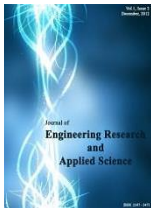
Journal of Engineering Research and Applied Science
Available at www.journaleras.com
Volume 12 (1), June 2023, pp 2255-2263
ISSN 2147-3471 © 2023



Friction and Wear Performance of the Ultra-High Molecular Weight Polyethylene Polymer with ANN Analysis

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Accepted 19 April 2023

Abstract

This study presents the friction and specific wear performance of the ultra-high molecular weight polyethylene (UHMW-PE) under conditions of dry sliding, egg albumen, and Hank's balanced salt solution with hyaluronic acid lubrication (HASS+HA). The friction and wear tests were conducted using the equipment with pins on stainless steel discs. The coefficients of friction were obtained in dry, egg albumen, and HASS+HA sliding conditions at sliding speeds of 0.5, 1.0, and 1.5 m/s under applied loads of 50, 100, and 150 N. Specific wear rates were obtained in dry, egg albumen, and HASS+HA sliding conditions at 0.4, 0.8, and 1.2 m/s sliding speeds rate under 38, 88 and 138 N applied loads. The results showed that the coefficient of friction for UHMW-PE is more significantly influenced by the sliding speeds and applied loads under dry rather than egg albumen and HASS+HA lubrication sliding conditions. Furthermore, both the coefficient of friction and specific wear rate values increased with the increment of applied load and sliding speed. For this study's applied load and sliding speed values, the lower specific wear rate was obtained using the HASS+HA lubricant, compared with the egg albumen and the dry sliding conditions. In addition, the applicability of artificial neural networks (ANN) analysis for predicting both the coefficients of friction and specific wear rate values of the material in different sliding conditions was studied. The neural network results were in agreement with the experimental results for the specific wear rate and coefficient of friction.

Keywords: *UHMW-PE, coefficients of friction, specific wear rate, ANN analysis*

1. Introduction

Due to its tensile strength, wear resistance, low friction coefficient, biocompatibility, long life durability, and chemical resistance ultra-high molecular weight polyethylene (UHMW-PE) polymer is now widely employed in medical applications and orthopedics industry such as orthopedic implants, the knee, hip, elbow, and wrist in the human body. Its numerous qualities, including reduced friction coefficient values, stronger wear resistance, chemical stability, biocompatibility, and high impact strength, enable high-quality performance [1, 2]. These characteristics make the material suitable for a variety of high-tech industrial uses. Knee joints are frequently employed in prosthetic applications and are the sole option for individuals who are utterly exhausted. The dimensions of prosthetic contact stresses and contact areas are determined by prosthesis geometry and kind of loading [3]. For applications in biomaterials, ultra-high molecular weight polyethylene polymer is a great material. It possesses great durability, good resistance to most biological solutions including chemical resistance, and a low friction coefficient in addition to being biocompatible [4]. It will be crucial to use UHMW-PE polymer to help people with joint problems feel less pain. The purpose of this experimental investigation is to examine the tribological characteristics of UHMW-PE polymer with commercial code GUR 1020 in various lubrication conditions in comparison to steel disc.

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ANNs have been used in many applications because of providing better and more reasonable solutions [5]. As a result, it is believed that ANN is an effective method for predicting the tribological behavior of UHMW-PE polymer. Few people have been researched in this field. A technique based on artificial intelligence, such as artificial neural networks (ANN) and general expression programming, is suggested by Sabouhi et al. [6] to assess the mechanical and physical characteristics of composites made of polymer and carbon nanotubes. In order to predict ionic polymer-metal composite (IMPC) bending behaviors, Zamyad et al. [7] developed a hybrid model of recurrent neural networks. They discovered that their model has acceptable accuracy and flexibility when compared to the experimental data. In a study on polymer composites, Velten et al. [8] used ANNs to forecast the wear volume of thermoplastics reinforced with short fibers and/or particles. An ANN model was given by Kurt and Oduncu [9] and used to compare the volume loss values of composite materials based on UHMW-PE. Their research has proven that the model and the outcomes of the experiments are quite consistent. An ANN was used by Abdelbary et al. [10] to research the wear mathematical model of a polyamide 66 polymer. They used the ANN's prediction of test outcomes to optimize their model. Gyurova and Friedrich [11] presented the prediction of sliding friction and wear properties of polymer composites based on a measured data set of 124 independent pin-on-disc sliding wear tests of polyphenylene sulfide (PPS) matrix composites by using artificial neural networks. During the design of fiber reinforced polymeric composites, Kazi et al. [12] used an integrated ANN to decrease the time and effort of material characterization for large numbers of samples.

