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Tribological Behavior of Ultra-High Molecular Weight Polyethylene Polymer with Artificial Neural Network Modeling

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Abstract

This study presents the tribological properties, wear and friction, of ultra-high molecular weight polyethylene under conditions of dry sliding and Hank's balanced salt solution lubrication. A pin-on-stainless steel disc apparatus was used for the friction and wear tests. Applied load conditions were 38, 50, 88, 100, 138, and 150N. Sliding speed conditions were 0.4, 0.5, 0.8, 1.0, 1.2 and 1.5 m/s. The results show that the coefficient of friction and the wear rate values decrease with the increase of applied load. The coefficient of friction and the wear rate values were highest under the dry sliding condition for the ranges of the sliding speed values and the applied loads tested in the study. In addition, the applicability of artificial neural networks (ANN) for predicting both the coefficients of friction and 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 wear rates and coefficients of friction.

1. Introduction

Ultra-high molecular weight polyethylene (UHMW-PE) polymer is used regularly in the orthopedics industry due to its superior wear and friction properties. It has many properties that allow for quality performance, like a lower friction coefficient value, higher wear resistance, chemical stability, and biocompatibility, and high impact strength [1–3] Because of these properties, UHMW-PE polymer is used in the industrial sector as well as in orthopedics. As the human body is highly sensitive, the properties of any biomaterials used in the various parts of the human body should be such that they do not disturb the various functions of the human body. One material with the properties needed to be used in the human body is UHMW-PE. The UHMW-PE polymer is used in orthopedic applications involving the knee, hip, elbow, and wrist in the human body. Generally, knee operations involving prosthesis technology are performed when the patient's joints have deteriorated. The prosthesis geometries and the types of forces acting on it determine the contacted area in the prosthetic component, the size of the contact stresses, and working conditions [4].

A good understanding of the factors affecting prosthesis use is important to reduce patients' pain and to extend the life of the joint replacement components.

The use of artificial neural networks (ANN) has been increasing in many applications to develop better and more reasonable solutions [5]. Therefore, an ANN can be used as an effective method for the prediction of the tribological behavior of medical-grade polymers. In the literature, there are a few ANN investigations on the tribological properties of polymer materials. Zamyad et al. [6] presented a hybrid model of recurrent neural networks for predicting ionic polymer-metal composite (IMPC) bending behaviors and found that their model has acceptable accuracy and flexibility when compared to the experimental data. Kurt and Oduncu [7] presented an ANN model, which was used to compare the volume loss values of UHMW-PE based composite materials. Their study has shown good

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consistency between their model and experimental results. Velten et al. [8] studied the prediction of the wear volume of fiber-reinforced polymeric bearing materials by an ANN prediction model. They used an ANN structure that has two inputs and one output; mechanical properties and test conditions being the inputs, and wear volume being the output. Abdelbary et al. [9] studied the wear mathematical model of a polyamide 66 polymer using an ANN. They optimized their model using the ANN's prediction of test results. They found good accuracy results when comparing the simulation results to the experimental test data. Rajesh et al. [10] provided an ANN model of surface roughness during the machining of Multiwall Carbon Nanotube (MWCNT) nanocomposites, demonstrating that an ANN is a dependable tool for predicting and simulating machining response. Sabouhi et al. [11] proposed a method that uses an artificial intelligence model in combination with generic expression programming to evaluate the mechanical and physical behaviors of carbon/polymer nanotube composites. They showed that their model was used to predict satisfactory results for the elastic modulus values of the polymer-carbon nanotube composites in their studied ranges. Zhang et al. [12] predicted the coefficient of friction and the wear rates for polyamide 4.6 (PA 4.6) composites with reinforced glass fiber on a measured database using a feed-forward artificial neural network (ANN) model. According to their results, the predicted values had acceptable accuracy when compared to experimental test values. Khan et al. [13] used an ANN to model the mechanical behavior of cross-ply laminated fiber-reinforced polymer composites (FRPCs), demonstrating that an ANN is a reliable tool for predicting composite mechanical behavior. The study by Lada and Friedrich [14] predicted the wear performance and friction properties of polymer composites based on their obtained data, collected from 124 independent the pin-on-disc (POD) wear tests of polyphenylene sulfide (PPS) composites, by using artificial neural networks (ANNs) and they found their ANN model profiles were consistent with their experimental data for the characteristic tribological properties. Kazi et al. [15] employed an integrated ANN to reduce the time and effort of material characterization for large numbers of samples during the design of fiber-reinforced polymeric composites. Pajchrowski et al. [16] applied an ANN taught by reinforcement learning on an adaptive controller design for electric drive. ANN studies can be used on the tribological performance of polymer materials which have limited studies in the literature.

