Using ANN and OA techniques to determine the specific wear rate effectors of A356 Al-Si/Al₂O₃ MMC

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Abstract
In the present work, it’s required to obtained the wear rate effectors’ values of A356 Al-Si/Al₂O₃ composite (Al₂O₃ wt%, applied load, hardness, and sliding distance) required to obtain a certain specific wear rate. So, the specific wear behavior of cast and heat-treated A356 Al-Si/Al₂O₃ metal matrix composites (MMC) were investigated as a function of its effectors. Five weight fractions of Al₂O₃ particles were used to produce specimens using stir casting. Two different hardness are obtained for each fraction (casted and heat-treated specimens). Sliding wear tests were done under three loads (20, 30, and 40 N), four sliding distances (310, 620, 930 and 1240 m) at constant speed (1 m/min). Experimental results indicated that the specific wear rate is generally reversed proportional to Al₂O₃ percentage. The impact of Al₂O₃ percentage was eliminated with the grown of applied load. Increasing the applied load decreases the specific wear rate, up to 20% Al₂O₃. However, at 25% Al₂O₃ the applied load increases the specific wear rate with a small graduation. Moreover, the heat treatment process improves the hardness and specific wear behavior of the casted MMC. Both Artificial neural network (ANN) and multiple regression techniques were used to predict the wear rate. The orthogonal array technique (OA) used in selecting the data set to train ANN and obtained a 2nd degree regression equation. ANN gives more realistic prediction then the regression equation. So, at the end, an algorithm is designed and tested to determine the weight fraction and other wear rate effectors for A356 Al-Si/Al₂O₃ MMC to obtain a certain wear rate, according to the uncertainty of the ANN. The used algorithm for obtaining the wear rate effectors provides a very good choices to produce a certain wear rate’s value, with error less than 1%.

Keywords A356Al-Si alloys • Al₂O₃ particles • MMC • Heat-treatment • Stir casting • Specific wear rate • Artificial neural networks • Orthogonal array technique

1 Introduction
Recently, extensive work concerned the material science field was directed to the forming of new lightweight materials having improved specific strength, stiffness, fatigue, creep and wear resistance[1]. Metal matrix composites (MMC) are considered as most promising in accomplishing improved mechanical properties as tensile, flexural, and tribological properties due to the presence of nano or micro-sized reinforcement particles embedded into the matrix. Reinforcements result in better strength and hardness with a loss of some ductility [2, 3].

Aluminum-matrix composites (AMC) filled with whiskers and particles are commonly used for high performance applications as in military, aerospace, automotive, and electricity industries owing to their improved mechanical and physical properties [2]. The aluminum alloy (A356Al-Si) is considered as one of the most widely metal matrices in MMC. It is characterized by its ductility, low cost, good strength, ease of handling, excellent casting characteristics and resistance to wear and corrosion. In MMC, soft alloy based on aluminum can be highly resistant by embedding
mostly hard particles as Al2O3 and SiC. The application of Al2O3 or SiC particles filled Al-alloy as the metal matrix in MMC in the automotive and aircraft industries. The MMC based on Al-alloy reinforced with Al2O3 or SiC particles is progressively increasing for pistons, connecting rods, disc brake rotors, cylinder heads applications, where the tribological properties of these MMC are very important [4–7]. Furthermore, the volume to weight ratio of these MMC was minimized so produces better fuel efficiency. Moreover, MMC reinforced with particulate cost less than MMC reinforced with fiber due to the lower cost of the particulates [8].

Various techniques was used to fabricate MMC including melt techniques, powder metallurgy, and squeeze casting [9]. Stir casting is considered a liquid state method of fabrication of MMC, as a hard particule is blended with molten metal matrix homogeneously via mechanical stirrer [10]. The stir casting process is the most cost-effective method for fabricating liquid state aluminum matrix composite [11, 12]. As compared to solid-state methods, stir casting process has some essential advantages as better bonding formation between metal matrix and particle interface, simplicity, mass production, easier control of metal matrix structure, low cost, suitability for adding high weight fraction of reinforcement and the wide choice of constituent materials [13].

