Comparison of Artificial Neural Network and Response Surface Methodology in the Prediction of Springback and Bend force in Air Bending of Electrogalvanised Steel Sheets

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Abstract—This paper compares the springback and bend force prediction models based on artificial neural network and response surface methodology. The models were developed based on five level-half factorial central composite rotatable design of experiments conducted on air bending of electrogalvanised steel sheets with strain hardening exponent, coating thickness, die opening, die radius, punch radius, punch travel and punch velocity as the process parameters. The ANN model of springback and bend force was developed using a multilayer feed forward back propagation network, trained with a Levenberg-Marquardt (LM) learning algorithm. The predictive capability of the developed ANN model was compared with the second order RSM models of springback and bend force. The comparison shows that the ANN models provide more accurate prediction than the RSM models.

Index Terms—Artificial neural networks, Response surface methodology, air bending, electrogalvanised steel, springback, bend force.

I. INTRODUCTION

Sheet metal forming is one of the major near-net-shape processes for the manufacturing of automobile, aircraft, electrical components etc. Sheet metal bending, being an important sheet metal forming process, employs a press brake with proper tooling to produce different bend components. The flexibility of the bending process is improved by the air bending technique [1]. Flexibility is achieved in such a way that the different bend angles can be produced by solely controlling the punch travel into the die without the need for changing tool sets. Because of this versatility, the lead time is reduced in air bending technique and hence it is commonly used in sheet metal industries. Steel sheets are widely used to manufacture various parts in sheet metal industry, but the susceptibility to corrosion is their natural weakness. To overcome this, the uncoated steel sheets are substituted with galvanised steel sheets based on the improved corrosion resistance. Since electrogalvanised (EG) steel sheets have better formability [2] and surface quality, they are much preferred than hot dipped, in many of the industrial applications.

The two important subjects related to bending process are springback and bend force. During bending, when the bending stress is removed at the end of the deformation process, elastic energy remains in the bent part causing it to partially recover to its original shape. This elastic recovery is called springback. Bend force is the force needed to deform the sheet metal part to the required shape. The material geometry and properties (thickness, yield strength, Young's modulus, etc.), tooling geometry (punch radius, die radius, die opening, etc.) and process parameters (punch travel, punch velocity, etc.) have considerable influence on springback and bend force. Springback prediction is important to control the process and die design to achieve the desired shape of the product. The prediction of bend force provides a base to the designer for the die design and press selection.

Traditional trial and error methods are time consuming and expensive, while the development of theoretical models for springback/bend force is difficult and cumbersome due to the complexity of sheet bending process. Consequently, an empirical model developed based on experimental research is more useful in industrial applications. The empirical modeling techniques namely response surface methodology (RSM) and artificial neural network (ANN) become promising tools for prediction of springback and bend force because of their robustness and predictability. Very few literatures is available for the prediction of springback and bend force in air bending using this prediction tools. Narayanasamy and Padmanaban [3] developed a prediction model applying RSM, for bend force in air bending operation of interstitial free steel sheet. Forcellese et al [4] developed a neural network based punch displacement control system in air bending process of AA5754 aluminium alloy sheets to control springback. Inamdar et al [5] discussed the development of ANN model for predicting springback in air vee bending of metallic sheets. Garcia Romeu and Ciruna [6] described the application of neural networks for the prediction of springback, punch displacement and final bending radius. Narayanasamy and Padmanaban [7] compared the neural network model with regression model for the prediction of springback of interstitial steel sheets in air bending process. Fu et al [8] developed a back propagation neural network model to predict the springback for air bending of high-
strength sheet metal. The model is based on orthogonal test with input parameters such as sheet thickness, tool gap, punch radius, ratio of yield strength to Young’s modulus and punch displacement. The model yields satisfactory result in sheet metal air bending of a workpiece used as crane boom. In this paper, development of RSM and ANN models for predicting both springback and bend force has been attempted and the models are compared based on their prediction performance.

II. EXPERIMENTAL DETAILS

The input-output database required for the development of predictive models is obtained through bending experiments. The process of selecting appropriate set of data points is in such way that it maximises the accuracy of the prediction is known as design of experiments (DoE).

