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Optimization of Super Plastic Forming of Low Carbon Steel in Stretching setup advanced Techniques

G. Jagan Naik
Department of Mechanical Engineering
Jagruti Institute of Engineering and Technology
Hyderabad (T.S.) [INDIA]
Email: gjnaik1106@gmail.com

M. Devaiah
Department of Mechanical Engineering
Geethanjali College of Engineering & Technology
Hyderabad (T.S.) [INDIA]
Email:devaiah.malkapuram@gmail.com

ABSTRACT

Super plastic forming is a manufacturing process whereby stainless steel, titanium or aluminum sheet is blow formed into a die to produce very light and strong aerospace components of crucial importance is the prediction of the final thickness distribution and the pressure cycle necessary to maintain super plasticity. A finite element based solution to these problems and presents examples for typical components including diffusion bonding effects. The deep drawing process for high strength/low formability metals has an extensive industrial application but drawing at room temperature, it has serious difficulties because of the large amount of deformations and high flow stress of the materials. Drawing at the elevated temperatures decreases the flow stresses and increased formability of the materials hence deformations become easier]. Since elevated temperature results in decreased flow stresses and increased formability in the sheet, it allows deeper drawing and more stretching to form products .Stainless steels are very vast industrial applications due to its high strength. These materials are essentially non magnetic in the annealed condition and can be hardened only by cold working. They usually possess excellent cryogenic properties and good high-temperature strength and oxidation resistance. Austenitic stainless steel offer excellent corrosion resistance in organic, acid, industrial and marine environments. The non-magnetic properties combine with exceptionally high toughness at all temperatures makes these steel an excellent selection for many marine, nuclear and space applications. The determination of these conditions implies not only the usual mechanical characterization but also the performance during deep drawing process. The present work is aimed to investigate the limiting draw ratio (LDR) and the coefficient of friction of extra-deep drawing (EDD) steels at room temperature and at 200°C. Simulation and experimental results showed *an increase in the LDR as the temperature increases and the coefficient of friction was estimated by comparing the simulation and experimental load–displacement curve. The limiting drawing ratio (LDR) is defined as the formability of sheet metal. In the present investigation, deep drawing of different diameter circular blanks was used to find the LDR of drawn cups at different temperatures. Artificial neural network predictors for mechanical properties of cold rolling products [16-18] is Controlling product mechanical properties is an important stage in steel production lines. But their high cost. Artificial Neural Network (ANN). For monitoring product mechanical properties without need for expensive laboratory tests.*

Keywords:— *ASS, EDD, LDR, ANN*

I. Introduction

Sheet metal forming is a technique by which most body parts are produced in automobile and aerospace. In this process a thin sheet blank is subjected to plastic deformation using forming tools like punch, dies to conform to a designed shape without failure, which is an important aspect of the sheet metal to produce complex components. Many factors such as mechanical and metallurgical properties of sheet metal die and punch geometry, lubrication, sheet thickness, sheet roughness, punch speed etc. contribute to the success or failure of the forming to varying degrees in an independent manner [1]. Therefore, an understanding of the formability and failure of sheet metal is essential for the production of quality components.

Nowadays, in the modern industry, the deep drawing process is used extensively. This is a complex forming process which involves tension (cup wall), bending (punch and die corners) and compression (cup flange). Both high tensile strength and better ductility in compression are required for the deep drawing material [2]. The puch force is limited to the maximum tensile load that can be carried by the wall of the cup and this in turn limits the depth of flange that can be drawn [3].

The plastic forming of sheet metals is the production of certain materials under the right conditions, such as suitable stress rate and low pressure without wrinkles. In 1997, Mamalis [4] has investigated the deep drawing of cylindrical boxes with the effect of forming characteristic of the material simulation. Madison (2000) [5] has studied the simulation of tin metal forming in the Industry. Although the deep drawing process for high strength/low formability metals has an extensive industrial application but drawing at room temperature, it has serious difficulties because of the large amount of deformations and high flow stress of the materials[6]. Drawing at the elevated temperatures decreases the flow stresses and increased formability of the materials hence deformations become easier[7, 8]. Since elevated temperature results in decreased flow stresses and increased formability in the sheet, it allows deeper drawing and more stretching to form products [9].

