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IMPLEMENTATION OF ECHO STATE NEURAL NETWORK FOR SINGLE POINT TOOL WEAR ESTIMATION USING HYBRID ALUMINIUM SILICON CARBIDE METAL MATRIX COMPOSITE

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ABSTRACT

In this research work, estimation of tool wear for the CBN / PCD tool has been done by using Echostate Neural network during machining of Al6061 metal matrix composite. AN estimation percentage of 90.62% has been achieved.

1. INTRODUCTION

Aluminium matrix composites (AMCs) refer to the class of light weight high performance aluminium centric material systems. The reinforcement in AMCs could be in the form of continuous / discontinuous fibres, whisker or particulates, in volume fractions ranging from a few percent to 70%. Properties of AMCs can be tailored to the demands of different industrial applications by suitable combinations of matrix, reinforcement and processing route. Presently several grades of AMCs are manufactured by different routes. Three decades of intensive research have provided a wealth of new scientific knowledge on the intrinsic and extrinsic effects of ceramic reinforcement vis-a-vis physical, mechanical, thermo-mechanical and tribological properties of AMCs. In the last few years, AMCs have been utilized in high-tech structural and functional applications including aerospace, defence, automotive, and thermal management areas, as well as in sports and recreation. It is interesting to note that research on particle-reinforced cast AMCs took root in India during the 70's, attained industrial maturity in the developed world and is currently in the process of joining the mainstream of materials.

The term “composite” broadly refers to a material system which is composed of a discrete constituent (the reinforcement) distributed in a continuous phase (the matrix), and which derives its distinguishing characteristics from the properties of its constituents, from the geometry and architecture of the constituents, and from the properties of the boundaries (interfaces) between different constituents. Composite materials are usually classified on the basis of the physical or chemical nature of the matrix phase, e.g., polymer matrix, metal-matrix and ceramic composites. In addition there are some reports to indicate the emergence of Inter metallic-matrix and carbon-matrix composites.

Aluminium metal matrix composites are attractive because of their

- improved strength,
- stiffness,
- creep behaviour,
- wear resistance
- and low thermal expansion compared with the corresponding monolithic alloys

The peak particle sizes are at about 4.5 and 6 µm. Within measured S-N curves the fatigue life-time at given stress amplitudes of SiC /Al6061 is superior to that of $A1_20_3$ / AA6061 in the low-cycle fatigue region as well as in the high cycle fatigue region. The unique combination of low weight with high strength and wear resistance is a highly desired property in the automotive and aircraft industries.

2. PROBLEM DEFINITION

The research problem attempts to estimate the amount of tool wear during machining of AlSiC with PCD or CBN. During the process, the amount of remaining life time has to be estimated.

3. PROPERTIES OF Al 6061

The following are important properties of Al6061.

Properties	**Values**	**Conditions T (^{0}C)**
Density (×1000 kg/m^3)	2.7	25
Poisson's ratio	0.33	25
Elastic modulus (GPa)	70-80	25
Tensile strength (Mpa)	115	25
Yield strength (Mpa)	48	25
Elongation (%)	25	25
Hardness (HB500)	30	25
Shear strength (MPa)	83	25
Fatigue strength (MPa)	62	25
Thermal expansion (10^{-6}/ºC)	23.4	20-100
Thermal conductivity (W/m-K)	180	25
Electric resistivity (10^{-9}W-m)	37	25

Accepted wear limit for PCD and CBN are 0.25mm

Density (g/cc)	3.43	3.49
Compressive strength (GPa)	4.74	4.15-5.33
knoop hardness (GPa)	50	44-60

4. EXPERIMENTAL SETUP

Technical specifications	
Model	1050/1
Height for centers	175 mm
Swing over bed	335 mm
Swing over cross slide	175 mm
Swing over saddle	230 mm
Dist. between centers	800 mm
Movement of cross slide	200 mm
Threads No. / Range	
Inch	32/ 4-60 TPI
Metric	15/ 0.5-6 mm

The tool used is a single point indexable tips based on requirements. PCD contains a small amount of Cobalt as a result of the manufacturing process. If a PCD tool is subjected continuous and significant heating during cutting, the diamond is likely to transform back to graphite. In order to avoid this effect, the use of coolant is recommended. Due to the polycrystalline nature of PCD, it is impossible to create cutting edges as perfect as those of single crystal diamond. Even with the finest grade PCD, which has a particle size of 2 microns, it is not possible to machine plastics and produce optically flat surfaces.

