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Prediction of Stress Correction Factor for Welded Joints Using Response Surface Models

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ABSTRACT

While performing fatigue reliability analysis of the butt-welded joints it is vital to estimate the Stress Concentration Factor (SCF) at these joints. A common approach adopted by industry to estimate the SCF at weld toes is to perform Finite Element Analysis (FEA) of the welded joints for different pipe sizes, flanges, valves etc. The SCF are calculated for each size by separately when required and are very time consuming. Although FEA is known for its accurate SCF calculation, but due to its high computational expense and time-consumption, SCF evaluation for different parameters makes the aforementioned method quite laborious. As an alternative response surface models (RSM) may be used for accurate estimation of SCF. The two basic steps in constructing a RSM are training and testing. The first corresponds to fitting a model to the intelligently chosen training points, while the second step involves comparing the predictions of the RSM to the actual response. This paper examines the applicability of 12 different RSMs for estimating SCF. The training and testing data is generated using FEA in ANSYS. In order to compare the accuracy of the RSMs, three metrics, namely, Root Mean Square Error (RMSE), Maximum Absolute Error (AAE), and Explained Variance Score (EVS) are used. A case study illustrating the applicability of the proposed approach is also presented.

1. INTRODUCTION

Stress Concentration is a localized increase in stress around the stress raisers or irregularities in a geometry. The stress value around these irregularities is generally higher than the nominal stress. Tubular butt weld connections with unequal thickness and transition on outer diameter are quite common in offshore and subsea piping and its components including valves, fittings, connectors etc. Estimating the stress concentration factors at these weld joints plays crucial role for both static stress and fatigue reliability assessment. Though these SCF values for simpler geometries can be calculated using some empirical methods, Finite Element Analysis is more reliable and accurate to capture minor details or complex geometries. However, FEA can be computationally expensive, time consuming and might require skilled analysts to get more reliable and accurate results. Furthermore, FEA techniques are afflicted with the following constraints:

1. The accuracy and computing time required to solve a FEA simulation is dependent upon the finite element size (mesh density). This implies that simulations of finite element models constructed with fine mesh size deliver accurate results, nevertheless the simulations generally take longer computing time and vice-versa [1].
2. Generally, three types of error are attributed to FEA, namely: user error (which emanates due to inexperience of the analyst), modeling error (which arises due to erroneous representation of the real world phenomenon) and discretization error (originating due to inadequate mesh density which is unable to capture the solution appropriately) [2]. While the former two errors are in the hands of the analyst, the latter is inherent to FEA and must be separately quantified by the analyst for an accurate solution. Thus, quantification of discretization error increases the accuracy of FEA results however it further adds to the time required to run a FEA simulation.

In order to overcome the aforementioned shortcomings of FEA, if a group of models have similar geometrical features and only the dimensional parameters of these features are changing, then by doing limited number of assessments using FEA or from the data already available from previous analyses, Response Surface Models (RSMs) may be used to closely predict the SCF for any values of dimensional parameters for these weld joints. Previously, authors have used RSM to predict Stress Intensity Factor (SIF) for assessing fatigue degradation of offshore piping [3,4,5]. Thus, the main objective of this manuscript is to predict SCF of welded joints using RSMs. Different Machine learning (ML) algorithms are compared to each other and finally the most accurate model is used to estimate the SCF values.

The remainder of the paper is structured as follows: In Section 2, the manuscript discusses the SCF definition and various methods used to evaluate it. Thereafter in Section 3, a small discussion regarding the RSM is made. Subsequently, in Section 4, an illustrative case study is presented. Finally, conclusion and recommendations are provided in Section 5.

2. STRESS CONCENTRATION FACTOR

2.1 Definition

A stress concentration factor (SCF) can be defined as a stress magnification at a detail due either to the detail itself or to a fabrication tolerance, with the nominal stress as a reference value [6]. Numerically it can be written as:

$$\mathbf{SCF} = \frac{\text{Actual (or) peak stress at the hotspot}}{\text{Nominal stress}}$$

Stress concentrations at the tubular butt weld connections are due to eccentricities and transitions resulting from different sources. These may be classified as concentricity (difference in tubular diameters), differences in thickness of joined tubulars, out of roundness and center eccentricity. The resulting eccentricity may be conservatively evaluated by a direct summation of the contribution from the different sources. [7]

2.2 SCF Evaluation

SCFs due to misalignment at butt welds in plates were presented by Maddox [7] and have been included in fatigue design rules for plated structures for many years. A simple butt weld between two plates, as shown in Figure 1, is considered as an introduction to the derivation of SCFs for butt welds. It is assumed that the plates are welded together from plates of the same size, with an eccentricity, δ, and without angular misalignment [8]. The plates are subjected to a membrane loading per unit width N = σ_{nominal} *t, where σ_{nominal} is nominal stress and t = thickness of the plates.

