Expert Knowledge Systems to Ensure Quality and Reliability in direct digital Manufacturing Environments

Authors: E. M. Scheideler, A. Ahlemeyer-Stubbe

in: Elio Padoano, Franz-Josef Villmer, Proceedings 6 th International Conference September 29 and 30, 2016 Lemgo, Germany, Production Engineering and Management, Volume 01/2016 Publication Series in Logistics Department of Production Engineering and Management Ostwestfalen-Lippe University of Applied Sciences, Lemgo (Germany)

https://www.hs-owl.de/fileadmin/diman/Veroeffentlichungen/PEM_2016_Proceeding_2016_09_14_Inhaltsnavigation.pdf

ABSTRACT:

In the context of Industrie 4.0 respectively direct digital manufacturing, seamless process chains are an important factor. The objective is to shorten the time between quoting for individually designed products and their production and delivery. Therefore, reliable automated and fast evaluation procedures are needed to ensure the quality of the individually designed products in terms of product safety and reliability.

This paper aims to demonstrate how a metamodel, generated on simulated data, adapts to the type of product and delivers the required quality and evaluation procedure. The metamodel guarantees the requested characteristics of the final product without the consultation of human expert knowledge. As proof of concept, a simple, well-documented task from the field of construction has been chosen.

The estimation from of the metamodel will meet all safety requirements, is based on the individual input variables and is confirmed without expert interaction. Fast, reliable prediction models deriving from complex simulation models are indispensable conditions for direct digital manufacturing. Using metamodels in automation contexts will be a foundation of manufacturing in future.

KEYWORDS:

Simulation, Metamodel, Computer experiment, Design of experiments

1 INTRODUCTION

In future, manufacturing processes will have to be highly flexible and dynamic. Manufacturing companies are involved in networks that require agile collaboration between partners [1]. Therefore direct digital manufacturing needs digital data from the product and the manufacturing process. IT tools are needed and global networks are useful. Designers will use engineering tools (CAD, FEM etc.) for product design and optimization [2]. The product design is also part of direct digital manufacturing. So everyone involved in the design process will be part of this digital revolution.

Soon the prosumer will be a part of the design group. Prosumers are persons who combine the economic roles of producer and consumer. Usually prosumers have no expert knowledge. Therefore, reliable automated and fast evaluation procedures are needed to ensure the quality of the individually designed products in terms of product safety and product reliability. Fast and easy-to-use engineering tools could be one solution here.

Additionally customer needs and requirements are getting increasingly diverse while individual customer requirements become more and more important. The old concept of a consumer not being involved in the manufacturing process will change to the concept of prosumers who will play an active part in direct digital manufacturing [3]. Therefore suitable prosumer concepts and easy-to-use tools should be developed for direct digital manufacturing.

Today, human experts check, based on their experience, whether the consumer (client) desired product parameters are valid to create a product that meets the required safety level. If necessary, the expert adapts the product parameters after client consultation in order to fulfill the safety requirements. Depending on the specific application the review of the parameters is done with special and often complex simulation tools. In most cases a human expert is needed to run the simulation, which is often very time-consuming. An alternative approach is the use of metamodels. Metamodels are “simplified models from a model” where the results come from algebraic equations. They are normally used to replace time-consuming complex simulations. The metamodel technique can also provide the algorithm for simple engineering tools, which require only a small amount of knowledge. Statistical tools are also well known for building metamodels. The metamodel approach can be used with a new data stream [4] or a constant data base.

A metamodel that has these characteristics should only run on the client given parameters and information of the demanded characteristics or usages of the future product. In the description below, these parameters are called input variables. Parameters based on expert knowledge should be covered by the metamodel itself and not be influenced by client requirements.

2 METHODS

2.1 Metamodel of complex simulations as a fast expert knowledge system

Metamodels in the context of IT represent a simplified model of a complex computer analysis which is based on statistical methods. The aim of the metamodel is to predict the future behavior of a process without doing the complex computer analysis. The results of the metamodel are an approximation of the output variables defined by a functional relation based on statistics. Therefore the calculated results of the metamodel normally have an error or residual left over [5]. The metamodel will not be used to predict exact values, but helps to make decisions, e.g. whether the product design fulfills the safety requirements or not.