This study investigated the tribological properties, the friction and wear performance, of UHMW-PE polymer under conditions of dry sliding, egg albumen, and Hank's balanced salt solution with hyaluronic acid lubrication, (HASS+HA). The coefficients of friction under applied loads of 50, 100, and 150 N were obtained in dry, egg albumen, and HASS+HA conditions at sliding speeds of 0.5, 1.0, and 1.5 m/s. Specific wear values under 38, 88, and 138 N applied loads were in dry, egg albumen, and HASS+HA conditions at 0.4, 0.8, and 1.2 m/s sliding speeds. In this study, an artificial neural network that uses a back-propagation with the feed-forward structure was used as the analysis method in polymer materials. The data from the ANN analysis was compared to the experimental data. The results of the ANN analysis were consistent with the experimental data. In addition, the ANN analysis showed more accurate predictions of the experimental data. Generally, the ANN prediction of real values is more accurate than classic linear and non-linear assumptions. The results showed that the coefficient of friction for UHMW-PE is more significantly influenced by the sliding speeds and applied loads under dry sliding conditions rather than egg albumen and HASS+HA lubrication conditions. The coefficient of friction and specific wear rate values increased as the applied load and sliding speed increased.

2. Experimental Study

In this experimental study, UHMW-PE for the tribological tests according to ISO 5834 and ASTM F 648 compressed molded low calcium GUR 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. UHMW-PE as a polymer pin material is used as the material for the cylindrical pins, each with a 6 mm diameter and a length of 50 mm, and the counter-face material was used DIN X2 CrNiMo 17 13 2 stainless steel as a disc material. The basic properties of the material, as claimed by the supplier, are listed in Table 1.

Disc material was machined to 100 mm diameter and 5 mm thickness. The Vickers hardness (HV) 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 ultra-high molecular weight polyethylene polymer is shown in Table 2.

Table 1. Properties of UHMW-PE (GUR 1020) 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	~5x10^{6}g/mol

Table 2. Test parameters of UHMW-PE (GUR 1020) polymer

Test parameters		Values
Applied load, N	Coefficient of friction	50, 100, 150
	Specific wear rate	38, 88, 138
Sliding speed, m/s	Coefficient of friction	0.5, 1.0, 1.5
	Specific wear rate	0.4, 0.8, 1.2
Humidity, RH		56±2%
Ambient temperature, °C		20±2
Dropping velocity of water, drops/min		20

2.1. Tests and the Tribometer

Pin-on-disc **(**POD) was used on a wear test machine to examine the sliding wear of the UHMW-PE polymer. The coefficient of friction (μ) of the UHMW-PE polymer was directly obtained from the equipment that records the μ value by using the following formula.

$$\mu = \frac{F_s}{F_n} \tag{1}$$

where F_n is the applied load, F_s is the frictional force on the polymer pin material. Generally, the specific 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 specific wear rate (Wr) of ultra-high molecular weight polyethylene polymer samples.

$$W_r = \frac{\Delta m}{\rho\, F_n\, L} \tag{2}$$

The worn particles were removed from the polymer samples by the completion of 2 km of sliding distance corresponding to the number of turns before and after each run. The coefficient of friction tests of UHMW-PE polymer material were performed at the sliding speed of 0.5, 1.0, and 1.5 m/s under the applied loads of 50, 100, and 150 N for dry, egg albumen, and HASS+HA conditions. The wear tests of UHMW-PE polymer material were performed at the sliding speed of 0.4, 0.8, and 1.2 m/s under the applied loads of 38, 88, and 138 N for dry, egg albumen, and HASS+HA conditions. Friction and wear tests were carried out at room temperature. Figure 1 shows a schematic diagram of the pin-on-disc wear test device. As shown in Figure 1, the pin-on-disc wear device is specially designed and manufactured for tribological tests.

