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Experimental and artificial neural network study of heat formation values of drilling and boring operations on Al 7075 T6 workpiece

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Drilling operation is one of the most important processing among the manufacturing processes. Manufacturing processes usually contain the drilling operation. Because of the importance of drilling operation, it has been accomplished drilling and boring experimental study. Al 7075 T6 workpieces has been used for this experimental study. For this material heat formation is important while the processing the material because this material changes its specification after certain temperature. Especially heat changes have been observed during the drilling and boring processes. In this study, firstly experimental setup has been accomplished then collected the heat formation data while the processing Al 7075 T6. Data have been collected from eleven different points on the workpiece. After that these data have been interpreted by statistical methods. Annova analysis has been applied to these data. However, no significant results were obtained with the Annova analysis. For this reason; data have been interpreted with artificial neural network system. Different cutting speeds and feed rates have been taken into consideration that are processing the drilling operations. The main goal is to predict the heat formation that is at any point on workpiece Al 7075 T6. So designers and manufacturers do not need do any calculation or experiment to determine the heat formation values on workpiece Al 7075 T6.

Keywords: Drilling, Boring, Heat formation, Artificial neural network, Al 7075 T6

Drilling operations are used widely in manufacturing operations. For this reason, this study is interested in manufacturing processes and especially drilling and boring operations. While many of machine parts are producing, these parts operate the drilling operations. These operations are important for approval machine parts produce. Every operation is subjected to some unwanted stresses on workpiece. Generally heat occurs when the workpiece is machined with drilling operations. The experimental studies have been reported in the literatures and experimental set-up has been designed for drilling tests. With this aim, an experimental study have been planned, set-up and accomplished. Three different sized drilling tools have been used in these tests. Cutting depth is constant that is 10 mm. A total 45 experiments have been accomplished and heat changes have been determined on workpieces. Each experiment contains ten drilling processes. In this study, it is investigated according to cutting speed and feed rate parameters. Firstly workpieces are drilled the diameter of 6 mm after then the holes enlarged with 7 mm and 8 mm diameter drilling tools respectively.

Thermal models depend upon many experimental data such as cutting force or torque, chip thickness, chip-tool contact length, and effective shear stress for each segment of the cutting edge. In order to measure those parameters and temperatures during the drilling processes, specially devised experimental set-ups were required. These problems have constrained the application of the developed models[1,2]. Agapiou and Stephenson[3] developed a method of computing temperatures for drills with arbitrary point geometries based on drilling torque and material properties.

Lin and Ting[4] used thrust force and torque signal to monitor the drill flank wear using regression model. They used the neural network model to study the drill wear and observed that the training error in case of sample mode converges faster than that in case of batch mode[5]. In another study, monitored the tool wear based on current signals of spindle motor and feed motor using regression model[6].

Ahn and Chung[7] developed a real-time estimator of the temperature distribution and the thermal expansion of a ball screw system using the IHP. They studied the one dimensional heat transfer problem modelled with continuous state equations using the concept of modal analysis and mode reduction[7]. Manish and Chandrashekhara[8] developed delamination prediction of thick composite-beam by neural networks[8]. Li ***et al***.[9] proposed hybrid learning for

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monitoring of drill wear using a combination of fuzzy system and neural network. Hashmi ***et al***.[10] proposed a fuzzy model for correlating the drilling speed with hardness of work material. They have used triangular membership function with fuzzy rule base in there analysis[10]. Tsai and Wang[11] compared the performance of electric discharge machining (EDM) utilizing various neural networks, and found that the RBFN model gives the correct results. Tsao[12] used the radial basis function network (RBFN) and adaptive based radial basis function network (ARBFN) to predict the flank wear, and compared their results with experimental observation. Lo[13] described the tool state in turning operation using artificial neuro fuzzy inference system (ANFIS) architecture, and concluded that higher accuracy could be achieved in the case of triangular and bell shape membership function. Marek Balazinski ***et al***.[14] used three artificial intelligence (AI) methods: feed forward back propagation neural network, fuzzy decisions support system and an artificial neural network based fuzzy inference system to monitor the flank wear in turning operation.

Multiple objectives linear programming models for optimizing drill hole quality with different cutting conditions such as speed and feed rate was proposed by Kim and Ramulu[15]. Obikawa and Shinozuka[16] used unsupervised and self-organizing neural network adaptive resonance theory (ART2) for monitoring of flank wear in high-speed machining operation.

Some researchers[17,18] have studied to estimate the temperature distribution and heat sources in manufacturing processes. El-Sonbaty ***et al***.[17] reported that over 100,000 holes are required in a small engine aircraft, mostly for fasteners. Conventional high speed steel and cemented carbide drills are widely employed in the machining of polymeric composite materials, albeit a number of research works have indicated that traditional twist drills are unsuitable to cut fiber reinforced materials, which require tools with special edge preparation. The inadequate selection of the tool geometry results in higher temperature due to friction between the principal and secondary clearance faces and the work material, accelerated tool wear rates and higher thrust force and torque values, which lead to poor hole quality and surface damage[17].

Drilling is one of the most common and fundamental machining processes. Worn drills produce poor quality holes and in extreme cases a broken drill can destroy an almost finished part. A drill begins to wear as soon as it is placed into operation. As it wears, cutting forces will increase, the temperature of the drill rises and this accelerates the physical and chemical processes associated with drill wear and therefore drill wears faster. Different types of drill wear, such as flank wear, crater wear and chisel edge wear and margin wear, can be observed on drill because of the geometry of the drill and the cutting conditions vary along the cutting lips from the margin to the chisel edge[18].

Singh ***et al***.[19] used back propagation neural network for prediction of flank wear of high-speed steel (HSS) drill in a copper workpiece using spindle speed, feed rate, drill diameter, thrust force and torque as input parameters and maximum flank wear as output parameter in a neural network.

Panda ***et al***.[20] used back propagation neural network for prediction of flank wear of HSS drill in a mild steel workpiece using the spindle speed, feed rate, drill diameter, thrust force, torque and chip thickness as input parameters and maximum flank wear as output parameter to neural network and concluded that inclusion of chip thickness as an input parameter to network leads to better prediction of flank wear.

