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Prediction of Forming Limit Diagram for Ti-6Al-4V Alloy Using Artificial Neural Network

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Abstract

In sheet metal industries, the ability to predict and avoid failures, such as necking, fracture and wrinkling are of great importance. It is important to work within the safe strain region to avoid these failures. The forming limit diagram (FLD) is the most appropriate tool to obtain the safe strain region for every sheet metal in different strain conditions and ration. In this paper, significance of important process parameters namely, punch speed, blank holder pressure (BHP) and temperature on FLD of a Ti-6Al-4V alloy are investigated. Taguchi technique was employed to identify the influence of these parameters on major strain and minor strain. The finite element model of deep drawing process has been built up and analyzed using Dynaform version 5.6.1 with LS-Dyna version 971 as solver. The simulations have been performed in Taguchi order to obtain the values of major strain and minor strain. Furthermore, the values of major and minor strain is predicted using artificial neural network (ANN) considering input parameters as punch speed, blank holder pressure (BHP) and temperature and normalized distance of a cup. Forming limit curve is drawn by using Keeler's equation considering the properties of Ti-6Al-4V at various forming temperatures. It is observed that the predicted strain values are in good agreement with the experimental data.

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Keywords: Ti-6Al-4V; Deep Drawing; FEA, Taguchi Method; FLD; ANN.

1. Introduction

Over the years, titanium and its alloys have proven themselves to be superior and cost effective materials for a wide range of applications in various industries, such as aerospace, automobile, marine and biomedical (Poondla N, Srivatsan T.S. , Patnaik A., 2009).

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Ti–6Al–4V alloy has an attractive combination of characteristics in terms of high mechanical properties, elevated corrosion resistance and low density, which consider it an excellent alternative for various fields of application(Seshacharyulu et al., 2000; Vanderhasten et al., 2007). The plastic forming is one of the main forming technologies to fabricate titanium components that can not only reduce the cost due to machining, but also enhance the performance of the products (Chen and Chiu, 2005). However titanium alloys are difficult to form because of their high deformation resistance, low ductility at room and low elevated temperature, large anisotropy and strong microstructural sensitivity to processing, which confine the size, precision and quality of titanium products and consequently lead to the increase of production costs and cycle times(Luo et al., 2010).

The sheet metal forming process is dependent on large number of parameters and their interdependence(Padmanabhan et al., 2007). These are material properties, machine parameters such as tool and die geometry, work piece geometry and working conditions. Research and development in sheet metal forming processes requires lengthy and expensive prototype testing and experimentation in arriving at a competitive product. A successful sheet metal forming operation can be carried out if the major strain and minor strains are within formability range. Determination of major strains and minor strain with all set of variation of process parameters are very laborious and tedious work. Therefore numerical investigations are very much useful tool for the prediction of major and minor strain.

In the present investigation, an attempt has been made to study the effect of these three important process parameters namely punch speed, blank holder pressure (BHP), and temperature on forming limit diagram. Taguchi method of experimental design was used to plan the numerical simulations. In Taguchi design, after the experiments are designed with various combinations of process parameter levels. Finite element (FE) simulations were carried out to predict the deformation behavior of the blank sheet. These FE simulations results were treated as input to artificial neural network to predict major strain and minor strain at any combination of process parameters within considered range of process parameters used in simulations. Artificial neural network developed is used to observe forming limit diagram at different combinations of process parameters which reduced the extra simulation time.

1.1. Finite Element Simulations

Taguchi proposed several methods to experimental designs called Taguchi method. This method utilizes an orthogonal array, which is a form of fractional factorial design containing a representative set of all possible combination of experimental conditions. Using Taguchi method, a balanced comparison of levels of the process parameters and significant reduction in the total number of required simulations can both be achieved. Taguchi L_9 orthogonal array was used to study the effect of three process parameters in nine experiments shown in Table 1 and

