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NEURAL NETWORK APPLICATION TO THE RECONFIGURABLE MULTIPOINT FORMING PROCESS

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ABSTRACT

Multipoint forming of thin sheets plates is based on the discrete die-punch reconfigurable tooling concept. The paper is concerned with the application of the neural network method in studying the springback phenomenon in multipoint forming. The method of neural network is first presented. An algorithm based on FEM and neural network modeling is then presented. Using the FEM simulation, the springback values for a simply curved geometry are obtained. On this basis, a neural network is trained, using as input parameters the rubber thickness, the rubber elastic modulus and the pins stroke and as output the springback in width and height defined. The conclusions obtained from the neural network modeling certify the validity of the developed method.

KEYWORDS: multipoint forming, modelling, FEM, neural network, sheet metal

1. Introduction

The reconfigurable multipoint forming (RMPF) is a relatively new sheet metal manufacturing method used in small batch production. The technology is known also as MPF - Multipoint Forming [6, 7, 9, 10, 15] or DDF - Digitized Die Forming [1-3].

In this manufacturing method, a pins matrix approximates the continuously active surfaces of the conventional die (Figure 1). In the pins matrix each pin is vertically aligned according to the part geometry.

Fig. 1. *Multipoint forming die subassembly*

Different methods have been proposed for the multipoint forming process study. One of them refers to neural networks.

Neural networks technique as a field of artificial intelligence is an effective method to solve complex technical problems, proved to be applicable in many areas including that of plastic deformation.

Artificial neural networks (ANN) have the advantage that they can deduce general principles of a functional model of a given set of data, extracted from training data. They may also respond to insufficient entries, unlike other supervision computer techniques. Neural networks ability to obtain experimental data relation is a major advantage in their use. In addition, by comparing the input and output of the network there can be observed trends and provided explanations for the behavior obtained.

ANN is an information processing system and has some characteristics similar to the biological neural networks. A neural network is characterized by:

a) network architecture (model connections between neurons / nodes);

b) the method of determining the connection weights (the training algorithm);

c) activation function.

Depending on the topology, neural networks can be classified into two categories, with back propagation (recurring or "feedback") and spread before ("feedforward") information. In networks with propagation type "feedforward" a neuron output is sent to other neurons without receiving any input information from neurons from upper layers.

Most RNA use a multilayer architecture with back propagation of error. So the knowledge gained from training experiences are applied to upper layers, allowing the network to take further decisions, to make new classifications and predictions. The first layer and last one have inputs and output nodes corresponding to input variables and target variables respectively. Neurons in the hidden layers are providing interconnections between input and output neurons. There is no particular rule, but in general, the number of the hidden layer nodes is assumed to be a number around:

$$N = 2n + 1 \tag{1}$$

where N is the number of the hidden layer nodes while n is the number of input parameters.

A hidden layer of neurons uses the weighted sum of the previous layer and a nonlinear function that allows RNA to solve complex problems quickly and easily. RNAs aim to achieve optimal weights, to get the best value for the output layer nodes. Below (Figure 2) is shown schematically a neural network with three layers.

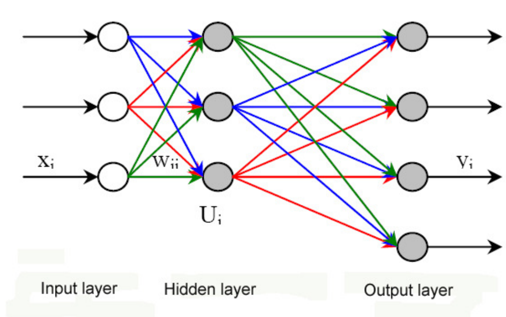

Fig. 2. *Neuronal network with 3 layers*

RNA is essentially based on two basic concepts:

a) operation to the level of independent processing units;

b) the existence of a learning law.

Algorithms based on neural networks are parallel algorithms and calculation is also parallel.

Techniques based on neural network techniques can be classified into supervised and unsupervised.

In the first category of methods, training is called supervised because are known both the input and output system parameters. The system is modeled using a neural network and the weights between layers are initialized with random values. By comparison between the known input parameters and the output parameters obtained from the application of network input data set, an error signal is obtained, by means of which are determined and adjusted the weights of the network layers to minimize a performance criterion.

Unsupervised learning methods do not use known output quantities in the neural network training stage, using the input quantities only to adjust the weights. In this way, the output classes can be constructed corresponding to certain entries in the data set, or outputs such as "winner takes all", where the output neuron with the highest activity is declared the winner and is activated, the other output neurons of the layer being not activated. This process is called self-organization and can be successfully applied in pattern recognition problems.

A back propagation neural network was trained on the basis of these simulation studies. Networks prediction was compared with the simulation results.

