NordDesign 2012
August 22 – 24, 2012
Aalborg, Denmark

Visualization of simulation-data-based metamodels during the product synthesis

Philipp Ziegler, Alwin Schummer, Sandro Wartzack
Chair of Engineering Design
Friedrich-Alexander University of Erlangen-Nuremberg (FAU)
Martensstraße 9, D-91058 Erlangen
GERMANY
ziegler@mfk.uni-erlangen.de

Abstract
This research work focusses on visualization techniques to support the product developer at the product synthesis, which can be implemented in a design support tool. The method uses metamodels, which predict approximatively product properties from combinations of characteristics. The metamodel is fitted to simulation data. The visualization enables a deeper comprehension of the correlations between product characteristics and product properties as well as among the properties.

Keywords: Visualization, metamodels, design support tool, sheet-bulk metal forming

1 Introduction

In accordance to WEBER [1] the relevant core-activities during the product design process can be identified as product synthesis steps and product analysis steps, respectively. In the synthesis step the product characteristics and parameters are generated with respect to the requirements where as the product properties and thus the fulfilment of the requirements are evaluated in the analysis step.
If the product does not fulfil the demanded requirements a further synthesis step (design interaction) is needed. For this step it is important for the designer to know the correlations between the characteristics which he can specify directly and the product properties which result from the specified characteristics. This knowledge enables him to identify the relevant and decisive characteristics and parameters in order to optimize the product.
Prerequisite for knowing the correlations is a knowledge transfer between the analysis expert and the designer. Due to the fact that the necessary analyses (simulations or tests) are time consuming (lack of information in early design phases, external service companies need external flow of information, experts are not available, etc.) the iteration loops between synthesis and analysis and thus the product optimization process can be considered to be quite slow. Consequently new ways have to be found to support the product developer by analysing the product's properties and to provide the correlation between characteristics and properties.

2 Motivation

In the product development process, the product has to fulfil demanded requirements. To achieve them, the product developer can modify certain parameters. According to the "Characteristics-Properties Modelling" (CPM) of WEBER [1] these parameters are called characteristics. If a requirement is put on a characteristic, the product developer only has to adjust it. If the requirement is not directly adjustable, it is called a property. A lot of properties and characteristics are correlated to each other. The idea is to configure the characteristics in a way that the correlated properties fulfil the requirements, this is called “Property-Driven Development” (PDD) [1]. One way to analyse the correlations between characteristics and properties is to perform computer-simulations. Explorating the simulation-data with statistical methods is an adequate next step. A common and suitable method is regression analysis, which calculates a prediction model (with a small error) for the values of the product properties by known product characteristics combinations. The prediction model is also denoted as metamodel. If the metamodel characterizes the correlations between several characteristics and properties, it is called multidimensional and multivariate [2]. If the metamodel additionally is nonlinear, the exploitation of the characteristics-properties- correlations and furthermore a derivation of instructions for modifying the product characteristics needs an additional metamodel-analysis step. In statistics, visualization techniques have a long tradition in exploiting the included information of data. This paper focusses on appropriate visualization techniques to support the configuration of the product characteristics to optimize the product properties.

3 State of the Art

3.1 Metamodels

Statistical Methods are widely used in engineering design to analyse the functional relationship between a vector of design variables (characteristics) x and a vector of responses (properties) y of a computer simulation. The main approach is to calculate an *approximation* of the simulation-intern relationship. If the relationship has the form [3]

$$y = f(x),$$

a ‘model of the model’ or metamodel of the relation is given by

$$\hat{y} = g(x) \text{ and so } y = \hat{y} + \varepsilon,$$

where ε is the sum of approximation and measurement errors. Usually regression analysis is used for calculating the metamodel. Some metamodels calculate for every property a separate metamodel, others calculate one metamodel which predicts all property values together. The benefits of the metamodel are

- prediction of the properties for known characteristics combinations
- a better understanding for the relationship between characteristics and properties
- faster implementation of optimization, correlation- and robustness analysis algorithms

Sensitivity Analysis

“Sensitivity analysis studies the relationships between information flowing in and out of the model” [4]. In the context of metamodels there are two important sensitivities: local and global sensitivity. This paper focusses on global sensitivities, as they consider interactions between the characteristics. For robustness analysis the global variance-based sensitivity of SOBOL is an adequate technique [5]. Sensitivity measures have the form

$$\begin{pmatrix} s_{11} & \cdots & s_{1m} \\ \vdots & \ddots & \vdots \\ s_{n1} & \cdots & s_{nm} \end{pmatrix},$$

where the influence of every characteristic on every property is characterized.

