Neural network wear prediction models for the polymethylmethacrylate (PMMA)

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The aim of this work is to design and study the feasibility of neural network model that simulates the wear of PolyMethylMethAcrylate (PMMA) under different working conditions, such as sliding distance, crack angle relative to sliding direction, crack length and the contact area. Four different feed-forward Neural Network (NN) models are proposed. The first NN is trained to simulate the wear volume of PMMA due to a certain sliding distance. The second is a model of the wear volume when the contact area is included as a second parameter. The third NN is trained to simulate the wear volume and adding the crack angle as third parameter. The fourth NN considered more over the crack length as parameter. Another model of NN based on the generalized regression is developed to simulate the wear against the four previous parameters. The time needed for training both models, the accuracy and strength are compared together. Both models predict the wear volume loss with absolute mean relative error less than 0.088. However the generalized regression NN model is superior with respect to the training time. It is less than 0.001 of the time needed to train the feed-forward NN.

يهدف البحث الي تصميم واختبار شبكة عصبية كنموذج يحاكي التآكل في البوليميثيل ميثاكريليت PMMA في ظروف التشغيل المختلفة،مثل مسافة الانزلاق واتجاه الشرخ بالنسبة لإتجاه الانزلاق وطوله ومساحة التلامس. تم تصميم اربع شبكات عصبية ذات تقدم أمامي اولها دربت على محاكاة حجم التآكل كدالة من مسافة الانزلاق. اما الثانية فقد دربت لإيجاد حجم التآكل مع ادخال مساحة التلامس اضافة للأولى . أما الثالثة فقد دربت بإضافة اتجاه الشرخ كعنصر ثالث مكمل للمؤثرات السابقة. الشبكة العصبية الرابعة اضافت طول الشرخ كعنصر رابع. صمم نوع آخر من الشبكات العصبية من النوع الارتداد العام (generalized regression) تحاكي التآكل في ظروف تشغيل مختلفة من العناصر السابقة. وفي جميع الأحول تم قياس الوقت اللازم للتدريب ومقارنة النوعين من الشبكات من حيث الدقة . وقد وجد ان النموذجين يحاكيان التآكل بصورة مرضية الآ أن طريقة الارتداد العام تتفوق في سرعة تدريبها حيث يلزمها فقط ٠,٠٠١ من الوقت اللآزم لتدريب الشبكة الأمامية التقدم.

Keywords: Wear model, Neural network, Polymer, Wear prediction

1. Introduction

The analysis of tribological data is always done by applying one of two classical models; the empirical and the phenomenological-models. In the empirical model method a relation between the affecting variables are postulated a-priori [1], such as relations between wear volume, sliding distance and contact area. On the other hand, in phenomenological modeling the quantitative relations are derived from the first principals [2]. For this reason such models are preferable and reliable. However the difficulty and mathematical complications of obtaining such models for wear is a drawback. Neural network has recently a great potential in modeling tribiological material behaviors. That is because the ease of its construction and testing by MATLAB software [3] and its ability to simulate complicated nonlinear systems. Jones et al. [4] introduced a pioneering work for the prediction of the wear volume in fretting experiments using neural network.

Another work in this research field has been performed at IVW [5] on the ANN modeling and ANN prediction of wear volume of short fiber composites. As a continuation of this research Zhang et al. [6,7] developed a back-propagation neural network trained to predict the wear properties of composites. An Artificial Neural Network (ANN) approach was applied by Zhang et al. [8] as well, to the wear data of three polymers, i.e. PolyEthylene (PE), PolyURethane (PUR) and an Epoxy modified by hygrothermally decomposed PolyURethane (EP-PUR). Three independent datasets of erosive wear measurements and characteristic properties of these polymers were used to train and test the neural networks. For the first two materials, the impact angle of solid particle erosion and some characteristic properties were selected as ANN input variables. Where as the third one, material compositions, were also involved as additional ANN input variables.

