Future Generation of Communication and Internet of Things (FGCIOT)

Journal homepage: http://fgciot.semnaniau.ac.ir/

PAPER TYPE (Research paper)

Neural network in predicting the mechanical strength of Al6061/SiC composites used in aerospace industries

Seyed Rahim Kiahosseini*

Department of Engineering, Damghan branch, Islamic Azad University, Damghan, Iran

Article Info

Article History:
Received: 1 November, 2023
Revised: 14 January, 2024
Accepted: 20 February, 2024

Keywords:
Fiber Type, Heat Treatment, Yield Strength, Ultimate Tensile Strength, Elastic Modulus

*Corresponding Author's Email Address:
rkiahoseyni@yahoo.com

Abstract

Aluminum composites have received attention in the aerospace industry due to their strength-to-weight ratio. In this research, the effect of three parameters, the percentage and type of SiC reinforcing material and the type of thermal cycle of composite manufacturing on the elastic modulus, yield strength and ultimate strength of Al/SiC composite have been investigated. For this purpose, the information related to composite with Al6061alloy reinforced with SiC particles was extracted. After normalizing the input and output information, the perceptron recurrent network was designed and it was tried to extract the optimal parameters by changing different parameters of the network such as the frequency of network training, changing the learning coefficient of the network and weight and bias coefficients and comparing the sum of squared errors in different conditions. Finally, by defining the adaptive learning coefficient in the network, it was tried to improve the speed and accuracy of the network. The results showed that by repeating the network training 10000000 times, the sum of squares of error was reduced to the range of 7-10. Also, the lowest error sum of squares is related to the learning coefficient α=0.002. The results related to the definition of the adaptive learning coefficient showed that if the network is trained 100,000 times, the training speed decreases to 60,000 times with the same error for the adaptive learning coefficient and the constant learning coefficient. In other words, if the adaptive learning coefficient is used, the training speed and error reduction will be higher than using the constant learning coefficient.

Introduction

Metal matrix composites reinforced by particles have received a lot of attention due to their remarkable practical properties[1-4]. These composites are made by various methods such as powder metallurgy and casting[5-9]. Although the manufacturing mechanism of these materials affects their behavior and properties, other parameters such as the size of particles added to the background can also affect the behavior of the composite. Various researches have been conducted on the effect of particle size[10]. percentage and shape on the properties of metal-based composites[11-14]. Also, studies have been conducted with the aim of predicting the properties of composites by means of modeling and simulation. For example, Lange et al.[15] have studied the effect of compressive force at ambient temperature on the density of composites made of aluminum powder and steel. Sridhar et al.[16] and Kim et al.[17] studied the yield stress of composites made of metal powders after different manufacturing mechanisms such as three-dimensional compression and isostatic cold

Doi:

pressing. In general, a lot of research has been done on composites and a lot of money has been spent in this regard. In order to reduce research costs and increase the accuracy of results, modeling the properties and behavior of composites by means of artificial neural network has been the focus of researchers. Genel and his colleagues[18] modeled and investigated the tribological properties of zinc-aluminum composite reinforced with alumina. In other researches, studies such as the effect of semi-solid extrusion of aluminum-based composite on its behavior[19], predicting the fatigue life of composites with multi-dimensional layer reinforcing materials[20] and predicting the effect of production parameters on properties Carbon/carbon composite[21] has been made. In this research, an attempt has been made to predict the effect of the type and percentage of SiC and the heat treatment of the Al6061/SiC composite on its mechanical behavior by means of the perceptron neural network.

Research materials and methods

In order to analyze the data extracted from the sources and predict the behavior of the Al6061/SiC composite, the backpropagation neural network (BP) was used. The network is shown in Fig 1 and 2.

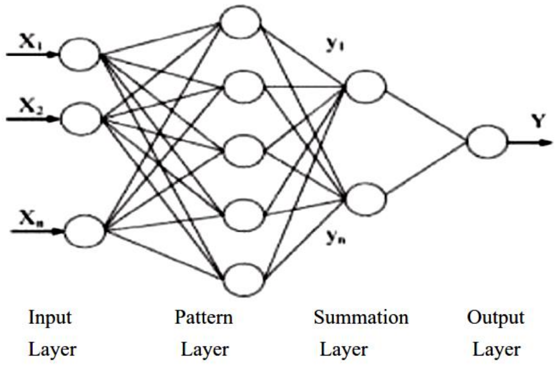


Fig.1: Schematic picture of a neural network[22].

