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Investigation of erosive wear behaviour of tungsten carbide cobalt coated metal matrix composites using ANN

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Abstract

An artificial neural network (ANN) model was employed on erosive wear result of aluminium 7034 T6 reinforced with different weight percentage of Al_2O_3 and SiC with tungsten carbide cobalt (WC-Co) coated composites. WC-Co in the form of powder was pretreated before coating, to identify the inflence of pretreatment on the substrate. The WC-Co coating was deposited with high velocity oxy fuel (HVOF) sparay method. The microstructural examination was carried through scanning electron microscope (SEM) and to identify the elemental composition of coated specimens, energy dispersive X-ray analysis (EDX) was used. These material charecterisation shows that pretreated WC-Co coated Al 7034 T6 composites at 500 μm size exhibit thick closely packed, low porosity and good adhesion of membrane, while specimen at 400 μm size showed properties opposite to the 500 μm size speciemen. To predict the erosive wear behaviour of WC-Co coated Al7034 T6 composite, neural network model uses the parameters such as impact velocity, stand-off-distance, erodent temperature, impingement angle, the weight percentage of reinforcement and coating thickness. It is found that predicted values from the artificial neural network can be compared with the experimental result values.

1. Introduction

The recycling characteristic of aluminium surpasses the use of all the other materials. Aluminium has a tendency of developing oxide film which protects against corrosion. This oxide film may get rupture by increasing or decreasing the level of pH. But the use of aluminium under sea water is really a challenging one. Researchers [1,2] have found that removal of material from the surface of the substrate by erosion is greater than the removal of material by corrosion. Waistage of material from the surface of manganese bronze propellers are greater than the bronze propeller. It is found that these erosion losses meant for the development of the improved, more resistant alloys. These new propeller alloys, stronger and more wear resistant. These high erosion losses have cause to the development of the improved, more resistant alloys. The newer propeller alloys, though more costly, are stronger and much more resistant to wastage. The propeller can be protected from failure by suitable sophisticated coatings and utmost care should be taken from corrugation of paint on the surface of a propeller blade, it disturbs the flow of water over the edge of the blade and greatly enhances erosion wear in that area. Coatings should be able to protect the structure against the erosion-corrosion environment and from external foreign particle impact.

Generally, coatings have smooth surfaces on the substrate material. SEM study [3] showed that coating powder consists of uneven size and shape of grains. Porosity level in coating plays an important role for high temperature resistance coatings. The presence of porosity in the coating is subjected to corrosion and erosion of coated substrate. High velocity oxy-fuel spray (HVOF) coating has proved to be the most efficient way of producing coatings in terms of reducing the porosity level. [4]. Cheng-Hsun Hsu et al. [5] suggested that using annealed CrAlSiN coating can significantly improve the wear resistance of JIS SKD61 tool steel. Sahraoui et al. [6] studied the microstructural behaviour of ordinary steel (AFNOR 25CD4) substrates with WC-12% Co coated by HVOF method. They reported that porosity level in the coating is substantially decreased to even less than 1%. Guilemany et al. [7] reported that nano coatings on the G41350 steel subjected to decarburization due

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to the surface to voulme ratio effect compared to conventional method of coating. Hence an attempt has been made to develop micron meter sized coatings on the aluminium 7034T6 composites. Composite boat propellers provide, good performance, durable, and inexpensive in use. Exhaustive literature work is available on the use of composites for under sea water components [8,9]. Very few studies are available on the use of aluminium based composites operating under sea water. The oxidizing property of aluminium based composite makes it a suitable candidate for erosion –corrosion applications. But it is a challenging task under sea water condition. So this work aims at developing Aluminium 7034T6 composites. The fabrication method and mechanical properties of aluminium 7034T6 composites are reported in our previous studies [10].

