A DECISION SUPPORTING FRAMEWORK BASED ON TREND ANALYSIS OF INTERDISCIPLINARY DISTRIBUTED AEC SYSTEMS

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ABSTRACT

Consequences of a decision made by a planner (e.g. a project manager, or an engineer) within an interdisciplinary collaborative environment can hardly be foreseen. For example, such a scenario is represented by a planning process in AEC. In particular, during certain planning stages alternatives have to be considered which significantly influence the overall result. Today's AEC planning procedures can be very much improved by predicting simulation methods to judge about the quality impact of certain design or planning modifications. Also, proper interpretation of data is very crucial to give suitable insight into the characteristic consequences of individual planning decisions. An analysis' result of that data reveals the magnitude of dependency between different product model parameters (e.g. wall width or column distance) and chosen output quantities like cost or stresses in a certain part of the model. This enables a planner to simulate different conditions (e.g. load cases during the construction phase) or to vary single parameters and predict the impact on his observed quantities. Therefore, trends of these quantities are computed for every variation of the model to support the planner in decision taking.

This contribution presents a framework to bring together various disciplines in a dedicated environment, to control workflow between them and to analyze the produced data.

KEY WORDS

collaborative engineering, product model, sensitivity/trend analysis, agent technology

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INTRODUCTION

Efficiency of a planning process is a prerequisite for the success of a product in AEC. Mistakes or suboptimal decisions can lead to severe negative influences on the ongoing planning process and therefore on the whole product. As a consequence, prediction of planning decisions contributes to achieve a better result.

The idea of simulating the planning process is well known in automotive and aerospace industry. There are many techniques to support designers, which are already implemented. They are frequently used to apply multidisciplinary design optimization (see Sobieszczanski-Sobieski and Riley 1987 and Kroo 2004). However, in AEC most problems arise because of heterogeneity of the working environments of the planning participants and because of the prototypical character of products in AEC. The most important discrepancy is that in AEC there is hardly any discipline-spanning in-house-manufacturing. Different disciplines are distributed to various companies and locations, which usually don't work together for any longer than the duration of one project. Thus, the effort to adjust their systems for co-operation for every new project is usually too high to work economically.

An agent based communication environment allows flexible and scalable implementation of such a co-operative scenario. Furthermore, co-operation with existing agent communication systems is facilitated by using the FIPA standardized Agent Communication Language (FIPA-ACL) for message transfer.

For analysis of planning situations we apply methods from the field of sensitivity analysis, which are typically used in optimization disciplines (e.g. structural or topology optimization). Additionally, Design of Experiments (DOE) and Response Surface Methods (RSM) are used. Applying these methods the level of impact (consequences) to particular planning parameters can be estimated, which arise by alteration of specified input parameters.

COLLABORATIVE ENVIRONMENT

GENERAL

Several projects, like iCSS[3], ArKos[4] or ISTForCE[5] are dealing or dealt with environments for collaborative work in AEC. However, we developed our own framework because we need additional features like dynamic workflow management or analyzing support for certain parts of a planning process.

A collaborative environment (CE) in our context needs to be capable to include workflow, involved planners and underlying product model data for a certain scenario. A scenario is set up by an analyst who defines the possible changes of product model data (variants). Afterwards, affected planners have to process this information and provide the CE with their results. Lastly, the analyst will pick up the data and do an analysis of that process

[3] http://cib.bau.tu-dresden.de/icss/
[4] http://www.arkos.info/
[5] http://www.istforce.com/

resulting in an assessment of consequences and pointing out alternatives for the accomplished modifications.

