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Prediction of Tool Wear for Ball End Nose in Milling Inconel 718 Using a Feed Forward Back Propagation Neural Network

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ABSTRACT

In a machining process, detecting tool wear before failure is an important step towards avoiding unscheduled machine downtime. Tool wear occurs during the machining process, due to an interaction between the edge of the cutting tool and the work piece. Particular attention should be given to the progression of tool wear, because it causes breakages of the cutting tool, and consequently affects the work piece's accuracy and production time. Furthermore, high quality machined parts is required, in order to fulfil current demands. This paper proposes several architectures of single and multi-layer back propagation neural network methods, to predict tool wear progression within the end milling process of Inconel 718. The end milling process was carried out in a cryogenic environment, with cutting parameters of cutting speed, V_c (140 - 170 mm/min), feed rate, F_z (0.05 - 0.1 mm/tooth), axial depth of cut, ap (0.3 - 0.5 mm), and radial depth of cut, ae (0.2 - 1 mm). A coated carbide end ball nose, with a diameter of 5 mm, was used as a cutting tool. The cutting forces exerted during the milling process were measured using a strain gauge based dynamometer in x, y, and z directions. In order to apply a feed forward back propagation neural network method to predict tool wear; V_c, F_z, ap, ae, and the resultant force (F_R), were taken as inputs, and tool wear was obtained as an output. Levenberg-Marquardt's training method was used in this study. The performance of the back propagation neural network was evaluated using R^2 and Mean Absolute Percentage Error (MAPE). The ANN structures; which have the smallest value of MAPE and R^2 value close to one, were chosen as the best structure to predict tool wear. The results showed that the neural network's 6-10-1 structure of back propagation neural network gave the best results for tool wear prediction in this study, with a MAPE value of 6.440%. Meanwhile, the ANN structure 6-8-1 gave the highest R^2 value of 0.9689.

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INTRODUCTION

Using an extremely high cutting speed and a high feed rate to increase production rate is unwise, since the tool wear of cutting tools increases with increased cutting speed and feed rate. Tool wear influences the quality of machined products. The tool life of cutting tools used in traditional machining operations depends on many factors, such as cutting speed, feed rate, depth of cut, tool material, and the type of cutting fluid applied. It is vital to set the optimum cutting parameters to achieve the longest tool life; whilst maintaining the quality of the machined product. Worn tools cause low quality machined products and may even cause damage to the machine itself. According to Snr (2000), the condition of a tool is an important factor in the metal cutting process, as this will cause the cost to be much higher, as a result of waste components, damage to the machine tool, and unscheduled downtime. The current rapid growth of the manufacturing industry requires shorter production times that can produce quality products at lower costs. This can be achieved using high cutting speeds and high feed rates. However, by using high cutting speeds and feed rates, the cutting temperature in the cutting zone is high; which immediately shortens tool life and affects dimensional accuracy of the machined parts (Da Silva *et al*., 2011).

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To avoid worn tools being used during the metal cutting process, a tool conditioning monitoring system must be used. A tool conditioning monitoring system is often used based on machining output parameters, such as cutting force, vibration, acoustic emission, noise, heat, surface finish, etc., (Teti *et al*., 2010).

The tool wear monitoring technique can be divided into two categories, namely direct and indirect (Teti *et al*., 2010). Using cameras to acquire visual wear of tools is a direct method. Unfortunately, the direct inspection of tools during the machining process is not suitable, because work pieces and debris may block the camera's view during tool monitoring (Abu-Mahfouz, 2003). An indirect method is a method that has less precision than the direct method, but is less complex and more suitable (Teti *et al*., 2010). An example of an indirect method is to use a sensor to monitor tool wear. Many types of sensor signals can be used to monitor tool wear through cutting force, vibration, acoustic emission, sound cutting temperature, ultrasound, and so on.

