Response Surface Metamodel to Predict Springback in Sheet Metal Air Bending Process

Jaber E. Abu Qudeiri, Fayez Y. Abu Khadra, Usama Umer, and Hussein M. A. Hussein

***Abstract*—The springback amount in the air bending process is influenced by a number of material's geometrical parameters. To predict the springback a multidimensional function should be approximated. In this paper a response surface metamodel is utilized for this purpose. A verified nonlinear Finite Element (FE) algorithm is developed to generate the training data. Then, the generated training data will be used to train RSM. The FE algorithm is developed based on the updated Lagrangian formulation. To select the training data for the RSM, computer generated D-optimal designs are utilized.**

***Index Terms*—Metamodels, springback, response surface, D-optimal designs.**

I. Introduction

An accurate analysis of springback in the bending process is crucial to determine the punch displacement required to achieve a required bend angle after springback. A number of analytical models based on the material properties and the tool geometry are available to predict springback. Most of the analytical models proposed are based on many simplified assumption due to the complexity of the problem, however, they do not provide accurate predictions. Powerful finite element method has been used to simulate the sheet bending processes and springback prediction. However, carrying out accurate and technically meaningful finite element analysis requires highly skilled and experienced people and is relatively time-consuming. Using the concept of metamodeling to develop an accurate approximation for springback prediction is easy and fast. The term "metamodel" emphasizes a technique that can find a relationship between a measure value and the input which affect this measured value. Using the metamodels technique, acceptable approximation for functions can be done fast. Many metamodeling techniques were built for various applications [1]-[5].

The Response Surface (RS) methodology [6], [7] is one of the techniques that can be used to construct fast approximations of complex simulation models. An interpolation method known as Kriging is becoming widely used for the design and analysis of computer experiments [8], [9].

Manuscript received December 25 2014; revised April 30, 2015. This work was supported by Fatima Alnijris Research Chair for Advanced Manufacturing Technology.

Jaber E. Abu Qudeiri, Usama Umer, and Hussein M. A. Hussein are with the Advanced Manufacturing Institute, King Saud University, Riyadh, Saudi Arabia (e-mail: jqudeiri@ksu.edu.sa, uumer@ksu.edu.sa, hhussein@ksu.edu.sa).

Fayez Y. Abu Khadra is with the Mechanical Engineering Dept., King Abdulaziz University, Rabigh, Saudi Arabia (e-mail: f_Khadra@yahoo.com).

In this paper, a Response Surface Metamodeling (RSM) technique is used to fit simulation model data through regression models to predict the springback in the air bending process.

II. Procedure Response Surface Metamodeling

The general procedure required to implement any metamodel are applied through the following four steps [10].

Step 1: Identify the space of the design and select design factors.

Step 2: Choose the sample point and generate a predictive model.

Step 3: Perform simulation code sample point identified in step 2.

Step 4: Construct the predective model

Mathematically, for a response, *y*, and a vector of independent factors *x* influencing *y*, the function of y in term of *x* is defined by (1).

$$y(x) = f(x) + \varepsilon \tag{1}$$

where *y(x)* is the function of interest, *f(x)* is the polynomial approximation of *x* and *ε* is the normally distributed random error with zero mean and *σ*2 standard deviation. The RS approximating function for curvature is given by (2).

$$\hat{y} = \beta_0 + \sum_{i=1}^{k} \beta_i X_i + \sum_{i=1}^{k} \beta_{ii} X_i^2 + \sum_{i=1}^{k} \sum_{j=1, i<j}^{k} \beta_{ij} X_i X_j \tag{2}$$

Usually, the least squares regression analysis is used to determine the parameters in (2). [6].

The success of the metamodel fitting depends mainly on the design of experiments, thus, we have to pay more attention in selecting the experimental runs of the simulation codes to avoid poor metamodel approximation. Some statistical packages employ optimality criteria to reduce the number of runs. Optimality criteria [6] were born out of the need to optimize processes. They are used for screening designs due to their flexibility in designing experiments given only the number of runs desired, the number of factors, and their numbers of levels. Many of the optimality criteria used in RSM have calculations involving the X^TX matrix. The *X* matrix is related to the design matrix where each experimental run is a row, and each factor is a column in the matrix.

To validate a metamodel, it should be checked against independent data [10]. Many criteria are available to choose the suitable approximation to the RS surface among the

DOI: 10.7763/IJMMM.2015.V3.208

candidate metamodels. In this study, predictive capabilities of metamodels are assessed by using the standard deviation (STDV). The STDV can be calculated using (3).

$$STDV = \sqrt{\frac{\sum (y - \hat{y})^2}{n}} \tag{3}$$

y and $\hat{y}$ are measured and predicted values of the response, respectively.

