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Archives of Applied Science Research, 2010, 2 (1) 310-317
(http://scholarsresearchlibrary.com/archive.html)

ISSN 0975-508X
CODEN (USA) AASRC9

Application of Neural Networks in Preform Design of Upsetting Process Considering Unequal Interfacial Frictional Conditions

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Abstract

Design of the optimum preform for near net shape manufacturing is a crucial step in upsetting process design. In this study, the same is arrived at using artificial neural networks (ANN) considering different unequal interfacial friction conditions between top and bottom die and billet interface. Back propagation neural networks are trained based on finite element analysis results considering four unequal interfacial frictional conditions and varying geometrical and processing parameters, to predict the optimum preform for commercial aluminum. Neural network predictions are verified for three new problems of commercial aluminum and observed that these are in close match with their simulation counterparts.

Keywords: Artificial neural network; Preform; finite element; upsetting; deformation

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Introduction

Upsetting is an important metal forming operation. It is a class of bulk forming operation where large deformation is given to the material for shape and property modification. The major issue, which restricts imparting large deformation to the billet, is the bulging induced tensile stress which later results in cracking. Bulge is also undesirable from near net shape manufacturing point of view as it will require secondary processing like trimming. To obtain the near net shape, preform design of the billets is a powerful solution. Considerable amount of literature are available on the preform design in forging process.

Roy et al. (1994) report application of neural networks in interpolation of preform shapes in plane strain forgings. Ranatunga et al. (1996) present preform designing techniques based on the upper bound elemental technique (UBET) with evidence of effective material usage and extended overall die-life. Lee et al. (1997) report application of an upper-bound elemental technique in preform design for asymmetric forging which is validated through experiments. Liu et al. (1998) present a preform design method which combines the FEM & upper bound based reverse simulation technique. The billet designed using this technique achieves a final forging with minimum flash. Ko et al. (1999) describe a new method of preform design in muti-stage metal forming processes considering workability limited by ductile fracture. Neural networks and Taguchi method are used for minimizing the objective function. Srikanth et al. (2000) present a continuum sensitivity analysis approach for the computation of the shape sensitivity, which is later used for the purpose of preform design and shape optimization in forging process. Chang et al. (2000) propose reverse simulation approach clubbed with finite element analyses for preform design. Bramley et al. (2001) report a new method named as tetrahedral upper bound analysis which enables a more realistic flow simulation to be achieved. Antonio et al. (2002) presents an inverse engineering formulation together with evolutionary search schemes for forging preform design. Shim et al. (2003) presents optimal preform design for 3D free forgings using sensitivity approach and FEM. Tomov et al. (2004) reports preform design of axisymmetric forging using FE software FORM-2D. Ou et al. (2004) reports finite element (FE) based forging simulation and optimization approach in order to achieve net-shape forging production for aero engine components. Effects of die-elastic deformation, thermal distortion and press-elasticity were considered. Poursina et al. (2004) proposes a FEM and GA based preform design procedure for axisymmetric forgings in view to achieve high quality products. Thiyagarajan et al. (2005) presents a 3-D preform shape optimization method for the forging process using the reduced basis technique. Repalle et al. (2005) presents reliability-based optimization method for preform shape design in the forging. Antonio et al. (2005), reports an inverse approach for preform design of forged components under minimal energy consumption using FEM and genetic algorithms. Park and Hwang et al. (2007) reports preform design for precision forging of rib type aerospace components using finite element analysis. Poshala et al. (2008) carried out formability analysis and its experimental validations for aluminum preforms using neural network. Haluk Tumer et al. (2008) optimised die and preform to minimize hardness distribution in back extrusion process using Nelder-Mead search algorithm integrated with the finite element model.

Although substantial literature on preform design is available, they address it as individual problem considering one or few parameters. The main objective of this study is to devise a generalized procedure of preform design considering various parameters. For this, neural network has been used for preform design of the upsetting process. In this study effect of critical factors including different preform shapes, interfacial friction conditions, and their effect on the final deformed profiles are studied using FE simulation. Four cases of unequal interfacial friction conditions are considered for the same. Based on the simulation results, a back propagation neural network is trained to provide guidelines for selection of parameters to result in near net shape manufacturing. Neural network predictions are being verified with three numerical examples for commercial aluminum.