Moreover, for enhancing the mechanical and tribological properties of MMC suitable heat treatment can be attained. Attempts was made to improve tensile strength, toughness, and hardness of AMC and AMC reinforced with hard particles by altering the metal matrix microstructure with heat treatment. Research on sliding wear behavior indicated wear resistance of the alloy or MMC are enhanced by heat treatment [14–17]. Consequently, it is noteworthy to investigate the wear behavior of A356Al-Sialloy reinforced with hard particulates after heat treatment [15].

Prediction of the resulting specific wear for the material under study is most important because it reduce much more time and money for specialists. And determination of the effectors that gives certain value of specific wear rate for material is of great importance for them. There were many techniques used in prediction engineering parameters, such as multiple regression and Artificial neural network (ANN). The regression techniques are the most popular technique and could be obtained in different forms (linear, quadratic equation et.). While, ANN technique is considered as a time saving, efficient, and accurate computational method used for modeling complex nonlinear problems. This method is considered as an enthralling mathematical tool used for solving complicated problems that are difficult to approach linearly.

The ANN technique has been approved and used to simulate complex problems in both engineering and science fields [18]. Many researchers were used ANN to predict the mechanical, tribological and the physical properties of composite materials. ANN is a powerful approach used to predict complex engineering data relations and functions [1]. Standard orthogonal arrays (OAs) are an experimental design technique, inverted by Taguchi, to eliminate the number of full factorial experiment set into a smaller number of experiments (in the present work the number of experiments was reduced from 120 to 24) [19]. This OA technique ensure that all levels (values of the factors) of all factors (system inputs parameters) are represented equally.

The present work aimed to obtain an effective routine for predicting wear rate of A356 Al-Si/Al2O3 under different conditions and weight percentage of Al2O3. So, the hardness and specific wear rate, as cast and heat treatment conditions were studied. Five weight fractions of Al2O3 particles were used to produce specimens using stir casting. The wear test is performed with three different loads, 4 sliding distances and 2 different hardness, for each Al2O3 percentage under constant velocity. A selected data set, according to OA technique, was used in obtaining linear and quadratic equations and training ANN to predict the wear rate. The uncertainty of the predicted results of the all techniques were calculated. Then, an algorithm is designed and verified to determine the weight fraction and other wear rate effectors for A356 Al-Si/Al2O3 MMC to obtain a certain wear rate, with the best technique.

2 Experimental procedure

2.1 Materials of MMC and preparation of specimens

A356 aluminum alloy (Mg-0.3, Si-7.1, Mn-0.01, Cu-0.02, Ni-0.01 by weight%) was supplied by Egyptalum Company, Egypt and was selected as matrix material. However, and Al2O3 supplied by El-Gomhouria, company, Egypt and was used as reinforcement. The Al2O3 particles has an average diameter of 60–80 μm.

The MMC (A356 with 0, 10, 15, 20 and 25 wt% Al2O3) was fabricated using stir casting at 750 °C. The Al2O3 particles was heated at 900 °C before addition to Al–Si molten metal and magnesium amount of 1 wt% was added into the composite melts to enhance the wettability. Stirring process were carried out during the Al2O3 adding and for five minutes after finishing at 700 rpm.

Some of MMC specimens were heat-treated by treating the solution at 540 °C for 8 h, subsequently, water quenching was conducted at 60 °C, and then isothermal
aging at 155 °C was performed [20]. One hundred and twenty specimens of 9 mm diameter and 15 mm height is prepared for wear test. Half of them as casted and the other half is heat-treated. Each specimen is grinded against 800 abrasive paper to ensure the full contact of the specimen with the machine disk.

2.2 Wear characterization of MMC specimens

The specimens were tested under dry sliding conditions on pin and disk machine. The pin was withdrawn from its holder after each test and cooled to ambient temperature. It was cleaned lightly by a brush to get rid of loose wear debris and after that the pin was weighed using a digital balance having accuracy of 0.0001 g. The measurement of weight loss of the pin was taken during the wear test after different sliding distances (310, 620, 930 and 1240 mm) at three different loads (20, 30, and 40 N). The sliding wear tests were done at a sliding speed of 1 m/s. Each test was repeated three times and the average value of the weight loss after each sliding distance was considered for analysis of wear behavior. The volumetric wear rate and specific wear rate was calculated by using the formula Eqs. (1) and (2), respectively [21]:

Wear rate = \( V/\rho D \) (mm\(^3\)/m) \hspace{1cm} (1)

SWR = Wear rate/L (mm\(^3\)/N m) \hspace{1cm} (2)

where SWR is the specific wear rate, \( \rho \) is the density of material, \( V \) is the weight loss, \( D \) is the sliding distance, and \( L \) is the applied load.