In the present work, neural network models are developed to predict the wear volume of PMMA under different conditions of sliding distances, contact areas, different crack lengths and different crack angles. The networks are trained based on experimental data obtained by Helmy et al. [9], and the designed ANN models are tested with a group of data not included in the experimental work.

2. Feed-forward neural network wear volume predication model

Starting the treatment of the problem by suggesting a simple feed-forward ANN consists of 4 layers $\{35 - [5 - 2]_2 - 1\}$; the input layer has neurons of the tansigmoidal type, the two hidden layers and the output layer have purelinear neurons. This NN is trained by the group of data number 1 in table 1. This consists of 18 measured data values for wear volume V_m against sliding distance X. The applied load is 103.8 N, the contact area is 139 mm^{2}and the sliding speed S equals to 0.24 m/s. The Levenberg Marqurdit [10] training method is applied until a normalized mean squared error between the measured data and that obtained from the ANN was N_e $=6 *10^{-32}$ i.e. zero. The CPU time on Pentium IV 750 MHz computer and 256 MB RAM was 14.27 s. The NN is tested with 10 data not included in the experimental work. To measure the quality and the strength of the NN, the values for the predicted wear volume are compared with that obtained from the equation of the best line fitting of the experimental data. The resulted mean absolute relative error is 0.0264.

Fig. 1 shows the measured wear volume, the obtained wear volume from the trained NN and the predicted wear volume for test data against sliding distance.

The results of the previous NN were encouraging to introduce the contact area with the sliding distance as input parameters for prediction of wear volume. A feed-forward NN $\{50 -[1\ 5]_1 - 1\}$ is considered. The input layer neurons are tan sigmoidal, the hidden and output layers contain purelinear neurons. Only one hidden layer is used in order to compromise the CPU time needed for training. The first two groups of data in table 1 are used in the training of the suggested NN. These are 27 measured data values for two different contact areas 139mm^2 and 63.5 mm^2. The load and the sliding speed are the same as before. A minimum normalized mean squared error of N_e $=9.67*10^{-5}$ is obtained after CPU time of 2475 s. Naturally the CPU time is much longer than that of the first NN. This is due to the increase of the input parameters and the input data. Applying more than one hidden layer increases the CPU time dramatically.

The NN was tested by introducing 10 data not included in the experimental work. The predicted values were compared with that calculated from curve fitting of the experimental results. The mean relative absolute error in this case is E_m = 0 .0208. Fig. 2 shows the measured wear volume, the obtained wear volume from the trained NN and the predicted wear volume for test data against sliding distance for contact areas of 139 and 63.5 mm^2.

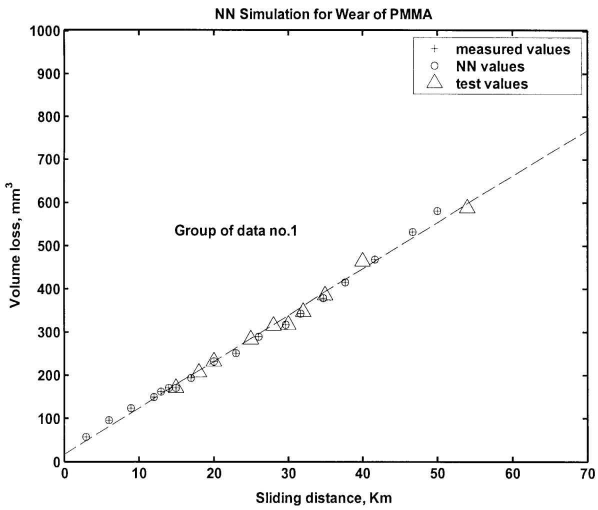

Fig. 1. ANN prediction model of wear loss volume of PMMA against the sliding distance.

