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Multi-Objective Genetic Algorithm Based Optimization of Age Hardening for AA6063 Alloy

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Abstract. The present article attempts to optimize the process parameters of artificial ageing for an AA6063 Al-Mg-Si alloy using multi-objective genetic algorithm (MOGA) to simultaneously achieve the maximum ultimate tensile strength (UTS) and percentage of elongation (%El). For this, a feed-forward multi-layered perceptron artificial neural network (ANN) has been developed which is trained by the scale conjugate gradient back propagation algorithm. The dataset required for the model has been compiled from the experimental results of this study, as well as, from the open literature. The network consists of solutionizing time and temperature, storage time/pre-ageing, rate of quenching, ageing time and temperature as input variables and UTS, %El as their outputs. The developed ANN model establishes the interrelationships between the input and output variables which can serve as objective functions for the optimization, following the theory of Pareto-optimality. The Pareto solution generated from MOGA between UTS and %El assists to conclude that the desired combination of high strength and ductility has been achieved through slow cooling after solutionizing, high pre-ageing time and high temperature of ageing. Furthermore, the designed heat treatment schedule through MOGA has been applied to the selected alloy on an experimental basis which shows satisfactory results.

1. Introduction

Age hardenable aluminium alloys are the attractive materials for various applications because of their excellent combination of mechanical properties. Al-Mg-Si alloys are an important group in both cast and wrought form whose mechanical properties can be enhanced by varying the amount of alloying elements [1], *via* thermal treatment [2] and by thermo mechanical processing [3]. To achieve these, huge experimental efforts had to be put in, which is a costly affair and requires lot of manpower as well. Therefore, the modern day engineers are primarily focused towards designing the materials through optimization techniques [4]. In case of age hardenable Al alloys, optimization of the microstructure is a challenging task as it is governed by the process involving some critical parameters such as: (i) solutionizing temperature [5], (ii) solutionizing time, (iii) quenching medium, (iv) rate of quenching [6], (v) deformation [7,8], (vi) ageing temperature [9], and (vii) ageing time [9].



Establishing the complex inter-relations between these parameters would assist in designing the alloy. In this regard, researchers from past couple of decades have been employing the optimization techniques like multi-objective genetic algorithms (MOGA) based artificial neural networks (ANN) in different areas [10–12] to overcome the difficulty posed by complex non-linear relationships in processing the materials [13]. Song et al. [10] have employed an ANN model to investigate the aging dynamics of 7175 alloy. Back propagation feed-forward neural network has been used by providing three inputs nodes *i.e.*, different values of deformations in percentage, various solution and aging times, 10 nodes in hidden layer and the experimental hardness values were the only output provided for training the network. After training and generalization the hardness values and their associated relative errors are obtained. Su et al. [12] have used artificial neural network along with genetic algorithm to optimize and predict the artificial aging process parameters of Cu-Cr-Zr-Mg alloy to obtain hardness and electrical conductivity. It has been identified that reports on designing of age hardenable alloy with enhanced properties using intelligent based methods are scanty in the open literature; to the best knowledge none are related to AA6063 Al-Mg-Si alloy.

The present investigation deals with the optimization of parameters for the heat treatment schedule to attain optimum strength and ductility for an AA6063 alloy using artificial neural network (ANN) and multi-objective genetic algorithm (MOGA) in tandem. A large set of data including various heat treatment parameters as inputs and ultimate tensile strength and percentage of elongation as outputs are collected from previous literature to train the ANN. Objective functions from ANN are supplied to MOGA for the optimization process. The suitability of the model has been examined by applying the designed heat treatment schedule on experimental basis.

