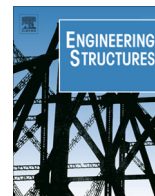




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# A numerical-informational approach for characterising the ductile behaviour of the T-stub component. Part 2: Parsimonious soft-computing-based metamodel

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## ABSTRACT

The accuracy of the component-based method relies heavily on the characteristic response of their constitutive elements. To properly assess the deformation capacity of the whole connection, modelling the complete force–displacement curves of the components, from the initial stiffness to fracture, is necessary. This paper presents a numerical-informational method for calculating the ductile response of the T-stub component. In order to reduce the intensive computation of the finite element (FE) method, the results of numerical simulations are used to train a set of metamodels based on soft-computing (SC) techniques. These metamodels are capable of predicting, with a high degree of accuracy, the key parameters that define the force–displacement curve of the T-stub. In addition, a feature selection (FS) scheme based on genetic algorithms (GAs) is included in the training process to select the most influential input variables. This scheme leads to overall and parsimonious metamodels that improve the method's generalisation capacity.

The mean absolute error (MAE) in the prediction of each key parameter reports values below 5% for both validation and test results. This demonstrates the strong performance of the SC-based metamodels when comparing them with the FE simulations. Finally, this hybrid method constitutes a suitable tool to be implemented in non-linear steel connections software.

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## 1. Introduction

In recent decades research into structural steel connections have been focused on accurately approximating the actual behaviour of the moment–rotation curve. A reliable and accurate response of the connection is essential to avoid a structural collapse during extreme situations, such as seismic loads or fire conditions. In addition, a detailed and in-depth knowledge of the characteristic response provides valuable information for optimisation purposes, reducing costs and enhancing the robustness and reliability of the steel connection within the whole frame.

Until now, numerous methods have been developed to estimate the moment–rotation curve of bolted connections, as briefly described in our companion paper. One of the earlier attempts was based on curve fitting models [1–5], which adjust the

parameters of the moment–rotation curve from experimental beam-to-column tests and analytical expressions. Advances in the statistical, machine learning and artificial intelligence techniques facilitated the inclusion of more sophisticated approximation models in the civil engineering domain.

Artificial neural networks (ANNs) are one of the most widely known approximation models. Several studies can be found in the literature on the assessment of beam-to-column connections using this technique. The first studies estimating the response of cast-in-situ beam-to-column joints were performed by Jadid and Fairbairn [6], based on the results of 34 experimental tests. Stavroulakis et al. [7], demonstrated that ANNs models are also able to accurately estimate the response of single web-angle bolted connections. In this case, only six experimental tests were conducted to create the training dataset. A total of 21 experiments were utilised by Anderson et al. [8] to develop a simple ANN with seven inputs and two outputs: the ultimate moment and the corresponding joint rotation. Both values were required to define the bilinear moment–rotation response of minor axis steel connections. Lima et al. [9] also addressed the capacity of ANNs when predicting

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the behaviour of welded, endplate and double angle bolted connections. The initial stiffness and the bending moment resistance were correctly estimated with only two ANNs for each connection type. In 2010, Kim et al. [10] presented a comparative study between mechanical and informational modelling of steel connections. They proposed a new mechanical-informational model for determining the non-linear hysteretic behaviour of bolted connections [11]. Again, the use of ANNs is a key factor to including some underlying effects that are extremely difficult to model with mechanical approaches. Finally, ANNs have also been very useful when predicting the response of steel connections under fire conditions. The work performed by Al-Jabri and Al-Alawi [12,13] is especially noteworthy as it obtained great accuracy with training data from a total of 29 experiments at elevated temperatures.

Some drawbacks can be easily detected in the aforementioned ANNs models. Firstly, the use of reduced experimental datasets is often not enough to train good performing prediction models. A detailed characterisation of a bolted connection requires an elevated number of model inputs related to the connection layout, geometry and the mechanical properties of materials. According to the *curse of dimensionality* phenomenon [14], more experiments would be required to maintain model accuracy as the number of inputs increases. However, a reduced number of tests can be affordable given the high costs incurred by conducting experimental work. In addition, experimental data are probabilistic by nature mainly due to the variability of specimens' mechanical properties. Systematic errors inherent to testing machines also contribute increasing this variability. Thus, the use of experimental data introduces a source of uncertainty that is difficult to quantify in the model performance.

