UNIVERSITATEA TEHNICĂ DIN CLUJ-NAPOCA

INTRARE NR. 16787
IEŞIRE
DATA: 25.06.2019

Catre,

Consiliul de Administratie al Universitatii Tehnice din Cluj-Napoca

Subsemnatul Turcu Antoniu Claudiu, avand functia de Sef lucr. Dr. Ing. Ref. ec., in cadrul Departamentului de Electroenergetica si Management, contest prin prezenta avizul Biroului juridic referitor la analiza dosarului de concurs pentru ocuparea postului de Conferentiar, poz. 8, din urmatoarele considerente:

1. Avizul negativ se refera la urmatoarea situatie de fapt: numarul de lucrari indexate in baze de date ISI este 6 si nu 7, care este minimul necesar pentru a fi eligibil.
2. Lucrarile indexate ISI atasate dosarului meu este in numar de 8, cu urmatoarele mentiuni:

- Una din lucrarile indexate ISI nu se regaseste in baza de date WOS, desi lucrarea respectiva este citata de alte 3 lucrari de specialitate, ale caror copii le atrasez prezentei;

- Cealallta lucrare stiintifica la care fac referire a fost transmisa jurnalului Technical Gazette - Tehnički Vjesnik in anul data de 09.12.2014. A trecut de toate comisiile de revizuire, versiunea finala fiind publicata pe pagina personala a unuia din autori in data de 06.09.2017. Din ultimele discutii purtate cu chairman-ul si cu editorul sef al jurnalului, lucrarea urma sa fie publicata in numarul 3 din iunie 2019, din acest motiv lucrarea regasindu-se in lista mea. Din motive independente de mine, lucrarea nu a fost publicata in acest numar, avand promisiunea ca pana la data de 01.07.2019 sa am, oficial, confirmarea de publicare primita de la consiliul editor. Atasez, de asemenea, dovada de revizuire a prezentei lucrari la care fac referire.

In speranta unui raspuns favorabil, va asigur de toata consideratie mea!

Cluj-Napoca,

26.06.2019

Sef lucr. Dr. ing. Ref. ec. Antoniu Claudiu TURCU

TEHNIČKI VJESNIK
TECHNICAL GAZETTE
Scientific professional journal of technical faculties of the Josip Juraj Strossmayer University of Osijek, Croatia

Sorin Dumitru GROZAV (Log out)

Home
Paper
Profile
Info

Article data | Review | Messages

Paper Id: TV-20141209182117

Title: ARTIFICIAL NEURAL NETWORKS MODEL FOR SPRINGBACK PREDICTION IN THE BENDING OPERATIONS

Submitter: Sorin Dumitru GROZAV

Authors: Florica Serban, Sorin Grozav, Vasile Ceclan, Antoniu Turcu

Keywords: springback, finite element simulation, artificial neural networks

Abstract: The main purpose of this work is to develop an Artificial Neural Network (ANN) model for springback prediction in the free cylindrical bending of metallic sheets. The proposed ANN model was developed and tested under the Matlab program. The input parameters of the proposed ANN model consist in the sheet thickness, punch radius, and friction coefficient. The output parameter is the springback coefficient. Training, testing and validation of the model were performed using 126 data sets obtained by Finite element analysis (FEA). ANN was trained by Levenberg

- Marquardt back - propagation algorithm. The performance of the ANN model was evaluated using statistic measures. The predictions of the ANN model comparing with those of FEA had quite low root mean squared error (RMSE) values and the model performed well with the coefficient of determination values. This shows that the developed ANN model has a good potential to be used as a tool for springback prediction.

No. pages:	6
No. figures:	9
No. tables:	2
No. photographs:	0
No. references:	18
Category:	Applications of Fuzzy Theory in Industrial Engineering (Industrial Engineering Research and Development)
Original file:	[06.09.2017] TV-20141209182117-R.docx [06.09.2017] TV-20141209182117 New 06.09.2017.docx [21.01.2015] TV-20141209182117.docx [09.12.2014] Grozav_Paper_Rev.docx
Review file:	[06.09.2017] TV-20141209182117-R.pdf [06.09.2017] TV-20141209182117 New 06.09.2017.pdf [21.01.2015] TV-20141209182117.pdf [09.12.2014] Grozav_Paper_Rev.docx
Status:	Reviewed

Abandon

Paper Submission Tool

Numerical Simulations for Estimating the Effective Permittivity of Matrix Dielectric Mixtures

R. Creţ and L. Dărăbant

Abstract– **The paper presents the result of the numerical and analytical computation of effective permittivity of some matrix mixtures, considering different concentrations, size, shapes, distances and orientation of the inclusions in the host media. The numerical computation of the effective static permittivity ef is done using the Finite Element Method (FEM), that will alow us to consider these influence factors. We performed a comparison between numerical and analytical results and we emphasize a formula for estimating the effective permittivity for this type of mixtures.**

Index Terms– **effective permittivity, composites, numerical simulation**

I. INTRODUCTION

THE use of composite materials for electrical, mechanical and thermal applications was extended, especially due to their improved mechanical properties (a unique combination of low density and high mechanical resistance). Their main advantage consists in the possibility of designing them for special purposes. Composite materials continue to evolve, due to technological development that leads to an improved and more precise manufacturing process. A rising importance is now attributed to the study of their electrical properties, as they can be used as dielectrics in insulating systems. Since the size and weight of the insulation system plays an important role in its cost, creating a light and cheap composite, with the same electrical properties as traditional materials, would represent a major achievement.

The most studied composites are binary mixtures, composed by a polymer that represents the matrix, and organic or non-organic inclusions, spatially distributed in the host media. If there are analytical formulas available to estimate the effective permittivity for a reduced volume percent of the inclusions in the mixture, for a large amount of inclusions – that represents the case of polymer composites used in insulating systems – a numerical simulation is required to asses their behavior. Using MAXWELL 2,3D, created by ANSOFT corporation, one can compute – using the Finite Element Method (FEM) – the electric field and electric displacement in any point of a domain, making it possible to asses the effective (real) permittivity of the mixture, - ε_{ef}.

The literature [1, 2, 3, 4, 6, 9, 10] shows that effective permittivity depends not only on the shape, size and distance between inclusions, but also on their orientation with respect to the applied electric field. The simulations performed for matrix mixtures also considered these influence factors.

II. COMPUTATION METHODS FOR STATIC EFFECTIVE PERMITTIVITY

The key parameter to be computed in order to determine dielectric properties of mixtures is the electric field distribution E(x ,y, z) in the computation domain. The most appropriate method to perform this numerical computation for dielectric mixtures is the Finite Element Method (FEM) [1, 5, 7, 10].

Once we know the distribution of the electric field, this can be used in several ways to compute the effective permittivity. One approach is based on Ampère's law, given by:

$$\nabla\left(\left(\Sigma - j\sigma/\omega\varepsilon_0\right)^{-} E\right) = 0, \tag{1}$$

valid for a time variable electric field, $E = E_0 \exp(j\omega t)$.

