VIRTUAL FORMING AND GAGE THICKNESS OPTIMIZATION OF SHEET METAL COMPONENTS

Raghu Echempati[1,a], Bernadetta Kwintiana Ane[2,b] and Dieter Roller[2,c]

[1]*Department of Mechanical Engineering, Kettering University, Flint, MI – 48504 USA*

[2]*Institute of Computer-aided Product Development Systems, Universitätsstr. 38, D-70569 Stuttgart, Germany.*

Email: [a]*rechempa@kettering.edu,* [b]*ane@informatik.uni-stuttgart.de,* [c]*roller@informatik.uni-stuttgart.de*

With the advent of high-speed computers more and more theoretical research in manufacturing area is transferred to technology that enable complex CAD modeling and solution of the nonlinear, large deformation finite element problems. All OEMs require their suppliers to use the simulation tools before prototypes are made on the shop-floor. Virtual simulations help produce an array of acceptable designs some of which give information on identifying and setting the optimum values of the forming process parameters. This paper discusses the application of rotatable orthogonal array (OA) and 5-axes response surface methodology (RSM) to identify the optimum values related to metal forming of an example part with thickness as the response.

Keywords: Metal forming, design of experiments (DOE), response surface methodology (RSM), orthogonal array (OA), optimization.

1. INTRODUCTION AND BRIEF REVIEW OF LITERATURE

For complex sheet metal parts, typically, there will be 3 to 6 different stages of forming operations before a final product is made. Each forming stage involves separate die and punch tool set (see Figure 1), that costs several thousands of dollars to manufacture and to assemble. With tens and thousands of sheet metal parts (outers, inners, etc.) for a typical automobile, and for several car and truck models, billions of dollars are spent annually by the die design departments and other transportation industries. Reduction of cost and cycle time to manufacture these parts are of paramount importance leading to a lot of research in innovative production and optimization methods involving modern light weight and strong materials for the car body panels. Besides sheet metal forming, machining operations and other forming processes such as hydro-forming, forging, extrusion and drawing are some of the applications of large deformation mechanics. Large deformation software programs use one-step or incremental time marching integration solvers to predict many forming characteristics so that the cost of prototype operations of sheet metal parts can be reduced. Sheet metal forming characteristics such as thinning, rupture (or splitting), wrinkling, etc., can be predicted and controlled with high level of confidence using the simulation tools such as Abaqus/Explicit (Simula), AutoForm (AutoForm Engineering), HyperForm (Altair Hyperworks), Dynaform/LS-DYNA (ETA/LSTC), Pam-Stamp (ESI Group), etc.

Application of DOE and RSM procedures to study the inter-relation between several forming parameters has been reported by many researchers. Both these methodologies have been used for several other applications within the design and manufacturing areas. Due to space limitations, the brief literature presented in this section is limited only to select references in the sheet metal forming area. All the references are grouped into three categories: Statistical methods for DOE and RSM methodology

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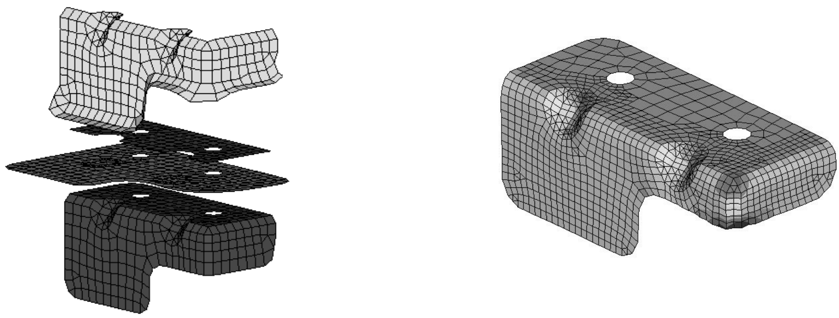

Figure 1. Thinning contour plot from LS-DYNA showing 19.5% thinning at the corner of the formed part (blank) [25].

are reported in [1–10]. Sample references on basics and analysis of metal forming processes are reported in [11–15]. Applications of the DOE and RSM methodologies to sheet metal forming are reported in [16–25]. Finally, references on 5-axes RSM are reported in [26–28].

