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Full Length Research Paper

The analysis of humidity factor in cestamide materials on surface roughness with the help of artificial neural network

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Cestamide, an engineering plastic, is used in many areas of industry today. Apart from its excellent mechanic features; it also has a negative feature, namely dehumidification. It is necessary to detect cutting conditions of dehumidified cestamide materials for metal cutting. After the process of humid and dry cestamides under same cutting conditions, the change of average surface roughness quality is studied by performing some experiments. For this, after keeping materials in humid and dry environment, cestamide materials are processed with same kind of cutting tool in (1, 1.5, 2, 2.5, 3 mm) chip thickness (a_p), (90, 110, 130 m/min) cutting speed (V_c) (100, 120, 140,160 mm/min) feed rate (f) and then average difference of surface roughness values are detected. Moreover, an Artificial Neural Network (ANN) modelling is developed with the results obtained from the experiments. For the training of ANN model; material type, cutting speed, cutting rate and depth of cut parameters are used. In this way, average surface roughness values except for the mentioned experiment could be estimated. Experimental results and ANN model results show that, different average surface roughness values are obtained for applying same processing conditions humidity factor on cestamide materials. It is observed that a case which is based on different variables such as average surface roughness can be estimated in acceptable error rate with the help of ANN model.

Key words: Artificial neural network (ANN), cestamide materials, average surface roughness.

INTRODUCTION

Usage of engineering plastics has been constantly increasing together with technological innovations. Today, it has a wide range of usage from aerospace industries to construction industry. There are different types and characteristics of engineering plastics. Polyamides are one of these most widespread plastic types (Davim et al., 2009). The type which is obtained as casting and whose mechanical features are improved with additives is called cast polyamide or cestamide with its specific industrial name. Cestamide takes place of many metals being a cheap, easily processed, light, high-resistant, abrasion resistant and quiet working engineering material. It is more preferred because is cheaper than metals such as aluminium, copper and brass.

Many studies have been carried out for different characteristics of polyamides since 1960’s when they got to be used as an engineering material to this day. Some of these studies are based on their friction condition (Adams, 1963). Friction force of dry cestamides which do not contain any lubricant are lower than other metals. In order to decrease this friction force even more; different lubricant are added in cestamide materials (Samyna et al., 2007; Palabiyik and Bahadur, 2000; Samyn and Tuzolana, 2007; Liu et al., 2006).

With the feature of adding lubricant in the cestamide materials; operating life of machine elements such as frictional bearings, shafts, slides and cams are extended. Cestamide materials are processed with metal cutting. Workability of different polyamide types, cutting force and surface roughness observations are other area of experiment. A lot of parameters such as cutting types, cutting speed, cut of depth; material used etc. can be effective on cutting force and surface quality (Davim et

Table 1. Physical features of cestamide.

Properties	Unit	Test Method		Value
		DN	ISO	
Specific gravity	gr/cm^3	53479	1183	1.15
Service temperature	0 ℃	53461	75	100
Melting point	0 ℃	-	-	190
Thermal elongation	$1/K{*}10^5$	53752	-	8-9
Pulling resistance	N/Mm^2	53455	527	55 - 85
Pulling elongation	%	53455	527	-
Breaking resistance	N/mm^2	53455	527	88 - 90
Breaking elongation	%	53455	527	10 - 40
Stroke resistance	Kj/m^2	53453	179	-
Elastic module	N/mm^2	53452	178	3900 - 4200
Water absorption	%	53495	62	6 - 7
Resistance as per volume	Ω X cm	53482	167	$> 10^{15}$
Resistance as per surface	Ω	53482	167	$> 10^{12}$
Dielectric resistance	KV/mm	53481	243	80 - 100
Shore	Skala D	53505		85
Rockwell	Skala	-	2039-2	M88
Ball Notch 358/30	N/Mm^2	53456	2039-1	110-160

al., 2009; Mata et al., 2006). Studies carried out upon surface roughness are studied on a wide range from micro cutting conditions to the effect of cutting parameters upon surface roughness (Wang et al., 2005). Generally; cutting conditions, cutting tool geometry, cutting tool type, usage of coolant, rigidity of machine tool, cutting method and the type of material used have effects on average surface roughness in metal cutting process. Cutting parameters feed rate, depth of cut, cutting speed, cutting edge number of cutting tool have effects on cutting process (Ertakin et al., 2003; Dabade et al., 2003).