There have been many scientific applications of both drilling operation and statistical method. New materials should be explored for their machinability abilities[21,22].

Many products are produced through the drilling process. With increasing demands on drill accuracy and higher production rates, it is important to better understand the process. In some countries drilling has been reported to account for nearly 50% of all machining operations[23].

Manufacturing industries are trying to reduce the operation cost as well as better quality of product. So, automation with online monitoring in metal cutting operation is a new approach toward improvement of the quality of the product as well as reduction of the overall cost of the product. Monitoring of drill wear is an important issue since wear on drill affect the hole quality and tool life of the drill[24].

The other studies especially related to Hidden-Markov model, Taguchi method and machinability specifications[25,26].

Experimental Set-up

For measurement of thermal formation on the workpiece; firstly, a clamping fixture has been designed and manufactured. Clamping fixture has been produced by Ç1040 (AISI 1040) material. All surfaces of clamping fixture have been manufactured with machining operation then processed grinding operations. Clamping fixture's surfaces have position tolerances. It has been noticed that there are vibration effects during the experiment duration. For this aim, workpiece has been located rigid position. Workpiece has been jointed by contra nuts. So rigid position has been obtained. Experiment material properties are given in Table 1.

This fixture were drilled for tip of thermocouples. Hole distances are 10 mm one to another hole. 16 hole have been drilled to locate the thermocouples. So, thermal changes have been measured during the drilling operations. Thermocopules were connected the fixture than workpiece was being clamped the fixture (Fig. 1).

Different drilling tips are used drilling operations. Operations have been accomplished 3 steps. High speed steel (HSS) drill bits that are 6 mm, 7 mm and 8 mm diameter, have been used for drilling hole in AL 7075 T6 plates. Primarily holes have been drilled 6 mm, than enlarged with 7 mm and 8 mm drilling tools. Total 450 holes have been drilled on workpieces. AL 7075 T6 is used for workpieces. Workpieces dimensions are 100×40×10 mm. J types of thermocouples have been used for experimental studies. These types of thermocouples working range is 0-850°C. ADAM-3016 has been used for convert to voltage from data. ADAM-3016 working range is 0-10 V. It produces analog outputs. Analog data have been saved through Advantech PLC-812 PG data connection card. Heat values have been obtained at 11 different points during the experiments. All data have been collected to PC that has MMX-200 processor and 256 MB ram memory. To collect and convert to data, it has been prepared a QB software (Fig. 2). Experiments were performed on milling machine that is PREIFER F105 CNC (BORVERG). It has 30 kW power. It has CNC HEIDENHAIN TNC 155 control unit. To calibrate thermal stresses, it has been used TES Electric-Electronic Corp TP-D05 (-150 ~ +150 °C) probe. All experminetal set-ups were calibrated that are noise, temperature, vibration, etc. Figure 3 shows CNC machine and experimental set-up.

Experimental values have been measured as voltage. Then these voltage values have been converted (V) to temperature (°C). Thermocouple values have been calibrated and found by Eq. (1) (Fig. 4):

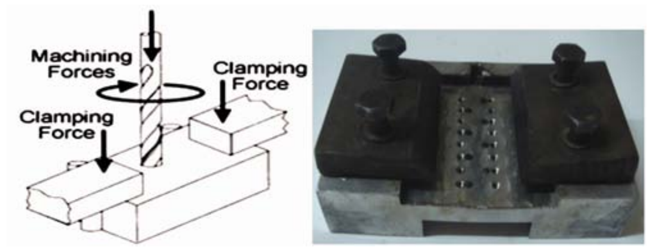


Fig. 1 – Schematic and photographic image of clamping fixture

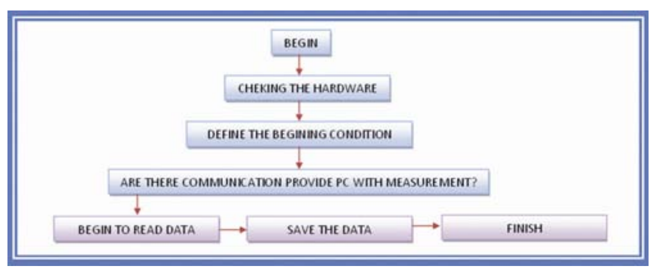


Fig. 2 – Software algorithm

Fig. 3 – CNC milling machine

Table 1 – AL 7075 T6 chemical composition limits

Hardness Brinell	Al	Mg	Si	Cr	Mn	Ti	Cu	Fe	Zn
150	87.1 - 91.4	2.1 - 2.9	Max 0.4	0.18 - 0.28	Max 0.3	Max 0.2	1.2 - 2	Max 0.5	5.1 - 6.1

$$T = 75.721 * V - 36.223 \qquad \dots (1)$$

here T is temperature (°C) and V is voltage value (V).

Tables 2 and 3 show the experimental details. Table 2 emphasises the measurement details, Table 3 shows cutting parameters. In these experiments have not been used the cutting liquid. Figure 5 shows photographic image of work pattern and connection with the thermocouples on workpiece Al 7076 T6.

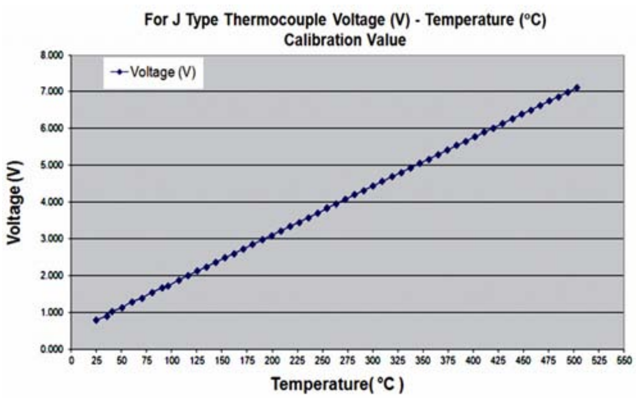


Fig. 4 – Voltage (V) - temperature (°C) calibration value

Artificial Neural Network Model

Artificial neural network

The concept of artificial neural networks has emerged with the idea that is simulate the brain's operating principles of digital computers. The studies were made with mathematical modeling of biological neurons that make up the brain cells.The results of these studies revealed the neighboring neurons, each neuron receives some information and this information converted into an output according to the demands of the dynamics of biological neurons[27].