In this work, erosive wear behaviour of WC-Co coating by HVOF spray method has been investigated. The effect of erosive wear parameters such as impact velocity, standoff distance, impingement angle, erodent temperature and filler content was analysed. To study the correlation between erosive wear results and the predicted result, artificial neural network (ANN) model was used. In order to tackle the complex problems into a simpler one, ANN is the best approach to achieve this [11]. ANN structure consists of a number of nodes and interconnection between the nodes. Nodes can be treated as an analytical element which receives the inputs, processes it and generate an output. ANN consists of 3 input layers, 8 hidden layers, and an output layer. Feed forward back propagation algorithm was used to solve the problem. A large number of data may be used to get the accurate solution of the problem by using computational methods [12]. Therefore the aim of the present study is to evaluate the erosive wear behaviour of WC-Co coating by HVOF spray method at different operating conditions and to predict the experimental values with the ANN generated values. Neural network fitting tool was used to train the network and evaluated its performance using mean square error. SEM and EDAX charecterisation techniques were used to analyse the erosive wear behaviour of aluminium 7034T6 composites with different weight percentage of WC-Co coatings.

2. Material and methods

The components were polished with embry paper before coating to avoid the presence of dust particles. The WC-Co film membrane was deposited on a 20 ×10 mm aluminium 7034 T6 composite by HVOF method. A novel method of pretreatment of WC-Co was adopted to identify the influence of pre treatment of coated compostes. The powder was cleaned with alcoholic agent and dried for nearly an hour then subjected to pretreatment for a temprature range of 950°C to 1250°C in an oven. The pretreatment method was adopted in a asimilar manner as adopted by [13]. The WC-Co coating in the form of fine particles was accelerated at a supersonic velocity on a substrate material. The coating composition consists of 88% of WC and 12% of Co. The composition of WC-Co coating is shown in Table 1. The measurement of coating thickness was done by digital thickness gauge which uses the principle of eddy current. WC-Co coating was prepared at a variying coating thickness of 400 µm size and 500µm size respectively. The average coating thickness considered here is 500 µm. Micro hardness test [10] was carried out to study the hardness of the coated composites. To study the elemental composition of the composites (EDAX) was used. SEM was used to identify the material charecterisation of the composites. Porosity plays a crucial role while developing high temprature corrosion resistance coating. Porosity mesurement can be done by imaze analyser which is equipped with SEM avialable at IISC Bangalore. Porosity for coated components was found to be in the range of 1.3-1.8%.

Table 1. The composition of WC-Co coating.

Coating Powder	Size
88% of WC and 12 % of Co	Approximatley 10 µm

2.1 Erosion wear

The solid particle slurry erosion tests were carried out using a self-fabricated air-jet erosion test as reported in our previous studies [10]. Percentage composition of specimens subjected to erosive wear is shown in Table 2. Different erosive wear parameters selected for erosion test is shown in Table 3.

Table 2. Percentage composition of specimens.

Sample	Sample code	Hardness (HV)[10]
Pure aluminium 7034 T6		190
Aluminium7034 T6 + 3%Al_2O_3 + 3% SiC		240
Aluminium7034 T6 + 6%Al_2O_3 + 3% SiC	[M1]	256
Aluminium7034 T6 + 9%Al_2O_3 + 3% SiC	[M2]	285

Table 3. Parameters selected for erosion test.

Control Factor	Level				
	1	2	3	4	Units
A: Impact velocity	5	10	15	20	m·sec^{-1}
B: Stand-off-dist	30	40	50	55	mm
C: Erodent temp	35	70	100	120	ºC
D: Impingement angle	30	45	60	90	◦
E: Filler content	0	3	6	9	wt%
F: Coating thickness	500	400	500	400	µm

2.2 Neural network analysis for erosive wear prediction

Neurons are the fundamental units of the network system. The shape of the neuron depends on its specified function. A network is an approach used to solve the complex problems into simpler one. Nodes can be used as a computational element to process the input and generate an output. Artificial neural network is a computational model used to copy the activity performed by human brains. It is the most important branch of Artificial Intelligence used to solve the complex problems which are highly impossible by human beings in a conventional way. At the same time, ANN produces accurate and better results. ANN is an emerging field of engineering developed just before few decades and has proven to be useful for solving complex problems in the various fields of engineering such as engine management systems, stock market prediction, research etc. This wide range of applications differentiates the ANN from control system and optimization techniques [14]. Erosive wear analysis was done using a well known statistical tool called artificial neural network with the help of MATLAB (R2011a) as reported by Zhu et al. [15]. A feed forward back propagation multilayer network was modeled using MATLAB. The sequence of steps involved in ANN model was a collection of data, processing of data, designing, training, and testing, simulation and prediction of data, finally an analysis of predicted data. ANN model was used to predict the erosive wear rate of the aluminium 7034T6 composites. The controlling factors selected for input/output data collection for ANN training model were impact velocity A, stand-off-distance B, erodent temperature C, impingement angle D, filler content E, coating thickness F, while the output data consists of erosive wear rate only. The controlling factors selected for the study is shown in Table 3. The maximum and minimum levels of the experimental data were set to a threshold of +1 and -1 respectively. MATLAB helps to build the suitable standard back propagation multilayer feed forward network. The network consists of the input layer (impact velocity A, stand-off-distance B, erodent temperature C, impingement angle D, filler content E, coating thickness F) single hidden layer with 7 neurons and output layer (erosive wear rate) respectively. The network was constructed to predict the erosive wear rate for different input parameters. The constructed network is shown in Figure 1. It is suggested that no standard method select the number of neurons in the hidden layer

