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Wear Behavior Prediction for Cu/TiO_2 Nanocomposite Based on Optimal Regression Methods

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The present study investigated the effects of the addition of the TiO_2 nanoparticles with different weight percent on the copper nanocomposites' abrasive wear behavior. In addition, optimal machine learning regression (OMLR) methods are used to detect the copper nanocomposites' abrasive wear behavior. The powder metallurgy method is used to fabricate the Cu/TiO_2 nanocomposite specimens with 0, 4, 8, 12 wt% TiO_2. The abrasive wear behavior of fabricated specimens is evaluated experimentally using a pin on the desk apparatus. The abrasive wear results are used to predict the abrasive wear behavior of the fabricated composites using OMLR methods. OMLR methods are implemented and carried out using MATLAB/software. The OMLR methods use the input parameters of TiO_2, sliding distance and load, and the weight loss due to abrasive wear as an output to build their optimal models. OMLR methods were successfully detected with small errors, especially GPR methods. The results of the proposed GPR were compared with those obtained from the ANN model with the efficacy of the GPR model. The experimental results demonstrated that the weight loss in test specimens decreased with increasing wt% of TiO_2 addition. This reflected improvements in the wear resistance of copper nanocomposites compared to pure copper.

Keywords: *Nanocomposites, copper, TiO_2 particles, wear behavior, optimal machine learning regression methods, ANN.*

1. Introduction

Copper (Cu) is widely used in industrial applications. Copper becomes a hopeful selection for a wide range of applications due to its superior thermal and electrical conductivity. These applications include heat exchangers, high voltage switches, and combustion chamber liners. However, copper and its alloys' low wear resistance and strength limit the use of copper and its alloys in applications that need great mechanical properties[1-3]. The addition of hard reinforcements such as ZrO_2, ZrB_2, Al_2O_3, and TiO_2 have improved the hardness and wear properties of the composite's materials[4-6]. Cu as a metal matrix and TiO_2 particles as a reinforcement is promising composite material due to their excellent mechanical and physical properties[7]. Studies in recent times focused on estimating the nanoparticles' effect on the mechanical properties and wear resistance of metal matrix nanocomposites. Most of these studies focus on the different nanoparticles reinforcing addition to producing metal matrix nanocomposites, leaving only a few studies that focused on the TiO_2 addition effect on Cu's mechanical properties and wear behavior[8]. Moghanian et al.[7] studied the effect of addition 1-3wt% of TiO_2 to copper. They found that, the hardness of Cu/TiO_2 nanocomposite increased by increasing TiO_2 amount. Sorkhe et al.[9] the hardness of Cu/TiO_2 nanocomposite increased by increasing nano particles up to 5 wt%TiO_2. Ning et al.[10] stated that the wear properties improve of a coated layer of Cu/TiO_2 composite when the reinforcements are distributed uniformly in the matrix. Warrier and Rohatgi[11] revealed the dispersions of reinforcement particles. TiO_2 could increase the mechanical properties of Cu. Akarapu[12] presented that the wear resistance of coated layer of Cu/TiO_2 composite is better than coated layer $Cu–Al_2O_3$ composite. Moghanian et al.[7] reported that the increase in sliding distance causes the increase in the rate of wear volume loss of Cu/TiO_2 nanocomposite, specifically when TiO2 particles content in the copper matrix is low.

Megahed et al.[13] concluded that Analysis of Variance (ANOVA) and Artificial Neural Network (ANN) exposed

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that the weight fraction percent of Al_2O_3 particles and the sliding distance are the main factors that influence the wear rate, however the effect of load is relatively small. Atta et al.[14] detected to obtain an effective routine for predicting wear rate of A356 Al-Si/ Al_2O_3 under different conditions and weight percentage of Al_2O_3. They use both Artificial neural network (ANN) and multiple regression techniques were used to predict the wear rate. ANN gives prediction that is more realistic then the regression equation. Abd El-Aziz et al.[15] also found that the applied load exposed a small effect on the wear rate of high-Cr cast iron when they used ANNs to predict the wear rate of high Cr cast iron. Suresh et al.[16] used surface' response methodology and developed mathematical models of different factors such as particles Wt%, applied load, and the sliding distance. To check the validity of the developed model, an analysis of the variance method was used. They found that this mathematical model was established for a specific wear rate, which was expected at a 99.5% confidence level. Rashed and Mahmoud[17] predicted the wear behavior of metal matrix composites A356/SiC using the ANN approach. The ANN model was developed using wear test parameters such as the effect of particles size, particles weight percent, applied load, and temperature. Fathy and Megahed[18] used the ANNs technique to predict the abrasive wear rate of nanocomposite materials Cu/Al_2O_3. They observed that load and Al_2O_3 vol% effectively influence the Cu/Al_2O_3 nanocomposite wear rate. The prediction of the wear rate of composite materials has been commonly investigated. However, there are insufficient reports related to predicting the wear rate of the copper nanocomposite using Optimized machine-learning methods (OMLR) methods. OMLR has been recognized as a powerful predictive tool for data-driven multi-physical modelling, leading to unprecedented insights and an exploration of the system's properties beyond the capability of traditional computational and experimental analyses. OMLR offers a wider scope for effectively analysing the behaviour of resulting composites with limited experimentation or computationally intensive realizations of expensive models[19]. The present investigation is intended to fabricate nanocomposites materials, copper, as a matrix, and nano-TiO_2 particles as reinforcements. Nanocomposites are reinforced with 0, 4, and 8, 12 wt.% Nano-TiO_2 particles fabricated using the powder metallurgy method. Pin-on-disk wear tests were used to study the effects of TiO_2 nanoparticles' addition on the abrasive wear behavior of Cu nanocomposites. The weight loss obtained from the abrasive wear tests was used in the datasets formation inserted into the four optimal machine learning regression (OMLR) methods to predict the copper nanocomposites' abrasive wear behavior. The OMLR methods are decision tree (DT), ensemble method (EN), support vector machine (SVM), and Gaussian process regression (GPR). The four OMLR methods are carried out and implemented using the 2020b MATLAB/package regression learner toolbox.

