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A new model based on evolutionary computing for predicting ultimate pure bending of steel circular tubes

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ABSTRACT

In this study, the feasibility of using evolutionary computing for modelling ultimate pure bending of steel circular tubes was investigated. The behaviour of steel circular tubes under pure bending is complex and highly non-linear, and the literature has a number of solutions, most of which are difficult to use in routine design practice as they do not provide a closed-form solution. This work presents a new approach, based on evolutionary polynomial regression (EPR), for developing a simple and easy-to-use formula for prediction of ultimate pure bending of steel circular tubes. The EPR model was calibrated and verified using a large database that was obtained from the literature and comprises a series of 104 pure bending tests conducted on fabricated and cold-formed tubes. The predicted ultimate pure bending of steel circular tubes using this model can be obtained from a number of inputs including the tube thickness, tube diameter, steel yield strength and modulus of elasticity of steel. A sensitivity analysis was carried out on the developed EPR model to investigate the model generalisation ability (or robustness) and relative importance of model inputs to its output. Predictions from the EPR model were compared with those obtained from artificial neural network (ANN) models previously developed by the authors, as well as most available codes and standards. The results indicate that the EPR model is capable of predicting the ultimate pure bending of steel circular tubes with a high degree of accuracy and outperforms most available codes and standards. The results also indicate that the performance of the EPR model agrees well with that of the previously developed ANN models. It was also shown that the EPR model was able to learn the complex relationship between the ultimate pure bending and most influencing factors, and render this knowledge in the form of a simple and transparent function that can be readily used by practising engineers. The advantages of the proposed EPR technique over the ANN approach were also addressed.

1. Introduction

Circular hollow steel tubes have good energy absorption characteristics under pure bending, thus, have been used in several large-scale engineering applications such as offshore pipelines and platforms; chemical and nuclear power plants; and land-based pipelines. The deformation of circular tubes under bending exhibits significant changes to their cross section profile along the tube length through what is known as *ovalisation* [1,2]. This phenomenon is highly non-linear and makes the behaviour of circular tubes under pure bending very complex. An accurate prediction of the ultimate capacity of steel circular tubes under pure bending using the conventional analytical solutions requires rigorous mathematical procedures that are difficult to achieve from the pragmatic point of view. Most available methods for predicting the ultimate pure bending of circular tubes [3–7] incorporate several assumptions to simplify the problem and to make it amenable to a solution, which in turn, affect the prediction accuracy. In this respect, artificial intelligence (AI) techniques such as artificial neural networks (ANNs) and evolutionary polynomial regression (EPR) are more efficient, as they do not need incorporation of any assumptions or simplifications. Unlike most available statistical methods, AI techniques do not need predefined mathematical equations of the relationship between the model inputs and corresponding outputs and rather mainly use the data to determine the structure of the model and unknown model parameters, enabling the limitations of most existing modelling techniques to be overcome.

In a previous paper by the authors published at the same journal [8], ANNs were successfully used to develop ANN-based models for predicting the ultimate pure bending of steel circular tubes. However, ANNs have the advantage that the obtained network structure is usually complex as the acquired knowledge is represented in the form of a set of weights and biases that are difficult to interpret; thus, ANNs are always criticised of being *black boxes* [9]. Due to their lack of ability to provide insights of how model inputs affect outputs, ANNs neither consider

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nor explicitly explain the underlying physical processes of the problem at hand. Consequently, ANNs usually fail to give a transparent function that relates the inputs to outputs, making it difficult to understand the nature of the input–output relationships that are derived [10]. The main objective of the current work is to explore the feasibility of utilising a relatively new AI technique, i.e. evolutionary polynomial regression (EPR), for developing an accurate, simple and transparent model for prediction of the ultimate pure bending of steel circular tubes. The predictive ability of the developed EPR model was examined by comparing its results with experimental data, and with those obtained from the ANN models previously developed by the authors as well as most available codes and standards.

Despite the fact that the EPR is similar to ANNs in the sense that both techniques are based on observed data (i.e. data driven approaches); however, unlike ANNs, EPR can return a simple mathematical structure that is symbolic and usually uncomplicated [11]. The nature of the obtained EPR models permits global exploration of expressions, which provides insights into the relationship between the model inputs and corresponding outputs, i.e. allows the user to gain additional knowledge of how the system performs. An additional advantage of EPR over ANNs is that the structure and network parameters of ANNs (e.g. number of hidden layers and their number of nodes, transfer functions, learning rate, etc.) should be identified a priori and are usually obtained using ad hoc, trial-and-error approaches. However, the number and combination of terms, as well as the values of EPR modelling parameters, are all evolved automatically during model calibration. At the same time, the prior physical knowledge based on engineering judgement or human expert can be incorporated into EPR to make hypotheses on the elements of the objective functions and their structure, enabling refinement of the final models.