[16]. Arbitrarily we selected 07 neurons in the hidden layer. The suitable architecture of the network was found from MATLAB software. The MATLAB was used to train the network using a function called 'train' to modify the weights interconnected between the neurons till the preferred error level is achieved. The present work trained the network above 1000 iteration. For the best performance, Levenberg-Marquardt [LM] algorithm was used [17]. The 70% of selected data was used for training the network and 15% for validating and testing the network. In order to minimize the error between experimental and predicted value, weights and biases were adjusted. The training was stopped when mean square error reaches to a value of 0.0001 [18].

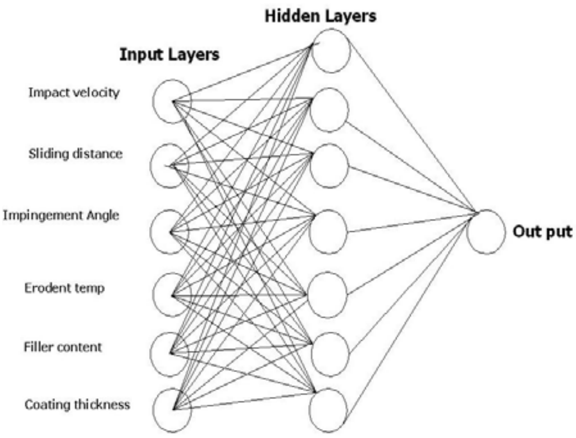


Figure 1. Neural network structure.

3. Results and discussion

In order to obtain good performance, a large number of data sets were collected from the erosive wear test result as shown in Table 4. Figure 2 shows the comparative analysis between experimental and predicted data sets. All the data sets used perfectly fit with the 45° line and are visible on that line clearly. Therefore it is evident from the above graphs of training, testing and validation that experimental and predicted values are almost nearer values hence it is confirmed that trained ANN gives an output with a minimum percentage of error. Regression coefficient (R) was used to correlate the relationship between output and the target value. Studies [18,19] suggested that if R value is 1 then there exists a close relationship between output and the target value, zero indicates arbitrary relationship and greater than 0.9 represents the better quality. From the graph, it is revealed that the combined set of training, testing, and validation having R value greater that 0.99981 almost approaches to 1 which means that very least error and the selected network is suitable for error prediction. If R value is very less then we have to increase the number of neurons in the hidden layers in the neural network. Figure 3 shows the error values of a histogram with the default value of 20 Bins. The horizontal line represents the number bins in terms of an error and vertical line represents frequency instances. Feed forward back propagation helps in predicting the minimum number of the error. The histogram represents the frequency distribution of a bar chart. It is observed that for a maximum frequency level of 56 we can observe the zero error. Figure 4 shows the performance analysis for predicting the erosive wear of selected data sets. Neural network parameters such as feed forward back propagation, training function (TRAINLM), adaption learning function (LEARNGDM), performance function (mean square error), number of layers (1), number of neurons (10), and transfer function (LOGSIG) were selected and modified during prediction. For prediction following steps may be used. 1. A large number of data sets collected from the experimental result are to be preprocessed. 2. Train the selected neural network using training papmeters. 3. Analyze the performance of the selected neural network for best performance, if not satisfied then repeat the step 2. Training validation and testing will be repeated until it attains a minimum mean square error value. The predicted result was compared with the experimental values. Finally, select the trained ANN for prediction. One can acknowledge from Figure 4 that even for a few epochs say (2) the network reaches to an accuracy of 0.000000041.