2. Experimental Procedure

Metal matrix composites containing TiO_2 nanoparticles as reinforcements with an average particle size of about 80nm and pure Cu as a matrix was prepared using the powder metallurgy method. The nanocomposites specimens with different weight fractions of 0, 4, 8, and 12 wt. % of TiO_2 nanoparticles were produced, as shown in Figure 1. After carrying out the fabrication process, the nanocomposites are prepared to investigate microstructural and wear behavior. SiC abrasive emery papers, ranging from 180 to 1200 grit size, were used in-ground and polished the metallographic specimens. After that, the specimens were etched with a solution containing 75ml HCl, 25ml HNO_3, 5ml HF, and 25 ml H_2O to expose their microstructure constituents. The microstructure characteristics at the different positions on the specimen surface are investigated by using scanning electron microscope (SEM). A pin-on-disk is used to carry out the abrasive wear test. The abrasive wear test is performed against SiC abrasive emery papers, 400 grit size where the

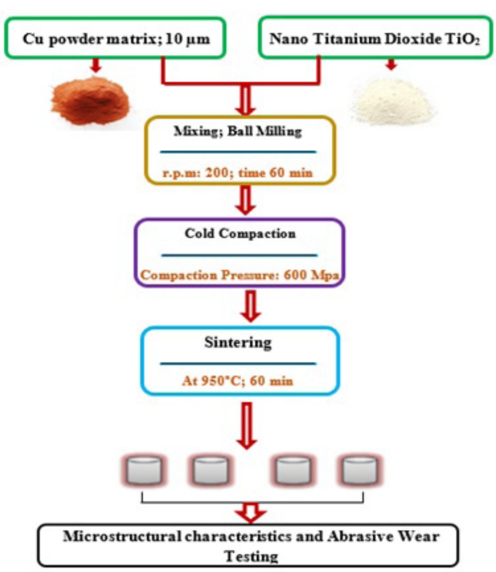


Figure 1. Flow chart and Schematic presentation showing the fabrication path of the present work.

sliding speed was constant at 1 m/s. The abrasive wear test is carried out under different conditions. These conditions were as follow:

- The applied loads: 5,10, 15,20, 25, and 30 N.
- The sliding distance 200, 400, and 600 m.
- The wear track diameter was kept constant at 80 mm.
- Circular specimens with a contact area of 176 mm^2

Microhardness tests is carried out after preparing the different specimens for metallographic examination using a VHS-1000 microhardnes testing machine at the load of 100g. Each value is the average of five readings.

TiO_2 nanoparticles with an average particle size of about 80nm as reinforcements and high purity Cu powder (99% purity and average particle size of 20µm) as a matrix were prepared to produce the required metal matrix composites (MMCs) by using powder metallurgy technique. The chemical analysis of the TiO_2 nanopowder was calculated using XRD measurements (Bruker D8 advance diffractometer with a Cu-tube operated at 40 KV and 40 mA). Figure 2 indicates the result of qualitative XRD peaks' profile and the phase analysis of TiO_2 nanopowder used as a reinforcement in the present research.

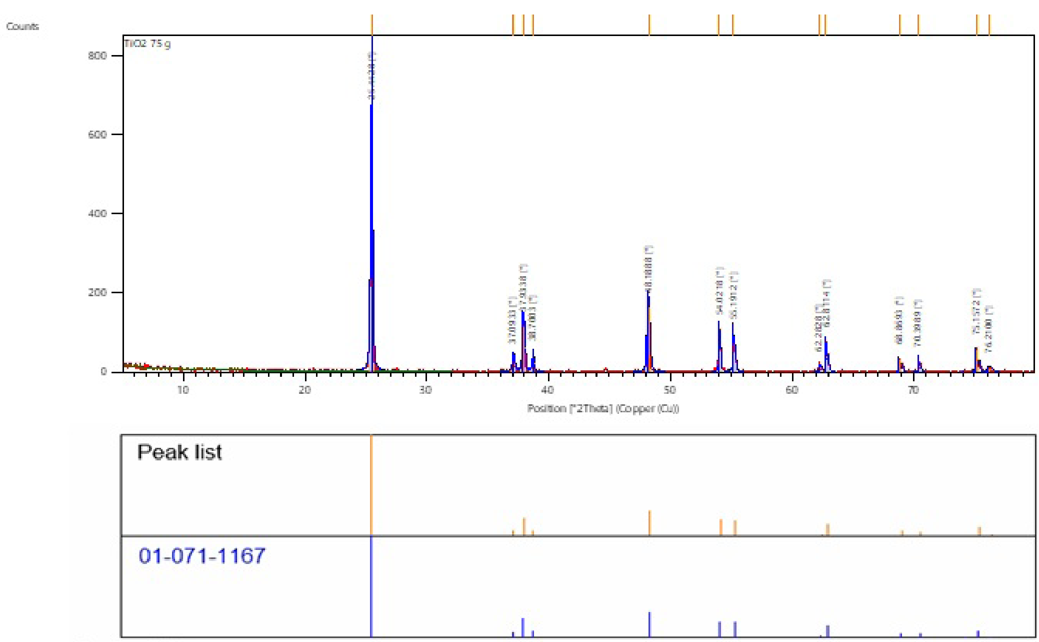
3. Optimal Machine Learning Regression Learner methods

This paper uses optimal machine learner regression (OMLR) methods to detect the abrasive wear behavior of copper nanocomposites. OMLR methods are implemented and carried out using MATLAB/software. The OMLR methods contain four approaches: decision trees (DT), Gaussian process regression (GPR), support vector machines (SVM), and ensemble regression (EN) methods. Each method of these four OMLR methods has several sub-regression algorithms. The DT method, as an example, has the following algorithms: fine tree, medium tree, and coarse tree. The OMLR methods are carefully applied in different regression applications. The OMLR method uses the input parameters of TiO_2, sliding distance and load as an input, and the weight loss due to abrasive wear as an output to build their optimal models. The 2020b MATLAB/software regression learner is used for building the OMLR methods[20]. The detecting scenario detects the abrasive wear behavior of copper nanocomposites in the flowchart shown in Figure 3. Firstly, all dataset samples are inserted and normalized using (1). The dataset samples are divided into two sets for training and testing purposes (67 samples for training and 29 samples for testing). The main optimizing parameters are selected, and one OMLR is selected. Then, the training process is carried out to obtain the optimal model of the selected OMLR method. The training and testing results are obtained for the selected OMLR method. The last three steps are repeated with other OMLR methods.

$$I_i = \frac{x_i - Min_j}{Max_j - Min_j} \tag{1}$$

where, I_i is the i[th] input of a certain variable, while Min_j and Max_j are the minimum and maximum values of that input variable samples.