Solving equation (1) for the electric field E(x,y) – in 2D – or E(x, y, z) – in 3D – the effective permittivity is obtained as:

- Method M1: knowing the average values of the electric field $\tilde{E}$ and of the electric displacement $\tilde{D}$:

$$\varepsilon_{ef} = \tilde{D} / \tilde{E} \tag{2}$$

- Method M2: from the electrostatic energy balance:

$$\frac{1}{2}\varepsilon_{ef}\tilde{E}^2 = \frac{1}{\Omega}\int_{\Omega}\frac{1}{2}E\cdot D\,d\Omega \tag{3}$$

In these equations, Ω represents the computation domain, and:

$$\tilde{E} = \frac{1}{\Omega}\int_{\Omega} E\cdot d\Omega; \quad \tilde{D} = \frac{1}{\Omega}\int_{\Omega}\varepsilon E\cdot d\Omega \tag{4}$$

III. ANALYTICAL METHODS FOR ESTIMATING THE EFFECTIVE PERMITTIVITY

The computation method for the average (effective) permittivity of the mixture is chosen as a function of the mixture's type (statistic or matrix) [3, 4, 5, 7, 8]. Most formulas are based on the theory of the average field. Among these, we used the following formulas to compute the permittivity of the matrix mixture:

$$\frac{\varepsilon_2-\varepsilon_{ef}}{\varepsilon_2-\varepsilon_1} = (1-q)\cdot\sqrt[3]{\frac{\varepsilon_{ef}}{\varepsilon_1}} \quad \text{(Bruggerman)} \qquad (5)$$

$$\varepsilon_{ef} = \varepsilon_1\left(1+\frac{mq(\varepsilon_2-\varepsilon_1)}{m\varepsilon_1+(\varepsilon_2-\varepsilon_1)(1-q)}\right) \quad \text{(Sillars)} \qquad (6)$$

$$\varepsilon_{ef} = \varepsilon_1\frac{(\varepsilon_2+2\varepsilon_1)+2q(\varepsilon_2-\varepsilon_1)}{\varepsilon_2+2\varepsilon_1-q(\varepsilon_2-\varepsilon_1)} \quad \text{(Maxwell–Wagner)} \qquad (7)$$

In the equations above, q represents the volume concentration of the inclusions, ε_{ef}, ε_1, ε_2 – the relative permittivities of the mixture, the host media and inclusions and m – a parameter equal to 3 for spherical inclusions or 6 for elliptic ones.

IV. GEOMETRICAL MODEL

The selected computation domain is the dielectric of a plane capacitor placed inside a homogenous field. The boundary conditions attributed to the model are those in figure 1. The influence of the distance between inclusions upon the effective permittivity of the mixture was studied using the model in fig. 2, where the host media is a rectangle of 50x25 µm and the relative permittivity ε_1=2.25. The inclusions are represented by infinitely long cylinders, of radius r = 2 µm and ε_2=3.78, the distance between them varying from 0 to 24 µm (d = 12r).

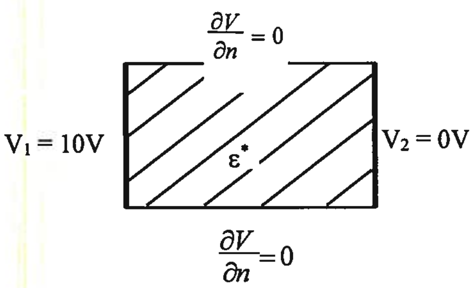
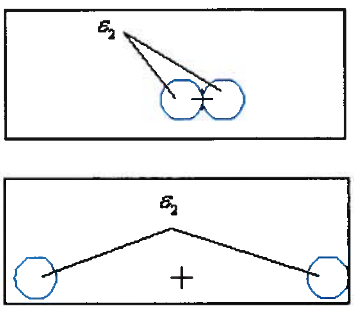


Fig. 1. Boundary conditions attributed to the computation model

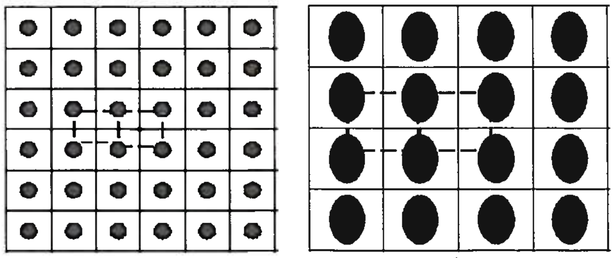
a.



b.

Fig. 2. Dielectric mixture with two cylindrical inclusions. He distance between them is: a) 0 µm; b) 24 µm

For the 2D case, we considered ordered matrix structures, having the same matrix of the host media (16x16 elements) but with different forms and concentrations of the inclusions. We considered cylindrical and ellipsoidal inclusions, according to models in figure 3 – a and b.



a. b.

Fig. 3. Fragment of the modeled matrix structures, with: a – cylindrical and b – ellipsoidal inclusions

The concentration of the inclusions was computed as the ration between the area of the inclusion and the area of the matrix square that hosts it, with formula $q_i = \pi r^2/l^2$ for cylindrical inclusions and $q_i = \pi ab/l^2$ for ellipsoidal ones.

For ellipsoidal inclusions, figure 4 shows the variation of the small semi-axis of the ellipse as a function of the large semi-axis, b = $f(a)$ for different values of the concentration. This allows us to easily establish the size of the ellipse when the concentration changes. The graphic was established considering a unit side of the square of the host matrix.

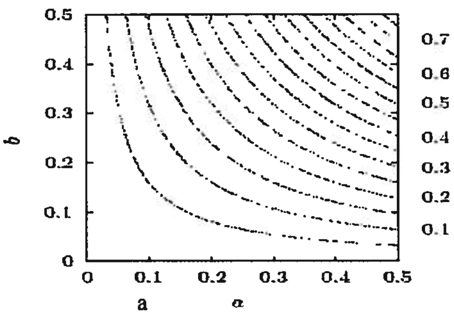
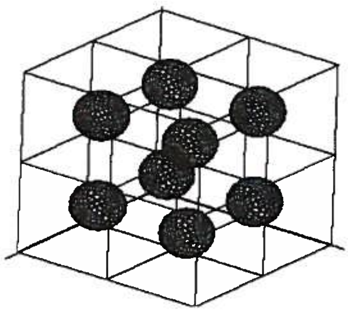
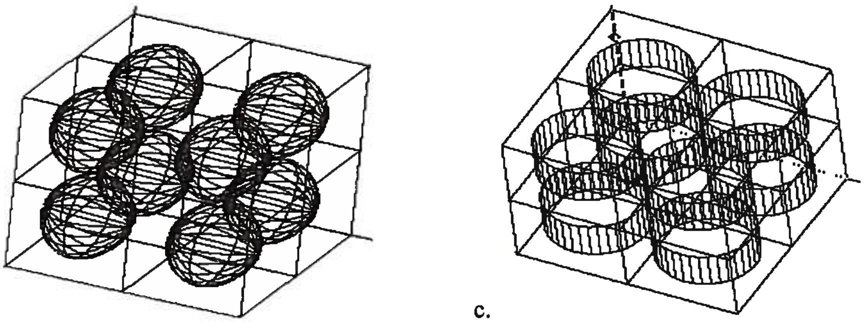


Fig. 4. Variation of the small semi-axis of the ellipse as a fuction of the large semi-axis for different concentrations

In 3D we modeled matrix mixtures with spherical, ellipsoid and cylindrical inclusions. The models that we studied are those in figure 5.



a.



b. c.

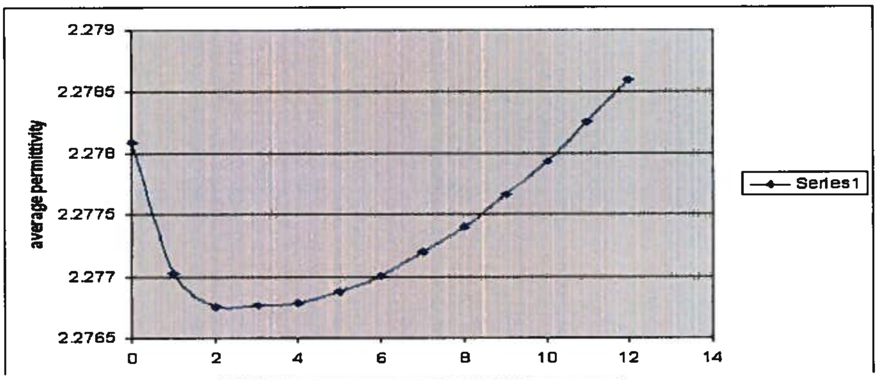
Fig. 5. The model of the mixture, with a- spheric, b – ellipsoide and c – cylindric inclusions

V. RESULTS AND DISCUSSIONS

The results of the numerical study regarding the influence of the distance between the inclusions upon the effective permittivity of the mixture with two cylindrical inclusions – the model in figure 2 – are given in table I. The distance between the inclusion is expressed in terms of multiples of the inclusion's radius (r=2μm). The variation of the effective permittivity of the mixture as a function of the distance between inclusions is given in figure 6.