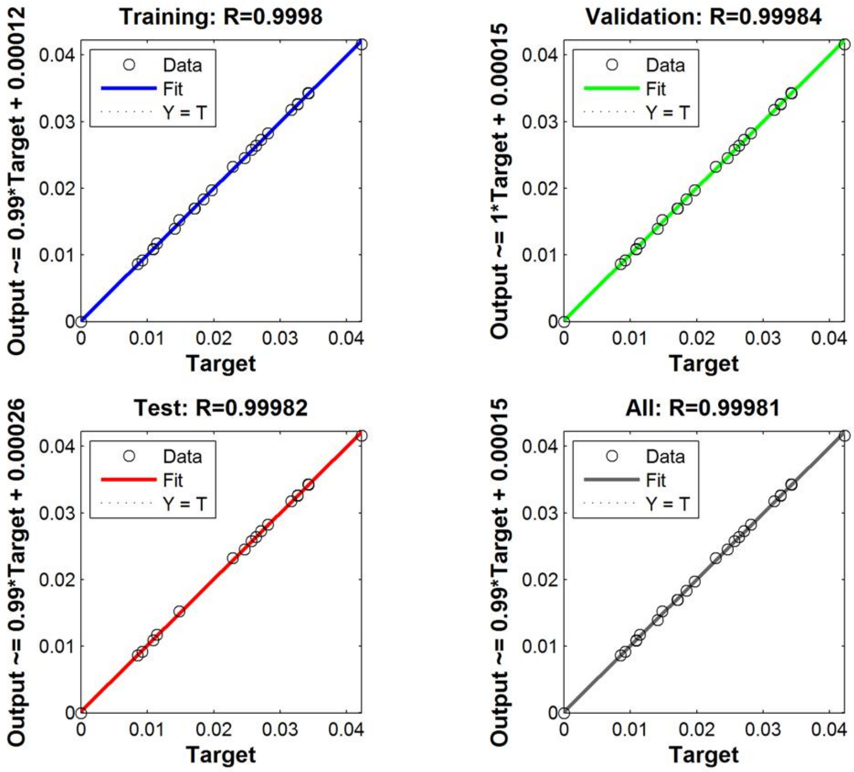


Figure 2. The relationship between experimental and ANN predicted values using LM algorithm.

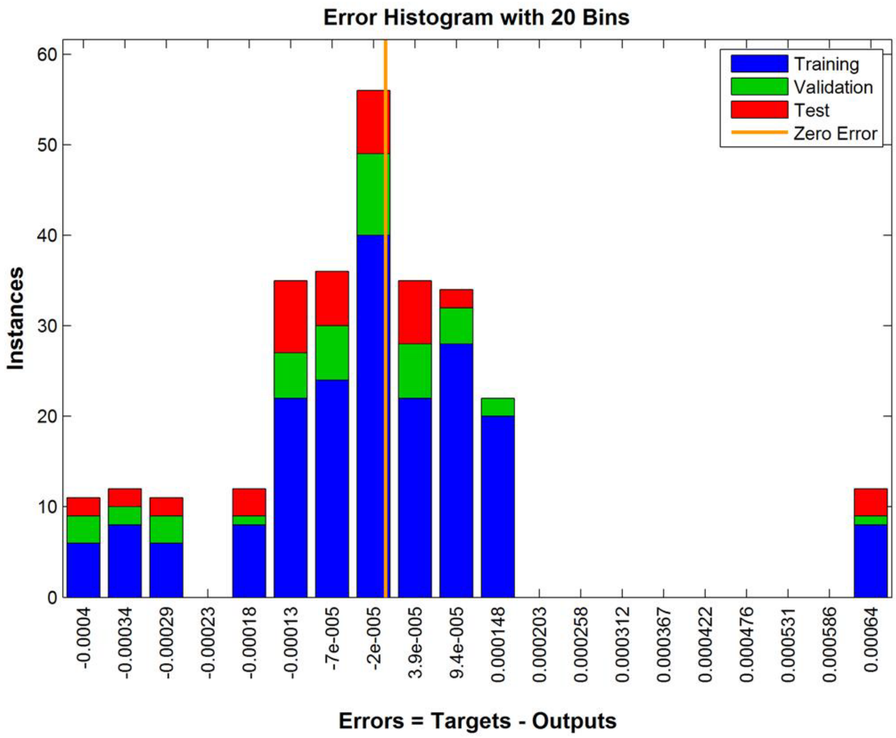


Figure 3. Error histogram in the ANN for LM algorithm.

