth of cut, lubricant, and others [7].

Although online roughness control applications are found in literature, a more common approach is the application of ANNs to offline control based on process parameters. Off-line quality techniques are considered an effective approach to improve product quality at a relatively low cost [8]. A survey on practical efforts for network topology optimization reveals a drive towards parameter optimization. Jiménez et al. [9], for example, used Focused Grid Search (FGS) techniques for classification problems.

Despite the enthusiasm of using ANN for roughness control, the results obtained are mixed: in many cases, authors deem networks performance as equal or even worse in comparison to other modeling techniques [3,10,11]. However, a close examination on literature reveals some issues such as basics of neurocomputing being disregarded in many works. A broad review [12] found that in more

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than 40% of papers dealing with surface roughness controlled by ANNs, networks are designed by trial and error and in less than 10% any effort to optimize network topologies could be positively identified. This paper proposes then a method for tuning optimized networks of Multi-Layer Perceptron (MLP) architecture applied here for Average Surface Roughness (R_a) control in machining processes. By combining two distinct techniques, Design of Experiments (DOE) and Focused Grid Search (FGS), this work manages to establish optimization decisions based on solid statistical criteria. It is innovative because of the sequential use of DOE arrangements for finding optimal model parameters. DOE is an applied statistical methodology whose use allows to plan experiments capable of generating appropriate data for an efficient statistical analysis, resulting in valid and objective conclusions [13].

The strategy adopted consists in the use of DOE arrangements to search for network configurations that benefits output control. This method addresses problems found with previous optimization attempts: (1) It imposes no restriction on the outer search limits; (2) It avoids the use of large intervals between levels of design factors adopted in experimental planning; (3) It addresses the simultaneous optimization of the selected design parameters; (4) It takes into consideration the effects of interaction among design factor levels; and (5) As an algorithm, it proposes a systematic design method for ANN practical use. The last one is pointed as a limiter and as a disadvantage in many works [14–17].

This paper is then organized as follows. Section 2 briefly reviews concepts of machining, surface roughness and the use of DOE for ANN optimization. Section 3 explains the work's reorientation toward Evolutionary Operations (EVOP). Section 4 presents the optimization method algorithm for ANN tuning in details. Section 5 shows the experimental strategy, and Section 6 approaches the two works selected for comparison. Section 7 shows and compares the results of the optimization method to the results of the works dataset were extracted for, and to the results of a software package intended to optimize ANN architectures. Conclusions and suggestions for further research are then presented in Section 8.

2. Background and literature review

Machining is a process that generates surfaces through removal of material, conferring form and dimension to a part. Turning is the most common machining operation [18], being characterized by simultaneous and continuous movement of part and tool. Turning is controlled by its movements, which are: feed, depth of cut and cutting speed. One of the main quality features resulting from machining process is the surface roughness, which can define functional behaviors of a part such as fatigue life, wear patterns, lubricant retention, or resistance to corrosion [10,19,20]. It is linked to machine tool errors, workpiece deformation, vibration, workpiece material inhomogenities, cutting edges shape and condition, chip formation, cutting parameters, and physicochemical mechanisms acting on workpiece grain and lattice structures [7]. As pointed out, it plays an important role in determining the quality of a machined product [21,22].

Roughness is then an indicator of process performance and must be controlled within proper limits for particular machining operations [23]. The process-dependent nature of roughness formation, along with many uncontrollable factors, makes difficult to keep it between desirable limits, i.e. to control it [7,19]. Operators use their own experience and machining guidelines in order to achieve the best possible surface finish [24].

Among the parameters to measure surface roughness, the most commonly used is Roughness Average (R_a). It is the arithmetic average of the absolute value of the heights of roughness irregularities from the mean value measured [25]. For discrete measurement, R_a can be defined as in Eq. (1) [26].

$$R_a = \frac{1}{n}\sum_{i=1}^{n} |y_i| \tag{1}$$

the roughness average (R_a) is typically measured in micrometers (μm), n is the number of samples in a given length, and $|y_i|$ stands for the absolute measured values of the peak and valley in relation to the center line average. According to international standards [27], machining processes can achieve roughness values ranging from 0.025 μm to 50 μm.

Efforts to model roughness involve analytical, experimental and AI techniques [28]. Theoretical and empirical models, however, suffer from a number of problems. Theoretical models take no account of imperfections in the real process, such as tool vibration or chip adhesion [20]. Empirical models have their application limited to very specific operational conditions. The experience in both cases is then poor, as stated in many works [29,30].

The use of ANNs in machining processes has been encouraged in a considerable number of papers. Authors sustain that ANNs are a good alternative to conventional empirical modeling based on linear regressions for surface roughness modeling [10], also maintain that neural networks are able to capture the turning characteristic of non-linearity [24]. In hard turning operations, some authors approaches the difficulty of generating explicit analytical models with the complex relationship among the parameters involved and, according to them, ANN pose a suitable and practical option for modeling [31].

There is no consensus, however, on the experience with ANN for roughness modeling. Some authors point to the lack of systematic design methods as a disadvantage [14]. Others claim that finding a good ANN architecture requires several modeling attempts, making it a time consuming activity [15,16]. Researchers also testify the need of large amounts of data for training and validation as restrictions to the practical application of ANN in machining processes [32].

The most popular approaches for ANN design are empirical search optimization (trial and error), pruning and constructive approach [33]. Trial and error is common practice in most works on the field of intelligent systems [17]. In more than 40% of the papers using ANN, network topologies are explicitly defined by trial and error; Clear optimization efforts are detected in less than 10% [12]. The application of statistics for network topology optimization is not widespread in literature. The few examples found shows that the full potential of this subject is not uncovered yet. This factor could contribute to such a mixed view of ANNs abilities controlling model roughness.

DOE technique is based on the concept of simultaneous variation of factors levels, in order to build forecasting models for relevant outputs [13]. An additional advantage is that DOE principles can be implemented in a well-defined and relatively low number of experiments [30]. It is one of the most important methodologies for researchers dealing with experiments in practical applications and its tools are incorporated in many statistical software packages that ease calculation and interpretation of results [34].

A DOE application for ANN optimization in machining process can be found in [31]. The authors employed a DOE arrangement called Taguchi to select the inputs for roughness prediction in CNC face milling process. In [35], the development of roughness prediction model for polymer blends machining using MLP trained by back-propagation is also proposed employing Taguchi. Besides roughness prediction, some DOE applications for network optimization can be found such as tool wear [36] or thickness