Modeling of Tool Wear Parameters in High-Pressure Coolant Assisted Turning of Titanium Alloy Ti-6Al-4V Using Artificial Neural Networks.

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ABSTRACT

Titanium alloy (Ti-6Al-4V) can be economically machined with high-pressure coolant (HPC) supply. In this study, an artificial neural network (ANN) model was developed for the analysis and prediction of tool wear parameters when machining Ti-6Al-4V alloy with conventional flow and high-pressure coolant flow, up to 203 bar. Machining trials were conducted at different cutting conditions for both rough and finish turning operations with uncoated carbide (K10 grade) and double TiAlN/TiN, PVD coated carbide (K10 substrate) inserts. The cutting parameters (cutting speed, feed rate, depth of cut, coolant pressure, and tool type) and the process parameters (cutting forces, feed force, machined surface roughness, and circularity) were used as input data set to train the three-layered feed-forward, back-propagation artificial neural networks. The networks were trained to predict tool life and wear rate separately. The results show that the correlation coefficients between the neural network predictions and experimental values of tool life, tool wear and wear rate were 0.996 and 0.999, respectively, suggesting the reliability of the neural network model for analysis and optimization of cutting process.

(Keywords: artificial neural network, titanium alloy, tool wear, machining, tool condition monitoring)

INTRODUCTION

Ti-6Al-4V alloy is one of the commonly used commercial grades of titanium alloys in aerospace and power industries. In recent years, the need for harder, stronger, tougher, stiffer, and more corrosion or oxidation and heat resistant materials has led to an increase in the development and application of superalloys such as titanium and nickel base alloys in the aerospace, automobile, chemical, and medical industries (SECO, 2002). These alloys are developed specifically for applications demanding exceptional mechanical and chemical properties at elevated temperatures. Titanium alloys are particularly known to exhibit high strength to density ratios and good corrosion resistance properties. Their ability to retain their mechanical properties such as hardness, strength, and toughness at elevated temperature makes them more difficult to machine. The low machinability of titanium alloys coupled with the high temperature generated at the cutting edge results in rapid tool wear of different types, such as adhesive, abrasive wear, and diffusive wear, hence leading to extremely short tool life and high cost of tooling. Research efforts are been geared towards exploring means of machining this difficult-to-machine alloys economically by optimizing the tool performance through tool condition modeling (TCM).

The tool condition modeling is required for the optimization of the machining operations and reduction of costs of tooling, workpiece, machine tool, time and labor and ultimately a reduction in the overall cost of production. The implementation of a tool condition modeling involves the acquisition several process parameters such cutting forces, vibration, acoustic emission, power, temperature, and roughness and roundness of the machined surface, which are measured during the machining operations. These measured signals, which are also influenced by the cutting parameters and external factors are then correlated with tool condition such as tool life, tool wear, wear rate and failure mode. The correlation between the measured signals and tool condition are known be complex and non-linear time-variant (Silva et al., 1998; 2000). In order to model this complex relationship various modeling techniques have been developed.

The earlier works on TCM systems were focused on the development of analytical models, which dependent upon large amounts of experimental data (Dimla et al., 1997; Lin et al., 2003). These methods are costly, time consuming, and fails to account for the complexity and variability in the nature workpiece, tooling, and cutting conditions. The need for a more accurate and reliable model for TCM has led researchers into exploring other methods such as multiple regression analysis (Ehmann et al., 1997), wavelet analysis (Wang et al., 2003), time series analysis, and frequency domain analysis (Bernhard, 2002). These methods have been applied in practical TCM in metal-cutting processes with limited degrees of success.

More recently, the application of Artificial Neural Network (ANN) in TCM is becoming more popular in the manufacturing industries. ANN is mathematical model consisting or networks of interconnected elements called ‘neurons’, which are designed to mimic the biological nervous systems. Like the human brain, when neural network is presented or trained with a given input and desirable output datasets, they can learn, assimilate, and reproduce the complex and non-linear relationships between the input and output dataset. Neural networks are generally applied for modeling complex functions and in pattern recognition or classification problems.

