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SCF Prediction using the Finite Element Method Coupled with Sobol Sampling and Bayesian Optimization

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Abstract

A comprehensive database was developed for stress concentration factors (SCF) in offshore tubular T-joints through a code that enables finite element (FE) modeling of a joint using graded mesh generation, load and boundary conditions for a range of geometric parameters. A mesh sensitivity study was conducted and the SCF computations were validated against existing experimental results. A parametric study was conducted to identify the best samples for training a neural network (NN) model. Bayesian optimization by Gaussian Process and Expected Improvement functions were employed to tune the hyper-parameters. A Sobol sampler was used to generate an initial set of points in the search space with the hyper-parameters including learning rate, batch size, number of layers, neurons, activation function and dropout. The optimization process generated a set of trial points using a balanced Sobol sampler, which was evaluated by an objective function that monitored validation loss to obtain the best hyper-parameters. Back-propagation based on a NN model was trained and tested to predict the SCF of T-joints by using the best hyper-parameters obtained from the model. SCF results were compared with parametric equations of Det Norske Veritas (DNV) and Lloyds Register (LR). Advantages of the proposed method have been highlighted.

Keywords: stress concentration factor, offshore structures, T-joints, finite element analysis, Sobol sequence, Bayesian optimization, neural networks

1 Introduction

Offshore jacket platforms are space frames built with welded tubular steel with vertical legs that are held by a transverse bracing system. Main cause of structural failures of offshore jacket platform has been attributed to fatigue damage. Computation of SCF is a key element in fatigue assessment. Empirical equations are often used to compute SCF, which are mostly on the safe side. Thus, FE analysis is recommended to justify extending structure's life.

Toprac and Beale [1] developed the empirical SCF equations for tubular joints by employing a small pool of steel joint data. Due to exorbitant expense of testing scaled steel models, Efthymiou [2] developed empirical equations using 150 cylindrical 3-dimensional FE models with PMBSHELL elements. LR developed SCF parametric formulae for simple tubular joints based on an experimental database of measured SCFs for steel joints and full-scale acrylic models. DNV and LR are the most widely used empirical equations in the offshore industry. Santacruz and Mikkelsen [3] showed that SCFs from FE models with solid elements are lower than those derived using shell elements. Empirical equations were created using FE models which either did not contain a weld geometry or modelled the geometry in a simplified form. Hectors and Waele [4] proved that geometry of weld significantly impacts magnitude of SCF, pattern of SCF distribution and the projected location of failure. They suggested that SCF can be ascertained by modelling solid joints with inclusion of the weld geometry. Effective service life of offshore structures can be well depicted with adoption of more precise SCF.

Choo and Qian [5] proposed NN based estimation of SCF in steel tubular X-joints based on 100 ABAQUS-FE models database with single hidden layer of 11 neurons. Xiao et.al [6] developed NN model to predict SCF in Concrete Filled Steel Tubular Y-joints. The proposed ground breaking approach integrates Sobol sequence sampling and Bayesian optimization, revolutionizing hyper-parameter optimization for NNs and enabling the discovery of optimal configurations that minimize loss. Cheng and Druzdzel [7] demonstrated that Sobol sequences outperformed Halton and Faure sequences in sampling methods for Bayesian networks as the number of dimensions increased. Bratley and Fox [8] examined the proposal by Antonov and Saleev [9] for an optimized variant of the Sobol sequence using Gray code. Utilization of Gray code in the Sobol sequence improved its performance, making it a valuable tool for applications requiring high-quality quasi-random number generation. Maass et al. [10] explored the influence of Sobol sequences on optimization of Back Propagation Neural Network (BPNN) architectures by including number of layers and nodes.

Potential of neural networks with the support of sufficient and accurate FE database can overcome limitations of empirical equations. In order to assist offshore design engineers to forecast accurate fatigue life, NN models for SCF prediction in tubular T-joints based on a sizable FE database are developed by incorporating Sobol sequence sampling and Bayesian optimization.

2 Mesh Sensitivity Study and FEA Validation

Tubular T-joints can be subjected to axial forces, in-plane bending, and out-of-plane bending. Typical tubular T-joint with non-dimensional geometrical parameters and loading mode is presented in Figure 1. Nominal stresses are the stresses in the structures under external loads that do not take into account the intricacy of the joint intersection. These stresses are primarily due to the bending and axial loads acting on tubular members. Hot-spot stresses occur due to deformation of tubular wall under applied external loads to maintain continuity at the intersection of chord and brace members. These stresses can be significant and may lead to joint fatigue failure. Positions of hot spot stress of tubular joints are in the way of weld toes on the sides of chord and brace. Hot spot locations considered for fatigue life assessment are chord-crown, brace-crown, chord-saddle and brace-saddle. Stresses in the extrapolation region are considered for computation of SCF. It is mentioned in DNV RP C203 [11] that hot spot stress can be obtained by extrapolation of stresses determined from FE analysis at specified locations from the weld toe.

