



UNIVERSITI PUTRA MALAYSIA

**NEURAL NETWORK MODEL AND FINITE ELEMENT SIMULATION
OF SPRINGBACK IN PLANE-STRAIN METALLIC BEAM BENDING**

FAYIZ Y. M. ABU KHADRA.

FK 2006 21

**NEURAL NETWORK MODEL AND FINITE ELEMENT SIMULATION OF
SPRINGBACK IN PLANE-STRAIN METALLIC BEAM BENDING**

By

FAYIZ Y. M. ABU KHADRA

**Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia,
in Fulfilment of the Requirement for the Degree of Doctor of Philosophy**

February 2006



Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfillment of the requirement for the degree of Doctor of Philosophy

NEURAL NETWORK MODEL AND FINITE ELEMENT SIMULATION OF SPRINGBACK IN PLANE-STRAIN METALLIC BEAM BENDING

By

FAYIZ Y. M. ABU KHADRA

February 2006

Chairman: Professor Abdel Magid Salem Hamouda, PhD

Faculty: Engineering

Bending has significant importance in the sheet metal product industry. Moreover, the springback of sheet metal should be taken into consideration in order to produce bent sheet metal parts within acceptable tolerance limits and to solve geometrical variation for the control of manufacturing process. Nowadays, the importance of this problem increases because of the use of sheet-metal parts with high mechanical characteristics. This research proposes a novel approach to predict springback in the air bending process. In this approach the finite element method is combined with metamodeling techniques to accurately predict the springback.

Two metamodeling techniques namely the neural network and the response surface methodology are used and compared to approximate two multidimensional functions. The first function predicts the springback amount for a given material, geometrical parameters, and the bend angle before springback. The second function predicts the punch displacement for a given material, geometrical parameters, and the bend angle after springback. The



training data required to train the two-metamodeling techniques were generated using a verified nonlinear finite element algorithm developed in the current research. The algorithm is based on the updated Lagrangian formulation, which takes into consideration geometrical, material nonlinearity, and contact. To validate the finite element model physical experiments were conducted. A neural network algorithm based on the backpropagation algorithm has been developed. This research utilizes computer generated D-optimal designs to select training examples for both metamodeling techniques so that a comparison between the two techniques can be considered as fair.

Results from this research showed that finite element prediction of springback is in good agreement with the experimental results. The standard deviation is 1.213 degree. It has been found that the neural network metamodels give more accurate results than the response surface metamodels. The standard deviation between the finite element method and the neural network metamodels for the two functions are 0.635 degree and 0.985 mm respectively. The standard deviation between the finite element method and the response surface methodology are 1.758 degree and 1.878 mm for both functions, respectively.

Abstrak tesis yang dikemukakan kepada Senat Univeristi Putra Malaysia
sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

**MODEL RANGKAIAN NUERAL DAN SIMULASI UNSUR TIDAK
TERHINGGA LENTURAN BALIK DALAM TERIKAN SESATAH
LENTURAN RASUK LOGAM**

Oleh

FAYIZ Y. M. ABU KHADRA

Februari 2006

Pengerusi: Profesor Abdel Magid Salem Hamouda, PhD

Fakulti: Kejuruteraan

Lenturan mempunyai kepentingan signifikasi di dalam industri produk kepingan logam. Lanjutan daripada itu kesan lenturan balik ke atas kepingan logam patut diambil kira untuk menghasilkan lenturan terhadap kepingan logam di dalam had toleransi yang munasabah dan menyelesaikan variasi geometrical untuk kawalan proses pembuatan. Kini, kepentingan permasalahan ini meningkat disebabkan oleh penggunaan kepingan logam yang mempunyai ciri mekanikal yang tinggi. Penyelidikan ini mencadangkan satu pendekatan novel untuk menganggarkan kesan lenturan balik didalam proses lenturan udara. Dalam pendekatan ini, kaedah unsur terhingga telah dikombinasikan dengan kaedah permodelan meta untuk menganggarkan kesan lenturan balik dengan mudah dan tepat.

