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Predicting The Hardness and Porosity of a Smart Alloy (Cu-Al-Ni) with Nanoparticles Added, Using Smart Neural Networks

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Abstract— This research is dealing with determining the best ratio between the experimental and predicting results and comparison between them by using the Artificial Neural Network (ANN) for the mechanical properties of Hardness and porosity of smart (83% Cu-13% Al-4% Ni) alloys by adding aluminum nanoparticles (0%, 5%, 10%, 15%). These mechanical properties have a main technological and commercial interest in industrial and aerospace applications, and also in high damping composites, sensors, actuators, and filters.Physical examinations were carried out (using electron microscopy (SEM) and X-ray diffraction), to ensure the presence of Martensite phase after heat treatment.The prediction process utilizing the ANN tool in Matlab R2020a software is separated into two stages: the first is to select the best network to predict the best outcomes for the experiment's inputs. In order to decrease the expense, effort, and time necessary to carry out numerous further trials in order to attain these findings, the second stage entails using this best network for comparison between the predicted and experimental results. The forward back propagation algorithm was used in all networks of ANN.Show the results that increasing the percentage of nanoparticle addition leads to an increase in Vickers micro hardness where its value was (136 HV) for the sample without addition, while it reached its maximum value (190.7HV) when 15% of the nanoparticles were added. The porosity test showed a reverse behavior from the hardness test, where the porosity increased when no nanoparticles were added, and its value was (21.54), while its value (3.245) when added was 15%.

Keywords— nanoparticles, Smart (Cu-Al-Ni) alloys, Artificial Neural Network.

1. Introduction

Shape memory alloys (SMAs) are substances that, when their temperature rises over their transformation point due to various environmental factors, can regain their original shape even after suffering severe plastic deformations [1]. They may easily be twisted into any desired shape, which they will maintain, and if their temperature falls below their transition point, they have very little yield strength [2]. Due to their distinctive characteristics, SMAs have significantly increased economic and technological value and are currently used in a wide range of applications, including industrial, medicinal, and aerospace applications [3]. The SMAs' special features are the thermoplastic martensitic transition, a reversible crystalline change. There are two solid phases that make up the martensitic transition. The first is austenite, the parent phase of the martensitic transition, and the second is martensite, the product phase, these are the two solid phases involved. The martensite phase, which is a solid phase, is formed as a result of the rapid cooling of the austenite phase after the necessary heat treatment [9].

The main purpose of finding the optimal percentage of the nano edition and using the network is to reduce manufacturing costs, time, and effort in practical experiments. ANN gave a wide range to the user by predicting and comparing the results for the samples to which nanomaterials were added, so ANN was preferred over other methods like Fuzzy Logic Model. ANN is a powerful computing system with a fundamental operating principle that is analogous to biological neural networks. A connection linked every neuron to another one in the body. Each liaison connection has a weight attached to it that contains information about the input signal. Since the weight often activates or inhibits the signal that is being conveyed, the neurons employ this information to address a specific issue. Each neuron has an internal case called an activation signal, which is used when the activation function and the input signals are combined to produce output signals [11].

Zahran, B., et.al., (2015), [12]: In this research, the ANN tool was employed to forecast how the ratios of the alloying elements (used as input variables) will affect the mechanical properties of aluminum alloys (output variable: hardness). The principal alloying elements (Cu, Si, Fe, Mn, and Mg) are used in varying percentages to create 10 various compositions of aluminum alloys. These alloys were examined in this research, and experimental findings indicate that the elements Fe & Cu individually had the best effects on hardness, as well as the optimum structure (Fe, Cu, Si, and Mn). In order to achieve the best result for hardness, the ANN tool has been used to assess the number of neurons in the hidden layer and the activation function.

Hasan and Ahmed (2016) [5]: ANN tools in the Matlab software were used to forecast new samples without creating them for a smart alloy (copper, aluminum, nickel). By using the sintering time as input and (SME%, hardness, and porosity) as output. Two networks were created using two distinct techniques: The first one uses three samples of data for training, predicts the remaining data, and then assesses the accuracy of the predictions using experimental data. The information from all five samples was used in the second approach. The outcomes of the predictions are utilized to train a larger final network. The final network is used to forecast the outcomes of the experiment. To compare mechanical qualities, two approaches for forecasting results and experimental findings were used. In sintering time, the relationship between SME% and hardness is indirect. However, the relationship between SME and porosity is direct.

Taher and Ahmed (2018) [9]: Matlab R2016a software employed ANN, to cut down on expenditures and experimentation. The (Cu-Al-Ni) SMAs behavior at varying the (Cu-Ni) & (Al-Ni) concentration ratios was very well predicted by the ANN. Where, for eight fresh R.St. % inputs for the same alloys utilized in the experimental work to explore the influence of (Cu-Ni), the average absolute error percentage between experimental and predicted outcomes of SME is 6.23%. A novel alloy that was not employed in the experimental effort to explore the effect of (Cu-Ni) has an average absolute error percentage between the experimental and projected results of hardness and porosity of 1.93%.