In this study, an artificial neural network that uses a back-propagation with feed-forward structure was used as the numerical analysis method except for when conducting traditional linear and non-linear analysis in polymer materials. This study will provide a new approach in the field of tribology, especially with regard to medical applications. This study investigated the tribological properties of medical-grade UHMW-PE polymer in different working conditions, namely dry sliding and Hank's balanced salt solution conditions. Tribological experiments were performed at 38, 50, 88, 100, 138 and 150N of applied load and 0.4, 0.5, 0.8, 1.0, 1.2 and 1.5 m/s of sliding speed. The coefficient of friction values and specific wear rate on the UHMW-PE material under these conditions were determined. The data from the ANN analysis was compared to the experimental data. At the end of the study, 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 than linear regression. Generally, the ANN prediction of real values is more accurate than classic linear and non-linear assumptions.

2. Experimental Study

2.1. Materials

In this study, a UHMW-PE polymer, classified as medical-grade for surgical implants according to ISO 5834 and ASTM F 648 compressed molded low calcium CHIRULEN 1020 (Quadrant PHS, Germany), was used as the base polymer material. The UHMW-PE polymer was also used as the material for the cylindrical pins, each with a 3 mm radius and a length of 50 mm. The counter-face material was used AISI 304L stainless steel which was machined to a radius of 5 cm and thickness of 0.5 cm. The Vickers hardness of the counter-face disc material had an average HV 297.

Before testing, each stainless-steel disc was cleaned with acetone. Table 1 lists the test parameters for the medical-grade UHMW-PE polymer material.

Table 1. Test parameters of medical-grade UHMW-PE polymer material.

Ambient temperature, ºC	21±2
Applied load, N	38, 50, 88, 100, 138, 150
Sliding speed, m/s	0.4, 0.5, 0.8, 1, 1.2, 1.5
Dropping velocity of water	20 drops/min
Humidity, RH	58±2%

2.2. The Tribometer and Tests

To test the sliding wear of the medical-grade UHMW-PE polymer, POD was performed using a wear test machine. The μ value (coefficient of friction) of the UHMW-PE polymer was calculated from the POD machine by using Eq. (1). The normalized wear volume divided by the sliding distance and the applied load is usually how the specific wear rate is determined. Eq. (2) was used to evaluate estimates of the specific wear rate, W_{sp}, of UHMW-PE polymer samples.

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

$$W_{sp} = \frac{V_{sp}}{F_n L} \tag{2}$$

where; F_n is applied load, F_s is frictional force on the polymer pin material, L is the sliding distance, V_{sp} (mass/density) is volume loss.

The mass and volume losses were obtained from each experimental measurement for different conditions and all samples.

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. In addition, stainless steel surfaces were polished to obtain a surface roughness of 0.25 μm by corundum paper for the friction tests. Before the steel discs and the flat-ended polymer pins were installed in the pin-on-disc wear test apparatus, they were cleaned using alcohol and acetone. For both the dry sliding and HBSS (Hank's balanced salt solution) conditions, the coefficient of friction and wear rate tests were performed at sliding speeds ranging between 0.4 to 1.5 m/s and applied loads ranging between 38N to 188N at a temperature of atmospheric ambient. A schematic drawing of the experimental apparatus for the wear test is given in Figure 1.