The main elements of an artificial neural network

Artificial neural networks consist of a large number of interconnected processing elements. Artificial

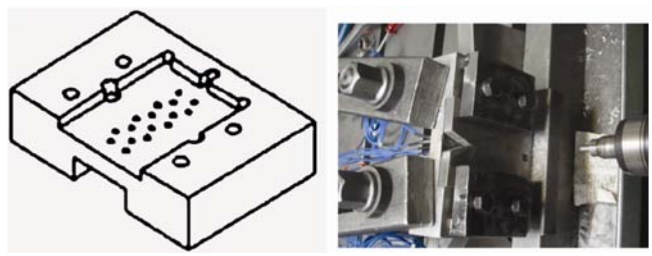


Fig. 5 – Photographic image of work pattern and connection with the thermocouples on workpiece Al 7076 T6

Table 2 – Heat measurement coordinates

J Type Thermocouple Coordinates	X	10	10	10	10	-10	-10	-10	-10	-10	-10	-10
	Y	15	35	55	75	25	45	85	15	35	55	75
	Z	0	0	0	0	0	0	0	8	8	8	8

Table 3 – Drilling experiment parameters

Cutting tool diameter (***d***, mm)	Cutting speed (***v***, mm/min)	Feed rate (***f***, mm/rev))	***n*** (rpm)	Cutting tool diameter (***d***, mm)	Cutting Speed (***v***, mm/min)	Feed rate (f-mm/rev))	n (rpm)	Cutting Tool Diameter (d-mm)	Cutting Speed (v-mm/min)	Feed rate (f-mm/rev))	n (rpm)
6	12	0.1	637	7	12	0.1	546	8	12	0.1	478
6	12	0.11	637	7	12	0.11	546	8	12	0.11	478
6	12	0.12	637	7	12	0.12	546	8	12	0.12	478
6	12	0.13	637	7	12	0.13	546	8	12	0.13	478
6	12	0.14	637	7	12	0.14	546	8	12	0.14	478
6	14	0.1	743	7	14	0.1	637	8	14	0.1	557
6	14	0.11	743	7	14	0.11	637	8	14	0.11	557
6	14	0.12	743	7	14	0.12	637	8	14	0.12	557
6	14	0.13	743	7	14	0.13	637	8	14	0.13	557
6	14	0.14	743	7	14	0.14	637	8	14	0.14	557
6	16	0.1	849	7	16	0.1	728	8	16	0.1	637
6	16	0.11	849	7	16	0.11	728	8	16	0.11	637
6	16	0.12	849	7	16	0.12	728	8	16	0.12	637
6	16	0.13	849	7	16	0.13	728	8	16	0.13	637
6	16	0.14	849	7	16	0.14	728	8	16	0.14	637

neural networks processing elements are called simple nerves. An artificial neural network contains a large number of interconnected nodes. Nerve is the basic unit of an artificial neural networks. Artificial neural is so simple than biological nerves. Figure 6 shows an artificial neural network algorithm. All artificial neural networks are derived from this basic structure. The differences in the structure of artificial neural networks provide a different classification[28].

Training, learning and testing in artificial neural network

Training meaning of artificial neural networks, neural network, presented the problem of establishing the right connections between the input and output data provide and produce the correct outputs. This process continue to fall below a certain value that error between the foreseen output and desired output. Artificial neural networks learn like the human. The more samples are used for learning, the more accurate result is obtained[29].

When the learning of a certain input is entered, the network can make changes to data in order to give similar accurate answers. The error is difference between the output and expected output. After the training, the data network is tested that ANN has learned really to understand rather than memorize. In test section, unused data is used for control of accuracy value[30].

Levenberg-Marquardt method

The Levenberg-Marquardt method uses a search direction that is a solution of the linear set of equations[31,32]:

$$(\boldsymbol{J}(\boldsymbol{x}_k)^T \boldsymbol{J}(\boldsymbol{x}_k) + \boldsymbol{x}_k \boldsymbol{I})\boldsymbol{d}_k = -\boldsymbol{J}(\boldsymbol{x}_k)^T \boldsymbol{F}(\boldsymbol{x}_k) \quad \text{... (2)}$$

or, optionally, of the equations

$$(\boldsymbol{J}(\boldsymbol{x}_k)^T \boldsymbol{J}(\boldsymbol{x}_k) + {}_k \boldsymbol{diag}(\boldsymbol{J}(\boldsymbol{x}_k)^T \boldsymbol{J}(\boldsymbol{x}_k)))\boldsymbol{d}_k = -\boldsymbol{J}(\boldsymbol{x}_k)^T \boldsymbol{F}(\boldsymbol{x}_k) \quad \text{... (3)}$$

where the scalar λ_k controls both the magnitude and direction of $\boldsymbol{d}_k$. Set option ScaleProblem to none' to choose Eq. (2), and set ScaleProblem to 'Jacobian' to choose Eq. (3).

When λ_k is zero, the direction $\boldsymbol{d}_k$ is identical to that of the Gauss-Newton method. As λ_k tends to infinity, $\boldsymbol{d}_k$ tends towards the steepest descent direction, with magnitude tending to zero. This implies that for some sufficiently large λ_k, the term $\boldsymbol{F}(\boldsymbol{x}_k + \boldsymbol{d}_k) < \boldsymbol{F}(\boldsymbol{x}_k)$ holds true. The term λ_k can therefore be controlled to ensure descent even when second-order terms, which restrict the efficiency of the Gauss-Newton method, are encountered. The Levenberg-Marquardt method therefore uses a search direction that is a cross between the Gauss-Newton direction and the steepest descent direction. The solution for Rosenbrock's function converges after 90 function evaluations compared to 48 for the Gauss-Newton method. The poorer efficiency is partly because the Gauss-Newton method is generally more effective when the residual is zero at the solution[40,41]. However, such information is not always available beforehand, and the increased robustness of the Levenberg-Marquardt method compensates for its occasional poorer efficiency[33].

