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Optimization of spring back in U-die bending process of sheet metal using ANN and ICA

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Abstract. The controlling and prediction of spring back is one of the most important factors in sheet metal forming processes which require high dimensional precision. The relationship between effective parameters and spring back phenomenon is highly nonlinear and complicated. Moreover, the objective function is implicit with regard to the design variables. In this paper, first the influence of some effective factors on spring back in U-die bending process was studied through some experiments and then regarding the robustness of artificial neural network (ANN) approach in predicting objectives in mentioned kind of problems, ANN was used to estimate a prediction model of spring back. Eventually, the spring back angle was optimized using the Imperialist Competitive Algorithm (ICA). The results showed that the employment of ANN provides us with less complicated and time-consuming analytical calculations as well as good results with reasonable accuracy.

Keywords: U-die bending process; spring back angle; artificial neural network; imperialist competitive algorithm

1. Introduction

Due to the release of elastic stresses, the sheet metal tends to return to its original shape after unloading. This phenomenon is called "spring back". It plays an essential role in sheet metal forming processes in order to obtain a geometrically optimized shape. Accordingly, the spring back prediction in sheet metal forming is of great significance in industrial applications. There are several parameters affecting spring back, such as sheet thickness, depth of drawing, specimen orientation and forming speed.
Regarding the complicated and nonlinear relationship between the effective parameters in spring back phenomenon, having a theoretical model to perform spring back calculations is very challenging. Therefore, many researchers have employed Finite Element Method (FEM) and Artificial Neural Network (ANN) approaches to propose specific models to control and predict the spring back. Due to the time-consuming and numerous runs in finite element method, ANN which overcomes the complexities of FEM is preferred in many cases.

Karafillis and Boyce (1992, 1996) performed spring forward method in designing dies to obtain the desired final shape. Ruffini and Cao (1998) implemented a neural network control system to reduce spring back in a stamping process of aluminium. Cao *et al.* (2000) discussed the implementation of ANN approach for the first time. They used ANN to predict spring back in free V-bending sheet metal forming. Kim and Kim (2000) employed finite element simulations and ANN to predict spring back. Sun *et al.* (2006) used a closed-loop control system to develop a method for evaluating spring back during the metal forming process. Liu *et al.* (2007) used a GA-trained neural network to develop a model for spring back prediction in U-shaped bending. Kazan *et al.* (2009) used ANN to propose a prediction model for spring back in wipe bending process, where the training data for the neural network were calculated using finite element methods.

In the present paper, the spring back angle in typical U-die bending process is optimized using the Imperialist Competitive Algorithm (ICA). Because the calculation of spring back by actual experiments for any different value of effective parameters isn't economically reasonable and is in some level impossible to perform, we employed the powerful ANN approach to find the nonlinear relationship between effective parameters and spring back angle. In this regard, to obtain the relationship between different parameters such as sheet thickness, U-die depth and specimen orientation and spring back angle value, experimental tests were performed. Then, concluding results were used to train the appropriate neural network in order to predict spring back angle for other parameter values.

2. Artificial neural network approach

Artificial neural network approach is a simulation of the human brain in processing the mathematical information. ANN consists of a group of neurons (processor elements) and their connector linkages with adjustable weights related

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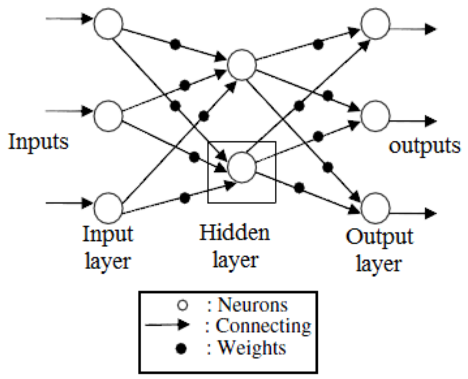

Fig. 1 The architecture of an artificial neural network

Fig. 2 An overview of the die used for U-die bending experiment

to the governing conditions of the problem. The neural networks have three kinds of layers, namely an input layer, hidden layers and an output layer. The obtained data from the experiments enter the neural network through the input layer. Layers included between the input and output layers are called "hidden layers". These layers receive the data from the input layer and send them to the output layer after processing them. Receiving data from the hidden layers, the output layer makes a vector as the output of the neural network. Fig. 1 shows the architecture of a typical neural network.

In this paper, 36 experimental tests were performed to find the required data for training the appropriate ANN as well as to predict and control the spring back angle. Accordingly, several aluminum sheets with the thicknesses of 0.5, 1, 1.5 and 2 *mm* were cut at different orientations to the rolling direction (0, 45 and 90°). Consequently, the U-die bending experiment was performed for die depths 20, 25 and 30 *mm* to find the spring back angles with the die shown in Fig. 2.