2.3 Hardness

The Brinell hardness values of the MMC were measured on polished specimens at a load of 10 kg. For MMC containing a soft metal matrix and a hard reinforcement phase (\( \text{Al}_2\text{O}_3 \)). The choice of a zone in the specimen for estimating the hardness value is very crucial. Consequently, regions predominant in the soft metal matrix or in the hard-reinforced phase must be avoided so the average hardness values were measured correctly. At least ten measurements were made for each tested sample.

3 Prediction techniques and data base

3.1 Prediction with ANN

ANN is a system simulates the human brain to learn a specific task. Now days, there is an extensive use of it for solving various problems in engineering. It is a powerful technique to predict complex engineering data relations and functions [22]. ANNs consist of number of nodes, which imitated the human neuron, arranged in number of layers. The most widely used algorithm of neural network is multilayer back-propagation one, more than 80% of the studies are used [23]. These types of neural networks consecutively contain input layer, one or more hidden layers and output layer, Fig. 1a. The nodes in any layer are connected to all the nodes in the next layer through weighted connection. Also, each node has its own remembrance weight which is connected to the bias node (its output value is 1). The nodes in hidden and output layers are composed of an integration function (collecting data from the previous layer into single value) and activation function (producing the node output to the next layer) Fig. 1b.

    The connections strength (weights) values are randomly selected then adjusted through a supervised learning (training) operation. The training operation has two paths, forward and backward paths. Through the forward path the difference between the net and the actual outputs is calculated. While, in the backward path the obtained error is propagated to modify the weights to minimize the net outputs errors. One of the most optimum and faster convergence training algorithms for the multilayer back-propagation is Levenberg–Marquardt learning algorithm [23–25].

Based on the previous paragraphs, the used ANN (to model the present work) is multilayer back-propagation. It has 4 nodes in the input layer, one for each wear rate effectors (\( \text{Al}_2\text{O}_3\% \), sliding distance, load and hardness), and one node in the output layer, the wear rate value. It has, also, one hidden layer, Fig. 2a. The structure of the nodes, hidden and output nodes, are composed of sum for the input signals, as integrated function, and sigmoid function as activated function, Fig. 2b. Levenberg–Marquardt learning algorithm is used to train this ANN. The training is carried out with different numbers of hidden layer’s nodes (4, 6, 8 and 10) to select the more suitable hidden layer’s number of nodes. This suitable number of nodes in the hidden layer is selected according to net performance (MSE) and correlation coefficient (\( R \)) between the net output and the actual resulting specific wear rate.

    The training was carried out with two techniques; the first one was the normal backpropagation technique (with training, validation and test data sets), the second technique was the leave-one-out procedure (with training and validation sets only). The second procedure repeated the training multiple times, each time leaving out a different subset of the data.
3.2 Multiple regression model

Multiple regression technique is used to get a predicted relation between the specific tool wear ($W$) of A356 Al-Si/Al$_2$O$_3$ composite with its effectors Al$_2$O$_3$% ($R$), applied load ($L$), hardness ($H$), and sliding distance ($D$). Through the present work the quadratic Eq. (3) was used to present this relation. Determination of the coefficients of regression ($a_0$ to $a_{14}$) are calculated according to the least square method (minimizing the sum of the square errors between the predicted and actual values).

$$W = a_0 + a_1R^2 + a_2L^2 + a_3H^2 + a_4D^2 + a_5R + a_6L + a_7H + a_8D + a_9RL + a_{10}RH + a_{11}RD + a_{12}LH + a_{13}LD + a_{14}HD$$

where $a_0$ to $a_{14}$ are the regression coefficients.

3.3 Preparation of regression and training data sets

As shown in the experimental work, there are 4 levels for the wt% and sliding distance (after excluding the wt% ratio 15%), 3 levels of load and two levels of hardness (treated or not treated specimens). This full matrix experimental data, 120 samples, is divided into four sets. The first set is selected according to the standard orthogonal arrays (OAs) [19] and used in training the ANN and regression operations. This group are selected according to OA $32 \times 2^1$ [26], which is eliminated to 24 samples after removing the samples of the 4th level of load, Table 1.

