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ORIGINAL ARTICLE

Investigation of the effect of machining parameters on the surface quality of machined brass (60/40) in CNC end milling—ANFIS modeling

Ibrahem Maher · M. E. H. Eltaib · Ahmed A. D. Sarhan · R. M. El-Zahry

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Abstract Brass and brass alloys are widely employed industrial materials because of their excellent characteristics such as high corrosion resistance, non-magnetism, and good machinability. Surface quality plays a very important role in the performance of milled products, as good surface quality can significantly improve fatigue strength, corrosion resistance, or creep life. Surface roughness (Ra) is one of the most important factors for evaluating surface quality during the finishing process. The quality of surface affects the functional characteristics of the workpiece, including fatigue, corrosion, fracture resistance, and surface friction. Furthermore, surface roughness is among the most critical constraints in cutting parameter selection in manufacturing process planning. In this paper, the adaptive neuro-fuzzy inference system (ANFIS) was used to predict the surface roughness in computer numerical control (CNC) end milling. Spindle speed, feed rate, and depth of cut were the predictor variables. Experimental validation runs were conducted to validate the ANFIS model. The predicted surface roughness was compared with measured data, and the maximum prediction error for surface roughness was 6.25 %, while the average prediction error was 2.75 %.

Keywords Brass · ANFIS · Surface roughness · CNC · End milling

I. Maher · A. A. D. Sarhan (✉)
Centre of Advanced Manufacturing and Material Processing, Department of Mechanical Engineering, Faculty of Engineering, University of Malaya, 50603 Kuala Lumpur, Malaysia
e-mail: ah_sarhan@yahoo.com

I. Maher
Department of Mechanical Engineering, Faculty of Engineering, Kafrelsheikh University, Kafrelsheikh 33516, Egypt

M. E. H. Eltaib · A. A. D. Sarhan · R. M. El-Zahry
Department of Mechanical Engineering, Faculty of Engineering, Assiut University, Assiut 71516, Egypt

1 Introduction

Brass is one of the first two metals most widely used by humans, copper and its alloy (brass) and gold [1]. Brass is specified because of the unique combination of properties, it is stronger and harder than copper, easy to form into various shapes, a good conductor of heat, and is generally resistant to corrosion from salt water. Owing to these properties, brass is usually a first-choice material for many components in equipment made in general. In the electrical and precision engineering industries, brass is also used to make pipes and tubes, weather stripping, and other architectural trim pieces, screws, radiators, musical instruments, and cartridge casting for firearms [2].

In the milling process, surface roughness plays a vital role in how products perform, and it is also a factor with great influence on manufacturing cost. It describes the geometry of the machined surface, and combined with surface texture, it can play an important role on the operational characteristics of the part (e.g., fatigue, corrosion, fracture resistance, and surface friction). To achieve a desirable surface quality value, the part must be machined more than once. Therefore, the desired surface finish is usually specified, and appropriate processes are selected to attain the required quality [3].

To achieve a desired surface finish, a good predictive model is required for stable machining. The number of surface roughness prediction models available in literature is very limited [4]. Most surface quality prediction models are empirical and generally based on laboratory experiments. In addition, it is practically very difficult to control all factors as required to obtain reproducible results [5, 6].

Actual surface roughness monitoring can be accomplished either by intensive post-process inspection, an in-process surface roughness measuring device, or a surface roughness prediction system. Although post-process inspection is the easiest to implement, it cannot prevent the parts from being

processed before a defective batch is discovered. In-process measurement of surface roughness requires adding sensitive sensors to a hostile environment. Ultimately, the surface roughness prediction system can be used to determine the surface roughness indirectly [7–9].

Several techniques including multiple regression, Taguchi, fuzzy logic, artificial neural network (ANN), and adaptive neuro-fuzzy inference system (ANFIS) have been used to predict surface roughness in various cutting processes [10–16].

