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Prediction of Geometrical Instabilities in Deep Drawing Using Artificial Neural Network

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Abstract: Geometrical instabilities like wrinkling and necking are 2 major defects in deep drawing process. Because of them, drawability is greatly reduced leading to huge lose of material and money. Friction has an important bearing on wrinkling and necking. Hence their prediction is of utmost importance in deep drawing process design. In past such prediction were made via trial and error approaches based on shop floor experiences. But such approaches are crude and time consuming. To overcome these difficulties, Artificial Neural Network (ANN) has been used in this study. Neural networks are trained based on finite element simulated data. Limiting strain hardening exponent for the success of deep drawing, are arrived at from FE simulations. It has been shown that proposed approach is powerful and fast in predictions of geometrical instabilities in deep drawing process.

Key words: Deep drawing, wrinkling, thinning, finite element, neural network

INTRODUCTION

Deep drawing is a class of sheet metal forming process used for manufacturing of cups, beverage cans etc. Major defects in deep drawing are wrinkling and necking, which restrict the depth of drawing. Wrinkles are the surface defects in the form of small waves and folds. Wrinkling of the flange or the edges of the cup results from the buckling of the sheet as a result of the higher circumferential compressive stresses. Eighty percent of the part failure in automotive pressing can be attributed to wrinkling of the flange or corner region (Dieter, 1989). The other common failure is the thinning near the punch radius, which may lead to fracture. Thinning depends upon die, punch radius and blank holder force. Prediction and prevention of wrinkling and necking are few of the most important steps for the deep drawing process design (Rao, 1998). Friction plays an important role on these defects. There existence a limiting friction beyond which deep drawing can't take place, as frictional force will be so large and it would not allow the sheet to move leading to necking and fracture. In previous days predictions of these defects were carried out via trial and error method supported by shop floor experiences. But such techniques were time consuming and costly affairs due to large number of try outs on shop floor. Application of numerical techniques like finite element method in such studies, have become very popular due to their being of non-destructive nature. Moreover, they are fast, accurate and economical. Doege *et al*. (1995) predicted necking and wrinkling in sheet metal forming using Continuum Damage Mechanics (CDM) approach. Ahmetoglu *et al*. (1997) determined wrinkling and fracture limits and developed blank holder forces control methods to eliminate defects, improve part quality and increase the draw depth in deep drawing of aluminum alloys. Chu and Xu (2001) analysed the onset of flange wrinkling of a deep drawing cup considering it as an elasto-plastic bifurcation problem. Correia *et al*. (2002) predicted wrinkling in the deep-drawing process of anisotropic metal sheets and showed the attainment of critical wrinkling conditions were significantly affected by the influence of anisotropy on the stress state and sheet curvature developed in the wall prior to bifurcation. Analytical and numerical investigations of wrinkling in deep-drawn anisotropic metal sheets, were carried out by Correia *et al.* (2003). Singh and Ravi (2003) used Artificial Neural Network (ANN) to predict the thickness along a cup wall in hydro-mechanical deep drawing. Cloth, Lee and Chun (2005) investigated the variation of deep drawability of STS-304 using FE simulations and attributed the wrinkles found at the corner of the blank to the unbalanced inflow of the sheet metal between the step edges. Zhang *et al*. (2006) analyzed the conditions of process defects such as flange wrinkling and ruptures. Experiments were carried out to verify the computer simulation results. In this study, artificial neural network is applied for prediction of geometrical instabilities in deep drawing. Finite element analyses results of 9 sets of varying strength coefficient (K), strain hardening exponent (n) and friction coefficients

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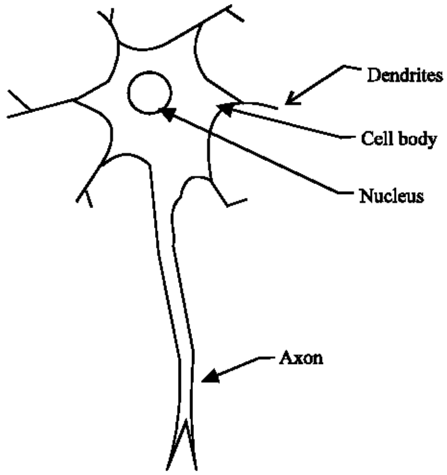

