Physical and Mechanical Properties Estimation of Ti/HAP Functionally Graded Material Using Artificial Neural Network

Dr. Jawad K. Oleiwi
Materials Engineering Department, University of Technology/Baghdad.
Email: jawadkad@yahoo.com
Dr. Rana A. Anaee
Materials Engineering Department, University of Technology/Baghdad.
Sura A. Muhsin
College of Materials Engineering, University of Babylon/Babylon

Received on: 8/9/2015 & Accepted on:19/5/2016

ABSTRACT

This study presents the effort in applying neural network-based system identification techniques by using Back- propagation algorithm to predict some physical mechanical properties of functionally graded and composite samples from Ti/HAP, these samples were fabricated by powder metallurgy method at various volume fraction of hydroxyapatite and at n equal (0.8, 1, and 1.2). Because of important of advanced materials such as FGMs as alternative industrial material, it is necessary to measure the physical properties of these materials such as porosity, density, hardness, compression …etc. Therefore the ANN will be used to estimate these properties and give a good performance to the network.

Keywords: Ti/HAP; ANN; FGM; Physical properties.

INTRODUCTION

An artificial neural network (ANN), often just called a neural network, is a mathematical model inspired by biological neural networks. A neural network consists of an interconnected group of artificial neurons, and it processes information using a connectionist approach to computation [1].

Complex nonlinear input-output relationships that used in many applications can be applied on neural network because the important feature of neural networks is that they have the ability to learn complex nonlinear input-output relationships, many steps can be applied as the sequential training procedures, and adapt themselves to the data. Many applications of neural networks, pattern classification tasks are represented in [2,3]. Classification and clustering tasks can be done perfectly by learning process of the neural network which consist of updating network architecture and connection weights. Recently, pattern solving recognition problems have been depending on neural network models because of their apparently low dependence on domain-specific knowledge and due to using learning algorithms efficiently by practitioners.

Neural network architectures hardware implementation can be mapped to hardware implementation by using electronic devices. The novel structure of the information processing system which is inspired by the way biological nervous systems, such as the brain, process information. It consists of a large number of neurons (processing components) which woks to solve definite problems. Learning in biological systems contains regulations process of the synaptic contacts that exist between the neurons, this learning can be used to adjust the weights in mathematical model, contact the artificial neurons each together for data classification and pattern recognition and recognition applications [4-8].

In the advanced materials applications, the functionally graded materials (FGMs) are used due to their significant characteristics like bio implant application. Due to the lack of suitable

https://doi.org/10.30684/etj.34.12A.1
2412-0758/University of Technology-Iraq, Baghdad, Iraq

fabrication method for the FGMs, the impact of the outcomes was still limited until present time although many of theoretical works on designing and investigating the performance of FGMs were reported since 1970's.

There are many researches highlighted fabrication and characterization of metal/metal and metal/ceramic FGMs in addition to study their physical, chemical and mechanical properties[9-18].

In this work, the functionally graded materials were fabricated at three (n) values which calculated according to Wakashima et al. as follows [9]:

$$(z) = \left(\frac{\quad}{\quad}\right) \qquad \ldots(1)$$

where $V_{1(z)}$ is the local volume fraction of phase 1 and for the phase 2 is:

$$V\ (z) = 1 - V_1(z) \qquad \ldots(2)$$

where (z_1) and (z_2) are border regions of pure phase 1 and phase 2 respectively, z is distance from pure Ti (phase 1) to pure HAP (phase 2) and exponent (n) is a variable parameter, and the magnitude of which determines the curvature of $V_1(z)$.

In this work the ANN was used to obtain the physical properties of the fabricated Ti/HAP FGMs by powder metallurgy method after limit the n at 0.8, 1 and 1.2 according to mathematical calculations with five layers for FGM.

Proposed Work

Three-layer ANN is used to obtain the properties of the Ti/HAP FGM in this work for all datasets. According to the classification problem, the total number of neurons for every hidden layer must be set. Number of input layer and output layer usually come from number of attribute and class attribute. However there is no appropriate standard rule or theory to determine the optimal number of hidden nodes.

In this work, trial and error has been used to determine number of hidden neurons. The activation function used to calculate output for each neuron is sigmoid activation (transfer function equation) except input neuron.

Tables (1) and (2) represent the input parameters and the target parameters sets of the fabricated FGM and composite samples respectively. In the input sets, **n** is a variable parameter which represent the exponent of eq. (1), $V_{2\ (z)}$ is a percent of volume fraction for hydroxyapatite, p represents the pressure applied to press the layers, and **Ts** is the sintering temperature of fabrication. The fabrication happens under 138 MPa pressures and 1000°C temperature. While in the output sets, **P** is the porosity, **D** is the density (g/cm^3) and **H** is the hardness (kg/mm^2), compression (MPa) , Elastic modulus (GPa) and Poisson's ratio.