Table 1 presents the results of the experiment. In this table, *NS* represents the sample number, *t* the thickness, *D* the die depth, θ the specimen orientation to the rolling direction and *SB* the spring back angle.

According to the fact that applying a 2-layer neural network (with one hidden layer) enables us to model any nonlinear relationship with the desired accuracy (Hormik *et al*. (1989), a 2-layer neural network was used in the present paper. Sheet thickness, drawing depth and specimen orientation to the rolling direction are considered as the ANN inputs while spring back angle acts as the ANN output. Considering the dependence of neural network to how to select the test and training data, two different sets of test and training data were chosen to train two different

Table 1 Input data to the neural network using the U-die bending experiment

NS	t (*mm*)	D (*mm*)	Teta (*deg*)	SB (*deg*)	NS	t (*mm*)	D (*mm*)	Teta (*deg*)	SB (*deg*)
1	0.5	20	0.0	11.9	19	1.5	25	90	7.9
2	1	25	45	7	20	2	30	0.0	1.5
3	0.5	30	90	4.2	21	0.5	20	90	15.2
4	2	30	45	1.7	22	1	25	0.0	5.4
5	0.5	25	90	12.5	23	2	25	0.0	2.2
6	1	30	0.0	4	24	0.5	25	45	11.6
7	1.5	20	90	7.8	25	1	30	90	6.5
8	0.5	30	45	10.7	26	1.5	20	45	7
9	1	20	0.0	8.9	27	2	25	90	2.8
10	1.5	25	45	7.1	28	0.5	30	0.0	6.1
11	0.5	20	45	14	29	1.5	25	0.0	6.3
12	1	25	90	7.4	30	2	30	90	2
13	1.5	30	0.0	3.5	31	1	20	45	10.4
14	2	20	90	3	32	2	20	0.0	2.5
15	1	30	45	6	33	0.5	25	0.0	8.4
16	1.5	20	0.0	5.6	34	1	20	90	11.2
17	2	25	45	2.4	35	1.5	30	45	3.8
18	0.5	30	90	11.5	36	2	20	45	2.7

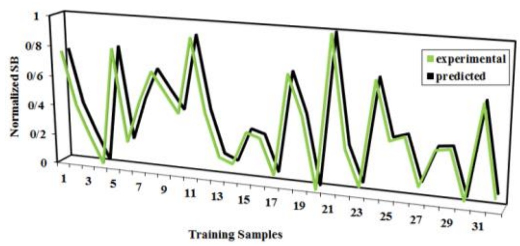

Fig. 3(a) Comparison of experimental and predicted spring back values by ANN for train data in Type 1 neural networks

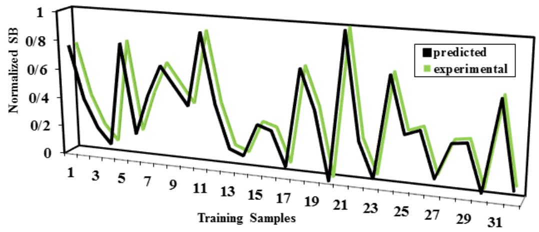

Fig. 3(b) Comparison of experimental and predicted spring back values by ANN for train data in Type 2 neural networks

types of neural networks. In the first set, samples 4, 33, 34 and 35 and in the second set, samples 33 through 36 in Table 1 was chosen as the test data while other entries were selected as training data.

Furthermore, various neural networks (with one hidden layer and between 3 to 6 neurons) were trained for these 2 sets of input data where the optimum networks are selected for set 1 and set 2. The architecture of the ANN along with the activation functions used in the chosen models is presented in Table 2.

