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Prediction of welding residual stresses using machine learning: Comparison between neural networks and neuro-fuzzy systems

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ABSTRACT

Safe and reliable operation of power plants invariably relies on the structural integrity assessments of pressure vessels and piping systems. Welded joints are a potential source of failure, because of the combination of the variation in mechanical properties and the residual stresses associated with the thermomechanical cycles experienced by the material during welding. This paper presents comparative studies between methods based on artificial neural networks (ANN) and fuzzy neural networks (FNN) for predicting residual stresses induced by welding. The performance of neural network and neuro-fuzzy systems are compared based on statistical indicators, scatter plots and several case studies. Results show that the neuro-fuzzy systems optimised using a hybrid technique can perform slightly better than a neural network trained using Levenberg-Marquardt algorithm, primarily because of the inability of the ANN approach to provide conservative estimates of residual stress profiles. Specifically, the prediction accuracy of the neuro-fuzzy systems trained using the hybrid technique is better for the axial residual stress component, with root mean square error (*RMSE*), absolute fraction of variance (R^2) and mean absolute percentage error (*MAPE*) error of 0.1264, 0.9102 and 22.9442 respectively using the test data. Furthermore, this study demonstrates the potential benefits of implementing neuro-fuzzy systems in predicting residual stresses for use in structural integrity assessment of power plant components.

1. Introduction

Residual stresses can be generated in pressure vessel and piping systems as a consequence of manufacturing process such as welding. Structural integrity assessment of welded components must take account of residual stresses remaining in the welded joint as well as the applied service loading conditions. Tensile residual stresses in engineering structures can be detrimental as they can initiate cracks or accelerate growth of pre-existing cracks during service. Engineering fracture assessment procedures such as R6 [1] and API-579 [2] provide guidelines on the treatment of residual stresses. In undertaking safety assessments of welds, estimations are generally made of the residual stresses, and in order to provide both simplicity and conservatism, yield levels of residual stresses may be assumed. These estimated residual stress distributions in welded components can then lead to conservatism in the predicted plant life and may unfavourably affect the life extension scenarios of operating power plants.

The use of mechanistic approaches such as finite element modelling [3] often rely on the modeller's choice of assumptions and there is significant uncertainty owing to the inherent complexity of the welding process. Moreover, finite element simulation requires extensive computational requirements and tedious non-linear analysis of the welding process, limiting its application to safety-critical components that require a high standard of validation [4]. The finite element approach for predicting weld residual stresses requires comprehensive data such as the physical and thermo-physical properties from room temperature up to the melting point, parameters for all beads deposited during welding, and tensile and cyclic stress-strain data of weld and parent material [5]. A series of round-robin activities have been undertaken recently for the improvement of the numerical techniques in order to reliably characterise the distribution of residual stresses in structural welds [6,7].

With the development of residual stress measurement techniques, both non-destructive and destructive, extensive experimental data are readily becoming available on residual stresses in welds. Neutron diffraction [8] is a popular non-destructive technique that can be used to determine the residual stress distribution in thick-section welds because of its high depth of penetration and

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good spatial resolution that is capable of resolving high strain gradients. Neutron diffraction is based on the principle of Bragg's law to measure the changes in lattice spacing of the material's crystallographic planes. By contrast, destructive methods such as the contour method [9] and deep hole drilling [10] are based on the principle of stress relaxation that occurs during cutting or drilling operations. However, characterisation of residual stresses to high confidence levels is notoriously difficult owing to the innate scatter in welding residual stress [11]. Undertaking residual stress measurements using multiple experimental techniques is crucial for robust validation of analytical or finite element models [12].

The substantial amount of data accumulated in recent years can be utilised for the application of data-driven models to predict the residual stresses in weldments; thereby finding potential applications in structural integrity assessment of power plant components. Machine learning techniques such as artificial neural networks (ANNs) and adaptive neuro-fuzzy inference systems (ANFIS) have been increasingly used as alternative prognostic methods for modelling complex problems associated with engineering systems. Recently, ANNs have been applied to predict welding-induced residual stresses [13,14] where the prediction was expressed as a distribution plot providing realistic uncertainty bounds. Ahmadzadeh et al. [15] presented ANNs for predicting residual stress distributions obtained from finite element data in gas-metal-arc weldments using a Levenberg-Marquardt training algorithm. The application of hybrid models based on support vector regression and neuro-evolutionary computing have also been proposed [16,17] using datasets accumulated from finite element simulation. Na et al. developed a fuzzy neural network model for prediction of residual stresses in dissimilar metal welds using data from parametric finite element analysis [18]. More recently, Koo et al. [19] estimated the residual stresses in dissimilar metal welds in nuclear power plants using cascaded support vector regression. Alamaniotis et al. [20] studied the application of probabilistic kernel machines for predictive monitoring of welding residual stress in circumferentially welded pipes. The outcomes of these studies for predicting the residual stress state of weldments have been promising. However, there have been inadequate studies comparing the performance of different data-driven techniques for predicting residual stress distribution of welded components.