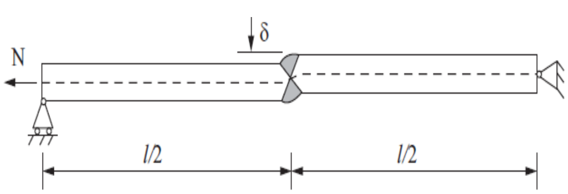

Figure 1. Typical buttweld in Unstiffened Plates [6]

The stress concentration, frequently referred to at an unstiffened plate weld joint, is given as:

$$SCF = \frac{\sigma_{tot}}{\sigma_{\text{nominal}}} = \frac{\sigma_{\text{nominal}} + \sigma_b}{\sigma_{\text{nominal}}} = 1 + 3\,\frac{\delta}{t}$$

Researchers have used analytical expressions for stress concentration factors for these connections are presented based on classical shell theory [9]. Several approximate formulas of SCF for various types of welded joints were based mainly on numerical results obtained using the finite element FE and the boundary element BE methods [11, 12, 13]. In the recent years researchers have tried to estimate SCF using ML [14, 15, 16] and the results seems to be promising.

3. RESPONSE SURFACE MODELS

3.1 Introduction

Response Surface Models (RSMs) (also known as surrogate models or meta models) are data-driven models that try to predict the complex input/output (I/O) behavior of an underlying system, by using a limited set of computationally expensive simulations (CES) [17]. The two basic steps in constructing a RSM are training and testing. The first corresponds to fitting a model to the intelligently chosen training points, while the second step involves comparing the predictions of the MM to the actual response [18]. RSMs act as a 'curve fit' to the training data (generated by an expensive simulation code, FEA in this case) and thereafter may be used to estimate the quantity of interest without running the expensive simulation code. The RSMs must not be mistaken as a simplified version (with low reliability) of the CES; conversely, MMs emulate the behavior of the CES as accurately as possible, coupled with low computational cost [19]. The main idea of using RSMs as a replacement to the FEA is based on the fact that, once built, the RSMs will be faster than the FEA, while still being usefully accurate [20]. In the aforementioned context, RSMs may be used to predict the SCF of welded joints.

3.2 Different RSMs Employed

The most commonly used RSMs in the engineering domain are parametric machine learning models (such as linear and polynomial regression), and non-parametric models such as support vector regression (SVR), Gaussian Process Regression (GPR), Gradient boosting, Gaussian Process Regression, k-NN, Decision tree etc. The mathematical background and theory of the various MMs used in this manuscript are discussed briefly in the sub-sections of [21].

In this paper uses 12 different surrogate models, namely multi-linear regression (MLR), LASSO regression, Ridge regression, Bayesian ridge, kNN, Decision tree regressor, Random Forest, AdaBoost, Gradient boosting, Bagging, Gaussian Process Regression (GPR), and support vector regression (SVR) is used to estimate the SCF of Butt welded joints. The performance of 12 algorithms is compared using three different metrics namely, Root Mean Square Error (RMSE), Maximum Absolute Error (MAE), and EVS are used. GPR emerged as the best fit, hence it was finally used to estimate estimate the SCF.

4. CASE STUDY

4.1 SCF Calculation

In this manuscript SCF calculation is performed using two different methods. First is using FEA and second is RSM. These methods are expounded in the following sub-sections. For a typical buttweld transition for joining pipe ends of unequal thickness (same ID), as Per ASME B31.8 (Appendix I) [7] Mandatory end Preparations for joining pipe ends by buttwelding, acceptable design for unequal wall thickness is given by the limits on certain dimensional parameters are given below and shown in Figure 2. Figure 2 also shows the two possible hotspots for the given butt-weld joint.

