TECHNICAL UNIVERSITY OF CLUJ-NAPOCA

ACTA TECHNICA NAPOCENSIS

Series: Applied Mathematics and Mechanics
Vol. 56, Issue I, March, 2013

APLICATION OF FUZZY EXPERT SYSTEM IN DEEP DRAWING OF CYLINDRICAL CUPS

Florica Mioara ŞERBAN, Ciprian CRISTEA, Emilia SABĂU, Vasile CECLAN, Glad CONŢIU

Abstract: *Thickness is one of the major quality characteristics of drawn parts. In this paper a fuzzy expert system is designed to predict the thickness along cup wall in deep drawing of cylindrical cups. After using the finite element results for training and testing, the developed fuzzy system was applied to new data for prediction of thickness distribution in deep drawing of cylindrical cups. The prediction results were compared with finite element simulation. The results show that de fuzzy expert system can accurately predict the thickness variation of drawn cups.*
Key words: *deep drawing, finite element simulation, fuzzy expert system.*

1. INTRODUCTION

Deep drawing is one of the most frequently used forming procedures in the production of metallic parts. This process is widely used in a variety of industrial areas like production of automobile body parts, aerospace and consumer products.

Thickness is one of the major quality characteristics of drawn parts. Thickness is unequally distributed in the part after deep drawing. In general the minimum thickness value is located at the region of punch radius and outside the die corner, and the maximum thickness at the flange area. The existence of thickness variation from the production stage may lead to failure in the part. Therefore is important for manufacturers to know the value of thickness along the wall cup especially the minimum and maximum value of thickness. Several papers in the past were focused on the analysis of the thickness distribution in deep drawing processes. Singh [15] used finite element simulation, artificial neural networks, support vector regression method and experiments in order to obtain the cup thickness distribution along the cup wall in hydro-mechanical deep drawing. Padmanabhan [10] use finite element method combined with Taguchi technique to determine the relative influence of each process parameter die radius, blank holder force and friction coefficient on the deep-drawing of a stainless steel axi-symmetric cup. The analysis of variance (ANOVA) was carried out to examine the influence of process parameters on the thickness variation of the circular cup and their percentage contribution.

Raju [12], determined that the die shoulder radius has major influence followed by blank holder force and punch nose radius on the thickness distribution of the deep drawn cup of AA 6061 sheet using TAGUCHI's signal-to-noise ratio.

In this paper a fuzzy expert system is designed to predict the thickness distribution in deep drawing process of cylindrical cups. The input data sets for training and testing the fuzzy expert system were obtained by finite element method.

2. FINITE ELEMENT SIMULATION OF THE DEEP-DRAWING PROCESS

Deep drawing process for cylindrical parts was simulated with DYNAFORM [21] software which uses the explicit LSDyna solver. Various sets of parameters were used in the simulation. These variable parameters used for the simulation of the deep drawing process are given below:

- punch radius R_p=5; 8; 10; mm;
- die fillet radius R_d=5; 8; 10; mm;

- blank holder force F=35; 40; 45kN.

The material used in the present work for numerical simulations is a CQ steel. The initial thickness for the blank is 1mm.

Because the local thickening (up to 25% of the nominal thickness) of the sheet is often met in deep drawing processes [17, 18] the die surface was offset at 1.25 * sheet thickness in order to generate the corresponding surfaces of the punch and blank holder. Figure 1 shows the obtained geometric models.

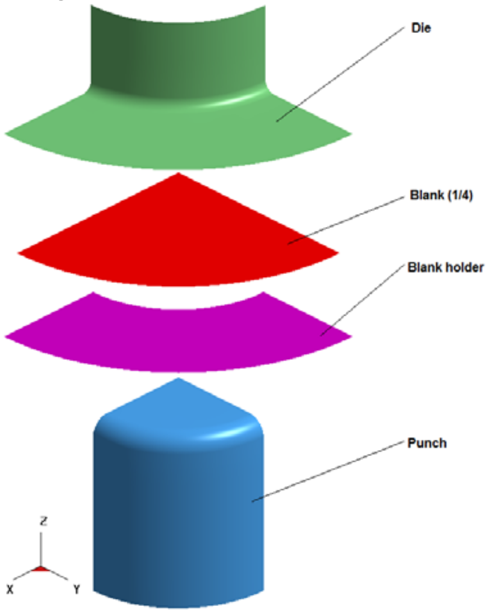

Fig. 1. Tooling used in deep drawing.

