Neural network-based estimation of stress concentration factors for steel multiplanar tubular XT-joints

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Abstract

The hot-spot stress method for fatigue design of tubular joints relies on the accurate predictions of the stress concentration factors (SCF) at the brace to chord intersection areas. At present, SCFs are predicted based on established empirical equations. An alternative approach using a neural network-based model has been developed in this paper to estimate the SCFs of multiplanar tubular XT-joints. The neural network software, Stuttgart Neural Network Simulator, was used for the purpose. To train and test the network, an SCF database was built up using the finite element method (FEM). The database covers a wide range of geometrical parameters for the XT-joints. Three axial load cases were considered. The geometrical properties of the tubular joints were used as the training input data. The FEM SCFs are used as the training output data. Different network configurations are also tested for the best possible results. The results show that a trained neural network can indeed predict the SCFs for the various load cases with a higher level of accuracy.

Keywords: Neural network; Stress concentration factors; Tubular joint; Fatigue
1. Introduction

Steel offshore structures used for the extraction of oil and gas are composed of tubular members welded together to form three-dimensional space structures. Such structures are susceptible to localized fatigue failure [1] at the welded connections as a result of the high stress concentration at these brace to chord intersection regions and the large number of stress cycles experienced during their operational life spans. For the welded tubular joint, the hot-spot stress method has evolved as the most suitable means for practical fatigue design purposes [2]. In order to ensure that the structure is adequately designed, it is necessary to be able to accurately predict the hot-spot stresses around the welded connections where cracks are likely to start and propagate.

Considerable effort has been expended in the past decades on the development of procedures for determining the fatigue endurance of the tubular joints, which are a common feature of current offshore fixed steel platforms. A major advance has been the replacement of S–N curves based on “punching shear stresses” by those based on “hot-spot stresses”. This latter procedure involves the use of “hot-spot” stress concentration factors (SCFs) which relate the extrapolated stress at the “hot spots” of the weld toe of the joint intersection areas to the nominal stress in one of the members.

The stress distributions in tubular joints are complex, since the magnitude of the hot-spot stress is dependent on the geometric parameters of the joint. In offshore structures, this problem is further aggravated, as there are often numerous joints with different sizes and geometries. Although the finite element method (FEM) is a good tool for analysing the various joint configurations, extensive use of this method is not feasible owing to the high computer cost and extensive computation time involved in a normal day-to-day design office operation. The common design solution is to use an established set of empirical equations to estimate the ratio of the hot-spot stress at the joint connection to the nominal stress of the loading members, known as the SCF equations. These equations express the SCFs as a function of the geometric parameters of the joint and are generally applicable to a particular loading condition. However, for each type of load case involved, there will be many individual equations involved for the various parameters at the different critical locations.

Various empirical equations have been proposed for calculating these SCFs from the geometric parameters of the tubular joints. To date, most of the parametric SCF formulae developed are to determine the hot-spot stress in the uniplanar joints. However, multiplanar joints are an intrinsic feature of the three-dimensional offshore structures. The multiplanar effect plays an important role in the stress distribution at the brace to chord intersection areas of the spatial tubular joints [3]. For such multiplanar joints, the parametric stress formulae for simple uniplanar tubular joints may not be applicable in the SCF prediction.

In this paper, a new and alternate approach has been developed, known as the artificial neural network for the estimation of stress concentration factors for the multiplanar tubular XT-joints. Neural networking is a newly emerging technology with very wide applications ranging from engineering to psychological aspects. A
neural network software called SNNS (Stuttgart Neural Network Simulator) [4] is used for this purpose. It has been trained using the database obtained by the FEM. The training database was built up from FEM analyses for 64 XT-joints covering a wide variety of geometrical parameters. SCF results generated from the final network were compared with the original FEM SCF database and those obtained using the parametric equations proposed in a previous study [5]. Comparison of the results confirmed that the final neural network is reliable and accurate.