α can vary from 14º to 30º
x can vary from 0 to 0.5t
Max. allowed **δ** =2.38 mm

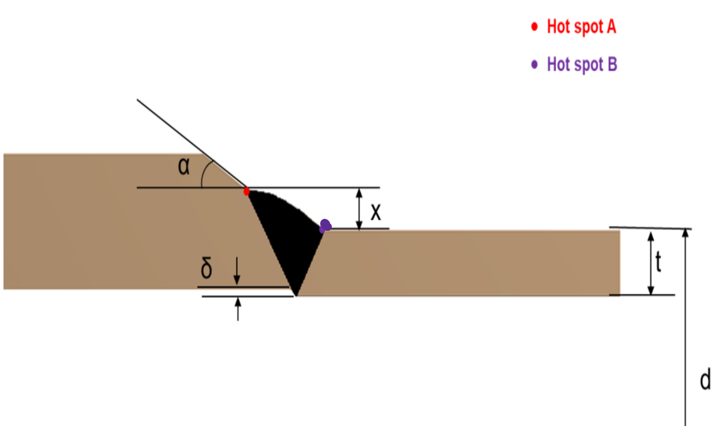

Figure 2. Typical buttweld transition for joining pipe ends of unequal thickness (same ID)

4.1.1 Finite Element Modelling

A finite element model is prepared using the commercially available FEA software ANSYS 19.2 [22]. The finite element model of the buttweld joint with transition from larger pipe OD to smaller pipe OD is modeled as shown in Figure. 3. The material and Geometric properties used during the analysis is shown in Table 1 in Annex A. The weld cap is also modeled with a flank angle of 15º and toe radius of 5mm. The extent of the local model has been chosen such that effects due to the boundaries (fixed point) on the structural detail considered are sufficiently small and reasonable boundary conditions can be formulated.

Two different mesh sizes were used in the analysis, with the mesh around the weld being more refined than rest of the geometry. The reason for a finer mesh at the weld toe is to obtain mesh convergence and a more accurate solution. Higher order elements with hex-dominant meshing are used for building the model. The material behavior is assumed to be linear elastic. Meshing details for one of the models is shown in the Figure 3.

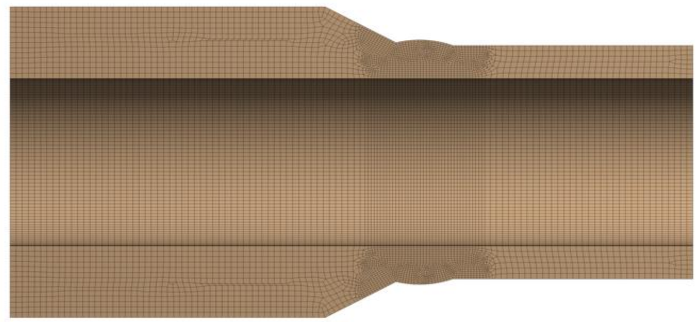

Figure 3. Finite element model for the butt weld transition with refined mesh at weld area.

A uniaxial tensile load is applied on the smaller pipe side and fixing the larger side. Boundary conditions for one of the models are shown in the Figure 4.

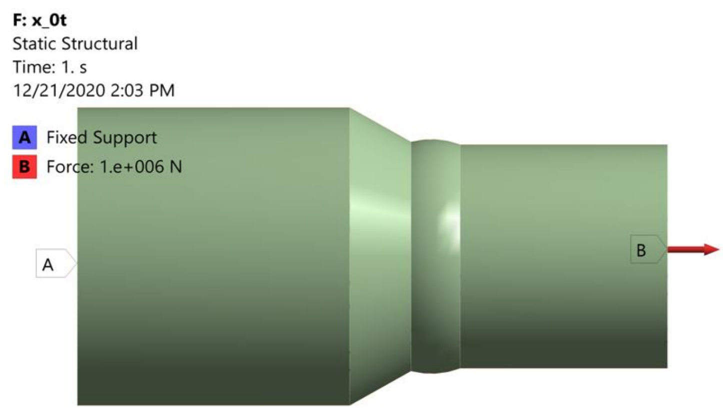

Figure 4. FEM model showing the boundary conditions

Based on the peak stress values obtained at hotspots A and B as shown in the Figure 5, SCF at these hotspots were calculated by dividing the peak stress from FEA with analytical nominal stress at that cross-section. FEA stress results and SCF calculations for one of the models with configuration (d = 200 mm, t = 30 mm, x= 3 mm, α= 30º) or (t/d=0.15, α= 30º and x/t =0.1) is shown in the Figure 5.

$$\textbf{SCF at Hotspot} = \frac{\text{Actaul stress at hotspot (FEA)}}{\text{Nominal stress}}$$

Similarly, FEA has been done for different models by changing the variables α, x and t as shown in the Figure 2. δ is maintained as 2.38 mm in all the models. SCF calculated for all these different models are recorded in Table 2 and Table 3.