2. Algorithm for studying the deformation process in multipoint forming

Due to the large number of parameters that influence the process of multipoint forming, the performance optimization of the deformation conditions requires a large number of experiments carried out under specific conditions.

The analysis showed that the studied process is described by a large number of parameters, which have a nonlinear variation and are interdependent on each other.

In these circumstances it is difficult to achieve a mathematical model describing the process faithfully studied.

Therefore, to convert data obtained by simulating with FEM the multipoint forming process with interpolator, in manufacturing and design knowledge, an algorithm was developed for predicting the deformation behavior material in the process. The algorithm is shown in Figure 3.

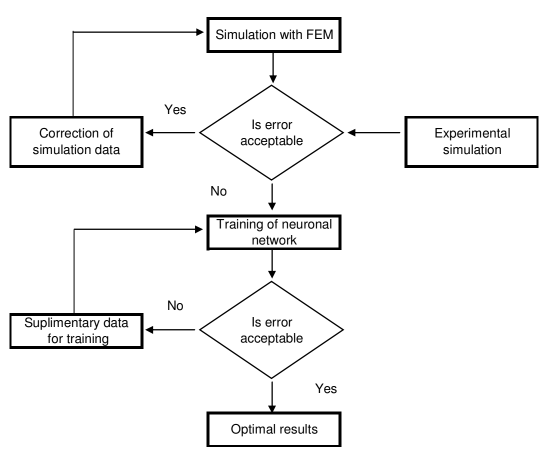

Fig. 3. *Neuronal network algorithm based on FEM*

3. FEM model and process simulation

The FEM model is presented in Figure. 4.

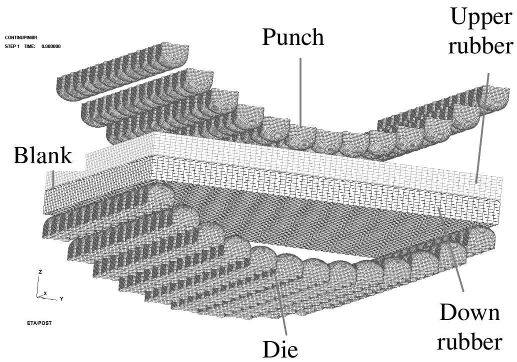

Fig. 4. *Reconfigurable multipoint forming tooling FEM model*

The tooling was modeled as rigid surfaces using the simulation program DYNAFORM-PC. No blankholder was used. In the model between the active elements and the blank were included two interpolators (upper and down rubber). No blankholder was used so the ends of the rubbers are free to expand.

The upper die and lower one consist of 100 pins for each, disposed face to face, both on *x*-direction and *y*-direction.

The part geometry is a simply curved part with an interior radius of 95 mm, a width of 120 mm (maximum depth is 21.345 mm) and a length of 130 mm. The blank was a rectangular plate with the dimensions of 120x130 mm.

The punch speed was 100 mm/second. A Coulomb friction law was used with a friction coefficient of 0,125.

For simulation were used 4-node Belytschko-Tsay shell elements, which provide five integration points through the thickness of the sheet metal.

The material used in experiments was mild steel, with a thickness of 1 mm. The yielding of the material was modeled using a power law, as:

$$\sigma = K\,\varepsilon^{n} \tag{2}$$

According to the material characteristics, for simulation the *n*-value = 0,22 and *K* = 648 MPa. The *R*-values were set to: R_{00} – 1,87; R_{45} – 1,27; R_{90} – 2,17.

For rubber interpolator was chosen a material type Elvax 460. The properties of the material were: density, ρ – 0.946 g/cm^3; hardness Shore ASTM D2240 scale B – 40 and scale A – 80; tensile strength, *Rm* – 18 MPa; elongation – 750%; stiffness, *k* – 43 MPa; Poisson ratio, ν – 0.499. Solid elements were used for the discretization of the rubber interpolator. The interpolator was modelled as an elastic material, *MAT_ELASTIC (LS-DYNA Type 1). The rubber flexural moduli varied between 14 and 44 MPa. The thicknesses of the rubbers varied between 2 and 10 mm. The simulations were done also with different punch strokes (Table 1).

Table 1. *FEM simulation parameters*

Nr. crt.	Rubber thickness, [mm]	Pins strokes, [mm]	Rubber elastic modulus, [MPa]
1.	2	17	14
2.	3	18	24
3.	4	19	34
4.	5	20	44
5.	6	21	
6.	7	22	
7.	8	29	
8.	9	30	
9.	10		

The geometry of part is affected by the rubber presence in terms of profile radius and depth.