2. Finite element simulation

2.1. Finite element modeling

For welded tubular joint stress analysis by means of the finite element method, the accuracy of results depends on the use of element type, mesh refinement, integration scheme, weldment shape modeling and boundary conditions. In each case, some guidelines are available from the existing research literature. The weldment modeling produces the most realistic SCF results. Thus the weldment was included in the numerical models in this study. Romeijn [6] carried out a systematic study and recommended the use of a 20-node solid element with a reduced integration scheme. The element length along the brace–chord intersection should be less than one-sixteenth of the total length of the intersection area. Such valuable recommendations were also considered. In addition, a preliminary study was carried out on the mesh refinement method, the weldment size effect, and the chord end condition effect to obtain reliable numerical results. To make full use of the advantage of the structural and load symmetry properties, the one-quarter joint model was proposed in this study. The 20-node three-dimensional isoparametric brick element was used. The element has three translational degrees of freedom $u_x$, $u_y$, and $u_z$ at each of the nodes. The hardware platform used for this study is the SUN Workstation SPARC Station 20. The finite element software is MARC K6.2/K7.2 with the pre- and post-processing package Mentat 2.3/3.2.

The numerical models of the XT-joints were created based on a former FE model which has been verified by the experimental SCF results obtained from the investigation of a large-scale XT-joint specimen [7]. Fig. 1 illustrates the verified XT-joint FE models. Under balanced loading, only one-quarter of the joint needs to be modeled. For easy reference, the three braces of the joint are denoted as West-, North- and East-Brace (hereafter W-, N- and E-Brace).

2.2. Mesh refinement and integration scheme

A convergence study was necessary to find out the proper mesh refinement for the SCF calculation. FEM models with element number of 921, 1114, 1199, 1447, 1901 for the one-quarter XT-joint specimen were simulated under N-brace axial, IPB and OPB loadings. The model with 1199 brick elements, as shown in Fig. 1, was finally selected for the SCF study. In this model, much attention was given to
the mesh refinement at the brace-chord intersection areas: along the weldment at both brace and chord side, 40 elements were used to simulate one whole circular intersection weldment, along the direction perpendicular to the weld toe, the width of the first two row elements were kept as small as “0.8T” or “0.8r” at the chord or brace side, which was two times the minimum extrapolation distance from the weld toe, refer to Table 1, as recommended by CIDECT [8]. The element sizes of the other areas were enlarged gradually, as shown in Fig. 1.

As to the integration scheme, the reduced integration scheme (MARC Element 57, 2*2*2) was found to be suitable for the SCF study. This is consistent with the recommendations given by Romeijn et al. [9] and CIDECT [8].

2.3. Weldment modeling

Owing to the importance of the weldment to the stress distributions at the welded joint intersection areas, the weldment was included in the FE model with the use of

Table 1
Extrapolation region recommended by CIDECT [8]

<table>
<thead>
<tr>
<th>Chord side</th>
<th>Brace side</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crown location (1)</td>
<td>Saddle location (2)</td>
</tr>
<tr>
<td>$R_{ch}=0.4T$</td>
<td>$R_{ch}=0.4T$</td>
</tr>
<tr>
<td>$R_{ch}=4$ mm</td>
<td>$R_{ch}=4$ mm</td>
</tr>
<tr>
<td>$R_{ch}=0.4\sqrt{aRT}$</td>
<td>$R_{ch}=5^\circ$</td>
</tr>
</tbody>
</table>
3-D solid elements. Such weldment was consistent with the offshore industry practices as specified in the AWS Code D1.1 [10] and is illustrated in Fig. 2.

