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Prediction the Limiting Drawing Ratio in Deep Drawing Process by Back Propagation Artificial Neural Network

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***Abstract*—**In this paper back-propagation artificial neural network (BPANN) with Levenberg–Marquardt algorithm is employed to predict the limiting drawing ratio (LDR) of the deep drawing process. To prepare a training set for BPANN, some finite element simulations were carried out. die and punch radius, die arc radius, friction coefficient, thickness, yield strength of sheet and strain hardening exponent were used as the input data and the LDR as the specified output used in the training of neural network. As a result of the specified parameters, the program will be able to estimate the LDR for any new given condition. Comparing FEM and BPANN results, an acceptable correlation was found.

***Keywords*—**BPANN, deep drawing, prediction, limiting drawing ratio (LDR), Levenberg–Marquardt algorithm

I. Introduction

THE correlation of the LDR of a sheet metal with its material properties and process parameter has been activated by industrial necessity for improving drawability. Attempts to evaluate The LDR value have been made by many researchers. Chan [1] predicted the LDR using an elasto-plastic finite-element method (FEM) and compared it with the experimental result. Leu [2] derived a simple and accurate equation to show the effects of the normal anisotropy value (R) and the strain-hardening exponent (n) on the LDR. Tung predicted LDR by abductive networks under the process parameters such as blank holder force, the profile radius of the die, the clearance between the punch and the die and the friction coefficient [3].In this work, a neural network model is coupled with a finite element analysis to predict the limiting drawing ratio (LDR) of the deep drawing process. In this way, the LDR can be determined for different process parameters, die and punch radius, die arc radius, friction coefficient, thickness, yield strength of sheet, strain hardening exponent by finite element analysis, using ANSYS software. The employed finite element analysis is capable of considering the effects of various parameters. These results then be used to training the neural network. Comparing FEM and ANN results, an acceptable correlation was found

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II. Deep Drawing Process

The deep drawing process is a sheet metal process where sheet metal is formed into a desired shape, usually by mechanical or hydraulic presses.

It is widely used in industries such as automobiles, airplanes, etc. The design and control of a deep drawing process depends on not only the workpiece material, but also on the condition at the tool workpiece interface, the mechanic of plastic deformation, and the equipment used.

The limiting drawing ratio (LDR) is commonly used to provide a measure of the drawability of sheet metal, The LDR defined as the ratio of the maximum blank diameter to the punch diameter, without failure.

The LDR is affected by many material and process parameters, such as the strain hardening exponent, friction, the profile radius of the die and punch, etc

Fig.1 shows the deep drawing operation under consideration that a circular blank of original radius R_0 and thickness t_0 is deep drawn by the flat-bottomed punch through a die opening of radius r_1 with a constant clearance blank-holder. Radially symmetrical properties and rigid–plastic strain-hardening material are assumed.

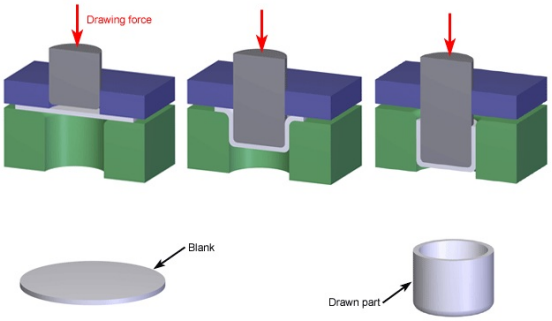


Fig.1 Schematic of deep drawing process

The friction effect is considered in the analysis. Under plane-strain conditions, the thickness in the flange region of deep drawing is invariable. All dimensions of tool geometries are measured along with the middle line of the thickness of the deformed sheet .The strain-hardening characteristic of sheet metal is assumed to follow the form:

$$\bar{\sigma} = K\bar{\varepsilon}^{n} \quad (1)$$

III. Finite Element Simulation

There are numerous influencing parameters, but according to the experimental and simulation results, the primary ones

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are punch radius (r_1), die radius(r_2), die arc radius (r_d), friction coefficient (m), thickness (t_0),yield strength of sheet (σ_y) and strain hardening exponent (K ,n) Through 20 sets of finite element analysis under different working condition the input data achieved (Table.I). At the same time in order to confirm the validity of the neural network model, an extra three simulation are carried out under different condition from the above 20 sets (Table.II). Because of the existing symmetry, only one quarter of the workpiece is considered in the modeling (Fig.2). The tooling surface of die was modeled using rigid- body model. Simulations were carried out from the sheet of diameter 100 mm with the diameter progressively increasing by 5 mm until the sheet was fractured.