A numerical computer method that has been introduced is an artificial neural network. Current advances in computing techniques have resulted in an artificial neural network that is well-known in the work of modelling, forecasting, and decision-makers, in the process of forecasting (Vrabel *et al*., 2012).This method is becoming very popular in industry and financial circles, because it has the ability to classify and optimize a process (Dimla *et al*., 1997). Many researchers have applied the neural network method to predict the phenomenon's of the machining process. Abu Mahfouz (2003) applied neural network to detect drilling wear using a vibration signal. Choudhury *et al*., (1999) and Chungchoo & Saini (2002) used the neural network method in their research of the online monitoring of tool wear in turning operations. Prediction of surface roughness profiles for milled surfaces using artificial neural network has be done by El-Sonbaty *et al*., (2008). Özel & Nadgir (2002) studied the prediction of flank wear by using the back propagation neural network modelling of cutting hardened H-13 steel with chamfered and honed CBN tools.

The objective of this study is to apply a feed forward back propagation neural network method to predict tool wear progression during the end milling process of Inconel 718. The type of cutting tool used in this study was a tungsten carbide ball end nose with multi-layer Physical Vapour Deposition (PVD) Titanium Aluminium Nitride TiAlN in a cryogenic environment. The cutting force applied to the work material was measured using a strain gauge sensor that gave signals in x, y, and z axis's. A back propagation neural network requires the cutting condition parameters, which include cutting speed (V_c), feed rate (F_z), axial depth of cut, radial depth of cut, spindle speed, and the resultant force, to be used as inputs to trained and predict the output i.e., the tool wear progression. The best back propagation neural network structure, with the least number of errors, will be chosen as the structure to predict tool wear.

Back Propagation Neural Network:

As a numerical computational method, the back propagation neural network tool is able to recognize patterns or connects of a non-linear relationship. The neural network itself is defined as a numerical computer system model that copies a human brain and nervous system (Asiltürk & Çunkaş 2011; Petri, Billo & Biclanda, 1998). In other words, artificial neural networks are able to learn and pattern recognition. An artificial neural network is structured with an input layer, a hidden layer, and an output layer. Each layer contains neurons that link with each other to form a network.

An artificial neural network method is able to model the human brain's ability to learn, think, remember, and solve problems. The neural network consists of several layers of non-linear processing units that relate one another. The input layer, which contains input neurons, will be processed by neurons in a hidden layer to the output layer (Abu-Mahfouz, 2003).

The purpose of using a feed forward back propagation algorithm in a neural network method is to make the neural network learn from the training data. The back propagation application uses supervised learning; whereby the algorithm needs both inputs and outputs for the training process. The training process begins with random weights. The goal is to adjust the weight so that the error between the actual output and the expected output is minimized. In this study, the training method used to train the data was Levenberg-Marquadt. Levenberg-Marquardt's training method was developed by Kenneth Levenberg and Donald Marquardtz as a numerical solution to the problem of minimizing non-linear functions, and is suitable for small to medium size problems (Beale, Hagan & Demuth, 2013). The back propagation neural response can be changed according to the environment. This is supported by Ezugwu *et al*., (1995), who state that when added as an input of a network, it will adjust its value to produce a consistent response, known as the learning process. Furthermore, to produce the best artificial neural network model structure, the number of neurons in the hidden layer must be modified again and again, until it can produce the best artificial neural network model (Sonbaty *et al*., 2008). Kavzoglu (1999) and Kaya *et al*., (2011) state that there are no certain methods that can be used to determine the best structure of an ANN. To determine the best structure of an ANN, trial and error through experimentation is the best way.

Advantages of a neural network include, it has very fast learning rate, and it is able to perform interference separation and process data in parallel. Furthermore, the method of artificial neural network model is capable of representing large input and output ranges (Dimla *et al*., 1997). Meanwhile, Vrabel (2013) states that neural network is able to represent linear or non-linear relationships and learn these relationships directly from the modelled data. Figure 1 shows the basic back propagation neural network architecture.