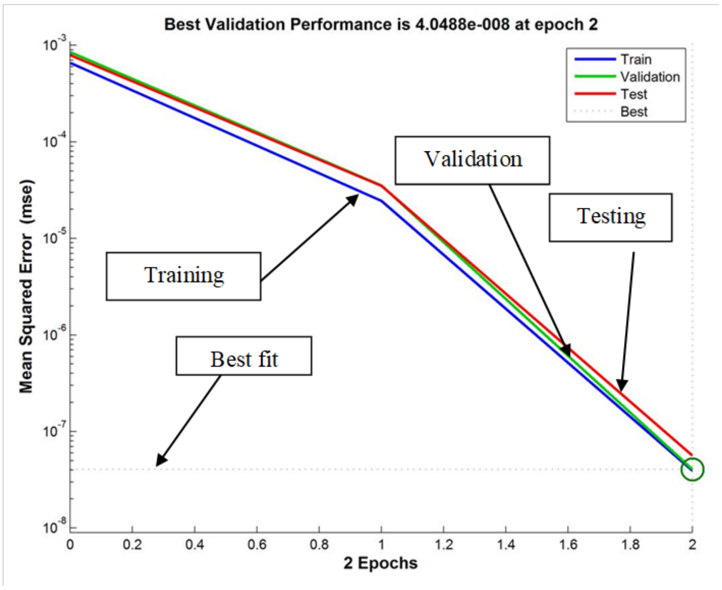


Figure 4. Performance plot in the ANN for LM algorithm.

Table 4. Erosive wear test results for wear prediction.

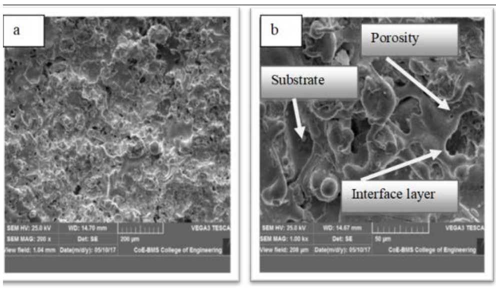
Impact velocity	5	10	15	20	5	10	15	20	5	10	15	20	5	10	15	20
Stand-off distance	30	40	50	55	30	40	50	55	30	40	50	55	30	40	50	55
Erodent temp	35	70	100	120	35	70	100	120	35	70	100	120	35	70	100	120
Impingement angle	30	45	60	90	30	45	60	90	30	45	60	90	30	45	60	90
Filler content	0	3	6	9	0	3	6	9	0	3	6	9	0	3	6	9
Coating thickness	500	400	500	400	500	400	500	400	500	400	500	400	500	400	500	400
Experimental erosive wear rate	0.009	0.077	0.065	0.01	0.089	0.095	0.092	0.13	0.15	0.19	0.067	0.110	0.19	0.08	0.2	0.167
ANN predicted	0.008	0.076	0.059	0.08	0.078	0.086	0.085	0.09	0.14	0.17	0.067	0.109	0.17	0.05	0.19	0.166

Table 4. Erosive wear test results for wear prediction. (Continued)

Impact velocity	5	10	15	20	5	10	15	20	5	10	15	20	5	10	15	20
Stand-off distance	30	40	50	55	30	40	50	55	30	40	50	55	30	40	50	55
Erodent temp	35	70	100	120	35	70	100	120	35	70	100	120	35	70	100	120
Impingement angle	30	45	60	90	30	45	60	90	30	45	60	90	30	45	60	90
Filler content	0	3	6	9	0	3	6	9	0	3	6	9	0	3	6	9
Coating thickness	500	400	500	400	500	400	500	400	500	400	500	400	500	400	500	400
Experimental erosive wear rate	0.15	0.17	0.18	0.2	0.175	0.16	0.12	0.145	0.135	0.11	0.244	0.044	0.175	0.16	0.12	0.145
ANN Predicted	0.149	0.168	0.178	0.198	0.174	0.159	0.198	0.143	0.133	0.10	0.234	0.042	0.167	0.158	0.198	0.139