Stainless steels are very vast industrial applications due to its high strength. These materials are essentially non magnetic in the annealed condition and can be hardened only by cold working. They usually possess excellent cryogenic properties and good high-temperature strength and oxidation resistance. Austenitic stainless steel offer excellent corrosion resistance in organic, acid, industrial and marine environments. The non-magnetic properties combine with exceptionally high toughness at all temperatures makes these steel an excellent selection for many marine, nuclear and space applications. Various investigations have recently carried out to understand the properties of these materials at high temperature. These properties are essential to carry out FE studies while drawing the material in warm conditions. ANN model are also developed to calculate these properties at unknown temperatures [10-11].

Despite the large application of stainless steel in industry there is still s lack of knowledge about its formability and fracture in particular for the austenitic stainless steel (ASS) 316. These facts have led to the thorough study and understand the formability behaviour of this material and its nature of fracture. The determination of these conditions implies not only the usual mechanical characterization but also the performance during deep drawing process [12-15]. The limiting drawing ratio (LDR) is defined as the formability of sheet metal. In the present investigation, deep drawing of different diameter circular blanks was used to find the LDR of drawn cups at different temperatures.

Artificial neural network predictors for mechanical properties of cold rolling products [16-21] is Controlling product mechanical properties is an important stage in steel production lines. But their high cost. Artificial Neural Network (ANN)[15-21]. For monitoring product mechanical properties without need for expensive laboratory tests. In view of the following, in the proposed research following objectives are earmarked.

II. Development Technology and Economic Factor of Constitutive Models

2.1 Technological and economic factors

The hardening of material is practically inexistent and spring-back is zero; these features characterise a very good finished product, with dimensional accuracy, avoiding finishing interventions. In the aerospace industry, superplastic forming has been used for thirty years.

The forming process is expensive, the working temperature is very high (60% of melting temperature), the average size of grains must be less than 10 μm, the strain rate less than 10-2 s-1. Materials with small grain size have a very expensive treatment. The different heat treatment kinds employed contributed to the improvement of the alloy mechanical properties. According to the alloys characteristic, the applied cooling rate and alloy additions seem to be a good compromise for mechanical properties. (L.A. Dobrzański, 2009)

The traditional forming limit diagram is described by a curve in a plot of major strain vs. minor strain. This curve defines the boundary between elastic or stable plastic deformation (lower curve) and unsafe flow (upper curve). The risk of failure is determined by the distance between the actual strain condition in the forming process and the forming limit curve. (J. Majak, 2007)

The possibility of using SPF is limited by the slow strain rates, which is an intrinsic characteristic of the process and must be localised inside the area of the available forming risk; that slow strain makes the lead time long. To use the SPF technology, it is necessary to take into account both technological and economic factors.

2.2 Metallurgical Requirements of Materials for Superplastic Forming

❖ Very fine grains: d < 10;

❖ High resistance to grain growth;

❖ Strain rate has a very pronounced effect on the flow stress σ_e .

❖ High resistance to pore formation

Table 2. Change in Microstructure in the Three Rate Zones (Sieger & Werle, 1994)

Zone I	Zone II	Zone III
Flow stress is almost inde-pendent of strain rate, low m values, only small deforma-tions possible	Strain rate has a pronounced effect on flow stress, high m values, large deformations pos-sible	Flow stress is almost independ-ent of strain rate, low m values, only small deformations pos-sible
Limited elon-gation of indi-vidual grains	Almost no elon-gation of individ-ual grains; Whole groups of grains glide as a packet; Grains move along parallel planes and a few exchanges of neighboring grains occur.	Individual grains heavily deformed due to multiple slide.

2.3 Behaviour of Flow Stress, m Value and Fracture Elongation within the Three Zones at Superplasticity

As summarized in table 2, the logarithmic strain rate has a very strong effect on flow stress in zone II. Both elongation at rupture and the m value also have their maxima in this zone. Zone I is rate insensitive, hence m and the attainable rupture elongation have their minimum values here. Similar conditions exist in zone III, i.e. low gradient of the flow stress curve with increasing strain rate. The m value also decreases in this zone. In summary, super plastic forming behaviour only occurs in the region of rate zone II. The m coefficient increases with a strain rate up to the maximum, as can be observed in figure 1.

In zone 1, the speed influence on the deformation mechanism is very low, and the exact indication of this fact is still not very well understood. The results in this region are often limited and inconsistent. (Samekto, 2005) From the viewpoint of microstructure, the limited elongation of individual grains occurs in this zone.

