

Research Article





Friction and wear performance of medical grade UHMWPE polymer with numerical analysis

Abstract

In this study, the tribological behavior of medical grade ultra-high molecular weight polyethylene (UHMWPE) polymer was used. A pin-on-disc wear test machine was used for the tribological tests. Medical grade UHMWPE as a polymer pin material and DIN X2 CrNiMo 17 13 2 stainless steel as a disc material were used. Friction and wear tests were done under distilled water, egg albumen and dry sliding conditions at 0.5, 1.0 and 2.0 m/s sliding speeds and under 50, 100 and 150 N applied loads. The results showed that the coefficient of friction (COF) for medical grade UHMWPE is more significantly influenced by the sliding speeds and applied loads under dry sliding condition rather than distilled water and egg albumen lubrication conditions. Furthermore, both the COF and wear rate values increased with the increment of applied load and sliding speed. For the range of applied load and sliding speed values of this study, the lower wear rate values were obtained using an egg albumen lubricant when compared to distilled water and dry sliding conditions. In this study, numerical analysis contains an artificial neural network (ANN) and linear regression respectively. In addition, both of numerical methods compared with experimental results for predicting both COF and wear rate values of medical grade UHMWPE polymer material in different sliding conditions. The developed ANN method is presented in the study. ANN results showed that the predicted data are perfectly suitable with experimental results than linear regression results.

Volume 2 Issue 2 - 2018

Kemal Ermis, Huseyin Unal

Faculty of Technology, Applied Science University, Turkey

Correspondence: Kemal Ermis, Sakarya Applied Science University, Faculty of Technology, Esentepe Kampusu, Adapazari, Turkey, Email ermes@sakarya.edu.tr

Received: October 22, 2018 | Published: November 16, 2018

Keywords: UHMWPE, polymer, friction, wear, ANN, regression

Introduction

Ultra-high molecular weight polyethylene (UHMWPE) polymer is widely used in medical applications such as orthopedic implant in recent years due to its tensile strength, bio-compatibility, low friction coefficient, long life durability, chemical resistance and wear resistance. In addition, it is also successfully used in engineering application such as bearing material applications. ^{1,2} These properties enable the material to be used in a range of high-tech industrial applications. Knee joints are the only solution for patients who are completely worn out and are commonly used in prosthetic applications. Prosthesis geometry and type of loading determine the size of prosthetic contact stresses and contact areas.3 On the other hand, the tribological performance of the prosthetic material is very important in applications where wear occurs. In such applications, there should be no abrasion or very low wear and the debris particles produced mustn't be toxic. Excessive wear on prosthetic materials causes the loosening of the prosthesis in the bone. This causes pain in the patient, makes life difficult and can reduce the quality of life.

UHMWPE polymer is very useful material for bio-material applications. It has bio-compatibility, excellent resistance to most biological solutions such as chemical resistance, high toughness and low friction coefficient.⁴ Understanding the wear and friction properties and mechanical properties of the UHMWPE polymer will be important to reduce the pain of patients suffering from joint discomfort.

ANNs have been increased to use predict for engineering applications due to finding more suitable and better.⁵ Therefore, the ANN is getting an efficient method for the prediction of the tribological behavior of medical grade polymer. There are a few studied in this

area. Sabouhi et al.6 are proposed a method for the polymer-carbon nanotube composites by using artificial neural networks (ANN) and they evaluated the mechanical and physical properties on the composites. They found that their model was a successful prediction on elastic modulus values of polymer-carbon nanotube composites in their studied range. Velten et al.7 were studied to predict wearing on polymer composites by using artificial neural networks and found the effect of the wear volume on reinforced thermoplastics having short fiber with particles. They used an ANN model and applied on wear volume results depending on the mechanical properties and the test conditions. Zhang et al.8 have predicted wear rate and COF short fibre reinforced polyamide by using measured data by using a multiplelayer feed forward neural network. They showed that the predicted data was good acceptable when comparing with the experimental values. Lada & Friedrich⁹ presented the prediction results on the polymer composites for sliding friction and wear rate. They used a pin-ondisc test machine to get data for sliding wear rate of poly-phenylene sulfide matrix composites by using artificial neural networks (ANNs). They found their model has good agreement comparing with test results. Artificial neural network analysis (ANN) is performed on the tribological behavior of medical grade, GUR 1020, medical grade UHMWPE polymer by using a feedforward with back propagation structure of neural network structure. Artificial neural networks results show good agreement comparing with real test data. A good structure with well-trained the artificial neural networks is provided to be very suitable results to get an optimum design of composite materials and particular tribological applications. Also, it can give a lead to systematic parameter studies.