The blank and the tools geometry are axisymmetric. For reason of computing time a 3D analysis modeling only a quarter of the deep drawing process is achieved. This assumption led to a considerable shortening of computing time. Adequate boundary conditions must be imposed along the symmetry axes. These symmetry axes are defined as the global X and Y axes in the FE mesh; the global Z axis is parallel to the punch displacement direction.

The orthotropy of the sheets has imposed the choice of the material model.

For sheet metal forming processes, the friction influences the material flow and the final strain distribution. The constant friction condition is assumed at all tool interfaces.

The elements used were 4-node Belytschko-Lin-Tsai [21] shell elements, which provide five integration points through the thickness of the sheet metal. The tooling was modeled using rigid surfaces.

The existence of thickness variation in the deformed part may lead to the damage acceleration because it may cause stress concentration. Figure 2 shows the thickness variation of the drawn cup at the different location from the center of the drawn cup calculated in the post-processor. The numerical results show a thinning tendency of the sheet at the connection with the flat region of the part, and the thickening tendency towards the top of the cup which is mentioned in the literature [13, 16].

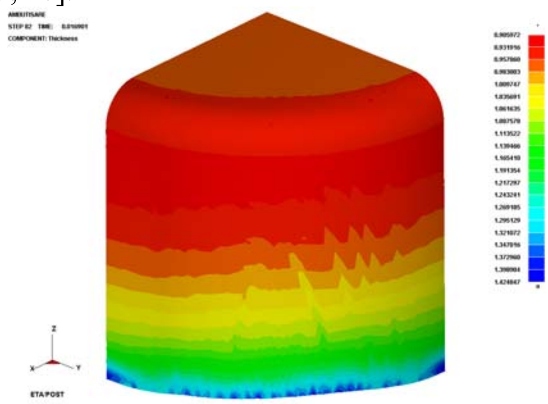

Fig. 2. Simulated deep-drawing process of cylindrical cups (thickness distribution)

The forming limit curve [1] used by eta/Post postprocessor to estimate the risk level of forming is shown in Figure 3. The lower curve shown in the left side of the diagram represents the forming states with the risk of crack (the possible occurrence of necking) and the curve located above defines the states inducing the crack of the material. It can be observed that the entire part surface is located in the safety area.

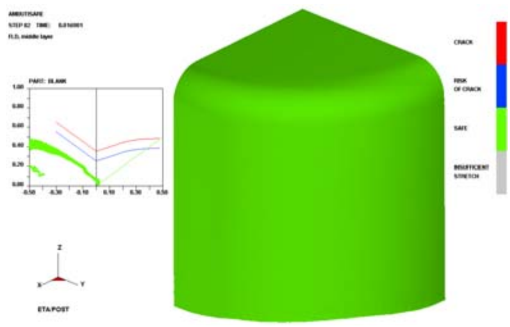

Fig. 3. Evaluation of the risk level of the strains in the final stage of the deep-drawing operation

Figure 4 shows the variation diagram of the punch load.