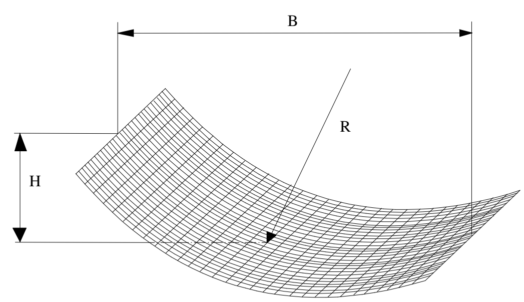

Fig. 5. *Parameters for springback definition*

The blank deformation was evaluated in terms of springback. The springback could be defined function of the three parameters presented in Figure 5.

The springback was calculated using the relation:

$$\Delta S = \frac{V_i - V_f}{V_i} \tag{3}$$

where: ΔS is the value of the springback, *S* is one of the three parametrs; V_i – initial value of one of the three parametrs; V_f – final value of one of the three parameters.

In Table 2, there are presented only some of the values of rubber thickness (for thickness from 2 to 7 mm). Also, the values of springback on the width and height direction are considered. (Table 2).

Tabel 2. *Springback values using FEM simulation and Neural Networks modelling*

Crt. no.	Rubber thickness [mm]	Pins strokes [mm]	Rubber elastic modulus [MPa]	FEM simulation		NNTmodeling		Error [%]	
				ΔB	ΔH	ΔB	ΔH	ΔB	ΔH
1.	2	21	14,00	0,034	-0,326	0.034	-0.301	-1.0	7.8
2.	2	21	24,00	0,032	-0,258	0.033	-0.267	-3.9	-3.5
3.	2	21	34,00	0,031	-0,246	0.031	-0.233	0.2	5.4
4.	2	21	44,00	0,029	-0,225	0.030	-0.221	-1.9	2.0
5.	2	23	14,00	0,030	-0,234	0.030	-0.229	-0.9	2.2
6.	2	23	24,00	0,026	-0,192	0.026	-0.188	-3.3	2.0
7.	2	23	34,00	0,021	-0,146	0.021	-0.130	-2.9	11.2
8.	2	23	44,00	0,016	-0,109	0.017	-0.086	-8.1	21.1
9.	2	25	14,00	0,030	-0,234	0.030	-0.225	-2.3	4.0
10.	2	25	24,00	0,026	-0,192	0.025	-0.177	1.1	7.9
11.	2	25	34,00	0,021	-0,146	0.021	-0.134	-2.4	8.3
12.	2	25	44,00	0,016	-0,109	0.017	-0.086	-6.2	20.5
13.	3	22	14,00	0,032	-0,260	0.031	-0.247	2.9	4.7
14.	3	22	24,00	0,029	-0,223	0.029	-0.219	0.5	1.9
15.	3	22	34,00	0,026	-0,187	0.026	-0.185	-0.7	0.8
16.	3	22	44,00	0,023	-0,155	0.022	-0.143	2.4	7.6
17.	3	23	14,00	0,026	-0,196	0.026	-0.193	0.2	1.3
18.	3	23	24,00	0,020	-0,141	0.020	-0.131	0.8	6.7
19.	3	23	34,00	0,013	-0,076	0.014	-0.061	-3.8	19.7
20.	3	23	44,00	0,010	-0,044	0.011	-0.027	-11.9	38.6
21.	4	23	14,00	0,030	-0,233	0.031	-0.225	-1.9	3.5
22.	4	23	24,00	0,024	-0,166	0.026	-0.170	-7.0	-2.6
23.	4	23	34,00	0,017	-0,101	0.018	-0.089	-3.5	11.7
24.	4	23	44,00	0,012	-0,054	0.012	-0.038	-5.1	28.8
25.	5	21	14,00	0,020	-0,115	0.019	-0.123	3.6	-7.0
26.	5	21	24,00	0,010	-0,039	0.012	-0.044	-14.6	-13.1
27.	5	21	34,00	0,010	-0,018	0.010	-0.020	3.5	-11.5
28.	5	21	44,00	0,014	-0,014	0.010	-0.016	31.1	-12.1
29.	5	22	14,00	0,036	-0,294	0.037	-0.295	-2.3	-0.2
30.	5	22	24,00	0,034	-0,271	0.035	-0.270	-3.0	0.3
31.	5	22	34,00	0,032	-0,247	0.033	-0.243	-2.6	1.8
32.	5	22	44,00	0,030	-0,223	0.031	-0.218	-2.0	2.2
33.	5	23	14,00	0,033	-0,256	0.033	-0.254	-2.0	0.8
34.	5	23	24,00	0,028	-0,195	0.029	-0.197	-3.7	-1.1
35.	5	23	34,00	0,022	-0,132	0.023	-0.129	-4.6	2.4
36.	5	23	44,00	0,015	-0,073	0.018	-0.079	-15.7	-7.9
37.	6	21	14,00	0,038	-0,322	0.038	-0.315	-0.8	2.2
38.	6	21	24,00	0,036	-0,304	0.037	-0.293	-0.9	3.7
39.	6	21	34,00	0,035	-0,287	0.035	-0.276	-0.3	3.9
40.	6	21	44,00	0,034	-0,268	0.035	-0.266	-1.8	0.6
41.	6	23	14,00	0,034	-0,274	0.035	-0.269	-0.7	2.0
42.	6	23	24,00	0,030	-0,220	0.030	-0.210	0.6	4.4
43.	6	23	34,00	0,026	-0,177	0.025	-0.154	2.4	13.3
44.	6	23	44,00	0,019	-0,105	0.020	-0.105	-3.9	0.3
45.	7	20	14,00	0,036	-0,293	0.037	-0.300	-2.0	-2.2
46.	7	20	24,00	0,036	-0,289	0.036	-0.284	-0.8	1.9
47.	7	20	34,00	0,034	-0,274	0.035	-0.273	-2.2	0.2
48.	7	20	44,00	0,034	-0,266	0.035	-0.267	-2.5	-0.5