Dua teknik permodelan meta, iaitu rangkaian neural dan respon permukaan model meta telah digunakan dan dibandingkan untuk menentukan secara tepat dua fungsi dimensi kepelbagaian. Fungsi pertama menganggarkan kesan lenturan balik jumlah sesuatu bahan, parameter geometri dan sudut

lenturan sebelum lenturan balik. Fungsi kedua menganggarkan pergerakan tumbukan untuk sesuatu bahan, parameter geometri dan sudut lenturan balik sesudah kesan lenturan balik. Data latihan yang diperlukan untuk melatih dua teknik permodelan meta telah diambil dengan menggunakan model unsure terhingga bukan linear dimana ia adalah berasaskan formulasi terkini Lagrangian yang mengambil kira geometri, sifat bukan linear bahan dan jalinan. Untuk menentu-sahkan model unsur terhingga ini, ujikaji fizikal telah dijalankan. Satu algoritma rangkaian neural yang berasaskan propagasi terbalik algoritma telah dibangunkan. Penyelidikan ini menggunakan rekabentuk D-optimal yang diambil dari komputer untuk memilih contoh latihan bagi kesemua teknik permodelan meta tersebut dan untuk membuat perbandingan diantara permodelan yang boleh dianggap adil.

Keputusan daripada penyelidikan ini menunjukkan penganggaran lenturan balik FEM adalah persamaan baik dengan keputusan ujikaji dan deviasi piawai ialah 1.213 darjah. Keputusan juga mendapati rangkaian neural model meta adalah lebih tepat daripada respon permukaan model meta. Deviasi piawai diantara FEM dan rangkaian neural model meta bagi dua fungsi adalah 0.635 darjah dan 0.985 mm. Deviasi piawai diantara FEM dan methodologi respon permukaan ialah 1.758 darjah dan 1.878 mm untuk kedua-dua fungsi tersebut.

ACKNOWLEDGMENTS

I would like to express my sincere gratitude and deep thanks to my supervisor Professor Dr. Abdel Magid Salam Hamouda for his kind assistance, support, advice, encouragement and suggestions throughout this work and during the preparation of this thesis.

I would like to express my appreciation to Associate professor Shamsuddin Sulaiman and Dr. Elsadig Mahadi for their help, suggestions and assistance during the preparation of this thesis.

Finally, I would like to express my indebtedness to my family. My thank you goes especially to my father and my brother Fawwaz, for their moral and financial support.




I certify that the examination Committee has met on 22th February 2006 to conduct the final examination of Fayiz Y. M. Abu Khadra on his Doctor of Philosophy thesis entitled "Neural Network Model and Finite Element Simulation of Springback in Plane-Strain Metallic Beam Bending" in accordance with Universiti Pertanian Malaysia (Higher Degree) Act 1980 and Universiti Pertanian Malaysia (Higher Degree) Regulations 1981. The committee recommends that the candidate be awarded the relevant degree. Members of the Examination Committee are as follows:

Napsiah Ismail, PhD
Associate professor
Faculty of Engineering
Universiti Putra Malaysia
(Chairman)

Barkawi Sahari, PhD
Professor
Faculty of Engineering
Universiti Putra Malaysia
(Internal Examiner)

Wong Shaw Voon, PhD
Associate Professor
Faculty of Engineering
Universiti Putra Malaysia
(Internal Examiner)

Elsayed A. Elsayed, PhD
Professor
Faculty of Engineering
Rutgers University
(External Examiner)



HASANAH MOHD. GHAZALI
Professor/Deputy Dean
School of Graduate Studies
Universiti Putra Malaysia

Date: **26 APR 2006**

This thesis submitted to the senate of Universiti Putra Malaysia and has been accepted as fulfillment of the requirement for the degree of Doctor of Philosophy. The members of the Supervisory Committee are as follows:

Abdel Magid Salam Hamouda, PhD
Professor
Faculty of Engineering
(Chairman)

Shamsuddin Sulaiman, PhD
Associate Professor
Faculty of Engineering
Universiti Putra Malaysia
(Member)

Elsadig Mahadi, PhD
Lecturer
Faculty of Engineering
Universiti Putra Malaysia
(Member)



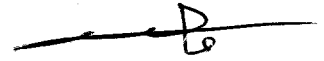
AINI IDERIS, PhD
Professor/Deputy Dean
School of Graduate Studies
Universiti Putra Malaysia

Date: **11 MAY 2006**



DECLARATION

I hereby declare that the thesis is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any degree at UPM or other institutions.



