 CMC, vol.8, no.3, pp.133-149, 2009

Identification of Materials Properties with the Help of Miniature Shear Punch Test Using Finite Element Method and Neural Networks

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Abstract: This paper describes an approach to identify the mechanical properties i.e. fracture and yield strength of steels. The study involves the FE simulation of shear punch test for various miniature specimens thickness ranging from 0.20mm to 0.80mm for four different steels using ABAQUS code. The experimental method of the miniature shear punch test is used to determine the material response under quasi-static loading. The load vs. displacement curves obtained from the FE simulation miniature disk specimens are compared with the experimental data obtained and found in good agreement. The resulting data from the load vs. displacement diagrams of different steels specimens are used to train the neural networks to predict the properties of materials i.e. fracture and yield strength. Two different feed forward neural networks have been created and trained in order to predict the Fracture toughness and yield strength values of different steels. L-M algorithm has been used in the networks to form an output function corresponding to the input vectors used in the network. The trained network provides the output values i.e., fracture toughness and yield strength of unknown input values, which are within in the range of data that is used for the training of network.

Keyword: Fracture toughness; yield strength, miniature, shear punch test, FEM, Neural Network, and ABAQUS.

1 Introduction

Shear punch test technique is the most suitable test technique to determine the degraded mechanical and fracture properties of structural members of Nuclear power plant, steam power plants, chemical industry etc. The material behavior of structural components changes due to in service loading, aging, irradiation embrittlement and some other influences. That requires an in situ monitoring of the material state. In order to determine material parameters at various locations e.g. in weldments or gradient materials, the size of the material taken out for a test specimen should be very small but representative. In the miniature shear punch test (MSPT), a disk like specimen of 10mm diameter 0.50mm size is deformed in a miniaturized deep drawing experiment. The measurable output is the load displacement curve of the punch, which contains information about the elasto-plastic deformation behavior and about the strength of material [Mao, Shoji and Takahashi (1987); Takahashi, Shoji, Mao, Hamaguchi, Misawa, Saito, Oku, Kodaira, Fukaya Nishi and Suzuki (1988)].

This technique provides the data regarding the properties of a material by using a small volume of material where as conventional test specimens need a large volume of material. Neural network (NN) technique has been used to predict the mechanical properties of different steels using the data obtained from the simulation of shear punch test. NN predicts the mechanical properties of materials accurately compared to the existing empirical relations. More recently a neural network (NN) model is developed for the analysis and prediction of the mapping between degradation of chemical element and electrochemical parameters during the corrosion process [Pidaparti and Neblett (2007)].

Miniature specimen techniques include a wide variety of types and techniques as described by [Husain et al (2004), Lucas (1990), Cheon and Kim

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(1996)] tensile test, micro hardness, small punch ball, spherical, and hemispherical head indentation, bend, fracture, impact, and fatigue. Manahan et al (1981) and Huang et al (1982) were among the earliest to study the small Punch test technique for the determination of mechanical properties of irradiated materials from small circular disks. These techniques largely involve loading a supported disc or coupon with an indenter or punch, deforming it to failure, and analyzing the resulting load-displacement data. Load-line displacement at failure is converted to an effective failure strain.

Foulds and Viswanathan (1994) described the determination of material toughness of in service low alloy steel components by small punch test. [Foulds, Waytowitz, Parnell and Jewell (1995)] in their investigation estimated the material fracture appearance transition temperature (FATT) of a range of components in fossil power plant and carried out fracture toughness evaluation by using small punch test. [Se-Hwan, Jun-Hwa, Jun and Kim (1994)] in their paper evaluated 16 Mev proton irradiation effects on a fusion reactor candidate material (12Cr-Mov steel) in terms of changes in energy up to failure by small punch tests. Very recently, an inverse approach based on depth-sensing instrumented indentation tests is proposed by Qian et al [Qian, Cao, Zhang, Rabbe, Yao and Fei (2008)] to determine Young's modulus, yield strength and strain hardening exponent of the stress-strain curve can be described using a power function.

[Husain (2003)] investigated on the small punch techniques. Specimens of 10mm diameter and 0.5mm thickness of different materials have been experimented and FE simulation was also performed. Small punch tests were performed on the following materials:

- Medium carbon steel (MS)
- Non-shrinkable steel (D3)
- Structural steel (STS)
- Chromium hot work steel (H11)

Different types of specimen shapes used in this investigation are (i) Circular (ii) Square (iii) Rectangular. Small punch experimental studies of circular disk (10mm diameter, 0.5mm thick), square shape, and rectangular shape miniature specimen were also studied. The four different steels are selected for the preparation of miniature samples. A new empirical correlation for the estimation of yield strength is established. The proposed empirical relation is the function of miniature specimen geometry, inner dimensions of specimen holder (dies) and the punch tip diameter.

Very little work is done in the area of applying neural network for the prediction of mechanical behaviour. [Ince (2004)] used the neural network technique in the area of material science. In that study a neural network method has been used after identifying some variables that could be expected to influence the fatigue growth rate in nickel based super alloys. [Abendroth and Kuna (2003)] described an approach to identify plastic deformation and failure properties of ductile materials. The experimental method of small punch test is used to determine the material response under loading [Timmel, Kaliske, Kolling and Mueller (2007)].

The present study carries out small punch test simulation of four different materials of thickness ranging from 0.20mm to 0.80mm. The numerical study pertains to the finite element modeling and simulation of miniature samples adopting small punch test technique with the help of ABAQUS computer code [Sharifi and Gakwaya (2006)]. Neural network technique is used to predict the mechanical properties of different steels using the data obtained from the simulation of shear punch test of different specimens. These neural networks work based on the history of data available. This network forms an output function based on the data provided to the network during the training i.e. input vectors and target values. Different weights 'w' and biases 'b' will be assigned to the input data 'p' provided to the network .The sum of 'w*p' and 'b' are transferred to a transfer function to estimate a output function. The weights and biases will be updated until the function formed approaches the function that can be formed by the available target values. There are different algorithms that are used with these networks in order to estimate an output function. L-M algorithm has been used in the present study, because of its test convergence.