III. Case Study: The Springback in the Bending Process

A. Air Bending Process

Sheet metal bending process consists of loading and unloading stages as shown in Fig. 1.

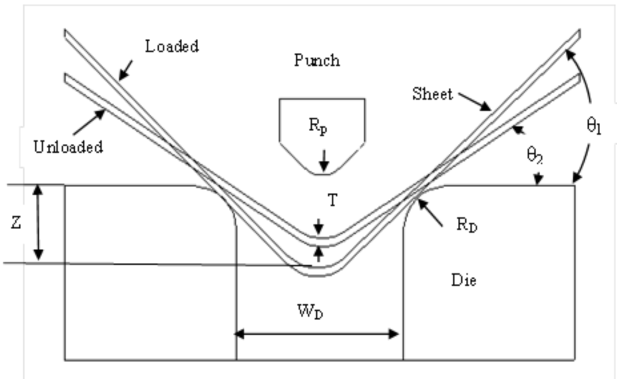


Fig. 1. Air bending process.

Due to the mechanical relaxation, the sheet bending angle becomes different after removing the applied load. The change of the angle is called springback and given by (4).

$$\Delta\theta = \theta_1 - \theta_2 \tag{4}$$

In this research, the input variables to the RSM metamodel include material parameters and geometrical parameters. The RSM can be defined by the nonlinear relation given in (5).

$$\Delta\theta = f(E, \sigma_y, k, n, t, R_p, R_d, W_d, \theta_1) \tag{5}$$

where E is the Young' modulus, σy is the yield strength, k is the strength coefficient, n is the strain hardening coefficient, t is the sheet thickness, Rp is the punch radius, Rd is the die radius, Wd is the die width, and is the bend angle prior to springback. The *FE* analysis is simplified to a 2*D* plane strain problem. A four-node, iso-parametric, and quadrilateral plane strain element is used. This element can be used for linear and nonlinear analysis. The nonlinear *FE* equation is solved by using full Newton-Raphson method.

B. Training Examples

Creating and validating a RSM required a database including designs and their corresponding performance characteristics, these database is called training examples. The required training data for the RSM should be selected so that it can provide a wide range of information between the inputs and outputs. The numerical runs should be chosen carefully to avoid inaccurate approximation. FE method is used to generate many training examples randomly. These training examples are divided into two groups. The first group is for training and the second group is for testing. From the training examples group, some bending cases are selected using computer-generated designs [6], [11]. These designs employed optimality criteria to reduce the number of computational cycles. Many of the optimality criteria used in the response surface method have calculations involving the X^TX matrix. The X matrix refers to the design matrix, each row in the matrix represents one experiment and each column represents one factor. The D-optimality is considered as optimality criterion [6]. The regression equation matrix can be written as show in (6).

$$b = (X^T X)^{-1} X^T y \tag{6}$$

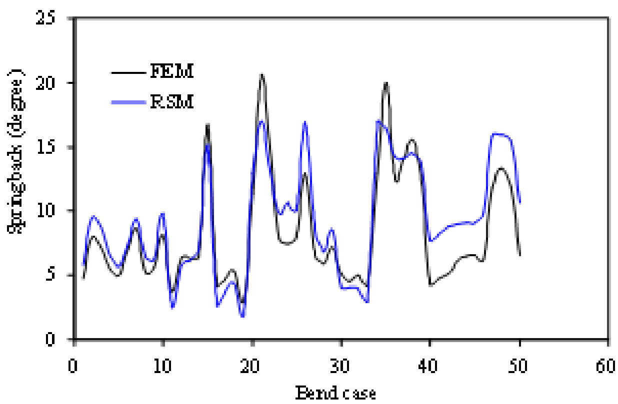
where b is a vector includes of regression equation coefficients relating a response vector y to the factors and interactions compose the X matrix. D-optimality minimizes the variance of the vector b coefficients in the regression model by maximizing the determinant of the X^TX matrix. The variance of vector b coefficients is given by (7).

$$Var(b) = \sigma^2_{response} (X^T X)^{-1} \tag{7}$$

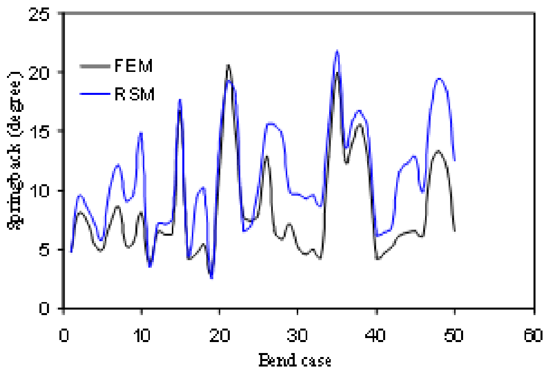
where σ^2 is the variance of the response and is dependent on the y vector. The $(X^TX)^{-1}$ is dependent only on the experimental setup. $(X^TX)^{-1}$ can be minimized by maximizing the determinant of the X^TX matrix. To select training examples using the D-optimality criterion a model must be specified.This research considers four models, namely, linear (*L*), linear+squares (*LS*), linear+interactions (*LI*), and the full quadratic (*FQ*) model.