Eight experiments (third of the training set) for both validations set (which determine the performance of the ANN) and test set (which test the ANN) were randomly selected from the chosen 4 levels of the wt%, sliding distance, loads and 2 levels of hardness. The ANN’s training operation was carried out with NeuroSolutions 5 software [27] with batch training. All the data are normalized, pre-
processed, to the range between 0.15 and 0.85. The rest of the data were used to confirm the uncertainty of the prediction. This was, also, done for normal training and Leave-one procedures.

| Data type   | Input data | Measured wear rate (mm³/m) | Obtained ANN’s for 4-8-1 structure | Multiple regression |
|-------------|------------|----------------------------|-------------------------------------|---------------------|
|             |            |                            | Output                      | Error               | Output                      | Error               |
| Training set|            |                            | 0.018                        | 0.01743             | 0.019151                   | 0.001151            |
|             |            |                            | 0.041                        | 0.04010             | 0.041202                   | 0.000202            |
|             |            |                            | 0.071                        | 0.07135             | 0.069543                   | 0.00146             |
|             |            |                            | 0.017                        | 0.01838             | 0.015732                   | 0.00127             |
|             |            |                            | 0.038                        | 0.03739             | 0.037253                   | 0.00075             |
|             |            |                            | 0.063                        | 0.06518             | 0.065063                   | 0.002063            |
|             |            |                            | 0.012                        | 0.01120             | 0.012556                   | 0.000556            |
|             |            |                            | 0.0216                       | 0.01703             | 0.020553                   | 0.00105             |
|             |            |                            | 0.035                        | 0.037253            | 0.037253                   | 0.000202            |
|             |            |                            | 0.06064                      | 0.060728            | 0.001151                   | 0.000134            |
|             |            |                            | 0.03653                      | 0.036073            | 0.036073                   | 7.35E-05            |
|             |            |                            | 0.05768                      | 0.058444            | 0.058444                   | 0.00056             |
|             |            |                            | 0.06818                      | 0.067729            | 0.067729                   | 0.000729            |
|             |            |                            | 0.03195                      | 0.034401            | 0.034401                   | 0.000401            |
|             |            |                            | 0.04555                      | 0.046855            | 0.046855                   | 0.00015             |
|             |            |                            | 0.04884                      | 0.046222            | 0.046222                   | 0.00078             |
|             |            |                            | 0.01009                      | 0.010805            | 0.010805                   | 0.00019             |
|             |            |                            | 0.01987                      | 0.020791            | 0.020791                   | 0.000121            |
|             |            |                            | 0.03951                      | 0.035387            | 0.035387                   | 0.000187            |
|             |            |                            | 0.00899                      | 0.010729            | 0.010729                   | 0.000027            |
|             |            |                            | 0.01339                      | 0.012034            | 0.012034                   | 0.001034            |
|             |            |                            | 0.03032                      | 0.027874            | 0.027874                   | 0.00113             |
|             |            |                            | 0.08064                      | 0.084472            | 0.084472                   | 0.001472            |
|             |            |                            | 0.05155                      | 0.055711            | 0.055711                   | 0.001711            |
|             |            |                            | 0.03322                      | 0.03344             | 0.03344                    | 0.00056             |
|             |            |                            | 0.01210                      | 0.014132            | 0.014132                   | 0.000132            |
|             |            |                            | 0.04512                      | 0.044146            | 0.044146                   | 0.000146            |
|             |            |                            | 0.01418                      | 0.016926            | 0.016926                   | 0.000207            |
|             |            |                            | 0.02469                      | 0.029289            | 0.029289                   | 0.000228            |
|             |            |                            | 0.01759                      | 0.010225            | 0.010225                   | 0.000478            |
| Validation set|            |                            | 0.083                        | 0.084472            | 0.084472                   | 0.001472            |
|             |            |                            | 0.05155                      | 0.055711            | 0.055711                   | 0.001711            |
|             |            |                            | 0.03322                      | 0.03344             | 0.03344                    | 0.00056             |
|             |            |                            | 0.01210                      | 0.014132            | 0.014132                   | 0.000132            |
|             |            |                            | 0.04512                      | 0.044146            | 0.044146                   | 0.000146            |
|             |            |                            | 0.01418                      | 0.016926            | 0.016926                   | 0.000207            |
|             |            |                            | 0.02469                      | 0.029289            | 0.029289                   | 0.000228            |
|             |            |                            | 0.01759                      | 0.010225            | 0.010225                   | 0.000478            |
| Test set    |            |                            | 0.077                        | 0.075344            | 0.075344                   | 0.00166             |
|             |            |                            | 0.073                        | 0.075306            | 0.075306                   | 0.002306            |
|             |            |                            | 0.019                        | 0.014701            | 0.014701                   | 0.00043             |
|             |            |                            | 0.00739                      | 0.069051            | 0.069051                   | 0.001051            |
|             |            |                            | 0.03031                      | 0.028046            | 0.028046                   | 0.000495            |
|             |            |                            | 0.00887                      | 0.009753            | 0.009753                   | 0.00025             |
|             |            |                            | 0.01573                      | 0.014825            | 0.014825                   | 0.00117             |
|             |            |                            | 0.02153                      | 0.026368            | 0.026368                   | 0.005368            |