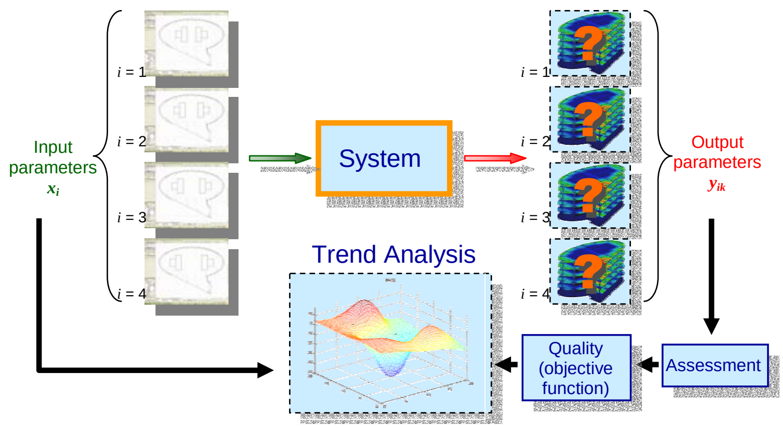

Figure 1: System analysis

Depicted in Figure 1 is an overview of the analyzing procedure. In- and output of the system consists of several variants (i) and are the basis for an analysis, which is called Trend Analysis (see below). The CE is encapsulated in the System and treated as a black box in this view.

Heterogeneity and different demands of planner applications make generic interfaces highly essential. Therefore, development of an integration mechanism for involved planners is necessary. Furthermore, workflow management should not be handled statically by the analyst himself. A more dynamic workflow as well as product data management model has to be introduced.

The "System" depicted in Figure 1, is realized as an agent based CE, which possesses all the postulated properties. In the following a brief overview of the features is given. This framework was developed over the last 2 years. For more details refer to Lähr and Bletzinger (2005).

AGENT TECHNOLOGY

Agent technology is a methodology for handling network communication on a very high level of abstraction. A software agent is an independent computer program, which is able to autonomously interact with its environment. Decisions to be made are based on its perceptions and contribute to reach its goal. For detailed information see Woolbridge and Jennings (1995) and Ferber (1999).

To integrate the different involved persons (planners and analyst) the class of proxy agents is introduced. A proxy agent (PA) represents the participating person or institution (e.g. structural engineering or cost analysis) within the agent environment (multi agent system). Accordingly, a PA has to act as an interface to external, planner specific software, which mostly has been approved over a long time. The left hand side of Figure 2 illustrates this integration mechanism. This technique is also known as software wrapping. A software wrapper is a thin software program or module that converts program-specific input and output operations into generic sets of commands that apply to a wide range of programs.

Workflow management is based on an event handling framework and displayed on the right hand side of Figure 2. Data transfer and management is handled by a product model agent, which is not explained here, explicitly. The authors would like to refer to a previous publication (Lähr and Bletzinger 2005) for detailed information on that topics.

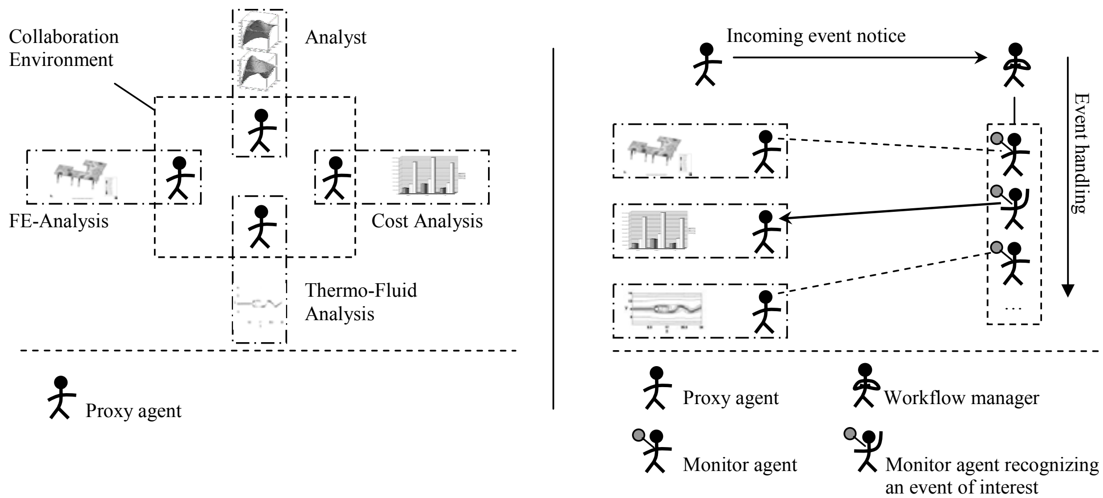

Figure 2: Integration mechanism on the left hand and workflow management on the right hand side.

