Fuzzy logic based model for predicting surface roughness of machined Al–Si–Cu–Fe die casting alloy using different additives-turning

Mohsen Marani Barzani [a,*], Erfan Zalnezhad [a], Ahmed A.D. Sarhan [a,c], Saeed Farahany [b], Singh Ramesh [a]

[a] Department of Mechanical Engineering, AMMP Center, Faculty of Engineering, University of Malaya, 50603 Kuala Lumpur, Malaysia
[b] Department of Materials, Manufacturing and Industrial Engineering, Faculty of Mechanical Engineering, Universiti Teknologi Malaysia, 81310 UTM Skudai, Malaysia
[c] Department of Mechanical Engineering, Faculty of Engineering, Assiut University, Assiut 71516, Egypt

ARTICLE INFO

Article history:
Received 12 April 2014
Received in revised form 28 August 2014
Accepted 7 October 2014
Available online 1 November 2014

Keywords:
Fuzzy logic
Aluminum
Turning
Surface roughness
Antimony
Bismuth

ABSTRACT

This paper presents a fuzzy logic artificial intelligence technique for predicting the machining performance of Al–Si–Cu–Fe die casting alloy treated with different additives including strontium, bismuth and antimony to improve surface roughness. The Pareto-ANOVA optimization method was used to obtain the optimum parameter conditions for the machining process. Experiments were carried out using oblique dry CNC turning. The machining parameters of cutting speed, feed rate and depth of cut were optimized according to surface roughness values. The results indicated that a cutting speed of 250 m/min, a feed rate of 0.05 mm/rev, and a depth of cut of 0.15 mm were the optimum CNC dry turning conditions. The results also indicated that Sr and Sb had a negative effect on workpiece machinability. The workpiece containing Bi exhibited the lowest surface roughness value, likely due to the formation of pure Bi that acted as lubricant during turning. A confirmation experiment was performed to check the validity of the model developed in this paper, and the predicted surface roughness came had an error rate of only 5.4%.

1. Introduction

Aluminum–silicon alloy is used extensively in the automotive and aerospace industries [1] due to its excellent castability, good thermal conductivity, low expansion coefficient, and good corrosion resistance. Al–Si castings constitute 90% of the total aluminum cast components produced [2,3]. Silicon appears as a flake-like morphology in hypoeutectic Al–Si alloys and it easily facilitating fractures and decreased fracture elongation. Using a modification melt treatment that adds modifier elements such as strontium (Sr) and sodium (Na) is common practice. Modification melt treatments changes the flake morphology to a fibrous form, resulting in increased elongation and casting ductility [4].

Most Al–Si parts require some processing prior to assembly. Understanding the machining characteristics of a workpiece is crucial for predicting surface quality after machining [5]. Compared to conventional Al–Si alloys cutting techniques, dry machining is an environmentally sustainable alternative owing to the absence of cutting fluids [6]. However, cutting speeds, feed rates, and the depth of the cut must be adjusted to achieve the best surface roughness and to realize cost reductions [7–9].

* Corresponding author. Tel.: +60 379674593; fax: +60 379675330.
E-mail addresses: marani.mohsen@gmail.com (M. Marani Barzani), e.zalnezhad@gmail.com (E. Zalnezhad), ah_sarhan@um.edu.my (A.A.D. Sarhan), fsaeed2@live.utm.my (S. Farahany), ramesh79@um.edu.my (S. Ramesh).

http://dx.doi.org/10.1016/j.measurement.2014.10.003
0263-2241/

Nomenclature

dX_n	fuzzy subsets distinctive	a	triangular fuzzy triplet
Y_n	fuzzy subsets distinctive	b	triangular fuzzy triplet
Z_n	fuzzy subsets distinctive	c	triangular fuzzy triplet
W_n	fuzzy subsets distinctive	D_0	the output value in numerical form
λ_{Xn}	corresponding membership functions	e_i	individual error
λ_{Yn}	corresponding membership functions	H_m	measured value
λ_{Zn}	corresponding membership functions	H_p	predicted value
λ_{Wn}	corresponding membership functions	A	model accuracy
$\vee$	minimum operation	N	total number of data set teste
$\wedge$	maximum operation	v	cutting speed (m/min)
C_n	centre of the *n*th	f	feed rate (mm/rev)
σ_n	width of the *n*th	d	depth of cut (mm)