The OMLR methods optimal parameters can be implemented by grid search, Bayesian optimization (BO), and random



Pattern List:

Visible	Ref. Code	Score	Compound Name	Displacement [°2Th.]	Scale Factor	Chemical Formula
*	01-071-1167	88	Titanium Oxide	0.170	0.965	TiO2

Figure 2. Qualitative XRD analysis of Nano-Titanium Oxide (TiO_2) used as a reinforcement in Cu-based nanocomposites.

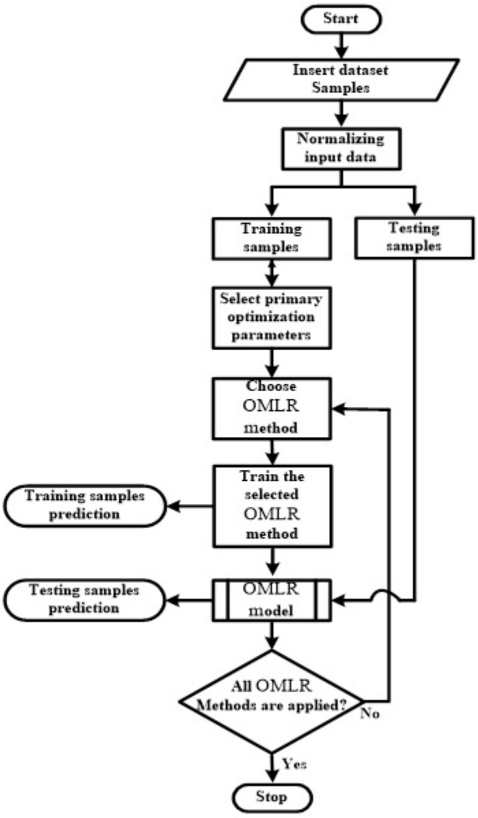


Figure 3. Solution methodology Flowchart.

search. The BO approach is the famous approach used for optimization problems to select and calculate the optimal parameters of the machine learning regression methods[21]. BO is used to evaluate the hyperparameter space while using a probabilistic technique to build the optimal model based on prior estimation. The probabilistic model carries out the final step to estimate the optimal parameters using the probability values of its position to select the parameters related to the highest probability[22]. The BO approach details were introduced in William et al.[22] and Jia et al.[23]. The primary optimization parameters selected before the training process are shown in Table 1, and the OMLR optimal parameters of methods are introduced in Table 2.

The comparisons of the four OMLR methods are carried based on four regression statistics variables, mean square error (MSE), root mean square error (RMSE), R-Squared error, and mean of absolute error (MAE) that evaluated as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - y_{ip}\right)^2 \quad (2)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - y_{ip}\right)^2} \quad (3)$$

$$R - Squared = 1 - \frac{\sum_{i=1}^{n}\left(y_i - y_{ip}\right)^2}{\sum_{i=1}^{n}\left(y_i - \underline{y}\right)^2} \quad (4)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - y_{ip}\right| \quad (5)$$

Table 1. Primary selected optimal parameters of OMLR methods during the training stage.

Optimizer	**Bayesian optimization**
Acquisition function	Probability of improvement
Maximum number of iterations	30
Number of cross folds	10

Table 2. Statistical analysis of the OMLR methods during the training process.

Method	**DT**	**SVM**	**GPR**	**EN**
RMSE	0.036615	0.015836	0.0090196	0.013607
MSE	0.001341	0.000251	8.1353e-5	0.000185
R-Squared	0.71	0.95	0.98	0.96
MAE	0.031387	0.01298	0.0064381	0.010337
Training time (s)	28.3	134.94	65.122	393.01
Prediction speed (obs/s)	3500	3100	3400	87

where, n is the total number of dataset samples, y_i and y_{ip} are the output and OMLR predicted output of the i^{TH} dataset sample, respectively. $\overline{y}$ is the mean of all actual values.

Table 2 presents the different statistical variables for OMLR methods during the training stage. The statistical values of the different methods illustrate the effectiveness of the GPR method compared to other methods. Table 3 presents the optimal parameters of the four OMLR methods as obtained from the optimization process that depends on the training dataset samples. For example, the optimal parameters of the GPR method are: Sigma is 0.001667, Basis function is Constant, the Kernel function is Nonisotropic Exponential, and the Standard size is true, while the optimal parameters of the SVM method are: Box constraint is 5.216, Epsilon is 0.0044073, a Kernel function is Linear, and Standard size is true.

Figure 4 introduces the MSE of the different OMLR methods against the number of iterations through the optimization process that depends on the training dataset samples. It illustrates that the GPR method has a minimum MSE of 8.1353e-5, while the DT method has the highest MSE of 0.001341.

Figure 5 shows the predicted response against the true response of the four OMLR methods through the training process. It illustrates that the GPR methods predict better than the other three methods.

4. Results and Discussions

4.1. Microstructure characteristics

SEM microstructure and EDS spectrum of nanocomposite with 8wt.% of TiO_2 nano particles is shown in Figure 6. In shown the figure, SEM micrograph illustrates the two dissimilar regions in the microstructure of Cu containing 8wt.% of TiO_2 nanocomposite, the first one revealed the Cu-matrix and the second displays dispersed nano TiO_2 particles in Cu matrix. Nanocomposite with 8wt.% of TiO_2 nanoparticles and corresponding EDS spectrum

Table 3. Optimal parameters for each OMLR methods.

