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Estimation of stress concentration factor in butt and T-welded joints utilizing artificial neural network-based models

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Summary. In this study, the capability of artificial neural network-based models in estimation of stress concentration factor of welds in form of butt-welded joints (single-V and double-V) and T-welded joints (as-welded and TIG-dressed conditions) was investigated. The joints were analyzed under axial-tension and bending load cases. A large set of finite element models were used for each configuration in order to train, validate and test the corresponding networks. The estimations by the neural network- based models yielded the results with higher accuracy for all configurations compared to the available parametric equations. The proposed models also cover the joints with broader range of local weld parameters.

Key words: stress concentration factor, butt weld, T-joint, artificial neural network

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Introduction

It is not possible to eliminate the presence of structural discontinuities in real components. These spots, which act as stress raisers, are usually critical locations susceptible to crack initiation and growth. Originating in the work of Neuber, the concept of a stress concentration factor (SCF) has been well defined and systematically studied to enable assessment of the severity of notches and their effects on structural integrity. Advancements in stress measurement techniques have resulted in more accurate equations covering a wider range of configurations, for example, welded components, which have more affecting parameters than non-welded components. A number of parametric equations can be found in literature for SCF calculation of T-welded joints and are reviewed by Brennan et al. [1]-[2]. Some of the equations were originally proposed for calculation of SCF in T-welded and cruciform joints, but they are used interchangeably for butt welds in single-V and double-V forms. The most

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recent parametric equation for SCF estimation of butt welds is proposed by Kiyak et al [3].

This study uses the artificial neural network (ANN) technique to simulate the relationship between basic variables and the SCF in single-V and double-V butt joints and as-welded and TIG-dressed T-joints experiencing axial-tension and bending load cases (figure 1).

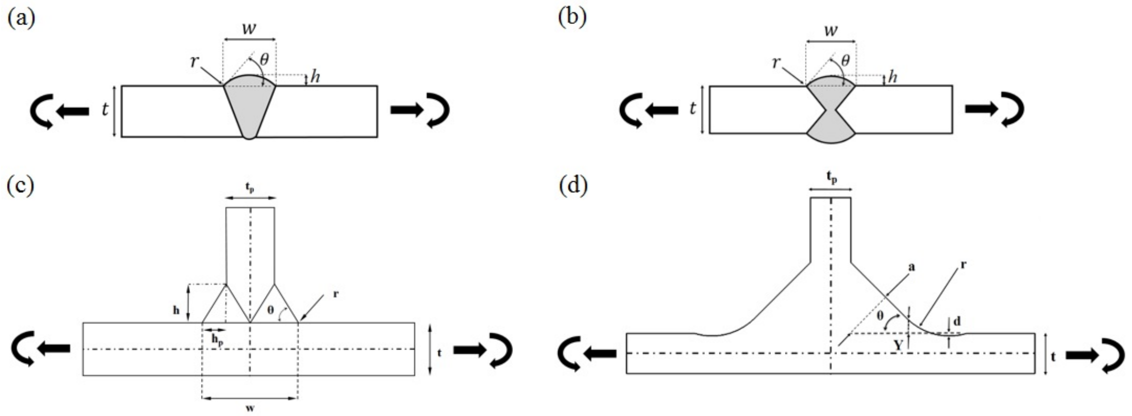

Figure 1. Investigated configurations in the current study: (a) single-V, (b) double-V butt welds and (c) as-welded, (d) TIG-dressed T-joints.

Taguchi method of design of experiments is used to design the combination of factors required for analysis and modeling. The Finite Element (FE) models are analysed to examine the profiles and used in training, validation and testing of the networks. The validity ranges of the analysed configurations are shown in Table 1.

Table 1. Considered weld parameters and their ranges in butt and T-welded joints

	Plate thickness (t) (mm)	Weld toe radius (r) (mm)	Reinforcement height (h), Weld leg size (h_p) (mm)	Flank angle (θ) (°)	Undercut depth (d) (mm)
Single-V & double-V butt joint	$5 \le t \le 30$	$0.1 \le r \le 4$	$1 \le h \le 3$	$10 \le \theta \le 70$	-
As-welded T-joint	$6 \le t \le 30$	$0.05 \le r \le 5$	$6 \le h_p \le 22$	$30 \le \theta \le 60$	-
TIG-dressed T-joint	$6 \le t \le 10$	$2 \le r \le 6$	-	$45 \le \theta \le 55$	$0.1 \le d \le 0.25$

