ORIGINAL ARTICLE

A novel approach for the prediction of bend allowance in air bending and comparison with other methods

Hasan Kurtaran

Received: 6 September 2006 /Accepted: 19 February 2007 / Published online: 17 March 2007 \oslash Springer-Verlag London Limited 2007

Abstract Air-bending is a major sheet-metal forming operation, where precise prediction of the developed shape is a key factor for the accuracy assessment of the final shape for the part after bending. To predict the blank shape, accurate estimation of the bend-allowance (BA) is necessary, which can be defined as the length of the un-stretched fiber at the bent state of shape. There are several different approaches to find the BA values depending on either experience-based or knowledge-based techniques. In this paper, a brief summary is provided for different approaches to find the BA values by comparing their advantages as well as, their drawbacks. They are evaluated in terms of accuracy, efficiency and ease of implementation for integrated CAD/CAM environment. Then, a novel approach; by using higher order response surface (RS) fitting for the prediction of BA during air-bending is demonstrated. This technique is in general found very promising as an integrated tool for both CAD interfaces, as well as CNC machine tools. The RS predictions, which are generated from over 1,000 bending experiments using combinations of bending radius, bending angle and material thickness, are built for different orders and are compared to Artificial Neural Network (ANN) models that are also trained by using the same experimental data.

Keywords Air-bending . Artificial neural network . Response surface model

H. Kurtaran (***)

Department of Design and Manufacturing Engineering, Gebze Institute of Technology, PK. 141, Gebze-Kocaeli, Turkey e-mail: hasan@gyte.edu.tr

1 Introduction

Bending can be defined as "the plastic deformation of a sheet-metal along a straight line" [\[1](#page-9-0)]. The most common bending operation is air-bending, which is basically a free bending process that usually can be conducted by using a press-brake as shown in Fig. [1.](#page-1-0)

Even though, air-bending is one of the most inaccurate methods of all, this process is widely used among other sheet-metal forming methods. The reasons are obvious:

- The tooling is simple and can be used for more than one flange and for more than one part even with a different thickness.
- There is no need to change the dies and the tooling to obtain different bending angles.
- Relatively smaller forces are needed.

However, consistent and repeatable air-bending processes comprise some critical details; such as the necessity of accurate and adaptive control of the punch stroke, which is the factor determining the bending angle and eventually the amount of spring-back. Developing machine tool technologies overcome this problem with the help of new generation controllers equipped with advanced algorithms [\[2](#page-9-0)–[4](#page-9-0)]. CNC press-brakes are preferred for this kind of operations, where narrow bands of tolerances can be achieved for the bending angles and flange lengths.

Air-bending process causes dramatic changes in the initial blank size and the shape depending on the material thickness, bending angle, bending radius, properties of the material and the tooling. Effects of tooling geometry, bending angle, bending radius and material properties on the air-bending process have been investigated extensively [\[5](#page-9-0)–[15\]](#page-9-0). Several numerical, experimental and analytical approaches have been proposed for this purpose. A very big portion of these research concentrate on springback predictions in air-bending operations. Compared to the

Fig. 1 Air-bending with press-brake

springback effect, very limited research has focused on BA predictions [\[16](#page-9-0), [17](#page-9-0)].

Analytical models use simple equations while numerical techniques mostly use finite element method (FEM) or onestep solvers to predict the developed length in air bending operations. FEM is usually computationally expensive but provide extremely accurate plasticity information by incorporating advanced constitutive equations. However, with the involvement of predicting the amount of spring-back, iterative solvers usually have to use explicit-implicit transition, which can be challenging and loosing its practicality. One-step solvers, however, use simple geometric relations to predict an initial shape for the part. This method can be very efficient with the lack of accurate plasticity calculations. It would be very impractical to employ FEM at the preliminary design stage and couple this method with a CAD/CAM tool since it will require excessive amount of time to predict the initial geometry. One-step solvers, on the other hand, can easily be used for this purpose.

As an alternative to the numerical methods, several analytical or semi-analytical methods are developed. However, in most of the earlier analytical approaches, the shift of the neutral fiber and the thickness change accompanying the bending process are neglected [\[1](#page-9-0), [7,](#page-9-0) [8](#page-9-0), [18,](#page-9-0) [19\]](#page-9-0). Most of those methods also usually make simplifying assumptions such as; plain-strain deformation, rigid-plastic or simple power law plasticity material models, isotropic material, rigid tooling etc. As a result, the applications of these solutions are not quite adequate for a whole range of sheet materials and development of a practical and efficient tool is crucial.