2. Database generation

The dataset for the present study has been acquired from the open literature as well as through the experimentation concerning the AA6063 alloy. A total data of 214 numbers comprising of solutionizing temperature, solutionizing time, rate of quenching, storage/pre-ageing time at ambient temperature, stretching/working, ageing temperature and ageing time as input parameters and ultimate tensile strength and total elongation as output parameters. For the experiments, AA6063 Al-Mg-Si alloy hot extruded rods of 16 mm diameter have been procured on commercial basis. Solutionizing of specimens have been carried out at $525\text{ }^{\circ}\text{C} \pm 2\text{ }^{\circ}\text{C}$ for 2 h and quenching in ice water followed by exposing them at different ageing temperatures of 100-250 $^{\circ}\text{C}$ for 0.083 to 1008 h.

Ageing response of the selected alloy has been assessed by measuring the micro hardness using a Vickers hardness tester (VMHT Leica, Germany) at a load of 2 Kgf for dwell time of 10 s. At least ten readings have been taken on each sample and the average values along with the standard error are reported. Uniaxial tensile tests have been carried out on specimens (Gauge length - 25mm and Gauge diameter - 6mm) using servo hydraulic controlled Universal testing 8801 Instron machine at a crosshead speed of 1.92mm/min which is equal to a nominal strain rate of 0.001 ms^{-1} . A minimum of three tests have been performed on each ageing condition and the obtained tensile properties stored in software are utilized in this model. The dataset used for developing the models are presented in table. 1 consists of the maximum, minimum, mean and the standard deviation values of each variable.

3. Results and discussion

3.1. Development of models

The present study utilizes a feed forward multi-layered perceptron network trained by standard scale conjugate back propagation algorithm [14,15]. Initially, the normalization of inputs and outputs has been carried out within the range of -1 to 1 using the following equation:

$$x^N = a + \frac{(x - x_{\max})(b - a)}{x_{\max} - x_{\min}} \quad (1)$$

where, the normalized value of x is represented as x^N , the values of a and b are given as -1 and 1 respectively; x_{\max} and x_{\min} are the maximum and minimum values of x .

Table 1. Summary of the minimum, maximum, mean and standard deviation values of input and output variables used in the developed model.

Parameters	Min	Max	Mean	Std. dev
<i>Input variables</i>				
Solutionizing temperature (°C)	480	580	515.0342	26.46726
Solutionizing time (h)	0.5	4	1.335616	0.759105
Rate of quenching (°C s ⁻¹)	0.231	4.25	2.668933	1.956332
Storage/pre-ageing time at RT (h)	0	720	267.4521	347.9414
Stretching / Working (%)	0	75	24.68493	28.90693
Ageing temperature (°C)	130	400	174.9247	34.60936
Ageing time (h)	0.016	200	17.00589	33.11995
<i>Output variables</i>				
Ultimate tensile strength (MPa)	128.1	309.1	258.46	38.54
Total elongation (%)	10.5	34.8	22.24	5.636

Later, a tangent hyperbolic transfer function which is a summation of the normalized inputs, x_i^N in combination with the weights, w_{ji} in addition with the bias value, b_j is supplied as input to the hidden neuron (h_j) whose expression is given as:

$$h_j = \tanh\left(\sum w_{ji}x_i^N + b_j\right) \quad (2)$$

here, the suffixes j and i denote the hidden and input neuron numbers respectively.

The output is given by the following equation as:

$$y = \sum W_j h_j + b \quad (3)$$

The developed network has been trained to obtain the optimum input-output relation by minimizing the error function through iterative process. This process has been carried out by comparing the target values with the obtained output values followed by arbitrarily varying the individual weights given as input and output to the hidden neurons [16,17].

Two independent ANN models have been developed which maps the input variables to the UTS and %El. The optimum number of hidden nodes in a single hidden layer of the two developed ANN models for UTS and %El are 46 and 35, respectively. The scatter plots in Fig. 1 show a reasonably good prediction of the target versus output values of UTS and %El based on the developed ANN models. The relation in Figs. 1(a) and (b) has been used as an objective function for further optimization studies.