RSM has been used by Stander [16], Jakumeit [17], Naceur [18] and Zhang [19]. Tang and Chen [20] used robust design models for cylindrical cup drawing process by integrating the RSM methodology. Shivpuri and Wang [21] carried an optimal design of spatially varying frictional constraints in reducing the risk of failure due to wrinkling and thinning. They used an FEM-based genetic algorithm approach (NSGA-II) to determine the deterministic Pareto front for multiple design alternatives, and a trade-off strategy is used to identify an optimal design.

Marrettaa, *et al.* [22] proposed a multi-objective optimization problem integrating the FEM, RSM and Monte Carlo Simulation methods. Echempati, *et al.* [23–25] used the DOE and RSM methodologies to sheet metal forming application to optimize the thickness of example aluminum cups and for instrument panel (IP) components. The work reported in this paper is based on the work done for the IP component previously in reference [24], in which only two or three critical variables were considered for the study. Figures 1 shows the tool set up of an example automobile IP component and the thinning contours. The acceptable value of thinning for steel material is around 20% to 23% after which splitting generally occurs.

The critical factors that contribute to thinning and other output parameters are: material properties, contact surface friction, blank holding pressure, punch velocity and blank size. However, in practice, and for more complex parts such as fenders and instrument panels (IP), there are more than 20 variables that affect successful forming. Optimizing the critical forming parameters would be helpful not only to increase life, reduce the weight of the parts, but also to reduce the scrap. DOE and RSM methodologies are used to help in studying the interaction between the various forming parameters and to identify the most influencing factors that affect the drawing operations, for example. Many large deformation software tools such as those mentioned above, do not, however, incorporate DOE/optimization modules embedded in them for easy interaction by the user. This is a topic of continuous research by the software developers.

To date, however, the capability of RSM to depict the responses is still limited within R^3 Euclidean space which consists of two treatment factors only. As the number of factors increase, the problem of excessive number of observations emerges that makes the designs become inefficient and impractical. Furthermore, the factorial designs do not give equal precision for the fitted responses at points that are at equal distances from the design center. Investigating an optimal response of more than two factors cannot be done visually. These constraints create a possibility to fall into the trap of 'local optima'. In view of this, Ane and Roller [26–28] introduced the 5-axes response surface model based on a rotatable Orthogonal Array (OA) L_9 (3^4). This model enables both numerical and visual analyses of four factors at three different levels simultaneously. Thus, it provides better analysis in identifying an optimal response, in terms of 'global optima'. The developed model has been validated with available data from the literature. There are numerous other works available in the literature on applying the DOE and RSM to metal forming applications. However, due to space limitations not all references are given here.

2. BACKGROUND OF THE OPTIMIZATION STUDY OF METAL FORMING PROCESSES

For any successful forming operation, one of the objectives is to optimize the sheet thickness. In theory, the mechanical properties like the yield strength, tensile strength, elongation and hardness do not change significantly if either the thickness or the initial blank geometry is changed. However, in practice and during forming these properties do change and hence there is a range (min and max) on these properties that were already well documented in the handbooks and the literature for HSS, aluminium and many other sheet materials. The power law of plasticity is an example to mathematically represent how the stress in the sheet varies as it is being deformed (strained). Depending on the exact composition and the type of material being formed, well established failure criteria (for example, Hill's criteria) have been reported in the literature [11–15]. These material models predict how the material parameters such as strain hardening exponent (n), plasticity modulus (K) and anisotropy parameter (R) change as the sheet undergoes permanent deformation to assume the final shape of the formed part (for example the fender of an automobile). There are numerous other variables, for example, those related to stamping press machine, friction between the contacting bodies, initial blank size and shape, etc., that influence if a sheet is formable without any defects. Some of these defects include thinning and rupture (function of material properties, die and punch geometry, binder force, punch velocity), wrinkling (due to excessive compressive forces in one direction of the sheet), loose metal, etc. There are other kinds of quantifiable defects that the Die-Engineering personnel use to define and to declare if the forming was successful. It takes many man-hours to set these forming parameters both in the virtual and in real forming for successful drawing of a part. With many sheet metal parts in an automobile scenario, the trial-and-error approach to obtain the first successful draw can be tedious.