PCD tools are relatively expensive, compared with conventional cutting tools. Poor quality materials, which have inclusions that break conventional cutting tools, or work holding systems that do not locate and hold the part securely, are likely to have the same effect on PCD tools but at a greater cost.

Metal matrix composite (MMC) materials, Aluminium reinforced with Silicon carbide particles or filaments can be machined with PCD, but as the SiC content increases the tool life reduces and materials with more than 30% SiC are practically impossible to machine other than by grinding or EDM. The size of the workpiece is 55 x 250m length. The turning experiments were conducted and the readings are given in Table-1.

5. ECHOSTATE NEURAL NETWORK

An artificial neural network (ANN) is an abstract simulation of a real nervous system that contains a collection of neuron units, communicating with each other via axon connections. Such a model bears a strong resemblance to axons and dendrites in a nervous system. Due to this self-organizing and adaptive nature, the model offers potentially a new parallel processing paradigm. This model could be more robust and user-friendly than the traditional approaches. ANN can be viewed as computing elements, simulating the structure and function of the biological neural network. These networks are expected to solve the problems, in a manner which is different from conventional mapping. Neural networks are used to mimic the operational details of the human brain in a computer. Neural networks are made of artificial 'neurons', which are actually simplified versions of the natural neurons that occur in the human brain. It is hoped, that it would be possible to replicate some of the desirable features of the human brain by constructing networks that consist of a large number of neurons. A neural architecture comprises massively parallel adaptive elements with interconnection networks, which are structured hierarchically.

Artificial neural networks are computing elements which are based on the structure and function of the biological neurons. These networks have nodes or neurons which are described by difference or differential equations. The nodes are interconnected layer-wise or intra-connected among themselves. Each node in the successive layer receives the inner product of synaptic weights with the outputs of the nodes in the previous layer. The inner product is called the activation value. The activation value is passed through a non-linear function. When the vectors are binary or bipolar, hard-limiting non-linearity is used. When the vectors are analog, a squashed function is used. Some of the squashed functions are sigmoid (0 to 1), tanh (-1 to +1), Gaussian, logarithmic and exponential.

A network with two states of a neuron (0 or 1, and -1 or 1) is called 'discrete', and the same with a continuous output is called 'analog'. If, in a discrete network at a particular time 't', the state of every neuron is updated, the network is said to be synchronous. If the state of only one neuron is updated, the network is said to be asynchronous. A network is feed forward, if there is no closed chain of dependence among neural states. The same network is feed backward, if there is such a closed chain. When the output of the network depends upon the current input, the network is static (no memory). If the output of the network depends upon past inputs or outputs, the network is dynamic (recurrent). If the interconnection among neurons change with time, the network is adaptive; it is called non-adaptive. The synaptic weight updation of the networks can be carried out by supervised methods, or by unsupervised methods, or by fixed weight association networks methods. In the case of the supervised methods, inputs and outputs are used; in the unsupervised methods, only the inputs are used; and in the fixed weight association networks methods, inputs and outputs are used along with pre-computed and pre-stored weights. Some of the supervised learning algorithms are the perceptrons, decision-based neural networks, adaptive linear element (ADALINE), multi layer perceptron, temporal dynamic models and hidden Markov analysis. The various unsupervised learning algorithms are neo-cognition, self-organizing feature map, competitive learning, adaptive resonance theory (ART) and the principal component analysis. The fixed weight networks are Hamming net, Hopfield net and the combinatorial optimization. The total pattern recognition system constitutes instantiation space, feature extraction, training the network, and the testing the network.