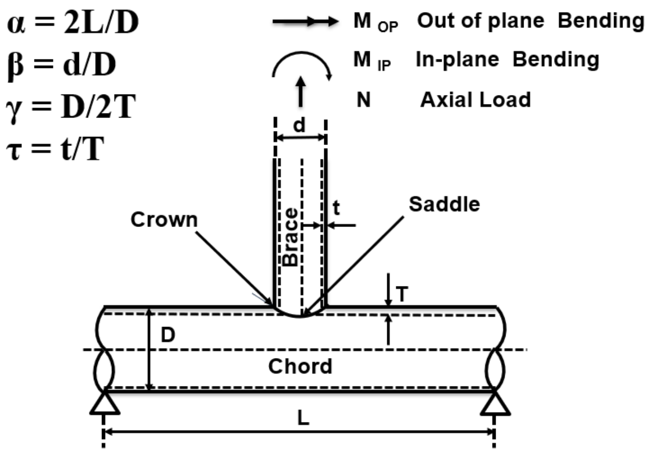

Figure 1: Geometric Parameters and Mode of Loading.

Twenty-noded three-dimensional solid elements are used to simulate tubular joints including the weld geometry. Modulus of Elasticity and Poisson's ratio of steel are considered to be 200 GPa and 0.3, respectively. Because there exists symmetry in material, size, shape, orientation, and boundary conditions; one-fourth of the geometry is modelled using the Ansys Parametric Design Languauge (APDL) code. Weld geometry is modelled based on requirements suggested by American Welding Society (AWS) D1.1 standard [12]. A finer mesh is implemented for numerical simulations in areas surrounding the weld region, while a coarser mesh is used for regions farther away. Displacements in the X,Y, and Z directions at all nodes pertaining to chord end were arrested for simulating the fixed-fixed boundary for all loading conditions. Unit pressure is applied at the brace-end for axial loading. By applying appropriate stresses at the associated nodes, linear stress variation with zero stress at the neutral axis is simulated. Unit pressure is also applied at the extreme point for both in-plane and out-of-plane bending. Planes of symmetric and asymmetric boundary conditions are used to simplify FE analysis. Mesh sensitivity is conducted to identify optimum mesh controls to save computation time in creating the database without affecting accuracy of results. A mesh convergence study is performed on a 700 mm chord diameter joint, as an example, with mean non-dimensional geometric parameters. Key mesh controls for study are: number of elements across thickness of chord and brace members. Three models are studied with one, two and three elements each across the thickness of the chord and brace member. SCF at all the locations for three loadings are plotted in Figure 2. It can be observed from the plot that the second model is apt for the FE analysis because the SCFs become stable from second to third model at all locations for all loading.

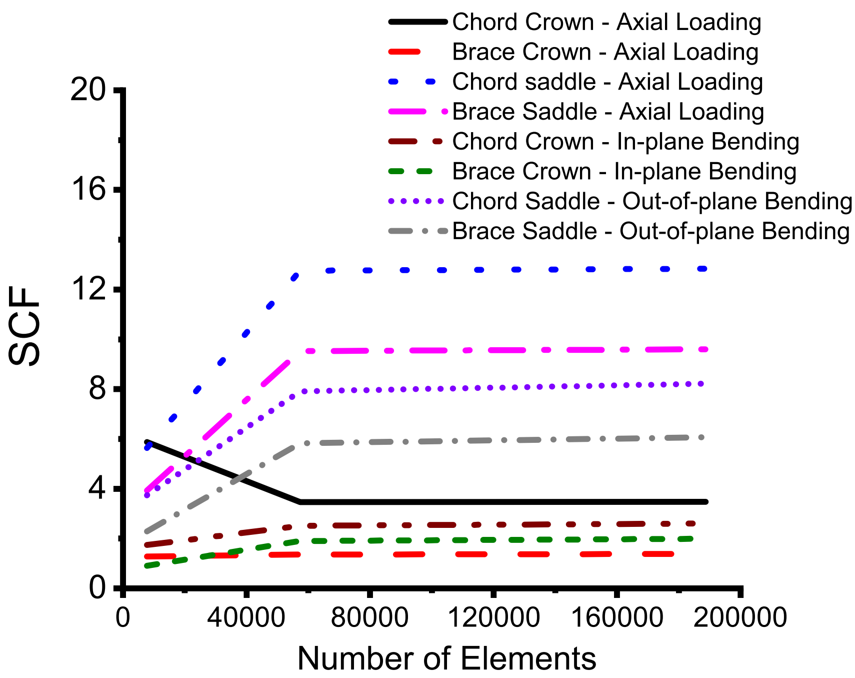

Figure 2: Mesh Convergence Plot for all Loadings.