In zone 3, Individual grains are heavily deformed due to multiple slide; sensitivity coefficient m usually assumes values close to 0.2 and strain hardening coefficient n is bigger than 3, thus the creep rates are sensitive to changes in grain size. The predominant mechanism of deformation is the conventional dislocation movement, such as the movement of atoms and gaps. (Samekto, 2005)

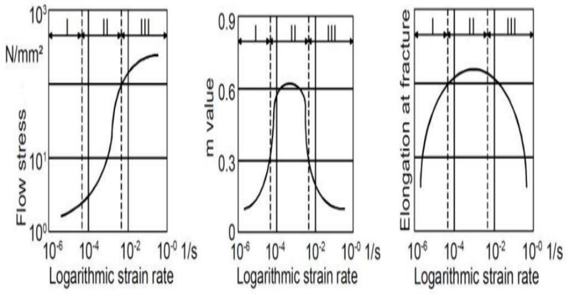

Figure 1 - Relation between Flow stress, Elongation at fracture and m with strain rate. Adapted (Siegert & Werle, 1994))

In zone 2, the existence of a stationary region is known, in which the strain rate is constant. It is commonly accepted that the existence of the steady state is the result of a balance between hardening and softening. The maximum value of m is and should be equal to or greater than 0.5. This value places the superplasticity phenomenon in this zone. (Samekto, 2005)

It is important to make explicit that there is currently no single model that is able to describe all the metallurgical and mechanical aspects involved in the SPF process. The parameters obtained by mechanical tests are not always exactly reproduced during forming, in which certain features observed during the tests are undesirable, such as Cavitation. The refinement of parameters such as temperature, time of shaping, thickness of the wall, backpressure, control model implemented and control monitoring conditions, is a barrier to the SPF process optimization. (Marinho, 2011).

III. Finite Element Simulation

Finite element method has been extensively used in forming operations to optimize various process variables in order to produce defect free parts. Generally, in any operation large amount of time is consumed in trial and error method and there are high chances that the tools are to be redesigned whenever the desired products are not obtained. Hence, this trial and error method involves lot of expenditure and loss of valuable time. To overcome this problem, process modeling by computer simulation called finite element method (FEM) has been introduced which simulates the actual process and thus saves time and money. Many commercial codes are available for finite element analysis in metal forming such as Dynaform, Abacus, Nike 2D. The finite element analysis in the present work is done using a commercially available code Dynaform version 5.6.1 with LS-Dyna version 971 solver with coupled thermal analysis for deep drawing at elevated temperature. The code is developed for applications such as sheet metal forming, automobile crashworthiness, occupant safety and underwater explosions. It is a non-linear dynamic simulation package which can simulate different types of sheet.

Metal processes like deep drawing, stretching, bending, hydro forming, stamping, etc. to predict stresses, strains, thickness distribution, etc. and the effect of various design parameters of tooling on final product can be studied. The input models like die, blank, blank holder and punch were constructed in pre-processor. After surface is generated, fine meshing is done on the surface of the tool components and on the blank and automatically the nodes are created. Fine meshing is done on the blank to obtain accurate results. The complete model in the pre-processor is shown in figure 2. The blank and the tool components were meshed using Belytschko-Tsay shell elements as it takes less computational time, around 30–50% less time than others [18]. Material properties that are calculated at room temperature and 200°C on UTM machine which is coupled with the furnace are used to run the simulation. Barlat's yield criteria is chosen as material model in simulation both at room temperature and at 200°C because Barlat's criterion incorporates the effect of both normal and planar anisotropy in the yielding behavior of the material at both the temperatures the material is anisotropic.

Deep drawing process was simulated at room temperature and 200°C using explicit finite element code LS-DYNA. The coefficient of friction was estimated both at room temperature and at 200°C by overlapping the load vs. displacement graphs obtained in simulation and in experimentation while drawing the blank of same diameter. LDR was calculated both at room temperature and at 200°C and it was found that simulated results