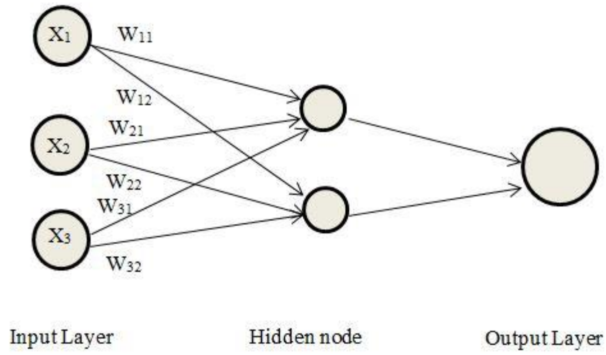

Fig. 1: Typical neural network structure (Petri *et al*., (1998).

MATERIALS AND METHODS

In this study, a CNC milling machine (DMC 635 V Ecoline) was used to perform the end milling operation. These CNC millings are able to reach a spindle speed of 8000 RPM. This milling machine also has a magazine containing 20 station hardware peripherals, with high motor power of 13 KW. The work material used was Inconel 718. Inconel 718 is a nickel-based super alloy that is widely used to produce things that have a resistance to high temperatures and corrosion. It is widely used to produce components in the aerospace industry, particularly components in the hot sections of gas turbine engines. Inconel 718 is composed of 0.49 Al, 18.3 Cr, 18.7 Fe, 3.05 Mo, less than 0.005 P, 53.0 Ni, 1.05 Ti, less than 0.002 S, 0.004 B, 0.051 C, 0.08 Si, 5.05 Cb.Ta, 0.30 Co, 0.04 Cu, and 0.3 Mn.

The cutting tool used in this study was a coated ball nose end milling (Titanium aluminium nitride (TiAlN)). The cutting tool's geometry was 10 mm diameter, 11^{o} relief angle, 0^{o} radial rake angle, -3^{o} axial rake angle, 3.97 µm thicknesses, and 90^{0} approach angle. The cutting parameters of cutting speed, feed rate, spindle speed, axial depth of cut, and radial depth of cut, are shown in Table 1. Cryogenic, which is liquid nitrogen, was used as a cooling liquid in this study to enhance tool life.

Table 1: Cutting condition parameters.

No of experiment	Cutting Speed m/min	Feed rate mm/tooth	Axial depth of cut (mm)	Radial depth of cut(mm)	Spindle speed RPM
1	170	0.1	0.5	0.25	5224
2	140	0.1	0.3	0.75	4735
3	170	0.05	0.3	1	5749

The milling process was conducted until the tool wear reached the value recommended by ISO 8688-2; which states that the end point of tool life is achieved when flank wear (VB) is equal to 0. 3 mm average for all teeth, or 0.5 mm on an individual tooth. Therefore, in this study, a complete run for one cutting condition was achieved when flank wear reached 0.5 mm.

An Olympus SZ51 microscope was used to measure tool wear, and was able to magnify the tool wear image in the range 8 - 40X. Tool wear was measured twice and the average value was recorded. Meanwhile, the cutting force used in this study was measured with a strain gauge sensor. Omega SGD-3/350-LY11 strain gauges, with 350 Ohms resistance, and a tolerance of +/- 0.35 % were used in this study. Strain gauge sensors were located at four places of the octagonal rings. These strain gauges were used to measure the deformation of the octagonal ring in the x, y, and z axis's. The analogue signals from the strain gauges were then amplified using a data acquisition module NI 9237, then transferred to a personal computer via a USB connection.

The Levenberg-Marquardt optimization method was used to train the data obtained from the experiment. Forty one items of data were used to train using the Levenberg-Marquardt method, with the maximum number of epochs of 1000. The Levenberg–Marquardt method was designed to approach second-order training speed without having to compute the Hessian matrix. The ANN structure directly influences the training time. The higher number of neurons in the hidden layer resulted in a large ANN structure, which therefore required more time to train. Moreover, the number of neurons in the hidden layer must be chosen correctly to avoid the effect of too few neurons causing underfitting. Meanwhile, too many neurons in the hidden layer will cause overfitting. Figure 2 shows the architecture of the neural network used in this study.

