ISSN: 2278-0181
PECTEAM - 2K18 Conference Proceedings

Modeling the Correlation Between Cutting and Process Parameters in Machining of Ni Based UDIMET Alloy Using Artificial Neural Network

[1]T. Mayavan, [2] S. Thamizh Selvan, [3] J. Srinivas, [4] P. Sriram
[1,2,3,4]Department of Mechanical Engineering,
Panimalar Engineering College

***Abstract*—An artificial neural network (ANN) model was developed for the analysis and prediction of the relationship between cutting and process parameters during high-speed turning of nickel –based, UDIMET720, alloy. The input parameters of the ANN model are the cutting parameters: Speed, feed rate, depth of cut, cutting time and coolant pressure. The output parameters of the model are seven process parameters measured during the machining trials, namely tangential force (cutting force, Fz), axial force (feed force, Fx), spindle motor power consumption, machined surface roughness , average flank wear (VBmax) and nose wear (VC). The model consists of a three layerd feedforward backpropagation neural network. The network is trained with pairs of inputs/outputs datasets generated when machining UDIMET 720 alloy with triple (TiCN/Al2o3/TiN) PVD-coated carbide (K 10) inserts with ISO designation CNMG 120412. A very good performance of the neural network, in terms of agreement with experimental data, was achieved. The model can be used for the analysis and prediction of the complex relationship between cutting conditions and the process parameters in metal-cutting operations and for the optimization of the cutting process for efficient and economic production.**

I. INTRODUCTION

The aerospace industry employs superalloys for their superior mechanical and thermal properties (primarily their mechanical strength that high temperatures). The very same properties dictating their use inmanufacturing of aerospace components result in slow cutting speeds and rapid tool wear in comparison to machining of conventional steels. In general machining of high temperature alloys presents many difficulties. The higher yield strengths of these materials induce higher cutting forces during machining. These higher cutting forces, in conjunction with their strain-hardening, often induce high cutting temperatures, which affect tool life and resultant microstructure.

UDIMET 720 is a nickel-based alloy solid solution strengthened with tungsten and molybdenum, and precipitation hardened with titanium and aluminum, which is produced by vacuum-induction melting, to close chemical composition tolerances and further refined by vacuum-arc remelting. Ingots are remelted by consumable arc for optimum control of homogeneity and microstructure. Carbon, boron, and zirconium are carefully balanced to optimize grain boundary precipitation and properties. This alloy exhibits typical nickel-based alloy characteristics, such as high strength and metallurgical stability. It has a melting range of 1194–1338º C and a density of 8082.6 kg/m³, and possesses excellent mechanical properties at high temperatures. The maximum useful service temperature for an extended period of time is believed to be 982º C. This has been demonstrated by impact strength retention after long exposures at elevated temperatures.

UDIMET 720 also shows good oxidation and corrosion resistance, making it useful in gas turbine blade and disc applications. Among the applications are blades for aircraft, marine and land-based gas turbines and rotor discs. Conventional machining techniques used for iron-based alloys may be used. This alloy however, has an increased propensity for work- hardening during machining and has higher strength and "gumminess" not typical of steels, which make machining much more difficult. Heavy duty machining equipment and tooling should be used to minimize chatter or work-hardening of the alloy.

UDIMET alloy 720 can be machined by conventional machining processes, but cannot be machined economically on light machine tools nor machined at the high operating speeds used for ordinary steel. UDIMET 720 has very low thermal conductivity (about 20 W/mK for the temperature up to 600◦ C as opposed to about 50 W/mK for steel), which traps the heat at the cutting edge during a machining process, making the tool life relatively short. In particular, UDIMET 720 machining conditions are limited by microstructural deformation. The post processed microstructure has a direct effect on part life. Machining at high velocities will result in increased deformation and part rejection. Cutting speeds have to be very low because of this reason (Special metals, 2007).

Furthermore, low thermal conductivity and related localization of temperature at the cutting zone lead to attendant difficulties in machining and hence efficient temperature control techniques are needed to improve machinability. Even though new advanced cutting materials have resulted in higher cutting speeds, some of these superalloys, such as Titanium alloys, are still primarily machined by carbide cutting tools due to their superior compatibility (Rao and Shin, 2002). The high temperatures occurring during machining of these superalloys lead to solution and diffusion wear in tool materials such as Sialon and Cubic Boron Nitride. This limits the cutting speeds that can be used with these advanced materials (Richards and Aspinwell, 1989).