A few researchers have pointed out that an increase in cutting speed results in higher cutting temperatures during Al–Si alloy machining in addition to a decrease in surface roughness due to less built-up edge (BUE) formation [10]. Free-cutting aluminum alloys developed by adding free-machining elements (FME) is the most common metallurgical technique used to improve the machinability of these alloys [11]. In order to accurately predict the quality of a machined surface after turning, the machinability of the material concerned must be known. Machinability depends on the type of material, its microstructure, and machining states. Yang et al. [12] reported an improvement of wear resistance after the addition of antimony (Sb) and strontium (Sr) to A357 cast alloy. Bismuth (Bi) is considered to be a free-machining element for aluminum alloys. Additionally, Bi has a refining effect on the silicon morphology in Al–7%Si–0.4%Mg alloy [13,14].

The traditional method of achieving low surface roughness at various machining parameters entails using a trial and error approach, which is very time-consuming. Hence, a reliable systematic approach for predicting surface roughness at different cutting conditions is required that would cover all parameter and only require low number of experiments [15]. When exact mathematical information is not available, soft computing techniques are the best way to analyze experimental results. However, these techniques do have a few drawbacks including approximation, partial truth, met heuristics, uncertainty, and inaccuracy.

Many researchers utilized artificial intelligent (AI) methods because these methods are capable of predicting and modeling phenomena. Artificial neural network (ANN) adaptive network-based fuzzy inference system (ANFIS) and fuzzy logic methods are the most popular examples of AI methods [16–19]. Fuzzy logic which is a method for identifying systems, is widely used in machine monitoring and diagnostics [20]. Nandi et al. [21] used a fuzzy logic (FL) model to predict surface roughness and cutting power for drilling Aluminum AA1050. Lo [22] concluded that a fuzzy logic models can accurately predict surface roughness. Ramesh et al. [23] used fuzzy logic to improve productivity by the controlling forces encountered during turning processes.

Fuzzy logic was introduced by Zadeh [24] and it successfully uses the fuzzy set theory. Fuzzy logic acts as an extension of set theory by using the characteristic function replacement of a set through a membership function with values ranging from 0 to 1. Fuzzy modeling is used when subjective knowledge and expert suggestions are important for defining objective functions and decision variables [24]. Compared to other AI methods, developing fuzzy logic methods are easier and they do not require a large investment in software and hardware resources. For turning process, results can be obtained by conducting only a few experiments. Out of all the AI approaches, fuzzy logic methods are appropriate for predicting parameters such as surface roughness using a limited amount of training data. The purpose of this study was to predict surface roughness following the machining of Al–11.3Si–2Cu–0.4Fe die casting alloy that was treated with different additives including Sr, Bi, and Sb and by using an artificial intelligence technique (fuzzy logic). The Pareto-ANOVA optimization method was used to obtain optimum parameter conditions during the machining process.

2. Experimental procedure

2.1. Workpieces material

The chemical composition of Al–Si–Cu–Fe die cast alloy is shown in Table 1. Initially, the material was cut into small pieces, dried, and melted in a 2 kg SiC crucible using an electric resistance furnace. Then a weighted bismuth, antimony and strontium in the form of pure metallic shots (99.99 wt.%), pure metallic granules (99.99 wt.%, and an Al–10Sr rod master alloy, respectively, were introduced separately into the fully molten alloy. The levels of Bi, Sb, and Sr were selected based on the author's previous study in which the optimum concentration for each additive was determined using a combination of computer aided cooling curve thermal analysis (CA-CCTA) and microscopic inspection [25]. The author found that the optimal concentration for modifying or refining the eutectic Al–Si phase with Bi and Sb, and Sr were 1 wt%, 0.5 wt% and 0.04 wt%, respectively [25]. After adding the additive elements, the molten

Table 1
Chemical compositions of the fabricated workpieces (wt.%).

Element	Si	Cu	Zn	Fe	Mn	Mg	Ni	Cr	Bi	Sb	Sr	Al
Base alloy	11.3	1.99	0.82	0.35	0.33	0.27	0.06	0.036	–	–	–	Bal.
Bi-containing	11.2	1.65	0.82	0.41	0.35	0.28	0.04	0.032	0.85	–	–	Bal.
Sb-containing	11.3	1.82	0.80	0.43	0.31	0.25	0.06	0.030	–	0.42	–	Bal.

metal was kept for 15 min for complete melt homogenization. Prior to casting, the alloys were stirred and the surface was skimmed to remove dross and other impurities. The molten alloy was then poured at a temperature of 730 °C (±5 °C) into cylindrical permanent molds to fabricate workpieces.