The present paper describes the study, carried out with the following objectives:

- To develop the finite element models using ABAQUS computer code to simulate the process of small punch specimen test technique and carrying out engineering analysis of large deformation of different size miniature samples.
- To create and train a neural network for the prediction of fracture toughness.
- To create and train a neural network for the prediction of yield strength.

2 Simulation of Miniature Shear Punch Test Using FEM

The numerical study pertains to the finite element modeling and simulation of miniature samples adopting small punch test technique with the help of ABAQUS computer code [Gao, Zheng and Yao (2006), Charrabarty and Cagin (2008)]. The circular miniature samples of four different materials with different thickness are simulated using finite element method. Direct finite element analyses on different thickness specimen are carried out in the present study. The special contact algorithms between miniature sample plate and tip of rigid punch (to simulate experimental situation) as slave surface and analytical master surface respectively has been used for the study. ABAQUS explicit finite element analysis approach has been employed to simulate 3-D model of the miniature samples of different thickness. The quasi-static punch loads are used to simulate the small punch experimental procedure with the help of time amplitude increments option of the code [Panthi, Ramakrishnan, Pathak and Chouan (2007), Samantha and Ghosh (2008)]. The 3-D finite element analysis provides the load-displacement curves/data, Von-Misses stresses, equivalent plastic (fracture) strain, and contact pressure at the surface. The finite element results of 0.5mm thickness specimen are validated by comparing with results published in the literature [Husain (2003)].

The small punch test using circular disk shape miniature specimens is simulated to follow the actual SP experimental test procedure. The dimensions of the circular shape miniature specimens are considered according to the inner borehole of the dies (specimen holder) i.e. 4mm diameter. The circular disk specimens of 4mm diameter and thickness ranging from 0.2mm to 0.8mm with an interval of 0.1mm are modeled. In order to make the problem more tractable, a three-dimensional finite element model is simulated to follow the actual situation as in small punch test experiments. The three dimensional model of miniature disk specimen is descretized and the mesh is generated using three dimensional isoparametric hexahedron elements.

The miniature disk specimen are modeled and descretized with 8-node brick isoparametric solid elements as shown in Figure. 1. The hemispherical headed rigid punches are modeled by analytical rigid surface option. The tip diameter used for the punch is 2.309mm.Simulation of the small punch test follows the physical procedure as closely as possible, with the miniature specimen fixed between a lower die and an upper die plate by six clamping screws. To simulate this condition of small punch test on the model of the miniature sample, all the circumferential nodes were constrained (remain fixed or have Zero displacement) by boundary conditions option encaster (rigidly fixed). In such case all peripheral nodes are constrained completely and thus cannot move in any direction. Due to this reason, in the finite element model, the diameter of circular disk sample is considered according to borehole of the dies i.e., 4mm.

The hemispherical headed punch is modeled as a rigid body constrained to translate only in the vertical direction normal to miniature sample at a prescribed quasi-static loading using the time amplitude with small incremental step technique. The load is applied at the reference node (NODE NO 1). The reference node is constrained in two

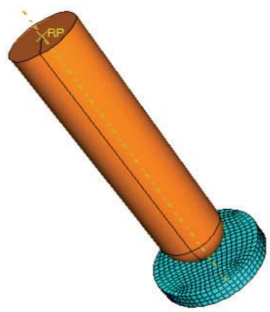

Figure 1: Miniature circular disc specimen of 0.4mm thickness and rigid punch

horizontal directions but is free to move in vertical direction to pierce slowly the sample normal surface at center. Each element of the deformable mesh is characterized by the true stress- true plastic strain relation of the material, as obtained from standard uni- axial tensile test. The tensile specimens are subjected to standard tensile test under continuous loading up to failure. in the ABAQUS input file is important. The nominal stress-strain curve for each material obtained from standard Uniaxial test is used by converting the test data defining material plastic behavior in to the appropriate input format for ABAQUS.

The following assumptions are considered for small punch test simulation of miniature specimen finite element analysis.

The hemispherical headed indenters are considered to be rigid because high strength steel is used as the material.

The friction between the specimen and the indenter is included in the calculation. The friction factor used is 0.1; this choice had only a minor effect on the load vs. displacement curve.

It is considered that the boundary condition is very close to a rigid fixed boundary condition, because the small punch specimen is fixed firmly by six clamping screws, in between the dies.

The present finite element analysis using ABAQUS is very versatile and gives a wide spectrum of information concerning the small punch test, e.g. von-Misses stresses, equivalent plastic strain, contact pressure, deformation, logarithmic strain components, different stress components, load till failure, full field displacement, load vs. displacement curves, and von-Misses stress vs. equivalent plastic strain curves etc.

2.1 Load- Displacement Behavior of Circular Specimens

During the deformation process in finite element analysis, the rigid hemispherical headed punch moves slowly (quasi-statically) by pressing the miniature disk specimen normally under the tip of punch until all the elements under the punch are badly damaged (distorted). The deformation behavior during punching is closely monitored at each incremental step. A typical run for the finite element analysis of the problem comprise of nearly 512 elements and 846 nodes and require about more than 100 small incremental steps. CPU time required for completion of the simulation is generally about 50-75 minutes on the HP workstation. The computer memory required to store the results of these simulation for each case varied from 20-30 MB. It is also noticed that the increasing the mesh density increases the CPU time drastically.

Figure 1. shows the un-deformed finite element models for circular shape miniature specimens with different thick-nesses. It is observed that the computed load vs. displacement curve from FEM and from SP experiments are in good agreement on an average but generates moderate gaps between two values after substantial deformation. In a similar way finite element analysis is carried out for small specimens of different thick- nesses. The minor differences between two curves can be attributed to crack initiation before the load approaches its maximum. And a limitation of small strain theory in the ABAQUS program would also cause such difference at a high deformation stage.