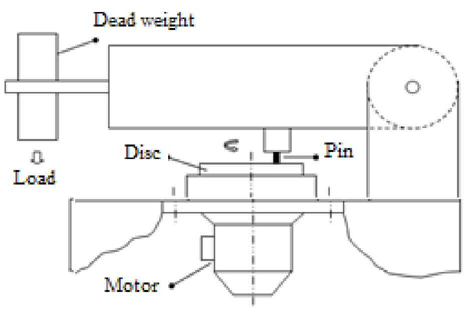

Figure 1. A schematic drawing of the experimental apparatus for the wear test.

The wear test apparatus included a pin sample holder and a variable speed, the variable-speed motor delivers unidirectional motion to the turntable, and thus to the disk sample. To apply forces to the sample in the pin-on-disc, the pin sample was rigidly coupled to a pivoted loading arm, which was supported by bearing arrangements. The force of friction was measured using a transducer installed on the loading arm. During the test period, data was collected every second. A microprocessor-controlled data collecting device was employed in this study to record friction force data at a rate of 35 times per minute on average. The mass loss was measured by weighting the pin with a precision scale, with an accuracy of ± 0.0001 g. The obtained mass was converted into a volume using the density of the sample. Mass loss measurements were used to calculate the specific wear values. Sliding wear data was the average of more than three runs.

3. Artificial Neural Network (ANN) Modelling

A well-trained ANN can be used to create an optimal material design for certain tribological applications. For tool wear estimation on dry hard turning processes of AISI4140 steel, Rajeev et al. [17] used an ANN model with a feed-forward neural network design. Ufnalski and Grzesiak [18] found that special measures should be taken to properly evaluate the performance of the controller because of the nature of the artificial neural network training process. Generally, the back-propagation algorithm is used for the multi-layered, feed-forward network training of models. Ermis [19, 20] developed a new algorithm for training. An ANN model was developed in this study to predict tribological data, the coefficient of friction, and the specific wear rate. The learning and training processes were carried out using an ANN model having a back-propagation and feed-forward configuration. The computer code, developed using C++ programming, was used to solve the ANN model algorithm. This algorithm formulation is shown below:

The training data sets were normalized between 0.1 and 0.9 to use the procedure. All the connection values of the weights were adjusted to threshold values and small random to obtain a training model and network outputs.

The net input for the jth node was calculated on the hidden layer,

$$\mathrm{Net}_j = \sum_{i=1}^{n} W_{ij} X_i - \theta_j \tag{3}$$

where; W_{ij} is the weight's connection value from the ith node to the jth node, j is the hidden layer node, i is the input layer node and x is the input. Θ_j is the threshold between the input and the hidden layer.

Various activation functions are used to develop networks, the usage of which depends on a variety of factors, including how quickly the function changes when the function's argument changes, the interval where the functions are well behaved, or simply personal preferences. Sigmoid is one of the most commonly used activation functions. The activation function of the logistic sigmoid is used in this network structure.

The output was calculated for the j^{th} node at the hidden layer:

$$H_j = f_h\left(\sum_{i=1}^{n} W_{ij}X_i - \theta_j\right) \quad \text{where} \quad f_h(x) = \frac{1}{1+e^{-\lambda_h x}} \tag{4}$$

where; H_j represents the hidden layer's neuron vector. f_h the logistic sigmoid's activation function from the input layer to the hidden layer. λ_h is a factor that is managing the gradient of the sigmoid function in the hidden layer.

At the hidden layer, the net input for the k^{th} node was calculated:

$$Net_k = \sum_j W_{kj}X_j - \theta_k \tag{5}$$

where; W_{kj} is the weight connection value from the j^{th} node to the k^{th} note, and k is the output layer. The threshold between the hidden and output layers is θk.

At the output layer, the output was calculated for the k^{th} node:

$$Y_k = f_k\left(\sum_{j=1}^{n} W_{kj}X_j - \theta_k\right) \quad \text{where} \quad f_k(x) = \frac{1}{1+e^{-\lambda_k x}} \tag{6}$$

where; Y_k is the output of the output layer neurons. The logistic sigmoid's activation function from the hidden layer to the output layer is $f_{k(x)}$. λ_k is a variable that controls the sigmoid function's gradient in the output layer.

