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CONSIDERATIONS ON ARTIFICIAL NEURAL NETWORKS IN THE STRESS CONCENTRATION FACTORS FOR TUBULAR JOINTS

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ABSTRACT

This paper describes an alternative approach to calculate stress concentration factors using artificial neural networks. Neural networks have the ability to learn and turn this knowledge helpful for future use. Encourage this approach the needless of find out a mathematical expression between input and output data. Finite element simulations of tubular joints that complete the data set consider the common geometrical parameters of chord and brace members, and also the parameters defining the 3D geometry of the weld fillet. The procedure proposed represents an improvement in the tubular joints evaluation, both because it takes into account the effects of the weld geometry in the calculus of stress concentration factors and also provides another manner to extrapolate it.

INTRODUCTION

Tubular joints in offshore structures are connected by welding the end of brace members onto the external surface of the chord, causing high stress gradient in the welding zone. Accordingly, the stress peak achieves several times the nominal stresses of the brace members. The Stress Concentration Factor (SCF) is a measure frequently used to quantify that peak in the welded joint.

Since the evaluation of the SCF for all offshore tubular joints seems to be impracticable, the main procedure accepted to accomplish that task is based on the following steps: a data set with some particular joints is organized and the SCF is evaluated for that joints. Further, semi-empiric expressions are formulated in order to achieve the SCF for similar joints. According to Gurney (1968), these expressions have the general formulation:

$$FCT = C.\alpha^{a}.\beta^{b}.\gamma^{c}.\tau^{d}.(sin\theta)^{n} \qquad (1)$$

where C is a constant, a, b, c, d and n are adjustable exponents and α, β, γ, τ and θ are non-dimensional geometrical parameters defined in the Fig. 1. In this sense, several parametric expressions are available for the calculation of SCF, each one with its own characteristics.

The stress concentration in welded tubular joints, however, is a difficult task to be modeled. Consequently, comparison of the existing parametric equations for similar joints sometimes shows considerable differences. This is due to the different definitions of hot spot stress that have been used and also to the difficulties of establishing *a priori* a mathematical expression to associate geometrical parameters and the SCF. Moreover, if welded geometry parameters were added in the mathematical model, the problems to formulate an expression raise. Since the phenomenon is highly complex, these are likely the leading sources of unsuitable results in several joints.

These difficulties lead us to research an alternative approach to deal with the SCF estimate, which bring an improved manner to compose the data set and to evaluate the SCF.

In the same manner that occurs in SCF evaluation by regression approach, a data set was taken from Finite Element (FE) analysis. The FE model used in this work, however, takes into account the weld fillet geometry by using three-dimensional isoparametric elements. Three-dimensional (3D) elements are shown to provide more accurate modeling of joints when compared to the commonly used shell elements, mainly because of their 3D nature. Accordingly, the stiffness of joint is more appropriately represented, since the weld fillet geometry works reducing the stress gradient, smoothing out the stress flow between brace and chord member. Furthermore, the SCF evaluation is straightforward achieved, without the need of extrapolating results, as prevalently occurs with shell element models.

In the second phase, instead of regression expressions, Artificial Neural Networks (ANN) were applied in the SCF evaluation. The use of ANN is motivated by the needless of found an expression to associate the geometrical parameters to the SCF.

Neural networks are mathematical models useful to handle complex tasks, with capacity of learning from a data set and turn the stored knowledge useful for subsequent use. The term "neural network" refers to a collection of neurons, their connections and the connection strengths between them. The knowledge is acquired during the *learning process* by changing the connection weights in order to reduce an error function.

In this work ANN were trained for axial force and in plane bending moment (IPB) load cases. The applied data set contains Y joint configurations with several combinations for both members and weld geometrical parameters. The results were compared with existing expressions and some expected behavior of stress distribution were also checked.

GENERATION OF DATABASE SET

FINITE ELEMENT MESHING

As larger platforms are designed and installed in increasingly deep water, the prediction of hot spot stress near the welds used in these connections has also been extremely difficult to evaluate by experimental procedures. In addition, over the past thirty years the computer machine speed has increased, allowing the development of efficient solvers and automatic meshing programs. Hence, since the early 1970s the finite element method has been the most used process in the calculus of SCF expressions. Several computer programs for automatic meshing tubular joints has been developed, initially based on flat shell elements and later with the inclusion of 3D element (Liaw,1987).