3 Neural Networks

An Artificial Neural Network (ANN) is an information-processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. NNs, like people, learn by example. A NN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons. In a simple neuron as shown in Figure 2., the scalar or vector input ‘p’ is transmitted through a connection that multiplies its strength by the weight ‘w’, to form the product w*p. This argument is fed as an input to the transfer function, which produces output ‘a’. In the neuron with bias, the bias is simply added to the product w*p. The bias is much like a weight, except it has a constant input of one. Sum of the w*p and bias ‘b’, is fed as the input to the transfer function, which produces output. Weights and biases are both adjustable parameters of the neuron. The central idea of neural network is that such parameters can be adjusted so that the network exhibits some desired or interesting behavior. Thus, networks can be trained to do a particular job by adjusting the weight or bias parameters, or perhaps the network itself will adjust these parameters to achieve desired end.

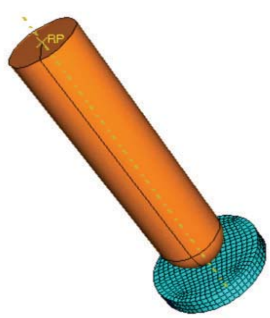

Figure 2: A simple neuron

3.1 Transfer functions

There are many transfer functions of which the following three are mostly used transfer functions. They are

- Linear transfer function
- Log-sigmoid transfer function
- Tan-sigmoid transfer function

3.2 Selection of Algorithm

It is very difficult to know which training algorithm will be the fastest for a given problem. It will depend on many factors, including the complexity of the problem, the number of data points in the training set, the number of weights and biases in the network, and the error goal. In general, on networks, which contain up to a few hundred weights the Levenberg-Marquardt, algorithm will have the fastest convergence. This advantage is especially noticeable if very accurate training is required. The quasi-Newton methods are often the next fastest algorithms on networks of moderate size. Of the conjugate gradient algorithms, the Powell-Beale procedure requires the most storage, but usually has the fastest convergence. Rprop and scaled conjugate gradient algorithm do not require a line search and have small storage requirements. They are reasonably fast, and are very useful for large problems. The variable learning rate algorithm is usually much slower than the other methods, and has about the same storage requirements as Rprop, but it can still be useful for some problems. There are certain situations in which it is better to converge more slowly. In most of the problems, first L-M algorithm is recommended. If this algorithm requires too much memory, then any one of the conjugate gradient methods are recommended.

3.3 Training of neural networks

Training of a general neural network consists of following steps

a. Creating neural network

b. Initializing weights and biases

c. Training the neural network

d. Simulation for new inputs

3.3.1 Creating neural network

A trainable feed forward neural network can be created using an in-built function ‘newff’. It requires four inputs and returns the network object. The first input is an R by 2 matrix of minimum and maximum values for each of the R elements of the input vector. The second input is an array containing the sizes of each layer. The third input is a cell array containing an array containing the names of the transfer functions to be used in each layer. The final input contains the name of the training function to be used. The following command creates two-layer network.

Net=newff ([min,max].[m,n],{'tansig', 'purelin'}, 'trainlm')

3.3.2 Initializing weights and biases

Before training a feedforward network, the weights and biases must be initialized. The initial weights and biases are created with the command 'init'. This function takes a network object as input and returns a network object with all weights and biases initialized. For feedforward networks there are two different layer initialization methods which are normally used, one is 'initwb and second one is 'initnw'.

The initwb function causes the initialization reverts to the individual initialization parameters for each weight matrix and biases. For the feedforward networks the weight initialization is usually set to rands, which sets weights to random values between -1 and 1. It is normally used when the layer transfer function is linear.

The function initnw is normally used for layers of feedforward networks where the transfer function is sigmoid. It is based on the technique of Nguyen and Widrow and generates initial weights and bias values for a layer so that the active regions of the layer's neurons will be distributed roughly evenly over the input space.

3.3.3 Training

A neural network can be trained for function approximation, pattern association, or pattern classification. The training process requires a set of examples of proper network behavior i.e., network inputs 'p' and target outputs 't'. During training the weights and biases of the network are iteratively adjusted to minimize the network performance function. The default performance function for the feed forward networks is mean square error "mse' i.e., the average squared error between the network outputs and the target outputs 't'.

In the present study two different neural networks are trained to predict the Fracture Toughness and yield strength of various steels. They are

1. Neural Network for prediction of Fracture Toughness
2. Neural Network for prediction of yield strength

4 Training of Neural Network to Predict Fracture Toughness & Yield Strength

In this study of prediction of fracture toughness using neural network, fracture toughness values of four different materials have been taken from the literature. These fracture toughness values are used as the target values, and thickness of specimen before and after deformation have been used as input vectors in the neural network training (**Table 1**).

A neural network has been created using 'newff' function. 10 hidden layers and one output layer have been used to get good approximation of the output function. A function called 'minmax' has been used to calculate the minimum and maximum values of each input vector. Transfer functions 'tansig', 'purelin' have been used in the hidden layer and output layer correspondingly. The linear transfer function, which used in the output layer, allows the output range to fall outside -1 and 1. L-M algorithm has been used to train the neural network. A default initialization is used in this study. The default initialization function for the feedforward network is initlay, which allows each layer to use its own initialization function for the network.