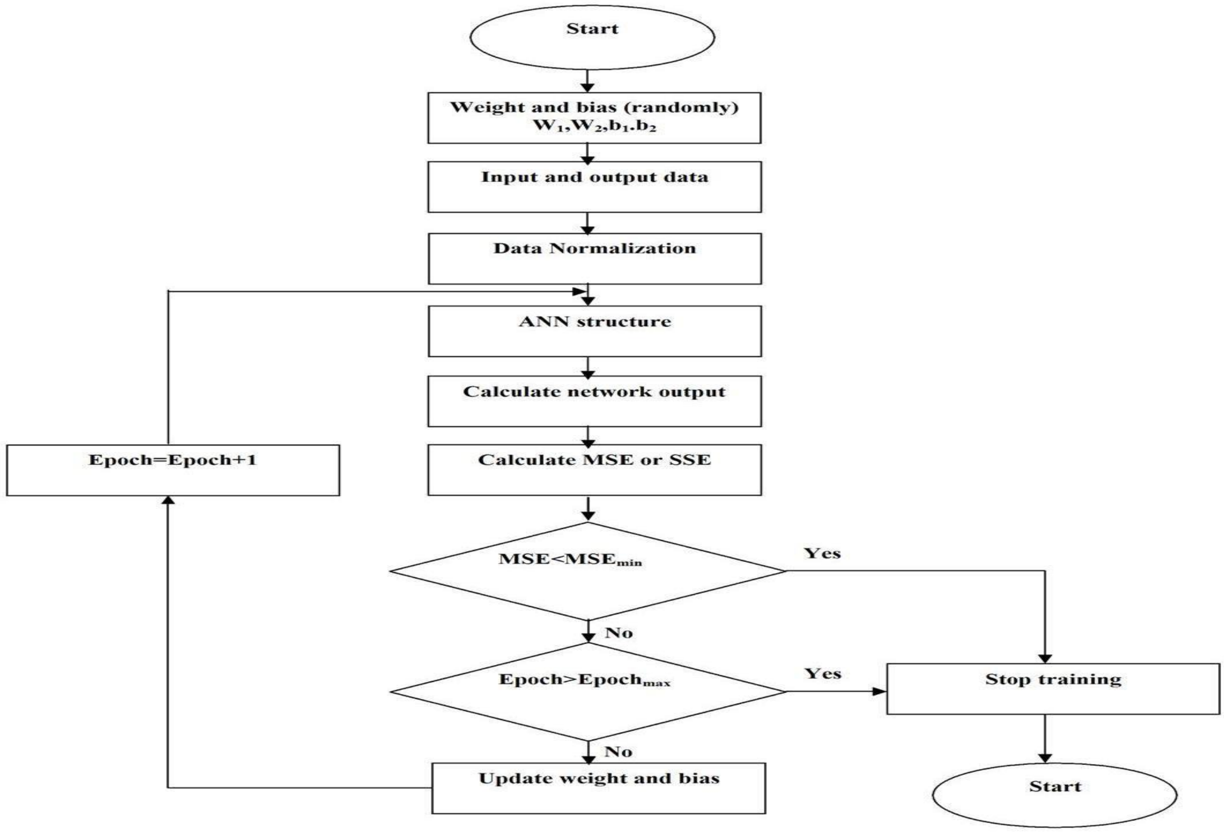


Fig. 2:Schematic representation of ANN training process.

Future Generation of Communication and Internet of Things (FGCIOT)

Journal homepage: http://fgciot.semnaniau.ac.ir/

Also, in order to design the recurrent perceptron neural network, the technical report of the American Space Agency (NASA)[23] was used according to Table 1 and the effect of three parameters SiC percentage, SiC type and type of heat treatment on Ultimate strength, yield strength and Young's modulus (Elastic modulus) for Al/SiC composite was identified with Al6061 base, which is widely used in the aerospace industry.

