A. SAGBAS, F. KAHRAMAN, U. ESME

ISSN 0543-5846
METABK 48(2) 117-120 (2009)
UDC – UDK 621:620:539.036.311.517.004=111

MODELING AND PREDICTING ABRASIVE WEAR BEHAVIOUR OF POLY OXY METHYLENES USING RESPONSE SURFACE METHODOLGY AND NEURAL NETWORKS

Received – Prispjelo: 2008-05-14
Accepted – Prihvaćeno: 2008-09-15
Preliminary Note – Prethodno priopćenje

In this study, abrasive wear behaviour of poly oxy methylenes (POM) under various testing conditions was investigated. A central composite design (CCD) was used to describe response and to estimate the parameters in the model. Response surface methodology (RSM) was adopted to obtain an empirical model of wear loss as a function of applied load and sliding distance. Also, a neural network (NN) model was developed for the prediction and testing of the results. Finally, a comparison was made between the results obtained from RSM and NN.

Key words: abrasive wear, poly oxy methylene, neural network, responce surface methodology

Primjena metode odzivnih površina i neuronskih mreža za modeliranje i procjenu otpornosti na abrazijsko trošenje poly oxy metilena. U radu je istraživano abrazijsko trošenje poly oxy metilena (POM), za različite uvjete ispitivanja. Za procjenu parametara modela i odziva, primijenjen je centralno kompozitni plan pokusa. Primjenom metode odzivnih površina dobiven je matematički model ovisnosti gubitka mase o primijenjenom opterećenju i putu klizanja. Također, primjenom neuronskih mreža, razvijen je model za procjenu i testiranje rezultata. Na kraju su uspoređeni rezultati modela, dobiveni metodom odzivnih površina i primjenom neuronskih mreža.

Ključne riječi: abrazijsko trošenje, poly oxy metilen, neuronske mreže, metoda odzivnih površina

INTRODUCTION

Abrasive wear is defined wear due to hard particles or hard protuberances forced againts and moving along a solid surface. This defination encompasses several different mechanisms by which material removal occoures. The five types of wear are abrasive, adhesive, erosion, fatigue and fretting. The abrasive wear of polymeric materials is the interest and the subject of quite number of literature. Sahin [1] carried out experiments to analyze the influence of applied load, abrasive grain size and sliding distance on weight loss of metal matrix and its composite using Taguchi method. Sahin and Ozdin [2] investigated the abrasive wear behaviour of aluminium based composites using pin on disc type of machine and developed in terms of the applied load, sliding distance and particle size using factorial design. Sahin [3] studied wear behaviour of aluminuim alloy and its composites reinforced by SiC particles using statistical analysis and he expressed in terms of applied load, sliding distance and particle size using a linear factorial design approach.

Franklin [4] focused on the wear performances of several engineering polimer based materials under dry reciprocating sliding conditions to estimate the wear. Lin and Chou [5] used to response surface method to express the wear rate parameter and reciprocal of the contact temperature as a function of sliding speed and applied load. The solution predicted by the polynomials were compared with the experimental results. Farias et al. [6] studied the sliding wear of austenitic stainless steels. They adopted to obtain an empirical model of wear rate as a function of applied load and sliding velocity using RSM. Shipway and Ngao [7] investigated the abrasive behaviour of polimeric materials in microscale level. They concluded that the behaviour rates of polymers dependent critically on the polymer type. Durmus et al. [8] used neural networks for the prediction of wear loss and surface roughness of AA 6351 aluminium alloy. Zhang et al. [9] applied an ANN model to predict the erosive wear of three polymers. Unal et al. [10] studied abrasive wear behaviour of aliphatic polyketone (APK), polyoxymethylene, ultrahigh molecular weight (UHMWPE) polyethylene, polyamide 66 (PA 66), and 30 % glass fibre reinforced polyphenylene sulfide (PPS+30 %GFR) engineering polymers at room temperature using pin on disc. Tests were at 1 m/s test speed, load value of 10 N and different sliding distances. Liu et al.[11] studied the influence of the parametres; sliding distance, contact pressure and sliding speed on the wear performance of polyamide and UHMWPE using statistical wear analysis.

A. Sagbas, F. Kahraman, U. Esme, Tarsus Technical Education Faculty, Mersin University, Tarsus, Turkey

The aim of the present work was to investigate the abrasive wear behaviour of POM (delrin) under various testing conditions. RSM was adopted to obtain an empirical model of wear loss (response) as a function of applied load and sliding distance (input factors). RSM and NN models were developed to predict abrasive wear behavior of delrin. Comparison of the RSM model with NN was made to determine the performance of the developed models.