In the training of neural network original thickness and reduced thickness of 50 samples has been given as input and fracture toughness values as targets. During the training by L-M algorithm the weights and biases of the network are iteratively adjusted to minimize the network performance function. The default performance func-

Table 1: Input data used to train the NN for the prediction of Fracture Toughness

Material	Thickness of specimen (mm)	Reduced thickness of specimen (mm)	Fracture Toughness MPa qrt (m)
H11	0.2	0.0294	230.63
	0.3	0.0934	230.63
	0.4	0.1385	230.63
	0.6	0.1673	230.63
	0.7	0.2125	230.63
STS	0.2	0.0624	220.77
	0.3	0.0888	220.77
	0.5	0.1152	220.77
	0.6	0.1278	220.77
	0.7	0.1397	220.77
	0.8	0.1419	220.77
MS	0.2	0.0319	122.29
	0.3	0.0599	122.29
	0.4	0.1233	122.29
	0.5	0.1273	122.29
	0.6	0.1372	122.29
	0.7	0.1419	122.29
D3	0.2	0.0281	44.04
	0.3	0.1427	44.04
	0.4	0.1933	44.04
	0.5	0.2179	44.04
	0.7	0.3254	44.04

tion feed forward network is mean square error mse i.e., the average squared error between network outputs and the target outputs. More than 3000 epochs or iterations have been used to form precise output function. The training of neural network will come to halt whenever any one of the performance function, mse, and gradient reaches its minimum value. Then the network is said to be trained. After the network has been trained, thickness and reduced thickness of any unknown steel can be given to the network in order to get the fracture toughness of that particular material.

For the determination of yield strength, creation of network and all other process are similar to the above procedure but the training data contains the thickness of specimen and the yield load, which is calculated from the load-displacement diagram. After the training of the network, the yield strength of any material can be obtained by giving the thickness and yield load of that particular material (**Table 2**).

5 Results and Discussion

In the present study, the finite element analysis and simulation of the small punch test technique is successfully carried out on different miniature specimens of different thickness of four materials using the ABAQUS code. The FEM load vs. displacement curves of 0.5mm thick specimens are compared with the load-displacement curves taken from literature [Husain (2003]. These simulated models have been used to obtain wide range of information. The SP experimental method provides only the load-displacement curves where as the finite element method provides a lot of information such as deformation behavior of miniature specimens, load-displacement curves, von-mises stress, equivalent plastic strain, logarithmic strain components, contact stress etc.

The load at the breakaway (P_y) from the linearity can be used to estimate the yield strength (σ_y) of the material. The reduced thicknesses of all

Table 2: Input data used to train the NN for the prediction of yield strength

Material	Thickness of specimen (mm)	Breakaway load (N)	Yield strength (MPa)
H11	0.2	30	484.02
	0.3	75	484.02
	0.4	325	484.02
	0.6	625	484.02
	0.7	825	484.02
STS	0.2	40	475
	0.3	65	475
	0.5	460	475
	0.6	600	475
	0.7	750	475
	0.8	950	475
MS	0.2	30	323.22
	0.3	45	323.22
	0.4	270	323.22
	0.5	400	323.22
	0.6	580	323.22
	0.7	590	323.22
	0.8	825	323.22
D3	0.2	25	478.03
	0.3	60	478.03
	0.4	310	478.03
	0.5	490	478.03
	0.7	800	478.03

the specimens also have been calculated by subtracting the maximum deflection of upper surface of specimen from the maximum deflection of the lower surface of the specimen. These breakaway load and reduced thickness are used in the neural network to predict the mechanical properties. The load displacement curves of different miniature samples with different thickness obtained from FE simulation are shown in Figure 3 to Figure 19. The Deformed simulated miniature disk shape specimens of 0.50mm and 0.60mm thickness are shown in Figure 20 and Figure 21.

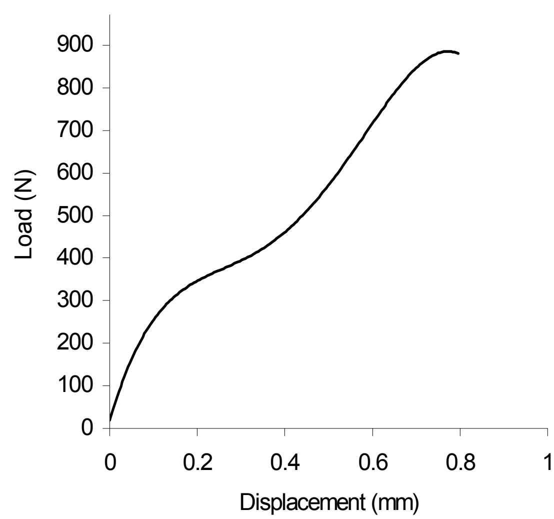

Figure 3: Load-displacement diagram of 0.4mm thick D3 specimen

5.1 *Prediction of mechanical properties using neural network*

Two neural networks for the prediction of fracture toughness and yield strength of different steels have been trained. The fracture toughness and yield strength of four different materials are predicted and are found in good agree-