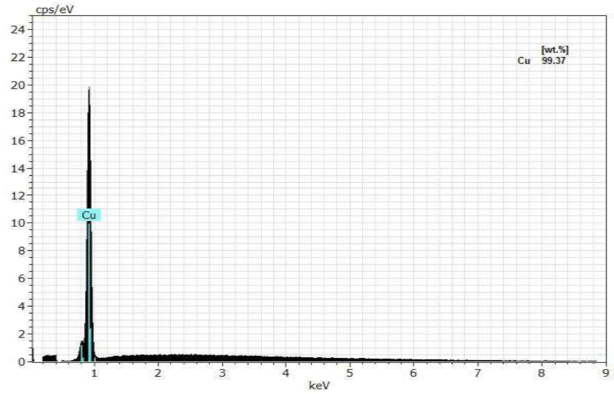
Haydar Al-Ethari and Shahad Ali (2020) [6]: This research focused on (Ni-Ti) shape memory alloy reinforced with nanoparticles was the main topic of this essay. The goal of the current research is to better understand how copper and silver nanoparticles are used to reinforce Nitinol. By applying the powder metallurgical method and a determined acceptable compacting pressure of two directions at 650 MPa while sintering for five hours at 850 C in an argon gas furnace, a base alloy consisting of (55% Ni + 45 % Ti) has been created. Samples containing 0.5 weight percent of Ag or Cu nanoparticles were also produced. Microhardness and porosity were among the mechanical and physical characterizations. The findings demonstrated that the hardness value increased to 287 Hv (0.5 wt. % Cu) and (0.5 wt. % Ag) combined, while for the same percentage alloy, the porosity reduced to (23.1).

Raed N. Razooqi, and Saad J. Ahmed (2021), [7]: The research presented a study of the influence on the physical and mechanical properties when adding Ag nanoparticles to NiTi-based alloy, with various volumetric percentages of Ag (0, 8, 9, 10, 11, and 12) %. Powder metallurgy was used to prepare the samples. Mixing, compacting uniaxial compacted at a pressure of 850 MPa (1 min) (in one direction), and sintering were the three primary processes in the procedure. The results revealed that as the Ag concentration increased, the porosity decreased, and the hardness, increased, the maximum hardness value was (280 Hv) at 11% Ag content.

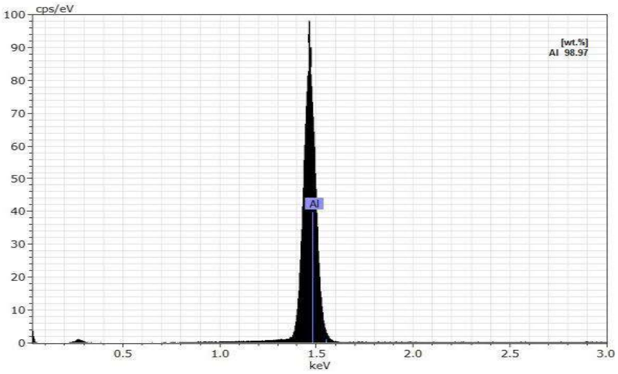
2. Database and a model of an artificial neural network (ANN model)

2.1 Material

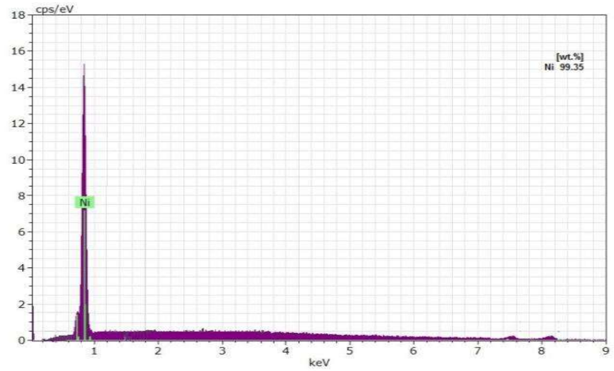
The powder metallurgy method was used to manufacture four smart (83% Cu-13% Al-4% Ni) alloys with different concentrations that depended on the percentage of adding aluminum nanoparticles (0, 5, 10, and 15) %. Two samples were manufactured from each weight and addition, as shown in table (1), the seventh column shows the final weights of the samples. They contain (Cu, Al, and Ni) powders that have the purity of (99.5 Cu, 99 Al, and 99.5 Ni) % and an average particle size (44) micrometer (-325 mesh), and Aluminum nanoparticle with purity (99.9) % and an average particle sizes (40) nanometer, as shown in the figure (1)



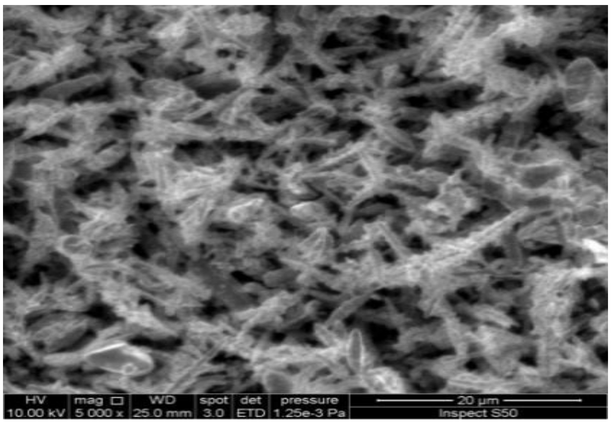
(Cu)



