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SHORT COMMUNICATION

Application of Neural Network in Sheet Metal Bending Process

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ABSTRACT

The sheet metal bending is an important form of sheet metal forming process, widely used in various industrial applications like aircraft, automobiles, household items, power industries, etc. This study predicts the responses of the sheet metal bending process using artificial neural network. Based on 44 cases analysed using finite element method, a neural network was trained. Sheet thickness and die radius were the input, and stresses, strains, springback, loads, etc were the output for the neural network. The trained neural network was tested for five new patterns. It was found that most of the results were quite close to the simulation results. Such a technique of response prediction helps in reducing the computational time.

Keywords: Bending, springback, finite element, residual stress, plastic strain, neural network, sheet metal forming

1. INTRODUCTION

Bending is the process by which a straight length is transformed into a curved length. It is a very common forming process for changing sheets and plates into channels, drums, tanks, etc[1]. The two major problems of bending are cracking at the tension side and the springback after release. The smaller the radius of curvature, the greater the decrease in thickness on bending. The problem of springback is encountered in all metal forming operations, but can be most easily recognised and studied in bending. The sheet metal bending is a complex elasto-plastic deformation process involving small to moderate deformation and large rotation. Prominent material and geometrical parameters which affect the bending process are Young's modulus, strain-hardening coefficient, yield stress, die and punch radius, die gap, sheet thickness, etc. Material anisotropy and Bauschinger effect enhance the complexity of the problem. Considering all these factors, the governing differential equations become so complex that these cannot be solved by any analytical solution. Computer simulation of the sheet metal bending process is getting wide popularity in recent years due to their ease, quickness and economy. At present, there are many commercial softwares in the market which especially deal with the sheet metal forming process. Selection of an appropriate software should be done judiciously based on criterion given[2,3]. Although computer simulation has many advantages over its experimental counterpart, it demands expertise. There are not many who can do realistic simulation work and there is a need for automation in response prediction for the given bending conditions. In recent times, the artificial neural networks have proven to be effective tools for predicting responses in metal forming[4-6]. In this study, the efficacy of the neural

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network in response prediction of the sheet metal bending process is taken up and a set of simulation studies on sheet bending, considering varying dimensions of the sheet, were carried out[7]. The springbacks obtained from the simulation were in good agreement with the experiments[8]. A back propagation neural network was trained on the basis of these simulation studies. Network's prediction was tested for five new patterns and its responses were compared with the simulation counterparts.

2. ARTIFICIAL NEURAL NETWORK

The artificial neural network (ANN) attempts to imitate the learning activities of the human brain. The human brain is composed of approximately 10^{11} neurons (nerve cells) of different types. In a typical neuron, one can find the nucleus, where the connections with other neurons are made through a network of fibres 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.

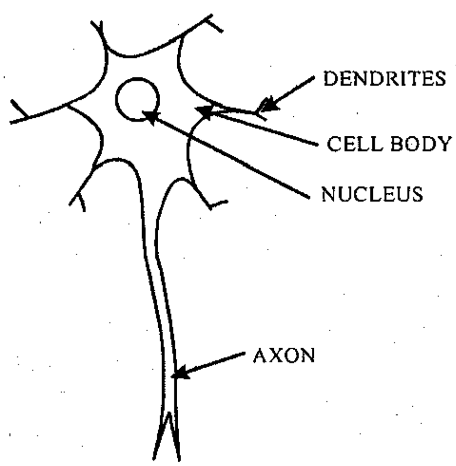

Figure 1. Typical biological neuron

In an 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

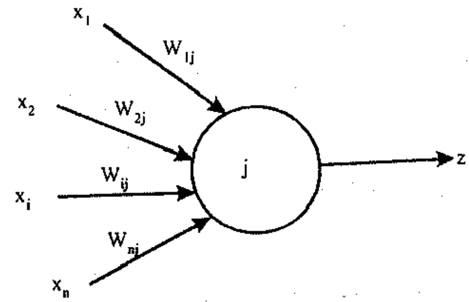

Figure 2. Single processing unit

paths (Fig. 2). The weighted value is passed on to the neuron, where it is modified by the threshold function, such as sigmoid function (Fig. 3). The