Table 1
Experimental data groups for different sliding areas, crack angles and crack lengths

Data group	Area of contact mm^2	Crack angle, deg.	Crack length, mm	No. of measured values	Equation of best line fits the measured data
1	139	-	Without crack	18	V=10.7428*X+15.7246
2	63.5	0	Without crack	9	V=47.4749*X +422.073
3	63.5	Specimen rotated 90	Without crack	9	V=28.4736*X +198.095
4	63.5 +63.5	0	Infinite crack	9	V=40.0311*X-10.0567
5	63.5 +63.5	90	Infinite crack	17	V=11.1963*X+90.0383
6	127	0	6	6	V=48.7308*X+23.789
7	127	0	10	10	V=44.1326*X-29.9521
8	127	0	12	10	V=40.9669*X+32.7007
9	127	0	13	10	V=42.4247*X+34.9241
10	127	0	14	10	V=41.2052*X+21.0507
11	127	0	15	10	V=42.4284*X+4.01829
12	127	0	16	10	V=41.0773*X+43.7602
13	127	90	6	10	V=27.2539*X+13.568
14	127	90	10	16	V=23.0329*X+20.2152
15	127	90	5	17	V=14.7309*X+113.231

To include the crack angle as a third input parameter, a feed-forward NN is designed consisting of 4 layers; one input layer of sigmoidal neurons, two hidden layers with purelinear neurons and one output layer with one purelinear neuron { 50- $[8\ 5]_2$-1}. This construction is obtained after a number of trials to maintain good accuracy of the trained NN and suitable training time. The input data are the first five groups of measured data in table 1. These represent the case without crack with area 139 mm^2 and the case with and without infinite crack for crack angles of 0^o and 908 and contact area of 63.5 mm^2 and (63.5+63.5) mm^2. The minimum normalized mean squared error reached is N_e =9.07*10^{-2} in CPU time of 2926 *s*.

Testing the NN by introducing 25 data not included in the experimental work and comparing it with that calculated from equations of the best fitting lines of the experimental results. The mean relative absolute error in this case is *Em*=0.0652. Fig. 3 shows the measured wear volume, the obtained wear volume from the trained NN and the predicted wear volume for test data against sliding distance for the first five groups of measured data given in table 1.

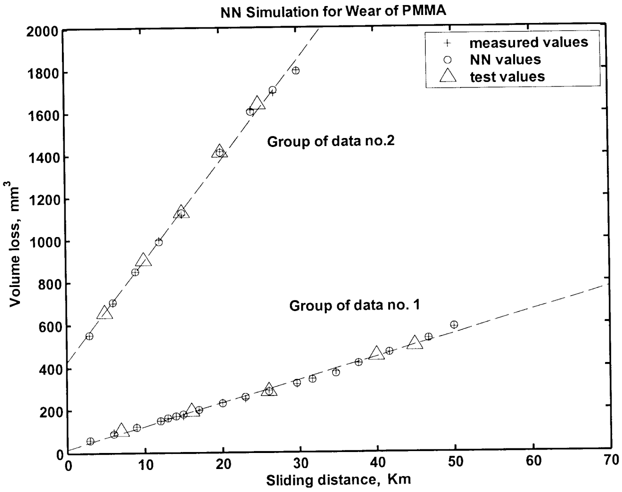

Fig. 2. ANN prediction model of wear loss volume of PMMA against sliding distance for different contact areas.

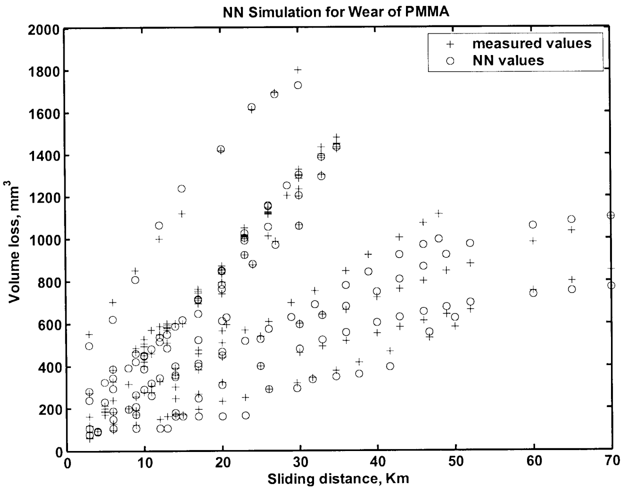

Fig. 4. ANN prediction model of wear loss volume against sliding distance for different contact areas, crack angles and crack lengths.