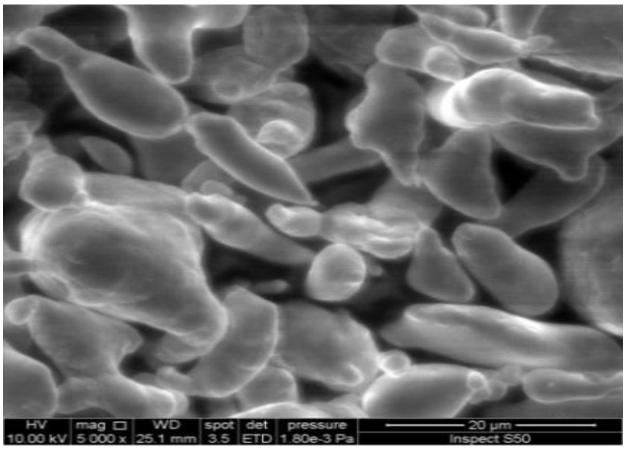
(Al)



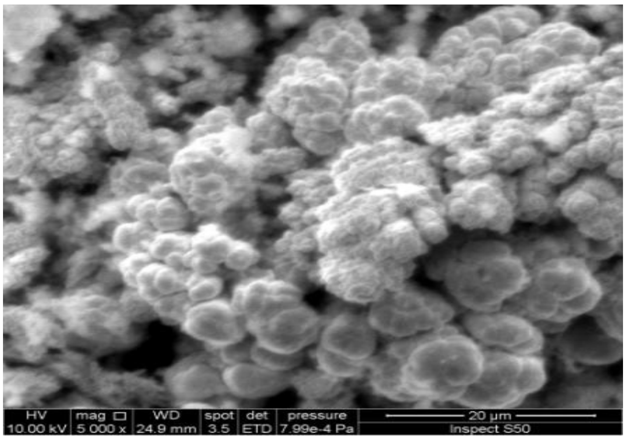
(Ni)



(Cu)



(Al)



(Ni)

Figure 1: EDX, and SEM examination raw material: Cu, Al, and Ni

Table 1: Distribution of weight of materials

<table>
<tr><th>No. of sam-ple</th><th>Cu (83%) (gm)</th><th>Al (13%) (gm)</th><th>Ni (4%) (gm)</th><th>Nano (gm)</th><th>Qty. of sam-ple</th><th>sample weight (gm)</th></tr>
<tr><td>S1</td><td rowspan="4">2.49</td><td rowspan="4">0.39</td><td rowspan="4">0.12</td><td>0</td><td rowspan="4">2</td><td>3</td></tr>
<tr><td>S2</td><td>0.019</td><td>3.019</td></tr>
<tr><td>S3</td><td>0.039</td><td>3.039</td></tr>
<tr><td>S4</td><td>0.058</td><td>3.058</td></tr>
</table>

The manufacturing process included four stages (mixing, compacting, sintering, and heat treatment).

The mixing stage included two stages to ensure a homogeneous distribution of the mixture with the nanomaterial. As for the pressing process, it took place under constant pressure (650 MPa), and in one upward direction.

After the process of pressing and obtaining (green compact), the process of sintering and heat treatment begins, which is carried out in the inert (argon) gas and is in several stages as shown in figure (2)

Figure 2: (a) Electrical furnace with an inert gas system, and (b) Samples after heat treatment

Also known as solid-state sintering is a heat treatment performed on green compact in an atmospheric furnace at temperatures between 0.7 and 0.9 degrees Celsius over the melting temperature of the material, the goal of this technique is to bind the alloy particles together using a plastic and diffusion flow mechanism, resulting in increased strength and hardness [8]. Figure (3) shows the sintering process steps.

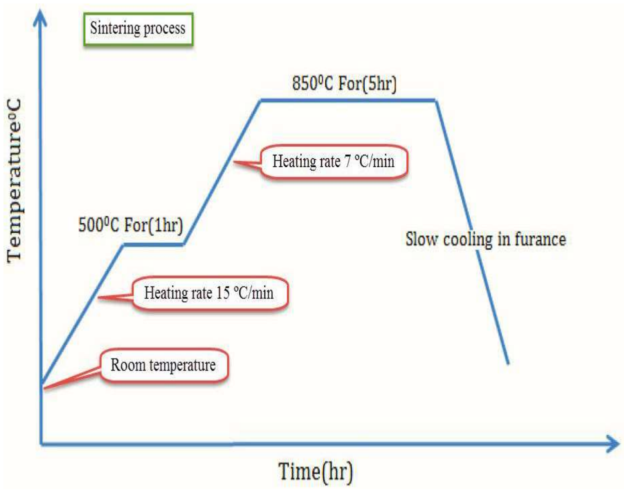


Figure 3: Diagram of sintering process steps [10]

Physical tests were carried out on the samples that were manufactured to find out the phase responsible for the creation reliability of this type of alloy, which included:-

1. Scanning Electron Microscopy: The layers of martensite following heat treatment were demonstrated using this test. As shown in figure (6).