Multilayer networks often use the log-sigmoid transfer function logsig. The function logsig generates outputs between 0 and 1 as the neuron's net input goes from negative to positive infinity. Alternatively, multilayer networks can use the tan-sigmoid transfer function tansig. Sigmoid output neurons are often used for pattern recognition problems, while linear output neurons are used for function fitting problems. The linear transfer function purelin is shown Fig. 7.

Results and Discussion

Experimental results

In this study, the effects of heat formation parameters that are cutting speed, feed rate and cutting tool dimater for drilling the material Al 7075 T6 have been investigated. Total 45 experiments have been performed to commetment of these parameter

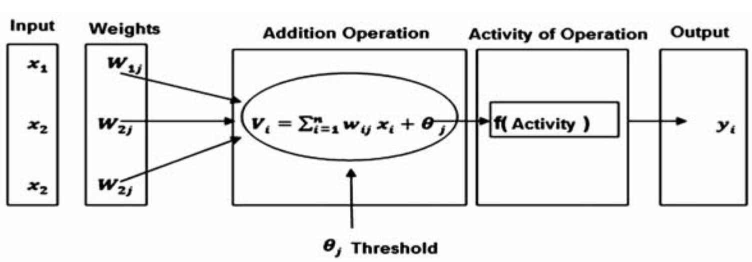


Fig. 6 – An artificial neural network

effects of heat formation on the workpiece. Eleven thermocouples have been located at different coordinates on the workpiece Al 7075 T6. So heat formation has been measured at 11 diffrerent points. To measure the heat values, firstly experiment set-up has been established. The heat values have been measured at 11 different locations on the workpiece. It has been accomplished the experiment that have 45 different workpieces, 11 measurement point every workpiece, 10 holes each workpiece, 6 mm, 7 mm and 8 mm drilling and boring tests . The experiment variables are cutting tool diameter (***d,*** mm), cutting speed (***v***, mm/min), feed rate (***f***, mm/rev), revolution per minute (***n***, rpm), thermocouple location coordinates (***x,y,z***) for 11 thermocouple points and heat value. It has been read 60 data per minute for every thermocouple point. Total 48 column × 3185 line data have been obtained in the experiment. Average values have been taken into account for ANN. So reading data errors have been reduced to minimum. 48 column × 3185 line data have been converted to 7 column × 435 line data. It is enough for modelling with ANN. These data have been divided into some groups. 70% data have been used for the training, 15% data have been used to check the validation results and 15% data have been used for the test results.

Firstly ANNOVA analysis has been accomplished ($\boldsymbol{R}^2$=0.26775402, adjusted $\boldsymbol{R}^2$= 0.25748889). This analysis result is not appropriate to interpret the experiment result. In the Annova analysis only tool diameter and cutting speed have some meaning for the analysis. Every parameter has been investigated the effects of each other. Only tool diameter and cutting speed have been effected heat formation values. So this analysis seems partial factorial design. Annova analysis has not been given the contriubition of the experiment result. For this reason artificial neural network model has been modelled in this study. There were different ANN models tried especially RBF and MLP models. The best results have been obtained by the MLP model (Fig. 8).