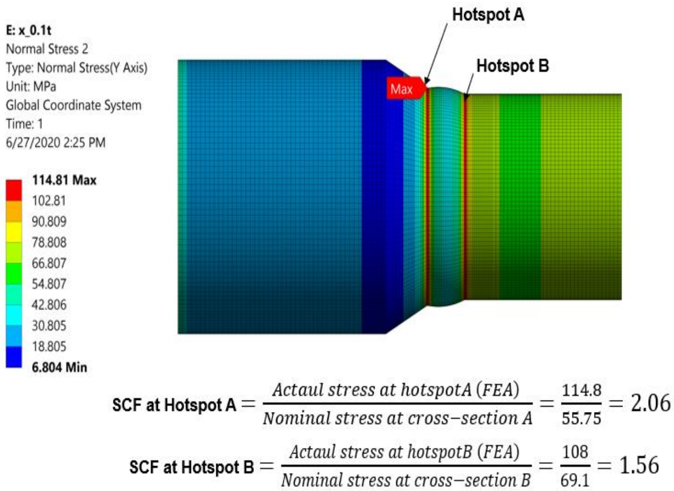

Figure 5. Stress analysis results from FEA showing the peak stresses at hotspots.

4.1.2 Response Surface Model

Two different data sets corresponding for hotspot A and hotspot B generated from FEA are used to train and test the performance of different RSMs. The dataset is shown in Table 2 and Table 3 in Annex A. A correlation matrix for the data set is shown in Figure 6 and 7. From Figure 6, it can be seen that angle and t/d have positive correlation with SCF while x/t has a negative correlation coefficient with SCF. Furthermore, it can be seen from Figure 7 that all the input variables have positive correlation with SCF, with x/t being the most correlated variable to SCF. For both the hotspots, 'x/t' is most correlated variable to SCF. However, hotspot A is having a negative correlation unlike hotspot B. This is because the stress raiser at the weld toe for hotspot A would flatten more with increase in value of 'x', thus decreasing the SCF. This is the other way around for the hotspot B, thus resulting in positive correlation.

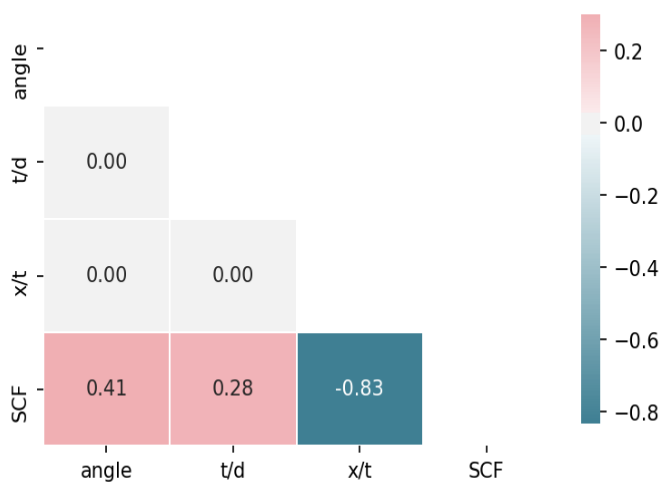

Figure 6 Correlation Coefficients Between Different Variables for Hotspot A

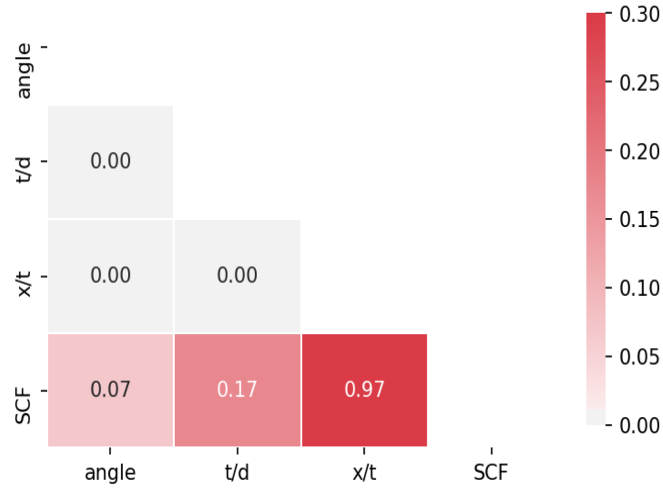

Figure 7 Correlation Coefficients Between Different Variables for Hotspot B

4.2 Result Discussion

Since, we had limited number of data, therefore K-fold cross validation technique was used to evaluate different ML models. In order to compare the accuracy of the regression algorithms, three metrics, namely, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Explained Variance Score (EVS) are used. Mathematically, these are written as:

$$RMSE = \sqrt{\frac{\left(\sum_{i=1}^{n}(y_i - \hat{y}_i)^2\right)}{n}}$$

$$MAE = \frac{\sum_{i=1}^{n}|y_i - \hat{y}_i|}{n} \quad (1)$$

$$EVS = 1 - \frac{Var(y_i - \hat{y}_i)}{Var(y_i)}$$

The regression model which has lowest value of RMSE and MAE and for which EVS are closer to 1 is the most accurate model. The value of the three metrics for 12 algorithms for the analysis has been shown in Table 4 (for hotspot A) and Table 5 (for hotspot B). From Table 4 and Table 5, it is seen that Gaussian Process (highlighted by red color) is the most accurate algorithm as it has lowest errors (i.e. RMSE, MAE) and scores (EVS) closest to 1.

As, GPR is the most accurate algorithm out of all the competing ones, so the values of the actual Relative Volume (from experiments) and the predicted Relative Volume for three validation datasets have been plotted and presented in Figure 10, 11 and 12.

Table 4: Different RSMs Comparison for Hotspot A

Response Surface Model	RMSE	MAE	EVS
MLR	0.063	0.043	0.976
LASSO	0.0147	0.109	0.783
Ridge	0.106	0.081	0.908
BayesRidge	0.062	0.042	0.977
SVM	0.101	0.069	0.944
kNN	0.217	0.0185	0.865
Tree	0.151	0.135	0.809
RandomForest	0.07	0.059	0.984
Bagging	0.065	0.058	0.984
AdaBoost	0.172	0.162	0.872
GaussianProcess	0.047	0.033	0.984
GradientBoosting	0.106	0.086	0.962

Table 5: Different RSMs Comparison for Hotspot B

Response Surface Model	RMSE	MAE	EVS
MLR	0.053	0.044	0.887
LASSO	0.173	0.161	0.538
Ridge	0.108	0.098	0.744
BayesRidge	0.053	0.044	0.886
SVM	0.103	0.09	0.7
kNN	0.146	0.132	0.726
Tree	0.022	0.02	0.985
RandomForest	0.013	0.011	0.992
Bagging	0.012	0.009	0.993
AdaBoost	0.02	0.016	0.981
GaussianProcess	0.008	0.008	0.994
GradientBoosting	0.009	0.008	0.993