Compares the LDR value obtained by FEM simulation with that obtained experimentally [4], proving that the model proposed herein is accurate in determining the LDR of deep drawing process.

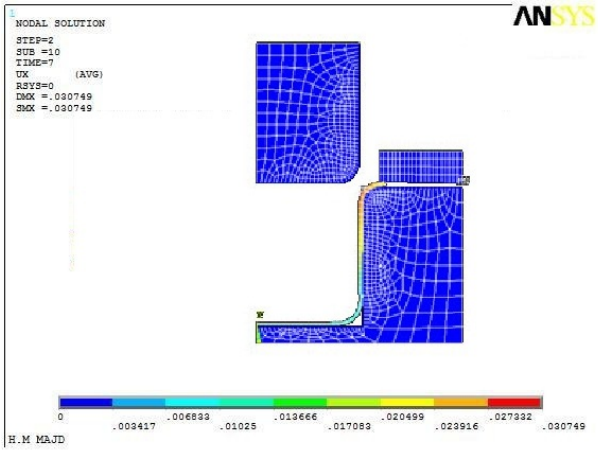


Fig. 2 FEM simulation

IV. Neural Networks

An artificial neural network is a parallel distributed information processing system. It stores the samples with distributed coding, thus forming a trainable nonlinear system. The main idea behind a neural network approach resembles the human brain functioning. Given the input and the expected outputs, the program is self adaptive to the environment so as to respond to different inputs rationally. The objective of this paper is to investigate the prediction of LDR in deep drawing process, by training a BPANN.The neuron can be classified into three types: input, output, hidden neurons. Input neurons are the ones that receive input from the environment, such as punch radius (r_1), die radius(r_2), die arc radius (r_d), friction coefficient (m), thickness (t_0), yield strength of sheet (σ_y) and strain hardening exponent (K ,n) in this study. Output neurons are those that send the signals out of the system, like LDR. As the activation function, Sig activation function has been used, which is continuous, nonlinear, monotonic non-decreasing and S shaped function (equation 2). [5]

$$f(x) = \frac{1}{1+e^{-\beta x}} \tag{2}$$

In this study, the back propagation, which is a widely used algorithm, is used in the training step. Back propagation is a systematic method for training multilayer artificial neural networks. It has a strong mathematical foundation based on gradient descent learning. Elman BP network train with the back propagation algorithm is used. Elman networks are back propagation networks, with the addition of a feedback connection from the output of the hidden layer to its input. This feedback path allows Elman networks to learn to recognize and generate temporal patterns, as well as spatial patterns [6]. For an Elman to have the best chance at learning a problem it needs more hidden neurons in its hidden layer than are actually required for a solution by another method.

This model has four layers including, an input layer, two hidden layer and an output layer. In this work, different number of hidden units has been employed to obtain the optimum number of hidden units. The experiments show that number of 12 units in the hidden layer is enough to reach the desired accuracy (Table.III).

Training of the neural network was done in MATLAB, using Sig and TRAINLM function. TRAINLM is a network training function that updates weights and bias values in a back propagation algorithm according to Levenberg–Marquardt optimization. Levenberg–Marquardt algorithm is a highly efficient method for solving non-linear optimization problems [7], [8]. The trained network model showed error of 1.7%, 2.59% and 3.8% while testing with the 3 data sets (Table. 2).