In this work an automatic meshing program was used to produce the data set, which makes use of isoparametric solid elements (brick-8 nodes), with incompatible modes and quadratic integration model the tubular joint geometry. Using solid elements the complex geometry of weld fillet was represented, working as a stress gradient smoother. Furthermore, modeling the tubular joint with solid elements avoid the use of extrapolation procedures to attain the SCF, since the welded geometry is also modeled. So, as showed in the next item, with a correct choice of load magnitude acting in the brace member, the SCF is performed straightforward in the post-processing phase. In addition, the variability in weld geometry is likely to be a major cause of the observed scatter in fatigue life data (Engesvik,1988).

Therefore, the influence of either the groove angle and the gap between chord and brace were included as non-dimensional geometrical parameters, as depicted in the Fig. 1. A typical Y joint from the automatic meshing program used in this work is portrayed in Fig. 2.

MODEL CHARACTERISTICS

The automatic meshing program used works by taking some non-dimensional geometrical parameters that define the welded tubular joint handled. In this sense, the classical parameters β, γ, τ, θ and α (the later for axial force load case) are specified by the designer as well as the parameters that describe the welded geometry.

It is important to mention the inclusion of the *Sec* parameter, representing the position of SCF along the welded joint length. Considering that the FE solver provides stresses in all nodal points of the model, that parameter permits the study of stress distribution along the weld length. Consequently, the joint design can be improved, since the maximum SCF for the various load cases do not occurs at the same point.

About 250 models were analyzed, determining a data set with almost 9000 points. The data set was produced by varying the non-dimensional parameters showed in Table 1 and calculating the von Mises stresses for each configuration. The variables used represent the geometrical ratios found in traditional regression analysis approach and, also, the weld fillet geometry. The latter, as depicted in Fig. 1, is represented by the groove angle and the gap between the chord and the brace members. Moreover, the position of stresses along the weld fillet was considered as a percentage value, which vary from 0% at the crown heel to 100% at crown toe, as depicted in Fig. 3.

Table 1 – Parameters Range

Parameter	Minimum	Maximum
β	0.4	0.8
τ	0.4	0.8
γ	10	20
α	2.8	3.2
θ	50	90
α_S	10	45
G/t	0.2	0.8
Sec	0	100

The loads applied in the brace was enough to produce unitary membrane tension far from the joint and, accordingly, hot spot stress was obtained direct from FE post-processing. The axial force and IPB moment load cases were carried out. Gibstein (1987) showed that in IPB load is applied there are no meaningful differences whether the boundary conditions is considered clamped or simply supported. Thus, in all FE models we consider the primary member ends clamped.

The data were fulfilled after almost 1000 hours of processing, using a *Pentium 166 MHz* computer, and the solver and post-processing of ALGOR (1997) software. After some convergence tests, we noticed that 40 divisions of weld fillet along its length were enough to overcoming the problem of refine the solid mesh employed, as illustrated in Fig. 4.

NEURAL NETWORKS

ARCHITECTURE

Artificial neural networks are an attempt to simulate the functioning of human brain by virtue of massive parallel processing artificial neurons and a learning rule (Lipmann,1987). The term 'neural network' refers to a group of neurons, and the connection strengths between them. One by one, the artificial neurons can perform trivial functions, but altogether, connected in form of a network, they are capable of solving complex tasks.

A typical artificial neuron is depicted in Fig. 5. As showed, the neuron j receives signals from other neurons through the connections between them. Each incoming signal is multiplied by its connection strength, so that, the neuron acquires a sum of outputs of all neurons to which it is connected. Thus, the weighted sum is compared with a threshold of the neuron j, and if the summation exceeds the threshold the neuron sends a signal to other forward-connected neurons. The output of a typical neuron is performed by a non-linear function of weighted sum, as shown in Eq. (2).

$$y_j = F\left(\sum_i x_i . w_{ij} - \theta_j\right) \tag{2}$$

where F is a non-linear function, x_i and w_{ij} are the inputs and the weights from ith input node to jth node and θ_j is the threshold value for the j neuron.

The most commonly threshold function F used is the logistic function showed in Fig. 6. Named logistic function, it adds non-linear characteristics to the neuron, which is essential in multi-layer networks. Further, as shown by Eqs.(3) and (4), its derivative is straightforward, an important feature to learning process.

$$F = \frac{1}{1 + e^{-y}} \tag{3}$$

$$F' = F(1 - F) \tag{4}$$

The neuron depicted in Fig. 5 can be arranged in a network in a variety of ways by changing the number of neurons and/or layers. An illustrative multi-layer feed-forward network is depicted in Fig. 7. This is the most used neural network for the sake of its remarkable capability of deal with non-linear input-output mapping of general function and its easy implementation.