2. XRD X-ray diffraction: The martensite phase's presence was verified using this technique. As shown in figure (7).

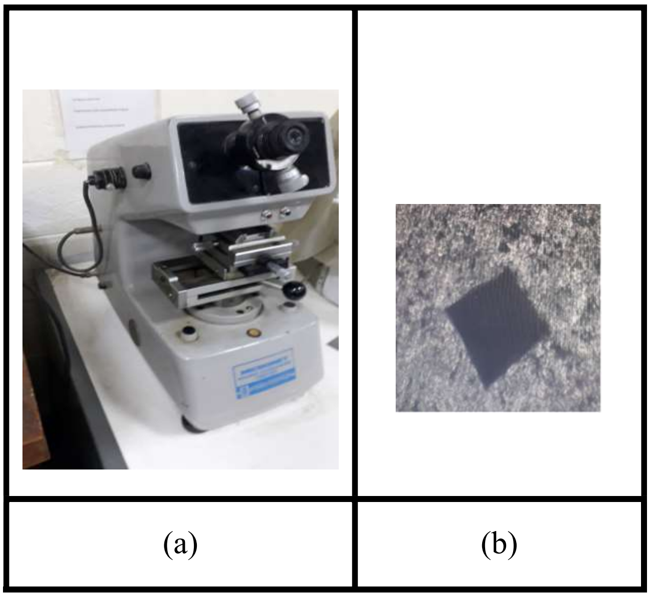


Figure 4: Vickers micro-hardness

Figure 5: Porosity testing

Mechanical tests were carried out, which included the Vickers Micro-Hardness test and porosity test, the micro-hardness test was conducted on eight samples divided into two groups, and three readings were performed for each sample, and then the average was taken between every two samples as shown figure (4). This test was performed in which a 400 g force was applied to the sample for 20 seconds. The results are shown in table (2)

To perform the porosity test, use the 3 digit-sensitive balances (type KERN 770) under vacuum as indicated in the figure (5). The porosity test was done on eight samples divided into two groups, and two readings were performed for each sample, and then the average was taken between every two samples as shown in table (3).

2.2 collecting of data and database construction

The process of data processing and organizing is done by utilizing artificial intelligence. ANN uses neurons to simulate the predicted data, and thus ANN is playing a role similar to the role of the human brain. Incoming input signals are either from the input source or from the hidden layers multiplied by a certain value called weight; the value of the next output signal depends on the weight value. The sum of the input signal values in their weights is named the transfer function (or activation function). The output value of the neural network is determined by this function, as shown in figure (8) & equation (1).

$$.Y = \sum_{i=1}^{m}(Wi * Xi) \qquad (1)$$

Wi = weights.

Xi = input variable value.

m = input variable number.

Y = transfers function value.

ANN is featured from other algorithms, because they can understand the data, perceive how the system works and they possess the ability to predict new data [11].

2.3 ANN application to mechanical property analysis

ANN is a system design that shows the inputs, outputs, and components, which are neurons, as well as how they are connected, similar to the human brain. The weights are a method of inter-neuron communication that serves as the primary control for adjusting anticipated output values until they converge on the desired value or to reduce the difference between predicted and actual outputs. The forward back spread algorithm's equation for modifying weights is an equation (2)

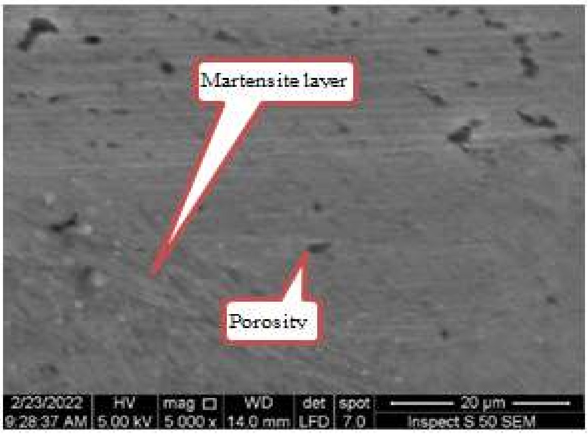
Wnew = Wold + Ar (desired - output) * input (2) [12].