OMLR Method	Optimal Parameters
DT	Min. leaf size: 4
SVM	Box constraint: 5.216
	Epsilon: 0.0044073
	Kernel function: Linear
	Standard size: true
GPR	Kernel function: Nonisotropic Exponential
	Sigma: 0.001667
	Basis function: Constant
	Standard size: true
EN	Ensemble method: LsBoost
	Learning rate: 0.027684
	Number of learners: 499
	Min. leaf size: 3
	Predictors numbers of to sample: 1

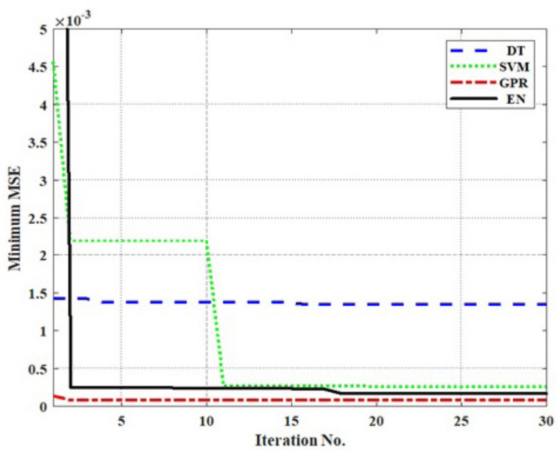


Figure 4. Minimum MSE of DT, SVM, GPR, and EN methods against iteration numbers through the optimization process in the training stage.

analysis of elements composition are given in Figure 6. This confirms the existence of TiO$_2$ nanoparticles in Cu-matrix structure. Higher magnification of typical SEM micrographs and corresponding EDS spectrum analysis of Cu containing 12%TiO$_2$ nanocomposite with line analysis and EDS mapping are displayed in Figure 7a-i. As indicated in this figure, the surface scanning results obtained by line analysis and elemental EDS mapping of Cu, Ti, and O elements existing in nanocomposites display a uniform distribution of nano TiO$_2$ particles in the structure of nanocomposite. But, some of these particles were agglomerated with increasing in wt.% of TiO$_2$ particles. In the figure, it is clear that copper covers almost the entire surface of nanocomposites microstructure. The results of surface scanning for Ti and oxygen show that these two elements are present less in the microstructure of the nanocomposite material and the surfaces they inhabit are inter-lapping, which corresponds to the existence of dispersed nano TiO$_2$ in the microstructure. The presence of larger amount of second dispersed phase particles and homogeneous dispersion of TiO$_2$ in the Cu-matrix for the nanocomposite specimens was appeared also in Figure 6.

4.2. Microhardness

Microhardness results of the tested specimens are shown in Figure 8. As shown in the figure, the microhardness increases with increasing TiO$_2$ Nanoparticles. The microhardness of pure Cu was 53 HV, and increased to 91 HV, in Cu nanocomposite with 12 wt% TiO$_2$. The addition of 4 wt.% TiO$_2$ Nanoparticles enhances pure hardness of Cu by 28.3%. Moreover, by adding of 12wt.% TiO$_2$ Nanoparticles enhances the microhardness of pure Cu by 71.7%. This improvement in the hardness of Cu/TiO$_2$ nanocomposites is due to the hardness of pure TiO$_2$ nanoparticles was higher than that of pure Cu. Ning et al.[10] prepared the Cu/TiO$_2$ nanocomposite coatings with different contents of nano TiO2 particles. The nanocomposite coating Cu/25wt.% TiO$_2$ presented considerably enhanced microhardness of 218.7 Hv.

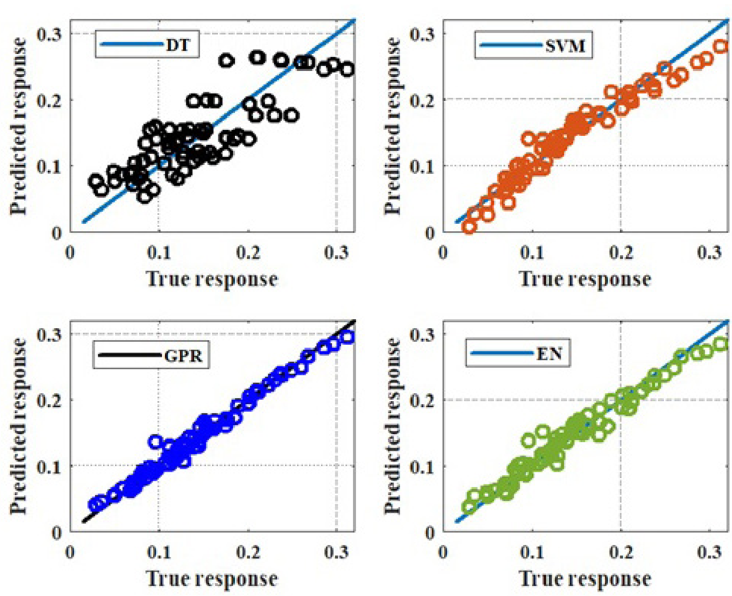


Figure 5. Predicted response against the true response of the different OMLR methods through the training period.