2. Overview of evolutionary polynomial regression

Evolutionary polynomial regression (EPR) is a hybrid regression technique that is based on evolutionary computing developed by Giustolisi and Savic [12]. In recent years, EPR has been applied successfully to some problems in civil engineering [e.g. 9,13,14] and have shown high potential. It constructs symbolic models by integrating the soundest features of numerical regression, with genetic programming and symbolic regression [15]. The following two steps roughly describe the underlying features of the EPR technique, aimed to search for polynomial structures representing a system. In the first step, the selection of exponents for polynomial expressions is carried out, employing an evolutionary searching strategy by means of genetic algorithms [16]. In the second step, numerical regression using the least square method is conducted, aiming to compute the coefficients of the previously selected polynomial terms. The general form of expression in EPR can be presented as follows [12]:

$$y = \sum_{j=i}^{m} F\left(X, f(X), a_j\right) + a_o \tag{1}$$

where: y is the estimated vector of output of the process; m is the number of terms of the target expression; F is a function constructed by the process; X is the matrix of input variables; f is a function defined by the user; and a_j is a constant. A typical example of EPR pseudo-polynomial expression that belongs to the class of Eq. (1) is as follows [12]:

$$\hat{Y} = a_o + \sum_{j=i}^{m} a_j \cdot (X_i)^{ES(j,1)} \ldots\ldots (X_k)^{ES(j,k)} \cdot f\left[(X_i)^{ES(j,k+1)} \ldots\ldots (X_k)^{ES(j,2k)}\right] \tag{2}$$

where: $\hat{Y}$ is the vector of target values; m is the length of the expression; a_j is the value of the constants; X_i is the vector(s) of the k candidate inputs; ES is the matrix of exponents; and f is a function selected by the user.

EPR is suitable for modelling physical phenomena, based on two features [17]: (i) the introduction of prior knowledge about the physical system/process — to be modelled at three different times, namely before, during and after EPR modelling calibration; and (ii) the production of symbolic formulas, enabling data mining to discover patterns which describe the desired parameters. In the first EPR feature (i) above, before the construction of the EPR model, the modeller selects the relevant inputs and arranges them in a suitable format according to their physical meaning. During the EPR model construction, model structures are determined by following some user-defined settings such as general polynomial structure, user-defined function types (e.g. natural logarithms, exponentials, tangential hyperbolics) and searching strategy parameters. The EPR starts from true polynomials and also allows for the development of non-polynomial expressions containing user-defined functions (e.g. natural logarithms). After EPR model calibration, an optimum model can be selected from among the series of models returned. The optimum model is selected based on the modeller's judgement, in addition to statistical performance indicators, namely the coefficient of determination. A typical flow diagram of the EPR procedure is shown in Fig. 1 [18], and detailed description of the technique can be found in Giustolisi and Savic [12].

3. Development of EPR model

In this work, the EPR model was developed using the computer-based software package EPR TOOLBOX Version 2.0 [19]. The following steps were used for model development.

3.1. Model inputs and outputs

Four variables were presented to the EPR as model inputs including the tube thickness, t, tube diameter, d, steel yield strength, f_y, and modulus of elasticity of steel, E. The single model output is the ultimate pure bending, M_u.

3.2. Data division and pre-processing

The data used to calibrate and validate the EPR model were obtained from the literature and include a series of 104 ultimate pure bending tests, 49 tests were conducted on fabricated steel circular tubes and 55 tests on cold-formed tubes. The 49 tests of fabricated tubes comprise a number of 27 tests reported by Sherman [2,20], 10 tests by Schilling [21], 4 tests by Jirsa et al. [22] and 8 tests by Korol and Huboda [23]. The 55 tests of cold-formed tubes were reported by Elchalakani et al. [24–27]. Details of the data used were previously published in Shahin and Elchalakani [8].

The available data were randomly divided into two sets: a training set for model calibration and an independent validation set for model verification. As recommended by Masters [28] and Shahin et al. [29], the data were divided into their sets in such a way that they are statistically consistent and thus represent the same statistical population. The statistics of the data used in the training and validation sets are given in Table 1, which include the mean, standard deviation, minimum, maximum and range. In total, 80% of the data (i.e. 84 records) were used for model training and 20% (i.e. 20 records) for validation. It should be noted that, like all empirical models, EPR performs best when they do not extrapolate beyond the range of the data used for model training; consequently the extreme values of the available data were included in the training set, as shown in Table 1.

3.3. Model optimization

Following the data division, they were presented to the EPR for model training and a set of internal model parameters were tried in an attempt to arrive at an optimal model, by selecting the related internal parameters for evolving the model. The optimization phase was undertaken as