Effects of Copper Content, Annealing Temperature, and Aging Time on the Hardness of Aluminium Alloys Using Artificial Neural Networks Analysis

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Abstract

Problem Statement: In this study the effect of annealing, aging temperature, aging time and copper content on the hardness of aluminium alloys, using mathematical modelling tools of Artificial Neural Networks (ANN) was analyzed.

Aim and Objective: The predicted model should be used for prediction of hardness in particular groups of alloyed copper only, because of the discontinuous character of input data.

Approach: A data established for different series of aluminium alloys using Neural network with the back-propagation (BP) learning algorithm had been applied to predict hardness, where annealing temperature, aging temperature, aging time and copper content have been defined as the input Parameters of ANN. The output layer of the ANN model consists of hardness.

Conclusions: Results show that the improved model could apparently decrease the prediction errors, and raise the accuracy of the prediction results. This model can also predict the hardness within an average error less than 1%.

Keywords: Aluminium alloy, Copper, Ageing time, Heat treatment,Hardness, Nneural Networks.

1 Introduction

The heat treatment process can be classified into two processes, including solution heat treatment and aging. By aging the solution heat-treated alloy to a certain temperature, the strength and hardness of aluminium alloy expected to be further increased and accompanied by a clear drop in ductility compared to non heat treated alloy. This improvement in the properties of aluminium alloys expected to be depend on the precipitated phases during heat treatment. This will be investigated and analyzed by microstructure and creep testing of the heat treatment alloys compared with the non-heat treated.

Recently, aluminium alloys have attracted the attention of many researchers as promising structural materials for the automotive industry or aerospace applications. Especially, 6xxx aluminium alloys have been studied extensively because of their benefits such as medium strength, formability, weldability, corrosion resistance, and low cost, compared to other aluminium alloys [1, 2]. The 6061 Al-alloy has been used in the automotive industry for the fabrication of several types of automobile parts, such as wheels, panels and even in the vehicle structure [3]-[6]. It is expected that substitution of such aluminium alloys for steels will result in great improvements in the energy economy, recyclability and life-cycle cost. However, it is necessary to improve the strength and the formability of aluminium alloys for further applications for industries [7]. Also, enhancing creep properties of aluminium alloys at elevated room temperature and should be taken in consideration.

The properties of various aluminum alloys can be altered by specific designated heat treatment. Some aluminum alloys can be treated in liquid phase to increase their strength and hardness. The heat treatment process can be classified into two processes, including liquid phase's heat treatment and artificial aging. This consists of heating the alloy to a temperature between 460 and 530°C at which all the alloying elements are in solution. By heating the solution heat-treated material to a temperature above room temperature and holding it there, the precipitation accelerates and the strength is further increased compared to natural aging and accompanied by a clear drop in ductility. This is called "artificial aging", "age hardening" or just "aging" and is generally carried out at temperatures up to approximately 200°C (for 6000-alloys generally between 160 and 230°C)[8]-[12].

The addition of copper only increases the strength and hardness of the alloy. Al-Cu-Mg-Si alloys come in the series of precipitation hardenable alloys. Alloys 2014, 2024 and 2017 with content Cu 4-8% result in increasing the hardness.

2 Methodology

A methodology of the computer-aided determining relationship between copper aging temperature,aging time and hardness of heat treated aluminum alloys. To resolve the problem ANN soft word were used. Classification problems were evaluated by the consideration mainly the values of mistakes and correct answers of ANN system for test data. On the basis of collecting data by the ANN, to analyze the input data, to get the optimum hardness of alloying elements range.

3 Data collection and database construction

The performance of an ANN model depends upon the dataset used for its training. Therefore, for a reliable neural network model a significant amount of data as well as powerful computing resources are necessary. Some experimental data on mechanical properties of aluminium alloys at different conditions are collected from the literature, and some of these date are shown in table 1.

The data were divided in a proportion of 75% for the learning set and 25% for the validation set. It is recommended that the data be normalized between slightly offset values such as 0.1 and 0.9.

One way to scale input and output variables in interval [0.1,0.9] is as [14]:

$$Pn = 0.1 + (0.9 - 0.8) * (P - Pmin)/(Pmax - Pmin), \tag{1}$$

where Pn is the normalized value of P, which is of a maximum and a minimum value given by Pmax and Pmin, respectively [14]. The collected data designed for formation of a numerical model determining: hardness Vickers number in relation to the annealing temperature, ageing temperature, ageing time and Cu content.