As showed in Fig. 7, the network consists of an input layer, an output layer and hidden layers. The input layer commonly receives an input vector as well as the output layer is associated to output vector. In this work the input vector is associated to the non-parametric parameters showed in Table 1. The output layer is related to von Mises stresses performed by the solver for each configuration. One has the input and output variables of the phenomenon handled, so that the number of neurons required in the correspondent layers is direct. On the other hand, choose of the number of hidden layers and the number of neurons in the hidden layer neurons is the most difficult part in the network process.

Although it is proved that any functional relationship can be mapped using a network with a single hidden layer and with a sufficient number of nodes (Wasserman,1989) and despite of efforts of some researchers to get an approximate formula (Haykin,1994), there is no reliable method for this purpose. In practice, the trial-and-error method has been the most used process to define the hidden layers.

The weighted connections among neurons of each layer and the threshold parameters are used in the learning process, i.e., an iterative process to carry out an input-output mapping function for the FE data. The learning process is commonly performed by *back-propagation* algorithm, which is fundamentally an error minimization technique. The best input-output mapping is achieved by changing the weights coefficients and threshold parameters in a supervised learning process, i.e., using the actual output to check the network output.

BACK-PROPAGATION ALGORITHM

Back-propagation algorithm is covered in details in several works(Haykin,1994), (Wasserman,1989). The basic structure, however, can be condensed in some steps, as showed by Lipmann(1987):

1. Initialize the weights and the thresholds to some random values.
2. Present a new continuous-valued input vector $\{X_0, X_1, \ldots, X_{n-1}, X_n\}$ and specify the desired outputs $\{d_0, d_1, \ldots d_{n-1}, d_n\}$.
3. Calculate the actual output, says o_j. At each node, calculate the weighted sum of the inputs and use the sigmoid non-linearity defined by equation 2.
4. Adapt weights: using a recursive algorithm at the output node and working back, adjust the weights by

   $$W_{ij}(t+1) = W_{ij}(t) + \eta\delta_j x_j$$

   where W_{ij} is the weight from ith node to jth node, δ is the error at jth node, and η is the gain term constant.

   If j is an output layer node then

   $$\delta_j = (d_j - o_j).o_j.(1 - o_j)$$

   If j is an hidden layer node then

   $$\delta_j = X_j(1 - X_j)\sum_k(\delta_k W_{kj})$$

   where the summation is performed over all the nodes in the layer above the node j.
5. Repeat by going to step 2 until an expected convergence value is attained .

RESULTS.

The stresses provide by ANN were compared with FE analysis results. In this sense, an usually adopted procedure is to divide the data in two sets: the training set and the testing set. The earlier is used to teach the network and the later is used to assure that the network can recognize patterns that it have never seen before.

Therefore, the designer can determine whether the network found the intrinsic relations between input and output data or just "memorize" the training set.

In this work, we randomize the data and separate the testing set and the training set in the proportion of 1:4. In the IPB load case, the average error over the training set was 2 % and 9 % considering the testing set. Similarly, we have , 3 % and 12 % in the axial force load case.

The network configuration obtained for the axial force presents 2 hidden layers, one near the input layer with 15 neurons and other near the output with 5 neurons. It was used as input variables the parameters showed in the table 1. Likewise, for the IPB load case the network also presents 2 hidden layers, with 30 and 20 neurons, respectively.

The ANN results were compared with the formulations of Kuang (1975), and UEG (1985). As showed in Figs. 8 to 11, the agreement with the formulations is acceptable, since there are errors evolved with both procedures. It is worth to mention that FE analysis using shell elements produce excessive SCF values, either for the absence of the weld fillet or the difficulties to obtain experimental data.

ADVANTAGES AND DRAWBACKS

The main purpose here is to constitute an alternative tool to calculate the SCF, which concepts avoid the need of place a mathematical expression. The neural network, after trained, is able to accomplish such task straightforward.

It was proved that feed forward neural networks, with one hidden layer, can approximate complex functions (Wasserman, 1989). However, there are no reliable suggestions about the hidden layer structure, i.e., the number of hidden layers and the how many neurons in each one. In fact, we have adjusted more than 10 networks until attain appropriated formations. The trial-and-error method still remains as the most used approach to produce some useful results with ANN. Hence, the training process, considering both load cases took about 300 hours of time processing, using a *Pentium 166MHz*.

A drawback of neural network approach is the final result exposition. Neural networks store the knowledge in a different fashion, compared with traditional regression equations. Certainly, the generalization, i.e., querying the network about training patterns that it has never seen during the training time, is performed by a weighted sum using a lot of network parameters. Consequently, isolated effects of the network parameters on the calculated SCF are difficult to visualize. Besides, the range of sigmoid function is 0 to 1, so that one have to scale output values to that range to get an suitable comparison. In fact, the replace of a simple computation of a final regression expression by an routine program represents a disadvantage that can be easier defeated.