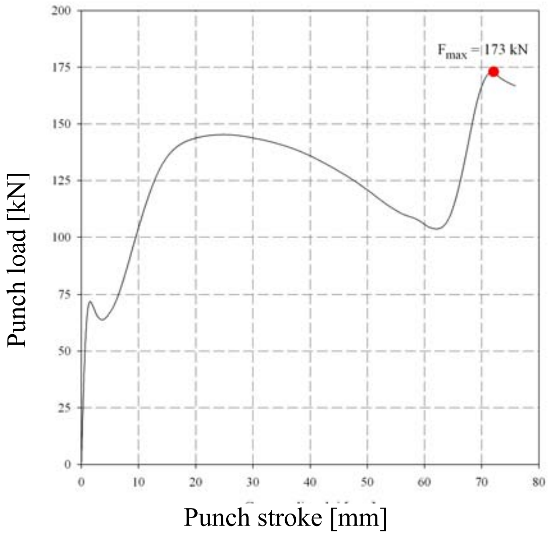

Fig. 4. Punch load versus stroke

It can be noted that maximum of 173 kN is reached at a stroke of about 72 mm.

3. Fuzzy expert system

The contribution of fuzzy logic and rule-based reasoning has found various applications in the control of industrial processes, modeling of complex systems and the development of Fuzzy inference systems [6, 7]. Due to their wide usages, fuzzy inference systems are also known as fuzzy expert systems, fuzzy rule-based systems, fuzzy associative memories, or fuzzy systems [4].

An expert system is a computer system employing expert knowledge to attain high levels of performance in solving the problems within a specific domain area. By encapsulating expert knowledge and experience, expert system enables organizations to support important decision-making and improve organization productivity [8].

The main difference of these systems with other software is that they process knowledge instead of data or information [2]. In order to construct the knowledge database methods such as fuzzy logic, artificial neural networks (ANN), or neuro-fuzzy are used.

A fuzzy set is a set whose elements might only partially belong to that set, an element of a fuzzy set naturally belongs to the set with a membership value in the interval [0, 1], as opposed to the more classical nonfuzzy set, where the elements are either completely inside or completely outside of the set [11]. To deal with vagueness of human thought, Zadeh (1965) first introduced the fuzzy set theory, which was oriented to the rationality of uncertainty due to imprecision or vagueness. A major contribution of fuzzy set theory is its capability of representing vague data. The theory also allows mathematical operators and programming to apply to the fuzzy domain. A fuzzy set is a class of objects with a continuum of grades of membership. Such a set is characterized by a membership function, which assigns to each object a grade of membership ranging between zero and one. In this theory, the membership of the members of the set is determined by U(x) function where x stands for a specific member and U is the fuzzy function which indicates the membership grade of x in the set ranging from 0 to 1 and is shown by $\mu(x)$ $(A = \{(x, \mu(x)) \mid x \in U\})$ [19].

In this approach, triangular membership function has been used.

4. Development of fuzzy expert system for thickness prediction

In general, designing a fuzzy system is composed of [4, 5]:

Step 1. Identifying pertaining input and output variables. Besides, the meaningful linguistic states along with appropriate fuzzy sets for each variable ought to be selected.

Step 2. Introducing a fuzzification method for input variables that expresses the associated measured uncertainty. The purpose of the fuzzification method is to interpret measurements of input variables which are expressed by a real number.

Step 3. Formulating pertaining knowledge in terms of fuzzy inference rules. There are two principal ways in which relevant inference rules can be determined. One way is to elicit them from experienced humans and the other way is to obtain them from empirical data by suitable learning methods, usually with the help of neural networks.

Step 4. Combining measurements of input variables with relevant fuzzy rules to inference

regarding the output variables in which the purpose of inference engine will be obtained.
Step 5. Ascertaining a suitable defuzzification method to convert the aggregated fuzzy set of implications into a real number.

In this paper a fuzzy expert system was created using MATLAB Fuzzy Logic Toolbox.

4.1 Fuzzification

Fuzzification simply refers to the process of taking a crisp input value and transforming it into the degree required by the terms. If the form of uncertainty happens to arise because of imprecision, ambiguity, or vagueness, the variable is probably fuzzy and can be represented by a membership function. If the inputs generally originate from a piece of hardware, or drive from sensor measurement, then these crisp numerical inputs could be fuzzified in order for them to be used in a fuzzy inference system [3, 14].