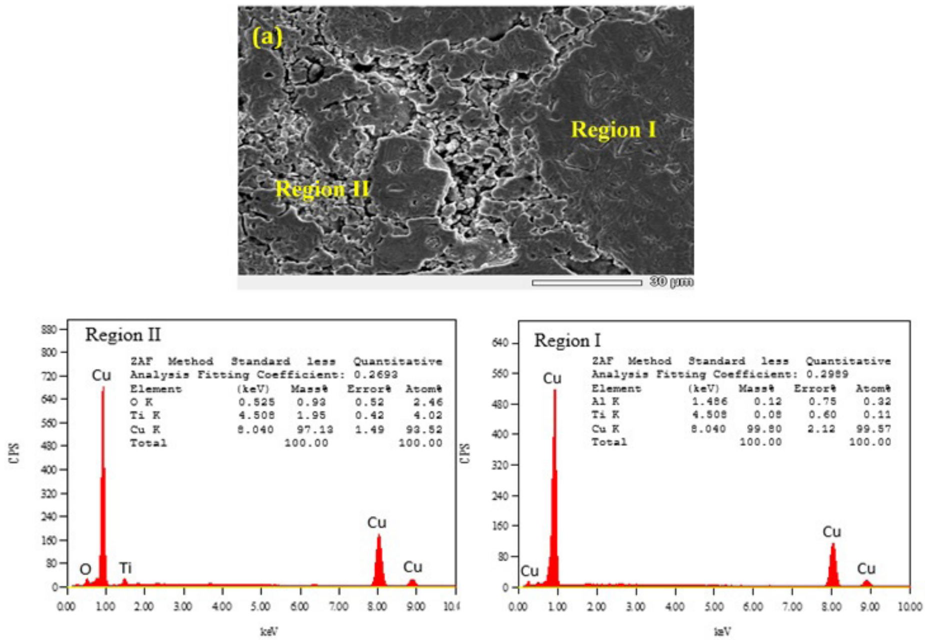


Figure 6. EDS analysis of nanocomposite containing Cu/8%TiO_2 of different regions of SEM in (a).

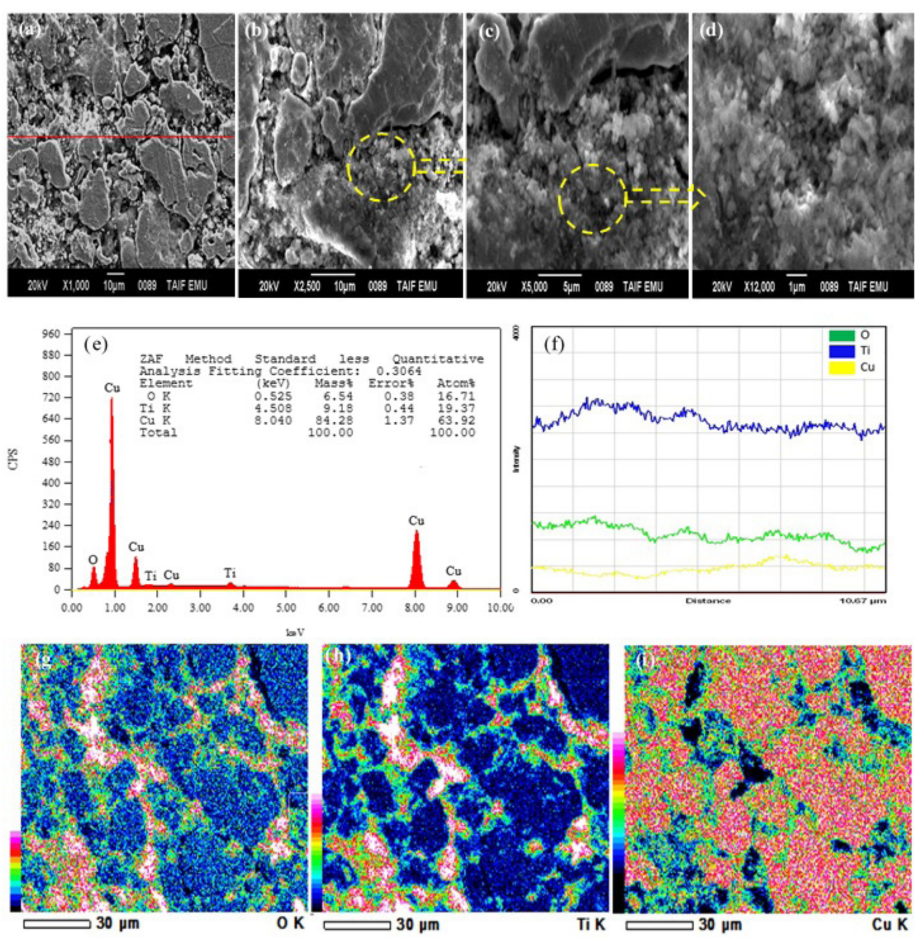


Figure 7. (a) The SEM micrographas images of 12 wt.% TiO2 nanocomposite; (b), (c), (d) Detailed regions of (a), with higher magnifications; EDS spectrum analysis of (a); (f) EDS Line analysis in (a); and (g), (h), (i) EDS mappings of Cu, Ti, and O elements present in (a).

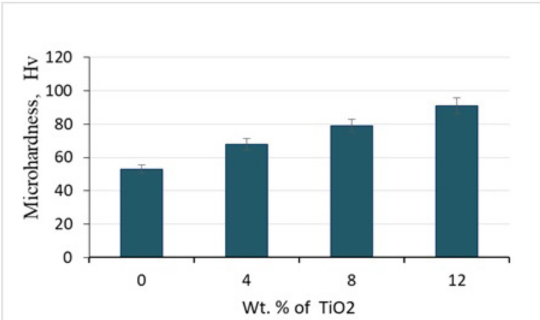


Figure 8. The measured microhardness of Cu-TiO_2 Nano composites with different wt. % of TiO_2 nanoparticles.

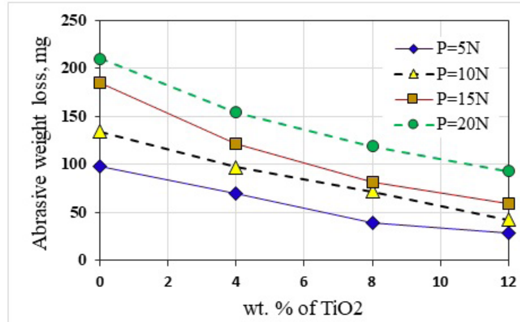


Figure 9. Correlation between abrasive weight loss (mg) and nano-TiO2 content at sliding distance of 200m and different applied loads.