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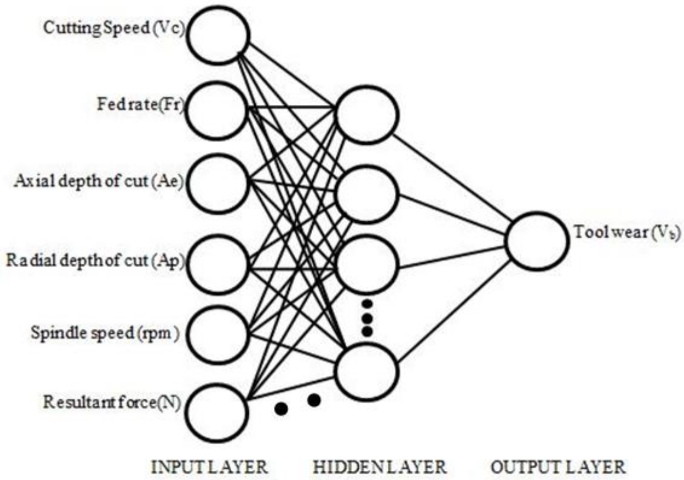

Fig. 2: Architecture of the neural network.

RESULT AND DISCUSSION

Besides the five cutting condition parameters that were used as inputs, the resultant force is also used to represent the cutting force for all directions (i.e., x, y, and z), which is defined in Equation 1. All of these parameters will be used to obtain tool wear progression.

$$F_r = \sqrt{F_x^2 + F_y^2 + F_z^2} \tag{1}$$

Where, F_r = Resultant force, F_x = cutting force acting in x direction, F_y = cutting force acting in y direction, F_z = cutting force acting in z direction.

Table 2 shows the calculated resultant force value for each run and the tool wear value obtained from the milling operation. The findings from Table 2 show that the cutting force, which is the resultant force, increased with the increasing tool wear. This was due to the worn cutting tool that was used during the milling operation, which required a large cutting force. The graphs of resultant force and tool wear for each experiment are represented in Figure 3.

Table 2: Resultant force and tool wear values for all cutting conditions.

Experiment 1			Experiment 2			Experiment 3		
Run	Resultant force (F_r)	Tool wear (mm)	Run	Resultant force (F_r)	Tool wear (mm)	Run	Resultant force (F_r)	Tool wear (mm)
1	284.48	0.102	1	353.02	0.13	1	323.50	0.144
2	94.97	0.115	2	208.11	0.134	2	251.00	0.1675
3	274.87	0.118	3	325.66	0.134	3	366.58	0.179
4	250.45	0.142	4	289.45	0.1375	4	372.32	0.197
5	359.05	0.145	5	396.26	0.139	5	442.43	0.303
6	417.11	0.230	6	503.30	0.151	6	614.74	0.3275
7	811.85	0.389	7	533.65	0.163	7	531.72	0.3275
8	955.39	0.400	8	608.60	0.157	8	555.47	0.356
9	860.57	0.413	9	540.66	0.169	9	590.77	0.383
10	1004.45	0.422	10	339.10	0.171	10	804.95	0.459
11	1025.60	0.421	11	529.03	0.175	11	689.98	0.489
12	1090.24	0.441	12	586.17	0.1945	12	829.34	0.64
13	1048.82	0.474	13	653.68	0.24			
14	1410.42	0.548	14	618.52	0.307			
			15	892.23	1.035			

Meanwhile, tool wear progression is comprised of four stages, which are 1) flank wear formation, 2) notch wear, 3) chipping, and 4) flaking. Figure 4 shows the sequence of these four stages. Figure 4(a) shows the flank wear occurring near to the depth of cut line, while Figure 3(b) shows the notch wear that occurs when the pitting starts to form due to the repetitive cyclic load. A chipping formation, as shown in Figure 4(c), appears when the pitting condition becomes worst. When the cutting temperature increases, flaking begins to form (as shown in Figure 3(d)).