3.2 Visualization

Visualization is a methodology in the field of Database Exploration. According to KEIM [6] is "Database Exploration (…) the process of searching and analysing databases to find implicit but potentially useful information". The publication of statistical data visualization began with PLAYFAIR in the 18th century. There e.g. bar charts and pie charts were invited, long before FISHER [7], the pioneer of modern statistics. FISHER was the founder of the Design of Experiments, which is a powerful toolbox for data collection and data exploitation. With this method it became possible to analyse the correlations between several parameters including interactions between these parameters. In visualization, there are two terms for multi-parameter visualization: multidimensional and multivariate (mdmv). Multidimensional refers to the dimensionality of the independent dimensions (characteristics) while multivariate refers to the dimensionality of the dependent variables (properties) [2].
In the end of the seventies, TUKEY invited his exploratory data analysis [8]. In combination with the arrival of the personal computer a new era of data visualization started. Exploratory data analysis guides people to visually decode information from data and with the personal computer a powerful machine for data analysis was available for a lot of scientists. Based upon the new possibilities, a lot of visualization techniques for multidimensional and multivariate data were invited in the following decades [8,9].
Multidimensional and multivariate data visualization challenges with the boundedness of two-dimensional screens, the incompatibility of simplicity and accuracy of complex information and the paradoxon of the assessment of effectiveness [2]: "We do not know what valuable knowledge is present in the data, so we hope to gain insight by visualizing it. Nevertheless, if we known nothing about the pattern or relationship to be shown in the data representation, we can never assess the effectiveness of a particular visualization technique." Visualization techniques can be divided into four classes [2]:

Geometric projection
These techniques base upon projections and transformations of the mdmv-datasets to lower dimensions. The projected data then is visualized. Geometric projection methods are good for detecting outliers and for correlation analysis amongst different dimensions. A typical representative of this class is the scatterplot matrix (see chapter Work Methodology).
Pixel-oriented techniques
The principle behind pixel-oriented techniques is to characterize an attribute value of the data by a pixel based on some color scale. For n dimensions of the dataset, n colored pixels are necessary to visualize one data item. These methods are powerful but require a lot training. Subsequently no technique of this class will be used.
Hierarchical display
The hierarchical methods subdivide the data space into smaller segments and visualize these subspaces in a hierarchical way. As different dimensions of the data are threated differently, these techniques require training. The worlds within worlds method e. g. is an appropriate technique for multidimensional metamodels (see chapter Work Methodology).
Iconography
Iconographic techniques map each mdmv data item to an icon. The icon represents several data-parameters by several features. Considerations of graphical features are pre-attentive, what makes them catchy for humans. The star glyph is an example for an iconographic technique (see chapter Work Methodology).

4 Work Methodology

4.1 Framework

The starting point of our methodology is a simulation-dataset

$$\begin{pmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{pmatrix}, \quad \begin{pmatrix} y_{11} & \cdots & y_{1o} \\ \vdots & \ddots & \vdots \\ y_{m1} & \cdots & y_{mo} \end{pmatrix},$$

with n varied input parameters (characteristics) and o outputted parameters (properties), where m simulations were performed. The values of the input parameters previously were defined by a sampling. The sampling determines, which values of the several characteristics are combined with each other. First of all the simulation-dataset is visualized (see Figure 1) to get a first impression about the range of the properties and indications for correlations between characteristics and properties. For this purpose the box-plot and scatterplot matrix technique will be used. In the next step a metamodel is fitted to the simulation-data to predict property values for not simulated characteristics combinations (see Figure 1). For visualizing the metamodel a mdmv *function* visualizing method is necessary. The worlds within worlds technique fulfils this requirement, it can visualize functions as a surfaces. Finally, sensitivity analysis methods are applied to calculate the sensitivity of the properties with regard to the characteristics (see Figure 1). The calculated values are visualized by bar plots and star plots. All visualizations are shown in figure 2.