Table (1) Input and target parameters for FGM at P 138 MPa and T_s 1000°C.

Input for FGM

n	0.8	0.8	0.8	0.8	0.8	1	1	1	1	1	1.2	1.2	1.2	1.2	1.2
V_z	0	32.9	57.4	79.4	100	0	25	50	75	100	0	18.9	43.5	70.8	100

Output of FGM

P	0.70	0.70	0.70	0.70	0.70	0.69	0.69	0.69	0.69	0.69	0.68	0.68	0.68	0.68	0.68
D	6.3223	6.3223	6.3223	6.3223	6.3223	6.7716	6.7716	6.7716	6.7716	6.7716	7.9983	7.9983	7.9983	7.9983	7.9983
H	312	330	350	375	453	309	325	340	365	445	306	320	330	360	440

Pison's ratio	Elastic modulus	Absorbance	Compression
0.32	110.3	2.4105	100
0.30	80.3	2.4105	100
0.29	64.03	2.4105	100
0.28	51.57	2.4105	100
0.27	40	2.4105	100
0.32	110.3	3.1935	110
0.30	86.55	3.1935	110
0.29	68.61	3.1935	110
0.28	53.97	3.1935	110
0.27	40	3.1935	110
0.32	110.3	2.9335	118
0.31	91.68	2.9335	118
0.29	72.87	2.9335	118
0.28	56.28	2.9335	118
0.27	40	2.9335	118

Table (2) Input and target parameters for composite samples.

Input for composite

n	0.8	1	1.2
V_z	35.9	30	26.9
P	138	138	138
T_s	1000	1000	1000

Output for composite

P	0.23	0.22	0.12
D	3.3383	3.5253	3.7707
H	375	350	330
Compression	106	115	125
absorbance	1.0525	0.8445	0.5735
Elastic modulus	78.12	82.59	84.99
Poisson's ratio	0.301	0.305	0.306

Results and Discussion

The parameters of Back-propagation algorithm are set to the momentum coefficient α =0.9 and the learning rate η =0.54. The initial weights and biases are randomly generated between [-0.45, 0.45].

In the training process, three cases are discussed in this work .During training, the ANNs were presented FGM physical and mechanical properties as output data.

There are seven output variables in the training data set. Output variable values are assigned in the Tables (1) and (2).

The ANN scheme trained by BP is as shown in Figure (1). There are 7 output variables in the training data, dependent on the input data, in this case the input processing element is 4 neuron, and 10, and 30 hidden neurons based on trial and error.

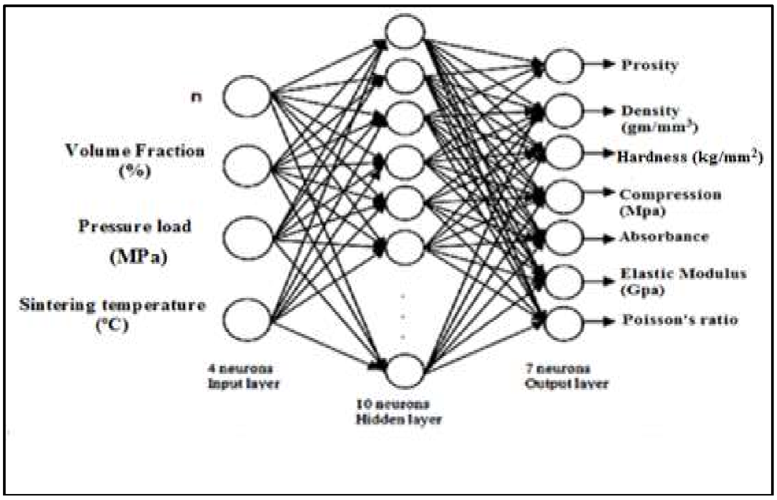
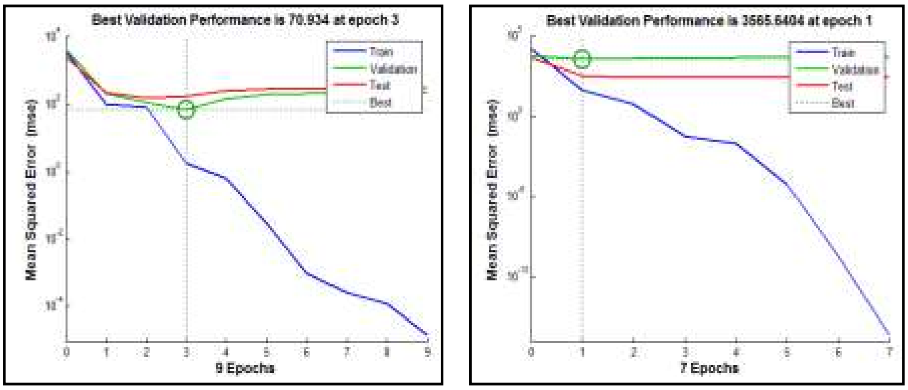


Figure (1): Training ANN Using BP.