Advances in cutting tool technology have led to the introduction of coated and uncoated carbide, ceramic, CBN/PCBN and PCD tools with adequate hot hardness and toughness to withstand elevated temperatures generated at high –speed conditions. Also, machining techniques, such as ramping (or taper turning), high-pressure coolant (HPC) delivery system, hot machining, cryogenic machining and the use of self-propelled rotary tooling (SPRT), have been developed in recent years. A good understanding of the behavior and the relationship between the work piece materials, cutting tool materials, cutting conditions and the process parameters is an essential requirement for the optimization of the cutting process. In this regard, a significant number of investigations have been carried out to understand the complex relationship between the cutting conditions and the process parameters in high speed machining of nickel-based, UDIMET 720 alloy from both empirical and theoretical standpoints. Empirical models relating tool wear and the components forces as functions of cutting speed and coolant concentration when machining nickel based, nimonic C-263, alloy with PVD-coated carbide tools have been reported[4]. Similarly, several experimental and analytical studies have been conducted on high –speed machining of nickel based, UDIMET 720, alloy[5-8]. It must be pointed out, however, that these techniques are both costly and time consuming. Computer-based models, on the other hand, offer a more efficient and cost-effective method in modeling the complex process parameters.

Artificial neural networks (ANNs) are one of the most powerful computer modeling techniques, based on statistical approach, currently being used in many fields of engineering for modeling complex relationships which are difficult to describe with physical models. ANNs have been extensively applied in modeling many metal-cutting operations such as turning, milling and drilling[9-12]. However, this study was inspired by the very limited or no work on the application of ANNs in modeling the relationship between cutting conditions and the process parameters during high-speed machining of nickel –based, UDIMET 720,alloy.

II. MODEL DESCRIPTION

When There has been continual increase in research interest in the applications of ANNs in modeling and monitoring of machining operations[13,14]. The input/output dataset of the model is illustrated schematically in Fig.1. The input parameters of the neural network are the cutting conditions, namely cutting speed, feed rate, cutting time and the coolant delivery pressure. The output parameters are seven of the most important process parameters, namely component forces (tangential or cutting force, Fz and axial or feed force, Fx), spindle motor power consumption, machined surface roughness, and tool wear (average and maximum flank wear as well as nose wear). The five basic steps used in general application of neural network adopted in the development of the model: assembly or collection of data; analysis and pre-processing of the data; design of the network object; training and testing of the network; and performing simulation with trained network and post processing of results.

A. *Experimental/collection of input/output dataset*

Machining tests were conducted on an 11KW CNC lathe with a speed range from 18 to 1800 rpm, which provides a torque of 1411Nm. 200mm diameter and 300mm long cast solution treated, vacuum inducted melted and electroslag remelted nickel-based, UDIMET 720, alloy bars were used as workpiece. The chemical composition and physical properties of the work piece are given in Tables 1 and 2, respectively. Before conducting the machining trials, upto 3mkm thickness of the top surface of each bar was cleaned in order to eliminate any skin defect that can adversely affect the machining result. Triple (TiCN/Al2o3/TiN) PVD-coaed carbide (K 10) inserts with ISO designation CNMG 120412412 were used for the machining trials. The physical properties and Nominal chemical Composition of the inserts are given in table3. Cutting conditions, typical of rough turning of nickel based alloys in the manufacturing industry employed in the machining trials are shown in Table 4. During the machining trails, the component forces were measured using a piezo-electric tri-axial dynamometer (Type 9257B). Signals from the dynamometer were conditioned through charge amplifiers (Type 5001) with in built low-pass filters of 680 Hz cut-off frequency. The RMS values of the signals were sampled at a rate of 200kHz with a two-channel digital oscilloscope. The power consumption of the spindle motor was measured with a multifunction three-phase power meter. The roughness of the machined surface was measured after each test with a stylus-type instrument. Readings were taken at three different locations and the average value was recorded. Tool wear: average (VB) and maximum (VBmax) flank wear, and nose wear (vc) were measured with a travelling microscope connected to a digital readout device at a magnification of x25. The tool rejection criteria for roughin operation were used in the machining trials.