The alternative experimental approach includes conducting a number of bending experiments using the available machine tools and creating bending tables for general usage. Even though, the accuracy depends on the precision of the measurements before and after the bending process, this approach can be very accurate. However, testing can be very time consuming and costly at the beginning. The biggest advantage of this method is to isolate the machine or tooling dependency of the results and once the bending tables are created, they can be easily and efficiently applied for CAD/CAM environment. One of the most important drawbacks for this method is not to be able to test every airbending scenario because of time and cost limitations. Then, depending on the algorithm used, CAD/CAM interface will have to find a corresponding BA value by interpolation. Considering a highly non-linear relation, this approach can also be misleading.

In this study, effective methods are discussed to be efficiently used as a supplementary Computer Aided Process Planning (CAPP) tool for air-bending operations. Within the context of this study, DIN-6935 standard equation, ANN and novel higher order response surface models are considered and compared with each other for accuracy and efficiency. ANN and Response Surface models exploit a massive air-bending experimental data during construction phase. Details of methods are given in the following sections.

2 Overview of bend allowance calculations

During the bending operation, initial length of the part differs from the bent total length, depending on the material thickness, bending angle, bending radius, properties of the material and the tooling. Figure 2 represents how to calculate a developed length (L_0) for bending by using a factor called as K. In this study, K indicates bend allowance throughout the text.

Sheet-metal part designer generally tries to achieve functional-technical and aesthetic requirements for the final part. However, the developed flat length of the part is needed for the manufacturing stage in order to design a blanking die or to transfer the flat borders into CAM environment to be used for nesting or optimizing the layout on rolled sheet, which later can be punch pressed. Figure [3a](#page-2-0)

Fig. 2 Calculation of the development length after air-bending and bend allowance

Fig. 3 (a) final shape, (b) developed flat model, (c) nested manufacturing model

represents such an experimental sheet metal part that contains different flanges and features, Fig. 3b is the developed flat model of this part, and Fig. 3c is the optimized manufacturing model for the flat layout of the model on a piece of sheet panel in standard dimensions.

In this section, experimental and an empirical approach given by DIN-6935 [[19\]](#page-9-0) are compared for calculating the BA for mild steel with a tensile strength of 40 kg/mm².

2.1 Experimental approach

Within the context of this approach, a large number of airbending experiments are conducted for mild steel to generate a data table corresponding to BA values for different bending angles, material thickness and bending radius [\[20](#page-9-0)]. Each specimen is measured before and after the bending operation and the BA values are directly found from the relation that is shown in Fig. [2](#page-1-0). Test ranges are choosen between 0.8–50 mm for thickness (T), 183 mm for bending radius (Rp) and $0-165^{\circ}$ (0°, 15°, 30°, 45°, 60°, 75°, 90°, 105°, 120°, 135°, 150°, 165°) for the bending angle (θ). Bending experiments for angles greater than 165 \degree are not conducted since the values are found to be negligible for this particular material. The R_P/T ratio is kept to be bigger or very close to unity for a successful airbending operation. Also, to satisfy a good manufacturability, the following testing assumptions in Eq. 1 and Table 1 are followed for the tooling. It can be easily seen from Fig. 4 that the same part actually can be obtained by using different tooling in air-bending. So, it is very

Table 1 Corresponding tooling for a given thickness

Tooling			
T Thickness (mm)	$0.6 - 2.5$	$3 - 8$	$10 - 50$
W Die Opening (mm)	67	87	10T

important to keep these technological variables consistent during testing.

$$
R_P = 0.16W\tag{1}
$$

The calculated BA values are utilized in preparing a data table for general usage. The bend allowance table created in this study includes a total of 1,064 experimental results. A subset of the data table corresponding to 90° bending experiments is shown in Table [2](#page-3-0) and in Fig. [5](#page-4-0). The cases with no values in Table [2](#page-3-0) correspond to air-bending operations that are not reasonable in terms of manufacturability or practical reasons. The table can be easily exploited in a CAD software to obtain a developed length.

From Fig. [5](#page-4-0), it is seen that BA values show high local nonlinearities in the experiment range. In Fig. [5a](#page-4-0), flat surfaces on the top correspond to a region that the experiments are not conducted for. It is clear from Fig. [5](#page-4-0) that when thickness, radius and bending angle are all considered as parameters, the hypersurface corresponding to BA will be much more nonlinear and challenging to find a good fitting predictive model. In the next sections several models are investigated for fitting capability and accuracy in predicting BA experimental data.

