

# Comparison of Artificial Neural Network Model and Response Surface Methodology for Springback Prediction

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**Abstract.** In sheet metal manufacturing, the ability to predict failures, such as springback, wrinkling and thinning, are of high importance. The objective of this study is to compare the response surface methodology (RSM) and the artificial neural network (ANN) model for predicting springback during the deep drawing process. In this investigation, friction coefficient, punch speed and blank holder force were considered as input variables. Sample data were planned by the complete factorial design and obtained via numerical simulation. To compare the RSM and ANN models, a goodness-of-fit test was performed. The results of the two methods are promising and it is found that the ANN results are more accurate than the RSM results.

## 1 Introduction

Deep drawing, as an essential process in the metal forming industries, is most commonly employed in the automotive and appliance industries. One of the most important and deleterious failures in this process is springback which is defined by difference between the goal shape and the shape achieved after the tool retraction [1]. The impact of different parameters that cause this failure mode are: coefficient of friction between the blank and the tools, punch speed, blank holder force, mechanical properties of the material and the geometrical characteristics of the tools namely punch and die radius [2].

Therefore, the prediction of springback becomes an essential requirement in the stamping process design [3]. So far, there are various popular surrogate models, such as Radial Basis Function (RBF), Response Surface Methodology (RSM), Artificial Neural Network (ANN) and Kriging [4]. Bahloul et al. [5] applied RSM to predict sheet thinning rate and punch forces in incremental forming. Tool dimensions, wall tilt angle, vertical pitch size and material thickness considered as problem inputs. Kotkunde et al [6] proposed an ANN model to predict the Forming Limit Diagram for aluminium Alloy. Punch velocity, temperature, blank holder force and normalized distance of a cup are considered as input parameters.

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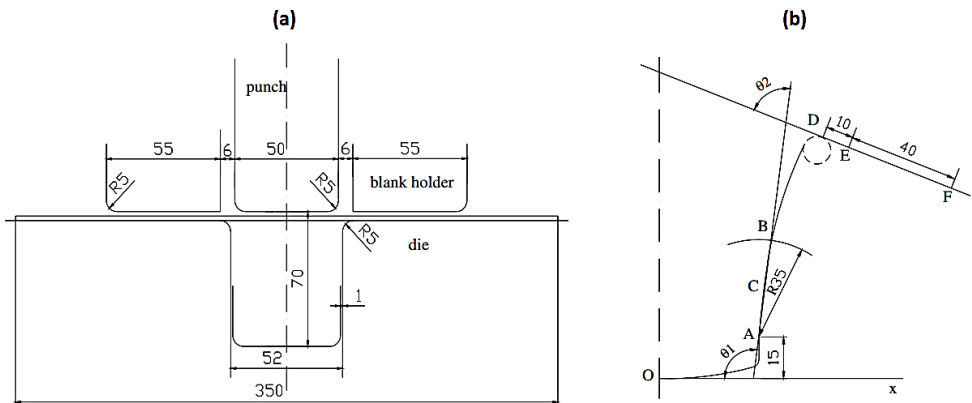
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## 2 Case study and Methodology

The objective of this investigation is to predict the influence of deep drawing parameters namely friction coefficient between blank holder and blank, blank holder force, friction coefficient between die and blank, and punch velocity that have the strongest effect on springback values. Fig.1 shows the 2-D drawing bending problem of NUMISHEET'93 and measure method of springback [7]. The main reason for choosing this reference problem is that U-profile shape is a prevalent characteristic of deep drawn pieces that are present in numerous high springback automotive components [8]. Based to their level of influence, three levels are chosen for friction coefficient between die and blank ( $\mu_d$ ) and friction coefficient between blank holder and blank ( $\mu_h$ ), and two levels for blank holder force (BHF), and punch velocity (vp), as indicated in Table 1. In order to predict the springback, RSM and ANN methods are selected. To collect sample data for ANN and RSM training, a series of simulations were performed based on a full factorial design. The full factorial design method consists in improving the accuracy of Meta model prediction through its principle of applying all levels of factors with all possible interactions. Therefore, for Meta-models training, 36 sets of samples were carried out.