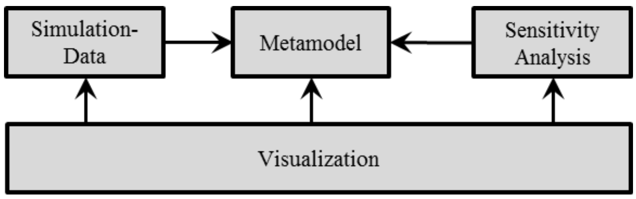

Figure 1 Framework of the Visualization Methodology

4.2 Simulation-data visualization

First of all it must be said that the validity of the following data exploration extends only over the ranges of all simulated characteristics values. Outside of this parameter area no reliable exploration can be done. Two visual techniques for exploring the simulation-data are used: a star glyph of the property values and a scatterplot matrix of the characteristics-properties correlations. The star glyph is an iconographic visualization technique. In this case the single axis contain box plots of the property values. A box plot displays the scattering of a single parameter. In this case the most important information from the properties box plot is the median and the range of the properties. Furthermore it indicates a general robustness of the properties regarding *all* varied characteristics. Additionally the geometric projection technique “scatterplot matrix” will be applied. The scatterplot matrix plots every property with their values from the simulation against every characteristic in a single scatterplot in form of a point cloud. The scatterplot indicates direct correlations between characteristics and properties. If several characteristics have a significant impact on a property, the point cloud of the single scatterplots can have a confusing form. Furthermore the scatterplot does not indicate interaction effects between the characteristics.

4.3 Metamodel, correlation and sensitivity calculation

A feed-forward artificial neural net with backpropagation learning algorithm, one hidden layer and sigmoid transfer-functions [10] is the selected metamodel. This is a common metamodel, which can approximate very general correlations between parameters. As sensitivity measures pearson and spearman correlation coefficients as well as main and total effect of the global sensitivity according to SOBOL [4] were calculated. The pearson correlation coefficient measures the linear correlation between parameters, the spearman correlation coefficient the monotone correlation. The global sensitivity index indicates the main contributing characteristics for deviations of the properties, what is important for robustness analysis. Therefore distributions of the characteristsics are necessary informations for the sensitivity calculation. If the distributions of the characteristics are not known, a geometric sensitivity analysis can be done [5].

4.4 Metamodel, correlation and sensitivity visualization

For the metamodel a mdmv *function* visualization technique is necessary. The hierarchical display method “worlds within worlds” is a powerful 3D-rendering technique [2]. The technique consists of a response surface (one property regarding two characteristics) which is embedded into additional three-dimensional coordinate systems (three additional characteristics). The correlation between any number of characteristics and one property can be analyzed simultaneously. This technique can be applied for every property separately. The worlds within worlds method displays the property value for characteristics combinations and the growth of the value by changing single as well as several characteristics. With this technique *one* property can be controlled very good.

Furthermore, the two correlation coefficients and the sensitivities are visualized by bar charts. As they are normalized, the correlation coefficients have values between -1 and 1, the sensitivity measures between 0 and 1. By visualizing these three measures, different features of the correlation (linearity, monotony and influence on the property distribution) between characteristics and properties can be explored.

At least, the correlation coefficients and the sensitivities are evaluated and a correlation list for the order of the characteristics influence on the properties will be created. These list will be visualized by a star plot (a kind of star glyph), an iconographic visualization technique. The areas enclosed by the characteristics show their importance for the property values.