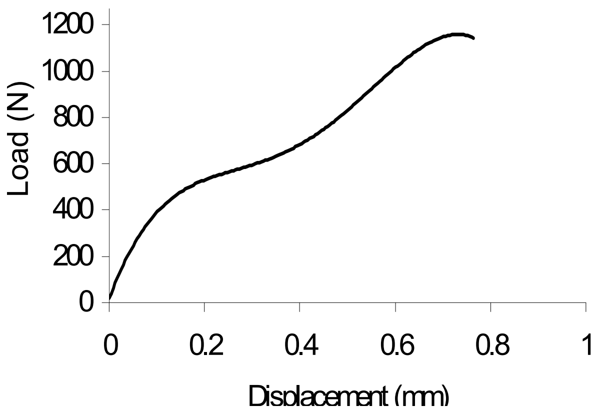

Figure 4: Load-displacement diagram of 0.5mm thick D3 specimen

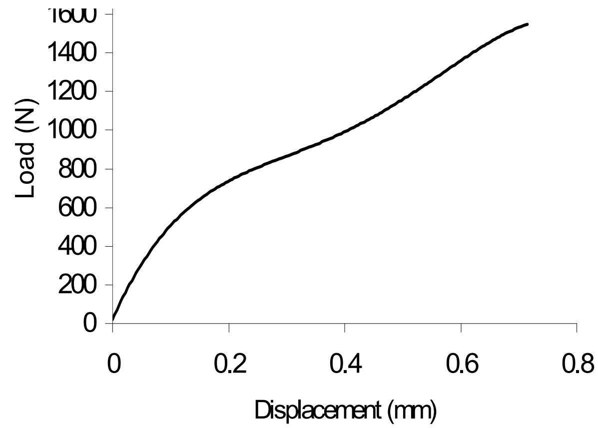

Figure 5: Load-displacement diagram of 0.6mm thick D3 specimen

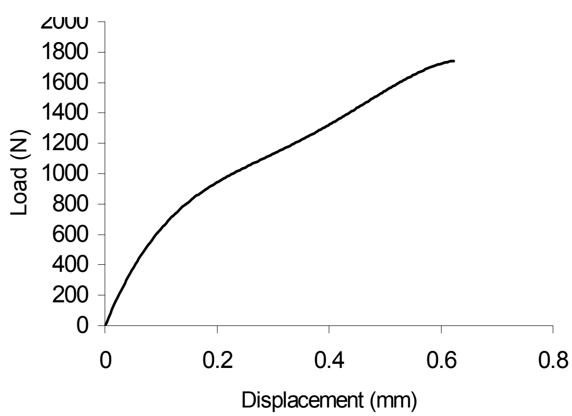

Figure 6: Load-displacement diagram of 0.7mm thick D3 specimen

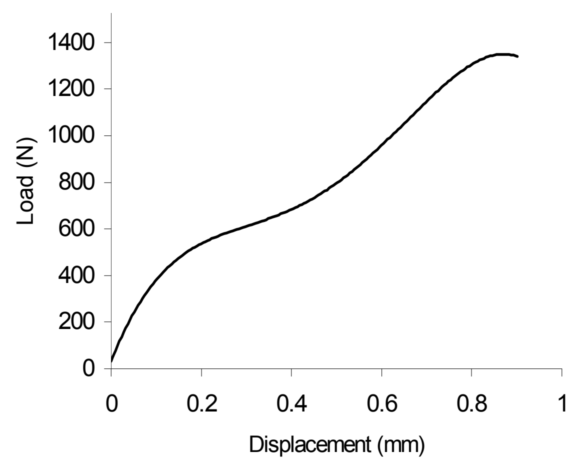

Figure 7: Load-displacement diagram of 0.5mm thick H11 specimen

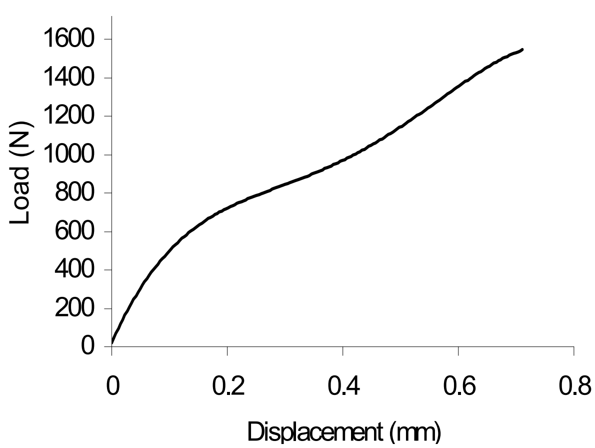

Figure 8: Load-displacement diagram of 0.6mm thick H11 specimen

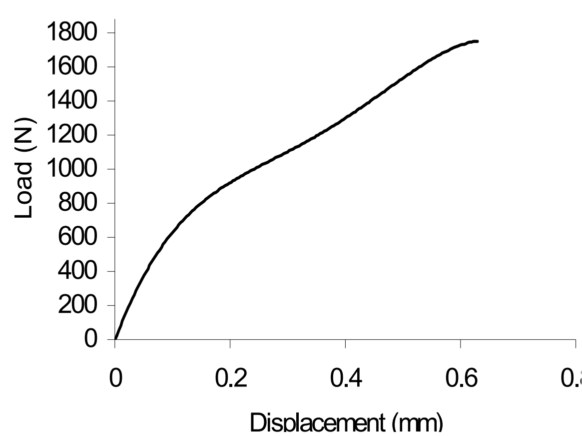

Figure 9: Load-displacement diagram of 0.7mm thick H11 specimen

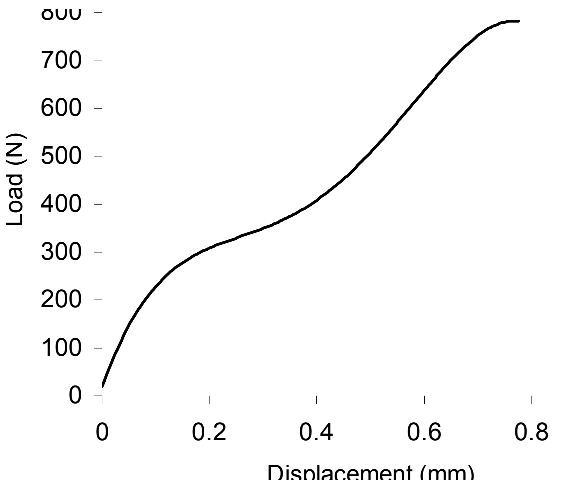

Figure 10: Load-displacement diagram of 0.4mm thick MS specimen

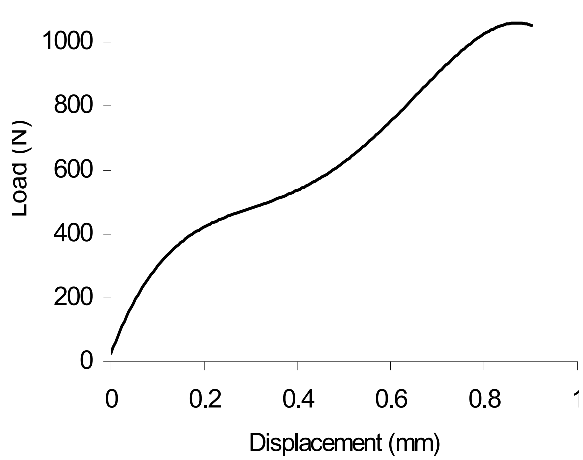

Figure 11: Load-displacement diagram of 0.5mm thick MS specimen

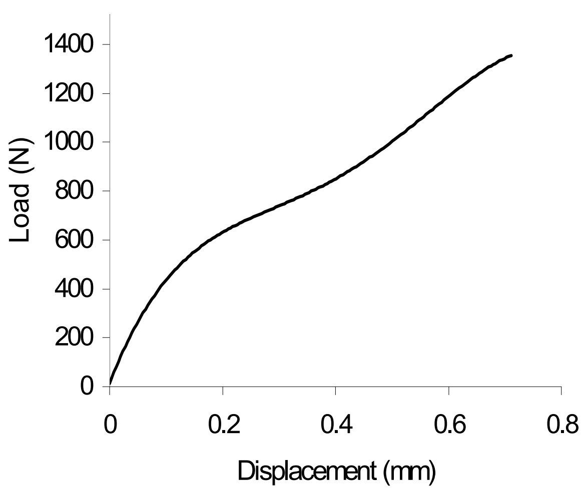

Figure 12: Load-displacement diagram of 0.6mm thick MS specimen

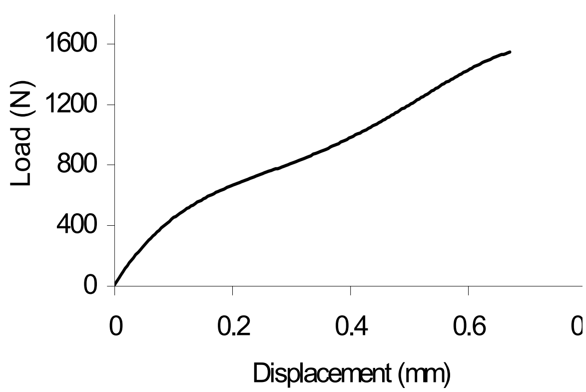

Figure 13: Load-displacement diagram of 0.7mm thick MS specimen

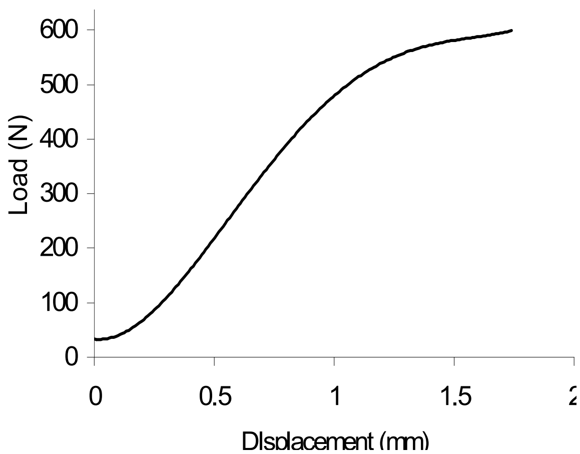

Figure 14: Load-displacement diagram of 0.3mm thick STS specimen

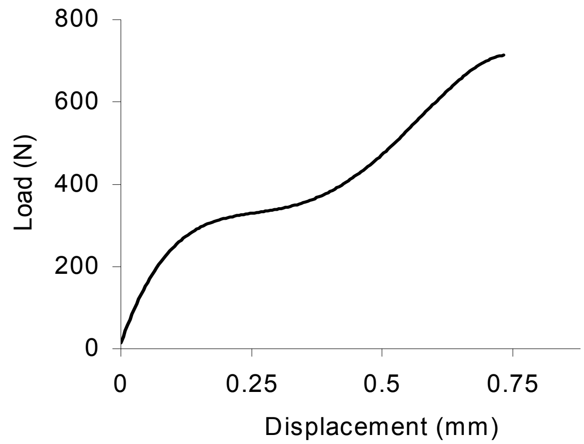

Figure 15: Load-displacement diagram of 0.4mm thick STS specimen

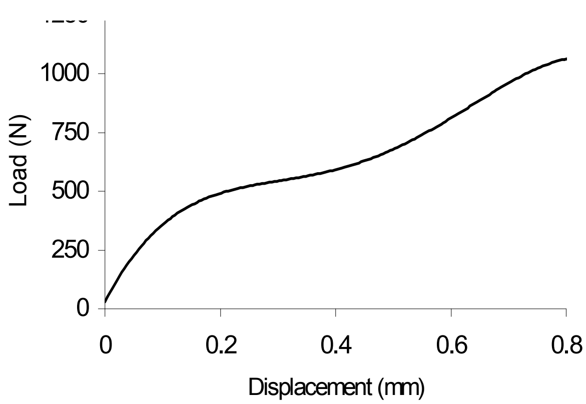

Figure 16: Load-displacement diagram of 0.5mm thick STS specimen

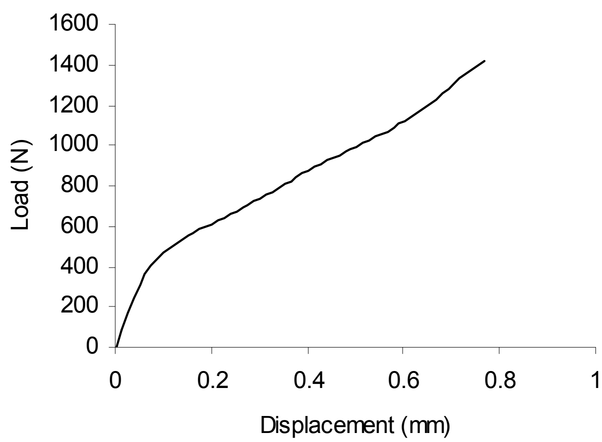