In view of the above discussions, most forming analysis engineers use predetermined value of the design and the forming variables to reduce the virtual simulation times, only to possibly go through another round of simulations based on the results of (real) prototype testing on the shop-floor, before the final forming analysis report for production are released. Due to the fact that both the press settings and the tools used for (the real) prototype forming may sometimes be different than the production settings and production tools, often formability problems still exist that are usually only solved by the production engineers. Friction between the contacting surfaces (mainly between the blank and the binder, and the blank and the die) is not only not uniform (both in magnitude and in location), but it also changes during forming which is not possible to measure or to input as a mathematical function into simulation software. Problems get magnified when draw beads are present and either multi-stage or progressive forming is involved. In view of these difficulties, many forming companies have developed in-house designs to identify the upper- and lower-bound values for each critical forming parameter, and for each sheet metal part. They do virtual simulations using randomly selected values within the upper- and lower-bound levels until they obtain the first successful simulation. However, the first successful simulation may not be an optimum design. Since the goal is to successfully form a part by initially using the smallest blank (sheet) and to maintain constant thickness after drawing, there exists an optimum combination of the forming variables that yield the lightest part. However, the optimized thickness may not be available as a standard gage. Thus, it is confusing to satisfy the conflicting requirements of all the forming process variables.

The objective of this paper to enlighten some of these issues and show how virtual forming together with DOE and RSM studies may be useful to understand the interactions between these variables and to better design a forming product.

3. RSM RESEARCH METHODOLOGY

In this paper a single design has been selected based on performing the following simulations (see Table 1):

(i) Run full-factorial ($3^5 = 243$ runs) simulation,

Table 1. List of Factors-levels.

Factors	Factors	Levels		
		Low (−1)	Average (0)	High (+1)
1	Metal thickness (mm)	1.0	1.5	1.75
2	Binder holding force (kN)	20,000	35,000	60,000
3	Punch velocity (SPM)	60	150	250
4	Strain hardening exponent	0.15	0.20	0.28
5	Friction coefficient	0.08	0.15	0.30

(ii) Based on the result of the optimal factors-levels combination obtained in the previous step, do further analysis under assumption of a single metal thickness using OA L_9 (3^4, i.e., 4 factors 3 levels), where the data is extracted from the same full-factorial design. Therefore, it can be safely assured that both data (i.e. in full-factorial and OA L_9) come from a similar probability distribution. This eliminates the chance of a typical heterocedasticity error to occur.

Simulation is performed using a set of hypothetical data. In generating the data and to avoid typical error due to multicollinearity and autocorrelation, the data is built randomly using a random number generator instead of an interpolation technique.

Generally speaking, the true response function is always unknown [1]. Therefore, prior studies need be made to identify a region in the factor space that most likely produces optimal responses. Applying the factors-levels combination, calculation is done using the second-order polynomial regression

$$\hat{y} = \alpha + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \sum_{i=1}^{k} \sum_{j=i+1}^{k} \beta_{ij} x_i x_j + \varepsilon \tag{1}$$

Here, $\widehat{y}$ is the estimated response on metal thinning, α: constant; x_i, x_j: treatment factors i and j; β_i: coefficient of linear effect of factor i; βij: coefficient of quadratic effect of factor i; β_{ij}: coefficient of interaction between factors i and j; and ε: error terms. Park [4] found that in most cases the fitted second-order polynomial regression is an adequate model used to approximate the relationship between a response and a number of treatment factors. Experimental design for fitting a second-order response surface must involve at least three levels of each factor. In this regard, the 3^k full-factorial or 3^{k-p} fractional factorial design is a proper design [4, 5, 7, 8].

In the statistical analysis, the fittability of the polynomial regression model in fitting the experimental data is measured using the signal-to-noise (S/N) ratio that applies 'nominal-is-best' as the target,

$$S/N(\theta) = 10 \log_{10} (\tau^2/\sigma^2) \tag{2}$$

$$\sigma^2 = \frac{\sum_{i=1}^{n-1} (\hat{y}_i - \tau)^2}{(n-1)} \tag{3}$$

Here, τ^2: thinning target $= 1\,\text{mm}$, σ^2: variance, and n: number of samples. Then, the analysis of variance (ANOVA) is performed to study the behavior of each treatment factor towards the responses, when they are changed according to the assigned level.

After the optimal combination of factors-levels has been found, a confirmatory experiment is applied using the orthogonal array (OA) L_9 (3^4) as described in Table 2. An orthogonal array (OA) is a fractional factorial matrix which assures a balanced comparison of levels of any factor or interaction of factors. An OA is balanced when each level of a factor has an equal number of occurrences with each level of the other factors [2]. Hence, the OA L_9 (3^4) is a well-suited fractional factorial design which allows rapid estimation of the individual factor effects through the use of a relatively small amount of data without the fear of distortion of results by the effect of other factors [3, 5, 6].