Fig. 1: A typical biological neuron

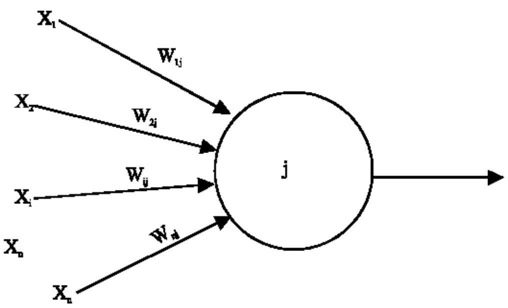

Fig. 2: A single processing unit

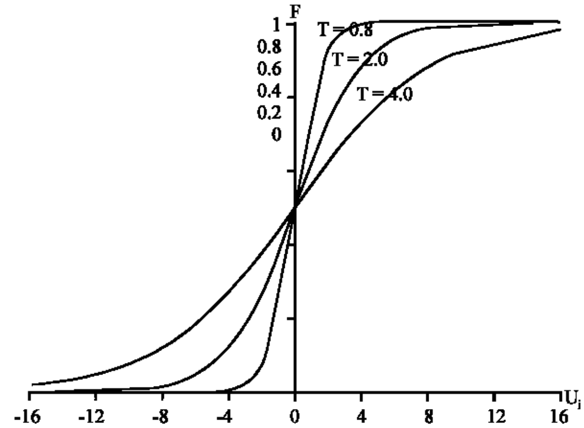

Fig. 3: The sigmoid function

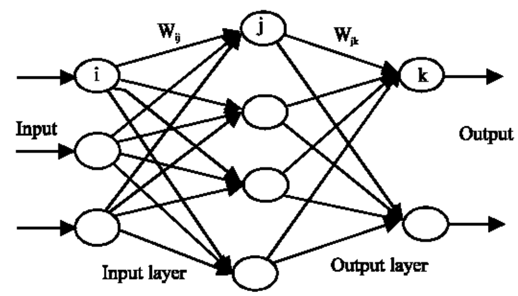

Fig. 4: Neural network

are used for training of the network. For each case, limiting strain hardening exponent for deep drawing to take place are predicted from FE simulation in iterative manner. The trained network is validated for 2 new sets of parameters. It is found that ANN predictions are in close match with the FE results.

Artificial neural network: Artificial neural network attempts to imitate the learning activities of the brain. The human brain is composed of approximately 10^{11} neurons (nerve cells) of different types. In a typical neuron, we can find the nucleus, where the connections with other neurons are made through a network of fibers called dendrites. Extending out from the nucleus is the axon, which transmits, by means of a complex chemical process, electric potentials to the neurons with which the axon is connected to (Fig. 1). When the signals received by the neuron equal or surpass their threshold, it "triggers", sending the axon an electric signal of constant level and duration. In this way the message is transferred from one neuron to the other. In an Artificial Neural Network (ANN), the artificial neuron or the processing unit may have several input paths corresponding to the dendrites. The units combine usually, by a simple summation, the weighted values of these paths (Fig. 2). The weighted value is passed to the neuron, where it is modified by threshold function such as sigmoid function (Fig. 3). The modified value is directly presented to the next neuron. In (Fig. 4) a 3-4-2 feed forward back propagation artificial neural network is shown. The connections between various neurons are strengthened or weakened according to the experiences obtained during the training. The algorithm for training the back propagation neural network can be explained in the following steps:

Step 1: Select the number of hidden layers, number of iterations, tolerance of the mean square error and initialize the weights and bias functions.

Step 2: Present the normalized input -output pattern sets to the network. At each node of the network except the nodes on input layer, calculate the weighted sum of the inputs, add bias and apply sigmoid function

Step 3: Calculate total mean error. If error is less than permissible limit, the training process is stopped. Otherwise,

Step 4: Change the weights and bias values based on generalized delta rule and repeat step 2.

