Prediction Micro-Hardness of Al-based Composites by Using Artificial Neural Network in Mechanical Alloying

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Abstract

Aluminum composites are one of the most important alloys with a wide range of properties and applications. In this paper, we predict the micro-hardness of aluminum-based alloys by artificial neural method (ANN). First, the effective parameters in mechanical alloying include weight percentage and micro hardness of reinforcement materials, milling time, the ball to powder weight ratio, vial speed, the pressure of presses, sintering time and temperature, selected for inputs and micro-hardness of Al composite considered as the output. A feed-forward back propagation artificial neural network designed with 16 and 10 neurons in the first and second hidden layers, respectively. The created network with the mean percentage error of 5.6% was able to predict micro hardness of the Al composites. Finally, the effect of each parameter was determined by sensitivity analysis which volume fraction of alloying elements, milling speed and sintering time had the highest impact on the micro hardness of Al-based composites.

Keywords: Aluminum Alloys, Prediction Micro Hardness, Artificial Neural Network, Mechanical Alloying.

1. Introduction

Noble properties of aluminum like low density, malleability, machinability, good electrical and heat conductivity, and high corrosion resistibility; turn the Al-based alloys to the most commonly used composites than other MMCs (metal matrix composite) [1]. Hence, Al-alloys have various applications such as automobile manufacturing [2], aerospace applications [3], circuits [4], fuel cells [5], etc.

On the one hand, low strength is the known weakness of the Al, and on the other; reinforcement materials usually improve the main phase properties such as strength, toughness, electrical and heat conductivity. Variety methods exist for producing Al composites such as casting [6], ultrasonic cavitation [7], severe plastic deformation (SPD) [8] and mechanical alloying (MA) [9].

Among these ways, MA due to low temperature, simplicity and cheapness of the process, being eco-friendly and homogenous dispersion of the second phase, has a particular position for the production of Al composites. Different materials in Al alloys could apply as reinforcement phases; such as Cu, Mg, Mn and, Si. Despite the simplicity of the mechanical alloying, each alloying element and effective MA factors owing to various interactions between the matrix and the second element has a different impact on the micro hardness of Al-composites.

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Estimation the micro hardness of the Al composites lead to optimizing using of the MA for synthesizing Al-alloys.

Various computational modeling have been proposed for numerous materials engineering optimization and prediction, such as artificial neural network [10], Taguchi [11], and Genetic Algorithm [12]. ANN due to the suitability of categorizing large datasets, approaching different parameters and achieving a precise solution, has been used widely. Indeed, ANN is one of the most powerful modeling tools for approaching different datasets and reaching an exact solution [13-15].

This modeling technique is based on learning and subsequently the prediction of output responses. Moreover, ANN has been a lot of applied in MA and owing to the different significant parameters in the mechanical alloying, it can help to predict desired outputs.

In this paper, we collect important factors in the MA method include weight percentage and micro hardness of reinforcement materials, milling time, the ball to powder weight ratio (BPR), the vial speed, the pressure of presses, sintering time and temperature, and micro-hardness of Al-composites from valid related papers.

Then, the gathered data were used to design an artificial neural network for prediction the micro hardness of different Al alloys. Finally, the Neurosolution program was used for specifying the most important parameters on the micro hardness of Al composites in the MA method.

2. Materials and Methods

In order to predict the hardness of Al-based alloys, the experimental data were extracted from valid international reports [16-24] and collected in (Table. 1.).

Table. 1. The collected dataset with detail of effective parameters in the MA method for producing Al-based composites.