Table 2. Orthogonal Array (OA) L9 (4^3).

RUN	Binder holding force (x_2)	Punch velocity (x_3)	Strain hardening exponent (x_4)	Friction coefficient (x_5)
1	−1	−1	−1	−1
2	−1	0	0	0
3	−1	1	1	1
4	0	−1	0	1
5	0	0	1	−1
6	0	1	−1	0
7	1	−1	1	0
8	1	0	−1	1
9	1	1	0	−1

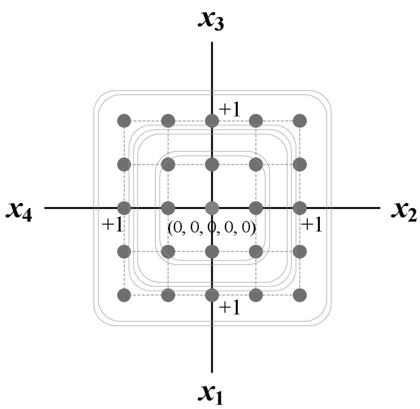

Figure 2. Nonconcentric Circle Contour.

In this confirmatory stage, the analysis is focused on a certain level of metal thickness in order to observe the effect of the remaining factors on the measured responses. Afterwards, simulation is run with data drawn from the prior full-factorial design in order to preserve the data being consistent comes from a single population and under the same probability distribution.

According to Ane and Roller [26–28], the OA L_9 (3^4) fits to the of 5-axes response surface model. However, the design is not rotatable since the contours associated with the variance of the predicted responses, var [$\hat{y}(x_i)$], are not concentric circles [28] as depicted in Figure 2.

Rotatability is an important property in the exploration of response surface because the precision of the estimated surface neither depends on the orientation of the design with respect to the true response, nor the direction of searching for the optimal condition. A design is rotatable if the estimated responses have equal precision at all points in the factor space that are equidistant from the design center. Maintaining the rotatability property requires variance of the predicted responses being constant at points equal distant from the design center [1, 5].

According to Mason *et al.* [9], design points for more than two factors should lie on a sphere, or a hypersphere, in four or more dimensions. Therefore, another two axial points need to be added on the y-axes, as well as another two design centers. The axial points are determined as $\alpha = (n_F)^{0.25} = (9)^{0.25} = 1.73$, where n_F represents the number of factorial points, which equals 9 in the design of OA L_9 (3^4). Table 3 describes the additional axial points. Figure 3 illustrates the additional incomplete block design which consists of six axial points and six additional design centers. Combining the OA L_9 (3^4) and the incomplete block results in a rotatable design.

Table 3. Additional Axial Points.

Binder holding force	Punch velocity	Strain hardening exponent	Friction coefficient
(x_2)	(x_3)	(x_4)	(x_5)
+1.73	0	0	0
0	+1.73	0	0
0	0	+1.73	0
0	0	0	+1.73

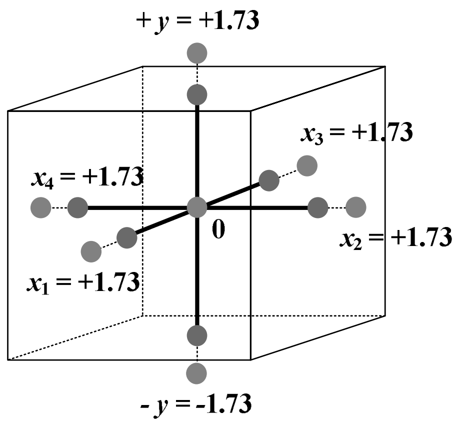

Figure 3. Incomplete Block Design.

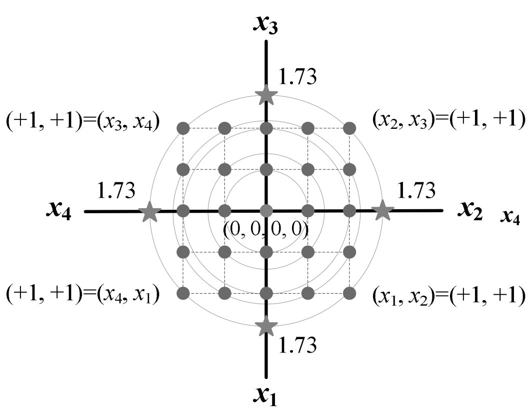

Figure 4. Rotatable OA L_9 (3^4).