Artificial Neural Networks

Artificial neural network attempts to imitate the learning activities of the brain. In an artificial neural network (ANN), the artificial neuron or the processing unit may have several input paths corresponding to the dendrites in the biological neuron as shown in figure1. 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-

Step1 – Select the number of hidden layers, number of iterations, tolerance of the mean square error and initialize the weights and bias functions.
Step2 – 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
Step3-Calculate total mean error. If error is less than permissible limit, the training process is stopped. Otherwise,
Step4 –Change the weights and bias values based on generalized delta rule and repeat step 2.
The mathematical formulations of training the network can be found in Ref. 21.

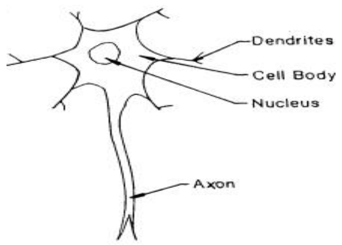


Fig.1: A typical biological

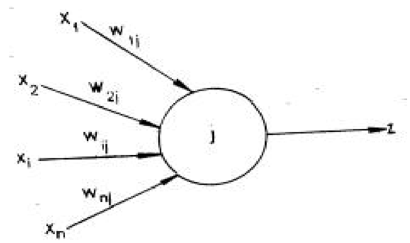


Fig.2: A single processing unit

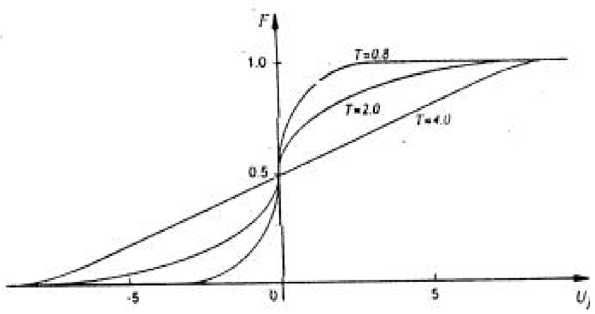


Fig.3: The sigmoid function

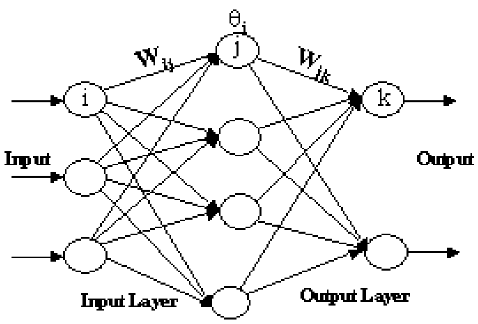


Fig.4: Neural network

Methodology

In Fig.5, schematic undeformed and deformed billets are shown. Let top, middle and bottom diameters of these billets are to be a, b c, and a_1, b_1, c_1 respectively. Their diameter ratios with respect to top diameter, can be expressed as R_1=b/a, R_2=c/a and $r_1=b_1/a_1$, $r_2=c_1/a_1$. It is obvious that for near net shape manufacturing, r_1 and r_2 should be one. Since deformed profiles depend on geometrical and frictional conditions, large numbers of variation of these parameters are accounted. Four sets of interfacial frictional parameters and 38 sets of geometrical conditions making total 152 combinations are considered in this study for commercial aluminum. Finite element simulations of these cases are carried out to obtain the deformation behavior. Based on these results, back propagation neural networks are trained to predict desired preform for given f_t, and f_b values to result in near net shape upsetting.