TABLE1
Chemical Composition of UDIMET720

Element	C	Cr	Co	Mo	W	Ti	Al	B	Zr	Ni
Wt(%)	0.025	18	14.75	3	1.25	5	2.5	.030	.035	bal

TABLE 2
Physical Properties of UDIMET720

Tensile strength σт (MPa)	Yield strength Σy (MPa)	Elongation Є(%)	Reduction of area φ (%)	Vickers Hardness HV
1385	1025	10	11.9	466

Co (vol.%)	WC (vol.%)	TaC (vol.%)	NbC (vol.%)	Hardness (HV)	Grain size (µm)	KIC [MPa (m⁻½)]	Coating thickness (µm)		
							TiCN	Al2O3	TiN
17.1	81	1.2	0.6	2000	1.7	14	4	1	0.5

in accordance with ISO Standared 3685. An insert was rejected and further machining discontinued when any or a combination of the following criteria is reached:

- Average flank wear≥0.4mm
- Maximum flan wear ≥0.7mm

- Nose wear≥0.5mm
- Surface roughness≥6.0µm

B. *Pre-Processing of input/output data set*

Use one space after periods and colons.

The generalization capability of the neural network is essentially dependent on: (i) the selection of the appropriate input/output parameters of the system; (ii) the distribution of the dataset; and (iii) the format of the presentation of the network. For this model, the input parameters used are the four main cutting parameters, while the output dataset are seven process parameters. In total, 20 machining tests were conducted and a total of 102 input/output dataset pairs were collected during the machining tests. The experimental design and the data distribution of the input/output dataset for each testare given in Table .

Prior to the use of the datasets, principal component analysis was performed, using the Matlab subroutine prepca, to test the correlation between the input and output dataset. Result shows that each of the four selected cutting parameters (input dataset). Before training the network, the input/output atasets were normalized within the range of ±1, using the Matlab subroutine premnmx. The normalized value (xi) for each raw input/output dataset (di) was calculated as

$X_i=2/d_{max} - d_{min} (d_i-d_{min})-1$

where d_{max} and d_{min} are the maximum and minimum values of the raw data.

Table 4
Cutting parameters

Machining conditions	
Cutting speed (m/min)	20, 30, 40 and 50
Feed rate (mm/rev)	0.25 and 0.30
Depth of cut (mm)	2.0-3.5 (ramping)
Coolant pressure (bar)	110,150, and 203
Coolant concentration (%)	6.0
Cutting geometry	
Cutting tool insert	CNMG 120412
Tool holder	MSLNR 252512
Approach angle (°)	40.0
Side rake angle (°)	0.0
Clearence angle (°)	6.0
Back rake angle (°)	-5.0
Cutting fluid type	
Emulsion oil (alkanolamine salts of the fatty acids and dicyclohexylamine	

C. *Neural Network design and training*

The network architecture or features such as number of neurons and layers are very important factors that determine network. For this model, standared multilayer feedforward backpropagation hierarchical neural networks were designed with MATLAB 6.1 Neural Network Toolbox[15]. The networks consist of three layers: the input, hidden layer, and output layer. In order to determine the optimal architecture, four different networks with different number of layers and neurons in the hidden layer were designed and tested. In general, the networks have four neurons in the input, corresponding to each of the four cutting parameters and one neuron in the output layer, correspondin to each of the process parameter. Networks with one or two layers and with 10 or 15 in the hidden layer(s) were used as shown in table. For all networks linear transfer function 'purelin' and tangent sigmoid transfer function 'tansig' were used in the output and hidden layer, respectively. Seven different networks were designed for each of the process parameters.

The networks were trained with Levenberg-Marquardt algorithm. This training algorithm was chosen due to its high accuracy in similar function approximation[3,15]. In order to improve the generalization of the network, different 'regularisation' schemes were used in conjunction with the Levenberg-Marquardt algorithm. The automatic Bayesian regularization and the Early stopping regularization were used (see Table 5).

For training with the Levenberg-Marquardt combined withBayesian regularisartion, the input/output dataset, consisting was divided randomly into two categories: training dataset, consisting of two thirds of the input/output dataset and test dataset, which consists of one-third of the data. When the networks were trained with Levenberg-Marquardt combined with Early stopping, the input/output dataset was divided in three sets: training set, one-quarter as test and one-quarted as validation set.