TABLE I.
VARIATION OF THE EFFECTIVE PERMITTIVITY WITH DISTANCE BETWEEN CYLINDRICAL INCLUSIONS

d	0	r	2r	3r	4r	5r	6r
ε_{ef}	2.2780936	2.2770272	2.2767622	2.2767622	2.2767829	2.2768781	2.2770056
d	7r	8r	9r	10r	11r	12r	
ε_{ef}	2.2772030	2.2774020	2.2776700	2.2779325	2.2782590	2.2785934	



[redacted]

Fig. 6. Variation of the effective permittivity with distance between the inclusions

Numeric computation of the effective permittivity was performed for matrix structures where the host media has dielectric constant ε_1=4, inclusions ε_2=6,5 and the side of the square l is 20 μm. The computation methods for ε_{ef} in electrostatic regime were: M1 – with equation (2) and M2 – with equation (3), using MAXWELL 2,3D software.

Numerical results obtained for mixtures with cylindrical inclusions of different concentrations (figure 3 a, b) are given in table 2. They were compared with those computed analytically with formulas (5), (6), and (7).

Based on the analysis of the results in table II, one can conclude that the numerical values are closes to those computed with Maxwell-Wagner formula.

For ellipse inclusions and a concentration of q =$0,3$ we draw – figure 7 - the variation of the effective. permittivity as a function of the angle between the direction of the electric field and the large semi-axis of the ellipse – defined in figure 8.

For 3D modelling we considered models in figure 5, with the same concentration of the inclusions, q_i = $0,3$. For ellipsoids and cylinders, we also considered the two main directions of applying the external electric field, which is parallel or perpendicular to the axis of the inclusion.

TABLE II

ANALYTICAL AND NUMERICAL VALUES OF THE EFFECTIVE PERMITTIVITY FOR MATRIX MIXTURES WITH CYLINDER INCLUSIONS, FOR DIFFERENT CONCENTRATIONS

q	Erori Brugermenn-M1 (Errors)	Sillars	Maxwell-Wagner	M1	M2
0.1	0,007795	4,2240	4.2105	4.1946	4.1510
0.2	0,015241	4,4423	4.4285	4.3977	4.3127
0.3	0,021452	4,6528	4.6545	4.6114	4.4892
0.4	0,026104	4,8520	4.8888	4.8367	4.6836
0.5	0,028625	5,0344	5.1320	5.0752	4.9002
0.6	0,028519	5,1901	5.3846	5.3284	5.1457
0,7	0,016232	5,2102	5,6470	5,5999	5,4329
0.785	0,017321	5,3219	5.8783	5.8467	5.7193
	Analytical methods			**Numerical methods**	

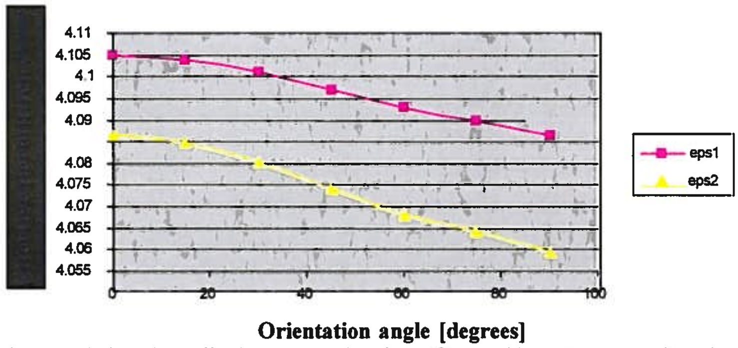


Fig.7. Variation of the effective permittivity of the mixture with respect to the orientation angle

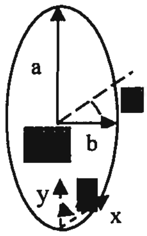


Fig. 8. Defining the orientation angle of the ellipse with respect to the external electric field

The effective permittivities of the mixtures, computed numerically, are given in table III. Depending on the orientation, errors are equal to 1,739% for cylindrical inclusions and 0,021% for ellipsoidal ones. Therefore, we can establish that the influence of the orientation of the inclusion in the applied field upon the permittivity is stronger for cylindrical inclusions.

TABLE III

EFFECTIVE PERMITTIVITY OF MATRIX MIXTURES WITH SPHERIC, ELLIPSE AND CYLINDER INCLUSIONS, FOR TWO DIRECTIONS OF THE APPLIED ELECTRIC FIELD

INCLUSION'S TYPE		M1	M2
Sphere		4.62973539	4.53322938
Cylinder	$\beta = 0^o$	4.59880429	4.464654958
	$\beta = 90^0$	4.67800461	4.604837551
Ellipsoid	$\beta = 0^o$	4.61337827	4.535562429
	$\beta = 90^0$	4.61230341	4.533102822

VI. CONCLUSIONS

In case of dielectric matrix mixtures, the influence of concentration, size, shape, distance and orientation of inclusions on the effective permittivity of the binary mixture is confirmed. One can conclude that the most significant is the influence of the orientation of the inclusion with respect to the applied electric field, in case of elliptic inclusions, but especially in case of cylindrical inclusions.

The results obtained with the numerical computation method M1 are closer to those computed with Maxwell-Wagner formula, the one indicated in the literature for estimating ε_{ef} for this type of mixtures.

VII. REFERENCES

[1] C. Brosseau, A. Beroual, "Effective Permittivity of Composites with Stratified Particles", *Journal of Physics*, 2001.

[2] P. Clauzon, L. Krahenbuhl, A. Nicolas, "Effective Permittivity of 3D Lossy Dielectric Composite Materials", *IEEE Transactions on Magnetics*, vol. 35, nr. 3, 1999.

[3] R. Creţ, "Contribuţii la studiul dielectricilor neomogeni", *Teză de doctorat*, Cluj-Napoca, 2004;

[4] R. Creţ, L. Creţ, "Numerical Computation of Dielectric Permittivity of Mixtures", *J. Optoelectronics and Advanced Materials*, nr.3, 2004.

[5] R. Creţ , E. Simion, M. Pleşa, D. D. Micu, "Numerical Modelling of Non-Homogenous Dielectrics with Very Different Permittivities of the Components", *Proceedings of the Conference Metamaterials 2007*, Rome, Italy,. 2007.

[6] R. Creţ, A. Turcu, D. Ştet, D. D. Micu, "Study of the Factors that Affect the Effective Permittivity of the Dielectric Mixtures", *Proceedings of the International Conference „Materials for Electrical Engineering" - 6th Edition of MmdE*, 2008.

[7] R. Creţ, L. Dărăbant, A. Turcu, M. Pleşa, "Numerical Simulations and Experimental Analysis of Polimer Based Non-homogeneous Dielectrics", *J. Optoelectronics and Advanced Materials*, nr. 5,nov. 2009.

[8] B. M. Tareev, "Fizika Dielectriceskih Materialov", *Energoizdat*, Moskva, 1982.

[9] E. Tuncer, S. M. Gubanski, "Dielectric Proprieties of Different Composite Structures", *SPIE*, vol. 4017, 2000;

[10] E. Tuncer, Y. V. Serdyuk, S. M. Gubanski, "Comparing Dielectric Properties of Binary Composite Structures Obtained with Different Calculation Tools and Methods", *CEIDP*, Canada, 2001.