4.3. Wear behavior

Figure 9 displayed a correlation between nanocomposites' abrasive weight loss (mg) and TiO_2 nanoparticles at different applied loads. From the figure, it is clear that the weight loss of the nanocomposites reduced with increasing the percent of TiO_2 nanoparticles and increased with the increase in the applied load. This reflected that the wear resistance of Cu improved by adding TiO_2 nanoparticles. Pure Cu showed the highest weight loss (98 mg), while nanocomposite with 12 wt% TiO2 showed the lowest weight loss (29 mg) at the applied load of 5 N, as shown in Figure 9. This may be caused by the existence of hard nanoparticles that raise the hardness of the material. The same tendency was achieved in the case of different loads. Figures 10-12 show a correlation between abrasive weight loss (mg) of nanocomposites with different nano-TiO_2 contents and applied loads at a different sliding distance. In general, the increase in applied load at various sliding distances increases the weight loss due to the greater penetration of the indenter in the test specimen, enabling a higher metal removal rate[6]. For nanocomposites, the weight loss is reduced with the addition TiO_2 nanoparticles with different weight percentages at the same load, leading to improved wear resistance. The abrasive wear resistance is enhanced due to the hard ceramic nanoparticles' addition to the soft copper matrix[4,5]. This enhanced wear resistance is due to TiO2 nanoparticles reinforcement with a good load-bearing capacity and higher hardness than Cu due to the better bonding between Cu and TiO_2 nanoparticles[9-12].

4.4. Prediction of OMLR methods

4.4.1. OMLR methods predicting performance

The OMLR models (GPR, DT, SVM, and EN methods) predict the abrasive wear behavior of copper nanocomposites (WBCN) of the 29 experimental dataset samples. The predicting output of the four OMLR methods is expressed in Table 4. The results illustrate a good prediction of the four OMLR methods. The GPR method has the highest predicting results compared to other methods.

4.4.2 OMLR Comparisons with ANN Method

Artificial neural networks (ANNs) are commonly used for classification and regression activities. The ANN has mainly three layers, as displayed in Figure 13. The first layer is the input layer, the second layer is the hidden layers, and the third layer is the output layer[24,25]. Each layer includes

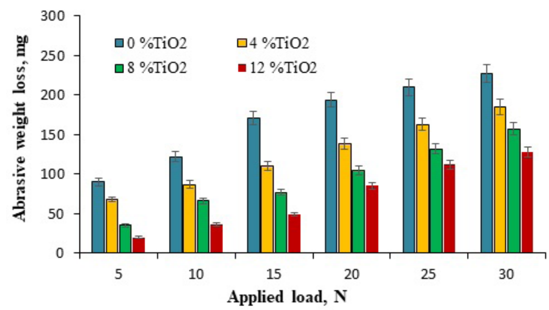


Figure 10. Correlation between abrasive weight loss (mg) and applied loads at different nano-TiO2 contents and sliding distance of 200m.

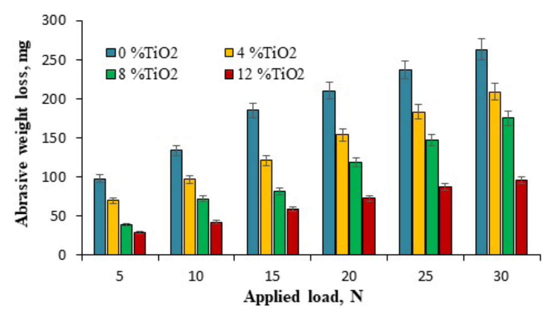


Figure 11. Correlation between abrasive weight loss (mg) and applied loads at different nano-TiO2 contents and sliding distance of 400m.

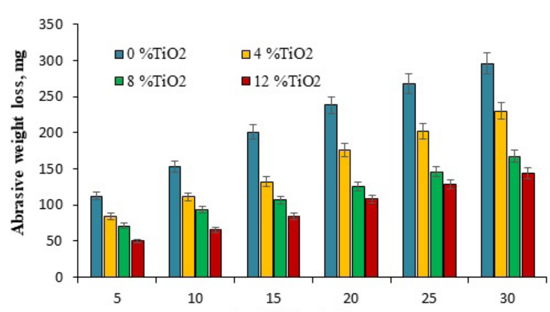


Figure 12. Correlation between abrasive weight loss (mg) and applied loads at different nano-TiO2 contents and sliding distance of 600m.

Table 4. Predicting results of the OMLR methods with the 29 testing dataset samples.

TiO_2	Sliding distance	Load	WBCN	DT	SVM	GPR	EN
0	200	20	0.194	0.2577	0.179	**0.1872**	0.1819
0	400	30	0.263	0.2577	0.2492	**0.2618**	0.2501
4	800	5	0.11	0.1105	0.117	**0.1095**	0.115
4	200	30	0.185	0.1939	0.1955	**0.1912**	0.1932
8	400	25	0.147	0.1492	0.1508	**0.1417**	0.1461
0	800	5	0.132	0.1466	0.153	**0.1378**	0.1489
4	200	15	0.11	0.0918	0.1167	**0.1113**	0.1113
12	600	10	0.056	0.0737	0.0536	**0.0627**	0.0695
8	600	30	0.167	0.1492	0.1948	**0.1779**	0.1752
8	400	5	0.039	0.0462	0.0457	**0.0515**	0.0533
0	400	5	0.098	0.1466	0.1178	**0.101**	0.109
12	400	10	0.042	0.0737	0.036	**0.0437**	0.0417
0	200	15	0.171	0.1466	0.1527	**0.1586**	0.1563
12	400	20	0.093	0.1247	0.0885	**0.0892**	0.086
4	800	20	0.198	0.1939	0.1959	**0.1911**	0.1891
12	600	20	0.108	0.1247	0.1062	**0.1054**	0.1149
0	200	30	0.227	0.2577	0.2316	**0.2334**	0.2245
4	400	25	0.183	0.1939	0.1869	**0.1831**	0.1832
8	600	15	0.107	0.0737	0.1159	**0.1066**	0.1005
4	200	10	0.087	0.0918	0.0904	**0.0866**	0.0907
8	800	25	0.168	0.1492	0.1861	**0.1681**	0.1694
4	600	15	0.132	0.0918	0.1519	**0.1397**	0.1335
12	600	25	0.128	0.1247	0.1324	**0.1234**	0.1293
12	200	10	0.036	0.0737	0.0183	**0.034**	0.0481
8	200	20	0.105	0.1492	0.1069	**0.1053**	0.1065
8	200	10	0.066	0.0737	0.0544	**0.0553**	0.0645
0	800	15	0.221	0.1466	0.2056	**0.2158**	0.2174
12	200	5	0.02	0.0462	-0.008	**0.0233**	0.0316
12	400	25	0.077	0.1247	0.1148	**0.1069**	0.1009
RMSE				0.03037930	0.014926	**0.008044**	0.00946485
MSE				0.00092290	0.000223	**6.4706E-05**	8.9583E-05
R-Squared				0.7314	0.9454	**0.9822**	0.9724
MAE				0.02390345	0.011821	**0.005472**	0.00735862