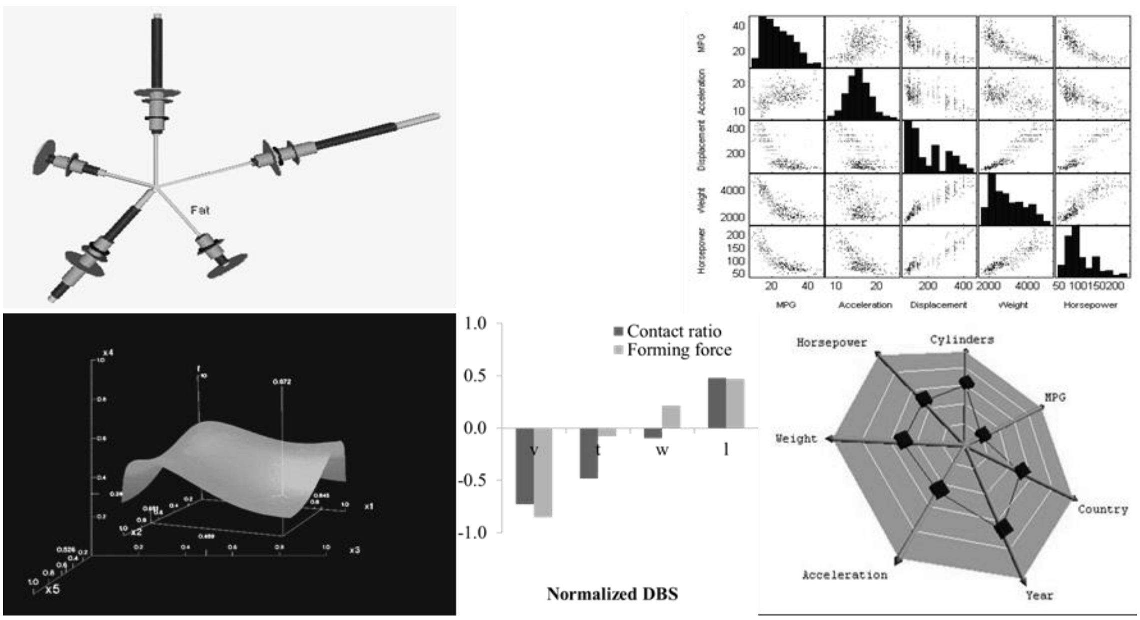

Figure 2 Star glyph (u.l., for reference see [2]), scatterplot matrix (u.r., for ref. see [2]), worlds within worlds (d.l., for ref. see [2]), bar- and star plot (d.r. , for ref. see [2])

5 Case Study

5.1 Sheet-bulk metal forming

The transregional collaborative research centre 73 (SFB/TR 73) aims to connect the advantage of cold bulk forming to thin sheet metal parts and therefore creates a new manufacturing technology, named “sheet-bulk metal forming” (SBMF). It is defined as the “plastic change of the shape of a plain semi-finished product with both two- and three-axial strain and stress conditions” [11]. Parts produced with this production method should stand out with lightweight design and the conjunction of multiple functions. Furthermore material and energy-usage in the manufacturing process would decrease. The subproject B1 “Self-learning engineering assistance system” of SFB/TR 73 is the basis for the automatic and data-mining based knowledge-aquistion that is done in this paper.

Table 1 Simulation parameters

Parameter	Symbol	Unit	Range
Spindle speed	n	1/min	[2000;20000]
Feed per tooth	f_z	-	[0;0.5]
Axial immersion depth	a_p	mm	[0;0.3]
Corner radius	r	mm	{0;3}
Contact pressure 1	A_{closed}	GPa	[0;0.5]
Contact pressure 2	A_{max}	Gpa	[0;0.5]
Contact pressure 3	$A_{closed\ (max)}$	Gpa	[0;0.5]
Chatterclass	c	-	{0;4}

5.2 Simulation-data about frictional behaviour of surface structures

Important aspects of sheet-bulk-metal forming are the friction properties between the tool and the metal blank during the forming process. They influence the material flow during the forming process. Milling the surface of the forming tool, self-excited vibrations can be intentionally invoked to apply tailored friction ([12]). Figure 3 right shows possible surface structures. To predict the frictional behaviour of the milled surface, a contact simulation using a halfspace model was created ([13]). Halfspace models are Finite Element surface meshes. Their calculation time is much shorter than for volume meshes.

With the contact simulation a statistical analysis of the correlations between product and process characteristics and product properties was performed [14]. The spindle speed n, the feed per tooth f_z and the axial immersion depth a_p of the forming process were varied. Furthermore, the corner radius r of the milling tool was varied (see Figure 3). A couple of 100 characteristics combinations were created with a Latin Hypercube Experimental Plan, which combines the single varied parameters randomly with each other. With the Minimax condition the most suitable was selected. The simulation was performed due to the Experimental Design and three contact pressures (A_{closed}, A_{max} and $A_{closed\ (max)}$) as well as the chatterclass c was measured.