Apart from excellent mechanical features, cestamide materials have the characteristic of dehumidification up to 7%. Although process conditions have not changed for dehumidified cestamide material, the expected average surface roughness value may change. Experiments were carried out to confirm this result as well.

ANNs have been studied for many years in the hope of achieving human-like performances in solving problems that are generally ill defined and that require a great amount of processing. Human brain carries out this using millions of neurons working together. Similarly, an ANN consists of many computational elements, operating in parallel, connected by links with variable weights that are typically adapted during the learning process. Developed of detailed mathematical models began in the 1960s but only in recent years have the improvements in the science of ANNs allowed the development of manufacturing applications (Forcellese et al., 1998).

During the last ten years, there has been a substantial increase in the interest on ANNs. Neuron is the fundamental processing element of a neural network. An artificial neuron is model whose components have direct analogs to components of an actual neuron. ANNs have been used successfully in solving complex problems in various fields of Engineering, Economics, Neurology, Mathematics, Medicine, Meteorology, and many others. Some of the most important ones are in pattern, sound and speech recognition, in the identification of explosives in passenger suitcases and in the identification of military targets (Kalogirou, 1999; Chouai et al., 2002).

Aim of this study is to apply ANN to estimate surface roughness of dry and humid cestamide materials in different cutting parameters. Experimental data and ANN test data are compared and they are illustrated in a graph. Conclusions are drawn by using these results.

EXPERIMENTAL

Cestamide material in 46 mm plates that is used in the experiments is supplied from Polimersan firm. It is named as POLİKES® - PA6 G (cestamide) in firm product catalogue. Cestamide obtained in plates are cut in dimensions of 112 × 82 × 46 mm. and they are kept in humid and dry place. Physical features of cestamide are given in Table 1.

Humid and dry samples are processed in TMC500 CNC vertical machining centre. Cycle of bench can be adjusted between 60 and 6000 cycle/min. Carbide cutting tools used in experiment have 14 mm diameter. This cutter produced in the standards of DIN, has four cutting edge, the features of 30° helix angle, 87.7% WC rate, 12.3% cobalt rate, TRS 4200 MPa, 92.5 HRA Rockwell rigidity, 0.5 µm particle size, high abrasion and effect ability. Cutting tools are bound to spindle with the help of pincers. By using of cutting parameters; cutting speed, feed rate, depth of cut and humid/dry cestamide material in milling process; average surface roughness are detected. Schematic picture of experiment setting is depicted in Figure 1.

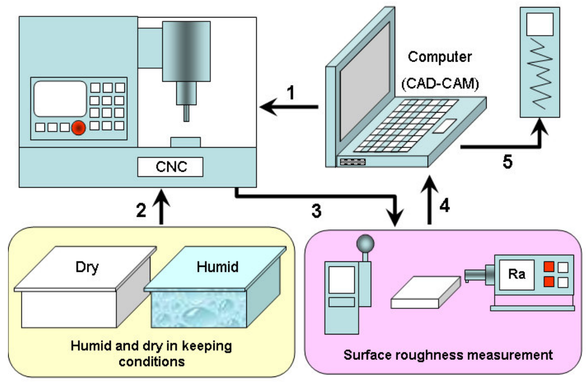

Figure 1. Schematic picture of experiment setting.

Table 2. Cutting conditions.

Cutting factor	Symbol	Levels				
Feed rate (mm/min)	f	100	120	140	160	
Depth of cut (mm)	a_p	1	1.5	2	2.5	3
Cutting speeds (m/min)	V_c	90	110	130		
Material	M	Humid	Dry			

Table 3. Some of the average roughness values that are measured.