TREND ANALYSIS

As already mentioned the variety of options for a designer (planner) in a complex, multidisciplinary context is immense and mostly unmanageable. We define such a context as a system, which is influenced by several participating independent system designers. If we take into consideration that each designer can be a specialist in a certain field our system has to be able to handle multidisciplinary data as well as communication.

In this section we will discuss an approach for a system designer's decision support. We introduce the role of an analyst, who performs a system analysis. If we transfer all that to AEC, any person who can potentially influence our system can be an analyst. This can be a planner as well as a project manager. In that case our system can encapsulate the planning procedure of a building project, for example. Clearly, the quality of an analysis depends on the accuracy of the system's model. Since the model interactions are very complex and in general, cannot be exploited it is possible to achieve results of approved accuracy. Consequently, we aim at a coarser goal, namely the trends of the system behaviour for a specified design variety.

SENSITIVITY ANALYSIS

Sensitivity analysis (SA) is applied in several disciplines, like social, economic and financial engineering science. Basically, sensitivity analysis is useful when using a surrogate model for a real system or process. Saltelli et.al. (2000). state that SA is a prerequisite for modeling. Typically, SA treats the question how a system's output behaves by varying the same system's input.

Particularly, there is to be distinguished between screening methods, local and global methods. Screening methods are used to identify significant system parameters. One of the simplest applications of screening methods is the one-at-a-time (OAT) method. Their major limitation is the neglecting of parameter interaction (Saltelli et al. 2000). Local sensitivities of a system are imagined at best as partial derivatives with respect to the input parameters. The system has to be known as a function to directly derive the sensitivities from. Otherwise, methods like finite-difference approximation support obtaining the slopes of the calculated system. Considering "real" systems, an analyst is faced with the influence of noise variables. There are uncertainties, like measurement errors, rounding errors, etc., and can't be controlled directly. Therefore, global methods of sensitivity analysis are applied to cover the total scope of input parameters. The goal remains the same, namely to analyze the system alteration by variation of input parameters.

System input is represented by input parameters and system output by response parameters, accordingly. Actually, additional parameters like fixed and noise parameters influence the system. Fixed parameters are constant during an analysis and noise parameters can vary arbitrarily within a certain range, as described above. A certain configuration of input parameters is called system configuration or design. The totality of input parameter combinations over their complete ranges defines a design space.

The goals of a SA are

- to identify essential input parameters that significantly affect the system response (response parameters),
- to eliminate certain input parameters by identifying parameters that cause hardly any system response alteration,
- to identify design space regions (system configurations) where the system behaves critical w.r.t. certain input parameters.

In the context of this contribution there doesn't exist an analytical solution at any point in the design space. For this reason many of the relations between the examined parameters can not be expressed analytically. In most cases it is not even known if they influence each other at all. Analysis of these relations is one of the main goals of the SA application in this context. Typically, all known information is based on discrete configurations (designs) of the design space. Hence, SA is applied on a surrogate model, which was created by this discrete system information. Obviously, the amount (number of known designs) of information directly controls the accuracy of the model.

I/O-Strategy

In multidisciplinary environments a designer typically has limited or even no knowledge about disciplines. In our environment such a designer plays the role of the analyst to learn more about the multidisciplinary project he is working on. We suppose the analyst initially has completely no idea how the system answer will look like if he changes some parameters.

The question arises where to start and what about the magnitude of change. Generally, there are two strategies he could embark, which both have different pros and contras. Hence, a hybrid strategy is introduced to combine as many pros as possible.

For presentation purposes all strategies will be explained based on a three dimensional system design space. It is set up by two input parameters x_1, x_2 and one system response Y. In fact, we can treat more than on system response (see Section Assessment).

