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Computational intelligence based design of age-hardenable aluminium alloys for different temperature regimes

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ABSTRACT

Computational intelligence based approaches are used in tandem to design novel age-hardenable aluminium alloy, which would utilize the effect of all precipitate forming elements together, crossing the limit of the compositions defined within different series. A pool of data is created from the tensile properties of age-hardenable aluminium alloys in the 2XXX, 6XXX and 7XXX series. Based on the testing temperature the data is segregated, and different models for the tensile properties in the different temperature regimes are developed using Artificial Neural Network (ANN). The inherent relation between the composition and processing variables with the mechanical properties are explored using sensitivity analysis (SA). In order to design alloys with the conflicting objectives of high strength and adequate ductility, Multi-Objective Genetic Algorithm (MOGA) is used to search optimum solutions using the ANN models as the objective functions. The Pareto solutions from MOGA and the SA results are used along with prior knowledge of the alloy systems to design age-hardenable aluminium alloys with improved mechanical properties at different temperature regimes. The designed composition, which is beyond any of the age-hardenable series, has been developed experimentally, with encouraging results and interesting observations.

1. Introduction

Aluminium alloys that respond to heat treatment are the age-hardenable or precipitation hardened alloys. At elevated temperature, the second phase dissolves in the solid solution, which precipitates upon quenching and ageing at a lower temperature. For an aluminium alloy to be age hardened the second phase must be soluble at elevated temperatures, but must show decreasing solubility with decreasing temperature. This second condition of decreasing solubility with temperature puts a limit on the number of useful precipitation-hardened alloy systems [1]. With proper alloying and heat treatment, hardness in precipitation hardened alloy can be increased to nearly 40 times as compared to pure aluminium alloys. Therefore, it is one of the most important strengthening mechanisms in aluminium [2]. The common age hardenable alloys are the Al–Cu (2XXX), Al–Mg–Si (6XXX) and Al–Zn–Mg (7XXX) series of alloys, which have specific stable and metastable precipitates and their fixed precipitation sequences for each system. To improve the properties of these alloys, several attempts have been made for years through minor additions [3–5] or through thermal [6–8] or thermomechanical processing [9–14].

The performance of an alloy might be improved only if the boundaries of the series of alloys could be crossed and if the effects of the precipitates of the different series could be incorporated. But such effort has never been reported by any previous worker. In this work, attempts have been made to design alloys with improved mechanical properties having such composition, which can have precipitates of all the three age hardenable alloy series. Experimental trial-and-error method to search for suitable chemical composition and processing parameters that will lead to the desired material properties is tedious, time consuming and costly, with no warranted results. On the other hand, unveiling the mathematical interrelationships between the composition and processing parameters with the materials properties of the alloy will make it possible to computationally design an alloy possessing the optimal combination of strength and ductility [15]. The complex correlation being difficult to describe through any physical model, data-driven models have been used extensively in the materials engineering domain [16–18] to successfully find such complex correlations leading to effective materials design. Applications of this computational approach to the design of Al alloys and composites have also been reported [19–25]. While computational intelligence techniques, particularly using rough and fuzzy set theories have seen wide application in mapping the complex composition–processing–property relationships [26–28], Artificial Neural Network (ANN) [29,30] seems to be the most widely used paradigm in this domain to satisfactorily extract non-

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Table 1
List of input and output variables with their minimum, maximum, mean and standard deviation values at low, room and high testing temperature respectively.

Variables	Symbols	Low testing temperature				Room testing temperature				High testing temperature			
		Min	Max	Mean	Std dev	Min	Max	Mean	Std dev	Min	Max	Mean	Std dev
Silicon (wt.%)	Si	0.1	0.9	0.43	0.22	0.1	1.4	0.60	0.35	0.18	0.9	0.48	0.19
Iron (wt.%)	Fe	0.12	1.1	0.51	0.26	0.12	1.1	0.51	0.24	0.3	1.1	0.58	0.22
Copper (wt.%)	Cu	0.1	6.3	2.35	1.98	0.1	6.3	1.95	2.13	0.1	6.3	2.58	2.15
Manganese (wt.%)	Mn	0	0.8	0.29	0.23	0	0.8	0.31	0.26	0	0.8	0.29	0.23
Magnesium (wt.%)	Mg	0.02	2.7	1.38	0.83	0	2.8	1.07	0.77	0	2.7	1.17	0.84
Chromium (wt.%)	Cr	0	0.3	0.12	0.09	0	0.4	0.10	0.10	0	0.3	0.12	0.09
Nickel (wt.%)	Ni	0	2	0.12	0.43	0	2	0.13	0.47	0	2	0.14	0.47
Zinc (wt.%)	Zn	0.1	6.8	1.84	2.64	0.05	6.8	1.11	2.11	0.1	6.8	1.33	2.38
Zirconium (wt.%)	Zr	0	0.18	0.01	0.05	0	0.18	0.02	0.05	0	0.18	0.02	0.05
Titanium (wt.%)	Ti	0	0.2	0.12	0.06	0	0.2	0.11	0.07	0	0.2	0.12	0.06
Testing temperature (°C)	T_{test}	−269	−28	−105.5	74.2					100	371	229.8	92.7
Solutionizing temperature (°C)	T_{soln}	468	540	508.4	21.8	468	565	517.5	23.7	468	540	507.9	22.9
Ageing temperature (°C)	T_{age}	24	205	149.6	51.2	24	240	123.8	70.4	24	205	140.7	60.8
Ageing time (hours)	t_{age}	1	72	31.2	26.7	1	72	36.2	30.0	1	72	31.2	26.6
Cold work	cw	0	1	0.21	0.41	0	1	0.18	0.39	0	1	0.24	0.43
Yield strength (MPa)	YS	97	745	402.8	145.2	90	540	300.5	118.1	10	470	124.5	118.9
Ultimate tensile strength (MPa)	UTS	165	876	483.6	150.7	152	605	371.2	116.4	16	505	151.0	136.2
%Elongation	%El	5	44	15.3	6.9	6	24	14.5	4.6	8	125	48.7	30.8