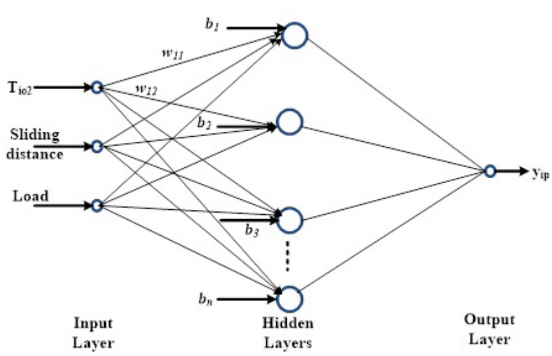


Figure 13. ANN structure configuration.

numerous neurons. The input layer has several neurons equal to the number of input variables or features; the hidden layers have several neurons selected to obtain the greatest predicting accuracy, while the numbers of neurons are equal to the output variable numbers in the output layer[24].

The relation between the output p (y_{ip}) value and the input variables i (I_i) can be identified as follows:

$$y_{ip} = G\left(\sum_{i-1}^{n} w_{im} I_i - b_m\right) \tag{6}$$

where G is the nonlinear function gain used in the hidden layers, w_{im} is the ith input (I_i) weight and b_m is biased of its output m.

The ANN training process is carried out using one of two algorithms. The first algorithm is Levenberg-Marquardt (LM) and the second algorithm is Bayesian regularization (BR)[24]. The LM algorithm is used in this work for the training stage. Ten neurons are selected for the hidden layer of the ANN model. The training dataset samples (67 samples) are divided into three sets for the training (47 samples), testing (10 samples), and validation (10 samples) stages. The minimum MSE error with the validation dataset samples is 0.00011953 at eight epochs, as shown in Figure 14. The percentage accuracy of training, validation, testing, and all dataset samples is 99.92, 97.68,

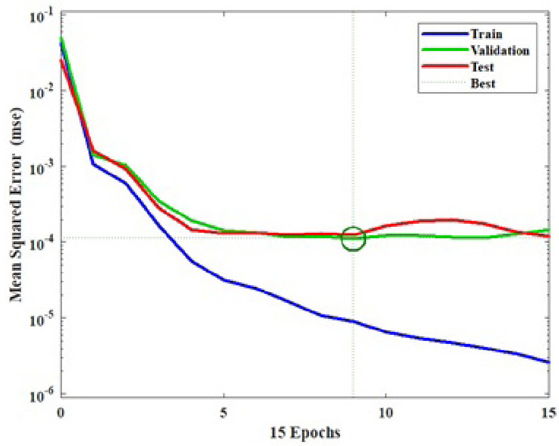


Figure 14. MSE against epoch numbers during the training process of the ANN model.

98.08, and 99.53, respectively, as shown in Figure 15. The backpropagation type is the more well-known ANN type used in the regression process[25].

The ANN model is implemented to predict the abrasive wear behavior of copper nanocomposites with the test dataset samples. Table 5 compares the proposed GPR and the ANN models with the testing samples (29 samples). The results illustrate that the GPR predicting results are close to the weight loss of copper nanocomposites under abrasive wear conditions. In contrast, the predicting results of the ANN have a greater difference from the actual weight loss of copper nanocomposites under abrasive wear conditions. The overall RMSE, MSE, R-Squared, and MAE of the proposed GPR and ANN models based on the 29 testing samples are (0.008044, 6.4706e-5, 0.9822 and 0.005472) and (0.013722, 0.000188, 0.9407, and 0.010941), respectively. The results demonstrate the efficacy of the proposed GPR model compared to the ANN model.