In the present study, based on the previous work done on this field by various researchers [9-19], seven important and independently controllable process parameters which strongly influence the springback and bend force have been identified. They are strain hardening exponent, coating thickness, die opening, die radius, punch radius, punch travel and punch velocity.

The design matrix considered in this study is a five level central composite rotatable design (CCRD) consists of half replication of 27(128/2 = 64) design points plus 10 center points and 14 (2X7) star points. The rotatability value is calculated by taking the fourth root of number of design points. The upper level of a factor is coded as +2.82 and the lower level as -2.82 for designing the experiments. The intermediate coded values are obtained from the equation as

\[ z_i = \frac{x_i - x_{i0}}{d_i} \]  

where \( x_i \) is the actual parameter value, \( x_{i0} \) is the parameter value corresponding to zero level and \( d_i \) is the incremental parameter value. The actual and coded values of the process parameters are listed in Table 1.

The substrate used in this study is Aluminium Killed Draw Quality (AKDQ) steel sheet. AKDQ steel sheet is a widely used sheet metal in automotive, electrical and other domestic applications because of its excellent formability and low cost. The steel sheet was electro galvanised for various coating thickness such as 4 µm, 7µm, 10µm and 14µm. The blanks from the steel sheets were cut to the required dimensions of 120 mm x 40 mm x 1mm and the edges were cleaned to remove the burrs. As the strain hardening exponent n values (0.211, 0.219, 0.232, 0.206 and 0.227) belong to five different orientations 0°, 22.5°, 45°, 67.5° and 90° respectively, the blanks were prepared in the five directions. The experiments were conducted in a 40T Universal Testing Machine (UTM) and the tooling (dies and punches) was made of hardened steel.

The experimental setup for bending is shown in Fig.1. The punch was mounted in the upper arm of UTM and the die was placed on the lower platform. The sheet blanks were positioned on the die with necessary care. The punch traveled to the required depth for bending the sheet and the digital meter attached to the UTM was used to measure the punch travel. The larger edge of the bent sample was coated with black ink and the impression of the profile was taken carefully on a thick white paper supported by a board. Two impressions were taken before unloading and after unloading. The impressions of the sheet were scanned and converted into digitised images. The digitised images were imported to CAD software and the lines were drawn on the edges of the legs of images using the software. The necessary angles were measured using CAD software [18]. The difference between the bend angles during loading (\( \theta_i \)) and after unloading (\( \theta_f \)) gives the springback angle (\( \Delta \theta \)). The bend force was measured by the digital display of load cell arrangement. The sheets were bent to different depths by controlling the punch travel.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Parameter levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>Strain hardening exponent (n)</td>
<td>0.206, 0.211, 0.219, 0.227, 0.232</td>
</tr>
<tr>
<td>Coating thickness (t) in µm</td>
<td>0, 4, 7, 10, 14</td>
</tr>
<tr>
<td>Die opening (W_d) in mm</td>
<td>40, 55, 60, 65, 80</td>
</tr>
<tr>
<td>Die radius (R_d) in mm</td>
<td>3, 5, 6.5, 8, 10</td>
</tr>
<tr>
<td>Punch radius (R_p) in mm</td>
<td>4, 8, 10, 12, 16</td>
</tr>
<tr>
<td>Punch travel (t_p) in mm</td>
<td>5, 12, 15, 18, 25</td>
</tr>
<tr>
<td>Punch velocity (V_p) in mm/s</td>
<td>0.2, 0.45, 0.6, 0.75, 1</td>
</tr>
</tbody>
</table>

The experimental setup for bending is shown in Fig.1. The punch was mounted in the upper arm of UTM and the die was placed on the lower platform. The sheet blanks were positioned on the die with necessary care. The punch traveled to the required depth for bending the sheet and the digital meter attached to the UTM was used to measure the punch travel. The larger edge of the bent sample was coated with black ink and the impression of the profile was taken carefully on a thick white paper supported by a board. Two impressions were taken before unloading and after unloading. The impressions of the sheet were scanned and converted into digitised images. The digitised images were imported to CAD software and the lines were drawn on the edges of the legs of images using the software. The necessary angles were measured using CAD software [18]. The difference between the bend angles during loading (\( \theta_i \)) and after unloading (\( \theta_f \)) gives the springback angle (\( \Delta \theta \)). The bend force was measured by the digital display of load cell arrangement. The sheets were bent to different depths by controlling the punch travel.
where \( d \), \( n \), \( Y \), and \( T \) are determined as:

\[
\Delta \theta = \text{Springback Angle} \\
\theta = \text{Bend Angle (After Unloading)} \\
\theta_0 = \text{Bend Angle (During Loading)} \\
\Delta \theta = \text{Springback Angle}
\]

