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Development of an artificial neural network model for criticizing the burr formation during flat bottom drilling of CuZn38As brass alloy considering cutting tool geometry

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Abstract

The approved laws and regulations on restricting the use of Lead in the products' chemical composition, have made the industries to come up with development of low-lead brass alloys as an innovative solution during the last years. These alloys are the most predominantly utilized materials in pumping, drinking water industry. However, as alternatives for the conventional brass alloys, they contain lower machinability. Most of the components need to be aesthetic and compact. Therefore, the designed components have complex geometries. Flat bottom drilling is one of the new processes which is generally taken advantage in machining of these components. In this study, artificial neural networks (ANN) modelling, have been deployed to investigate the effects of the cutting tool geometries including axial rake, radial rake angles and edge radius as well as plunging angle to the work material focusing on the burr formation. A multilayer feed-forward ANN using error back-propagation training algorithm has been employed for this purpose. The results revealed possible reduction of burr formation on both the entry and exit sides of the low-lead brass alloy.

Keywords: Flat bottom drilling; brass; Artificial neural network; Burr.

1. Introduction

Brass alloys are broadly used in such as electric and electronics, automotive and sterile and plumbing industries [1]. In order to make the machining processes simpler and more productive, customarily elements are added to the alloying compositions, one of which is Lead (Pb) [1]. However, in the consideration of the environment and human health, some laws have been accepted and published according to the restriction on the usage of this element in some applications [2-5]. These restrictions have resulted in deterioration of the machining properties of brass alloys [2, 6-9].

Long continuous chips, undesired burrs and lower part quality, higher needed cutting forces and torques are the most common unsolved problems in machining of these types of alloys. Different properties of the low-lead and lead-free brass alloys as compared to leaded ones in terms of ductility and strain rates has been studied by Hofmann et al. [10]. Drilling of forging brass with a special tungsten carbide drilling tool was studied by Timata et al. [11]. They measured the exit burr height and workpiece diameter at diverse spindle speeds and feed rates. Their ANOVA results show that spindle speed and feed

Nomenclature

PA	plunging angle	BHEN	burr height at entry
RRA	radial rake angle	BWEN	burr width at entry
ARA	axial rake angle	BHEX	burr height at exit
CER	cutting edge radius	BWEX	burr width at exit

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rate on exit burr height and workpiece diameter were statically at noteworthy of level. Johansson et al. [12] investigated the burr formation, cutting forces and cutting resistance for traditional free-machining leaded alloy and brass alloys with low lead content, material properties. Hua et al. [13] investigated the effects of cutting-edge geometry, and workpiece hardness, cutting conditions such as feed rate and cutting speed. They indicated that sharpen edge in addition to chamfer cutting edge and higher feed rate help to increase both compressive residual stress, hardness, and penetration depth in hard turning operations. This study extends the field of research by applying artificial neural networks (ANNs) to predict the required parameters for drilling stainless steel with a certain depth and diameter of blind holes, and it also pre-simulates the drilling result of these predicted parameters before actual laser processing. Karnik et al. [14] carried out a comparison of the burr size predictive models based on artificial neural networks (ANN) and response surface methodology (RSM) for machining AISI 316L stainless steel considering work material with cutting speed, feed, and point angle as the process parameters. Their comparison indicates that the ANN models provide more accurate prediction compared to the RSM models. Kolesnyk et al. [15] investigated the effects of drilling parameters on drilling temperature and hole quality in CFRP/Ti alloy stacks by applying an artificial neuron network (ANN). cutting speed, feed rate, and time delay factors were their inputs and drilling temperature, hole diameter, and out of roundness were considered as outputs.

Considering the available conducted studies in the literature, it is seen that most of the investigations are related to standard cutting tools in laboratory circumstances and none of them is about high-performance tools used in industry. However, most of the industrial components need to be aesthetic and compact besides their complex shape regarding to the functionality. Flat bottom drilling is one of the new processes which is generally taken advantage in machining of these components having superiority to conventional drilling tools. They can be deployed in inclined and vertical plunging as well as their capability in working on curved and inclined surfaces. In this study, artificial neural networks (ANN) modelling, have been deployed to investigate the effects of the cutting tool geometries including axial rake, radial rake angles and edge radius as well as plunging angle to the work material considering burr formation.

2. Methodology

2.1. Experimental setup

In this study, CuZn38As (CW511L) low-lead brass alloy billets with the chemical compositions and technical specification described in Table 1 having a diameter of 35 mm and 86 mm in length materials were hot forged at 730±10˚ C with 11 m/s stroke by 550-ton eccentric press machine.