2.2 Empirical approach

One of the many commonly used empirical BA calculation methods is given by DIN-6935 for mild steel. Just like other analytical or empirical approaches this method is also based on the estimation of the position of the neutral axis

Fig. 4 Variable tooling for an identical part

Fig. 5 a) BA versus thickness and radius and b) isosurface curve for BA

after bending and ignores the contribution of the tooling and operational variables. The method gives Eq. 2 as the position of the un-stretched fiber depending on the bending radius and thickness.

$$
\chi = 0.65 + \frac{1}{2} \lg \frac{Rp}{T}
$$
 (2)

After estimating the position of the neutral axis, the appropriate values of BA (represented with K) for bending angles up to 90° are calculated with Eq. 3 as below:

$$
K = \pi \left(\frac{180 - \theta}{180}\right) \left(Rp + \frac{T}{2}\chi\right) - 2(Rp + T) \tag{3}
$$

For bending angles between 90° and 165°, Eq. 4 is offered.

$$
K = \pi \left(\frac{180 - \theta}{180}\right) \left(Rp + \frac{T}{2}\chi\right) - 2(Rp + T)tg
$$

$$
\times \frac{180 - \theta}{2} \tag{4}
$$

And, for angles greater than 165° BA is accepted to have no effect on the developed length.

2.3 Comparison of experimental and empirical approach

BA predictions from DIN-6935 standard are compared with the experimental data in Fig. 6. Figure 6 is obtained by considering BA values at each combination of parameters. Each combination is referred to as data set number in Fig. 6 and in this study. Total 1,052 data set is used. Root mean square (RMS) error in Fig. 6 indicates a statistical measure of fitting capability. For more clear comparison of DIN-6935 standard with experiments, the predicted values for 12 randomly chosen parameter combinations are given in Table [3.](#page-5-0) It can be observed that the empirical values that are offered by DIN-6935 do not match with the experimental BA values at some parameter combinations and there is a need for a better estimation for a given tooling and operation parameters.

3 Computer aided process planning implementation

Sheet metal parts are typically produced by a sequence of bending operations, where the most common procedure is air-bending because of its advantages that are mentioned earlier. This sequence should be planned and executed

Fig. 6 Comparison of DIN-6935 BA prediction with experimental data (RMS Error=2.848)

accordingly to maintain a cost-effective manufacturing process with limited time and expected quality constraints. CAPP is crucial to take advantage of the flexibility in airbending process. This, however, requires state-of-the-arts algorithms that can couple CAD/CAM/CIM/PDM [[21,](#page-9-0) [22](#page-9-0)].

The novel approach that is proposed in this paper can both be coupled with CAD/CAM softwares, which have sheet-metal design modules. The developed lengths can be generated automatically depending on the experimental bend-allowance values for each press-brake and tooling that can be used. However, the power of the system lies on the approximate predictions of BA values by using ANN or higher order RS models.

3.1 Artificial neural network model

ANN is known as a fitting method to an available data. It has high flexibility in fitting a data set and therefore they are utilized very often in creating approximate models. Despite its powerful fitting capability, design of an effective ANN architecture is often a trial and error process. Also training of a neural network model is computationally costly.

In this study, after several trials, an optimum, custom designed ANN architecture consisting of two hidden layers with 100 neurons for each as shown in Fig. 7 are found to capture the highly nonlinear nature of the problem and produce accurate BA predictions. The designed ANN architecture is trained using back propagation algorithm with Matlab Neural Network Toolbox [[23](#page-9-0)]. Sigmoid (logistic) function is chosen as activation (transfer) function in this study as below:

$$
out_j = f(net_j) = \frac{1}{1 + e^{-net_j}} \tag{5}
$$

During training phase 1052 data sets are used. These data sets are referred to as training data set in this study. ANN training is conducted for 300,000, 600,000, 1,000,000 and 1,500,000 training iterations. After training predictive capability of ANN is compared for 1052 training data sets in Fig. [8](#page-6-0) and for 12 randomly selected experimental data, which are not used in training (the same data with the preceding section) in Table [4](#page-6-0). Comparison in Fig. [8](#page-6-0) corresponds to the case of 1,500,000 training iterations. As seen from Table [4](#page-6-0), ANN predictions with higher number of training iterations are in good agreement with the experimental data and can be used as a precise predictive tool for other air-bending applications. Also from Table [4](#page-6-0), it is clear that the number of training iterations affect both computational cost and accuracy of an ANN prediction.