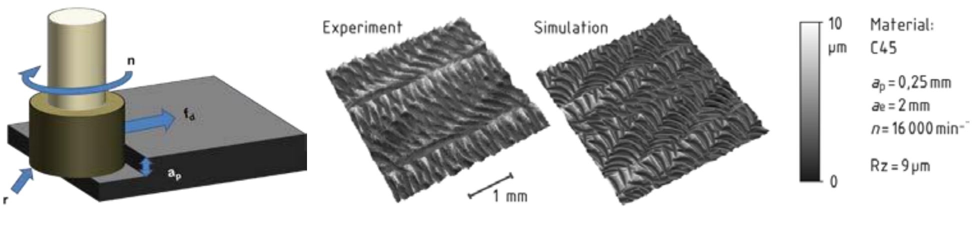

Figure 3 Varied parameters of the simulation (l.), tool surface example (r., [14])

5.3 Visualization

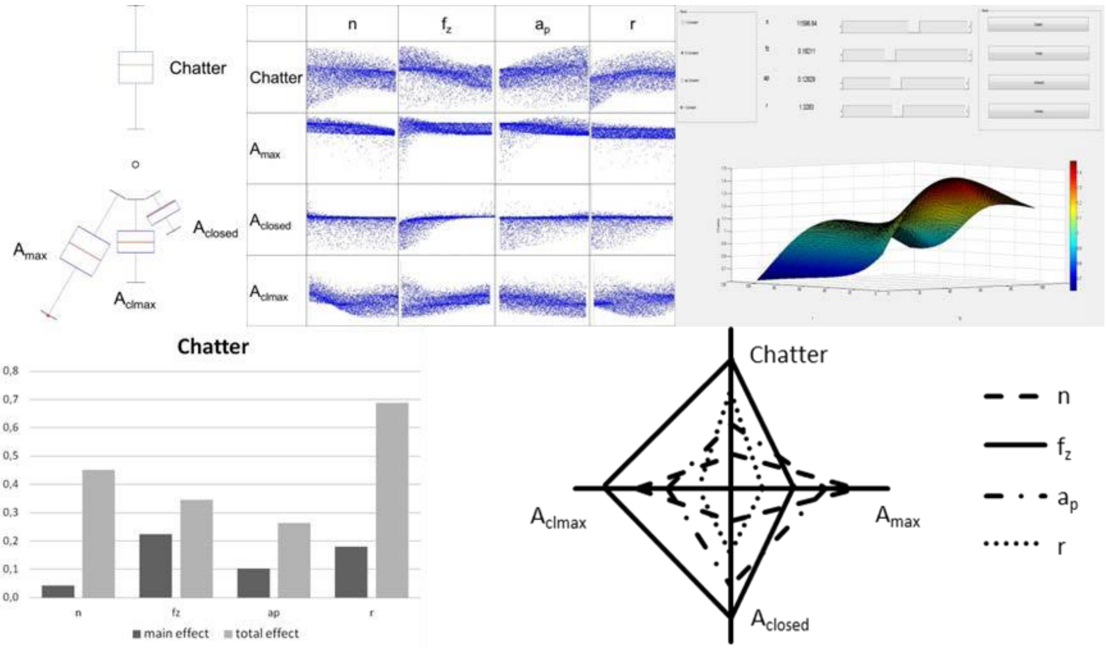

Figure 4 Visualized properties and characteristics-properties correlations

5.4 Interpretation of the results

The first visualization technique seen in figure 4 is the star glyph box plot. The chatterclass has a different scale as the other three parameters and is arranged separately. All properties are symmetric distributed in the simulation-dataset except A_{closed}, where the lower quantile is very short. Due to the equally distributed simulation sample this states nonlinear correlations between characteristics and A_{closed}. Second, the scatterplot-matrix (u. m.) shows the correlations between single characteristics and properties without interactions between the characteristics. Noticeable is the fact that A_{max} is nearly constant – it can be overlooked in the following. The worlds within worlds method is shown here with slide control parallel axis (u. r.), not orthogonal ones. The surface is strongly nonlinear for f_z and r. In the fourth picture (d. l.), the main- and total sensitivity indices for the chatterstrength are shown. The height of the bars show the strongest contributors, the difference between main- and total effect of the single characteristics the strength of the interactions between the characteristics. The last picture shows the rank of the contributing characteristics for varying the properties. As the line for f_z has the biggest area included, it is the general main contributor.