Table 1: Effect of tempering temperature, percentage and kind of SiC on the mechanical properties of Al/SiC composite[23]

Alloy	No.	SiC content (%wt.)	SiC Particles Shape[a]	Tempering Type[b]	Elastic modulus (GPa)	yield strength (MPa)	Ultimate strength (MPa)
6061	1	10	1	1	77	141	250
	2	10	1	2	83	311	373
	3	15	3	1	81	121	215
	4	15	3	2	90	295	359
	5	20	1	1	106	208	311
	6	20	1	2	96	321	423
	7	20	2	1	103	168	261
	8	20	2	2	99	316	385
	9	20	3	2	108	356	428
	10	30	1	1	112	334	406
	11	30	1	2	110	309	406
	12	30	3	1	112	222	329
	13	30	3	2	118	382	439
	14	40	3	2	134	428	457

a) 1: whisker structure 2: Needle structure 3: Spherical structure

b) 1: E type treatment 2: T6 Treatment

There are two computational paths in the BP algorithm. The first path is called the forward path and the second path is called the return path[24, 25].

Doi:

A- Forward path:

this route is expressed by the following equations.

a=p(k) (1)

a1+1(k)=F1+1(W1+1(k)a1+b1+1(k))1= 0,1,….L-1 (2)

a(k)=aL(k) (3)

In this way, as we can see, the parameters of the network do not change during the execution of calculations, and the stimulus functions act on each neuron, that is:

$F_{1+1}(n(k))=[f_{1+1}(n_1(k)\ldots f_{1+1}(n_{s1}+i(k)))]T$ (4)

B- Return path:

In this path, the sensitivity vectors are returned from the last layer to the first layer. The following equations express the dynamics of the return path[24]:

$$\mathrm{\delta^L(k) = -2F^L(n)e(k)} \quad (5)$$

$$\mathrm{\delta^L(k) = F^1(n^1)(w^{1+1})^T\delta^{1+1}, 1 = L-1, \ldots, 1} \quad (6)$$

$$e(k) = t(k) - a(k) \quad (7)$$

In other words, on the way back, work starts from the last layer, the output layer, where the error vector is available. Then, the error vector is distributed from the right to the left from the last layer to the first layer, and the local gradient is calculated neuron by neuron with a recursive algorithm. In this way, the network parameters will not change[24].

C- Adjusting the parameters:

Finally, the weight matrices and bias vectors of the MPL network are adjusted with the following relations:

$$W^1(k+1) = W^1(k) - \alpha\delta^1(k)(a^{1-1}(k))^T \quad (8)$$

$$b^1(k+1) = b^L(k) - \alpha\delta^1(k), 1 = 1,2, \ldots, L \quad (9)$$

We note that after applying each input-output pair as a learning pattern, the input vectors (input pattern) do not change during the above three steps. For this reason, the number of iteration step k is practically equivalent to the application of the k th model to the network[24].

D- Stopping:

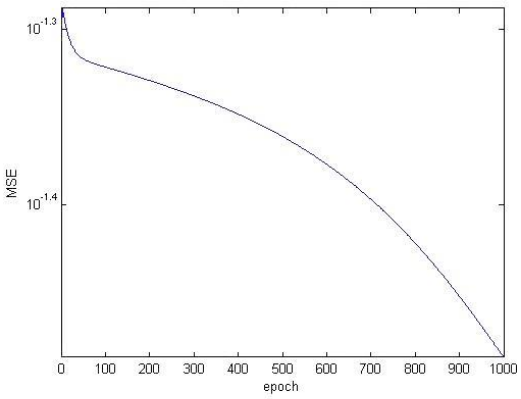
In order to stop repeating the BP algorithm, the following two indicators can be used simultaneously[24].

1- The average error square in each cycle or Epoch (the sum of the error squares for all learning patterns) is less than a predetermined value, or the form of changes in network parameters after each cycle is very small. It should be noted that each cycle is equal to the number of repetitions, equal to the number of learning samples. For example, if there are 100 learning sample data, the cycle is repeated for 100 steps.

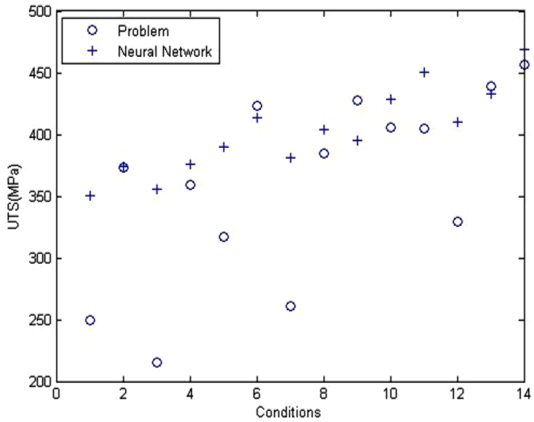
2- The soft gradient of the error is too small: the soft gradient of the error should be smaller than a predetermined circuit.