Depth of cut (mm)	Cut. Speeds (m/min)	Feed rate (mm/min)	Material	
			Dry	Humid
			Ra µm	Ra µm
1	90	100	0.77	2.483
1	110	120	0.857	1.247
1	130	100	0.553	2.106
1.5	90	120	2.34	3.261
1.5	110	160	2.618	2.749
1.5	130	160	2.461	2.984
2	110	120	1.259	0.912
2.5	130	120	1.614	0.996
2.5	130	160	2.78	2.62
3	90	100	1.821	1.374
3	130	120	1.334	1.122

Experiment samples that are kept as humid and dry are processed in cutting conditions specially designed for CNC environment. Coolant is not used while carrying out experiment. Cutting conditions are given in Table 2.

Average surface roughness values are recorded on computer while performing the experiment. Portable surface roughness measurement equipment (MarSurf PS1) is used for the measurement of roughness. Measurement needle has the measurement diameter of 2 µm and pressure force is averagely 0.7 mN. Measurement scanning length is adjusted to 5.6 mm. Some average roughness values are tabulated in Table 3. There is an air conditioning in CNC laboratory where the measurements are carried out and average room temperature is 21 ± 1°C. The processes are carried out in CNC laboratory in 45% relative humidity condition. After 30 days of keeping materials in water to obtain humid 7% dehumidification is carried out on average.

ARTIFICIAL NEURAL NETWORKS AND SELECTED MODEL

Neural networks operate like a 'black box' model and do not require detailed information about the systems. On the other hand, they learn the relationship between the input parameters and the controlled and uncontrolled variables by studying previously recorded data, similar to the way a non-linear regression might perform (Kalogirou et al., 1999). The output of a specific neuron is a function

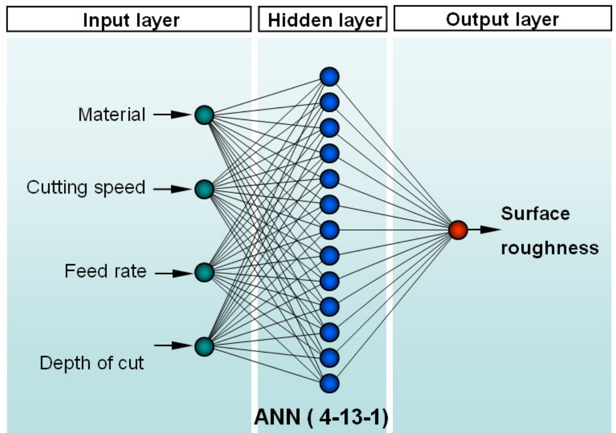

Figure 2. ANN architecture used for 13 neurons in a single hidden-layer.

Table 4. Error values of the ANN approach for average surface roughness used in training and testing.

Hidden number	TRAINING			TEST		
	RMSE	R^2	MAPE	RMSE	R^2	MAPE
12	0.0034	0.9999	1.2563	0.0035	0.9935	0.0848
13	0.0021	0.9999	0.3326	0.0030	0.9949	0.0831
14	0.0616	0.9983	5.0772	0.0545	0.9975	1.7953
15	0.0035	0.9968	0.5400	0.0054	0.9983	0.1024
16	0.0085	0.9972	0.9164	0.0134	0.9992	0.3400

of the weighted input, the bias of the neuron and the transfer function. A neural network consists of a number of neurons and in a typical network there are input layer, hidden layer or layers and output layer. In its simple form, each single neuron is connected to other neurons of a previous layer through adaptable synaptic weights. Knowledge is usually stored as a set of connection weights. The error is described by the root-mean-squared error (RMSE) and defined as follows:

$$RMSE = \left(\left(1/n \right) \sum_{j=1}^{n} \left| p_j - m_j \right|^2 \right)^{0.5} \quad (1)$$

In addition, the absolute fraction of variance (R^2) and mean absolute percentage error (MAPE) are defined, respectively, as follows:

$$R^2 = 1 - \left(\frac{\sum_{j=1}^{n} (p_j - m_j)^2}{\sum_{j=1}^{n} (m_j)^2} \right) \quad (2)$$

and

$$MAPE = \frac{1}{n} \sum_{j=1}^{n} \left(\left| \frac{p_j - m_j}{m_j} \right| \right) \cdot 100 \quad (3)$$

Where p is the predicted value, m is the measured value; n is the pattern number (Bechtler et al, 2001).