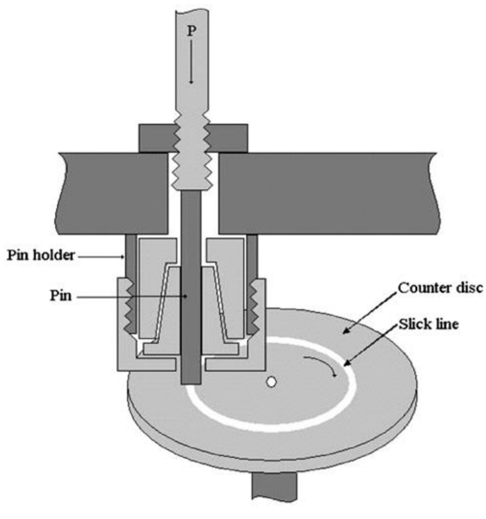

Figure 1. Schematic diagram of the friction and wear test device

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 as shown in Figure 1. To enable loads to be supplied to the polymer pin sample, this loading arm is supported by bearing arrangements. A load cell positioned on the loading arm measured the friction force during the test. For a period of sliding wear testing time, the friction force readings on the loading arm were calculated as the average of 30 measurements recorded every one second. A data acquisition system controlled by a microprocessor was employed for this. Mass loss measurements of the pin material were used to calculate the wear rates of ultra-high molecular weight polyethylene polymer material. Data on the materials' specific wear rate and coefficient of friction are derived from the average of at least three runs.

3. Artificial Neural Network(ANN) Analysis

A well-trained ANN can be used to create an optimal material design for UHMW-PE polymer applications. The back-propagation algorithm that is the focus of recent studies on modeling is the most suitable method for training multi-layer feed-forward networks. The algorithm for training a back-propagation network was developed based on different kinds of literature [13–15] by Ermis [16–18]. In this study, an ANN model for the prediction of tribological data, the coefficient of friction and the specific wear, is performed. A feed-forward back-propagation ANN approach is used for the training and learning processes. A computer code in the C^{++} programming language is developed to solve the ANN model algorithm and summarized as follows:

1. Present a training pattern and propagate it through the network to obtain the outputs

2. Initialization: Initialize all weights to small random values and threshold values: set all weights and threshold to small random values. Usually, the training sets are normalized to values between –0.9 and 0.9 during processing.

3. The net input to the j^{th} node in the hidden layer

$$net_j = \sum_{i=1}^{n} w_{ij} x_i - \theta_j \tag{3}$$

where; i is the input node, j is hidden layer node, x is the input, w_{ij} weights value connection from the i^{th} input node to the j^{th} hidden layer node and θ_j is the threshold between the input and hidden layers.

4. The output of the j^{th} node in the hidden layer:

$$h_j = f_h\left(\sum_{i=1}^{n} w_{ij} x_i - \theta_j\right) \quad and \quad f_h\,(x) = \frac{1}{1+e^{-\lambda_h x}} \tag{4}$$

where h_j is the vector of hidden-layer neurons, $f_{h()}$ is a logistic sigmoid activation function from the input layer to the hidden layer, and λ_h is the variable that controls the slope of the sigmoidal function.

5. The net input to the kth node in the hidden layer

$$net_k = \sum_{j} w_{kj} x_j - \theta_k \tag{5}$$

where k represents the output layer, w_{kj} is the weights connection from the j^{th} hidden layer node to the k^{th} output layer and θ_k is the threshold connecting the hidden and output layers.

