Materials and Design 31 (2010) 336–342

Contents lists available at ScienceDirect

Materials and Design

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

Assessment of the effect of existing corrosion on the tensile behaviour of magnesium alloy AZ31 using neural networks

V. Kappatos *, A.N. Chamos, Sp.G. Pantelakis

Laboratory of Technology and Strength of Materials, Department of Mechanical Engineering and Aeronautics, University of Patras, Panepistimoupolis Rio, 26500 Patras, Greece

ARTICLE INFO

Article history:
Received 18 May 2009
Accepted 8 June 2009
Available online 10 June 2009

Keywords:
Magnesium alloy
Mechanical properties
Corrosion damage
Neural networks

ABSTRACT

A concept has been devised to assess the effect of existing corrosion damage on the residual tensile properties of structural alloys and applied for the magnesium alloy AZ31. The concept based on the use of a radial basis function neural network. An extensive experimental investigation, including metallographic corrosion characterization and mechanical testing of pre-corroded AZ31 magnesium alloy specimens, was carried out to derive the necessary data for the training and the prediction module of the developed neural network model. The proposed concept was exploited to successfully predict: the gradual tensile property degradation of the alloy AZ31 to the results of gradually increasing corrosion damage with increasing corrosion exposure.

1. Introduction

The multifarious variables that are involved in corrosion of structures in-service are convoluted, complex and interacting [1]. On the other hand, traditional approaches to understanding and assessing the effects of corrosion on structural components rely on classic textbooks models of general corrosion and the metallographic characterization of corrosion damage.

In recent years, a number of incidents (e.g. Aloha, 1988) and the results of various investigations, e.g. [2], provided evidence that the assessment of the effects of corrosion damage on residual strength and integrity of structural components operating in corrosive environment is a problem far more complex than anticipated [1–4].

The development of methodologies capable of facing the above problem requires a comprehensive understanding and characterization of corrosion damage mechanisms and relies heavily on the existence of sufficient experimental data. However, limited experimental data exist in published literature on the mechanical performance of corrosion damaged structural alloys. Examples of such data, mostly obtained from materials subjected to accelerated laboratory corrosion conditions and only very rarely from materials corroded in service may be found, e.g. in [3–10]. Essential cause for the limited amount of such data available is that their production is time consuming and expensive.

The use of Neural Networks (NN) to make predictions of the mechanical properties of alloys is a relatively new concept, but one that has received considerable interest in recent years [11–17]. In [11], the authors have introduced three different back-propagation NN models which can predict the (i) impact toughness of quenched and tempered steels exposed to various postweld heat treatment cycles, (ii) simulated heat affected zone toughness of pipeline steels resulting from in-service welding and (iii) hot ductility and hot tensile strength of microalloyed steels. In [12], some results of the research connected with the development of a new approach based on artificial intelligence for predicting the volume fraction and mean size of the phase constituents occurring in steel after thermomechanical processing and cooling are presented. A NN model was used to predict mechanical properties of dual phase steels and sensitivity analysis was performed to investigate the importance of the effects of pre-strain, deformation temperature, volume fraction and morphology of martensite on room temperature mechanical behaviour of these steels [13].

In [14], a NN was developed for the analysis and simulation of the correlation between the properties of maraging steels and composition, processing and working conditions. The input parameters of the model consist of alloy composition, processing parameters (including cold deformation degree, ageing temperature and ageing time), and working temperature. The outputs of the NN model include property parameters, namely: ultimate tensile strength, yield strength, elongation, reduction in area, hardness, notched tensile strength, Charpy impact energy, fracture toughness and martensitic transformation start temperature.

In [15], a model for predicting the mechanical properties of the alumina matrix ceramic was established by means of a NN, using

* Corresponding author.
E-mail addresses: kappatos@mech.upatras.gr (V. Kappatos), hamosa@mech.upatras.gr (A.N. Chamos), pantelak@mech.upatras.gr (Sp.G. Pantelakis).

0261-3069/$ - see front matter © 2009 Elsevier Ltd. All rights reserved.
doi:10.1016/j.matdes.2009.06.009

hardness, elastic modulus, density, as well as content of the matrix material and additives, as the input parameters of the network model. The output parameters of the NN are flexural strength and fracture toughness of the composite ceramic materials. In [16], a model was developed for the analysis and prediction of the correlation between processing (heat treatment) parameters and mechanical properties in titanium alloy by applying NN.

A NN was trained and used to predict fatigue life for specified sets of loading and environmental conditions, using a data base of 1036 fatigue tests for carbon and low-alloy steels in [17]. It covers an adequate range of compositional and structural parameters, loading strain rate, temperature, and water chemistry. By finding patterns and trends in the data, the NN can estimate the fatigue life for any set of conditions.

In the present work, a concept to assess the effect of existing corrosion damage on the tensile behaviour of the wrought magnesium alloy AZ31 has been devised. The concept relies on the exploitation of Radial Basis Function (RBF)-NN. For the developing of the NN, extensive experimental investigation has been carried out including corrosion characterization and measurements of mechanical properties degradation after several corrosion exposure times.