Ar = learning rate

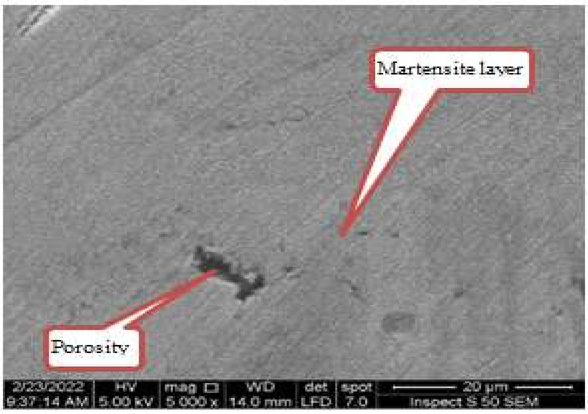
3. Results and discussions

3.1 Determine Best Hardness and Porosity Prediction Network

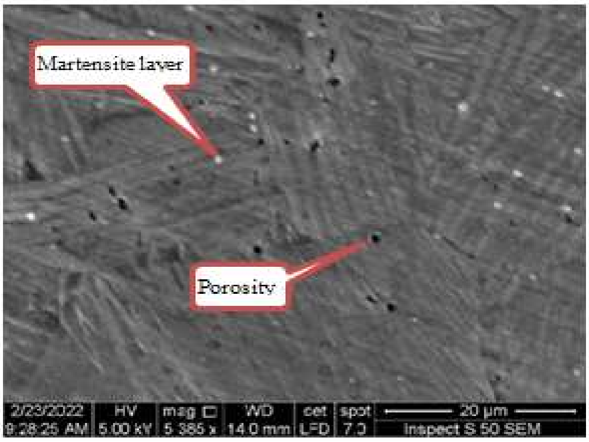
By training these ANN to forecast the results of the hardness and porosity properties of SMA samples based on the impact of changes in the concentrations percentage of the aluminum nanoparticle, the best network in ANN was selected. In this particular work, only three of the four samples (S1, S2, and S3) were used to train the ANN and predict the output of the fourth sample (S4) using simulation, as indicated in table (3). With a variety of nanoparticles added to the base alloy, the four samples' concentration ratios of Cu, Al, and Ni were used to create the network, which had three outputs: hardness (134, 164.9, and 180.4) and porosity (21.140, 19.01, and 9.217). The number of neurons, the number of hidden layers, and the type of transfer function were all varied repeatedly, resulting in changes to the constructed network. The best target of regression (0.99065) was produced by the following network, which was recognized as the best (4 inputs, 1 hidden layer, 16 neurons, Tansigmoid, and 2 outputs), as shown in figure (8).