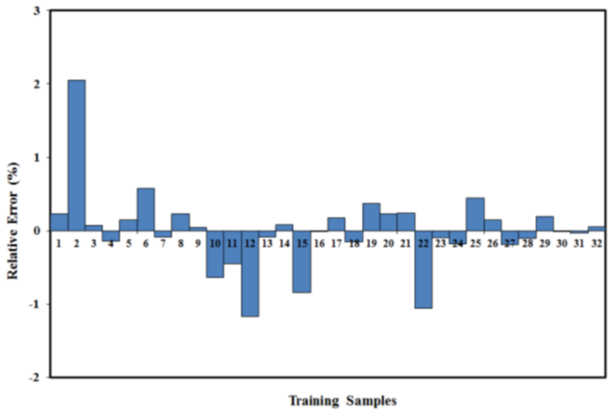

Fig. 4(a) Relative error of ANN training samples for Type 1 neural networks

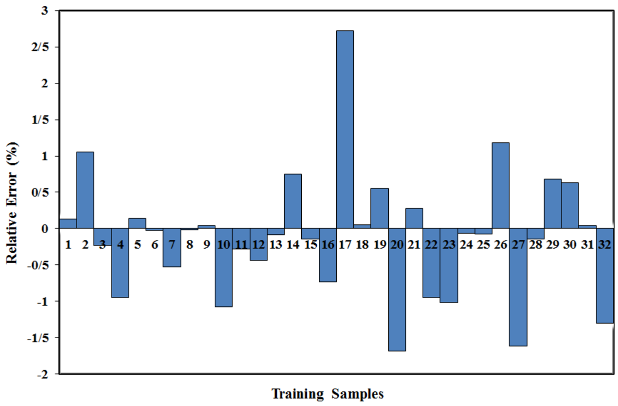

Fig. 4(b) Relative error of ANN training samples for Type 2 neural networks

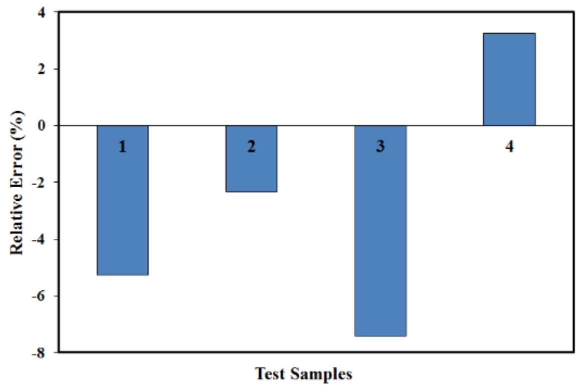

Fig. 5(a) Relative error of ANN test samples for Type 1 neural networks

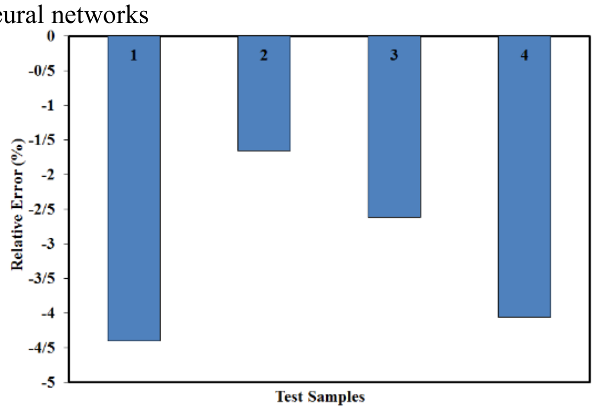

Fig. 5(b) Relative error of ANN test samples for Type 2 neural networks

Table 2 ANN architecture and functions

Network	Feed-forward back propagation network
Training method	Supervised training
Transfer function	Log-Sigmoid function
Training function	Levenberg–Marquardt
Learning function	Gradient descent
Performance function	Mean squared error

A comparison of predicted values by ANN with experimental data which were used to train Type 1 and Type 2 neural networks, are presented in Figs. 3(a) and 3(b). At these figures, normalize SB is determined by Eq. (1).

$$Normalized\ SB = \frac{SB - SB_{min}}{SB_{max} - SB_{min}} \tag{1}$$

Where SB_{min} and SB_{max} are the minimum and maximum values of spring back in experimental tests.

In Figs. 4(a) and 4(b), the relative error for training data of Type 1 and Type 2 neural networks is shown, respectively. Moreover, the relative errors between predicted values of spring back and experimental test samples is presented for Type 1 and Type 2 neural networks in Figs. 5(a) and 5(b), respectively.

It can be observed that the errors between experimental and predicted values by ANN for train samples are insignificant, therefore it is concluded that the neural network has been extended well for both types.

3. Spring back optimization by ICA algorithm

After finding the appropriate trained ANN for spring back angle prediction in terms of different aforementioned parameters, one can use mentioned ANN models as the objective function for ICA to optimize the spring back angle. This algorithm was proposed by Atashpaz-Gargari and Locus (2007) which develops a robust meta heuristic optimization algorithm using the socio-political evolution of humanity as a source of inspiration.