To characterize corrosion average and maximum pit depth as well as pitting density were measured. In the proposed model, these characteristics are used as input parameters in a NN, in order to correlate the corrosion damage to the tensile properties of the corroded material. The developed NN was used for predicting the time dependency of the tensile mechanical properties degradation on the basis of corrosion damage characteristics.

2. Experimental work

2.1. Material

The experimental investigation was carried out for the magnesium structural alloy AZ31. It was received in sheet from of 2 mm nominal thickness. The material is characterized as high-purity (hp), as the concentration of the contaminants (Fe, Ni and Cu) was held under certain limits. After the rolling procedure the material was subjected to annealing (O-temper) at 300 °C for 30 min. The chemical composition of the alloy is shown in Table 1.

2.2. Corrosion tests

To characterize corrosion damage and derive the necessary input data for the NN a number of metallography specimens were exposed to salt spray fog for different exposure times. The exposure times selected for the corrosion tests were 0.5, 3, 6, 12, 24, 48 and 72 h. For the tests rectangular metallography specimens having 100 mm × 50 mm dimensions were cut from the longitudinal direction of the AZ31 sheet. Corrosion damage was predicted by calculating maximum, average and standard deviation of pit depth, average and standard deviation of pitting density, geometrical configuration of the pits in terms of their aspect ratio as well as pitting factor as the ratio of maximum to average pit depth.

2.3. Tensile tests

For deriving data to train the NN, a series of tensile tests was carried out following to the exposure of AZ31 tensile specimens to salt spray fog for different exposure times. The tensile tests were machined in longitudinal direction according to the ASTM E8 M specification with 50 mm gauge length and 12.5 mm gauge width at the reduced cross-section. For the tests servo hydraulic MTS 250 KN machine was used for the tensile tests. The tests were carried out according to ASTM E8 M with a constant elongation rate of 2 mm/min. A data logger was used to store the data in a digital file.

Evaluated have been the properties: yield strength (R_p) (0.2% proof stress), tensile strength (R_m), elongation to fracture (A_f), and strain energy density (W) (tensile toughness). In the present work, strain energy density has been calculated as the integral of the engineering tensile stress–strain curves up to elongation to fracture. Involving engineering stress–strain curves instead of true stress–true strain curves for calculating W is justified as the observed tensile necking at the elongation to fracture has not been appreciable.

Table 1
Chemical composition of magnesium alloy AZ31.

	Al	Zn	Mn	Fe	Ni	Cu	Mg
AZ31	3.06	0.80	0.25	0.003	<0.001	0.001	Bal.

2.4. Corrosion testing procedure

Prior to the corrosion exposure, the surface of the specimens were chemically cleaned in order to remove any oily lubricant, left from the rolling process of the material. Two subsequent solutions were used. The first treatment was immersion of the test specimens for 1 min to a solution contained 10% HNO_3 and ethanol. Then the test specimens were immediately immersed for another minute in a solution containing 10% NaOH and 90% distilled water. Afterwards the test specimens were dried and immediately inserted to the corrosive environment.

For the corrosion tests, the accelerated salt spray fog environment has been used. The salt spray tests were conducted according to ASTM B117 specification. The corrosive solution was prepared by dissolving five parts by mass of sodium chloride in 95 parts of distilled water. The pH of the salt solution was such that when atomized at 35 °C the collected solution was in the pH range from 6.5 to 7.2. The pH measurement was made at 25 °C. The temperature at the exposure zone of the salt spray chamber was maintained at 35 ± 1 °C. After the exposure the specimens were cleaned according to ASTM G1 specification. The solution used contained 200 g chromium trioxide (CrO_3), 10 g silver nitrate ($AgNO_3$), 20 g barium nitrate ($Ba(NO_3)_2$) and reagent water to make 1000 mL. The pre-corroded tensile specimens were immersed in the above solution for about 1 min to remove the corrosion products from their surface and then immediately dried.

3. Experimental results

3.1. Corrosion damage characterization

Representative cross-sections of the metallography specimens after different exposure times in the salt spray environment can be seen in Fig. 1. At short exposure times prevailing mechanism is the development of wide and shallow pits as it can be seen for the example of the 3 h corrosion exposure in Fig. 1a,b. For 24 h corrosion exposure time, some wide and shallow pits are still present (Fig. 1c) yet narrow and deep pits are mostly observed (Fig. 1d).

A light microscope Leica DM LM had been used to measure the average and maximum pit depth of the metallography specimens for the investigated exposure times. The average value of the pit depth was determined by the average of 30 pit depth measurements in each metallography specimen. The surface of each plate was divided into sections of 100 mm^2 in order to measure the pitting density and to calculate the pitting factor. The pits depth and density were measured and classified according to the standard ASTM G46.

The dependency of pitting density and pit depth on the investigated corrosion exposure times can be seen in the graphs of Fig. 2.