



MODELING OF SHOT-PEENING EFFECTS ON THE SURFACE PROPERTIES OF A (TiB + TiC)/Ti-6Al-4V COMPOSITE EMPLOYING ARTIFICIAL NEURAL NETWORKS

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Abstract

Titanium matrix composites (TMCs) have wide application prospects in the field of aerospace, automobile and other industries because of their good properties, such as high specific strength, good ductility, and excellent fatigue properties. However, in order to improve their fatigue strength and life, crack initiation and growth at the surface layers must be suppressed using surface treatments. Shot peening (SP) is an effective surface mechanical treatment method widely used in industry which can improve the mechanical properties of a surface. However, artificial neural networks (ANNs) have been used as an efficient approach to predict and optimize the science and engineering problems. In the present study the effects of SP on TMC were modeled by means of ANN and the capability of the ANN in predicting the output parameters is investigated. A back-propagation (BP) error algorithm is developed for the network training. Data of experimental tests on the (TiB + TiC)/Ti-6Al-4V composite are employed in order to train the network. The volume fractions of the reinforcements (TiB + TiC) were 5 % and 8 %. ANN testing is accomplished using different experimental data that were not used during the network training. The distance from the surface (depth) and SP intensity are regarded as input parameters and residual stress and hardness of the Ti-6Al-4V before and after the SP and adding reinforcements are gathered as the output parameters of the network. A comparison was made between experimental and predicted data. The predicted results were in good agreement with experimental ones, which indicates that developed neural network can be used for modeling the SP process on TMCs.

1 INTRODUCTION

Titanium matrix composites (TMCs) have attracted considerable interest due to their attractive properties over titanium alloys, such as high elastic modulus, high strength, superior creep and fatigue resistances at ambient and elevated temperatures.¹⁻⁴ The fabrication of TMCs using in-situ technology is simple and does not result in the pollution of an interface.^{5,6} TMCs can be reinforced with continuous fibers, whiskers or particles.⁷ As is well known, the mechanical properties of the composites depend on matrix, reinforcement and reinforcement/matrix interface, which bonds the formers together.⁸ Compared with continuous fibers, TMCs reinforced with whiskers or particles exhibit more isotropic behaviors. The fabrication of these materials is more convenient and cost effective; therefore, they have drawn extensive attention recently.⁹ Titanium monoboride (TiB) whiskers and titanium carbide (TiC) particles offer high modulus, relative chemical stability, and high thermal stability, while maintaining similar density and thermal expansion coefficient to those of the titanium matrix, as well as clean interfaces without any unfavorable reaction between the precipitates and the titanium matrix.

TMCs co-reinforced with TiB whiskers and TiC particles have been fabricated and investigated for their mechanical properties¹⁵⁻¹⁷ and have been extensively demonstrated to possess superior mechanical properties over the single TiB or TiC reinforced discontinuously reinforced titanium matrix composites (DRTMCs).¹⁸⁻²¹ As an effective and important surface-treatment method, shot peening (SP) can introduce high residual compressive stress (RCS) and microstructure variation at near surface layers, which can enhance their fatigue properties compared to non-peened materials. The process of SP involves the bombardment of spherical balls of a hard material against the surface of components, which induces the strong elastic-plastic deformation at the surface and sub-surface regions. In the deformation layers, high RCS and microstructure refinements are introduced after SP. The residual stresses and hardness are very important properties of materials after the SP treatment. In the field of science and engineering, artificial neural networks (ANNs) are some of the most important research areas. ANN is a modeling tool to solve linear and nonlinear multivariate regression problems.²² Recently, ANN models were widely utilized to interpret and correlate the variable relationships in complex nonlinear data sets. The present study proposes a new approach based on



ANNs to investigate the effects of SP process on mechanical and metallurgical properties (TiB + TiC)/Ti-6Al-4V composite. Residual stress and hardness were modeled by ANN. 20 data of experimental tests results from the total of 30, are used to train the networks, while in the networks testing 10 different experimental data which were not used during training are used. Since the experimental results did not include the training sets the performance of the ANN is evaluated in a fine way.