4. Visual examination of eroded coated surfaces

Scanning electron microscopy (SEM) of eroded surfaces was used to study the surface morphology of coated specimens. After the erosion experimentation, the eroded specimen (M1 and M2) was analyzed using EDX (Energy dispersive X-ray analysis) is shown in Figures 5 and 6. EDX analyses the elemental or chemical charecterisation of the coated samples. Figure 5(c) shows the elemental analysis of Aluminium7034 T6+6%Al_2O_3+3% SiC composites. Figure 6(c) shows the elemental analysis of Aluminium7034 T6+9%Al_2O_3+3% SiC composites. The specimens were coated with the 400 µm and 500 µm size of WC-Co coating. It is evident from Figures 5 and 6(c) that W is the major element among all the other elements of C, O, Co, Fe, and Al. It is also observed that no adverse reaction has been identified in the elemental composition of the substrate. Therefore, it is evident that W is responsible for good adhesion between matrix and reinforcement resulting in further improvement in the erosive wear resistance of the composites. Interface layer plays a vital role in determining the mechanical properties of the composites [20]. Hence care should be taken in analyzing the Interface layer. EDAX helps in examining the newly formed erosive wear surfaces and identify the porosity on the interface layer. From Figure 5(b) specimen coated at 500 µm size shows less porosity compare to Figure 6(b) because interface layer carried the load transfer due to erosive wear parameters. It is also observed from the elemental composition table that, the weight percentage of carbon reduces and gradually diffuses in to the matrix. It is also observed from Figure 6(b) that more surface is eroded and exposes SiC than the Figure 5(b) this is due to the principal effect of W over other elements. Many authors [20,21] reported that conventional method of the coating does not make any changes in the visibility of carbide but the reduction in the particle size to the micro or nano level difficult to measure the grains exists in the matrix. The presence of cobalt in the WC-Co enhances the poor film adhesion and low resistant quality. Hence to improve the quality of adhesion between substrate and the coating, pretreatment method has been adopted. Due to thermal spraying, degradation reaction takes place and dissolution of WC occur [22]. Porosity was found to be 1.8% ± 0.2% for the micron sized coating. The presence of porosity can be very easily identified across the boundaries of the WC as shown in Figure 6(b) and also it shows more wear damage such as micro- cratering than Figure 5(b). Verdon et al. [23] stated that micro- cratering is also one of the parameters responsible for wear damage due to erosion.



Element	Atomic %	Weight %
CK	57.89	18.80
OK	21.57	9.33
AlK	1.12	0.82
FeK	2.57	3.88
CoK	4.92	7.84
WL	11.93	59.32

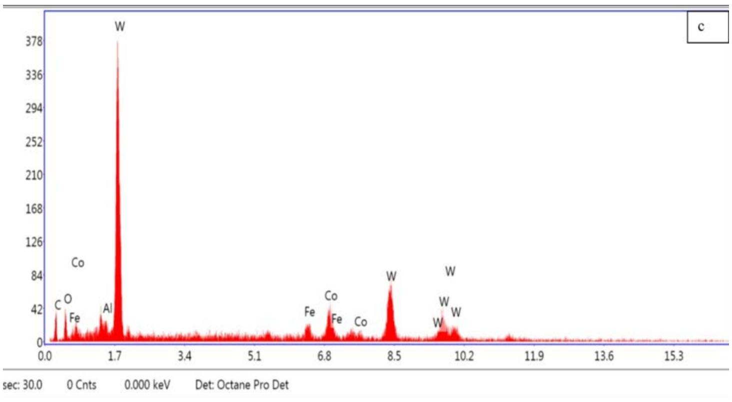
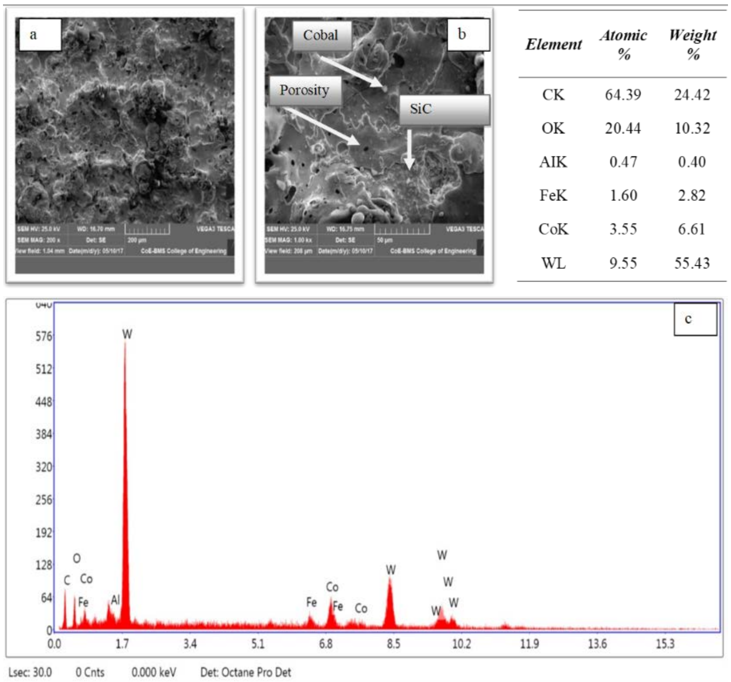