No	Composite	Reinforcement (wt %)	Reinforcement Hardness (HV)	Milling Time (h)	BPR	Vial Speed (RPM)	Pressure (MPa)	Sintering Temperature (K°)	Sintering Time (h)	Final Micro Hardness (HV)	Reference
1	Al-Al_4C_3	2	498	10	6	450	650	873	5	100	[16]
2	Al-Al_4C_3	2	498	20	6	450	650	873	5	140	[16]
3	Al-Al_4C_3	2	498	30	6	450	650	873	10	220	[16]
4	Al-Al_4C_3	2	498	10	6	450	650	873	20	175	[16]
5	Al-Al_4C_3	2	498	30	6	450	650	873	20	290	[16]
6	Al-Al_4C_3	2	498	20	6	450	650	923	5	150	[16]
7	Al-Al_4C_3	2	498	30	6	450	650	923	5	200	[16]
8	Al-Al_4C_3	2	498	30	6	450	650	923	10	310	[16]
9	Al-Al_4C_3	2	498	10	6	450	650	923	20	200	[16]
10	Al-Al_4C_3	2	498	20	6	450	650	923	20	270	[16]
11	Al-Al_4C_3	2	498	30	6	450	650	923	20	350	[16]
12	Al-Al_4C_3	2	498	20	6	450	650	873	10	180	[16]
13	Al-Al_4C_3	2	498	10	6	450	650	923	10	160	[16]
14	Al-AlB_2	15	2500	4	7	300	49	600	60	175	[17]
15	Al-AlB_2	50	2500	4	7	300	49	600	60	295	[17]
16	Al-AlB_2	15	2500	4	7	300	49	900	60	160	[17]
17	Al-AlB_2	50	2500	32	7	300	49	600	60	370	[17]
18	Al-AlB_2	15	2500	32	7	300	49	900	60	250	[17]
19	Al-AlB_2	50	2500	32	7	300	49	900	60	500	[17]
20	Al-AlB_2	50	2500	4	7	300	49	900	60	400	[17]
21	Al-AlB_2	15	2500	32	7	300	49	300	60	145	[17]
22	Al-MgB_2	15	2600	4	7	300	49	900	60	170	[17]
23	Al-MgB_2	50	2600	4	7	300	49	900	60	315	[17]
24	Al-MgB_2	15	2600	4	7	300	49	300	60	150	[17]
25	Al-MgB_2	50	2600	4	7	300	49	300	60	220	[17]
26	Al-MgB_2	15	2600	4	7	300	49	600	60	180	[17]
27	Al-MgB_2	50	2600	32	7	300	49	300	60	360	[17]
28	Al-MgB_2	15	2600	32	7	300	49	600	60	250	[17]
29	Al-MgB_2	15	2600	32	7	300	49	900	60	270	[17]
30	Al-MgB_2	50	2600	32	7	300	49	900	60	460	[17]
31	Al-Fe	2.5	130	20	10	300	375	600	120	220	[18]
32	Al-Fe	10	130	20	10	300	375	600	120	370	[18]
33	Al-Fe	15	130	20	10	300	375	600	120	440	[18]
34	Al-Fe	20	130	20	10	300	375	600	120	600	[18]
35	Al-Fe	2.5	130	20	10	300	375	400	120	130	[18]
36	Al-Fe	5	130	20	10	300	375	400	120	140	[18]
37	Al-Fe	15	130	20	10	300	375	400	120	170	[18]
38	Al-Fe	20	130	20	10	300	375	400	120	180	[18]
39	Al-Fe	5	130	20	10	300	375	800	120	170	[18]
40	Al-Fe	10	130	20	10	300	375	800	120	180	[18]
41	Al-Fe	20	130	20	10	300	375	800	120	500	[18]
42	Al-AlN	2.5	1100	25	20	270	1500	873	20	183	[19]
43	Al-AlN	5	1100	25	20	270	1500	873	20	186	[19]
44	Al-AlN	10	1100	25	20	270	1500	873	60	185	[19]
45	Al-AlN	5	1100	25	20	270	1500	873	60	198	[19]
46	Al-Al_3Ti	10	145	20	10	300	375	673	120	140	[20]
47	Al-Al_3Ti	15	145	20	10	300	375	673	120	210	[20]
48	Al-Al_3Ti	20	145	20	10	300	375	673	120	340	[20]
49	Al-Al_3Ti	5	145	20	10	300	375	673	120	100	[20]
50	Al-Al_3Ti	20	145	20	10	300	375	573	120	270	[20]
51	Al-Al_3Ti	5	145	20	10	300	375	573	120	110	[20]
52	Al-AlB_2	50	2600	20	7	300	49	573	60	430	[21]
53	Al-AlB_2	15	2600	20	7	300	49	673	60	240	[21]
54	Al-AlB_2	15	2600	20	7	300	49	573	60	190	[21]
55	Al-AlB_2	15	2600	20	7	300	49	573	60	200	[21]
56	Al-AlB_2	50	2600	20	7	300	49	673	60	370	[21]
57	Al-AlB_2	50	2600	20	7	300	49	673	60	450	[21]
58	Al-AlB_2	15	2600	20	7	300	49	773	60	160	[21]
59	Al-AlB_2	50	2600	20	7	300	49	773	60	350	[21]
60	Al-AlB_2	50	2600	20	7	300	49	773	60	470	[21]
61	Al-AlB_2	15	2600	20	7	300	49	873	60	170	[21]
62	Al-AlB_2	15	2600	20	7	300	49	873	60	280	[21]
63	Al-AlB_2	50	2600	20	7	300	49	873	60	500	[21]
64	Al-SiC	10	2400	24	20	200	38	823	60	270	[22]
65	Al-SiC	2	2400	24	20	200	38	823	60	120	[22]
66	Al-SiC	5	2400	24	20	200	38	823	60	160	[22]
67	Al-SiC	7	2400	24	20	200	38	823	60	190	[22]

