Solid State Sciences 14 (2012) 1426–1430

Contents lists available at SciVerse ScienceDirect

Solid State Sciences

journal homepage: www.elsevier.com/locate/ssscie

Prediction of the mass gain during high temperature oxidation of aluminized nanostructured nickel using adaptive neuro-fuzzy inference system

M. Hayati [a,b,*], A.M. Rashidi [b], A. Rezaei [c,d]

[a] Computational Intelligence Research Center, Razi University, Tagh-E-Bostan, Kermanshah 67149, Iran
[b] Faculty of Engineering, Razi University, Tagh-E-Bostan, Kermanshah 67149, Iran
[c] Department of Biomedical Engineering, Faculty of Medicine, Kermanshah University of Medical Sciences, Kermanshah, Iran
[d] Isalmic Azad University, Gilan-e-Gharb Branch, Gilan-e-Gharb, Iran

ARTICLE INFO

Article history:
Received 24 February 2012
Received in revised form
15 July 2012
Accepted 29 July 2012
Available online 5 August 2012

Keywords:
Adaptive neuro-fuzzy inference system
Modeling
Mass gain
Aluminized nanostructured nickel

ABSTRACT

In this paper, the applicability of ANFIS as an accurate model for the prediction of the mass gain during high temperature oxidation using experimental data obtained for aluminized nanostructured (NS) nickel is presented. For developing the model, exposure time and temperature are taken as input and the mass gain as output. A hybrid learning algorithm consists of back-propagation and least-squares estimation is used for training the network. We have compared the proposed ANFIS model with experimental data. The predicted data are found to be in good agreement with the experimental data with mean relative error less than 1.1%. Therefore, we can use ANFIS model to predict the performances of thermal systems in engineering applications, such as modeling the mass gain for NS materials.

1. Introduction

Metals and alloys with the grain size at the nanometer scale exhibit unusual behavior compared to their bulk counterparts [1]. The atom and ion transport phenomena in the solid state of materials is an example, which is the interesting property of nanostructured (NS) materials [2–5]. Diffusivity of NS materials is several orders of magnitude higher than coarse-grained materials. For example, the values of measured diffusivity of NS copper at 80 °C and 120 °C are 2×10^{-18} m^2/s and 1.7×10^{-17} m^2/s, respectively, which they are about 16 or 14 orders of magnitude larger than the bulk diffusivity of coarse-grained copper [4]. Similarly enhanced diffusivities were also reported for solute diffusion in other materials [5]. Such unusual property has generated interest in NS materials for potential applications in the diffusion process such as gas nitriding of steel, aluminizing coating, and high temperature oxidation [6–9]. It is observed that the aluminizing time needed for the onset of formation of aluminide coating on NS nickel at 475 °C is approximately 4 times shorter than the bulk nickel [8]. Also, the results reported by Si et al. [9] indicate that the growth rate constants of aluminide coating formed on NS steel are about 20 and 10 times greater than coarse-grained samples at 500 °C and 600 °C, respectively. However, to meet the technological demands in these areas, resistant to high temperature oxidation is an important factor which should be investigated. A combination of experimental results and prediction models provides a useful approach to estimate the mass gain of coated materials when they exposed in oxidized environmental. As a result, the stability and long term performance of used materials under environmental oxidation at high temperatures can be determined using modeling frameworks. Adaptive neuro-fuzzy inference system (ANFIS) is a powerful tool for modeling the material processing and properties. This modeling frameworks has been recently used by many authors in various fields, for example, the control of Telbot [10], modeling of photovoltaic power supply [11], prediction of wear rate [12], the effect of vacuum sintering conditions [13], flow stress [14,15], elastic constant [16], the compressive strength [17], the peak pressure load of concrete pipes [18], fatigue crack growth rates and fatigue life [19,20], grain size of NS nickel coatings [21], the dielectric properties [22], modeling of heat transfer [23–25] and prediction of flow fields and temperature distributions [26]. However, the authors were not found the published documents, which dealing with the application of ANFIS framework to predict the mass gain during high temperature oxidation of aluminized metals. In this work an ANFIS model for the prediction of mass gain during high temperature oxidation is presented using experimental data obtained for aluminized NS nickel.

* Corresponding author. Computational Intelligence Research Center, Razi University, Tagh-E-Bostan, Kermanshah 67149, Iran. Tel.: +98(831) 4274535; fax: +98(831) 4274542.
E-mail address: mohsen_hayati@yahoo.com (M. Hayati).