4 Developing the ANN Model

Neural neworks are typically organized in layers. Layers are made up of a number of interconnected 'nodes' which contain an 'activation function'. Patterns are presented to the network via the 'input layer', which communicates to one or more 'hidden layers' where

Table 1: Database

Annealing Temperature	Hardness Out-Put (HV)	Aging Temperature	Aging Time	Cu%
496	128	190	6	5.65
515	76	185	4	5.8
315	184	195	3	4.58
315	128	160	4	4.32
495	69	190	4	4.9
420	155	190	8	4.26
495	113	170	12	4.4
535	129	230	4	5.95
510	156	190	3	4.91
450	162	200	10	4.2
575	115	190	21	4.27
520	175	180	14	4.28
525	138	185	14	5.35
450	154	200	4	4.2
530	177	205	2	4.3
490	167	150	32	3.6
450	160	200	10	4.2
535	168	125	8	6
570	160	173	24	2.5
510	191	165	8	4.45
495	184	195	5	4.58
535	190	190	10	7
525	125	190	4	4.32
450	162	200	10	4.2
515	158	185	4	5.3
496	137	190	26	6.3
515	158	185	4	5.3
495	184	195	5	4.58
415	180	190	8	4.26
495	180	190	4	4.9
450	162	200	10	4.2
525	170	185	12	8
525	155	185	12	6
525	140	185	12	4
500	190	160	24	5
495	168	190	5	4.46
535	114	210	4	5.95
490	144	190	13	3.5
535	87	165	18	6.48

the actual processing is done via a system of weighted ‘connections’. The hidden layers then link to an ‘output layer’ where the answer is output as shown in the graphic Figure:1.

Multilayer feedforward network models with one hidden layer can approximate any complex nonlinear function provided sufficiently many hidden layer neurons are available.

Therefore, in this study, multilayer feedforward network models containing one hidden layer were used. Determination of optimum number of the hidden layer neurons is very important in order to predict accurately a parameter using by ANNs. However, there is no theory how many hidden layer neuron need to be used for a particular problem.

The best approach to find the optimum number of hidden neurons is to start with a few numbers of neurons and then slightly increasing the number of neurons. During this process for each hidden neuron number the performances of the network models are monitored according to chosen performance criteria. Finally, in order to relieve the training difficulty and balance the important of each parameter during training process, the examinational data were normalized.

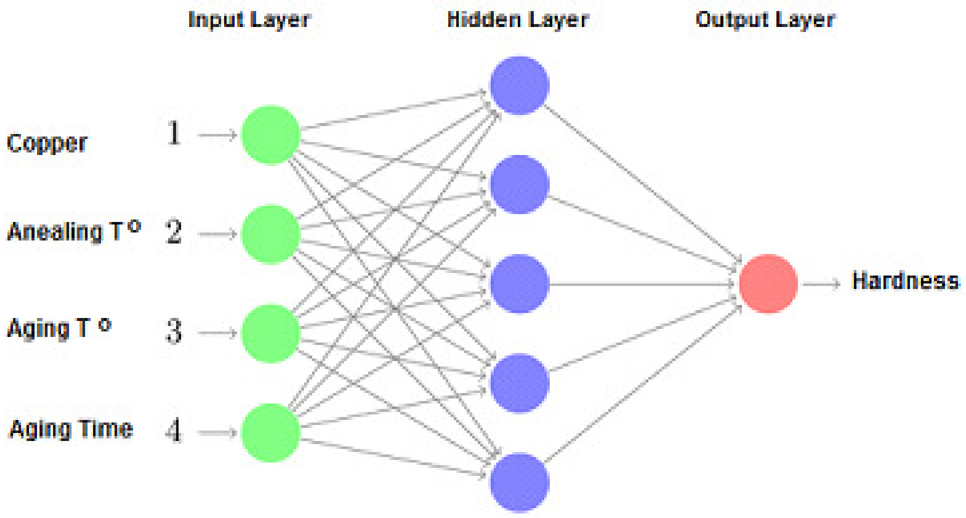

Figure 1

5 Results and discussions

Different pre-process parameters have important influences on the predicted results. The effort was made for improving pre-processes of the ANN model. Model of neural network was used to verify correctness of experimental mechanical properties including Vickers hardness, Multi Layers were applied for calculations — Multi Layerceptron (MLP). The number of nodes in input was defined as four: Copper content, annealing temperature, aging temperature, and aging time. The output layer were defined as hardness.

6 Performance and evaluation

The neural network output was calculated then performance computed that is the mean square error (MSE) illustrated in equation (2).

$$mse = \frac{\frac{1}{2}\sum_{i=1}^{n}(t_i - o_i)^2}{N} \tag{2}$$

Where t_i and o_i are the predicted and observed values of output respectively. In figures (2, 3, 4, 5, 6, 7) the hardness values predicted by model are compared with those of experimental results which collected in table (1) from the literature. The values predicted by ANN are in very good agreement with the ones obtained by experimentally in table (1).