6. The output of the kth node in the output layer:

$$y_k = f_k\left(\sum_{j} w_{kj} x_j - \theta_k\right) \quad and \quad f_k\,(x) = \frac{1}{1+e^{-\lambda_k x}} \tag{6}$$

where y_k is the output of output-layer neurons, $f_{k()}$ is a logistic sigmoid activation function from the hidden layer to the output layer, and λ_k is variable that controls the slope of the sigmoid functional.

7. Compute errors:

The output layer error between the target and the observed output:

$$\delta_k = -\left(d_k - y_k\right) f'_k \;\; and \;\; f'_k = y_k (1 - y_k) \tag{7}$$

where δ_k is the vector of errors for each output neuron and d_k is the target activation of the output layer. δk depends only on the error (d_k-y_k) and f'_k is the local slope of the node activation function for output nodes.

The hidden layer error:

$$\delta_j = f'_h \sum_{k=1}^{n} w_{kj} \delta_k \quad and \quad f'_h = h_j (1 - h_j) \tag{8}$$

where δ_j is the vector of errors for each hidden layer neuron. δ_k is a weighted sum of all nodes and f'_h is the local slope of the node activation function for hidden nodes.

8. Adjust the weights and thresholds in the output layer:

$$w_{kj}^{(t+1)} = w_{kj}^{(t)} + \alpha\delta_k h_j + \eta\left(w_{kj}^{(t)} - w_{kj}^{(t-1)}\right) \quad (9)$$

$$\theta_k^{(t+1)} = \theta_k^{(t)} + \alpha\delta_k \quad and \quad \theta_j^{(t+1)} = \theta_j^{(t)} + \alpha\delta_j \quad (10)$$

where α is the learning rate, η is the momentum factor and t is the time period. The learning rate and the momentum factor used to allow the previous weight change to influence the weight change in this time period, t. These calculation steps repeat until the output layer error is within the desired tolerance for each pattern and neuron.
The neural network has back-propagation, feed-forward, three-layer configuration that it use in friction coefficient and specific wear rate estimation as shown in Figure 2.

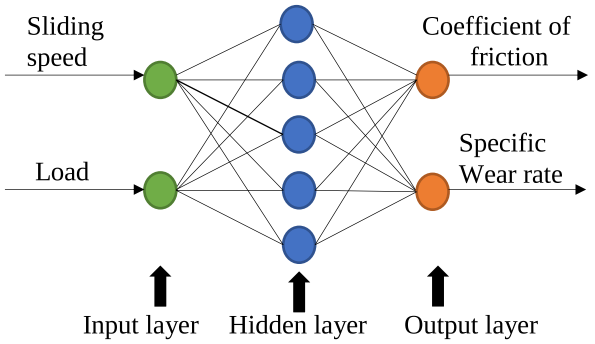

Figure 2. A three-layer feed-forward back-propagation neural network for the coefficient of friction and specific wear rate.

The two input parameters, the applied loads and sliding speeds, and the two output terms, the coefficient of friction and the specific wear rate, were used in the network structure. The weights, biases, and hidden node numbers are altered to minimize the error between the output values and the current data. In order to obtain the least error convergence, the configurations of the ANN are set by selecting the number of hidden layers, nodes, the learning rate, and the momentum coefficient. 54 cases were formed out of data and further grouped into 6 data sets, the dry, the egg albumen, and HASS+HA for the coefficient of friction and the specific wear. All data are separated into 2 groups, the first group consists of 6 sets of selected data randomly which were used to the train network (25% of all data) and the second group consists of 6 cases that are used to verify the ANN model. The ANN model is utilized by using 2 of inputs, two outputs, and five hidden layers. In the algorithm, the learning rates and momentum coefficients are 0.6 for learning processes, in which 350,000 iterations are used to obtain good fits.
The layered structure of the ANN model for the specific wear rate and the coefficient of friction are shown in Figure 3.

