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

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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 works 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
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]:

\[
(z) = \left(\frac{z}{L}\right)^n \quad \text{...(1)}
\]

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

\[
V(z) = 1 - V_{1(z)} \quad \text{...(2)}
\]

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), \(V_{z(z)}\) 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, 1000°C.**

**Input for FGM**

| \(V_1\) | \(n\) | \(V_{z(z)}\) |
|---|---|---|
| 0 | 0.8 | 32.9 |
| 35.7 | 0.8 | 57.4 |
| 0.8 | 1 | 79.4 |
| 0.8 | 25 | 100 |
| 0.8 | 50 | 75 |
| 1 | 0.8 | 1 |
| 1 | 25 | 1 |
| 1 | 50 | 75 |
| 1 | 100 | 1 |

**Output of FGM**

| \(P\) | \(D\) | \(H\) |
|---|---|---|
| 6.3223 | 330 | 312 |
| 6.3223 | 350 | 357 |
| 6.3223 | 453 | 309 |
| 6.3223 | 309 | 325 |
| 6.7716 | 340 | 6.7716 |
| 6.7716 | 365 | 6.7716 |
| 6.7716 | 445 | 6.7716 |
| 6.7716 | 406 | 7.9983 |
| 6.7716 | 320 | 7.9983 |
| 6.7716 | 330 | 7.9983 |
| 6.7716 | 360 | 7.9983 |
| 6.7716 | 440 | 7.9983 |

Table (2) Input and target parameters for composite at P 138 MPa and T, 1000°C.

**Input for Composite**

| \(V_1\) | \(n\) | \(V_{z(z)}\) |
|---|---|---|
| 0 | 0.8 | 32.9 |
| 35.7 | 0.8 | 57.4 |
| 0.8 | 1 | 79.4 |
| 0.8 | 25 | 100 |
| 0.8 | 50 | 75 |
| 1 | 0.8 | 1 |
| 1 | 25 | 1 |
| 1 | 50 | 75 |
| 1 | 100 | 1 |

**Output of Composite**

| \(P\) | \(D\) | \(H\) |
|---|---|---|
| 6.3223 | 330 | 312 |
| 6.3223 | 350 | 357 |
| 6.3223 | 453 | 309 |
| 6.3223 | 309 | 325 |
| 6.7716 | 340 | 6.7716 |
| 6.7716 | 365 | 6.7716 |
| 6.7716 | 445 | 6.7716 |
| 6.7716 | 406 | 7.9983 |
| 6.7716 | 320 | 7.9983 |
| 6.7716 | 330 | 7.9983 |
| 6.7716 | 360 | 7.9983 |
| 6.7716 | 440 | 7.9983 |
The parameters of Back-propagation algorithm are set to the momentum coefficient $\alpha = 0.9$ and the learning rate $\eta = 0.54$. 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.
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.

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).
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.

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