Between the experimental output and the target, the output layer error was computed.

$$\delta_k = -\left(D_k - Y_k\right)f'_k \quad \text{where} \quad f'_k = Y_k(1 - Y_k) \tag{7}$$

where; D_k is the target activation of the output layer. δ_k is the vector of errors for each output neuron, and it only depends on the faults in the output layer between the target activation and the output. f'_k is the node activation function's local slope in the output nodes.

The error in the hidden layer was calculated as follows:

$$\delta_j = f'_h \sum_{k=1}^{n} W_{kj}\delta_k \quad \text{where} \quad f'_h = H_j(1 - H_j) \tag{8}$$

where; δ_j is the vector of errors for each neuron in the hidden layer, H_j is the hidden layer's neuron vector, and δ_k is the weighted sum of all nodes. In the hidden nodes, f'_h is the local slope of the node activation function.

In the output layer, the weights and thresholds were adjusted:

$$W_{kj}^{(t+1)} = W_{kj}^{(t)} + \propto \delta_k H_j + \eta\left(W_{kj}^{(t)} - W_{kj}^{(t-1)}\right) \tag{9}$$

$$\theta_k^{(t+1)} = \theta_{kj}^{(t)} + \propto \delta_k \text{ and } \theta_j^{(t+1)} = \theta_j^{(t)} \propto \delta_j \tag{10}$$

Where α is the learning rate, t is time, and η is the momentum factor.

For each neuron and pattern, all calculation steps were repeated until the output layer error was within the required tolerance. The learning rate and the momentum factor were utilized to allow the prior weight change to affect the weight change in this phase.

The neural network has back-propagation, feedforward, and a three-layer configuration for use in friction coefficient and specific wear rate estimation, as shown in Figure 2.

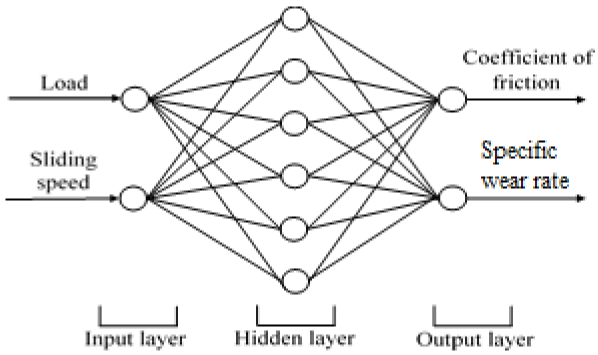

Figure 2. A three-layer feed-forward back-propagation neural network for the coefficient of friction and specific wear rate.

In the network structure, two input parameters applied loads and sliding speeds, and two output parameters, coefficients of friction and wear rate values, were used. To reduce the error between current data and output values, the weights, biases, and hidden node numbers were examined. The ANN configurations were set by selecting the hidden layer's numbers, nodes, the momentum coefficient, and the learning rate values to achieve the least error convergence. 18 data sets were evaluated for the cases. All data were separated into two groups. The first group has two sets of data randomly selected from the HBSS and dry sliding conditions to test. One of them was used for network training (67% of all cases) and the other set was used to test the validation of the ANN model. The layered structure of the ANN model for the specific wear rate and the coefficient of frictions are shown in Figure 3.

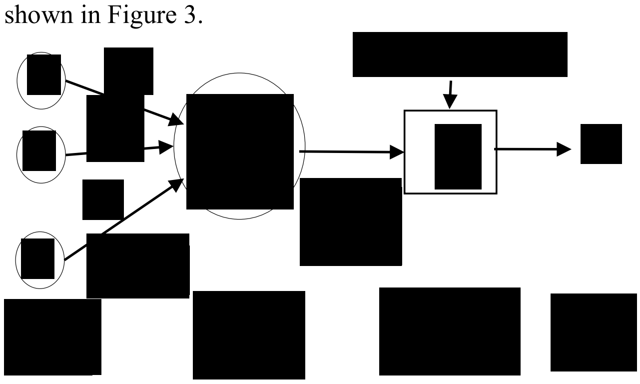

Figure 3. The ANN model's layered structure for the specific wear rate and the coefficient of friction.