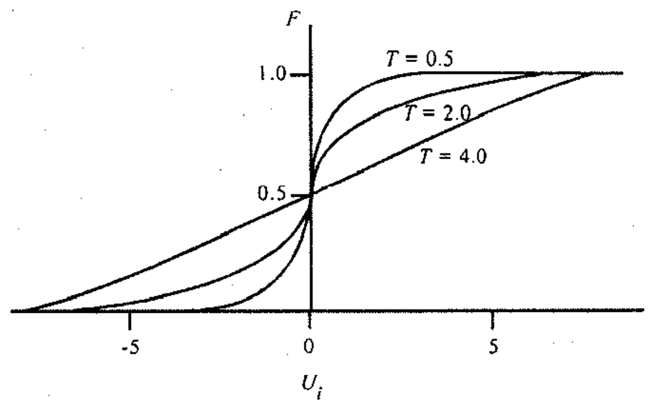

Figure 3. Sigmoid function

modified value is directly presented to the next neuron. In Fig. 4, a 3-4-2 feed-forward back propagation ANN is shown. The connections between the various neurons are strengthened or weakened according to the experiences obtained during the training. The algorithm for training the back propagation neural network is explained in the following steps:

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

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

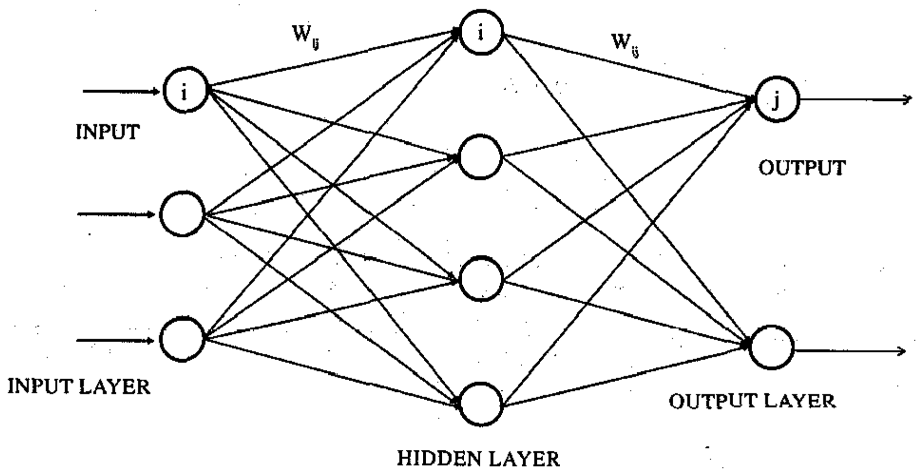

Figure 4. Neural network

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

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

The mathematical formulations of training the neural network have been given by Hertz and Krogh[9].

3. FINITE ELEMENT ANALYSIS

The finite element modelling of punch-sheet-die setup was carried out using a preprocessor[10] named DIEMESH. In this, the die is modelled using two reverse circular curves to avoid sharp corners which create convergence problems in contact algorithm. The mesh file generated through DIEMESH is used by the finite element modelling software[11-14] directly. The finite element model of the die punch system is shown in Fig. 5. The simulation of the sheet metal bending process is carried out using indigenous software RRLFEM capable of handling large strain and large rotation plasticity. Loading on the sheet is applied through punch by displacement boundary condition. The sheet, which is made of steel, has the following material properties:

(a) Young's modulus (E) = 190 GPa

(b) Yield strength (σ_Y) = 295 MPa

(c) Strain-hardening coefficient (n) = 0.17

(d) Poisson ratio (ν) = 0.3

Post-yielding behaviour of the flow curve is expressed by the following power equation:

$$\sigma/\sigma_y = (\varepsilon/\varepsilon_y)^n$$

where σ_y and ε_y are the yield stress and the yield strain.

Using software RRLFEM, a number of sheet metal bending problems considering different thicknesses and radii were analysed. The following parameters were considered for the analysis:

Thicknesses(mm) = 20, 30, 40

Sector angle = 90°

Die radii (mm) = 120, 150, 180, 210, 240, 500, 700, 1100, 1200, 1300, 1400, 1500, 2500, 3175, 3500, 5000, 6100, 7000

The complete bending of the sheet was carried out in 500 incremental steps. Stress distribution

