Original Article

Experimental and numerical investigation of formability for austenitic stainless steel 316 at elevated temperatures

Syed Mujahed Hussaini a *, Swadesh Kumar Singh b, Amit Kumar Gupta a

a Department of Mechanical Engineering, Birla Institute of Technology and Science, Pilani, AP, India
b Department of Mechanical Engineering, Gokaraju Rangaraju Institute of Engineering and Technology, Hyderabad, AP, India

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A B S T R A C T

Sheet metal forming at elevated temperature is not much used in industries but it is going to be a very important process in the future. The present work is aimed to investigate the formability of austenitic stainless steel 316 at elevated temperatures. Limiting drawing ratio and thickness of the drawn cup are the indicators of formability in deep drawing. In the present investigation circular blanks are deep drawn at room temperature, 150 °C and 300 °C using a 20 ton hydraulic press coupled with a furnace. Finite element simulations are carried out using Dynaform with LS-Dyna solver. Simulations and experimental results show an increase in the limiting drawing ration as the temperature increases and a decrease in the thickness of the drawn cup without any fracture. An artificial neural network model is developed for the prediction of the cup thickness at different locations. Based on the input variables, such as distance from the center of the cup, temperature and LDR, a back propagation neural network model to predict the thickness as output was develop. The comparison between these sets of results indicates the reliability of the predictions. It was found that there is a good agreement between the experimental and predicted values.

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1. Introduction

Deep drawing is one of the important sheet metal forming process. Most of the sheet metal components are being produced in nuclear, automotive, aerospace and domestic applications by this process. In this, a thin sheet metal blank undergoes plastic deformation by forming tools such as punch, dies and gets a desired shape without fracture. This is one of the important methods of the sheet metal forming to produce complex components. Factors including mechanical and metallurgical properties of sheet metal, die, punch geometry, lubrication, sheet thickness, punch speed, etc. contribute to the success of the forming to varying degrees in an interdependent manner [1]. Therefore, an understanding of the formability of sheet metals is essential for the production of quality components.

In the deep drawing process, the sheet metal blank is subjected to the different types of stresses. Metal blank undergoes tension (cup wall), bending (punch and die corners) and compression (cup flange). Higher tensile strength and good ductility in compression are required properties for successful deep drawing the material. The flange of the cup undergoes radial tensile stresses due to the pulling of the blank into the die cavity by the punch and compressive hoop stresses due
to the reduction in the circumference. Wrinkles occur on the flange of the blank because of the compressive hoop stress. The blank-holder is provided with suitable force to prevent this to happen [2]. Cup wall undergoes longitudinal tensile stress, as the punch transmits the drawing force through it. Tensile hoop stress also builds in the flange due to the punch action. The punch force is limited to the maximum tensile load that can be carried by the wall of the cup. This maximum force limits the depth of flange that can be drawn [3].

Deep drawing of high strength metals at room temperature is a little difficult, because of the large deformation and high flow stresses of the materials. Whereas drawing at elevated temperatures leads to the decrease in flow stresses, relieves residual stresses and made the drawing easier [4,5]. It allows deeper drawing and more stretching in the final products [6,7]. Stainless steels are extensively used in industries for different applications due to its very good properties. Most of these materials are essentially nonmagnetic in the annealed condition and can be hardened only by cold working. These steels have higher oxidation resistance together with high strength and possess excellent cryogenic properties. Austenitic stainless steels offer excellent corrosion resistance in organic, acid, industrial and marine environments. The non-magnetic properties combined with exceptionally high toughness at all temperatures make these steels a good selection of cladding material in nuclear reactors.

Mechanical properties are required to carry out finite element (FE) analysis of forming the material at different conditions. Constitutive models and artificial neural networks (ANN) model were developed using these data to calculate these properties even at unknown temperatures [8,9]. Despite the large applications of stainless steel in the industry there is still a lack of understanding about its formability conditions at elevated temperatures, particular for austenitic stainless steel (ASS) 316. Formability of this material can be estimated through specific characteristics of the sheet undergone during the deep drawing process [10,11]. The limiting drawing ratio (LDR) is one of the commonly used characteristic of the formability, which can be measured in deep drawing. The LDR is the ratio of maximum blank diameter to maximum cup diameter, which can be produced in a single stroke without failure or fracture. Thickness of the drawn cup is also an important factor which governs the quality of the cup. In the present study LDR and the thickness of the drawn cup were found through finite element simulations using the explicit finite element code, LS-Dyna. These simulations are validated by performing the deep drawing experiments on the blanks of the same size used in simulations and compare the results. The thickness of the experimentally drawn cup was measured at the LDR. Using these thickness data an artificial neural network (ANN) model was developed to predict the thickness of the cup at unknown temperature, LDR with higher correlation coefficient and less error.