Meta heuristic algorithms are quite powerful and qualified for obtaining the solution of engineering optimization problems (Arjmand *et al.* (2018)). Recently, the researcher used of the ICA in many engineering problems such as Khabbazi *et al.* (2009), Mozafari and Abdi (2010), Kaveh and Talatahari (2010), Hosseini *et al.* (2010), Nazari-Shirkouhi *et al.* (2010), Sabour *et al.* (2011), Sheikhi *et al.* (2012) and Ding *et al.* (2017).

Like other meta heuristic optimization algorithms, ICA starts with initial design variables. Each particle of the population is called a “country” and they are divided into two groups: the imperialists and their colonies. The countries with much power (less costs) are chosen as imperialists and the rest are considered as colonies. In fact, each imperialist represents the local or global optimal points. Colonies are in the possession of an imperialist. The more details and fully explained the procedures of this

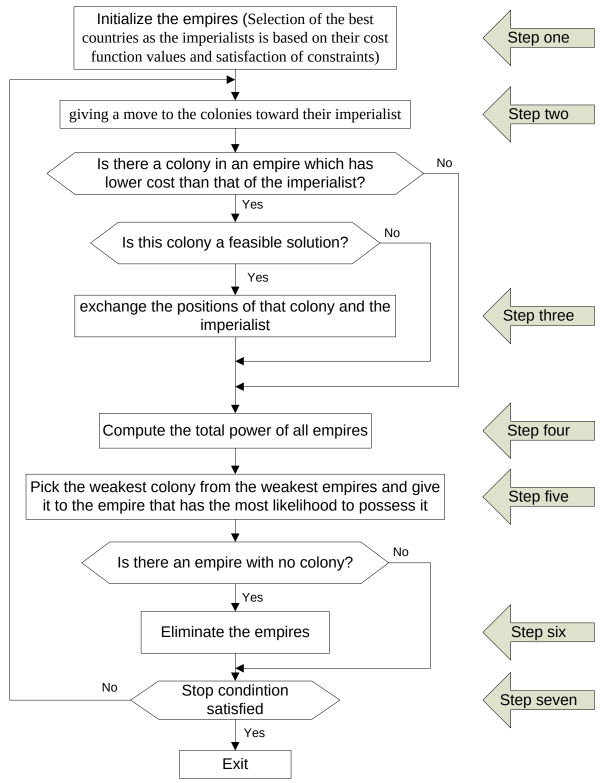

Fig. 6 Flowchart of the ICA (Sheikhi and Ghoddosian 2013)

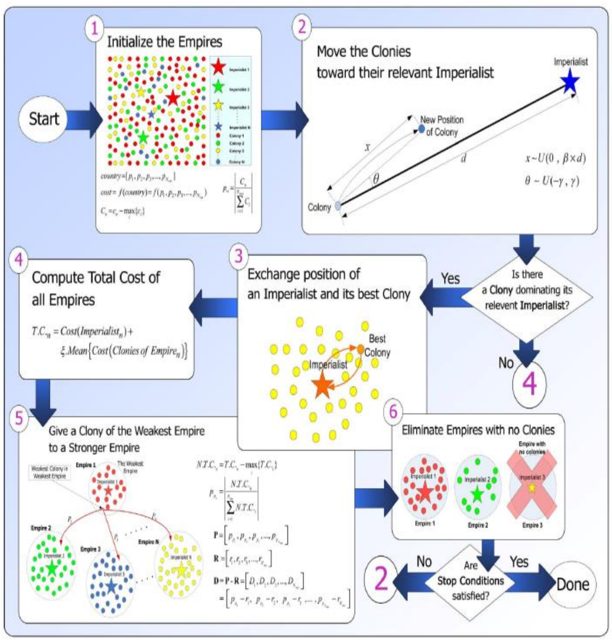

Fig. 7 The main steps of the ICA (Mozaffari *et al*. 2012)

Table 3 The results of spring back optimized angle using ICA

Neural Network	Spring back (*deg*)	Specimen orientation (*deg*)	Depth drawing (*mm*)	Thickness (*mm*)
Type 1	1.5	0.0	30.0	2.0
Type 2	1.5	0.0	30.0	2.0

algorithm is provided at Nazari-Shirkouhi *et al.* (2010) and Hosseini and Al Khaled (2014).