Dynamic computational models require the ability to store and access the time history of their inputs and outputs. The most common dynamic neural architecture is the time-delay neural network (TDNN) that couples delay lines with a nonlinear static architecture where all the parameters (weights) are adapted with the backpropagation algorithm. Recurrent neural networks (RNNs) implement a different type of embedding that is largely unexplored. RNNs are perhaps the most biologically plausible of the artificial neural network (ANN) models. One of the main practical problems with RNNs is the difficulty to adapt the system weights. Various algorithms, such as backpropagation through time and real-time recurrent learning, have been proposed to train RNNs; however, these algorithms suffer from computational complexity, resulting in slow training, complex performance surfaces, the possibility of instability, and the decay of gradients through the topology and time. The problem of decaying gradients has been addressed with special processing elements (PEs).

The echo state network (ESN), Figure-1, with a concept new topology has been found by. ESNs possess a highly interconnected and recurrent topology of nonlinear PEs that constitutes a "reservoir of rich dynamics" and contain information about the history of input and output patterns. The output of these internal PEs (echo states) are fed to a memoryless but adaptive readout network (generally linear) that produces the network output. The interesting property of ESN is that only the memory less readout is trained, whereas the recurrent topology has fixed connection weights. This reduces the complexity of RNN training to simple linear regression while preserving a recurrent topology, but obviously places important constraints in the overall architecture that have not yet been fully studied.

The echo state condition is defined in terms of the spectral radius (the largest among the absolute values of the eigenvalues of a matrix, denoted by (|| ||) of the reservoir's weight matrix (|| W || < 1). This condition states that the dynamics of the ESN is uniquely controlled by the input, and the effect of the initial states vanishes. The current design of ESN parameters relies on the selection of spectral radius. There are many possible weight matrices with the same spectral radius, and unfortunately they do not all perform at the same level of mean square error (MSE) for functional approximation.

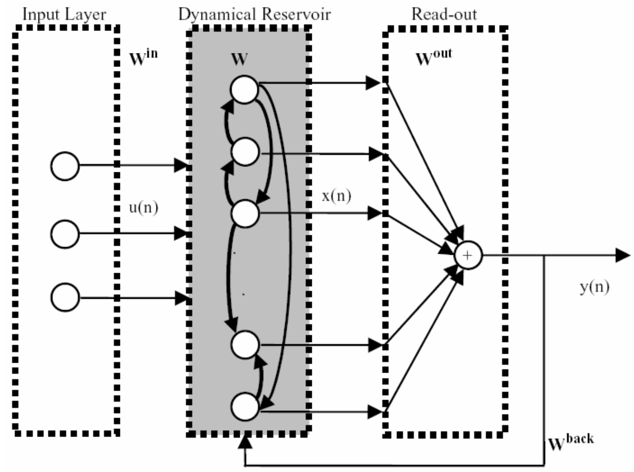

Figure-1. An echo state network (ESN). ESN is composed of two parts: a fixed weight

(|| W || < 1) recurrent network and a linear readout. The recurrent network is a reservoir of highly interconnected dynamical components, states of which are called echo states. The memory less linear readout is trained to produce the output.

Consider the recurrent discrete-time neural network given in Figure-1 with M input units, N internal PEs, and L output units. The value of the input unit at time n is $u(n) = [u_1(n), u_2(n) \ldots u_M(n)]^T$,
The internal units are
$X(n) = [x_1(n), x_2(n), x_N(n)]^T$, and
Output units are $y(n) = [y_1(n), y_2(n) \ldots y_L(n)]^T$.
The connection weights are given

- in an (N x M) weight matrix $W^{back} = W_{ij}^{back}$ for connections between the input and the internal PEs,
- in an N × N matrix $W^{in} = W_{ij}^{in}$ for connections between the internal PEs
- in an L × N matrix $W^{out} = W_{ij}^{out}$ for connections from PEs to the output units and
- in an N × L matrix $W^{back} = W_{ij}^{back}$ for the connections that project back from the output to the internal PEs.

The activation of the internal PEs (echo state) is updated according to

$$x(n+1) = f(W^{in} u(n+1) + Wx(n) + W^{back} y(n)) \qquad \ldots\ldots (1)$$

Where $f = (f1, f_2 \ldots f_N)$ are the internal PEs' activation functions.