The used ANN structure of a multi-layer is shown in Figure 2. It consists of four input layers, one hidden layer, and one output layer. The examples in this study are numerical values recorded during the experiment and 100 patterns were obtained from the experiments. Here, an ANN model was used to predict of surface roughness. Inputs for the network are material, feed rate, depth of cut, and cutting speeds; the output is average surface roughness.

The experimental results were used to train and test. It was used 100 experimental results, from the total of 120, as data sets to train the network, while 20 results were used as test data. The architecture of the ANN becomes 4 -13 - 1, 4 corresponding to the input values, 13 for the number of hidden layer neurons and 1 for the output. The back-propagation learning algorithm has been used in feed-forward, single hidden layer. A computer program has been performed under MATLAB 6.5. In the training, it used an increased number of neurons (from 12 - 16) in a single hidden-layer. When the network training successfully ended, the network was tested with test data. Some statistical methods, R^2, RMSE and MAPE values have been used for comparison. Some selected sample data sets used for training and testing the network is shown in Table 4.

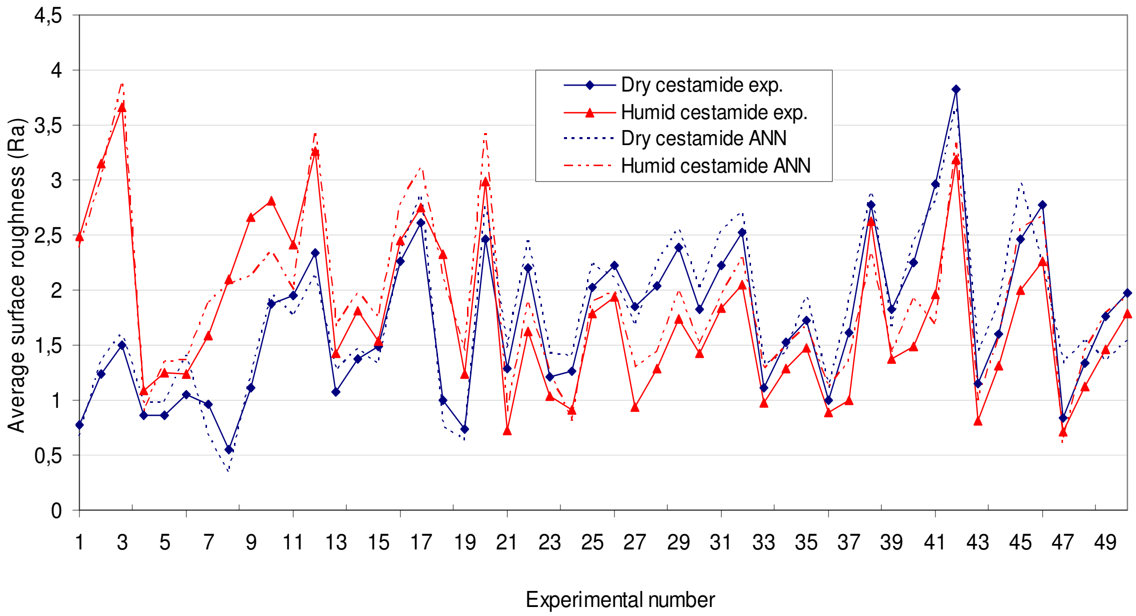

Figure 3. Measured and ANN predicted test data results of surface roughness.

RESULTS AND CONCLUSIONS

In this study, workability of humid and dry cestamide materials on CNC bench and the difference observed in surface quality after the process are studied. Average surface roughness values are measured and recorded. Some of the average surface roughness values detected are given in Table 3 comparatively.

It is known that cutting speed, depth of cut and feed rate factors that are observed during the process of dry cestamide materials have effect on the formation of surface roughness value. What is attractive in here is the change of surface roughness value in the same process conditions in humid cestamide materials. Experimental results are used for training in different algorithms and neuron numbers after conveying them to artificial neural networks.

Numerical results obtained from experimental and the related parameters have been used to train the network. The material, feed rate, depth of cut, cutting speeds and surface roughness has been used to train the network. Initially, thirteen hidden neurons in a single hidden-layer have been used for all the algorithms. Then, the number of neurons has been increased. The results revealed the optimum hidden number changes for different algorithms. In this study, the fastest learning is obtained with the LM algorithm. Statistical values such as RMSE, R^2, and MAPE of surface roughness are given in Table 4 for hidden number neurons. The LM algorithm with 13 neurons has produced the best results.