Experimental results which are available in the existing literature are identified and FE analysis is performed to find SCF of selected tubular T- joints as mentioned in Table 1. SCF at all locations for the out-of-plane bending obtained are compared with experimental results, which are presented in Figure 3. Variation of SCF between FE results and the test results can be attributed to a discrepancy in the location used to extrapolate the stress in the test. Further, differences in the weld profile might exist between the FEA code and the test model. Atteya and Mikkelsen [14] found SCFs determined through FE analysis to be dependent on various factors, including mesh size, element type, method used to compute SCF and the modelled weld profile. It is verified from comparison of FE based SCF results with experimental results that the code developed by the authors for FE modelling and analysis of steel tubular T-joints

Model No.	Code/ Literature	D (mm)	α	β	γ	τ
1	T23/1 (OTH) [13]	168	10.5	0.53	13.4	0.86
2	T24/3 (OTH) [13]	168	10	0.53	13.3	0.51
3	T204C (OTH) [13]	457	10.2	0.25	14.3	0.4
4	Santacruz [3]	250	12	0.5	14	1

Table 1: Details of Validation Models for Out-of-plane Bending.

can predict the SCF very well. The FEA based database is generated using a full factorial combination of geometric parameters, covering the entire parameter range. For cross-validation of the neural network model, a randomly generated data-set is created, with count equivalent to 20% of the total number of combinations in the full factorial design. Sobol Sequence Sampling Method and Bayesian Optimization Technique is used to find the best hyper-parameters of the NN model for SCF prediction.

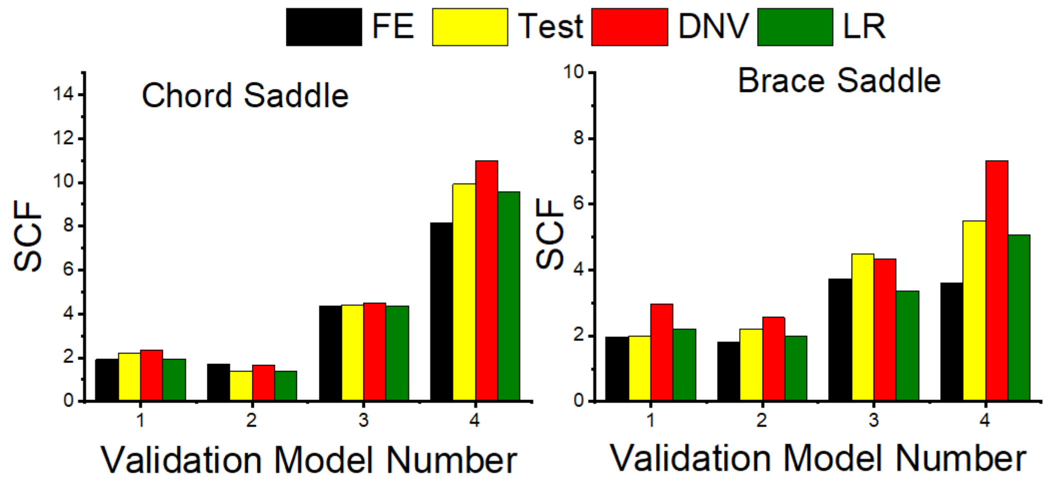

Figure 3: Comparison of SCF for FEA Validation for Out-of-plane Bending.