Results and Discussion

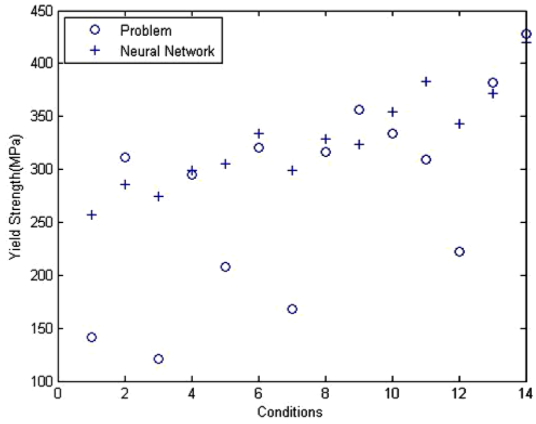
The results of the preliminary design of the multilayer perceptron neural network (MLP) in two layers to investigate the effect of three parameters SiC percentage, SiC type and tempering temperature on the elastic modulus, yield stress and ultimate stress of Al/SiC composite based on Al6061 with initial estimation of coefficients Weight and bias were coded in MATLAB software environment. In this case, the learning coefficient α = 0.5 and the training frequency was considered 1000 times. In order to increase accuracy in network training, the input and output data were normalized. For this purpose, all the data were divided to the maximum amount of data. The results of the network design with the available data are shown in the form of diagrams in Figure 3.



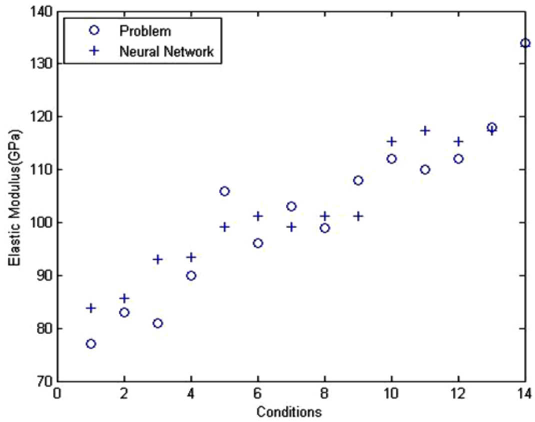
(a)



(b)



(c)



(d)

Fig. 3: the experimental results and the results of the two layers MLP neural network training of the composite Al / SiC, a) the number of errors in terms of education, b) Chart ultimate strength, c) the yield strength charts, D) elastic modulus chart.

According to Figure (3-a), it can be seen that with 1000 times of network training, the sum of squares of MLP network error has decreased. By using the two-layer feedback perceptron network, it is possible to estimate the Al/SiC composite behavior with the laboratory data, and there are training conditions. The sum of error squares in this condition was obtained as MSE = 0.0325824651108248.

The results related to the final strength, yield strength and elastic modulus of the Al/SiC composite in Figures 3b, c and d show that although the network error is decreasing, the laboratory results have a significant difference with the results of training. This issue shows the need to investigate different parameters of the neural network, such as the change in the training frequency and the change in the learning coefficient. Then, by changing the neurons of the first layer, it was tried to reduce the sum of squared errors in network training. By changing the number of neurons in the designed network code, we tried to get the appropriate number of neurons with the least sum of squared errors. For this purpose, the weight and bias coefficients were randomly changed with different neurons, and after running 20 times for each situation, the average of the sum of squared errors was obtained as shown in Table 2. According to these results, the selection of 8 neurons for Al/SiC composite manufacturing conditions can be appropriate in neural network design.