Figure 1 Experimental Setup

### III. RSM Modelling

Response surface methodology adopts mathematical and statistical techniques to evaluate the relationship between a cluster of controlled experimental factors and a response. RSM provides an approximate relationship between the response \( Y \) and the independent variables \( x_i \), which is based on the observed data from the process. The optimal response can be obtained from this methodology even when there is minimal information about the process.

\[
Y = f(x_1, x_2, x_3, \ldots, x_n) + \varepsilon \quad (2)
\]

where \( \varepsilon \) denotes an error component.

As air bending is a non-linear process [6], a linear polynomial is unable to predict the response accurately, and therefore the second-order model (quadratic model) is found to adequately model the process [20].

Second order non-linear models have been developed to predict springback and bend force which are of the following form

\[
Y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_i x_i^2 + \sum_{i,j} \beta_{ij} x_i x_j + \varepsilon \quad (3)
\]

where \( Y \) Response, i.e., springback and bend force

\( \beta \) Coded values for parameters

The values of the regression coefficients as defined above are determined as:

\[
b = \left( X^T X \right)^{-1} X^T Y \quad (4)
\]

where \( b \) Matrix of parameter estimates

\( X \) Matrix of model terms evaluated at \( n \) data points

\( Y \) Matrix of the measured response

<table>
<thead>
<tr>
<th>Responses</th>
<th>Springback</th>
<th>Bend Force</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sum of squares</td>
<td>0.048</td>
<td>0.0301</td>
</tr>
<tr>
<td>Degrees of freedom</td>
<td>24</td>
<td>51</td>
</tr>
<tr>
<td>Mean Squares</td>
<td>0.000884</td>
<td>0.000484</td>
</tr>
<tr>
<td>F-ratio (Calculated)</td>
<td>1.166</td>
<td>1.172</td>
</tr>
<tr>
<td>F-ratio (Table value)</td>
<td>2.82</td>
<td>2.806</td>
</tr>
</tbody>
</table>

The experimental data were analysed to obtain the coefficients of polynomials using MINITAB 15 software. The experimental data were analysed to obtain the coefficients of polynomials using MINITAB 15 software. The p value approach is used for testing the significance of coefficients. According to this, the coefficients are tested at 0.05 level of significance (95% confidence). The analysis of variance technique (ANOVA) is employed to check the adequacy of the developed models at a 95% confidence level. As per this technique, the calculated value of \( F \) ratio for the lack-of-fit must be lesser than its standard value for a desired level of confidence level. Here, both the springback and bend force models are adequate in non-linear form, as the \( F \) ratio of both the models is less than the standard value for 95% confidence level, as illustrated in Table II.

The final mathematical models for the springback and bend force given in terms of factors, as

\[
Y_i = 151.5028 - 1256.9472 c + 0.7578 d - 0.4065 W_c - 0.8244 R_c - 0.1744 n - 0.2558 t \\
- 5.496 W_c + 2785.0397 t^{1/3} + 0.0071 c + 0.0019 W_c + 0.0991 R_c + 0.0348 n + 0.0667 t + 6.355 W_c \\
- 2.5333 c + 1.0056 d + 3.2095 R_c - 1.0423 n - 0.9879 t - 0.0085 W_c - 0.0093 R_c \\
- 0.0243 t + 0.0021 c - 0.0032 W_c + 0.0055 R_c - 0.0023 W_c + 0.0033 R_c + 0.0118 W_c \\
- 0.0169 R_c + 0.0088 t + 0.0017 W_c - 0.0421 t + 0.0057 R_c 
\]

\[
(5)
\]