**Table 1.** Design variable with their levels

Level	BHF	vp	$\mu_d$	$\mu_h$
1	10	1	0.05	0.05
2	14	10	0.15	0.15
3	-	-	0.3	0.3



[Spring back]

$\theta_1$ : Angle between O-X and A-B

$\theta_2$ : Angle between A-B and E-F

[Curvature]

$\rho$ : Defined by the radius of a circle through A, B and C

[Point]

A: 15mm from O-X

B: 35mm from point A

C: Middle point of the straight line A-B

D: End of die's curve

E: 10mm from D

F: 40mm from E

**Fig. 1.** 2-D draw bending problem of NUMISHEET'93: (a) profile and (b) measure method of springback

### 3 RSM MODELLING

The response surface methodology is a meta model based on design of experiment and least squares error fitting. The RSM regression model can be defined by the equation below:

$$\hat{y} = \beta_0 + \sum_{j=1}^n \beta_j x_j + \sum_{j=1}^n \beta_{jj} x_j^2 + \sum_{i=1}^{n-1} \sum_{j=i+1}^n \beta_{ij} x_{ij} \tag{1}$$

where:

- $m$  is the number of design variables
- $\hat{y}$  is the estimated output
- $x_{ij}$  are the variables that influence the output
- $\beta_{ij}$  are regression coefficients

As shown in equation 1, a second-order polynomial model was constructed in the MINITAB software to obtain the relation between the output value and the input parameters. The ANOVA result for springback is presented in Table 2.

$$\hat{y} = 139,4 - 2,440 * BHF + 1,039V_p + 37,5\mu_d - 46,0\mu_h - 383\mu_d * \mu_d - 9,42V_p * \mu_d - 9,28V_p * \mu_h - 430\mu_d * \mu_h \tag{2}$$

**Table 2.** Analysis of variance (ANOVA) results for RSM model

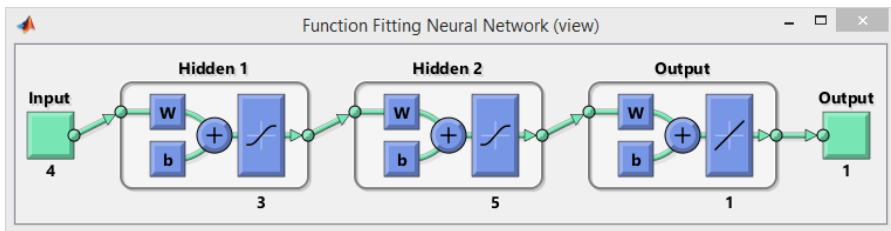
Source of variance	Degree of freedom	Sum of squares	Mean squares	F value	P value
Regression	8	36068,1	4508,52	45,41	0,000
<i>BHF</i>	1	857,2	857,22	8,63	0,007
<i>V<sub>p</sub></i>	1	125,6	125,59	1,27	0,271
<i>μ<sub>d</sub></i>	1	16,4	16,42	0,17	0,687
<i>μ<sub>h</sub></i>	1	156,9	156,90	1,58	0,219
<i>μ<sub>d</sub> * μ<sub>d</sub></i>	1	260,3	260,29	2,62	0,117
<i>V<sub>p</sub> * μ<sub>d</sub></i>	1	682,6	682,61	6,88	0,014
<i>V<sub>p</sub> * μ<sub>h</sub></i>	1	662,4	662,42	6,67	0,016
<i>μ<sub>d</sub> * μ<sub>h</sub></i>	1	742,3	743,35	7,48	0,011
error	27	2680,6	99,28	-	-
Total	35	38748,7	-	-	-

### 4 ANN MODELLING

The artificial neural networks are one of the most suitable meta-models to solve metal forming problems [9]. ANN are biologically derived from neural process of the human brain and they have a parallelly distributed structure with a high number of neurons and connections. Every link point from one node to another and is assigned with a weight.