FAYIZ Y. M. ABU KHADRA

Date: 21/04/ 2006

TABLE OF CONTENTS

	Page
ABSTRACT	II
ABSTRAK	IV
ACKNOWLEDGMENTS	VI
APPROVAL	VII
DECLARATION	IX
LIST OF TABLES	XIII
LIST OF FIGURES	XIV
LIST OF ABBREVIATIONS	XIX
 CHAPTER	
1 INTRODUCTION	1
1.1 Background	1
1.2 Problem Statement	2
1.3 Research objectives	4
1.4 Thesis Organization	5
 2 LITERATURE REVIEW	 6
2.1 Plasticity	6
2.1.1 Yield Criteria	7
2.1.2 Strain Hardening Laws	9
2.1.3 The Plastic Flow Rule	12
2.2 Bending and Springback	14
2.2.1 Bending	14
2.2.2 The Elastic– Perfectly plastic Bending Mechanics	17
2.2.3 Existing Research	21
2.3 Application of FEM to Sheet Bending Process	38
2.3.1 Geometric Nonlinearities	39
2.3.2 Contact and Friction	43
2.3.3 Element Type	46
2.3.4 Solver type	48
2.3.5 Existing Research	51
2.4 Metamodeling Techniques	55
2.4.1 Neural Networks	56
2.4.1.1 Basic Concepts	57
2.4.1.2 Learning Method	59
2.4.1.3 Multi-Level Perceptron	60
2.4.1.4 Application of Neural Network	63
2.4.2 Response Surface Methodology	65
2.4.2.1 Mathematical Form for the RSM Models	65
2.4.2.2 Design of Experiments for RSM Models	67



2.5	Genetic Algorithm	68
2.6	Summary	71
3	METHODOLOGY	73
3.1	The Structure of the Study	73
3.2	Experimental study	75
3.2.1	Materials	75
3.2.2	Tooling	77
3.2.3	Experimental Procedure	78
3.3	Finite Element Analysis	79
3.3.1	Springback Simulation	79
3.3.2	Finite Element Software	80
3.3.3	Validation of the Finite Element Model	80
3.4	Metamodeling	81
3.4.1	Metamodels A and B	81
3.4.2	Training Examples	83
3.4.3	Neural Networks	83
3.4.4	Response Surface Methodology	86
3.5	Error Measures	89
3.6	Summary	91
4	FINITE ELEMENT RESULTS FOR SPRINGBACK IN BENDING	92
4.1	Experimental Work	92
4.1.1	Overview	92
4.1.2	Results and Discussion	96
4.2	Finite Element Model	100
4.2.1	Basic Assumptions	100
4.2.2	Element Type	101
4.2.3	Finite Element Procedure	103
4.2.4	Material Behavior	106
4.2.5	Contact	109
4.2.6	Loading and Unloading	111
4.2.7	Convergence Criteria	112
4.2.8	Mesh Sensitivity	113
4.2.9	Effect of the Number of Increments	114
4.3	Validation of the Finite Element Model	116
4.3.1	Material Behavior	116
4.3.2	Punch Load Displacement Relation	117
4.3.3	Springback Amount	118
4.3.4	Accuracy of the Finite Element Model	121
4.4	Stresses Analysis of the Bending Process	123
4.4.1	Equivalent Von Mises Strain and Stress	123
4.4.2	Residual Stress	126
4.5	Parametric Study	129
4.5.1	Effects of Material Parameters on Springback	129
4.5.2	Effect of Geometrical Parameters on Springback	133