In order to use statistical methods to find relations between the input variables and the output variables, data sets are necessary. The quality of the statistical model depends to the number of given data sets and the distribution of the input variables [6]. The fastest way to achieve a reliable and valuable metamodel is to use a minimum number of complex computer analyses. Here the complexity and the nonlinearity between the input variables and the response have to be taken into account. The well-known methods to design computer experiments can be used.

2.2 Design of computer experiments

The design of experiments requires a method on how to do physical test systematically. Computer experiments differ from physical experiments in the way, that repeated computer simulations with an identical set of input variables result in identical output variables. That means, that a single observation on a given set of inputs provides perfect information about the final result. With this advantage in mind, the design strategy for computer experiments should fulfill two principles [7]:

1. Design should not take more than one observation at any set of inputs [7].
2. The design should provide information about all portions of the experimental region [7].

The space-filling design fulfills the two above mentioned principles. It includes different design methods such as Latin Hypercube, Maximum Entropy, Uniform, Fast, Flexible Filling and more. The method that will be used depends heavily on the application [8].

2.3 Statistical modeling

After selecting an appropriate experimental design and finishing the necessary computer runs, the next step is to launch the model fitting process.

Many alternative models and methods exist here. Most prevalent in the literature are the response surface, neural networks, including learning and kriging [9]. In this case the response surface method was chosen, because it is widely used and implemented in common statistical tools in order to keep the mythologies as simple as possible.

In computer experiments the response vector y is influenced by a vector of independent factors x (y=f(x)). There are no random errors. Since the true response surface function f(x) is usually unknown, a response surface g(x) is created to approximate f(x). Frequently used response surface approximation functions are low-order polynomials [9].

The parameters of the polynomials are usually determined by least square regression analysis by fitting the response surface approximations to existing data sets [9]. The validation of the simplified prediction model is a crucial success factor.

3 CASE STUDY

The aim of the paper is to show how the theoretical framework discussed above can be used in the context of construction. In this case a very simple, well-researched area of construction is chosen, because it is easier to obtain real and proven validation data and to compare the results with others [10]. As proof of concept the task of vision panels in facades or doors from the field of construction was chosen. The main research concentrated on the resistance of the glass to soft body impact and its safety properties after fracture.

The test scenario is generally determined by an impact test, for example as defined in the European standard EN 12600 [10]. In the last 10 years calculation methods using transient, implicit or explicit finite-element methods have been developed. They simulate the experimental results very well. These methods now form a part of the design method according to the German standard DIN 18008-4 'Glass in building – design and construction rules – part 4 [11]: additional requirements for barrier glazing'.

To use this calculation method, complex software tools and detailed expert knowledge is required. The expert must have knowledge about the program, the material parameters, element size, drop height and so on. The use of expert knowledge leads to an increase in time and costs. It also does not improve the process when used in automated actions.

To get a rough idea of whether the chosen vision panel might fulfill the required safety standards apart from physical trails, two simulation methods are normally suggested: the more reliable calculation using the finite element method. The second method uses analytical equations and substitute input values taken from charts. To combine the advantages of both methods, i.e. being reliable, fast and capable of being used without expert knowledge, would represent a third possibility.

The main question here is: is it possible to find a metamodel which allows to take a decision on whether vision glass panels are resistant to a soft body impact? The second question addresses the issue if this decision should be rather made by the human mind with very little expert knowledge, as in the case of sales people, or automatically proofen in an automated ordering process via the Internet.

3.1 Metamodel development

Beginning with the input parameters, it is important to consider the geometry of the vision panel, i.e. the height, the width and the thickness of the glass. The strength of the glass is also a very important parameter. There are three different glass types with different strengths – see Table 1.

Table 1: Allowable stress (DIN 18008) [12] for soft impact.

GLASS TYPE	*ALLOWABLE STRESS*
Float	81 MPa
HST (heat-strengthened glass)	119 MPa
FT (ESG) (fully toughened glass)	168 MPa

Due to the fact that the user of the metamodel needs only little expert knowledge, the common known glass type should replace the input for the glass strength.