There is lots of study about wear of polymer and especially medical grade polymer material. In addition, there are also a lot of studies





61

about the prediction of the tribological performance of polymers but there are a few studies about artificial neural networks (ANN) of medical grade polymer materials in the literature. In this experimental study the aim is to investigate the tribological performances of GUR 1020 commercial code UHMWPE polymer in different lubricant environments against steel disc. The wear tests were done on a pinon-disc wear machine. DIN X2 CrNiMo 17 13 2 stainless steel disc was used as a counter-face material. Tribological experiments were performed in dry media conditions, distilled water and egg albumen lubricant environments. The tribological tests were done under various loads such as 50N, 100N and 150N, and at three different speeds, such as 0.5, 1.0 and 2.0 m/s, at ambient temperature. Wear rate values were obtained for the GUR 1020 medical UHMWPE at dry conditions and different lubricated conditions such as distilled water and egg albumen. In the study, numerical analysis contains an artificial neural network ANN and linear regression respectively. In addition, both of numerical methods compared with experimental results for predicting both COF and wear rate values of medical UHMWPE polymer in different sliding conditions. The developed ANN method is presented in the study. ANN results showed that the predicted data are perfectly suitable with experimental results than linear regression results.

Experimental details

Materials

In this experimental study, medical grade UHMWPE for surgical implants according to ISO 5834 and ASTM F 648 compressed molded low calcium GUR (CHIRULEN) 1020 (Quadrant PHS, Germany), was used as the base material. The basic properties of the material, as claimed by the supplier, are listed in Table 1. The diameter and length of UHMWPE polymer pin material is 6 mm and 50 mm respectively. X2 CrNiMo 17 13 2 stainless steel disc material with DIN symbol was used as a counter-face material. Disc material was machined to 100 mm diameter and 5mm thickness. The Vickers hardness of the counter-face disc material is average HV 297. Before friction and wear testing, each pin and steel disc materials were cleaned with alcohol. Tribological test condition of the ultra-high molecular weight polyethylene thermoplastic polymer is shown in Table 2.

Table I Properties of GUR 1020 UHMWPE polymer

Properties	Unit
Tensile stress at yield (tensile strength)	>21MPa
Tensile stress at break (ultimate tensile strength)	>35MPa
Elongation at break	>300%
Tensile modulus	~720MPa
Shore-Hardness D, 15 s value	60-65
Water absorption at 23°C until saturation	<0,01%
Sterilization, Superheated steam 121/134°C	No
Sterilization, Gamma (inert atmosphere)	yes
Sterilization, Ethylene oxide	yes
Sterilization, Gas plasma	yes
Average molecular weight (average molecular mass) according to Margolie's equation	-5×10 ⁶ g/mol

Table 2 Test parameters of GUR 1020 UHMWPE polymer material

Test parameters	Values
Applied load, N	50, 100, 150
Sliding speed, m/s	0.5, 1.0, 2.0
Humidity, RH	56±2%
Ambient temperature, °C	21±2
Dropping velocity of water, drops/min	20