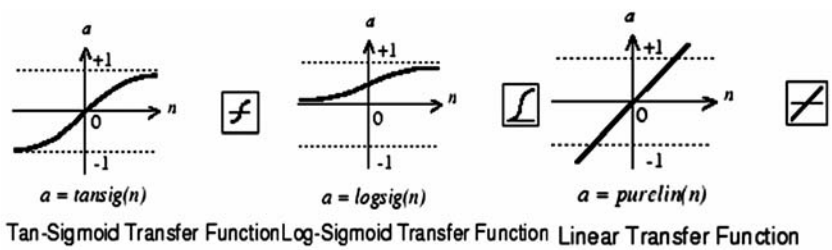


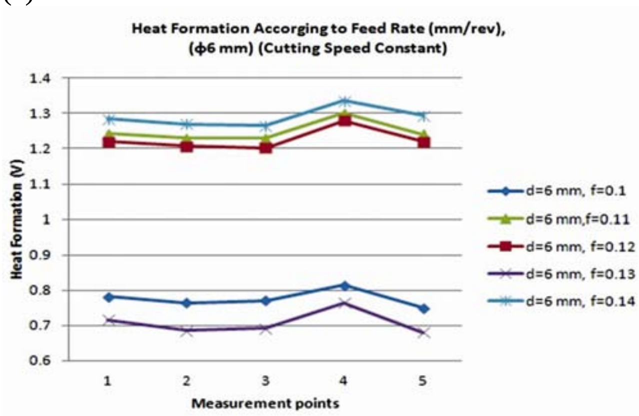
Fig. 7 – Used ANN functions

Net. name	Training perf.	Test perf.	Training error	Test error	Training algorithm	Hidden activation	Output activation
MLP 6-16-1	0.497860	0.602457	0.026070	0.025400	BFGS 5	Exponential	Logistic
MLP 6-28-1	0.498187	0.605923	0.025727	0.025883	BFGS 4	Exponential	Sine
RBF 6-39-1	0.509418	0.616413	0.025302	0.025400	RBFT	Gaussian	Identity
MLP 6-42-1	0.520252	0.603794	0.024941	0.025934	BFGS 13	Exponential	Tanh
MLP 6-92-1	0.521467	0.605494	0.025158	0.025382	BFGS 12	Exponential	Identity
RBF 6-22-1	0.521834	0.609073	0.024865	0.025903	RBFT	Gaussian	Identity
MLP 6-23-1	0.570185	0.609523	0.023073	0.025446	BFGS 29	Exponential	Identity
RBF 6-56-1	0.572631	0.610307	0.022965	0.025939	RBFT	Gaussian	Identity
RBF 6-49-1	0.589861	0.623508	0.022281	0.025150	RBFT	Gaussian	Identity
MLP 6-22-1	0.597940	0.602831	0.021957	0.025730	BFGS 37	Exponential	Exponential
RBF 6-79-1	0.612849	0.647078	0.021336	0.024048	RBFT	Gaussian	Identity
RBF 6-96-1	0.613516	0.609811	0.021308	0.025542	RBFT	Gaussian	Identity
MLP 6-80-1	0.672569	0.650933	0.018740	0.023578	BFGS 63	Exponential	Logistic
MLP 6-49-1	0.905952	0.868016	0.006132	0.009665	BFGS 75	Logistic	Sine
MLP 6-9-1	0.916851	0.948799	0.005451	0.003915	BFGS 64	Tanh	Identity
MLP 6-13-1	0.959814	0.953407	0.002728	0.003688	BFGS 149	Logistic	Logistic
MLP 6-32-1	0.966638	0.951429	0.002243	0.003720	BFGS 133	Logistic	Sine
MLP 6-51-1	0.968354	0.963399	0.002129	0.002879	BFGS 125	Logistic	Identity
MLP 6-33-1	0.978804	0.963877	0.001435	0.002809	BFGS 141	Logistic	Tanh

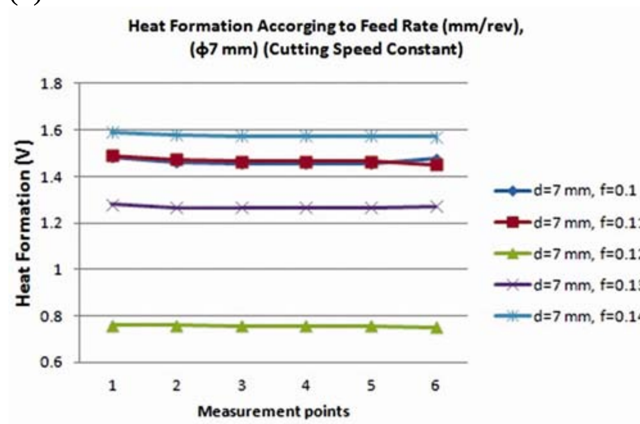
Fig. 8 – Determination of ANN model

Experimental results have been interpreted effects of tool diameter, feed rate and cuttting speed values. When the cutting speed has been constant, maximum heat has been formed at ***f***=14 mm/rev. It was valid for tool diameter 6, 7 and 8 mm. Minimum heat value was formed at ***f***=14 mm/rev for the tool diameter 7 and 8 mm. But minimum heat value was formed at ***f***=13 mm/rev for the tool diameter 6. In the study, workpieces have been drilled for the tool diameter 6 mm then boring with 7 and 8 mm. These values have been showed in Fig. 9 (a-c). When the drilling tool diameter, cutting speed and feed rate were variable, maximum heat value has been formed that is state 1 (***d***=6 mm, ***v***=12 mm/min, ***f***=0.1 mm/rev), state

(a)



(b)



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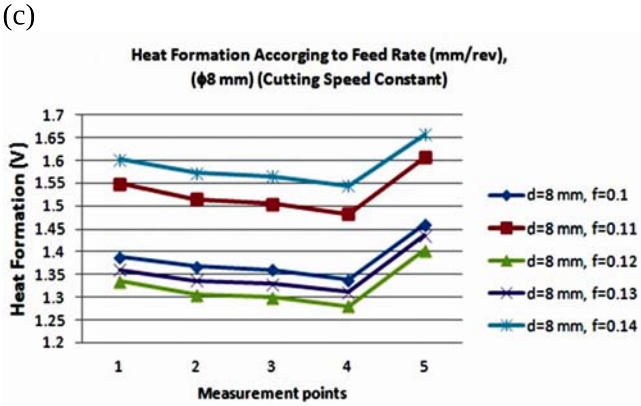
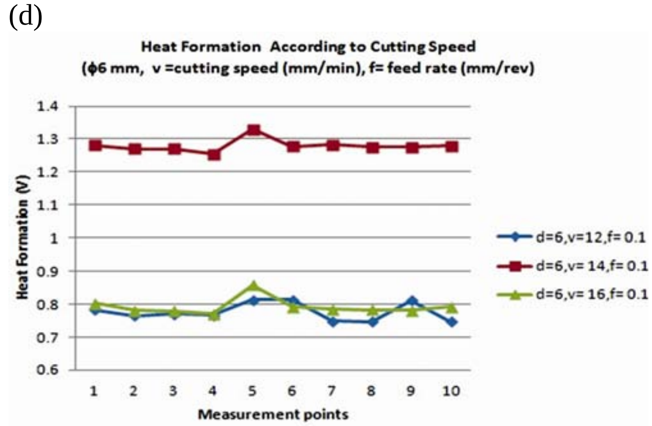
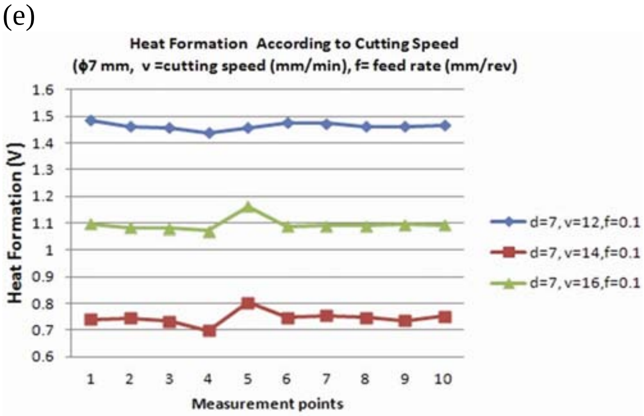


(d)



(e)



(f)