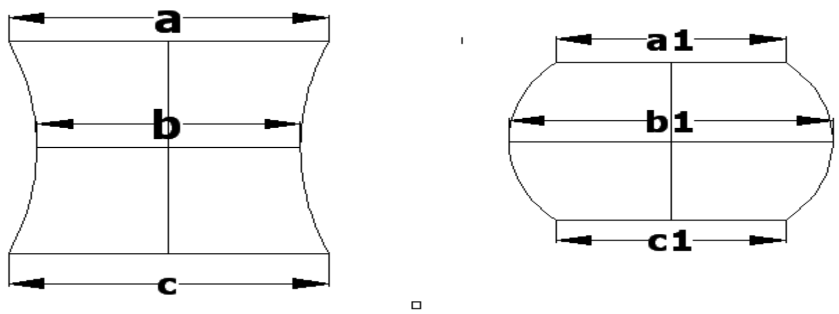


Fig.5: Initial and final shapes of billet

Geometrical, Material and Processing Parameters

Cylindrical specimens of 40 mm top diameter and 40 mm height are used for simulation studies of commercial aluminum. The central and bottom diameters are considered as 28, 30, 32, 34 36, 38 and 39 mm. In this way center and top diameter ratio and bottom and top diameter ratio (R_1 and R_2), also named as preform ratios, comes out to be 0.7, 0.75, 0.8, 0.85, 0.9, 0.95 and 0.975 respectively. Four combinations of interfacial frictions, Coulomb friction, at top and bottom surfaces of billet and platens considered for simulation studies are given in Table 1.

Table.1: Frictional conditions at die and billet interface

S.No	f_t(Friction between top die and billet interface)	f_b(Friction between bottom die and billet interface)
1	0.2	0.1
2	0.3	0.2
3	0.4	0.2
4	0.4	0.3

The 38 cases of geometric parameters accounted in the study. Material properties of commercial aluminum have been obtained by conducting tensile tests. Specimens of gauge length 80 mm, prepared as per ASTM standard, are tested in a Shimadzu make Universal Testing Machine (UTM). The test and tested specimens of commercial aluminum are shown in Fig.6. The engineering stress & strain are converted into their true counterparts using standard relationships (Kalpakjian and Schmid ,2004). Based on these results, material modeling is carried out. The post yielding behaviour is modeled using the power law equation (Meyers and Chawla, 1997):

$$\sigma = k\varepsilon^n$$

Where k is the strength coefficient and n is the hardening exponent. The material properties evaluated and adapted for FE simulation are given in Table 2.

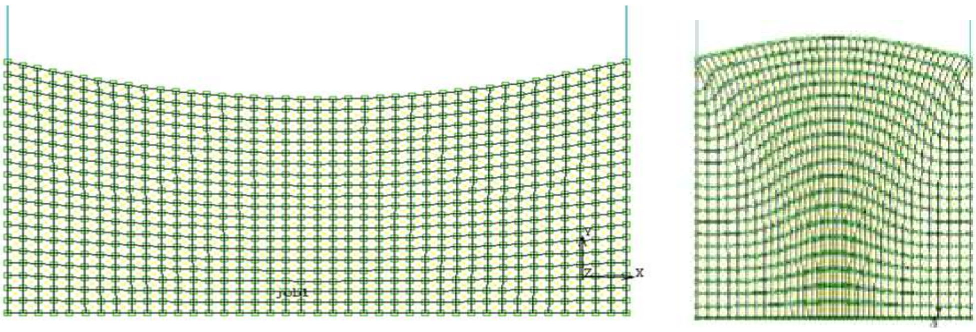
Fig.6: Tensile specimens (Before & after test)

Table.2: Material Properties

Properties	Commercial Aluminum
Youngs modulus (E)MPa	7×10^4
Poisson's ratio (ν)	0.33
Strengthcoefficient (K)MPa	225.4
Hardening exponent (n)	0.095