2.4. SCF extraction and extrapolation method

In the FEM stress analysis, the edge nodal stress is obtained by averaging those stresses calculated from neighboring elements. The stresses at the weld toe nodes obtained by this method are not always reliable due to the structural discontinuities at the brace–chord intersection areas, especially at the chord side. To get realistic SCFs at the weld toe hot-spot locations, the values of the hot-spot stresses must be obtained by extrapolating the stress values at the nodes inside the extrapolation region. For the tubular XT-joints the linear extrapolation method can be sufficient [8,11]. Fig. 3 illustrates the SCF extraction process for the hot-spot location “O” (at chord side) with the linear extrapolation method. In this figure, “O” and “B” are edge nodes, “A” and “C” are mid-nodes of the two nearest elements. The mesh
refinement, as mentioned above, ensures that nodes A and B are always within the extrapolation region. The stress distribution line can be obtained by fitting the stresses at the two nodes A and B. The chord-side hot-spot stress at node “O” \( (\sigma_{O,Extra}) \) can then be obtained by extrapolating along the stress distribution line to the weld toe. By keeping the nominal stress value as one, the value of the extrapolated stress at “O” is just the SCF value. In addition, the stress at node C provided a reference for monitoring the stress distribution.

2.5. Load cases and the definition of hot-spot stress

For the finite element SCF analysis of the XT-joints in this paper, three balanced brace axial loads were analysed. Fig. 4 illustrates the three load cases. SCFs at the six-weld toe saddle locations, Nsch, Nsbr, Ws1ch, Ws1br, Ws2ch and Ws2br, were derived for each of the load cases. Fig. 5 shows the definition of these hot-spot locations. SCFs at spots other than the typical locations can be derived by symmetry analysis.

In this paper, the definition of the hot-spot stress complied with the recommendations from the “New guidelines for fatigue design of HSS connections” [11]. The stress components perpendicular to the weld toe were adopted for the SCF calcula-
lations, and this enabled the SCF predictions for the multiplanar XX-joint under arbitrary combined loading by using the superposition method and the numerical or equation SCF results under basic brace and chord load cases. As to the nominal stress, the definition adopted in this paper was:

1. For axial member loading, the nominal stress was obtained by dividing the force by the cross-sectional area of the member that carries the load directly;
2. For bending loads, the nominal stress was derived from simple beam theory using the maximum moment arm of the load-carrying member. For simplification in deriving the SCFs, a value of unity was assigned to the nominal stress of the calculated load cases.

2.6. Geometrical parameter validation range

In total, 64 multiplanar XX-joint models were generated and analysed. These joints cover a wide range of geometrical parameters with the objective of capturing the relationships between the SCFs and the geometrical parameters of these XT-joints. The detailed geometric parameters of these joint models are listed in Table 2. The definitions of the non-dimensional geometric parameters are:

\[ \alpha = \text{chord length to radius ratio (2L/D);} \]
\[ \beta = \text{brace to chord diameter ratio (d/D);} \]
\[ \gamma = \text{chord radius to thickness ratio (D/2T);} \]
\[ \tau = \text{brace to chord thickness ratio (t/T).} \]

In this paper, the valid ranges of the geometrical parameters are within ranges adopted typically in practice. The detailed ranges of the parameters are \( \alpha = 14, 0.3 \leq \beta \leq 0.6, 15 \leq \gamma \leq 30, \) and \( 0.4 \leq \tau \leq 1.0. \)

From the FEM stress analyses on the 64 XT-joints, a database of SCFs at the six typical saddle locations under load case 1 to 3 was built up. It was used to train the neural network in the following sections.

3. Neural networks

Neural networks [12,13] are systems that typically consist of a large number of simple processing units called neurons. A neuron generally has a high-dimensional input vector and one single output signal which is usually a non-linear function of the input vector and a weight vector. This weight vector is adjusted in a training phase by using large sets of examples and a learning rule. The learning rule adapts the weight of all neurons in a neural network to learn an underlying relation in the training examples. Thus it is clear that this method of finding a function to be performed by a system is completely different from programming a function.