Table 2: Dependence of mean square error to number of back propagation Perceptron Neural Network neurons for Al / SiC composite

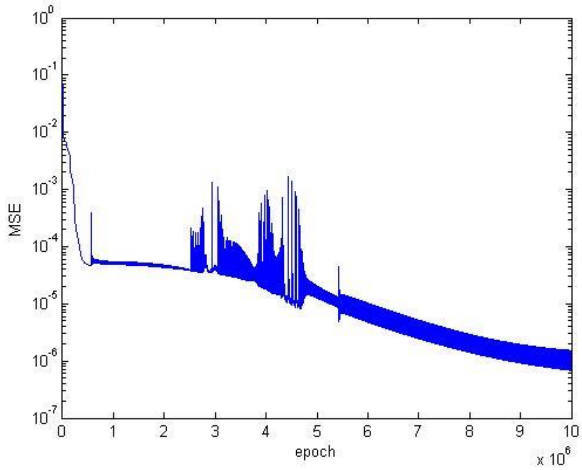
Number of neurons	Mean squared error
1	0.0278635155188623
2	0.0267445761356187
3	0.0302594017312537
4	0.0344077839583995
5	0.0256311891193074
6	0.0243489990873295
7	0.0236088564293812
8	0.0235668894948894
9	0.0269826702232628
10	0.0277143768756384

One of the effective parameters to reduce the sum of squares of errors in the feedback perceptron network is the change in the repetition frequency of training. For this purpose, the neural network code was executed with epoch change and the results of Table 3 were obtained. In all stages, the learning coefficient α=0.05 was considered.

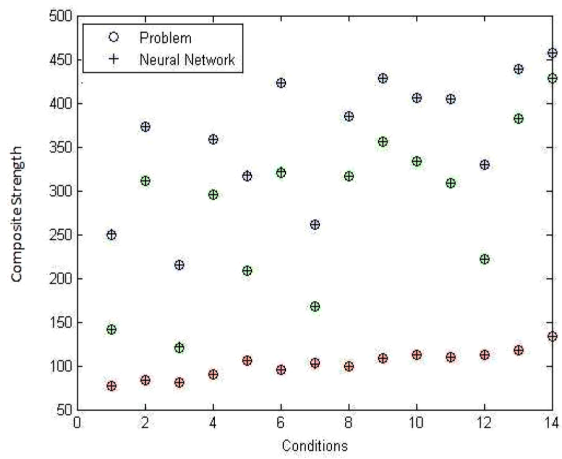
Learning coefficient training was modified. In this way, if the average of the sum of squares of our 5 periods before the last was higher than the last period, the learning coefficient was multiplied by 1.00015 and otherwise it was divided by 1.00015.

Table 3: Dependence of mean square error to number of back propagation Perceptron Neural Network trainin for Al / SiC composite

Training repetition times	Mean squared error
10	0.0418
100	0.0399
1000	0.0236
10000	0.0099
100000	0.0062
1000000	10^5
10000000	10^7



(a)



(b)

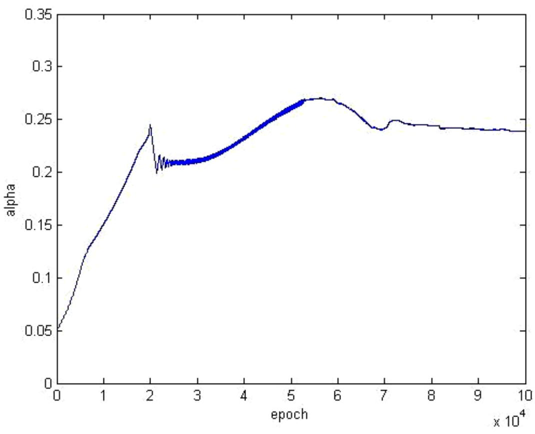
Fig. 4: Comparison of experimental results and the results of backpropagation artificial neural network training with the number of training 10 million times, a) the sum of squares of error in terms of frequency of occurrence, b) matched experimental results with the results of the neural network of the composite Al / SiC.

Figure 4 shows the results of the sum of squared errors and the comparison of the results obtained from neural network training with laboratory results after 10,000,000 times of network training. It can be seen that by increasing the repetition of the training, the sum of squares of the error has decreased and also the laboratory results are in acceptable agreement with the results of the neural network. In this way, the weight and bias coefficients were modified to an acceptable level. In order to increase the accuracy and speed of the training of the backward perceptron neural network, a variable learning coefficient was used according to the sum of squared errors in each network training cycle. For this purpose, the learning coefficient was corrected by calculating the average sum of squared errors in our 5 consecutive periods before the last training of the network and comparing it with the last training. In this way, if the average of the sum of squares of our 5 periods before the last was higher than the last period, the learning coefficient was multiplied by 1.00015 and otherwise it was divided by 1.00015.