The rotatable design leaves the variance unchanged when the design is rotated about the center $(x_1, x_2, x_3, x_4, y = (0, 0, 0, 0, 0)$. Variance of the predicted response $\mathrm{var}[\hat{y}(x_i)] = f'(x_i)(X_i'X_i)^{-1}f(x_i)\sigma^2$ is a function only of the distance of the point from the design center and is not a function of the direction. Therefore, contours of constant standard deviation of the predicted response $\sigma[\hat{y}(x)]$ are concentric circles as illustrated in Figure 4. Finally, by translating the rotatable design using the transformation algorithm [26–28] a 5-axes spherical factors space can be derived as depicted in Figure 5. Afterwards, a heuristic "hill climbing" method [4] can be performed to seek the optimal factors-levels combination on the spherical region that is expected to be the true global optima. But this is not discussed in this paper.

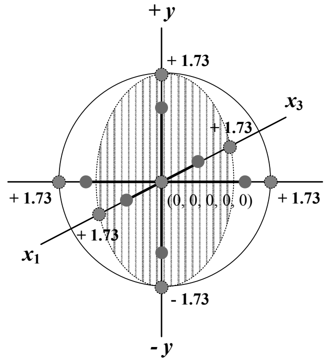

Figure 5. A 5-axes Spherical Factors Space.

4. DISCUSSION OF RESULTS

The procedure in doing the simulation is as follow:

First, the statistical simulation based on the full-factorial model is run in order to get coefficients for identifying the best-fit mathematical function. Using the identified mathematical function, the "global minima" is calculated. In our case, the value of global minima is found at $y = 0.087$, which is recognized as a "saddle point". Genetic Algorithm is then run using the same objective function to find the best combination of the control-factors. It is found that x_1, x_2, x_3, x_4, x_5 are respectively, 0, 0, 0, 1, and 1.

In the next step, full-factorial model is divided into 3 independent building blocks based on variable x_1 (i.e., the metal thickness at 1, 1.5, and 1.75 mm). Each building block is modified into a "Rotatable OA L_9 (3^4)" design, and then transferred onto a new codified scale between 0 to $+1.73$. The statistical simulation and the Genetic Algorithm are repeated for each building block in the same manner as explained in the previous paragraph to obtain the global minima at $y = 0.059$, and the best combination of the control-factors: x_2, x_3, x_4, x_5 are respectively, 1, 0, 0, 1, and 1. In order to avoid the infeasible (or negative) response values for y, the value of x_1 needs to be adjusted in each building block. In our case, x_1 at Level 0 (zero) produced reliable result. 3D graphs are generated independently between 2 factors for analyzing the correlation between pair of factors. Later, those graphs will be transformed into the 5-axes response surface graph.

5. CONCLUSIONS

In this paper, a research methodology based on 5-axes response surface model is briefly described to understand how it can be used to set the critical metal forming parameters of an example IP component. By optimizing the forming variables a sheet metal component that has minimum percentage thinning can be obtained. However, all the optimum variables may not be achieved in practice, but this methodology helps in identifying and understanding the interaction between those variables so that the real and virtual sheet metal experiments using the CAE tools such as HyperForm or LS-DYNA can be set up. Simulation times using DYNA and/or by real experiments can be reduced using this Quality Engineering tool. More work will be done in future to validate some of the statistical results for the real sheet metal parts.