Here, all f_i's are hyperbolic tangent functions $\frac{e^x - e^{-x}}{e^x + e^{-x}}$.

The output from the readout network is computed according to

$$Y(n+1) = f^{out}(W^{out} x(n+1)) \qquad \ldots\ldots(2)$$

Where

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$f^{out} = (f_1^{out}, f_2^{out}, ..., f_L^{out})$ are the output unit's nonlinear functions [15-16] generally; the readout is linear so f^{out} is identity.

6. IMPLEMENTATION

This process is achieved by using Echostate network.

Decide the input features of the registered image.
Fix the target values.
Set no. of inputs = 2;
Set no. of reservoir = 20;
Set no. of output = 1
Create weight matrix (no. of reservoirs, no. of inputs) = random numbers -0.5
Create weight backup matrix (no. of outputs, no. of reservoirs) = (random numbers -0.5)/2
Create weight not (w0) (no. of reservoirs, no. of reservoirs) = (random numbers -0.5)
Create temp matrix (Te) (no. of reservoirs, no. of reservoirs) = random numbers
Calculate w0 = w0.* (te <0.3)
Calculate w0 = w0.* (w0 <0.3)
Follow the heuristics
v = eig (w0)
lamda = max(abs(v))
w1= w0/lamda
w = .9* w1
Create network training dynamics
state = zeros(no_reservoir,1)
desired = 0;
For loop
 Input = x (i: i+nipp-1)
 F = wt_input* input'
 TT = w*state
 TH = wt_back' * desired
 next_state = tanh(F+TT + TH)
 State = next_state
 Desired = x (i+nipp-1)
desired_1 = desired
end

Echostate neural network (testing)

Network testing

Input = x (i: i+nipp-1);
F = wt_input* input';
TTH = wt_back' * output_d;
next_state = tanh(F + w*state + TTH);
State = next_state;
Output (i) = (wout'*state);

7. RESULTS

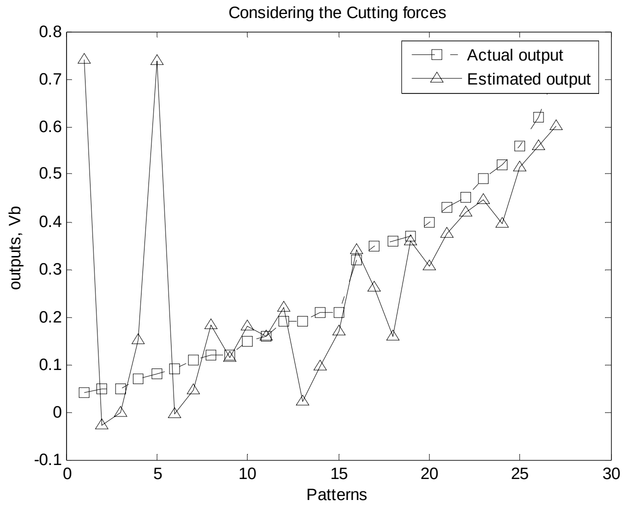

Figure-2. Estimation of Vb using ESNN considering cutting forces.

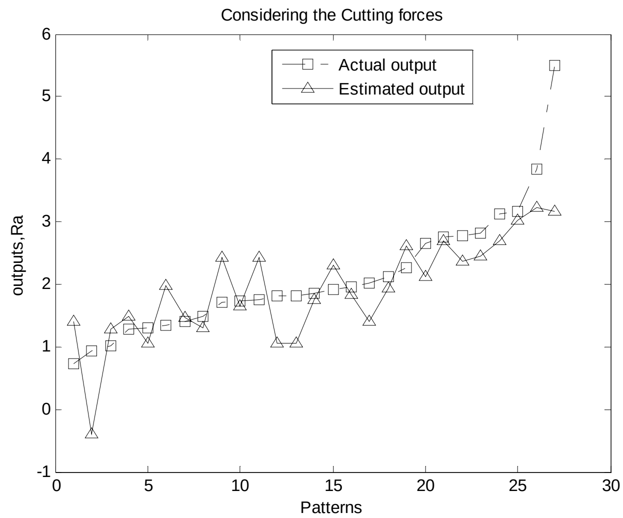

Figure-3. Estimation of Ra by ESNN considering cutting forces.