Table 1: Geometrical parameters

S.No	Parameter	Value
1	Die radius	50.75 mm
2	Punch radius	48.5 mm
3	Blank radius	82.5 mm
4	Punch corner radius	19.5 mm
5	Die corner radius	21.5 mm
6	Drawing ratio	1.6
7	Blank thickness	2 mm
8	Stroke length	60 mm

MATERIALS AND METHODS

Geometrical parameters: The various geometrical parameters are considered in this study are given in Table 1.

The blank diameter, using these data, may be calculated using following formula (Ghosh, 2001).

$$D = \sqrt{(d - 2r)^2 + 4\, d\,(h-r) + 2\pi\, r\,(d - 0.7r)}$$

where,

r = Corner radius of the punch.
h = Height of the stroke.
d = Outer diameter of the die.
D = blank Diameter.

This is valid for $d \leq 10r$

Based on the above formula, the blank radius comes out to be 88.5 mm and the same is considered in this study. The ratio of punch-corner radius to die corner radius has been kept less than 1.

Material parameters: Aluminum alloy 2024 is considered in this study. The Young's modulus and Poisson's ratio are 7.8×10^4 N mm^{-2} and 0.33, respectively. The power law is used for material modeling in the post yielding range.

$$\sigma = K\,\varepsilon^n$$

Here σ represents the effective stress, ε the strain, K strength coefficient and n is strain hardening exponent. For most metals n lies between 0.10 and 0.50.

The various coefficients of the power law considered in this study are,

Strain hardening coefficient (K) : 650, 690, 725 MPa
Strain hardening exponent (n) : 0.1, 0.15, 0.2, 0.25, 0.3, 0.35, 0.4, 0.45 and 0.5

Finite element analysis: Axi-symmetric modeling of the punch, die and blank for the deep drawing process simulation have been carried out. Tools are modeled as rigid body whereas blank is considered as deformable which is discretized into finite element. Four nodded quadrilateral elements are used for FE modeling. There are 20 elements and 80 nodes in the FE model (Fig. 5). With deformation the finite element mesh deforms, remeshing is badly needed for smooth running of FE analysis. The current mesh parameters are automatically transferred on the newly generated FE mesh. In this study, advanced front quadrilateral meshing technique has been employed for remeshing. Coulomb's friction is adopted in this study. Three values of the friction coefficients viz. 0.1, 0.15 and 0.2 are considered. Punch velocity is considered as 1 mm sec^{-1} and punch stroke is 60 mm. The die is kept fixed, transfer of forces among them is accounted through contact algorithm when the punch draws the blank into the die. The 3 dimensional expanded model is shown in Fig. 6.

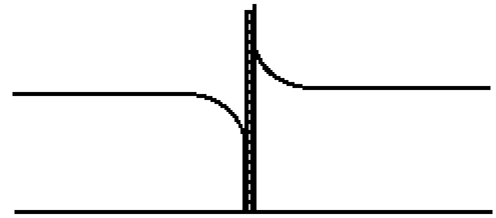

Fig. 5: Initial mesh diagram

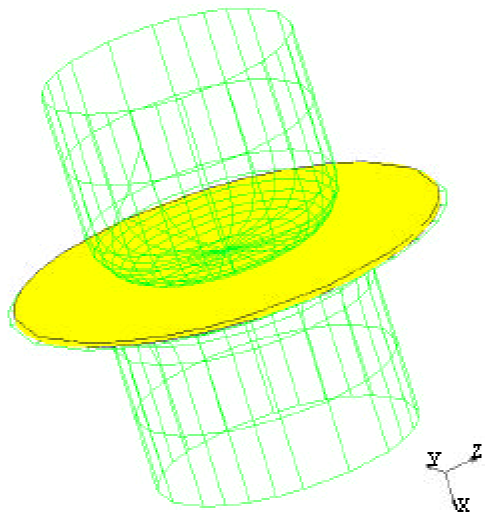

Fig. 6: Expanded view of the die, punch and blank

Prediction of limiting hardening exponent: There exist a limiting strain hardening exponent corresponding to each frictional condition. Below this value, drawabilty will be less than that is needed to overcome frictional forces. To calculate limiting hardening exponent, for given friction condition, n value is increased in the increment of 0.05 until deep drawing is successful. Initial n is taken as 0.1. Hence, for each K and f values, there is a unique n. These data is tabulated in Table 2. Using these 9 sets of data, a backpropagation neural network is trained to predict the