1293-2558/$ – see front matter
http://dx.doi.org/10.1016/j.solidstatesciences.2012.07.029

2. Experimental procedure

NC Nickel samples with average grain size of about 25 nm were prepared from Watts bath by direct current electroplating under galvanostatic conditions. The details of electrodeposition procedure can be found in Ref. [27]. Aluminizing treatment was carried out at 500 °C for 6 h in a resistance furnace, using a homogenous mixture of 98 wt.% Al powder as masteralloy source and 2 wt.% NH_4Cl as an activator [8]. After removal, the coated specimens were cleaned and then heated for 2 h at 750 °C in an inert atmosphere of argon for achieving the Ni_2Al_3/NiAl coating structure. After aluminizing, oxidation tests were carried out in static air for various durations at 800 °C, 900 °C and 1000 °C. Prior and after the oxidation experiments, the samples were weighted to a precision of ±0.1 mg. Mass gain per unit area (W) was calculated according to:

$$W = \frac{\Delta w}{A} = \frac{w_{\mathrm{af}} - w_{\mathrm{pr}}}{A} \tag{1}$$

where w_{af} and w_{pr} are weight of samples prior and after the oxidation, respectively, and A is the total area surface of samples, which is exposed in environmental oxidation at high temperatures.

3. Adaptive neuro-fuzzy inference system

3.1. ANFIS architecture

ANFIS is an adaptive network which permits the application of neural network topology together with fuzzy logic [10]. The goal of ANFIS is to find a model which will simulate correctly the inputs with the outputs. Among many fuzzy inference system (FIS) models, the Sugeno fuzzy model is the most widely applied one for its high interpretability and computational efficiency [12]. For simplicity, we assume that the FIS has two inputs (x, y) and one output (f). For a first order Sugeno fuzzy model, a typical rule set with fuzzy based "if–then" rules can be expressed as follows [13]:

Rule1: If x is A_1 and y is B_1, then $f_1 = p_1x + q_1y + r_1$
Rule2: If x is A_2 and y is B_2, then $f_2 = p_2x + q_2y + r_2$

p_i, q_i, r_i are linear output parameters (consequent parameters) where $i = 1,2$. The corresponding equivalent ANFIS architecture is shown in Fig. 1.

The five layers of the ANFIS structure are defined as follows [11–16]:

Layer 1. This layer contains adaptive nodes with node functions described as:

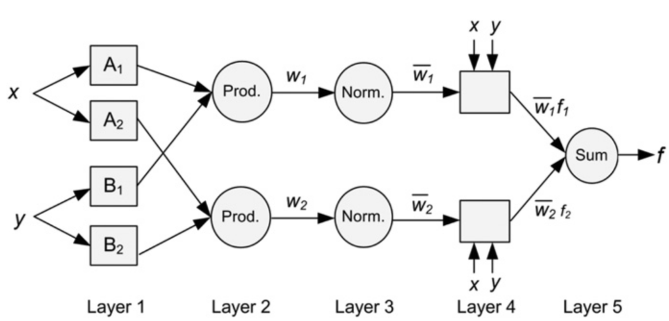

Fig. 1. ANFIS structure for a two-input Sugeno model.

$$O_{l,i} = \mu_{Ai}(x), \quad i = 1,2 \tag{2}$$

$$O_{l,i} = \mu_{Bi-2}(x), \quad i = 3,4 \tag{3}$$

where i is the membership grade of a fuzzy set (A_1, A_2, B_1, B_2) and $O_{l,i}$ is the output of the node i in a layer l. Also, $\mu_A(x)$ and $\mu_B(y)$ are the membership functions with maximum and minimum equal to 1 and 0, respectively. Typical membership functions are Bell and Gaussian functions given by Eqs. (4) and (5), respectively,

$$\mu_A(x) = \frac{1}{1 + \left|\frac{x - c_i}{a_i}\right|^{2b_i}} \tag{4}$$

$$\mu_A(x) = \exp\left(-\frac{0.5(x - a_i)^2}{b_i^2}\right) \tag{5}$$

where a_i, b_i and c_i are called the premise parameters.

Layer 2. Each node in this layer is a fixed node, which represent the firing strength of each rule. The output of this layer is given by:

$$O_{2,i} = w_i = \mu_{Ai}(x) \times \mu_{Bi}(y), \quad i = 1,2 \tag{6}$$

Layer 3. Every node of this layer calculates the ratio of the ith rule's firing strengths to the sum of all rule's firing strengths. The output of this layer is called normalized firing strengths and is given by:

$$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2}, \quad i = 1,2 \tag{7}$$

Layer 4. The output of the layer 4 is given by:

$$O_{4,i} = \overline{w_i}f_i = \overline{w_i}(p_ix + q_iy + r_i), \quad i = 1,2 \tag{8}$$

where $\overline{w_i}$ is a normalized firing strength from layer 3 and $\{p_i, q_i, r_i\}$ is the modifiable parameter set (consequent parameters).

Layer 5. This layer is simple summation of the outputs of layer 4, which computes the overall output as the summation of all incoming signals:

$$O_{5,1} = \sum_{i=1}^{2} \overline{w_i}f_i = \frac{w_1f_1 + w_2f_2}{w_1 + w_2} \tag{9}$$

ANFIS uses a hybrid learning algorithm to identify the parameters sets (adaptive parameters and consequent parameters). If the modeling is carried out properly, then the difference between the predicted outputs and observed ones, should give us the lowest possible level of error. The adjustment of modifiable parameters is a two-step process. In the first process, which is called forward pass, the adaptive parameters are assumed to be constant and the consequent parameters are identified by the least-squares estimation. In the second process, which is called backward pass, the consequent parameters are assumed to be constant and the