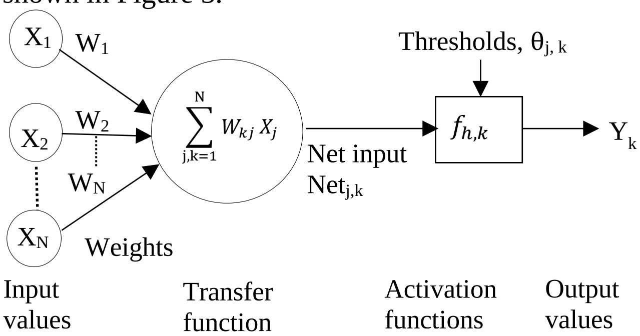

Figure 3. The ANN model's layered structure for the specific wear rate and the coefficient of friction.

The three error measurement metrics are used to compare the performance of different ANN designs in terms of consistency [19]. Three parameters were used for the performances of the ANN configuration. These parameters were the mean relative error percentage (MRE %), the relative standard deviations of error (STD), and the absolute fraction variance of error (R^2). Their formulations are defined as follows

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

$$\mathrm{STD} = \sqrt{\frac{\sum_{i=1}^{n}\left(A-\bar{A}\right)^2}{n-1}} \quad (12)$$

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

where A = (P-D)/D. P and D Parameters are the experimental data and the estimated output from the modeled ANN respectively. The arithmetic mean of the numbers is $\bar{A}$, whereas the estimated output value is y_i, the experimental data is a_i, and the data number is n.

4. Results and Discussion

The results show that with the increase of applied load, both the coefficient of friction and the specific wear rate values decrease under all lubrication conditions for the UHMW-PE polymer. This study investigated the applicability of artificial neural networks (ANN) for predicting both specific wear rate values and coefficients of friction of medical-grade UHMW-PE polymer in different sliding conditions. The results show that the data predicted by the ANN analysis is consistent with the experimental test results. Comparison of the mean relative error percentage (MRE %), the absolute fraction variance of error (R^2), and the relative standard deviations of error (STD) for the coefficient of friction and the specific wear rate are shown in Table 2 and Table 3, respectively.

Table 3. Comparison of MRE, R^2, and STD for the coefficient of friction

Test Condition	Coefficient of friction			
	Load (N)	Sliding speeds (m/s)	Experimental results	ANN model results
Dry sliding	50	0.5	0.2050	0.2053
	50	1.0	0.2200	0.2201
	50	1.5	0.2300	0.2295
	100	0.5	0.1900	0.1907
	100	1.0	0.2000	0.1985
	100	1.5	0.2100	0.2107
	150	0.5	0.1800	0.1799
	150	1.0	0.1950	0.1975
	150	1.5	0.2050	0.2056
The mean relative error, MRE (%)				1.0209
The relative standard deviations of error, (STD)				0.2237
The absolute fraction variance of error (R^2)				0.9974
Egg albumen	50	0.5	0.1360	0.1362
	50	1.0	0.1470	0.1469
	50	1.5	0.1540	0.1540
	100	0.5	0.1300	0.1297
	100	1.0	0.1400	0.1401
	100	1.5	0.1500	0.1500
	150	0.5	0.1250	0.1251
	150	1.0	0.1350	0.1350
	150	1.5	0.1450	0.1450
Mean relative error, MRE (%)				0.0731
The relative standard deviations of error,(STD)				0.1488
The absolute fraction variance of error (R^2)				1.0000
HBSS+HA Hank's balanced salt solution with hyaluronic acid lubrication	50	0.5	0.1059	0.1058
	50	1.0	0.1150	0.1149
	50	1.5	0.1250	0.1249
	100	0.5	0.1025	0.1024
	100	1.0	0.1090	0.1089
	100	1.5	0.1160	0.1159
	150	0.5	0.0990	0.0989
	150	1.0	0.1080	0.1079
	150	1.5	0.1120	0.1119
Mean relative error, MRE (%)				0.0092
The relative standard deviations of error, (STD)				0.1178
The absolute fraction variance of error, (R^2)				0.9999

The ANN model has 1.0209, 0.0731and 0.0731 of the mean relative error percentage results (MRE %) in dry, egg albumen, and HASS+HA respectively as shown in Table 2. For the coefficient of friction, the ANN model has 0.3677% of the average mean relative error and 0.9991 of the average mean absolute fraction of variance (R2) for all conditions. The average absolute fractions of variances are almost 1.0 at all conditions.