Web of Science

Cited References: 14

(from Web of Science Core Collection)

From: STUDY OF THE FACTORS THAT INFLUENCE THE EFECTIVE PERMITTIVITY OF THE DIELECTRIC MIXTURES ...More

Select Page Export... Add to Marked List

Find Related Records >

1. Title: [not available]
   By: BROSSEAU C
   J APPL PHYS Published: 2001

   Times Cited: 1
   (from Web of Science Core Collection)

2. Title: [not available]
   By: BROSSEAU C
   J PHYS D Published: 2001

   Times Cited: 1
   (from Web of Science Core Collection)

3. **Effective permittivity of 3D lossy dielectric composite materials**
   By: Clauzon, P; Krahenbuhl, E; Nicolas, A
   Conference: 8th Biennial IEEE Conference on Electromagnetic Field Computation (IEEE CEFC 98) Location: TUCSON, ARIZONA Date: JUN 01-03, 1998
   Sponsor(s): IEEE
   IEEE TRANSACTIONS ON MAGNETICS Volume: 35 Issue: 3 Pages: 1223-1226 Part: 1 Published: MAY 1999

   Times Cited: 12
   (from Web of Science Core Collection)

View Abstract ▼

4. **Numerical Simulations and experimental analysis of polimer based non-homogeneous dielectrics**
By: Cret, R.; Darabant, L.; Turcu, A.; et al.
Journal of Optoelectronics and Advanced Materials Pages: 932-937 Published: 2009
[Show additional data]

Times Cited: 2
(from Web of Science Core Collection)

5. **Numerical computation of dielectric permittivity of mixtures**
By: Cret, R; Cret, L
Conference: 4th International Workshop on Materials for Electrotechnics Location: Bucharest, ROMANIA Date: MAY 26-28, 2004
JOURNAL OF OPTOELECTRONICS AND ADVANCED MATERIALS Volume: 6 Issue: 3 Pages: 1045-1048 Published: SEP 2004

View Abstract ▼

Times Cited: 4
(from Web of Science Core Collection)

6. Title: [not available]
By: CRET R
THESIS Published: 2004

Times Cited: 2
(from Web of Science Core Collection)

7. Title: [not available]
By: DIXON GD
CERAMIC B Volume: 6 Published: 1973

Times Cited: 1
(from Web of Science Core Collection)

8. **Dielectric properties of (1-x)(Mg0.95Co0.05)TiO3-xCaTiO(3) ceramic system at microwave frequency**
By: Huang, CL; Pan, CL; Hsu, JF
MATERIALS RESEARCH BULLETIN Volume: 37 Issue: 15 Pages: 2483-2490 Article Number: PII S0025-5408(02)00792-4
Published: DEC 1 2002

View Abstract ▼

Times Cited: 37
(from Web of Science Core Collection)

9. **Effective permittivity of mixtures: Numerical validation by the FDTD method**
By: Karkkainen, KK; Sihvola, AH; Nikoskinen, KI
IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING Volume: 38 Issue: 3 Pages: 1303-1308 Published: MAY 2000

Times Cited: 173
(from Web of Science Core Collection)

View Abstract ▾

10. **DIELECTRIC SCREENING MODEL FOR LATTICE VIBRATIONS OF DIAMOND-STRUCTURE CRYSTALS**
By: MARTIN, RM
PHYSICAL REVIEW Volume: 186 Issue: 3 Pages: 871-& Published: 1969

Times Cited: 209
(from Web of Science Core Collection)

11. Title: [not available]
By: TAREEV BM
FIZIKA DIELECTRICESK Published: 1982

Times Cited: 2
(from Web of Science Core Collection)

12. **Dielectric mixtures: Electrical properties and Modeling**
By: Tuncer, E; Serdyuk, YV; Gubanski, SM
IEEE TRANSACTIONS ON DIELECTRICS AND ELECTRICAL INSULATION Volume: 9 Issue: 5 Pages: 809-828 Published: OCT 2002

View Abstract ▾

Times Cited: 184
(from Web of Science Core Collection)

13. **Dielectric properties of different composite structures**
By: Tuncer, E; Gubanski, SM
Conference: Conference on Polymers and Liquid Crystals Location: SZCZYRK, POLAND Date: SEP 24-27, 1998
Sponsor(s): Tech Univ Lodz, Text Inst; Tech Univ Lodz, Inst Polymers; Tech Univ Lodz, Inst Phys; USAF European Off Aerosp Res & Dev; USA Res Dev & Standardizat Grp; Comm Sci Res; Stefan Batory Fdn; SPIE; SPIE Poland Chapter
POLYMERS AND LIQUID CRYSTALS Book Series: PROCEEDINGS OF THE SOCIETY OF PHOTO-OPTICAL INSTRUMENTATION ENGINEERS (SPIE) Volume: 4017 Pages: 136-142 Published: 1999

View Abstract ▾

Times Cited: 2
(from Web of Science Core Collection)

14. **Comparing Dielectric Properties of Binary Composite Structures Obtained with Different Calculation Tools and Methods**
By: Tuncer, E.; Serdyuk, Y. V.; Gubanski, S. M.
Conference: CEIDP Location: Canada
COMP DIELECTRIC PROP Published: 2001

Times Cited: 2
(from Web of Science Core Collection)

Select Page

Export...

Add to Marked List

Key: = Structure available.

Web of Science

Cited References: 10

(from Web of Science Core Collection)

From: Considerations about the Influence of Some Factors Related to the Geometric Characteristics of Inclu ...More

Select Page Export... Add to Marked List Find Related Records >

1. **Determination of the effective permittivity of dielectric mixtures with the Transmission Line Matrix Method**
By: Blanchard, C.; Porti, J.A; Morente, J.A.; et al.
Journal of Applied Physics
[Show additional data]
Times Cited: 1 *(from Web of Science Core Collection)*

2. **Effective Permittivity of Composites with Stratified Particles**
By: Brosseau, C.; Beroual, A.
Journal of Physics Published: 2001
Times Cited: 1 *(from Web of Science Core Collection)*

3. **Effective permittivity of 3D lossy dielectric composite materials**
By: Clauzon, P; Krahenbuhl, E; Nicolas, A
Conference: 8th Biennial IEEE Conference on Electromagnetic Field Computation (IEEE CEFC 98) Location: TUCSON, ARIZONA Date: JUN 01-03, 1998
Sponsor(s): IEEE
Times Cited: 12 *(from Web of Science Core Collection)*

IEEE TRANSACTIONS ON MAGNETICS Volume: 35 Issue: 3 Pages: 1223-1226 Part: 1 Published: MAY 1999

View Abstract ▾

4. **Numerical Simulations and experimental analysis of polimer based non-homogeneous dielectrics**
By: Cret, R.; Darabant, L.; Turcu, A.; et al.
Journal of Optoelectronics and Advanced Materials Pages: 932-937 Published: 2009
[Show additional data]

Times Cited: 2
(from Web of Science Core Collection)

5. **Numerical computation of dielectric permittivity of mixtures**
By: Cret, R; Cret, L
Conference: 4th International Workshop on Materials for Electrotechnics Location: Bucharest, ROMANIA Date: MAY 26-28, 2004
JOURNAL OF OPTOELECTRONICS AND ADVANCED MATERIALS Volume: 6 Issue: 3 Pages: 1045-1048 Published: SEP 2004

View Abstract ▾

Times Cited: 4
(from Web of Science Core Collection)

6. Title: [not available]
By: Dinulovic, M.; Rasuo, B.
Dielectric Proprieties Modeling of Composite Materials Published: 2009
Publisher: University of Belgrade Press

Times Cited: 1
(from Web of Science Core Collection)

7. **Modeling and Simulation of Dielectric Mixtures using Finite Elements Method**
By: Farcas, C.; Cret, R.; Petreus, D.; et al.
Conference: Proceeding of the IEEE 16th International Symposium for Design and Technology in Electronic Packaging (SIITME)
P IEEE 16 INT S DES Pages: 385-388 Published: 2010
[Show additional data]

Times Cited: 1
(from Web of Science Core Collection)

8. Title: [not available]
By: Tareev, B.M.
Fizika dielectriceskvo materialov Published: 1982
Publisher: Energoizdat

Times Cited: 1
(from Web of Science Core Collection)

9. **Dielectric mixtures: Electrical properties and Modeling**
By: Tuncer, E; Serdyuk, YV; Gubanski, SM
IEEE TRANSACTIONS ON DIELECTRICS AND ELECTRICAL INSULATION Volume: 9 Issue: 5 Pages: 809-828 Published: OCT 2002
View Abstract

Times Cited: 184
(from Web of Science Core Collection)

10. **Comparing Dielectric Properties of Binary Composite Structures Obtained with Different Calculation Tools and Methods**
By: Tuncer, E.; Serdyuk, Y. V.; Gubanski, S. M.
Conference: CEIDP Location: Canada
COMP DIELECTRIC PROP Published: 2001

Times Cited: 2
(from Web of Science Core Collection)

Select Page Export... Add to Marked List

Key: = Structure available.