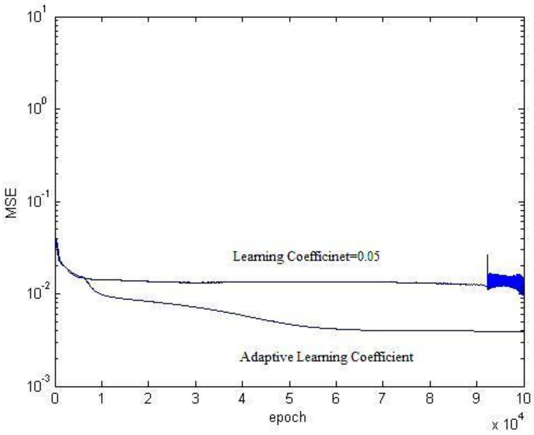
The graph of adaptive changes of the learning coefficient according to the number of network training is shown in Figure 5-a. It can be seen that by increasing the number of training up to 70,000 times, the learning coefficient increases in a fluctuating manner, and with the further increase of network training cycles, the fluctuations of the learning coefficient are reduced and tends to relatively constant values. These results show that the designed network has the ability to adapt the learning coefficient. Figure 5-b shows the sum of error squares according to the number of network training in the two cases of adaptive learning coefficient and fixed learning coefficient of 0.05. It can be seen that if the adaptive learning coefficient is used up to 10000 cycles, the sum of squared errors is almost equal to the fixed learning coefficient of 0.05, but with the increase in the number of training cycles, the sum of squared errors in the adaptive mode is reduced at a suitable rate, and wants acceptable values. As a result, by using the adaptive learning coefficient, the learning speed of the neural network will increase and the network error will decrease.

With these conditions, it can be claimed that with artificial neural network, it is easy to predict the effect of three parameters, percentage, type of SiC and type of heat treatment of Al6061/SiC composite on mechanical properties such as elastic modulus, yield stress and final strength. .

It is worth noting that, as shown in the flowchart of Figure 2, the initial weight and bias for training the perceptron neural network were considered random, which will have a non-theoretical effect on the exact values of the sum of squared errors. Therefore, considering that the training speed of the network depends on the initial guesses of weight and bias, by repeating the execution of the codes written in MATLAB software, although the prediction of the results was obtained with acceptable accuracy, but the repeatable behavior of the network error was not visible.



(a)



(b)

Fig. 5. a) behavior adaptive learning coefficient based on the number of cycles neural network training, b) the sum of squared errors versus the number of cycles of training the neural network with adaptive learning coefficient and constant learning factor 0.05.

Conclusion

By changing different parameters of the network to increase the accuracy of training with information related to Al/SiC aerospace composite, the following results were obtained:

- The dispersion of the primary data is such that in order to train the network, it is necessary to train the network 10,000,000 times.

- The learning coefficient as an effective parameter on the speed and accuracy of recurrent perceptron network training at α=0.002 has the lowest error in the presence of modified weight and bias.

- The number of neurons is also an effective parameter on the accuracy of network training. The best number of neurons in which the least training error was observed was related to the network with 8 neurons.

- By using the adaptive learning coefficient in the network training process, it was observed that the network error decreased and the network training speed increased significantly.

- Perceptron neural network results can be used with proper accuracy to predict the behavior of Al/Si composite with Al6061 base.

References

[1] Jung, H.K., et al., Analysis of anisotropy in elastic constants of SiCp/2124 Al metal matrix composites. 1999. 41(12): p. 1261-1267.

[2] Goujon, C. and P. Goeuriot, Solid state sintering and high temperature compression properties of Al-alloy5000/AlN nanocomposites. Materials Science and Engineering: A, 2001. 315(1-2): p. 180-188.

[3] Ahmadifard, S., et al., Fabrication of A5083/SiC surface composite by friction stir processing and its characterization. In Persian, Journal of Science and Technology of Composites, 2015. 2(4): p. 36-31.

[4] Ahmadian, H., et al., Mechanical properties of Al-Mg/MWCNT nanocomposite powder produced under different parameters of ball milling process. Diamond and Related Materials, 2022. 121: p. 108755.

[5] Dehestani, M., E. Adolfsson, and L.A. Stanciu, Mechanical properties and corrosion behavior of powder metallurgy iron-hydroxyapatite composites for biodegradable implant applications. Materials & Design, 2016. 109: p. 556-569.