Error’s average (40 samples)  
Errors’ sample standard deviation (40 samples)
4 Obtaining the wear rate effectors

This section aimed to get the values of wear rate effectors (wt%, sliding distance, load and the heat-treated state) that can achieve a certain value of wear rate, through the obtained prediction technique. Figure 3 shows the flowchart for getting these values. The first two steps are discussed in the previous section. To improve the well-anticipated for these values, the probable range of the more suitable prediction technique’s output error should be defined within the inputs’ ranges and defined level of confidence. The Uncertainty, which is a result’s property, describes the period inside which the true results are mostly expected to fall according to defined probability [28].

There are many factors define the uncertainty quality such as; test knowledge, measured value, equipment and measuring procedure [29]. Through this work only the uncertainty of the predicted technique itself will be considered. The other factors such as; the uncertainty of the inputs values and the experiment surrounding circumstances will not be taken into consideration. According to JCGM 100:2008 [29] the value of standard uncertainty of the prediction’s output error ($u$) is calculated according to Eq. (4), Fig. 3 step 3.

$$u = ku_c (W)$$

where $k$, coverage factor, depends on prediction technique’s error probability distribution and confidence level. $u_c$, is the sample standard deviation of the prediction technique’s output error.

The value of $k$, according to 40 specimens (Table 1), t-distribution and level of confidence more than 99%, is 3.33. So, the error range ($E$) will be calculated with Eq. (5), Fig. 3 step 4.

$$E = \bar{E} \pm u$$

where $E$ is the prediction technique’s output error and $\bar{E}$ is the average error three selected data sets.

The required specific wear rate value is entered ($w$), step 5. The effectors’ ranges are entered by the user, then a matrix of the inputs is constructed. The obtained prediction technique was run to obtain the resulting wear, steps 6 and 7. The rest of the flowchart shows that, the calculation of the upper and lower limits of the required wear rate ($w_1$ and
w_2) and comparing it with the obtained results of the full matrix to get a set of effectors combination to achieve the required wear rate.

5 Results and discussion

5.1 The hardness of the composite

5.1.1 Effect of Al_2O_3 ratio

As mentioned before the Al_2O_3 is added with four different weight percentage (wt%); 10, 15, 20 and 25%. Figure 8 shows the effect of reinforcement ratio on the hardness of the Al-Si alloy, which increase its hardness. This improve directly proportion with Al_2O_3 ratio. The hardness of casted composite is growing with percentages up to 137% of the casted Al-Si alloy hardness with a rate of about 3.7 VHN/1% of reinforcement. This can be referred to the reduction in the grain size and raising of plastic constraint of Al-Si alloy [30]. This depression in the grain size of Al-Si alloy with the growing Al_2O_3 ratio is noted with the scan showed with Fig. 5a–c. It is clearly showed the depression size of the matrix grains by the increase of reinforcement percentage (0, 15 and 25, respectively). It, also, shows fairly distribution of the reinforcement particles, with comparatively agglomeration in the higher percentage.

5.1.2 Effect of heat treatment procedure

Figure 4 presents the impact of heat treatment sequence in the hardness of the Al-Si alloy-Al_2O_3 composite. The figure displayed that the heat treatment enhances the hardness of heat-treated Al-Si alloy up to 112% at increasing rate of 3.5 VHN/1% V_f and between 15 and 144% of the casted Al-Si alloy. The enhancement of heat treated composite’s hardness above the Al-Si alloy (casted or heat treated) is, also, due to the change in the grain size and plastic constraint of Al-Si alloy, which can be reported with the comparison between Figs. 5a–c and 6a, b.