Figure 17: Load-displacement diagram of 0.6mm thick STS specimen

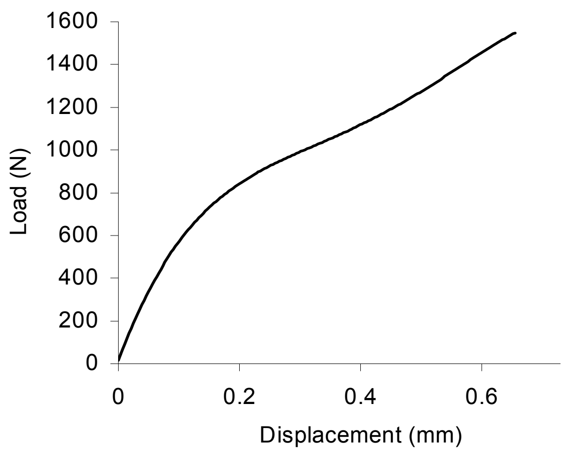

Figure 18: Load-displacement diagram of 0.7mm thick STS specimen

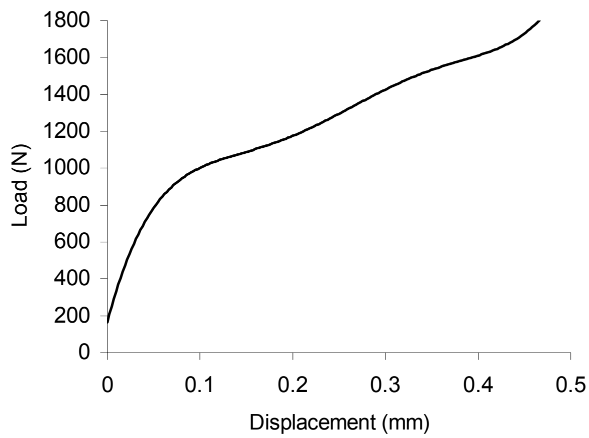

Figure 19: Load-displacement diagram of 0.8mm thick STS specimen

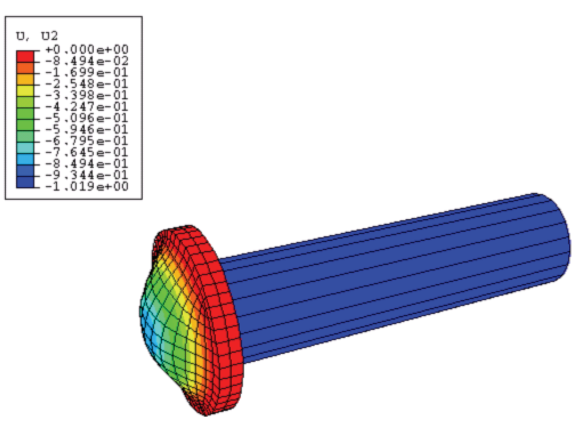

Figure 20: Deformed miniature disk shape specimen of 0.5mm thickness

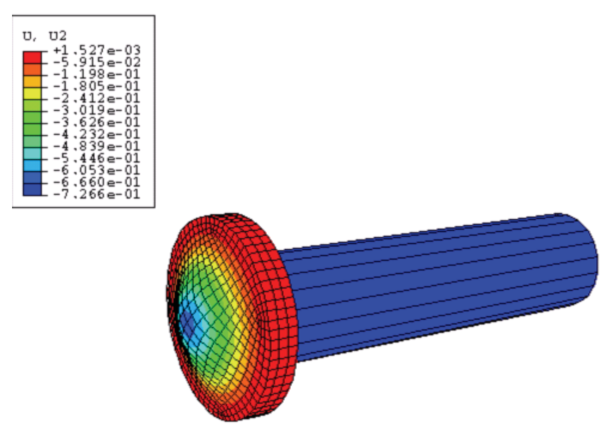

Figure 21: Deformed miniature disk shape specimen of 0.6 mm thickness

ment respectively with the fracture toughness measured from the standard three-point bend test and yield strength measured from standard tensile test. These properties were found using neural networks containing 2 inputs, 10 hidden units and 1 output unit. These neural networks were trained with 25 simulated load-displacement curves. Neural networks are able to generate an approximated function for the material parameters depending on the shape of the load-displacement curve of the punch. For the four different materials i.e., hot worked chromium steel, non-shrinkable die steel, medium carbon steel and structural steel, sets of material parameters have been found, that determine the material behavior reasonably well. The values of fracture toughness and yield strength obtained from neural network also compared with the values obtained from different empirical relations existing in literature.

5.1.1 Existing Correlations For The Prediction of Fracture Strain