The parameters of training algorithm (BP) are the same parameter. The maximum number of iterations (epoch)=1000 and (MSE=10e-6). The performance of FNNBP of datasets with 10, and 30 hidden neurons .

Figure (2) shows how the network's performance improved during training. Performance is measured in terms of mean squared error, and shown in log scale. It rapidly decreases as the network has trained. Performance is shown for each of the training, validation and test sets. The version of the network that did best on the validation set is was after training. As seen in Figure (2) in the training, the MSE decrease as the number of hidden neurons increase.

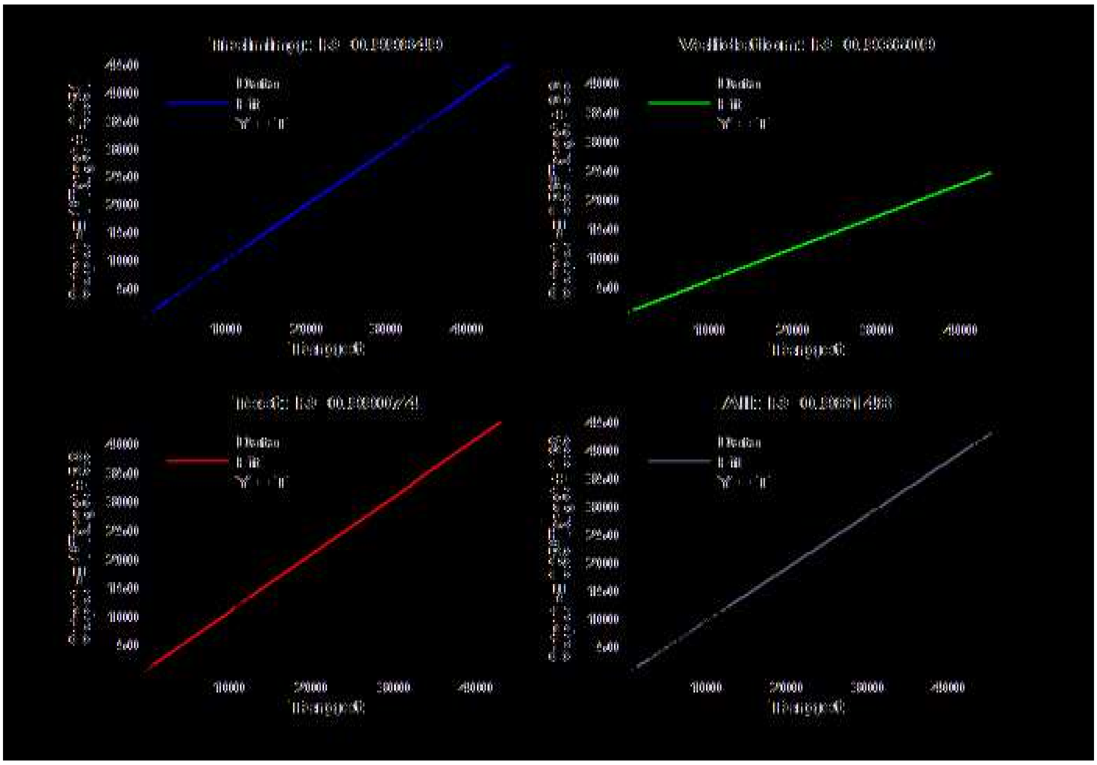


(a) (b)