**Table 3.** Characteristics of the neural network architecture

<b>Network type</b>	Feed forward neural network
<b>Number of hidden layers</b>	Two
<b>Number of neurons in input layer</b>	Four
<b>Training rule</b>	Back propagation
<b>Transfer function</b>	Sigmoid transfer function in hidden and output layers
<b>Number of neurons in hidden layers</b>	3–5
<b>Training termination</b>	Minimum mean square error



**Fig. 2.** Schematic illustration of the proposed ANN

Meta-modelling with an ANN technique entails the design of the networks architecture, like learning rate, number of hidden layers, learning method and number of neurons in every layer. Table 3 shows the design characteristics of the neural network architecture. Due to the results of various trials, a two-hidden layer structure with five neurons in the second and three neurons in the first was found to be the most suitable for the problem in question.

## 5 RESULTS AND DISCUSSION

In this work, RSM and ANN techniques are used to predict springback during the deep drawing process. These Meta-models are compared based on statistical indicators such as normalized root mean square error (NRMSE), mean absolute percentage error (MAPE) and R-squared coefficient (R<sup>2</sup>), and. These indicators are measured according to the following equations:

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \tag{3}$$

$$MAPE = \left( \frac{1}{n} \sum_{i=1}^n \frac{|y_i - \hat{y}_i|}{|\hat{y}_i|} \right) * 100 \tag{4}$$

$$NRMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} * \frac{1}{y_{max} - y_{min}} \tag{5}$$

With  $n$  is the number of experiment data sets,  $\hat{y}_i$  is the corresponding obtained value for the real value  $y_i$ ,  $\bar{y}$  is the average score of the data. A greater  $R^2$  score signifies a more precise surrogate model, while a greater NRMSE or MAPE value signifies a poorer surrogate model. The  $R^2$  value gives a picture of how well the model regression variables take into account the variability of the model output value. The MAPE is used to quantify the magnitude of the error in percent and the NRMSE is a metric for the relative accuracy of the Meta model.

Table 4 presents the accuracy assessment of the response surface methodology and the artificial neural network techniques using the chosen statistical measures. The  $R^2$  values of the neural network and the RSM models were determined to be 0.98 and 0.93, respectively. In addition, the NRMSE values of the neural network and the RSM models were calculated to be 0.0182 and 0.0785, respectively and the MAPE values of ANN and RSM models were determined to be 2.88 and 14.7353, respectively. Following these three error criteria, it is very clear that the ANN technique gives a better precision than the RSM model. However, evaluating the goodness of fit based only on training sample points cannot be sufficient. Therefore, the validation of the meta-model precision is also done by a set of additional  $k$  points, which were not considered for training. To provide a clearer picture of the surrogate model's accuracy, the average relative error ( $e_{avg}$ ) and the maximum relative error ( $e_{max}$ ) are also implemented as shown below:

$$e_{max} = \max_{i \in K} \left( \frac{|y_i - \hat{y}_i|}{|y_i|} \right) \tag{6}$$

$$e_{avg} = \frac{1}{K} \sum_{i=1}^K \frac{|y_i - \hat{y}_i|}{|y_i|} \tag{7}$$

Table 5 lists the accuracy assessment of the ANN and RSM techniques for test data. The maximum relative error values of the neural network and the RSM models were determined to be 0.075 and 0.22, respectively. The average relative error values of the neural network and the RSM models were determined to be 0.036 and 0.073, respectively. It is clearly demonstrated that the ANN model provides the best accuracy. Therefore, this tool was selected to link the springback and the input variables.

**Table 4.** Comparison of RSM and ANN prediction results for training data

Statistical criterion	ANN	RSM
$R^2$	0.98	0.93
MAPE	2.88	14.7353
NRMSE	0.0182	0.0785

**Table 5.** Comparison of RSM and ANN prediction results for test data

Statistical criterion	ANN	RSM
$e_{max}$	0.075	0.22
$e_{avg}$	0.036	0.073

## 6 CONCLUSIONS

In this article, springback was predicted using the neural network technique and the response surface methodology and the results achieved by the two techniques were matched to numerical results to study the closeness of the predictions with the numerical results. These meta-models are able to consider the effect of punch speed, blank holder force and friction coefficient on springback. It can be seen that both techniques are promising and the results of ANN are more precise than those of RSM. ANN model can be a strong basis for springback optimization and compliant product design. It would be interesting in a future study to take some other parameters, namely deformation exponent, punch radius and die radius that were not included in this study.

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