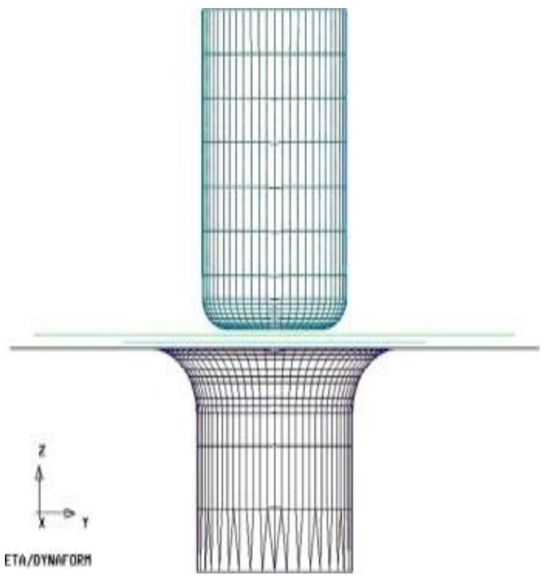

Figure 3.2. Assembly of tools in the pre-processor

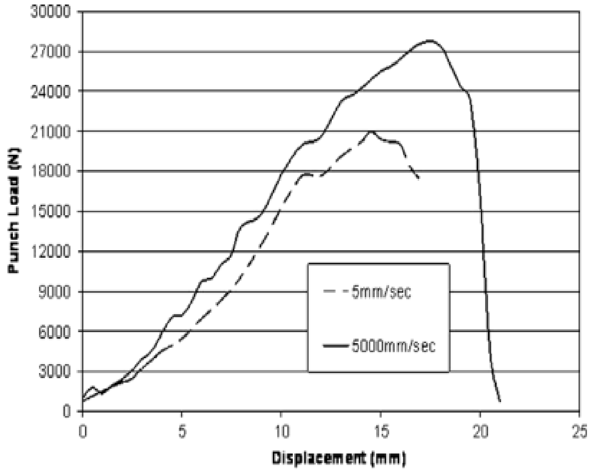

Figure 3. Punch load vs. displacement diagram from the simulation at two different punch speeds

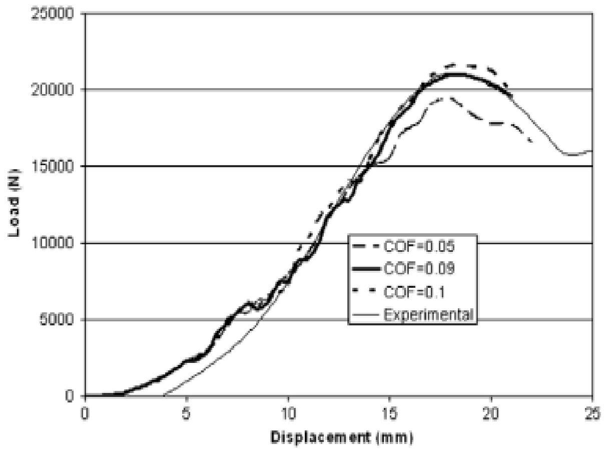

Figure 4. A Comparison of Punch Load vs. Displacement diagram from the simulationat different coefficient of friction and from experiments at room temperature. coefficient of friction

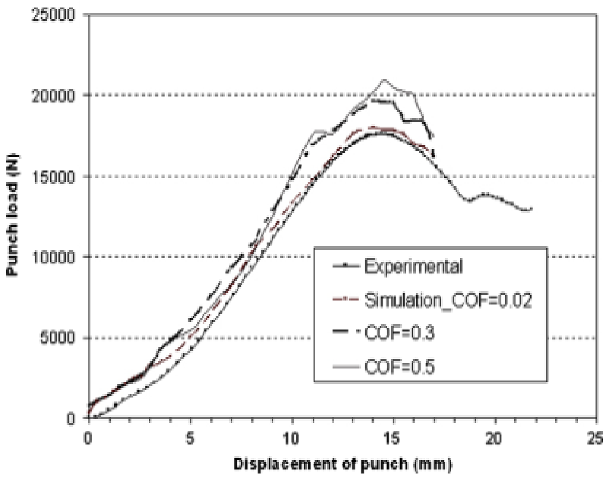

Figure 5. A comparison of punch load vs. displacement and from experiments at 200°C. diagram

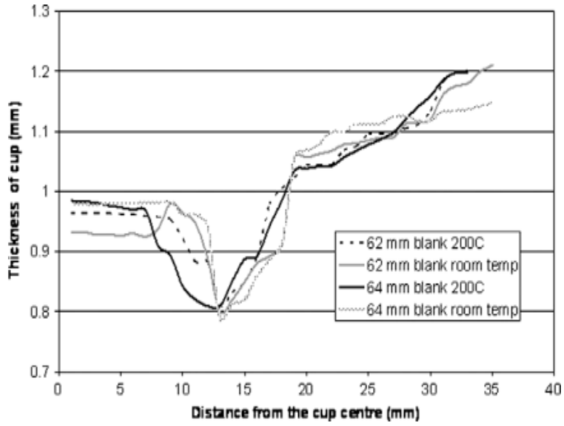

Figure 6. Comparison of thickness distribution of experimentally drawn cups of 62 from the simulation at different and 64 mm diameter blank for room temperature and at 200°C.