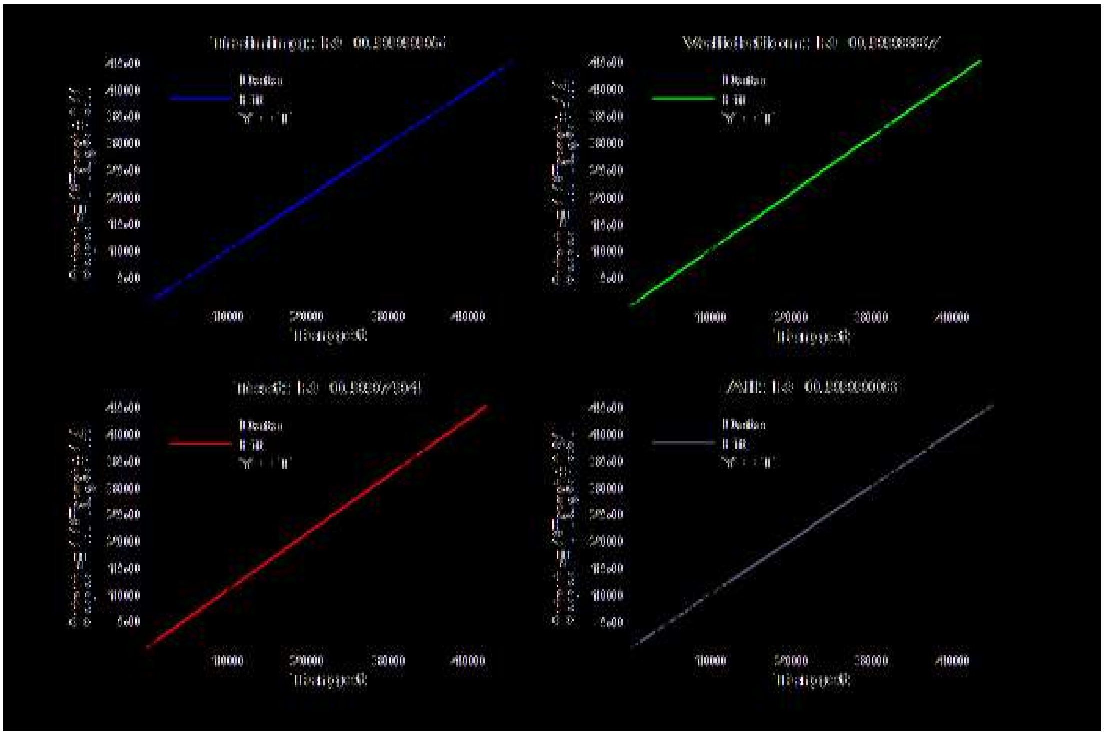
Figure (2): Performance of ANN with (a) 10 hidden neurons (b) 30 hidden neurons.

Figure (3) shows the regression plot measure of how well the neural network has fit the data . Here the regression is plotted across all samples. The regression plot shows the actual network outputs plotted in terms of the associated target values. If the network has learned to fit the data well, the linear fit to this output-target relationship should closely intersect the bottom-left and top-right corners of the plot. If this is not the case then further training, or training a network with more hidden neurons, would be advisable. As shows in Figure (3) by increase the hidden layers the output of ANN is fit to the target data.

The simulation results of and FNNBP for all datasets training with three different hidden neurons are shown in Table (3).



(a) 10 hidden neurons



(b) 30 hidden neurons

Figure (3): Regression of output of FNNBP network with (a)10 hidden neurons (b)30 hidden neurons.

Table (3): Results of FNNBP with different number of hidden neurons.

Parameters	FNNBP (10 hidden neurons)	FNNBP (30 hidden neurons)
Learning Iterations	9	7
Error Convergence	1.46 e-5	2.3 e-14
Convergence Time	1.8 e+000 sec.	1 sec
No. of Initial Weights	1 set	1 set
Gradient	0.291	1.33 e-5
Mu	1 e-8	1 e-10
Accuracy (%)	98.5	99.89

From Tables (1) and (2), the results show that 30 hidden neurons FNNBP with convergence time is faster, where it takes 1 seconds at 7 iterations compared with 10 hidden neurons, where it takes 1.8271 e+000 seconds at iteration 9 for overall learning process. For the correct accuracy percentage, it shows that as the hidden neurons increased the accuracy increased with 98.5 % for 10 hidden neurons compared to 99.89 % for 30 hidden neurons.

Processing in the estimation stage is similar to the classification stage, except that estimation stage also incorporates steps to match the input unknown parameters with those reference parameters in the database by neural network. The classification is achieved by train ANN.

Table (4): Estimation performance on test data using BPANN

Training type	ANN structure	Estimation rate 3 attempt	Average of Estimation
BPANN	4:10:7	93.31%	91.4%
	4:30:7	98.5%	96.74%

Table (4) shows that the FFANN blocks are robust enough in handling the image variations. During the estimation phase, the Neural Network is explored for robust output values in the presence of wide variations.

CONCLUSION

Artificial neural network is a simple algorithm that seems to be effective for estimation of physical properties of functionally graded material. The adjustment of ANN parameters gives an acceptable results . Some properties of fabricated materials can be calculated by ANN with simple and speed method.