3.2. Process parameter optimization with genetic algorithm

The superior performance of age-hardenable Al alloys can be achieved through simultaneous improvement of the strength and ductility. A simultaneous enhancement of these two properties, however, is conflicting with each other. Thereby, the multi-objective genetic algorithm (MOGA) [18] has been used for optimizing the individual objective functions of ultimate tensile strength and percentage of total elongation, which can be expressed in general form as:

$$\max\left[\sum W_j \left\{ \tanh\left(\sum_{x_i^{LB} \leq x_i \leq x_i^{UB}} w_{ji}x_i + b_j\right) \right\} + b\right] \quad (4)$$

where, x_i symbolizes the variable for which the maximization search is attempted within the search space, x_i^{LB} and x_i^{UB} as lower and upper bounds respectively.

The genetic search for conflicting objectives has been performed based on the principle of Pareto-optimality. The optimized Pareto-front developed using MOGA for ultimate tensile strength and percentage of total elongation is presented in Fig. 2. The suitable Pareto-front is identified by running

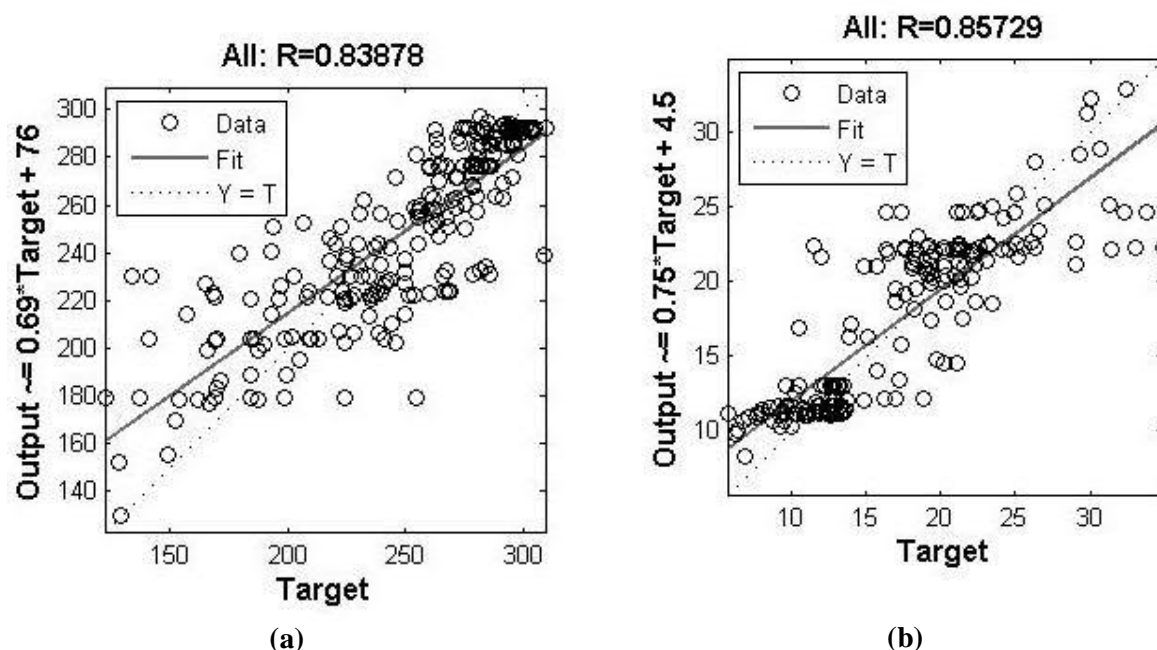


Figure 1. Illustrating the scatter plots for (a) ultimate tensile strength and (b) total elongation of the targets and output values from the designed model.

the genetic algorithm for various population sizes and numbers of generations to ensure the sub-optimal solutions are not achieved. For the present scenario, population size of 279 has been chosen for 279 generations. Where, the Pareto solutions are positioned in an ascending order with the elongation. In the present case, the lower solution numbers represent maximum UTS and higher solution numbers represent minimum %El.