Based on experimental observation that fracture in small punch (SP) test specimen occurs after membrane stretching, the fracture strain ε_{qf} can be calculated by using membrane theory proposed by Chakraborty (1970).

$$\varepsilon_{qf} = \ln\left(\frac{t_0}{t^*}\right) \tag{1}$$

Where t^* is the minimum thickness at fracture point and t_0 is the initial thickness of the miniature specimen

The biaxial fracture strain can be estimated from the empirical relation using small punch test, suggested by Kameda [1994] is as follows.

$$\varepsilon_{qf} = 0.12\left(\frac{\delta^*}{t_0}\right)^{1.72} \tag{2}$$

Where δ^* is maximum deflection at fracture

Similarly, another empirical relationship proposed by [Mao, Shoji and Takahasi (1997)] is as follows

$$\varepsilon_{qf} = 0.15\left(\frac{\delta^*}{t_0}\right)^{1.5} \tag{3}$$

[Husain (2003)] proposed the relation for fracture strain in case of circular shape miniature specimen as

$$\varepsilon_{qf} = 1.688\left[\ln\left(\frac{t_0}{t^*}\right)\right]^{1.24} \tag{4}$$

5.1.2 Existing Correlations For The Prediction of Fracture Toughness

The experimental correlation between equivalent fracture strain and fracture toughness (J_{IC}), based on the single specimen technique proposed by Takahashi et al (1980), is linear, as follows:

$$J_{IC} = 280\varepsilon_{qf} - 50 \quad (\text{for } \varepsilon_{qf}\rangle 0.2) \tag{5}$$

Where J_{IC} is in $\left(kJ/m^2\right)$.