Also, it is noted that the hardness of heat-treated composite is growing up the of casted one, that reinforced with the same wt% ratio, with ratios decreased from about 15 to 3% with of wt%. This lowering in the growing effect of the heat treatment can be attributed to the dislocation density, Fig. 6a, b, of Al-Si alloy particles as an effect of the thermal contraction through the cooling of the specimens in the heat treatment operations. The impact of this dislocation density is diminishing with the grow of Al_2O_3 volume fraction [30] which leads to reduce the improvement of the hardness in the higher volume fraction of Al_2O_3.

5.2 MMC specific wear rate

5.2.1 The Al_2O_3 percentage effect

The specific wear rate (SWR) is generally reverse proportional to the Al_2O_3 percentage which means that the growing of wear resistance with the raising in the ratio of reinforcement. The effectiveness of the Al_2O_3 is propagated at higher distance. This can be noted with the slope of the curves with the same marks in Fig. 7a–c regardless of applied load. The slope of curves with square mark, represent distance 1240 m, have the most inclination while the falling of curves with circle mark, represent distance 310 m, have the least one. This is counting on the increase in the specimen hardness due to the Al_2O_3 percentages. This notice is reduced with the increase of the applied load, this is remarked with the falling of the graphs with the same marks. The impact of Al_2O_3 ratio is eliminated with the grown of applied load.

Raising in the applied load (in the rage under studied) improves (reduces) the SWR in spite of friction distance, compare the different images in Fig. 7a–c with the same symbols [31]. This reduction is reduced with the raise of Al_2O_3 contents, which can be recorded by comparison different curves in Fig. 7a–c from left (lower contents) to right (higher one). At 25% Al_2O_3, the SWR trend is reversed, compare the left side in the three portions of Fig. 7. This can be attributed to the strain hardening cased in the material due to the applied load [32]. Also, it can be contributed to increase in delamination which involves subsurface deformation, crack nucleation and crack propagation, which produce greater wear. This is noted by the presents of fine powder in the wear debris. Figure 8 shows a microstructure for the worn surface of specimens with different Al_2O_3 percentages, which shows the increase in the delamination with high Al_2O_3%.
5.2.2 The applied load effects

Figure 9 shows that almost the increase in the applied load decreases the SWR, up to 20% Al₂O₃. Also, the distance of friction magnifying this effect, curves Fig. 9a–d respectively. While, at 25% the applied load increases the SWR with a small graduation. The reverse relation between the applied load and SWR can be attributed to the strain hardening of the specimen due to the applied load. While at the high reinforcement contents which has higher hardness values, sec 5.2, beside the applied force, which increase the contact between them, increase the friction between the pin.
Fig. 8 The worn surface a Al-Si alloy, b–e Al-Si alloy 10, 15, 20 and 25 wt% Al₂O₃, respectively.

Fig. 9 Effect of applied load on Specific Wear rate at different distances a 310 m, b 320 m, c 930 m and d 1240 m.
and the disk. This high friction induced heat that can raise the temperature at the contact surface to a value such softening the matrix and make a server wear [31]. Also, the frictional heating causes an oxidation of the surface, with wear occurring through the removal of oxide fragments.

5.2.3 The effect of the sliding distance

The SWR is directly proportional to sliding distance, as all. The reinforcement ratio and the applied load reduce the effect of the sliding distance on the SWR, Fig. 10a–c. The ascent of the SWR with the sliding distance decay with the growing of both reinforcement and load. The improving of the SWR with the raising in Al₂O₃ percentage is due to the increase in the material hardness. While this progress of SWR with the rise of the pressure on the specimen is due to the strain hardening occur in sample with this load.

5.2.4 Effect of heat treatment procedure

The heat treatment process improves the SWR of the Al-Si alloy-Al₂O₃ composite, as shown in Fig. 11a–d. This progress is reduced with the growing of the Al₂O₃ contents, which is consistent with the effect of it on the specimen hardness. And despite of the growth of the SWR at 25% Al₂O₃ with increase of both load and distance the heat treatment process improves it in the same way. This improvement is due to the increase of hardness and refine of the grain size as a result of this.