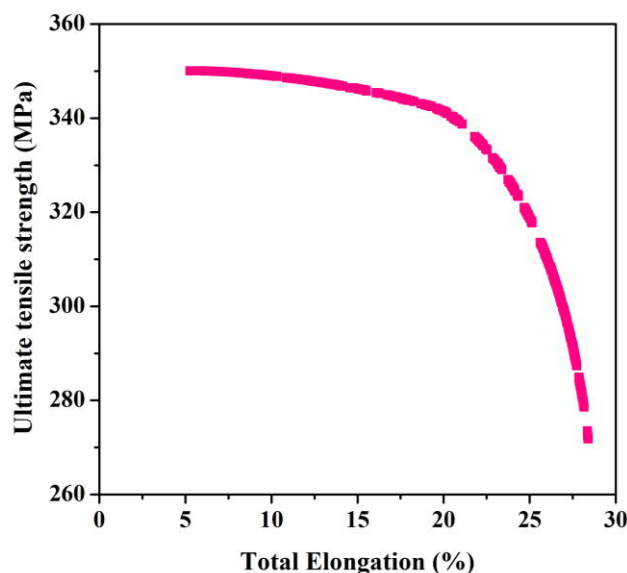


Figure 2. The Pareto-front of percentage total elongation and ultimate tensile strength generated using multi-objective genetic algorithm.

The non-dominated Pareto-solutions generated from multi-objective optimization studies are sorted with increasing strength and different input parameters for each solution as presented in Fig. 3. For

each solution number the variation in the input parameters are identified and related with the change in the UTS and %El. It can be observed from Fig. 3 that the rate of quenching, storage time, and ageing temperature are found to highly influence the strength and ductility of AA6063 alloy. It is a fact that the best combination of strength and ductility is achieved when the Mg_2Si precipitates are completely dissolved in the matrix before ageing [19]. Here the solutionizing temperature of $480^\circ C$ and solutionizing time of 4 hr have been chosen for the optimization study and is almost same for all solutions. The rate of quenching is found to influence the variation in the UTS values. Higher quenching rate is preferred for higher strength and lesser ductility (Fig. 3a). Vacancies that are generated while forming the single-phase solid solution gets trapped with fast quenching and serve as diffusion sites for solute atoms in forming of fine precipitation; the maximum strength is attributed to this phenomenon. Whereas, the slow quenching generates less number of precipitates during ageing which are easily sheared by the dislocations accounting to high elongation [20]. The UTS is maximum when the storage time is as minimum as possible at lower ageing temperatures (Fig. 3b).