The ANN model has 0.0059, 0.0026, and 0.0285 of the mean relative error percentage result (MRE %) in dry, egg albumen, and HASS+HA respectively as shown in Table 3. For the specific wear rate, the model has 0.0123% of average mean relative error and 1.0 of the absolute fraction of variance (R2) for all conditions as shown in Table 4. The average absolute fractions of variances are almost 1.0 at all conditions for the specific wear rate as shown in Table 4. These results show very good agreement with experimental results.

Table 4. Comparison of MRE, R^2, and STD for the specific wear rate

Test Condition	Specific wear rate			
	Load (N)	Sliding speeds (m/s)	Experimental results, (10^{-6})	ANN Model results (10^{-6})
Dry sliding	38	0.4	4.2000	4.1997
	38	0.8	5.9000	5.9001
	38	1.2	7.0000	7.0000
	88	0.4	3.2000	3.2006
	88	0.8	3.6000	3.5996
	88	1.2	6.0000	5.9999
	138	0.4	2.8000	2.8000
	138	0.8	3.1000	3.0998
	138	1.2	3.8000	3.8001
The mean relative error, MRE (%)				0.0059
The relative standard deviations of error, (STD)				4.6669
The absolute fraction variance of error (R^2)				1.0000
Egg albumen	38	0.4	3.7000	3.7001
	38	0.8	4.6000	4.5998
	38	1.2	5.1000	5.1004
	88	0.4	2.0000	1.9996
	88	0.8	2.8000	2.8003
	88	1.2	3.6000	3.5998

	138	0.4	1.7000	1.7009
	138	0.8	2.3000	2.2993
	138	1.2	2.6000	2.6002
Mean relative error, MRE (%)				0.0026
The relative standard deviations of error (STD)				3.3470
The absolute fraction variance of error (R^2)				1.0000
HBSS+HA Hank's balanced salt solution with hyaluronic acid	38	0.4	2.8000	2.8003
	38	0.8	3.5000	3.4993
	38	1.2	3.7000	3.7012
	88	0.4	2.4000	2.3998
	88	0.8	2.7000	2.7010
	88	1.2	2.8000	2.7991
	138	0.4	1.3000	1.3006
	138	0.8	2.0000	1.9993
	138	1.2	2.3000	2.3008
Mean relative error, MRE (%)				0.0285
The relative standard deviations of error (STD)				2.7696
The absolute fraction variance of error (R^2)				0,9999

Comparisons of the frictional coefficient results of the ANN model with experimental data at 50 N, 100 N, and 150 N of the load various sliding speeds under dry sliding, distilled water, and egg albumen conditions are shown in Figures 4, 5, and 6 respectively. The coefficient of friction and specific wear rates of medical-grade UHMW-PE polymer under the HBSS+HA lubricated condition was lower than the dry and egg albumen sliding conditions. Figures show that ANN results are good agreements with experimental data.

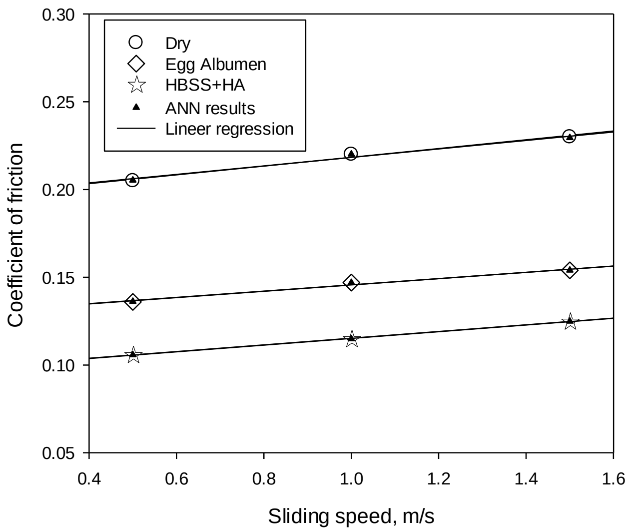

Figure 4. Comparison of the coefficient of friction between the experimental data and the ANN model at 50N of applied load under various sliding speeds.