ISSN 1330-3651 (Print), ISSN 1848-6339 (Online)
doi

ARTIFICIAL NEURAL NETWORKS MODEL FOR SPRINGBACK PREDICTION IN THE BENDING OPERATIONS

Original scientific paper
The main purpose of this work is to develop an Artificial Neural Network (ANN) model for spring back prediction in the free cylindrical bending of metallic sheets. The proposed ANN model was developed and tested under the Mat lab program. The input parameters of the proposed ANN model consist in the sheet thickness, punch radius, and friction coefficient. The output parameter is the spring back coefficient. Training, testing and validation of the model were performed using 126 data sets obtained by Finite element analysis (FEA). ANN was trained by Levenberg – Marquardt back – propagation algorithm. The performance of the ANN model was evaluated using statistic measures. The predictions of the ANN model comparing with those of FEA had quite low root mean squared error (RMSE) values and the model performed well with the coefficient of determination values. This shows that the developed ANN model has a good potential to be used as a tool for spring back prediction.

Keywords: *spring back, finite element simulation, artificial neural networks.*

Model umjetne neuronske mreže za predviđanje elastičnog povrata nakon savijanja

Izvorni znanstveni članak
Glavna svrha ovog rada je razviti model umjetne neuronske mreže (ANN) za predviđanje elastičnog povrata pri slobodnom cilindričnom savijanju metalnih limova. Predloženi ANN model razvijen je i testiran uz pomoć Matlab programa. Ulazni parametri predloženog ANN modela su debljina lima, polumjer žiga i faktor trenja.Izlazni parametar je koeficijent elastičnog povrata. Obuka, testiranje i validacija modela su provedeni pomoću 126 skupova podataka dobivenih pomoću analize konačnim elementima (FEA). Levenberg - Marquardt iterativni algoritam natrag-naprijed je korišten za treniranje ANN modela. Učinkovitost ANN modela procijenjena je pomoću statističkih metoda. Predviđanja ANN modela u usporedbi s onima dobivenom FEA analizom imala su prilično malu vrijednost pogreške korijena srednjeg kvadrata (RMSE) i model se izvodio dobro s koeficijentom determinacije vrijednosti. To pokazuje da razvijeni ANN model ima dobar potencijal da bude korišten kao alat za predviđanje elastičnog povrata.

Ključne riječi: *elastični povrat, simulacija konačnim elementima, umjetne neuronske mreže.*

1 Introduction

Modelling is a powerful tool in almost all fields of applications and engineering instead of doing laboratory tests for saving time and cost. It is widely established that for modelling large-scale complex processes, soft computing methodology can be effectively used, since this technique is basically designed to exploit the tolerance for imprecision, uncertainty and partial truth. The evolution of soft computing techniques helps in understanding various aspects of nonlinear systems and thereby making it possible to model them besides predicting their future response [1]. Soft computing is a collection of methodologies like fuzzy inference system (FIS), artificial neural networks (ANNs) and genetic algorithm (GA), designed to tackle imprecision and uncertainty involved in a complex nonlinear system [2], [3] .

In the last two decades, researchers explored the potential of artificial neural networks (ANNs) as an analytical alternative to conventional techniques [4], [5]), which are often limited by strict assumptions of normality, linearity, homogeneity, and variable independence [6]. Thus ANN was used by researchers in different engineering fields to solve various problems.

Xu [7] developed an ANN model to predict the ultimate bearing capacity of tubular T-joint under fire. In [6] a back-propagation neural network and an adaptive neuro-fuzzy inference system model were developed to predict the moment capacity of ferro cement members. ANN models were used in [8] in order to predict the mechanical properties of ST14 steel in an attempt to save product quality control costs and time. Zgoul [9] developed an ANN model for characterizing the rate dependent behaviour of adhesive materials. The developed model was used to predict true strain, true stress, strain rate, and modulus of elasticity under different conditions. Duan et al. [10] use ANN for predicting the compressive strength of recycled aggregate concrete prepared with varying types and sources of recycled aggregates. ANN and adaptive neuro-fuzzy inference system methods were employed in [1] in order to make prediction on the mechanical properties of glass fibre reinforced polymers. The adaptive neuro-fuzzy inference system and ANN model were used in [11] for the buckling analysis of slender prismatic columns with a single non-propagating open edge crack subjected to axial loads. Baseri et al. in [12] proposed a fuzzy learning back-propagation algorithm to predict the spring back in V-die bending process using the data generated by experimental observations. The performance of the model in training and testing is compared with those of the constant learning rate back-propagation and the variable learning rate back-propagation algorithms. Liu in [13], developed a technique based on ANN and a genetic algorithm to solve the problem of spring back in the U-shaped bending. Nasrollahi and Arezoo in [14] used the finite element method (FEM) to simulate the spring back in wipe bending for perforated components. The results were used as training data for two artificial neural networks. Fu in [15] used ANN to predict the punch radius based on the results of air-bending experiments of sheet metals. A genetic algorithm was used to optimize the weights of neural network and then, with the predicted punch radius and other geometrical parameters of a tool, 2D and 3D ABAQUS finite-element models were established, respectively. Kazan in [16] developed a predictive model of spring back in wipe-bending processes using ANN based on FEM to obtain the teaching data.

Spring back is a very important factor that influences the quality of the bent parts, thus an accurate determination of this parameter is very important for manufacturers. Nowadays the time to market and low cost are essential for any manufacturers to fight concurrence.

Some authors [17] have made diagrams on which the spring back coefficient can be determined but they are not universal and cannot be applied in any deformation circumstances or any material. Experimentally determination of spring back involves high costs and time. Finding the methods that fast and accurate predict the spring back without the need of experimental tests is a goal for any company that produces parts obtained by bending operations. Finite element method is often used in spring back prediction but in some cases especially in the case of complex parts it may be time consuming. Therefore, in this paper an artificial neural network model is proposed as an alternative to solve the spring back problem prediction in the free cylindrical bending of metallic sheets. The proposed ANN model is validated in comparison with FEM results proving its high accuracy and predictive capabilities.

2 Obtaining data set for spring back coefficient prediction

In order to obtain the data set for training, validation and testing of the ANN model, free cylindrical bending experiments and Finite Element (FE) simulation of the free cylindrical bending process were performed.

2.1 Experimental procedure

Technological free cylindrical bending experiments were performed using a free cylindrical bending device (fig. 1) with 7 different radii of the active elements 10,15,20,25,30,35,40 mm. The bending device was installed on a universal mechanical testing machine INSTRON 1196.

Figure 1. Set-up of the bending device.

The tests were performed on rectangular samples with dimensions of 25x10mm cut from aluminium alloy EN AW 6016 with the thickness of 1.25mm. The profile of the bent specimens was measured on a Werth Benchtop VideoCheck® IP 400 coordinate measuring machine (fig. 2). The measurement results were used to determine the spring back coefficient.