5.3 Prediction models

As mentioned in Sect. 3, the trained structure of ANN is 4-x-1, where x is the number of nodes in the hidden layer. X is taking as 4, 6, 8 and 10 nodes. Each network structure is trained 20 times with different initial weights, for both training techniques. After finishing training, the networks with which has min MSE, Min error and higher correlation coefficient (R) of all the trained networks is selected to simulate the experimental results. For normal training technique, the structure of this network is 4-8-1 and its outputs are shown in Table 1 beside the experimental results with its obtained error and the error average and sample standard deviation. While, for Leave-one-out technique, the most suitable structure is 4-8-1. Also, the resulting multiple regression polynomial is given with Eq. (6).

\[
W = -0.25375022 - 0.00057256 R^2 + 2.40598E - 06 L^2 \\
- 4.27276E - 05 H^2 \\
- 2.01873E - 08 D^2 - 0.024393028 R \\
- 0.000136754 L + 0.006861138 H \\
+ 0.000119873 D + 9.24752E - 05 RL \\
+ 0.00303436 RH + 1.29092E \\
- 06 RD - 1.49577E - 05 LH + 1.56253E - 06 LD \\
- 8.81367E - 07 HD
\]

(6)

Table 2 shown the MSE, R and \( R^2 \) for all groups of the experimental data and all predictions’ techniques, according to Sect. 3.2. The values of R and \( R^2 \) for the ruling set of data are more than 0.99 for both ANNs training methods and regression polynomial, and the MSEs of all are less than \( 10^{-5} \). While R of the rest samples is 0.9851 and 0.981for ANNs training methods and 0.9687 for the regression. The MSE were 1.20E-5, 1.44E-5 and 1.98E-5 respectively. This means that the ANN with the normal training technique would give the best simulation, between the used techniques, to the under-study engineering phenomena. Because of the smallest values of R and MSE it produces. Figure 12 shows the distribution of error percentages for ANN’s results. The figure shows that

![Fig. 10](image-url) 

**Fig. 10** Effect of sliding distance on specific wear rate at different loads a 20 N, b 30 N, and c 40 N
80% of the samples has less than 15% error, which reflect the accuracy of the prediction.

5.4 Obtaining the wear rate effectors

From the previous section, the ANN 4–8-1 structure will be used to execute the routine described in Fig. 3. Table 1 shows the average of the training, test and validation sets (40 samples) overall error (−0.000199) and the overall standard deviation (0.002304) of the ANN’s results with respect to the experimental results. The value of uncertainty (σ) is ±0.0076, Eq. (1). So, the error upper limit is 0.007403 and lower limit is −0.00787, Eq. (5), with a level of confidence more than 99%. Figure 13 shows the distribution of the both ANN’s and multiple regression’s errors and the expected upper and lower errors limits. The figure displayed that for ANN’s results 119 of 120 samples; laid between these errors’ limits (99.2%), while the

| Set type                | ANN’s results (normal training) | ANN’s results (Leave-one-out training) | Multiple regression |
|-------------------------|---------------------------------|---------------------------------------|---------------------|
|                         | MSE | R   | R²  | MSE | R   | R²  | MSE | R   | R²  |
| Training set (24 samples) | 3.94E-06 | 0.9953 | 0.9906 | 1.12E-06 | 0.9989 | 0.9978 | 1.02E-06 | 0.9987 | 0.9974 |
| Validation set (8 samples) | 9.66E-06 | 0.9907 | 0.9815 | 1.46E-07 | 0.9999 | 0.9998 |       |       |       |
| Test set (8 samples)    | 4.57E-06 | 0.9973 | 0.9946 | 1.14E-05 | 0.993 | 0.986 |       |       |       |
| All above sets (40 samples) | 5.21E-06 | 0.9948 | 0.9897 | 2.97E-06 | 0.9972 | 0.9944 | 4.05E-06 | 0.9960 | 0.9920 |
| The rest data (80 samples) | 1.20E-05 | 0.9851 | 0.9704 | 1.44E-05 | 0.981 | 0.962 | 1.98E-05 | 0.9687 | 0.9383 |
multiple regression technique showed that many samples lies out that limits. Despite of the \( R \) and MSE, Table 2, nearly the same for both. Which means that the ANN is presents the experimental data with a very good manner.