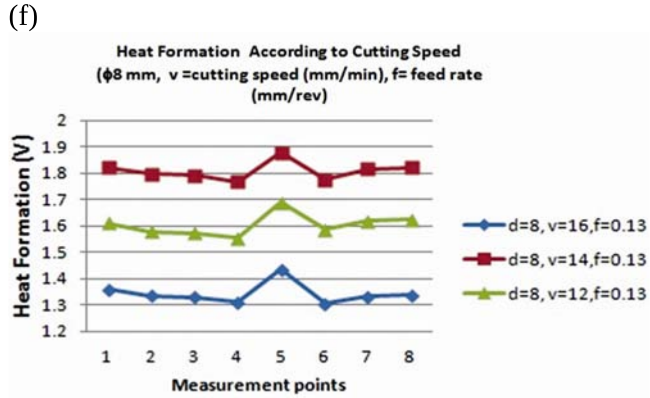


Fig. 9 – Comparision of heat formation; drilling tool diameter, cutting speed and feed rate changes (a, b, c) cutting speed constant, (d,e,f) cutting speed and feed rate variable

2 (***d***=7 mm, ***v***=12 mm/min, ***f***=0.1 mm/rev) and state 3 (***d***=8 mm, ***v***=14 mm/min, ***f***=0.13 mm/rev). These values are shown in Fig. 9 (d-f).

Performance of ANN model

There are many commercial ANN software. In this study, Matlab Neural Network Toolbox has been used to obtain the neural network model. There are seven inputs (cutting tool diameter, time, cutting speed (***v***), Feed rate (***f***), location points ***x,y,z***) and one output (heat formation (voltage-(***V***)). In the model, multi-layer feed forward perceptron (MLP) was used in the analysis. It was used tansig (hyperbolic tangent sigmoid transfer function), logsig (log-sigmoid transfer function) and purelin (linear transfer function) fuctions on the Matlab software. Levenberg-Marquardt training method was used in the ANN model. Figure 10 shows the ANN model.

Table 4 shows the comparison of experimental values and Matlab neural network predictions. The error amounts used for the analysis of the three statistical values. These are the statistical errors of the root mean square error (RMSE), absolute fraction of variance (R^2) and mean error percentage (MEP), respectively. RMSE value is found smaller than 0.015558 and R^2 is 0.999774 and MEP is around

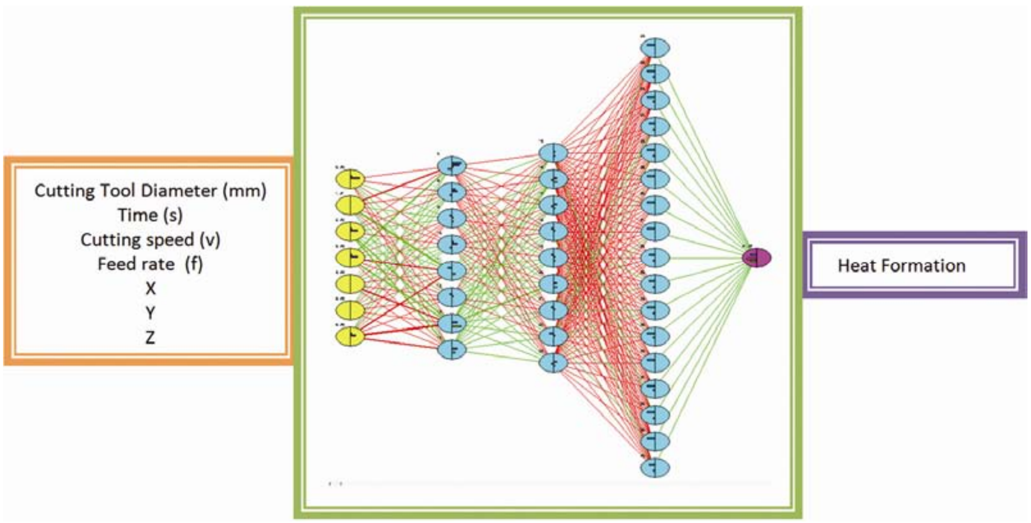


Fig. 10 – ANN model

Table 4 – ANN test data

Cutting tool diameter, mm	Cutting speed (*v*), mm/min	Feed rate (*f*), mm/rev	X	Y	Z	Experiment (Heat), V	ANN TEST (MATLAB) (Heat), V	RMS	R^2	MEP
6	12	0.1	-10	85	0	0.749569	0.759250	0.009681	0.999837	-0.01275
6	14	0.11	-10	75	8	1.049519	1.033961	0.015558	0.999774	0.015047
6	16	0.12	10	15	0	1.105628	1.119596	0.013969	0.999844	-0.01248
6	12	0.13	-10	15	8	0.682796	0.683421	0.000625	0.999999	-0.00091
6	14	0.14	-10	75	8	0.867093	0.870442	0.003349	0.999985	-0.00385
6	12	0.11	10	75	0	1.1945	1.193596	0.000904	0.999999	0.000757
6	16	0.13	10	35	0	0.911006	0.917320	0.006314	0.999953	-0.00688
7	16	0.12	10	75	0	1.707183	1.710183	0.003001	0.999997	-0.00175
7	12	0.13	-10	15	8	1.277083	1.282234	0.005151	0.999984	-0.00402
7	16	0.14	-10	75	8	0.857157	0.866099	0.008942	0.999893	-0.01032
7	14	0.11	10	35	0	1.579623	1.584456	0.004833	0.999991	-0.00305
7	12	0.13	-10	75	8	1.28008	1.273830	0.00625	0.999976	0.004907
7	14	0.14	10	15	0	1.641693	1.633279	0.008414	0.999973	0.005152
7	14	0.12	-10	75	8	1.652046	1.641860	0.010186	0.999962	0.006204
7	16	0.13	10	15	0	1.709499	1.709838	0.000339	1	-0.0002
8	12	0.1	10	15	0	1.388701	1.378700	0.010001	0.999947	0.007254

0.015047 for the training and test data, respectively. Simply, RMSE, $\boldsymbol{R}^2$ and MEP values are obtainable throughout the following equations:

$$\mathrm{RMSE} = \left[\frac{1}{p}\sum_j \left| t_j - o_j \right|^2\right]^{1/2} \quad \dots (3)$$

$$\mathrm{RMSE} = \left[\left|0.749569 - 0.759250\right|^2\right]^{1/2} = 0.015558$$