Numerical simulations rather than experimental tests allow the aforementioned problems to be partially resolved. The finite element (FE) method has demonstrated its ability to mimic the behaviour of bolted connections with a high degree of accuracy, as was noted in the companion paper. Additionally, given the deterministic nature of numerical simulations, they do not suffer from random errors, unlike the experimental tests. However, despite growing computing power, the intensive computational effort required to run the simulations still represents a significant weakness. Nowadays, using FE models to calculate bolted connections is not a cost-effective solution for the daily work of the structural engineers.

A way to overcome the drawback of the high computational cost consists of approximating the response of the complex FE code through analytical functions. These so-called *metamodels* or *surrogate models* are based on the relation between the input variables and simulation results. Several approximation techniques are available to this end, such as the response surface methodology, ANNs, support vector regression (SVR) and the kriging interpolation method. Díaz et al. [15] employed the latter for the cost-optimisation of two examples of bolted end-plate connections. Mashrei et al. [16] developed ANNs and adaptive neuro-fuzzy inference system (ANFIS) to predict the moment capacity of ferrocement members. Both ANFIS and ANNs appear to be reliable and easy methods for the prediction of the capacity of structural elements. In this sense, the work of Gholizadeh et al. [17] to predict the critical load carrying capacity of castellated steel beams merits special attention. The authors also employed ANFIS in combination with exhaustive search to determine the most influential inputs of the model. The results showed that the proposed method outperforms back-propagation neural networks in terms of both accuracy and computational effort.

This paper introduces a numerical-informational method for predicting the response of components in bolted connections. This hybrid approach constitutes a fusion between the FE method and metamodels based on soft-computing (SC). Specifically, a combina-

tion of SVR and genetic algorithms (GAs) is employed to achieve overall and parsimonious metamodels. Parsimony generally leads to higher generalisation capacity and lower prediction errors. This can be accomplished by selecting the metamodels with lower complexity and fewer inputs.

The case study developed herein is the well-known T-stub component, which constitutes the main source of deformability in the beam-to-column bolted connections. A SC-based metamodel is implemented to predict the complete force–displacement response of this component. To this end, input/output information necessary for the metamodel training process is directly extracted from the refined FE model described in the companion paper.

The paper is organised as follows: Section 2 provides a general framework for the hybrid methodology proposed herein. Basic concepts of data generation and computer experiment design are described in Section 3. In Section 4, the force–displacement curve of the equivalent T-stub is characterised by means of a modified Richard-Abbott function. Section 5 explains the background of the metamodeling technique. The optimisation process for tuning the metamodel parameters is also introduced, as well as the procedure to select the most relevant input features. Then, the results of the training and testing process are reported and discussed in Section 6. And finally Section 7 draws conclusions and makes suggestions for future research.

## 2. Methodology

A numerical-informational method is presented on the basis of an *evolutionary process* reported by Krishnamurthy [18]. The common denominators of this process are outlined as follows:

1. Design of an idealised model of the connection: FE model, rigid frame, etc.
2. Development of the equations that govern the connection behaviour (using regression analysis of parametric data or structural mechanics).
3. Model validation against experimental tests.
4. Simplifications of the governing equations to make them suitable for practical application.

However, significant advances have already been made not only in numerical simulation, but also in statistics and computer science. The present study takes these advances into consideration, and in addition proposes a hybrid approach that may represent a significant update of the first three points of Krishnamurthy's process. A general scheme is depicted in Fig. 1. Particularly, the hybrid approach is mainly derived from a combination of a numerical model based on FE analysis and an informational SC-based metamodel.

On the one hand, the numerical model of the T-stub component comprises the first part of this work and is described in its entirety in the companion paper. The primary feature of the refined FE model is the simulation of the progressive damage by means of a non-linear continuum damage mechanics model. Thus, the overall response of the equivalent T-stub is accurately defined from the initial stiffness up to the fracture.

On the other hand, the informational model encompasses all the stages of a metamodel-based methodology. Firstly, a design of computer experiments (DoCEs) is used to generate a representative dataset of T-stub configurations. This dataset should cover the ranges of dimensional parameters and mechanical properties most commonly used in practice. The T-stub configurations of the input dataset are introduced to the refined FE model in order to run the simulations. As a result, the force–displacement curve for each sample of the DoCE is obtained and stored. These curves are

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