In this paper the fuzzification of inputs parameters are in triangular fuzzy numbers. The input of the fuzzy expert system based on finite element simulation is composed of punch radius R_p, die fillet radius R_d, blank holder force F and wall region W.

For example, the punch radius input variable in fuzzy expert system is shown in figure 5. Two linguistic variables as ‘‘small’’ and ‘‘large’’ are defined for this input parameter and the range is between 5 and 10. The linguistic variables of all inputs parameters are shown in Table 1. The output of this system is thickness T that includes three linguistic terms as ‘‘small’’, ‘‘medium’’, and ‘‘large’’.

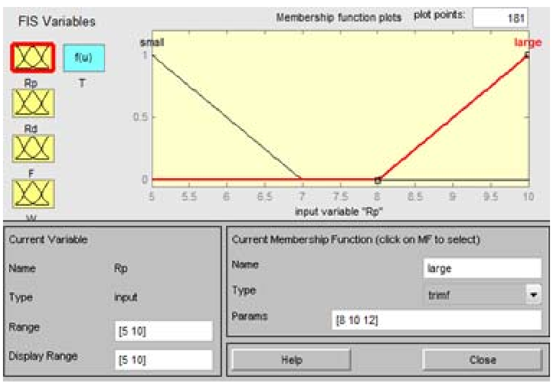

Fig. 5. Punch radius input variable in fuzzy expert system for thickness distribution

Table 1

Fuzzy input variables

Linguistic variables	Range	Linguistic values
Punch radius	[5 10]	Small, Large
Die fillet radius	[5 10]	Small, Large
Blank holder force	[35 45]	Low, High
Wall region	[1 21]	Small, Medium, Large

4.2 Fuzzy inference engine

The relationship between fuzzy input and output variables were developed using Takagi – Sugeno - Kang fuzzy if–then rules. Rules in this fuzzy system are like [5, 20]:

If x_1 is A_1 **AND/OR** x_2 is A_2 **Then** $y = f(x1,x2)$

where A_1 and A_2 are fuzzy sets and y is a (usually linear) function of crisp variables.

The fuzzy rules were developed based on industrial data, discussion with experts in cold forming and reference literatures.

The number of fuzzy rules in a fuzzy system is related to the number of fuzzy sets for each input variable. Thus 24 rules are formulated for thickness distribution, as an example:

Rule 1: ***If*** *punch radius is small and die fillet radius is small and blank holder force is high and wall region is small* ***Then*** *the thickness is small.*

The rule base of designed fuzzy expert system for thickness distribution in deep drawing of cylindrical cups can be seen in Figure 6.

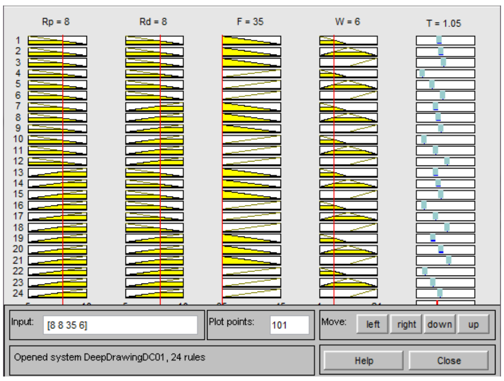

Fig. 6. Fuzzy rule base view of the fuzzy expert system for thickness distribution

4.3. Defuzzification

Sometimes it is useful just to examine the fuzzy subsets that are the result of the composition process, but more often; this fuzzy value needs to be converted to a single number

– a crisp value. The process of computing a single number which represents the best outcome of the fuzzy set evaluation is called defuzzyfication [9].