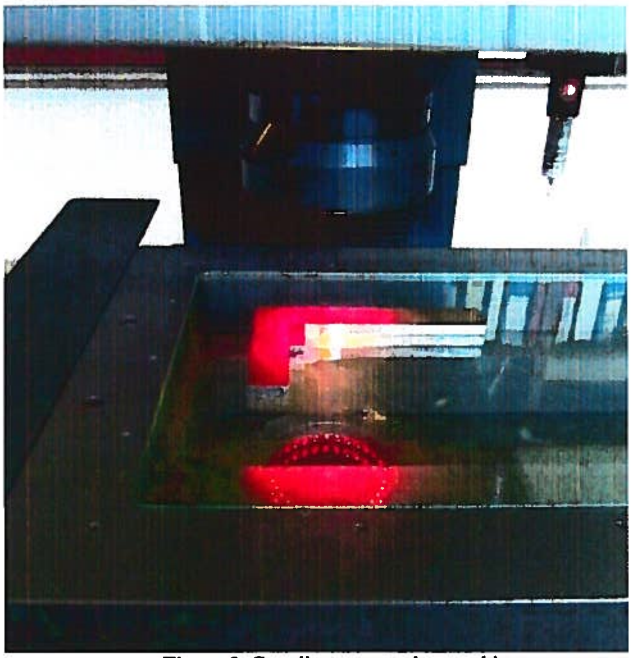


Figure 2. Coordinate measuring machine

With the device shown above, six bending experiments for each determination were made and an average of that six individual values was calculated. The accuracy of the part after bending was defined from the spring back coefficient K calculated using Eq.(1) found in reference (Smith, 1990).

$$K = \frac{R_1 + t/2}{R + t/2}, \quad (1)$$

Where: R-Part radius, R1- Die radius, t- Thickness of the sheet metal.

2.2 Finite element analysis

Finite element simulation is justified by the need of enriching the experimental data to a volume that enables training, validation and testing of the ANN model.

The Finite Element (FE) simulation of the free cylindrical bending process of metallic sheets was carried out using ABAQUS/Standard program. Numerical tests focused on the investigation of the elastic recovery dependence on the mechanical properties, the nominal sheet thickness, bending radius and the friction between the specimen and active elements of the die. The variable parameters used for the simulation are as follows:

- sheet thickness t=0.6; 0.8; 1; 1.25; 1.5; 2 mm;
- punch radius r_p=10; 15; 20; 25; 30; 35; 40 mm;
- friction coefficient μ=0.01; 0.09; 0.15.

The methodology consisted in repeating the simulation of the free cylindrical bending process, covering a range of values representative for each of the above-mentioned parameters.

In order to automatize the simulation tests, a monitoring program was developed. It repeatedly launched the program ABAQUS/Standard, providing each time another set of parameters of the bending process. Once a numerical test is finished, the monitoring program extracted from the corresponding output file the coordinates of two nodes located on the median fibre of the specimen. More precisely, the coordinate of node 1 located on symmetry axis of the specimen and of node 15 located at the middle of the bent region (fig. 3) were used for this determination.

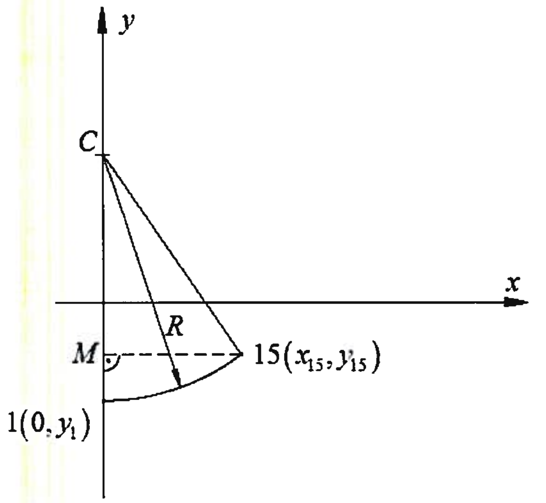


Figure 3. Geometric scheme used for the determination of the radius after removing the part from the bending die.

Using the coordinates of these nodes shown in fig. 3 we can determine the radius attained after the extraction of the bent part from the bending die:

$$R = \frac{x_{15}^2 + (y_{15} - y_1)^2}{2 \cdot (y_{15} - y_1)} \tag{2}$$

Having the radius after removing the part from the bending die the spring back coefficient K is computed using Eq. 1. Using this methodology, the data sets obtained by experimental procedure were significantly increased.

The finite element mesh used to discretize the raw part had: 26 equidistant nodes and 25 finite elements B21 (Beam elements with two nodes). The active areas of tools (punch, die) are defined in an analytical manner. The positions of these tools are controlled by two nodes of reference. The type of contact between the raw part and tools is the Coulomb, friction coefficient being the same for both punch and die.

The hardening law adopted in the simulation was Swift:

$$\sigma_c = C(\varepsilon_0 + \varepsilon_p)^n \tag{3}$$

In order to be sure on the correctness and representatively of the numerical results, the predictions of the program ABAQUS/Standard were compared with experimental data previously obtained (fig. 4 and Table 1).

where the relative error (RE) was calculated as follows:

$$RE = \left| \frac{predicted - \exp erimental}{\exp erimental} \right| \cdot 100 \quad [\%] \tag{4}$$

Table 1 Comparison of the spring back prediction provided by FE Simulation and experiments.

	Punch radius (mm)	Springback coefficient (-)		Relative error (%)
		Experimental	FEM prediction	
1	10	0,9635	0,9819	1,91
2	15	0,9149	0,9104	0,50
3	20	0,8976	0,9019	0,49
4	25	0,8800	0,8743	0,65
5	30	0,8670	0,8489	2,08
6	35	0,8442	0,8273	2,01
7	40	0,8181	0,8084	1,20

The comparison showed relative errors less than 2,1% (Table 1), confirming the validity of the simulations. Therefore the FEA results are sufficiently accurate and can be used as data set for training and testing the ANN model.

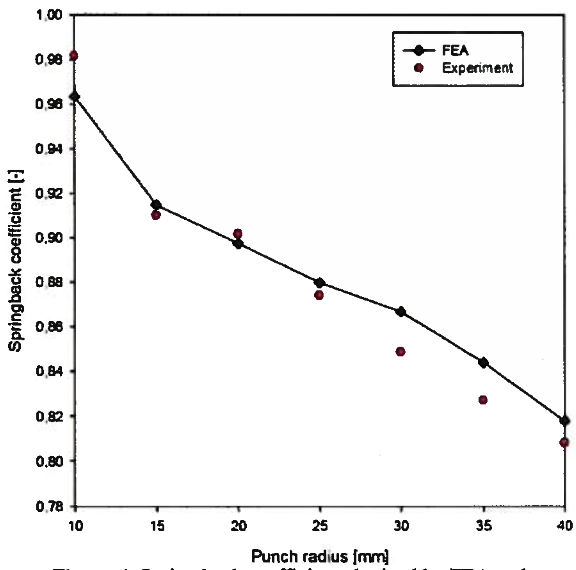


Figure 4. Spring back coefficient obtained by FEA and experiments

3 Neural network model for spring back prediction

Artificial neural network is a mathematical model that can learn and generalize the things learned. It makes a mapping function from input to output, giving information about practical phenomena. Because of the non-linear properties of neural networks, they are suitable for describing complex non-linear phenomena which linear modelling techniques fail to describe. Basically, all the processes that have an adequate number of measured data can be modelled by ANN [18].

3.1 Data set for ANN

In order to predict the spring back coefficient, the neural network is developed using Mat lab Software. Generally, the selection of the network inputs is a difficult problem. The network outputs are clearly imposed by the specificity of the problem analysed, whereas the inputs are not. The spring back phenomenon depends on many factors some of them being strongly correlated. Therefore in this work to develop the neural network model 3 input parameters were chosen (sheet thickness, punch radius, friction coefficient) and one output (spring back coefficient) directly imposed by the application (target). All of the input and target of the ANN are called the data sets.