4.6	Conclusions	136
5	RESULTS FOR NEURAL NETWORK METAMODELS	138
5.1	Neural Network Program	138
5.1.1	Activation Function	138
5.1.2	Normalization of the Input-Output Sets	139
5.1.3	Initial weights	140
5.1.4	Calculation of the Layers Response	140
5.1.5	Updating the Weights	141
5.1.6	Stopping Criteria	142
5.1.7	The Neural Network Program	144
5.2	Application of the Neural Network Program to the Springback Problem	146
5.2.1	Optimum Parameters for the Metamodels	146
5.2.2	Accuracy of the Metamodels	154
5.3	Integrated Metamodel Genetic Algorithm Optimization	157
5.3.1	Encoding and initialization of GA	157
5.3.2	Selection	158
5.3.3	Crossover	158
5.3.4	Mutation	160
5.3.5	Results and Discussion	160
5.4	Conclusions	163
6	RESULTS FOR RESPONSE SURFACE METAMODELS	164
6.1	Importance of the Inputs Parameters	164
6.1.1	General Sensitivity Analysis	164
6.1.2	Analysis of Variance	166
6.2	Response Surfaces	171
6.2.1	Design Selection	171
6.2.2	Comparison between the NN and the RSM Models	178
6.3	Discussion	189
6.4	Conclusions	191
7	DISCUSSION AND CONCLUSIONS	193
7.1	Summary and Conclusions	193
7.2	Achievement of the Objectives	195
7.3	Robustness of the Methodology	197
7.4	Contributions	198
7.5	Recommendations for Future Research	198
	REFERENCES	200
	APPENDIX	209
	BIODATA OF THE AUTHOR	225



LIST OF TABLES

Table		Page
4.1	List of sheets used and their properties	95
4.2	Effect of material and geometrical parameters on springback	135
5.1	Optimum parameters for the two metamodels	139
6.1	Experimental layout of Taguchi table L 27 and the calculated springback	168
6.2	Analysis of Variance for springback	169
6.3	Error metric for the different models for metamodel A	180
6.4	Error metric for the different models for metamodel B	185



LIST OF FIGURES

Figure		Page
2.1	Schematic of the isotropic hardening rule	9
2.2	Different strain hardening laws	11
2.3	Schematic of the kinematic hardening rule	12
2.4	Yield surface and normality criterion 2-D stress space	13
2.5	Air bending process	16
2.6	V-bending Process	16
2.7	Wiping bending (straight flanging)	17
2.8	Moment–curvature relationship during loading and unloading	18
2.9	Stress distribution during the different stages in the bending process	20
2.10	Normalized springback obtained theoretically $(\alpha_f/\alpha_0)_{\text{theoretical}}$, vs. normalized springback found experimentally $(\alpha_f/\alpha_0)_{\text{experimental}}$	32
2.11	Description of Motion	41
2.12	Individual Neuron Structure	58
2.13	A three-layered neural network	61
2.14	Learning algorithm of a neural network	62
2.15	Flow chart for genetic algorithm	70
3.1	Flow chart describes this study	74
3.2	Standard tensile specimen	76
3.3	The tool used for the bending test	78
3.4	Air bending process	82
3.5	Finite element applied for training the neural network	85
3.6	Steps to construct a response surface model	87
4.1	Stress-strain curves for S3	95

4.2	Experimental Springback angle as a function of the bend angle before springback ($W_d = 40$)	98
4.3	Experimental Springback angle as a function of the bend angle before springback ($W_d = 50$ mm)	99
4.4	Experimental Springback angle as a function of the bend angle before springback ($W_d = 60$ mm)	99
4.5	Finite element model	101
4.6	Gaussian integration points for element type 11	102
4.7	Von Mises yield Surface	108
4.8	Schematic of Isotropic Hardening Rule	110
4.9	Punch Control	111
4.10	Effect of number of element on the springback angle	114
4.11	Effect of the number of increments in unloading stage on the springback angle	115
4.12	Effect of the number of increments in loading stage on the springback angle	115
4.13	Nodes must follow the constitutive relation	116
4.14	Comparison punch load-displacement for S3	118
4.15	Experimental bend for S3 ($W_d = 40$)	119
4.16	Finite element model bend S3 ($W_d = 40$)	119
4.17	Bending angle versus springback angle for material S1 ($W_d = 40$)	120
4.18	Bending angle versus springback angle for material S7 ($W_d = 50$)	120
4.19	Comparison between the finite element and experimental springback angle for all bend cases used in this study	121
4.20	Deformation history and the Equivalent Von Mises Stress (MPa)	124
4.21	Deformation history and total equivalent plastic strain (mm/mm)	125
4.22	Predicted stress as under loading and after unloading through the sheet thickness	127