The ANN model was utilized by using the two inputs, two outputs, and nine hidden layers. The learning ratios and the momentum coefficients setup default to 0.7 for the learning processes in the ANN model. For this process, 300,000 iterations were used to achieve good consistency in the algorithm. The three error measuring parameters given by Sablani [21] are utilized to compare the performance of the various ANN configurations. 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), the absolute fraction variance of error (R2). Their formulations are defined as follows:

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

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

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

Where; A = (P-D)/D. Parameter D and P 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 wear rate values decrease under both dry sliding and HBSS lubrication conditions for the UHMW-PE polymer. For the range of speed and load values tested, the wear rate value and the coefficient of friction were higher under the dry sliding condition than the HBSS lubrication condition as shown in Figure 4 and Figure 5. Comparisons between the experimental data and the estimations by the ANN model for the coefficient of friction values at 50, 100, and 150N of applied load and various sliding speeds for both the dry sliding and HBSS lubrication conditions are shown in Figure 4.

The average friction factor was 0.2039 for the dry sliding condition and 0.1150 for the HBSS lubricate condition. The ratio of dry sliding to HBSS lubricate was 1.8 for the friction factor as shown in Figure 4. The average specific wear rate value was 4.40 for the dry sliding condition and 3.14 for HBSS the lubrication condition.

Comparisons between the experimental data and the estimations by the ANN model for the wear rate at 38 N, 88 N, and 138 N of applied load and various sliding speeds for both the dry sliding and HBSS lubrication conditions are shown in Figure 5.

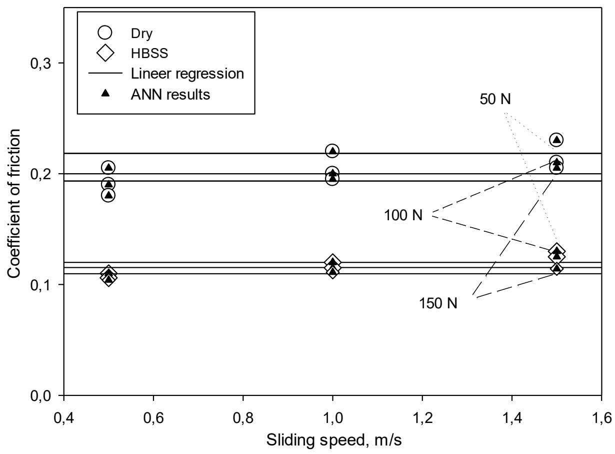

Figure 4. Comparisons of the coefficient of friction values between the experimental data and the ANN model estimations at 50N, 100N, and 150N of applied load under various sliding speeds.

The ratio of dry sliding to HBSS lubrication was 1.4 for wear rate as shown in Figure 5.

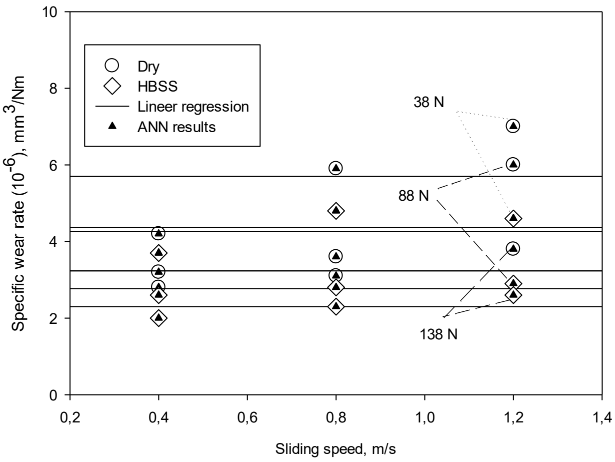

Figure 5. Comparison of the specific wear rate values between the experimental data and the ANN model estimated at 38N, 88N, and 138N of applied load under various sliding speeds.

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 are shown in Table 2 and the specific wear rate are shown in Table 3.