Trial and error strategy

The analyst starts from scratch (Figure 3a) and chooses a system configuration, which seems feasible for him. After a system evaluation he obtains a discrete result (Figure 3b). By changing some input parameters he may get a different result from another system computation (Figure 3c). Comparing both results, i.e. using finite difference method, he gets information about how the result changed and the level of impact to the response Y with respect to the input parameters. From that he can define a new system configuration by extrapolation or by hand (see Figure 3d). Depicted in Figure 3e the chosen and evaluated design reveals further behaviour of Y. He may decide to stop the system analysis when he got satisfying data.

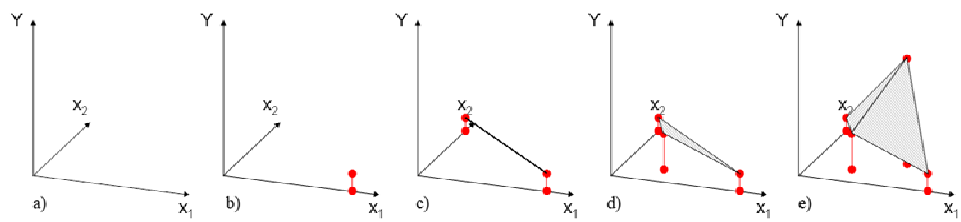

Figure 3: Trial & Error strategy.

Pros	Cons
direct control and awareness of variants	interpretation of a high-dimension design space is very complex
engineering experience of the analyst can be applied	many user (analyst) interactions during analysis

DoE-Strategy

DOE is a methodology to choose the location of the sampling points, used to accomplish statistical experiments. To make an expedient statement of a statistically derived model a certain number of experiments is to be processed. This number can be controlled by using different strategies like e.g. full factorial, fractional factorial designs as well as Latin hypercube sampling (Box and Draper 1987). Again, starting from scratch (Figure 4a) the analyst has now to configure certain parameters depending on the corresponding DoE-method. This will lead to a certain grid pattern (Figure 4b). Each system is evaluated individually yielding related system response data (Figure 4c). Based on this data a surrogate model is approximated and represents the system behaviour for the defined range of the input parameters (Figure 4d). Depending time necessary for an individual analysis this procedure can be very time consuming.

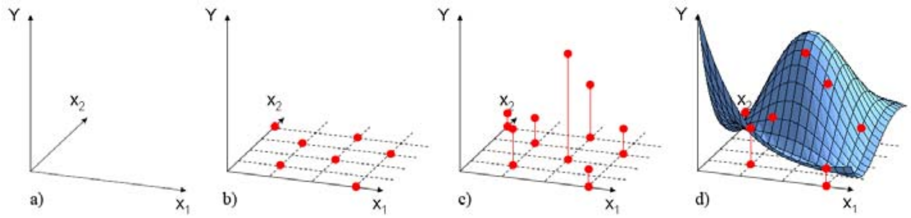

Figure 4: DoE-Strategy.

Pros	Cons
achievement of a system behaviour in a defined system design space	interpretation of a high-dimension design space is very complex
very few user interactions during analysis	no user interaction possible during analysis → computation of potentially irrelevant system design points → high amount of necessary computation time

Hybrid DoE supported interactive strategy

This strategy tries to combine both aforementioned procedures. The DoE-strategy is condensed to very simple and comprehensive designs. Firstly, this reduces the knowledge of the analyst about these statistical methods, which is usually very irritating for users taking the role of the analyst. Secondly, it turned out that coarse information of the system design space is sufficient very often. If necessary, refinement can be.

Compared to the "trial and error"-strategy (Figure 3) the hybrid approach supports the analyst by suggesting a new design point (Figure 5b and Figure 5d) that could most probably reveal much information about the system. User interaction is possible after each design support, so the analyst can decide whether to accept the suggested point or to choose another one. Again he ends up with a model of the system behaviour as an approximated surrogate model.