Finite element modeling

Studies showed that the difference in geometrical stiffness of single-V and double-V butt welds leads to different SCF values which makes this differentiation necessary to apply separate SCF equations for each form under axial-tension and bending load cases. The numerical modelling for stress analysis was performed using a 2D finite element model in ABAQUS. A second-order reduced integration quadrilateral element was used in mesh definition for all loading cases. All the stress calculations were made using elastic material behaviour defined by elastic modulus, E=200 GPa, and Poisson's ratio, υ= 0.3. All configurations were postulated as fully penetrated joints and exposed to axial-tension and bending loads.

Implementation of artificial neural networks

In this study, a multilayer perceptron (MLP) feedforward network is applied that utilizes a commonly used supervised training algorithm, a backpropagation algorithm (BPA) in conjunction with other optimization algorithms such as gradient descent. The best architecture of the network was obtained by trying different numbers of hidden layers and neurons. The artificial neural network architecture and functions used in the ANN model in this work are summarized in Table 2 for butt-welded joints and Table 3 for T-welded joints.

Table 2. Architecture and functions of the implemented ANN for butt-welded joints

Network	Feedforward backpropagation network
Training function	Levenberg–Marquardt
Learning function	Gradient descent with momentum weight & bias learning function
Transfer function	Tan sigmoid & Linear transfer function
Performance function	Mean squared error
Feedforward neural network type	Fitting networks (Fitnet)
Number of input layer units	4
Number of hidden layers	2
Number of first hidden layer units	6
Number of second hidden layer units	3
Number of output layer units	1

Table 3. Architecture and functions of the implemented ANN for T-welded joints

Network	Feedforward backpropagation network
Training function	Levenberg–Marquardt
Learning function	Gradient descent with momentum weight & bias learning function
Transfer function	Tan sigmoid & Linear transfer function

Performance function	Mean squared error
Feedforward neural network type	Fitting networks (Fitnet)
Number of input layer unit*	4
Number of hidden layers	2
Number of first hidden layer units	3
Number of second hidden layer units	2
Number of output layer units	1

*In a TIG-dressed profile, the number of inputs are equal to 5.

After the network has been established and primary arrangements defined, such as the number of inputs, outputs, hidden layers and transfer functions, the weights and biases of the system are initialized. These weights are pre-defined by the network during the training process, mainly through the BPA. Variation of weights and biases is accomplished in accordance with the training function and is carried out in the transfer functions. In the network used in this study, mean-squared error was found to give the most desirable performance. The number of input and output data sets that are allocated to the network during the training is *Q*. Weights are iteratively adjusted by the algorithm so that outputs (o_k) will be as close as possible to their output patterns (d_k) based on the input patterns. For a neural network with a total number of outputs *K*, the mean squared error (MSE) function is to be minimized:

$$MSE = \frac{1}{Q \times K} \times \sum_{q=1}^{Q} \sum_{k=1}^{s} k[d_k(q) - o_k(q)]^2 \qquad (1)$$

Results

Figure 2 shows the comparison of the SCF estimations of butt-welded joints by finite element, ANN-based model and the empirical equation by Kiyak et al [3]. It can be seen from figure 2a that the trained networks were able to estimate the SCF values with a considerably higher degree of precision (coefficients of determination were greater than 99.9% in all load cases and configurations). The equation proposed by Kiyak et al. [3] however, did not yield equally accurate estimations and discrepancy increased in joints with higher SCFs (figure 2b). A possible explanation for this discrepancy compared to FE results and its absence in their original study could be the utilization of remote nominal stress in calculation of SCF instead of the linearized through-thickness stress as used in current study. Evaluation of errors on SCF estimations showed that using the nominal stress instead of linearized through-thickness stress yields error in the same range as reported in their study (≤ 3.5 % to 4.4% depending on the configuration and load type). Detailed information can be found in Ref. [4].