Figures (2, 3) present the comparison between measured and predicted results for hardness for one factor input Cu, which gave bad perfermonce and bad regression, but shows that the high content of Cu icrease the hardness of aluminium alloys.

Figures (4, 5), show butter performans and regression where the input are ageing temperature, aging time and copper content.

Figures (5, 7) show the best performance and regression where we have four input, annealing temperature, temperature, aging time and copper content, the agreements between the predicted and measured values indicate that this approach is useful in modelling the mechanical properties of hardness in heat treatment technique.

The annealing temperature play a big role and have high effect on hardness and other mechanical properties.

Using neural network exhibit excellent accuracy in predicting the mechanical properties out-puts, and there are many contributing factors in heat treatment process that cannot be considered in the mathematical modeling but they can be easily incorporated in neural-network modeling.

In this work the composition of elements were not included, which also have an influence on mechanical properties.

7 Conclusions

1. The mechanical properties of Al-Cu alloys largely depend on the annealing temperature, aging temperature and aging time. Thus, these factor play a vital role in mechanical properties. Cu content in Al-Cu alloys affects the mechanical properties. With increasing Cu content, the hardness increases due to precipitation hardening.

2. Results show that the improved model could apparently decrease the prediction errors, and raise the accuracy of the prediction results.

3. The predicted results were found to be in good agreement with the experimental data.

One factor: copper

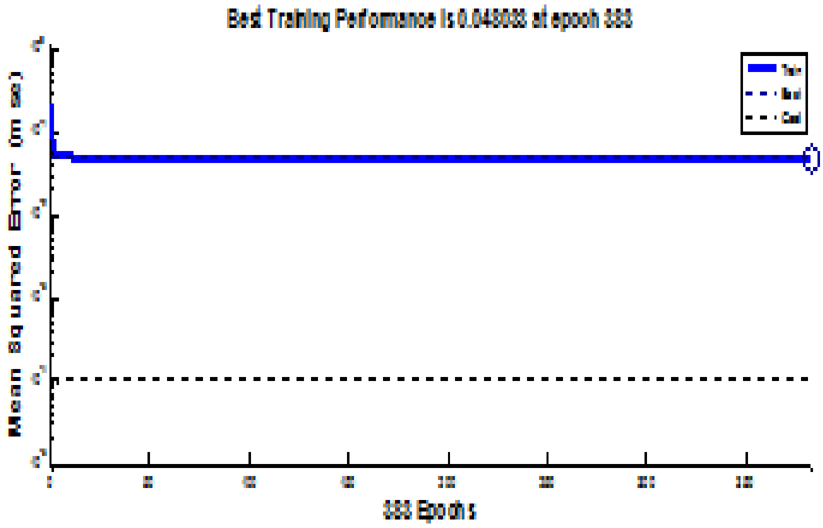

Figure 2: Performance (learning curve) of neural network

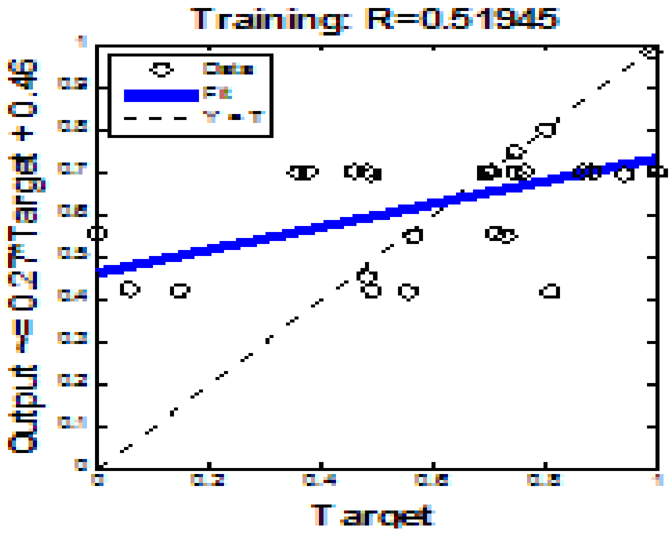

Figure 3: Regression

Three factors: copper, aging temperature and aging time

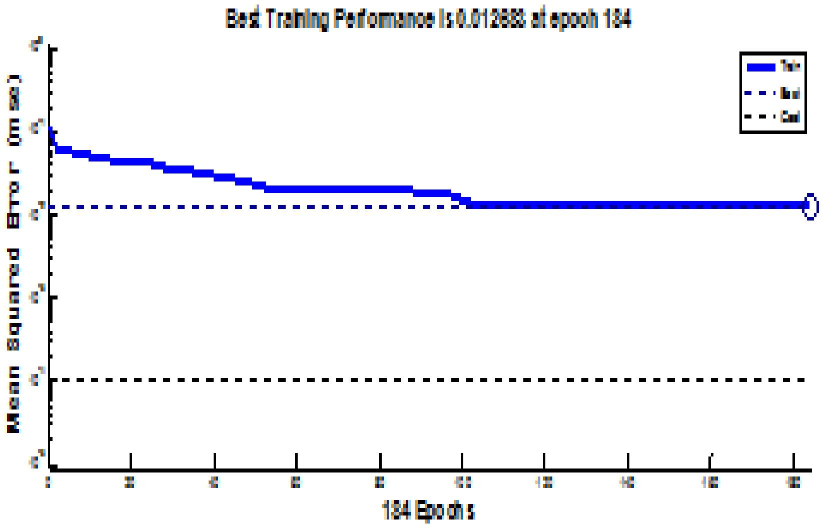

Figure 4: Performance (learning curve) of neural network

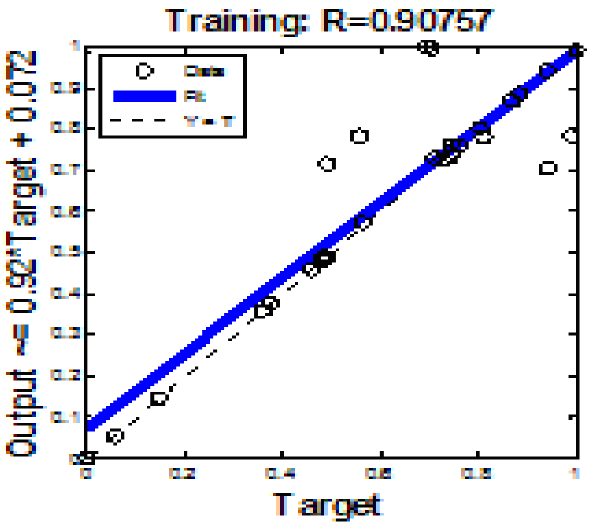

Figure 5: Regression

Four factors: copper, aging temperature , aging time and annealing temperature

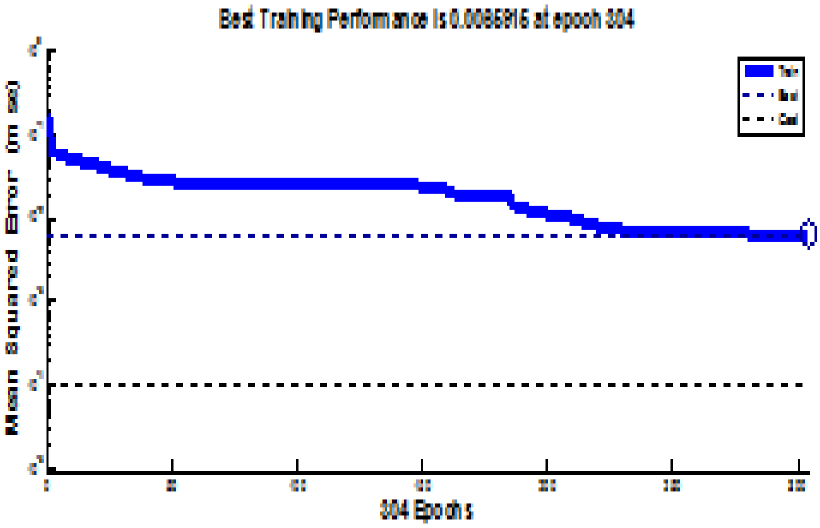

Figure 6: Performance (learning curve) of neural network

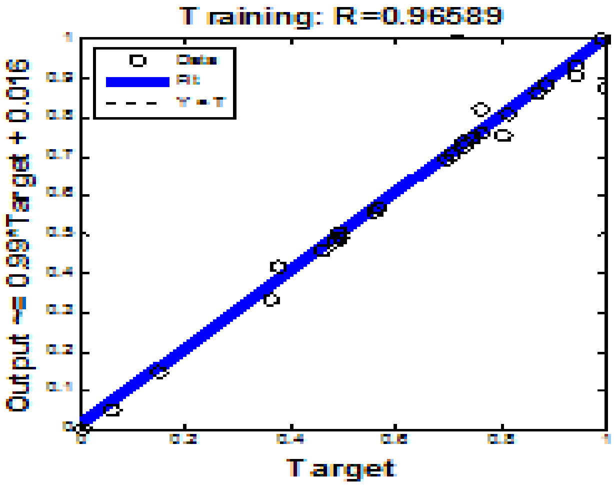

Figure 7: Regression

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