Ø8 mm and two teeth flat carbide bottom drills with 6˚, 8˚, 10˚ of radial rake angle, and -2˚, 0˚, 2˚ of axial rake with were designed and manufactured in ANCA grinding machine. Thereafter, the tools were subjected to drag finishing operation. Subsequently, tools with 10, 15 and 20 µm of cutting-edge radii were obtained. The geometry of the designed cutting tools is illustrated in Fig. 1. These tools were utilized to make through all holes on CW511L brass alloy with various plunging angles of 90°, 60° and 45°. The cutting speed and feed rate for the vertical plunging experiments were 100 m/min and 0.125 mm/rev whereas these values were 70 m/min and 0.066 mm/min for inclined plunging tests, respectively. The experiments were performed with internal coolant with 25 Bar pressure. The machining tests were carried out on Fanuc Robodrill α–D21MiB5 four axis CNC machine with the demonstrated setup in Fig. 2. The burr heights and width have been measured at both cutting tool entry and exit using Mitutoyo Contracer CV-2100M4 and Keyence digital optical microscope form four areas. A schematic of the formed entry and exit burrs on the hole due to the cutting tool contact is shown in Fig. 3. The measurements of the formed burrs have been executed from four parts of the hole, and the average value has been reported in this paper.

Table 1 Chemical composition of the studied brass alloys [16]

Composition	Cu	Zn	Pb	Fe	Ni	Al	As	Sn
CuZn38As (CW511L)	61.7 62.9 63.4	Rem.	0.2	0.1	0.3	0.05	0.05	0.1

Technical specifications	Structure	Elasticity Modulus (GPa)	Density (g/cm^3)	Machinability
	α, β	~100	8.41	40%