Table 3 shows the algorithm’s inputs. After constructing the ANN’s input data set (\( W \)) and produce their predicted values, the algorithm selects the samples that had wear rate between the upper and lower limits for the required wear rate (0.0686 and 0.0534 mm³/m). Table 4 shows the algorithm’s selected results sorted with the nearest predicted wear rate. The results showed that the nearest four predicted values had actual errors less than 1%, while the following nine had errors less than 10%. The results showed that the near is the predicted wear to the required one, the smaller is the obtained error.

### 6 Conclusions

The main goals of the present work are to help specialists to;

1. Predict the specific wear rate of A356 Al-Si/Al₂O₃ MMC.
2. Constructing and testing an algorithm to obtain effectors to achieve a certain specific wear rate for A356 Al-Si/Al₂O₃ MMC.

The results of the wear rate test of A356 Al-Si/Al₂O₃ MMC, its modeling with ANNs’ and multiple regression with OA technique, and the obtained algorithm for achieving the specific wear rate effectors by the obtained ANN, supported the following conclusions;

1. ANN model gave higher performance in prediction the specific wear rate of A356 Al-Si/Al₂O₃ MMC than multiple regression with low number of samples selected by orthogonal array technique.
2. Multilayer back-propagation ANN with sigmoid activation function, single hidden layer and Levenberg–Marquardt learning algorithm modeled the specific wear rate of A356 Al-Si/Al₂O₃ MMC.
wear rate prediction with confidence level more than 99%.

3. The normal training technique with OA technique produced higher performance (lower MSE and higher $R^2$) in the exterior samples than Leave-one-out technique.

4. ANN with OA technique modeled the specific wear rate with a very small MSE and high $R$ and $R^2$ values.

5. ANN model used to choose the specific wear rate’s effectors (its input vector) with an algorithm with high degree of accuracy.

6. AL$_2$O$_3$ contents in A356 Al-Si/Al$_2$O$_3$ MMC improved its hardness with direct relation and its specific wear rate with inverse relation.

7. Heat treatment of A356 Al-Si/Al$_2$O$_3$ MMC improved its hardness and reduced specific tool wear with ratios decreased with the increase of Al$_2$O$_3$%.

8. Applied load improved the specific wear rate up to 20% Al$_2$O$_3$ and worsened it for 25% Al$_2$O$_3$.

9. Specific wear rate is increased with the increase of sliding distance. This trend is eliminated with the increase of the applied load.

Table 4: The specific wear rate algorithm’s obtained results sorted with the nearest predicted wear rate

| Required wear rate (mm$^3$/m) | Obtained wear rate effectors | Predicted wear | Actual wear | Error% |
|-------------------------------|-------------------------------|----------------|------------|--------|
| AL$_2$O$_3$% Sliding distance Load Hardness | | | |
| 0.061 | 10 | 1240 | 30 | 115.56 | 0.060819 | 0.06 | 0.30 |
| 20 | 1240 | 40 | 144.44 | 0.060636 | 0.06 | 0.60 |
| 15 | 1240 | 30 | 121.48 | 0.060486 | 0.061 | 0.84 |
| 10 | 1240 | 20 | 100.00 | 0.060482 | 0.057 | 0.85 |
| 0 | 930 | 20 | 67.41 | 0.058321 | 0.059 | 4.39 |
| 0 | 930 | 30 | 77.78 | 0.057677 | 0.059 | 5.45 |
| 0 | 930 | 40 | 77.78 | 0.064395 | 0.059 | 5.57 |
| 15 | 930 | 40 | 121.48 | 0.057383 | 0.05 | 5.93 |
| 0 | 930 | 30 | 67.41 | 0.064841 | 0.064 | 6.30 |
| 10 | 930 | 40 | 100.00 | 0.065181 | 0.063 | 6.85 |
| 10 | 930 | 30 | 100.00 | 0.05643 | 0.052 | 7.49 |
| 15 | 1240 | 40 | 130.37 | 0.066568 | 0.061 | 9.13 |
| 20 | 1240 | 40 | 151.11 | 0.055199 | 0.054 | 9.51 |
| 10 | 930 | 40 | 115.56 | 0.054264 | 0.051 | 11.04 |
| 0 | 1240 | 20 | 77.78 | 0.068185 | 0.067 | 11.78 |
| 15 | 1240 | 30 | 130.37 | 0.053522 | 0.055 | 12.26 |

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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