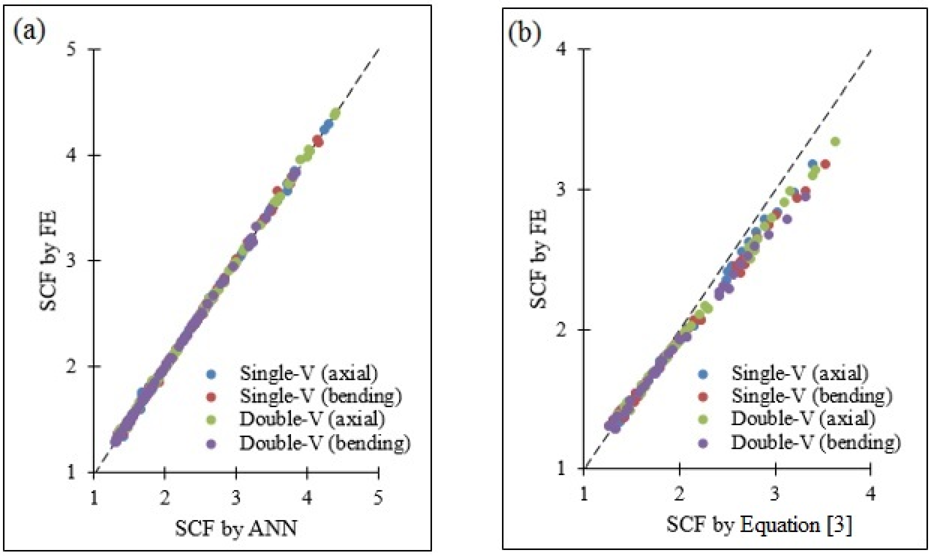

Figure 2. Comparison of estimated SCF values by (a) ANN and (b) parametric equation of Kiyak et al. [3].

Figure 3 illustrates the SCF values of T-welded joints in as-welded condition predicted by the ANN-based model and empirical equations by Brennan et al. [1]-[2] compared with the FE results. The results of this joint type in TIG-dressed condition are not presented because of the non-availability of appropriate parametric equation for comparison. More detailed results can be found in Ref. [5].

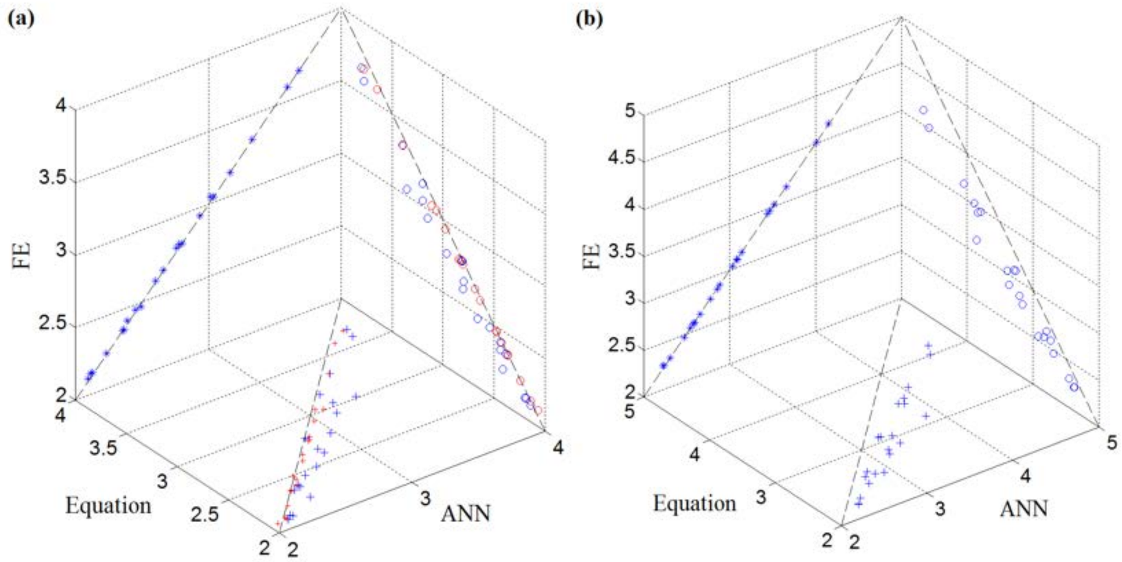

Figure 3. Comparison of estimated SCF values by FE, ANN and parametric equations of Brennan et al. [1]-[2] for as-welded T-joints under (a) axial tension and (b) bending load cases.

The red circles in figure 3a indicate the estimations made by the modified version of the original equation proposal by Brennan et al. [1]-[2]. It can be seen that the accuracy of the newly proposed equation is improved compared with the older equation and results are closer to the SCF estimations by FE.

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