2.2. Cutting tool and tool geometry

A Kennametalphysical vapor deposition (PVD) insert (ISO catalogue number VBGT110302F) with a TiN-coated, a radius of 0.2 mm, a relief angle of 5° and a rake angle of $\gamma = 0°$, and Grade KU10 was mounted on a holder designated by SVJBL-1616H1. The workpieces were machined using different cutting speeds (70, 130, and 250 m/min) and feed rates (0.05, 0.1, and 0.15 mm/rev) with a constant cutting depth of 0.5 mm. All machining conditions were selected based on the tool maker's recommendations. Each experiment was repeated two times and a new cutting insert was used for each set of conditions to ensure the accuracy of the surface roughness. The experimental scheme is illustrated in Fig. 1.

2.3. Experiment details

A number of factors and levels used in the experiments are shown in Table 2. The parameters used in this study included feed rate, cutting speed, and workpiece parameters. Additionally, three levels were used for the feed rate and cutting speed and a fourth level was used for the workpiece (base alloy, Bi, Sr, Sb). Machining an Al–Si–Cu–Fe die cast alloy was completed using a CNC turning machine (ALPHA 1350S) with an 8.3 kW power drive and a 6000 rpm maximum spindle speed. The surface roughness values were measured immediately after the turning process at five different locations on the circumference of the workpiece using a surface roughness tester (Mitutoyo-Formtracer CS 5000) with an accuracy rate of ±0.01 μm. The average surface roughness was calculated and used in an analysis of the workpiece morphology after machining. A Field Emission Scanning Electron Microscopy (FESEM) Supra-35VP, Carl Zeiss and an Atom Force Microscopy (AFM) model SPM-9500J2 with the contact tip cantilever were also used to record surface characterization. Images were captured from a $5 \times 5\ \mu m^2$ scanning area. Each measurement was repeated five times and the average surface roughness value was reported.

Table 2
Factors and levels used in the experiments.

Factors	Level 1	Level 2	Level 3	Level 4
(*A*) Cutting speed (m/min)	70	130	250	–
(*B*) Feed rate (mm/rev)	0.05	0.1	0.15	–
(*C*) workpiece	Base alloy	Containing Bi	Containing Sr	Containing Sb

3. Experimental results

The surface roughness of the machined samples was measured with a hybrid surface contour measuring machine. An evaluation of the machined surface finish

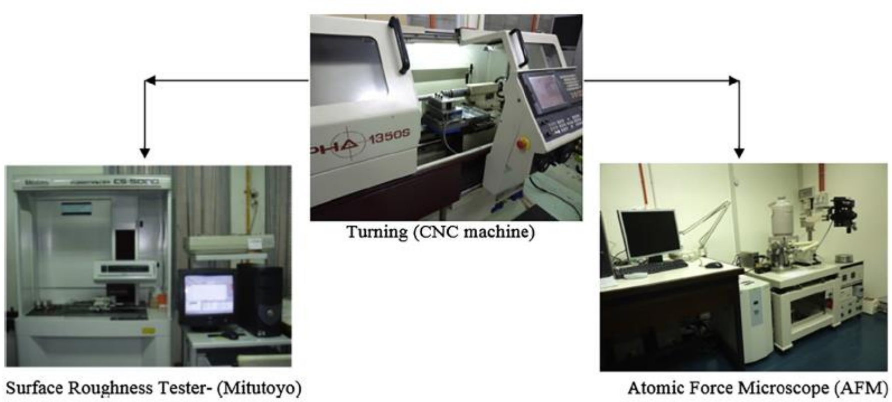

Fig. 1. Experimental scheme.