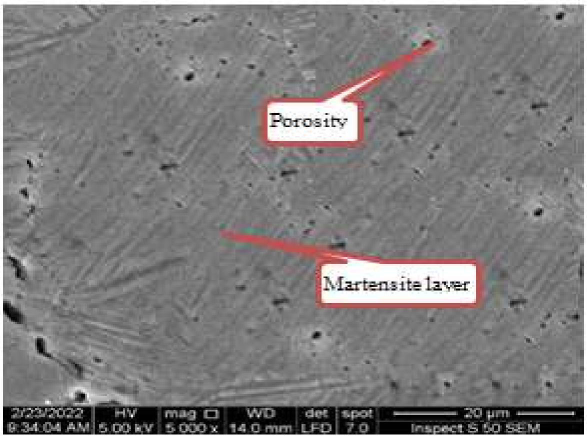
S1



S2

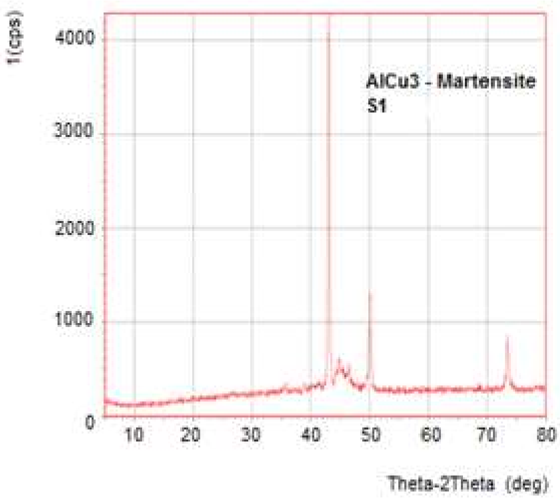


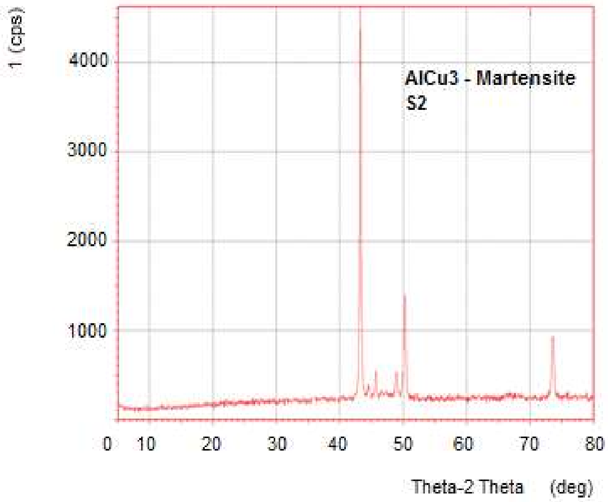
S3

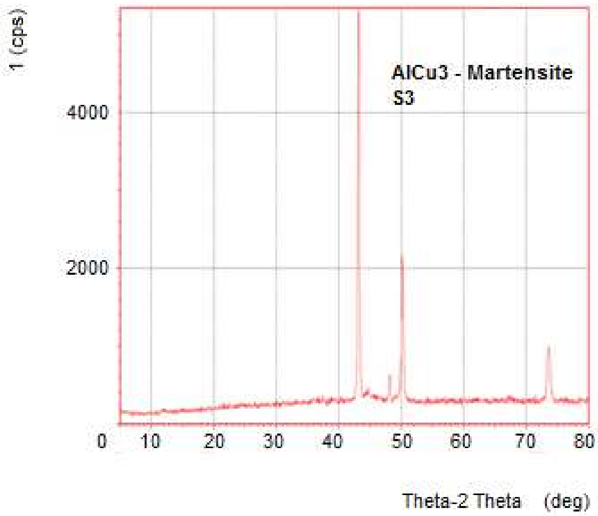


S4

Figure 6: The results of SEM testing of the manufacturing samples, to ensure the formation of the martensite phase







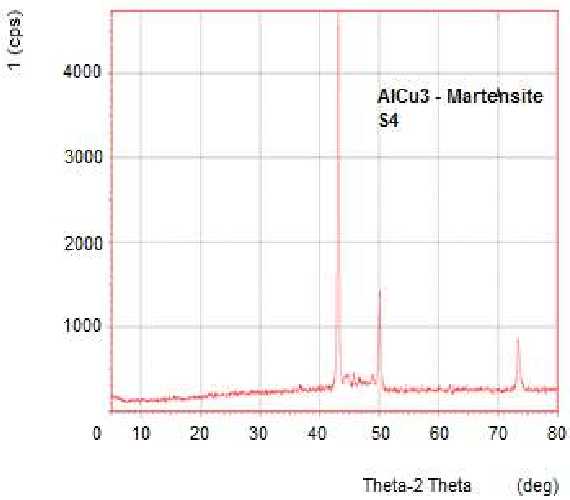


Figure 7: X-Ray Diffraction test results of the manufacturing samples, to ensure the formation of the martensite phase

Table 2: Results of Vickers Micro-Hardness testing

Sample No.	chemical composition	HV			Final HV (Average)
S1	without nanoparticle	130.9	135.8	132.2	134
S2	with 5% Al- nanoparticle	166.7	165.4	164.4	164.9
S3	with 10% Al- nanoparticle	182.6	181.2	179.6	180.4
S4	with 15% Al- nanoparticle	192.6	190.8	192.9	191.8

Table 3: Porosity Results

Sample No.	chemical composition	Porosity %		Final Porosity %
S1	without nanoparticle	19.573	22.708	21.140
S2	with 5% Al- nanoparticle	18.105	19.915	19.01
S3	with 10% Al- nanoparticle	8.404	10.031	9.217
S4	with 15% Al- nanoparticle	3.533	2.732	3.132

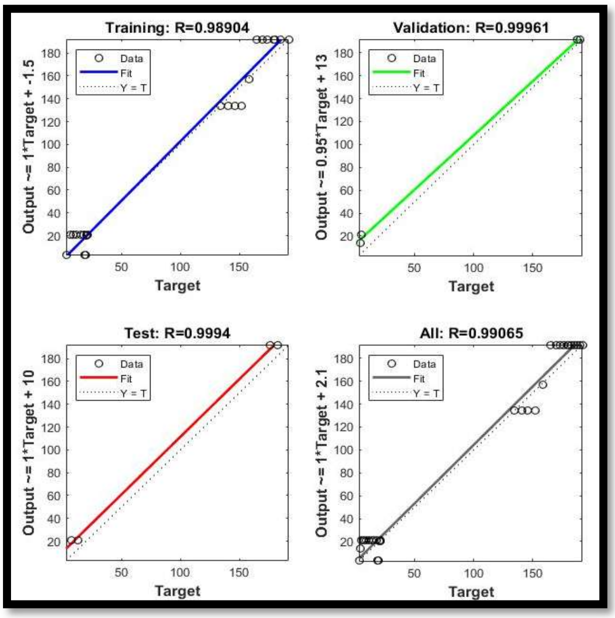


Figure 8: The best target of regression

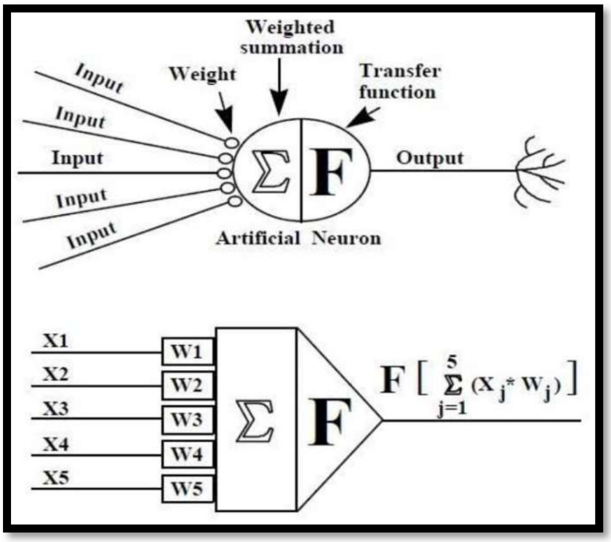


Figure 9: The single artificial neuron functions [8]