EXPERIMENTAL PROCEDURE

The experiments were carried out to analyze the influence of testing parameters on the wear loss of test samples. For the experiments delrin material was used as the sample material. Test samples with rectangular cross section were prepared in the form 15×120×10 mm. Three replications of each factor level combinations were conducted resulting in a total of 120 tests. Wear tests were carried out on designed arrangement test apparatus by using a lathe shown in Figure 1.

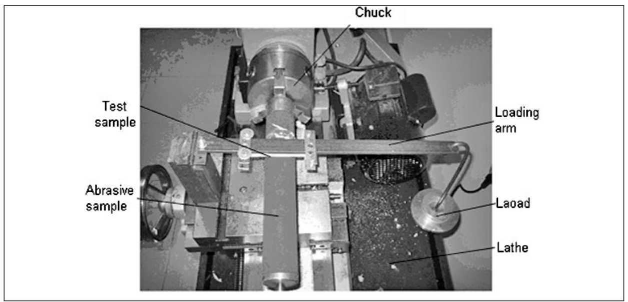

Figure 1. Abrasive wear test apparatus

AT 280 type experimental lathe set was used to evaluate the abrasive wear characteristics of test materials. Steel bar with 40 mm diameter and 400 mm length and was held in a three jaw chuck and supported by a sample in the tailstock. The abrasive SiC paper was fixed on the steel bar. Each test was performed with a new abrasive paper. Abrasive paper with 220 grit size was used for all the experiments. Test samples were placed on loading arm in the apparatus. The samples were loaded against the abrasive medium. For each sample, dry wear test was run at room temperature with normal loads from 8 to 22 N, sliding distances from 36,8 to 214,4 m. Samples were weighted by analytical scales with 0,01 g sensitiveness. After each test, the loss in mass was recorded. The wear loss was computed from the mass loss of the sample.

Design Expert software v6.0 was used for RSM, Qwiknet v2.23 software was used for NN modeling. A number of experiments based on two factor-five level CCD technique was carried out in order to collect wear loss values. RSM and NN models were developed to predict abrasive wear behavior of delrin. Also, a comparison between RSM and NN was made to determine the performance of the developed models.

PREDICTION TECHNIQUES

Response Surface Methodology

RSM is a collection of mathematical and statistical techniques that are useful for the modeling and analysis of problems in which a response of interest is influenced by several variables and objective is to optimize this response. RSM consist of a group of techniques used in the empirical study of relationships between one or more measured responses and a number of input factors It comparises: designing a set of experiments, determining a mathematical model and determining the optimal value of the response to beter understanding of the overall system behaviour [12]. The empirical relationship is freqeuntly obtained by fitting polynomial models. First and second order experiment designs are set up with the purpose of the collecting data for fitting such models. The first order polynomial model can be expressed by the general Equation 1.

$$y = \beta_0 + \sum_{j=1}^{k} \beta_j x_j + \varepsilon \qquad (1)$$

where y is response, $\beta_0, \beta_1, \ldots, \beta_k$ are the unknown regression parameters, $x_1, x_2, \ldots x_k$ are the input factors, k is the number of input factors, ε is random error.

CCD was used to describe response and to estimate the parameters in the model. This design consist of a factorial portion and axial portion and a centre point. Applied load and sliding distance were considered as model variables. The levels of model variables were shown in Table 1.

Table 1. **Experimental factors and levels for CCD**

Levels	Applied load /N	Sliding distance/m
-1,41	8	36,8
-1	10	62,8
0	15	125,6
+1	20	188,4
+1,41	22	214,4

Neural Network Modeling

In recent years, neural networks have become a very useful tool in the modeling of the input-output relationships of complicated systems. A large number of researchers reported application of NN models in predictions of wear loss. Neural networks have an excellent ability to learn and to generalize the complicated relationships between input and output variables [13]. There are several applications of neural networks such as back-propagation network (BPN) and general regression neural network (GRNN). In general, BPN seems to be the most utilized neural network. BPN is composed of many interconnected neurons that are often grouped into input, hidden and output layers. The neurons of the input layer are used to receive the input vector of the system and the neurons of the output layer are used to generate the corresponding output vector of the system.