Figure 5. Eroded surface morphology of WC-Co coated specimen (M2 of 500µm): SEM micrographs at (a) 200x, (b) 1000x magnification and (c) EDX micrographs.



Element	Atomic %	Weight %
CK	64.39	24.42
OK	20.44	10.32
AlK	0.47	0.40
FeK	1.60	2.82
CoK	3.55	6.61
WL	9.55	55.43

Figure 6. Eroded surface morphology of WC-Co coated specimen (M1 of 400μm): SEM micrographs at (a) 200x, (b) 1000x magnification and (c) EDX micrographs.

5. Conclusions

WC-Co coatings were deposited on specimen M1 and M2 by using HVOF method. The coating provoides good adhesion on the surface of the specimens. The coated specimens were subjected to erosive wear by using self fabricated erosive wear test rig. EDX was used to identify the composition of the elements in a coated substance. It is found that no adverse reaction was observed in a specimen and W was the major elemental composition in a coating among other elements. The erosive wear result of aluminium 7034 T6 reinforced with different weight percentage of Al_2O_3 and SiC with tungsten carbide cobalt WC-Co coated composites was investigated and compared using ANN. Erosive wear rate of aluminium 7034 T6 reinforced composites was predicted by a suitable trained neural network based on minimum mean square error method. It is found that experimental and ANN predicted values were well fit with each other. The neural network has proved a good agreement with the experimental values. Surface morphology of coated specimens was analyzed using SEM. It is found that porosity level decreased and erosion resistance was increased for M2 specimen as compared to specimen M1. This may be due to the dominant role of W over other elements and reduction in the weight percentage of C.

References

[1] H. Yu, Y. Zhengy, and Z. Yao, "Cavitation erosion corrosion behaviour of manganese-nickel-aluminum bronze in comparison with manganese-brass," *Journal of Materials Science and Technology Shenyang*, vol. 25, pp. 758-766, 2009.

[2] T. Yan, L. Tan, D. Xiong, X. Liu, B. Zhang, and K. Yang, "Fluoride treatment and in vitro corrosion behavior of an AZ31B magnesium alloy," *Materials Science and Engineering C*, vol. 30 pp. 740–748, 2010.

[3] Z. B. Qi, B. Liu, Z. T. Wu, F. P. Zhu, Z. C. Wang, and C. H. Wu, "A comparative study of the oxidation behavior of Cr_2N and CrN coatings," *Thin Solid Films*, vol. 544, pp. 515–520, 2013.

[4] A. Dent, S. DePalo, and S. Sampath, "Examination of the Wear Properties of HVOF Sprayed Nanostructured and Conventional WC-Co Cermets with Different Binder Phase Contents," *Journal of Thermal Spray Technology*, vol. 114, pp. 551-558, 2002.

[5] C.-H. Hsu, W.-C. Huang, Y.-P. Lee, and W.-Y. Ho, "Effect of nitrogen atmosphere heat treatment on structure and wear behavior of CrAlSiN nanocomposite film," *Surface &*

Coatings Technology, vol. 320, pp. 230–234, 2017.

[6] T. Sahraoui, S. Guessasma, M. A Jeridane, and M. Hadji, "HVOF sprayed WC–Co coatings: Microstructure, mechanical properties and friction moment prediction," *Materials & Design*, vol. 31(3), pp. 1431-7, 2010.