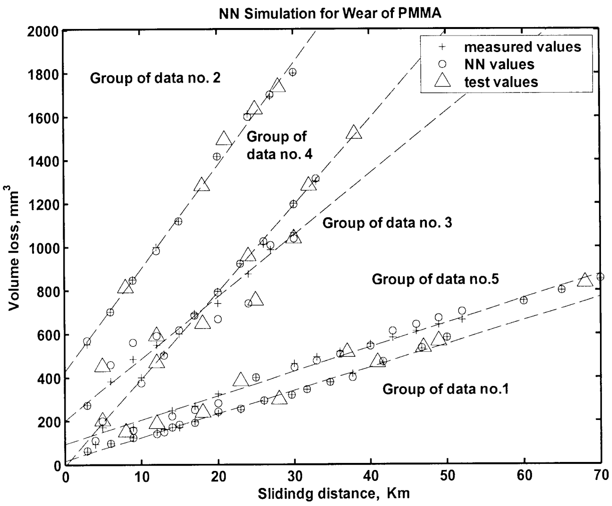

Fig. 3. ANN prediction model of wear loss volume against sliding distance for different contact areas and crack angles.

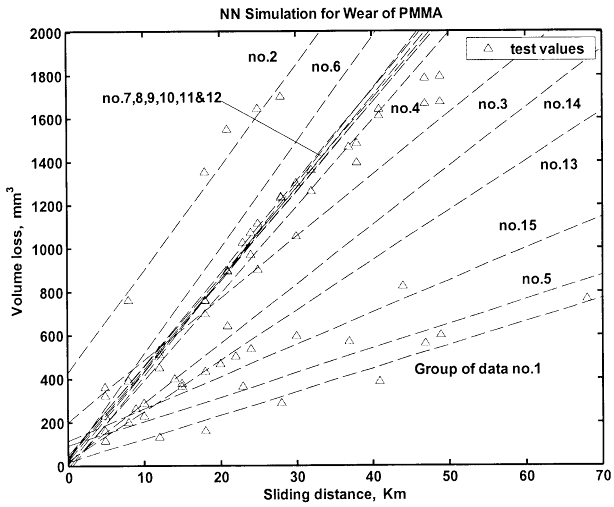

Fig. 5. Predicted volume loss for data not included in the experimental work.

An optimized feed-forward NN structure is synethesized to include all the operating conditions. It consists of 4 layers {35-[8 5]$_2$-1}. This NN is trained by all the group of data given in table 1. The data presents 171 measured values, and it is considering the sliding distance, the contact area, the crack angle and the crack length as input parameters. The training proceeded until the sum of the mean squared error is minimum; this equals to N_e =0.0038. The CPU time was 2048 seconds.

The strength of the NN is tested by 75 values that not included in the experimental work but in the same data range. The wear volume loss predicted by the NN is compared with that obtained from the equations of the best fitting of the experimental data. The mean absolute relative error is calculated as 0.088. (figs. 4,5).

Observations on the training method of Levenberg Marqurdet:

1. The training CPU time is relatively long. However the method is suitable specially for training of networks by huge number of data,

because it needs less memory in computer compared to other training techniques.
2. The minimization process is difficult, so the computer program must be allowed to execute a large number of training epochs.
3. The mean squared error function seems to have flat surfaces before a valley can be reached as shown in fig. 6 where between 20 and 300 epochs very small improvement in the objective function is obtained. The same trend is clear for the region between 300 and 500 epochs. If the training is stopped early in the region less than 300 epochs or 500 epochs, the obtained NN will not simulate the wear process accurately. So the training process must continue for a large number of epochs even it shows no considerable improvement in the objective function.