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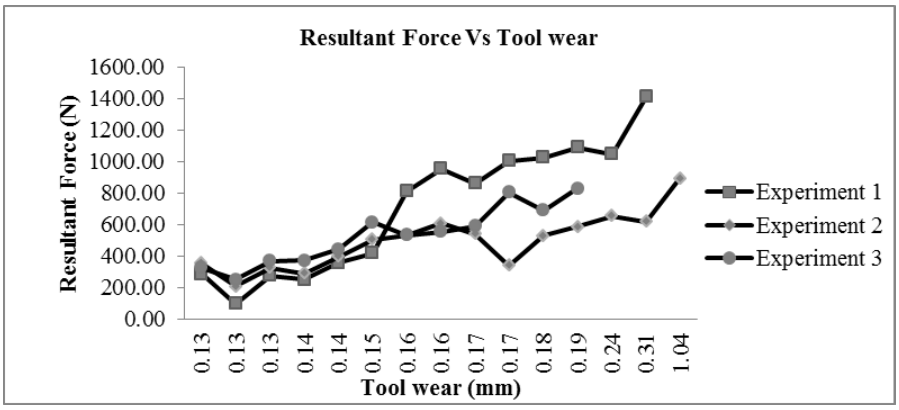

Fig. 3: Relationship between resultant force and tool wear for 3 experiments.

Using MATLAB 2008, tool wear was predicted using the feed forward back propagation neural network method. Graph in Figures 5 shows the comparison of tool wear values between the target values from the experimental work and the predicted value from the feed forward back propagation neural network method for some of neural network structures. The figures show that it is difficult to determine which ANN structure gives the best predicted tool wear value in this study. Hence, another method was needed to determine the best ANN structure. Regression analysis is one method that can be used to assess the performance of the ANN structure's prediction. A regression value near to 1 indicates a good linear relationship between predicted tool wear and the experiment's tool wear value. Graphs in Figure 6 shows some of the regression lines and R^2 values for each ANN structure. The ANN structure 6-8-1 had the highest R^2 value of all at 0.9689. The ANN structure 6-8-1 was able to give best prediction value; closest to the experimental value used in this study.

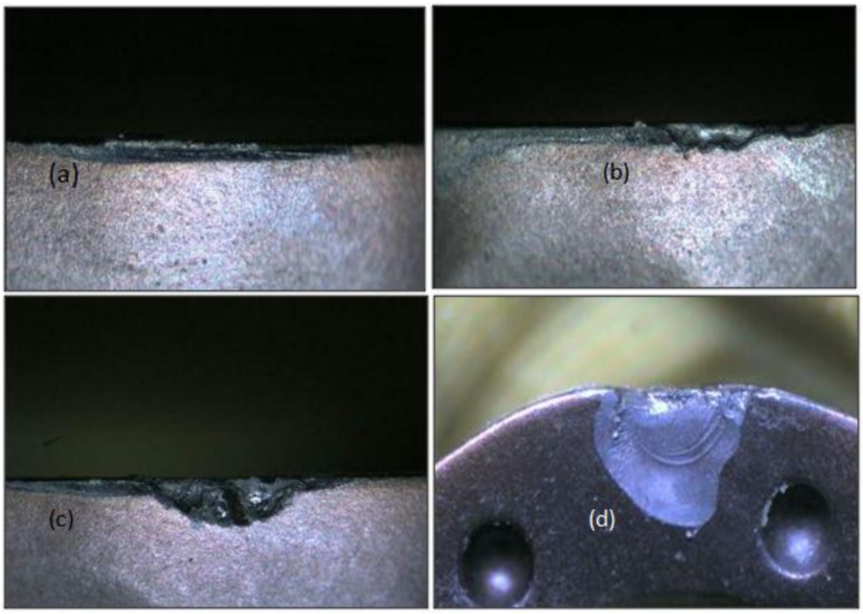

Fig. 4: Four stages of tool wear progression: a) Flank wear formation b) Notch wear formation c) Chipping formation d) Flaking formation.