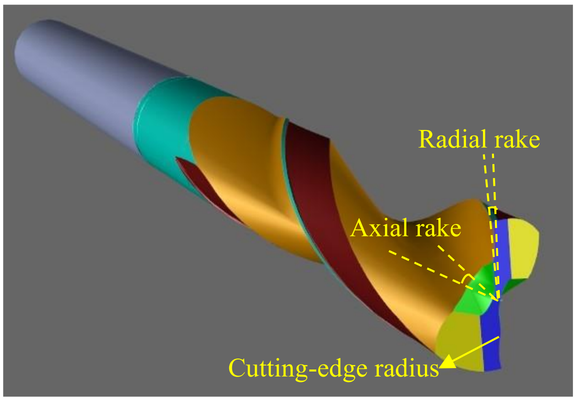

Fig 1. The designed flat bottom drill cutting tool

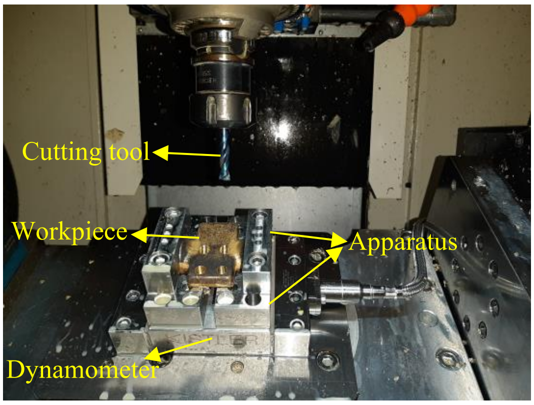

Fig 2. The experimental setup

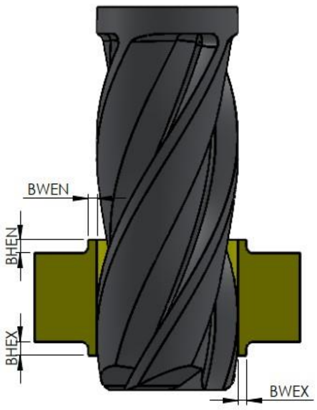

Fig 3. The schematic of the formed burrs

2.2. Artificial neural networks (ANN) modeling

A multilayer perceptron (MLP) is formed of minimal three layers as seen in Fig. 4. The inputs (I_i) are assigned within the input layer as and the yields (R_i) are obtained within the output layer. Inside layers known as hidden layers are performing among the input and output layer; and their number can be more noteworthy than one. Learning is fulfilled when the relationship between a predetermined arrangement of input-output sets is established. A neural organize can be a computational structure, comprising of several profoundly interconnected preparing units called neurons. The neurons entirety weighted inputs and after that applies a straight or non-linear work to the coming about whole to decide the yield and the neurons are orchestrated in layers and are combined through over the top network. Back propagation arrange is an ordinary ANN that has been broadly utilized in numerous inquire about areas. BPNs have various leveled feed forward arrange engineering, and the outputs of each layer are sent straightforwardly to each neuron within the layer above [17]. The complex connections between machined hole quality and influencing parameters may not be expressed by any analytic model. Conventional modeling strategies are for the most part depended on presumptions for demonstrate simplifications, and hence may lead to wrong results. On the other hand, the characteristic of the ANN strategy makes it reasonable for modeling the quality expectation of machined holes, and thus is utilized in this paper as the modeling tool.

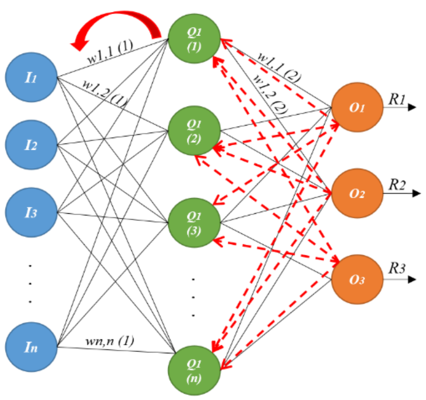

Fig. 4. The schematic of neural network model and back propagation algorithm [18]

Eq. 1 and Eq. 2 express the net input to unit i in layer $m+1$, the output of unit, respectively. f stands for the activation function of neurons in $(m+1)^{th}$ layer [18].

$$n_i^{m+1} = \sum_{j=1}^{S^m} w_{i,j}^{m+1} R_j^m + Q_i^{m+1} \tag{1}$$

$$R_i^{m+1} = f^{m+1}(n_i^{m+1}) \tag{2}$$

3. Results and discussions

The images of the formed entry burrs for the tool having 6° of radial rake, 2° of axial rake angle and 10 µm of cutting-edge radius is demonstrated in Fig. 5 for different plunging angles. It is seen that the maximum burr heights and widths at both entry and exit were measured as 583.601, 216.59, 164.515 and 52.144 µm in 90° of plunging angle with the tool having 10°, 0° radial and axial rake angles and 20 µm of cutting-edge radius. In general, increasing the radial rake angle and cutting-edge radius has resulted in intensifying of the formed burrs at bot entry and exit of the holes. This can be attributed to increase in the contact area of the tool surface with the workpiece and lower chip evacuation seen as swell up on the surfaces. Although very small values, but this trend is also valid for the axial rake angle. For training the designed models the experimental data tabulated in Table 2 were used. Normalization is a strategy utilized in neural systems so that all the information shows a consistent relationship. Otherwise, the neural network may assume that a value is more critical than the other since its arithmetic value is greater. This occurrence can aggravate the generalization ability of the network and result in overfitting. Therefore, all the obtained data were normalized; and transformed so that their mean value become equal to zero and the standard deviation equal to one. After the normalization process all inputs are equally significant for the training of the network. In our model, %70, %10, %20 of the data was utilized for training, validation and testing, respectively. All the data set for training, validation and testing were selected randomly. In common, as large number of neurons within the hidden layer causes over fitting and littler number of neurons causes under fitting, ideal number of neurons is to be selected in arrange to extend the network execution. The most excellent performance is recognized by the neurons resulting the least MSE. The model was 1-2-1; consisted of 1 input, 2 hidden and 1 output layers. The first layer, first and second hidden layers and last layer had 4, 8, 2 and 4 nods, respectively. Trial, and error strategy was adopted in arrange to predict the best performance. The gradient descent back propagation with adaptive learning was selected as a training function TRAINGD and LEARNGDM were deployed for learning function and mean squared error (MSE) was chosen for the performance validation. The MSE of training of the selected ANN was about 0.005 in 59 epochs as demonstrated in Fig. 6. A linear fit between the output of the developed model results. As expected, validation and testing group MSEs are higher than that of the training group. The best linear fit function is expressed as: Output=0.99*Input+ 2.937, while the correlation confidence coefficient was calculated, R=0.9124. This result demonstrates that the neural network can predict a satisfying level for the required output data. Fig. 7 shows the compared results between measured and predicted results by ANN.