3 Initial Sobol Sequence Sampling Method

A feed-forward BPNN is employed in the present study consisting of an input layer with four neurons representing geometric parameters of steel tubular T-joints. Network also includes an output layer with one neuron corresponding to SCFs at chord-crowd, brace-crown, chord-saddle and brace-saddle locations. Determination of the optimal hyper-parameters can be a challenging task because their values rely on problem and data-set characteristics. Thus, a Sobol sequence of all hyper-parameter combinations is generated to obtain the optimal NN model with fine-tuned hyper-parameters and a sample of Number of Neurons density plot is shown in Figure 4 for brevity. Such

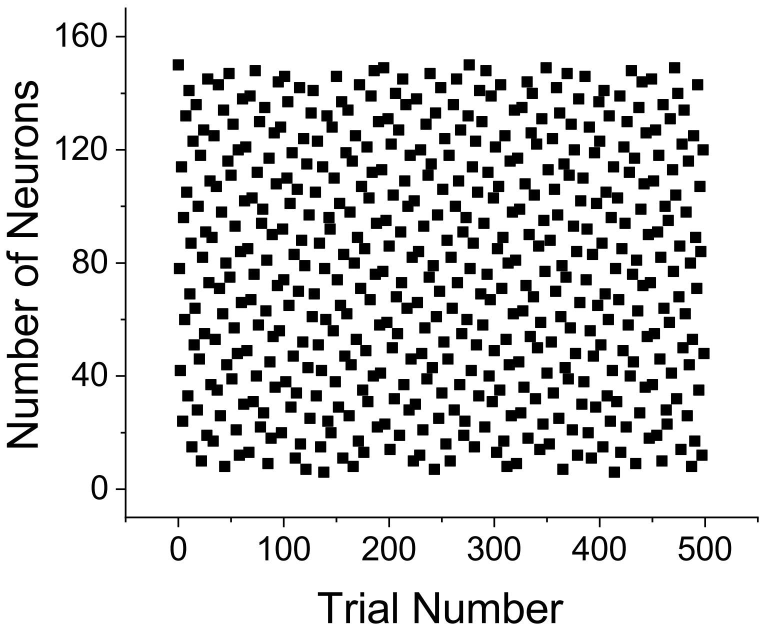

Figure 4: Number of Neurons generated using Sobol Sequence Sampling Method.

a sequence with use of a Gray code handles non-uniform distributions via point transformation. Thus the code becomes suitable for applications requiring non-uniform sampling, such as optimizing learning rate and dropout in a study. Saltelli et al [15] suggested that number of points (N) required for a balanced Sobol sequence should be at least:

$$N = 4 * D * (2^M) \tag{1}$$

A balanced Sobol sequence with a maximum level of Sensitivity, M = 4 and dimensionality, D = 6 for the present case requires a minimum of 384 points for sensitivity index estimation. 500 trial points were found adequate for hyper-parameter tuning in Bayesian optimization. The Sobol sequence trial points in Bayesian optimization generated evenly spaced initial points, reducing evaluations and thus improving robustness.

4 Sequential Bayesian Optimization Framework

Sequential Bayesian optimization maintains a probabilistic model, typically a Gaussian Process, capturing function evaluation uncertainty represented by Root Mean Squared Error (RMSE) between the true and the predicted metrics. Minimization of RMSE provides model's loss function. Gaussian Process model includes a mean function for expected values and a covariance function for smoothness and correlation. It estimates the next point by using acquisition function with updation from new evaluation which balances exploration and exploitation and computes expected improvement (EI) over the current best value. The EI is computed as follows:

$$EI(x) = max(y - y_{best}, 0) * p(y|x) \quad (2)$$

where x is the point to evaluate, y is the predicted value of the surrogate model, y_{best} is the best value so far, and $p(y|x)$ is the probability of observing y at x. The acquisition function selects the point maximizing expected improvement, leading to an iterative optimization process. The Framework employs density plots of optimization points to identify regions of concentrated clusters signifying hyper-parameter configurations with consistently lower validation losses for Out-of-plane Bending (OPB) case. This information aids in selecting optimal hyper-parameters for improved performance across multiple loading conditions at specific locations.

5 Results and Discussions

Prior to training the model, all input and output data points were scaled to the range of 0 and 1. Scaling of data ensures consistent and standardized features, facilitating neural network convergence and equal contribution of all features for optimal performance. Additionally, removal of data-points with SCFs less than 0.5 from the training data-set helped in the elimination of noise and outliers that hinder the learning process. The testing data-set was split into two subsets: one for cross-validation to fine-tune hyper-parameters and another for independent testing. This ensured a reliable assessment of the model's generalization on unseen data. After obtaining the optimal hyper-parameter combination through Bayesian optimization, selected weights at the epoch, over-fitting or under-fitting was advantageously prevented. This approach achieved a balance between capturing data patterns and maintaining generalization, resulting in optimal performance. Comparison of NN vs FEA, DNV, LR and % Under/Over Prediction by 95% is tabulated in Table 2.