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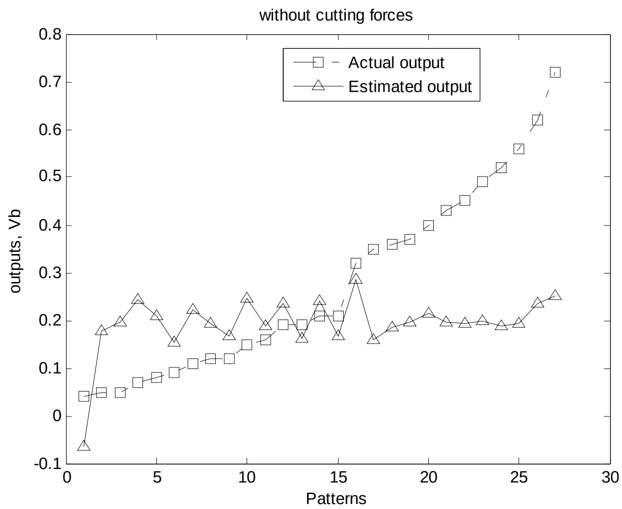

Figure-4. Estimation of Vb using ESNN without considering cutting forces.

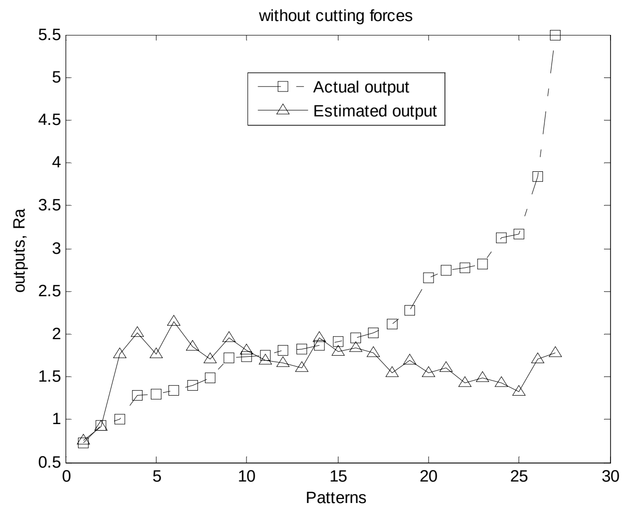

Figure-5. Estimation of Ra by ESNN without considering cutting forces.

8. CONCLUSIONS

In this research work, the estimation of tool wear of CBN / PCD on Al MMC machining and their machinabilty behavior were studied and analyzed using Echostate neural network. The percentage of estimation was achieved to be 90.62%.

REFERENCES

J. Paulo Davim, N. Muthukrishnan. 2008. Optimization of machining parameters of Al/SiC-MMC with ANOVA and ANN analysis. J. Materials Processing Technology.

N. Muthukrishnan, M. Murugan, K. Prahlada Rao. 2007. An Investigation on the machinability of AlSiC metal matrix composites using PCD inserts. Int. J. Adv. Manuf. Technology.

K. Palanikumar, R. Karthikeyan. 2006. Assessment of factors influencing surface roughness on the machining of AlSiC particulate composites.

I.A. Ibrahim, F.A. Mohamed, E.J. Lavernia. 1991. Particulate reinforced metal matrix composites- A review. J. Mat. Sci. 26: 1137-1156.

F. Dolauy. 1986. Increasing focus on silicon carbide-reinforced aluminum composites. Light Metal Age. 6: 7-14.

N. Tmoac, K. Tonnessen. 1992. Machining of particulate aluminium matrix composites. Ann. CIRP. 41(1): 55-58.

K. Weinert. 1993. A consideration of tool wear mechanism when machining metal matrix composites. Ann. CIRP. 42(1): 95-98.

G.A. Chadwick, P.J. Health. 1990. Machining metal matrix composites. Met. Mat. 2: 73-76.

M.K. Brun, M. Lee. 1985. Wear characteristics of various hard materials for machining SiC-reinforced aluminum alloy. Wear. 104: 21-29.