Indeed, the main drawback in neural networks approach is the training time. As the hidden layers structure is unknown, trial-and-error method is still the best method to find out an suitable solution. Besides, the learning algorithm is based in the *steepest descent method*, with some modifications in order to increase the performance. This method may leads the surface of error function to flat regions, and the training almost paralyze. Sometimes a simple modification in the learning parameters is enough to increase the training speed. Otherwise, the structure of hidden layers need to be altered.

CONCLUDING REMARKS

The use of ANN to evaluate SCF was reported. The results encourage future works in order to compare the performance of ANN with others geometrical joints and/or out plane bending moment load case. In fact, we are not proposing a strong modification in the fatigue life evaluation procedures once the tool we are using need to be better assessed.

Another noticing point is the 3D solid FE models. With the increased performance of computers, the prohibitive costs evolved in FE analysis have been reduced, so that automatic meshing programs for 3D solid models can be used to produce new tubular joints data. Moreover, the SCF value is achieved straightforward, avoiding the extrapolation normally associated with shell models.

In this work, the authors purpose a review of traditional method of evaluation the SCF, in the sense of substitute the traditional concepts which usually groups stresses and/or its effects by components. Moreover, we purpose the modeling of the actual joint geometry, in order to quantify, as better as possible, the tri-axial stress that occurs in the hot spot.

In the light of the work on SCF evaluation reported above, the following conclusions can be placed:

- The weld geometry inclusion affects the SCF value. As showed in Fig. 8, in some cases the SCF vary by 25% with the groove angle, allowing a better assessment of fatigue life.
- The including of *Sec* parameter as the SCF position in the weld length permits a more rationally association of different load cases. It is known that the SCF position in the axial force case moves from crown to saddle, as the heel angle increase. Such expected result was confirmed as depicted in Fig. 12, as well as for the IPB moment load case (Fig. 13).
- The final network result is a set of numbers composed by weights and thresholds. The structure of that output difficulties the utilization of neural networks as a tool that can be accessed quickly, since the user will need at least a microcomputer. On the other hand, it is an easy task the programming of an algorithm to perform the comprised algebra.
- A suggestion for future work, is the application of neural networks for another joint types (K, X, DK, etc.) and in the ultimate capacity evaluation of tubular joints, usually performed combining experimental and FE data, followed by a regression expression.
- Using 3D solid model automatic meshing was the key step to carry out the data basis. This work would have no meaning if we had to produce each solid mesh one by one.

NOMENCLATURE

ANN	= Artificial Neural Networks.
D , d	= chord and brace diameters.
G	= *gap* in the weld root between chord and brace.
L	= chord length.
SCF	= stress concentration factor.
Sec	= % of weld fillet length stem from crown heel.
T, t	= chord and brace thickness.
W_{ij}	= weight between neurons *i* and *j*.
α	= 2L/D.
β	= d/D.
γ	= D/2T
τ	= t/T.
θ	= angle between brace and chord (*hell*).
α_S	= weld fillet groove angle.
η	= learning rate.
δ_j	= error value at neuron *j*.
θ_j	= neuron *j* threshold.

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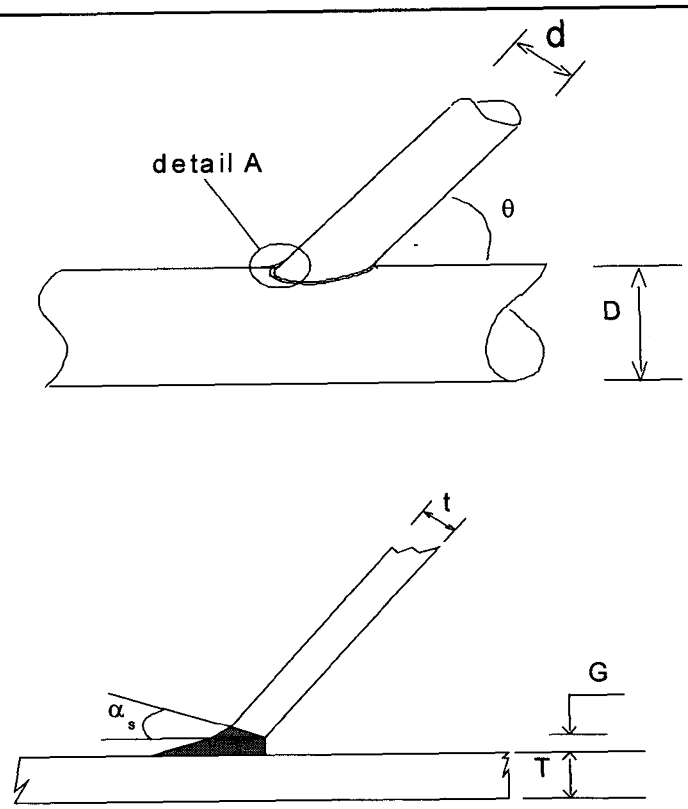

detail A

where:

L length of chord between constraints.