D. *Testing and Performance of the network*

The performance capability of each network was examined based on the correlation coefficient between the network predictions and the experimental values using the training, test and entire dataset. The best results, obtained from 10 different trials using different random initial weights and biases, for each process parameter are listed in table5. Generally, as shown in the table, networks with two hidden layers and 10 neurons in each layer, trained with Levenberg-Marquardt algorithm combined with Bayesian regularization, gave the best performance of the networks. It can also be seen that the increase in the number of neurons in the hidden layer from 10 to 15 has no significant improvement on the performance of the networks. Thus, network having two layers and 10 neurons in each hidden layer (4-10-10-1), trained with Levenberg-Marquardt algorithm and Bayesian regularization, was chosen as the optimum network and used for development of this model. The performance of the model for prediction of surface roughness using the training and entire dataset is shown in fig.2. the correction coefficient of 0.99 was obtained between the entire dataset and the model predictions. The percentage error of the model prediction was also calculated as the percentage difference between the experimental and predicted value relative to the experimental value. The error distribution of the model for the prediction of surface roughness using the entire dataset is shown in fig.3. the error has a uniform distribution pattern about zero with a mean value and standared deviation of – 0.87 and 7.16%, respectively. The result shows that 84% of th entire dataset have the percentage error ranging between ±10%. Acceptable results were also obtained for all the other process parameters. This demonstrated that the models have high accuracy for predicting the process parameters.

III. SIMULATION AND RESULTS

A. *Effect of cutting conditions on the process parameters*

Based on the optimized network parameters, ANN model was developed to predict each process parameter based on the cutting conditions, with a high degree of accuracy within the scope of cutting conditions investigated in the study. This, the influence of the cutting conditions on the process parameters can be studied using the model.

A.1. Effect of cutting speed on the process parameters

Cutting speed is one of the most important cutting parameters in metal-cutting operations. Its influence on the process parameters: surface roughness, cutting force, feed force, power consumption, average flank wear, maximum flank wear and nose wear over the speed range of 20-50m/min was examined using the neural network model at constant feed rate of 0.25mm/rev, coolant pressure of 110 bar and cutting time of 312s. results of the neural network predictions and the experimental values are shown in Fig. 4 (a)-(g). Fig. 4 (a) shows that the predicted surface roughness increased significantly with increasing cutting speed. The deterioration experienced in the machined surface with increase in cutting speed can be attributed to the presence of chatter and tool wear at higher speed conditions. The pattern of the predicted component forces (cutting and feed force) was similar as illustrated in Fig. 4(b) and (c).it can be seen that the cutting force reduced significantly (Fig. 4(b)), relative to the feed force (Fig.4(c)) when the cutting speed increase in cutting speed, from 20 to 35m/min. Further increase in cutting speed, from 35 to 50 m/min, resulted in rapid increase in both cutting and feed forces. The effect of cutting speed on component forces is in two contrasting phenomena. On one hand, as the cutting speed increase, the tool-chip contact length decrerases and the temperature at the cutting zone increases, leading to softening of the workpiece material[16]. There is, therefore a reduction in the shear strength of the workpiece, hence, the drop in component forces. On the other hand, as the cutting speed increase above 30m/min, tool wear increases, consequently increasing the component forces[17]. These, therefore, suggest that the optimum cutting speed is 35m/min.

Fig. 4 (d) shows that the predicted power consumption dropped slightly with increase in cutting speed from 20 to 25m/min and then increased exponentially with increase in cutting speed from 25 to 50m/min.The trend can then be explained by the corresponding reduction and increase in both component forces and tool wear. In terms of minimum power requirement, the optimum cutting speed is found to be 25m/min. the predicted tool wear, as shown in fig. 4(e) – (g), followed a similar pattern. A partially linear reduction in average flank wear (Fig.4(e)), maximum flank wear (Fig. 4 (f)) and nose wear (Fig .4(g)) was obtained with increase in cutting speed from 20 to 30 m/min. No significant difference was observed in both average flank wear and nose wear unlike gradual increase in the maximum flank wear. Further increase in cutting speed above 35m/min resulted to a general increase in all the tool wear modes, suggesting that the optimum cutting speed at which minimum process parameters can be obtained is in the range 25-35 m/min.