Fig. 7 Neutral network architecture

Fig. 8 Comparison of ANN bend allowance prediction with experimental data (RMS Error=0.179)

3.2 Response surface model

RS models are often referred to as least-square fitting of polynomial models to a response data based on statistical design of experiment (DoE) method [[24](#page-9-0)]. They are commonly used in creating global approximations for responses that are not known analytically or explicitly in terms of parameters. Recently, linear and second order (quadratic) RS models have been effectively coupled with optimization methods to enable the automated design of parts and structures with CAD softwares [\[25](#page-9-0)].

To investigate the power of RS models (especially higher order RS models) in predicting bend allowance values, a computer program in C programming language is devel-

oped. Main motivation in developing this program was the limitation of traditional linear or quadratic RS models in predicting highly nonlinear responses and the lack of availability of any generic program for higher order RS models to the author's knowledge. The developed program has the capability of creating multi-variable polynomials up to 10th order if sufficient data exist. The program is tested in different studies and produced good predictive results for variety of responses [\[26](#page-9-0), [27](#page-9-0)].

Generic form of RS models up to 10th order with all interaction terms for bend allowance prediction can be written as below:

$$
K = a_0 + a_1 R + a_2 T + a_3 \theta + a_4 R^2 + a_5 T^2 + a_6 \theta^2
$$

+ a_7 RT + a_8 T \theta + a_9 R \theta + \dots + a_m R^{10}
+ a_n T^{10} + a_p \theta^{10} (6)

where, *ai* are tuning parameters. RS models of varying orders from first-order to 10th order are created and tested for BA with the developed program. Predictive capability of RS models of varying orders is compared for 1052 training data sets in Fig. [9](#page-7-0) and for 12 randomly selected experimental data, which are not used in training (the same data as the preceding section) in Table [5.](#page-8-0)

From Table [5](#page-8-0), it is seen that although the predicted values do not match very well with the experiment at some selected parameter combinations, the fitting capability of RS models gets higher with the polynomial orders in terms of RMS error.

Table 4 Comparison of ANN bend allowance predictions with experiments

Random set number	Thickness T (mm)	Radius R_p (mm)	Bend angle θ (\degree)	Bend allowance, K				
				ANN prediction (mm)			Experiment (mm)	
				Number of iterations $(\times 1,000)$				
				300	600	1000	1500	
	0.8		30	-0.24	-0.24	-0.26	-0.25	-0.30
2	1	1.3	15	0.18	0.13	0.13	0.13	0.20
3	1.2	1.3	30	-0.51	-0.55	-0.57	-0.57	-0.60
4	3	4	45	-2.03	-2.03	-2.04	-2.06	-2.10
5	5	5	165	-0.91	-0.95	-0.95	-0.93	-0.90
6	6	8	$\mathbf{0}$	3.23	3.89	3.92	3.89	3.90
7	12	10	75	-18.61	-19.65	-19.61	-19.51	-19.00
8	20	20	105	-25.67	-26.77	-26.58	-26.52	-27.00
9	25	41	15	12.70	13.05	13.79	14.28	14.00
10	25	65	15	38.87	36.97	37.00	37.27	38.00
11	40	53	135	-23.97	-24.08	-24.54	-24.81	-24.00
12	50	65	150	-19.44	-19.14	-19.41	-19.38	-18.00
Computational time (hour)				35	70	116.7	175	

Bend Allowance, K (mm)

e) 9th order RS model (RMS Error = 1.271), f) 10th order RS model (RMS Error = 1.125)

Fig. 9 Comparison of RS models with experimental data for bend allowance prediction

4 Comparison of fitting of models

RMS error criterion is often used in statistics as an indicator of fitting capability of models. Table [6](#page-8-0) compares the fitting errors of all models used in this study. From Table [6,](#page-8-0) it is seen that ANN fits best to the highly nonlinear experimental BA data. ANN is followed by higher order RS models. The higher the RS model the higher the predictive capability (i.e., the lower the RMS error). DIN-6935 standard given by Eq. [\(2](#page-4-0)–[4](#page-4-0)) has slightly better fitting capability from lower order RS models but lower capability than higher order models.

5 Conclusions

Experience or knowledge based methods that can be used for bend allowance calculation in CAD/CAM software environment are discussed in this study. They are compared with each other for accuracy, efficiency, and ease of implementation. Within the context of this study, experimental (data table approach), empirical, ANN, and RS approaches have been considered. ANN is found to be the most accurate method of all. Empirical method follows ANN in accuracy. RS models produce the least accurate BA predictions.

Regarding computational cost, empirical and RS model are the most efficient methods. They can produce results immediately. ANN model is computationally costly in training phase. However, once ANN model is trained it can be effectively used. Experimental approach that is based on air-bending experiments can also be a very efficient way of calculating bend allowance if standard bending operations with the same tooling and set-up can be followed during the application.