2 EXPERIMENTAL PART

The experimental data are obtained from Xie et al.²³ The materials of (TiB + TiC)/Ti-6Al-4V (TiB:TiC = 1:1 (vol.%)) were fabricated via in-situ technology. Two types of theoretical total volume fraction of reinforcements (TiB + TiC) were 5 % and 8 %. The SP treatment was performed using an air-blast machine. The related information of used SP process is demonstrated in Table 1. The Almen specimens are A type and the diameter of peening nozzle was 15 mm and the distance between nozzle and sample was 100 mm. In order to obtain the depth distribution of the residual stress and hardness, the thin top surface layers were removed one by one via the method of chemical etch with a solution of water, nitric acid, and hydrofluoric acid in the ratio 31:12:7.

The results indicate that the increased reinforcements and SP intensities enhance the surface roughness after SP. Both the compressive residual stresses and hardness increase with the increase of the SP intensity, which is mainly due to the plastic deformation and high dislocation density in the near surface layer. Moreover, the reinforcement particles can act as the block sources during dislocation movements. After an appropriate SP treatment, the increased CRS and hardness are beneficial to industrial applications A table shows the obtained values of the experimental results on (TiB + TiC)/Ti-6Al-4V for 30 different samples.

3 ARTIFICIAL NEURAL NETWORKS

Artificial intelligence (AI) systems such as artificial neural networks (ANNs) have found many applications in science and engineering problems in the past decade. The concept of an ANN has emerged with the idea that it simulates the operating principles of a human brain. The first studies were made with mathematical modeling of biological neurons that make up the brain cells.²⁴ Basically, the brain functions with a very dense network of neurons. The brain contains a lot of neurons connected to each other by many interconnections. A neuron consists mainly of the following parts: dendrite, cell body and axon.²⁵ Dendrite gets the signals from various other neurons to the neuron and carries them to the cell body for processing, after that an axon carries the signal from the cell body to various other neurons. Similarly, the neural units in the artificial neural network are developed as a very approximate model of the natural biological neurons.²⁶ Figure 1 shows a natural biological neuron (Figure 1a) and an artificial neuron (Figure 1b) that is a computational and mathematical model of the biological neuron. A single neuron computes the sum of its inputs, which are multiplying with a variant called the weight, adds a bias term, and drives the result through a generally nonlinear transfer function to produce a single output termed the activation level of the neuron.

An ANN model is created by interconnection of many of the neurons in a known configuration. The primary elements characterizing the neural network are the distributed representation of information, local operations and non-linear processing. Structurally, every ANN is made up of three sections: input, hidden and output layers.²⁷ The structure of an ANN model is determined by the number of its layers and the number of nodes in each layer and the nature of the transfer function.^{28,29} Selecting the optimum architecture of the network is one of the challenging steps in ANN modeling. The term "architecture" refers to the number of layers in the network and the number of neurons in each layer. However, there is no straightforward method to estimate the optimal number of hidden layers and neurons in each layer.^{30,31} Thus trial-and-error methods have been used by many researchers to determine such case-dependent parameters for studies involving ANN-based models.³²

3.1 Training of ANN

The training of the ANN is performed by adjusting the connection weights. It is performed by iteratively adjusting the weights (w) of the connections and biases (b) in the network in order to minimize a predefined cost function.³⁶ The ANNs are trained with a training set of input and known output data. An ANN is better trained as more input data are used. The performance of an ANN is generally based on the parameters' architecture and the setting. As was mentioned, one of the most difficult tasks in studying ANNs is finding an appropriate architecture. This task is performed via trial and error and the number of middle layers and neuron presented in each layer is being identified. Appropriate designation of the initial amounts of weights and biases is very effective on the performance of network

and the time of calculation. But there is not a reasonable law and process to identify a suitable architecture. The only step which is very time consuming is the trial and error. One can get an idea by looking at a problem and decide to start with simple networks; going on to complex ones until the solution is within acceptable limits of uncertainty. Furthermore, the point that must be considered in training of the network is the rate of input and output data scattering. In this study all values of each input and output data parameters are divided to maximum absolute value of them and normalized also the used data are dimensionless. The normalized data are in range of $[-1, +1]$. In the present study, a feed forward ANN based on back propagation (BP) error algorithm, which is the most popular one in training of ANNs is used. BP is a descent algorithm, which attempts to minimize the error during iterations.