68	Al-SiC	1	2400	20	10	260	570	523	60	83	[23]
69	Al-SiC	1	2400	2	5	360	570	523	60	88	[23]
70	Al-SiC	1	2400	20	5	360	570	523	60	85	[23]
71	Al-SiC	1	2400	2	5	260	570	523	60	47	[23]
72	Al-SiC	1	2400	20	10	360	570	523	60	88	[23]
73	Al-MWCNT	0.25	2400	1	5	300	950	823	180	51	[24]
74	Al-MWCNT	0.25	2400	2	5	300	950	823	180	52	[24]
75	Al-MWCNT	0.75	2400	2	5	300	950	823	180	77	[24]
76	Al-MWCNT	0.75	2400	1	5	300	950	823	180	69	[24]
77	Al-TiB2	20	3400	1	10	360	35	277	10	206	[25]
78	Al-Al_4C_3	2	498	30	6	450	650	873	5	210	[16]
79	Al-Al_4C_3	2	498	20	6	450	650	873	20	260	[16]
80	Al-Al_4C_3	2	498	10	6	450	650	923	5	140	[16]
81	Al-Al_4C_3	2	498	10	6	450	650	873	10	140	[16]
82	Al-Al_4C_3	2	498	20	6	450	650	923	10	225	[16]
83	Al-AlB_2	50	2500	4	7	300	49	300	60	200	[17]
84	Al-AlB_2	15	2500	32	7	300	49	600	60	210	[17]
85	Al-AlB_2	50	2500	32	7	300	49	300	60	320	[17]
86	Al-MgB_2	15	2600	32	7	300	49	300	60	165	[17]
87	Al-MgB_2	50	2600	4	7	300	49	600	60	350	[17]
88	Al-MgB_2	50	2600	32	7	300	49	600	60	415	[17]
89	Al-Fe	5	130	20	10	300	375	600	120	230	[18]
90	Al-Fe	10	130	20	10	300	375	400	120	150	[18]
91	Al-Fe	2.5	130	20	10	300	375	800	120	160	[18]
92	Al-Fe	15	130	20	10	300	375	800	120	300	[18]
93	Al-AlN	10	1100	25	20	270	1500	873	20	190	[19]
94	Al-AlN	2.5	1100	25	20	270	1500	873	60	195	[19]
95	Al-Al_3Ti	10	145	20	10	300	375	573	120	130	[20]
96	Al-Al_3Ti	15	145	20	10	300	375	673	120	150	[20]
97	Al-MgB_2	15	2600	20	7	300	49	673	60	200	[21]
98	Al-MgB_2	50	2600	20	7	300	49	573	60	340	[21]
99	Al-MgB_2	15	2600	20	7	300	49	773	60	230	[21]
100	Al-MgB_2	50	2600	20	7	300	49	873	60	340	[21]
101	Al-SiC	1	2400	2	10	260	570	523	60	99	[23]
102	Al-SiC	1	2400	20	5	260	570	523	60	138	[23]
103	Al-SiC	1	2400	2	10	360	570	523	60	108	[23]
104	Al-MWCNT	0.5	2400	1	5	300	950	823	180	64	[24]
105	Al-MWCNT	0.5	2400	2	5	300	950	823	180	76	[24]