The most commonly used neuron is shown in Fig. 6. Each neuron input \( x_1 - x_n \) is
<table>
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<tr>
<th>Joint</th>
<th>$\beta$ (dD)</th>
<th>$\gamma$ (D/2T)</th>
<th>$\tau$ (T/T)</th>
<th>Joint</th>
<th>$\beta$ (dD)</th>
<th>$\gamma$ (D/2T)</th>
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</table>

weighted by the value $w_{1-w_n}$. The bias is much like a weight, except that it has constant input of 1. "w" is an adjustable scalar parameter of the neuron. The output, $y$, is obtained by summing the weighted inputs to the neurons, passing the results through a non-linear activation function. The central idea of a neural network is that such parameters can be adjusted so that the network exhibits some desired or interesting behavior.
3.1. The multilayer neural network

The most popular neural network is the multilayer network as shown in Fig. 7, which is rather powerful. The layer that produces the network output is called the output layer. The layer that receives input is called the input layer. This input layer receives data from the outside world, in the form of data files, program files, etc. They send the information to the second layer, called the hidden layer. This hidden layer is a layer containing the hidden neurons in between the input and output layers. It is part of the large internal abstract pattern, which represents the neural network's solution to any problem.

There can be more than one hidden layer, depending on the amount of input data that the network is going to train. Finally, the output neurons will send information with regard to the neural network's response to the input data. For example, a network of three layers can be trained to approximate any function arbitrary well. The input layer is essentially a direct link to the inputs of the first hidden layer.

The outputs of each node in a layer are connected to the inputs of all the nodes in the subsequent layers. Data flows through the network in one direction only, from...
input to output. Hence this type of network is called a feedforward network [12]. The network is trained in a supervised fashion. This means that during training, both the network inputs and outputs are used. The most popular algorithm used for training the multilayer perception is the backpropagation algorithm.

Neural networks and specifically those of the backpropagation type have attracted the attention of many investigators in a large variety of fields, including structural engineering, due to their ability to provide generalizations for a wide spectrum of applications. Some of these applications involve the prediction of seismic hazards [14], structural analysis simulations [15], and systems and applications of neural networks in civil engineering [16].

3.2. Preparation of the data

The SCF database built up from the FEM could be used directly in the training of the neural network. All the SCF data sets had to be transformed into an SNNS readable format before a network could be trained. First, the data have to be scaled down to fall between the range of 0.1 and 0.9. This was done by using simple algebraic equations to scale down the data involved as input and output data.

3.3. Network configuration

To carry out training successfully, the basic structure of the network has to be defined properly. The basic structure here comprises the number of input units, output units and hidden units and the ways they are arranged in space.

- **Number of input units:** As defined in the pattern file, there were three input units in the basic structure. These three input units corresponded to the three geometric parameter used to determine the hot-spot stresses. All networks that were defined will have the three input units arranged in one layer.
- **Number of output units:** There are altogether six typical hot-spot locations for the tubular XT-joints. The SCFs at the six hot-spot saddle locations will correspond to the six output units.
- **Number of hidden units:** The hidden layer of the basic structure plays the most important role in the neural network training. Thus extra consideration has to be given to choosing the correct number of hidden units and their arrangement. It was found that when there are too few hidden units, the speed of the training was increased but the accuracy achieved was not as satisfactory. The network cannot adjust its weight to the training data. This is because reducing the number of hidden units will reduce the interconnection of the network. On the other hand, an increase in the number of hidden units will improve the accuracy but the network will take a longer time to train. Moreover, the network will tend to "memorize" the training data, resulting in a case of good training performance but poor generalization. In other words, the network has lost its generalization capability; it cannot handle unfamiliar inputs. Thus the minimum numbers of hidden units would be the number of output units, i.e. six hidden units for all the load cases.
The maximum number of hidden units was fixed at 10 to reduce the possibility
of over-generalization of the network. Finally, eight different network structures
were used to train the data and the best network was to be used. These eight
network structures are shown in Table 3.

3.4. Training of the neural network

Once the data sets were prepared, training of the network can start. Training was
done for a number of cycles or epochs. All training patterns were presented once
during each cycle. The backpropagation algorithm has been used in this work. Each
cycle of training consists of a forward pass and a backpropagation.