Comprehensive reviews of such applications in turning operations have been reported by Bernhard (2002) and Dimla et al. (1997). The complexity of the metal-cutting processes coupled with the diverse cutting conditions and the nature the acquired signals and associated external disturbances are the major setbacks in the implementation of reliable practical TCM in metal-cutting operations. In order to improve the generalization capabilities of the systems, different techniques have been proposed by many researchers such as direct measuring methods (Dimla et al., 1997; Lin et al., 2003) and indirect monitoring methods (Dimla et al., 1997; Lin et al., 2003; Bernhard, 2002; Dan and Mathew, 1990; Ezugwu et al., 1995; Liu et al., 1998).

HPC is currently being used in the manufacturing industries to enhance the machinability and chip breakability of superalloys such as Ti-6Al-4V alloy (Marchado, 1990; Christer, 2003). Little or no work has as has been done on the development practical TCM systems with ANN for turning of Ti-6Al-4V alloy with HPC supply, hence this study.

MATERIALS AND METHODS

<u>Machining trials</u>

Machining trials were conducted on an 11 kW CNC Lathe with a speed range from 18 - 1800 rpm, which provides a torque of 1411 Nm. Ti-6Al-4V (IMI 318) alloy bar with 600 mm diameter and 300 mm long was machined with uncoated carbide inserts coded T1 and T2 and a double TiAlN/TiN, PVD coated carbide insert coded T3. All the inserts used had the ISO designation CNMG 120412.

The chemical composition and physical properties of the workpiece and cutting inserts are given in Tables 1-3, respectively. The followings cutting geometry were employed during the trials: Tool holder: MSLNR 252512, Approach angle: 40^o, Side rake angle: 0^o, Clearance angle: 6^0, Back rake angle: -5^0.

During the machining trials, a general purpose coolant containing alkaline salts of the fatty acid (Tri-(2-Hydroxyethyl)-Hexahydrotriazine), with a concentration of 6% by weight, was supplied with convectional flow (2.7 l/min) and at high pressure of 70 bar (16.9 l/min), 110 bar (18.5 l/min) and 203 bar (24 l/min). Cutting conditions typical of rough and finish turning of titanium alloys in the manufacturing industry were employed in the machining trials. The following cutting conditions were employed in this investigation:

Roughing: Cutting speed (m min^{-1}): 80, 90, 100, 110,120; Feed rate (mm rev^{-1}): 0.2; Depth of cut (mm): 2.0; Coolant supply pressure (bar): 70; Coolant concentration (%): 6.0

Finishing: Cutting speed (m min^{-1}): 100, 110,120, 130; Feed rate (mm rev^{-1}): 0.15; Depth of cut (mm): 0.5; Coolant supply pressure (bar): 110, 203; Coolant concentration (%): 6.0.

The component forces (cutting force, F_z and feed force F_x) were measured using a piezo-electric tri-axial dynamometer (Type 9257B). The roughness (Ra) of the machined surface was measured with a stylus type instrument, while the circularity was measured with a dial gauge.

Table 1: Chemical Composition (% wt) of Ti-6Al-4V Alloy.

Chemical Element	Al	V	Fe	O	C	H	N	Y	Ti
Min.	5.50	3.50	0.30	0.14	0.08	0.01	0.03	50ppm	Balance
Max.	6.75	4.50	-	0.23	-	-	-	-	-

Table 2: Physical Properties of Ti-6Al-4V Alloy.

Tensile Strength (MPa)	0.2% Proof Stress (MPa)	Elongation (%)	Density ($g.cm^{-3}$)	Melting Point (°C)	Thermal Conductivity ($W.m^{-1}.K^{-1}$)	Measured Hardness* (HV_{100})
900-1160	830	8	4.50	1650	6.6	Min. = 341, Max. = 363

Table 3: Physical Properties and Chemical Composition of Cutting Inserts.