3. Generalized regression neural network wear volume predication model

A generalized regression NN [3] is designed based on two layers. The input layer has a radial basis neurons and the second layer has purelinear ones. This network is trained to respond with the measured values of the volume loss against the four operating condition parameters. The fifteen groups of measured data given in table 1 with 171 measured values for different sliding distances, contact areas, crack angles and crack lengths, are the training data. The trained NN is tested with the same values of data used in testing the feed-forward NN. These data are not included in the experimental work. It is important to notice that the training time is in the order of one second.

The accuracy of fitting the experimental data and the accuracy of predicting the test values are depending on the chosen value of the spread factor for the radial basis functions. The spread factor, is a constant that each bias in the first layer is set to 0.8326/spread. This gives radial basis function that cross 0.5 at weighted inputs of +/- spread. This determines the width of an area in the input space to which each neuron responds. A certain value of that spread factor can give minimum mean absolute relative error for the test values (values which are not included in the experimental data). It is important to notice that the test values are compared with the theoretical values obtained from the equations that realize the best fit of the experimental data (see table 1).

Fig. 7 shows the normalized sum squared error of the trained data, the mean absolute relative error of the test data and the CPU time needed for the training process against the radial basis spread factor. From fig. 7 a spread factor having a value of 2 gives a minimum value for the mean absolute relative error for the test data equals to 0.0849. The time needed for the training is 1.8 seconds and the normalized mean absolute error is 0.0004. This error increases drastically as the radial basis spread factor increases. The values obtained from the NN trained with a spread factor equals to 2 and the test values are shown in figs. 8, 9.

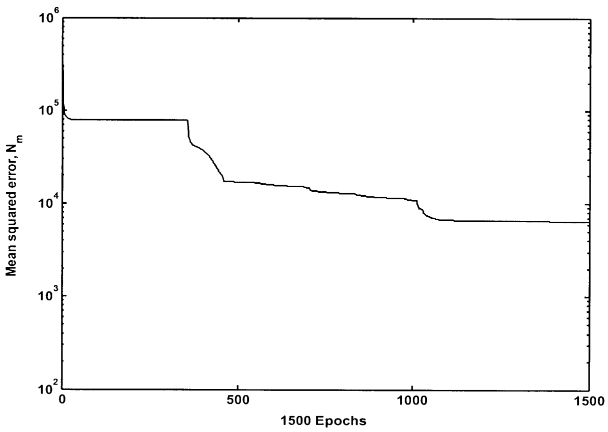

Fig. 6 Training with Levenberg Marqurdet method.

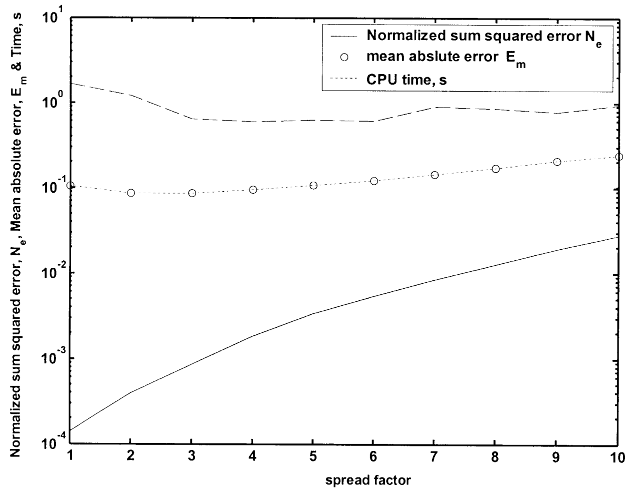

Fig. 7. Effect of spread factor on errors and CPU time.