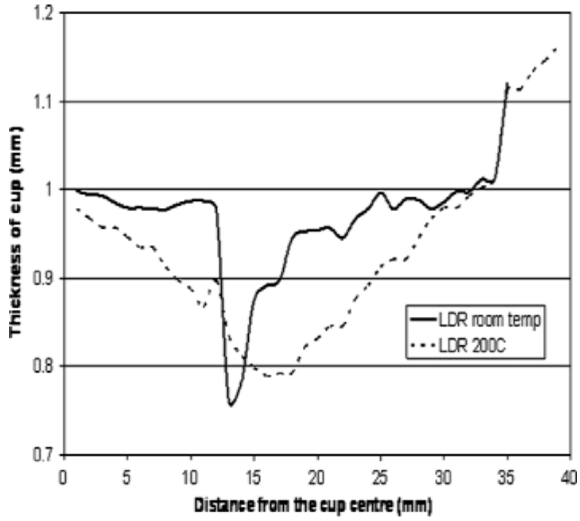

Figure 7. Comparison of thickness distribution of experimentally drawn cups at miting draw ratio (LDR) for room temperature and at 200°C.

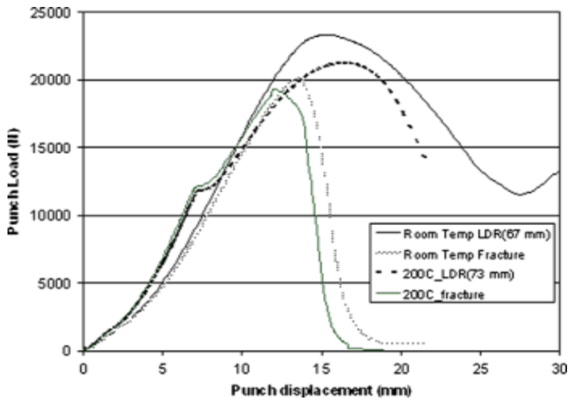

Figure 8. A comparison of experimental punch load vs. displacement diagram for deep drawing at room temperature and at 200°C for constant blank diameter.

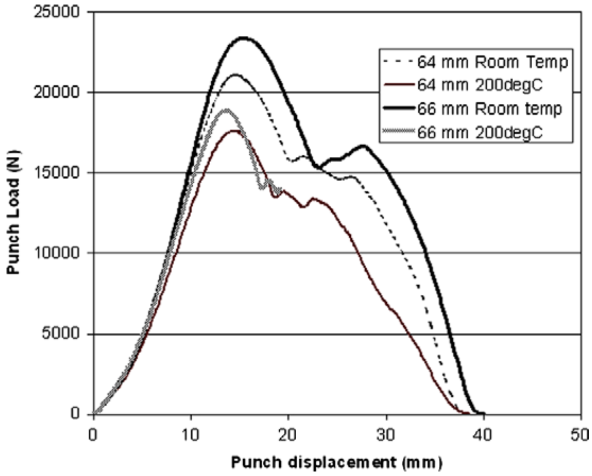

Figure 9. A comparison of experimental punch load vs. displacement diagram for deep drawing at room temperature and at 200°C at limiting draw ratio (LDR).

IV. Artificial Neural Networks (ANN) Model

Artificial Neural Networks methods are very valuable in processes where a complete understanding of the physical mechanisms is very difficult, or even impossible to acquire, as in the case of manufacturing processes where no satisfactory analytical model exists. The greatest advantage of ANNs is their ability to be used as an arbitrary function approximation mechanism that 'learns' from observed data. It can represent and capture complex non-linear relationships between inputs and outputs [18]. Lietal. [19] established the predicting model for the calculation of flow stress of Ti-15-3 alloy based on the ANN method. Reddy et al. [20,21] attempted to develop aback propagation neural network model to predict the flow stress of Ti–6Al–4V alloy for any given processing conditions.