Tool Grade	Physical Properties			Chemical Composition (wt.%)			Coating (µm)	
	Hardness Vickers (HV)	Density ($g.cm^{-3}$)	Substrate Grain Size (µm)	WC	Carbides	Co	TiAlN	TiN
T1	1760	14.95	1.0	93.8	0.2, (Ta, Nb) C	6	-	-
T2	1753	14.92	0.68	93.7	0.3, Cr_2C_3	6	-	-
T3	1760	14.95	1.0	93.8	0.2, (Ta, Nb) C	6	3.5	0.5

Tool wear for each machining trials was measured with toolmaker microscopy at a magnification of 25x. Tool life and failure mode(s) were determined using the ISO Standard 3685 tool rejection criteria for roughing and finishing operations (Table 4).

Table 4: Tool Rejection Criteria.

Rejection Parameters	Rejection value ≥ (mm)	
	Roughing	Finishing
Average flank wear	0.4	0.3
Maximum flank wear	0.7	0.4
Nose wear	0.5 or 0.4	0.3
Notching at the depth of cut line	1.0	0.6
Surface roughness (µm)	-	1.6

Design of Neural Network

Neural Network Toolbox for MATLAB® (Math Works, 2001) was used to design the neural network. The basic steps adopted in the design are as follows: experimentation and collection of data; analysis and pre-processing of data; design of the neural network; training and testing of the neural networks; simulation and prediction with the neural networks; and analysis and post-processing of predicted result.

The input/output datasets were collected during the machining trials, which consists of five cutting parameters: cutting speed; feed rate; depth of cut; coolant pressure; and tool type, and four process parameters: cutting force, feed force, surface roughness, and circularity of the machined surface, while the output dataset consists of three parameters: tool life; tool wear; and wear rate. Prior to the training of the network, the input/output datasets ware normalized to values between –1 to +1 using the MATLAB® function 'premnmx'. The *i*th normalized input/output dataset then becomes:

$$x_i = 2\frac{d_i - d_{\min}}{d_{\max} - d_{\min}} - 1 \qquad (1)$$

where, x_i is the *i*th normalized input/output dataset, d_i is the *i*th raw input/output dataset, while d_{min} and d_{min} are the minimum and maximum raw input/output dataset.

A standard back-propagation multiplayer feed-forward network was designed using the

MATLAB® function 'newff'. The network consists of three layers: input layer; hidden layer; and output layer. A typical architecture of a 3-layered feed-forward back-propagation hierarchical network is shown in Figure 1. The number of neurons in the input and output layers are determined generally by the number of input and output variables, which in case are 9 and 3 respectively. The number of neurons in the hidden layer was varied from 10, 15, and 20. The log-sigmoid transfer function 'logsig' was used in the hidden layer, while linear transfer function 'purelin' was used in the output layer.

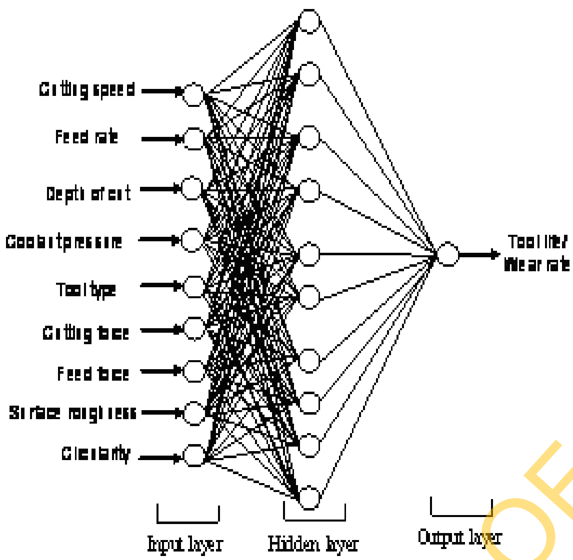


Figure 1: A Typical Network Structure (9-10-1) used for Prediction of Tool Life and Wear Rate.

The network was trained automatically with the MATLAB® function 'train' with the 'weights' and 'biases' initialized to random values. Before the training, the data set was divided randomly into training and test data set. 75% of the data set was used as training set, while the remaining 25% was used in testing of the network. In order determine the optimum network generalization capability, two different training algorithms were used: the resilient back-propagation (trainrp); and the Levenberg-Marquard with Bayesian regularization (trainbr). During the training the 'weights' and 'biases' of the network are adjusted so as to minimize the mean square error (MSE) between the expected and the predicted values.