A.2. Effect of feed rate on the process parameters

The effect of feed rate on the process parameters are presented in Fig.5 (a)-(g). Fig. 5(a) shows a reduction in the surface roughness value when the feed rate increased from 0.24 to 0.28 mm/rev, contrary to expectation. This reduction in nose wear with increasing feed rate up to 0.27mm/rev (Fig. 5 (g)). This clearly shows that nose wear has a big influence on the surface roughness generated. Further increase in feed rate above 0.28mm/rev gave a rapid increase in the surface roughness value. This result indicates that the optimum feed rate is 0.28mm/rev. an increase in feed rate produces a linear increase in both component forces and the power consumption (Fig.(b) – (d)). The average flank wear increased with increased in feed rate up to .28mm/rev, and subsequently leveled off with further increase (Fig. 5(e)), while the maximum flank wear increased steadily with increasing feed rate (Fig.5(f)). On the other hand, nose wear reduced when the feed rate increased from 0.24 to 0.27mm/rev and increased with further increase in feed rate (Fig. 5(g)). It can therefore be concluded that the optimum feed rate, corresponding to the minimum surface roughness and nose wear, is within the range of 0.27 and 0.28 mm/rev.

A.3. Effect of coolant pressure on the process parameters

The delivery pressure is considered as one of the most important factors in a high-pressure assisted jet cooling system. The reduction in the temperature at the cutting edge, improvement in tool life and chip breakability achieved with this system depend to a great extent on the delivery presuure[18]. The influence of coolant pressure on the process parameters is shown in Fig. 6(a)-(g). Fig.6(a) shows that the predicted surface roughness remained constant with increase in coolant pressure from 110 to 130 bar. It then increased with increase in coolant pressure from 130 to 170 bar before dropping rapidly when the pressure increase from 170 to 210 bar. There was a steady reduction in cutting force with increase in pressure (Fig. 6 (b)) due probably to reduction in the tool-chip contact length due to the hydraulic wedge created by the HPC jet at tool-chip interface[19]. A slight increase in feed force was obtained when the pressure increased from 110 tp 150 bar followed by a rapid reduction when the pressure increased from 150 to 210 bar (Fig (c)). The power consumption dropped steadily with increase in the coolant pressure (Fig (d)), similar to the cutting force. This can also be attributed to the reduction in both tool-chip contact length. Fig (6(e)-(f) shows the effect of coolant preesure on tool wear. An initial increase was observed in both the average and maximum flank wears with increasing coolant pressure. Further increase in pressure above 150 bar generally lowered the predicted flank wear. An initial reduction in nose wear was obtained with increase in pressure up to 130 bar followed by a steady rise up to 190 bar after which there was a reduction with further increase in pressure from 190 to 210 bar (Fig .6(g)).

A.4. Effect of cutting time on the process parameters

The influence of cutting time on the process parameters is shown in Fig.7(a)- (g). Fig .7(a) shows that increase in cutting time has no defined influence on the surface finish generated. Prolonged machining results in steady increase in both component forces, power consumption, average and maximum flank wears, and nose wear as illustrated in Fig. 7(b) – (g).

It is important to note that the experimental values for all the process parameters were very close to the predicted values, expect for the predictions of the component forces (Fig. 4 (b) and (c) – 7 (b) and (c) where the differences were high due to the low correlation coefficient between the measured and the predicted values from the model, which are 0.6595 and 0.7913 for cutting force and feed force, respectively, while that for other process parameters are in excess of 0.9 (table 5). This shows that the model prediction has a high degree of acuuracy.

IV. CONCLUSION

1. The multilayer network with two hidden layers having 10 'tangent sigmoid' neurons trained with Levenberg- Marquardt algorithm combined with Bayesian regularisaion was found to be the optimum network for the model developed in this study.
2. A good performance was achieved with the neural model, with correlation coefficient between the model prediction and experimental values ranging from 0.6595 for cutting force to 0.9976 for nose wear prediction.
3. The optimum cutting speed at which minimum process parameters were obtained is in the range of 25 – 35 m/min, while the optimum feed rate, corresponding to the minimum surface roughness and nose wear, is within 0.27 and 0.28 mm/rev.
4. A consistent reduction in cutting force was achieved with increase in coolant pressure due to reduction in tool-chip contact length as a result of the hydraulic wedge created by the coolant jet at the tool-chip interface. The effect of coolant pressure on tool performance is more pronounced on the maximum flank wear than other wear modes.
5. Prolonged machining results in steady increase in both component forces, power consumption, average and maximum flank wear and nose wear

ACKNOWLEDGMENT

One of the authors, D.A.Fadare, is grateful to the John D. and Catherine T. MacArthur Foundation Grant through the University of Ibadan, Nigeria for funding the staff development program during which this study was conducted.