The tribometer and tests

Pin-on-disc sliding wear test machine was used for the sliding wear study of medical grade UHMWPE polymer. The coefficient of friction (µ) of the UHMWPE polymer was directly obtained from the equipment that records the u value by using the following formula

$$\mu = Ff / F n \tag{1}$$

In the formula, Ff is frictional force and Fn is the applied load on the sample. Generally, the wear rate is defined by the fact that the wear loss (Δm) is divided by the normal load (Fn), the sliding distance (L) and the polymer pin density (ρ). The following formula was used to estimate the wear rate (Wr) of ultra-high molecular weight polyethylene polymer samples;

$$Wr = \Delta m / FnxLx\rho \tag{2}$$

The polymer samples were cleaned by using a soft brush to remove the worn particles before and after each run of 2km sliding distance. In addition, friction surfaces of stainless steel were polished by corundum paper to obtain a surface roughness of 0.25 µm. The UHMWPE polymer pin samples and stainless steel discs were cleaned with alcohol and then installed in the pin-on-disc wear test device. The tribological tests of UHMWPE polymer material were performed at the sliding speed of 0.5, 1.0 and 2.0m/s under the applied loads of 50N, 100N and 150N for dry sliding condition and distilled water and egg albumen conditions. Friction and wear tests were carried out at room temperature Figure 1 shows a schematic diagram of the pin-ondisc wear test device. As shown in Figure 1, pin-on-disc wear device is specially designed and manufactured for tribological tests. As shown in this figure, the device consists of a table made of stainless steel which is mounted on a turntable and a variable speed electric motor which provides the unidirectional motion to the turntable, hence to the disk sample and a pin sample holder which is rigidly attached to a pivoted loading arm. This loading arm is supported in bearing arrangements to allow loads to be applied to the polymer pin sample. During the test, friction force was measured by a load cell which is mounted on the loading arm. The friction force readings on the loading arm were taken as the average of 30 readings every one second for a period of sliding wear testing time. For this, a microprocessor controlled data acquisition system was used. The wear rates of ultra-high molecular weight polyethylene polymer material were calculated from mass loss measurements of the pin material. Wear rate and COF data of the materials are obtained from the average of at least three runs.

Artificial neural network structure

Recently, the backpropagation structure is applied training feedforward networks to modeling and the method is the most suitable method for these studies. The feedforward network with backpropagation structure was developed from available different kinds of literature. 10-14 An artificial neural network modeling to the prediction of tribological data, the friction and the wear, is performed for this study. An artificial neural network is performed for processes of the learning and training structures. Developed the codes of the computer using visual C program used for solve the model network structure. The method is explained following.

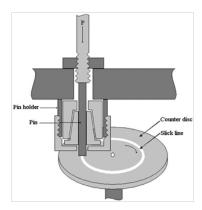


Figure 1 Schematic diagram of the friction and wear test machine.

- A. Compose a training model and advance over the network to obtain outputs
- Set the start: all weights adjust to small random and the threshold value. The training group data group sets are normalized to values between 0.1 and 0.9 for processing.
 - Net inputs to on the hidden layer's jth nodes

$$NET_{j} = \sum_{i=1}^{n} W_{ij} X_{i} - \theta_{j}$$
 (3)

 $NET_{j} = \sum_{i=1}^{n} W_{ij} X_{i} - \theta_{j} \tag{3}$ where; NET_j is the net input to hidden layer, w_{ij} is weight values connection from the ith input nodes to the jth nodes on hidden layer, x_i is the input node value, θ_i is the threshold between input layer and hidden layer. i and j are nodes on input and hidden layers.

D. The output of the jth nodes on the hidden layer:

$$V_{j} = f_{h} \left(\sum_{i=1}^{n} W_{ij} X_{i} - \theta_{j} \right)$$
 and $f_{h} \left(X \right) = \frac{1}{1 + e^{-\lambda_{h} X}}$ (4)

where; V_i is the neuron vectors on hidden layer, f_h is a logisticsigmoid activation function from input layer to hidden layer, λ_h is a variable, it controls the slope of the sigmoid function on hidden layer

The net inputs on hidden layer's kth nodes

$$NET_k = \sum_{i=1}^{n} W_{kj} X_i - \theta_k$$
 (5)

where; Net_k is the net input to hidden layer, w_{kj} is weight values connection from the jth nodes on hidden layer to the kth nodes on output layer and θ_k is the threshold between the hidden layer and output layer.