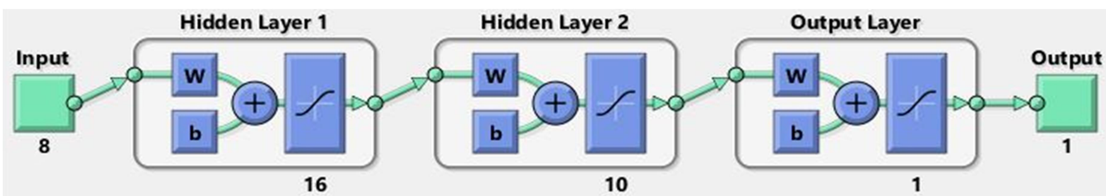

Fig. 1. Diagram of the designed ANN architecture.

2.1. ANN Modeling Procedure

ANN network generally contains interconnected units known as neurons or nods. Neurons are the smallest computing elements which interconnected to weighted links and they aggregate into layers. These layers affect their input information and can be trained by a process [26, 27]. Indeed, ANN consist of input layers, output layers, and hidden layers and neuron signals transmitted several times from input to the output. The training process of ANN continuous intermittently by changing weights until the network could approach the desired output and reaches to the acceptable error.

After training, the network can predict the output of untrained data by using the designed model that was learned at the training step. The relationship of neurons can be expressed by relation Eq. (1). [28-31]:

$$x = \sum_{i=1}^{p} w_i x + b \qquad \text{Eq. (1).}$$

Where the output x produced by the neuron in the layer, p is the number of elements in the layer, $w_i x$ is the weight, and b is the offset or bias. 77 and 28 data sets were used for the train and test of the network, respectively. Feed-forward backpropagation (FFBP), which is one of the most suitable ways for the training of the network in ANN, was used for training the model. This method presents effective solutions for approaching different factors in order to find a solution [14, 28]. The number of neurons in the hidden layers during the training process was determined by trial and error. This network includes an input layer, two hidden layers and, an output layer. There are 16 and 10 neurons in the first and second hidden layers, respectively. The input variables are weight percentage and micro hardness of reinforcement materials, time of milling, the ball to powder weight ratio, vial speed, the pressure of presses, sintering time and temperature; and micro-hardness of Al-composites considered as the output (Fig. 1.). provides information about the schematic diagram of the ANN model configuration. The network modeling was written in MATLAB software version R2014a and the Levenberg–Marquardt (LM) algorithm [29] was used to train the network. Furthermore, the log-sigmoid transfer function was applied as an activation function for hidden and output layers. The data sets have been normalized between 0.1 to 0.9 for homogenization according to relation Eq .(3). [31]:

$$N= 0.8\left(\frac{x-x_{min}}{x_{max}-x_{min}}\right)+0.1 \qquad \text{Eq .(3).}$$

Where x_{max} and x_{min} are the maximum and minimum values of the parameters, respectivelly.
The root mean square errors (RMSE) for the designed network was computed by Eq. 4. [31]:

$$\mathrm{RMSE}=\frac{1}{\mathrm{N}}\sum_{1}^{\mathrm{N}}\left(\frac{|\text{Actu value}-\text{Predicted value}|}{\text{Actual value}}\times 100\right) \text{Eq.(4).}$$

Where N is the total number of training patterns.