The neuron evaluates the inputs and determines the strength of each one through its weighting factor, i.e. the larger the weight between two neurons, the stronger is the influence of the connection. The result of the summation function can be treated as an input to an activation function from the output of the neuron. The output of the neuron is transmitted along the weighted outgoing connections to serve as an input to subsequent neurons. To modify the connection weights properly, a supervised learning algorithm involving two phases is employed [14].

Modeling of the wear loss with neural networks is composed of two phases: training and testing of the neural networks with experimental wear data. The training and test data have been prepared using experimental patterns. Applied load and sliding distance have been used as input layer, while the wear loss was used as output layer. BPN used in this study is shown in Figure 2. For each input pattern, the predicted values were compared with the respective measured average values and the absolute percentage error was computed.

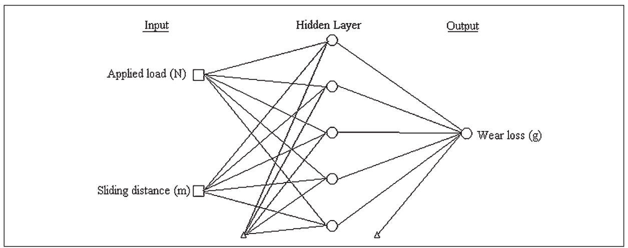

Figure 2. BPN network used for predicting wear loss

RESULTS AND DISCUSSION

Experimental levels for process variables were selected according to a CCD due to its good statistical properties such as orthogonality and rotatability. This design has 9 different design points (Table 2) for all combinations of process variables. Regression equations obtained from RSM analysis based on experiments for the wear loss of delrin can be expressed in Equation 2.

$$y = 0{,}2400 + 0{,}0502x_1 + 0{,}0489x_2 \qquad (2)$$

where x_1 and x_2 are coded variables

Regression analysis indicates that the first order regression model adequately represents wear loss in terms of process variables. Since the coefficients of the applied load and the sliding distance are positive, the weight loss increases with increasing the applied load and increasing the sliding distance. The sliding distance have a close effect on the wear loss when compared to the applied load effect. The relationship between wear loss, applied load and sliding distance shown in Figure 3.

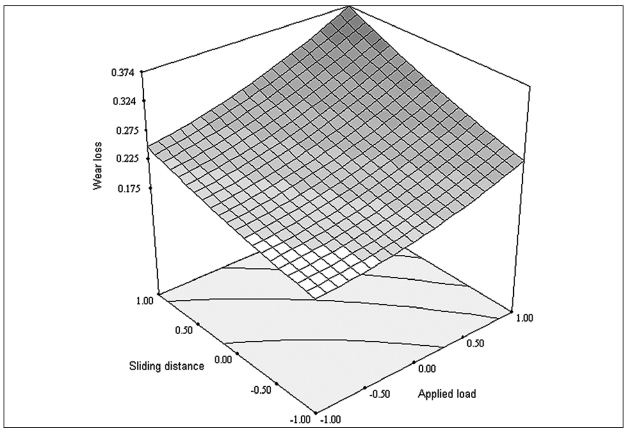

Figure 3. 3 D surface graph for wear loss

Experimental results used for training and testing the BPN model are shown in Table 2 and Table 3, respectively. Table 4 shows comparison of BPN and RSM results.

Table 2. **Experimental data for testing set**

Exp.no	Load / N	Sliding distance/ m	Wear loss/ g
32	10	62,80	0,16
33	20	62,80	0,23
34	10	188,40	0,26
35	20	188,40	0,38
36	8	125,60	0,20
37	22	125,60	0,35
38	15	36,80	0,21
39	15	214,40	0,31
40	15	125,60	0,24

According to the statistical analysis adjusted R-square value is obtained for RSM and BPN as 0,91, 0,99 respectively. BPN model was developed utilizing experimental measurements. A feed forward neural network based on BPN is a multilayered architecture made up of one or more hidden layers placed between the input and output layers.

Results show the ability of the both BPN and RSM in generalizing system characteristics by predicting values close to the actual values. In the prediction of wear loss avarege error for BPN and RSM was found to be as 3,42 % and 9,09 % respectively.