F. The output on the output layer's kth nodes

$$OUT_k = f_k \left(\sum_{j}^{n} W_{kj} X_j - \theta_k - \right) and f_k \left(X \right) \frac{1}{1 + e^{-\lambda_k X}}$$
 (6)

where; OUT_k is the neuron's output of from output layer, F_k is a logistic sigmoid activation function from hidden layer to the output layer, λ_k is a variable, it controls the slope of the sigmoid-function on the output layer.

G. Computed error values between the output and the obtained output on output layer:

$$\varphi_k = -\left(t_k - OUT_k\right) f_k^1 \text{ and } f_k^1 = OUT_k\left(1 - OUT_k\right) \tag{7}$$

where; φ_k is the vector errors from each output neurons, t_k is the

target activation of the output layer, f'_{k} is the local node's activation slope of function from output nodes.

For errors on the hidden layer

$$\varphi_{j} = f_{h}^{1} \sum_{k=1}^{n} W_{kj} \varphi_{k} \text{ and } f_{h}^{1} = V_{j} \left(1 - V_{j} \right)$$
 (8)

where; φ_j is the vector's error from every hidden neurons, φ_k is a sum of weighted the nodes, f'_h is the local node's activation function slope from hidden nodes.

H. Regulation of thresholds and weights on output layer

$$W_{kj}^{t-1} = W_{kj}^{t} + \delta \varphi_{k} V_{j} + \alpha \left(W_{kj}^{t} - W_{kj}^{t-1} \right)$$
 (9)

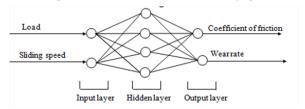
$$\theta_k^{t-1} = \theta_k^t + \delta \varphi_k \text{ and } \theta_i^{t-1} = \theta_i^t + \delta \varphi_i$$
 (10)

where; δ is the multiplier learning value, α is the multiplier momentum value and t is the time. The multiplier learning value and the multiplier momentum value are used to change the previous weights to adjust the weight values in the time cycles. These procedures repeat to obtain the errors of the output layer inside the target tolerance for each step.

The feedforward and backpropagation structure of neural network within a three-layer for the COF and wear rate are shown in Figure 2.

Figure 2 The feedforward and backpropagation artificial neural network within a three-layer schema for input and output variables.

The two input variables are the load and sliding speed. The two



output variables, the COF and the wear rate, were used at the network structure. The weights, number of nodes and biases make adjustments to minimize errors between the target values and the valid data. the configurations structure of the neural network are set by selecting the multiplier learning value, the multiplier momentum coefficient, number of hidden to obtain the least error convergences. 54 situations were created from data and then it was divided into six groups. These groups are the dry, the distilled water and the egg albumen for the COF and the specific wear. All data are separated into two groups, the first group selected randomly from a quarter of all data which were used for training of the neural network. The second group selected randomly from rest of training data of all data which were used for verifying the ANN model. Initialize of the model network are the two inputs, two outputs, and nine hidden layers. The multiplier of learning values and the multiplier momentum coefficients are 0.6 for learning processes. The processes run with 500,000 iterations to obtain well fit in the structure. Generally, more than one error measuring parameters are used for evaluation of the performance neural network.15 In this study, three error measuring parameters; mean relative error (MRE), the standard deviations in the relative (STD) errors and the absolute fraction of variance (R2) are used for evaluation of the performance various neural network.