Table 2: Input and output parameters

	Input parameters		Output parameters		
S.No.	K	n	f	Sheet thickness (mm) Section 1	Sheet thickness (mm) Section 3
1	650	0.10	0.10	2.41	1.39
2		0.25	0.15	2.40	1.38
3		0.50	0.20	2.36	0.96
4	690	0.10	0.10	2.42	1.43
5		0.30	0.15	2.40	1.36
6		0.50	0.20	2.40	1.28
7	725	0.10	0.10	2.41	1.26
8		0.35	0.15	2.37	1.46
9		0.50	0.20	2.36	0.98

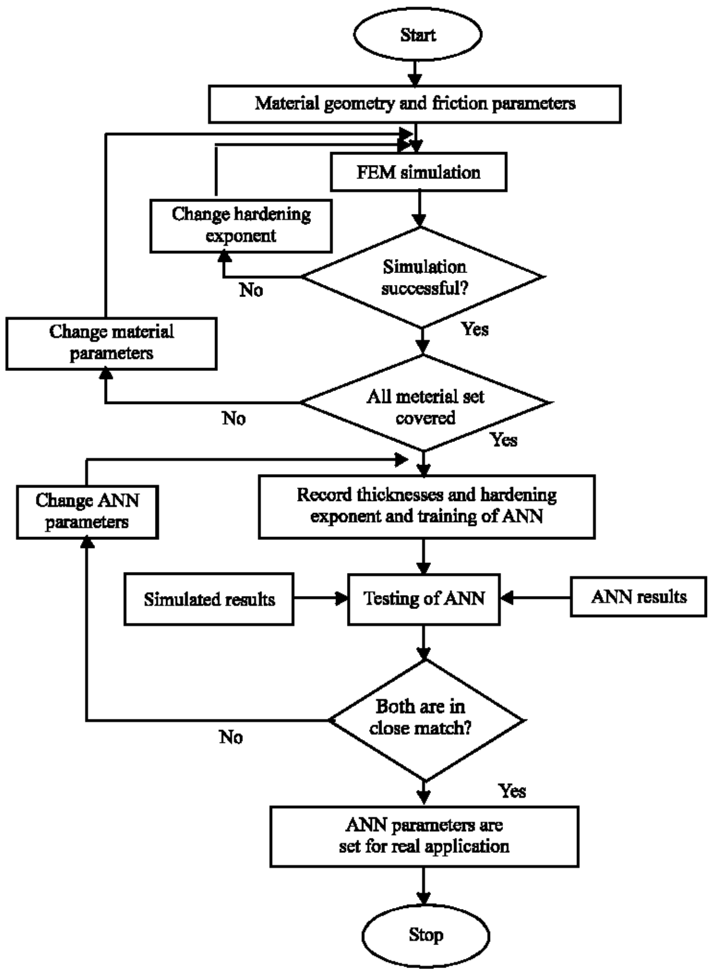

Fig. 7: Flow chart for instability prediction

friction and sheet thicknesses. Based on these results selection of lubricants can be made to reduce the friction.

Application of artificial neural network: Nine sets of data, obtained from above mentioned FE analyses, were used for training the network. A 2-6-3 size of backpropagation neural network has been used for the modeling. Input parameters are K and n whereas output parameters are friction and sheet thicknesses at sections 1 and 3. The error limit is 0.03 and it took 573463 epoches to converge to this limit. Trained network is tested for two unknown patterns to validate the approach. The flowchart of the whole prediction process is given in Fig. 7. The training and testing patterns are given in Table 1 and 2. It can be observed that predicted results are quite close to the simulated ones.