Table 4: Training the network of hardness and porosity for: (a): Input the results experimental for (S1, S2, and S3) and (b): Without input the results experimental for (S4)

(a)

	Four inputs %				Experimental Output		Four inputs %				Predicted Output	
	Cu	Al	Ni	Nano	Hardness	porosity %	Cu	Al	Ni	Nano	Hardness	porosity %
S1				0	134	21.14				0	136	21.54
S2	83	13	4	5	164.9	19.01	83	13	4	5	166.7	18.632
S3				10	180.4	9.217				10	181.2	8.923

(b)

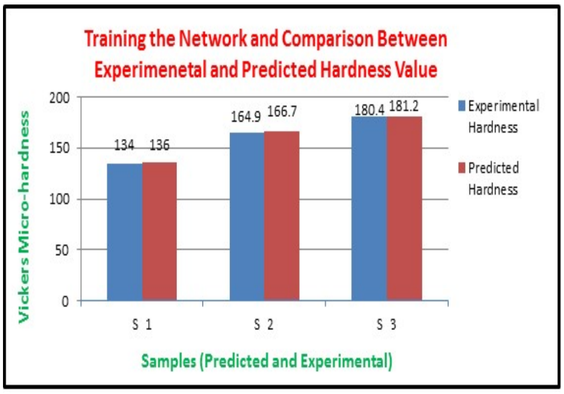
	Four inputs %				Experimental Output		For inputs %				Predicted Output	
	Cu	Al	Ni	Nano	Hardness	porosity %	Cu	Al	Ni	Nano	Hardness	porosity %
S4	83	13	4	15	191.8	3.132	83	13	4	15	190.7	3.202

The results of the Hardness values used to train the network and to compare the experimental and predicted values are shown in tables (3) and figures (10). In figure (10) the prediction results (red column) showed a gradual increase in hardness when increasing the nanoparticle weight ratio (136, 166.7, 181.2, and 190.7). When comparing with the experimental results shown in the same figure (blue column), it was found that there is a slight variation between the predicted and the practical results, which are summarized as follows:

In the first sample (S1) (134) was the percentage of variance (1.4%) and in the second sample (S2) (164.9) was the percentage of variance (1%), the third sample (S3) (180.4) was the percentage of variance (0.4%), and the fourth sample (S4) (191.8) was (0.5%) between the expected and experimental results. This means that the lowest error percentage was obtained.

The results of the predicted hardness of the three samples (red column) (S2), (S3), (S4) compared with the basic predicted sample (S1) showed the percentage increase as follows (18.4%) (24.9) (28.6%) respectively, when increasing the percentage of nanoparticle added to them.

(a)



(b)

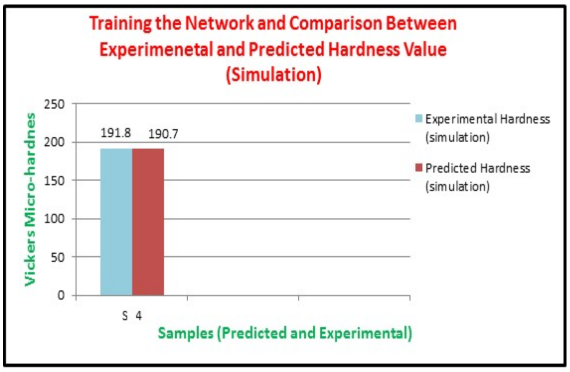


Figure 10: Training the network and comparison between experimental and predicted hardness value: **(a):** Input the results experimental for (S1, S2, and S3) and **(b):** Without input the results experimental for (S4)

The results of the porosity values used to train the network and to compare the experimental and predicted values are shown in tables (3) and figures (11).

The prediction results (red column) in figure (11) showed a decrease gradually in porosity when increasing the nanoparticle weight ratio of (21.54 S1, 18.632 S2, 8.923 S3, and 3.485 S4). When comparing with the practical results shown in the green column of the same figure, it was found that there is a slight difference between the predicted results and the practical results.

In the base sample (S1), a difference (1.8%) and in the second sample (S2) a difference of (1.9%), the third sample (S3), a difference of (3.1%) and the fourth sample (S4), a difference (3.4%) between the predicted and experimental results.

The results of the predicted porosity of the three samples (red column) (S2), (S3), (S4) compared with the basic predicted sample (S1) showed the percentage decrease as follows (13.5%) (58.5%) (84.9%) respectively, when increasing the percentage of nanoparticle added to them.