C. Experimental Results

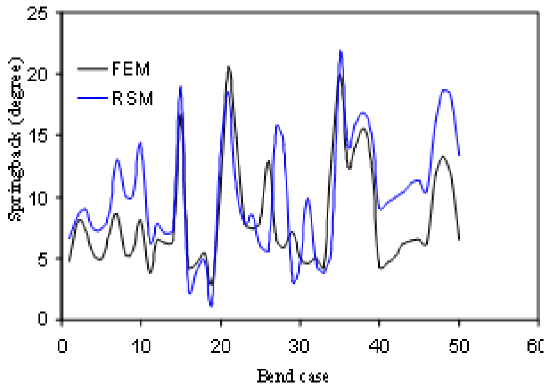
To evaluate the predictive power of the response surface metamodel. The prediction of this method is compared with the FE mthod. The second group of training examples is used to test the predictive performance of the metamodels. The results are given in Fig. 2. The figures compare the predictive performance of the RSM metamodeling technique to the finite element method prediction for the test bend cases.



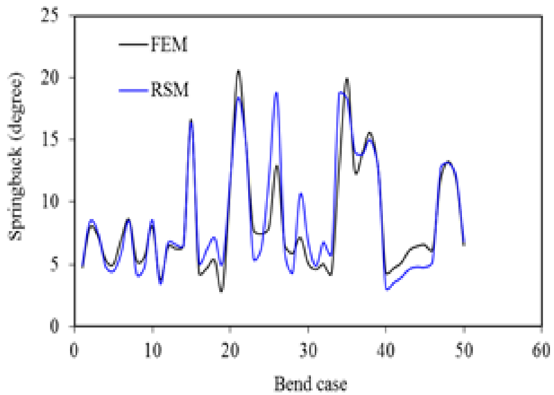
a. Selected based on linear model.



b. Selected based on linear+squares (LS).



c. Selected based on linear +interactions (LI).



d. Selected based on full quadratic (FQ).

Fig. 2. Comparison between the different models for springback design.

Comparing the four figures, it can be see that selecting the design point according the D-optimality criterion affects the predictive performance of the RSM metamodeling technique.

IV. Conclusion

The classical response surface modeling requires the specification of a polynomial function such as linear or second full quadratic to be regressed. The number of terms in the polynomial is limited to the number of experimental design points. D-optimality is a mathematical method, which can be utilized in the planning of the experiments. It might be helpful in achieving better understanding of models and more effective utilization of resources. D-optimality criterion can also be used in studying structure of a model or comparing structures of models. In this paper using training data selected by the D-optimality criterion, response surface model was constructed and compared with FEM, as a result, springback amount can be predicted accurately using the response surface metamodeling.The results obtained show that the full quadratic response surface metamodel gives the best ccuracy for springback compared to the finite element method prediction.

Acknowledgment

The authors would like to thank Fatima Alnijris Research Chair for Advanced Manufacturing Technology for the financial support.

References

[1] R. A. F. Valente, A. A. Campos, J. F. Carvalho, and P. S. Cruz, "Parameter identification and shape optimization," *Optimization and Engineering*, vol. 12, no. 1-2, pp. 129-152, 2011.

[2] A. Chamekh, S. B. Rhaiem, H. Khaterchi, H. B. Salah, and R. Hambli, "An optimization strategy based on a metamodel applied for the prediction of the initial blank shape in a deep drawing process," *The International Journal of Advanced Manufacturing Technology*, vol. 50, no. 1-4, pp. 93-100, 2010.

[3] F. M. Alam, K. R. McNaught, and T. J. Ringrose, "A comparison of experimental designs in the development of a neural network simulation metamodel," *Simulation Modeling Practice and Theory*, vol. 12, no. 7-8, pp. 559-578, 2004.

[4] T. W. Simpson, J. D. Poplinski, P. N. Koch, and J. K. Allen, "Metamodels for Computer based Engineering Design-survey and recommendations," *Engineering with Computers*, vol. 17, no. 2, pp. 129-150, 2001.

[5] R. Jin, W. Chen, and T. W. Simpson, "Comparative studies of metamodeling techniques under multiple modeling criteria," *Structural and Multidisciplinary Optimization*, vol. 23, no. 1, pp. 1-13, 2001.