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REFERENCES

1. Box G.E.P. and Hunter J.S., "Multifactor experimental design for exploring response surfaces", Annals of Mathematical Statistics 1957, 28, pg 195–241.
2. Taguchi G., "System of experimental design. Quality Resources 1 and 2", New York: American Supplier Institute; 1987.
3. Peace G.S., "Taguchi methods: A hands-on approach", Addison-Wesley Publishing Company, Inc., 1993.
4. Park S.H., "Robust design and analysis for quality engineering", Chapman and Hall, 1996.
5. Kuehl R.O., "Design of experiments: Research design and analysis", 2nd ed. Pacific Grove: Duxbury Press, 2000.
6. Amago T., "Sizing optimization using response surface methods in FOA", R&D Review of Toyota CRDL 2001, 37(1), pg 1–7.
7. Montgomery D.C., "Design and analysis of experiments", John Wiley & Sons, Inc., 2001.
8. Myers R.H. and Montgomery D.C., "Response Surface Methodology Process and Product Optimization using Designed Experiments". John Wiley and Sons, Inc., New York, USA, 2nd ed., 2002.
9. Mason R.L., *et al.*, "Statistical design and analysis of experiments with applications to engineering and science", 2nd ed., John Wiley & Sons, Inc., 2003.
10. National Institute of Standards and Technology (NIST). In: Engineering Statistics Handbook, USA (Department of Commerce), 2003.
11. Wagoner R.H. and Chenot J.L., "Metal Forming Analysis", Cambridge University Press, 2005.
12. Kobayashi S. and Altan T., "Metal Forming and the Finite-Element Method", Oxford University Press, 2005.
13. Hosford W.F. and Caddell R.M., "Metal Forming", Cambridge University Press, 2007.
14. Banabic D., "Sheet Metal Forming Processes: Constitutive Modelling and Numerical Simulation, 1st Ed., Springer, 2009, ISBN: 978-3-540-88112-4.
15. Juneja B.L., "Fundamentals of Metal Forming Processes", New Age International, 2010.
16. Stander N., "The successive response surface method applied to sheet-metal forming", Proceedings, First MIT Conference on Computational Fluid and Solid Mechanics, pg 481–485, June 12–15, 2001.
17. Jakumeit J., Herdy M. and Nitsche M., "Parameter optimization of the sheet metal forming process using an iterative parallel Kriging algorithm", Springer Berlin, ISSN 1615-147X, V 29, N 6, June 14, 2005, pg 498–507.
18. Naceur H., Ben Elechi S. and Batoz J.L., "On the Design of Sheet Metal Forming Parameters for Springback Compensation", VIII International Conference on Computational Plasticity (COMPLAS VIII), Barcelona, 2005.
19. Zhang W., "Design for Uncertainties of Sheet Metal Forming Process", Doctoral Dissertation, The Ohio State University, 2007.
20. Tang Y. and Chen, J., "Robust design of sheet metal forming process based on adaptive importance sampling", Journal Structural and Multidisciplinary Optimization Publisher Springer Berlin ISSN 1615-147X (Print), V 39, N 5, November, 2009, pg 531–544.
21. Shivpuri R. and Zhang W., "Robust design of spatially distributed friction for reduced wrinkling and thinning failure in sheet drawing", *Materials & Design*, V 30, N 6, June 2009, pg 2043–2055.
22. Marretta L., Ingaraoa G. and Di Lorenzo R., "Design of Sheet Stamping Operations to Control Sprinback and Thinning: A multi-objective Stochastic Optimization Approach", *International Journal of Mechanical Sciences*, V 52, N 7, July 2010, pg 914–927.
23. Echempati R. and Sathya Dev, V.M.S., "Statistical Design Study of Aluminum Forming", Proceedings of NUMISHEET 2002 Conference, October 21–25, 2002, Jeju Island, S. Korea, pg. 665–670.
24. Fox A. and Echempati R., "Modelling, Forming, Modal Analysis, and Gauge Optimization of Sheet metal Parts", Proceedings of the ASME 2009 International Manufacturing Science and Engineering Conference (MSEC2009), October 4–7, West Lafayette, Indiana, USA 2009.
25. Echempati R. and Fox A., "Integrated Metal Forming, Vibration Analysis, and Thickness Optimization of Sheet Metal Parts", Proceedings of TMCE 2010 Conference held in Ancona, Italy, May 2010, pg 731.
26. Ane B.K., Roller D. and Watanabe C., "To Go Beyond From the Local Optima: Developing 5-axes Response surface Graph based on OA L9", Jamshidi, M., Cox, D., Nahavandi, S., Jamshidi, J. S. (Eds.), Robotics, Manufacturing and Automation (Proceedings of WAC 2006), TSI Press, San Antonio, pg 245–250.
27. Ane B.K. and Roller D., "Geometric Constraint Modelling System: Development of 5-axes Response Surface Graph. Proceedings of WAC 2008, TSI Press, San Antonio, pg. 1–6, ISBN: 978-1-889335-38-4.
28. Roller D. and Ane B.K., "Geometric Constraint Modelling: Boundary Planar B-spline Curves and Control Polyhedra for 5-axes Response Surface Graph", *Computer Aided Geometric Design* 26(5), 2009, pg 493–509.