Statistical error amount,

$$R^2 = 1 - \left[\frac{\sum_j (t_j - oj)^2}{\sum_j (o_j)^2}\right] \quad \dots (4)$$

$$R^2 = 1 - \left(\frac{(0.749569 - 0.759250)^2}{(0.759250)^2}\right) = 0.999774$$

Average percent error,

$$\mathrm{MEP}\,\% = \frac{\sum_j \left(\frac{t_j - o_j}{t_j} \times 100\right)}{p} \quad \dots (5)$$

$$\mathrm{MEP}\,\% = \frac{0.749569 - 0.759250}{0}.759250 \times 100 = \%$$

0.015047

Figure 11 shows that training performance of the model. This is a result of MATLAB. According to graph; training percentage is maximum. This shows that the training value can acceptable rate. The result value is so close to 1. Performance of an ANN model is connected with the deviation between the actual output values and output values. Figure 12 shows ANN results; training, validation and test.

Figure 13 shows that ANN error histogram 20 Bins, Fig. 14 shows validation performance and Fig. 15 emphasises function fit for output. According to graphs; Training target, training output, validation target, validation outputs, test target, test output are compatible with the the experimental values. These values show that the ANN model is completely overlapped with actual values.

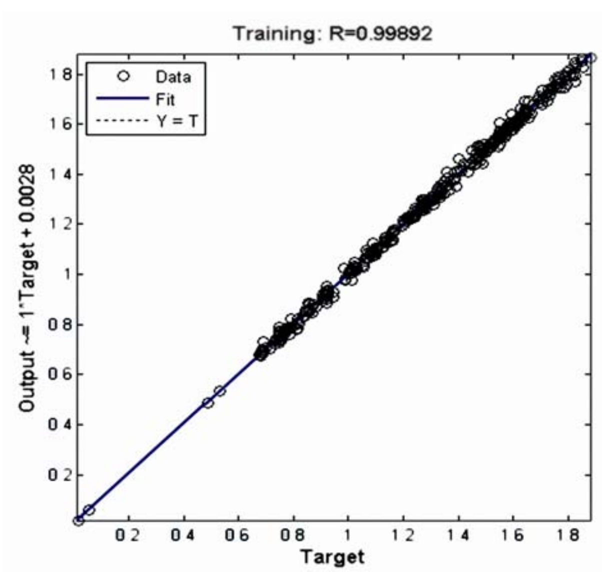


Fig. 11 – ANN training result

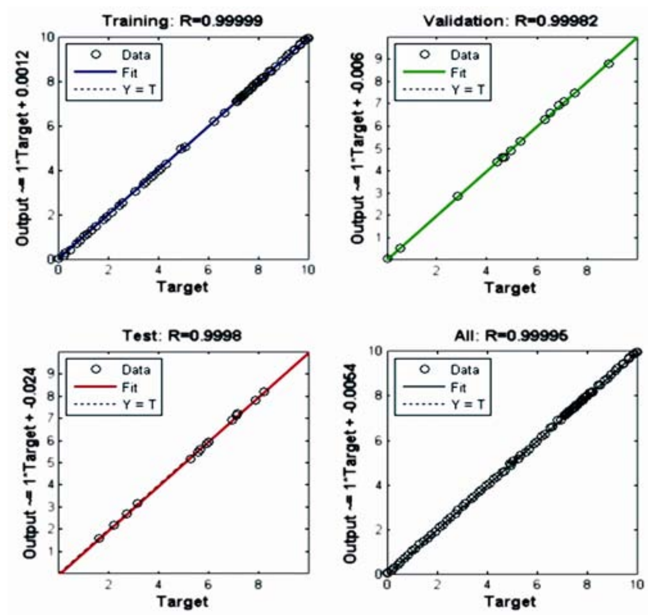


Fig. 12 – ANN results, training, validation and test

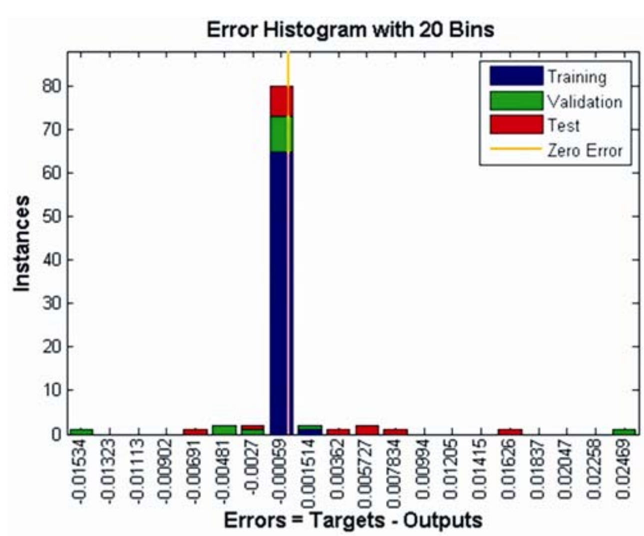


Fig. 13 – ANN error histogram 20 bins

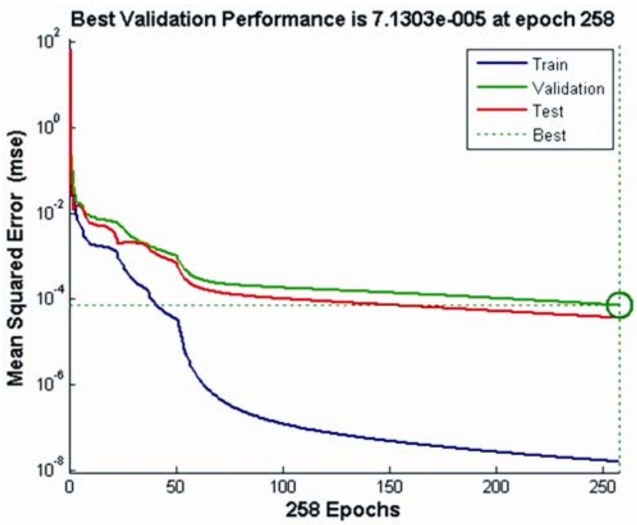


Fig. 14 – ANN vadidation performance

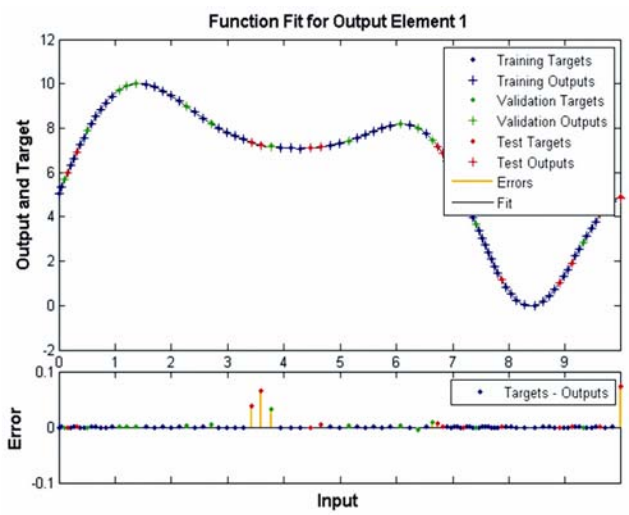


Fig. 15 – ANN function fit the output and ANN error histogram

Conclutions

In this study, heat formation on AL 7075 T6 has been investiagted experimentaly while the driling and boring processes. ANN model has been developed for predicting the heat values on workpiece. These analyses have been modelled with MATLAB neural network toolbox. The optimal configuration of the ANN consisted of three layers with LM neural networks approach Statistical analysis results are RMSE = 0.015558, R^2 = 0.999774 and MEP % = 0.015047. Experimental results and ANN model results are in good agreement with each other. The ANN based on calculation can be used to predict the heat values according to drilling parameters. In conclusion, heat formation can be predicted without requiring experimental study. ANN models can provide both simplicity and fast calculation. It is shown that ANN models can be used as an effective and an alternative method for the experimental studies and can contribute with regard to both time and economical optimization of the machining.

References