CONCLUSION

RSM and BPN can be succesfully employed to describe the abrasive wear behaviour of delrin. Linear regression equations was developed for predicting wear loss within selected experimental conditions using RSM. The wear loss of delrin increased with increasing applied load and sliding distance. The deviation from the actual value for BPN was smaller than RSM model. Results from RSM and BPN model will allow to im-

Table 3. **Experimental data for training set**

Exp.no	Load/ N	Sliding distance/ m	Wear loss/ g
1	8	62,80	0,14
2	8	99,60	0,17
3	8	188,40	0,23
4	8	277,30	0,26
5	10	99,60	0,19
6	10	125,60	0,23
7	10	277,30	0,30
8	12	62,80	0,18
9	12	99,60	0,20
10	12	125,40	0,24
11	12	188,40	0,27
12	12	277,30	0,31
13	15	62,80	0,19
14	15	188,40	0,27
15	16	62,80	0,20
16	16	99,60	0,22
17	16	125,40	0,26
18	16	188,40	0,29
19	16	277,30	0,33
20	18	62,80	0,23
21	18	99,60	0,25
22	18	125,40	0,30
23	18	188,40	0,33
24	18	277,30	0,38
25	20	99,60	0,27
26	20	125,40	0,33
27	20	277,30	0,45
28	22	62,80	0,24
29	22	99,60	0,28
30	22	188,40	0,40
31	22	277,30	0,47

Table 4. **Comparison of BPN and RSM results**

Exp. No	BPN Model		RSM Model	
	Predicted	Error	Predicted	Error
32	0,17	6,25	0,141	-11,88
33	0,24	4,35	0,241	4,78
34	0,25	-3,84	0,239	-8,08
35	0,36	-5,26	0,339	-10,79
36	0,21	5,00	0,169	-15,50
37	0,34	-2,86	0,310	-11,43
38	0,21	0,00	0,170	-19,05
39	0,30	-3,22	0,309	-0,32
40	0,24	0,00	0,240	0,00
Average error: 3,42 %	*Average error: 9,09 %*			

prove determination of the average wear loss value and to understand in a short time the behaviuor of the experimental results. Results show that, BPN is a good alternative to empirical modeling based on linear regressions.

REFERENCES

[1] Y. Sahin: Optimal Testing Parameters on the Wear Behaviour of Various Steels, Materials&Design 27(2006), 455-460.

[2] Y. Sahin, K.A.Ozdin: Model for the Abrasive Behaviour of Aluminium Based Composites, Materials&Design 29(2008), 728-733.

[3] Y. Sahin: Wear Behaviour of Alluminium Alloy and its Composites Reinforced by SiC Particles Using Statistical Analysis, Materials&Design 24 (2003), 95-103.

[4] S.E. Franklin: Wear Experiments with Selected Engineering Polymers and Polymer Composites Under Dry Reciprocating Sliding Conditions, Wear 251 (2001),1591-1598.

[5] J. F. Lin, C.C. Chou: The Response Surface Method and the Analysis of Mild Oxidational Wear, Tribology International 35 (2002),771-785.

[6] M.C.M. Farias, R.M. Souza, A.Sinatora, D.K. Tanaka: The İnfluence of Applied Load, Sliding Velocity and Martensitic Transformation on the Unlubricated Sliding Wear of Austenitic Stainless Steels, Wear 263 (2007), 773-781.

[7] P.H. Shipway, N.K Ngao: Microscale Abrasive Wear of Polymeric Materials, Wear, 255 (2003),742–750.

[8] H.K Durmus, E. Ozkaya, C Meric: The Use of Neural Network for the Prediction of Wear Loss and Surface Roughness of AA 6351 Aluminium Alloy, Materials&Design, 27 (2006), 56-159.

[9] Z. Zhang, N.M., Barkoula, J.Karger-Kocsis, K.Friedrich: Artificial Neural Network Prediction on Erosive Wear of Polymers Wear, 255 (2003), 708-713.

[10] H.Unal, U. Sen, A. Mimaroglu: Abrasive Wear Behaviour of Polimeric Materials, Materials&Design, 26 (2005),705-710.

[11] C. Liu, L. Ren, R.D. Arnell, J. Tong: Abrasive Wear Behavior of Particle Reinforced Ultrahigh Molecular Weight Polyethylene Composites, Wear 225 (1999),199–204.

[12] R.H Myers, D.C., Montgomery: Response Surface Methodology: Process and Product Optimization Using Designed Experiments, John Wiley & Sons Inc., New York 2002.

[13] S.C. Juang, Y.S. Tarng, H.R.Li: A Comparison Between the Back-Propagation Counter-Propagation Networks in The Modeling Welding Process, Journal of Materials Processing Technology, 75 (1998), 54–62.

[14] J.A. Freeman, D.M. Skapura: Neural Networks: Algorithms, Application and Programming Techniques, Wesley, New York 1991.

Note: The responsible translator for Englisch Language is A. Sagbas.