4.23	Stress along the sheet for the inner fiber	128
4.24	Stress along the sheet for the outer fiber	128
4.25	Effect of the young's modulus on the springback amount	131
4.26	Effect of the yield strength on the springback amount	131
4.27	Effect of the strength coefficient on the springback amount	132
4.28	Effect of the strain hardening constant on the springback amount	132
4.29	Effect of the die width on the springback amount	134
4.30	Effect of the die radius on the springback amount	134
4.31	Effect of the punch radius on the springback amount	136
5.1	Sigmoid function	139
5.2	Flow chart of the neural network approximator program	134
5.3	Structure of the neural network program	145
5.4	Structure of the neural network metamodels	147
5.5	Effects of the number of neurons in the hidden layer on the standard deviation for metamodel A	150
5.6	Effect of the number of neurons in the hidden layer on the STDV and RMSE for metamodel B	150
5.7	Effect of learning factor on the standard deviation for metamodel A	151
5.8	Effect of learning factor on the standard deviation for metamodel B	151
5.9	Effect of normalization range on the STDV and RMSE for metamodel A	152
5.10	Effect of normalization range on the STDV and RMSE for metamodel B	152
5.11	RMSE versus the number of iteration for the two metamodels	153
5.12	Comparison between the NN metamodel and FEM springback	155
5.13	Comparison between the NN displacement and the FEM displacement	155

5.14	Comparison between the NN and the experimental springback	156
5.15	Comparison between the NN and the experimental displacement	156
5.16	Optimization loop	159
5.17	Springback for the initial population	161
5.18	Springback for the final population	162
5.19	Average and best fitness as function of the generation number	162
6.1	Results of general sensitivity analysis for springback	166
6.2	Results of the analysis of variance for springback	171
6.3	Available design points in the database	175
6.4	Selected points using the D-optimality criterion based on linear (L) model	176
6.5	Selected points using the D-optimality criterion based on linear +squares (LS) model	176
6.6	Selected points using the D-optimality criterion based on Linear +Interaction (LI) model	177
6.7	Selected points using the D-optimality criterion based on Full quadratic (FQ) model	177
6.8	Comparison between the different models for springback design selected based on linear model (L)	181
6.9	Comparison between the different models for springback design selected based on linear+squares (LS) model	181
6.10	Comparison between the different models for springback design selected based on linear+ interactions (LI) model	182
6.11	Comparison between the different models for springback design selected based on full quadratic (FQ) model	182
6.12	Standard deviation for the different neural network models for springback	183
6.13	Standard deviation for the different response surface models for springback	183



6.14	Comparison between the different models for springback design selected based on linear model (L)	186
6.15	Comparison between the different models for springback design selected based on linear+squares (LS) model	186
6.16	Comparison between the different models for displacement design selected based on linear+interactions (LI) model	187
6.17	Comparison between the different models for springback design selected based on full quadratic (FQ) model	187
6.18	Standard deviation for the different NN models for displacement	188
6.19	Standard deviation for the different RSM models for displacement	188



LIST OF ABBREVIATIONS

E	Young's modulus of elasticity
K	Strength coefficient
N	Strain hardening exponent
M	Bending moment
1/P	Curvature
T	Sheet thickness
N	Poisson's ratio
θ	Bend angle
W	Work done
Z	Distance from neutral axis
ANN	Artificial neural networks
NN	Neural networks
FEM	Finite element method
FEA	Finite element analysis
M	Bending moment
RESIDUAL	Residual stress
F	Deformation gradient
$d\bar{\epsilon}^p$	Equivalent plastic strain increment
$\bar{\sigma}$	Equivalent stress
μ	Friction coefficient
Δv	Sliding velocity
LMS	Least Mean Squares algorithm
MSE	mean square error
MLP	Multilevel perceptron
$\beta_0, \beta_1, \beta_2$	Regression coefficients
ϵ	Approximation error
B	Coefficient vector
$\Delta\theta$	Springback
θ_1	Bend angle before springback
θ_2	Bend angle after springback