4. Application of neural network

The results of 96 case studies were used for training a back propagation neural network, with 3 inputs and 2 outputs. The input and output data required for training the neural network is given in Table 2.

The input parameters were the rubber thickness, the rubber elastic modulus and the pins stroke. The output parameter was the springback.

The bias factors were 0.385. The neural network was trained for average error tolerance of 0.0004. It converged in 200000 cycles.

Figure 5 presents the neural network designed:

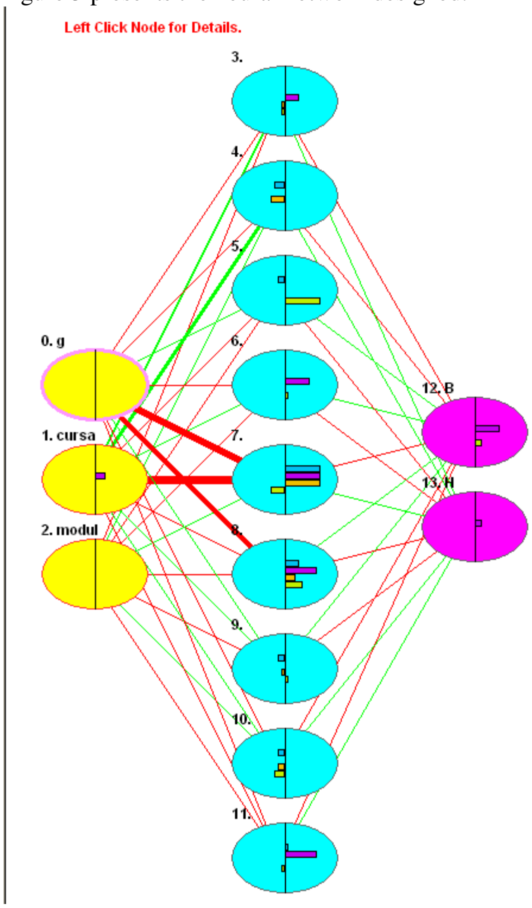

Fig. 5. Neural network used in training data

5. Results and discussions

The trained neural network has been used for predicting the responses of input data.

The learning rate was 0.6 and the momentum was 0.8.

The importances of the input columns were:

pins stroke 212.6892;

rubber thickness 163.3509;

rubber elastic modulus 16.4012.

6. Conclusions

This paper presents the application of neural network to study the springback in multipoint forming. First, the process is modelled using the finite element method. The numerical experiments give a data set of springback values. Then using neural network modelling, the data set is trained. The average error is 0.66 per cent for B and 1.95 per cent for H. 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 ΔH, whereas minimum error is in the ΔH prediction too.

This method will help in the quick determination of the behavior of sheets in the multipoint forming. The optimum parameters obtained by neural network, will be further checked using the finite element analysis.

This will reduce the simulation time and also the costs with the FEM simulations, and will help in the designing of a well-balanced multipoint forming process.

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Aplicarea rețelelor neuronale în procesul de formare multipunct

—Rezumat—

Formarea multipunct a tablelor subțiri se bazează pe conceptul de matriță reconfigurabilă multipunct. Această lucrare prezintă aplicarea metodei rețelelor neuronale în studiul fenomenului de revenire elastică în cazul formării multipunct.

În prima parte a lucrării se prezintă metoda rețelelor neuronale. De asemenea este prezentat un algoritm de modelare bazat pe FEM şi pe rețele neuronale. Utilizând simularea FEM, sunt obținute valorile revenirii elastice pentru o geometrie a piesei cu simplă curbură. Pe baza valorilor obținute a fost antrenată o rețea neuronală, utilizând ca parametri de intrare grosimea interpolatorului de cauciuc, modulul de elasticitate al cauciucului şi cursa pinilor. Ca date de ieşire au fost considerate revenirea elastică în lățime şi înălțime. Concluziile obținute pe baza interogării rețelei neuronale certifică validitatea metodei prezentate.