L. Cronjage, D. Merister. 1992. Machining of fibre and particle-reinforced aluminium. Ann. CIRP. 4(1): 63-66.

M.E. Merchant. 1945. Mechanics of the metal cutting process. Appl. Phys. 16(6): 267-318.

N. Kanetake. 1990. Analytical study on deformation behaviour of metal matrix composites. Mat. Proc. Tech. 24: 281-289.

T. Mori, K. Tanaka. 1973. Average stress in matrix and average elastic energy of materials with misfitting inclusions. Acta Metal. 21(5): 571-574.

Zhou Zhao, Song Zhijian, Xu Yingkun. 1991. Effect of microstructure on the mechanical properties of an Al alloy 6061-SiC particle composite. Mat. Sci. Eng. 132: 83-88.

K. Tanaka, T. Mori. 1970. The hardening of crystals by non-deforming particles and fibres. Acta Metal. 18(8): 931-941.

Zhou Zehua. 1992. Metal cutting theory. Mechanical Engineering Publishing House of China. p. 5.

D.J. Lloyd. 1994. Int. Mater. Rev. 39(1): 1.

I.A. Ibrahim, F.A. Mohamed, E.J. Lavernia. 1991. J. Mater. Sci. 26: 1137.

J.I. Song, H.D. Bong, K.S. Han. 1995. Scripta Metal. Mater. 33(8): 1307.

M.L. Ted Guo, C.-Y.A. Tsao. 2000. Compos. Sci. Technol. 60: 65.

A.B. Gurcan, T.N. Baker. 1995. Wear. 188: 185.

M. Gupta. 2003. Metastable Aluminum-Titanium Materials. US Patent. 6, 623, 571.

S.F. Hassan, M. Gupta. 2002. J. Mater. Sci. 37: 2467.

S.F. Hassan, M. Gupta. 2003. Mater. Sci. Technol. 19: 253.

V.V. Ganesh, M. Gupta. 2000. Mater. Res. Bull. 35: 2275.

V.V. Ganesh, C.K. Lee, M. Gupta. 2002. Mater. Sci. Eng. A 333: 193.

V.V. Ganesh, M. Gupta. 2001. Scripta Mater. 44: 305.

M. Gupta, M.O. Lai, C.Y. Soo. 1995. Mater. Res. Bull. 30(12): 1525.

1991. Powder Diffraction File, International Center for Diffraction Data, 1601 Park Lane, Swarthmore, PA, USA.

N. Srikanth, D. Saravanaranganathan, M. Gupta, L. Lu, M.O. Lai. 2000. Mater. Sci. Technol. 16(3): 309.

W.D. Callister Jr. 1994. Materials Science and Engineering: An Introduction. 3rd Ed., John Wiley and Sons Inc.

M. Hansen, K. Anderko. 1958. Constitution of Binary Alloys. McGraw-Hill Book Company, New York, USA. pp. 139-142.

M.J. Donachie. 1988. Titanium: A Technical Guide. ASM International, USA.

M. Gupta, Yee Chung-E, T.S. Francesca, Srivatsan. 2003. Mater. Manuf. Processes. 18(6): 891.

R.E. Reed-Hill. 1964. Physical Metallurgy Principles. 2nd Ed., D. Van Nostrand Company, New York, USA. pp. 267-325 and 753-755.

R. Morrell. 1985. Handbook of Properties of Technical and Engineering Ceramics, Part 1: An Introduction for the Engineer and Designer. Pub: Her majesty's Stationary Office, London. p. 70.

V.V. Ganesh, P.K. Tan, M. Gupta. 2001. J. Alloys Compd. 315: 203.

R.J. Perez, J. Zhang, M.N. Gungor, E.J. Lavernia. 1993. Metall. Trans. A 24, 701.

M. Gupta, F. Mohamed, E. Lavernia, T.S. Srivatsan. 1993. J. Mater. Sci. 28: 2245.

L. Tao, F. Delannay. 1998. Acta Mater. 46(18): 6497.

M. Gupta, S. Ling. 1997. Mater. Des. 18(3): 139.

M. Bauccio (Ed.) 1993. Metals Reference Book. 3rd Ed., ASM International Publication, Materials Park, OH, USA. p. 311.

E.A. Brandes, G.B. Brook (Eds.). 1998. Smithells Light Metals Handbook. Butterworth-Heinemann, Great Britain. p. 55.