FE Simulation

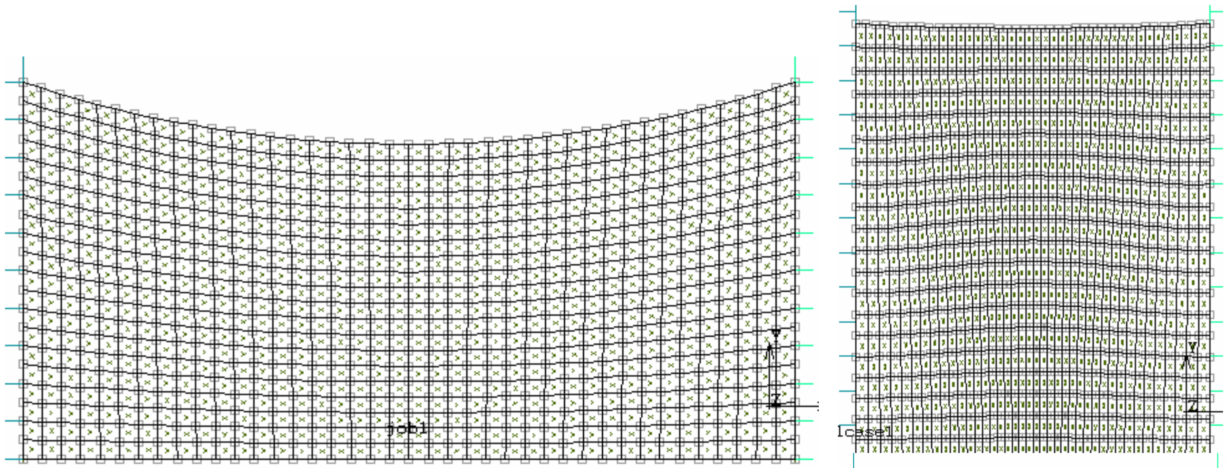
Finite element analyses of the upsetting process are carried out using MSC.Marc software (Ref 22). Curved profiles of specimens are modeled as arcs between top, middle and bottom diameters using ARC command of the software. Taking advantage of the symmetrical conditions, axisymmetrical formulation is adopted. Four nodded quadrilateral elements are used for the FE modeling. There are 800 elements and 861 nodes in the model. Considering the variation in 38 geometrical cases and four cases of frictional conditions, total 152 cases are simulated for commercial aluminum. Punch and die are modeled as rigid bodies. Bottom die is fixed whereas punch is movable which is given the displacement boundary condition. The entire commercial