Table 3: Testing parameters

	Input			Output					
			Friction	Sheet thickness (mm) section 1			Sheet thickness (mm) section 3		
S.No	K	n	coefficient (f)	ANN	FEM	Error (%)	ANN	FEM	Error (%)
1	670	0.18	0.13	2.40	2.40	0.00	1.39	1.38	0.72
2	710	0.34	0.15	2.38	2.39	0.42	1.45	1.39	4.32

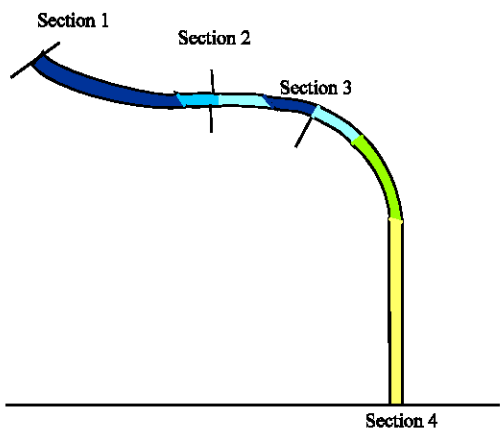

Fig. 8: Sectional view of deformed blank

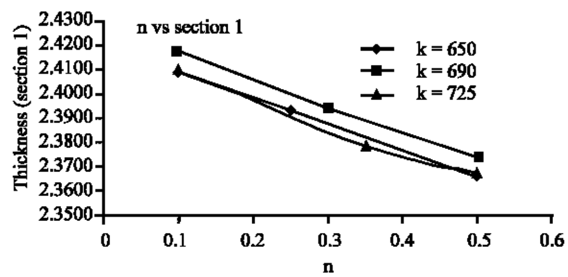

Fig. 9: Graph between strain hardening exponents (n) Vs sheet thickness at section 1

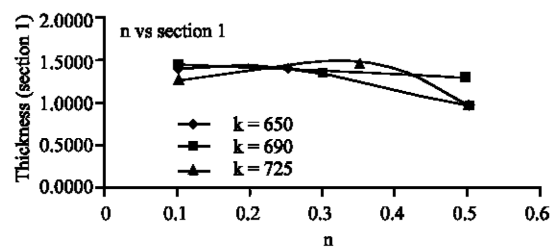

Fig. 10: Graph between strain hardening exponents (n) Vs sheet thickness at section 3

RESULTS AND DISCUSSION

The Finite Element Simulations for the deep drawing processes were carried out using Msc.SuperForm 2005 software. Results in terms of friction and thickness distributions were collected and given in the Table. 2. A deep drawn blank is shown Fig. 8. It can be observed that section 1 experiences thickening due to large compressive strains, whereas section 3 experiences thinning due to tensile strain. These are the two locations where wrinkling and necking take place. The plot of thickness distribution at section 1 with different n and k values are shown in Fig. 9. Thickening is maximum at lowest n and minimum at the highest n values. It clearly indicates the need of the blank holder to avoid possible wrinkling. At section 3 (Fig. 10), it is observed that the sheet is under various stresses as the corner punch radius has drastic influence on thinning of this section. Lower K and higher n values result in the minimum thinning. Thickness distribution in the sheet and required friction for drawing to happen as predicted by neural network is given in Table 3. It can be observed that maximum error at section 1 is 0.42% which is quite small. Maximum error in thickness prediction at section 3 is 4.32%. It is also observed, at constant friction, requirement of hardening exponent would go up with increase in K values. Friction predictions are also quite important. If friction is more than of the limiting value, drawing can't take place. In case of high friction, suitable lubricant may be employed. In this way application of neural network helps in material and process design for deep drawing.

CONCLUSION

In this study effect of material and processing parameters on the deep drawability is studied. Numerical experimentations were carried out using FEM to generate the database to be used for the training of the neural network. Safe strain hardening exponent limit is arrived at through FE simulations. Using these data, a back propagation neural network was trained. The trained network is validated for two unknown patterns and results are compared with FEM counterparts. It is observed both are in good match. Hence, neural network can be a powerful tool for material and process design for industrial applications.

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