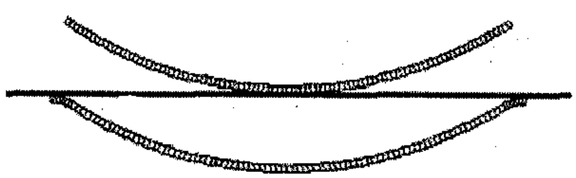

Figure 5. Finite element model

Table 1. Training patterns

Case No.	Input: Thickness (mm)	Input: Radius (mm)	Output: Effective stress (MPa)	Residual stress (MPa)	Springback (mm)	Plastic strain	Residual plastic strain	Load (kN)
1	20	120	569.8	569.9	130.962	0.0746	0.0748	52.60
2	20	150	539.6	541.9	198.287	0.0541	0.0566	59.51
3	20	210	534.3	323.2	223.275	0.0511	0.0500	87.15
4	20	240	524.4	278.8	254.004	0.0458	0.0443	95.39
5	20	500	482.7	154.6	526.212	0.0320	0.0305	154.20
6	20	1100	480.1	171.6	1133.930	0.0273	0.0253	411.60
7	20	1300	464.4	305.1	1376.000	0.0224	0.0164	527.30
8	20	1400	474.8	196.6	1420.910	0.0255	0.0239	495.40
9	20	1500	469.5	181.0	1557.390	0.0239	0.0223	498.00
10	20	2500	470.3	127.9	2564.430	0.0241	0.0222	687.90
11	20	3175	459.8	116.6	3291.870	0.0213	0.0192	822.20
12	20	3500	458.1	214.4	3624.330	0.0207	0.0191	1114.00
13	20	5000	415.4	110.2	5279.040	0.0116	0.0149	1710.00
14	20	6100	445.2	196.6	6282.350	0.0175	0.0160	1862.00
15	20	7000	449.8	213.3	7780.180	0.0186	0.0172	1868.00
16	30	120	614.0	587.2	176.500	0.1174	0.1177	46.98
17	30	150	580.7	585.1	191.891	0.0834	0.0900	62.24
18	30	180	553.9	543.4	232.888	0.0634	0.0635	65.45
19	30	210	550.3	482.0	227.132	0.0608	0.0602	78.93
20	30	240	539.5	326.9	253.202	0.0541	0.0528	91.15
21	30	1100	467.2	152.0	1152.630	0.0232	0.0213	395.60
22	30	1200	469.9	161.9	1246.580	0.0240	0.0221	403.30
23	30	1300	441.9	159.7	1397.380	0.0168	0.0151	445.00
24	30	1500	449.0	161.5	1682.680	0.0184	0.0167	529.30
25	30	2500	439.0	140.9	2682.190	0.0161	0.0143	828.10
26	30	3175	437.4	139.3	3409.140	0.0158	0.0142	1023.00
27	30	5000	438.6	151.2	5235.540	0.0160	0.0142	1674.00
28	30	6100	438.1	138.8	6356.240	0.0159	0.0141	1841.00
29	30	7000	451.2	190.9	7073.100	0.0189	0.0173	2188.00
30	40	120	599.7	588.4	158.915	0.1197	0.1226	49.74
31	40	150	616.5	591.4	223.002	0.1201	0.1209	53.43
32	40	180	572.1	576.8	210.667	0.0764	0.0815	70.01
33	40	210	567.6	570.3	239.864	0.0728	0.0758	85.09
34	40	240	550.5	547.9	358.986	0.0612	0.0620	80.95
35	40	1100	470.8	173.5	1184.640	0.0243	0.0225	379.60
36	40	1200	465.8	159.4	1277.560	0.0228	0.0209	423.70
37	40	1300	451.1	199.5	1425.130	0.0189	0.0172	438.00
38	40	1400	454.4	149.7	1514.890	0.0197	0.0179	498.70
39	40	1500	443.7	150.0	1644.830	0.0172	0.0154	445.70
40	40	2500	424.7	134.7	2786.720	0.0133	0.0116	722.20
41	40	3175	446.8	141.4	3377.720	0.0179	0.0160	935.40
42	40	3500	426.6	137.9	3865.080	0.0136	0.0120	1070.00
43	40	5000	423.1	178.5	5649.060	0.0130	0.0110	1308.00
44	40	7000	433.5	150.1	7400.430	0.0149	0.0132	1983.00

in one such bent case is shown in Fig. 6. After release of the punch, due to elastic recovery, there was considerable springback. Due to this, the final sheet radius was considerably higher than the die radius. The final radii of the released sheet were calculated[7] as follows:

If (X_1, Y_1) and (X_2, Y_2) are the coordinates of the two nodal points on the bent sheet then, radius of the bent curve may be calculated as

$$\text{Radius } (R) = \{(X_2-X_1)^2 + (Y_2-Y_1)^2\} \ / \ 2(Y_2-Y_1)$$

In the same way, two such radii were calculated using different nodal points and the average of these was taken as the final radius. The released sheet and the residual stresses in the above compressed sheet are shown in Fig. 7. Based on this approach, results of 44 sheet metal bending cases considering varying sheet thicknesses and die radii were analysed. Five other cases were also analysed for validation of neural network predictions.