[6] R. H. Myers, D. C. Montgomery, and C. M. A. Cook, *Response Surface Methodology: Process and Product Optimization Using Designed Experiments*, 3rd ed., New York: John Wiley & Sons, 2009.

[7] MSC. Marc, Volume A: Theory and User Information. (2012). [Online]. Available: http://www.geology.um.maine.edu/user/scott_johnson/share/MarcDocs/MarcDocs/docs/vola/vola.pdf

[8] A. J. Booker, J. E. Dennis Jr., P. D. Frank , D. B. Serafini , V. Torczon, and M. W. Trosset, "A rigorous framework for optimization of expensive functions by surrogates," *Structural Optimization*, vol. 17, no. 1, pp. 1-13, 1999.

[9] J. Sacks, W. J. Welch, T. J. Mitchell, and H. P. Wynn, "Design and analysis of computer experiments," *Statistical Science*, vol. 4, no. 4, pp. 409-435, 1989.

[10] J. P. C. Kleijnen and R. G. Sargent, "A methodology for fitting and validating metamodels in simulation," *European Journal of Operational Research*, vol. 120, no. 1, pp. 14-29, 2000.

[11] G. E. P. Box, W. G. Hunter, and J. S. Hunter, *Statistics for Experimenters*, John Wiley & Sons, NY, 1978.

Jaber Abu Qudeiri obtained BSc. degree in mechanical engineering from the University of Jordan, Japan in 1992, and the M.Eng. and Ph.D. degrees in industrial engineering from the Gifu University, Japan in 2005 and 2008, respectively.

He worked as an assistant professor at Philadelphia University in Jordan from Sept. 2008 to Aug. 2010 then worked as an assistant professor at King Abdulaziz University from Sept. 2010 to Aug. 2012. In Sept. 2012, he joined the Advanced Manufacturing Institute, King Saud University. His current research interests include modeling and optimization of manufacturing systems, optimization of sequence of operations in CNC, predict springback in sheet metal bending process

Dr. Abu Qudeiri is a member of Jordan Engineers Association. He was a member of the organizing committee of the second, third and seventh Jordanian International Mechanical Engineering Conference and a member of the Scientific Committee of Mechanical Engineering Division of Jordan Engineers Association, (1994-2000) and a member of the Technical Program Committee of the International Conference on Science, Technology, Engineering and Management 2014. Dr. Abu Qudeiri has a letter's patent registered at Ministry of Industrial and Tried under No. P/1775. Also, he has a best paper award at ICACTE 2014.

Fayiz Abu Khadra obtained BSc. degree in mechanical engineering from the University of Darmstadt in 97, Germany and MSc and Ph.D. degrees in mechanical engineering from UPM University, Malaysia in 2003 and 2006, respectively

He worked as an assistant professor at Philadelphia University in Jordan from Sept. 2006 to Aug. 2010. He joined King Abdulaziz University-Rabigh in Sept. 2010. His current research interests include finite element method, modeling and optimization of manufacturing processes and metamodeling techniques. Dr. Abu Khadra is a member of Jordan Engineers Association.

Usama Umer obtained his B.E and M.S degrees in mechanical engineering from NED University of Engineering and Technology, Karachi, Pakistan in 1998 and 2002 respectively. He did Ph.D. in manufacturing and automation from Beijing Institute of Technology, Beijing, China in 2007.

He worked as quality assurance officer in Philips/Whirlpool from Oct. 1998 to April 2002. He started teaching career in Nov. 2002 as instructor in National University of Science in Technology (NUST), Pakistan. After Ph.D. he rejoined NUST as assistant professor in July 2007. Presently he is working as an assistant professor in advanced manufacturing institute at King Saud University Riyadh, Saudi Arabia since Sep. 2012. His research interests include high speed machining, modeling and simulation of manufacturing operations, laser beam machining and optimization methods in manufacturing.

Hussein Mohamed Abdelmoneam obtained his BSc., M.Sc., and Ph.D. degrees in production engineering (CAD and expert system in sheet metal blanking dies) from the Helwan University, Cairo, Egypt. He worked as an assistant professor in King Saud University in Center of Manufacturing Technology Transfer "CMTT" from December 2009 till August 2011, since Sept. 2011 he is working as assistant professor in Advanced Manufacturing Institute "AMI" in the same university. His current research interests include computer aided engineering and its applications in sheet metal dies, fixture design and planning, inspection planning, process planning (sheet metal and machined parts), feature recognition, bus skeleton design, bus welding fixture design, automotive body-in-white design, machining and modeling.

Dr. Hussein is a member of Egyptian Engineers Syndicate, Egyptian International Mechanical Engineering. He has more than 40 publications in International Conferences such as AMPT, GCMM and ICTP and in peer-reviewed journals such as I-Mech-E Part B, and IJAMT.