G.E. Fougere, L. Riester, M. Ferber, J.R. Weertman, R.W. Siegel. 1995. Mater. Sci. Eng. A 204: 1.

A.R. Boccaccini, G. Ondracek, P. Mazilu, D. Windelberg. 1993. J. Mech. Behav. Mater. 4: 119.

V.V. Ganesh, M. Gupta. 2001. Mater. Sci. Technol. 17: 1465.

M.D. Huda, M.S.J. Hashmi, M.A. El-Baradie. 1995. Key Eng. Mater. 104-107: 37.

C.P. Ling, M.B. Bush, D.S. Perera. 1995. J. Mater. Process. Technol. 48: 325.

N. Eustathopoulos, M.G. Nicholas, B. Drevet. 1999. Wettability at High Temperatures (Pergamon Materials Series, Vol. 3), Elsevier Science Ltd., UK. pp. 175-197.

M.R. Krishnadev, R. Angers, C.G. Krishnadas Nair, G. Huard. 1993. J. Met. 45: 52.

M. Gupta, M.O. Lai, D. Saravanaranganathan. 2000. J. Mater. Sci. 35: 2155.

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Table-1. Experimental data.

S. No.	**Volume fraction** (%)	**Speed** (m/min)	**Feed mm/rev**	**Depth of cut** (mm)	**F_x N**	**F_y N**	**F_z, N**	**Machining time** (min)	**Flank wear V_b** (mm)	**Specific energy x 10^{-3}w.s /mm**	**Surface roughness R_a µm**
1	10	50	0.2	0.5	35	65	70	2	0.03	15.19	1.71
2	10	50	0.4	1.5	40	65	75	5	0.14	20.47	3.83
3	10	50	0.6	2.5	40	75	80	8	0.31	25.11	5.48
4	10	100	0.2	1.5	50	75	90	5	0.15	13.53	1.85
5	10	100	0.4	2.5	45	85	105	8	0.35	17.05	3.12
6	10	100	0.6	0.5	60	90	110	2	0.04	11.88	2.65
7	10	150	0.2	2.5	40	80	65	8	0.36	13.03	1.74
8	10	150	0.4	0.5	45	80	70	2	0.04	9.362	1.73
9	10	150	0.6	1.5	45	90	85	5	0.18	12.23	2.81
10	15	50	0.2	1.5	50	90	85	8	0.39	38.24	2.11
11	15	50	0.4	2.5	40	105	105	2	0.07	16.88	2.75
12	15	50	0.6	0.5	45	110	105	5	0.19	41.03	3.17
13	15	100	0.2	2.5	50	125	190	2	0.08	11.16	1.34
14	15	100	0.4	0.5	40	75	95	5	0.21	27.87	1.81
15	15	100	0.6	1.5	60	80	125	8	0.49	29.90	2.78
16	15	150	0.2	0.5	55	85	130	5	0.21	21.30	1.01
17	15	150	0.4	1.5	60	150	210	8	0.52	23.48	1.82
18	15	150	0.6	2.5	60	100	115	2	0.09	10.09	2.02
19	25	50	0.2	2.5	60	90	125	5	0.35	42.83	1.48
20	25	50	0.4	0.5	55	85	140	8	0.56	87.50	1.91
21	25	50	0.6	1.5	60	100	120	2	0.11	32.88	2.27
22	25	100	0.2	0.5	25	70	85	8	0.62	57.86	0.93
23	25	100	0.4	1.5	60	100	125	2	0.12	22.34	1.30
24	25	100	0.6	2.5	70	100	115	5	0.43	33.49	1.95
25	25	150	0.2	1.5	50	80	105	2	0.12	17.07	0.72
26	25	150	0.4	2.5	50	85	100	5	0.45	26.29	1.28
27	25	150	0.6	0.5	25	70	90	8	0.72	52.28	1.40