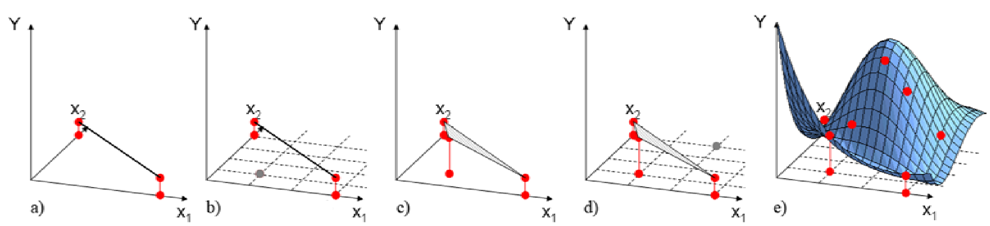

Figure 5: Hybrid DoE supported interactive strategy

ASSESSMENT

When monitoring a system in a multidisciplinary context the question arises how to assess results. Usually, more than a single response parameter *Y* (RP) will change on varying system input *X*. Additionally, considering design objectives and constraints boundaries or constraints of certain RPs have to be regarded.

We realized system behaviour assessment by introducing preference functions (PF) and weighting. Application of PFs results in a dimensionless quantity defined as quality loss for each RP. This can be seen as normalized scaling and allows combination of several RPs based on weighted summation.

PFs are operators acting on RPs. They can take any evaluable form. Actually, an analyst is free to choose any PF. Due to clarity a set of PF classes are defined, which can be applied to RPs. Up to now there are three basic classes :

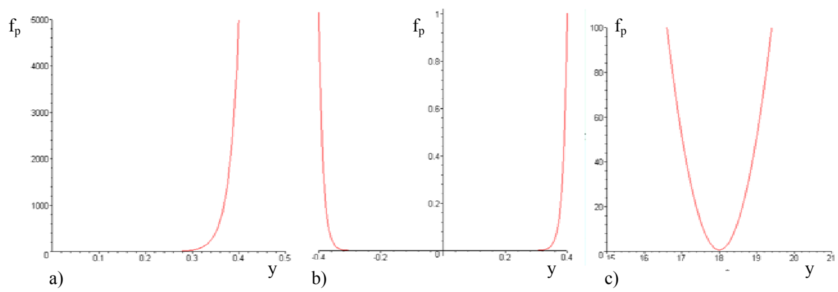

Figure 6: Preference functions.

- one sided boundary class (OBC) → $f_p = e^{a(y-b)}$ (Figure 6a)
- two sided boundary class (TBC) → $f_p = e^{a(-y-b)} + e^{c(y-d)}$ (Figure 6b)
- optimal value class (OVC), → $f_p = ay^2 + by + c$ (Figure 6c)

The configuration parameters (a,b,c,d) are calculated from specific information obtained from the user (feasible region, boundaries, optima, etc.).

A digital boundary class may be an appropriate candidate for an extension here. This and other classes will be addressed to further developments of this framework.

Although PFs are normalized and dimensionless compared to the related RPs their absolute values may differ very much among each other, as demonstrated in Figure 6. That is in particularly true for sided boundaries where the PFs are activated within a small transition zone.

As mentioned above, PFs transform RP values to a quality loss. They yield low values for good quality and vice versa. It can be said that they prefer feasible or acceptable RP values by converting them to low PF values.

Finally, an explicit weighting can be applied by introducing a weighting parameter g_k:

$$Q(\overline{X}) = \sum_{k=1}^{m} g_k \; f_p(y_k(\overline{X}))$$

Above, a general expression for an assessed and weighted quality Q is presented with respect to a system configuration $\overline{X}$. The index k runs from 1 to m, which is the number of RPs (y_k.).

QUALITY ANALYSIS

A quality analysis in this context means the overall result of a system analysis, including several system evaluations. It is always represented in an n-dimensional design space, where n depends directly on the number of system parameters (input and response parameters). For a demonstrative explanation we chose 2 input variables x_1, x_2 and the system quality loss Q. Consequently we get a 2-dimensional system design space for the results.