[7] J. M. Guilemany, S. Dosta, J. Nin, and J. R. Miguel, "Study of the properties of WC-Co nanostructured coatings sprayed by high-velocity Oxyfuel," *Journal of thermal spray technology*, vol. 14(3), pp. 405-413, 2005.

[8] A. M. S. Hamouda, S. Sulaiman, T. R. Vijayaram, M. Sayuti, and M. H. M. Ahmad, "Processing and characterization of particulate reinforced aluminium silicon matrix composite," *Journal of Achievements in Materials and Manufacturing Engineering*, vol. 25, pp.12-16, 2007.

[9] N. Miyazaki, "Solid particle erosion of composite materials: A critical review," *Journal of Composite Materials*, vol. 50 (23), pp. 3175-3217, 2016.

[10] M. Pasha and M. Kaleemulla, "Taguchi approach to influence of processing parameters on erosive wear behaviour of Al7034-T6 composites," *Transactions of Nonferrous Metals Society of China*, vol. 27, pp. 2163−2171, 2017.

[11] S. C. Vettivel, N. Selvakumar, and N. Leema, "Experimental and prediction of sintered Cu–W composite by using artificial neural networks," *Materials and Design*, vol. 45, pp.323–335. 2013.

[12] L. A. Dobrzański and R. Honysz, "Application of artificial neural networks in modelling of normalised structural steels mechanical properties," *Journal of Achievements in Materials and Manufacturing Engineering*, vol. 32 :1, pp. 37-45, 2009.

[13] X. Shen, X. Wang, F. Sun, and C. Ding, "Sandblasting pretreatment for deposition of diamond films on WC-Co hard metal substrates," *Diamond & Related Materials*, vol. 73, pp. 7–14, 2017.

[14] J. A. Lee, D. P. Almond, and B. Harris, "The use of neural networks for the prediction of fatigue lives of composite materials," *Composites: Part A*, vol. 30:11, pp. 59–69, 1999.

[15] Z. Jiahua, S. Yijun, F. Xin, W. Huaiyuan, and L. Xiaohua, "Prediction on tribological properties of carbon fiber and TiO2 synergistic reinforced polytetrafluoro ethylene composites with artificial neural networks," *Materials & Design*, vol. 30, pp. 1042-9, 2009.

[16] Z. Zhang and K. Friedrich, "Artificial neural networks applied to polymer composites: a review," *Composites Science and Technology*, vol. 63, pp. 2029–2044, 2003.

[17] K. L. Rutherford, P. W. Hatto, C. Davies, and I. M Hutchings, "Abrasive wear resistance of TiN/NbN multi-layers: measurement and neural network modelling," *Surface and Coatings Technology*, vol. 86–87, pp. 472–9, 1996.

[18] S. P. Jones, R. Jansen, and R. L. Fusaro, "Preliminary investigation of neural network techniques to predict tribological properties," *Tribology Transactions*, vol. 40:2, pp. 312–20, 1997.

[19] S. A. Kalogirou, "Artificial neural networks in renewable energy systems applications: a review," *Renewable, and Sustainable Energy Reviews*, vol. 5:4, pp. 373–401, 2001.

[20] J. Musil andJ. Vlček, "Magnetron sputtering of hard nanocomposite coatings and their properties," *Surface Coating Technology*, vol. 142–144, pp. 557–566, 2001.

[21] P. Patsalas, C. Charitidis, and S. Logothetidis, "The effect of substrate temperature and biasing on the mechanical properties and structure of sputtered titanium nitride thin films," *Surface Coating Technology*, vol. 125, pp. 335–340, 2000.

[22] J. M. Guilemany, J. M. de Paco, J. Nutting, and J. R. Miguel, "Characterization of the W2C Phase Formed during the HVOF Spraying of a WC-12Co Powder," *Metallurgical, and Material Transaction A*, vol. 30, pp. 1913-1921, 1999.

[23] C. Verdon, A. Karimi, and J. L. Martin, "A Study of High Velocity Oxy- Fuel Thermally Sprayed Tungsten Carbide Based Coatings Part 1," *Microstructures, Material Science and Engineering A*, vol. 246, pp. 11-24, 1998.