The main input parameters which represent the minimum level of knowledge for designing the glass are:

Table 2: Used parameters.

PARAMETER	*SYMBOL*	*VALUE*	*TYPE*
Glass height	h	500 mm – 3000 mm	Continuous
Glass width	b	500 mm – 2500 mm	Continuous
Inclination	α	0°-90°	Continuous
Glass thickness	d	6 mm -24 mm	Continuous
Glass type	gt	Float, HST, FT	Categorical

The output results should answer the question whether the clear four-sided glass panel is able to resist the soft impact (as ruled in –DIN 18008) or not.

After the input parameters are set, the design of experiment is created with the space-filling design and in detail with the fast filling function. This function is chosen because it allows the use of categorical input variables. In this case no additional rules for the parameter are taken into account. For example, the glass thickness is available on the market in steps only, i.e. not every thickness is available. Due to the fact that the metamodel is built from data sets which are derived from the computer simulation, this is not important.

Fig. 1 shows the distribution of the input variables in the design space. It can be clearly seen that all input variables are spread out as far as possible over the design space.

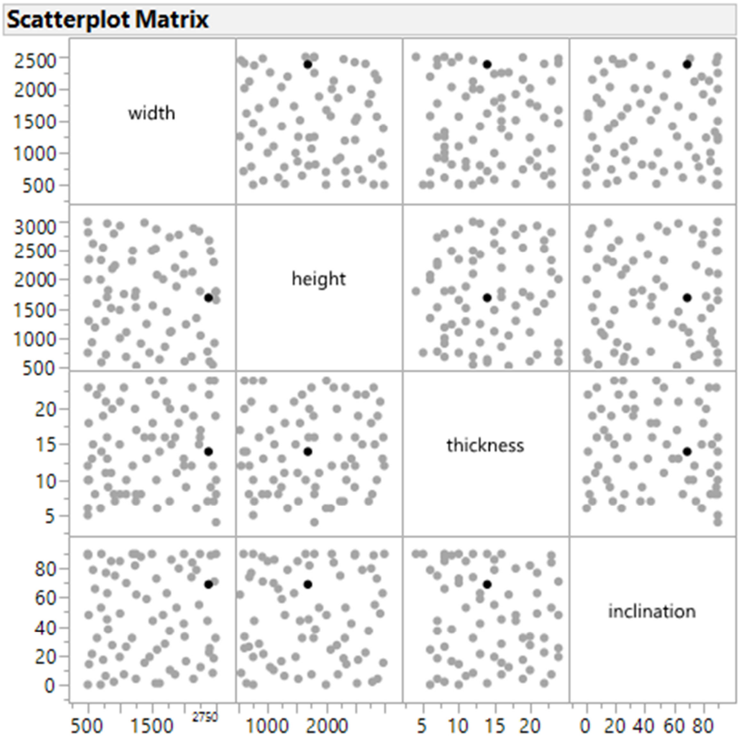


Figure 1: Scatterplot of space-filling design.

As a computer program for the simulation of the transient soft impact SJ-Mepla [13] is used, an expert explores how to do the simulation. The results from the complex simulation are verified by testing [14]. The stresses calculated with this program for all input parameters are the results from the computer simulation. To determine whether the vision glass panel restrains the load from the soft body impact, we have to build an output value of a yes / no event. Therefore, the outcoming resistance factor which is the relation between the stresses occurring in the glass form the calculation, and the allowable stresses of the glass type can be used.

$$F_R = \frac{\sigma_{Ed}}{\sigma_{Rd}} \quad (1)$$

F_R resistance factor

σ_{Ed} first principal stress to occur

σ_{Rd} allowable stress

If the resistance factor is $F_R \leq 1$, the design is resistant against soft impact. If F_R is > 1, the occurred stresses in glass are higher than the allowable stresses, that means the glass is likely to break and a safety issue might occur.

Bringing all input parameters and output results from the simulation completed with the resistance factor in one data sheet, makes it possible to build a statistical model. First steps are: a screening analysis. The results are shown in the half normal plot (Fig. 2). The glass type and the glass thickness, especially the glass type Float, have a major impact on the result.