D chord and brace diameters.

d brace diameter.

T chord thickness

t brace thickness.

G gap between chord and brace in the weld root.

α_s groove angle.

θ included angle between chord and brace.

$\alpha = 2L / D$

$\beta = d / D$

$\gamma = D / 2T$

$\tau = t / T$

Figure 1 - Geometrical parameters definition.

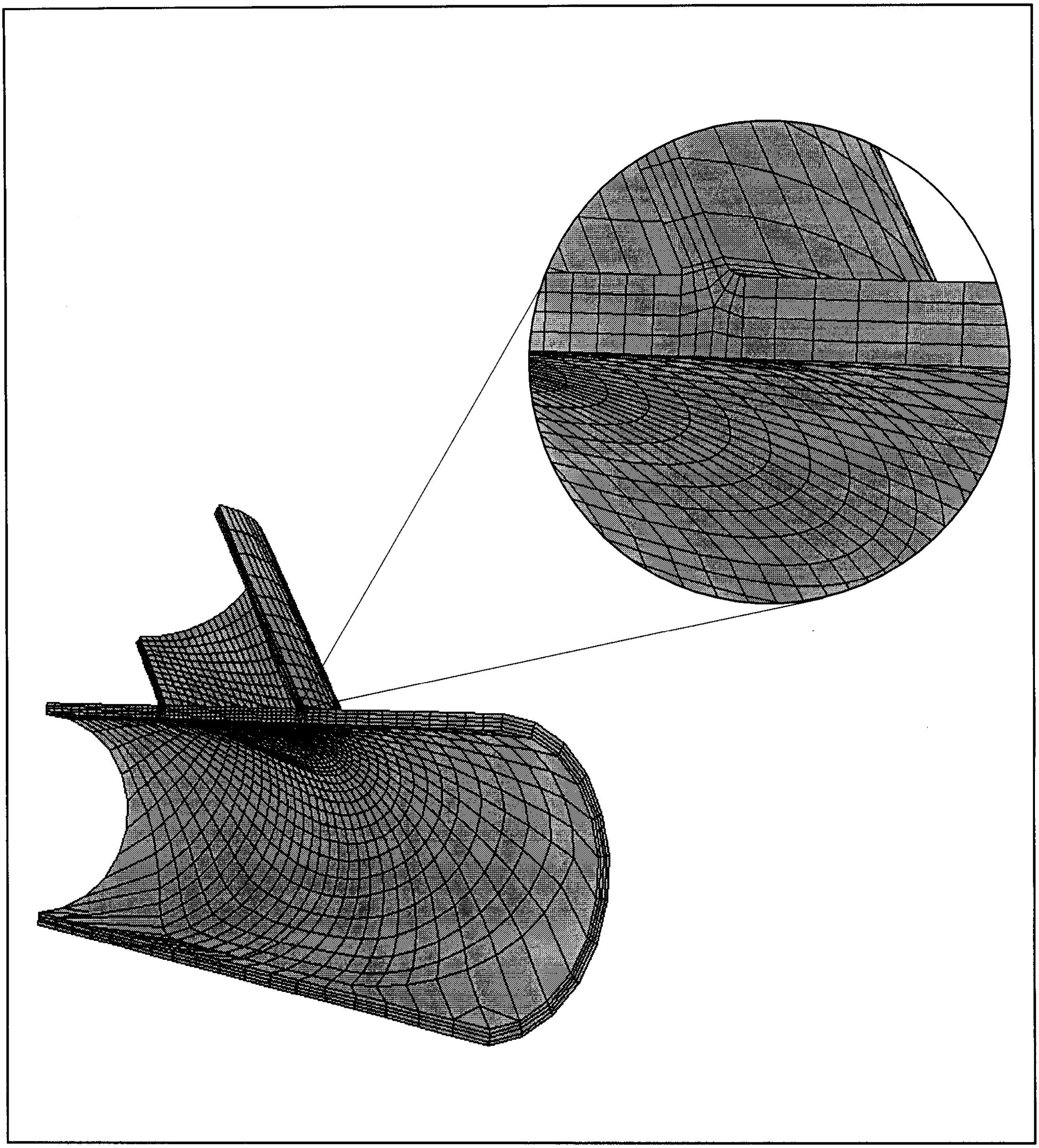

Figure 2 An example of automatic meshing joint.