The performances of neural network configurations were compared with experimental results using MRE, STD and R2 in Table 3 are defined respectively as follows:

Table 3 Comparison of MRE, R^2 and (STD) for the COF and the wear rate

Tribological test	Load	Sliding speeds (m/s)	Coefficient of f	riction	Wear rate	
Conditions	(N)	(*****)	Experimental results	ANN model results	Experimental results (10-6)	ANN model results (10 ⁻⁶)
	50	0.5	0.205	0.205115	4.33	4.326
Dry sliding	50	1	0.22	0.219815	6.14	6.1458
	50	2	0.23	0.230053	7.39	7.3878
	100	0.5	0.19	0.189916	3.32	3.3269
	100	1	0.2	0.200023	3.74	3.7373
	100	2	0.22	0.220078	6.28	6.2774
	150	0.5	0.18	0.179941	2.91	2.9158
	150	1	0.195	0.195127	3.32	3.3068
	150	2	0.21	0.209893	3.94	3.9479
	Mean rela	ative error, MRE (%)		4,47		1.485
	Standard	deviations in the rela	tive (STD)	0.21805		4.87562
	Absolute	fraction of variance (R ²)	0.999998		0.999969
	50	0.5	0.16	0.160057	3.52	3.5195
Distilled water	50	1	0.169	0.168929	4.05	4.0507
	50	2	0.19	0.190008	5.97	5.9698
	100	0.5	0.15	0.149924	2.78	2.7814
	100	1	0.158	0.158088	3.14	3.1386
	100	2	0.17	0.169979	4.05	4.05
	150	0.5	0.14	0.140028	2.22	2.2193
	150	1	0.153	0.152956	2.76	2.7605
	150	2	0.16	0.160004	3.45	3.4498
	Mean rela	ative error, MRE (%)		2,79		2.06
	Standard deviations in the relative (STD)			0.1709		3.76413
	Absolute fraction of variance (R ²)			0.999999		0.999999
	50	0.5	0.136	0.136156	3.83	3.83
Egg albumen	50	1	0.147	0.146866	4.56	4.5603
	50	2	0.154	0.154046	4.84	4.8399
	100	0.5	0.13	0.129738	2.14	2.1388
	100	1	0.14	0.140146	2.65	2.6506
	100	2	0.15	0.14999	3.47	3.4699
	150	0.5	0.125	0.125105	1.64	1.6422
	150	1	0.135	0.134988	2.27	2.2696
	150	2	0.145	0.144976	2.73	2.7303

Tribological test	Load	Sliding speeds (m/s)	Coefficient of friction	Wear rate	
	Mean rela	ative error, MRE (%)	7,3	2.76	
	Standard	deviations in the relat	tive (STD) 0.14872	3.31523	
	Absolute	fraction of variance (R ²) 0.999992	0.999998	

$$MRE = \frac{1}{n} \sum_{i=1}^{n} ABS(C)$$
 (11)

$$STD = \sqrt{\frac{\sum_{i=1}^{n} \left(C - \overline{C}\right)^{2}}{n-1}}$$
 (12)

$$R^{2} = 1 - \left[\frac{\sum_{i=1}^{n} (e_{i} - t_{i})^{2}}{\sum_{i=1}^{n} (t_{i})^{2}} \right]$$
 (13)

Where, B is equal to $\left(C_{pre} - C_T\right)/C_T$. The parameter C_{pre} is the predicted output from the artificial neural network model depending on input values while B_T is the target output (experimental results), e_i is the target output, t_i is the experimental result, n is the number of data values and C is the arithmetic mean of the numbers.

Results of the neural network model

The experimental results are compared with the neural network as shown in Table 3. The three error measuring parameters; MRE, STD and R² are showed that the development model is very well agreements with experimental results. The model has 4.47, 2.79 and 7.3 of the mean relative error percentage (MRE %) result in dry sliding, distilled water, and egg albumen respectively. The average MRE% is 4.853. Absolute fractions of variances are almost 1.0 at all conditions and average the standard deviation in the relative errors (STD) is 0.18589 at all conditions for the COF with comparing experimental results. For the wear rate; The ANN model has 2.102 of the average mean relative error percentage (MRE %), and absolute fractions of variances are almost 1, and the average standard deviations in the relative (STD) errors is 3.985 results dry sliding, distilled water, and egg albumen respectively. The average MRE% is 4.853 in all conditions. Absolute fractions of variances are almost 1 at all conditions and average the standard deviation in the relative errors (STD) is 0.18589 at all conditions by comparing experimental results.

