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Indirect model for roughness in rough honing processes based on artificial neural networks

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ABSTRACT

In the present paper an indirect model based on neural networks is presented for modelling the rough honing process. It allows obtaining values to be set for different process variables (linear speed, tangential speed, pressure of abrasive stones, grain size of abrasive and density of abrasive) as a function of required average roughness Ra. A multilayer perceptron (feedforward) with a backpropagation (BP) training system was used for defining neural networks. Several configurations were tested with different number of layers, number of neurons and type of transfer function. Best configuration for the network was searched by means of two different methods, trial and error and Taguchi design of experiments (DOE). Once best configuration was found, a network was defined by means of trial and error method for roughness parameters related to Abbott–Firestone curve, Rk, Rpk and Rvk.

1. Introduction

Many variables influence responses such as surface roughness or material removal rate in abrasive machining processes. Since such processes are complex and non linear, statistical techniques of design of experiments have great difficulties to model them. Another option to overcome non linearity of abrasive machining processes consists of using artificial intelligence techniques [1]. Artificial neural networks (ANN) have provided satisfactory results in machining processes like turning [2] or milling [3]. Moreover, different authors showed an improvement in results obtained when using artificial neural network models with respect to statistical models [4,5]. Neural networks have also been proved to be useful for modeling grinding processes. For example, Sathyanarayanan et al. [6] predicted surface finish, force and power from feed rate, depth of cut, and wheel bond type by means of ANN. Liao established a model for flat finishing process with diamond stones using ANN [7]. Li, Mills and Rowe developed ANN for selecting grinding wheels in finishing operations [8]. Ben Fredj et al. predicted roughness parameters Ra and Rt from cutting speed, depth of cut, grain size of abrasive and number of passes, in cylindrical grinding process, using data from design of experiments (DOE) to train neural networks [5].

Honing is a mechanical process in which material is removed by means of friction between abrasive stones and the workpieces' surface, thanks to simultaneous rotation and translation movements. This leads to a cross-hatch pattern on the workpieces' surface, which is very important in order to retain oil as well as to reduce friction between surfaces that are in contact. Hegemier and Steward demonstrated that honing and plateau-honing processes produce the best surface finish on cylinders for four stroke diesel engines, since they optimize oil consumption, minimize ring wear and liner wear [9]. Drozda [10] and ASM [11] proved that honing is currently the only process that is able to achieve the double requirement for surface finish and cross-hatch pattern that are necessary for manufacturing cylinder liners. Relative speed of the two parts as well as pressure of abrasive stones on the workpiece's surface determine material removal rate and surface roughness of the liner. Other parameters that influence surface finish and productivity are those related to the abrasive stone: type of abrasive material, grain size and density of abrasive, as well as bond employed.

Regarding ANN applied to honing processes, Feng et al. used networks with three hidden layers and BP learning algorithm for obtaining roughness parameters related to Abbott–Firestone

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Nomenclature

ANN	artificial neural networks
$A(i, k)$	matrix containing differences between real and simulated values for each one of the k validation tests and each one of the i variables
$B(k)$	vector containing differences between real and simulated values for each one of the k validation tests
BP	backpropagation algorithm
DE	density of abrasive according to ISO6104:2013
Dif(%)	relative difference between real and simulated values
DOE	design of experiments
GS	grain size of abrasive according to FEPA
mqe	mean quadratic error between real and simulated roughness values
n	number of validation tests
N	number of neurons of the best neural network
PR	pressure of abrasive stones on the workpieces' surface (N/cm^2)
Ra	average roughness (μm)
Rk	core height (μm)
Rpk	reduced peak height (μm)
Rvk	reduced valley height (μm)
ti	real value for roughness (μm)
tDE(i)	vector containing real values for DE for each one of the i validation tests
tGS(i)	vector containing real values for GS for each one of the i validation tests
tPR(i)	vector containing real values for PRS for each one of the i validation tests
tVL(i)	vector containing real values for VL for each one of the i validation tests
tVT(i)	vector containing real values for VT for each one of the i validation tests
tV(i)	real process value of the ith pattern corresponding to roughness
Vi	each one of the process variables
VL	linear speed (m/min)
VT	tangential speed (m/min)
yi	simulated value for roughness (μm)
yDE(i)	vector containing simulated values for DE for each one of the i validation tests
yGS(i)	vector containing simulated values for GS for each one of the i validation tests
yPR(i)	vector containing simulated values for PR for each one of the i validation tests
yVL(i)	vector containing simulated values for VL for each one of the i validation tests
yVT(i)	vector containing simulated values for VT for each one of the i validation tests
yV(i)	simulated process value of the ith pattern corresponding to roughness (μm)