REFERENCES

[1] Farhad Bilal Baha'addin, “Kurdistan Engineering Colleges and Using of Artificial Neural Network for Knowledge Representation in learning process”, International Journal of Engineering and Innovative Technology (IJEIT), Vol. 3, Issue 6, December 2013, pp. 292-300.

[2] A.K. Jain, J. Mao, and K.M. Mohiuddin, “Artificial Neural Networks: A Tutorial”, Computer, 1996, pp. 31- 44.

[3] T.Kohonen, “Self-Organizing Maps”, Springer Series in Information Sciences, Berlin, Vol. 30, 1995.

[4] Syed Ayaz Ali Shah, Azzam ul Asar and S.F. Shaukat, “Neural Network Solution for Secure Interactive Voice Response”, World Applied Sciences Journal, Vol. 6, No. 9, 2009, pp. 1264-1269.

[5] Wenjin Dai and Ping Wang, “Application of Pattern Recognition and Artificial Neural Network to Load Forecasting in Electric Power System”, Third International Conference on Natural Computation, Nan Chang University, China Vol. 01, ICNC 2007, 381-385.

[6] Shahrin Azuan Nazeer, Nazaruddin Omar, Khairol Faisal Jumari and Marzuki Khalid, “Face detecting using Artificial Neural Networks Approach”, First Asia International Conference on Modeling & Simulation, Washington, DC, USA, 2007.

[7] Lin He, Wensheng Hou, Xiaolin Zhen and Chenglin Peng, “Recognition of ECG Patterns Using Artificial Neural Network”, Sixth International Conference on Intelligent Systems Design and Applications, Vol. 2, 2006.

[8] Hongwei Yang, Chen He, Wentao Song and Hongwen Zhu, “Using Artificial Neural Network Approach to Predict Rain Attenuation on Earth-space Path”, Antennas and Propagation Society International Symposium, IEEE-Vol. 2, 2000.

[9] J. N. Reddy, “Analysis of functionally graded plates”, Int. J. Numer.Meth. *Eng.*, Vol. 47, 2000, pp. 663-684.

[10] Fumio Watari, Atsuro Yokoyama, Mamoru Omori, Toshio Hirai, Hideomi Kondo, MotohiroUo, and Takao Kawasak,” Biocompatibility of materials and development to functionally graded implant for bio-medical application”, Composites Science and Technology, Vol. 64, 2004, pp. 893–908.

[11] L. Jaworska, M. Rozmus, B. Królicka, A. Twardowska, “Functionally graded cermets”, Journal of Achievements in Materials and Manufacturing Engineering, Vol.17, Issue 1-2, July-August (2006).

[12] Victor Birman and Victor Birman, “Modeling and Analysis of Functionally Graded Materials and Structures”, Applied Mechanics Reviews, Vol. 60, Sep. (2007), pp. 195-216.

[13] Takafumi Toda, Masahiro Kou, Satoru Fujimoto, Osamu Fukumasa and WataruOohara, “Production of high quality Ti-HAP functionally graded coating using well-controlled thermal plasmas”, J. Plasma Fusion Res., Vol. 8, 2009.

[14] M. S. EL-Wazery, A. R. EL-Desouky, O. A. Hamed, N. A. Mansour, Ahmed. A. Hassan, “Preparation and Mechanical Properties of Zirconia / Nickel Functionally Graded Materials”, Arab Journal of Nuclear Sciences and Applications, Vol. 45, No. 2, 2012, pp. 435-446.

[15] Rasheedat M. Mahamood, Esther T. AkinlabiMember, IAENG, MukulShukla and SisaPityana, “Functionally Graded Material: An Overview”, Proceedings of the World Congress on Engineering, Vol III, July 2012, pp. 4-6.

[16] Siti Nur Sakinah Jamaludin, Faizal Mustapha, Dewan Muhammad Nuruzzaman and Shah Nor Basri, “A review on the fabrication techniques of functionally graded ceramic-metallic materials in advanced composites”, Scientific Research and Essays, Vol. 8, No. 21, 4 June 2013, pp. 828-840.

[17] Duraid Fadhil Ahmed, “Artificial Neural Network Control of Chemical Processes”, Eng. and Tech. Journal, Vol.32, Part (A), No. 1 , 2014, pp. 176-196.

[18] Abbas H. Issa, “Artificial Neural Networks Based Fingerprint Authentication”, Eng. and Tech. Journal, Vol.33, Part (A), No. 5 , 2015, pp. 1255-1271.