6 Discussion and Summary

The introduced composition of visualization techniques combined with metamodels and sensitivity analysis presented significant relationships between the considered parameters in the case study. The star glyph box plot is a first indicator for the strength and the nonlinearity of the correlations between characteristics and properties. Furthermore, the scatterplot matrix shows the the direct correlation without considering interactions between the characteristics. Both techniques indicate, which parameters can be dropt out for the next step. The worlds within worlds method is appropriate for analysing one property precisely, while the sensitivity visualization shows all correlations with interactions between characteristics for ranges of characteristics (e.g. spindle speed between 6000 and 10000 min^{-1}). If finally a ranking of the correlation strength between the single parameters is done, the star plot method suitable visualizes this ranking.

Acknowledgement

This work was supported by the German Research Foundation (DFG) within the scope of the Transregional Collaborative Research Centre on sheet-bulk metal forming (SFB/TR 73). Thanks to Rouven Hense and Franz Hauer for providing the simulation-dataset for the case- study.

References

[1] Weber, C., “CPM/PDD – An Extended Theoretical Approach to Modelling Products and Product Development Processes”, *Proceedings of the 2nd German-Israeli Symposium on Advances in Methods and Systems for Development of Products and Processes* (ed. by Bley, H.; Jansen, H.; Krause, F.-L.; Shpitalni, M.), TU Berlin / IPK, 07.-08.07.2005, pp. 159-179

[2] Chan, W., “*A Survey on Multivariate Data Visualization*”,Technical Report, available at http://www.cse.ust.hk/~wallacem/winchan/research/multivis-report-winnie.pdf, 2006

[3] Simpson, T. W., Peplinski, J. D., Koch, P. N., Allen, J. K., „Metamodels for Computer-based Engineering Design: Survey and recommendations“, *Engineering with computers*, Vol. 17 (2), 2001, pp. 129-150

[4] Saltelli, A., Chan, K., Scott, E. M., „*Sensitivity Analysis*“, Wiley & Sons Ltd., New York, USA, 2000

[5] Ziegler, P., Breitsprecher, T., Walter, M., Westphal, C., Wartzack, S., „Application of sensitivitives on simulation-data-based metamodels during the product synthesis“, *Proceedings of the 12th International Design Conference (Design 2012)*, Dubrovnik, Croatia, 21.-24.05.2012

[6] Keim, D. A., „Visual Techniques for Exploring Databases“, *Proceedings of the 3rd International Conference on Knowledge Discovery and Data Mining Tutorial Program*, 1997

[7] Fisher, R. A., „*The Design of Experiments*“, Oliver and Boyd, Edinburgh and London, UK, 1935

[8] Tukey, J. W., „*Exploratory Data Analysis*“, Addison-Wesley, 1977

[9] Cleveland, W., “*Visualizing Data*”, AT&T Bell Laboratories, Murray Hill, NJ, Hobart Press, 1993

[10] Hagan, M. T., Howard, B. D., Beale, M. H., “*Neural network design*”, PWS Publishing Company Boston, USA, 1996

[11] Röhner, S., Breitsprecher, T., Wartzack, S., „Acquisition of design-relevant knowledge within the development of sheet-bulk metal forming”, *Proceedings of the International Conference of on Engineering Design – ICED11*, T. McAloone (Ed.), Technical University of Denmark, Kopenhagen, 2011

[12] Biermann, D., Surmann, T., Odendahl, S., Steiner, M., Hense, R., Rausch, S., “Creating Functional Surface Structures by Milling using Self-Excited Tool Vibrations”, *Proceedings ASPE 2011 Spring Topical Meeting – Structured and Freeform Surfaces*, 6.3.-8.3.2011, Charlotte, North Carolina, USA, pp. 55-58

[13] Hauer, F., Vierzigmann, H.-U., Willner, K., Engel, U., “Numerical simulation of friction in metal forming using a halfspace model, *Proceedings of the 14th International ESAFORM Conference of Material Forming*, v. 1536, 2011, pp. 1741- 1746

[14] Breitsprecher, T., Hense, R., Hauer, F., Wartzack, S., Biermann, D., Willner, K., „Acquisition of heuristic knowledge for the prediction of the frictional behavior of surface structures created by self-excited tool vibrations“, *Key Engineering Materials*, Vols. 504-506, 2012, pp. 963-968