Artificial neural network general gives better results with comparing the other numerical methods, So artificial neural network can use all sciences. Comparisons of the COF results of the developed neural network model with experimental data at 50 N, 100 N, and 150 N of the load various for dry sliding condition and distilled water and egg albumen conditions are shown in Figure 3–5 respectively. Comparisons of the wear rate results of the developed neural network model with experimental data at 50 N, 100 N, and 150 N of the load various for dry sliding condition and distilled water and egg albumen conditions are shown in Figure 6–8 respectively. Figures show that ANN results are good agreements with experimental data. Linear regression analyses are performed to compare with ANN results using

fraction of variance (R^2) as shown in Table 4. Average the fraction of variance for ANN results has a 0.9999 both the COF and the wear rate. Average of linear regression results have 0.9516 for the COF and 0.9526 for the wear rate results for as shown in Table 4.

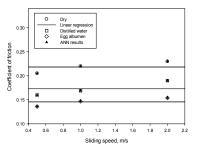


Figure 3 Comparison of the friction coefficient results of the ANN model with experimental data at 50N of the load various the sliding speeds.

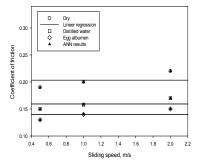


Figure 4 Comparison of the friction coefficient results of the ANN model with experimental data at 100N of the load various the sliding speeds.

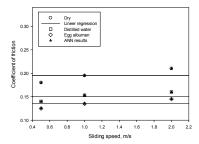


Figure 5 Comparison of the friction coefficient results of the ANN model with experimental data at 150N of the load various the sliding speeds.

Table 4 Comparison of absolute fraction of variance (R2) for ANN and linear regression results for the COF and the wear rate

Load (N)	Tribological test conditions	Coefficient of friction		Wear rate	
		Linear regression	ANN model results	Linear regression	ANN model results
50	Dry sliding	0.9097	0.9999	0.9152	0.9999
	Egg albumen	0.9024	0.9999	0.8171	0.9999
	Distilled water	0.9986	I	0.9841	1
,	Dry sliding	0.992	10,000	0.9597	0.9999
	Egg albumen	0.9642	0.9999	0.9968	1
	Distilled water	0.9943	1	0.9969	1
Dry sliding Egg albumen Distilled water	Dry sliding	0.9651	0.9999	0.9946	1
	Egg albumen	0.9632	0.9999	0.9236	0.9999
	Distilled water	0.8748	0.9999	0.9857	0.9999
	Average fraction of variance (R2)	0.9516	0.9999	0.9526	0.9999

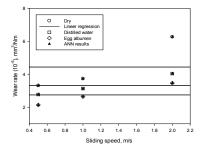


Figure 6 Comparison of the wear rate values results of the ANN model with experimental data at 50N of the load various the sliding speeds.

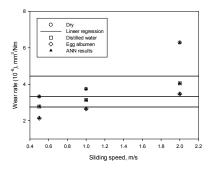


Figure 7 Comparison of the wear rate values results of the ANN model with experimental data at 100N of the load various the sliding speeds.

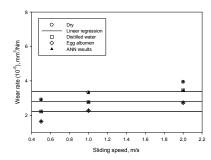


Figure 8 Comparison of the wear rate values results of the ANN model with experimental data at 150N of the load various the sliding speeds.

Conclusion

The following conclusions can be drawn from the tribological study.