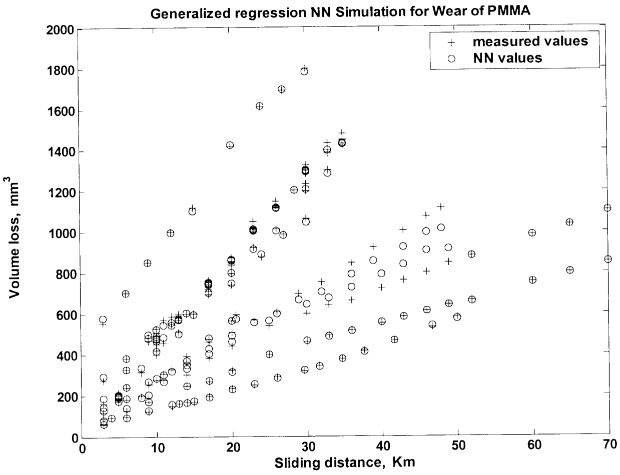

Fig. 8. Measured NN predicted wear volume loss for different sliding distances, contact areas, crack lengths and crack angles as input parameters.

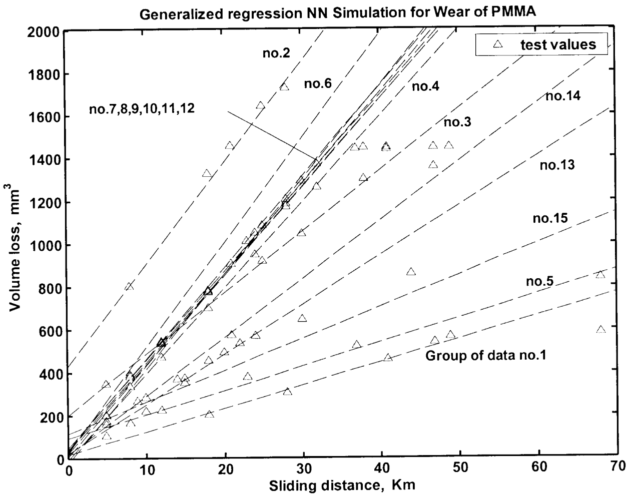

Fig. 9. NN predicted wear volume loss for test data compared with the straight lines fitting the experimental data.

4. Conclusions

This work starts with a feed-forward NN that simulates the volume wear loss of the PMMA due to different sliding distance. The NN is modified to simulate the same output for different sliding distance and contact areas, then the crack angles and crack lengths are added. The four feed-forward networks show good accuracy for the simulation. The NN strength was acceptable for data values not included in the experimental work. The experimental work is always needed to realize the data needed for training the NN. If the experimental work is chosen to be optimum and in the same time covers a wide range of working conditions, the NN trained with such data can cover large spectrum of data that are not experimentally done. This saves time and effort to obtain that data experimentally.

The generalized regression NN is superior in both training time and accuracy and may be the solution for the cases including more input parameters such as the shape of the crack tip and the condition of sliding, whether it is wet or dry.

Nomenclature

E_m Mean absolute relative error $= \frac{\sum_1^n Abs(V_{pn} - V_f)}{n\ V_f}$,

n Number of measured data,

N_m Mean squared error = $\frac{\Sigma(V_m - V_{nm})^2}{n}$,

N_e Normalized mean squared error $= \frac{\Sigma(V_m - V_{nm})^2}{\Sigma\ V_m^2}$,

S Sliding speed, m/s,

V_m Measured wear volume loss, mm^3,

V_{nm} Wear volume loss obtained from the trained neural network for a measured value V_m, mm^3,

V_{pn} Predicted wear volume loss obtained from the neural network for value not included in the experimental work, mm^3, ,

V_f Value of the volume wear loss obtained from the best fit line for the experimental data, mm^3, and

X Sliding distance, km.

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