Bend force

\[
Y = 51.41 - 299.629 c - 0.2929 d - 0.3636 W_c + 0.0595 R_c - 0.085 c - 0.823 V_p \\
+ 721.323 t^{1/3} + 0.0071 c + 0.002 W_c + 0.006 R_c + 0.002 t - 0.005 t + 0.3101 c \\
- 0.671 n - 0.029 W_c + 0.664 R_c - 0.312 n - 0.044 R_c + 0.026 V_p \\
+ 0.001 W_c R_c - 0.001 W_c + 0.003 R_c + 0.011 R_c + 0.039 V_p 
\]

\[
(6)
\]

where \( n \) is strain hardening exponent, \( t \) is coating thickness, \( W_c \) is die opening, \( R_c \) is die radius, \( R_p \) is punch radius, \( t_p \) is punch travel and \( V_p \) is punch velocity.

### IV. ANN Modelling

#### A. ANN Approach

An Artificial Neural Network (ANN) is an information processing system that is inspired by information processing of the biological nervous system (brain). ANN has a parallelly distributed architecture with a number of information processing elements called neurons which are interconnected by connection links. A multilayer neural network has an architecture that consists of an input layer, one or more hidden layers and an output layer. The input layer receives input data and after processing it, sends them to the hidden layer. The hidden layer processes the data and sends a response…
to the output layer. The output layer accepts the responses and produces the result. The network which has an information flow from input layer to output layer in forward direction is known as feed-forward network. Since the ‘intelligence’ of the network exists in the values of the weights between neurons, a method of adjusting the weights is needed to solve a particular problem. The process of modifying the weights in the connections between network layers with the objective of achieving the expected output is called ‘learning’ or ‘training a network’. The backpropagation (BP) algorithm is the most widely used learning algorithm.

The principal steps in the learning process are given below:

Step1: Initialise all the weights of the links to random values.
Step2: Present the input - desired output pattern sets for updating the weights and bias. The equation for updating weights and bias is

\[ w_{ji}^{t+1} = w_{ji}^{t} + \Delta w_{ji}^{t+1} \]  \hspace{1cm} (7)

where \( w_{ji} \) Weight of the link connecting neuron j to i, \( z \) is the learning step and \( \Delta w_{ji}^{t+1} \) is the \((\pm)\) incremental change in the weight. The weight change is determined by a learning algorithm.

Based on LM learning algorithm, the weight change can be written as

\[ \Delta w_{ji}^{t+1} = \left[ J^T J + \mu I \right]^{-1} J^T e + \alpha (w_{ji}^{t} - w_{ji}^{t-1}) \] \hspace{1cm} (8)

where \( J \) is Jacobean matrix that contains first derivatives of the network errors with respect to the weights and biases, \( \mu \) is the adaptive training parameter, \( I \) is the identity matrix, \( e \) is the vector of network errors and \( \alpha \) is the momentum term.

The use of a momentum term in the backpropagation algorithm is primarily to overcome the possible trap to local minima and also to overcome the oscillations during the training of the network. Moreover, the use of a small momentum helps in increasing the network training convergence with the LM algorithm.

Step 3: After presenting the patterns, compute the mean square error (MSE) of all outputs as:

\[ MSE = \frac{1}{Q \times K} \sum_{q=1}^{Q} \sum_{k=1}^{K} (d_{kq} - y_{kq})^2 \] \hspace{1cm} (9)

where \( Q \) is the number of sets of input-output data, \( K \) is the total number of outputs.

Step 4: If \( MSE < MSE_{target} \) then stop, else go to step 2. If the new MSE is smaller than that of the preceding, then reduce the training parameter \( \mu \) by \( \mu^* \). If the MSE is increased, then increase \( \mu \) by \( \mu^* \).

After the training stage, the ANN learning performance is evaluated by running it using the test data set, which is not included in the training set. If the network responds correctly to the inputs, the generalisation of network is confirmed.