### Table 1 – Chemical composition of ASS 316.

<table>
<thead>
<tr>
<th>Element</th>
<th>Fe</th>
<th>Cr</th>
<th>Ni</th>
<th>Mo</th>
<th>Si</th>
<th>Mn</th>
<th>Cu</th>
<th>Co</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>Composition (wt%)</td>
<td>67.69</td>
<td>16.63</td>
<td>10.85</td>
<td>2.42</td>
<td>1.28</td>
<td>0.38</td>
<td>0.21</td>
<td>0.21</td>
<td>0.018</td>
</tr>
</tbody>
</table>

2. Material and experimentation

Material used in this study was ASS 316 sheet of 1.0 mm thickness. Chemical composition of ASS316 sheet metal blank was measured and listed in Table 1. This alloy contains 2.42% molybdenum which enhances the corrosion resistance in marine conditions. This steel is more resistant to general corrosion, pitting and crevice corrosion than the conventional chromium-nickel austenitic stainless steels such as Alloy 304. Resistance to corrosion in the presence of chloride or other halide ions is enhanced by higher chromium (Cr) and molybdenum (Mo) content. This alloy also offers higher creep, stress-to-rupture and tensile strength at elevated temperatures. It is almost complete austenitic phase and small quantities of ferrite also may present. Due to the presence of these phases it has excellent toughness besides high strength. These combinations of properties provide the excellent fabricability and formability to the material.

The deep drawing experiments were carried out on the experimental test rig shown in Fig. 1. This test rig is specially designed for deep drawing operations which can be performed at elevated temperatures. Complete punch and die set-up is made with Inconel-600 to prevent the materials to change dimensions at higher temperatures. An induction furnace was developed to heat the blank to a maximum temperature of 300 °C. Two sets of furnaces were installed on a 20 ton hydraulic press as shown in Fig. 2. One furnace is utilized to heat the blank and another is attached to the lower die for heating the die to the required temperature and maintain this temperature. A continuous coolant supply is provided.
Deep drawing was performed at room temperature, 150 °C and 300 °C on the circular blanks of different diameters. The experimental conditions of the deep drawing at different temperatures are mentioned in Table 2. Various cups drawn from different blank sizes ranging from a diameter of 64–74 mm at different temperatures are shown in Fig. 3. LDR at these temperatures were estimated experimentally. The drawn cup was cut in the center and made into two halves. The thickness of the cup was measured at an interval of 1 mm along the cross section using a digital micrometer. The thickness variation of the drawn cup from the center of the base to the top of the wall was determined. The study of thickness distribution enables to analyze the safe blank thickness that can be drawn without fracture.

### 3. Finite element simulation

Finite element methods have been extensively used in forming operations to optimize various process variables in order to produce defect free parts. In forming 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 desired products are not obtained. Hence, this trial and error method involves a lot of expenditure and loss of valuable time. To overcome this problem, process modeling using computer simulation by finite element method (FEM) has been introduced which simulates the actual process. Many commercial softwares are available for finite element analysis in metal forming including Dynaform, ABAQUS, Nike 2D, etc. The finite element analysis in the present work is done using Dynaform version 5.6.1 with LS-Dyna, version 971 solver for deep drawing with the material properties at elevated temperatures. It is a non-linear dynamic simulation package which can simulate different types of sheet metal processes to predict stresses, strains, thickness distribution and the effect of various design parameters of tooling on the final product.

The input models, such as die, blank, blank holder and punch were constructed in pre-processor dynaform. After the surface was created, meshing was generated on the surface of

<table>
<thead>
<tr>
<th>Table 2 – Deep drawing experimental conditions.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Temperature</td>
</tr>
<tr>
<td>-------------------</td>
</tr>
<tr>
<td>Room temp</td>
</tr>
<tr>
<td>150 °C</td>
</tr>
<tr>
<td>300 °C</td>
</tr>
</tbody>
</table>