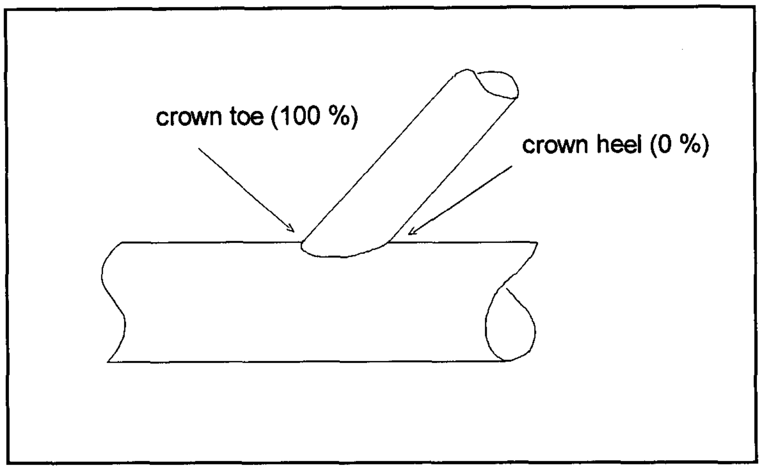

Figure 3 Position of stress value as a weld length percentage

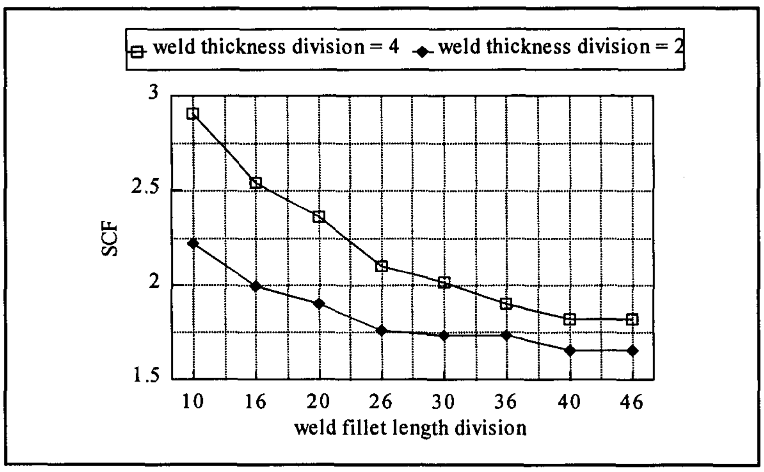

Figure 4 - Mesh convergence test.

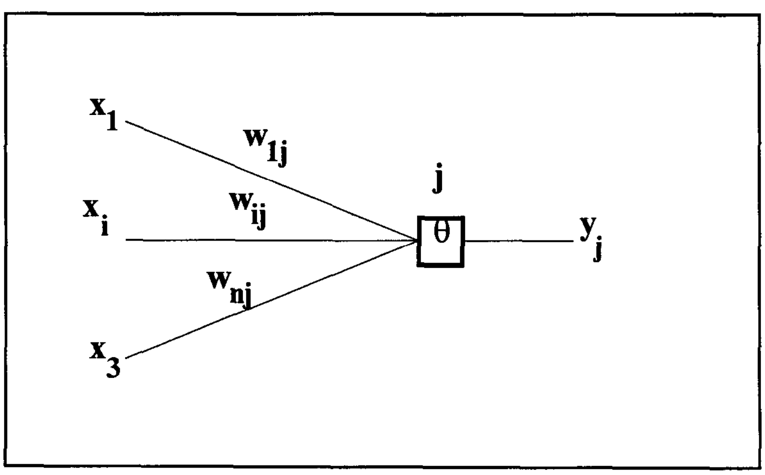

Figure 5 - An illustrative artificial neuron.