The neural network model demonstrated excellent performance with all data points were residing within the 95% confidence band, affirming the model's reliability. These results signify a perfect balance, avoiding over-fitting or under-fitting and highlighting the model's strong generalization capabilities. The NN based SCFs showed a 90% correlation with DNV based SCFs at the crown-saddle location, indicating good agreement. The NN captured accurate SCF behavior compared to the DNV equation. The R-squared score between the NN and LR SCFs is approximately 76%, suggesting the LR equation tends to over-predict SCFs. At the brace-saddle location, the NN and DNV SCFs have an R-squared score of around 68% and the NN and LR SCFs have an R-squared score of about 88.5%. For brevity, comparison of proposed NN models with DNV and LR at brace saddle for OPB are shown in Figures 5 and 6, respectively. DNV equation under-predicts for lower SCFs whereas LR equation over-predicts for higher SCFs for brace-saddle location which results in disparity in fatigue life derived between SCFs based on DNV and LR equation.

Observations	FE		DNV		LR	
	Chord-Saddle	Brace-Saddle	Chord-Saddle	Brace-Saddle	Chord-Saddle	Brace-Saddle
R2 Score	99.42	99.47	89.74	68.2	75.9	88.59
% of Under-prediction	16.09	4.01	71.42	78.25	9.4	54.36
% of Over-prediction	29.29	21.21	19.71	18.36	84.8	28.34

Table 2: Comparison of NN vs FEA, DNV, LR and % Under/Over Prediction by 95%.

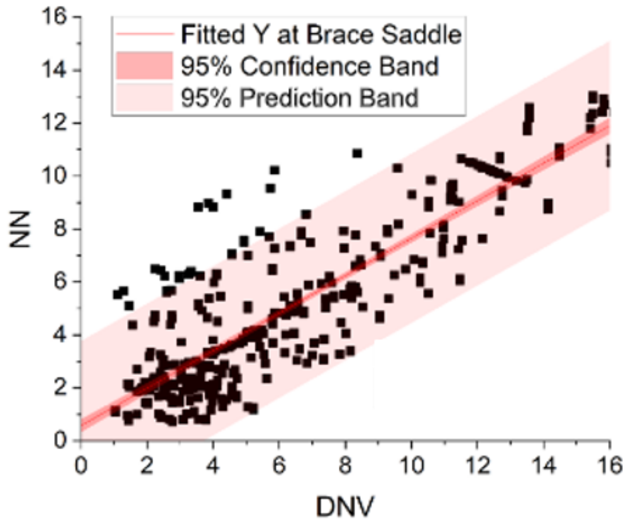

Figure 5: Comparison of Proposed NN Models with DNV at Brace Saddle for OPB.

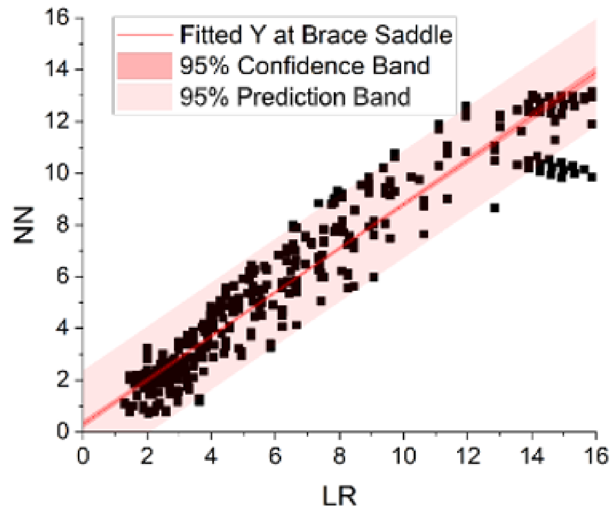

Figure 6: Comparison of Proposed NN odels with LR at Brace Saddle for OPB.

6 Conclusions

Results of present research demonstrated the superior performance of the NN model for predicting SCFs. The study's reliability is bolstered by including validated literature points utilizing DNV extrapolation techniques and optimized mesh configurations. Incorporation of solid elements in SCF prediction models is found to be crucial for accurate results, highlighting the limitations of empirical equations. Combination of Sobol sampling and Bayesian optimization has been proved to be a powerful approach for optimization problems. Sobol sampling provided insights into influential input variables, while Bayesian optimization efficiently searched for the best hyperparameters. Successful application of these methods in this study suggests their potential for further applications in regression problems. DNV and LR equations exhibit limitations such as under-prediction and over-prediction of SCFs. It is envisaged that use of the proposed NN models for the computation of SCF in the offshore industry would potentially prevent fatigue life overestimation or underestimating the in-situ capacity leading to safe, practical and economical designs.

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