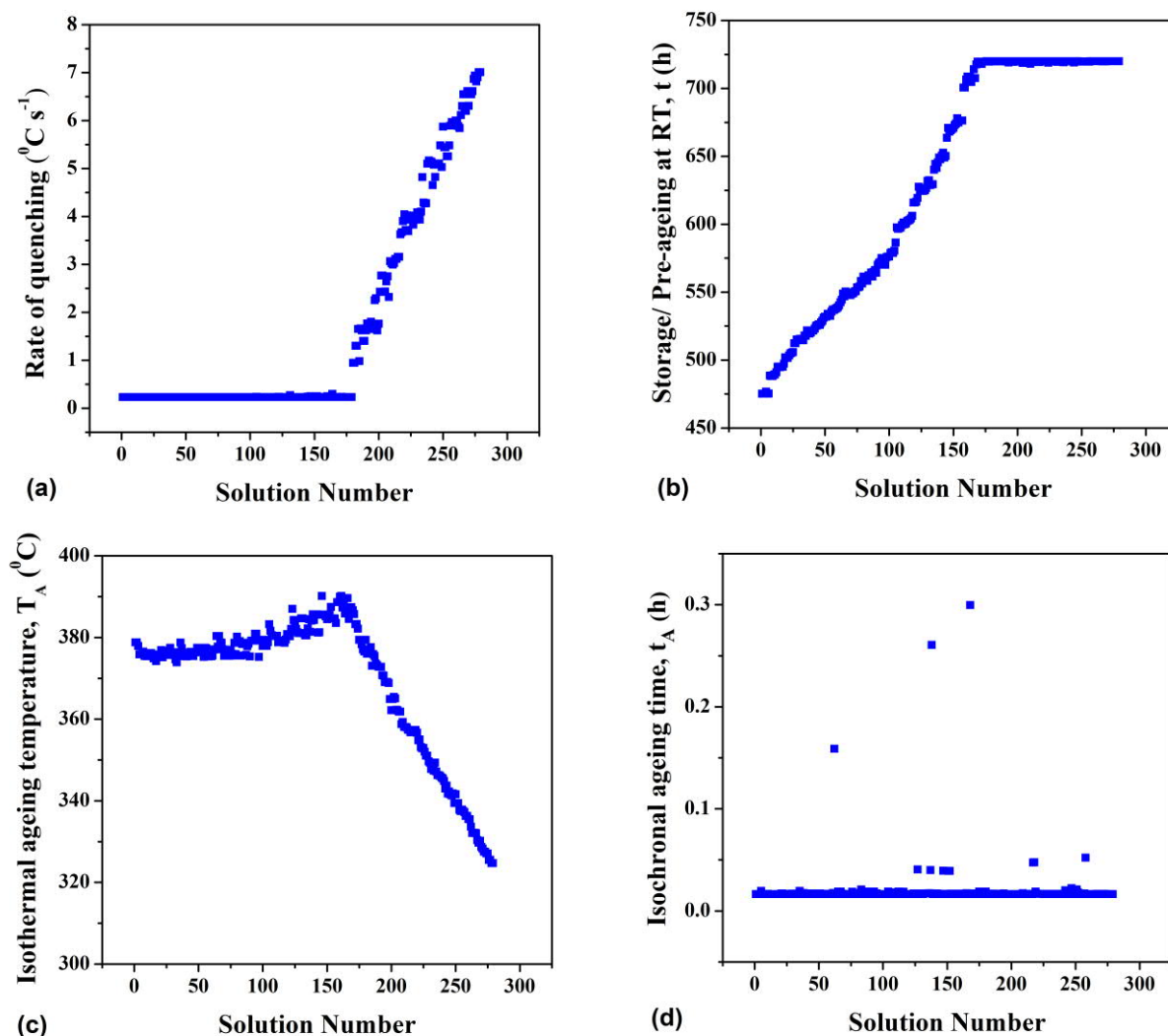


Figure 3. The optimized Pareto-front of (a) rate of quenching, (b) storage/pre-ageing time, (c) ageing temperature, and (d) ageing time against the solutions, numbered for increasing ultimate tensile strength and decreasing percentage of total elongation.

Pre-aging at room temperature generates Guinier-Preston (GP) zones, which provides more precipitation sights during subsequent artificial ageing and thus increases the strength. It is seen that

higher ageing temperature is preferred for higher ductility (Fig. 3c). Higher ageing temperatures leading to over-ageing due to coarsening of the precipitates provide more space for dislocation movement and thus higher ductility. For almost all solutions the ageing time was same (Fig. 3d).

To summarize, the analyses of optimum solutions reveal that slow cooling after solutionizing, high pre-ageing time and ageing at high temperature lead to the balance between high strength and ductility. The heat treatment schedule designed through these models has been applied to the selected alloy on experimental basis which shows satisfactory results.

4. Conclusions

The scheme of designing an alloy for the simultaneous achievement of optimum strength and ductility is convoluted. Therefore, for this objective the present article is directed at optimizing the artificial ageing process parameters for AA6063 alloy through computational intelligent based techniques such as artificial neural network model and multi-objective genetic algorithm (MOGA) in tandem. The interrelations established from the developed ANN models are found to satisfactorily serve as the objective functions for the MOGA. The Pareto solutions suggests that for AA6063 balanced strength of 344 MPa and ductility of 22% can be achieved by lower rate of quenching after the solution treatment and higher storage time before ageing and higher temperature of ageing.

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