The mean square error is computed as:

$$MSE = \frac{1}{Q}\sum_{k=1}^{Q} e(k)^2 = \frac{1}{Q}\sum_{k=1}^{Q} \left(t(k) - a(k)\right)^2 \quad \textbf{(2)}$$

where, Q is the number of the input/output dataset, e(k) is the network error, t(k) is the experimental value and a(k) is the network predicted value.

The training was terminated when the MSE = 0.001 or when the number of iterations is equal 1000. The performance of the networks with different number of neurons in the hidden layer trained with different algorithms are tested with the correlation coefficient between the predicted and the experimental values for training, test and whole dataset.

RESULTS AND DISCUSSION

The performances of the networks in terms of their correlation coefficients between the predicted and the experimental values are listed in Table 5. Based on the performance of the network and the training convergence time the network with 20 neurons in the hidden layer trained with the Levenberg-Marquard with Bayesian regularization algorithm was chosen as the best network.

The performance of the network for the prediction of tool wear rate, tool life and tool wear using the entire dataset are shown in Figure 2. The correlation coefficient between the predicted and the experimental values using the entire dataset for the prediction of tool life and tool wear rate are 0.996 and 0.999 respectively. Therefore the generalization capability of the network prediction can be ranged in the order: wear rate > tool life.

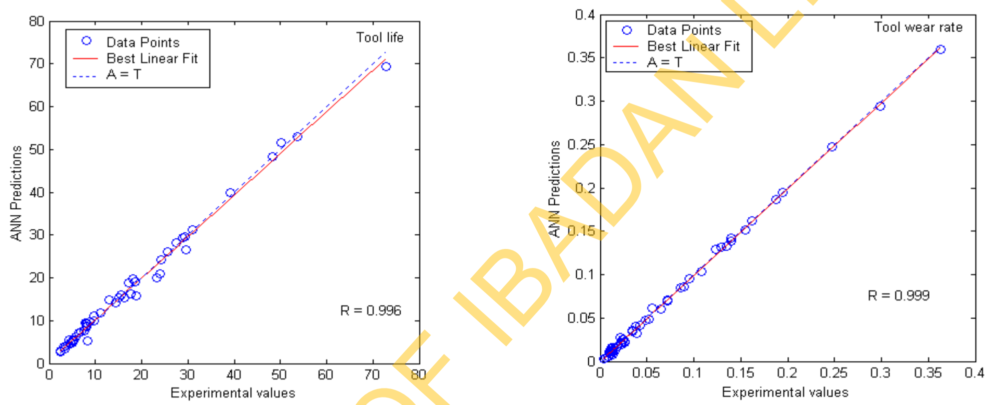
The percentage error of the network model was also calculated as the percentage difference between the experimental and predicted value relative to the experimental valve:

$$error(\%) = \frac{N_{Exp} - N_{Pre}}{N_{Exp}} \times 100 \quad \textbf{(3)}$$

where N_{Exp} is the experimental value and N_{Pre} is the predicted value from the neural network. The statistical analyses of the error distribution are shown in Figure 3.