Once the optimum results were achieved for all load cases, they were compared
with the targeted results to show the feasibility of using the neural network as a
replacement for the established equation. The three different load cases were com-
bined to train a single network that can be used to predict SCFs for all load cases
when the three parameters $\beta$, $\tau$ and $\gamma$ are known. The procedure will repeat from
stage 1 to stage 4 with varying conditions. All the results obtained for the different
load cases, different training data sets and the combined load cases are presented in
the next section.

3.5. Training termination consideration

In SNNS, training is done by the specification of the number of cycles or epochs.
Each round of training consists of a forward pass and a backpropagation. Training
is considered to have one epoch after the network has “seen” the whole training set.
There are two stopping criteria for the training process:

(a) termination upon reaching a specified number of epochs;
(b) termination upon the squared error becoming less than its allowed value speci-
fied by the user.

<table>
<thead>
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<th>Input units</th>
<th>Hidden units</th>
<th>Output units</th>
</tr>
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<td>7</td>
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<td>8</td>
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However, there may be difficulties in achieving criterion (b) as not all networks will converge to the required squared error. Moreover, the squared error will definitely get smaller when more epochs are run but this does not imply that the network had been well trained; in fact, it may be overtrained. Thus criterion (a) was adopted. All networks were trained 1000 epochs for each run and training was terminated when it reached 15 000. It was found that the squared error stabilized after 15 000 cycles, i.e. additional training of the network would not improve the squared error. A typical error graph is shown in Fig. 9.

4. Results and discussion

As mentioned earlier, the SCF database was generated using the FEM. Eight trial neural networks were used and the best network with least root mean square error
was selected. Neural network number 8 with two hidden layers with five nodes in each layer was found to be best.

The trained neural networks for three different load cases were used to estimate the SCF using the test data. SCFs for the six hot spots were compared with those obtained from the finite element method. SCFs obtained from the equations proposed in a previous study [5] have also been compared with those obtained from the finite element method. From Figs. 8–10, it can be clearly understood that the SCFs obtained from the trained neural network show better agreement with those from the FEM compared with those obtained from the established equations. For load cases 2 and 3, the network SCF data points are very close to those from the FEM. The trend lines for these data points align almost exactly on the theoretical line. For load case 1, it can be seen that the network approximates SCFs better than the established equation with the data points with the trend line deviating slightly from the theoretical line.

Hence the results have proven that a neural network can be used to replace the
equations to estimate the SCFs on the six saddle points with a higher accuracy and reliability for the three load cases of axial and combined axial loading. However, there will be three different neural networks to replace the three different load cases. Thus to take one step further, the three load cases were combined together and one network was being trained to provide all the 18 different SCFs at the six saddle points. In this approach, the three load cases were added together linearly, i.e. there would be three input data, corresponding to the three geometric parameters, and 18 output data. The first six outputs were the six SCFs for load case 1, the second six outputs will correspond to the six SCFs for load case 2 and the last six outputs will correspond to the six SCFs for load case 3.

As can be seen from the graph in Fig. 11, the estimation of the SCFs for all the load cases at the six saddle points using one network was very close to the SCFs formulated using the FEM. The graph of the FEM results versus the equation results was also drawn to make a comparison. It can be easily concluded that the 20 estab-
lished equations for finding the SCFs could be replaced by one neural network, which can give a higher accuracy of estimation.

5. Conclusion

The main objective of this work was to introduce a new and alternative approach of using a neural network for the estimation of the SCFs for multiplanar tubular XT-joints. An SCF database was built up from the FEM analyses of 64 multiplanar tubular XT-joints. Six typical saddle hot spots were considered under three different axial load cases. This SCF database was used to train and test the neural network.

For the neural network, three networks were used to approximate the SCFs for the three load cases and then a single network was used. It was found that both approaches could approximate SCFs with an error of less than 10%. The results were
especially good for the single network for all the load cases with an error of 5–6% consistently for the entire network tested. The neural networks can, therefore, replace the time-consuming finite element analysis and the approximate empirical equations and yet accurately estimate the stress concentration factors for the fatigue design of the tubular joints.

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