There are several defuzzyfication methods. In this approach fuzzy results of inference process are defuzzyfied by weighted average method. In the weighted average defuzzyfication method the output of each rule is weighted [4]. For example regarding the *j*th rule

Rj: **If** x_1 is A_j **AND** x_2 is B_j **Then** $y_j=f_j(x_1,x_2)$ the weight w_j is computed as $w_j = ANDmethod(\mu_{A_j}(x_1),\mu_{B_j}(x_2))$ where $\mu_{A_j}(\cdot)$ and $\mu_{B_j}(\cdot)$ are membership functions of A_j and B_j, respectively, and the AND method is the operation defined by the AND operator which is usually the ''min'' operation. Then the final output of the system will be obtained by

$$final\ output = \sum_j w_j y_j / \sum_j w_j \quad (1)$$

To calculate the final output according to Figure 6, after entering the data sets of deep drawing process to each of the 24 rules, an output is resulted from each of the rules. In the first right column from Figure 6, first 24 rectangular represents the outputs of the 24 related rules while the last rectangular is the total summation of outputs of the rules calculated by Eq. (1). This amount pointed by a vertical line in Figure 6 represents the final output.

5. Results and discussion

The defuzzyfication values resulted from weighted average method are very close to that obtained by finite element analysis judging against the statistical criteria used for performance analysis of the fuzzy system. These parameters are root mean square error (*RMSE*) and square of the correlation coefficient (R^2) as shown in table 2.

Table 2

Statistic criteria of designed fuzzy system

Training set		**Testing set**	
RMSE	**R^2**	**RMSE**	**R^2**
0.0028	0.999846	0.001705	0.999946

It can be noticed that all results of the two criteria showed better fit in the testing set than in the training set.

6. CONCLUSION

In this paper, an expert system has been built to predict the thickness distribution along the cup wall in deep drawing of cylindrical cups. The developed expert system has been applied to the available finite elements data sets. The inputs of the fuzzy expert system were punch radius, die fillet radius, blank holder force, wall region and the output was thickness along the cup wall of the drawn cup. The expert system was trained using a number of input data sets including a variety of conditions, and then it was applied to unknown data to predict the thickness distribution. The results show that the system worked well in predicting the thickness distribution for any other drawing conditions. The application of fuzzy expert system in the deep drawing process is expected to improve the process.

This work may be improved in the future by considering more input parameters such as anisotropy.

7. ACKNOWLEDGMENT

This paper was supported by the project "Development and support of multidisciplinary postdoctoral programs 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."

8. REFERENCES

[1] Banabic, D., Dörr, I.R. *Deformabilitatea tablelor metalice subțiri. Metoda curbelor limită de deformare*, Editura O.I.D.I.C.M., Bucureşti, 1992.

[2] Darlington K., *The essence of expert system*, Prentice Hall, Essex, 2000.

[3] Fasanghari, M., Montazer, G. A., *Design and implementation of fuzzy expert system for Tehran Stock Exchange portfolio recommendation*, Expert Systems with Applications, vol. 37, no. 9, pp. 6138–6147, 2010.