Mean Average of Percentage Error (MAPE) is another method used to determine the best tool wear prediction of an ANN structure. It may lead to a more accurate result for the tool wear prediction of an ANN. The MAPE formula is given: MAPE = $\left|\frac{VB_{target}-VB_{predicted}}{VB_{predicted}}\right|$ x 100

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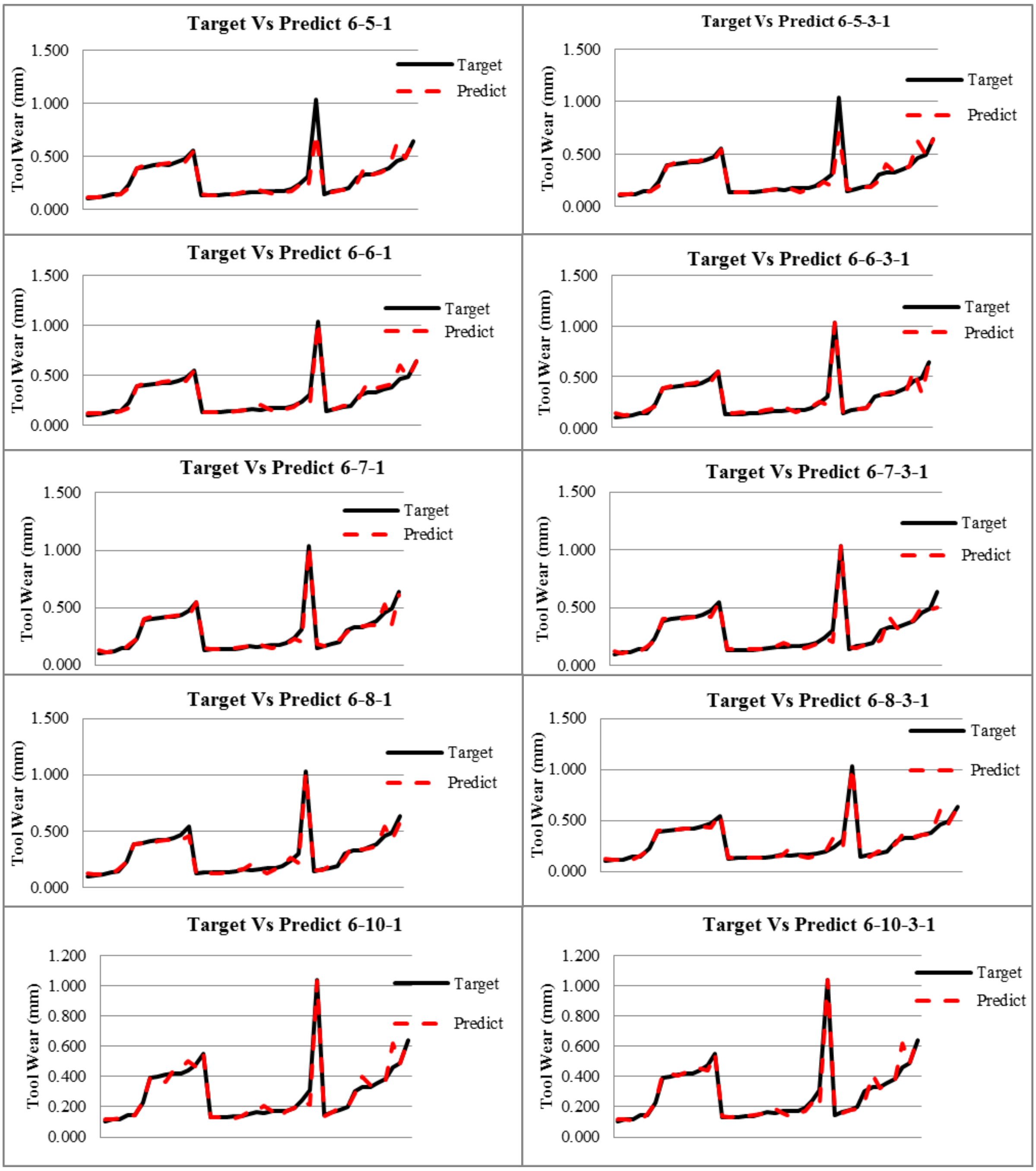

Fig. 5: Comparison between target and predict values for various structures as indicated in the graphs.