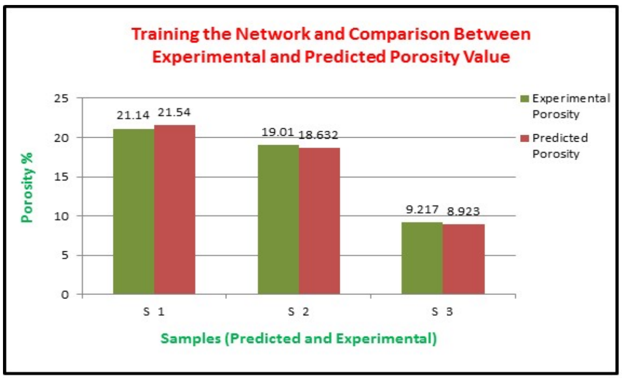
$$\text{Percentage of variance} = \frac{\text{S max} - \text{S min}}{\text{S max}} \quad (3)$$

S. max= Maximim Sample

S. min = Minimum Sample

ANN tool is used to predict the best input variables values to obtain the optimal properties by the least number of experiments to reduce the costs, effort, and time. To evaluate the ANN performance using the performance measure: percentage of variance to compare between the experimental results and predicted results. In ANN, the predicted values were in good agreement with the empirical values as indicated in the references [5, 10, and 12].

(a)



(b)

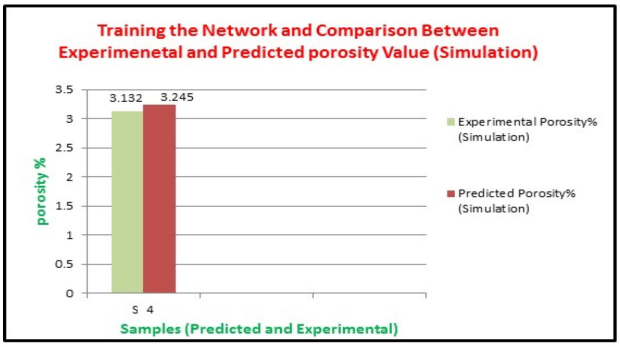


Figure 11: Training the network and comparison between experimental and predicted porosity value for: **(a):** Input the results experimental for (S1, S2, S3) and **(b):** Without input the results experimental for (S4)

4. CONCLUSION

Vickers microhardness test of the samples under study, the increase in the percentage of nanoparticle addition increases the microscopic hardness, where its value was (134) for the sample without addition, while it reached its maximum value (191.8) when 15% of the nanoparticles were added. In general, it can be said that increasing the percentage of nanoparticle addition leads to an increase in hardness.

The porosity test showed a reverse behavior from the hardness test, where the porosity increased when no nanoparticles were added, and its value was (21.14), while its value (3.132) when added was 15%.

ANN demonstrated excellent predicting of the behavior of (Cu-Al-Ni) SMAs at the ratios of nanoparticle concentrations changed, where were got the numerous properties of predicted results for the new alloys without manufacturing them to reduce effort, cost, and time.

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تنبؤ الصلادة والمسامية لسبيكة (Cu-Al-Ni) الذكية مع إضافة جسيمات نانوية باستخدام الشبكات العصبية الذكية.

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الخلاصة – يتناول هذا البحث تحديد أفضل نسبة بين النتائج العملية والتنبؤ والمقارنة بينهما باستخدام الشبكة العصبية الاصطناعية للخصائص الميكانيكية للصلادة والمسامية للسبائك الذكية (83٪ Cu-13٪ Al-4٪ Ni). بإضافة جسيمات الألمنيوم النانوية بنسبة (0٪ ، 5٪ ، 10٪ ، 15٪). هذه الخصائص الميكانيكية لها اهتمامات تكنولوجية وتجارية كبيرة مثل التطبيقات الصناعية والفضائية ، وكذلك في مركبات التخميد العالية ، وأجهزة الاستشعار ، والمشغلات ، والمرشحات.تم إجراء الفحوصات الفيزيائية (باستخدام المجهر الإلكتروني (SEM) وحيود الأشعة السينية (XRD) ، للتأكد من وجود مرحلة مارتينسيت بعد المعالجة الحرارية.تنقسم عملية التنبؤ باستخدام أداة ANN في برنامج Matlab R2020a إلى مرحلتين: الأولى هي تحديد أفضل شبكة للتنبؤ بأفضل النتائج لمدخلات التجربة. ومن أجل تقليل النفقات والجهد والوقت اللازم لإجراء العديد من التجارب الإضافية لتحقيق هذه النتائج ، تستلزم المرحلة الثانية استخدام هذه الشبكة المثلى للمقارنة بين النتائج المتوقعة والنتائج التجريبية. تم استخدام خوارزمية الانتشار الخلفي الأمامي في جميع شبكات ANN.بينت النتائج أن زيادة نسبة إضافة الجسيمات النانوية يؤدي إلى زيادة في الصلادة حيث كانت قيمتها (136) للعينة بدون إضافة ، بينما بلغت أعلى قيمة (190.7) عند إضافة 15٪ من الجسيمات النانوية. أظهر اختبار المسامية سلوكاً عكسيًا عن اختبار الصلادة حيث زادت المسامية عند عدم إضافة جزيئات نانوية وبلغت قيمتها (21.54) بينما يبغت قيمتها (3.245) عند أضافة 15٪.

الكلمات الرئيسية – الجسيمات النانوية ، السبائك الذكية (Cu-Al-Ni) ، الشبكة العصبية الاصطناعية.