Σ_Y	Yield strength
R_P	punch radius
R_D	die radius
W_D	die width
Z	Punch displacement
STDV	Standard Deviation
Y	Measured response
\hat{y}	Predicted response
R^2	Pearson's correlation ratio
RE	Relative error
UTS	ultimate tensile strength
$\dot{\tau}_{ij}$	Jaumann rate of the Kirchoff stress
$\dot{\epsilon}_{ij}$	Strain rate
S_f	Surface on which traction prescribed
\dot{t}_i	Rate of the normal traction
v_i	Velocity
δL_{ij}	Velocity gradient
H'	Strain-hardening rate
α	Constant equal to 1 for plastic state and 0 for the elastic state
σ'_{ij}	Effective stress deviatoric part of σ_{ij}
$\bar{\sigma}$	Effective stress
U	Nodal displacement vector
K_T	Current tangent stiffness matrix
F	External load vector
I	Internal force vector
B_K	Stress-displacement matrix
V_K	Element volume
ΔT	Time increment
$\sigma_1, \sigma_2, \sigma_3$	Principal Cauchy stresses
σ'_{ij}	Deviatoric Cauchy stress

$\ F_{\text{residual}}\ _{\infty}$	Magnitude of the maximum residual load
$\ \delta u\ _{\infty}$	Incremental displacement
TOL	Preset tolerance
C ₁ AND C ₂	Constant
V_{ji}	Input/hidden weights
W_{kj}	Hidden/output weights
R	Random vector
δ_{ok}	Error signal term
F	Activation functions
Z	Single pattern vector
O _K	Output from the k _{th} neuron
D _K	Target output
GA	Genetic algorithm
IN	Input parameters
OUT	Output features
ANOVA	Analysis of variance
SS	Sum of squares
Seq SS	Sequential sums of squares
Adj MS	Adjusted mean squares
Σ^2	Variance of the response
L	Linear model
LS	Linear+squares model
LI	Linear+interactions model
FQ	Full quadratic model

CHAPTER 1

INTRODUCTION

1.1 Background

Bending in manufacturing of engineering metal sheet parts is a cost effective technique since it allows the elimination of machining and welding operations. The components produced by the sheet-metal bending range from simple to complex shapes and can be as small as certain parts for the electronic industry or as large as car bodies for the automotive industry.

Sheet metal air bending processes are one of the most frequently used manufacturing operations in industry. Air bending is a forming process with great flexibility compared to other die bending processes. With the use of only one tool set it is possible to bend sheets of various thickness and mechanical properties to different bending angles. As the tooling is retracted, the elastic strain energy stored in the material recovers to reach a new equilibrium and causes a geometry distortion due to elastic recovery, the so-called springback. Springback refers to the shape discrepancy between the fully loaded and unloaded configurations. Springback depends on a complex interaction between material properties, part geometry, die design, and processing parameters.



Nowadays, the importance of the springback problem increases because of the use of sheet-metal parts with high mechanical characteristics. The capability to model and simulate the springback phenomenon early in the new product design process can significantly reduce the product development cycle and cost.

1.2 Problem Statement

Analytical models based on materials properties and tool geometry are available to predict springback. Most of the analytical models based on a lot of simplifying assumptions due to the complexity of the problem and do not provide accurate predictions. One accurate way to predict the springback is to use the finite element method (FEM).

The finite element method is a powerful numerical technique that has been applied in the past years to a wide range of engineering problems. More recently FEM has been used to model fabrication processes. When modeling fabrication processes that involve deformation, such as sheet metal bending, the deformation process must be evaluated in terms of stresses and strain states in the body under deformation including contact issues. The major advantage of this method is its applicability to a wide class of boundary value problems with little restriction on work piece geometry. However, sheet metal forming simulation using the finite element method involves material, geometric and contact nonlinearity, which make simulation of the forming process computationally expensive.

Moreover, finite element simulation applied to the sheet metal bending process becomes a trial-and-error process in which a set of input factors is used to predict a set of output performance measures. If the desired performance is achieved, a good system design has been attained. Otherwise the process is repeated until a satisfactory set of performance measures is obtained. Unfortunately, the iterative nature of this process can result in both high computing cost and difficulties in interpretation and prediction of the results.

In order to overcome these problems this study develops a novel approach using finite element method combined with metamodeling techniques so that the springback can be accurately predicted.

One of the main objectives of a metamodel is to accurately represent the input-output relationships over a wide range of the parameter space, while being computationally more efficient than the underlying finite element simulation model. Furthermore, the concept of metamodels can be useful to facilitate understanding the relationships between springback and the factors that influence the springback. In this research, two metamodeling techniques namely the neural network and the response surface methodology are used and compared to approximate two multidimensional functions used to predict the springback and the displacement required to achieve a certain bend angle after springback.