![Fig. 3 – Drawn cups from different diameter and at different temperatures.](image-url)
the tool components and the blank. Fine meshing was done on the blank to obtain accurate results. The complete tooling model of the pre-processor is shown in Fig. 4. The blank was meshed using Belytschko-Tsay shell elements as it takes less computational time, around 30–50% less than others [13]. The tool components were considered as rigid bodies so they were meshed using solid elements. Material properties which were given as input to dynasty to run the simulation were measured at different temperatures with the universal testing machine (UTM) coupled to the furnace. The properties of austenitis stainless steel (ASS) 316 that were found from UTM at different temperatures and friction at the blank and tool interface are shown in Table 3. Friction in deep drawing under warm conditions can be reduced by using molybdenum as a lubricant, which was calculated by Singh et al. [4] at various temperatures. Simulations were repeated by changing the size of the blank and temperature. The blank holding force was changed with temperature but speed was maintained 1 m/min similar to those of the experiments.

Barlat’s yield criteria were chosen as the material model in the simulations. This criterion incorporates the effect of both normal and planar anisotropy in the yield behavior of the material. This model was developed by Barlat et al. [14] for modeling the sheets with anisotropic materials under plain strain conditions. This material model allows the use of Lankford parameter in 0°, 45° and 90° to the rolling direction for the determining of anisotropy. The anisotropic yield criterion for plane stress is defined as:

$$\phi = a|K_1 + K_2|^m + a|K_1 - K_2| + c|2K_2|^m = 2\sigma_y^m$$  \hspace{1cm} (1)

where $\sigma_y$ is the yield stress and $K_1$ are given by

$$K_1 = \frac{\sigma_x + h\sigma_y}{2} \quad \text{and} \quad K_2 = \sqrt{\frac{\sigma_x + h\sigma_y}{2} + \rho^2\tau_{xy}^2}$$  \hspace{1cm} (2)

The anisotropic material constants $a$, $c$, $h$ and $p$ were obtained through $R_0$, $R_{45}$, $R_{90}$.

4. Development of ANN model

Artificial neural network (ANN) is a powerful data information treatment system which tries to simulate the neural network structure of the human brain. It can form complex non-linear relationships between inputs and outputs. 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 into the results into an output value. Currently, there are diverse training algorithms available. Among the various kinds of ANN approaches that have existed, the back propagation (BP) learning algorithm has become the most popular in engineering applications. BP algorithm is based on minimization of the quadratic cost function by tuning the network parameters. The mean square error (MSE) is considered as a measurement criterion for a training set. Specially, BP neural network is the most suitable tool for treating non-linear systems.

BP algorithms were applied to train a feed forward neural network, which are reliable and most commonly utilized. In this investigation, the input variables of ANN were temperature, LDR and distance from the center of the cup, while the output variable was thickness. A feed forward network was developed and trained with the back propagation algorithm, as shown in Fig. 5. Before training the network, the input and output datasets had been normalized within the range of 0.05–0.95 to prevent a specific factor from dominating the learning for the ANN model. The main reason for normalizing the data matrix was that the variables have been measured in

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**Fig. 4** – Construction of tooling in the pre-processor.

**Fig. 5** – Schematic illustration of the neural network architecture.
different units. These were recast into the dimensionless units to remove the arbitrary effect of similarity between the objects. Thus, using Eq. (3), the experimental data were normalized to make the neural network training more efficient prior to the use of the datasets. Where \( X_{\text{min}} \) and \( X_{\text{max}} \) are the minimum and maximum values of \( X \) which are the normalized data of the corresponding \( X \). Once the best trained network is found, all the transformed data return to their original value using Eq. (4).

\[
X_n = 0.05 + 0.90 \frac{X - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}}
\]  

(3)

\[
X = X_{\text{min}} + \left( X_n - 0.05 \right) \frac{X_{\text{max}} - X_{\text{min}}}{0.9}
\]  

(4)

The architecture of ANN selection requires choosing both the appropriate number of hidden units and the connections thereof. The desirable network architecture contains as minimal as possible hidden units and connections necessary for a good approximation of the true function. In most of the applications of ANN, this selection was done using a trial-and-error procedure. The number of hidden layers determines the complexity of neural network and precision of predicted values. If the architecture is too complex, it may not converge during training or the trained data may be over fitted. In another way, the trained network might not have sufficient ability to learn the process correctly. Therefore, various network structures with varying number of neurons in hidden layer were examined. Fig. 6 shows the influence of the number of neurons in hidden layer on the network performance. The value of mean square error (MSE) was used to check the ability of a particular architecture. It was observed that the mean square error of the network decreases to the minimum value when the number of neurons was 15. This indicates that a network with 15 neurons in hidden layer can exhibit the best performance.