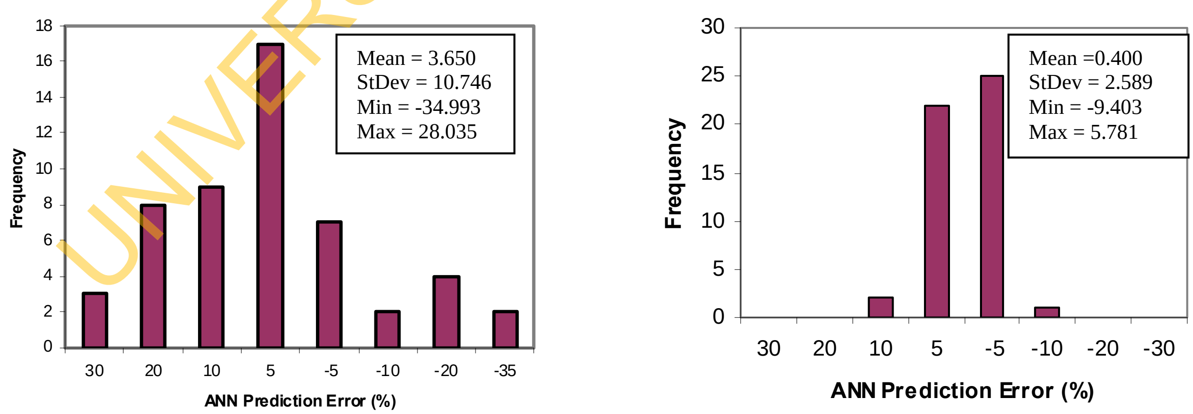
Table 5: Correlation Coefficient between ANN Predicted and Experimental Values of the Training, Test, and Whole Data Sets, for Different Training Algorithms and Network Topology.

Training Algorithm	**Resilient Back-Propagation**			**Levenberg-Marquard with Bayesian Regularization**		
Network Structure	4-10-1	4-15-1	4-20-1	4-10-1	4-15-1	4-20-1
Tool Life						
Training	0.987	0.996	0.997	0.997	0.997	0.996
Test	0.988	0.996	0.996	0.997	0.995	0.998
Whole	0.987	0.996	0.997	0.996	0.997	0.996
Tool Wear Rate						
Training	0.990	0.995	0.999	0.994	0.998	0.999
Test	0.997	0.998	1.000	0.996	0.999	1.000
Whole	0.992	0.995	0.999	0.994	0.998	0.999



(a) (b)

Figure 2: Correlation Between the Neural Network Predicted Values and Experimental Values using the Entire Dataset for Prediction of: (a) Tool Life and (b) Tool Wear Rate.



(a) (b)

Figure 3: Error Distribution of the Neural Network Predictions for; (a) Tool Life and (b) Wear Rate.

The results show that the error has a uniform distribution pattern about zero with mean values and standard deviation of 3.650 and 10.746% and 0.400 and 2.589 for prediction of tool life, and wear rate, respectively. The results also show that 68.6 and 100% of the entire dataset have the percentage error of ranging between ±10% for prediction of tool life, and wear rate, respectively. This demonstrated that the model has high accuracy for predicting the tool life and wear rate.

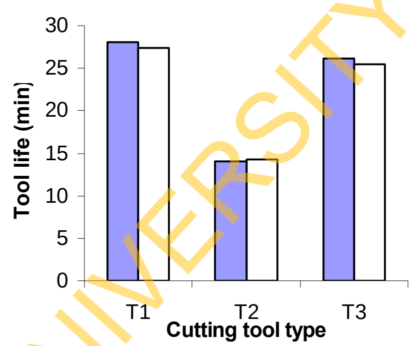
Comparison of ANN Prediction and Experimental Data:

The generalization capacity of the ANN model for monitoring of tool life, tool wear and wear rate was examined for different cutting conditions. Tool life, tool wear, and wear rate were predicted for cutting tool for typical rough and finish turning operation. The neural network predictions and experimental values are shown in Figure 4. The results show that the neural network predictions are in good agreement with the experimental data. This shows that the neural model can be used successfully for monitoring wear conditions of different cutting tools during rough and finish turning operations.

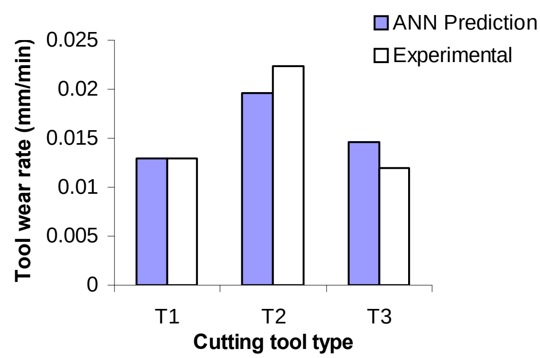
ANN Prediction for Rough Turning Operations:

The performance of the neural model was further examined for rough turning at different cutting speeds and coolant applications (convectional and at high pressure of 70 bar), for cutting insert (T1), feed rate = 0.2 mm/rev and depth of cut = 2.0 mm. The neural network predictions and experimental values for tool life, tool wear and wear rate are shown in Figure 5.