3.2 Implementation of ANN

In this paper the effects of the SP process on surface properties including of (TiB + TiC) / Ti-6Al-4V composite were modeled by means of an ANN. In implementation of the ANN distance from the surface (depth) and SP intensity are regarded as inputs and the residual stress and hardness are gathered as outputs of the networks. Different networks with different architecture and network parameters were trained for the prediction of residual stress and hardness. Figure 3, for an example, represents the schematic architecture of ANN for modeling of the mentioned output parameters: a four-layer feed forward with BP algorithm with full interconnection. This neural network model has a powerful input-output mapping capability. With the use of enough hidden neurons, it can effectively approximate any continuous nonlinear function. In the considered network, two inputs are logged into the input layer to determine the two outputs. In the ANN methodology, the sample data is often subdivided into training and testing sets. The distinctions among these subsets are crucial. Ripley defines the following: Training set: a set of examples used for learning that is to fit the parameters of the classifier. Testing set: a set of examples used only to assess the performance of a fully-specified classifier.

4 RESULTS AND DISCUSSION

In order to train the ANNs in this study, the obtained experimental test results on shot peened (TiB + TiC)/Ti-6Al-4V composite specimens are employed. Different networks were trained to achieve the optimum structure (OS) in order to generate a model function (MF). After the OS is selected and the MF is generated, operation of the network is tested with the use of them (OS & MF).

In the network testing, 10 different sample data (data of samples 21–30) which were not used during training are employed. Therefore, the whole experimental results did not comprise in the training. For investigative purposes, out of 30 samples data, 67 % data had taken for training and 33 % data for testing. Several networks have been trained with different architecture to find the OS of ANNs, to predict the regarded outputs, with the best performance and the highest PCC, the least RMSE, MRE and MAE. Related information of some the different trained networks for modelling of matrix hardness are shown in Table 4.

In modeling of residual stress, according to the Figure 8a, the minimum and maximum (min., max.) determined relative errors for matrix, 5 % reinforcement and 8 % reinforcement are (0.000, 0.2633), (0.0103, 0.1714) and (0.0099, 0.2616), respectively. Based on Figure 8b, similarly minimum and maximum calculated REs for matrix, 5 % reinforcement and 8 % reinforcement in modeling of hardness are (0.0015, 0.0587), (0.0026, 0.0870) and (0.0023, 0.0919), respectively.

MAE are very close to 0 and they are in little intervals and their ranges are [0.0597, 0.1976], [0.0194, 0.1228] and [0.0382, 0.14715], respectively. So, it is concluded that networks are trained finely and adjusted carefully. Likewise in network testing the values of PCC are more than 99.6 % and it is observed that values of testing PCC have a negligible reduction in comparison with the training. Moreover, the values of testing RMSE, MRE and MAE are in a tiny span as well and their ranges are [0.0647, 0.2071], [0.0276, 0.1342] and [0.0440, 0.1780], respectively. Based on the achieved values for the statistical errors for both training and testing samples it is concluded that the error values are acceptable and implementation of ANN is accomplished in a good way.

In residual stress modeling for each case of network training and testing, the obtained values for 5 % TiB + TiC., matrix and 8 % TiB + TiC and in modeling of hardness, achieved values for matrix, 5 % TiB + TiC and 8 % TiB + TiC have the smallest errors, respectively. Distributions of the residual stress and hardness from the shot-peened



surface to the bulk material (25-300 μm) for SP intensity of (0.00, 0.15 and 0.30) which are achieved by OS and MF of the used ANN modeling in this paper.

5 CONCLUSION

In present study the application of ANNs was investigated, aiming to create models to predict and optimize the SP process effects with different intensities on the residual stress and hardness of a (TiB + TiC)/Ti-6Al-4V composite. Experimental data show that both the residual stress and the hardness were increased with an improvement of the SP intensities. Residual stress and hardness were modeled using ANN for three cases: matrix, 5 % TiB + TiC and 8 % TiB + TiC. The obtained results indicate that statistical errors for RSME, MRE and MAE are in very small range and so close to 0. Moreover, the values of PCC for all of the regarded output parameters in implemented networks are more than 99 %. According to the achieved results, it can be concluded that when the ANNs are tuned in a good way and adjusted carefully, the modeling results are in reasonable agreement with the experimental results. Therefore, using ANNs, instead of costly and time consuming experiments, decreases the costs and the need for special testing facilities, and the ANNs can be employed to predict and optimize the SP effects on the residual stress and the hardness of TMCs.

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