trivial relationships between the properties and processing routes of different materials systems.

The objective of the present paper is to design novel age hardenable Al alloys with optimum mechanical properties; i.e. good strength and adequate ductility. The objectives of maximizing strength and ductility are however mutually conflicting, which can be computationally approached as a multi-objective optimization problem [31,32] and solved through genetic algorithm (GA) [33], a well-established

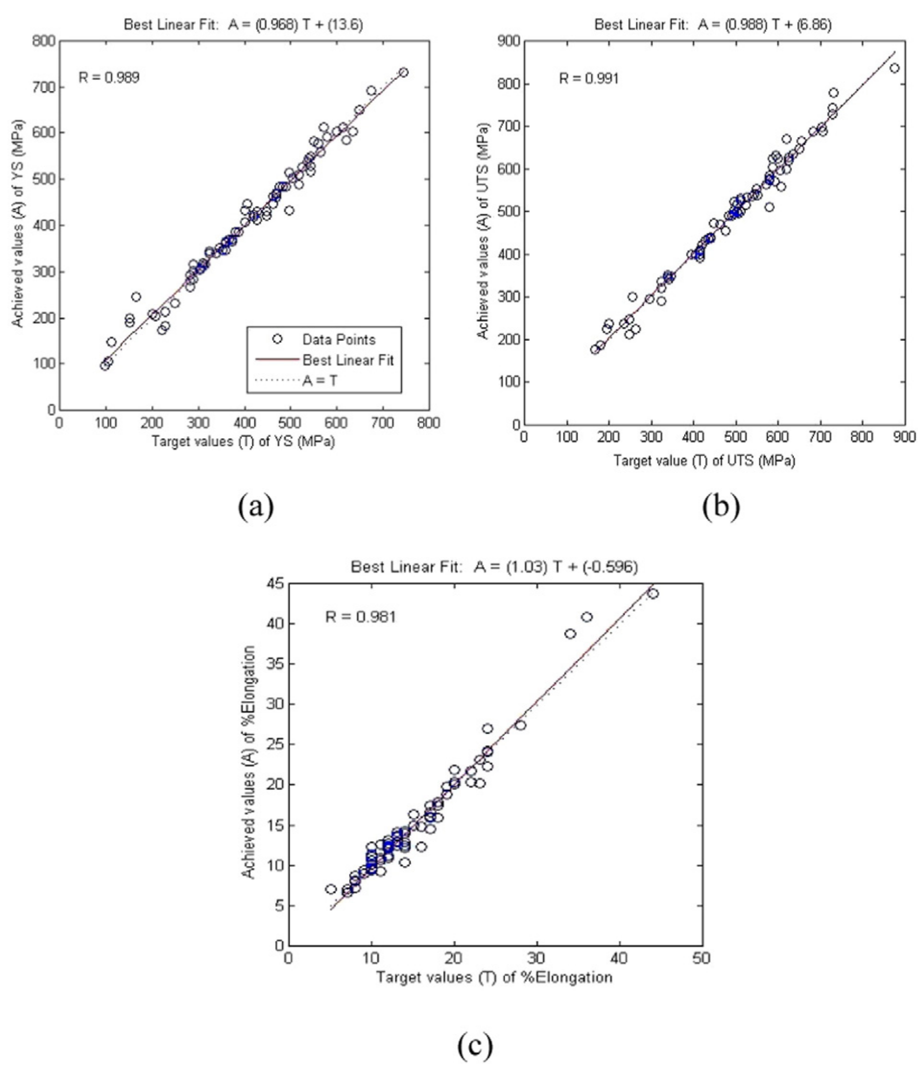

Fig. 1. Scatter plot for low temperature showing target vs achieved values for (a) YS, (b) UTS and (c) %El as predicted by ANN models.