[6] Liu, Z.Y., et al., Fabrication of CNT/Al composites with low damage to CNTs by a novel solution-assisted wet mixing combined with powder metallurgy processing. Materials & Design, 2016. 97: p. 424-430.

[7] Wang, X.J., et al., Processing, microstructure and mechanical properties of micro-SiC particles reinforced magnesium matrix composites fabricated by stir casting assisted by ultrasonic treatment processing. Materials & Design, 2014. 57: p. 638-645.

[8] 8. Sarvari, M. and M. Divandari, Melt-Solid-Gas behavior in the interface of Al/Mg composite produced by centrifugal casting. In Persian, Journal of Science and Technology of Composites, 2015. 2(3): p. 82-75.

[9] Borzouyi Kutenayi, S., S. Kiahosseini, and M. Talebpour, The effect of caspian sea water on corrosion resistance and compressive strength of reinforced concrete containing

different SiO2 pozzolan. International Journal of Engineering, 2017. 30(10): p. 1464-1470.

[10] Rahnama, H. and M.M. Shokrieh, Exact micromechanical stress analysis of long fiber composites under uniform tensile loading. In Persian, Journal of Science and Technology of Composites, 2015. 2(3): p. 10-1.

[11] Walker, E.E., The properties of powders. Part VI. The compressibility of powders. Transactions of the Faraday Society, 1923. 19: p. 73-82

[12] JIANG, L., et al., Thermal analysis for brake disks of SiC/6061 Al alloy co-continuous composite for CRH3 during emergency braking considering airflow cooling. Transactions of Nonferrous Metals Society of China, 2012. 22(11): p. 2783-2791.

[13] Knowles, A.J., et al., Microstructure and mechanical properties of 6061 Al alloy based composites with SiC nanoparticles. Journal of Alloys and Compounds, Volume 615, Supplement 1, 5 December 2014, Pages S401-S405, 2014. 615: p. S401-S405.

[14] Alhajeri, S.N., et al., Microstructure and microhardness of an Al-6061 metal matrix composite processed by high-pressure torsion. Materials Characterization, Volume 118, August 2016, Pages 270-278, 2016. 118: p. 270-278.

[15] Lange, F.F., et al., Deformation consolidation of metal powders containing steel inclusions. Acta Metallurgica et Materialia, 1991. 39(2): p. 209-219.

[16] Sridhar, I. and N.A. Fleck, Yield behaviour of cold compacted composite powders. Acta Materialia, 2000. 48(13): p. 3341-3352.

[17] Kim, K.T. and J.H. Cho, A densification model for mixed metal powder under cold compaction. International Journal of Mechanical Sciences, 2001. 43(12): p. 2929-2946.

[18] Genel, K., S.C. Kurnaz, and M. Durman, Modeling of tribological properties of alumina fiber reinforced zinc–aluminum composites using artificial neural network. Materials Science and Engineering: A, Volume 363, Issues 1–2, 20 December 2003, Pages 203-210, 2003. 363(1-2): p. 203-210.

[19] Muthukrishnan, N. and J.P. Davim, Optimization of machining parameters of Al/SiC-MMC with ANOVA and ANN analysis. Journal of Materials Processing Technology, 2009. 209(1): p. 225-232.

[20] Vassilopoulos, A.P., E.F. Georgopoulos, and V. Dionysopoulos, Artificial neural networks in spectrum fatigue life prediction of composite materials. International Journal of Fatigue, 2007. 29(1): p. 20-29.

[21] Li, H., et al., Numerical simulation of chemical vapor infiltration of propylene into C/C composites with reduced multi-step kinetic models. Carbon, 2005. 43(14): p. 2937-2950.

[22] Kumar, C.S., et al., Failure strength prediction of glass/epoxy composite laminates from acoustic emission parameters using artificial neural network. Applied Acoustics 2017. 115: p. 32-41.

[23] Danels, D.L.M. and C.A. Hoffman, Microstructure and Orientation effects on Properties of Discontinuos Silicon Carbide/Aluminum Composites. 1984, NASA: USA. p. 1-30.

[24] Menhaj, M.B., Computational Intelligence Fundamentals of Neural Networks. Vol. 5. 2009, Tehran: In Persian Amirkabir University of Technology. 716.

[25] Safaei Kuchaksaraei, J., Artificial intelligence in cancer diagnosis and treatment methods. Future Generation of Communication and Internet of Things, 2023. 2(3): p. 35-42