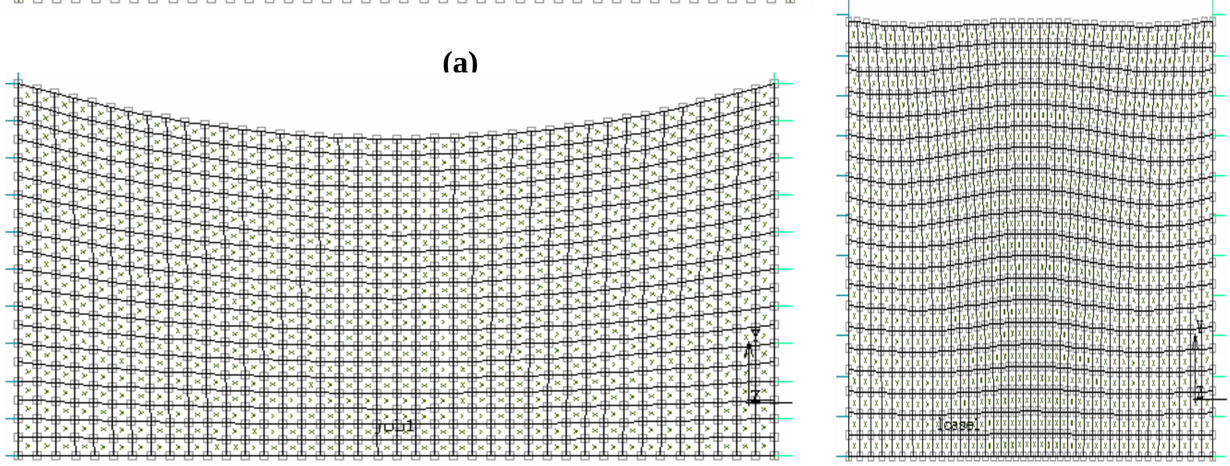
(a) **(b)**

Fig.7: FEM models (a) before deformation (b) after deformation

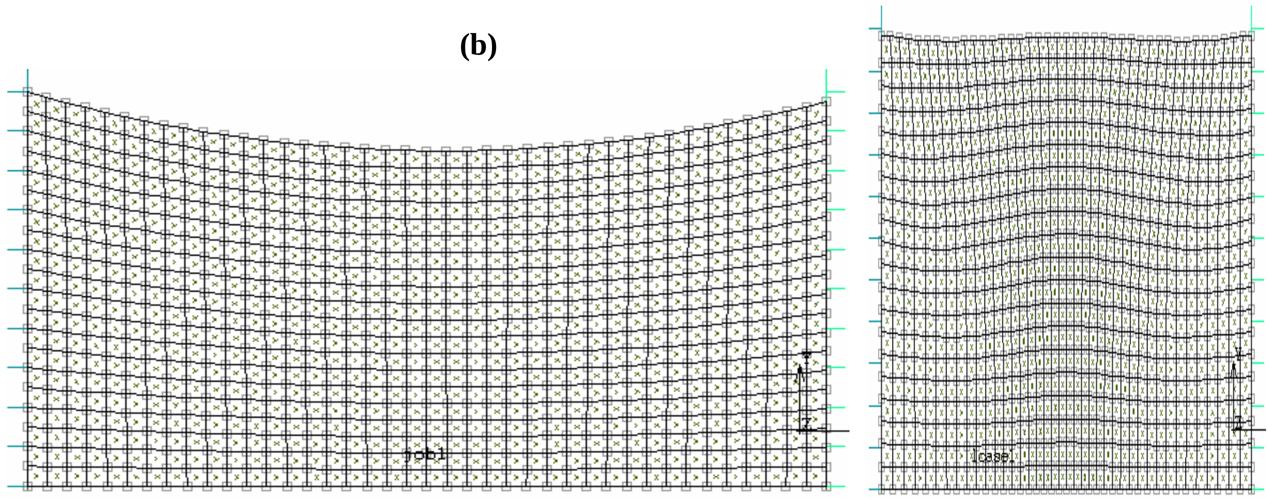
Aluminum billets are identically deformed to final height of 28 mm viz. 30 % reduction in height. A typical FE and deformed models are shown in Fig.7. Geometrical parameters of deformed and undeformed conditions for all the 152 cases are recorded separately for commercial aluminum.



(a)



(b)



(c)

Fig8: Initial and deformed shapes of aluminum (a) f_t= 0.28, f_b= 0.20, R_1= 0.835, R_2=1 (b) f_t= 0.3, f_b=0.25, R_1=0.86, R_2=1 (c) f_t=0.35, f_b=0.30 R_1=0.83,R_2=0.975

Numerical Validation

FE results in terms of diameter ratios are used for training neural networks. One 4-6-2 back propagation neural network for commercial aluminum has been used for the training. f_t, f_b, r_1, r_2 are input and R_1,and R_2 are output parameters. The error limit is 0.001 and it took 1537695 epochs to converge the desired limit. The trained network is being tested for three new problems of commercial aluminum upsetting to show the efficacy of the neural network predictions. The input parameters for them are given in Table3. The predicted preforms (R_1 and R_2 values) are used for validation through FE simulation. The 'r_1 and r_2' values predicted are very close to the near net shape manufacturing. Maximum error is 1% which is very less. The initial and final deformed meshes for these cases are shown in Fig8. It can be observed that deformed profiles are close to the near net shapes of perfect cylinders.

Table.3: Numerical Validation of ANN for commercial aluminum

S.No	f_t	f_b	R_1	R_2	$r_{1(Actual)}$	$r_{1(FEM)}$	%Error	$r_{2(Actual)}$	$r_{2(FEM)}$	%Error
1	0.28	0.20	0.835	1	1	0.99	1	1	0.999	0.1
2	0.30	0.25	0.86	1	1	0.998	0.2	1	0.999	0.1
3	0.35	0.30	0.825	0.975	1	0.995	0.5	1	1.003	0.3

Conclusion

In this study artificial neural networks have been used for the design of preforms for the cylindrical billet upsetting. Based on the results of 152 FE simulations a back propagation neural network is trained for commercial aluminum. Trained networks are first verified with three numerical examples. It is found that simulation and network predictions are in close match. This study also demonstrates that ANN can be effectively used for preform design. It is hoped, this study will help design engineers in fast and reliable predictions of optimum preforms under different unequal interfacial friction conditions for net shape manufacturing.

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