Each neural network is composed of an input layer, an output layer and one or more hidden layers, which are connected by the processing units called neurons. Each neuron works as an independent processing element, and has an associated transfer function, which describes how the weighted sum of its inputs is converted to the results into an output value. Amidst the fact that there are diverse training algorithms available, an ANN with back propagation algorithm is adapted in this case to model flow stress behavior at elevated temperatures. The mean square error (MSE) is considered as a measurement criterion for a training set.

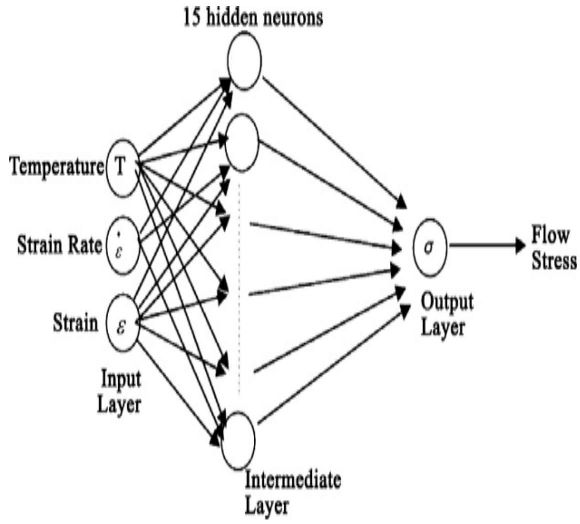

Figure 10. Plot of Mean Square error vs No. of intermediate neurons in the ANN Architecture.

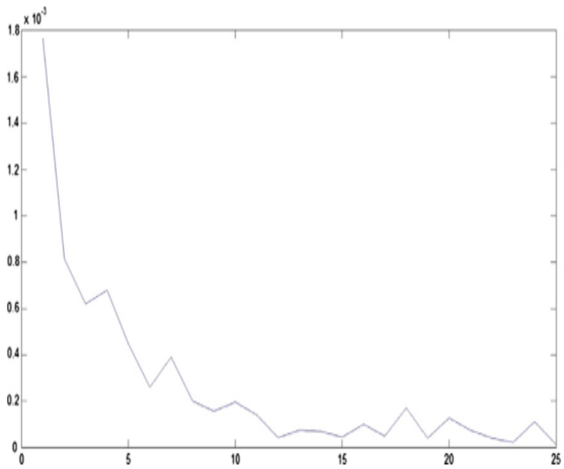

Figure 11. The Artificial Neural Network architecture

For this particular case, the input variables of ANN include stain, strain rate and deformation temperature, while the output variable is flow stress. Before training the network, the input and output datasets have been normalized to the range of 0.05–0.95 in order to prevent any specific factor dominating the learning curve of the ANN model. Moreover, as the variables have been measured in different units, normalizing the data matrix helps to recast them into the dimensionless units so as to remove the arbitrary effect of similarity between the objects. Thus, the experimental data was normalized to make the neural network training more efficient prior to the use of the datasets using Eq. (7).

X n= 0:05 + 0:90*(X – X min / X max -X min) (7)

where X min and X max are the minimum and maximum values of x and xn is the normalized data of the corresponding X. Once the best trained network is found, all the transformed data returns to their original value using Eq. (8).

X= X min + (X n - 0.05) * (X max - X min) / 0.90 (8)

The next step in modelling using ANN is deciding the ANN Architecture, which requires choosing appropriate number of hidden units. As the number of hidden layers determines the complexity of the neural network, various numbers of hidden layers were examined and the value of the mean square error was used to check the ability of a particular architecture. It is observed that the mean square error decreases to a minimum at 15 neurons and the same has been shown in figure 10. While having more number of neurons shows a decrease in the mean square error, in order to avoid over fitting, 15 intermediate neurons has been chosen.

Hence, the developed ANN, shown in figure 11, consists of three input neurons (corresponding to temperature, strain and strain rate), one intermediate hidden layer with fifteen neurons and one output neurons (flow stress). The hidden layer uses a hyperbolic tangent sigmoid (tansig) transfer function, while the output layer uses a linear (purelin) transfer function to map the output parameters. The results obtained from the experimental setup have been used to train the network. The data consisted of total 168 data points for the proper training of the network using

Levenberg – Marquardt function (trainlm). 10% (16) of the data was used as a testing data while the remaining 90% (152) was used to train the model. These data were chosen randomly using in built functions of MATLAB. The neural network toolbox of MATLAB software package is used for training and testing the given data.