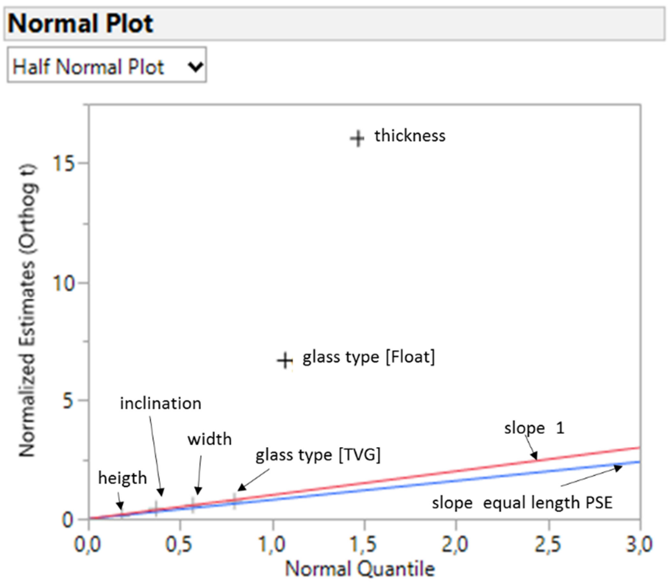


Figure 2: Half normal plot of a screening.

As mentioned in chapter 2, the response surface method is used to build the model. The statistical evaluation is done with the software tool JMP pro.

Fig. 3 shows the distribution of the residual. The residual average is near zero and median is slightly larger (0.002). This is a good indicator of the model quality. The belonging confidence interval indicates as well that the residues are likely to be small.

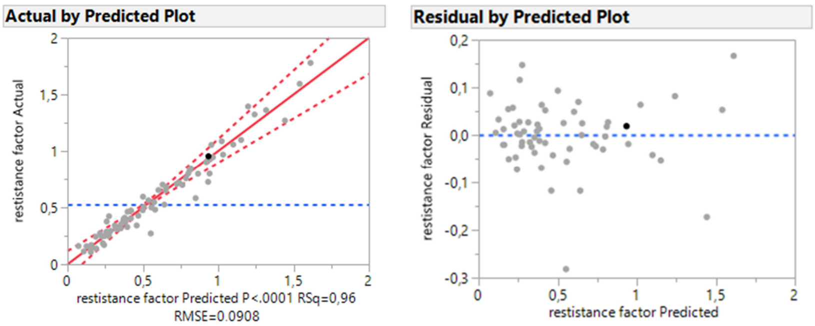
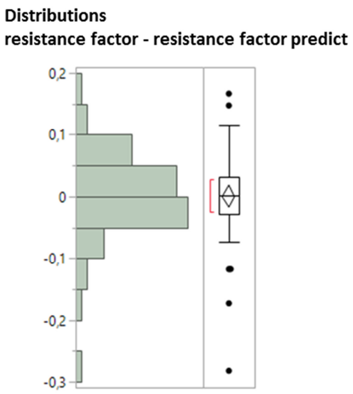


Figure 3: Predicted resistance factor / calculated resistance factor.



Quantiles

100.0%	maximum	0,1662913444
99.5%		0,1662913444
97.5%		0,1562385302
90.0%		0,0803602082
75.0%	quartile	0,0313271697
50.0%	median	0,0021889508
25.0%	quartile	-0,028194557
10.0%		-0,068311244
2.5%		-0,224727226
0.5%		-0,281913531
0.0%	minimum	-0,281913531

Summary Statistics

Mean	1,036e-16
Std Dev	0,0699126
Std Err Mean	0,0090257
Upper 95% Mean	0,0180603
Lower 95% Mean	-0,01806
N	60

Figure 4: Residual by predicted resistance factor.

The metamodel is supposed to deliver an early and robust estimation. Therefore it seems to be sensible to follow a very conservative approach to define the threshold when a vision glass panel is seen as safe. This indicates to put a greater security layer around the prediction. The standard deviation of 0.069 was chosen.

$predicted\_F_R < 1 - 0.0069$	The vision glass panel is predicted to be safe.
$1 - 0.069 < predicted\_F_R < 1 + 0.0069$	The vision glass panel needs detailed simulation by experts.
$1 + 0.069 < predicted\_F_R$	The vision glass panel is predicted to be not safe. Changing the glass thickness or glazing type might be a solution.