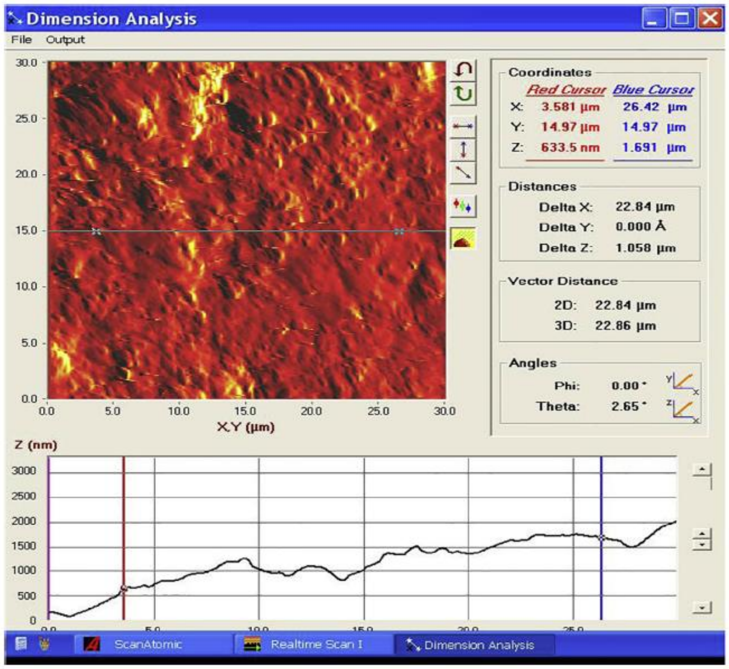

Fig. 2. AFM image analysis software.

was created using an AFM image analysis software over a $5 \times 5\ \mu m^2$ scanning area (Fig. 2). Fig. 3 presents the FESEM images and AFM topographical images of the machined surface of Al–11.3Si–2Cu–0.4Fe workpieces and for workpieces containing Bi, Sb, and Sr at a cutting speed of 250 m/min and a feed rate of 0.15 mm/rev. The images revealed that the workpieces with Bi had the best surface roughness of about 1 µm (Fig. 3c). In the 3D images, hills and valleys are observed and the workpiece containing Bi had the lowest hills (Fig. 3d). By contrast, the Sr-containing workpiece had the greatest surface roughness value of 3.8-µm (Fig. 3g) and the highest hills in the 3-D image (Fig. 3h). Moreover, the images show that surface tearing in Sr containing workpieces was greater than for workpieces composed of other additives or the base alloys.

4. Fuzzy Logic

Fuzzy logic is a continuous conversion from true to false conditions, as opposed to the separate true–false transition seen in binary logic. The possibilities presented in fuzzy logic provides a measure of a subset's potential ability to belong to another subset. Fuzzy logic has an extensive scope and range of applications compared to other statistical methods. In engineering applications, fuzzy logic utilizes this continuous subset membership transition to change wavy numeric problems into fuzzy linguistic territories. Fuzzy logic employs conventional language to define variables and fuzzy linguistic rules to describe relationships as opposed to working with numeric variables and mathematical functions. Fuzzy logic makes it possible to use accrued experience and knowledge in the rules-of-thumb form that cannot be incorporated into mathematical formula. The most notable use of fuzzy logic is to simulate complex and non-linear systems while maintaining the physical inferences and effects of every variable. In this study, the fuzzy rule base contained a group of IF–THEN declarations for thirty-six rules with three inputs, feed rate (A), cutting speed (B) and workpiece (C) with one output (surface roughness (D)). The general structure of fuzzy argumentation for the three inputs and one output of the fuzzy logic unit were defined as follows:

$$\text{Rule 1}: \text{ if } A \text{ is } X_1 \text{ and } B \text{ is } Y_1 \text{ and } C \text{ is } Z_1 \text{ then } D \text{ is } W_1$$

$$\text{Rule 2}: \text{ if } A \text{ is } X_2 \text{ and } B \text{ is } Y_2 \text{ and } C \text{ is } Z_2 \text{ then } D \text{ is } W_2$$

$$\text{Rule n}: \text{ if } A \text{ is } X_i \text{ and } B \text{ is } Y_j \text{ and } C \text{ is } Z_k \text{ then } D \text{ is } W_m \quad (1)$$

X_i, Y_j, Z_k, and W_m are fuzzy subsets distinctive by their corresponding membership functions, λ_{Xi}, λ_{Yj}, λ_{Zk}, and λ_{Wm}, respectively and n represents the rule's number. Table 3 portrays the value of surface roughness which measured by surface roughness tester. Moreover, it shows a description of all If-THEN rules. As shown in Table 3, Rule 1 is typically selected as follows:

$$\text{Rule 1}: \text{ if } A \text{ is Low and } B \text{ is Low and } C \text{ is } 1, \text{ then } D \text{ is good.}$$

Link to Full-Text Articles :

http://www.sciencedirect.com/science/article/pii/S0263224114004679