REFERENCES

[1] E.O>Ezugwu, Advances in the machining of nickel and titanium base superalloys, Keynote paper presented at the japan society for presion Engineering Conference 2004, pp.1-40.
[2] Secrotechnical guide, Turning difficulty – to – cut alloys.
[3] S. Malinov, W. Sha, J.J. Mckeown, Modelling the correlation between processing parameters and properties in titanium alloys using artificial neuralnetwork, comput. Mater. Sci.21(2001) 375-394.
[4] E.O.Ezugwu,K.A. Olajire, J. Bonney, Modelling of tool wear based on component forces, Tribol. Lett. 11(1)(2001).
[5] E.O. Ezugwu, J. Bonney, Effect of high – pressure coolant supply when machining nickel – base, UDIMET 720, alloy with coated carbide tools, Proceedings of AMPT 2003, 8-11 july 2003, Dubin, Ireland, pp.787 -790.
[6] E.O. Ezugwu, J. Bonney, Effect of high – pressure coolant supply when machining nickel – base, UDIMET 720, alloy with coated carbide tools, J. Mater. Process. Technol. 153-154 (2004) 1045 -1050.
[7] J. Bonney, High-speed machining of nickel-base, UDIMET 720, alloy with ceramic and carbide cutting tools using conventional and high-pressure coolant, PhD Thesis, London South Bank University, 2004.
[8] E.O. Ezugwu, A.R. Machado, I.R. Pashby, J.Wallbank, The effect of high-pressure coolant supply when machining a heat-resistant nickel-based superalloy, Lubr.Eng. 47 (9)(1991) 751-757.
[9] E.O. Ezugwu, S.J. Arthur, E.L. Hines, Tool wear prediction using artificial neural networks, J. Matter. Process. Technol.49 (1995) 255-264.
[10] T.L. Liu, W.Y. Chen, K.S. Anantharaman, Intelligent detection of drill wear, Mech. Syst. Signal Process. 12(6) (1998) 863-873.
[11] D.E. Dimla Sr., P.M. Lister, On-line metal cutting tool condition monitoring. II: Tool-state classification using multi-layer perceptron neural networks, Int. J. Mach. Tool Manuf. 40 (2000) 769-781.
[12] D.E. Dimla sr., Application of perceptron neural networks to tool-state classification in a metal-turning operation, Eng. Appl. Artif. Intell. 12 (1999) 471-477.
[13] B. Sick, On-line and indirect tool wear monitoring in turning with artificial neural networks: a review of more than a decade of research, Mech. Syst. Signal Process. 16 (4) (2002) 487-546.
[14] D.E.Dimla Jr., P.M.Lister, N.J. Leighton, Neural network solution to the tool condition monitoring problem in metal cutting – a critical review of methods, Int. J.Mach. ToolsManuf.37 (9)(1997) 1219-1241.
[15] H.Demuth, M. Beale, Neural Network Toolbox User's Guide, Version 4 (Release12), The Mathworks, Inc., 2000.
[16] B. Mills, A.H. Redford, Machinability of Engineering Materials, Applied Science Publishers, Barking, Uk, 1983.
[17] X.S. Li, I. Low, Cutting forces of ceramic cutting tools in: X.S. Li, I. Low (Eds.),, Advanced Ceramic Tools forMachining Application – 1 , Key Engineering Materials Vol. 96, Trans Tech Publications, Aedermannsdorf, Switzerland, 1994, pp.81-136.
[18] C. Richt, Turning Titanium – Developments in Applicatio Technology, Sanvik Coromant, Sandviken, Sweden, 2003.
[19] M.Mazurkiewicz, Z.Kubala, J. Chow, Metal machining with high pressure water-jet cooling assistance – a new possibility, J.Eng. Ind.111 (1989) 7-12.