5. Results and discussion

Deep drawing simulations were performed in LS Dyna as per the real conditions. Fig. 7 shows the drawn cup from the blanks of 66 mm diameter at room temperature conditions and forming limit diagram (FLD) of the cup. FLD is a graph between the minor strain and major strain of the sheet metal. Possibility of fracture in the cup can analyze and can be compared with the forming limit curve (FLC), which appeared in FLD. It shows that the strain in the cup is below FLC, which indicates that the drawing is in the safe zone. There is no indication of fracture in the cup walls. Thickness of the cup at punch corner was reduced to 0.91 mm without necking. At room temperature when 67 mm blank was drawn, the strain in the cup has crossed the FLC as shown in Fig. 8 which is not safe. The thickness at punch corner was reduced to less than 0.2 mm and leads to fracture. This fracture occurred at the punch corner due to increase in the tensile strain. At room temperature maximum of 66 mm diameter blank can be drawn into 30 mm cup without fracture; hence LDR is 2.2.

These simulation results were experimentally validated on deep drawing test set-up shown in Fig. 2. Experimentally drawn cups from 64 mm and 66 mm diameter blanks at room temperature are shown in Fig. 3. The next higher size of the blank fracture was occurred around the punch corner during drawing as shown in Fig. 9. Thickness of the cup at LDR was measured and presented along the distance as shown in Fig. 10. Thickness distributions in the simulations were well matched with the experiments. These experiments confirmed the FE predictions which show that the LDR at room temperature is 2.2. It can be observed from Figs. 8–10 that necking in the drawn cup occurred near punch corner. Being a hard material, the effect of the maximum stress region and convergent on stress contour ratio lines can be seen at the cup bottom where the thickness of drawn cup was lower than the original sheet thickness (1 mm). Increase in the thickness of the cup wall above 1 mm was due to the compressive hoop stresses in radial direction [15].

![Fig. 6 – Influence of hidden neurons on the network performance.](image1)

![Fig. 7 – Drawn cup at room temperature from φ66 mm blank and FLD by FEM.](image2)

![Fig. 8 – Fracture in the cup drawn from φ67 blank and FLD at room temperature.](image3)
Finite element simulations were performed on the blank of diameter higher than 66 mm at elevated temperatures. As the temperature was increased, the higher sizes of the blanks can be deep drawn without fracture. Maximum of 70 mm diameter blank can be deep drawn safely at 150 °C as shown in Fig. 11. Further increase in temperature to 300 °C maximum of 75 mm blank can be deep drawn safely. At the temperature of 150 °C the LDR was 2.33 and is further increased to 2.5 at 300 °C. These simulated results were experimentally validated and found a good agreement between them. At elevated temperatures, cups were drawn from the higher size of the blanks without fracture on the experimental set-up as shown in Fig. 3. Due to the increase in temperature, there is a decrease in mean flow stress which results in increase in the LDR of the sheet.

Thickness distribution of experimentally drawn cups at LDR was compared with simulated cup thickness as shown in Figs. 12 and 13. It was found that there is a good correlation between them. It was also observed that as the blank diameter increased, there was an increase in the punch load to draw the cup and hence it increased the thinning effect of the cup. Whenever the temperature of the blank increases strength of the material decreases so BHF should be decreased. BHF plays an important role and greatly influence the quality of cup in

Fig. 11 – Drawn cups at 150 °C from Ø70 mm and 300 °C from Ø75 mm by FEM.
Fig. 13 – Thickness distributions of drawn cup at 300 °C.

Fig. 14 – Comparison between thickness experimental and predicted values for the training.

Figs. 14 and 15 represent the predicted versus experimental flow stress values for the training and testing datasets, respectively. The correlation coefficient was found to be 0.9976 for the training dataset and 0.9954 for the testing dataset. This indicates a very good correlation between experimental and predicted thickness values. The results imply that the developed ANN model for austenitic stainless steel 316 is consistent with what is expected from the fundamental theory of hot deformation. Recently researchers [17] modeled DSA phenomenon using ANN and prediction of flow stresses were made very accurately. Singh and Gupta [8] also supported that ANN model can be applied to serrated flow and flow stresses can be predicted very accurately once sufficient input data is calculated in the DSA region by experiments. In the present research the ANN predicted the thickness distribution of the drawn cup at any unknown temperature to a very close accuracy.

