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Comparison of Artificial Neural Network and Multiple Regression Analysis Techniques in Predicting the Mechanical Properties of A356 Alloy

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Abstract

The mechanical properties of aluminium alloy castings, such as EL%, YS and UTS, are controlled by the casting and heat treatment variables, alloy's composition, and melt treatment. Despite the abundance of literature data, the large number of the controlling parameters has made it difficult to predict and model the mechanical properties by the conventional techniques. Another obstacle encountered when making such a prediction is the complex kinetics and interactions that exist among the many variables. The goal of this study was to develop Artificial Neural Network (ANN) and Multiple Regression models to predict the mechanical properties of A356 alloy from the processing variables. Several standard multi-layer ANN models were developed and trained using data from the literature and experimental results. A series of nonlinear regression models were also developed and the results were compared with the predictions made by the ANN models. Due to the complexity of A356's solidification behaviour, the nonlinear regression produced results that were not as accurate as those produced by the ANN model. Unlike the nonlinear regression analysis, ANN can simplify the modelling process by eliminating the need to define a function. The results indicate that ANN is a suitable modelling technique for predicting mechanical properties of castings based on the alloy chemistry and processing variables.

Keywords: Artificial Neural network; Regressionn Analysis; Prediction; Mechanical Properties; Casting, Aluminium Alloys; A356

1. Introduction

Al-Si and Al-Si-Cu alloys have been widely used in various applications because of their high strength-to-weight ratio and good corrosion and casting characteristics. The mechanical properties of cast alloys can be improved by controlling the alloy chemistry as well as casting and heat treatment variables. Heat treatment involves solutionizing at temperatures close to the eutectic temperature followed by quenching and then a combination of natural and artificial aging. The improvement in mechanical properties after heat treatment is mainly due to the formation of precipitates during aging and to the changes in the shape of Si particles. Melt treatments, such as grain refinement (by Ti and B additions), eutectic modification (by Sr or Na additions) or tramp/trace elements (Sn, Sc, Fe, etc.) could also influence the mechanical properties. Other critical variables are the casting microstructure (dendrite arm spacing or DAS, grain size, etc.) and defects (porosity and inclusions), all of which are dictated by the melting and casting processes.

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Due to the large number of controlling metallurgical variables, it is difficult to accurately predict the mechanical properties of aluminium 3xx alloys from these variables. Another obstacle encountered when making such a prediction is the complex kinetics and interactions that exist between the many variables. As a result of these complex interactions, it is difficult to establish the relationships that exist among the variables. It is also important to assess the significance of each variable and their interactions, and leave out those that are not significant. In the present study, two approaches were taken to correlate between the mechanical properties and these controlling variables. Moreover, only the two most common casting methods, i.e., sand and permanent mould casting processes, were considered.

2. Database

The data used in these analyses were collected from published papers on sand and permanent mould cast A356 aluminum alloys [1-13]. Since the mechanical properties are influenced by porosity and inclusions, only the reliable sources, where melts were degassed and melt cleanliness was controlled, were used. The data were collected in such a way to obtain a good range in dependant and independent variables. For the permanent mould, the values of wt%Si and natural aging temperature remained constant at 7 and 25^{o}C, respectively. As a result, the values associated with Si and natural aging temperature did not affect the regression results. Similarly, in the sand mould case four independent variables (Na, Sn, Sb, and natural aging temperature) were fixed. Some of the data used in this work are plotted in Figure 1. It is seen that the data exhibit a wide variation in the yield stress (YS) and ultimate tensile strength (UTS) allowing the analysis to correlate the controlling variables with these properties and establish a predictive model.

3. Mathematical Approaches

3.1 Multiple Linear and Nonlinear Regression Models

As the first step in attempting to predict the mechanical properties of A356 alloy, multiple linear and nonlinear regression analysis techniques were used. Mould type, chemical composition, grain refinement, Si modification, and heat treatment conditions were the model variables. Separate models were developed for YS, UTS and El%. Moreover, sand and permanent mould data were treated separately, and individual models were developed for each case. The weight percent of Si, Cu, Mg, Fe, Ti, Sn and Na or Sr were treated as the independent variables. The heat treatment variables consisted of solutionizing time and temperature, quench temperature, natural aging time, and artificial aging time and temperature. The multiple regression analysis was performed using a Microsoft Excel add-in that generates a model by using the least squares method to fit a line through a set of observations [14]. In the case of nonlinear analysis, a number of functions was defined to describe the relationships between the input and each output variables. Logarithmic terms were used to model certain treatment conditions. The functions for the nonlinear regression model were initially defined according to equation 1:

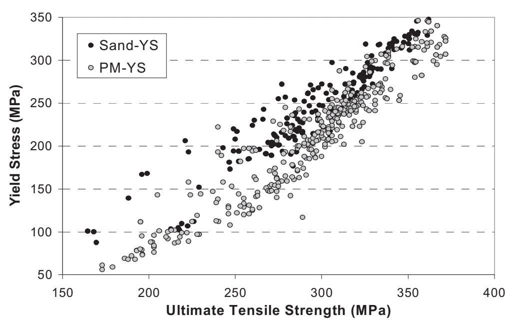

Fig. 1. YS and UTS from literature data for A356 under different casting and heat treatment conditions [1-13].

$$Y = \sum_i \left(a_i x_i + b_i x_i^2\right) + c_i Log(x_i + \varepsilon) + D \tag{1}$$

where Y is the mechanical property, a_i, b_i, c_j, and D are parameters, $\varepsilon = 1.0\text{x}10^{-5}$ to prevent Log(0) from taking place, and x_i represents the input variables (wt%Si, Cu, Mg, Fe, Sr, Na, Ti, Solutionizing time and temperature, natural aging time, artificial aging time and temperature). The logarithmic function was mainly added to better correlate to the precipitation hardening time or temperature. The parameters were calculated by minimizing the adjusted R^2 through an iterative approach. Due to the complexity in developing a nonlinear model with a large number of variables, the number of variables was reduced to create a simpler model without augmenting the error. For example, an analysis of the permanent mould case showed that the weight percent of Cu and Sn did not have much of an impact on the model, and thus were removed from the model. This means that any of the other variables may have a larger influence on the properties and thus the influence of Cu and Sn is minimal, or the data used for the present model did not have a wide enough range. The interactions between variables are also important in developing a nonlinear model. Our analysis showed that the interactions between heat treatment time and temperature are critical, and their interactions can be expressed in the form of $Log(X_i+\varepsilon)*Log(X_j+\varepsilon)$, where the time and temperature are denoted by x_i and x_j, respectively The model with the largest adjusted R^2 value was chosen.