Based on the calculated MAPE for all structures shown in Table 3 below, the ANN 6-10-1 structure had the lowest average MAPE value at 6.44%. Theoretically, a MAPE value of 0% is accepted as an excellent result and has an accuracy of 100%; and vice versa. The 6-10-1 ANN structure was able to predict tool wear more accurately than any other ANN structure.

Table 3: Average Mean Absolute Percentage Error (MAPE) for each ANN structure.

Average Mean Absolute Percentage Error (MAPE) for ANN structure (%)											
6-5-1	6-5-3-1	6-6-1	6-6-3-1	6-7-1	6-7-3-1	6-8-1	6-8-3-1	6-9-1	6-9-3-1	6-10-1	6-10-3-1
8.776	8.895	8.080	8.898	8.833	8.733	8.118	8.298	7.994	8.105	6.440	8.281

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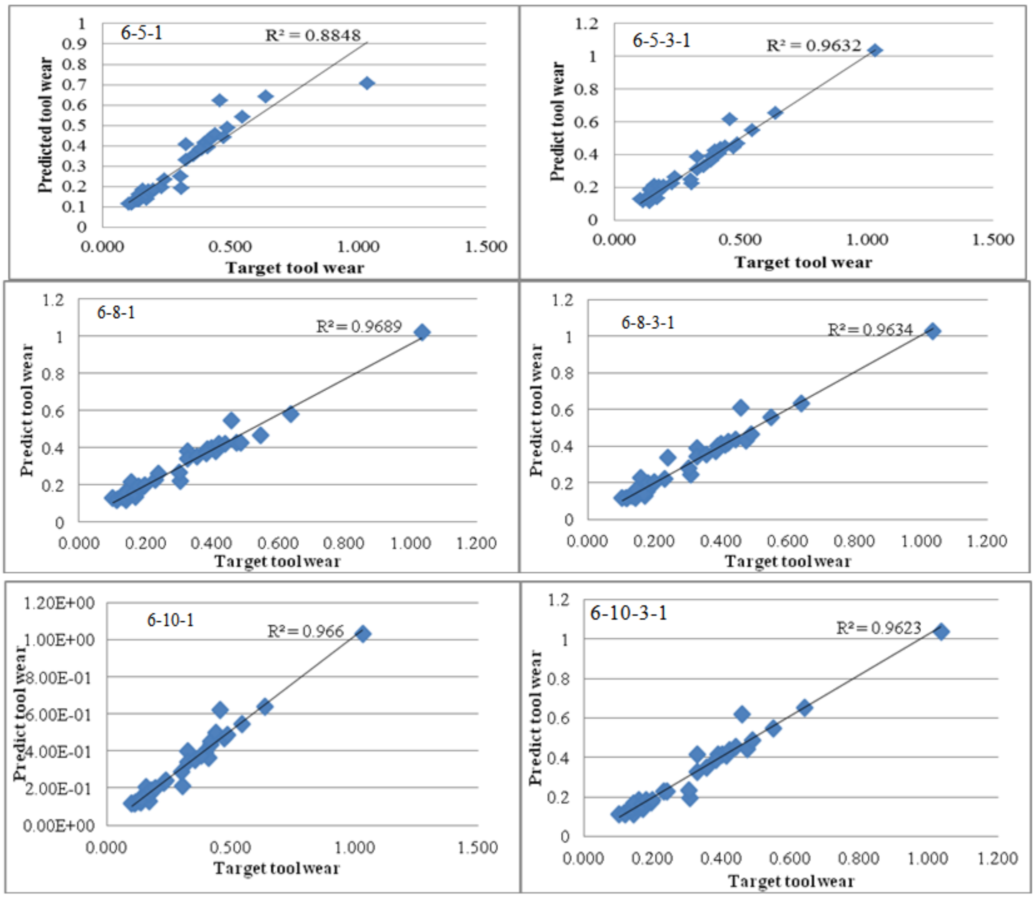

Fig. 6: Linear regression for various structures as indicated in the graphs.