For roughing operations the results show that the neural network predictions have a very good agreement with the experimental values for all the tool wear parameters: tool life (Figure 5(a)) and wear rate (Figure 5(b)). It can be seen from Figure 5(a), that tool life decreases with increase in cutting speed for both conventional and 70 bar pressure coolant supplies as expected. Increase in cutting speed leads to increase in the temperature at the cutting zone thus accelerated tool wear and consequent reduction in tool life. It can also be seen that longer tool life are obtained when machining with 70 bar coolant pressure relative to conventional cooling at lower speeds of 80 – 110 m/min.

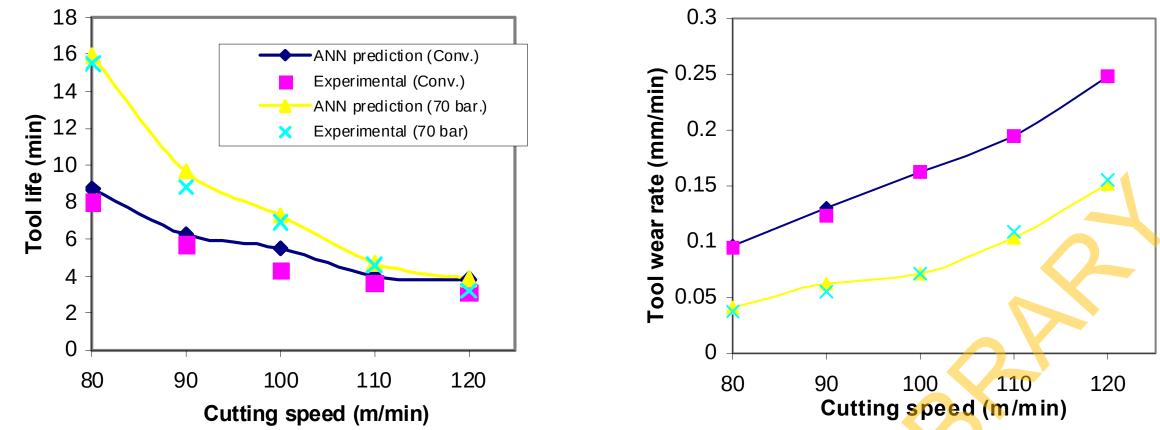


(a)



(b)

Figure 4: Neural Network Predictions and Experimental Values for Tool Life (a) and Wear Rate (b) for Different Cutting Tool Type.



(a) (b)

Figure 5: Experimental Values and Neural Network Predictions of the Influence Cutting Speed on Tool Life (a) and Wear Rate (b) for Different Coolant Applications, Cutting Insert (T1), f = 0.2 mm/rev, and d = 2.0 mm.

Figure 5 (b) shows that tool wear rate increased almost linearly with increasing speed for both conventional and 70 bar pressure cooling. The wear rate for conventional cooling are consistently higher than that of 70 bar coolant pressure. It can be seen that the difference in wear rate between the conventional and 70 bar coolant pressure cooling are fairly constant at the cutting conditions investigated.