To validate the results, additional data that is not part of modeling is necessary.

3.2 Validation of the model

To prove the validity of the metamodel, additional simulation runs are performed to create data sets that were not part of the model generation. The data set from DIN18008 is used for validation as well.

In the predicted plot (Fig. 5), the resistance factor, which is calculated with the finite element model, is plotted over the predicted resistance factor. The data marked with a cross (VAL) is the data used for validation. These data sets are randomly chosen values. The data marked with a dot (DIN) is validation data from the German standard, table B.1 [11]. In table b1 of the German standard, the vision glass panels are listed with a minimum and a maximum amount for the width and height. For the validation of the metamodel only the maximum possible values for the glass panel dimension are taken. The resistance factors of these data sets are in the area of 1 (see Fig. 5). Therefore, the predicted resistance factor should also be near 1 in the area of uncertainty. The metamodel is able to identify these sets.

The dots (DOE, marked with a circle) are the datasets which are used to build the statistical model.

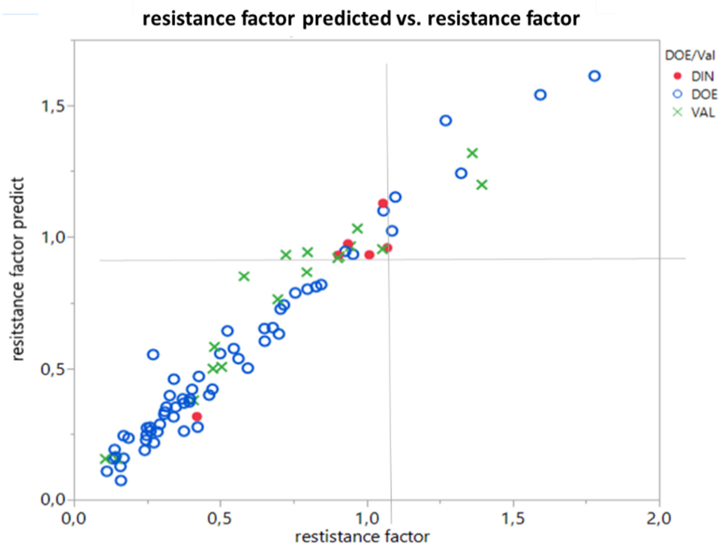


Figure 5: Predicted resistance factor over calculated resistance factor with validation.

Using the forecast rules (item 3.1) two visual glazing from the validation data set (VAL) fail to pass (see table 3).

Table 3: Comparison results.

	REAL			*PREDICTED*		
	Failed	Detailed investigation necessary	Fulfill requirements	Failed	Detailed investigation necessary	Fulfill requirements
DOE	7	0	53	6	3	51
VAL	3	0	15	2	5	11
DIN	3	0	3	1	4	1

In those cases the customer has to choose a greater glass thickness or a different glass type. For seven data sets the forecast is not clear, i.e. detailed investigation has to be carried out, or the customer has to choose a greater glass thickness. If detailed simulation is performed, the result shows that for some data sets the design fulfills the requirement, and for some it does not (see table 3, column REAL). Nine glazing panels are safe. Looking in detail at the data set from the German standard (DIN), detailed investigation of the four data sets is required, as elaborated before. Data sets taken from the German standard have a close resistance factor. After a detailed investigation two data sets of the four will have results that failed, while the other two data sets fulfill the safety requirements.

From 84 data sets the metamodel identifies 63 items that fulfill the requirements and 9 vision glazing that would fail. For 12 data sets detailed investigation is necessary, something that will usually be performed by an expert.

The advantage offered by the metamodel is obvious. Instead of testing or calculating a complex 84 vision panels, it is only necessary to perform a more detailed calculation for 12 models. Alternatively, these 12 will be provided with a new parameter setup such as increasing glass thickness to meet the criteria. This will reduce time and cost. This also means that architects and sales representatives are able to determine at a very early stage of the project which setup will suit the plans for the project.