3.2 ANN architecture

In this paper the developed ANN model consists of one input layer having 3 neurons, where input data (sheet thickness, punch radius and friction coefficient) is presented to the network, one hidden layer and an output layer with one neuron representing spring back coefficient of the free cylindrical bent sheet. The structure of the proposed ANN model is shown in fig. 5.

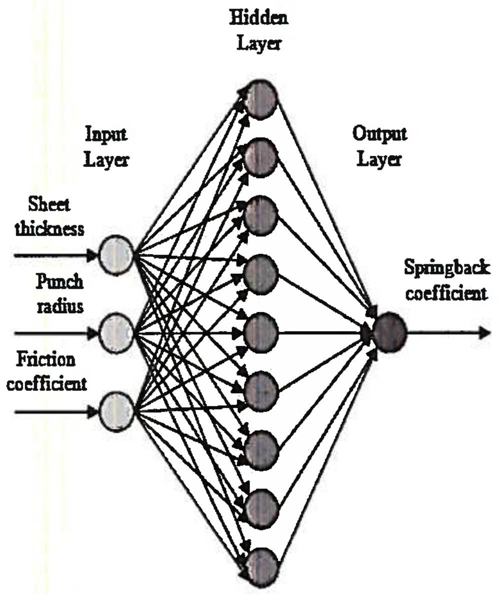


Figure 5 The proposed ANN model for springback prediction

The back-propagation neural network was trained by 107 data sets and tested by 19 data sets. In the training process the connection weights are assigned in order to reduce the error between the predicted and actual target value to a satisfactory level. This process is carried out through the minimization of the defined error function by updating the connection weights. The neural network was trained using Levenberg – Marquardt back-propagation algorithm. Once the training process is finished the neural network should be a model able to predict the target value given the input pattern. After the training of the network the model with all the parameters including the connection weights were tested using a data set that was not used in the training phase. For the tests set, the deviations of the ANN outputs from the finite element method (FEM) data (target) were determined using standard statistical analyses, to evaluate the accuracy of the proposed ANN model in predicting the spring back coefficient in the free cylindrical bending process. The statistical measures used are the root mean squared error (RMSE) and the coefficient of determination (R2) calculated using Eqs. (5) and (6) as follows:

$$RMSE = \sqrt{\frac{1}{N} \times \sum_{i=1}^{N} (a_i - p_i)^2} \tag{5}$$

$$R = \frac{n\sum ap - (\sum a)(\sum p)}{\sqrt{n(\sum a^2) - (\sum a)^2}\sqrt{n(\sum p^2) - (\sum p)^2}} \tag{6}$$

where: a is the actual value from experiments, p is the predicted value by models and N is the number of patterns.

The trials showed that the best network architecture and parameters that maximize the R^2 values and minimize the RMSE are as follows:

Number of input layer neurons =3
Number of hidden layers =1
Number of hidden layer neurons=9
Number of output layer neurons =1
Learning rate =0.3
Momentum rate =0.9

3.3 Results

The network has been trained continually through the updating weights until the error goal is 1.34×10^{-4}. The change of the error performance of the network during the training process is shown in Fig. 6. The expected value of the error performance of the network has been reached after 8 iterations, thus the training of the network is finished as shown in fig. 6.

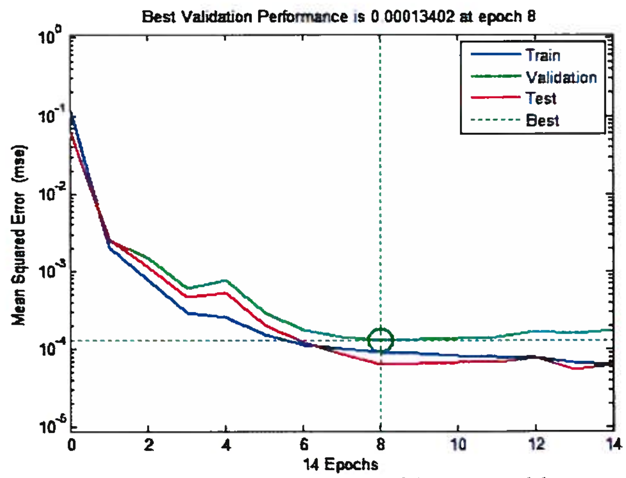


Figure 6 Mean square error (MSE) of the ANN model

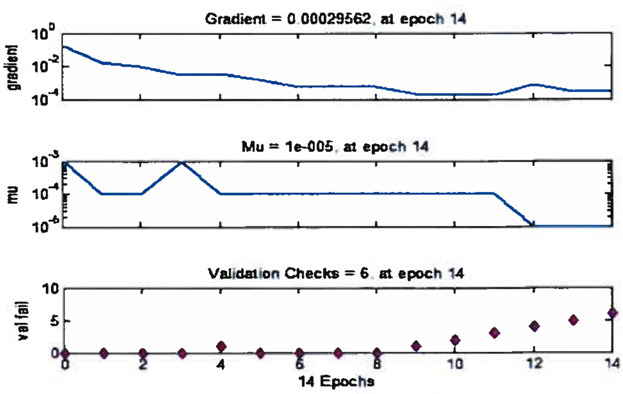


Figure 7 The training process of the ANN

The training process of the neural network is presented in fig. 7.

The developed model was evaluated by the squared regression (R2) and root mean squared error (RMSE) values.

Table 2 Comparison of the actual values with predicted results obtained from ANN model

No.	FEM	ANN	Relativ error RE
1	0,9753	0,9795	0,0043
2	1,0293	1,0283	0,0010
3	0,9873	0,9874	0,0000
4	0,9031	0,9030	0,0001
5	0,8861	0,9017	0,0176
6	0,8093	0,8027	0,0082
7	0,8601	0,8710	0,0126
8	0,8769	0,8939	0,0194
9	0,6429	0,6565	0,0212
10	0,8503	0,8498	0,0006
11	0,8749	0,8730	0,0021
12	0,8870	0,8907	0,0042
13	0,8190	0,8188	0,0003
14	0,8097	0,8065	0,0039
15	0,8360	0,8324	0,0043
16	1,0460	1,0445	0,0014
17	0,8840	0,8861	0,0025
18	0,9104	0,9262	0,0174
19	0,8743	0,8795	0,0060

Fig. 8 (a,b,c,d) shows the regression (R) analyses of the data as criteria of model accuracy. The regression values measure the correlation between outputs and targets. The following regression plots display the network outputs with respect to the targets for training, validation and testing sets. Fig.8a shows the regression analysis of the training data. The correlation coefficient of regression analysis of the training data is 0.99496. The regression analysis of the validating data is shown in Fig. 8b. It can be noticed that the correlation coefficient of regression analysis of the validating data is 0.99246.

The regression analysis of the testing data is presented in Fig. 8c. The correlation coefficient of regression analysis of the testing data is 0.9967. Finally, Fig. 8d shows the total regression for proposed ANN. In this case the correlation coefficient of regression analysis of all the data is 0.99459. All the correlation coefficients of regression analysis from Fig. 8 have the value close to 1(R value of 1 means a close relationship). It can be concluded from this fact that the proposed neural network could learn the relationship between the input parameters and the output parameter.

In this paper, the performance of the ANN model was also evaluated by relative error (RE) calculated using Eqs. (4).

The results obtained for relative errors (RE) are shown in Table 2. One may notice that the constructed ANN model provides good prediction performances being able to fit most of the spring back coefficient values close to the target spring back coefficient. All the 19 testing data sets have relative errors less than 0.0212. This means that the results obtained by ANN model are in good agreement with the results obtained by FEM showing the accuracy of the model.