The flowchart and main steps of ICA are proposed in

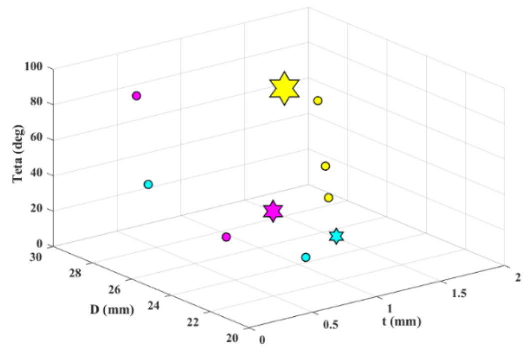

Fig. 8 Initial population of the countries

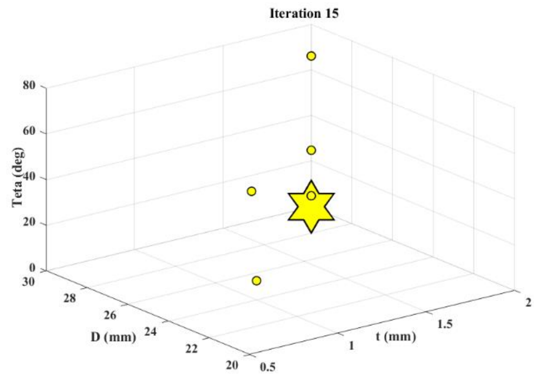

Fig. 9 Population arrangement of countries in the 15th iteration

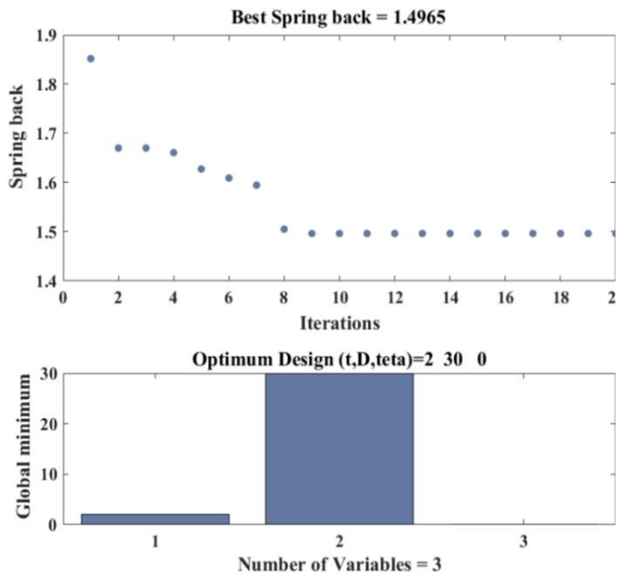

Fig. 10 The process of reaching to optimized spring back angle

Fig. 6 (Sheikhi and Ghoddosian 2013, and Sabour *et al.* 2011) and Fig. 7 (Mozaffari *et al*. 2012) respectively.

In this paper, 10 countries were chosen which 3 of them were selected as the imperialists. The variation range for the effective variables was within [0.1, 2] millimetres for sheet thickness, [20, 30] millimetres for die depth and [0, 90] degrees for the specimen orientation to the rolling direction.

The parameters tuning such as β, γ and ξ that used in

ICA are 2.0, 0.3 and 0.1 respectively (Sheikhi and Ghoddosian 2013). The arrangement of our initial population is shown in Fig 8. The stars depict the imperialists and circles represent the colonies.

The more is the power of an empire, the bigger is the star representing that. The stars depict the imperialists and circles represent the colonies. The more is the power of an empire, the bigger is the star representing that.

Fig. 9 shows the position of countries in the 15th iteration. As it can be observed from this figure, there exists just one empire and all the colonies belong to one imperialist. However, as we proceed in the mentioned algorithm, all the colonies move toward the remained imperialist and will have the same cost and power as their imperialist. The process of reaching to the optimized spring back angle in the first 20 iterations is shown in Fig. 10.

The results of the spring back optimized angle using ICA in conjunction with the trained ANN are provided in Table 3 for both neural networks."

4. Conclusions

It can be seen that ICA converged to the desired value for effective parameters. As the algorithm converges to the optimized value for spring back, it can be concluded that the ANN has provided precise values of fitness function for all ranges of different variables. This implies the good training of the neural network.

From the results provided in Table 3, it is observed that the optimized spring back values obtained from employing ICA in conjunction with both neural networks were the same. However, the ANN can be trained with more training samples in the vicinity of optimized value, or with less training samples while checking the generalizability by choosing test data in that vicinity. In the current paper the aforementioned procedure was employed by using both training alternatives and same optimum results were reached. Therefore, even if we don't have the final optimum range, we can rely on our neural network by choosing the appropriate test samples providing that the generalizability of the network is completely met. Regarding the results of the performed experiments and the optimum results for spring back angle obtained from ICA, it can be inferred that choosing a thicker sheet, deeper depth and smaller specimen orientation to the rolling direction, one can obtain a smaller spring back angle.

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