3.4 Outcomes

The case study shows that those complex simulation models, which need a lot of expert knowledge can be transferred into metamodels. These metamodels use input parameter which represent the minimum knowledge for designing the glass. The results are not exact values for example the stresses in the glass. The result is the decision if the required safety is fulfilled or not. The found algorithm can be used to build a fast and easy to use engineering tool which work in the background during a client makes the order for visual glazing. During the order process the customer gets a direct information if his desired design fulfills the required safety standards.

The implementation of the model is fast and easy to use engineering tools might generate a great economic impact. With such simple tools architects or facade planners can check in an early stage of a project if the glazing they like to use fulfills the requirements. Also sales people use such tools for a fast forecast during a sales discussion.

Predictive modelling can be used to reduce complexity to support decision making. Even in highly regulated industries the predictive analytics can be used to reduce time needed to run complicated analyses. It also enables non-experts or even customers to make reliable decisions themselves.

The statistical model is essentially an approximation however the accuracy and precision can be improved by increasing the size and complexity of the experimental design. The statistical model can also be a signal when to revert to the more precise, time-consuming and complex top of the range analysis.

4 OUTLOOK

The results above show that metamodels can be used to obtain a first impression of the suitability of the material and design of the product. This enables the industry to take decisions at an early stage of complex construction products. In future projects the metamodel can be spread to complex problems in the field of construction. It will be proved that, with different loads such as climatic loads, wind loads and different shapes, the metamodel will provide a reliable estimation so that the industry might use them as a forecast planning method more generally.

In summary, building a metamodel shortens the simulation time with only a small loss of information and without expert knowledge.

Finally it can be said that using metamodel instead of complex and time consuming simulation tools is at the beginning of the direct digital manufacturing a way to give the prosumer the possibility to do the design responsibly.

REFERENCES

[1] Kubler, S., Holmström, J., Främling, K., & Turkama, P. (2016) Technological Theory of Cloud Manufacturing. In Service Orientation in Holonic and Multi-Agent Manufacturing: 267-276. Springer International Publishing.
[2] Westkämper, E., Spath, D., Constantinescu, C., & Lentes, J. (Eds.). (2013) Digitale Produktion. Springer-Verlag.
[3] Strähle, J., Wagner, Y. (2016) Prosumer concepts in the outdoor fashion industry. International Journal of Economics, Commerce and Management, Vol. IV, Issue 2:59-83.
[4] Zhou, Q., Shao, X., Jiang, P., Gao, Z., Wang, C., & Shu, L. (2016) An active learning metamodeling approach by sequentially exploiting difference information from variable-fidelity models. Advanced Engineering Informatics, 30(3), 283-297.
[5] Acosta, D. A., Restrepo, D., Durango, S., & Ruiz, O. E. (2013) Design of computer experiments applied to modeling of compliant mechanisms for real-time control. Engineering with Computers, 29(3), 329-343.
[6] Ahlemeyer-Stubbe, A., & Coleman, S. (2014) A practical guide to data mining for business and industry. John Wiley & Sons.
[7] Santner, T. J., Williams, B. J., & Notz, W. I. (2013) The design and analysis of computer experiments. Springer Science & Business Media.
[8] Grayson, J., Gardner, S., & Stephens, M. (2015) Building Better Models with JMP Pro. Sas Institute.
[9] Simpson, T. W., Poplinski, J. D., Koch, P. N., & Allen, J. K. (2001) Metamodels for computer-based engineering design: survey and recommendations. Engineering with computers, 17(2): 129-150.
[10] Schneider, J., Schula, S. (2015) Simulating soft body impact on glass structures. Proceedings of the Institution of Civil Engineers-Structures and Buildings, 1-16.
[11] DIN 18008-4 (2013) Glass in Building- Design and construction rules- Part 4: Additional requirements for barrier glazing.
[12] DIN 18008-1 (2010) Glass in Building- Design and construction rules- Part 1: Terms and general bases.
[13] SJ, Mepla (2013) Theory manual version 3.5. Aachen: SJ Software GmbH.
[14] Brendler, S., (2007) Rechnerisches Bemessungskonzept für absturzsichernde Glastafeln. Dissertation, Technische Universität Carolo-Wilhelmina Braunschweig.