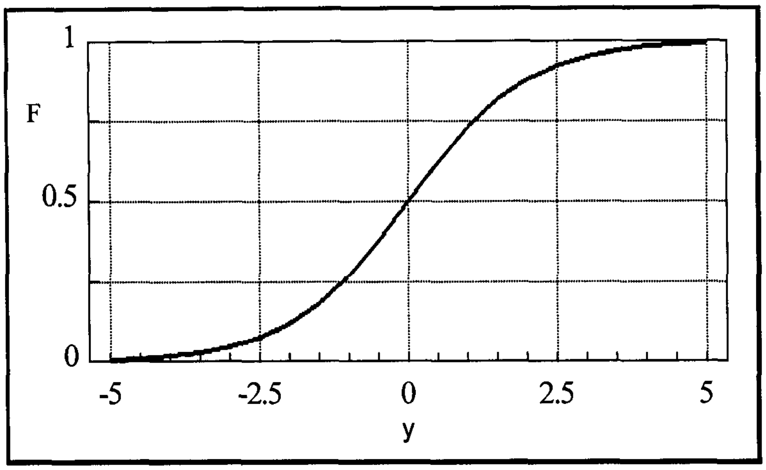

Figure 6 - Sigmoid Activation Function

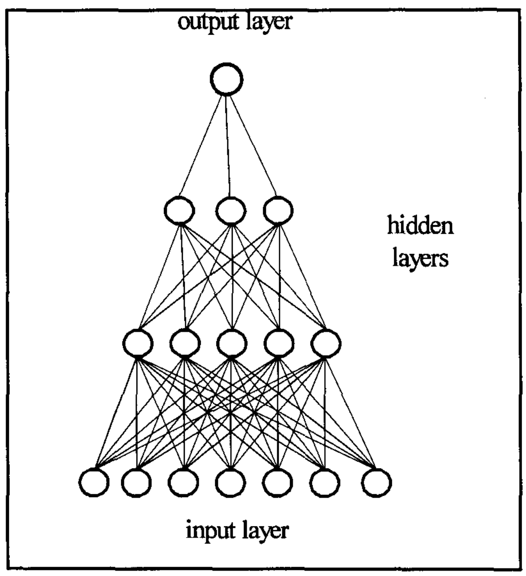

Figure 7 - A typical multi-layer neural network.

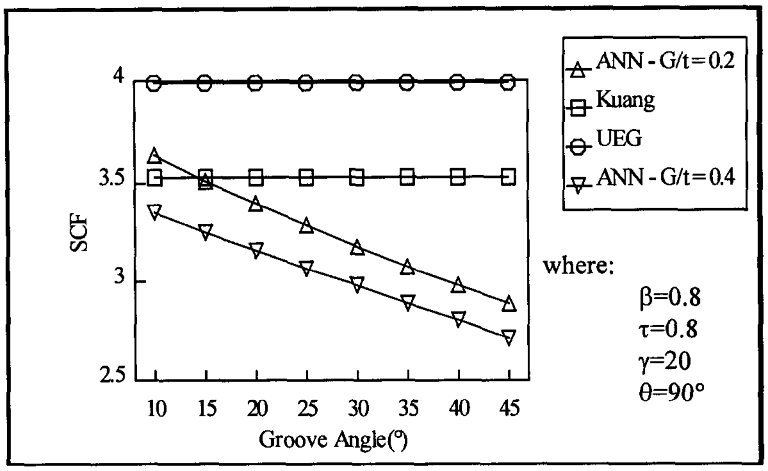

Figure 8 - Comparison of results. In plane bending moment case.

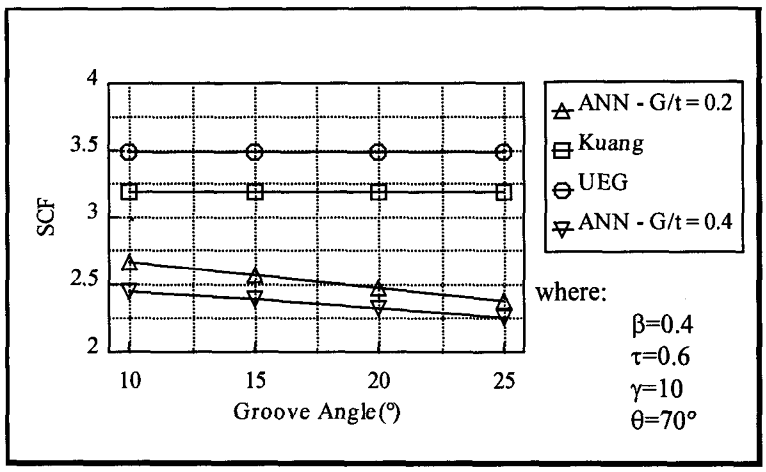

Figure 9 - Comparison of results. In plane bending moment case.

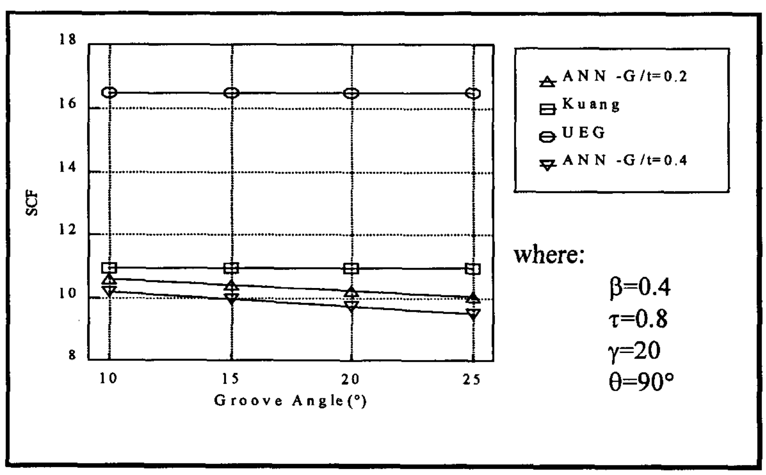

Figure 10 - Comparison of results. Axial force case.