References

- 1. Suchy I (1997) Handbook of die design, McGraw-Hill, New York
- 2. Forcellese A, Gabrielli F, Ruffini R (1998) Effect of the training set size on springback control by neural network in an air bending process. J Mater Process Technol 80–81:493–500
- 3. Inamdar M, Date PP, Desai UB (2000) Studies on the prediction of springback in air vee bending of metallic sheets using an artificial neural network. J Mater Process Technol 108:45–54
- 4. Elkins KL, Sturges RH (2001) Design of a sensor for on-line measurement of loaded bend angle for pressbrake control. Robot Comput-Integr Manuf 17:329–340
- 5. Livatyali H, Kinzel GL, Altan T (2003) Computer aided die design of straight flanging using approximate numerical analysis. J Mater Process Technol 142:532–543
- 6. Wang C, Kinzel G, Altan T (1993) Mathematical modeling of plane-strain bending of sheet and plate. J Mater Process Technol 39:279–304
- 7. Prasad YKDV, Somasundaram S (1993) A mathematical model for bend-allowance calculation in automated sheet-metal bending. J Mater Process Technol 39:337–356
- 8. Heller B, Kleiner M (2006) Semi-analytical process modeling and simulation of air bending. J Strain Anal Eng Des 41:57–80
- 9. Vin de JL, Streppel AH, Singh UP, Kals HJJ (1996) A process model for air bending. J Mater Process Technol 57:48–54
- 10. Anokye-Siribor K, Singh UP (2000) A new analytical model for pressbrake forming using in-process identification of material characteristics. J Mater Process Technol 99:103–112
- 11. Streppel AH, Lutters D, Brinke ET, Pijlman HH, Kals HJJ (2001) Process modeling for air bending: validation by experiments and simulations. J Mater Process Technol 115:76–82
- 12. Antonelli L, Salvini P, Vivio F, Vullo V (2007) Identification of elasto-plastic characteristics by means of air-bending test. J Mater Process Technol 183:127–139
- 13. Fei D, Hodgson P (2006) Experimental and numerical studies of springback in air v-bending process for cold rolled TRIP steels. Nucl Eng Des 236:1847–1851
- 14. Bruni C, Forcellese A, Gabrielli F, Simoncini M (2006) Air bending of AZ31 magnesium alloy in warm and hot forming conditions. J Mater Process Technol 177:373–376
- 15. Singh UP, Maiti SK, Date PP, Narasimhan K (2004) Numerical simulation of the influence of air bending tool geometry on product quality. J Mater Process Technol 145:269–275
- 16. De Vin LJ (2001) Expecting the unexpected, a must for accurate brakeforming. J Mater Process Technol 117:244–248
- 17. De Vin LJ (2000) Curvature prediction in air bending of metal sheet: J Mater Process Technol 100:257–261
- 18. Bremberger M (1965) Stanzerei Handbuch. Hanser, München
- 19. DIN 6935 standard (1969) Supplementary sheet 1–2, cold forming by press brake and cold bending of flat rolled steel - cold forming and cold bending of flat rolled steel products calculated compensating values for different bending angles
- 20. Ozcelik B, Buyuk M (2001) An experimental approach for determining the bend allowance in air-bending process: 2nd Int Conference on Design and Production of Dies and Molds, Kuşadası, TURKEY, 21-23 June 2001
- 21. Duflou JR, Vancza J, Aerens R (2005) Computer aided process planning for sheet metal bending: a state of the art. Comput Ind 56:747–771
- 22. Choi JC, Kim BM, Kim C (1999) An automated progressive process planning and die design and working system for blanking or piercing and bending of a sheet metal product. Int J Adv Manufac Technol 15:485–497
- 23. Matlab User Manual (2002) Version 6.5 Release 13, The Math-Works, Inc
- 24. Box GEP, Draper NR (1987) Empirical model-building and response surface. Wiley, New York
- 25. Stander N, Roux WJ, Eggleston T, Craig KJ (2006) LS-OPT version 3.1 user's manual. Livermore Software Technology Corporation, CA, USA
- 26. Oktem H, Erzurumlu T, Kurtaran H (2005) Application of response surface methodology in the optimization of cutting conditions for surface roughness. J Mater Process Technol 170(1– 2):11–16
- 27. Kurtaran H, Erzurumlu T (2006) Efficient warpage optimization of thin shell plastic parts using response surface methodology and genetic algorithm. Int J Adv Manufac Technol 27(5–6):468–472