It is observed that MAPE is 0.0831% in the testing and 0.3326% in the training; R^2 is 0.9999 in the testing, and 0.9949 in the training; the RMSE value is 0.003 in the testing and 0.0021 in the training. The highest MAPE is found to be 8.0965% for network of 16 hidden numbers.

Comparison of the measured and predicted surface roughness values are shown in Figure 3 for the test data, the values predicted by ANN are very close to measured values. The training epoch for each neural network is 30000. As shown Figure 4 the developed ANN gives a very accurate representation of R^2 values over the all range or working conditions.

Conclusion

Differences between average surface roughness values are detected after applying same process conditions on humid and dry cestamide samples. Generally it is observed that humidity rate is an important factor in the process of cestamide materials. These results are obtained from the experiment:

1. When the same process conditions are applied on humid and dry cestamides; the depth of cut increases as the surface roughness value also increase for dry cestamides although the depth of cut increases as the surface roughness value decrease for humid cestamides. Increment of the depth of cut in humid cestamide samples has positive effect on surface roughness. The reason of this is the decrement of heat and abrasion effect by the humidity of the material after increasing of depth of cut.
2. The best average for dry cestamide material is 0.533 µm on condition that surface roughness values depth of cut is 1 mm, cutting speed is 130 m/min and feed rate is

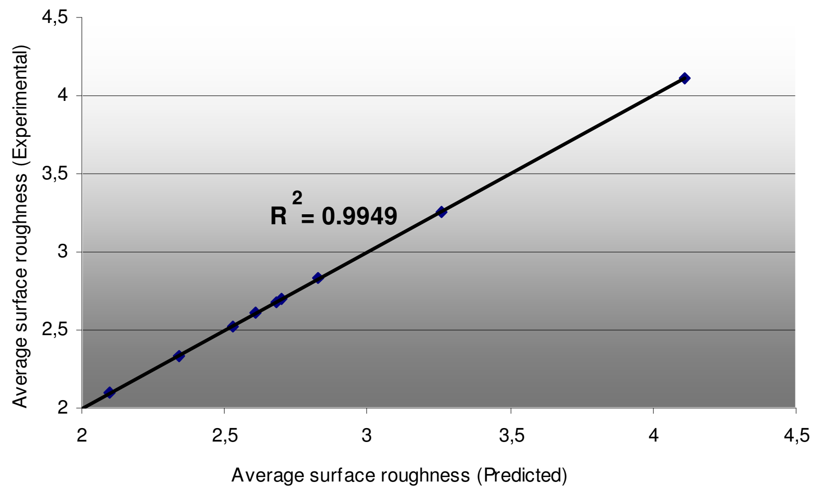

Figure 4. Comparison of measured and predicted surface roughness results for testing data.

100 mm/min. The worst result is 3.824 µm on condition that depth of cut is 3 mm, cutting speed is 90 m/min and feed rate is 160 mm/min.

3. The best average for humid cestamide material is 0.718 µm on condition that surface roughness values depth of cut is 3 mm, cutting speed is 130 m/min and feed rate is 100 mm/min. The worst result is 3.664 µm on condition that depth of cut is 1 mm, cutting speed is 90 m/min and feed rate is 140 mm/min.

4. According to experiment results; the best result is obtained when ANN with 4 input, 13 hidden layered and 1 output is used. Treatment and test data are coherent in 0.9949% rate. Experimental process of both humid and dry cestamides and treatment graphics drawn after ANN treatment are given in Figure 4. These results are in the acceptable error rate with the rate of 0.3326% and shows that ANN usage is suitable for the estimation of surface roughness value for the experiment results that have not been carried out yet.

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NOMENCLATURE

ANN, Artificial neural-network; **MAPE,** mean absolute percentage error; **RMSE,** root-mean-squared error; **R^2,** absolute fraction of variance; **m,** measured value; **n,** pattern; **f,** feed rate; **a_p,** depth of cut; **V_c,** cutting speeds; **R_a,** average surface roughness.

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