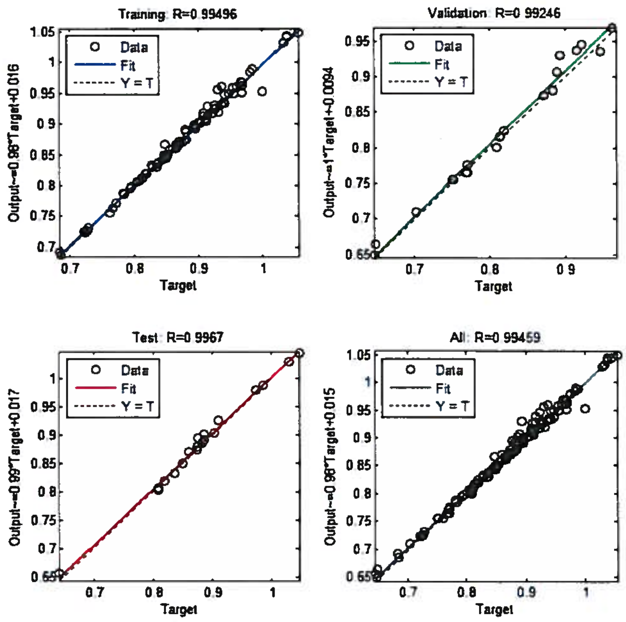


Figure 8. The data regression of the proposed ANN model

Fig. 9 presents a graphic comparison between the ANN output results and the target results obtained by FEM. It can be noticed that the most results predicted by ANN are very close to the results obtained by FEA demonstrating that the constructed ANN model is able to provide prediction of the spring back coefficient close to that of the FEA values.

The performance of the ANN model can still be improved by adding more parameters, such as materials properties.

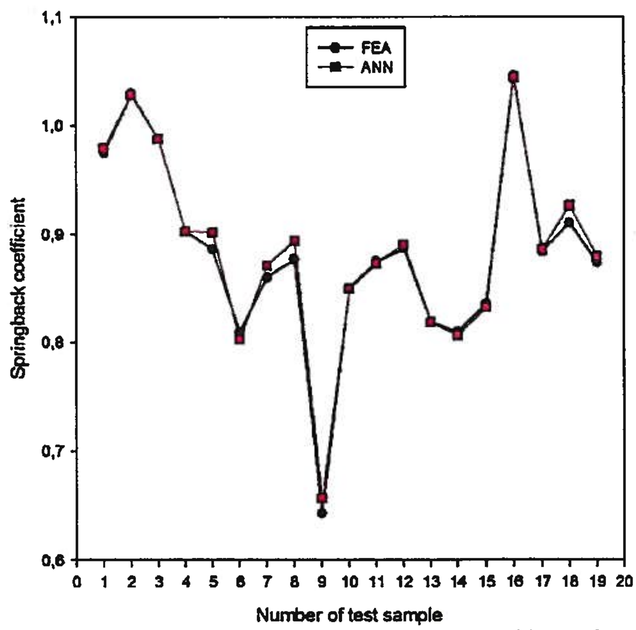


Figure 9. Comparison of the obtained results by ANN with FEA for spring back coefficient

4 Conclusions

In this study a back-propagation neural network model is developed to predict the spring back coefficient in the free cylindrical bending process of metallic sheets. A database of 126 tests obtained from FEM is used for training and testing this model, and 3 variables are selected as inputs to ANN model.

The proposed ANN model for characterizing the spring back phenomenon in the free cylindrical bending process of metallic sheets was successfully developed and used to predict the spring back coefficient. Results shown that the performances of the developed model are at a high level of accuracy judging against the root mean square error and the regression value.

A good agreement has been noticed between the predicted values by ANN and the targets values obtained by FEM. The computation time had significantly reduced using ANN model which is very important for bent parts manufacturers. Therefore the use of ANN technique in combination with FEM reduces time and cost of required experiments.

The approach proposed by the authors is able to provide accurate predictions, as proved by the comparison with experimental and FE results. In the future research, the authors intend to improve the ANN capabilities by adding more input parameters.

5 Acknowledgments

This paper was supported by the project "Development and support of multidisciplinary postdoctoral programmes in major technical areas of national strategy of Research - Development - Innovation" 4D-POSTDOC, contract no. POSDRU/89/1.5/S/52603, project co-funded by the European Social Fund through Sectorial Operational Programme Human Resources Development 2007-2013."

6 References

[1] Fazilat H., Ghatarband M., Mazinani S., Asadi Z.A., Shiri M.E., Kalaee M.R., Predicting the mechanical properties of glass fiber reinforced polymers via artificial neural network and adaptive neuro-fuzzy inference system, Computational Materials Science, 58, 2012, pp. 31–37.

[2] Dote Y., Ovaska, S. J., Industrial applications of soft computing: a review, Proceedings of the IEEE, 89, 2001, pp. 1243-1265.

[3] Kayak O., et al (Eds.), Fuzzy Inference Systems: A Critical Review, Computational Intelligence: Soft Computing and Fuzzy-Neuro Integration with Applications, Springer, Berlin, 1998.

[4] Hanna M. A., Ural D., Saygili G., Evaluation of liquefaction potential of soil deposits using artificial neural networks,. Engineering Computations, Emerald Publishers, 24, 2007, pp. 5-16.

[5] Padmini D., IiamparuthI K., Sudheer K.P., Ultimate bearing capacity prediction of shallow foundations on cohesionless soils using neurofuzzy models, Computer Geotechnics, 35, 2008,pp. 33-46.

[6] Mashrei M. A., Abdulrazzaq N., Abdalla T. Y., Rahman M.S., Neural networks model and adaptive neuro-fuzzy inference system for predicting the moment capacity of ferro cement members, Engineering Structures, 32, 2010, pp. 1723-1734.

[7] Xu J., Zhao J., Song Z., Liu M., Prediction of ultimate bearing capacity of Tubular T-joint under fire using artificial neural networks, Safety Science, 50, 2012, pp. 1495–1501.

[8] Ghaisari J., Jannesari H., Vatani M., Artificial neural network predictors for mechanical properties of cold rolling products, Advances in Engineering Software, 45, 2012, pp. 91–99.

[9] Zgoul M. H., Use of artificial neural networks for modelling rate dependent behaviour of adhesive materials, International Journal of Adhesion & Adhesives, 36, 2012, pp. 1–7.

[10] Duan Z.H., Kou S.C., Poon C.S., Prediction of compressive strength of recycled aggregate concrete using artificial neural networks, Construction and Building Materials, article in press, 2012.

[11] Bilgehan M., Comparison of ANFIS and NN models—with a study in critical buckling load estimation, Applied Soft Computing, 11, 2011, pp. 3779–3791.

[12] Baseri H., Bakhshi-JooybarI M., Rahmani B., Modeling of Spring-back in V-die Bending Process by Using Fuzzy Learning Back-propagation Algorithm, Expert Systems with Applications, 38, 2011, pp. 8894–8900.

[13] Liu W., Liu Q., Ruan F., Liang Z., Qiu H., Springback prediction for sheet metal forming based on GA–ANN technology, Journal of Materials Processing Technology, 187–188, 2007, pp. 227–231.

[14] Nasrollahi V., Arezoo B., Prediction of springback in sheet metal components with holes on the bending area, using experiments, finite element and neural networks, Materials and Design, 36, 2012, pp. 331–336.

[15] Fu Z., Mo J., Chen L., Chen W., Using genetic algorithm-back propagation neural network prediction and finite-element model simulation to optimize the process of multiple-step incremental air-bending forming of sheet metal, Materials and Design, 31, 2010, pp. 267–277.

[16] Kazan R., Firat M., Tiryaki A. E., Prediction of spring back in wipe-bending process of sheet metal using neural network, Materials and Design, 30, 2009, pp. 418–423.

[17] Smith, D. A., Die Design Handbook, 3rd ed., Society of Manufacturing Engineers, Dearborn, MI, 1990.