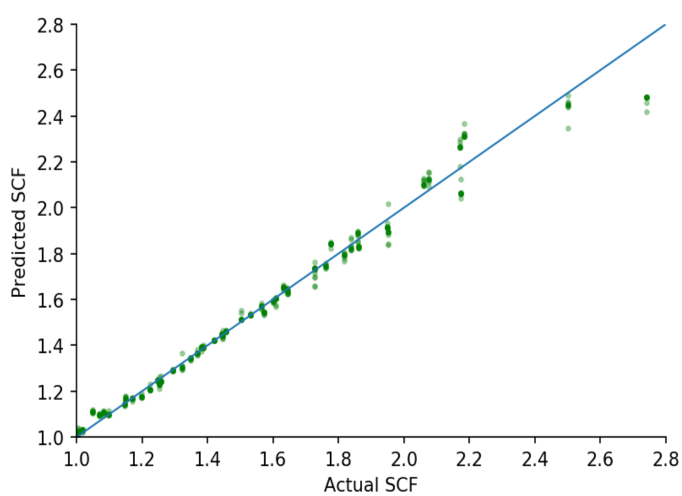

Figure 8 Actual vs. Predicted SCF value for Hotspot A

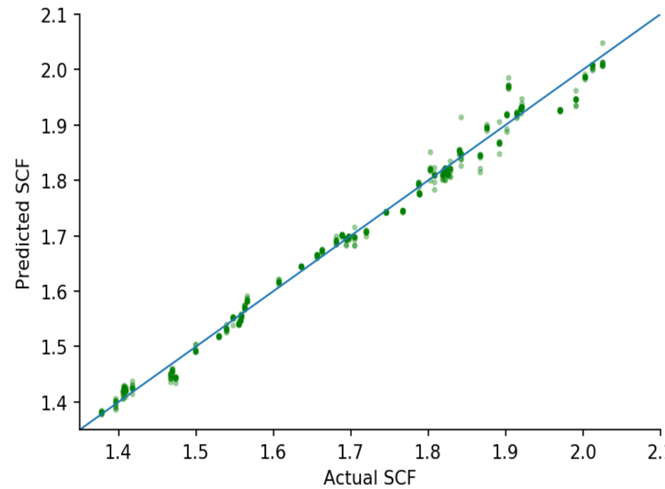

Figure 9 Actual vs. Predicted SCF value for Hotspot B

As can be seen from Figure 8 and Figure 9 that there are very few outliers and in general the trend between the actual and predicted SCF is almost linear, thus indicating good prediction accuracy of the GPR. Furthermore, in the future work authors wish to adaptively train the Gaussian Process regression to further increase the accuracy of the model.

5 CONCLUSION

The manuscript proposes the use of RSMs as a replacement to computationally expensive and time consuming FEA to predict the SCF of the welded joints. The viability of twelve different RSMs, was tested in the manuscript. Two different datasets (each having 54 instances) corresponding to different hotspot positions was used to train and test the different RSMs. The GPR models was found to be most accurate and was thus used to estimate the value of SCF with good accuracy. This proposed model can be used for SCF prediction for pipe welds with unequal thickness but within the limits specified for mandatory end preparations for acceptable design discussed in Section 4.

In the future work the accuracy of the GPR model can be further increased by adaptively training the model. Also, more geometric variables like weld toe radius, flank angle, undercuts and weld defects can be introduced in the analysis model.

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ANNEX A

Tab1e 1. Material and Geometry Properties of the model

Material Properties	*Value*	*Geometrical Properties (refer Figure 1)*	*Value*
Modulus of Elasticity	200 GPa	Offset at ID (δ)	2.38 mm
Poisson Ratio	0.3	Weld transition angle (α)	14º to 30º
Yield Stress/Tensile Stress	250 GPa/ 460 GPa	Thickness (x)	0 to 0.5 t

Tab1e 2. SCF at Hotspot A calculated from FEA

SCF - Hotspot A							
α (angle)	**t/d**	**x/t**					
		0	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**
14º	**0.2**	**1.84**	**1.64**	**1.46**	**1.29**	**1.15**	**1.02**
	0.15	**1.76**	**1.57**	**1.39**	**1.22**	**1.07**	**1.00**
	0.1	**1.60**	**1.42**	**1.25**	**1.10**	**1.01**	**1.00**
22º	**0.2**	**2.17**	**1.95**	**1.73**	**1.53**	**1.35**	**1.17**
	0.15	**2.08**	**1.86**	**1.63**	**1.45**	**1.25**	**1.05**
	0.1	**1.86**	**1.64**	**1.44**	**1.26**	**1.08**	**1.00**
30º	**0.2**	**2.74**	**2.18**	**1.95**	**1.73**	**1.50**	**1.32**
	0.15	**2.50**	**2.06**	**1.82**	**1.61**	**1.38**	**1.20**
	0.1	**2.17**	**1.78**	**1.57**	**1.37**	**1.15**	**1.00**

Tab1e 3. SCF at Hotspot B calculated from FEA

SCF - Hotspot B							
α (angle)	t/d	x/t					
		0	0.1	0.2	0.3	0.4	0.5
14^o	0.2	1.41	1.56	1.69	1.82	1.92	2.01
	0.15	1.40	1.54	1.66	1.79	1.88	1.97
	0.1	1.38	1.50	1.61	1.72	1.79	1.84
22^o	0.2	1.42	1.56	1.70	1.82	1.91	2.00
	0.15	1.41	1.55	1.68	1.81	1.89	1.90
	0.1	1.41	1.53	1.64	1.75	1.82	1.87
30^o	0.2	1.47	1.57	1.70	1.83	1.92	2.03
	0.15	1.47	1.56	1.69	1.82	1.90	1.99
	0.1	1.47	1.55	1.66	1.77	1.80	1.84