ANN and ANFIS models have been increasingly used for prediction and optimisation purposes using improved algorithms [21–24]. In this work, we present a novel application of ANN and ANFIS methods to predict residual stresses induced by welding for application in structural integrity assessment. The performance of ANN and ANFIS models can be effectively compared as the convergence criteria for training algorithms used in both neural networks and neuro-fuzzy systems is based on the minimisation of the error function over the given weight space. In supervised training, the error function is defined as the sum of square of the difference between the desired and predicted output vectors. The problem of mapping inputs to outputs by operating gradient descent to minimise the error can be reduced to a common optimization problem.

In this study, we present: (1) ANN and ANFIS models to predict through-thickness residual stress profiles using experimental data, described in section 2.2 and 2.3 respectively; (2) Section 3.1 presents performance comparison of the proposed techniques based on statistical indicators such as root mean square (RMSE), absolute fraction of variance R^2 and mean absolute percentage error (MAPE); (3) the generalisation ability of methods on test and training datasets (see section 3.1), and residual plots expressed as a function of individual input parameters (see section 3.2); and, (4) case studies demonstrating the efficacy of the ANN and ANFIS methods are discussed in section 3.3.

2. Material and methods

2.1. Database

Residual stress measurements in austenitic stainless steel girth welds collated over the last two decades were used to develop ANN and ANFIS models. These measurements were undertaken by diverse measurement techniques as part of UK nuclear power industry research programmes. The primary objective was to contribute to the knowledge gap in measured residual stress profiles, and to validate finite element simulations for assessing the structural integrity of engineering components. Neutron diffraction, the only non-destructive technique employed in this work, can achieve penetration depth of several centimetres and spatial resolution of the order of 1 mm in linear dimension. The contour method (CM) and deep hole drilling (DHD) methods were the preferred destructive techniques for measuring the through-wall distribution of the residual stresses in welded mock-ups. Detailed information about the experimental measurements can be found in [25].

A schematic diagram defining the stress components and geometry of a pipe girth weld is shown in Fig. 1. The measurement database covers a wide range of welding heat input Q (kJ/mm), wall thickness (t) and mean radius-to-wall-thickness ratio (R/t), which are considered to be the key input parameters controlling the residual stress distribution in circumferentially welded pipes [26]. Details of the welded samples and input parameters used to simulate the axial and hoop residual stress profiles are described in Table 1. The forecasting models were trained and tested using randomly selected samples. A total of 278 and 338 samples were obtained in the axial and hoop stress direction respectively, of which 80% of the data were used for training and the remainder for testing purposes.

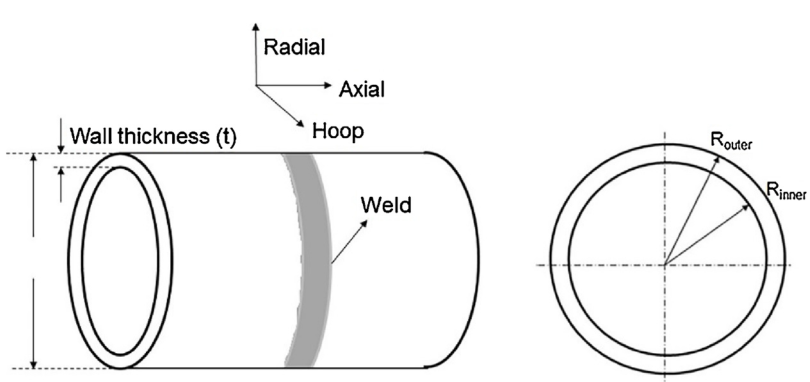

Fig. 1. Schematic illustration of a circumferential pipe-butt weld showing the residual stress components.