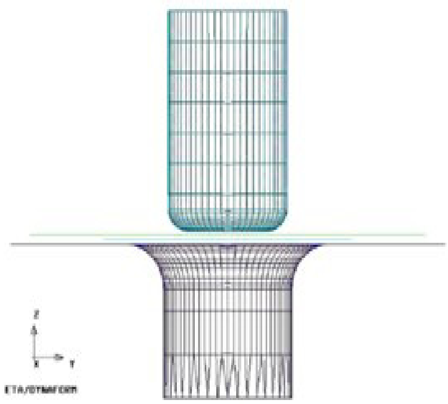

Fig. 1 Finite Element model of deep drawing setup

Table 2. The process parameters studied were, punch speed, BHP and temperature. Three levels (low, medium, high) were used for each parameter. The finite element analysis in the present work is done using Dynaform version 5.6.1 with LS-Dyna version 971 solver. The input models like die, blank, blank holder and punch were modeled in pre-processor. For present study, iso-thermal models are used. After surface is generated, fine meshing is done on the surface of the tool components and on the blank. Adaptive meshing is done on the blank to avoid inaccuracy due to large aspect ratio of element. The complete finite element model in the pre-processor is shown in Figure.1 The blank and the tool components were meshed using Belytschko- Tsay shell elements as it reduces computational time, around 30–50% less time than others(Singh et al., 2010). Properties of material such as strength coefficient (K), strain hardening exponent (n), and Lankford coefficients for 0^0,45^0, 90^0 orientations were calculated using uniaxial tensile test carried out at 150^0C, 300^0C and 450^0C at 0.01 s^{-1} strain rate. Three parameter Barlat's yield criterion is used as material model in simulation since it includes the effect of both normal and planar anisotropy in the deformation behavior of the material. The strain rate effect is not included in the Balart's three parameters model. The constant m for Ti-6Al-4V alloy required for three parameters Balart's yield criteria is obtained as 6. The coefficient of friction under the forming conditions is calculated by selecting appropriate plot obtained from simulation which gives a good match with the maximum punch force plot from the experimentation(Singh et al., 2010).

Table 1. Three Levels for Process Parameters

Parameters	1	2	3
Punch Speed (mm/s)	10	100	1000
Temperature (^{0}C)	150	300	450
BHP (Bar)	16	18	20

Table 2. Taguchi orthogonal array

Number	Punch Speed	Temperature	BHP
1.	1	1	1
2.	1	2	2
3.	1	3	3
4.	2	1	2
5.	2	2	3
6.	2	3	1
7.	3	1	3
8.	3	2	1
9.	3	3	2

1.2. Artificial neural network

The Artificial Neural Network (ANN) is an authoritative data information treatment system that captures complex non-linear interactions 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. Presently, there are different training algorithms available.

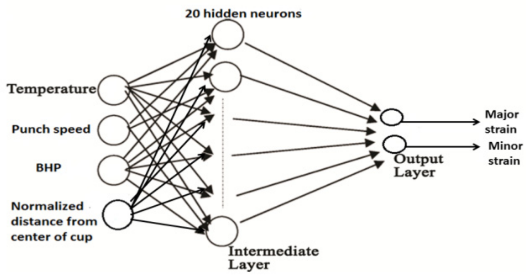

Fig. 2 Schematic representation of ANN architecture

Among the various kinds of ANN approaches that have existed, the back propagation (BP) learning algorithm has become the most popular in engineering applications. The BP trained ANN is the most suitable tool for treating non-linear systems. Hence, a back propagation algorithm was used to train a feed forward neural network, which is consistent and most commonly utilized (Amit Kumar Gupta, Swadesh Kumar Singh, Swathi Reddy, n.d.).

2. RESULT AND DISCUSSION

The simulations were carried out on 54 mm diameter blank in Taguchi order mentioned in Table 2. 3 parameter Barlat's yield model was used for the simulation. A section of simulated drawn cups was cut and values of major and minor strains were obtained from one edge of the cut to another edge. Forming limit curve is plotted using Keeler's formula is shown below. The values of strain hardening exponent (n) were calculated by performing tensile tests at 150^0 C, 300^0 C and 450^0 C.

$$FLD_0 = n \times (23.3 + 14.134 \times t)/21.0$$

The forming limit curve can be plotted by

$$\varepsilon_{major} = FLD_0 + \varepsilon_{minor} \times (0.02754 \times \varepsilon_{minor} - 1.1965) \qquad for \qquad \varepsilon_{minor} < 0$$
$$\varepsilon_{major} = FLD_0 + \varepsilon_{minor} \times (-0.008565 \times \varepsilon_{minor} + 0.784854) \qquad for \qquad \varepsilon_{minor} > 0$$