Similarly another empirical relationship for fracture toughness, suggested by [Mao and Takahashi (1987)], is

$$J_{IC} = 345\varepsilon_{qf} - 113 \quad (\text{for } \varepsilon_{qf}\rangle 0.4) \tag{6}$$

Where J_{IC} is in $\left(kJ/m^2\right)$.

[Husain (2003)] proposed the relation for fracture toughness in case of circular shape miniature specimen as

$$J_{IC} = 722.28\left(\varepsilon_{qf}\right)^{2.837} \tag{7}$$

For the results shown in Table 3–Table 5. The fracture strains are calculated from the following method:

1. Chakraborty (1970) (Eqn. 1)
2. Kameda et al (1994) (Eqn. 2)
3. Mao et al (1997) (Eqn. 3)
4. Husain (2003) (Eqn. 4) and
5. Present work

Using each of above fracture strains, the fracture toughness is calculated from the following method:

a. Takahashi et al (1980) (Eqn. 5)

b. Mao et al (1987) (Eqn. 6)

c. Husain et al (2003) (Eqn. 7)

d. Present work

The predicted mechanical properties of different materials by standard conventional tests, by empirical relations and as well as by the neural networks for four different materials are tabulated in Table 3 to Table 8.

Tables 3 to 5 gives the comparison of different studies made in order to predict the fracture toughness of different materials. It is observed that the present works seems to be very much close to the actual values where as in other studies there is a large variation.

Tables 6 to 8 gives the comparison of different studies made to predict the yield strength of different materials. It is observed that the variations of yield strength with actual values in the present study is more than the values predicted from the empirical relations established by Xu et al (1985) and are less than the values predicted from empirical relations established by Mao et al (1987).

It is observed that the fracture toughness values predicted by neural networks are more accurate than the fracture toughness obtained from the empirical relations. The accuracy of the neural network depends on the fracture toughness and yield strength data available. If more data input are available the prediction will be more accurate. It is observed that the input vector to train the neural networks also play an important role. To predict the fracture toughness value of steels various input parameter were considered. It is observed that the network in which, thickness of specimen and reduced thickness are used as input vectors is providing better results than the network, in which breakaway load, thickness of specimen and reduced thickness are used.

6 Conclusions

Following conclusions are drawn from the present study.

- It can be concluded that the load-displacement curves obtained from the FEM simulation of shear punch test using ABAQUS are in good agreement with the experimental curves available in the literature.
- It is observed that the plastic deformation occurs at the center of shear punch test specimens, after contact with the rigid indenter, but the location of maximum shear stress and maximum plastic deformation moves outward with increasing load due to the distribution of contact stress.
- The maximum value of von-mises stress occurs near the peripheral edges of the specimen.
- It can be concluded that the contact pressure between the hemispherical headed punch and the specimen is the highest at the edge of contact area after the breakaway point.
- It is observed that the mechanical properties predicted by neural networks are in good agreement with the experimental values. The variation of properties predicted by neural network with experimental values is much less compared to the variation of properties obtained by existing empirical relations.

The accuracy of prediction of properties by neural network increases by increasing the data for training the neural network.

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Table 3: Comparison of Fracture toughness of D3 steel predicted by different studies

Sl no	Fracture toughness Method proposed by	1	2	3	4	5
a	Mao et al (1987)	106.1	14.05	48.49	97.13	95.48
b	Takahashi et al (1988)	21.91	98.91	87.84	44.34	47.16
c	Husain (2003)	37.55	84.70	73.29	44.39	45.52
d	Present work			42.71		
e	Standard three point bend test			44.04		

Table 4: Comparison of Fracture toughness of STS steel predicted by different studies

Sl no	Fracture toughness Method proposed by	1	2	3	4	5
a	Mao et al (1987)	90.6	211.17	217.1	145.1	153.8
b	Takahashi et al (1988)	127.4	209.0	209.0	163.4	169.8
c	Husain (2003)	123.3	346.6	346.6	194.0	209.5
d	Present work			211.3		
e	Standard three point bend test			220.7		

Table 5: Comparison of Fracture toughness of H11 steel predicted by different studies

Sl no	Fracture toughness Method proposed by	1	2	3	4	5
a	Mao et al (1987)	115.4	52.38	10.79	173	167
b	Takahashi e al (1988)	142.7	108.8	98.59	184.2	180.1
c	Husain et al (2003)	150.1	96.59	84.34	248	236.7
d	Present work			219.82		
e	Standard three point bend test			230.63		

Table 6: Comparison of Yield strength of H11 steel predicted by different studies

Sl No	Empirical equations given by	σ_Y, Estimated by SPT	σ_Y, Estimated by standard tensile test	Percentage Error
A	Mao et al (1987)	331.20	482.02	31.57
B	Xu et al (1985)	438.84	482.02	9.33
C	Husain et al (2003)	471.59	482.02	2.56
D	Present work	443.75	482.02	7.93

Table 7: Comparison of Yield strength of D3 steel predicted by different studies

Sl No	Empirical equations given by	σ_Y, Estimated by SPT	σ_Y, Estimated by standard tensile test	Percentage Error
A	Mao et al (1987)	345.6	478.03	27.28
B	Xu et al (1985)	457.92	478.03	4.21
C	Husain et al (2003)	492	478.03	2.92
D	Present work	456.24	478.03	4.5

Table 8: Comparison of Yield strength of STS steel predicted by different studies

Sl No	Empirical equations given by	σ_Y, Estimated by SPT	σ_Y, Estimated by standard ensile test	Percentage Error
A	Mao et.al. (1987)	338.40	475	28.75
B	Xu et.al (1985)	448.38	475	5.6
C	Husain (2003)	481.84	475	1.44
D	Present work	430	475	9.47

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