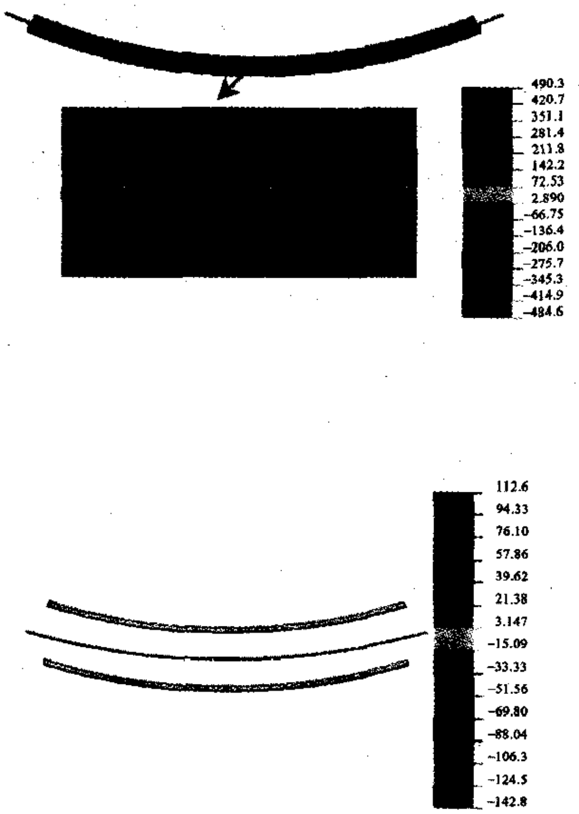

Figure 7. Residual stress in released sheet

4. APPLICATION OF NEURAL NETWORK

The results of 44 case studies were used for training a 2-8-6 back propagation neural network. The input and output data required for training the neural network is given in Table 1. The bias and weight factors were chosen randomly between –0.06 to 0.08. The neural network was trained for error tolerance of 0.115. It converged in 487654 epochs.

5. RESULTS & DISCUSSION

The trained neural network has been used for predicting the responses of unknown patterns. The input parameters of the unknown patterns are given in Table 2 and the corresponding neural network predictions are given in Table 3.

The maximum error in five predictions is 16 per cent. It can be observed from the tables that most of the time, neural network predictions are very close to the simulation results. These errors can be further reduced by reducing the tolerance limit and increasing the training patterns. Maximum error is in the prediction of plastic strain, whereas minimum error is in the effective stress. This may be due to the accumulation of training data around certain strains. The better the variation of training patterns, the better will be the predictions.

This approach of response prediction will help in quick determination of the behaviour of sheets in the bending process. The optimum geometrical parameters obtained by neural network, will be further checked using the finite element analysis. This will help in automating the design of sheet metal bending process.

Table 2. Testing patterns

Case No.	Thickness (mm)	Radius (mm)
1	20	180
2	20	1200
3	30	1400
4	30	3500
5	40	6100

Table 3. Predictions by neural network

S. No.	Effective stress (MPa)			Residual stress (MPa)			Springback (mm)		
	FEM	NNT	% (e)	FEM	NNT	% (e)	FEM	NNT	% (e)
1	538.00	542.30	0.80	422.00	417.90	0.97	245.00	211.8	13.55
2	471.00	456.70	3.01	207.00	180.90	12.61	1210.00	1288.66	6.50
3	454.00	454.30	0.07	177.00	154.60	12.65	1540.00	1532.00	0.51
4	431.00	433.90	0.68	148.00	147.50	0.34	3770.00	3671.05	2.62
5	433.00	427.30	1.32	151.00	152.10	0.73	6660.00	6370.50	4.34

S.No.	Plastic strain			Residual plastic strain			Load (kN)		
	FEM	NNT	% (e)	FEM	NNT	% (e)	FEM	NNT	% (e)
1	0.052	0.056	7.69	0.052	0.056	7.69	75.90	79.50	4.74
2	0.025	0.021	16.00	0.022	0.020	9.10	460	407	11.52
3	0.020	0.020	0.00	0.017	0.018	5.88	481	513.50	6.75
4	0.014	0.015	7.14	0.013	0.013	0.0	1170	1125	3.84
5	0.015	0.014	6.67	0.013	0.012	7.69	1910	1982	3.76

6. CONCLUSIONS

In this study, responses of sheet metal bending processes have been predicted using artificial neural network. The neural network is trained, based on the results of 44 cases analysed using the finite element techniques. Sheet thickness and die radius were taken as input and effective stress, residual stress, springback, plastic strain, residual strain, and punch load as output to the neural network. The trained neural network was tested for five new cases and compared with the finite element results. It was observed that the neural network gives quite close predictions of sheet forming responses. Such predictions help to reduce large computational time going into computer simulations. It can be handled even by novice in finite element analysis.

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Contributers

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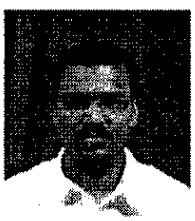

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