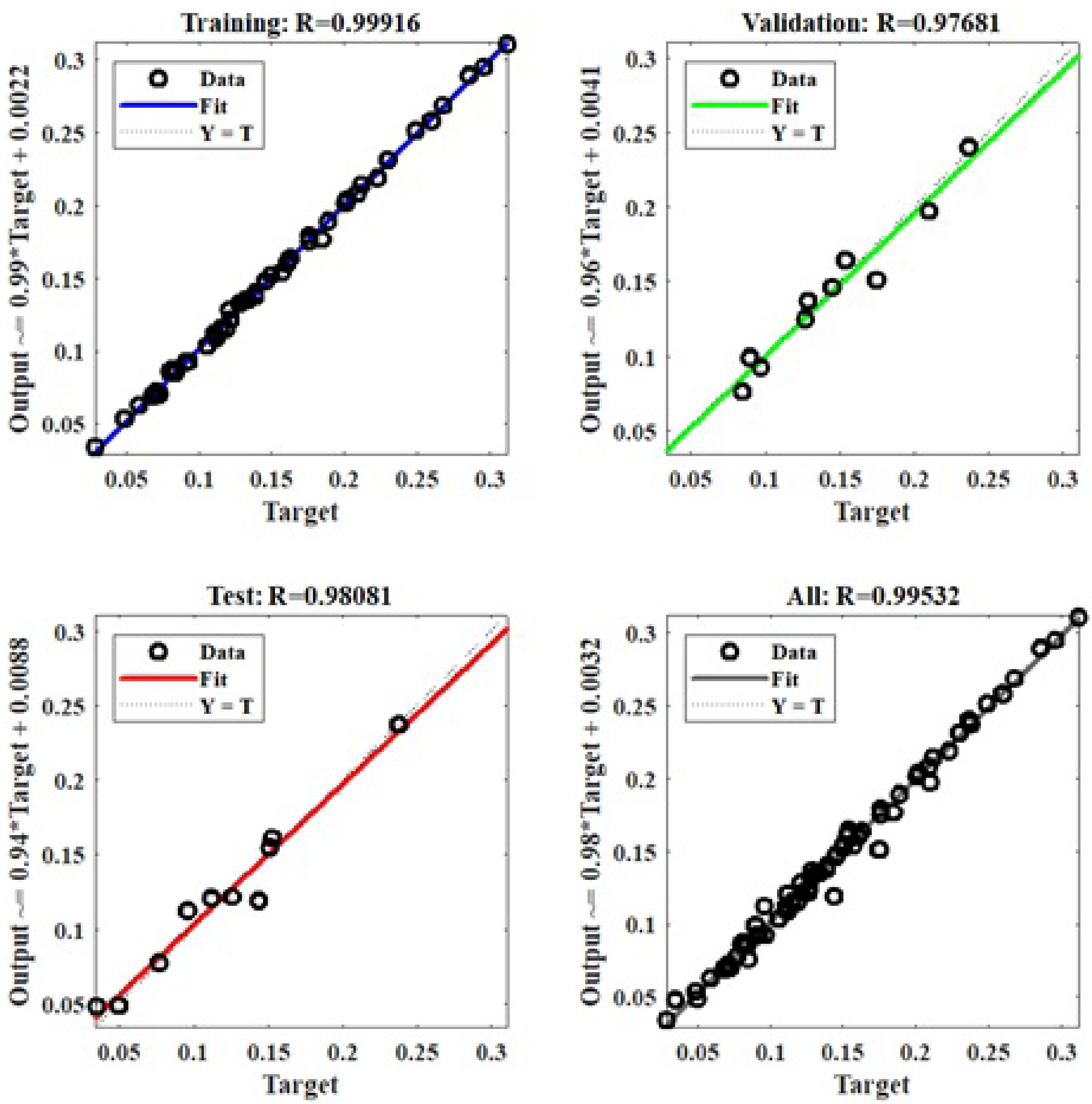


Figure 15. Percentage accuracy of the ANN model on the training, validation, testing stages, and wth the overall samples.

Table 5. The predicting results and the overall RMSE, MSE, R-Squared, and MAE for the proposed GPR model and the ANN model based on the 29 testing samples.

TiO_2	Sliding distance	Load	WBCN	GPR	ANN
0	200	20	0.194	**0.1872**	0.169
0	400	30	0.263	**0.2618**	0.26
4	800	5	0.11	**0.1095**	0.129
4	200	30	0.185	**0.1912**	0.1799
8	400	25	0.147	**0.1417**	0.1362
0	800	5	0.132	**0.1378**	0.1471
4	200	15	0.11	**0.1113**	0.1121
12	600	10	0.056	**0.0627**	0.0676
8	600	30	0.167	**0.1779**	0.1764
8	400	5	0.039	**0.0515**	0.0681
0	400	5	0.098	**0.101**	0.1001
12	400	10	0.042	**0.0437**	0.0445
0	200	15	0.171	**0.1586**	0.1438
12	400	20	0.093	**0.0892**	0.0785
4	800	20	0.198	**0.1911**	0.1842
12	600	20	0.108	**0.1054**	0.0973
0	200	30	0.227	**0.2334**	0.2183
4	400	25	0.183	**0.1831**	0.1903
8	600	15	0.107	**0.1066**	0.1058
4	200	10	0.087	**0.0866**	0.0894
8	800	25	0.168	**0.1681**	0.1672
4	600	15	0.132	**0.1397**	0.1447
12	600	25	0.128	**0.1234**	0.1052
12	200	10	0.036	**0.034**	0.0469
8	200	20	0.105	**0.1053**	0.1051
8	200	10	0.066	**0.0553**	0.057
0	800	15	0.221	**0.2158**	0.2187
12	200	5	0.02	**0.0233**	0.0408
RMSE				**0.008044**	0.013722
MSE				**6.4706E-05**	0.000188
R-Squared				**0.9822**	0.9407
MAE				**0.005472**	0.010941

5. Conclusions

Cu nanocomposites with different wt% of TiO_2 were fabricated, and abrasive wear behavior was evaluated experimentally under different conditions. These conditions were different loads (5-30 N) and sliding distances (200-600 m). The weight loss of the copper nanocomposites decreased with increasing the amount of TiO2 nanoparticles. On the other hand, the weight loss of pure copper and the nanocomposites increased with the increased applied load and sliding distance. Four optimal machine learning regression methods (OMLR) were implemented and carried out using MATLAB/software to predict the copper nanocomposites' abrasive wear behavior. The four OMLR methods were DT, GPR, SVM, and EN. The four methods were successfully detected with small errors, especially GPR methods. Furthermore, the ANN was implemented to detect copper nanocomposites' abrasive wear behavior. Four regression statistics factors (MSE, RMSE, R-Squared and MAE) were used to compare the results of the OMLR and ANN models. The results illustrated that the regression statistic factors of the GPR (best OMLR prediction method) were (0.0008044, 6.4706E-05, 0.9822 and 0.005472) while that of the ANN model were (0.013722, 0.000188, 0.9407 and 0.010941). Finally, the results of the proposed GPR model were effective for predicting wear behavior compared to other OMLR and the ANN model.

6. References

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