4.1. ANN model:

From figure 12, the R value for the training data is at 0.9983 and the R value for the testing data is 0.9930. The delta value for the testing data is 2.4215%. It can be clearly seen that the training and testing data fall almost on the same line showing very good prediction capability of ANN model.

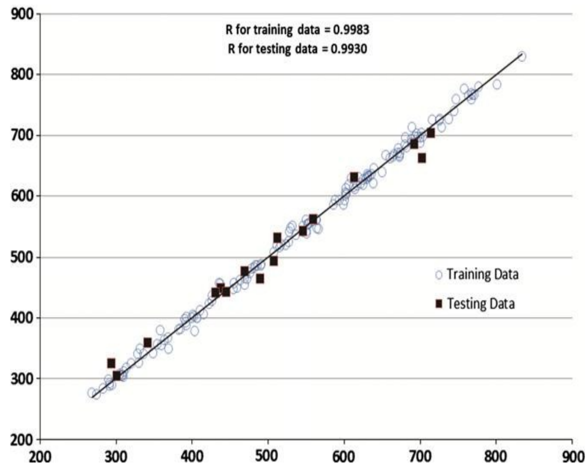

Figure 12. Plot of predicted vs. experimental stress for the Artificial Neural Networks model.

In this paper, a comparative study of the four constitutive models, namely JC model, modified ZA Model, modified Arrhenius type and ANN model, have been presented for the flow stress prediction in Austenitic Stainless Steel 316 at elevated temperatures. Based on the results and discussion, the following conclusions can be made:

1. From the correlation coefficient values, it can be concluded that modified ZA (R = 0.9879) and modified Arrhenius (R = 0.9852) models give better flow stress predictions in comparison to JC model (R = 0.9423), as JC model does not consider the coupled effects of strain, strain rate and temperature, while modified ZA model does consider these coupled effects. On the other hand, in modified Arrhenius model, Zener Hollman parameter (Z) considers the effects of temperature and strain rate on flow stress, while a nonlinear regression function is used to incorporate the strain effects.
2. The correlation coefficient of ANN model is 0.9930, which clearly shows that it very accurately reproduces the experimental flow stress. But, the present limitation of ANN model is its integration with FEM software, where it can converse with the FEM software with the ability to take input from and give output to it. Hence, further studies are required to develop this integration between ANN and FEM software.

The future work also involves flow stress studies beyond 350°C temperatures, where Austenitic Stainless Steel 316 enters into Dynamic Strain Aging (DSA) regime, in which the material behaves quite differently.

V. Conclusions

Deep drawing process was simulated at room temperature and 200°C using explicit finite element code LS-DYNA. The coefficient of friction was estimated both at room temperature and at 200°C by overlapping the load vs. displacement graphs obtained in simulation and in experimentation while drawing the blank of same diameter. LDR was calculated both at room temperature and at 200°C and it was found that simulated results are in good agreement with that of experimental ones. It was also found that while deep drawing at higher temperatures there is an increase in LDR value due to residual stress relieving and decrease in flow stress of material and while drawing at elevated temperatures there is uniformly distribution of thickness throughout the cup wall and this was justified both by using simulation and experimentation.

The mechanical properties of EDD steel like yield strength (YS), ultimate tensile strength (UTS), % elongation, strength coefficient (K) and work hardening exponent (n) were predicted using an Artificial Neural Network (ANN) model with feed forward back propagation. Temperature and orientation was treated as input layers and five mechanical properties are treated as output layers. The predicted results are in good agreement with the experimental data in the blue brittle region. This illustrates that ANN model gives highly accurate estimation of the mechanical properties in the region where the material properties behave abnormally. It was also observed that the load requirement in deforming the material increases in the blue brittle region and it was experimentally verified by conducting ironing tests. SEM studies were conducted on the UTM specimens in the three regions and it was found out that in the blue brittle region the primary mode of fracture is brittle.

In this context, we can implement ANN to the successful use of stainless steel, titanium and aluminum alloys in aerospace projects pushes some new technology processes forward, such as implementation ANN techniques for Superplastic forming.

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