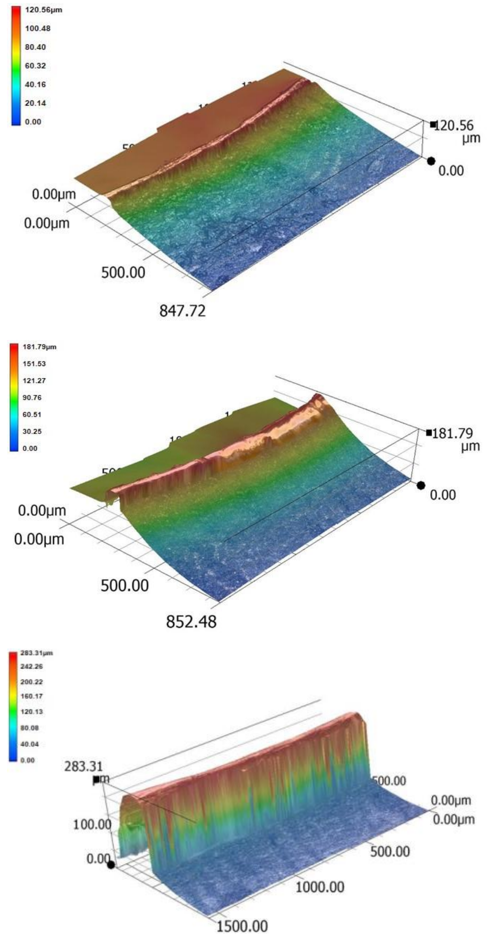

Fig. 5. The images of the formed entry burrs for the tool having 6° of radial rake, 2° of axial rake angle and 10 µm of cutting-edge radius; a) 45°, b) 60°, c) 90° of plunging angles

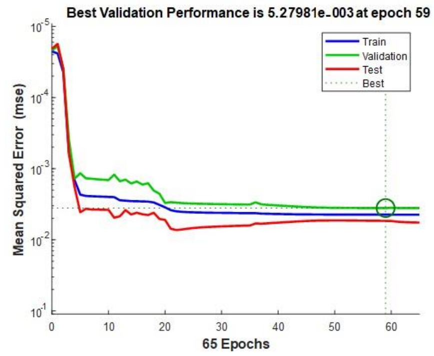

Fig. 6. The MSE of training of the selected ANN

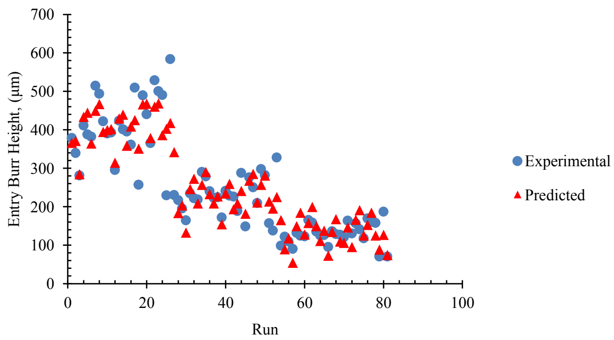

Fig. 7. Comparison between the measured and predicted results by ANN

Table 2. Measured experimental results in this study

PA(°)	RRA (°)	ARA (°)	CER (µm)	BHEN (µm)	BHEX (µm)	BWEN (µm)	BWEX (µm)
90	6	-2	10	378.480	142.651	109.953	34.521
90	6	0	10	339.420	130.942	99.563	31.687
90	6	2	10	281.220	110.323	84.082	26.698
90	8	-2	10	411.180	153.536	118.651	37.155
90	8	0	10	387.840	125.159	112.443	30.288
90	8	2	10	381.950	142.896	110.876	34.580
90	10	-2	10	514.600	140.65	146.161	34.037
90	10	0	10	493.898	138.549	140.654	33.528
90	10	2	10	421.940	143.954	121.514	34.836
90	6	-2	15	390.500	142.660	113.150	34.523
90	6	0	15	392.642	146.651	113.720	35.489
90	6	2	15	295.654	111.920	87.921	27.0846
90	8	-2	15	423.441	159.567	121.913	38.615
90	8	0	15	401.065	146.942	115.961	35.559
90	8	2	15	395.452	148.956	114.468	36.047
90	10	-2	15	360.948	197.269	105.290	47.739
90	10	0	15	509.580	188.651	144.826	45.653
90	10	2	15	256.970	162.354	77.631	39.289
90	6	-2	20	489.250	182.354	139.418	44.129

