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Flexural buckling load prediction of aluminium alloy columns using soft computing techniques

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ABSTRACT

This paper presents the application of soft computing techniques for strength prediction of heat-treated extruded aluminium alloy columns failing by flexural buckling. Neural networks (NN) and genetic programming (GP) are presented as soft computing techniques used in the study. Gene-expression programming (GEP) which is an extension to GP is used. The training and test sets for soft computing models are obtained from experimental results available in literature. An algorithm is also developed for the optimal NN model selection process. The proposed NN and GEP models are presented in explicit form to be used in practical applications. The accuracy of the proposed soft computing models are compared with existing codes and are found to be more accurate.

1. Introduction

The structural applications of aluminium members have experienced a fast growth in the last few years, mostly because these members exhibit several distinct advantages, namely high strength/weight ratios, corrosion resistance, pleasing appearance, ease of maintenance, fabrication versatility and, last but not least, increasingly competitive prices (Galambos, 1998; Goncalves & Dinar, 2004; Mazzolani, 2002; Roy, Beaulieu, & Bastien, 2001).

These advantages enable aluminium columns to be widely used in structural applications. The buckling phenomenon for aluminium columns is a complex task which involves various failure types and leads to difficulties in the prediction of critical buckling load. Particularly, for cases where plastic buckling is observed the process becomes too complicated. As in the case of flexural buckling of aluminium alloy columns, the behaviour of the aluminium section is determined by the stress–strain curves of the material. The stress–strain curves of aluminium alloys are nonlinear which can be modelled closely using the Ramberg–Osgood expression. Apart from the material nonlinearity, the production process also strongly affects the flexural buckling of aluminium alloy columns i.e. heat-treated aluminium alloys have significantly higher proof stresses yield strength than non-heat-treated aluminium alloys (Rasmussen & Rondal, 2000).

This study aims to present an alternative approach for flexural buckling load prediction of heat treated aluminium alloy columns by using soft computing techniques namely as NNs and GEP which has not been evaluated yet in this field so far. The accuracy of the proposed soft computing models are compared with available analytic expressions and related codes and are presented as explicit formulations.

2. Buckling of aluminium alloy columns

There has been significant experimental research on aluminium column testing in literature. A review of these studies can be found in Chou and Rhodes (1997), Singer, Arbocz, and Weller (2002). The flexural strength of aluminium alloy columns has been the scope of extensive experimental and numerical research conducted during the 1960s and 1970s at the European Convention for Constructional Steelwork (ECCS). As a result of these tests, reference column curves were proposed referred to as the ECCS a-, b- and c-curves for aluminium alloys (ECCS, 1978), where a- and b-curves were adopted by the ECCS, applying to heat-treated and non-heat-treated alloys, respectively. The reason why different curves were adopted for heat-treated and non-heat-treated alloys, respectively is the greater softening of non-heat-treated alloys compared to heat-treated alloys. Since the ECCS column curves were not suitable for design as they were in tabular form. An analytic expression was presented (Frey & Rondal, 1978; Rondal & Maquoi, 1979) and adopted by ECCS. Rondal (1980) expressed another simple expression based on a Perry-type column curve using an imperfection parameter given as:

$$\eta = \alpha(\beta - \lambda)(\lambda^2 - \lambda_0^2)^{1/2}. \quad (1)$$

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Nomenclature

e	nondimensional yield stress, ($e = \sigma_{0.2}/E_0$)	λ_1	parameter used to define the imperfection parameter (η)
E_0	initial elastic modulus	σ_u	ultimate stress of single test or mean of several tests conducted at the same length
n	exponent in Ramberg–Osgood expression	σ_{E_0}	flexural buckling stress based on E_0
α	parameter used to define the imperfection parameter (η)	$\sigma_{0.2}$	0.2% proof (or off-set) stress
β	parameter used to define the imperfection parameter (η)	φ	parameter used to define the nondimensional column strength (χ)
η	imperfection parameter	χ	nondimensional column design strength
λ	column slenderness, ($\lambda = (\sigma_{0.2}/\sigma_{E_0})^{1/2}$		
λ_0	parameter used to define the imperfection parameter (η)		