B. ANN Architecture

As neural network is a non-linear analysis tool, it maps the non-linear relationships with multiple interactions between input variables and springback/bend force in air bending in a better way [4,5,7]. Hence, a multilayer perceptron with back propagation training algorithm, widely used for engineering applications, is considered as a practical choice for this work. Single hidden layer is used for many practical problems since it can approximate any function which contains a continuous mapping from one finite space to another [21]. Hence single hidden layer is selected and the architecture of the ANN in this work has a three layer structure of one input layer, one hidden layer and one output layer. The number of neurons in input and output layers is 7 and 2, corresponding to the number of inputs and outputs. As a heuristic rule, the number of hidden layer neurons can be up to \( 2n+1 \) where \( n \) is the number of neurons in the input layer [22]. In this study, the number of neurons in the hidden layer is changed and the Mean Square Error (MSE) is evaluated. After several trials, the number of neurons which results least MSE is selected for hidden layers and is 14. The designed architecture becomes 7-14-2. The designed ANN architecture is shown in Fig. 2. Levenberg-Marquardt (LM) learning algorithm, the fastest method for training moderate-sized feed forward neural networks [23] is an efficient method for nonlinear problems [24]. This makes LM algorithm the much preferred one in this work. The transfer function is required to introduce the non-linearity characteristics into the network. Log-sigmoid function takes any real valued input and returns an output bounded between \([0,1]\). In backpropagation, it is important to calculate the derivatives of any transfer functions used. As it is differentiable, the function log-sigmoid is commonly used in back propagation networks [25]. Hence, log-sigmoid was chosen as the activation function for the present network.

C. ANN Training

The experimental design matrix of 88 bending experiments along with the experimental results of springback and bend force was used as the training set for the network. As the dimension and magnitude of the testing or training data are different, they should be normalised before applying in the network, so that they lie between 0 and 1. The 88 input-output pairs were fed into the computer and a computer pro
gram was performed in the MATLAB 7.0.1 software. The training was performed in batch mode with the following learning factors: Learning rate = 0.1; Momentum constant = 0.5; Target for MSE = 0.0000001; Maximum number of epochs = 1000. During training, the network compares its predicted value to the actual output and adjusts all the weights to improve the model. Once the MSE of the training data reached the target value, the training is terminated and the weights and biases are automatically saved by the program. The MSE target is achieved in 292 epochs and the variation of MSE during the training is shown in Figure 3.

![Figure 3. Variation of MSE during training the network](image)

The developed RSM and ANN predictive models were compared on the basis of their prediction accuracy. The measured values of springback and bend force from the 15 test experiments and the corresponding values of the ANN and RSM models were compared to test the interpolation of the prediction models. The accuracy of the developed models is assessed by means of absolute error function and it has been defined as

\[
\% \text{ Absolute error} = \left( \frac{V_m - V_{exp}}{V_{exp}} \right) \times 100 \tag{10}
\]

where \(V_m\) is the predicted value of the model and \(V_{exp}\) is the measured experimental value. Figures 4 and 5 illustrate the comparison of the error profiles for springback and bend force respectively, for 15 test data points.

The average absolute error for springback and bend force in ANN model is 1.24% and 1.41% while for RSM model it is 3.50% and 3.92% respectively. Despite the error being within the acceptable level for both the modeling techniques, ANN outperforms the RSM technique.

VI. DISCUSSIONS

Though the researchers [4-8] developed ANN models in air bending earlier, they concentrated mainly on the prediction of springback and not on bend force, which is another important parameter to be considered in air bending. The important parameters like die opening and die radius which are having major influence on springback and bend force have not been considered by Narayanasamy and Padmanabhan [7]. The main advantage of the present ANN is that it can be used as a computer aided tool for providing easy, quick and precise predictions in process design in air bending of electro galvanised steel. This work is a new attempt on electro galvanised steel sheet and it can be further extended for other types of coated steel sheets also.

CONCLUSIONS

This study described a comparative analysis of the two modeling approaches namely artificial neural network (ANN) and response surface methodology (RSM) for the prediction of springback and bend force in air bending of electrogalvanised steel. A five level central composite design of experiments was employed to create the input-output data pairs for developing both the models. The ANN model was based on a multilayer feed forward topology and trained with LM back propagation algorithm. The performance of the models was compared based on their prediction accuracy using a new set of 15 input-output pairs. The performance of the ANN model for predicting springback and bend force was found to be better than RSM models.
REFERENCES