Table 4 shows the experimental and the ANN model predicted thickness along with the associated absolute and percentage errors for randomly selected unseen testing dataset. The maximum percentage error was found to be 1.1%, which is considered to be very low. As the temperature of the material increases there will be decrease in the cup thickness due to the decrease in flow stress and work hardening coefficient. In general, the performance of any function fitting technique will be better if more numbers of data are taken near the domain boundaries. This ANN model predicts the thickness to very high accuracy.

<table>
<thead>
<tr>
<th>Temperature</th>
<th>By FEM</th>
<th>By experimentation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Room temp</td>
<td>2.2</td>
<td>2.2</td>
</tr>
<tr>
<td>150 °C</td>
<td>2.33</td>
<td>2.33</td>
</tr>
<tr>
<td>300 °C</td>
<td>2.5</td>
<td>2.47</td>
</tr>
</tbody>
</table>

Fig. 15 – Comparison between thickness experimental and predicted values for the testing dataset.
Table 5 – Comparison of ANN predicted vs. experimental thickness for the testing dataset.

<table>
<thead>
<tr>
<th>S.No.</th>
<th>Temp</th>
<th>LDR</th>
<th>Distance</th>
<th>Exp</th>
<th>Predicted</th>
<th>Error</th>
<th>% Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>50</td>
<td>66</td>
<td>7</td>
<td>0.902</td>
<td>0.913</td>
<td>0.011</td>
<td>1.1</td>
</tr>
<tr>
<td>2</td>
<td>50</td>
<td>66</td>
<td>20</td>
<td>0.997</td>
<td>1.002</td>
<td>0.005</td>
<td>0.5</td>
</tr>
<tr>
<td>3</td>
<td>50</td>
<td>66</td>
<td>23</td>
<td>1.019</td>
<td>1.017</td>
<td>0.002</td>
<td>0.2</td>
</tr>
<tr>
<td>4</td>
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<td>66</td>
<td>24</td>
<td>1.019</td>
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<td>0</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>50</td>
<td>66</td>
<td>30</td>
<td>1.056</td>
<td>1.054</td>
<td>0.002</td>
<td>0.2</td>
</tr>
<tr>
<td>6</td>
<td>150</td>
<td>70</td>
<td>6</td>
<td>0.915</td>
<td>0.915</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>7</td>
<td>150</td>
<td>70</td>
<td>19</td>
<td>0.925</td>
<td>0.926</td>
<td>0.001</td>
<td>0.1</td>
</tr>
<tr>
<td>8</td>
<td>300</td>
<td>74</td>
<td>11</td>
<td>0.859</td>
<td>0.856</td>
<td>0.003</td>
<td>0.3</td>
</tr>
<tr>
<td>9</td>
<td>300</td>
<td>74</td>
<td>17</td>
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<td>0.865</td>
<td>0.009</td>
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</tr>
<tr>
<td>10</td>
<td>300</td>
<td>74</td>
<td>18</td>
<td>0.866</td>
<td>0.878</td>
<td>0.012</td>
<td>1.2</td>
</tr>
<tr>
<td>11</td>
<td>300</td>
<td>74</td>
<td>25</td>
<td>0.949</td>
<td>0.951</td>
<td>0.002</td>
<td>0.2</td>
</tr>
</tbody>
</table>

6. Conclusions

In this study, formability of austenitic stainless steel 316 has been investigated by finite element analysis at different temperatures. Deep drawing process was simulated in explicit finite element code LS-DYNA. It was found that at room temperature limiting drawing ratio was 2.2. As the temperature was increased LDR increased to 2.33 at 150°C and further increased to 2.47 at 300°C. This increase in LDR is due to the decrease in mean flow stress at elevated temperatures. The thickness reduction of the cup was greater when drawn at higher temperatures but without fracture. The higher value of the work hardening exponent of this material at an elevated temperature leads to resistance to fracture of the cup at the punch corner. Increase in LDR and variation in thickness from the center of the cup to the top of the wall was greater due to higher formability at the elevated temperatures. ANN model was developed to predict the thickness of the drawn cup at LDR of unknown temperature with very low error and higher correlation coefficient. It was found that there is a good agreement between predicted and experimental results. ASS316 showed improvement in the formability at the temperature range 150–300°C and this was experimentally validated and justified.

Conflicts of Interest

The authors declare no conflicts of interest.

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