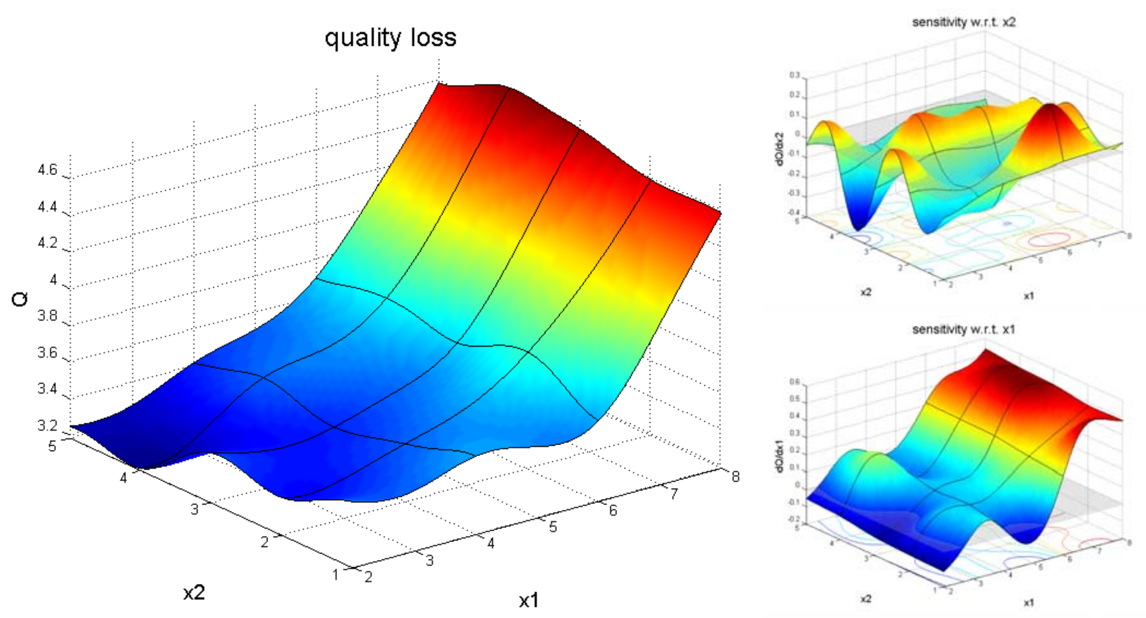

Figure 7: Quality loss Q over x_1 and x_2 and sensitivities w.r.t. x_1 and x_2

In Figure 7 the approximated surrogate model of the overall system quality loss function Q is shown. It is composed from the individual quality loss functions which in turn are related to the system response y as functions of the design parameter x_i. Lower quantities of the quality loss Q indicate more preferable solutions including conflicting objectives and constraints. The result presents an overview and allows for an assessment of the evaluated design space as well as for identification of interesting “unknown” regions. The analyst may decide if it’s worth to explore these regions or get a new idea for another system configuration and further improve his experience.

When exploring the design space observation of the sensitivity (partial derivative) of the solution with respect to input parameter at specified design points may be very interesting. For example, the magnitude of the result’s dependence from the input parameter or possible extrema w.r.t. that parameter can be evaluated. Sensitivity is computed as the partial derivation of the quality regarding to the input parameter. Right hand side of Figure 7 shows the sensitivities of the quality loss Q. Additionally, a zero plane, indicating robust system configurations and the iso lines for sensitivity are shown.

EXAMPLES

We would like to refer to publication of Krafczyk et. al (2006), which is published along with this contribution for several illustrating examples. In particular a, a multidisciplinary application in the context of fluid dynamics and structural mechanics is shown.

CONCLUSIONS

An analysis framework was presented to support planning decisions on basis of trend analysis in a heterogeneous planning environment in structural engineering.

In the next months we want to finish a prototype of the analysis framework. Afterwards, we are looking for industry partners to validate and test the developed methods against problems, which occur in daily engineering practice.

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