curve [12]. They also showed improvements in results obtained when using ANN with respect to statistical models [4]. Neagu and Dumitrescu used BP learning algorithm in three layer networks for modeling roughness, roundness and cylindricity as a function of process variables [13]. Wen et al. used ANN for solving multiobjective optimization of both quality and efficiency in the honing process of titanium parts [14]. Lawrence et al. used ANN for predicting roughness parameters related to Abbott–Firestone curve from image based parameters [15]. However, all previously mentioned papers solved the direct problem, in which values for responses, for example surface roughness, are predicted from known variables' values.

With respect to selection of best neural configuration, Zhong et al. stated that there is no exact solution for this purpose [16]. Although number of neurons is often obtained by means of trial and error approach, several attempts have been made to use systematic methods. For example, Pontes et al. used Taguchi design of experiments for selecting best configuration for neural networks used to predict roughness in turning processes [17]. Ortiz-Rodriguez et al. also used Taguchi DOE for designing neural networks [18]. They considered number of neurons in the first hidden layer, number of neurons in the second hidden layer, momentum and learning rate. Zanchettin et al. used design of experiments for identifyging most influential factors affecting a neuro-fuzzy inference system [19]. Mohana Rao et al. used genetic algorithms to optimize weights used in neural networks for modelling surface roughness in electro discharge machining [20]. On the other hand, Özel and Karpat presented a systematic approach for choosing number of hidden layers and number of neurons in turning processes, by using the output parameters of Bayesian regularization algorithm [21].

In the present paper the indirect problem is addressed for roughness in honing processes by means of ANN. This implies that input variable for the network is required roughness, and output variables are process' variables. Thus, from a certain number of input variables higher number of output variables must be predicted and this increases difficulty to achieve low error results. Alternative methods for solving the indirect problem are time series analysis [22] and real time procedures for regression models [23]. In the present paper, two models were obtained by means of ANN, one for average roughness Ra and the other one for roughness parameters related to Abbott–Firestone curve, Rk, Rpk and Rvk. Best ANN configuration was chosen as the one having lowest mean quadratic error mqe. Two different methods were used for this purpose: trial and error and Taguchi DOE. Indirect approach involves support for honing machine users in decision making when defining most appropriate values for the process variables to obtain required surface roughness. This will help users to reduce amount of experimental tests to be performed before serial production.

2. Experimental data

Experiments were conducted in a test machine with the aim of working under controlled and stable conditions. Input parameters that can be modified by the user are linear speed of the honing head VL (m/min), tangential speed of the workpiece VT (m/min), unlike industrial machines where usually the honing head rotates, and pressure of abrasive stones on the cylinders' surface PR (Fig. 1). Output signals of a.m. variables can be visualized and registered. In addition, two properties of the honing stones were varied: grain size of abrasive GS according to FEPA [24] (*Federation of European Producers of Abrasives*) and abrasive density DE according to ISO-6104:2005 [25]. Cubic boron nitride (CBN) stones were employed with metallic bond.

Minitab® 17 was used for all statistical analysis. A central composite design was defined, with a two-level fractional factorial design 2^{5-1} with 16 points and 1 central point. 10 face-centered axial points were added to the design in order to consider second order models. Total amount of experiments was 27. Two replicates were conducted for each experiment. Levels selected for the five variables are presented in Table 1.

Tests were performed on steel St-52 cylinders of length 100 mm, 90 mm external diameter and 80 mm internal diameter. It was assured that, for each experiment, honing time is long enough to completely erase previous machining marks. In addition, it was assured that the surface of the honing stone was completely