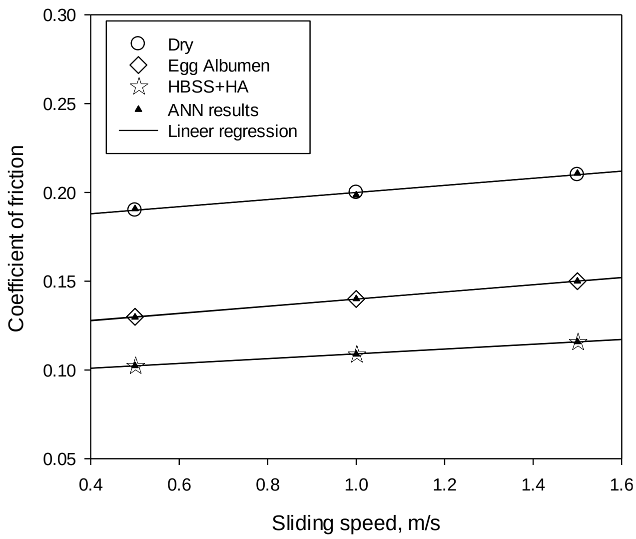

Figure 5. Comparison of the coefficient of friction between the experimental data and the ANN model at 100N of applied load under various sliding speeds.

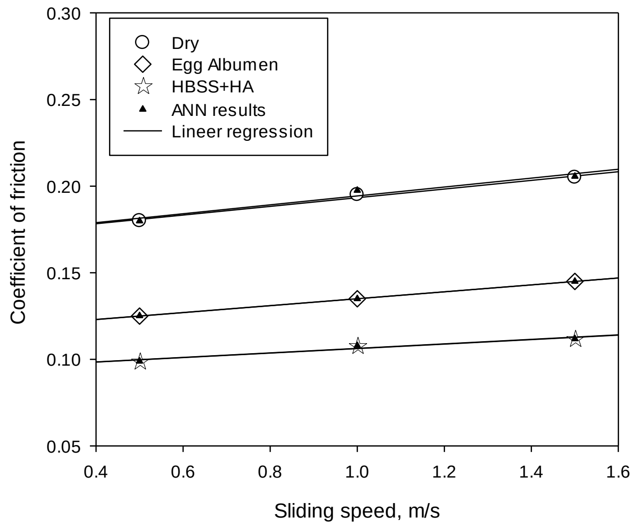

Figure 6. Comparison of the coefficient of friction between the experimental data and the ANN model at 150N of applied load under various sliding speeds.

Comparisons of the specific wear rate results of the ANN model with experimental data at 38 N, 88 N, and 138 N of the load various sliding speeds under dry, egg albumen, and HASS+HA conditions are shown in Figures 7, 8, and 9 respectively. The specific wear rate value and coefficient of friction were greater under the dry sliding condition than the egg albumen and HBSS+HA lubrication conditions over the range of speed and load values evaluated, as shown in Figures 7, 8, and 9.

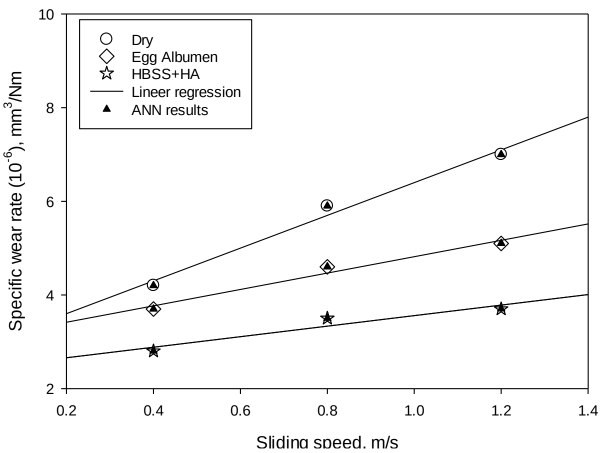

Figure 7. Comparison of the specific wear rate values between the experimental data and the ANN model estimated at 38N of applied load under various sliding.