Conclusion:

In conclusion, in this study, a feed forward back propagation neural network method was applied to predict tool wear. Vc, Ap, Ae, Fr, spindle speed, and resultant force, were applied as inputs to the feed forward back propagation neural network to predict the output of tool wear. Forty one pieces data were used to train the ANN; with 60% used for training, 20% used for validating, and 20% used for testing. Twelve different architectures of ANN were used in this study to determine the best ANN architecture to give the best prediction value of tool wear. The 6-8-1 ANN structure had the highest R^2 values, meaning that it was able to give a good linear relationship between predict and experiment tool wear. However, the 6-10-1 ANN structure had the lowest MAPE average, thus defining it as able to predict a value that has minimal errors between predict and experiment tool wear values, compared to other ANN structures.

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REFERENCES

Abu-Mahfouz, I., 2003. Drilling wear detection and classification using vibration signals and artificial neural network. International Journal of Machine Tools and Manufacture, 43(7): 707-720.

Asiltürk, İ., M. Çunkaş, 2011. Modeling and prediction of surface roughness in turning operations using artificial neural network and multiple regression method. Expert Systems with Applications, 38(5): 5826-5832.

Beale, M.H., M.T. Hagan, H.B. Demuth, 2013. Neural Network Toolbox ™ User ' s Guide R 2013 b.

Choudhury, S.K., V.K. Jain, C.V.V. Rama Rao, 1999. On-line monitoring of tool wear in turning using a neural network. International Journal of Machine Tools and Manufacture, 39(3): 489-504.

Chungchoo, C., D. Saini, 2002. On-line tool wear estimation in CNC turning operations using fuzzy neural network model, 42: 29-40.

Da Silva, R.B., J.M. Vieira, R.N. Cardoso, H.C. Carvalho, E.S. Costa, a.R. Machado, R.F. De Ávila, 2011. Tool wear analysis in milling of medium carbon steel with coated cemented carbide inserts using different machining lubrication/cooling systems. Wear, 271(9-10): 2459-2465.

Dimla, D., P. Lister, N. Leighton, 1997. Neural network solutions to the tool condition monitoring problem in metal cutting-a critical review.

Ezugwu, E.O., S. Arthur, E. Hines, 1995. Tool-wear prediction using artificial neural networks, 49: 255-264.

El-Sonbaty, I.a., U.a. Khashaba, a.I. Selmy, a.I. Ali, 2008. Prediction of surface roughness profiles for milled surfaces using an artificial neural network and fractal geometry approach. Journal of Materials Processing Technology, 200(1-3): 271-278.

Kavzoglu, T., 1999. Determining Optimum Structure for Artificial Neural Networks (September), 675-682.

Kaya, B., C. Oysu, H.M. Ertunc, 2011. Force-torque based on-line tool wear estimation system for CNC milling of Inconel 718 using neural networks. Advances in Engineering Software, 42(3): 76-84.

Özel, T., A. Nadgir, 2002. Prediction of flank wear by using back propagation neural network modeling when cutting hardened H-13 steel with chamfered and honed CBN tools. International Journal of Machine Tools and Manufacture, 42(2): 287-297.

Petri, K.I., R.E. Billo, B. Biclanda, 1998. A Neural Network Process Model for Abrasive Flow Machining Operations, 17(1): 52-64.

Snr, D.E.D., 2000. Sensor signals for tool-wear monitoring in metal cutting operations - a review of methods, 40: 1073-1098.

Teti, R., K. Jemielniak, G. O'Donnell, D. Dornfeld, 2010. Advanced monitoring of machining operations. CIRP Annals - Manufacturing Technology, 59(2): 717-739.

Vrabeľ, M., I. Mankova, J. Beno, J. Tuharský, 2012. Surface Roughness Prediction using Artificial Neural Networks when Drilling Udimet 720. Procedia Engineering, 48: 693-700.