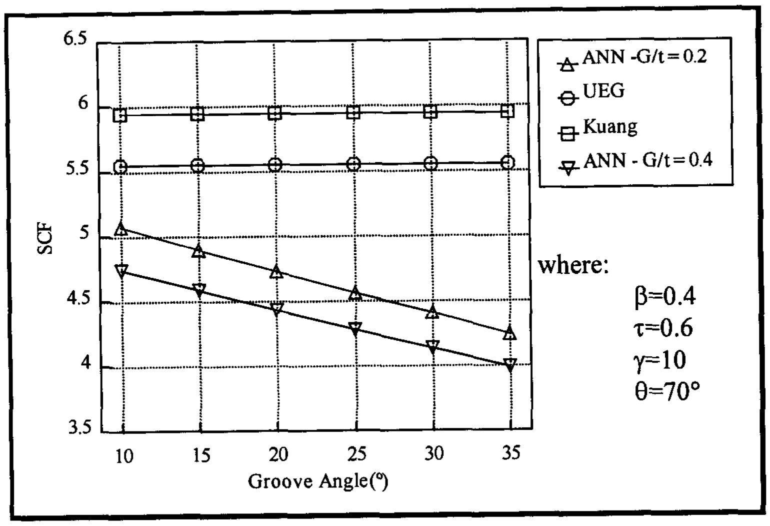

Figure 11 - Comparison of results. Axial force case.

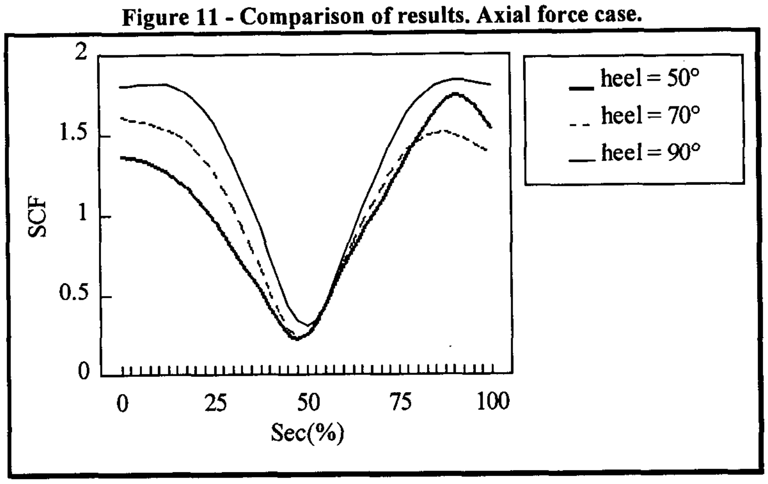

Figure 12 - Variation of SCF position in the weld length. In plane bending case.

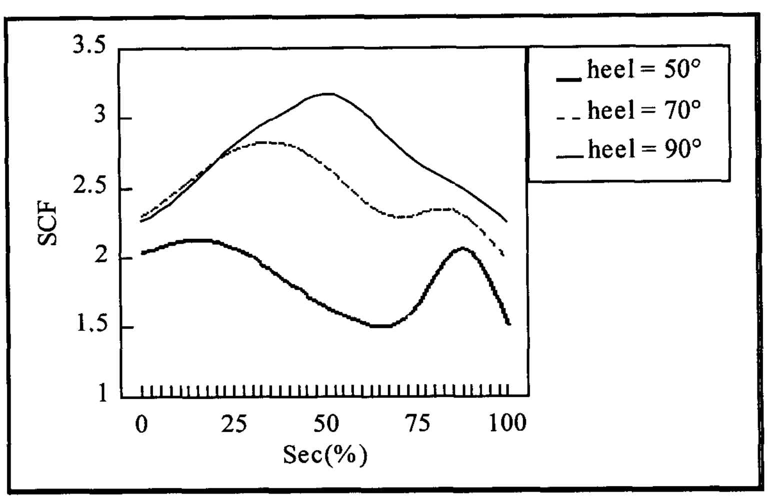

Figure 13 - Variation of SCF position in the weld length. Axial force case.