For columns failing by flexural buckling, the pre-standard Eurocode 9 (1998) uses the same Perry-type curve as that specified in Eurocode 3 (1992) and the same linear form of the imperfection parameter given as

$$\eta = \alpha(\lambda - \lambda_0). \tag{2}$$

Eq. (2) has also been adopted in the ISO (1992) recommendations. Moreover, Rasmussen and Rondal (1996) described a general design procedure applicable to metals and presented an appropriate form for round-house type materials given as:

$$\eta = \alpha(\lambda - \lambda_0)^{\beta} - \lambda_0. \tag{3}$$

This design procedure is subsequently applied to aluminium alloy columns by Rasmussen and Rondal (2000). The mechanical properties are firstly assumed in terms of the Ramberg–Osgood parameters, involving the initial Young's modulus (E_0), the 0.2% proof stress ($\sigma_{0.2}$) and the parameter (n) which controls the sharpness of the knee of the stress–strain curve. The Ramberg–Osgood parameters are assumed to have been obtained from curve fits of measured stress–strain curves obtained from stub column tests of the finished product. Secondly, a Perry curve is adopted as strength curve by modifying the imperfection parameter to be expressed by Eq. (3) where the constants α, β, λ_0 and λ_1 can be expressed in terms of Ramberg–Osgood parameters ($E_0, \sigma_{0.2}, n$) (Rasmussen & Rondal, 2000). Thus, the non-dimensional column strength is calculated using

$$X = \frac{1}{\varphi + \sqrt{\varphi^2 - \lambda^2}}, \tag{4}$$

$$\varphi = \frac{1}{2}(1 + \eta + \lambda^2), \tag{5}$$

where the constants α, β, λ_0 and λ_1 can be expressed in terms of material parameters i.e. in terms of

$$\alpha(n,e) = \frac{1.5}{(e^{0.6} + 0.03)\left(n\left(\frac{0.0048}{e^{0.55}}\right)^{1.4} + 1.3\right)} + \frac{0.002}{e^{0.6}}, \tag{6}$$

$$\beta(n,e) = \frac{0.36\exp(-n)}{e^{0.45} + 0.007} + \tanh\left(\frac{n}{180} + \frac{6 \times 10^{-6}}{e^{1.4}} + 0.04\right), \tag{7}$$

$$\lambda_0(n,e) = 0.82\left(\frac{e}{e + 0.0004} - 0.01n\right) \geqslant 0.2, \tag{8}$$

$$\lambda_1(n,e) = 0.8\frac{e}{e + 0.0018}\left(1 - \left[\left(\frac{n - 55}{n + \frac{6e - 0.0054}{e + 0.0015}}\right)^2\right]^{0.6}\right). \tag{9}$$

In Eqs. (5) and (6) χ and λ are defined as:

$$\chi = \frac{\sigma_u}{\sigma_{0.2}}, \tag{10}$$

$$\lambda = \sqrt{\frac{\sigma_u}{\sigma_{E_0}}}, \tag{11}$$

$$\sigma_{E_0} = \frac{\pi^2 E_0}{(L/r)^2}, \tag{12}$$

where $\sigma_{0.2}$, L and r are the ultimate stress, effective length and radius of gyration respectively (Rasmussen & Rondal, 2000). The accuracy of the procedure applied to aluminium alloys is demonstrated by comparisons with established numerical solutions. This study presents a significant contribution in this field by using soft computing techniques for the flexural buckling load prediction of aluminium alloy columns.

3. Soft computing techniques

The definition of soft computing is not precise. Zadeh (1994), the inventor of the term soft computing, describes it as follows:

"Soft computing is a collection of methodologies that aim to exploit the tolerance for imprecision and uncertainty to achieve tractability, robustness, and low solution cost. Its principal constituents are fuzzy logic, neurocomputing, and probabilistic reasoning. Soft computing is likely to play an increasingly important role in many application areas, including software engineering. The role model for soft computing is the human mind."

Soft computing can be seen as an attempt of collection of techniques that mimic natural creatures: plants, animals, human beings, which are soft, flexible, adaptive and clever. It can be described as a family of problem-solving methods that have analogy with biological reasoning and problem solving. It includes basic methods such as (FL), neural networks (NN), *genetic algorithms* (GA) and genetic programming - the methods which do not derive from classical theories. Soft computing can also be seen as a foundation for the growing field of computational intelligence (CI) as an alternative to traditional artificial intelligence (AI) which is based on hard computing (Koivo, 2000).

In many ways, soft computing represents a significant paradigm shift in the aims of computing – a shift which reflects the fact that the human mind, unlike present day computers, possesses a remarkable ability to store and process information which is pervasively imprecise, uncertain and lacking in categorisation (Dug & Changha, 2004).

Two soft computing approaches based on neural networks and genetic programming is the scope of this study which will described in this section.