90	6	0	20	440.365	165.548	126.415	40.062
90	6	2	20	365.455	134.950	106.489	32.657
90	8	-2	20	528.456	197.845	149.847	47.878
90	8	0	20	500.003	186.125	142.278	45.042
90	8	2	20	490.600	184.640	139.777	44.682
90	10	-2	20	229.340	194.659	70.282	47.107
90	10	0	20	583.601	216.590	164.515	52.414
90	10	2	20	230.684	197.446	70.639	47.781
60	6	-2	10	216.744	112.661	52.780	23.005
60	6	0	10	195.651	102.657	48.646	20.963
60	6	2	10	164.223	89.156	42.486	18.206
60	8	-2	10	234.402	120.654	56.241	24.638
60	8	0	10	221.798	100.607	53.771	20.544
60	8	2	10	218.618	111.261	53.147	22.719
60	10	-2	10	290.249	109.456	67.187	22.351
60	10	0	10	279.069	108.793	64.996	22.216
60	10	2	10	240.212	112.659	57.380	23.005
60	6	-2	15	223.235	110.367	54.052	22.537
60	6	0	15	224.3916	115.551	54.279	23.596
60	6	2	15	172.018	90.626	44.014	18.506
60	8	-2	15	241.023	136.542	57.539	27.882
60	8	0	15	228.940	115.330	55.171	23.550
60	8	2	15	225.909	117.980	54.576	24.092
60	10	-2	15	189.076	159.664	47.357	32.603
60	10	0	15	287.538	150.485	66.656	30.729
60	10	2	15	148.328	126.545	39.371	25.840
60	6	-2	20	276.560	142.365	64.504	29.071
60	6	0	20	250.162	125.216	59.330	25.569
60	6	2	20	209.710	104.000	51.402	21.237
60	8	-2	20	297.731	150.645	68.654	30.762
60	8	0	20	282.366	144.980	65.642	29.605
60	8	2	20	157.289	142.357	41.127	29.069
60	10	-2	20	138.208	150.017	37.387	30.633
60	10	0	20	327.509	163.268	74.490	33.339
60	10	2	20	98.934	152.147	29.689	31.068
45	6	-2	10	121.744	78.434	28.638	16.222
45	6	0	10	109.245	72.099	27.063	14.912
45	6	2	10	90.621	60.944	24.717	12.605
45	8	-2	10	132.208	84.322	29.957	17.440
45	8	0	10	124.739	68.971	29.016	14.265
45	8	2	10	122.855	78.566	28.778	16.250
45	10	-2	10	165.303	77.351	34.126	15.998
45	10	0	10	158.678	76.215	33.292	15.763
45	10	2	10	135.651	79.139	30.390	16.368
45	6	-2	15	125.591	78.439	29.123	16.223
45	6	0	15	126.276	80.598	29.209	16.670
45	6	2	15	95.240	61.808	25.299	12.784
45	8	-2	15	136.132	87.585	30.451	18.115
45	8	0	15	128.971	80.755	29.549	16.703
45	8	2	15	127.175	81.845	29.322	16.928
45	10	-2	15	120.534	107.982	28.486	22.334

45	10	0	15	163.696	103.320	33.924	21.370
45	10	2	15	130.461	89.093	29.736	18.427
45	6	-2	20	157.191	99.913	33.104	20.665
45	6	0	20	141.547	90.821	31.133	18.785
45	6	2	20	117.576	74.267	28.113	15.361
45	8	-2	20	169.736	108.294	34.685	22.398
45	8	0	20	160.632	101.951	33.538	21.087
45	8	2	20	157.623	101.150	33.159	20.921
45	10	-2	20	70.019	106.570	22.121	22.042
45	10	0	20	187.383	118.435	36.909	24.496
45	10	2	20	70.449	108.078	22.175	22.354

Conclusion

This study has applied artificial neural networks technique for predicting the burr height and width as machining performance response at both cutting tool entry and exit while flat bottom drilling of CW511L. the influences of the plunging, radial, axial rake angles and cutting-edge radius was taken into consideration. For this purpose, an AI model was proposed and validated with experimental results. The neural network was trained with experimental data acquired in vertical and inclined through all drilling tests. The results obtained indicated that the proposed ANN can successfully predict the burr sizes, within the limits of the input values by which it was trained. Moreover, during the experiments and measurements, the researchers found that burr size in terms of height and width was strongly affected by the plunging, radial rake angles as well as cutting-edge radius. The axial rake angle did not impress the results.

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