[4] Haji, A., Assadi, M., *Fuzzy expert systems and challenge of new product pricing*, Computers & Industrial Engineering, vol. 56, issue 2, pp. 616–630, 2009.
[5] Klir G. J., Yuan, B., *Fuzzy sets and Fuzzy logic: theory and applications*, Prentice-Hall, New-York, 1995.
[6] Lin, C., Chen, C., *New Product Go/No-Go Evaluation at the Front End: A Fuzzy Linguistic Approach*, IEEE Transactions on Engineering Management, 51(2), pp. 197–207, 2004.
[7] Machacha, L. L., Bhattacharya, P., A fuzzy-logic-based approach to project selection, IEEE Transactions on Engineering Management, 47(1), pp. 65–73, 2000.
[8] McCarthy, J., Some expert system need common sense, in Pagels H. R. (Ed.), *Computer culture: The scientific, intellectual and social impact of the computer*, New York Academy of Science, New York, 1984.
[9] Ngai, E. W. T., Wat F.K.T., *Design and development of a fuzzy expert system for hotel selection,* Omega, 31, pp. 275–286, 2003.
[10] Padmanabhan R., Oliveira M.C., Alves J.L., Menezes L.F., *Influence of process parameters on the deep drawing of stainless steel*, Finite Elements in Analysis and Design, vol. 43, issue 14, pp. 1062 – 1067, 2007.
[11] Piltan M., Mehmanchi E., Ghaderi S.F., *Proposing a decision-making model using analytical hierarchy process and fuzzy expert system for prioritizing industries in installation of combined heat and power systems*, Expert Systems with Applications 39(1), pp. 1124–1133, 2012.
[12] Raju S., Ganesan G., Karthikeyan R., *Influence of variables in deep drawing of AA 6061 sheet*, Transactions of Nonferrous Metals Society of China, 20(10), pp. 1856-1862, 2010.
[13] Rosinger Şt., *Procese şi scule de presare la rece. Culegere de date pentru proiectare,* Editura Facla, Timişoara, 1987.
[14] Ross, T. J., *Fuzzy logic with engineering applications*, John Wiley & Sons, Chicester, 2004.
[15] Singh S. K., Gupta A. K., *Application of support vector regression in predicting thickness strains in hydro-mechanical deep drawing and comparison with ANN and FEM*, CIRP Journal of Manufacturing Science and Technology, vol. 3, issue 1, pp. 66–72, 2010.
[16] Smith D.A., *Die Design Handbook,* Society of Manufacturing Engineers, Dearborn, 1990.
[17] Suchy I., *Handbook of Die Design (2nd ed.),* McGraw-Hill, New York, 2006.
[18] Tăpălagă I., ş.a., *Tehnologia presării la rece, vol. I*, Litografia Institutului Politehnic, Cluj-Napoca, 1985.
[19] Zadeh L. A., *Fuzzy sets*, Information and Control, 8(3), pp. 338–353, 1965.
[20] Zimmermann H. J., *Fuzzy set theory – and its applications (3rd ed.)*, Kluwer Academic Publishers, Boston, 1996.
[21] *** *eta/DYNAFORM. User's Manual (Electronic documentation, – release 5.6.1).* Engineering Technology Associates, 2008.

APLICATII ALE SISTEMELOR EXPERT FUZZY LA OPERAȚIA DE AMBUTISARE A PIESELOR CILINDRICE

Rezumat: Grosimea este una dintre caracteristicile principale de calitate ale pieselor ambutisate. In aceasta lucrare a fost elaborat un sistem expert fuzzy pentru predicția distribuției de grosime in procesul de ambutisare a pieselor cilindrice. Sistemul a fost antrenat si testat folosind seturi de date obtinute din simulare cu elemente finite. Rezultatele arata ca sistemul expert fuzzy poate prezice cu acuratete grosimea peretelui pieselor ambutisate.

Florica Mioara ŞERBAN, Postdoctoral researcher PhD. Eng., Technical University of Cluj-Napoca, Department of Manufacturing Engineering, 103-105 Muncii Bvb., 400641 Cluj-Napoca, E-mail: Florica.Groze@tcm.utcluj.ro

Ciprian CRISTEA, PhD. Eng., Department of Electrical Machines and Drives, Technical University of Cluj-Napoca, 26-28 Barițiu Street, 400027, Cluj-Napoca, E-mail: cristeaciprian1@gmail.com

Emilia SABĂU, Assist. PhD. Eng., Technical University of Cluj-Napoca, Department of Manufacturing Engineering, 103-105 Muncii Bvb., 400641 Cluj-Napoca, E-mail: Emilia.Sabau@tcm.utcluj.ro

Vasile CECLAN, Assist. PhD. Eng., Technical University of Cluj-Napoca, Department of Manufacturing Engineering, 103-105 Muncii Bvb., 400641 Cluj-Napoca, E-mail: Vasile.Ceclan@tcm.utcluj.ro

Glad CONȚIU, PhD. Eng., Technical University of Cluj-Napoca, Dept. of Manufacturing Engineering, 103-105 Muncii Bvb., 400641 Cluj-Napoca, E-mail: Glad.Contiu@tcm.utcluj.ro