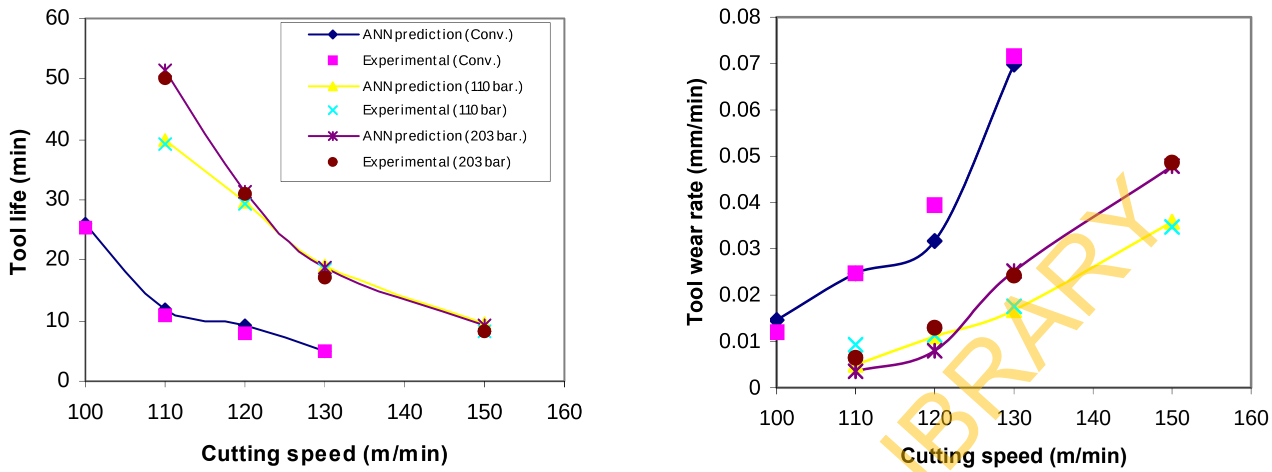
ANN Prediction for Finish Turning Operations:

The performance of the ANN model was tested for typical finish turning operations at different cutting speeds and cooling applications (up to 110 and 203 bar) when machining with T3 inserts at a feed rate of 0.15 mm/rev and a depth of cut of 0.5 mm. The results show that predicted values from the network tracked the experimental values with a very high accuracy level. Increase in tool life was achieved using high-pressure coolant delivery than with conventional cooling. Increase in coolant pressure led to increase in tool life when machining at lower cutting speeds (110 and 120 m/min). At higher cutting speeds from 120 – 150 m/min there was no different in tool life with increasing coolant supply pressure (Figure 6(a)). Figure 6(b) shows that wear rate increased with increasing cutting speed. The wear rate for conventional cooling are consistently higher in all cutting speeds relative to those obtained with high pressure coolant supplies. For high coolant applications, the wear rate for 110 bar are higher than for 203 bar, although there was no significant difference at lower speed conditions of 110 – 120 m/min. At higher speeds above 120 m/min, the wear rate at 203 bar are higher than at 110 bar, contrary to expectation. This phenomenon can be related to the significant difference in tool life observed at higher speeds above 120 m/min in Figure 6(a). These results demonstrated the existence of an optimum coolant pressure at 110 bar for high speed machining of Ti-6Al-4V alloy.

CONCLUSIONS

1. The multilayer neural network with 20 neurons in the hidden layer trained with Livenberg-Marquard algorithm combined with Bayesian regularization was found to be the optimum network for the model.

2. A good performance was achieved with the neural network model for both rough and finish turning operations, with correlation coefficient between the model predictions and experimental values of 0.996, 0.998 and 0.999 for tool life, tool wear and wear rate prediction, respectively.



(a) **(b)**

Figure 6: Effect of Cutting Speed and Coolant Pressure on Tool life (a) and Wear Rate (b) for Cutting Insert (T3) with f = 0.15 mm/rev and d = 0.5 mm.

3. Tool life decreases with increase in cutting speed for both conventional and high-pressure cooling. A 2-fold increase in tool life was obtained at lower speed of 80 m/min for 70 bar coolant pressure compared to conventional cooling, while a 4-fold and 5-fold increase were obtained at higher speed of 110 m/min with 110 and 203 bar, respectively.

4. The optimum coolant pressure, corresponding to the minimum wear rate was identified as 110 bar.

NOMENCLATURE

x_i	*i*th normalized input/output dataset.
d_i	*i*th raw input/output dataset.
d_{min}	minimum raw input/output dataset.
d_{min}	maximum raw input/output dataset.
Q	number of the input/output dataset.
$e(k)$	network error.
$t(k)$	experimental value.
$a(k)$	network predicted value.
N_{Exp}	experimental value.
N_{Pre}	ANN predicted value.

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