1 Agapiou J S & DeVries M F, ***Int J Mach Tools Manuf***, 30 (1990) 203-215.
2 Agapiou J S & DeVries M F, ***Int J Mach Tools Manuf***, 30 (1990) 217-226.
3 Agapiou J S & Stephenson D A, ***Trans ASME, J Eng Ind***, 116 (1994) 54-60.
4 Lin S C & Ting C J, ***Wear***, 180 (1995) 53-60.
5 Lin S C & Ting C J, ***Int J Mach Tools Manuf***, 36 (1996) 465-475
6 Xiaoli Li & Tso S K, ***Wear***, 231 (1999) 172-178.
7 Ahn J Y & Chung S C, ***Trans NAMRI/SME***, 20 (2000) 437-442.
8 Manish T V & Chandrashekhara K, ***Compos Sci & Technol***, 60 (2000) 1773-1779.
9 Li X, Dong S & Nenuvinod P K, ***Int J Adv Manuf Technol***, 16 (2000) 303-307.
10 Hashmi K, Graham I D & Mills B, ***J Mater Process Technol***, 108 (2000) 55-61.
11 Tsai K M & Wang P J, ***J Mater Process Technol***, 117(1) (2001) 111-114.
12 Tsao C C, ***J Mater Process Technol***, 123 (2002) 354-360.
13 Lo S P, ***Int J Adv Manuf Technol***, 19 (2002) 564–572.
14 Balazinski M, Czogala E, Jemielniak & Leski K J, ***Eng Appl Artif Intell***, 15 (2002) 73-80.
15 Kim D & Ramulu M, ***J Compos Struct***, 63 (2004) 101-114.
16 Obikawa T & Shinozuka J, ***Int J Mach Tools Manuf***, 44 (2004) 1311-1318.
17 El-Sonbaty I, Khashaba U A & Machaly T, ***Compos Struct***, 63(3-4) (2004) 329-338.
18 Sanjay C, Neemab M L & Chin C W, ***J Mater Process Technol***, 170 (3) (2005) 494-500.
19 Singh A K, Panda S S, Pal S K & Chakraborty D, ***Int J Adv Manuf Technol***, 28 (5-6), (2006) 456-462.
20 Panda S S, Singh A K, Chakraborty D & Pal S K, ***J Mater Process Technol***, 172 (2006) 283-290.
21 Gaitonde V N, Karnik S R, Achyutha B T & Siddeswarappa B, ***Indian J Eng Mater Sci***, 13(6) (2006) 484-488.
22 Natarajan U, Arun P & Periasamy V M, ***Indian J Eng Mater Sci***, 13(2) (2006) 103-109.
23 Haber-Haber R, Haber R, Schmittdiel M & del Toro R M, ***Int J Mach Tools Manuf***, 47(15) (2007) 2290-2297.
24 Panda S S, Chakraborty D & Pal S K, ***Appl Soft Comput J***, 8(2) (2008) 858-871.
25 Kilickap E l, ***Indian J Eng Mater Sci***, 17(4) (2010) 265-274.
26 Jayabal S & Natarajan U, ***Indian J Eng Mater Sci***, 17(6) (2010) 463-470.
27 Efe M Ö, Kaynak O, Yapay Sinir Ağları & Uygulamaları, (Boğaziçi Üniversitesi , İstanbul), 2000, pp. 3:1 (in Turkish).
28 Elmas Ç & Yapay Sinir Ağları, (Seçkin Yayıncılık, Ankara), 2003, pp. 27-37, (in Turkish).
29 Arslan A & İnce R, ***Eng Fract Mech***, 71(15) (1996) 2143-2159.
30 Yao X, ***Evolving artificial neural Networks***, Proc LEEE, (1999), p. 87.
31 Levenberg, K, ***Q Appl Math***, 2 (1944) 164-168.
32 Marquardt D, ***J Appl Math***, 11 (1963) 431-441.
33 ***MATLAB Helping Neural Network Toolbox***, 2012.