V. Conclusion

In this work, a four-layer back propagation network is developed to best fit this nonlinear engineering problem. Through comparison between the targeted value and training results with different neuron numbers in the hidden layers, an appropriate number of 12 is suitable to set up this network. For this nonlinear engineering problem, the appropriate algorithm is Levenberg -Marquardt because it can reach high accuracy. The error between the predicted value and targeted one is little. Using this network can save much time

TABLE I
FEM SIMULATION CONDITION

	punch radius (r_1) mm	die arc radius (r_d) mm	die radius (r_2) mm	friction coefficient (m)	thickness (t_0) mm	yield strength (σ_y) Mpa	k	n	(LDR)
1	30.75	8.5	39.25	0.1	1	155	610	0.263	2.13
2	30.75	8.5	39.25	0.2	1	155	610	0.263	2.11
3	30.75	8.5	39.25	0.1	1	157	612	0.248	2.13
4	30.75	8.5	39.25	0.2	1	157	612	0.248	2.10
5	30.65	8.6	39.25	0.1	1.2	138	619	0.264	2.20
6	30.78	8.6	39.38	0.1	1.2	138	619	0.264	2.22
7	30.78	8.6	39.38	0.2	1.2	138	619	0.264	2.16
8	30.86	8.6	39.46	0.1	1.2	138	619	0.264	2.12
9	30.86	8.6	39.46	0.2	1.2	138	619	0.264	2.09
10	30.86	5.4	39.26	0.2	1.2	171	622	0.228	2.03
11	30.86	8.6	39.25	0.2	1.2	171	622	0.228	2.07
12	30.86	10.6	41.46	0.2	1.2	171	622	0.228	2.08
13	30.86	12.6	43.46	0.2	1.2	171	622	0.228	2.12
14	30.86	14.6	45.46	0.2	1.2	171	622	0.228	2.15
15	26.48	6.79	33.27	0.05	0.88	258	631	0.238	2.40
16	26.52	6.74	33.27	0.05	0.79	203	631	0.238	2.43
17	26.55	6.71	33.27	0.05	0.73	300	631	0.238	2.37
18	26.55	6.71	33.27	0.05	0.73	292	631	0.238	2.39
19	26.25	6.84	33.27	0.05	0.99	276	631	0.238	2.36
20	26.42	6.85	33.24	0.05	1	244	631	0.238	2.33

TABLE II
TEST CONDITION

	punch radius (r_1) mm	die arc radius (r_d) mm	die radius (r_2) mm	friction coefficient (m)	thickness (t_0) mm	k	n	*yield strength* (σ_y) Mpa
1	30.65	8.6	39.25	0.2	1.2	619	0.264	138
2	26.47	6.80	33.27	0.05	0.90	631	0.238	202
3	30.75	8.5	39.25	0.15	1	610	0.262	155

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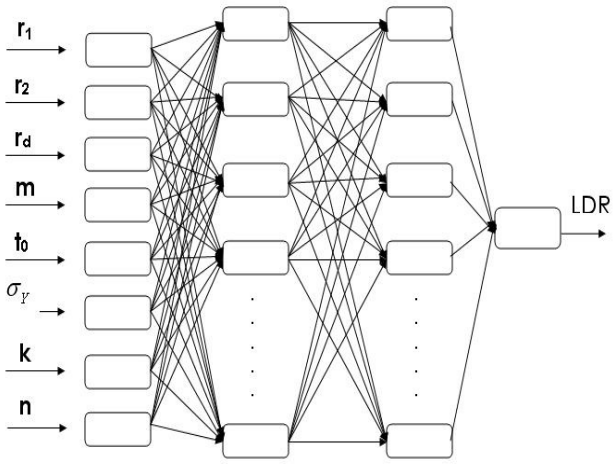


Fig. 3The structure of the neural network

TABLE.III
COMPARISON OF MEAN SQUARE ERROR USING DIFFERENT STRUCTURE OF ANN

Structure of ANN	*MSE* *Mean square error*
8-6-6-1	17712e-7
8-7-7-1	15230e-8
8-8-8-1	24583e-10
8-9-9-1	11243e-11
8-10-10-1	154477e-7
8-11-11-1	12402e-12
8-12-12-1	345258e-14
8-13-13-1	42433e-6
8-14-14-1	24131e-6

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