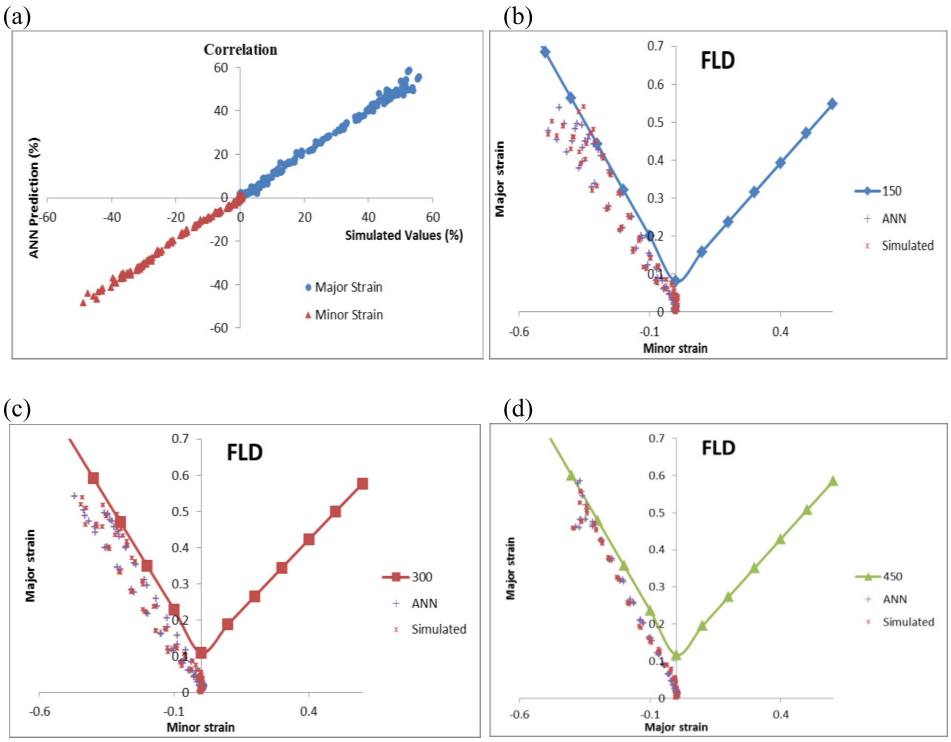

Fig. 3 (a) correlation of simulated and ANN data; FLD at (b) 150^0C (c) 300^0C (d) 400^0C

The Artificial Neural Network (ANN) is an authoritative data information treatment system that captures complex non-linear interactions between inputs and outputs. Hence major strain and minor strain data have been trained using ANN. 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. The ANN architecture used in this prediction is

4-20-2, having four input neurons, twenty neurons in the intermediate layer and two output neurons. The ANN model has an excellent capability to predict these data and the same can be seen with the correlation coefficient value (R) which is close to 0.99 for both major and minor strain. The absolute average error (Δ) for prediction of major and minor strain is 4.2% and 1.7% respectively. The ANN model also showed excellent predictability with least possible error in validation as well as testing sets. The correlation of simulated and ANN data is shown in fig.2 (a).

The input layers of neurons consisting of blank holder pressure, temperature, punch speed and normalized distance. Output layer of neurons consisted corresponding value of major strain and minor strain. The predicted values showed excellent correlation with simulated data. ANN prediction of major and minor strain was plotted along with forming limit curve. It is observed that at 150^0 C and higher punch speeds there is a fracture in cup due to necking. At 450^0 C, the cup was formed but at lower speed i.e.10 mm/s. Also ANN prediction showed that a cup can be drawn without failure in neck at 400^0 C at 100 mm/s. forming limit diagram at 150^0C,300^0C and 450^0C is shown in fig.2(b)(c)&(d).

A simulation was carried out at 400^0 C with 100 mm/s punch speed and 16 bar blank holding pressure on Ti-6Al-4V blank. It is observed that the forming limit diagram very well matches with major and minor strain plot obtained by ANN. Hence ANN network can be used to study the forming limit diagram so that forming operation can be successfully done at lowest possible temperature and highest possible punch speed. In this study, the input variables of the ANN include process parameters viz., punch speed, BHP, temperature and location of thickness along the cross section where the output variables are thickness distribution. The simulated result of deep drawn cup is shown in fig.3.

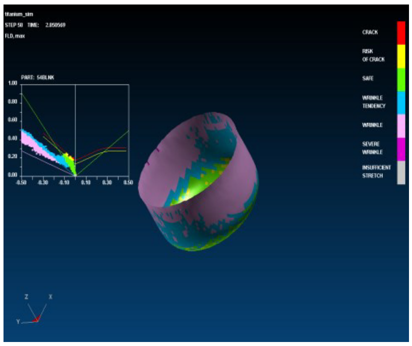

Fig. 4 Simulated deep drawn cup at 400^0C and 100mm/s punch speed

3. Conclusion

The ANN model has a good capability to predict these data and the same can be seen with the correlation coefficient value (R) which is close to 0.99 for both major and minor strain. The absolute average error (Δ) for prediction of major and minor strain is 4.2% and 1.7% respectively. Therefore, ANN can be effectively used to avoid experimental try-outs and FE simulations to observe the formability of Ti-6Al-4V sheet.

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