3. Results and Discussion

In order to verify the accuracy of the network performance, regression analysis was performed for training and testing data sets. The result of the regression analysis is shown in Fig. 2. According to this graph, the total regression (total regression of test, train, and validation) was 0.987. Better regression leads to less scattering between datasets and predicted values. Thereby, it is completely reasonable that the error percentage of the measured regression will be less and the obtained relation would be more accurate, due to being very close to 1. It can be seen that the artificial neural network has been able to reach a very close relation between the experimental variables and the prediction values and the network has been able to find an appropriate equation. For verification of the network, a comparison between experimental and predicted values datasets was carried out. Regarding Eq. 4., the average error of the network was calculated by 5.6%. Based on this result, it can be expected that the modeled ANN network can predict other similar results with such high accuracy and reliability. Moreover, with attention to the many variables involved in the MA, the proposed model reduces time and experimental research costs. The influence of each parameter can be determined by using sensitivity analysis. This analysis explains which of input more important than the other factors. Fig. 3. shows the result of Neurosolution from the sensitivity analysis of collected datasets. According to the results, the proportion of alloying elements, milling speed and sintering time have the highest impact function, respectively. In General, The enhancement amount of the reinforcement materials leads to an increase in the lattice parameter and micro-hardness. More percentages of alloying elements cause to work hardening of Al particles and so the hardness of the powders increased.

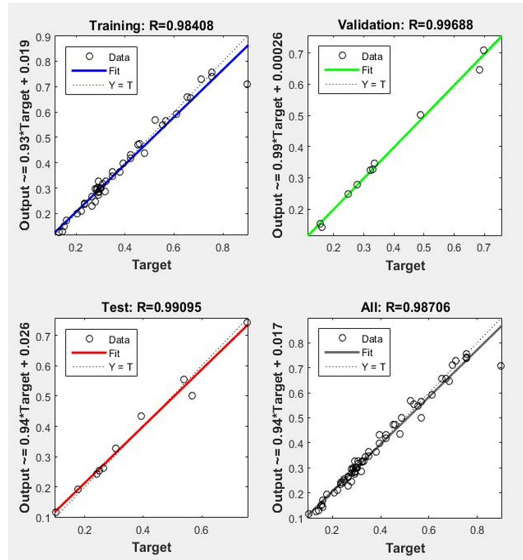

Fig. 2. Schematic of regression based on the designed ANN model for prediction micro hardness of Al-based alloys in the MA method.

The rich solid solution in aging will form a high volume fraction of coherent sediments, and crystalline defects provide preferred sites for sedimentation, consequently, these sediments prevent recovery and recrystallization [30]. During the ball milling of Al alloys, powder particles are severely deformed by the impact of the steel balls which leads to an increase in the local temperature and as a result, atomic diffusion occurs. Furthermore, the density of crystalline defects such as vacancies, dislocations, and stacking faults are greatly increased. Consequently, the particles get work hardening over time and as a result, the effects of work hardening expanded; hence it is reasonable that milling speed has a major effect on the hardness of the Al alloys. It should be noted that each parameter can minimize or maximize the others and affect the micro hardness of the Al- composites during MA.

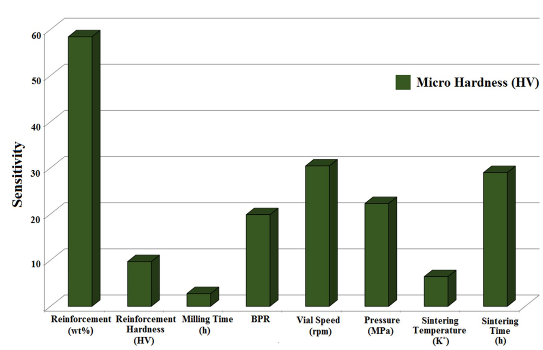

Fig. 3. Sensitivity analysis of the important parameters of the MA for fabrication AL-composite.

4. Conclusion

1. The ANN model with 16 and 10 neurons in hidden layers 1 and 2, respectively, is a useful method for the prediction of the micro hardness of Al-based composite synthesized by the MA method.
2. In this study, the designed ANN model predicted the micro hardness of Al alloys with an average error of 5.6%.
3. Results of the sensitivity analysis show that the proportion of alloying element, milling speed and sintering time have the highest impact on the micro hardness of Al composites, respectively.

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