- Under egg albumen conditions, the friction coefficient of medical grade UHMWPE polymer material is obtained lower than that of under the distilled water and dry lubrication conditions.
- b. The lowest wear rate is obtained 1.64x10⁻⁶mm³/Nm for ultrahigh molecular weight polyethylene polymer under the egg albumen lubricated conditions at the sliding speed of 0.5m/s and under the load of150N. In contrast, the biggest wear rate is also obtained for ultra-high molecular weight polyethylene polymer at the sliding speed of 2m/s and under the applied load of 100N and the dry sliding condition with a value of 6.280x10⁻⁶mm³/Nm.
- c. For among of lubrication media used in this experimental study, the wear rate is influenced highly by the variation of applied load and the lubrication media.
- d. Egg albumen is the most effective lubricant among the lubricants used in this experimental investigation.
- e. A feedforward and backpropagation artificial neural network structure are developed and applied for the COF and the wear rate on UHMWPE polymer.
- f. The present neural network model compares with experimental data and the artificial neural network has provided very well agreement for the COF and the wear rate with the experimental data.
- g. ANN model has 4.85% of mean relative error and 0.9999 of absolute fraction of variance (R²) for COF. Also, the model has 2.10% of mean relative error and 0.9999 of absolute fraction of variance (R²) for wear rate. The results are showed that the model is a perfectly acceptable method.

ANN model is better than linear regression with compared results.

Acknowledgements

None.

Citation: Ermis K, Unal H. Friction and wear performance of medical grade UHMWPE polymer with numerical analysis. MOJ Poly Sci. 2018;2(2):60–66. DOI: 10.15406/mojps.2018.02.00049

Conflict of interest

The authors declare there is no conflict of interest.

References

- Bartel DL, Burstein AH, Toda MD, et al. The effect of conformity and plastic thickness on contact stresses in metal-backed plastic implants. J Biomech Eng. 1985;107(3):193–199.
- Brach Del Prever EM, Bistolfi A, Bracco P, et al. UHMWPE for arthroplasty: past or future? J Orthop Traumatol. 2009;10(1):1–8.
- 3. Briscoe BJ, Sinha SK. Wear of Polymers. *J Eng Tribology Proc Inst Mech Engrs part J.* 2002;216(6):401–413.
- Chandrasekaran M, Loh NL. Effect of counter-face on the tribology of UHMWPE in presence of proteins. Wear. 2001;250(1-12):237–241.
- Lin TY, Tseng CH. Optimum design for artificial neural networks: an example in a bicycle derailleur system. Engineering Applications of Artificial Intelligence. 2000;13(1):3–14.
- 6. Sabouhi R, Ghayour H, Abdellahi M, et al. Measuring the mechanical properties of polymer–carbon nanotube composites by artificial intelligence. *International Journal of Damage Mechanics*. 2016;25(4):538–556.
- 7. Velten K, Reinicke R, Friedrich R. Wear volume prediction with artificial neural networks. *Tribology International*. 2000;33(10):731–736.

- Zhang Z, Friedrich K, Velten K. Prediction of tribological properties of short fiber composites using artificial neural networks. Wear. 2002;252(7–8):668–675.
- Lada AG, Friedrich K. Artificial neural networks for predicting sliding friction and wear properties of polyphenylene sulfide composites. *Tribology International*. 2011;44(5):603–609.
- Haykin S. Neural Networks: A Comprehensive Foundation. New Jersey, USA: Prentice Hall; 1998.
- Fausett L. Fundamentals of Neural Networks: Architecture Structures and Applications. New Jersey, USA: Prentice Hall, Englewood Cliffs; 1994
- Reed RD, Marks RJ. Neural Smithing: Supervised Learning in Feedforward Artificial Neural Networks. London: MIT Press; 1999.
- Ermis K. ANN modeling of compact heat exchangers. *International Journal of Energy Research*. 2008;32(6):581–594.
- Ermis K, Erek A, Dincer I. Heat transfer analysis of phase change process in a finned tube thermal energy storage system using artificial neural network. *International Journal of Heat and Mass Transfer*. 2007;50(15–16):3163–3175.
- Sablani SS, Kacimov A, Perret J, et al. Non-iterative estimation of heat transfer coefficients using artificial neural network models. *International Journal of Heat and Mass Transfer*. 2005;48(3-4):665–679.