Table 2. Comparison of MRE, R^2, and STD for the coeffici ent of friction

Test Condition	Coefficient of friction			
	Load (N)	Sliding speeds (m/s)	Experimental results	ANN model results
Dry sliding	50	0.5	0.205000	0.205295
	50	1.0	0.220000	0.220056
	50	1.5	0.230000	0.229521
	100	0.5	0.190000	0.190695
	100	1.0	0.200000	0.198500
	100	1.5	0.210000	0.210655
	150	0.5	0.180000	0.179855
	150	1.0	0.195000	0.197533
	150	1.5	0.205000	0.205640
The mean relative error, MRE (%)				0.388528
The relative standard deviations of error, (STD)				0.002163
The absolute fraction variance of error (R^2)				1.000000
HBSS (Hank's balanced salt solution)	50	0.5	0.110000	0.110000
	50	1.0	0.120000	0.120000
	50	1.5	0.130000	0.130000
	100	0.5	0.106000	0.105999
	100	1.0	0.115000	0.115001
	100	1.5	0.125000	0.124998
	150	0.5	0.104000	0.104000
	150	1.0	0.111000	0.111001
	150	1.5	0.114100	0.114101
Mean relative error, MRE (%)				0.000628
The relative standard deviations of errors (STD)				0.002164
The absolute fraction variance of errors (R^2)				1.000000

The modeled ANN has 0.388528 and 0.005873 for the MRE result for the friction coefficient and the wear rate, respectively, for the dry sliding condition. For the HBSS lubrication condition, the ANN model has 0.000628 and 0.002580 for the MRE result for the coefficient of friction and specific wear rate, respectively. Absolute fractions of variances were 1 under both conditions. STD were 0.002163 and 0.046676 for the friction coefficient and wear rate, respectively, for the dry sliding condition.

For the HBSS lubrication condition, the ANN model has 0.002164 and 0.046680 of STD for the friction coefficient and wear rate, respectively, which were consistent with the experimental results.

Table 3. 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	4.200000	4.199650
	38	0.8	5.900000	5.900125
	38	1.2	7.000000	7.000000
	88	0.4	3.200000	3.200575
	88	0.8	3.600000	3.599575
	88	1.2	6.000000	5.999875
	138	0.4	2.800000	2.800000
	138	0.8	3.100000	3.099775
	138	1.2	3.800000	3.800125
The mean relative error, MRE (%)				0.005873
The relative standard deviations of error, (STD)				0.046676
The absolute fraction variance of error (R^2)				1.000000
HBSS (Hank's balanced salt solution)	38	0.4	3.300000	3.299900
	38	0.8	3.700000	3.700025
	38	1.2	5.600000	5.600000
	88	0.4	2.400000	2.399825
	88	0.8	2.800000	2.799950
	88	1.2	4.400000	4.400038
	138	0.4	2.300000	2.300000
	138	0.8	2.800000	2.799950
	138	1.2	3.300000	3.299900
Mean relative error, MRE (%)				0.002580
The relative standard deviations of errors (STD)				0.046680
The absolute fraction variance of errors (R^2)				1.000000

5. Conclusions

The following are the conclusions of this study;

- The coefficient of friction and wear rate of medical-grade UHMW-PE polymer under HBSS lubricated condition was lower than the dry sliding condition.
- The highest wear rate was $7.\text{x}10^{-6}$ mm^3/Nm for the UHMW-PE polymer at 1.2 m/s sliding speed and 38 N of load under the dry condition. The lowest wear rate was $2.3\text{x}10^{-6}$ mm^3/Nm under the HBSS lubricated condition at 0.4 m/s sliding speed and 138 N load as shown in Table 3.
- For the range of lubricant conditions used in this investigation, the wear rate was highly influenced by the size of the applied load and the type of lubrication media. For the two lubricant conditions used in this tribological study, HBSS was a more effective lubricant than dry sliding.
- In this paper, we have suggested a new 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 wear rate values and the coefficient of friction by the ANN model were consistent with the experimental data.

• For the coefficient of friction, the ANN model has 0.194578% of average mean relative error and 1.0 of the absolute fraction of variance (R^2) for both conditions. Also, for wear rate, the model has 0.0042265 % of mean relative error and 1.0 of the absolute fraction of variance (R^2) for both conditions. The obtained results show that the use of the ANN for predicting the coefficient of friction and wear rate is a perfectly acceptable method.

Declaration of Ethical Standards

The authors of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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