The criterion variable is surface roughness and the predictor variables are controllable machining parameters, such as spindle speed, feed rate, and depth of cut and their interactions. These techniques were used in turning [17, 18], milling [19, 20], and drilling processes [21, 22].

ANFIS is a fuzzy inference system implemented in the framework of an adaptive neural network. By using a hybrid learning procedure, ANFIS can be used to construct an input–output mapping based on human knowledge as fuzzy if-then rules as well as predetermined input–output data pairs for neural network training. It provides a means for fuzzy modeling to learn information about the data set in order to compute the membership function parameters that best allow the associated fuzzy inference system to track the given input–output data [23, 24].

Recently, ANFIS has been applied to predict workpiece surface roughness in end-milling operation, yielding accuracy as high as 96 % [25] and average error up to 0.522 % [26]. It has also been used to predict surface roughness in turning operation, producing average error up to 0.38 % [27]. Lee et al. [28] employed ANFIS to establish the relationship between actual surface roughness and texture features of the surface image. Accurate surface roughness modeling can facilitate the effective estimation of surface roughness. The input parameters of a training model are spatial frequency, arithmetic mean value, and standard deviation of gray levels from the surface image, without involving cutting parameters (cutting speed, feed rate, and depth of cut). Experiments demonstrate the validity and effectiveness of fuzzy neural networks for modeling and estimating surface roughness. Empirical results also show that the proposed ANFIS-based method outperforms the existing polynomial-network-based method in terms of training and test accuracy of surface roughness. Hence, the aim of this work is to obtain optimal milling parameters (cutting speed, feed rate, and depth of cut) for minimal surface roughness while milling brass (60/40). ANFIS modeling is used to accomplish this objective.

2 Experimental setup

Surface roughness is the dependent variable, while cutting speed (n) in the range of 750–1,750 rpm, feed rate (f) ranging from 50 to 250 mm/min, and depth of cut (t) in the range of 0.3–0.7 mm were used as predictor variables, which were selected based on the tool manufacturer's recommendations (Table 1).

The experiments were performed using a ProLight2000 computer numerical control (CNC) end-milling machine. A high-speed steel four-flute end-milling cutter with a diameter of 7/16 in. (11.1 mm) was used for dry machining slots of brass (60/40) blocks under specific machining conditions (speed, feed, and depth of cut), as shown in Fig. 1. Brass (60/40) with Vickers hardness of 125 and a chemical composition of 60 % copper and 40 % zinc served as a workpiece material with 40×40×20 mm dimensions (Fig. 1). The surface roughness Ra (μm) was measured with a stylus-based profilometer (Surtronic 3+, 99 % accuracy).

3 Experimental results

A slot-milling test was carried out using the proposed experimental setup to investigate the surface quality. The average surface roughness Ra was calculated for three different measurements under the same conditions with a sampling length

Table 1 Measured Ra in microns (trained data set)

f (mm/min)	n (rpm)														
	500			750			1,000			1,250			1,500		
	t (mm)														
	0.1	0.2	0.3	0.1	0.2	0.3	0.1	0.2	0.3	0.1	0.2	0.3	0.1	0.2	0.3
60	0.79	0.86	0.91	0.33	0.41	0.43	0.28	0.36	0.34	0.28	0.33	0.28	0.28	0.29	0.28
120	1.28	1.39	1.44	0.74	0.81	1.2	0.43	0.51	0.61	0.34	0.41	0.48	0.34	0.39	0.4
180	1.43	1.64	1.82	1.01	0.93	0.88	1.01	0.92	0.84	1.0	0.92	0.82	0.93	0.91	0.8
240	1.79	1.76	2.03	1.29	1.19	1.05	0.89	1.18	0.96	0.85	0.87	0.93	0.82	0.89	0.92
300	1.77	1.84	2.28	1.65	1.55	1.57	1.23	1.29	1.09	1.07	1.02	1.01	1.06	0.92	0.98