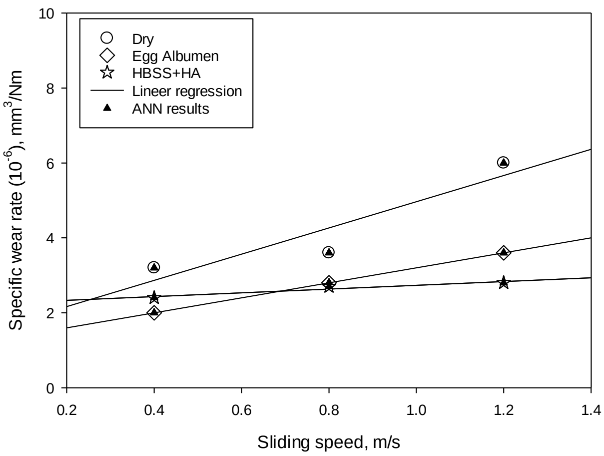

Figure 8. Comparison of the specific wear rate values between the experimental data and the ANN model estimated at 88N of applied load under various sliding speeds.

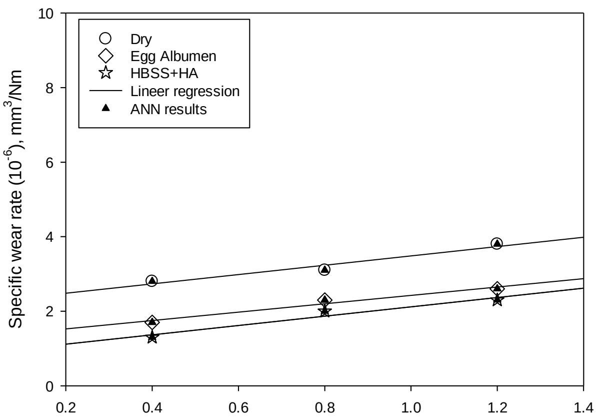

Figure 9. Comparison of the specific wear rate values between the experimental data and the ANN model estimated at 138N of applied load under various sliding speeds.

5. Conclusions

The following are the conclusions of this study;

- The coefficient of friction and specific wear rates of medical-grade UHMW-PE polymer under the HBSS+HA lubricated condition was lower than the dry and egg albumen sliding conditions.
- The lowest specific wear rate was obtained $1.3x10^{-6}$ mm^3/Nm under the HBSS+HA lubricated condition at 0.4 m/s sliding speed and 138 N load. In contrast, the highest specific wear rate was $7x10^{-6}$ mm^3/Nm for the UHMW-PE polymer at 1.2 m/s sliding speed and 38 N of load under the dry condition as shown in Table 4.
- For among of lubrication media used in this experimental study, the specific wear rate is influenced highly by the variation of applied load and the lubrication media. This tribological study is used for the three lubricant conditions, HBSS+HA was a more effective lubricant than dry and egg albumen sliding conditions.
- In this paper, we have suggested an artificial neural network (ANN) algorithm, which has feed-forward and backpropagation, to predict the specific wear rate and the coefficient of friction.
- The estimates for the specific wear rate values and the coefficient of friction by the ANN model were consistent with the experimental data.
- The present ANN model through comparisons with experimental data and find out that the ANN model has provided a better agreement for the coefficient of friction and the specific wear rate with the experimental data.
- For the coefficient of friction, the ANN model has 0.3677% of the average mean relative error and 0.9991 of average mean the absolute fraction of variance (R^2) for all conditions. In addition, the model has 0.0123% of average mean relative error and 1.0 of the absolute fraction of variance (R^2) for all conditions for specific wear rates. The obtained results show that the use of the ANN for predicting the coefficient of friction and specific wear rate is a perfectly acceptable method.

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